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EFFECTS OF R&D AND CAPITAL EXPENDITURE ON FIRM PERFORMANCE: EVIDENCE FROM TECHNOLOGY HARDWARE AND EQUIPMENT SECTOR *

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Abstract

Past research has shown positive association with accumulated R&D intensity with firm performance; however, the exact channel and magnitude of this influence seems to vary across sectors and depend on characteristics of the sample and the performance criteria chosen. Using observations from 163 firms operating on a global scale, our study focuses on the empirical relationship between R&D expenditure and firm performance in the global technology hardware and equipment sector (ICB Code 9570), in comparison to fixed capital expenditure based on a cross-sectional regression model. We find no significant association between past R&D expenditure from 2012 to 2016 and operating margin or net margin in 2017, while the impact of past capital expenditure is significant and positive. On the other hand, accumulated R&D appears to increase firm's future Tobin's Q or stock-price-to-book value; which reveals a strategic function of R&D expenditure in establishing investor optimism about the future revenue stream of the firm.

Keywords: Research and development, Capital expenditure, Firm performance, Technology hardware and equipment sector, Strategic management

ARGE ve Sermaye Harcamalarının Firma Performansına Etkileri: Teknoloji Donanımı ve Ekipmanı Sektörü

Öz

Geçmişteki araştırmalar, çoğunlukla firmanın birikmiş ARGE yoğunluğunun gelecekteki performansa olumlu katkısının olduğunu göstermiş olsa da; etkinin tam olarak hangi kanallardan gerçekleştiği ve boyutları sektörden sektöre farklılık göstermekte, seçilen örneklemin özelliklerine ve kullanılan performans kriterlerine göre değişmektedir. Çalışmada, teknoloji donanımı ve ekipmanı sektöründe (ICB Kod 9570) küresel düzeyde üretim yapan 163 firmaya ait gözlemler kullanılarak ARGE harcamaları ve firma performansı arasındaki ampirik ilişki bir kesit regresyon modeli aracılığıyla sabit sermaye harcamalarına göreli olarak incelenmiştir. 2017 yılına ait işletim kâr marjları ve net kâr marjları ile 2012-2016 arası ARGE harcamaları arasında istatistiksel olarak anlamlı bir bağlantı bulunamasa da, aynı döneme ait sabit sermaye harcamaları ile kâr marjları arasında anlamlı ve aynı yönde bir ilişki tespit edilmiştir. Öte yandan, geçmişteki ARGE yoğunluğunun bir yıl sonraya ait "Tobin's Q" ya da hisse değeri-varlık değeri oranını istatistiksel olarak anlamlı bir şekilde arttırdığı gözlemlenmiştir. Bu bulgu, ARGE harcamalarının kısa vadede kârlılığa doğrudan bir etkisi olmasa da, firmanın gelecekteki beklenen gelir akışı konusundaki yatırımcı iyimserliğini arttırma yönünde bir stratejik rol oynadıklarına işaret etmektedir.

Anahtar Sözcükler: Araştırma ve geliştirme, Sermaye harcamaları, Firma performası, Teknoloji donanımı ve ekipmanı sektörü, Stratejik firma yönetimi

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Effects of R&D and Capital Expenditure on Firm Performance: Evidence from Technology Hardware and Equipment Sector

Introduction

One of the most important changes in the standards for national income accounting in recent years was the capitalization of R&D spending. Capitalization refers to the inclusion of R&D expenditures into Gross Fixed Capital Formation (GDCF) account, and therefore treating R&D spending as an investment in fixed assets that are utilized in the production process repeated over the course of time. The former approach (which can be found in the European Systems of Accounts 1995 guidelines) was treating R&D output and imports as being exhausted within the period of purchase in the production process, similar to any intermediate good. Since the value added of any productive activity do not include the value of intermediate goods that are used up in the production process, R&D expenditures did not have any direct impact on the GDP and the contribution of R&D output to the total product was accounted for only indirectly.

The natural result of this revision is an immediate increase in the measured GDP: The Bureau of National Statistics in the US which have adopted the revised approach officially in 2013, reported a 3.5% difference between the GDPs for 2012 measured using the old method and the revised method (Moris et.al., 2015). For the OECD countries, the total impact of the revision on the level of GDP was on average 3.8%. However, despite the significant change in the level of GDP, the revision seems to have no effect on the growth rates of GDP: When the revised methodology is applied retrospectively to the GDPs measured between 1992 to 2012, the average change in the calculated growth rates were only +/- 0.1% with one exception in 2009 (van de Ven, Peter, 2015).

Even though, the inflation of any economic variable due to a change in the national accounts' calculation methodology may raise suspicion and seem like a political strategy to overstate the performance of the economic policies; capitalization of the R&D expenditures has its merits according to the economic growth literature. Treating the expenditure on R&D as intermediate or current expenses that are used up during the production process without any accumulating effects totally disregards the continuous contribution of the amassed know-how on the productivity, future profits and total sales of the firm. In this sense, R&D is similar to any fixed asset that is produced using labor and capital. Ownership rights of the resulting technology is well-defined, the outcomes of R&D activities are used repeatedly in the production process as they do not disappear at the end of the fiscal year. Like fixed capital, the contribution of R&D declines over the years due to newer technologies coming up; therefore, it is subject to depreciation (Grilliches, 1980).

Aside from theoretical justifications, the steady quantitative increase in the R&D expenditures in the last couple of decades is another motivation behind the capitalization of R&D spending in the national accounts. According to the UNESCO Institute for Statistics data, the ratio of global Gross Domestic Expenditure on R&D (GERD) to the world GDP have increased from 1.971% in 1996 to 2.227% in 2015 (UNESCO, 2015). For OECD members the corresponding ratios were 2.12% for 1996 and 2.55% for 2015. During the same period, fixed capital expenditure has in fact slightly declined on a global scale: from 23.527% of GDP in 1996 to 23.439% in 2015. The decline in capital expenditures was more significant for OECD countries; from 22.709% in 1996 to 20.971% in 2015. As a result of these trends the ratio of R&D expenditures to capital expenditures have increased from 8.3% to 9.5% globally, and from 9.3% to 12.2% for OECD economies during the same period (Galinda-Rueda & Verger, 2016).

The scale of R&D expenditures varies significantly across sectors. European Commission's the Economics of Industrial Research & Innovation (IRI) project publishes expenditure and sales data for the top 2500 firms with the highest absolute R&D expenditure annually on a global scale. The R&D spending in the IRI 2017 list is dominated by four sectors: pharmaceuticals and biotechnology, technology hardware and equipment, automobiles and parts, and software and computer services. These four sectors make up the top 62% of the total R&D expenditure across the 2500 firms: 19% by the firms in the pharmaceuticals and biotechnology sector, 16% from technology hardware and equipment sector, 15% from automobiles and parts, and 12% from software and computer services. As a side note, the combined share of these four sectors in the total capital expenditure is 31% (IRIMA, 2018). The distribution of R&D spending among sectors seems to be time consistent: The 2010 R&D Scoreboard prepared by UK Department for Business, Energy & Industrial Strategy (BIS, 2010) reports very similar shares for the leading four sectors on a global scale; only exception being the software and computer services which seems to have increased its share in total R&D expenditure from 7% to 12%.

This paper focuses on the empirical relationship between R&D expenditure and firm performance in the global technology hardware and equipment sector (THE), in comparison to capital expenditure. The firms included in our analysis were selected from the European Commission's Economics of Industrial Research & Innovation R&D Expenditure reports, that focuses on the global scale publicly traded firms with the highest amount of absolute R&D investment. Therefore, mid- or small-scale technology hardware and equipment producers are beyond the focus of this paper. It has been reported that returns to scale on R&D expenditures is related to the firm size, but the connection is weaker in the technology intensive sectors (Montresor and Vezzani, 2015). So, the generalizability of the results is problematic without further analysis including smaller scale enterprises. The technology hardware and equipment sector (Industry Classification Benchmark/ICB Code 9570) involves mainly of communications equipment (ICB 9578), computer hardware including peripherals and data storage (ICB 9572), electronic office equipment (ICB 9574), and semiconductors (ICB 9576). Technology hardware and equipment sector is one of the two main sectors of information and communications technology (ICT) manufacturers, along with the software and computer services sector. Therefore, THE consists producers of personal electronics and smart devices such as Apple and Nokia; semiconductor manufacturers such as Intel, Applied Materials Inc. and Nvidia; firms manufacturing and selling networking hardware and telecommunication equipment such as Cisco Systems and Qualcomm; and office equipment manufacturers such as Canon and Texas Instruments. It might be worthwhile to note that manufacturers of electronic leisure goods like TVs and entertainment systems are not included in THE; therefore, high technology firms like Sony and Panasonic are not included in our analysis.

Understanding the link between R&D expenditure and firm performance is naturally vital from a management point of view, but it is also important from an economist's perspective in evaluating the benefits from R&D direct and indirect support policies. Even though, the link was explored by a large number of studies, few of them concentrates in the technology equipment and hardware sector specifically, and ever fewer have a global scope as the current study. Shin et.al. (2009) uses international data from top 300 leading electronic businesses between 2000-2005 in order to analyze the influence of R&D spending on profits and firm value. However, their database includes not only the THE firms but also software firms such as Microsoft and consumer electronics firms such as Samsung. Another study by the same researchers (Shin et.al., 2017), repeat the model using data from 21 semiconductor firms that operate internationally. Ortega-Argilés et.al. (2009) explores the R&D-performance relationship for 203 European small-to-medium scale enterprises with the highest absolute R&D spending; 27 of which are THE firms. Their analysis uses a partition clustering algorithm and elaborates on sectorial composition of different clusters. We will compare the outcomes reported by these studies with our findings after we present the regression results below.

The next section will introduce the sample used in the analysis and identify the specific performance variables and related independent variables that are used in the model, as well as the details of the econometric model used. Justifications for the choice of the variables will also be given in Section 2, in the light of the related literature. Section 3 will present the empirical results from the econometric analysis, along with the possible economic interpretations of the findings for each performance variable. In the final section, concluding remarks will be presented and possibilities for further research will be discussed.

1. Theoretical Background, Data and Analysis Method

The sample consists of observations from 163 firms that are categorized in the "Technology and Hardware Equipment (THE) sector. As will be explained in more detail below, R&D and fixed capital expenditures by firms are treated in a cumulative fashion, so even though we are constructing a cross-sectional model without any time dimensions, the observations for R&D intensity and capital intensity are calculated using the reported values for years between 2012 and 2016. The dataset was created by selecting the THE firms from the "R&D ranking of the world top 2500 companies" data published every year by European Commission's Economics of Industrial Research & Innovation (IRI) Project (EU IRI, 2017). The source data, as the name suggest, presents R&D expenditures, capital expenditures and net sales of the 2500 top firms with the highest absolute R&D expenditures. This focus on "top firms" may clearly introduce a degree of selection bias favoring large-scale firms into our analysis, but a certain degree of selection bias is inevitable on the global scale considering data limitations. Another possible bias is in regards of survivorship: In order to ensure data continuity, firms that didn't make it to the IRI Top 2500 firms list in every single year between 2012 and 2017 were omitted in our analysis.

The data used in calculating firms' sale growth performance in 2017 were also extracted from the IRI dataset. The rest of the variables were taken from the end-of-the-year accounting reports issued by the firms at the end of 2017 and the stock market data from December 29th, 2017 which was the last day of trading for 2017. Further details about the calculation of the variables in our model will be given below, along with their definitions.

One of the main independent variables in the model is **R&D intensity (RDI)**-the ratio of R&D expenditure to the total sales revenue. Experimental research, product development and enhancement and the related operating costs are all included in the R&D expenditure. Normalization of monetary value of absolute R&D expenditures with respect to sales revenue is quite common in the related literature (see Gentry & Shen (2013), Kotabe et.al. (2002) and Belderbos et.al. (2004), for example). Another benefit of this normalization is getting rid of scale effects that may occur when dealing with firms with varying sizes with respect to sales revenue as no need arises to adjust observations according to the changing relative values of currencies within the period of interest.

Our second main independent variable is **capital intensity (CI),** which is measured as the ratio of (fixed) capital expenditures to the sales revenues. including purchases of property, plant and equipment; acquisition expenses and maintenance costs.

Both R&D intensity and capital intensity figures enter our analysis in a cumulative manner: All observations from 2012 to 2016 are aggregated to figure out the accumulated R&D intensity and capital intensity. Different rates of depreciations were applied to R&D intensity and capital intensity; more specifically 30% for R&D intensity and 20% for capital intensity. OEDC Productivity Database uses a fixed 10-year service life for R&D expenditures, which corresponds to a 20% annual depreciation rate (Schreyer and Zinni, 2018), however, empirical sector specific analysis reports varying but higher depreciation rates for THE sector (Hall, 2007; Warusawitharana, 2015). A more recent study by Li and Hall (2016) reports R&D expenditure depreciation rates close to 30% on average for THE. Although there have been numerous studies that empirically estimate R&D depreciation rates in high technology sectors, there are only few studies estimating physical capital depreciation rates for THE specifically. 20% depreciation rate we use is in accordance with the sector specific estimates by Nomura and Suga (2018) based on disposal surveys in Japan, as well as the manufacturing equipment service life durations estimated by Barth et.al. (2016). Naturally, the precise depreciation rates might vary across sub-sectors or even across individual firms with similar sub-sector, firm size, R&D and capital intensities; but calculating firm specific depreciation rates for the sample would necessitate building an additional complex estimation model which would be beyond the scope of the current study. However, it should be emphasized that the statistical significance and the values of the estimators are not sensitive to the depreciation rates chosen; increasing or decreasing the rates by 10 points for both R&D and capital intensity reveals no significant changes in our results.

For each firm, the (depreciated) cumulative value is calculated using the equation:

$$X = \sum_{t=0}^{4} (1 - \delta_i)^t x_t \qquad (1)$$

where x_t is the R&D or capital intensity in period t and X is the final figure that enters the regression for each variable; while δ_i equals to 0.30 for R&D intensity and 0.2 for physical capital intensity. The period indicator t takes the value 4 for the year 2012, 3 for 2013 and so on.

While applying a depreciation rate to the fixed capital values would seem trivial, applying depreciation to R&D expenditures might not be as intuitive at the first glance. Arguably, any novel technology or knowledge gained as a result of R&D spending is an intangible asset for the firm, and therefore not subject to any wear and tear like the physical capital stock. However, the R&D stock accumulated over the years cannot be expected to retain its contributions on firm's performance at a constant rate. While equipment and machinery lose their value due to wear and tear, the intangible know-how loses its impact over time as technologies become obsolete and new products are bound to be imitated by competing firms. On the other hand, applying a constant and arbitrary depreciation rate to both R&D and capital may seem like a stretch. Technically, the depreciation rate applied to R&D expenditures should capture the rate of decline in the contribution of past R&D expenditures on the firm's future private returns, if no further investments on R&D is made. Therefore, its value might potentially vary between firms and over the years for the same firm. However, as argued by Hall (2007) and Hall and Griliches et.al (1986), precise calculation of individual depreciation rates for each firm for each period requires vast amount of retrograde data and usually not worth the effort for sector-based analysis of multiple firms, since R&D series for a single firm usually displays close to random walk behavior over time (see Kafouros (2008) for a more detailed discussion on this issue).

Firm's size (Size), which is the ratio of total assets of the firm to its sales revenue within a given year, is another independent variable we use in our model in order to control for the effect of total assets acquired by the end of 2016 on the firms performance variable measured at the end of 2017. In calculating the size variable, total asset values from accounting reports were used along with sales revenue data from the IRI dataset.

Leverage (Lev) is also among the independent variables used. Leverage value of a firm is the ratio of total debt of the firm to the total assets. Leverage indicators were taken from accounting reports of the corresponding firms at the end of 2017. Controlling for leverage has critical importance for the performance variable *net profit margin*, defined by the ratio of net income over sales, since a high leverage ratio leads to high interest payments which directly lowers net income of a firm (Xu & Birge, 2008).

Usage of firm size and leverage as control variables is quite common in the literature regarding the connection between research and development expenditure or similar strategic investments and firm profitability and performance, especially after the influential paper by Jaffe (1986). Loch et.al. (1996), uses similar variables in analyzing the effect of technological innovation on firm performance in the electronics industry. More recently, Lee and Wu (2016) used a similar model for the effects of slack variables on R&D performance. Ho and others (2006) focus on R&D investment and firm size in relation to generating growth opportunities for the firm.

Four distinct dependent variables are used as measures of firm performance in our model:

Tobin's Q is a measure of firm's financial market performance, first suggested by Kaldor (1966). More precisely, Tobin's Q reflects the stock market's valuation of the future revenue flow potential of the firm and calculated as the ratio of the market value of the firm (current stock value) to the replacement value of the total assets of the firm (i.e. current total asset value). In the past, Grilliches (1979) suggested a positive and significant impact of accumulated R&D expenditure with Tobin's Q in various research-intensive sectors after reviewing sector-based empirical studies. Grilliches' generalized results were challenged by Erickson and Jacobson (1992) but it should be kept in mind that the later study focuses only on American and Japanese firms actively traded in the corresponding stock markets, and does not exclusively focus on sectors with high R&D intensity, such as pharmaceuticals, informational technology, or automobiles. More recently Bharadwaj and others (1999) finds strong relations between R&D intensity and stock market performance in the information sector, which in part includes THE. Collonly and Hirschey (2005), also reports significantly higher impact of R&D spending on Tobin's Q in large-scale firms compared to smaller firms, which serves as another justification to include firm size as an independent control variable in our model. Overall; since our model focuses on THE sector which is a high R&D-intensity sector, and only includes large-scale firms due to the nature of the dataset; in the light of similar empirical analysis in the existing literature we should expect significant positive relationship between accumulated R&D-intensity and stock market performance of the firm, captured by Tobin's Q.

Sales growth in 2017 is another dependent variable and firm performance indicator in our model. Morbey and Reither in their 1990 review article point out that while earlier studies failed to demonstrate any clear link between accumulated R&D expenditures and accounting profits, a significant positive link has been established between R&D and sales growth. Dugal and Morbey (1995) shows past R&D expenditure have a positive effect on sales growth consistently across sectors, even during the 1991 Recession. Among sector-based research, Nolan et.al.(1990) and Demirel & Mazzucatto (2012) reports similar results for the UK pharmaceuticals sector. Hall (1986) and Singh (1994) find past

R&D spending improves sales growth performance in manufacturing sectors of US and India, respectively. Sales growth is also interesting in its impact on the firm's future survivability and asset growth (see Ramaswamy et.al., 2008; Zheng et.al, 2015).

Operating margin at the end of 2017 is our first profit-related performance variable. Operating margin is calculated as the ratio of operating earnings (sales minus general and administrative expenses and costs of output sold) to the sales revenue. Operating margin has two advantages for analyzing profit performance on a global scale: (i) It is pre-tax, so any interference due to international differences in corporate tax policy is controlled for, and (ii) it is also pre-interest, therefore, does not depend on firm's current debt stock. Although, Hsieh et.al. (2005) finds positive relationship between past R&D intensity and subsequent operating margin for pharmaceuticals sector in US, broader-scale research such as Eberhart et.al. (2004) and Hall & Mairesse (2009) report no significant impact. Since there is no clear consensus in the literature, it is interesting to see whether the results of Hsieh et.al (2005) indicating a significant positive impact on operating profit margins in pharmaceuticals sector would be repeated for technology and equipment hardware equipment sector: As mentioned above; while the pharmaceuticals sector is typically characterized by high R&D expenditure and relatively low capital expenses, THE sector has a more balanced distribution of R&D and fixed capital investments (IRIMA, 2018).

Net margin at the end of 2017, on the other hand is the ratio of net income of the firm to its total sales. Net margin is different than operating margin, as it reflects the profit margin after tax and interest. Since interest costs are factored in, a negative relationship between the independent leverage variable and the net margin of the firm is to be expected. Also, any significant relationship between operating margin and R&D intensity or capital intensity should be expected to be valid for net margin if distortion caused by debt stock and tax policy differences are minimal. Naturally, it would be interesting to observe a systematic difference between the impact of R&D intensity on operating margin and on net margin, from a corporate finance and corporate trade policy standpoint. Remarkably, Shin et.al. (2017) has found a significant negative relationship between past R&D intensity and net profit margin in the semi-conductor industry. Even though their sample only consists of 21 firms, inclusion of net margin as a performance variable in our model was in part motivated by their results; as technology and equipment sector encompasses semiconductor producers and have similar characteristics in terms of R&D expenditure relative to fixed capital expenditure.

We also utilize **sub-sector dummies** for three of the four subsectors identified within the technology hardware and equipment sector: computer hardware including peripherals and data storage (**DumComp**), electronic office equipment (**DumOff**), semiconductors (**DumSem**), and communications equipment. These subsectors might potentially vary in terms of market structure and firm sizes. Summary statistics for the subsectors presented below in Table 2, for example, suggest electronic office equipment is highly concentrated with few leading firms similarly sized in terms of physical capital intensity such as Canon and Xerox similar in physical capital intensity, while the semiconductors industry is relatively competitive including many firms with various degrees of capital intensity. Time specific external influences, such as an isolated change in demand in a specific subsector in 2017, the year our performance variables were taken from, also need to controlled for. Application of subsector dummies will check for potential sub-sector specific effects on the dependent variables.

Table 1 below displays short definitions summary statistics for the variables used in our model. Table 2 presents the summary statistics for each subsector defined within the technology hardware and equipment sector; namely computer hardware including peripherals and data storage (ICB 9572), electronic office equipment (ICB 9574), semiconductors (ICB 9576), and communications equipment (ICB 9578).

Table 1. Variable definitions and Summary Statistics (All Subsectors Combined)

Variable	**Definition**	**Label**
Dependent		
Operating Margin	Operating income before Depreciation and R&D/Sales	OperM
Net Margin	Net income after operation costs, taxes and interest/Sales	NetM
Sales Growth	(Sales 2017/Sales 2016)-1	SalesG
Tobin's Q	(Market Value of Equity)/Total Assets	TobinQ
Independent		
R&D Intensity	Accumulated and Depreciated R&D Expenditures/Sales	RDI
Capital Intensity	Accumulated and Depreciated Capital Expenditures/Sales	CI
Firm Size	Total Assets/Sales	Size
Leverage	Total Debt/Total Assets	Lev
Sub-sector Dummy Variables		DumComp, DumOff, DumSem

Technology Hardware and Equipment Sector (ICB 9570)					163 Firms
Variable	**Mean**	**Median**	**Standard Deviation**	**Min.**	**Max.**
Operating Margin	7.8769	7.00	19.7372	-163.90	56.57
Net Margin	4.2169	5.15	20.4604	-180.72	45.04
Sales Growth	0.0732	0.0410	0.2076	-0.4899	0.9402
Tobin's Q	2.9778	2.45	2.7847	-10.68	19.74
R&D Intensity	0.3798	0.3273	0.2672	0.0121	1.6243
Capital Intensity	0.1902	0.1168	0.2439	0.0033	1.8559
Firm Size	1.3526	1.2865	0.7295	0.0013	4.1388
Leverage	0.1957	0.1819	0.1550	0.0000	0.7056

Table 2. Summary Statistics for Subsectors

Computer Hardware Including Peripherals and Data Storage (ICB 9572)					37 Firms
Variable	**Mean**	**Median**	**Standard Deviation**	**Min.**	**Max.**
Operating Margin	9.9565	5.95	14.9488	-19.92	56.57
Net Margin	6.5486	3.13	16.5561	-34.08	45.04
Sales Growth	0.1345	0.0508	0.2172	-0.1544	0.7718
Tobin's Q	3.1157	2.28	3.1407	0.00	19.74
R&D Intensity	0.2290	0.1658	0.1999	0.0129	0.8467
Capital Intensity	0.1622	0.1046	0.2001	0.0033	0.9265
Firm Size	1.3031	1.2931	0.7824	0.0015	3.5648
Leverage	0.2230	0.2172	0.1419	0.0000	0.5682

Electronic Office Equipment (ICB 9574)					9 Firms
Variable	**Mean**	**Median**	**Standard Deviation**	**Min.**	**Max.**
Operating Margin	6.3600	15.22	29.3497	-48.12	40.32
Net Margin	-4.0678	5.16	30.1847	-61.30	24.38
Sales Growth	-0.0349	0.0285	0.1801	-0.4899	0.1369
Tobin's Q	3.1578	1.90	3.1332	0.88	9.93
R&D Intensity	0.2570	0.1385	0.2238	0.0708	0.7832
Capital Intensity	0.1282	0.1492	0.0561	0.0553	0.2208
Firm Size	1.8683	1.9913	0.6873	0.3907	2.7181
Leverage	0.2652	0.2311	0.1847	0.0000	0.7056

Table 2. Summary Statistics for Subsectors (cont.)

Semiconductors (ICB 9576)					**70 Firms**
Variable	**Mean**	**Median**	**Standard Deviation**	**Min.**	**Max.**
Operating Margin	7.4234	7.70	23.7581	-163.90	39.58
Net Margin	3.7006	6.395	25.0836	-180.72	35.10
Sales Growth	0.0571	0.0455	0.1967	-0.4086	0.8914
Tobin's Q	2.7611	2.935	2.4504	-10.68	10.90
R&D Intensity	0.4772	0.4442	0.2894	0.0691	1.6243
Capital Intensity	0.2377	0.1324	0.3041	0.0173	1.6243
Firm Size	1.3163	1.2894	0.6655	0.0013	3.2005
Leverage	0.1836	0.1603	0.1623	0.0000	0.1603

Communications Equipment (ICB 9578)					**47 Firms**
Variable	**Mean**	**Median**	**Standard Deviation**	**Min.**	**Max.**
Operating Margin	7.2055	5.89	12.8403	-29.77	39.58
Net Margin	4.7366	4.64	10.3153	-27.21	35.10
Sales Growth	0.0697	0.0323	0.2071	-0.3572	0.9402
Tobin's Q	3.1574	2.22	2.8604	0.66	16.27
R&D Intensity	0.3782	0.3515	0.2160	0.0121	1.1139
Capital Intensity	0.1535	0.0938	0.1740	0.0221	1.0311
Firm Size	1.3470	1.1871	0.7476	0.018	4.1388
Leverage	0.1788	0.1628	0.1404	0.0000	0.5735

2. The Model

As mentioned above, we built our regression on cross-sectional firm level data, and only two of the independent variables, namely accumulated R&D intensity and fixed capital intensity, as calculated using data from years between 2012 and 2016 (see Equation 1 above). The rest of the variables are from the end of year 2017. The regression equation takes the form:

$$y_i = c + \beta_1 RDI_i + \beta_2 CI_i + \beta_3 SIZE_i + \beta_4 LEV_i + \beta_5 DumComp + \beta_6 DumOff + \beta_7 DumSem + \varepsilon_i \quad (2)$$

where c is the constant term, RDI_i is the accumulated R&D expenditure as a ratio of sales revenue, CI_i is the accumulated fixed capital expenditure as a ratio of sales revenue. $SIZE_i$ is the total asset to sales revenue ratio for 2017. LEV_i refers to the leverage in 2017 (dept to asset ratio) for the firms and the *DumComp*, *DumOff* and *DumSem* are sub-sectoral identifier variables for computer hardware, electronic office equipment, and semiconductor firms respectively. Identifier for communication equipment producers was omitted to avoid dummy trap.

Our dataset consists of 163 firms of various sizes, operating in 15 different countries. Furthermore, the technology and hardware equipment sector by definition includes firm operating in very different markets: Firms like Accton or ZTE operate in network systems industry; Nokia, Motorola, ZTE and others focus on telecommunication equipment; Intel and AMD primarily develop and produce micro-processors; Mediatek, ASE and others manufactures semi-conductors for different purposes. On the other hand, although our independent variables were chosen considering the related literature regarding sector-based firm performance analysis, a certain degree of collinearity between the predictors is to be expected given the variable definitions: For example, the value of total assets of the firm is used in calculating both leverage and size variable, albeit to a different effect; or a high R&D intensity might mean a high capital intensity if the firm is growing during the period of interest. Therefore, considering the characteristics of our data and the model we use, we test our data for multicollinearity and heteroscedasticity using Variance Inflation Test (Farrar & Glauber, 1967) and White Test (White, 1980) respectively.

In terms of multicollinearity, none of the variables reveals a Uncentered VIF value above 5, the highest value belongs to Firm Size with 4.6977. Since the commonly accepted "rule of thumb" in social sciences is eliminating regressors with VIF values above 10, we choose to keep all variables given the results of the test (see O'brien (2007) for a detailed discussion regarding multicollinearity and VIF test in social sciences).

Although, R^2 based White test indicator does not reveal any heteroscedasticity, the "Scaled Explained Sums of Squares" test indicator points to a significant degree of heteroscedasticity. Scaled explained sum of squares is based on a normalized version of the explained sum of squares from the auxiliary regression used in White test, therefore asymmetric results of these two indicators leads to a certain degree of ambiguity about heteroscedasticity (see Brooks (2014) for a more detailed take on the issue). It is worth mentioning that the same issue arises when Breusch-Pagan-Godfrey test is applied, as well.

In order to control for the impact of possible heteroscedasticity on standard errors, we use "robust least squares estimators" as suggested by White (1980). Theoretically speaking, usage of robust standard errors will not have any impact on the estimated coefficients if there is no heteroscedasticity but alter the results if there is significant heteroscedasticity in the data (Croux et.al.,2003; Wilcox & Keselman, 2004).

Another benefit of using robust least squares estimators is dealing with outlier problems in a systematic fashion. As the minimum and maximum values and standard deviations given in Table 1 and 2 suggests, there is a potential risk of outliers in our data set. However, instead of arbitrarily eliminating potential outliers, robust least squares methods offer a more systematic way for controlling extreme influences of potential outliers without eliminating the related observations using either Huber's or Tukey's Biweight influence functions (See McKean (2004) for a more detailed explanation).

3. Results

Table 3 presents robust least squares regression coefficient estimates for our model, separately for each of our four dependent performance variables. We report the "M-estimation" results first introduced by Huber (1973) with Huber Type-I standard errors; however, application of alternative estimation procedures, such as method of movements or "MM-estimation" suggested by Yohai (1987), does not alter the statistical significance of our results.

Table 3. Regression Results (M-Estimation with Huber Type I SE&CV)

	Constant	**R&D Intensity**	**Capital Intensity**	**Size**	**Leverage**	**DumComp**	**DumOff**	**DumSem**
Dependent Variable								
Operating Margin	-0.6484 (2.8753)	3.1292 (3.8046)	**10.4789 *** (3.8375)**	**5.0821 *** (1.2871)**	-3.0821 (6.1255)	1.1735 (2.6468)	**9.1419 ** (4.3632)**	1.3716 (2.2596)
Net Margin	-0.6078 (2.620871)	1.7107 (3.4679)	**8.0405 *** (3.4980)**	**4.7206 *** (1.1732)**	**-12.6732 ** (5.5834)**	2.9653 (2.4126)	6.0668 (3.9771)	1.7907 (2.0597)
Sales Growth	0.0263 (0.0382)	**0.1017 ** (0.0505)**	-0.0133 (0.0509)	-0.0201 (0.0171)	-0.0188 (0.0813)	0.0403 (0.0351)	-0.0055 (0.0579)	-0.0040 (0.0299)
Tobin's Q	**1.8699*** (0.3761)**	**1.0070 ** (0.4976)**	-0.2592 (0.5019)	0.1087 (0.1684)	0.1876 (0.8012)	-0.2838 (0.3462)	-0.8757 (0.5707)	0.2235 (0.2955)

(*) (**) (***) represents statistical significance at 10%, 5% and 1% respectively.

The first performance (dependent) variable presented in Table 2 is **operating profit margin**, or the ratio of the operating income of the firm before depreciation and R&D expenditures to sales revenue. Although, the estimated coefficient of accumulated (and depreciated) R&D intensity is positive, it is not statistically significant even at 10% confidence interval. On the other hand, capital intensity coefficient is positive and significant. Therefore, the results show no significant impact of past R&D expenditures on operating profit margin for the firms in the THE sector. Subsector dummy variable for the electronic equipment sector is positive and statistically significant for operating margin, indicating higher overall operation profits in the office equipment sector. No other sub-sector based differences were detected via the dummies as seen in Table 3.

The next independent performance variable we look at is **net profit margin**; the ratio of firm's net income (after depreciation, all operating costs, capital and R&D expenditure, corporate taxes and any interest payments) to sales revenue of the firm. Once again, no significant impact of accumulated R&D intensity has been found on net profit margin; but accumulated capital intensity has a significant and positive effect on net profits of the firms. It should be noted that firms' leverage (debt to assets ratio) has no significant impact on operating profit margins, but a negative and significant impact on net profit margin as expected, since net income is calculated after interest costs.

Results for profit margins is somehow in accordance with the related literature. Although, some research focusing on the pharmaceuticals sectors have reported significant relationship between past R&D intensity and subsequent profitability (Grabowski & Vernon, 1990; more recently Hsieh et.al., 2005) these results are not repeated for more broadly-defined sectors such as manufacturing (Hall & Mairesse, 2009). For the technology hardware and equipment sector and its subsectors specifically, Shin et.al. (2009) reports no significant relationship between R&D expenditures and profits in the short-term in the global electronics sector and Shin et.al. (2017) reports a negative significant relationship for 21 semiconductor producers. Ortega-Argiles et.al. (2009) once again reports no significant relationship between R&D expenditures and profitability for European technology hardware and equipment firms.

On the other hand, our model reveals a positive link between the R&D intensity accumulated between 2012 and 2016 with percentage increase in total sales (**sales growth)**, although it is barely significant in 10% confidence interval. As mentioned above, literature on R&D generally report a strong link between research investments and firms' revenue growth (Dugal & Morbey, 1995; Zheng et.al, 2015; Demirel & Mazzucatto, 2012; Hall, 1987). Therefore, while our results might be interpreted as confirming previous research on the subject, further analysis is clearly needed to establish a more robust association between R&D investments and future sales revenue growth in technology hardware and equipment firms. Time dimension of our current database is too limited for a panel data analysis (2012-2017), but a model with a time dimension supplemented with a broader database may lead to less ambiguous results than what is presented here.

The final performance variable in Table 2 is **Tobin's Q** (sometimes referred to as "price-to-book ratio"). Our regression results suggest a statistically significant positive link between past R&D intensity and next year's Tobin's Q values. Unlike profit margins or sales growth that reflect firms' current accounting performance, Tobin's Q indicates the anticipated future performance of the firm in the financial markets. One point that needs to be addressed about using Tobin's Q in regression analysis has to do with possible negative values of the variable. Since stock prices cannot go lower than zero, a negative Tobin's Q value means negative book value for the firm (due to financial distress experienced by the firm at the time). The common interpretation of Tobin's Q is that it reflects by how much the particular firm is *overvalued* or *undervalued* by the stock market; it is a measure of how much an investor buying the stock today will lose if the company goes bankrupt tomorrow (Wernerfelt & Montgomery, 1988). Therefore, while a very low but positive value indicates a clearly undervalued firm, a low and negative Tobin's Q most probably means the stock is overvalued, given the financial difficulties suggested by the negative book value. One solution to this problem might be using the absolute value or the squared value of the Tobin's Q variable. Fortunately, our sample has only one negative observation for Tobin's Q (belonging to NXP Semiconductors from Netherlands), so this issue is not a critical cause for concern in our regression. It should still be mentioned that using squared values of Tobin's Q improves the statistical significance of R&D intensity coefficient from 5% to 1% (results not shown in Table 2).

Past research has shown similar links between price to book ratio and R&D expenditures, especially in technology intensive sectors such as pharmaceuticals (Hsieh et.al, 2005) or information technology (Bharadwaj et.al., 1999).

Overall, our results only partially mirror the findings of related empirical literature: (i) Past R&D expenditure has no statistically detectable immediate impact on firm's profitability in the short run. On the other hand, capital expenditures along with a firm's total assets (size) has a significant effect on the next period profit margins; (ii) Although, our model reveals a positive relationship between R&D and sales growth, it is only significant at 10% confidence interval. So, our results neither confirms nor denies the empirical literature on high-tech firms. (iii) As anticipated, our model reveals a significant positive relationship firm's price-to-book ratio which reflects the optimism of financial markets towards the firm's future revenue stream, much more than fixed capital investment. High R&D expenditures with respect to sales revenue signals the firm is after the innovations that will bring in profits in the long run.

4. Comments and Suggestions for Further Research

Globally, technology hardware and equipment industry is second only to pharmaceuticals in terms of total R&D spending. It is natural to ask whether these investments are justified by short term profitability, at least as much as fixed capital investments. We built a cross-sectional regression model to test the impact of capital and R&D expenditures relate to size on the profit margins, sales growth and finally, the stock-market value of the firm relative to its assets value. We found while accumulated R&D investment have no impact on next year's profit margins, it has a net positive effect on stock value. Next question to ask might be whether the firms use R&D expenditures to signal determination to innovation and new technologies towards investors in order to gain market capitalization or acquire an advantageous position in potential future mergers, as suggested by Kothari et.al (2006) or Saad and Zantout (2017). On the other hand, there is a clean link established between firm productivity growth and R&D (Griffith et.al., 2004; Ortega-Argiles, 2015). Therefore, higher stock market to book value ratios may be a result of investors accurately anticipating increased future income flow as a result of the productivity increase, even though profit margins do not reflect any immediate rise in revenue, at least in the short run. The answer to the question is not only important from a business management perspective but also from a policy design angle: Since most governments provide public funds or tax incentives to encourage R&D activities directly, it is valid to ask whether these incentives bear any fruit in terms of increased profitability and competitiveness for the firms to allow them to expand and create jobs. In order words, it would be quite a different story if the increasing impact of R&D intensity on the expected future profitability by the stock markets is never realized in the years that follow, leading to overinvestment behavior by the firms partially in order to boost the price-to-book ratios today. R&D investments by their nature bear higher risks and uncertainty with respect to increasing firm's future performance compared to physical capital investments, however, immediate returns in terms of raising stock value might distort the efficiency of the allocation of investment resources between tangible and intangible forms of capital. Therefore, intangible asset accumulation decisions by firms cannot be interpreted solely on a performance and profitability basis, stock market performance and shaping investor expectations could also motivate investing in R&D and other intangible assets such as advertisement and brand recognition.

Naturally, the validity of our results is very restricted, given the data limitations and survivorship bias, as mentioned earlier. Although, the fact that most of our results parallel the predictions by previous researchers might be encouraging with respect to the precision of our results; a panel data analysis making use of a more inclusive dataset with broader time dimensions would answer these questions more accurately.

Extending the analysis to other similar sectors such as software and network services or automobiles, on the other hand, would allow a test for generalizability of the results across industries. Going the opposite way and increasing focus on the sub-sectors of technology hardware industry like semiconductors or telecommunication equipment is another possibility that would allow to capture the interdependent strategic aspects of R&D investments suggested by Teirlinck & Spithoven (2013) or Matsumura et.al. (2013).

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