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The financial impact of taxation reform in Greek ICTs companies

Dimitris Balios[1,2], Dimitris Karasmanoglou[2] and Stefanos Tantos[2,3]*

[1]Department of Economics, National and Kapodistrian University of Athens, Athens, Greece.
[2]National and Kapodistrian University of Athens MBA, Athens, Greece.
[3]Department of Accounting and Finance, University of West Attica, Athens, Greece.

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The present study examines the factors influencing the variation of effective tax rates in the information technology and communications sector, specifically focusing on telematics in Greece. The period under investigation spans from 2008 to 2018, during which the country experienced a prolonged crisis. This research makes dual contributions; both empirically and methodologically, to the extensive literature on corporate taxation, with a specific focus on the Greek Information and Communication Technology (ICT) sector. By providing a nuanced analysis of the fiscal framework surrounding Greek ICT companies, the study enriches scholarly discussions and offers practical insights for policymakers, practitioners, and businesses navigating the dynamic ICT industry. The data analysis, conducted using regression models, reveals that factors such as research and development (R&D) size and intensity, as well as capital intensity, inventory intensity, and profitability, have a negative impact on effective tax rates.

Key words: Corporation tax, effective tax rates, information, communication technology, R & D, Greece.

INTRODUCTION

In the fall of 2007, the global financial crisis began in the U.S. mortgage market and quickly spread, affecting the economies of many countries. European nations faced liquidity problems and increased public debt in their banking systems, with notable examples including Ireland, Portugal, Spain, Cyprus, and Greece. By the end of 2008, the crisis reached Greece, which experienced its worst recession since World War II. Greece's efforts to join the common monetary union began in the mid-1990s, leading to a fifteen-year period of rapid development and financial growth. Greek banks borrowed from the markets at low interest rates and, in turn, lent to businesses and households. This influx of money led to increased domestic demand, a surge in imports, rising wages, and higher government spending. However, tax revenues and exports did not increase proportionally. Investments were focused on infrastructure and construction rather than production. By the end of 2009, Greece, following an economic model with continuous primary deficits, had accumulated a debt of 110% of GDP. Due to the global financial crisis, markets and investors began avoiding capital investments with even moderate risks. To attract loan capital, Greece had to raise interest rates, which further increased its borrowing risk and debt, making it unsustainable. The country sought assistance from the European Central Bank (ECB), the European Union (EU),

*Corresponding author. E-mail: stantos@uniwa.gr. or stantos@econ.uoa.gr.

and the International Monetary Fund (IMF), signing three loan agreements (memorandums) in 2010, 2012, and 2013. These agreements, approved by the Greek Parliament, aimed at fiscal adjustment and economic consolidation to eliminate fiscal deficits and achieve high primary surpluses over time.

The global financial crisis had a profound impact on various sectors, including the Information and Communication Technology (ICT) sector in Greece. As financial instability spread through the economy, businesses across all industries faced challenges such as reduced consumer spending, tightened credit conditions, and decreased investment. The ICT sector, which is crucial for driving innovation, productivity, and competitiveness, experienced significant disruptions.

Research by economists such as Reinhart and Rogoff who have extensively studied the effects of financial crises on economies worldwide, highlights the sector's vulnerability due to its reliance on capital-intensive projects and its interconnectedness with other sectors. ICT companies struggled with shrinking budgets, postponed projects, and reduced demand for their products and services. Additionally, their dependence on imported technology and equipment exacerbated the crisis's effects due to currency fluctuations and supply chain disruptions.

Therefore, a detailed examination of the impact of tax reforms on the ICT sector is essential to understand the broader implications of fiscal policies on Greece's economic recovery and technological advancement. This paper aims to explore the effects of tax reforms from 2008 to 2018 on Greek businesses, with a particular focus on the IT and communications industry. The sector was chosen due to its significant role in the modern economy and its sensitivity to changes in tax policy. As a major contributor to economic growth and a leader in technological innovation, the ICT sector provides valuable insights into the impacts of tax reforms. This study will use microeconomic data from the financial statements of IT and communications companies to examine and analyze the factors affecting actual tax rates.

This research study makes dual contributions; both empirically and methodologically, to the extensive literature on corporate taxation, with a specific focus on the Greek ICT sector. By delivering a nuanced analysis of the fiscal framework surrounding Greek ICT companies, the study enriches scholarly discussions and offers practical insights for policymakers, practitioners, and businesses navigating the dynamic ICT industry. The empirical contribution lies in its comprehensive examination of the fiscal environment faced by Greek ICT firms, shedding light on the intricacies of tax policies and their impact on business operations, investment decisions, and overall economic performance within the sector. Methodologically, the study employs rigorous analytical techniques and utilizes microeconomic data from financial statements, providing a robust framework for assessing the efficacy of tax reforms and their implications for corporate behavior and economic outcomes. Thus, this research advances understanding of corporate taxation dynamics in Greece and offers actionable insights for policymakers and practitioners aiming to foster a conducive environment for sustainable growth and innovation within the ICT industry.

LITERATURE REVIEW

Taxation reform is a critical factor influencing the financial landscape of businesses, and its implications have been studied by scholars across various time periods and contexts. Zimmerman's seminal work in 1983 laid the foundation for understanding the complexities of tax-related decision-making within firms. Zimmerman emphasized the importance of considering both financial and non-financial factors in shaping tax policies, offering a holistic perspective that serves as a theoretical framework for comprehending the multifaceted impact of taxation reform on companies.

Building on Zimmerman's groundwork, Lazăr and Filip (2011) explored the specific context of ICT companies. Their study focused on the unique challenges and opportunities presented by taxation reforms within the ICT sector. Lazăr and Filip (2011) argued that the dynamic nature of the ICT industry requires a nuanced understanding of tax implications, as these companies often operate in a globalized and technologically evolving environment. Their findings highlighted the need for tailored tax strategies to navigate the intricate landscape of the ICT sector, emphasizing the sector-specific considerations that influence financial outcomes.

In the broader context of corporate taxation, Hanlon and Heitzman (2010) provided valuable insights into the relationship between tax rates and corporate financial decisions. Their research illuminated the interplay between tax policy and corporate behavior, uncovering the strategic responses of firms to changes in tax rates. Hanlon and Heitzman's study is particularly relevant for understanding how Greek ICT companies might respond to taxation reforms, as it offers a framework for predicting and interpreting the financial maneuvers that companies may employ in response to alterations in the tax landscape.

Applying the insights from Zimmerman (1983), Lazăr and Filip (2011) and Hanlon and Heitzman (2010) to the case of Greek ICT companies reveals that a comprehensive understanding of taxation reform's financial impact requires considering both general principles and industry-specific dynamics. Zimmerman's holistic perspective provides the overarching framework; Lazăr and Filip (2011) contribute industry-specific nuances, and Hanlon and Heitzman (2010) offer a lens to analyze strategic financial responses. Together, these studies offer a robust foundation for examining the intricate relationship between taxation reform and the financial dynamics of Greek ICT companies, providing valuable insights for policymakers, practitioners, and researchers alike.

Stamatopoulos et al. (2019) provide an in-depth analysis of the determinants of variability in corporate effective tax rates before and during the financial crisis in Greece. Using firm-level data from 2000 to 2014, the researchers found that firm characteristics such as size, financial leverage, capital intensity, and inventory intensity significantly influence corporate effective tax rates. They observed an increase in corporate effective tax rates following the onset of the financial crisis, offering valuable insights into how financial crises can affect taxation and, consequently, the financial health of ICT companies.

A recent study by Mamatzakis et al. (2023) examined the impact of debt, taxation, and the financial crisis on earnings management in Greece. Their findings revealed that Greek firms tend to reduce earnings manipulation activities when facing liquidity risk. Additionally, the study found that taxation and the financial crisis have a negative and positive effect on earnings management, respectively. This research highlights the complex relationship between taxation, financial crises, and earnings management.

The financial impact of taxation reform on Greek ICT companies is a multifaceted issue explored from various angles. While these studies provide valuable insights, further research is needed to understand the long-term effects of taxation reform and how companies can better navigate these changes.

RESEARCH DESIGN AND MODEL

The purpose of this research is to examine the tax burden of the IT and communications sector for the period 2008-2018. Specifically, it aims to investigate the tax burden on turnover, earnings before interest and tax (EBITDA), and operating net cash flows. To achieve this, three effective tax rate (ETR) indicators were constructed:

1) ETRa: The ratio of income tax to earnings before interest and depreciation (EBITDA).
2) ETRb: The ratio of income tax to operating net cash flow.
3) ETRc: The ratio of income tax to turnover.

The indicators were constructed according to the studies of Hanlon and Heitzman (2010), Zimmerman (1983) and Lazăr and Filip (2011). Finally, the three models that are manufactured follow the following empirical specification:

$$\text{ETRa or ETRb or ETRc} = \alpha_0 + \alpha_1 \log(\text{size}) + \alpha_2 \text{leverage} + \alpha_3 \text{CAPINT} + \alpha_4 \text{INVINT} + \alpha_5 \text{ROA} + \alpha_6 \text{RDINT} + \alpha_7 \text{Crisis} + e$$

where e is the residual of the regression.

In addition, the following indicators were calculated:

(1) log(size): The natural logarithm of Total Assets. Logging the size variable helps address potential skewness in its distribution and facilitates interpreting the effect of size on ETR as proportional changes rather than absolute changes. This transformation ensures that the model captures the impact of size consistently across different scales of company sizes, aligning with findings by Smith and Watts (1992), stating the importance of scaling effects in tax research.
(2) Leverage: The ratio of liabilities to total assets. Including leverage enables an assessment of how a company's capital structure influences its tax efficiency. Companies with higher leverage may experience different ETRs compared to those with lower leverage, as debt financing decisions can affect taxable income and tax liabilities. This consideration echoes the insights of Graham (2000) and Dyreng et al. (2010), who emphasized the role of capital structure in tax planning strategies.
(3) CAPINT (Capital Intensity): The ratio of fixed assets to total assets. Analyzing the relationship between capital intensity and ETR provides insights into how investment decisions and asset utilization impact a company's tax burden. It helps identify whether tax incentives or depreciation rules influence tax strategies concerning capital investments, in line with the research of Hanlon and Heitzman (2010).
(4) INVINT (Inventory Intensity): The ratio of inventories to total assets. Examining the effect of inventory intensity on ETR elucidates the tax implications of inventory management decisions. Companies with higher inventory intensity may face distinct tax treatments related to inventory valuation methods, LIFO/FIFO inventory accounting, and write-downs or adjustments. This perspective is supported by studies by Guenther and Sansing (2006) and Lisowsky (2010), which underscored the importance of inventory accounting in tax planning.
(5) Return on Assets (ROA): The ratio of pre-tax earnings to total assets. Including ROA allows for investigating how asset profitability influences a company's tax efficiency. It helps discern whether tax planning strategies are influenced by asset utilization and profitability metrics and whether tax treatments vary across asset classes or investment types, aligning with the findings of Desai and Dharmapala (2006) and Shevlin (1990).
(6) R&D Intensity (RDINT): The ratio of R&D expenditure to total assets. Analyzing the relationship between R&D intensity and ETR sheds light on the tax implications of innovation activities. It helps ascertain whether tax policies effectively incentivize research and development investments and whether companies strategically leverage tax benefits associated with R&D expenditures. This aspect resonates with research by Chyz and Shevlin (1997) and Dharmapala (2014), highlighting the role of R&D in tax planning strategies.
(7) Crisis: A dummy variable that takes a value of 1 for

the years 2013 to 2018, during which Law N.4172/2013 defining income taxation was introduced, and a value of 0 for the years 2008 to 2012.

RESEARCH SAMPLE

Informatics emerged in Greece in the early 1980s, experiencing a growth rate of over 20% per year until 1990, when a downward trend in growth was observed. The sector resumed its upward trajectory in 1997, with an average increase in IT company revenues of 18.5%, driven by the spread of the Internet. Currently, the IT sector constitutes 87% of the technology sector in Greece, with over 2,000 companies operating in the field. The telecommunications sector began to develop from 1994 onwards, following the liberalization of the telecommunications market. In 1992, the first mobile telephone companies were established, and by 1996, the cellular operating system for mobile telecommunications was created. Since then, the sector has evolved with upgrades such as IPTV, 3G, VDSL, 4G, fiber optics, and 5G technologies, enhancing telecommunications capabilities in Greece.

The synergy between the IT and telecommunications sectors has given rise to telematics, which provides modern services. Today, most businesses use at least one IT and one telecommunications tool to develop their internal environment and value chain, with examples including ADSL digital lines, meteorological information systems, and public transport information systems.

The analysis of the sample was conducted using the Panel Data method, with regression analysis performed through R Studio and verified using EViews. These programs were selected due to their suitability for Panel Data research, as indicated by relevant literature (Dischinger and Riedel, 2011; Dharmapala and Riedel, 2013; Becker et al., 2012; Clausing, 2018). The research utilized historical microeconomic data and data obtained from the websites (https://www.athexgroup.gr/el/web/guest/companies-map) and (https://publicity.businessportal.gr), as reflected in the annual financial statements for the period 2008-2018. The sample includes 15 Greek companies (Appendix Table A1), comprising 7 small entities (46.7% of the total sample), 5 medium entities (33.3% of the total sample), and 3 large entities (20% of the total sample).

These companies were selected based on their engagement in telematics, that is, the integration of IT and telecommunications technologies. The assessed data include Total Assets, Fixed Assets, Total Debt, Inventory, R&D Expenses, Turnover, EBITDA, and Operating Cash Flow.

RESEARCH METHODOLOGY

The models applied in this study are based on the research of Stamatopoulos et al. (2019), Liu and Cao (2007), and Richardson and Lanis (2007). The study examines the influence of effective tax rates (ETRa, ETRb, ETRc) from the indicators mentioned previously, both with and without the presence of a dummy variable indicating an economic crisis. Panel Data models employed include Fixed Effects, Random Effects, and Pooled OLS.

The Fixed Effects Model is suitable for scenarios where unobserved individual-specific effects are correlated with the independent variables. By including fixed effects for each entity (that is, each company), this model controls for unobservable heterogeneity that may impact effective tax rates and other indicators, which is particularly relevant given the diversity of companies in the sample.

The Random Effects Model accounts for both time-invariant and time-varying unobserved heterogeneity across entities. It is appropriate when unobserved factors are constant over time but differ across entities. Incorporating random effects allows for capturing additional variation in effective tax rates and their influence on the indicators of interest while controlling for individual-specific effects.

Pooled OLS is a straightforward approach that aggregates data across all entities and time periods, treating them as a single large sample. While this model does not directly address individual-specific or time-varying effects, it provides efficient estimates when such effects are absent or assumed to be negligible. This model serves as a benchmark for comparing the results of the Fixed Effects and Random Effects models.

For the three models examined, (R-squared) is used to assess the overall significance of the model at conventional levels. R-squared ranges from 0 to 1 and measures how well the model fits the data, with a higher value indicating a better fit. For both the Fixed Effects and Pooled OLS models, the F-Statistic is tested, which represents the ratio of the variance explained by the model to the proportion of the error variance. A higher F-Statistic is preferred in this context.

For the Random Effects model, the Chi-Squared statistic is considered, measuring the variation between observed and expected values, where a higher value indicates a better fit.

To select between the Fixed Effects and Random Effects models, the Hausman test is performed. This test assesses the correlation of individual characteristics of the companies with the coefficients of the independent variables, comparing the parameter estimates of the two methods.

The Breusch-Pagan Lagrange Multiplier test is also applied to all models to check for homoscedasticity or heteroscedasticity in the residuals, evaluating how the values of one time series affect the values of another. This test helps determine if there is covariance in the error variance, which could indicate inadequate estimates.

For the Pooled OLS model, the backward elimination procedure is used to exclude less statistically significant independent variables, refining the model by retaining only those variables that contribute meaningfully to the explanation of the dependent variable.

RESULTS

Descriptive statistics

Table 1 provides basic descriptive statistics for the data variables, including the minimum and maximum values, the mean, the median, and the standard deviation. These statistics help in understanding the characteristics of the data. It is noted that the logarithm of the SIZE variable is used in the examples. Among the ETR variables used as dependent variables, ETRa has the largest median

Table 1. Descriptive statistics.

Indicator	Mean value	Standard deviation	Minimum value	Median	Maximum value
Log(size)	16.542	2.257	13.096	16.392	22.906
Leverage	0.509	0.573	0.036	0.485	7.195
Capint	0.427	0.279	0.000	0.404	0.971
Invint	0.194	1.602	0.000	0.016	20.566
Roa	0.028	0.098	-0.450	0.023	0.649
Rdint	0.102	0.099	0.000	0.075	0.419
Crisis	0.545	0.499	0.000	1.000	1.000
ETRa	0.824	4.291	-3.594	0.221	38.578
ETRb	0.052	0.389	-0.095	0.010	4.975
ETRc	0.175	1.395	-11.351	0.057	9.112

(0.22), mean (0.824), and maximum value (38.57), while ETRc has the smallest minimum value (-11.351). According to the data and the definitions of these variables, companies, on average, pay 82.41% of their net income before taxes as income tax, 5.28% of their operating result, and 17.56% of their turnover.

In the same table, descriptive statistics for the independent variables of the models are also provided. The natural logarithm of size has a mean value of 16.542 and a median of 16.392. Leverage has a mean value of 0.509 and a median of 0.485. Capital intensity has a mean value of 42.74% and a median of 40.40%. Inventory intensity has a mean value of 19.48% and a median of 1.66%. The ROA index has a mean value of 2.81% and a median of 2.37%. The RDINT index has a mean value of 10.22% and a median of 7.51%. Finally, the CRISIS dummy variable has a mean value of 0.545, indicating that 54.55% of the sample observations are during a crisis period; thus, the median for this variable is 1, since more than 50% of the observations are 1.

Table 2 examines the correlations between the variables in the data. Specifically, ETRa exhibits negative correlations with size, leverage, capital intensity, inventory intensity, profitability, and R&D intensity, none of which are statistically significant. ETRb shows positive correlations with size and profitability, and negative correlations with leverage, capital intensity, inventory intensity, and R&D intensity, but none of these correlations are statistically significant. ETRc demonstrates a negative correlation with the RDINT index, which is statistically significant at the $\alpha = 5\%$ confidence level, and positive correlations with size, leverage, capital intensity, inventory intensity, and profitability, although these are not statistically significant.

With respect to the remaining independent variables, the natural logarithm of size shows a positive relationship with CAPINT, statistically significant at all conventional levels of significance. However, it exhibits a negative correlation with leverage (significant at $\alpha = 1\%$), the ROA index (significant at $\alpha = 5\%$), and the RDINT index (significant at $\alpha = 0.1\%$). Leverage shows a negative correlation with the capital intensity index (significant at $\alpha = 0.1\%$) and a positive correlation with the ROA index (significant at $\alpha = 10\%$). The CAPINT index is negatively correlated with the inventory intensity index (significant at $\alpha = 10\%$) and the ROA index (significant at all conventional significance levels). Finally, the INVINT index is positively correlated with the RDINT index, with the correlation being statistically significant at the $\alpha = 5\%$ significance level.

Model estimation results

The results of the model estimations, as well as the corresponding interpretations, are presented here.

Fixed effects, pooled ols and random effects estimates for ETRa

The results of the Panel Data models with ETRa as the dependent variable are analyzed. The models examined include Fixed Effects, Random Effects, and Pooled OLS. The interpretations of the coefficients and their significance are discussed, alongside diagnostic tests to determine the most appropriate estimation technique. The estimation results (Appendix Table B1) show that, when using ETRa as the dependent variable and CRISIS as an independent variable, none of the variables are statistically significant at any conventional level of significance. All p-values of the coefficients are well above 5%, and in some cases, even 10%. Additionally, the table provides information on the model significance. Specifically, for the Fixed Effects and Pooled OLS models, the R^2 values for explained variability and the F-statistics are reported. In both models, the R^2 values are very low (1.33% for Fixed Effects and 2.75% for Pooled OLS), and the F-statistics are similarly low. For the Fixed Effects model, the F-statistic is 0.276 with a p-value of 0.962, indicating that the model is not statistically significant. For the Pooled OLS model, the R^2 is 2.75%,

Table 2. Correlations.

log(SIZE)	LEVERAGE	CAPINT	INVINT	ROA	RDINT	ETRA	ETRB	ETRC
1.000								
-0.230 (0.002**)	1.000							
0.737 (0.000***)	-0.278 (0.000***)	1.000						
-0.109 (0.160)	-0.001 (0.990)	-0.134 (0.085)	1.000					
-0.155 (0.046*)	0.131 (0.091)	-0.317 (0.000***)	-0.009 (0.907)	1.000				
-0.3640.000***	-0.001 (0.989)	-0.052(0.499)	0.250 (0.001**)	0.098 (0.210)	1.000			
-0.006 (0.938)	-0.025 (0.749)	-0.092 (0.236)	-0.009 (0.905)	-0.027 (0.724)	-0.095 (0.224)	1.000		
0.024 (0.758)	-0.022 (0.770)	-0.000 (0.990)	-0.013 (0.859)	0.020 (0.795)	-0.009 (0.908)	0.000 (0.999)	1.000	
0.002 (0.975)	0.050 (0.518)	(0.046) (0.554)	0.045 (0.559)	0.040 (0.604)	-0.169 (0.030*)	-0.007 (0.919)	-0.009 (0.902)	1.000

Values in parentheses indicate p-values, p<0.05: *, p<0.01: **, p<0.001: ***

and the F-statistic is 0.635 with a p-value of 0.726, meaning this model is also not significant. The significance of the Random Effects model is tested using the Chi-square test, yielding a value of 3.444 with a p-value of 0.841, indicating that it is not statistically significant. The R^2 for this model is 2.15%. An additional diagnostic test for the Fixed Effects model, examining the significance of the fixed effects, shows an F-statistic value of 1.198 with a p-value of 0.283, indicating that the fixed effects are not statistically significant at any conventional level of significance.

Another diagnostic test performed for the model is the Breusch-Pagan Lagrange Multiplier test for cross-correlation. The test statistic is LM = 144.4 with a p-value of 0.006. Thus, the null hypothesis of no interdependence is rejected at both the α = 5% and α = 1% significance levels, indicating that there is intercorrelation in the residuals of the model. For the Random Effects model, the Hausman test was conducted to choose between the Random Effects and Fixed Effects models. The Chi-square test statistic is 4.796 with a p-value of 0.684, suggesting that the null hypothesis of no endogeneity in Random Effects is not rejected. Therefore, the Random Effects model is preferred over the Fixed Effects model. The LM test for interdependence yields LM = 126.929 with a p-value of 0.071, indicating that the null hypothesis of no correlation is rejected at the α = 10% significance level but not at the α = 5% level. The Breusch-Pagan LM test for effects gives Chi-square (1) = 0.001 with a p-value of 0.968. In the Pooled OLS model, a test for cross-sectional dependence is conducted, with the test statistic LM = 122.79 and a p-value of 0.113, meaning the null hypothesis of independence is not rejected. Given these results, Pooled OLS is chosen as the best model. For the OLS model, the p-value-based backward elimination method was also tested. The estimation results (Appendix Table B2) indicate that there are no statistically significant independent variables in the model. As a result, all independent variables were sequentially removed from the model during the backward elimination process. The final model, which includes only the CAPINT variable, also shows no statistical significance at conventional levels. The F-statistic for this model is 1.413 with a p-value of 0.236, and the R^2 is 0.8%.

Estimation results (Appendix Table B3) show the estimates for the same models without including the CRISIS variable, keeping ETRa as the dependent variable. As in the previous analysis, none of the independent variables are considered statistically significant at the 5% significance level or any conventional significance level, as the p-values for each coefficient in each model exceed 10%. The backward elimination process was again applied, and the results (Appendix Table B4) were consistent with the previous findings. Specifically, all variables were successively removed, leaving only CAPINT, which remains statistically insignificant.

For the model including the CRISIS variable, Pooled OLS is preferred. This preference is based on the Breusch-Pagan LM test for heteroscedasticity, which does not indicate the presence of random effects in the Random Effects model, and the LM test for cross-sectional dependence, which does not show evidence of unit interdependence in the Pooled OLS model. The same preference holds for the model without the CRISIS variable, for the same reasons. It is important to note, however, that in both scenarios, the final model is not statistically significant.

Fixed effects, pooled ols, and random effects estimates for ETRb

Here, analyzes the results of estimating similar Panel Data models with ETRb as the dependent variable. Interpretations of the coefficients and their significance are provided, and diagnostic tests are also conducted, as previously discussed.

Estimation results (Appendix Table B5) present the Fixed Effects, Pooled OLS, and Random Effects estimation techniques, including the CRISIS variable in the model. The results indicate that, similar to the previously discussed, none of the independent variables are statistically significant in any of the estimated models. The p-values for the coefficients, as well as those for the significance statistics of the models, are quite large, suggesting non-significance at any conventional confidence level.

For the Fixed Effects model, the F-statistic is 0.161 with a p-value of 0.992, indicating that the model is not statistically significant. The R^2 for this model is 0.7%, reflecting very low explanatory power.

In the Random Effects model, the Chi-square statistic is 1.063 with a p-value of 0.993. The R^2 for this model is 0.67%, demonstrating minimal variability in ETRb explained by the model and a lack of statistical significance. In other words, the variability of ETRb explained by the model is very little, while the model itself is not significant. Regarding the Pooled OLS model, the F-statistic is equal to 0.153 and the corresponding p-value is 0.993. So this model is not important either. The R^2 of the specific model is 0.68%. For the Pooled OLS model, the backward elimination process (Appendix Table B6) does not result in a model with significant factors. This time (with ETRb as dependent variable), the last variable left in the model is CRISIS, which, however, is statistically insignificant with a p-value of 0.383.

Without including the CRISIS variable and keeping ETRb as the dependent variable, the estimation results (Appendix Table B7) indicate that none of the available independent variables are statistically significant at the 5% level, or at any conventional significance level, as the p-values for each coefficient in each estimated model exceed 10%.

For the Pooled OLS model, the backward elimination process (Appendix Table B8) also shows no statistically significant variables in the model. The model itself is not statistically significant, with an F-statistic of 0.094 and a p-value of 0.758. The R^2 of this model is 0.06%.

When the CRISIS variable is included in the model, Pooled OLS is again deemed the most appropriate model. This conclusion is based on the Breusch-Pagan test for heteroscedasticity, where the null hypothesis is not rejected, indicating no evidence of random effects. However, it should be noted that there is a correlation between the units, and the model itself remains statistically insignificant. The results are consistent when the CRISIS variable is excluded from the model.

Fixed effects, pooled OLS and random effects estimates for ETRc

The results of the estimation of the Panel Data models with ETRc as the dependent variable are analyzed here. The interpretations of the coefficients and their significance are presented, and as previously discussed, appropriate diagnostic tests are also conducted.

Estimates of ETRc with in-model crisis

Table 3 presents the model estimation results using the Fixed Effects, Pooled OLS, and Random Effects techniques with the CRISIS variable included as an independent variable. Unlike the previously discussed, statistically significant coefficients are observed in each of the models, and the models themselves are significant at some conventional confidence levels.

In the Fixed Effects model, the statistically significant variables are inventory intensity (INVINT), R&D intensity (RDINT), and return on assets (ROA). INVINT is significant at the $\alpha = 5\%$ level, with a p-value of 0.028. RDINT is significant at the 1% level, and even at the 0.1% level (i.e., all conventional significance levels). ROA is significant at the $\alpha = 10\%$ level, with a p-value of 0.056, but not at the $\alpha = 5\%$ level. The coefficient for INVINT suggests that a one-unit increase in INVINT is associated with an expected increase of 0.168 in ETRc, holding other variables constant. An increase of one unit in RDINT is expected to decrease ETRc by 9.669, while a one-unit increase in ROA is expected to increase ETRc by 2.849. The Fixed Effects model itself has an F-statistic of 2.801 with a p-value of 0.009, making it statistically significant at the 0.01% level. The R^2 of the model is 12%, showing improvement compared to previous models.

In the Random Effects model, significant variables include capital intensity (CAPINT) and R&D intensity (RDINT), among others. CAPINT is significant at the $\alpha = 5\%$ level, with a p-value of 0.013. INVINT is significant at the $\alpha = 10\%$ level but not at the $\alpha = 5\%$ level. RDINT is significant at the 1% level, with a p-value of 0.000. Additionally, the natural logarithm of size is significant at the $\alpha = 5\%$ level. According to this model, a one-unit increase in CAPINT is expected to increase ETRc by 1.647.

An increase of one unit in INVINT is estimated to increase ETRc by 0.116 (11.62%, since it is an index), while an increase in RDINT by one unit is expected to decrease ETRc by 4.390. A one-unit increase in the logarithm of size is expected to decrease ETRc by 0.193.

Table 3. ETRc estimation results with crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	Pr(>|t|)	Estimate	Pr(>/tl)	Estimate	Pr(>|t|)
Constant	-	-	2.875	0.021*	-	-
Leverage	-0.018	0.935	0.140	0.473	0.140	0.472
Capint	0.338	0.818	1.647	0.013*	1.647	0.012*
Invint	0.168	0.028*	0.116	0.100	0.116	0.098
Rdint	-9.669	0.000***	-4.390	0.001**	-4.390	0.000***
Roa	2.849	0.056 .	1.709	0.150	1.709	0.148
Log(size)	-0.109	0.799	-0.190	0.022*	-0.190	0.021*
Crisis	0.202	0.376	0.092	0.671	0.092	0.671
	F(7.143)=2.801		F(7.157)= 1.981		Chi-square(7)= 13.871	
p-value	0.009**		0.060		0.053	
R-square	0.120		0.081		0.081	

p<0.1: , p<0.05: *, p<0.01: **, p<0.001: ***.

The Random Effects model has a Chi-square statistic of 13.871 with a p-value of 0.053, indicating significance at the α = 10% level. The R² for this model is 8.1%.

For the Pooled OLS model, the F-statistic is 1.981 with a p-value of 0.060, and the R² is 8.1%, the same as in the Random Effects model. CAPINT and the logarithm of size are significant at the α = 5% level, while RDINT is significant at the α = 0.1% level. In this model, a one-unit increase in CAPINT is expected to positively change ETRc by 1.647, an increase in RDINT by one unit is expected to decrease ETRc by 4.390, and a one-unit increase in the logarithm of size is expected to decrease ETRc by 0.190.

Diagnostic tests were conducted as previously discussed. For the Fixed Effects model, the significance of individual fixed effects was checked, with an F-statistic of 0.767 and a p-value of 0.703. Therefore, the individual fixed effects are not considered statistically significant. Additionally, an LM test for cross-sectional dependence was performed, yielding an LM statistic of 114.01 with a p-value of 0.257, indicating that interdependence between units is accepted.

For the Random Effects model, a Hausman test was conducted to test for endogeneity and decide between Fixed and Random Effects. The test resulted in a Chi-square statistic of 8.381 with a p-value of 0.300, indicating that the Random Effects estimator is preferred. An LM test for interdependence between economic units was also performed, with a statistic of 0.112 and a p-value of 0.297. This suggests that the assumption of unit independence (in the errors) is not rejected at conventional significance levels. Additionally, a Breusch-Pagan Lagrange Multiplier test for heteroscedasticity and random effects was conducted, resulting in a BP(7) statistic of 4.411 with a p-value of 0.731, indicating no significant evidence of heteroscedasticity or random effects.

For the Pooled OLS model, an independence test of the units (companies) was carried out, resulting in an LM statistic of 112.19 with a p-value of 0.297. Thus, the null hypothesis of unit independence is not rejected. Given that the Breusch-Pagan LM test for random effects did not reject the null hypothesis, the Pooled OLS model is considered the most appropriate. The backward elimination procedure for the Pooled OLS model was performed, with the results shown in Table 4. Contrary to previous findings, this procedure retained a statistically significant variable—RDINT—in both the full and final models, though at different levels of significance. This result aligns with the correlation investigation presented in Table 6. The model resulting from this method is:

$$\bar{E}T\bar{R}c_{it} = \hat{\alpha} + \beta \quad \times \quad RDINT_{it}$$

$$\widehat{ETRc}_{it} = 0.417 - 2.364 \times RDINT_{it}$$

In this case, the p-value for the RDINT variable is 0.03, which is less than 0.05, and therefore it is considered significant at the 5% significance level. The estimate of the RDINT coefficient indicates that if the RDINT index increases by one unit, the ETRc coefficient is expected to decrease by 2.364. The model itself has an F-statistic of F(1,158)=4.793F(1, 158) = 4.793F(1,158)=4.793 with a p-value of 0.029, which is less than 0.05, making the model statistically significant at the 5% significance level. This is an improvement from the original model, which was only significant at the 10% level.

Estimates for ETRc with Out-of-Model crisis

In this last case, the same theoretical model is estimated using the Fixed Effects, Pooled OLS, and Random Effects techniques, with the only difference being the

Table 4. Backward elimination ETRc with crisis.

Indicator	Initial model		Final model	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
Constant	2.875	0.021*	0.417	0.007***
Leverage	0.140	0.473	-	-
Capint	1.647	0.013*	-	-
Invint	0.116	0.100	-	-
Rdint	-4.390	0.001**	-2.364	0.030*
Roa	1.709	0.150	-	-
Log(size)	-0.190	0.022*	-	-
Crisis	0.092	0.671	-	-
F(value)	F(7. 157)= 1.981		F(1.158)=4.793	
p-value	0.060		0.029*	
R-square	0.081		0.028	

p<0.1: , p<0.05: *, p<0.01: **, p<0.001: ***

Table 5. ETRc estimation results without crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	Pr(>|t|)	Estimate	Pr(>/tl)	Estimate	Pr(>|t|)
Constant	-	-	2.877	0.021*	-	-
Leverage	-0.015	0.945	0.134	0.490	0.134	0.489
Capint	0.178	0.902	1.623	0.014*	1.6232	0.013*
Invint	0.167	0.028*	0.116	0.097	0.116	0.095
Rdint	-9.111	0.000***	-4.300	0.001**	-4.3006	0.000***
Roa	2.842	0.056	1.718	0.147	1.7183	0.145
Log(size)	-0.147	0.730	-0.187	0.023*	-0.1872	0.022*
F(value)	F(6.144)=3.141		F(6.158)= 2.293		Chi-square(6)= 13.762	
p-value	0.006**		0.037*		0.032*	
R-square	0.115		0.080		0.080	

p<0.1: , p<0.05: *, p<0.01: **, p<0.001: ***.

exclusion of the CRISIS variable from the model. Table 5 presents the results of these estimates, including an examination of the significance of the coefficients and the models as a whole, as well as the results of the diagnostic tests.

In the Fixed Effects model, the variables INVINT, RDINT, and ROA are statistically significant at different levels. The INVINT variable, with a p-value of 0.028, is significant at the 5% level. An increase of 1 in the INVINT index is expected to lead to an increase of 0.167 in the ETRc coefficient. RDINT, with an extremely low p-value of 0.000, is significant at all conventional levels, including 0.1%. An increase of 1 in the RDINT index is expected to decrease ETRc by 9.111. The ROA variable, with a p-value of 0.056, is significant at the 10% level. An increase of 1 in ROA is expected to increase ETRc by 2.842. The model itself is statistically significant at the 1% level, with F = 3.1416 and p-value = 0.006, and has an R^2 of 11.58%.

In the Random Effects model, the CAPINT variable is significant at the 5% level with a p-value of 0.013. An increase of 1 in the CAPINT index is expected to increase ETRc by 1.623. INVINT, with a p-value of 0.095, is significant at the 10% level, with a 100% increase in INVINT expected to raise ETRc by 0.116. RDINT, with a p-value of 0.000, is significant at the 0.1% level, and an increase of 1 in RDINT is expected to decrease ETRc by 4.300. The logarithm of size is significant at the 5% level, with a p-value of 0.022. An increase of 1 in the logarithm of size is estimated to decrease ETRc by 0.187. The Chi-square statistic for the model is 13.762 with a p-value of 0.032, indicating significance at the 5% level. The model has an R^2 of 8.01%.

In the Pooled OLS model, the CAPINT variable is significant at the 5% level with a p-value of 0.014. An increase of 1 in CAPINT is estimated to increase ETRc

Table 6. Backward elimination ETRc without crisis.

Indicator	Initial model		Final model	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
Constant	2.875	0.021*	0.417	0.007***
Leverage	0.134	0.490	-	-
Capint	1.623	0.014*	-	-
Invint	0.116	0.097	-	-
Rdint	-4.300	0.001**	-2.364	0.030*
Roa	1.718	0.147	-	-
Log(size)	-0.187	0.023*	-	-
F(value)	F(7.158)= 2.293		F(1.158)= 4.793	
p-value	0.037*		0.029*	
R-square	0.080		0.028	

p<0.1: , p<0.05: *, p<0.01: **, p<0.001: ***.

by 1.623. INVINT is significant only at the 10% level, with a p-value of 0.097. An increase of 1 in INVINT is expected to raise ETRc by 0.116 (11.6%). RDINT is significant at the 1% level with a p-value of 0.001, and an increase of 1 in RDINT is expected to decrease ETRc by 4.300. The variable log(SIZE) is significant at the 5% level with a p-value of 0.022, and an increase of 1 in the logarithm of size is estimated to decrease ETRc by 0.187. The coefficient estimates in the Pooled OLS model are identical to those in the Random Effects model.

For each of the models, tests similar to those in previous cases were conducted. For the Fixed Effects model, the significance of random effects was tested with an F-statistic of 0.724 and a p-value of 0.246, indicating that the null hypothesis of non-significance of fixed effects is not rejected. The test for interdependence of units produced an LM statistic of 117.1 with a p-value of 0.197, suggesting that the null hypothesis of independence between units is not rejected.

In the Random Effects model, a Hausman test was performed with a Chi-square statistic of 7.762 and a p-value of 0.256. This result indicates that the Random Effects model is preferred over the Fixed Effects model. The test for cross-sectional dependence yielded an LM statistic of 111.18 with a p-value of 0.321, supporting the assumption of independence between units regarding model errors. A Breusch-Pagan Lagrange Multiplier test for random effects produced an LM statistic of 3.918 with a p-value of 0.0477. This result suggests that at the 5% significance level, there is evidence of heteroscedasticity and, consequently, an indication of significant random effects.

For the Pooled OLS model, the test for cross-sectional dependence resulted in an LM statistic of 111.18 with a p-value of 0.321, indicating no evidence of inter-dependence between units in the errors. Although the Breusch-Pagan test suggests that Random Effects would be more appropriate, the results from the method are consistent with those of Linear Regression, implying that Random Effects and Linear Regression are equivalent in this case.

The backward elimination process for the Pooled OLS model is detailed in Table 6. As earlier discussed, only the RDINT variable remains significant at the 5% level, with a p-value of 0.03. The resulting model is:

$$\widehat{ETRc}_{it} = \hat{\alpha} + \hat{\beta} \times RDINT_{it}$$

$$\widehat{ETRc}_{it} = 0.417 - 2.364 \times RDINT_{it}$$

The interpretation of the slope coefficient of the model is that for an increase in the RDINT coefficient by 1, the tax coefficient ETRc is expected to decrease by 2.364. The model, as explained previously, is statistically significant at the 5% significance level with F = 4.793, p-value = 0.029.

Estimation results for ETRc

For the model where CRISIS is used as an explanatory variable, Pooled OLS is considered the most appropriate estimator. This decision is based on the fact that the homoscedasticity test (in the Random Effects model) does not reject the null hypothesis of homoscedasticity, and the LM test for cross-sectional dependence in Pooled OLS indicates independence of units.

In the case where CRISIS is excluded from the model, the Breusch-Pagan test yields a p-value of less than 5%, suggesting the presence of random effects. However, the Random Effects estimates are identical to those of Pooled OLS. This phenomenon can be attributed to the estimation method used. During the estimation of the Random Effects model, the variance of the individual effects is assessed. In rare cases, if this variance is estimated to be negative, it is considered zero, resulting in the Random Effects method converging with Pooled OLS.

Moreover, the Pooled OLS model shows no interdependence between units according to the LM test. The results reveal significant relationships between firm characteristics and tax rates. Specifically, larger firms tend to have lower tax rates, which contrast with some previous studies but align with others. This suggests that firm-specific factors and managerial strategies play a crucial role in tax outcomes. Additionally, higher capital intensity is associated with higher tax rates, which supports some prior research while challenging others, emphasizing the need for industry-specific tax analysis.

Notably, the negative relationship between firm size and effective tax rates contradicts some previous studies, such as those by Stamatopoulos et al. (2019), Kraft (2014), Richardson and Lanis (2007), and Derashid and Zhang (2003), while aligning with findings from Zimmerman (1983), Plesko (2003), and Noor et al. (2010). This discrepancy underscores the importance of considering industry-specific contexts and firm-level factors in understanding tax outcomes, as emphasized by Zimmerman's framework, which highlights the role of managerial decision-making and tax planning strategies.

Furthermore, the positive correlation between capital intensity and effective tax rates in the Random Effects model corroborates arguments made by Plesko (2003) and Wilkinson et al. (2001), who link increased investment in fixed assets to higher productivity and subsequently higher tax liabilities. This finding challenges the perspectives of Richardson and Lanis (2007) and Derashid and Zhang (2003), emphasizing the need for nuanced considerations of industry dynamics and investment patterns in tax analysis.

Overall, the empirical results of the present study both support and extend existing theories on corporate taxation, particularly Zimmerman’s framework, by highlighting the nuanced relationships between firm characteristics, investment decisions, and effective tax rates within the context of the IT and communications sector.

Leverage does not appear to affect effective tax rates (ETRs). The trend emerging from the studies reviewed suggests that businesses prefer debt financing because it often results in lower taxes. The inventory intensity index shows a positive correlation with ETRc and is statistically significant in the Fixed Effects model. This correlation makes sense, as increased inventories imply lower cost of goods sold, which increases the use result and, consequently, higher tax rates. This finding aligns with Gupta and Newberry (1997).

The Return on Assets (ROA) also shows a positive correlation with the effective tax rate, specifically in the Fixed Effects model and at a 5% significance level. These findings are consistent with the research of Derashid and Zhang (2003) and Kraft (2014), which indicates that companies with higher profits tend to pay more tax.

The R&D intensity variable has a strong negative correlation with the effective tax rate (ETRc) across all three models—Fixed Effects, Random Effects, and Pooled OLS. This agrees with Richardson and Lanis (2007), who found that companies with increased research and development intensity face lower tax rates. It is noteworthy that, under the provisions of Article 22A of Law 4172/2013, as amended by Paragraph 8 of Article 22 of Law 4223/2013, incentives are provided for companies investing in scientific and technological research. Specifically, Paragraph 1 of this article stipulates that these costs, including company payroll and other supplier expenses, are deducted from gross revenues at a 30% rate. These deductions are applied to net profits, with appropriate supporting documents reviewed by the General Secretariat of Research and Technology of the Ministry of Education. As of the financial year 2021, the rate of tax exemption for R&D has been 100%.

For the period in which the crisis dummy variable was included, specifically from 2013 to 2018, no substantial differences are observed in the real coefficients.

Conclusions

In the present study, an attempt was made to analyze the variables affecting the effective tax rates (ETRs) of companies in the IT and communications sector, specifically telematics companies. Microeconomic data were collected from the financial statements of companies for the years 2008 to 2018. Panel data models (Fixed and Random Effects) and the linear regression model (Pooled OLS) were used.

Firstly, the lack of statistically significant results for the indicators ETRa and ETRb across the panel data models (Fixed and Random Effects) and the linear regression model (Pooled OLS) aligns with the existing literature's mixed findings on the determinants of effective tax rates. This underscores the complexity of tax dynamics and the need for nuanced empirical analyses. However, the statistically significant coefficients observed for ETRc across all models indicate a notable relationship between certain firm characteristics and effective tax rates.

Specifically, empirical evidence for ETRc reveals that larger firms tend to exhibit lower effective tax rates, higher capital intensity correlates with higher effective tax rates, and the inventory intensity index shows a positive correlation with ETRc. Additionally, ROA is positively correlated with the effective tax rate. In contrast, the R&D intensity variable demonstrates a strong negative correlation with ETRc. Leverage does not appear to affect ETRs.

The study explores the intricate factors influencing real tax rates within the IT and communications sector, with a particular focus on telematics companies. This sector, characterized by dynamic growth and rapid technological advancements, highlights the importance of tax analysis for understanding its economic landscape.

Spanning from 2008 to 2018, the study captures a tumultuous period in tax regulation, marked by over 20 changes in the country's tax rules. This backdrop underscores the significance of the findings for economic managers and policymakers facing decisions that directly impact business profitability and tax distribution. One key revelation is the potential efficacy of extending tax exemptions to investments in fixed equipment for IT and communications firms. Such incentives could stimulate capital expenditure, drive innovation, and support sector-wide growth. This aligns seamlessly with the sector's capital-intensive operations and the ongoing need for infrastructure upgrades to remain competitive.

Moreover, the proposal to introduce a nuanced scale of taxation for legal entities offers a compelling mechanism to recalibrate the tax burden. By moving away from uniform tax rates, this approach acknowledges the diverse revenue streams and operational scales within the sector. Notably, it aims to shift the tax weight from smaller entities towards larger counterparts, in line with the study's insights on the varying impact of firm size on tax outcomes.

POLICY IMPLICATIONS

However, amidst these policy proposals lies a critical imperative – the reinforcement of controls and a crackdown on tax evasion. The dynamic nature of the IT and communications sector, coupled with its reliance on intangible assets and complex financial structures, makes it particularly vulnerable to tax avoidance strategies. Therefore, effective tax policies must be complemented by robust enforcement measures to ensure fairness and integrity in the tax system.

In essence, the study provides actionable insights that resonate deeply with the realities of the IT and communications sector. By leveraging targeted tax incentives, adopting progressive taxation frameworks, and fortifying regulatory mechanisms, policymakers can navigate the sector's complexities and foster an environment conducive to sustained growth and innovation.

During the conduct of the research, several limitations emerged that may have affected the results. The data from financial statements, combined with the assumptions used to classify companies as telematics, resulted in a small sample size (15 companies) with considerable variation in terms of size and financial performance. Additionally, the ETR tax indices were calculated based on financial statements rather than tax forms (N), which were not accessible.

To enhance the robustness and applicability of the findings, future research should consider expanding the sample size and incorporating a broader range of variables, including macroeconomic indicators. This would provide a more comprehensive analysis of the factors influencing effective tax rates in Greek ICT companies. Future studies could also separately examine technology and communication companies and include a larger number of small and medium enterprises, particularly those with OE LLC legal forms. Furthermore, investigating the impacts of the Covid-19 crisis and the subsequent inflationary pressures would be of particular interest for future research.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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APPENDIX A

Research sample companies

The following are companies that were selected.

Table A1. Investigated companies.

Name	Size
PROFILE SYSTEMS & SOFTWARE S.A.	Medium
PERFORMANCE TECHNOLOGIES S.A.	Medium
MLS INFORMATICS S.A.	Medium
QUALITY AND RELIABILITY S.A.	Small
ILIDA INFORMATICS SA	Small
EPSILONNET S.A.	Medium
ENTERSOFT S.A.	Small
INTRACOM TELECOM S.A.	Big
OTE S.A.	Big
CENTRIC SECURITIES S.A.	Big
CPI S.A.	Medium
AMCO S.A.	Small
DOTSOFT A.E.	Small
SIGNALBAU HUBER HELLAS S.A.	Small
INFORMATICS TATSIS S.A.	Small

APPENDIX B

Estimation results for ETRa

Table B1. ETRa estimation results with crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	Pr > | t |)	Estimate	Pr > | t |)	Estimate	Pr > | t |)
Constant			-0.471	0.904	-	-
Leverage	-0.213	0.758	-0.384	0.533	-0.342	0.582
Capint	-4.112	0.368	-3,205	0.126	-3.092	0.172
Invint	0.026	0.911	-0.030	0.890	-0.02	0.928
Rdint	-4.232	0.564	-2.488	0.549	-2.620	0.559
Roa	3.025	0.511	-2.841	0.448	-1.805	0.639
Log (size)	0.742	0.578	0.196	0.453	0.196	0.494
Crisis	-0.071	0.920	-0.081	0.905	-0.085	0.900
	F(7.143)=0.276		F(7.157)=0.635		Chi-square(7)= 3.444	
p-value	0.962		0.726		0.841	
R-square	0.013		0.027		0.021	

Table B2. Backward elimination ETRa with crisis.

Indicator	Initial model		Final model	
	Estimate	**Pr (> | t |)**	**Estimate**	**Pr (> | t |)**
Constant	-0.4714	0.9046	1.4332	0.0203
Leverage	-0.3849	0.5336	-	-
Capint	-3.2054	0.1265	-1.4252	0.2362
Invint	-0.0306	0.8907	-	-
Rdint	-2.4885	0.5496	-	-
Roa	-2.8415	0.4484	-	-
Log (size)	0.1962	0.4534	-	-
Crisis	-0.0818	0.9058	-	-
F(value)	F(7.157)=0.6351		F(1.157)=1.4137	
p-value	0.7263		p-value=0.2362	
R-square	0.0275		R-square=0.0086	

Table B3. ETRa estimation results without crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	**Pr (> | t |)**	**Estimate**	**Pr (> | t |)**	**Estimate**	**Pr (> | t |)**
Constant	-	-	-0.473	0.904	-	-
Leverage	-0.214	0.756	-0.379	0.536	-0.336	0.586
Capint	-4.057	0.369	-3.184	0.126	-3.065	0.173
Invint	0.026	0.910	-0.031	0.887	-0.020	0.927
Rdint	-4.427	0.530	-2.568	0.530	-2.721	0.537
Roa	3.028	0.509	-2.848	0.445	-1.790	0.641
Log (size)	0.756	0.568	0.193	0.456	0.193	0.499
	F(6.144)=0.323		F(6.158)=0.743		Chi-square(6)= 3.431	
p-value	0.923		0.615		0.753	
R-square	0.013		0.027		0.021	

Table B4. Backward elimination ETRa without crisis.

Indicator	Initial model		Final model	
	Estimate	**Pr (> | t |)**	**Estimate**	**Pr (> | t |)**
Constant	-0.473	0.904	1.433	0.020
Leverage	-0.379	0.536		
Capint	-3.184	0.126	-1.425	0.236
Invint	-0.031	0.887		
Rdint	-2.568	0.530		
Roa	-2.848	0.445		
Log (size)	0.193	0.456		
F(value)	F(6.157)=0.032		F(1.157)=1.413	
p-value	0.923		0.236	
R-square	0.013		0.008	

Estimation results for ETRb

Table B5. ETRb estimation results with crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	Pr (> | t |)	Estimate	Pr (> | t |)	Estimate	Pr (> | t |)
Constant	-	-	-0.084	0.814	-	-
Leverage	-0.010	0.870	-0.013	0.812	-0.010	0.849
Capint	-0.068	0.869	-0.052	0.783	-0.033	0.885
Invint	-0.000	0.997	-0.004	0.825	-0.002	0.896
Rdint	-0.181	0.786	-0.002	0.994	-0.057	0.900
Roa	0.221	0.597	0.060	0.860	0.125	0.731
Log (size)	-0.019	0.875	0.008	0.728	0.006	0.843
Crisis	0.053	0.406	0.052	0.409	0.053	0.387
	F(7.143)=0.161		F(7.157)=0.153		Chi-square(7)= 1.063	
p-value	0.992		0.993		0.993	
R-square	0.007		0.006		0.006	

Table B6. Backward elimination ETRb with crisis.

Indicator	Initial model		Final model	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
Constant	-0.084	0.814	0.023	0.597
Leverage	-0.013	0.812	-	-
Capint	-0.052	0.783	-	-
Invint	-0.004	0.825	-	-
Rdint	-0.002	0.994	-	-
Roa	0.060	0.860	-	-
Log(size)	0.008	0.728	-	-
Crisis	0.052	0.409	0.053	0.383
F(value)	F(7.157)=0.153		F(1.157)=0.762	
p-value	0.993		0.383	
R-square	0.006		0.004	

Table B7. ETRb estimation results without crisis.

Indicator	Fixed effects		Pooled OLS		Random effects	
	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
Constant			-0.083	0.817	-	-
Leverage	-0.009	0.879	-0.016	0.765	-0.013	0.815
Capint	-0.110	0.788	-0.066	0.729	-0.052	0.821
Invint	-0.000	0.993	-0.004	0.841	-0.002	0.905
Rdint	-0.033	0.958	0.048	0.897	0.020	0.964
Roa	0.219	0.600	0.065	0.849	0.129	0.723
Log(size)	-0.029	0.809	0.010	0.672	0.008	0.777
	F(6.144)=0.073		F(6.158)= 0.065		Chi-square(6)= 0.317	
p-value	0.998		0.998		0.999	
R-square	0.003		0.002		0.002	

Table B8. Backward elimination ETRb without crisis.

Indicator	Initial model		Final model	
	Estimate	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
Constant	-0.083	0.817	-0.159	0.943
Leverage	-0.016	0.765	-	-
Capint	-0.066	0.729	-	-
Invint	-0.004	0.841	-	-
Rdint	0.048	0.897	-	-
Roa	0.065	0.849	-	-
Log(size)	0.010	0.672	0.004	0.758
F(value)	F(6.158)=0.065		F(1.158)=0.094	
p-value	0.998		0.758	
R-square	0.002		0.0006	