Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

CONTABILIDADE, FISCALIDADE E FINANÇAS EMPRESARIAIS

MASTER´S FINAL WORK

DISSERTATION

HOW MANAGEMENT CONTROL SYSTEMS USAGE AFFECTS BUSINESS PERFORMANCE: EVIDENCE FROM PORTUGUESE FIRMS

INÊS BAPTISTA ÁGUAS

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SUPERVISION:
PROF. SOFIA MARGARIDA MORAIS LOURENÇO

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ABSTRACT

This dissertation studies the impact Management Control Systems (MCS) usage has on the financial performance of firms. MCS are seen as instruments that can be used by managers to achieve the company goals more easily, through an increase in efficiency and effectiveness of the operations performed.

To test this relationship empirically, data regarding firm characteristics was collected through a questionnaire targeted at Portuguese non-financial firms. Additionally, it was also gathered hard data comprising the financial performance of the firms between the years 2010 and 2020. Afterwards, Propensity Score Matching (PSM) was used to obtain a sample of comparable firms. Finally, a regression model was fitted to panel data comprising the sample of comparable firms by using the between regression estimator (between effects).

The results obtained reinforce the argument that MCS usage is beneficial to the financial performance of firms and helps them achieve their goals. Specifically, it was found that MCS have a significant and positive effect on Return on Equity (but not on Return on Assets). These results are robust to the PSM specifications but not to different specifications of regression models.

KEYWORDS: Management Control Systems; Performance; Propensity Score Matching; Panel Data

RESUMO

A presente dissertação estuda o impacto que o uso de Sistemas de Controlo de Gestão (SCG) tem na performance financeira das empresas. Os SCG são vistos como um instrumento que os gestores têm à sua disposição para mais facilmente atingirem os objetivos da empresa, através de um aumento de eficiência e de eficácia das operações realizadas.

Para testar esta relação foram recolhidos dados sobre as características das empresas através de um questionário direcionado a empresas portuguesas não financeiras. Adicionalmente, foram obtidos dados das demonstrações financeiras das empresas referentes à sua performance financeira no período de 2010 a 2020. Para se obter uma amostra de empresas comparáveis foi utilizado o *Propensity Score Matching* (PSM), aplicando-se depois sobre essa amostra um modelo de regressão ajustado a dados em painel, usando o *between regression estimator* (*between effects*).

Os resultados obtidos servem para reforçar o argumento de que a utilização de SCG é benéfica para a performance financeira das empresas e que as ajuda a atingir os seus objetivos. Especificamente, verificou-se que os SCG têm um efeito significativo e positivo na rendibilidade do capital próprio (mas não na rendibilidade do ativo). Estes resultados apresentam robustez face às especificações do PSM mas não a diferentes especificações de modelos de regressão.

PALAVRAS-CHAVE: Sistemas de Controlo de Gestão; Performance; *Propensity Score Matching*; Dados em Painel

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List of Abbreviations

AGRIC – Agriculture, animal production, hunting, forest and fishing

CEO – Chief Executive Officer

CFO – Chief Financial Officer

DECENT – Decentralization

ECO – Economic Group

EFA – Exploratory Factor Analysis

FINANCIALPOS – Financial Position

INDUSTRY - Industry, construction, energy and water

KMO – Kaiser-Meyer-Olkin

LNSIZE – Logarithm of Size

MCS – Management Control Systems

MCSCOUNT – Intensity of usage of MCS (score)

MCSINTENSITY – Intensity of usage of MCS (binary variable)

OLS – Ordinary Least Squares

PEU – Perceived Environmental Uncertainty

PEUDYN – Perceived Environmental Uncertainty: Dynamism

PEUHOST – Perceived Environmental Uncertainty: Hostility

PEUUNC – Perceived Environmental Uncertainty: Uncertainty

PSM – Propensity Score Matching

ROA - Return on Assets

ROC - Receiver Operating Characteristic

ROE – Return on Equity

STATE – State Corporate Sector

1. INTRODUCTION

We live in an extremely globalized world. With globalization comes increased competition since it is easy to access different markets in different points of the world (Altman & Bastian, 2021). Additionally, the environment is changing very rapidly, and what is popular today may not be tomorrow, therefore firms need to observe daily the changes that occur in the market (McLaughlin, 2021). Thus, firms need to have the ability to adapt, to improve the processes, to become more profitable, and to avoid being left behind (McLaughlin, 2021).

Managers possess many resources and many possibilities to use them in order to improve firm performance (Anthony et al., 2014). Since it is easy to get lost in the middle of so many options, studies that analyze the different tools available to managers, and the effect they have on performance, are helpful for decision making.

Management Control Systems (MCS) are tools that managers can implement and use in their firms with the aim of increasing long-term performance (Anthony et al., 2014). By providing firms and employees with relevant information, MCS help them achieve their goals in an effective and efficient way (Anthony, 1965).

However, researchers have difficulty in ascertaining the benefits of MCS usage in firms. Most studies focus on the contingency theory and on the fit between firm characteristics and specific MCS, however the results have been conflicting (Langfield-Smith, 2006; Otley, 2016).

Additionally, recent studies found that there is not the need for a specific alignment between firm characteristics and controls since there are multiple packages of MCS capable of fulfilling firm's needs (Bedford et al., 2016; Ittner et al., 2003). Nevertheless, it is critical to ascertain if MCS usage is or not beneficial to a firm, as Davila & Foster (2005, 2007) and Duréndez et al. (2016) have observed. This study follows this trend in the literature and focus on the usage of MCS as a driver of firm performance. Specifically, this study investigates whether there are performance differences between firms that have a high usage of MCS and those with a low usage. Thus, the research question of this thesis is: *Does MCS usage affect business performance?*

This question is answered by mimicking an experimental setting in an observational/retrospective study. Specifically, by using Propensity Score Matching (PSM), a control group and a treatment group are created, and a pre-experiment and an experiment period are defined (the first one goes from 2010 to 2014 and the second one from 2015 to 2020). More concretely, firms were divided in accordance with their MCS usage, with firms with a high MCS usage considered as part of the treatment group, and firms with a low MCS usage considered as part of the control group. In an experiment setting it is a prerequisite that firms are alike prior to the treatment so that they are comparable in the second period. PSM is used to make sure that at the beginning of the second period firms are alike in the two groups. So, at the outset, 2015, only firms that are similar (in relation to performance and other characteristics), although they have different MCS usage, are considered. The performance of the two groups is then compared in the experimental period (from 2015 onwards) relative to the pre-experiment period. If MCS usage has an impact on performance, the two groups should be different in the experimental period.

The information that was used to characterize firms came from a questionnaire with a sample of 1 762 Portuguese non-financial firms. Hard financial data was then collected for these firms between 2010 and 2020.

The results show that higher MCS usage has a positive and significant effect on Return on Equity (ROE), but not on Return on Assets (ROA). The significance of the effect is robust to different PSM specifications but not to different specifications of regression models.

This study contributes to the literature in several ways. First, this is one of the few studies that has a broad sample whereas previous studies have focused on a single industry and on large businesses (Ittner et al., 2003; King et al., 2010; Sandino, 2007). Second, this study uses hard financial performance in a panel data format, which is not common in prior studies that sometimes rely on self-ratings of performance, which can lack objectivity (Brownell & Merchant, 1990; Ittner et al., 2003). Third, because this study uses panel data, it overcomes the limitations of cross-sectional data. Moreover, measurement practices yield economic results with some lag, and therefore the linkage between management practices and improved firm performance may take time, which requires longitudinal data (Ittner et al., 2003; Jokipii, 2010; van der Stede, 2014).

This study has also practical relevance, namely for top managers aiming to improve the performance of their firms. This study shows that investments in MCS have a clear return in terms of firm performance.

This dissertation will comprise four more chapters. The next chapter presents the literature review and the development of the hypothesis. Chapter three describes the methodology and the data. The results and robustness analysis will be presented in chapter four. Lastly, chapter five comprises the conclusion, limitations, and suggestions for future research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Management Control Systems

MCS were initially defined by Anthony (1965) as a process that enables firms to achieve their objectives, which are established by strategic planning, in the most effective and efficient way. The definitions that followed emphasized this same idea that MCS are closely linked with the goals and strategy of a firm. Simons (1994, p. 170) defined MCS as the "formal, information-based routines and procedures used by managers to maintain or alter patterns in organizational activities" and Anthony et al. (2014, p. 1) defined management control as "the systematic process by which the organization's higher-level managers influence the organization's lower-level managers to implement the organization's strategies".

MCS are instruments that convey managers timely and reliable information, on the basis of which they make improved decisions (Hopwood, 1970) that affect employees' behavior (Flamholtz et al., 1985). MCS enable the efficiency and effectiveness of activities (Jokipii, 2010) and allow the goals of the firm to be achieved (Hopwood, 1970).

Usually, a firm does not implement only one system, but instead multiple MCS are chosen from a portfolio that encompasses formal and informal types of controls (Abernethy & Chua, 1996) and financial and non-financial measures (Ittner et al., 2003). These mechanisms can be used as planning, budgeting, resource allocation, measurement, feedback, or evaluation-reward controls, and taken together constitute the organizational control system (Flamholtz et al., 1985; Anthony & Govindarajan, 2014).

If MCS are designed with the purpose of achieving the same goal it can be considered that the organizational control system is internally consistent (Abernethy & Chua, 1996), which has a positive effect on performance (Gong & Ferreira, 2014). Thus, it can be misleading to analyse each MCS one by one without considering the existence of others (Bedford et al., 2016). For that reason, Otley (2016) makes a call for more studies taking into consideration MCS as a package, since many of the studies made until now did not look at MCS as a whole, but instead focused on a particular control (Abernethy & Brownell, 1999; Gosselin, 1997; Hoque & James, 2000)

2.2 Management Control Systems and Performance

One of the challenges of MCS is to increase the long-term performance of the organizations (Anthony et al., 2014). However, the implementation of MCS may not always be beneficial to a firm. When deciding to implement and use MCS, managers must weigh the pros and cons of such adoption (Davila & Foster, 2005). The benefits of MCS usage include increased information, efficiency, effectiveness, and coordination, while the costs can be in the financial form (resources are needed to implement and oversee the controls) or can come from the fact that the individual subject to the controls feels frustrated and limited, so that s/he neglects her/his job (Khandwalla, 1972).

Overall, the usage of MCS will only favour the firm if the benefits outweigh the costs, which will happen when the need for improved information is higher than the costs (Abernethy & Brownell, 1999). This identification of the effects of using MCS is hampered by the difficulty in relating management variables with business performance because of the intervention of organizational and environmental variables (contingencies) in this relationship (Simons, 1994).

The contextual factors of the business affect the decisions of firms related to MCS implementation since, depending on the specific situation of the firm, each control will have different costs and benefits. Therefore, different firms will use MCS differently, since MCS will impact each firm in their own way and there can be situations in which the rational decision is to adopt a control and others in which it is not to adopt it (King et al., 2010). The theory supporting these arguments is called contingency theory.

The main idea of contingency theory is that a one size fits all organization control system does not exist (Fisher, 1995), and instead each system should be a response to a set of contingencies (Abdel-Kader & Luther, 2008). Thus, the suitability of the management system to the external and internal environment of the firm is the key to its effectiveness (Ditillo, 2004; Haldma & Lääts, 2002). This means that MCS, through enhanced information, have the capability to help managers make decisions which will lead to the desired organizational outcomes, but only if MCS implementation and usage are appropriate to that firm (Chenhall, 2006). For example, for certain firms some of the MCS may be too formal and hinder creativity, which will affect performance negatively (Ittner & Larcker, 1997). Furthermore, the decision to implement a MCS is not only contingent on the cost-benefit analysis, but also on the personal incentives and preferences of the managers (King et al., 2010). The managers shape the MCS according to their ideas, so the portfolio of MCS implemented in a firm also reflects their vision (Naranjo-Gil et al., 2009; Naranjo-Gil & Hartmann, 2006, 2007).

Besides deciding on the MCS to implement, the manager is also the user of the information coming from the MCS and the one who makes decisions for the firm. When short terms goals of a manager are not congruent with long term company goals dysfunctional behavior may emerge (Otley, 1978). So, although it may be logic to think that the manager makes the best decisions for the firm so that all the MCS are implemented and used in a beneficial way to the firm, there are financial limitations as well as other stimulus affecting the manager and preventing the firm from using the optimal MCS for their business context (King et al., 2010).

Therefore, the decision to implement a certain MCS can be affected by a rational trade-off between costs and benefits, but also by other institutional and managerial factors. Additionally, contextual factors also play a role. Contingency theory has focused on these factors while trying to relate MCS to performance (Abernethy & Lillis, 1995). Contingency theory main argument is that there are no MCS that fit and benefit all companies equally (Fisher, 1995). Many studies corroborate this argument. For example, Haldma & Lääts (2002) find that external and internal contingencies are associated with changes in cost and management accounting practices. However, when performance enters the equation, there are contradictory findings (Abernethy & Lillis, 1995; Kim, 1988). Many studies try to find a match between contingencies and MCS that maximizes performance, yet this match is conflicting across studies (Langfield-Smith, 2006; Otley, 2016).

Additionally, recent studies, such as Bedford et al. (2016), find that there are multiple effective combinations of MCS. Otley (2016) argues that the creation of predictive knowledge is not possible in the dynamic environment faced by the MCS and, therefore, the need for contingency studies is questioned.

Since finding a link between MCS, contingencies and performance has been burdensome and problematic, it is relevant to follow the findings of Ittner et al. (2003) and verify if MCS usage is or not beneficial to a firm. Ittner et al. (2003) found that firms with higher measurement diversity (of financial and non-financial measures) than other firms following similar strategies show higher performance. These results do not support the need for alignment between the firm's strategy and its systems, since they find that more systems than those predicted by the model are beneficial *ceteris paribus*. This study questions the need for alignment and emphasizes overall MCS usage as the key to success.

This study follows a similar approach and focusses on the impact of MCS usage in a firm. Multiple studies have already found evidence of a positive influence of MCS usage on firms' performance (Davila & Foster, 2005, 2007; Duréndez et al., 2016) but they struggle with identification issues related with problematic data coming from cross-sectional data or limited panel data. The present study overcomes these limitations by using PSM and a large panel. From a theoretical standpoint, this study argues that, *ceteris paribus*, a higher usage of MCS should lead to a higher performance, such that MCS usage is a driver of competitiveness and organizational performance. Hence, the hypothesis for this study is the following:

H1: The usage of MCS has a positive effect on the financial performance of firms.

Financial performance is used to avoid problems of self-reported data and it is the type of performance that Simons (1987) used to define MCS effectiveness. For that reason, it is also the type of performance on which the literature has focused the most, more particularly on profit and return on investment (Otley, 2016).

2.3 The confounders affecting the link between MCS usage and Performance

The relationship between MCS usage and financial performance will be studied by taking into consideration possible confounders of that relation (variables that affect both performance and MCS usage), as can be seen in Figure 1. The non-inclusion of these confounding variables has been a weakness in many MCS studies (Kim, 1988). The choice of these confounders was done based on the literature. They will be described in the next sections.

2.3.1 Financial Position

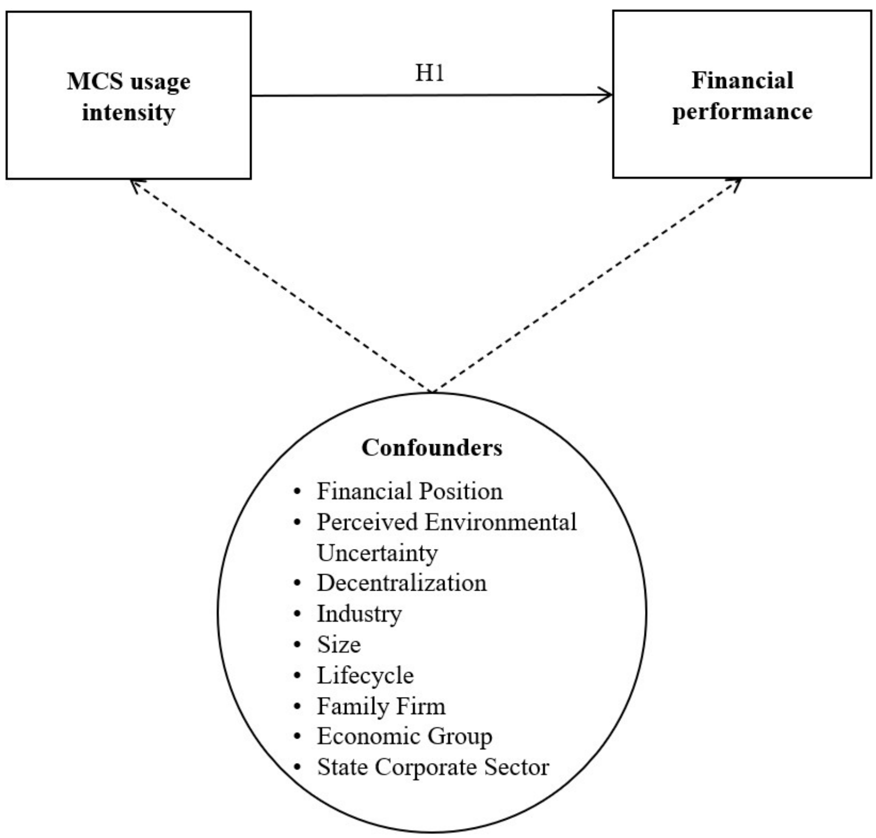

Figure 1 - Research Model

Langfield-Smith (2006) and Otley (2016) argue that financial performance is a contingent variable affecting MCS usage. On the one hand, firms with poorer financial performance may feel the need to implement MCS to revert their situation, on the other hand, MCS are costly and thus firms with better performance have the resources to implement them more easily.

In addition, financial performance is a potential outcome of the effectiveness of MCS usage (Duréndez et al., 2016).

2.3.2 Perceived Environmental Uncertainty

Perceived Environmental Uncertainty (PEU) has also been associated with the emergence of MCS in companies. This variable translates how managers evaluate the impact of various elements of the external environment. Uncertainty, hostility, and dynamism are the most common studied elements of PEU (Chenhall, 2006; King et al., 2010; Otley, 2016).

Jokipii (2010) found that environmental uncertainty has a significant effect on the internal control structure of a firm. Uncertainty needs to be coped with flexible and adaptable systems (Otley, 2016) because it requires broad scope and timely information (Chenhall & Morris, 1986).

Competition, and the hostility that it brings, increase the need for objective and appropriate information. In a competitive environment there is a strong need to control costs and to assess if all functional areas are meeting expectations, which implies an extensive usage of MCS (Khandwalla, 1972). This suggests that, as competition intensifies, the benefits outweigh the costs associated with the usage of these controls, so that a great extent of MCS usage in a firm facing weak competition may be damaging (Khandwalla, 1972). In addition, a more intensive and dynamic operating environment must be followed by a sophisticated and complex accounting system (Haldma & Lääts, 2002).

Lastly, the relationship of PEU with performance can be moderated by the use of MCS (Gul & Chia, 1994; Jokipii, 2010). On one hand, when PEU is low there is no need to implement more MCS since the information the firm already has is enough to make trustworthy decisions, and more information would lead to information overload (Chong, 1996), which would undermine performance. On the other hand, when PEU is high the environment is more complex, and more information is needed to make accurate decisions, MCS are more important.

2.3.3 Decentralization

In a centralized business decision-making is restricted to upper levels, while in decentralized businesses it is delegated to business units' managers (lower levels). In this latter case, managers have increased responsibility and they need MCS designed in a way to provide them with information relevant for decision-making (Abdel-Kader & Luther, 2008; Jokipii, 2010; King et al., 2010). In the former case, fewer MCS should be required, as top management team is more involved in the daily business operations (Abdel-Kader & Luther, 2008; Jokipii, 2010; King et al., 2010). Empirical studies find evidence to support these arguments (Abdel-Kader & Luther, 2008; King et al., 2010), but there are also non-statistically significant results (Jokipii, 2010).

2.3.4 Industry

The activities undertaken in each business have different levels of knowledge complexity and of task uncertainty. Task uncertainty is high when there are not established techniques for handling the task and when the tasks possess high variety or novelty (Abernethy & Brownell, 1997). These two factors influence the organizational control system (Abernethy & Brownell, 1997; Ditillo, 2004). In manufacturing companies present greater routine in the activities compared to other companies, then MCS will be different for this industry.

In addition, Ittner & Larcker (1997) found that, by industry, controls affect differently the performance of firms, so that they should be adapted to the industry in question. Duréndez et al. (2016) found that construction companies seem to use MCS to a greater extent than other sectors, however no significant differences were found between industry and service companies. Davila (2005) found that industry impacts significantly the emergence of MCS, with manufacturing firms being more likely to implement the systems.

2.3.5 Size

Several studies have found evidence that the larger the business the larger the extent of MCS usage (Davila, 2005; Davila & Foster, 2005, 2007; Duréndez et al., 2016; Haldma & Lääts, 2002; King et al., 2010). The rationale is that when a firm grows in complexity and number of employees, informal interactions no longer provide all the information needed for decision-making and MCS emerge as a solution to deal with such growth (Davila & Foster, 2005; Greiner, 1998; King et al., 2010). Additionally, larger firms have greater ease in getting the resources needed to invest in MCS (Abdel-Kader & Luther, 2008; King et al., 2010), which may also explain the higher usage of MCS by large firms.

Finally, size is also positively related with performance (Duréndez et al., 2016; Fama & French, 1995).

2.3.6 Lifecycle

Although Davila (2005) finds that age is associated with the emergence of MCS, age is not a great predictor of MCS usage since what defines the need for MCS is the growth of a firm (Greiner, 1998). Growth is related with the lifecycle of the firm, and not necessarily with the age, since each firm has its own pace and may face growth at a different age. This idea is corroborated by Duréndez et al. (2016) who finds that age is unable to explain the degree of MCS usage.

Support for lifecycle stage acting as a dependent variable for MCS usage was found by Moores & Yuen (2001) who obtained evidence that MCS formality changes across lifecycle stages. Auzair & Langfield-Smith (2005) also found that lifecycle stage influences MCS design.

2.3.7 Family Firms

Duréndez et al. (2016), Kotey (2005) and Speckbacher & Wentges (2012) found that non-family businesses use MCS to a greater extent, in comparison with family businesses. MCS seem to be less relevant to family businesses in comparison to non-family businesses since in the former the degree of information asymmetry is lower (Senftlechner & Hiebl, 2015). Being a family firm acts as a substitute for MCS usage (McCollom, 1988).

2.3.8 Economic Group

Organizations that are part of an economic group have the need to remain interconnected with the remaining firms of the group. Thus, to reduce the risk of information asymmetries, that is higher in this setting, they build systems that allow for high-quality exchanges of resources and information (Min et al., 2022). Consequently, this type of firms has a higher usage of MCS compared to firms that do not belong to a group.

2.3.9 State Corporate Sector

Firms belonging to the public sector are intrinsically different from private sector companies. Since public utility is the priority for these organizations, the set of objectives they possess is much more complex so that it is not adequate to simply translate the tools that are used in the private sector (Davila et al., 2012). In addition, there is high pressure to keep expenditure low (Felício et al., 2021).

These factors suggest that there is a higher need for MCS in this type of firms. However, since the competition to stay alive is less of a concern for these firms, they do not feel the urge to adopt the best MCS to survive (Felício et al., 2021), and the effect on MCS is dubious.

3. RESEARCH METHOD

3.1 Data Description and Survey Design

In order to test the research model, this study uses two sets of data. The first set refers to a survey put forward by a group of researchers, between 2012 and 2014, as part of a comprehensive study about the MCS usage in Portuguese companies.

Although questionnaires are a useful and simple tool to get large scale data, the way they are implemented can lead the data to suffer from response or surveyor biases, which leads to questioning the reliability of the results (van der Stede et al., 2006). To mitigate these problems and improve the quality of the instrument a series of actions were taken by the researchers (Dillman et al., 2016; van der Stede et al., 2006). For example, the group of researchers, specialists in the management control area, developed a survey grounded on the existing literature to increase the internal validity of the constructs. Additionally, a pre-test, with the goal of increasing the understandability of the survey, was performed, which resulted in correction of mistakes and ambiguities. Finally, a pilot test was done by a group of managers and management academics.

To distribute the questionnaire, data from Portuguese non-financial companies was requested to Informa D&B (a company that gathers corporate information). This request resulted in a target population of 34 659 companies, for which contacts were provided.

To obtain the name and e-mail of the person suitable to answer the survey (the person responsible for the management control of the firm), the companies were contacted by phone. In these contacts, some companies refused to take part in the study, others were insolvent, ceased activities, or belonged to the same economic group. Finally, for some firms the e-mail address obtained was not correct. Therefore, only 23 008 surveys were effectively sent, which corresponds to the survey population.

In order to increase the response rate, some measures were taken. Together with the survey an introduction letter was sent, in which the participants could find relevant information about the study and the follow-up of its results. Participants upon completion of the questionnaire were also eligible to win one of 8 vouchers ranging from 24.90 € to 89.90 €. Finally, up to 10 reminders were sent to improve the response rate.

In total 4 375 responses were received, which corresponded to a response rate of 19.02%. However, not all of them completed the questions necessary for this study, and therefore were dropped from all the analyses. Thus, the final sample for this study consists of 1 762 responses (7.66% response rate). The sample details can be found in Appendix 1.

The response rate obtained (7.66%) is compatible with the idea that response rates in management accounting survey research are declining as a result of an increase in the use of electronic surveys (Hiebl & Richter, 2018). Additionally, the large population size also contributes to this low rate since this variable is significantly and negatively associated with the response rate (Hiebl & Richter, 2018). However, the large survey population size (23 008) comes with a large number of usable responses (1 762), which is an important prerequisite to obtain a sample that resembles the survey population, and is important to test a theoretical relationship, which is the focus of this study (Hiebl & Richter, 2018). Even so, the low response rate, although less important in this context, still needs to be assessed in order to verify if the survey suffers from biases, which can affect the sample representativeness.

Non-response bias was ascertained by comparing the early (N = 475) and the late (N = 421) respondents, with a t-student test for independent samples with a Confidence Interval of 95%. As can be seen in Appendix 2, no significant difference is found between the two groups for the variables used in this study and therefore the concern of non-response bias is mitigated.

Descriptive statistics of the respondents (position occupied, experience in the position, professional experience, gender and age) can be found in Table I, while firm size statistics, measured by the number of employees, can be found in Table II. Overall, the profile of the respondent is a 41 years old male Chief Executive Officer (CEO) of a small firm, who spent 19 years working, and 11 in the current position.

The second set of data refers to hard financial data (2010 to 2020) from the companies that answered the survey. These data were obtained from Informa D&B.

Table I - Participants Profile

Position	N	Experience in the position (average of years)	Professional experience (average of years)	Age	Gender (N)	
					W	M
CEO	779	13.19	21.97	43.68	151	628
CFO	600	10.33	18.04	40.53	258	342
Controller	157	7.94	14.88	37.40	69	88
Owner	23	14.00	23.43	44.87	5	18
Other manager	72	8.45	15.14	37.71	32	42
Non manager	129	10.41	16.05	37.79	80	49
Total	**1 762**	**11.37**	**19.30**	**41.38**	**595**	**1 167**

Table II - Size of the Participants by Number of Employees

Number of employees	N	% of Total
Small: 10 - 49	1 316	74.69
Medium: 50 - 249	373	21.17
Large: more than 249	73	4.14
Total	**1 762**	**100**

3.2 Research Model

The major goal of this study is to document the effect of MCS usage in the firms' financial performance. To be able to make this analysis multiple steps need to be taken beforehand.

Firstly, there is the need to identify the treatment variable. In this study, MCS usage is considered the treatment variable. Therefore, firms with a high usage of MCS are considered subject to treatment and firms with a low usage of MCS are considered in the control group.

Second, in this study, assignment to treatment was not random (MCS is endogenous as firms decide the usage of MCS) and treatment is not the only variable differentiating the firms, so the nature of the data is observational.

Third, since firms self-select themselves into the groups there is the risk of selection bias (Tucker, 2010). Firms that have a high usage of MCS may possess characteristics that make them more likely to use MCS but that may also moderate the relationship between MCS intensity and performance. So, the characteristics in which these firms differ can be an explanation for the potential difference in performance between the firms, and not the MCS usage. Therefore, the performance of firms that have a high usage of MCS can only be compared with the firms that have a low usage intensity of MCS when these differences are accounted for, that is, when both groups being compared are not structurally different in internal and external characteristics (Villalonga, 2004).

Therefore, to solve endogeneity and self-selection issues, the researcher needs to use more sophisticated econometric methods, such as PSM (Rosenbaum & Rubin, 1983). PSM is a technique increasingly being used in accounting (Shipman et al., 2017; Tucker, 2010). In comparison to an Ordinary Least Squares (OLS) model, PSM is a more robust approach since it decreases reliance on assumptions regarding functional form given that it does not impose a linear relation between the outcome and the covariates (DeFond et al., 2017; Tucker, 2010). Therefore, the problem of endogeneity is better alleviated through a PSM model (Shipman et al., 2017). Many studies were able to show the effectiveness of matching methods in overcoming concerns with structural issues in the underlying data (Shipman et al., 2017).

Since PSM only addresses selection due to observables (Tucker, 2010), in this study it will be assumed that selection bias due to unobservables is not a major concern. It is possible to make that assumption since throughout the years many studies were developed regarding MCS use and performance, which mitigates the concern of unobservables. However, it is important to notice that the information processed in an empirical model is always limited in comparison to the reality in which managers base their managerial decisions (Tucker, 2010).

In this method, firms with a high usage of MCS will be matched to firms with which they share the same characteristics, but with low usage of MCS. This will lead to a smaller sample where differences in characteristics between groups are minimized (the two groups have similar distributions of covariates).

Given that finding firms with exactly the same characteristics is infeasible, since there are many characteristics on which treated and non-treated firms differ and that determine treatment assignment, and some of them are continuous (dimensionality problem), the match is made using the propensity score, the conditional probability of having a high usage intensity of MCS, given pre-treatment characteristics (Rosenbaum & Rubin, 1983). Therefore, the covariates that determine the probability of treatment will be aggregated in a score, the propensity score, which is a function of the observed covariates, surpassing the dimensionality problem (Villalonga, 2004). In fact, the firms will not be exactly matched on the propensity score but on the linear predictor of the propensity score, since it is normally distributed (Guo & Fraser, 2015).

Therefore, each treated firm will be matched to a non-treated firm with which it shares the same distribution of the full vector of variables X, so that for a given propensity score assignment to treatment can be considered random and bias due to all observed covariates is removed (Rosenbaum & Rubin, 1983). Afterwards, data from this non-randomized experiment can be analyzed as if it had come from a randomized experiment, since treatment will be the only variable differentiating the firms. This allows a clean identification of the treatment effect of MCS usage on performance.

The design choice of the PSM will be a one-to-one matching without replacement, in order to include only treatment and control observations a single time in the final sample, which is the most common method in finance and accounting studies (Shipman et al., 2017). Additionally, it is considered best practice to impose a caliper distance, since it restricts the maximum allowable distance between propensity scores for a successful match, which will improve covariate balance (Shipman et al., 2017). For that reason, a caliper distance of 0,2 times the standard deviation of the propensity scores is going to be imposed (Guo & Fraser, 2015). Therefore, each firm with high MCS usage will be matched to the nearest observation with low MCS usage, i.e., the most similar observation from the other group (still available) in terms of propensity score. Moreover, in a one-to-one match it is important to randomly sort the observations since the order will influence the matching. In additional analysis these choices will vary to evaluate the robustness of the results.

A common support region will not be directly imposed, that is, firms located outside the range between the minimum and maximum propensity score of the firms with high MCS usage will not be discarded from matching since imposing a common support region can possibly worsen the results because good matches at the frontier are lost (Becker & Ichino, 2002). Instead, since a caliper distance is imposed, it is possible to be sure that the match will not be in a far range.

The PSM is the first model (logit model) in this study. This model is used to calculate the propensity scores that will be used in the matching procedure. For this model cross-sectional data was used to assure that the firms that were going to be considered were alike prior to the experiment period. The beginning of the experiment period will be considered in 2015 since the survey was taken between 2012 and 2014. The nature of the data of the second model (outcome model) will be longitudinal and will comprise the periods between 2010 and 2020. The outcome model identifies the treatment effect, i.e., the effect of MCS usage on financial performance. This second model is a regression model that will be fitted to panel data using the between regression estimator (between effects). In this model, the matched sample will be used and it will be observed how in the experiment period, in comparison to the pre-experiment period, the firms with high MCS usage differ from those with less usage in terms of financial performance.

In this second model, the regressors used should be the same as the ones used in the first model (Villalonga, 2004). The variables considered in the PSM model are the ones that may be related to treatment and outcome and can potentially bring bias to the study (Shipman et al., 2017). Because they are omitted correlated variables, they should also be included in the second model. The use of a regression on the matched sample allows to mitigate the effect of any residual covariate imbalance and to adjust for any remaining differences between groups – doubly robust estimation (Shipman et al., 2017).

3.3 Description and Measurement of Model Variables

3.3.1 Dependent Variable

The variable of most interest in this study is the financial performance of the companies, that will be represented by ROE.

Data is available from the period before/during the survey, from 2010 to 2014, and the period of 6 years that followed the survey, that is from 2015 until 2020.

3.3.2 Treatment Variable

The treatment variable is the intensity of MCS usage (MCSINTENSITY). It is considered that with a high MCS usage/intensity a company is subject to treatment (and this variable will take the value 1 for that company), while a company that has a low MCS usage/intensity is not subject to treatment and is therefore in the control group (this company will take the value 0 in this variable).

Usage is different from implementation since a MCS is only truly being used when it is giving information to the managers and influencing its decisions and behaviors in the day to day of the firm. However, many studies have difficulty in ascertaining usage since asking solely about implementation is not asking about usage.

To measure usage there is the need to make a distinction between a firm that has the control implemented but does not use it, a firm that makes an occasional use of controls, and a firm that makes a weekly use. To do that, Khandwalla (1972) used a 7-point scale to measure the extent of usage of controls. The approach used in this study will follow this rationale.

To construct the treatment variable MCSINTENSITY data from two different questions of the questionnaire was taken into consideration. In a first step, it was asked the participants to identify in a set of 41 MCS (adapted from Chenhall & Langfield-Smith (1998) and Davila & Foster (2007)), the ones that were used/implemented in their firm. In a second step, if the participant answered positively about the usage of a certain control he had to report the regularity with which the control was used, with answers being in a scale of 1 (rarely used) to 7 (used daily). Then, a score of usage was computed for each firm (MCSCOUNT). This score of usage is computed by summing the answers relative to usage regularity of MCS. For example, imagine a firm that uses only 3 of the 41 controls, and says that relatively to the three controls one is used with a 5 regularity, another is used with 7, and the last one is a 2. For 38 of the controls it will be considered that the regularity of usage is 0, so that to compute the score it only needs to be summed the answers of the controls that are used, so that the score for this particular firm is 14. After computing the score for each firm, the median of all firms is calculated and it is considered that firms with a usage equal or above the median have a high usage/intensity of MCS, while the firms below the median have a low usage/intensity of MCS. So, MCSCOUNT is a discrete variable that will be used to construct the MCSINTENSITY binary variable.

3.3.3 Independent Variables

3.3.3.1 Financial Position

The financial position of the firm (used in the PSM) was assessed with a self-reported measure of firm performance. A 4 items question, adapted from King et al. (2010), was used, where the participants had to evaluate the ability the company had to reach its goals in the last three years through a Likert scale (1 = very poor performance; 7 = excellent performance). This subjective measure is used in the PSM because it was collected at the same time as the other items in the survey.

Given that this is a multi-item variable, there is the need for a factorial analysis to be performed. Thus, Exploratory Factor Analysis (EFA) with principal-component factors was used and its validity was confirmed via the Kaiser-Meyer-Olkin (KMO) criteria. KMO showed a value above 0.5 (0.781), which means that data are suited for factorial analysis (Kaiser, 1974). By following the rule that a factor should be kept if the *eigenvalue* shows a value greater than 1 (Marôco, 2014), only one factor was extracted (FINANCIALPOS), which explains 76.75% of the total variance, and whose *alpha cronbach* is 0.90, which shows good internal consistency (Cronbach, 1951; Hair et al., 2010). The respective construct was created as the arithmetic average of the items that constitute the factor. Appendix 3, Panel A, shows the weights and communalities of each item, the factor's eigenvalue and the % of variance explained.

3.3.3.2 Perceived Environmental Uncertainty

To capture the different aspects influencing the external environment of the firm three questions – measured through a Likert scale from 1 to 7 (1 = low PEU; 7 = high PEU) – were put to the participants. Through these questions, adapted from Gordon and Narayanan (1984), it is possible to capture the dynamism (PEUDYN), the uncertainty (PEUUNC), and the competition surrounding the firm (PEUHOST).

Due to the multi-item nature of these variables, EFA was also used. EFA with principal-component factors with orthogonal rotation as extraction method (consistent with previous research from Gordon & Narayanan (1984) and King et al. (2010)) was considered because it was assumed that the factors are uncorrelated (Hair et al., 2010).

The validity of EFA was confirmed by the KMO criteria (0.723). By following the rule of the *eigenvalue* above 1, three factors, corresponding to the previously mentioned dimensions, were extracted. The factors have a low internal consistency, but are in the limit of acceptance (*alpha cronbach* values between 0.60 and 0.74), and explain globally 57.59% of the total variance. Each factor is the arithmetic average of the items that belong to each factor (see Appendix 3, Panel B).

3.3.3.3 Decentralization

The variable decentralization (DECENT) was measured through a 6-item question (originally developed by Gordon and Narayanan (1984) and then adapted by multiple authors, such as King et al. (2010)). The participant had to assess the extent to which authority was delegated to its operational managers and/or employees through a Likert scale in which 1 meant no delegation and 7 meant total delegation.

The EFA with principal-component factors was validated by a KMO of 0.867. By following the eigenvalue above 1 rule of extraction only a factor was extracted. This factor explains 63.12% of the total variance and shows internal consistency since its *alpha cronbach* has the value of 0.88. The construct was built through the arithmetic average of the different items (see Appendix 3, Panel C).

3.3.3.4 Industry

The companies were classified according to the nature of the activities performed, in accordance with the classification made by INE (2007). In the PSM model, to limit the number of variables, the industries were grouped, and three sectorial dummies were created, one for agriculture, animal production, hunting, forest and fishing (AGRIC), one for industry, construction, energy and water (INDUSTRY) (reference category) and one for services (SERVICES). In the panel data model, to control for industry in the identification of the treatment effect, the two-digit code of INE (2007) was considered (INDUSTRYCODE).

3.3.3.5 Size

The size of the firm was measured each year by taking the natural logarithm of the number of employees (LNSIZE), which was obtained from Informa D&B. The size used in the first phase (PSM) of the analysis is the one that was taken from Informa D&B at the moment the survey was sent.

Number of employees is a proxy for dimension commonly used in the literature (Davila, 2005; Jokipii, 2010; King et al., 2010).

3.3.3.6 Lifecycle

Each company provided information in the questionnaire about the stage of the lifecycle in which it was. The available options come from the model proposed by Miller & Friesen (1984): birth (BIRTH), growth (GROWTH), maturity (MATURITY) (reference period), revival (REVIVAL) and decline (DECLINE).

3.3.3.7 Family Firms

The participants were asked to indicate whether their firm was a family firm, based on a definition of the European Commission - Enterprise and Industry Directorate-General (2009)[1]. Therefore, the variable family firm (FAMILY) is a dummy variable that takes the value 1 when the firm is a family business and 0 when it is not.

3.3.3.8 Economic Group

A dummy variable, in which 1 indicates that the firm belongs to an economic group and 0 if the opposite is true (ECO).

3.3.3.9 State Corporate Sector

A dummy variable, in which 1 indicates that the firm belongs to the state's business sector and 0 if it does not (STATE).

3.4 Descriptive Statistics of Variables

In Table I to III the descriptive statistics of the variables mentioned in the previous section can be found.

In the full sample (Table III) the MCSCOUNT ranges between 0 and 195, with the median being 38. Therefore, firms with a MCSCOUNT equal or above to 38 are considered firms with a high usage of MCS (treatment), and the ones below 38 are

[1] A firm, of any size, is a family business, if: (1) The majority of decision-making rights is in the possession of the natural person(s) who established the firm, or in the possession of the natural person(s) who has/have acquired the share capital of the firm, or in the possession of their spouses, parents, child or children's direct heirs. (2) The majority of decision-making rights are indirect or direct. (3) At least one representative of the family or kin is formally involved in the governance of the firm. (4) Listed companies meet the definition of family enterprise if the person who established or acquired the firm (share capital) or their families or descendants possess 25 per cent of the decision-making rights mandated by their share capital.

considered firms with a low usage of MCS (control). In the first group the average of MCS usage is 70.47 while in the second group it is 17.91.

Table IV shows the descriptive statistics for model variables regarding companies that have a high MCSINTENSITY, while Table V refers to companies that have a low MCSINTENSITY.

Firms with a high MCSINTENSITY rate the environment as more dynamic and hostile than firms with a low MCSINTENSITY. Decentralization is also higher for high MCSINTENSITY firms. Conversely the perception of uncertainty is similar between the two groups.

Family-owned firms are overrepresented in the low MCSINTENSITY group, since 74.7% of firms in that group are family owned, while the percentage in both conditions is 66.7%. Conversely, firms belonging to an economic group or to the state are overrepresented in the high MCSINTENSITY group (29.0% in high intensity vs 20.4% in the full sample and 1.3% in high intensity vs 1.0% in the full sample, respectively).

Regarding industry, 63.2% of firms with a high MCSINTENSITY are service companies and 36.0% of them are industry companies. In the low MCSINTENSITY group 50.3% are service companies and 47.7% are industry companies. Thus, it is more probable to find a service firm in the high MCSINTENSITY group.

With respect to the lifecycle, the stages that have a higher probability of having high MCSINTENSITY firms are growth and revival, since they are overrepresented in this group.

In relation to size, high MCSINTENSITY firms range between 10 and 6 613 employees, with the mean being located at 106 employees. In turn, low MCSINTENSITY firms' employees' range between 10 and 637, and have on average 33 employees. Therefore, all firms with more than 637 employees are high intensity users of MCS (there are 19 firms in this interval).

Lastly, firms with high usage of MCS report that they are more able to reach the goals proposed, and thus seem to be a priori in a better financial position. However, when looking at objective financial performance (ROE) this perception vanishes. In addition, when comparing the pre-experiment period and the experiment period only the low

MCSINTENSITY group shows an improvement in ROE. This provides preliminary evidence that does not support the expected relationship between MCSINTENSITY and performance. However, these results should be carefully analyzed as they come from bivariate analysis and, hence, they do not control for several variables that simultaneously affect performance.

Table III - Full Sample Descriptive Statistics

N = 1 762	**Min**	**Mean**	**Median**	**Max**	**Std. Dev**
MCSCOUNT	0	44.519	38	195	34.207
MCSINTENSITY	0	.506	1	1	.500
FINANCIALPOS	1	4.277	4	7	1.083
PEUDYN	1	4.397	4,5	7	1.314
PEUUNC	1	3.856	4	7	1.304
PEUHOST	1	4.421	4,5	7	1.165
DECENT	1	3.049	2.833	7	1.446
AGRIC	0	.014	0	1	.116
INDUSTRY	0	.418	0	1	.493
SERVICES	0	.569	1	1	.495
SIZE	10	70.304	22	6613	285.702
BIRTH	0	.016	0	1	.127
GROWTH	0	.135	0	1	.341
MATURITY	0	.546	1	1	.498
DECLINE	0	.215	0	1	.411
REVIVAL	0	.089	0	1	.284
FAMILY	0	.667	1	1	.471
ECO	0	.204	0	1	.403
STATE	0	.010	0	1	.101
ROE	-16 360.17	-0.996	.051	166.322	123.269
ROE 2010-2014	-1 867.67	-0.233	.043	166.322	21.761
ROE 2015-2020	-16 360.17	-1.698	.059	148.143	169.520

Table IV - MCS High Usage Sample Descriptive Statistics

N = 892	**Min**	**Mean**	**Median**	**Max**	**Std. Dev**
MCSCOUNT	38	70.474	63	195	28.598
FINANCIALPOS	1	4.461	4.25	7	1.093
PEUDYN	1	4.624	4.75	7	1.261
PEUUNC	1	3.854	4	7	1.300
PEUHOST	1	4.483	4.5	7	1.111
DECENT	1	3.248	3	7	1.330
AGRIC	0	.008	0	1	.088
INDUSTRY	0	.360	0	1	.480
SERVICES	0	.632	1	1	.482
SIZE	10	106.424	30	6613	395.495
BIRTH	0	.013	0	1	.115
GROWTH	0	.157	0	1	.364
MATURITY	0	.546	1	1	.498
DECLINE	0	.174	0	1	.379
REVIVAL	0	.110	0	1	.313
FAMILY	0	.590	1	1	.492
ECO	0	.290	0	1	.454
STATE	0	.013	0	1	.115
ROE	-16 360.17	-1.984	.057	125.887	173.655
ROE 2010-2014	-1 867.67	-.379	.050	125.887	28.527
ROE 2015-2020	-16 360.17	-3.477	.063	20.128	239.668

Table V - MCS Low Intensity Usage Sample Descriptive Statistics

N = 870	**Min**	**Mean**	**Median**	**Max**	**Std. Dev**
MCSCOUNT	0	17.908	18	37	11.495
FINANCIALPOS	1	4.088	4	7	1.040
PEUDYN	1	4.164	4.25	7	1.326
PEUUNC	1	3.858	4	7	1.308
PEUHOST	1	4.357	4.5	7	1.216
DECENT	1	2.846	2.5	7	1.530
AGRIC	0	.020	0	1	.138
INDUSTRY	0	.477	0	1	.500
SERVICES	0	.503	1	1	.500
SIZE	10	33.271	19	637	48.205
BIRTH	0	.020	0	1	.138
GROWTH	0	.111	0	1	.315
MATURITY	0	.546	1	1	.498

(Table V continuation)

	Min	Mean	Median	Max	Std. Dev
DECLINE	0	.256	0	1	.437
REVIVAL	0	.067	0	1	.250
FAMILY	0	.747	1	1	.435
ECO	0	.115	0	1	.319
STATE	0	.007	0	1	.083
ROE	-689.228	.003	.046	166.322	8.004
ROE 2010-2014	-689.228	-.084	.036	166.322	11.205
ROE 2015-2020	-77.188	.082	.055	148.143	2.851

The correlations matrix can be found in Appendix 4. Many of the covariates are significantly correlated with each other and with the dependent variables, however, none of them are problematic since the Variance Inflation Factor is around 1 for all the variables, not showing any multicollinearity concerns.

5. EMPIRICAL TESTS AND RESULTS

5.1 Model Analysis

Panel A of Table VI shows that the high MCSINTENSITY group and the low MCSINTENSITY group differ on multiple characteristics prior to matching. The last column of the panel reports the results of the test for the difference of means and shows that the two groups differ significantly on 13 of the 17 characteristics considered. Thus, PSM is needed to solve this ex-ante differences.

The first step in PSM is to construct a logit model that computes propensity scores. In this first stage model, the dependent variable will be the treatment variable previously described, MCSINTENSITY, a dummy variable measuring whether participants have a high usage of MCS or not. Since this model is in fact calculating the probability (propensity) of a firm to have a high usage intensity of MCS, the covariates chosen to integrate the model were the internal and external characteristics that prior literature suggests having an influence on the usage of MCS (Shipman et al., 2017), and whose measurement was described in the previous section.

Prediction model (first stage):

$$(1)\qquad MCSINTENSITY = \alpha_0 + \alpha_1 FINANCIALPOS + \alpha_2 PEUUNCERT + \alpha_3 PEUDYN + \alpha_4 PEUHOST + \alpha_5 DECENT + \alpha_6 AGRIC + \alpha_7 SERVICES + \alpha_8 SIZE + \alpha_9 BIRTH + \alpha_{10} GROWTH + \alpha_{11} REVIVAL + \alpha_{12} DECLINE + \alpha_{13} FAMILY + \alpha_{14} ECO + \alpha_{15} ESTATE + \varepsilon$$

Panel B of Table VI shows the first-stage estimates used to calculate the propensity score for each observation. The results of the logit model suggest that all of the variables other than PEUHOST, BIRTH, DECLINE and STATE are important predictors of whether firms are MCS high intensity users.

The model shows an accuracy of 73.8%, as can be seen by the area under the receiver operating characteristic (ROC) curve value. However, since the aim of the application of this model is to balance the confounding covariates between treatment and control groups, the power of the model is not the most relevant thing. A low accuracy would not be a problem since it would be an indication that the variables were, a priori, similar between the two groups (Shipman et al., 2017).

It is important to mention that the results obtained in this model are equivalent to the ones obtained when using a negative binomial regression that has as dependent variable the simple count of MCS (MCSCOUNT), which gives assurance to the performed division of firms between high and low intensity users of MCS.

To perform the matching, the PSM sample will focus on a subset of firms located between the propensity scores 0.2 and 0.8, since in the more extreme propensity scores overlap is rare. In this region there is greater overlap in the characteristics, which makes groups more comparable and reduces biases. Therefore, the inferences made in this study will only be valid for the range of propensity scores in the common support region, where there are treated and control firms possessing the same vector of characteristics.

Based on the propensity scores calculated in the logit model and on the matching technique specified, the final matched sample consists of 1 132 firms (566 in each group) that will be used to estimate the average treatment effect of MCS usage on performance if, and only if, the two groups can be considered comparable.

Table VI - Propensity Score Matching: MCS Usage Intensity

Panel A: Descriptive statistics for the high and low MCS usage intensity subsamples before matching

	MCSINTENSITY = 1 N = 892		MCSINTENSITY = 0 N = 870		
Variable	Mean	Std. Dev	Mean	Std. Dev	t-value
FINANCIALPOS	4.461	1.093	4.088	1.040	-7.34***
PEUDYN	4.624	1.261	4.164	1.326	-7.46***
PEUUNC	3.854	1.300	3.858	1.308	0.07
PEUHOST	4.483	1.112	4.357	1.216	-2.27**
DECENT	3.248	1.330	2.846	1.530	-5.89***
AGRIC	0.008	0.088	0.020	0.138	2.11**
INDUSTRY	0.360	0.480	0.477	0.500	5.02***
SERVICES	0.632	0.482	0.503	0.500	-5.50***
SIZE	106.424	395.495	33.271	48.205	-5.48***
BIRTH	0.013	0.115	0.020	0.138	1.00
GROWTH	0.157	0.364	0.111	0.315	-2.81***
MATURITY	0.546	0.498	0.546	0.498	0.00
REVIVAL	0.110	0.313	0.067	0.250	-3.21***
DECLINE	0.174	0.379	0.256	0.437	4.23***
FAMILY	0.590	0.492	0.747	0.435	7.12***
ECO	0.290	0.454	0.115	0.319	-9.40***
STATE	0.013	0.115	0.007	0.083	-1.37

Panel B: First stage prediction model (DV = MCSINTENSITY)

Parameter	Estimate	z-value	p-value
Intercept	-4.568	-10.47	0.000***
FINANCIALPOS	0.230	4.31	0.000***
PEUDYN	0.228	5.23	0.000***
PEUUNC	-0.078	-1.79	0.074*
PEUHOST	0.042	0.84	0.398
DECENT	0.093	2.42	0.015**
AGRIC	-0.897	-1.8	0.072*
SERVICES	0.732	6.52	0.000***
SIZE	0.594	9.15	0.000***
BIRTH	-0.191	-0.46	0.648
GROWTH	0.503	3.07	0.002***
REVIVAL	0.677	3.48	0.001***
DECLINE	-0.030	-0.21	0.833
FAMILY	-0.300	-2.53	0.011**
ECO	0.069	4.72	0.000***
STATE	-0.244	-0.44	0.661
N	1762		
R^2	0.140		
Area under the ROC curve	0.738		

Panel C: Descriptive statistics for the high and low MCS usage intensity subsamples after matching

	MCSINTENSITY = 1 N = 566		MCSINTENSITY = 0 N = 566		
Variable	Mean	Std. Dev	Mean	Std. Dev	t-value
FINANCIALPOS	4.263	1.055	4.232	1.040	-0.49
PEUDYN	4.404	1.259	4.415	1.256	0.15
PEUUNC	3.870	1.293	3.858	1.265	-0.16
PEUHOST	4.402	1.058	4.423	1.226	0.31
DECENT	3.005	1.280	3.019	1.557	0.16
AGRIC	0.009	0.094	0.007	0.084	-0.33
INDUSTRY	0.396	0.489	0.410	0.492	0.48
SERVICES	0.595	0.491	0.583	0.493	-0.42
SIZE	39.254	73.488	39.947	57.729	0.18
BIRTH	0.014	0.118	0.019	0.138	0.69
GROWTH	0.140	0.347	0.134	0.341	-0.26
MATURITY	0.560	0.497	0.541	0.499	-0.66
REVIVAL	0.076	0.265	0.090	0.287	0.86
DECLINE	0.210	0.408	0.216	0.412	0.22
FAMILY	0.710	0.454	0.680	0.467	-1.10
ECO	0.138	0.345	0.161	0.368	1.08
STATE	0.009	0.094	0.106	0.103	0.30

*, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests)
Panel A reports a balancing test that shows that there are significant differences between high intensity and low intensity MCS usage groups.

Panel B reports a logit model based on which the propensity scores of having a high usage intensity of MCS is calculated.

Panel C reports a balancing test that confirms that there is no significant difference between high intensity and low intensity groups, after matching.

To facilitate the interpretation the SIZE variable is presented as non-logarithmized values.

Thus, after conducting the matching, the distributions of the variables in the two groups are reanalyzed, as can be seen in Panel C of Table VI. It can be verified that the t-tests performed do not show significant differences between the two groups, i.e., the covariates have similar distributions in the two groups. Additionally, the logit model is re-estimated for the matched sample and, as expected, none of the variables is now significant. Thus, the quality of the match can be assured given that the goal of the PSM to originate a sample of comparable observations is achieved, since the balancing property holds (Becker & Ichino, 2002).

After this first phase (PSM), the second phase can begin where the identification of the treatment effect will occur. In this model, the variables POST and MCSINTENSITY will be added as independent variables. POST is a dummy variable that is equal to 1 if the observations belong to the period after the survey (0 otherwise), while MCSINTENSITY is the dummy variable used in the previous model as dependent variable. The key binary independent variable will be the interaction between MCSINTENSITY and POST. The dependent variable is the financial performance, measured with ROE, of the companies (i) between 2010 and 2020 (t).

As controls in this model, a variable representing the lagged performance is added, since the previous year performance will probably affect next year performance; the binary variables representing AGRIC and SERVICES are replaced by the specific two-digit industry code (INDUSTRYCODE), since performance is largely influenced by the specific industry a firm operates in and this allows to control for industry fixed effects; dummy variables are added for the years, as a way to control for year fixed effects; and all the firm characteristics measured in the survey and used in the first phase are also considered. Notice that these variables will be constant throughout the years as they were collected in a single point in time. The exception is the number of employees, for which yearly data was available in Informa D&B database.

Outcome model (second stage):

$$(2)\qquad \begin{aligned} PERFORMANCE_{it} = {} & \beta_0 + \beta_1 L.PERFORMANCE_{it} + \beta_2 MCSINTENSITY_i + \\ & \beta_3 POST + \beta_4 MCSINTENSITY_i * POST + \\ & \beta_5 FINANCIALPOS_i + \beta_6 PEUUNCERT_i + \\ & \beta_7 PEUDYN_i + \beta_8 PEUHOST_i + \beta_9 DECENT_i + \\ & \beta_{10} INDUSTRYCODE_i + \beta_{11} SIZE_{it} + \beta_{12} BIRTH_i + \\ & \beta_{13} GROWTH_i + \beta_{14} REVIVAL_i + \beta_{15} DECLINE_i + \\ & \beta_{16} FAMILY_i + \beta_{17} ECO_i + \beta_{18} ESTATE_i + \beta_{19} YEAR_{it} + \\ & \varepsilon_{it} \end{aligned}$$

This model is thus controlling for the initial differences between the companies, for the year effect and for the previous year performance effect.

The answer to the hypothesis is given by the coefficient of the interaction between MCSINTENSITY and POST, coefficient $\widehat{\beta_4}$. This coefficient estimates the average difference between firms with a MCSINTENSITY and firms with a low MCSINTENSITY between the experimental and pre-experimental periods, while controlling for all other independent variables.

Before analyzing the results of this model, it is crucial to run a model that only includes the performance of the companies from 2010 to 2014. The goal of PSM was to have in moment 0 (2015) firms that shared the same characteristics, and thus the performance of these companies before 2015 should be similar, so that MCSINTENSITY is not significant in a model taking only into consideration the years before 2015. This expectation was verified and, one more time, assurance of a good matching was attained.

It is now possible to observe the results of the second model, showed in Table VII. The usage of lagged performance led to the loss of nine firms, so that the matched sample now comprises 1 123 firms and 10 134 observations.

The significance of MCSINTENSITY*POST at 1% gives support to the hypothesis of this study. On average, a firm with high usage of MCS will exhibit a ROE 1.35 higher than a firm with low usage of MCS, between 2015 and 2020 in comparison to the years between 2010 and 2014.

Table VII - The Association Between MCS Intensity and Performance

	Matched Sample			Full Sample		
	Estimate	t-value	p-value	Estimate	t-value	p-value
Intercept	-0.235	-0.44	0.660	34.689	1.32	0.187
POST	0.841	0.50	0.619	53.890	0.49	0.624
MCSINTENSITY	-0.788	-3.82	0.000***	-24.935	-1.94	0.053*
MCSINTENSITY*POST	1.353	3.70	0.000***	43.557	1.93	0.054*
Controls		Yes			Yes	
Year Fixed Effects		Yes			Yes	
Industry Fixed Effects		Yes			Yes	
Lagged Dependent Variable		Yes			Yes	
n		10 134			15 810	
n of groups		1 123			1 752	
R^2						
- Within		0.0019			0.0002	
- Between		0.2973			0.0911	
- Overall		0.0001			0.0011	

*, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively (based on two-tailed tests)

Because of the downsides and risks of PSM (reduction of sample size and attrition bias) it is relevant to look at the results of this model when taking into consideration the full sample. These results are also reported in Table VII and show a more meaningful positive coefficient on MCSINTENSITY*POST, although only significant at 10%. The estimates obtained in this model are substantially different from the ones obtained in the first model. This happens since in this case the firms that do not have a propensity score between 0.2 and 0.8 are being considered. These cases can be considered outliers.

Additionally, this second model is also replicated to use as industry variables the dummy variables considered in the PSM model (AGRIC and SERVICES) instead of the INDUSTRYCODE. The model is robust to this change since the key coefficient MCSINTENSITY*POST is still significant and positive.

Thus, this study provides new evidence that suggests that a high usage of MCS has a positive effect on firms' performance.

5.2 Additional Results

5.2.1 Robustness Analysis: Testing Alternative PSM Models

The closeness of the match, the replacement, and the number of control firms matched to each treatment firm are all PSM specifications that affect the sample created. A different sample may lead to different conclusions, with multiple studies having already showed that the treatment effect of the estimates is sensible to the PSM model specification (DeFond et al., 2017; Shipman et al., 2017).

Since the results previously obtained are influenced by the design choice of the PSM, in this section the robustness of the results to those choices will be tested by creating twelve new models with alternative PSM specifications. By making this analysis it can be assessed if the results obtained are unique to the specification used.

In the first ten models the changing factor was the caliper distance, which ranged between 0.1 and 1, while it kept on being a one-to-one match without replacement. Changing the caliper distance creates a trade-off between bias (closer matches mean better matches, which minimizes differences in propensity scores and reduces bias) and variance (increases with lower caliper distance because the matched sample reduces). In all these cases the results are similar to those reported in the main model since the key variable (MCSINTENSITY*POST) is significant (at 1% in all cases) and in the same direction.

In the eleventh model replacement was allowed, while it kept on being a one-to-one match with a caliper distance of 0.2 times the standard deviation of the propensity scores. Matching with replacement reduces bias because each treated observation matches with the most similar control observation. In the last model, one to many matching was imposed (4 untreated observations are matched to each treated observation), replacement was still allowed and the caliper distance was the same as in the previous model. A one-to-many match will generally reduce the quality of some matches (increases bias), but may partially mitigate the issues with sampling variance (because of the larger matched sample size). The results obtained in these models show additional support for the hypothesis presented.

As it was mentioned, the different design choices bring different advantages and disadvantages and create different samples. By constructing different models with different PSM configurations it is possible to achieve reasonable assurance that the results obtained are robust to alternative design choices since in all the models the sign and significance of the results are not affected (Becker & Ichino, 2002).

It is important to mention that, although some of the samples created have covariates that are significantly different between the treatment and control group, the covariate balance is high in comparison to what it was before matching, which offers some assurance to proceed with the analysis (Shipman et al., 2017). Additionally, in all the specifications, the model between 2010-2014 did not show significance in the key variable, giving assurance to the match.

5.2.2 Alternative Performance Measures and Models

In alternative to fitting a regression model to panel data with the between regression estimator, a model with fixed effects and a model with random effects were constructed. In both models the results do not support the hypothesis. In the fixed effects model the coefficient is significant, but the sign is in the opposite direction. In the random effects model the coefficient is non-significant.

The model was also replicated for pooled data where instead of a between effects regression a pooled OLS regression with clustered standard errors by firm was used. In this case, there were no statistically significant coefficients.

Lastly, there were also no statistically significant results when different financial performance measures were used (ROA and Performance per employee, measured as net income/employee) as substitutes for ROE.

6. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This dissertation studies how MCS affect the financial performance of firms, by taking into consideration multiple confounding factors of this relationship.

The results obtained confirm the idea present in the literature that MCS have a positive effect on the financial performance of firms, since a positive and significant relationship is found between MCS and ROE (though not in ROA). Thus, this study corroborates Davila & Foster (2005, 2007) and Duréndez et al. (2016) findings regarding a positive effect of MCS usage on performance. These results are robust to PSM specifications but not to different specifications of regression models.

Although this study does not say which MCS a firm should implement based on its characteristics, it does say that, *ceteris paribus*, a higher usage of MCS is associated with higher performance than a lower usage of MCS. It is also important to notice that this does not by any means contradict the contingency theory and the need for alignment between MCS and firm characteristics. Instead, this study highlights the power of MCS usage to reach company goals. This information can now be used by managers during their decision making.

Additionally, this study does not say that all the controls that are being implemented in a firm contribute positively to its financial performance. It can be the case that some of the controls being implemented contribute negatively to the financial performance of the company. However, this study suggests that a package with more intensive use of MCS influences positively firm performance. Moreover, having a positive effect on performance is not the only reason why a control should be implemented, since they can have indirect effects and their benefits can come in various forms for the firm operations.

These results should be interpreted in light of their limitations. Some of the limitations can lead to future research. The first limitation refers to the use of survey data. Data originated from a survey can suffer from bias due to common method bias, non-response bias and low response rates, all problems that will impact the data and consequently the results obtained. Nevertheless, the design and implementation of the survey instrument, in accordance to research best practices, and the combination of hard financial data with survey data, mitigates these concerns.

The second limitation refers to the treatment variable. It was used a cut-off point (median) to make the split between high MCS usage and low MCS usage. By dichotomizing the continuous treatment variable there can be observations in the treated group that receive almost the same "amount of treatment" as observations that are in the untreated group (Shipman et al., 2017). This can diminish the size effect of the variable being studied and increase the likelihood of a false negative. A possible solution to this problem would be to match only "extremely" treated observations with the less treated ones. For example, match the ones that are below the first quartile of MCS usage with the ones that are above the fourth quartile of MCS usage. Alternatively, a multinomial logit could be used instead of the binary logit used to calculate the propensity scores.

The third limitation refers to MCS usage. MCS can be present in multiple companies, but that does not mean that they are used in the same way in all of those companies. Abernethy and Brownell (1999) argue that what will truly differ between companies is not which MCS are used, but how they are used. Thus, future studies could explore this idea of MCS usage intensity having an influence on performance, but distinguishing MCS according to the way they are used. For example, if they have a diagnostic or an interactive use (Simons, 1995). Additionally, some of the MCS may have been implemented in the firm in the last year, while some may have been implemented ten years ago, and this difference will certainly affect performance.

The fourth limitation refers to static nature of controls (firm characteristics). These controls were only measured in the survey and they were considered to have remained constant between 2015 and 2020. However, those characteristics may have changed, as well as the number of MCS used, which may have implications on performance. In those cases, the effect of MCS on performance may be deceptive. Future studies can incorporate the evolution of firm characteristics and MCS usage across time. Nevertheless, conducting a longitudinal survey is costly and difficult since over time non-response will increase (van der Stede et al., 2006).

The fifth limitation refers to PSM. Since PSM only has the power to control for selection bias coming from observed characteristics the contribution that this study offers are limited to the bias coming from the characteristics observed in this study. This study included a wide range of characteristics that have been studied in the MCS research. To increase the confidence that there are not unmeasured factors influencing the results, other studies could use other variables to perform the PSM, such as culture or strategy. A strong internal culture may be a substitute to the use of MCS (Otley, 2016), while strategy is the most studied contingent in the literature, and although it is questionable if it has an influence on the extent of MCS usage, it surely has on the optimal MCS needed for each strategy since different strategies have different information and feedback requirements (King et al., 2010).

Another downfall of PSM is its limited external validity. PSM excludes observations that lack a match, these observations are located at the upper range of the propensity scores, or at the lower range of the propensity scores. Thus, this particularity of PSM limits the ability to generalize the results obtained to observations outside of the sample used. In this study, since the overlap observed between the control group and the treatment group is substantial, it is possible to have some degree of comfort that the sample used approximates the population.

Finally, previous studies document that in small firms a statistically significant relationship between control and effectiveness is not able to be found, since formal controls may not be tailored to small businesses (Jokipii, 2010). Thus, the results obtained could have been stronger if only medium and large firms were considered, and possibly no results would have been found if only small firms were considered. Hence, it would be interesting to study these two groups separately.

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APPENDICES

Appendix 1 – Research Sample Details

Sample selection	**N**
Target Population	34 659
Excluded firms*	11 651
Surveys sent	23 008
Answered surveys	4 375
Excluded surveys**	2 613
Final Sample	**1 762**

*Excluded all firms that did not want to participate in the study, were in insolvency proceedings, belonged to the same economic group, or had an inaccurate e-mail address

**Excluded all firms that did not answer the questions related to: MCS implementation and frequency of usage, PEU, decentralization, lifecycle, family owned, performance, economic/state group

Appendix 2 – T-test for Two Independent Samples: Comparison Between the Early and Late Respondents

	t	df	Sig (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Lower	95% Confidence Interval of the Upper
MCSCOUNT	0.438	875.697	0.662	1.022	2.334	-3.558	5.602
MCSINTENSITY	0.361	878.956	0.718	0.012	0.034	-0.054	0.078
FINANCIALPOS	0.538	881.210	0.591	0.039	0.072	-0.102	0.181
PEUDYN	-0.216	878.859	0.829	-0.019	0.088	-0.192	0.154
PEUUNC	-0.701	874.676	0.484	-0.061	0.086	-0.230	0.109
PEUHOST	-1.221	851.791	0.222	-0.097	0.079	-0.253	0.059
DECENT	-1.153	863.670	0.249	-0.114	0.099	-0.307	0.080
AGRIC	0.969	870.289	0.333	0.007	0.008	-0.008	0.022
INDUSTRY	0.865	881.159	0.387	0.029	0.033	-0.036	0.093
SERVICES	-1.083	881.279	0.279	-0.036	0.033	-0.101	0.029
SIZE	-0.232	731.328	0.816	-5.976	25.715	-56.461	44.509
BIRTH	0.988	880.304	0.323	0.009	0.009	-0.009	0.027
GROWTH	0.738	887.768	0.461	0.0170	0.023	-0.028	0.062
REVIVAL	-1.152	848.907	0.250	-0.023	0.020	-0.062	0.016
MATURITY	-0.987	880.432	0.324	-0.033	0.033	-0.099	0.033
DECLINE	1.130	888.452	0.259	0.030	0.027	-0.022	0.082
FAMILY	0.258	877.865	0.797	0.008	0.032	-0.054	0.071
ECO	0.351	882.515	0.726	0.009	0.027	-0.043	0.062
STATE	0.719	884.114	0.473	0.005	0.007	-0.009	0.020

The early respondents group was created by selecting the companies for whom the number of reminder was lower, until 20% was reached. The late respondents group was created by selecting the companies for whom the number of reminders was highest, until 20% was reached. This criterion was used since the surveys were sent to the companies in different dates.

Appendix 3 – Exploratory Factor Analysis of Financial Position, Perceived Environmental Uncertainty and Decentralization

Panel A: Financial Position

Extraction method: Principal-component factors

	Factor Loadings	
	1	Communality
1. Performance		
Global performance of the company	0.89	0.79
Global productivity of the supply system	0.87	0.76
Global profitability of the company	0.86	0.73
Market share of the main products	0.89	0.78
Alpha Cronbach	0.90	
Eigenvalues	3.07	
% of variance	76.75%	

Panel B: Perceived Environmental Uncertainty

Extraction method: Principal-component factors, with orthogonal rotation (varimax)

	Factor Loadings			
	1	2	3	Communality
1. Dynamism of the external environment				
Economic Environment	**0.71**	0.03	0.12	0.51
Technological Environment	**0.63**	0.28	0.03	0.48
Legal Environment	**0.82**	0.1	0.11	0.70
Political Environment	**0.79**	0.01	0.07	0.63
2. Uncertainty of the external environment				
Actions developed by competitors in the last 3 years	0.12	0.16	**0.81**	0.69
Tastes and preferences of the consumers	0.07	0.06	**0.84**	0.71
3. Intensity of the external environment				
Price competition	0.11	**0.47**	0.24	0.29
Competition in the diversity of services and products marketed	0.06	**0.75**	0.17	0.59
Competition in order to have access to human resources	0.12	**0.77**	0.06	0.61
Competition in order to have access to suppliers	0.07	**0.73**	0.08	0.54
Alpha Cronbach	0.74	0.67	0.6	
Eigenvalues	2.25	2.02	1.48	
% of variance	22.50%	20.25%	14.84%	

Panel C: Decentralization

Extraction method: Principal-component factors	Factor Loadings	
	1	**Communality**
1. Degree of delegated authority		
Development of new products/services	0.65	0.42
Hiring and/or dismissal of employees	0.8	0.64
Selection of investments	0.85	0.71
Resource distribution in the budget	0.85	0.72
Products and services price	0.81	0.65
Operational management of the business	0.79	0.63
Alpha Cronbach	0.88	
Eigenvalues	3.79	
% of variance	63.12%	

Appendix 4 – Correlations Matrix

	MCSINTENSITY	**FINANCIALPOS**	**PEUDYN**	**PEUUNC**	**PEUHOST**	**DECENT**	**AGRIC**	**INDUSTRY**	**SERVICES**
MCSINTENSITY	1	0.167***	0.168***	-0.002	0.042*	0.177***	-0.050**	-0.119**	0.130***
FINANCIALPOS	0.172***	1	0.120***	0.008	0.049**	0.132***	0.012	-0.015	0.012
PEUDYN	0.175***	0.129***	1	0.249***	0.274***	0.160***	0.026	-0.054**	0.047**
PEUUNC	-0.002	-0.008	0.239***	1	0.301***	0.127***	-0.003	-0.003	0.003
PEUHOST	0.054**	0.045*	0.269***	0.314***	1	0.156***	-0.020	-0.048**	0.052**
DECENT	0.139***	0.131***	0.151***	0.125***	0.182***	1	-0.035	0.010	-0.002
AGRIC	-0.050**	0.012	0.023	-0.013	-0.027	-0.039	1	-0.100***	-0.135***
INDUSTRY	-0.119***	-0.020	-0.054**	-0.003	-0.043*	0.033	-0.100***	1	-0.973***
SERVICES	0.130***	0.017	0.048**	0.006	0.049**	-0.024	-0.135***	-0.973***	1
SIZE	0.128***	0.060**	0.011	-0.019	-0.037	0.044*	-0.013	0.017	-0.014
BIRTH	-0.024***	-0.015	-0.060**	-0.032	-0.038	-0.017	-0.015	-0.019	0.023
GROWTH	0.067***	0.130***	-0.015	-0.036	0.031	0.054**	0.083***	0.034	-0.053**
MATURITY	-0.000	0.165***	0.029	-0.008	-0.048**	0.035	-0.031	-0.020	0.028
REVIVAL	0.076***	0.055**	0.032	0.015	0.011	0.027	0.050**	0.007	-0.019
DECLINE	-0.101***	-0.342***	-0.026	0.039*	0.036	-0.101***	-0.061***	-0.003	0.017
FAMILY	-0.167***	-0.076***	-0.079***	0.010	0.034	-0.109***	-0.011	0.090***	-0.087***
ECO	0.218***	0.046*	0.051**	-0.026	-0.029	0.120***	0.001	-0.046*	0.045*
ESTATE	0.033	0.038	0.048**	-0.058**	-0.112***	-0.015	-0.012	0.017	0.014
ROE	-0.008	-0.005	-0.007	-0.010	0.006	-0.003	0.001	0.007	-0.007

	SIZE	BIRTH	GROWTH	MATURITY	REVIVAL	DECLINE	FAMILY	ECO	ESTATE	ROE
MCSINTENSITY	0.233***	-0.024	0.067***	-0.000	0.076***	-0.101***	-0.167***	0.218***	0.033	0.047***
FINANCIALPOS	0.063***	-0.013	0.133***	0.157***	0.051**	-0.332***	-0.074***	0.043*	0.037	0.111***
PEUDYN	0.067***	-0.052**	-0.011	0.022	0.033	-0.025	-0.077***	0.050**	0.050**	-0.004
PEUUNC	0.021	-0.026	-0.025	0.003	0.013	0.016	0.013	-0.023	-0.055**	-0.010
PEUHOST	-0.018	-0.034	0.029	-0.041*	0.010	0.030	0.033	-0.029	-0.087***	-0.014*
DECENT	0.140***	-0.010	0.059**	0.041*	0.020	-0.109***	-0.121***	0.134***	-0.009	0.016**
AGRIC	0.001	-0.015	0.083***	-0.031	0.050**	-0.061***	-0.011	0.001	-0.012	-0.008
INDUSTRY	0.168***	-0.019	0.034	-0.020	0.007	-0.003	0.090***	-0.046*	0.017	-0.059***
SERVICES	-0.168***	0.023	-0.053**	0.028	-0.019	0.017	-0.087***	0.045*	-0.014	0.061***
SIZE	1	-0.026	-0.047*	0.092***	-0.006	-0.060**	-0.126***	0.230***	0.107***	0.004
BIRTH	-0.013	1	-0.051**	-0.142***	-0.040*	-0.068***	0.006	0.034	-0.013	0.017**
GROWTH	-0.001	-0.051**	1	-0.432***	-0.123***	-0.206***	0.078***	0.032	0.010	0.102***
MATURITY	0.049**	-0.142***	-0.432***	1	-0.342***	-0.573***	-0.017	0.042*	0.047**	0.027***
REVIVAL	-0.011	-0.040*	-0.123***	-0.342***	1	-0.163***	-0.005	-0.014	-0.012	-0.015**
DECLINE	-0.047**	-0.068***	-0.200***	-0.573***	-0.163***	1	0.087***	-0.079***	-0.053**	-0.114***
FAMILY	-0,122***	0.006	-0.078***	-0.017	-0.005	0.087***	1	-0.274***	-0.132***	-0.058***
ECO	0.178***	0.034	0.032	0.042*	-0.014	-0.079***	-0.274***	1	-0.051**	0.027***
ESTATE	0.055**	-0.013	0.010	0.047**	-0.012	-0.053**	-0.133***	-0.051**	1	-0.013*
ROE	-0.000	0.002	-0.018**	0.009	-0.001	0.005	-0.004	-0.014	0.001	1

The correlation matrix was constructed for all variables, apart from ROE, with cross-sectional data, since in the panel data observations are not independent.
For ROE the correlations had to be performed with panel data. Pearson correlation can be seen above the diagonal, and Spearman below.