Exploring Quantitatively Corporate Financial Performance and Social Performance Relationship with Net Impact Method

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Abstract – **Measuring the impact of corporate actions on corporate social performance (CSP) is traditionally recognized to be notoriously difficult. This manuscript reports the results of a study using the Net Impact Method to quantify CSP and approximates corporate financial performance (CFP). We report findings on the CFP-CSP relationship and consider temporal lags between CFP measures and CSP impacts. Our findings are mostly supporting existing research but contrary to earlier research we find non-linear dynamics between CFP and CSP measures on some accounts. Although we used a limited dataset, our findings shed additional light on the CFP-CSP relationship.**

Keywords – corporate social performance, CSP, corporate financial performance, CFP, Net impact method

I. INTRODUCTION

Investigations of Corporate Financial Performance (CFP) and Corporate Social Performance (CSP) seldom delve into the actual measurement and category level of CSP due to a lack of proper measures [1]. ESG-based MSCI KLD has become the "de facto standard" in measuring CSP [4,5], but the heterogeneous nature of measures, the human involvement in the analysis, the various sources of data, and the issue of single composite measure make the use of MSCI KLD questionable in CSP development [3, 6, 7, 8, 9, 10]. Net Impact Method (NIM) has been proposed and designed for quantitative analysis and development of CSP [2, 3] in response to having quantifiable measures of CSP.

NIM is based on artificial intelligence technology analyzing scientific articles presenting positive and negative impacts of products and services. It consists of four dimensions, environmental (E), health (H), societal (S), and knowledge (K) dimensions. The dimensions consist of 19 categories which have positive and negative valences [2]. The categories under the E dimension are Greenhouse Gases (GHG), non-GHG, biodiversity, Waste, and Water. All of these have both positive (handprint) and negative (footprint) valences. Under dimension H there are diseases, diet, physical activity, relationships, and meaning and joy categories with both positive and negative impacts. Under dimension S there are positive impacts related to taxes, jobs, and societal infrastructure as well as both positive and negative impacts related to equality and societal stability and understanding among people. Under the K dimension, there is a negative impact category of scarce human capital, which considers human capital as a limited resource like raw materials. Moreover, the K dimension consists of positive impacts related to building knowledge infrastructure, creating knowledge, and distributing knowledge.

In earlier research, NIM has been used to investigate the CFP-CSP relationship on the dimensional level [1]. However, the dimensions are aggregate measures, and as such lower-level categories entail significant information on various aspects of CSP. Hence, we will investigate what is the CFP-CSP relationship at the category level and whether there are temporal lags in this relationship. We contribute to the literature investigating the sustainability impacts of company actions specifically as manifested in the CFP-CSP relationship.

II. METHODOLOGY

We investigate the explanatory power of predictor, CFP variables on dependent, CSP variables with backward elimination multiple regression models. Our predictor data considers yearly (2015-18) finance datasets of 150 small and medium size Finnish technology companies. Following [1], the variables used are company age, personnel growth in %, turnover growth in %, turnover per person in €, *v*alue add per person in €, and return on assets in %. The financial data was received from Asiakastieto Oy. Additionally, there are two dummy variables, a variable indicating whether the company belongs to the high or to low growth companies as well as a variable, indicating whether the company is a product or a service company.

The dependent NIM data of these companies was received from the company Uprigth Oy, the developer of the NIM. We selected from each dimension two categories with the highest mean values to consider the highest impact categories. Our variables include non-GHG gases and waste footprints under E, diseases footprints and diseases handprints under H, taxes and societal infrastructure handprints under S, and scarce human capital footprints and knowledge creation handprints under K. The variables were logarithmically transformed to meet the normality requirements of multiple regression.

Multiple regression models were built independently for each year. In the Appendices, Table A presents the descriptive statistics and correlations of the example year 2016 for independent variables, and Table B descriptive statistics and correlations of the transformed dependent variables.

III. RESULTS

A. *Environmental Impacts: Non-GHG gases footprints*

The 2015 model was the only statistically significant model with 8.8% explanatory power ($F=6.152$, $p<0.05$).

The model suggests that the lower the ROA % is, the larger the non-GHG gas footprint and that the higher value-added per person in €, the higher the non-GHG footprint. Further, the results suggest that the temporal lag for making a change is 3 or more years as the oldest model is the only significant model. (Table I)

TABLE I
Models explaining variance in Environmental impacts Non-GHG footprints (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company age				
Personnel Growth %				
Turnover Growth %				0.077 (0.001)
Turnover/ person €				0.133 (0.000)
Value add/ person €	0.169* (0.000)		0.167 (0.000)	
Return on assets %	-0.348** (0.006)		-0.143 (0.005)	
Product/ service		0.102 0.130)		0.150 (0.134)
Growth comp. (dummy)		0.076 (0.137)		
Constant	-0.459 (0.114)	-0.616 (0.114)	-0.674 (0.162)	-0.726 (0.134)
F	6.152	1.047	1.289	1.455
Sig	0.003	0.354	0.280	0.230
Adj. R^2	0.088	0.001	0.005	0.011

*p<0.1, **p<0.05

B. Environmental Impacts: Waste footprints

All 4/4 models were statistically significant with the explaining power from 4.7% to 8.4% (Table II).

TABLE II
Models explaining variance in Environmental impacts Waste footprints (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company age				
Personnel Growth %				
Turnover Growth %		0.224** (0.003)	0.164** (0.002)	
Turnover/ person €	0.137 (0.000)	0.185** (0.000)	0.195** (0.000)	0.195** (0.000)
Value add/ person €				
Return on assets %	-0.247** (0.004)	-0.198** (0.004)		
Product/ service	0.210** (0.122)	0.184** (0.121)	0.213** (0.123)	0.200** (0.124)
Growth comp. (dummy)				
Constant	-0.628 (0.115)	-0.714 (0.118)	-0.883 (0.123)	-0.818 (0.119)
F	5.032	3.997	4.317	4.395
Sig	0.002	0.004	0.006	0.014
Adj. R^2	0.083	0.084	0.067	0.047

*p<0.1, **p<0.05

The models suggest that companies with poorer financial performance measured with ROA create more waste than companies with higher financial performance. The results also suggest that product manufacturing companies create more waste than service companies and that maximizing the turnover per person tends to increase the waste. Two models also suggest that the higher the turnover growth % the higher the amount of waste created. The statistically most significant models are the 2015 and 2016 models, which suggest that the temporal lag for making a change is around 2-3 or more years.

C. Health Impacts: Diseases footprints

Two models were statistically significant at p<0.05. Of these one suggests that product manufacturing companies have higher disease footprints than service companies and that growth companies have higher diseases footprint than other companies. Statistically most significant model is the 2015 model, which suggests that the temporal lag is more than 4 years. (Table III)

TABLE III
Models explaining variance in Health impacts Diseases footprints LgH1N (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company age				
Personnel Growth %	-0.179* (0.003)		0.147* (001)	
Turnover Growth %				
Turnover/ person €				
Value add/ person €				
Return on assets %				
Product/ service	0.146 (0.095)	0.165* (0.093)	0.170* (0.093)	
Growth comp. (dummy)	0.157* (0.100)	0.125 (0.096)		
Constant	-0.842 (0.083)	-0.843 (0.082)	-0.827 (0.080)	-0.843 (0.082)
F	3.219	2.882	3.293	2.882
Sig	0.025	0.060	0.041	0.060
Adj. R^2	0.053	0.045	0.052	0.030

*p<0.1, **p<0.05

D. Health Impacts: Diseases handprints

Two models were statistically significant at p<0.05 with an explaining power of 4.4-6.1%. The statistically most significant model suggests that the higher the personnel growth % is the lower the diseases handprints and that the higher the ROA% the higher the diseases handprints. Results also suggest that the older the company, the higher its diseases handprints. The most statistically significant model is the 2015 model, but the latest models also show increasing explanatory power that might suggest concave temporal lag. (Table IV)

TABLE IV
Models explaining variance in Health impacts Diseases handprints LgH1P (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company	0.159	0.188*	0.167*	0.195*
age	(0.005)	(0.005)	(0.005)	(0.005)
Personnel	-0.207**		0.106	
Growth %	(0.005)		(0.001)	
Turnover		0.09		
Growth %		(0.003)		
Turnover/				
person €				
Value add/				0.144
person €				(0.000)
Return on	0.018*			
assets %	(0.005)			
Product/				
service				
Growth comp.				
(dummy)				
Constant	-1.326	-1.292	-1.269	-1.388
	(0.149)	(0.143)	(0.135)	(0.149)
F	3.282	1.938	2.161	3.211
Sig	0.024	0.149	0.120	0.045
Adj. R^2	0.061	0.016	0.020	0.044

*p<0.1, **p<0.05

E. Societal Impacts: Taxes handprints

All the models were statistically significant at p<0.05 with an explaining power of 11.0 to 17.0 %. The most significant 2015 model suggests that the higher the personnel growth % and ROA % higher the taxes, and the higher the turnover per person €, the lower the taxes. (Table V)

TABLE V
Models explaining variance in Societal impacts Taxes handprints LgS1P (standardized betas and standard errors in parentheses) Backward elimination.

	2015	2016	2017	2018
Company			-0.161**	-0.141*
age			(0.001)	(0.001)
Personnel	0.209**			
Growth %	(0.001)			
Turnover				0.193**
Growth %				(0.000)
Turnover/	-0.199**		-0.271**	-0.267**
person €	(0.000)		(0.000)	(0.000)
Value add/				
person €				
Return on	0.178**			
assets %	(0.001)			
Product/	-0.274**			-0.266**
service	(0.019)			(0.019)
Growth comp.				
(dummy)				
Constant	0.049	0.055	0.113	0.099
	(0.067)	(0.019)	(0.023)	(0.024)
F	8.193	6.794	7.946	7.680
Sig	0.000	0.000	0.000	0.000
Adj. R^2	0.170	0.110	0.123	0.153

*p<0.1, **p<0.05

Moreover, the 2015 and 2018 models also suggest that service companies pay more taxes than product manufacturing companies. 2017 and 2018 models further suggest that the younger the company is, the higher the taxes. The results suggest somewhat concave temporal lag as the oldest and newest models have the best explanatory power.

F. Societal Impacts: Societal infrastructure handprints

Three models are statistically significant at p<0.05 with an explaining power of 6.8 to 11.3 %. In the most significant 2018 model the higher the value added per person € and service companies, the higher the societal infrastructure handprints, and the higher the turnover growth % the lower the societal infrastructure handprints. As the latest models are statistically significant the temporal lag of societal infrastructure handprints is suggested to be equal to or less than 2 years. (Table VI)

TABLE VI
Models explaining variance in Societal impacts Societal infrastructure handprints LgS3P (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company				
age				
Personnel	0.144		-0.217*	
Growth %	(0.006)		(0.002)	
Turnover				-0.223*
Growth %				(0.002)
Turnover/			0.185*	0.215*
person €			(0.000)	(0.000)
Value add/		0.225*		0.275**
person €		(0.000)		(0.000)
Return on				
assets %				
Product/	-0.171	-0.194	-0.161	-0.257**
service	(0.226)	(0.247)	(0.218)	(0.259)
Growth comp.				
(dummy)				
Constant	-0.436	-0.840	-0.658	-0.638
	(0.186)	(0.351)	(0.255)	(0.279)
F	2.199	3.280	3.343	3.012
Sig	0.118	0.044	0.024	0.025
Adj. R^2	0.031	0.067	0.085	0.113

*p<0.1, **p<0.05

G. Knowledge Impacts: Scarce human capital footprints

All the models were statistically significant at p<0.05 with an explaining power of 31.6 to 47.1 %. In all the models, the higher the turnover per person, the lower the scarce human capital footprints. Moreover, in the 2017 and 2018 models the older the company the higher the scarce human capital footprints. Additionally, in the 2016 and 2017 models, service companies are suggested to have lower scarce human capital footprints. The latest models were equally significant, which suggests that the temporal lag is shorter than 2 years. (Table VII)

TABLE VII

Models explaining variance in Knowledge impacts Scarce human capital footprints LgK1N (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company			-0.112*	-0.109*
age			(0.002)	(0.002)
Personnel	0.125	0.165**		
Growth %	(0.002)	(0.001)		
Turnover				0.177**
Growth %				(0.000)
Turnover/	-0.668**	-0.683**	-0.698**	-0.680**
person €	(0.000)	(0.000)	(0.000)	(0.000)
Value add/	0.286**			
person €	(0.000)			
Return on		0.106		
assets %		(0.002)		
Product/		-0.109*	-0.115*	
service		(0.056)	(0.055)	
Growth comp.				
(dummy)				
Constant	-0.035	0.288	0.466	0.257
	(0.058)	(0.066)	(0.073)	(0.060)
F	19.346	31.662	44.069	43.972
Sig	0.000	0.000	0.000	0.000
Adj. R^2	0.316	0.472	0.471	0.471

*p<0.1, **p<0.05

H. Knowledge Impacts: Knowledge creation handprints

All the models were statistically significant at $p<0.05$ with the explaining power of 13.1 to 16.4 %. Service companies are suggested to contribute more positively to knowledge creation than product companies. In 3 of 4 models, the higher the personnel growth % the higher the knowledge creation handprints. In the two models the higher the turnover per person in €, the lower the knowledge creation handprints. The temporal lag does not seem to exist. (Table VIII)

TABLE VIII

Models explaining variance in Knowledge impacts Knowledge creation handprints LgK3P (standardized betas, standard errors in parentheses, and method: backward elimination)

	2015	2016	2017	2018
Company				
age				
Personnel	0.272**	0.264**		0.233**
Growth %	(0.005)	(0.002)		(0.001)
Turnover			-0.225**	
Growth %			(0.000)	
Turnover/		-0.191**		-0.211**
person €		(0.000)		(0.000)
Value add/	0.222**			
person €	(0.000)			
Return on				
assets %				
Product/	-0.298**	-0.319**	-0.332**	-0.320**
service	(0.173)	0.162	(0.162)	(0.163)
Growth comp.			0.158*	
(dummy)			(0.170)	
Constant	-0.806	-0.415	-0.370	-0.381
	(0.200)	(0.148)	(0.162)	(0.157)
F	6.278	9.703	7.744	9.219
Sig	0.000	0.000	0.000	0.000
Adj. R^2	0.164	0.163	0.131	0.155

*p<0.1, **p<0.05

IV. DISCUSSION AND CONCLUSIONS

Firstly, the most surprising results consider the temporal lag. The earlier research has suggested a one-year temporal lag for environmental impacts [1] on the dimensional level, but here we find 3-4 years for the two footprints at the categorial level. This may be explained by the unanalyzed environmental handprint categories. Our study confirms the results of the previous research [1] that the time lags of the health impacts are at least 4 years, but for the societal impacts, our results suggest concave dynamics. Further, the temporal lag of scarce human resources and the change in a company could be seen in 1-2 years after the change has been made. The results of knowledge creation handprints support the previous result of temporal lag being at least 4 years.

Secondly, the categorial models seem to show more sense-making than the dimensional-level models [1] due to their higher equivalence. Moreover, the specificity brought more explaining variables on the categorial level, which did not appear on the dimensional level. As far as the temporal lags are concerned, the category level also brought more detailed information.

Thirdly, from Table B it seems that companies generating non-GHG gases are also generating more waste and causing more diseases but correlating negatively with diseases handprints. Knowledge creation handprints correlate positively with taxes and scarce human capital but negatively with environmental footprints. It is fair to assume that knowledge-creating companies have more educated people, which are seldom product manufacturing companies and do not thus carry the environmental burden. Societal infrastructure handprints do not significantly correlate with any of the other impacts. Paying taxes seems to correlate with both environmental and health footprints. It seems also that companies with diseases footprints have also higher diseases handprints, which is an interesting result.

Finally, in the sample correlation table, ROA has a significant correlation ($p<0.01$) with the growth companies, two-year personnel growth, turnover growth, and value-added per person. (Table A). The phenomenon could be related to the fact that the growth company subset of the sample included also profitable high-growth companies. Value added per person correlated with turnover per person, personnel growth, and turnover growth, which is also a natural conclusion.

The purpose of this research was to quantitatively elaborate the previous CFP-CSP relationship explorations [1] by going deeper into the essence of the CSP at the category level. The findings strengthen the previous findings about the possible usefulness of the NIM in measuring the CSP. Especially NIM may be useful for developing corporate sustainability strategy as it shows opportunities for measuring the impacts of actions. The specificity of the CFP-CSP relationship, when going to the category level helps in designing the CSP strategy of the company.

The results also show interesting future research avenues, especially considering the temporal lag of actions influencing the CSP measures. Our contributions suggest that temporal lag in the relationship between CFP measures resulting from company actions and CSP measures is non-linear in nature and this needs to be investigated, in line with linear studies between CFP and CSP. Our study is limited in that the used dataset was from one national sub-sample and included only select categories. In sum, our results suggest that the CFP-CSP relationship using NIM could be explored quantitatively, and we call for additional research using NIM or similar methods to further our understanding of the relationship between corporate actions, CFP, and their impacts on CSP.

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APPENDICES

TABLE A

Correlations table for independent variables using 2016 numbers as an example

	N	Mean	SD	1	2	3	4	5	6	7	8	9
1LgE2N	126	-0.526	0.685	1								
2Prod/serv	149	0.72	0.451	0.11	1							
3GrwthCo	149	0.25	0.433	-0.04	0.08	1						
4Age16	149	24.51	15.608	0.08	0.07	-0.11	1					
5PG1614	149	6.702	29.256	-0.21*	0.04	0.34**	-0.15	1				
6TOG1614	149	10.494	28.82	-0.13	-0.03	0.37**	-0.21*	0.63**	1			
7TOP16	149	286048	480515	0.07	-0.18*	-0.05	-0.10	-0.02	0.04	1		
8VA16	122	81490	34288	0.06	-0.14	0.10	-0.21*	0.27**	0.34**	0.50**	1	
9ROA16	141	11.255	14.536	-0.10	0.04	0.24**	-0.16	0.31**	0.42**	0.01	0.48**	1

* Significant at the 0.05 level (2-tailed).

** Significant at the 0.01 level (2-tailed).

TABLE B

Correlation table for transformed dependent variables

	N	Mean	Std. Dev.	1	2	3	4	5	6	7	8
1LgE2N	123	-0.483	0.637	1							
2LgE5N	139	-0.514	0.655	0.73**	1						
3LgH1N	124	-0.684	0.460	0.59**	0.58**	1					
4LgH1P	115	-1.047	0.758	0.20*	0.33**	0.52**	1				
5LgS1P	149	0.013	0.111	-0.32**	-0.54**	-0.22*	-0.15	1			
6LgS3P	77	-0.635	0.929	0.14	0.04	-0.15	0.16	-0.00	1		
7LgK1N	146	-0.134	0.404	-0.34**	-0.50**	-0.24**	-0.25**	0.45**	-0.31**	1	
8LgK3P	135	-0.909	0.915	-0.30**	-0.51**	-0.31**	-0.09	0.67**	0.12	0.53**	1

** Significant at the 0.01 level (2-tailed).

* Significant at the 0.05 level (2-tailed).