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Department of Business and Management

Course of Corporate Strategies

"CEO and Managerial Capabilities Effects in the ICT industry: a variance decomposition simulation"

THESIS SUPERVISOR — GRADUATING

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AA. 2013/2014

To my parents

for the love and for always being there

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Abstract

How CEOs affect strategy and performance is obviously relevant to strategic management research. In this paper the evidence on CEO effect, associated with corporate managerial actions, is analyzed in depth, within a single industry and on a time period of reasonable length. In particular, this study addresses the issue of the relative degree of variance in ROA accounted for by year, corporate, a proxy for managerial decisions and the person of the CEO herself. Most of the earlier literature focused much more on one of the two factors, separately. Here I propose a model that encompasses both CEO and corporate level decision effects, the latter representing what managers implement and, especially, how they do that. Further, rather than considering a corporate level fixed effect, I have presented a time-varying one. Several tests on this model will be carried out in detail.
Contrary to previous literature, I find a negligible CEO effect, while management capabilities, as it was in earlier studies, account for a significant part of the variance explained, thus implying their prominence in profitability analysis research. I have also performed the interaction term between CEO and the managerial capability proxy variable and, interestingly, find it explaining a significant portion of variance in firm profitability. This finding would emphasize the organizational dimension of CEOs' actions. The concept of managerial capabilities is employed here to firmly restate the heterogeneity in managerial decisions and, consequently, their relatedness to firm performance in a changing external environment.

1) Introduction

The variance decomposition literature in strategic management has grown rapidly over the last several years (Rumelt, 1991; McGahan and Porter, 1997, 1999, 2002, 2003). Most of this work has concentrated on the percentage of firm performance explained by industry, corporate and firm effects (e.g. Schmalensee, 1985; Rumelt, 1991; Roquebert, Phillips, and Westfall, 1996; McGahan and Porter, 1997, 1999, 2002, 2003). Apart from Lieberson and O'Connor 1972, Weiner 1978, Thomas 1988 and Wasserman, Nohria, and Anand 2001 papers, there have been no other works that examined the percentage of variance in firm performance explained by CEO effects. Despite the different theoretical focus, methodological conventions and limits do apply to studies examining leader effects.

This study partitions the total variance in rate of return among firms within the same industry – gathered at the corporate parent level – time factors, factors associated with strategic decisions taken at the corporate level and, finally, factors related to those people taking decisions for the companies' growth: CEOs. As said before, a large body of past decades literature exists that uses variance decomposition analysis to examine the extent to which CEOs can influence their companies' performance. This debate has become relevant as it tries to examine the role of CEOs and the importance of leadership in general. Most of these studies show that CEOs do have the ability to influence their companies and this result has had many repercussions for both theory and empirical research. At this point, is also important to make clear the distance from literature about CEOs' compensation and the relationship between that and firms' performance - though it shows many points of contact – as this research does not take into account compensation level.

I estimate the time-varying corporate effect associated with corporate-level managerial decisions, restating and developing the concept of *dynamic managerial capabilities* (Adner, Helfat 2003), including the analysis of the *CEO effect* to test whether a significant change was brought into the original model. Theory and empirical evidence of connections to performance overflow within each paradigm, but, surprisingly, very little has been done to investigate the two and evaluate the relative effect of each on firm profitability. Despite the strong results in favor of CEO effects displayed by earlier studies, I find here the CEO to be negligible, while management actions seem to explain much of the performance's variance. I have also included the interaction term between CEO and management actions proxy into the model. Interestingly, the interaction term effect does assume significant values and this brings new insights to current research. More precisely, I argue that top leaders formulate a collective purpose that practically binds them in the organization with all the other active participants. This is not a new theme though. Selznick (1957) described how top leaders infuse values within an organization; Schein (1992) argued that top leaders help create an organization's culture. Again, Tichy and Cohen (1997) argued for the crucial role of top managers in deciding an organization's course of action with respect to technical and environmental change (Woodward, 1965; Lawrence and Lorsch, 1967; Thompson, 1967). What these entire studies share is that leadership effects are thought to be leveraged by an organization, resulting in substantial impact on a firm's performance, and this suggestion is somehow restated here and supported by statistical results.

2) Variance Decomposition Analysis

Variance Decomposition has always been treated, in previous papers, in its essentials, focusing the attention on the core variables representing the new versions of the model being employed. Here I want to propose a more exhaustive description, considering all relevant theoretical aspects first. This way, I believe, a clearer version of the model itself could be delivered and all new starters in this field of research may benefit from this. Thus, before going through the core statistical model, I would like to discuss about key theoretical points first. With that purpose, I first walk through the ANOVA technique from a theoretical point of view. I will then go through a quick literature review to address aspects of past relevant studies to the present research and then move forward to the framework in which this analysis is applied.

Analysis of Variance

Analysis of variance (ANOVA) is a method for decomposing variance in a measured outcome in to variance that can be explained (like experimental treatment assignment) and variance that cannot be explained, which is often attributable to a random error. In addition to using variance to measure effects on profitability, studies measure the importance of each effect considering its magnitude. Using this decomposition into component sums of square, it is possible to calculate particular test statistics that can be used to analyze the data.

Variance decomposition of firm returns in the strategy field was initiated by the pivotal paper of Schmalensee (1985) and further analyzed by Rumelt (1991). More precisely, an ANCOVA, analysis of covariance, is employed in this research (in some sense ANCOVA is a blending of ANOVA and regression). The general model assumes that each sample has the same number *J* of subjects: $|C_i| = J(i=1,\ldots\ldots,I)$ and, in its *linear* form, appears to be:

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$$

where $\mu_i = \mu + \alpha_i$ is the grand mean and represents the average of the population associated with the *i-th* experimental factor condition. The generic mean

$$\mu = \frac{\sum_{i=1}^{I} \mu i}{I}$$

represents the average of the parameters μ_i (i = 1,..., I) and denotes the level of the dependent variable selected as observational measure in assessing the induced effects - on the variable itself - by the experimental factor with I conditions (levels). The main effect of condition I is α, which stands for the differential effect of the *i-th* treatment or, more accurately, the difference between the expected μ_i and the generic mean μ,

$$\alpha_i = E(Y_{ij}) - \mu = \mu_i - \mu$$

since μ is a constant, the only source of variation in prediction comes from the *i-th* experimental conditions.

Finally, in contrast to predicted scores, the ε_{ij} term represents the discrepancy between actual and predicted results and could be different for each subject,

$$\varepsilon_{ij} = \mu_j - Y_{ij}$$

In the regression context, the sum of squares can be decomposed as follows (noting that Y_i is individual i's outcome, $\overline{Y}$ is the mean of the outcomes, $\hat{\overline{Y}}$ is individual *i*'s fitted value based on the ordinary least squares (OLS) estimates, and e_i is the residual):

$$\sum_{i=1}^{n}(Y_i - \overline{Y})^2 = \sum_{i=1}^{n}(Y_i - \overline{Y})^2 + \sum_{i=1}^{n} e_i^2$$

and the total sum of squares

$$SS_{total} = \sum_{i=1}^{n} (Y_i - \bar{Y})^2$$

can be decomposed in

$$SS_{regression} = \sum_{i=1}^{n} (Y_i - \bar{Y})^2$$

which is the variance explained by the regression and

$$SS_{error} = \sum_{i=1}^{n} e_i^2$$

which is the variance attributable to the error term (also referred to as unexplained variance). The final equation can be written as follows:

$$SS_{total} = SS_{regression} + SS_{error}$$

The equations above illustrate how the total variance measured in the observations can be decomposed into variance that can be explained by the regression equation and variance that can be attributed to the random error term in the regression model.

Analysis of variance is not restricted to use with regression models. The concept of decomposing variance can be applied to other models as well and in particular to an experimental model. At this point, another consideration has to be made: One-Way ANOVA is conducted with one independent variable (one factor) with more than two conditions. Two-Way ANOVA has two independent variables (two factors) and each factor can have multiple conditions.

ANOVA can also be thought of in terms of a model plus error. Here, the dependent variable values represent the data, the experimental conditions constitute the model and the component of the data not explained by the model, again, is represented by the error term. Typically, researchers applying ANOVA are interested in whether the mean dependent variable scores differ significantly. This is achieved by determining how much variation in the dependent variable scores is attributable to differences *between* the scores obtained in the experimental conditions, and comparing this with the variation in the dependent variable scores *within* each of the experimental conditions, that is the error term. With ANOVA the sum of squares expression can be written as:

$$SS_{total} = SS_{between} + SS_{within}$$

using the above decompositions, a summary analysis of variance table can be constructed

Source	***df***	***SS***	***MS***	***ANOVA Layout***
Regression	p	$SS_{Regression}$	$SS_{Regression}$ / p	between
Error	n – p - 1	SS_{Error}	SS_{Error} /n-p-1	within
Total	**n - 1**	$\mathbf{SS_{Total}}$		

Source: personal elaboration

In the regression context, the degrees of freedom for the regression are the number of parameters in the regression equation. The degrees of freedom for the error are n– p –1, while the total number of degrees of freedom is defined as $df_{\text{regression}}$ + df_{error}. MS stands for mean squared error which is defined as SS / *df* for each row in the table. The degrees of freedom for the model, in total, are the number of treatments less one, (I - 1) for I treatments. Finally, in order to assess whether the outcome of the model itself is statistically significant or not, we need to compare the so called F statistic with the p-value. To put it simply, the F-test determines if the means of the treatment groups are significantly different. The null hypothesis for an F-test is that all coefficients in our model are jointly not statistically distinguishable from zero.
The formula to get the F-test is:

$$\text{F} = \frac{explained\ variance}{unexplained\ variance} = \frac{SS_{regression}/p}{SS_{error}/n{-}p{-}1}$$

We can also define the R^2 with the following formula:

$$R^2 = \frac{SS_{regression}}{SS_{total}} = 1 - \frac{SS_{error}}{SS_{total}}$$

As I will show later, these estimates can easily be calculated with dedicated statistical software packages.

For what concerns the testing hypotheses, the ANOVA methodology implies that subjects' dependent variable values are best described by the experimental condition means. This may be expressed formally as

$$\alpha_i \neq 0 \text{ for some } i$$

that is equivalent to say that the effects of all of the experimental conditions do not equal zero. An equivalent expression in terms of the experimental condition means would be

$$\mu \neq \mu_i \text{ for some } i$$

which states that some of the experimental condition means do not equal the grand mean. Lastly, I would like to take into consideration the estimated effects by comparing full and reduced models in the ANOVA procedure, as this aspect becomes relevant later on in this research.

Basically, the comparison of full and reduced models applies a refined form of linear modeling processes to the analysis. As previously explained, these procedures are evaluated in terms of the relative proportions of variance attributed to model and error components. Taking the simplest full model described above with grand mean μ, the α parameter and the error term, that tests the hypotheses illustrated above, it is also possible to formulate a reduced model that omits any effect of the experimental conditions. Here, the reduced model is described by the equation

$$Y_{ij} = \mu + \varepsilon_{ij}$$

which uses only the grand mean of values *i* to account for the data. It presumes that subjects' dependent variable scores are best described by the grand mean of all scores. In other words, it states that the description of subjects' scores would not benefit from taking the effects of the experimental conditions (α_i) into account. The reduced version manifests the data description under the null hypothesis. By ignoring any influence of the experimental conditions, the reduced model assumes that the experimental conditions do not influence the data. This assumption may be expressed more formally as

$$\alpha_i = 0$$

that is the same as saying that the effect of all of the experimental conditions is zero. As done before, it is possible to express it with the grand mean

$$\mu = \mu_i$$

obviously, the model version providing the better data description should have the smaller error component. Moreover, any reduction in the size of the error component caused by including the effects of the experimental conditions should be reflected by an equivalent increase in the size of the model component. Presenting the full and reduced model equations together makes it even clearer

$$\text{Full model: } Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$$

$$\text{Reduced model: } Y_{ij} = \mu + \varepsilon_{ij}$$

any reduction in the error component from the full model to the reduced form can then be attributed exclusively to the inclusion of the experimental condition effects. I have inserted this discussion as it represents the main part of the statistical methodology explained in following paragraphs.

In the past, variance decomposition has involved the breakdown of both business-level or corporate level performance as a dependent variable, generally including many of the following elements in a descriptive model:

$$r_{ijt} = \mu + \alpha_i + \beta_j + \gamma_t + \phi_{ij} + \delta_{it} + \varepsilon_{ij} \quad (1)$$

where r_{ijt} denotes the rate of return of business or company operating in industry *i*, in time period *t*, (owned by corporation *j* if it is at business level). The α_i are industry effects, the β_j are corporate effects (if a business level variable is chosen), the γ_t are year effects, the ϕ_{ij} are business effects (from company operations contained in a singular industry), the δ_{it} are industry-year interaction effects, and the ε_{ijt} is the residual. Evidently, the model changes with respect to the dependent variable and the interaction terms analyzed.

Another point of discussion has been the ambiguous use of the term ‘firm’. Theoretically, a ‘firm’ is referred to as an autonomous competitive unit inside an industry but the term is also often used to indicate the legal entity; the ‘company’ or ‘corporation’. Because most empirical studies’ research is about large corporations, and because most large corporations are substantially diversified, legal or corporate ‘firms’ do blend into an individual theoretical competitive unit. Confusion may arise whenever one author uses the term ‘firm effects’ to indicate intra-industry dispersion among theoretical ‘firms’, and another author uses the same term to denote differences between corporations which are not explained by their patterns of industry activities. To reduce the ambiguity then, the term ‘firm’ should be avoided anytime a study looks for the two levels of analysis. Rather, the correct term to use, to denote that portion of a company’s operations which are wholly contained within a single industry, should be *‘business-unit’*.

Furthermore, the distinction between corporate and business strategy has also been distinguished in the past strategic management literature; this is not a matter of statistics but, merely, of economics. Typically, business strategy deals with the competition among single-business firms or individual businesses of larger firms within a particular industry or market. Corporate strategy deals with the ways in which a corporation manages a set of businesses together.

This argument has concerned resource-based view theorists as well. They argue that business-level resources are at least as important as industry level ones in determining competitive advantage within a specific market (e.g., Barney, 1991). However, The resource-based view contemplates a significant role for corporate strategy based on utilization of common resources by related businesses within a firm. This branch involves the study of interdependencies and is mainly focused on the exploitation of synergies between resources that share similar and compatible characteristics to create value for the firm.

For those researches that comprise both level of analysis, one of the most important elements to consider is the inclusion or exclusion of single-business firms. Statistically, corporate effects derive from multiple-business firms. As a result, many of the variance decomposition studies that include single business firms find corporate effects to be zero in those firms (McGahan, 1997). Thus, inclusion of single-business firms clearly masks the corporate effect: the more single-business firms are included in the sample, the smaller will be the estimated corporate effect. Conversely, when a study excludes single-business firms, the estimated corporate effect rises. This kind of confusion is avoided here as I only employ the effects associated with the corporate parent that, for preciseness, I call “Firm effect”.

Having said that, on the one hand, if a business level performance variable is selected, then the descriptive paradigm will include the corporate effect, which represents the performance at the consolidated level (the holding company performance). On the other hand, if the corporate level performance is used as a dependent variable, then the variance could be further decomposed at the business-segment or business-unit level, depending on the available information. While the models may be influenced and thus change based on these choices, there are effects that have been constantly tested across all relevant researches such as year and industry. Further, it is important to reaffirm here that the elements contained in a model depend upon the data at hand, in terms of quality and size.

Another point of discussion has concerned the type of measurement for the dependent variable employed. Basically, there are two main measurement types which have been verified and that are worth noting: Return on Assets, or ROA, and market share. As previously stated, these measurement types can refer to either corporate or business level. The majority of past research contributions use ROA as a dependent variable measure. Nevertheless, market share has also been tested but on business level only (Chang and Singh, 1997). Other approaches have been the one adopted by Wernerfelt and Montgomery (1988), among others, which replaces return on assets with Tobin’s q and the numerous corporate dummy variables with a single continuous measure of ‘focus’[1], and return on sales as in Lieberson and O’Connor (1972) and Weiner and Mahoney (1981). ROA indicates the profitability of a company with respect to its total assets. It gives an idea on how efficient the management of a company is, at using its assets, to generate earnings. It could be calculated either using net income or profit/loss before taxes. Market share is defined as the ratio of a firm’s sales, in a particular industry, divided by total industry sales.

For what concerns the other factors, studies often interpret the industry, business and corporate effects as reflecting ‘stable’ differences in business returns associated with each of these classes of effects. In practice, for the estimation of these effects, practitioners use

[1] Diversification, Ricardian rents, and Tobin's q, Cynthia A. Montgomery and BirgerWernerfelt, RAND Journal of Economics Vol. 19, No. 4, Winter 1988

differences in the average returns over the sample time period. Industry effects derive from differences between industries in the average of returns to individual businesses in each industry. Business effects typically derive from differences between businesses in the average of annual returns to each business. Therefore, only the average returns of businesses within a corporation matter (if that level of analysis is chosen) for the estimation of a corporate effect. Consequently, individual corporations do not need to have an impact on all the businesses they operate in to produce a ‘corporate effect’ (Brush and Bromiley, 1997). Corporate effects derive from differences between multiple-division corporations in the average of returns to individual businesses in each corporation. Year effects derive from differences between years in the average of returns to individual businesses. It represents year-to-year fluctuations in macroeconomic conditions that influence all corporations, or business units, equally. Each firm differs, to some extent, from the others, in each period of time and this is not uniform across time. That is, the firm, its strategy and the environment change over time.

Then a number of possible interaction effects could be assessed. One of the most used is the industry-year effect that represents the fact that industry effects may vary between years. Furthermore, it is crucial to consider that, at any given time, some firms are better prepared to deal with coexistent environment features than others. Hence, there is an interaction effect between individual firms and the contemporaneous environment, which is not captured by the fixed year effect. This has led practitioners to formulate models with the firm-year effect that I have included in my model.

Summing up, in order to deliver a complete overview of related literature, Table 1 below reports a summary of the results of the various empirical studies, including models adopted, investigated effects and methods employed. I have also reported, in Table 2, the results of the empirical “leadership studies” that estimate top management effects on the variance of profitability, as this is a central matter of this research.

Table 1. Summary of past variance decomposition studies

Study	Data base	Years included	Industry definition	Types of industries	Definition of a business
Schmalensee (1985)	FTC LOB[a]	1975	LOB ≅3 1/2-digit SIC	Manufacturing only	All co. business in each LOB category
Kessides (1987)	FTC LOB	Sample A: 1975 Sample B: 1974–1976	LOB ≅3 1/2-digit SIC	Manufacturing only	All co. business in each LOB category
Wernerfelt and Montgomery (1988)	Trinet/EIS; FTC; other sources	1976	2-digit SIC	Industrial and utility cos.	All co. business in each LOB category
Kessides (1990)	FTC LOB	1975	LOB ≅3 1/2-digit SIC	Manufacturing only	All co. business in each LOB category
Rumelt (1991)	FTC LOB	1974–1977	LOB ≅3 1/2-digit SIC	Manufacturing only	All co. business in each LOB category
Roquebert *et al.* (1996)	Compustat	1985–1991	4-digit SIC (broadly defined)	Manufacturing only	All co. business in each SIC code
McGahan and Porter (1997)	Compustat	1981–1994	4-digit SIC (broadly defined)	Non-financial	All co. business in each SIC code
McGahan and Porter (1998)	Compustat	1981–1994	4-digit SIC (broadly defined)	Non-financial	All co. business in each SIC code
McGahan (1997)	Compustat	1981–1994	4-digit SIC (broadly defined)	Non-financial	All co. business in each SIC code
Chang and Singh (1997)	Trinet/EIS	1981, 1983, 1985, 1987, 1989	i) 4-digit SIC (narrowly defined) ii) 3-digit SIC	Manufacturing only	All co. business in each: i) 4 digit SIC code; ii) 3 digit SIC code
Bercerra (1997)	Compustat	1991–1994	4-digit SIC (broadly defined): study also includes classification by broad world geographic area	None excluded	All co. business in broad world geographic area (multinational cos. only)

Source: " Does Corporate Strategy Matter?", EDWARD H. BOWMAN and CONSTANCE E. HELFAT, Strategic Management Journal

Table 2. Continued

Study	Firm size	Number of firms	Number of industries	Number of businesses	Number of businesses per firm	Dependent variable (annual data)
Schmalensee (1985)	Mkt share ≥ 1%	456	242	1,775	Avg. = 3.89	ROA per business
Kessides (1987)	Mkt share ≥ 1%	456	242	1,775	Avg. = 3.9	ROA per business
Wernerfelt and Montgomery (1988)	Not given	247[c]	Not reported	Not reported	Not reported	Tobin's q per company
Kessides (1990)	Mkt share ≥ 1%	456	242	1,775	Avg. = 3.89	ln(1-ROS) per business
Rumelt (1991)	Sample A: mkt share ≥ 1%	A: 457	A: 242	A: 1,774	Minium = 1 A: Avg. = 3.88	ROA per business
	Sample B: mkt share > 0	B: 463	B: 242	B: 2,810	B: Avg. = 6.07	
Roquebert *et al.* (1996)	Not given	94–114 in each sample (10 samples)	223–266 in each sample (10 samples)	387–451 in each sample (10 samples)	Minimum = 2 Avg. = 4.01	ROA per business
McGahan and Porter (1997)	Assets and sales ≥ $10 million	7,003	628	12,296	Minimum = 1 Avg. = 1.76	ROA per business
McGahan and Porter (1998)	Assets and sales ≥ $10 million	7,793	668	13,660	Minimum = 1 Avg. = 1.75	ROA per business
McGahan (1997)	Assets and sales ≥ $10 million	4,947	648	9,904	Minimum = 1 Avg. = 2.00	a: Tobin's q per co. b: ROA per business (manuf. only) c: ROA per co.
Chang and Singh (1997)[b]	Sample A: mkt share ≥ 1% Sample B: $2 million to $2 billion sales	A: 466 (3-digit); 475 (4-digit) B: 710 (3-digit); 693 (4-digit)	A: 137 (3-digit); 374 (4-digit) B: 137 (3-digit); 390 (4-digit)	A: 1236 (3-digit); 1531 (4-digit) B: 2663 (3-digit); 3070 (4-digit)	Minimum = 1 A. Avg. = 2.65 (3-digit); 3.22 (4-digit) B. Avg. = 3.75 (3-digit); 4.43 (4-digit)	Mkt. share per business
Bercerra (1997)	Within largest 100 U.S. cos. in 1994	41	11 industries 5 geographic areas	134	Minimum = 3, Max. = 5 Avg. = 3.27	ROA per business

Source: " Does Corporate Strategy Matter?", EDWARD H. BOWMAN and CONSTANCE E. HELFAT, Strategic Management Journal

Table 3. Continued

Study	Statistical technique[d]	Corporate effect	Business effect	Industry effect	Year effect	Industry × Year	Other interactions
Schmalensee (1985)	i) OLS hierarchical regression (ANOVA) ii) variance components	i) zero ii) not included	Mkt share effect: i) 0.2 to 0.6% ii) 0.6%	i) 18.8 to 19.3% ii) 19.5%	Not included	Not included	i) negative cov. bus. & ind. suggested ii) cov. bus. & ind: −0.6%
Kessides (1987)	OLS hierarchical regression (ANOVA)	A: 1 to 8%[e] B: 11 to 54%[f]	Mkt share effect: A: not reported B: 5 to 39%[f]	A: not reported B: 9 to 45%[f]	Not included	Not included	Not included
Wernerfelt and Montgomery (1988)	OLS hierarchical regression (ANOVA)	Corp. focus (relatedness): 0.2 to 3.7%	Mkt share effect: 0 to 2.3%	10.9 to 20.1%	Not included	Not included	Not included
Kessides (1990)	Weighted least squares with a mix of fixed and random effects—hierarchical regression[g]	5.1 to 9.8%	Mkt share effect: 6.6 to 27.5%[f]	4.7 to 25.2%	Not included	Not included	Not included
Rumelt (1991)	i) sequential analysis of variance ii) variance components[h]	i) A: 14.8 to 17.6% B: 10.9 to 11.6% ii) A: 0% B: 1.6%	i) A: 33.9 to 34.0% B: 41.3 to 41.4% ii) A: 47.2% B: 44.2%	i) A: 15.3 to 17.9% B: 9.8 to 10.3% ii) A: 7.3% B: 4.0%	i) A: 0% B: 0.1% ii) A: 0% B: 0%	i) A: 9.6 to 9.8% B: 6.8 to 7.1% ii) A: 8.9% B: 5.3%	i) Not included ii) cov. ind. & corporation; A: 0.76% B: 0%
Roquebert *et al.* (1996)	Variance components	17.9% (avg. across samples)	37.1% (avg. across samples)	10.1% (avg. across samples)	0.4% (avg. across samples)	2.3% (avg. across samples)	

Source: " Does Corporate Strategy Matter?", EDWARD H. BOWMAN and CONSTANCE E. HELFAT, Strategic Management Journal

Table 4. Continued

Study	Statistical technique	Corporate effect	Business effect	Industry effect	Year effect	Industry × Year	Other interactions
McGahan and Porter (1997)	i) sequential analysis of variance ii) variance components	i) 9.1 to 11.9% ii) 4.3%	i) 34.9 to 35.1% ii) 31.7%	i) 6.8 to 9.4% ii) 18.7%	Not included	Not included	i) Not included ii) cov. ind. and corp.: −5.5%
McGahan and Porter (1998)	OLS hierarchical regression[i] (ANOVA)	8.8 to 23.7%	32.5 to 59.1%	6.9 to 16.3%	0.2 to 1.1%	Not included	Not included
McGahan (1997)	Sequential analysis of variance[i]	a: corp. focus = 0 to 1% b: 8.3% c: corp. focus = 0 to 0.1%	Asset share effect: a: 35.3 to 66.0% b: 28.7% c: 14.8 to 31.2%	a: 21.6 to 29.4% b: 7.6% c: 8.6 to 10.6%	a: 0 to 2.9% b: 1.2% c: 1.7 to 2.1%	Not included	Not included
Chang and Singh (1997)	Variance components	3-digit SIC: A:0% B:1.6% 4-digit SIC: A:4.3% B:8.5%	3-digit SIC: A:15.2% B:13.7% 4-digit SIC: A:52.7% B:46.8%	3-digit SIC: A:1.6% B:3.1% 4-digit SIC: A:19.4% B:25.4%	3-digit SIC: A:2.4% B:1.0% 4-digit SIC: A:0.9% B:0.3%	3-digit SIC: A:6.2% B:11.4% 4-digit SIC: A:0.9% B:1.8%	Not included
		Sample B (4-digit SIC) Firm size large: 10.9% medium: 25.7% small: 6.3%	Sample B (4-digit SIC) Firm size large: 44.4% medium: 15.8% small: 15.6%	Sample B (4-digit SIC) Firm size large: 24.1% medium: 40% small: 59.4%	Sample B (4-digit SIC) Firm size large: 0.7% medium: 0% small: 0%	Sample B (4-digit SIC) Firm size large: 1.3% medium: 6.9% small: 12.5%	Not included
Bercerra (1997)	i) hierarchical regression (ANOVA) ii) variance components iii) repeated measures random factors (ANOVA)	i) 12% ii) 4.71% iii) 3.05 to 10.95%	i) not reported ii) 27.2% iii) not included	i) not given ii) Industry: 30.4% Geogr. area: 6.9% iii) Industry: 41.9% to 46.8% Geogr. area: 0 to 1%	i) not reported ii) not incl iii) not significant	i) not incl ii) not incl iii) significant	i) not included ii) none iii) year × corp. significant

Source: " Does Corporate Strategy Matter?", EDWARD H. BOWMAN and CONSTANCE E. HELFAT, Strategic Management Journal

Table 5. Leadership studies

Study	Data base	Years	Types of industries	Number of firms	Number of industries	Number of CEOs per firm
Lieberson and O'Connor (1972)	Moody's Industrial and Transportation Manuals	1946–1965	Selected less diversified industries (manuf., service, transportation)	167	13	Not reported
Weiner (1978)	Compustat and other sources	1956–1974	Manufacturing	193	Not reported	Avg. = 2.8
Weiner and Mahoney (1981)	Compustat and other sources	1956–1974	Manufacturing	193	Not reported	Avg. = 2.8
Thomas (1988)	Not given	1965–1984	U.K. retailing	12 (ranked in top 200 U.K. firms)	1	Not reported

Study	Dependent profitability variable	Statistical technique	CEO effect[a]	Firm effect[a]	Industry effect[a]	Year effect[a]
Lieberson and O'Connor (1972)	Return on sales per company	Sequential analysis of variance	14.5%	22.6%	28.5%	1.8%
Weiner (1978)	Return on sales per company	Sequential analysis of variance	8.7%	45.8%	20.5%	2.4%
Weiner and Mahoney (1981)	Return on assets per company	Regression combined with sequential analysis of variance	43.9%	Explanatory variables: firm size, capital/labor, debt/equity, % of earnings retained	Explanatory variables: industry sales, industry concentration	Explanatory variable: annual GNP
Thomas (1988)	Return on sales per company	Sequential analysis of variance	5.7%	83.2%	Not included	5.6%

Source: " Does Corporate Strategy Matter?", EDWARD H. BOWMAN and CONSTANCE E. HELFAT, Strategic Management Journal

Analysis and variables used

The first variance decomposition study that tried to examine how much CEOs influence company performance was that of Lieberson and O'Connor (1972). After that, a variety of similar new researches have been conducted (e.g. Weiner, 1978; Thomas, 1988; Wasserman, Anand, and Nohria, 2001).

Here, I employ the ANOVA variance decomposition, considering the following equation:

$$r_{iy}= \mu + \gamma_y + \varphi_i + \beta_i \Delta_j + \alpha_{ceo,y} + \phi_{iy} + \delta_{i\,t} + \varepsilon_{ijt} \quad (2)$$

where r_{it} denotes the rate of return of company *i* in year *y*. I use ROA at corporate parent level (consolidated level). The explanatory variables are μ, the average performance of all companies over the entire period. The γ_y are year effects or the premium (deficit) associated with year *y*; the φ_i is the premium (or deficit) associated with the company itself; $\beta_i\Delta_j$, is the time-varying corporate effect from one particular type of managerial decision; $\alpha_{ceo,y}$, which captures the premium (or deficit) associated with the CEO who leads the company in year y; the ϕ_{iy} are CEO and managerial interaction effects; the δ_{it} are firm-year interaction effects and the ε_{ijt} are random disturbances. With respect to equation (1), the above descriptive model adds a simple form of time-varying corporate effect of managerial decisions $\beta_i\Delta_j$. Further, the model includes $\alpha_{ceo,y}$ which is a dummy code that represents the CEO of a specific company. On the other hand, it drops variables such as industry and business-segment that were heavily employed in past research. The sizes of the individual effects are determined with a simultaneous ANOVA (McGahan and Porter, 2002).

Consistent with most previous works on CEO effects (e.g., Fitza 2013; Ahn et al., 2009; Crossland and Mackey, 2008; Hambrick, 2007; Wasserman et al., 2001; Thomas, 1988) as well as variance decomposition analyses in corporate effects in the strategic management literature (e.g., Bowman and Helfat, 2001; Brush and Bromiley, 1999; McGahan and Porter, 1997, 2002; Rumelt, 1991), I have used here the return on assets (ROA) for the dependent variable, as a measure of accounting-based firm performance. This measure is calculated as profit before taxes divided by total assets. As I have said before, there are studies that have utilized alternate measures such as market share for business effects or corporate focus variables for corporate effects. Bowman and Helfat (2001) offer a comprehensive review of these studies.

Obviously, there are limitations of using accounting-based measures as well (e.g. Fisher and McGown, 1983) but this approach is convenient for two primary reasons. First, it makes this study directly comparable to those previous works that adopted the same dependent variable (the majority of past work) and, second, because of the estimation of segment effects and industry effects for multi-divisional firms that require information on segment performance (segments of companies are not publicly traded thus making market-based measures of segment performance unavailable).

3) Empirical Setting

The Information Communication and Technology industry (ICT) provides the empirical setting for this study. The period initially considered was between 1992 and 2014.

The industry name was first coined by Dennis Stevenson in his 1997 report to the UK government and promoted by the new National Curriculum documents for the UK in 2000. The concept is now often referred to as computer networking or data network, the study of the technology used to handle information and improve communication. In addition to the subjects included in Information Technology (IT), ICT encompasses areas such as telephony, broadcast media and all types of audio and video processing and transmission. This environment better fits with the sample analyzed in this research that actually extends to a broader set of corporations, including those operating in the electronic and digital entertainment. What all these companies have in common is the scientific know-how based on software and telecommunication. Because this is a blurred operating area with undefined boundaries, focusing on businesses would be much better, to deliver a better understanding of companies' operations. In this scenario, all the companies face the same difficulties and there are a plenty of factors that could affect profitability.

The reasons I have chosen this kind of companies are several. ICT is reshaping the way the world's economies, governments and societies behave, interact and create value. ICT has to be intended as a must have tool to improve organizations' effectiveness and quality, reach higher level of efficiency and deliver better services to strengthen competition worldwide, across all sectors of the economy. In this highly competitive, fast paced environment - characterized by tremendous uncertainty– CEOs are deemed to find the best strategies to boost performance and shareholders' value. Resources could be really rare, talented people are essential and every kind of decision process is clearly time constrained. Taking all together, this is obviously one of the toughest environments to operate in and where CEOs' guidelines could be easily thought as indispensable, given the huge impact of their role and the repercussions of their decisions that shape companies' future.

3.1) Data

Companies that are required to follow specific U.S. Government disclosure reporting standards (like the FRS[2] in Adner-Helfat 2003) or Compustat's ExecuComp database have been the data sources for the vast majority of past variance decomposition studies. However, for what concerns the elaboration of this research, I could not benefit from such precious access. Having set the focus on the ICT industry, I have used a number of online sources, analyzing individual CEOs' curricula and checking for their affiliations.

My data sample includes a total of 50 companies over a 22-year time period. Financial data on companies' performance have been taken from Bureau Van Dijk's Osiris database. Some of the companies reported data for only part of this period, due to acquisitions, spin-offs and start-ups. If a company has had financial information available for only part of the period, I have excluded the company's data for that time frame from the analysis. If a company reported financial information for only part of a year, then company's data in that year have to be excluded. In addition, the analysis includes only parent companies because many of them do not own subsidiaries. For those corporations that do own domestic or foreign subsidiaries, Osiris Database does not include data, thus making impossible to correctly ascertain corporate and other effects. Table 3 lists the companies in this analysis.

As already mentioned, the dependent variable used in the decomposition of variance is annual return on assets (ROA). These data are taken from Osiris Financial Database and are expressed as profit and loss before taxes divided by total assets. CEOs, instead, are only those people in charge for that precise role (I have also included those CEOs in charge of chairmanship as usual in US). Any other member of the executive committee as well as any board member other than the CEO was taken out of the sample.

One of the main aspects that most influenced past research results was the confounding of CEO with the corporation. CEOs usually serve in that capacity in only one company, resulting in a complete overlapping with the corporation. These studies assess the effect of a particular CEO in a particular company at a particular time but have the limit to specify

[2] The Facility Registry Service provides quality facility data to support EPA's mission of protecting human health and the environment.

the CEO effect, linking it to company and time. I propose a generalized, independent version using a sample of CEOs who served in more than one company to overcome this confounding (see Appendix A). While this change can likely address these technical issues, other aspects of confounding will be nevertheless unresolved. For example, the experience of a CEO in one firm can undoubtedly influence the performance of the same CEO in subsequent firms. Moreover, there are other factors like the preference to hire CEOs with certain previous experience (outsiders) other than those coming from the inside the corporation (this condition applies to industries as well). Hence, a CEO performance effect in a certain firm will be contingent, to some degree, to different particular combinations and interactions of events, trends and, largely, to the internal organization of the firm itself.

Obviously, this sample is much more reduced compared to other studies' datasets but, even though the above mentioned conditions may impact final results, it proved to be robust from a statistical viewpoint.

Table 6. ICT company sample

Company name	time frame
Oracle	2004-2013
Selectica	2007-2013
Cisco Systems	1995-2013
Avistar Communications Corp	2007-2013
Polycom	2009-2013
Tandbergasa	2002-2006
SonicFoundry	2011-2013
Telco Systems	2011-2013
Comarco	2007-2010
Centura Software Corporation	1996-1998, 2013
Aruba Networks	2006-2013
ANADIGICS	1998-2008
TridentMicrosystems	2011-2012
Meru Networks	2012-2013
Lucent Technologies Inc	1996-2003
Cummins Inc.	1992-1995
Sun Microsystems	1999-2002
Motorola	1992-2011
Motorola Mobility	2011-2013
Kodak	1994-2013
Gemplus International	2000-2001
Avago Technologies	2006-2013
Integrated Device Technology	2005-2008
Integrated Circuit Systems	1999-2005
Computer Sciences	2012-2013

Misysplc	2006-2012
Ebay	1998-2008
Unisys Corporation	2008-2013
Gateway Inc	2006-2008
CompuCom	1999-2004
ALK Technologies	2011-2013
EA	2005-2013
HP	1997-2013
FriendFinder Networks	1996-1998
Majesco Entertainment Company	2004-2005
ADTRAN	2005-2007
Progress Software	2011-2013
AllscriptsHealth Solutions Inc	2010-2011
Vmware	2008-2013
Extreme Networks	2010-2013
Taleo Corporation	2005-2012
Symantec Corporation	2009-2012
NCR Corporation	2005-2013
Symbol Technologies	2002-2005
Terabeam Corporation	2000-2004
EMC	2000-2013
WangLaboratories	1993-1999
AMD	2011-2013
Lenovo	2009-2011
Verizon	2000-2011

Source: personal elaboration

As illustrated by the table above, due to the limited availability of data for these companies[3] and to the industry dynamics described above, I have registered missing years for each company record, implying an unbalanced dataset. At the beginning, my sample counted a total of 312 observations, downsized to 283 after the above stated considerations. To give a better grasp on the distribution of data used in my analysis, Table 4 highlights the descriptive statistics of my final dataset.

Table 7. Summary Statistics

```
           Firm      Performance         CEO           R.D              year
Cisco Systems: 19   Min.   :-81.320   Min.   : 1.00   Min.   :-49.324   Min.   :1992
Kodak        : 18   1st Qu.: -1.855   1st Qu.: 8.50   1st Qu.: -1.914   1st Qu.:2003
EA           : 15   Median :  5.180   Median :18.00   Median :  2.616   Median :2007
EMC          : 14   Mean   :  2.300   Mean   :18.11   Mean   :  1.807   Mean   :2006
Verizon      : 12   3rd Qu.: 11.015   3rd Qu.:27.00   3rd Qu.:  9.116   3rd Qu.:2011
ANADIGICS    : 11   Max.   : 71.310   Max.   :37.00   Max.   : 14.836   Max.   :2013
(Other)      :194
```

[3] Many of these companies are privately held and characterized by continuous organizational change.

3.1.1) Data on corporate level decision

Research & Development (R&D) spending has been chosen as a proxy for managerial decisions. These data have been taken from Osiris Financial Database that provides customized options for the types of indices to use. Particularly, more than a mere budget expense I have employed a campsite measure given by R&D expenditure for the period divided by the operating revenue. This index ties the static R&D budget to the revenues generated by the core activities of the firm. Additionally, this can also emphasize the organizational dimension in which strategic decisions occur.
$\beta_{i\Delta j}$ in equation (2) could be seen as a type of firm-year interaction effect that is tied directly to corporate managers with Δt representing a multiple-year time period that begins with the year in which a decision occurs in corporation *i* and terminates in the year prior to the next decision of the same type made by the same corporation. Clearly, it is time-varying, in the sense that corporate managers may make a series of decisions over time. For instance, corporate management may alter a company' s organizational structure and then subsequently alter it again if conditions change, as noticed in Adner-Helfat 2003. In that paper, $\beta j\Delta t$ stands for the time-varying corporate effect related to managerial decisions. They employed a dummy variable, identified in downsizing that, by the nature of the decision, had to have come from the corporate level of management. Practically, they coded all announcements in the *Wall Street Journal* and selected those highlighting management actions in the form of downsizing. Among the identifiable categories of downsizing decisions there were cost-cutting, layoffs, and financial as well as organizational restructuring. Some of these decisions included downsizing at a company-wide level and others targeted only particular businesses within the firm.
Here, I want to apply the same concept but, given the peculiarities of the selected industry, I am going to adopt a continuous quantitative variable with the aim of reaching a better explanatory fitting. This parameter represents the biggest issue of this study. While continuous variables typically offer more information than dichotomous variables, establishing validity for continuous variables, measuring something like managerial talent, could be extremely problematic. Yet, even if a good measure of managerial ability were available, this measure would have to vary over time to avoid being collinear with the fixed effect corresponding to each executive.

Anyway, R&D seems to be more appropriate at reflecting ICT managers' decision characteristics. This choice represents a substantial difference with Adner-Helfat's research. R&D reflects decisions at the corporate level of management and is about resource allocation and choice of businesses within the corporation. The R&D decisions generally reflected efforts by corporate management to increase profits, by selecting the most profitable product development projects or allocating resources to more profitable divisions. Variance decomposition, however, does not provide information about firm performance. Rather, the analysis shows whether the decisions account for a portion of the variance in performance, indicative of differences between firms in the level of performance. If all firms responded to changes in the external environment in the same way, at the same time, then R&D decisions would have no effect on the variance of performance. Variance decomposition can answer the question of whether there is heterogeneity in managerial responses and whether this accounts for a portion of heterogeneity in performance.

There are several advantages of using R&D over operating income. It targets only core business projects that are fundamental for firm's growth and, contrary to downsizing, would not affect extraordinary items that do not enter into the ROA formula (in that case a conservative approach should be taken in evaluating only longer lasting effects on operating cash flows). It represents one of the most leading measureable drivers on which CEO rely on in the ICT industry. Anyway, a decision of the type of downsizing would not have had much business sense in this context.

As I have pointed out, I use R&D divided by operating revenue and this estimate offers additional advantages. In fact, CEOs not only have to decide on the allocation of these funds among the best investment alternatives but they do have to be aware of the consequences that this choice has on the cash flows generated by the company's operations, implying a continuous and careful trade-off between growth and prudence. Then, there will be CEOs who are eager to make their companies thriving and would therefore take on a more aggressive approach. On the contrary, there could be CEOs who prefer to consolidate and defend the business and would more likely to take on a conservative approach. All depends by the specific contingent sub-environment that the company is facing inside the industry and by the type of CEO at the helm. Yet, these considerations can actually be regarded as both good and bad news as they widen the significance of the measure itself and, consequently, its application. But given the CEO-

organization focus of my analysis, this variable optimally works as a proxy for the strong linkage between the two.
Despite the good fitness displayed by this variable I would like to point out the limits too, as these represent mainly technical problems and are therefore crucial in evaluating final results. As I have mentioned before, this is a quantitative variable and, like firm performance, because of the specific nature of the industry and the poor availability of information in general, data do not cover all the years for each company in the sample.
Being a quantitative variable, R&D expresses higher explanatory power than a categorical variable but still presents technical limits for the ANOVA technique. There are no references in the past literature that used similar approaches, leaving this study to be a standalone example without direct comparable analyses. Taking a very conservative approach, I would say that results are obviously affected by the nature of these variables and in order to reach complete reliability on the ANOVA outcomes, further tests and research should be carried out with that respect. Anyway, in order to reduce the variability in the R&D observations, I have modified the distribution centering it on the mean.
In sum, I believe the benefits of using R&D over operating revenues clearly offset the disadvantages within the framework of this study.

3.2) Statistical Methodology

In the first part of the analysis, I will assess the size of year, company, R&D, CEO, as well as interaction effects, by applying a variance decomposition analysis. In the second part of the analysis, I will discuss in detail this traditional way of measuring these effects and show how it can be influenced by technical issues and by chance and random fluctuations.
Here, I employ a simultaneous ANOVA variance decomposition developed through the use of the R Statistical Software. As said before, there are studies that estimated CEO effects using a nested ANOVA. However, a nested ANOVA assumes that no covariance exists between the individual effects. This assumption may be too optimistic. A key advantage of a simultaneous ANOVA is the ability to control for such covariance between the CEO effect and all other effects.

Past studies and statistical methods

Before explaining the ANOVA methodology used in this research I will briefly review the components of variance (COV) and nested ANOVA and their results in past studies. I will take McGahan and Porter (1997a) work as example since they addressed several methodological issues. With regard to method, they tried to decompose variance using both components of variance and nested ANOVA techniques. The core result, obtained using the COV method, indicated that year, industry, corporate-parent, and business-specific effects accounted for 2%, 19%, 4%, and 32% of variance, respectively. The nested ANOVA indicated that the effects explained 0.3%, 7% – 9%, 9% – 12%, and 35% of variance, respectively. These sharp differences suggested the need for further research since the assumptions inherent in the COV and nested ANOVA methods were too restrictive.

The components-of-variance approach does not generate estimates of each effect, but uses summary statistics to assess the influence of variance in year, industry, business-specific, and corporate parent effects. Similarly, the nested ANOVA approach does not account for covariance between effects. For example, there is strong covariance between industry and corporate-parent effects as reported in McGahan and Porter (1997a) and this highlights flaws in the assumptions necessary to both approaches. Here, I do not have any industry effect and such covariance could arise only between CEO and firm effects. The simultaneous ANOVA instead allows for a full set of covariance effects and does not assume randomness in the model errors. In previous studies, the methods either assumed that the effects and their covariances were randomly generated or imputed all of the covariance either to the industry or to the corporate-parent effects. These covariances are not to be underestimated. For example, the covariance between industry and corporate-parent effects may indicate that a diversified firm may be more likely to expand into particular types of industries.

Following McGahan and Porter paper of 2002, I reproduce here a simultaneous ANOVA based on the same procedure. As in that study, the main difference between this model and those examined in the past is that it shows the incremental contribution to explanatory power of the firm and CEO effects while allowing for relationships in the processes that generate the effects. In fact, these two variables may result in overlapping when capturing portion of variance explained. In other studies this technical issue regards, mainly, corporate-parent and industry effects.

The technical problem lies in the fact that an ANOVA involves the examination of the incremental explanatory power of a specific set of effects and, hence, there is an inherent “nesting” quality to an ANOVA. However, there is no difference in the estimation procedure between the simultaneous ANOVA and nested ANOVA when particular types of effect are introduced into the model. One example is business-segment effect. Business-specific effects are somehow linear with both the industry and the corporate-parent effects, meaning that industry effect is numerically equivalent to the average of business-specific profits among industry players; similarly, the corporate-parent effect is equivalent to the average of business-specific profits among corporate members. This is not the case, however, when we are dealing with industry and corporate-parent effects. They are not linear by design, and there may be covariance between the effects in the data. Thus, nested ANOVA approaches impute all of the covariance to the first introduced effect. Rather, by estimating a simultaneous model that includes both industry and corporate-parent effects and comparing the results with models that include either industry or corporate-parent effects, it is possible to assess whether relationships between the industry and corporate-parent effects influence the results. Even though we know that components-of-variance estimation procedure generates estimates of the covariance between the industry and corporate effects, one should bear in mind that this result is based on an unusual assumption: COV models assume that the covariances as well as the effects are randomly generated. Thus, the approach does not account for systematic interactions such as the tendency of out-performer industries to host a disproportionate number of diversified firms, with respect to other industries, as noted by McGahan and Porter. This understanding was crucial for establishing the relationship between industry and corporate-parent effects on performance. Here, as I have already stated, the focus is much more on management capabilities and the persons of CEOs themselves. Yet, I have encountered the same statistical issues particularly when dealing with firm and CEO effects. However, I have fixed it using either the dedicated R procedure to neutralize the entry order of variables and, as I have said, the replication of the simultaneous ANOVA as in McGahan and Porter 2002. For clarity, I have entered CEO effect lastly in my model to avoid this confounding.

When it comes to CEO effects, prior variance decomposition studies used datasets with executives who were in charge for that role for no more than one corporation or industry. In this scenario, CEOs are said to be nested within industry and corporate effects. When a variable such as the CEO effect is perfectly nested within another variable (e.g. industry or corporate), almost all of the variance in the dependent variable imputed to leadership influences will be common to the industry or to the corporation. To avoid the problem of perfectly nested samples, only firms that had a CEO who worked for more than one company were included in my sample. For this particular study, leaders have to be CEOs and not be other members of the executive committee or members of the board. CEOs have to experience some extent of turnover; otherwise the effects attributed to them cannot be separated from corporate effects. In fact, if the same CEO is running a company for the totality of the data range, CEO effects and corporate effects for a given observation would perfectly match. Thus, if companies included in the dataset did not experience a turnover event, then all of the firm performance variance due to the CEO would be attributed to the corporate effect. Hence, all firms with no changes in the CEO position were excluded from the sample, overcoming a common limitation of prior empirical work in this area. More than dropping companies from the original dataset – that remains unchanged in this respect- this implied the elimination of specific records, for every company, corresponding to those CEOs who never took on the same role in other ICT companies or who left the industry. Dropping these records resulted in 29 observations being deleted from the sample and a final unbalanced dataset.

The R statistical software

I have performed the ANOVA procedure with R programming software. R is an open source environment for statistical computing[4]. As I have pointed out earlier, due to turnover CEOs, I have registered an unbalanced sample. When data is unbalanced, there are different ways to account for the ordering entry of variables in the ANOVA. Since we

[4] For an introduction refer to The R Project for Statistical Computing at Internet site http://www.r-project.org.

know that order matters for the final outcomes of the model, I have tried to neutralize it directly in R in order to yield more accurate results for the analysis.

There are at least three approaches, commonly called *Type I, II and III* sums of squares (SS). The correct type to use has led to an ongoing controversy in the field of statistics. However, at the end, it is all about testing different hypotheses about the data.

When data is balanced, the factors are said to be *orthogonal*, and types I, II and III all give the same results. The default procedure set in R is the Type I effect or the sequential sum of squares. However, this is the procedure that leads to unclear results as it tests the main effect of a factor and the main effect of the subsequent factor only *after* the main effect of the former. Because of the sequential nature and the fact that the factors are tested *in a particular order*, this type of sums of squares will give different results for different ordering schemes, depending on which main effect is entered first.

With Type II we still test for each main effect *after* the other main effect. The assumption of no significant interaction between the factors holds and, consequently, one should look at interaction first and only if the interaction between the two or more factors is not significant, continue with the analysis for main effects. If there is indeed no interaction, then type II is statistically powerful in assessing effects. From a computational point of view, this is equivalent to running a type I analysis with different orders of the factors, and taking the appropriate output. Finally, type III tests for the presence of a main effect *after* the other main effects and interactions. This is the most effective approach when dealing with significant interactions. Usually, the hypothesis of interest is about the significance of one factor while controlling for the level of the other factors. If the data is unbalanced, this leads to use type II or III sum of squares.

The anova or aov function in R implement a sequential sum of squares (type I). As indicated above, for unbalanced data, this is not merely a hypothesis of interest, since essentially the effect of one factor is calculated based on the varying levels of the other factors. In other words, the results are interpretable only in relation to the particular levels of observations that occur in the unbalanced dataset. As noted, using type II SS procedure it is possible to overcome this technical issue. The correct SS can be obtained using anova() and varying the order of the factors. Again, Type-II sums of squares are constructed following the principle of marginality. As an example, in a three-way ANOVA with factors A, B, and C, the Type-II test for the AB interaction assumes that the

ABC interaction is zero, and the test for the A main effect assumes that the ABC, AB, and AC interaction are zero, but not necessarily the BC interaction, since the A main effect is not marginal to this term. Type-III tests do not assume that terms that come first in order to the term in question are zero. For example, in a two-way design with factors A and B, the type-III test for the A main effect tests whether the population marginal means at the levels of A, averaged across the levels of B, are the same.

In sum, the analysis proposed in this paper presents advancements in the field of variance decomposition estimation. The sample of leaders is not perfectly nested within the industry and firm effects, statistical analysis is conducted with simultaneous ANOVA, firms that did not register CEO turnover were excluded from the sample and there is no difference between diversified and undiversified companies as well as no business-segment level data.

4) Results

In this section, I show the results of a simultaneous ANOVA approach for equation (2) also compared with the results of a variety of related models where restrictions have been imposed. I will also show the incremental explanatory power associated with year, Firm, R&D and CEO effects, as well as interaction effects, respectively. Table 5 and Table 6 report the significance of the effects to see whether all the effects are statistically significant and how much significant they are. I have performed this test twice, one with only the R&D inserted into the model and one with only the CEO.

Obviously, year and firm effects are largely significant as well documented by most of past studies. R&D proves to be statistically significant while CEO effects are negligible. The reason I have showed this table is to highlight a negligible statistical effect on the CEO, thus implying that every further analysis that could be made in that merit becomes irrelevant. The only deeper analysis I have performed is measuring the impact of CEOs taking into consideration time lag, as this will represent a major factor in considering the "effects" that their tenure have on firm's performance.

Table 8. Analysis of Variance table. Significance of effects (No CEO)

	Df	Sum Sq	Mean Sq	F value	Pr (>F)
year	21	12295	585.5	4.350	1.12e-08
firm	50	46482	929.6	6.908	< 2e-16
R&D	1	1645	1645.0	12.223	0.000576
Residuals	210	28262	134.6		

Source: personal elaboration

Table 9. Analysis of Variance table. Significance of effects (No R&D)

	Df	Sum Sq	Mean Sq	F value	Pr (>F)
year	21	12295	585.5	4.047	7.28e-08
firm	50	46482	929.6	6.426	< 2e-16
CEO	7	393	56.1	0.388	0.909
Residuals	204	29514	144.7		

Source: personal elaboration

Table 7 illustrates the full model, containing both R&D and CEO as well as interaction effects. Despite the negligible CEO effect displayed above, the interaction effect between R&D and CEO produces an interesting significant effect that plays a crucial role in the elaboration of this study. The interaction term between firm and year is statistically significant and describes that firm's performance is affected by fluctuations, among years, in the external environment.

Table 10. Analysis of Variance table. Significance of effects (Full model)

	Df	Sum Sq	Mean Sq	F value	Pr (>F)
year	21	12295	585.5	6.621	2.11e-12
firm	50	46482	929.6	10.512	< 2e-16
R&D	1	1645	1645.0	18.602	3.17e-05
CEO	7	617	88.1	0.997	0.436779
R&D:CEO	32	7014	219.2	2.479	0.000179
firm:year	42	9223	219.6	2.483	4.97e-05
Residuals	129	11408	88.4		

Source: personal elaboration

Summing up, all the effects other than the CEO are largely statistically significant. Even when the analysis is conducted without R&D, CEO effects are not statistically significant. I have run the analysis either with R&D alone or CEO alone to assess whether an overlapping exists among the two, such as the overlapping between firm and CEO. Indeed, the only way to see a statistically significant CEO is to enter it directly before firm. However, this would undoubtedly negatively affect final results.

Further, as I have mentioned before, I have illustrated the results of my analysis-of-variance as McGahan and Porter did in their 2002 research. Figure 1 shows this methodology and intuitively reports the advantages of its use, as it yields the neutralization of the order described in previous sections. I have performed the neutralization firstly with R Type III ad hoc procedure and found no difference in the results associated with the order generated by the default formula.

The mechanism illustrated by Figure 1 basically work in the following way.

Given a model of the form $Y = X_1 + X_2 + X_3 + X_4$, where Y stands for performance and the independent variables are year, firm, R&D and CEO, the following analysis is equivalent, from an analytical viewpoint, to do the following:

first consider the *null model*,

Y= 1

which is simply the equation with no factors. Then start adding factors taking the equation explained by one single factor:

$Y = X_1$,
$Y = X_2$,
$Y = X_3$,
$Y = X_4$,

then, take the equation with just two factors in the following way

$Y = X_1 + X_2$,
$Y = X_1 + X_3$,
$Y = X_1 + X_4$,

and so forth, trying all the combinations. Finally, the third step involves the following

$Y = X_1 + X_3 + X_4$, with X_2 taken out,

$Y = X_2 + X_3 + X_4$, with X_1 taken out,

$Y = X_1 + X_2 + X_3$, with X_4 taken out,

and so forth, trying all the combinations. At the end I get the *full model* comprised of all the factors together

$$Y = X_1 + X_2 + X_3 + X_4$$

Starting from the first line to the end, one can simply detect the impact that each single factor adds to the model, firstly alone and later after other factors are entered.

Bearing in mind the above process, looking at the scheme in Figure 1, the model at the bottom of the figure corresponds to the fully specified model in equation (2). Looking at the above strings, the model assumes the reduced form described in chapter 2. All the entries in Figure 1 correspond to models in which at least one class of effects is restricted to zero.

The serial correlation in residuals (ρ), and the ordinary and adjusted R^2 are shown for each model. Each line is accompanied by the probability at which an F-test rejects the corresponding restriction. In restricted models, the rate of serial correlation is higher because the residuals include the omitted effects. In the full model, the rate of serial correlation could be interpreted as the tendencies of shocks in a specific year to influence returns in the subsequent year.

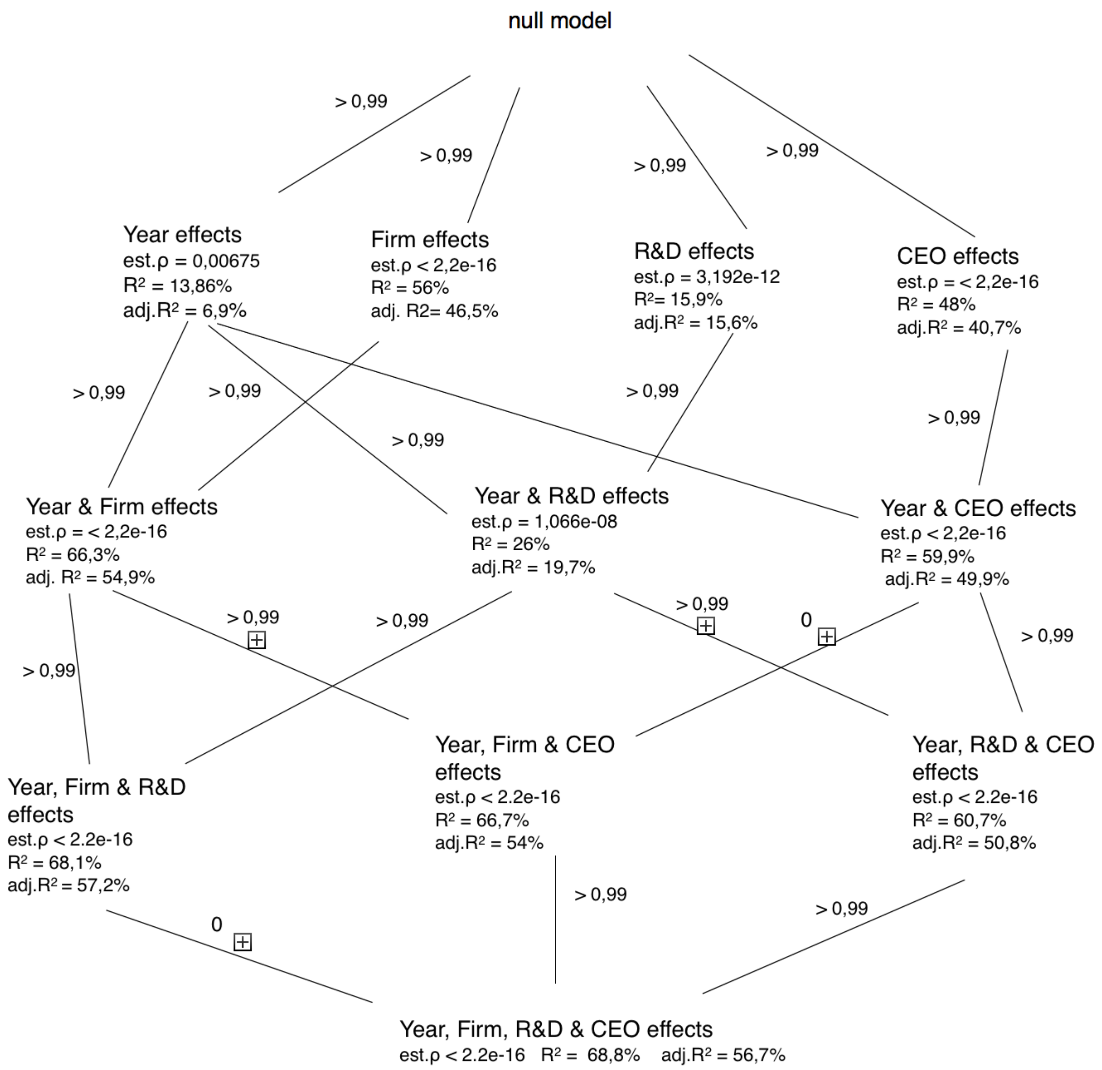

Figure 1 – Analysis of Variance of Equation 2

As said above, the figure shows the estimated rate of correlation, the R^2 and the adjusted R^2 in models that include various sets of effects. Each line is accompanied by a figure that represents the probability with which the model rejects the restriction indicated by comparing the two models. The model at the bottom of the figure includes year, firm, R&D, and CEO effects, and generates an R^2 of 0.688. The model immediately above it excludes the R&D effect, and generates an R^2 of 0.667. The difference in the explanatory power of the two models is significant at the 99% level, as indicated by the "> 0,99" that accompanies the restriction. Thus, the analysis shows that R&D effect adds significant explanatory power even in a model that already includes year, firm, and CEO effects.

The model at the bottom represents the fully specified version. The lines immediately above point to a model in which one type of effect is restricted. The first two of these lines are associated with restrictions on CEO and R&D effects, respectively. In the first case, the level of the F-test does not reject the restriction because most of the variance in the model is clearly captured by the firm effect (here these two effects could be seen as linear by design). In the second case the F-test rejects at 1% confidence, meaning that the portion of variance explained by the R&D factor is clearly relevant with this order. The third line points to a model in which firm effects are restricted. Again, the F -test rejects the exclusion with 1% confidence.

It is important to notice that by comparing models we are invoking the inherent nested nature of an ANOVA though. The description of this model as “simultaneous” ANOVA stems from the fact that each model reported in the figure is estimated while accounting for covariance between the estimated effects.

The next-highest group of lines corresponds to various restrictions in which three of the four effects are into the model. The first group of three lines is associated with restrictions on the model composed by year, firm, and R&D effects. The F-tests cannot reject the restriction on firm and R&D effects as they do provide significant R^2 increase. Similarly, the second group of three lines is associated with restrictions on the model that includes year, R&D and CEO effects. The F -tests cannot reject the restriction on R&D effects and on CEO effects. The reason, again, is the absence of firm in this paradigm. These results provide additional insight for CEO effects. The third group of three lines is especially important because it is associated with restrictions on the model that includes year, firm, and CEO effects and not R&D effects. Firm significantly contribute to explanatory power either when CEO effects are excluded or when they are plugged in. On the contrary, CEO effect does not add significant explanatory power to the model. The third-highest group of lines corresponds to restrictions on models with two sets of effects. CEO effect, this time, displays important explanatory power in the fixed-effects model. The remaining models also reject the exclusion of all effects, except in the cases of linearity by design. Again, these results suggest the overlapping between firm and CEO effects.

The final group of restrictions at the top of the figure provides information about the explanatory power of each type of effect on its own. When only one of the classes of effects is present, the F-statistic never rejects the restriction to the null model.

In sum, Figure 1 confirms that all but CEO types of effects— year, firm, R&D — are justified for inclusion in the full model. CEO effect provides explanatory power only when firm effects are moved away from the model. If CEO effects were introduced before firm and R&D effects, then Firm and R&D effects would still have had explanatory power, because CEO alone would not have captured all profit differences in the industry and among all companies.

Table 8 summarizes the results from Figure 1 about the increment to explanatory power by type of effect. To construct Table 8, I have calculated the increment to the ordinary and adjusted R^2 with effects introduced in the following order: year, firm, R&D and CEO. In addition to Figure 1, I have also included the interaction effects. I have followed the convention that takes the year effect as the first one and the corporate-parent as the second (here I have only corporate-parent level). This is such an economic convention that is based on economic characteristics of the variables included.

Table 11. Increment to Explanatory Power by Type of Effect

	Ordinary R^2	Adjusted R^2
year	13,86%	12,62%
firm	60,84%	60,28%
R&D	5,5%	4,14%
CEO	2,18%	0,77%
R&D:CEO	25,37%	22,60%
firm:year	44,70%	43,90%
Full model	87,14%	86,95%

Source: personal elaboration

The above results have been obtained with the "partialR2" function in R.

Note that the increment in model of year effects is over null model. The increment in model of year and firm effects are over model of year effects. Increment in model of year, Firm and R&D effects are over model of year and Firm effects and so forth to the increment in full model over null model.

Before discussing in detail the results presented, one should be aware that the right measure to look at is the adjusted R^2 as it yields more accurate results. The adjusted R^2

takes into account the number of observations *n* and the number of explanatory variables *p* in the model. Analytically, the adjusted R^2 measure is computed as follows

$$R^2_{adj} = 1 - [\,(1 - R^2)\frac{n-1}{n-p-1}]$$

where *n* = observations in the data sample and *p* = explanatory variables in the model. I am going to report the adjusted measures for increment in explanatory power.

Year effects add 12,6% to adjusted R^2. Firm effects add 60%, the biggest contribution, R&D effects add 4%, CEO effects add 0,77%, the interaction term R&D-CEO adds 22,60% and the interaction term between firm and year adds 43,90%. Finally, the entire model explains 86,95% of the variance. Firm effects are more important than any other type of effect. In order, looking at the explanatory variables, year effects are the most important (in many previous studies these effects were marginal), after firm, while R&D effects are quite important after year. CEO effects are relatively unimportant as one would have expected given the results showed in Table 5 and 6. Lastly, the interaction terms are both substantially important with the R&D-CEO term being a paramount linkage in this research. Thus, the findings in this study generally prove to be different from past literature.

I have also reported the same analysis conducted over a sample on which the time lag effects have been imposed. I have carried out the analysis considering only one level of time leg, precisely at one year. In order to do the analysis with any level of lag, it is necessary to exclude some observations from the data. In fact, if the lag is one year, then the first year of each CEO's tenure has to be deleted from the sample. Table 9 below shows the results. As in Lieberson and O'Connor's (1972) study, the CEO effect is larger when the CEO influence is lagged.

Table 12. Increment in explanatory power (incremental R^2) for each effect with no time lag and one-year lag

	No lag	One-year lag
year	13,86%	14,1%
firm	60,84%	70%
R&D	5,5%	10,9%
CEO	2,18%	3,54%
R&D:CEO	25,37%	34,8%
firm:year	44,70%	33%
Full model	87,14%	90,9%

As shown in Table 12, one-year lag results in a larger CEO effect. Specifically, the CEO effect increases from 2,18%, when measured with no time lag, to 3,54 percent, under ordinary R^2, when measured with a one-year time lag. Considering the adjusted R^2, this estimate increases from 0,77 to 1,82 percent, a more considerable impact than before but still too restricted to be considered an imperative effect. The interaction term R&D-CEO shows an increment as well, from 25,37 to 34,80 percent, meaning that, as one would expect, when CEO effect is postponed in time, the effects produced- considering managerial instruments - are amplified accordingly. On the contrary, the interaction effect between firm and year declines from 44,70 to 33 percent. Finally, the full model shows an increase, precisely from 87,14 to 90,9 percent.

As in previous table, the company effect accounts for the most variance (between 60,8% and 70%). Year effects account for substantial variance (13,8-14%) and R&D accounts for 5,5-10,9 percent of the variance.

Finally, Table 10 illustrates my results compared with those of previous studies concerning the same class of effects and, in particular, the CEO effect.

Table 13. Comparison of results with previous studies

	This study, no time lag	This study, one-year time lag	Lieberson & O'Connor (1972), two year time lag	Crossland &Hambrik (2007), no time lag	Wasserman et al. (2001),no time lag	Mackey (2008), no time lag
Year Effects	13,86%	14,1%	1,8%	3,6%	2,6%	0,7%
Firm Effects	60,84%	70%	28,5%	11,8%	6,3%	6,2%
R&D Effects	5,5%	10,9%	22,6%	19,1%	25,5%	7,9%
CEO Effects	2,18%	3,54%	32,1%	13,4%	14,7%	29,2%
Total Variance Explained	87,14%	90,9%	85%	47,9%	49,1%	44%

Source: M. Fitza 2013, Strategic Management Journal. Personal re-elaboration

ROA is the dependent variable for all studies in this comparison except for Lieberson and O'Connor who use profit margin. All studies are based on U.S. samples.

In Lieberson and O'Connor the two-year time lag is chosen because it resulted in the largest CEO effect. As illustrated, my results are somewhat negligible with respect to past studies that found, instead, considerable effects. It is important to notice that my results are not directly comparable to them though. My model comprises management capabilities effects and does not include industry effects. The R&D effects are found in the Hadner-Helfat research which is not included among the researches above. This element is paramount as it demonstrates how important strategic choices are for the organization but do not consent for direct comparison among the models above reported.

Analysis of a random sample

There is one more test that can be done to overcome some limits of previous studies on the accurateness of CEO effects that I want to report here. In particular, it is possible to determine the part of the CEO effect that can be explained by random fluctuations. However, due to the insignificant CEO effect derived by the reported results I have not run this test but, rather, I have only reported the statistical technique. With respect to this particular analysis, I am referring to Markus Fitza's work of 2013, the first research to pose the focus on this argument.

To investigate the part of the CEO effect that can be explained by chance, by randomness, an analysis in which ROA, as the dependent variable, is replaced by a random variable while everything else is held the same as in the empirical sample. The random variable could be easily created with the `rnorm` function in R. This random performance distribution is normally distributed with the same mean and the same standard deviation as the ROA used in the previous calculus. Further, to ensure that the specific features of a single new variable do not drive the results, this analysis can be conducted over n different random variables. Looking at M. Fitza's work, he found an average CEO effect based on these n analyses of 13,3 percent with a confidence interval around this mean of 12,8–13,8 percent. This 13,3 percent represents the statistical consequence that the CEO effect is inflated by the effect of randomness. In other words, if performance differences between different CEOs were only based on chance, then a variance decomposition analysis would on average find a 13,3 percent CEO effect. Thus, any CEO effect that is below this threshold cannot be distinguished from the effect of random chance. As a consequence, given the confidence interval to be significantly different from randomness, in statistical terms - that is with a p of less than 0,05 - CEO effect needs to be larger than the level emerged from this analysis.

This can be treated as a baseline effect. In fact, taking Fitza's results as reference, since randomness inflates the CEO effect, a CEO effect below or equal to 13,8 percent represents a CEO who had no influence over a company' s performance. Any CEO effect that is caused by CEO ability and leadership must be over and above this baseline.

The size of the baseline (the part of the CEO effect that cannot be distinguished from the effects of chance) depends on the number of observations per categorical variable in the model and, particularly, on the average length of CEO tenure. Intuitively, the longer the average CEO tenure, the less will the measurement of the CEO effect be inflated by chance.

As shown in Fitza's paper, running the same analysis over various sub-datasets with different average CEO tenures and selecting firms with low/high average CEO tenure yields different results. For example, in a dataset with average CEO tenure of eight years, the measured CEO effect (without considering time lag) is far higher than the measured CEO effect derived from a dataset with an average of four years after accounting for the level of randomness. These results indicate that both the CEO effect as well as the random effect increases with shorter tenure, confirming the notion that the size of the statistical artifact created by random fluctuations depends on the number of observations per categorical variable.

In my analysis I have found a robust CEO tenure of 5,75 or 6 years, comparable with that of Fitza's and thus worth proving for a comparative statistical analysis. Again, the very low CEO effect found in this study does not allow for such a test.

5) Discussion

In short, the empirical analysis conducted in this paper suggests that firm leaders account for 0,77% of the variance in corporate profitability. In other words, CEOs, on average, cannot substantially impact firm performance within the ICT industry. I want to stress the fact that CEOs, taken *individually* – that is the person of the CEO - cannot impact firm's performance. This impact has been deeply described in past studies drawing upon corporate strategies such as diversification, mergers and acquisitions. It has been even extended on business-segments through control exerted over product market strategies such as vertical integration, cost leadership, product differentiation of the segments as well as the management who run the business-segments and the accounting practices upon which assets and profits are allocated across segments.

CEO effects of 0,77 per cent of the variance in firm profitability are clearly different than most of the prior cited empirical studies of leadership effects (Lieberson andO'Connor, 1972; Thomas, 1988; Wasserman, Nohria, and Anand, 2001). While this prior work has demonstrated a relatively muted leadership impact, my research shows that this effect is somewhat negligible. Past studies showed CEO effects ranging from a low of 3,9% (Thomas, 1988) to a high of 14,7% (Wasserman, Nohria, and Anand, 2001), with biggest effects ranging from a low of 5% to a high of 15% of the variance (Salancik and Pfeffer, 1977). Similar researches have been tested on sports teams (instead of firms) as well and succession effects suggest that leaders do not impact team performance (Gamson and Becker, 1964; Eitzen and Yetman, 1972; Allen, Panian, and Lotz, 1979; Brown, 1982). My research estimates are coherent with this branch of research.

As I have said previously, CEOs' results may be influenced by a number of data sample characteristics. For example, the fact that a CEO has moved from a different industry matters as well as a move from a different company within the same industry. In my sample there are only CEOs who have moved at least once from an existing company of the same industry. In a parallel research, I have performed the same statistical analysis on the same dataset but including CEOs who had never moved from a company to another in the same ICT context. I have found significant succession effects. In particular, the fact that a CEO had been in more than one company proved to be statistically significant on firm's performance.

It is also crucial to notice that variance decomposition is not the only method for examining the linkage between CEO and organizational outcomes. In fact, the so called "structural models" that use theoretical variables to capture the specific industry, corporate or individual leadership effects on performance have also been employed (e.g. Weiner and Mahoney, 1981; Pfeffer and Davis-Blake, 1985). On the other hand, empirical studies investigating CEO performance linkage with structural methodologies are limited by their measures, samples and the same methodological limitations described above (e.g. perfectly nested samples). What are really needed are more structural studies of leadership effects to explain the *source* of the CEO effect. Structural methodologies will be helpful in explaining that leaders can have considerable impact on firm results.

With respect to perfectly-nested samples, we know they are a common feature of empirical studies in many other literatures within executive leadership such as executive compensation and succession. These samples confound individual, corporate, and industry heterogeneity. With that respect, adopting a sample with executive mobility to estimate the determinants of executive compensation would, for example, decompose the unobserved component of wages into person and firm effects, in the sense that the portion of the variance in wages due to executive ability and the portion of the wages due to unobservable firm heterogeneity can be explicitly estimated. In particular, within the succession literature, some works have drawn on samples with individual mobility and have found significant succession effects.

Previous work also pointed to the difference between "effective" and "ineffective" leaders. Practitioners have suggested that "effective" leaders are more able to influence firm performance than "ineffective" leaders do and hence, the proportion of "effective" leaders over "ineffective" ones in a sample will influence the degree of the CEO effect. The conclusion has been that while "ineffective" leaders might have no material impact on firm performance, they could destroy firm value, and hence, the presence of "ineffective" leaders in a sample, with "effective" leaders, will create more variance in the type of impact on firm performance (i.e. positive or negative).

Intuitively, significant CEO effects may mean that top executives behave differently and make different decisions even within the same or similar external environment. Further, large CEO effects may also suggest that they have their own unique styles in deciding how to manage the resources within the firm, as I have said before (e.g. aggressive versus conservative strategies or internal growth versus inorganic growth). These different styles are evident when CEOs decide whether to acquire or divest business units, layoff or hire employees, financially or organizationally restructure the firm, launch new products or enter new markets among other strategies and alliances. Just like industry and corporate effects derive by the number and type of industries a firm decides to operate in and how it competes in those industries, respectively, part of the CEO effect is dependent on how a firm chooses its competitive position. Then, in line with the resource-based view, corporate strategies and the executives who design and implement them may be important resources for the firm's ability to generate competitive advantage and create sustainable value.

In this context, I have presented these findings from a different perspective. Firm performance metrics might not always reflect the true value created by a strategic choice if the value is appropriated by an individual CEO and not by the organization members as a whole. CEOs influence organizational outcomes and vice versa. The results here presented show the impossibility for CEOs to appropriate economic rents.

Taking Adner-Helfat' paper as a yardstick, more than restating the importance of managerial decisions on firm performance, I have tried to see whether the person of the CEO, per se, would have generated the same impact. The answer is negative, in the sense that CEOs, on their own, are not capable to deliver the same results from a statistical point of view (portion of variance explained) as the R&D variable. These results are directly comparable with a branch of past literature regarding the study of CEOs' performance on organizations' returns. In fact, the interaction term between CEO and R&D shows significant statistical result and explain 22,60% of the variance in profitability, implicitly saying that CEOs do matter in reality but they have to be conceptualized in the organizational context. They deliver critical results for the firm through the cooperation of the entire corporate system. This shows why the linkage with the R&D variable is so powerful. R&D benefits are strictly connected to corporate key roles and the entire R&D process actually involves all the human and capital resources within the organization, especially in the ICT industry. Furthermore, the ICT environment consists of a number of different external and internal variables that can impact firm's achievements. That could be another possible explanation for CEOs' muted effects (or CEOs effects that do not manifest at all).

The reasons behind the R&D as the corporate managerial decision proxy equally support the results in Table 8. Here the final consideration is even broader. It is not the person of the CEO for his/her own sake who makes any difference on firm's performance but he or she, using proper managerial tools (strategies), along with all the other active organization participants. This is not new to business administration theorists and it is totally reinforced in this study.

6) Conclusions

My analysis contributes to the study of competitive heterogeneity by measuring the effect of specific corporate-level managerial decisions, driven by the so called dynamic managerial capabilities, on the variance of firm's performance. My analysis is further enhanced with the inclusion of CEO effects to assess whether interesting results were added to well renowned models. The analysis builds on the variance decomposition technique and focuses on the corporate level profitability.

Clearly, a complete understanding of the firm effect requires that research account for the impact of corporate strategy on firm performance. By definition, corporate strategy includes strategic decisions at the vertex of the organization. Strategic decisions generally need to change over time. For these reasons, this study investigated the impact of corporate strategic decisions on business profitability considering a variable that changed over time. I have adopted the R&D expenditure over operating income. I have found that even after accounting for other effects on the variance of profitability, corporate strategic decisions of this type do add statistically significant increment to explained variance. This finding provides further evidence that corporate strategy does in fact matter and this result directly links to Hadner-Helfat work on corporate strategy effect on firm performance. R&D decisions clearly came from top management and are one of the management tools CEOs can rely on. Despite facing similar conditions in the external environment, we can say that corporate managers - in different companies - made different decisions with that respect. I re-take the new concept of dynamic managerial capabilities to help explain differences in how managers respond to changes in the same external environment.

In particular, as stated in Hadner-Helfat 2001 research, there are three attributes of managers that underpin their dynamic capabilities, namely, *managerial human capital*, *managerial social capital*, and *managerial cognition*. Although past research has investigated each of these three attributes separately, much less effort has been directed towards their interactions and how they affect the ability of corporations to adapt and change. A better understanding of how these capabilities contribute to the time-varying corporate effect is yet to be seen and this could be a new point of study for future research.

On the contrary (and this is actually not directly investigated in Hadner-Helfat' paper) corporate managers do matter marginally. Taken individually, they do not provide for significant increase in explanatory power. When we consider a CEO without the management tools he/she needs for running the company, the simple fact the he or she is in charge for that position does not imply the he or she really impacts firm profitability, at least in this industry context. This paper suggests that CEO effects on the variance of firm performance may be as high as 3,54%. These results also agree with important theoretical perspectives in organizational studies that assume small CEO effects. Much of the executive compensation literature regards CEO compensation not commensurate with executive influence on firm results and much of the foundation of corporate governance theory suggests that firm differences arise due to heterogeneous governance practices in monitoring executives and not executive effects (Bertrand and Schoar, 2003). These and many other assumptions scholars have about organizations, based on small leadership effects, might accord with the empirical results found in this study.

Future research should focus on why some CEOs might matter more in influencing firm outcomes taking into consideration that variance decomposition is a crude method for controlling for the backgrounds and abilities of leaders.

My analysis indicates several new research topics for extending the variance-decomposition literature. Focusing on differences in the importance of effects within subpopulations can potentially mitigate the limitations of the decomposition method. For example, the influence of industry and corporate-parent effects is substantially different for high and low performers, as shown in McGahan and Porter (1997b, 1999).

The clearest opportunities for further research reside in exploring new data. For instance, comparable data on the accounting profits of firms in other parts of the world would yield insight on questions about the relationships between the national economic environment and industrial performance.

In this study I have also provided insights on the profitability of privately held firms and this may constitute an important contribute in making the entire research body more representative of the whole economy. Opportunities may also lie in exploring additional measures of firm performance, including stock-market return and market share. As I have pointed out in chapter 2, there have been past studies (Wernerfelt and Montgomery 1988 and McGahan 1999a) that used Tobin’s q to decompose variance and showed that industry effects are as important as in the accounting-profit studies.

Other approaches for analysis could be explored too. One would be to identify cross-sectional relationships between the industry, corporate-parent, and business-specific effects. The variation of business-specific effects within an industry may be related to the average performance of members (that is the industry effect) as indicated by McGahan 1999b. Industry characteristics may be related to diversity in the performance of incumbents as shown by Rivkin's 1997 study. Further, diversified corporate-parents may have invested in businesses with varied performance, whereas seasoned diversifiers may have similarly performing businesses. The propensity of a diversified company to enter high-performing industries may be related to the number of member businesses. Investigation of these relationships will shed light on how attractive industries emerge.

Additional research could be also needed on the inter-temporal relationships incorporated in effects. McGahan and Porter researches of 1997 (b) and 1999 address, broadly, the characteristics of these inter-temporal processes, but do not examine cross-sectional relationships in rates of serial correlation. Anyway, it is nevertheless true that both industry and business-specific effects derive by interaction in the strategies of rivals over time. The entry of diversified firms affects the evolution of a target industry. In the same way, diversifying firms may be attracted to particular kinds of industries. Decomposition of variance cannot address these issues because models would be over-specified if interaction terms were included for industry-year, corporate-parent-year, and business-specific–year effects. Anyway, further research on the interaction of effects over time will bring important insights to competitive process framework. Here, I have conducted similar analyses and these proved to be in fact critical with that respect.

In sum, my results indicate somewhat different results from major studies in the research stream. The literature's findings are generally robust. The robust findings, directly reconcilable to mine, suggest that the research has successfully shown that industry, corporate-parent, and business-specific influences are all important. New approaches should be needed to understand how industry, corporate-parent and business-specific influences interact.

Acknowledgements

I thank my Professor Alessandro Marino for his helpful and developmental review.
In addition, I am grateful to Giancarlo Ferrara for programming assistance and for providing valuable input at different stages of the development of this research.
All remaining errors are my own.

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APPENDICES

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APPENDIX A

CEO	ID
Safra A. Catz	1
Mark Hurd	2
Margaret C. Whitman	3
Jason Stern	4
John T. Chambers	5
Simon B. Moss	6
Bob Kirk	7
Andrew Miller	8
Gary R. Weis	9
Itzik Weinstein	10
Samuel M. Inman	11
Dominic P. Orr	12
BamiBastani	13
Henry B. Schacht	14
Edward J. Zander	15
George M. C. Fisher	16
Sanjay Jha	17
Antonio M. Perez	18
Mr. Hock E. Tan	19
Mr. J. Michael Lawrie	20
J. Edward Coleman	21
Barry J. Glick	22
John S. Riccitiello	23
Robert A. Altman	24
Carl J. Yankowski	25
Danny J. Windham	26
Philip M. Pead	27
Paul Maritz	28
Oscar Rodriguez	29
John S. Chen	30
Michael P. Gregoire	31
Enrique T. Salem	32
William Nuti	33
Daniel R. Hesse	34
Joseph M. Tucci	35
Rory Read	36
Ivan Seidenberg	37
Average Tenure	**5.74 years**