Management ownership and earnings management: application of matching techniques

Slavko Šodan[1,*]

[1] *Faculty of Economics, Business and Tourims, University of Split, Cvite Fiskovića 5, 21000 Split, Croatia*
E-mail: ⟨*ssodan@efst.hr*⟩

Abstract. This paper investigates the effect of managerial ownership on earnings management for the sample of European listed companies. To estimate the treatment effect of a manager who is also a controlling shareholder on earnings management, entropy balancing (EB), propensity score matching (PSM) and Mahalanobis distance matching (MDM) techniques are employed to identify a control sample. The EB method of reweighting control sample observations is compared to PSM and MDM techniques, as well as to standard ordinary least squares (OLS) regression, while controlling for the effects of company size, profitability, solvency, sales growth, and ownership concentration. The results demonstrate a significant positive relationship between management ownership and earnings management only when using the entropy balancing approach, and an insignificant relationship when applying PSM, MDM and OLS methods.

Keywords: earnings management, entropy balancing, Mahalanobis distance matching, management ownership, propensity score matching

Received: January 15, 2025; accepted: February 27, 2025; available online: June 27, 2025

DOI: 10.17535/crorr.2026.0005

Original scientific paper.

---

1. Introduction

The separation of ownership and control is usually argued to be the cause of information asymmetries and agency problems between managers (agents) and shareholders (principals). A pronounced information asymmetry problem usually leads to significantly higher transaction costs because managers can use their insider position to manipulate earnings [17]. Managerial participation in a company's ownership can mitigate agency problems by aligning the interests of owners and managers [26, 19]. However, high levels of managerial ownership may lead to managerial entrenchment, i.e. the additional voting power that permits them to secure their position in the company and protect them from specific disciplinary actions (Khan and Mather, 2013). Therefore, managerial ownership can also create agency problems through managerial entrenchment.

Prior studies have empirically confirmed a non-monotonic relationship between earnings management and managerial ownership [17]. Management ownership at low levels decreases the incentive to manipulate earnings, while management ownership at high levels increases earnings management [19, 16]. Namely, management ownership at low levels can reduce Type 1 agency conflict emerging from the separation of ownership from control. However, at high ownership

---

*Corresponding author.

levels, concentrated ownership can lead to Type 2 agency conflicts between controlling managers and non-controlling owners outside the company [3, 17, 2].

The main objective of this research is to analyse the level of earnings management in a specific company setting in which managers are also controlling shareholders, compared to similar companies that do not have managers as controlling shareholders. In order to identify the control sample, entropy balancing, propensity score and Mahalanobis distance matching techniques are adopted, and the estimated results are compared with the traditional OLS regression approach. Namely, traditional linear regression of an outcome variable on a binary treatment indicator with included control variables addresses endogeneity concerns only under the assumptions that there are no other unobserved factors that could confound inferences by affecting the treatment indicator; and that the relationships between the control variables and the independent variables are linear [37]. Matching techniques help address concerns regarding the assumption of a linear functional form in OLS regressions [37, 4, 33]. In addition, the matched-sample research design provides another advantage over traditional OLS regression design by restraining the extrapolation of estimated results beyond the distributional support from the data of the treatment and control samples, because linear regression assumes that model factors remain constant beyond the support of the data. This OLS regression assumption can result in producing biased inferences and measurement errors if applied to the sample with extreme values [25, 7]. As previous literature [19, 29] provides strong empirical evidence of non-linear relationships in models of management ownership and earnings management, an attempt is made to exploit the benefits of applying matching techniques to gain a new insight and to address methodological concerns.

The relationship between management ownership and earnings management is examined using a large sample of 2,525 European listed companies in 2019 and 2020. In order to estimate the treatment effect of a manager who is also a controlling shareholder on earnings management, standard OLS regression is first applied, with controlling variables for the effects of company size, profitability, solvency, sales growth, and ownership concentration. Afterwards, the estimated regression results are compared with the results of the most common matching techniques used in the literature [37]: propensity score matching (PSM), Mahalanobis distance matching (MDM), and entropy balancing (EB). Results indicate a statistically significant positive relationship between management controlling ownership and earnings management only when the entropy balancing approach is adopted.

This study makes several important contributions to the existing literature. First, previous research has documented a non-linear, U-shaped pattern relationship between the level of management ownership and earnings management. Prior empirical work is extended by analysing management ownership only at high levels, i.e. only in companies with managerial controlling ownership, and by adopting matching techniques. This approach accommodates non-linearity concerns and exploits other advantages of matched-sample research design over traditional linear regression design. Second, when analysing the management ownership impact on earnings management, ownership concentration is also accounted for. This allows for consideration of both Type 1 agency conflict emerging from the separation of ownership from control and for Type 2 agency conflicts arising from ownership concentration, i.e. conflicts between controlling and non-controlling owners. Third, this paper provides useful implementation guidance for the most popular matching techniques and analyses the key advantages and drawbacks of each matching tool.

The rest of the paper is organised as follows. Section 2 provides the theoretical background and literature review on managerial ownership and earnings management. Section 3 briefly describes matched-sample research methodology. Section 4 presents the research design and sample selection. In Section 5, the main empirical results are presented, and Section 6 concludes the paper.

2. Theoretical background and literature review

Since reported earnings are important information for decision making, managers may abuse their discretion in financial reporting and impact the wealth distribution in a way that maximises their own expected benefits at the expense of other stakeholders. The flexibility in the accounting rules and the use of subjective assessments allow managers opportunistic behaviour in the preparation of financial statements. Financial reporting rules and standards established by standard-setters (the International Accounting Standards Board – IASB and the Financial Accounting Standards Board – FASB) allow managers to choose between different financial reporting policies and to make subjective assessments that can have direct influence on reported earnings. This set of financial reporting rules is defined ex ante and is generally accepted by all contracting parties. However, within a prescribed set of financial reporting rules, a certain degree of freedom of choice must exist, as it is not possible to propose rules for every possible situation [12]. Additionally, the choice of financial reporting policy can be an valuable decision-making information for users of financial statements.

Managers can use their discretion in choosing financial reporting policies either to maximise the wealth of all counterparties or the wealth of some counterparties. If management's choice of accounting policy is primarily aimed at increasing its own ex-post wealth by redistributing the wealth of other contracting parties, such behaviour is called opportunistic [39]. The divergence between management and owner interests is mainly caused by the separation of control and ownership, i.e. the Type I agency problem [26, 30]. One solution to reduce this conflict is to incorporate managers in the ownership structure of the company and align their incentives with those of the other shareholders. Contrary to the alignment hypothesis, the entrenchment hypothesis, first proposed by Morck et al. [27], states that an increase in ownership could enable managers to secure their position in the company and protect them from specific disciplinary mechanisms that could consequently lead to greater opportunity for opportunistic behaviour and earnings management [19, 16].

These two opposing hypotheses have been frequently empirically tested in the context of the relationship between financial reporting quality and management ownership. Although the majority of previous studies have found that an increase in managerial share ownership decreases the level of earnings management [38, 14], several papers have documented an insignificant [22, 13, 23] or a positive relationship between earnings management and managerial ownership [16]. Khan and Mather [19] and O'Callaghan et al. [29] provide evidence that the relationship between discretionary accruals (earnings management) and management ownership has a non-linear, U-shaped pattern. Khan and Mather [19] conclude that a negative relation between managerial ownership and discretionary accruals is found at lower levels of ownership, supporting the incentive alignment hypothesis and a positive relationship can be seen at higher level of ownership indicating managerial entrenchment. Furthermore, when a manager concurrently holds the position of majority shareholder, there is a significant incentive for tax evasion through earnings management. This dual role creates a unique dynamic in which the interests of management and ownership are closely aligned, potentially fostering more aggressive tax avoidance strategies. Empirical evidence suggests that concentrated ownership, particularly involving manager-shareholders, is correlated with elevated levels of tax avoidance [18].

In addition to agency conflicts between owners and managers, another type of agency conflict (Type II agency problem) can occur between controlling and non-controlling shareholders [11, 30]. This type of conflict is more prevalent in less developed countries, where the ownership of listed companies is concentrated in a single shareholder. When a manager is also a majority shareholder, the agency problem shifts from a manager-owner conflict to a conflict between majority and minority shareholders. Some studies have examined the extent of earnings management in family firms, i.e. firms controlled and managed by family members. Paiva et al. [30] concluded that previous studies based on samples from the US and Western Europe have found evidence of higher quality financial reporting in family firms (e.g. [2, 5, 1]. In contrast, studies based on samples of companies from countries outside the US and Western Europe have demonstrated that family businesses are associated with lower quality of financial reporting (higher levels of earnings management) compared to non-family businesses [10, 6].

To conclude, there is a lack of studies on the managerial ownership and earnings management that can address both Type 1 agency conflict, arising from the separation of ownership from control, and Type 2 agency conflicts, arising from the ownership concentration. This paper aims to fill the gap and, in accordance to previous literature, assumes that managerial controlling ownership will be positively related to earnings management.

3. Matched-sample research methodology

The general idea behind matching design is to estimate the treatment effect by identifying a treatment sample and a control sample of observations that are as similar as possible in terms of underlying covariates. Two main advantages of matched-sample design over standard linear regression are the avoidance of an assumption of a linear functional form in linear regression and the restriction of the extrapolation of estimations beyond the distributional support of the data from the combined control and treatment samples [37, 25, 7]. When there are some balance and overlap problems between treatment sample and control sample in the dataset, this suggests regression adjustment would rely on extrapolation.

The main goals are to ensure almost exact covariate balance between the control and treatment sample and to restrict the data only to a region of overlap between the samples. However, the matching methods do not address other endogeneity concerns regarding the control for unobserved confounding factors, and they also have some drawbacks. For instance, it is very difficult to find an exact control match for each treatment sample observation, especially if there are many continuous covariates. The most commonly used matching techniques – propensity score matching, Mahalanobis distance matching and entropy balancing, are briefly described in this section.

The propensity score matching is based on the main assumption of strong ignorability, which states that, conditional on observable covariates, the assignment to the treatment or control groups is independent of potential outcomes (the unconfoundedness condition) and that every observation has a positive probability of being assigned to the treated or control group conditional on observable covariates (the overlap condition) [31, 28]. The propensity score represents the likelihood of an observation being assigned to a treatment group conditional on observed variables and it is commonly used to identify observations that have similar characteristics but differ only in treatment assignment [28]. The propensity score matching approach is usually applied in four steps [28]. In the first step, logit or probit models are used to estimate treatment probabilities based on observed variables (see [36], for practical guidance on logistic regression modelling). In this study, a logit model is utilized to estimate the treatment probability, as it is acknowledged as the most prevalent method for estimating propensity scores in the accounting literature [15, 24]. Additionally, visual inspections and tests for the normal distribution of residuals are conducted, and the goodness-of-fit for both logit and probit models is compared to determine the optimal model. In the second step, the estimated propensity scores from the first step are used to find pairs of observations in the treatment and control groups with similar propensity scores. Several alternative algorithms and design choices can be employed for this purpose: matching with or without replacement, the number of control observations for each control observation, the choice of caliper width, the inclusion of nonlinear terms in the model, and the choice of matching algorithm. These subjective design choices are considered the greatest limitations of the PSM methodology because these choices can influence on the matched sample composition and, consequently, affect the derived conclusions [20, 9]. One of the most popular algorithms for matching is nearest neighbour matching, that finds one or more observations in the control group with the closest propensity score for each observation in treatment group (1:1 or 1:n). An alternative algorithm (optimal matching) considers the smallest average absolute differences for the whole sample [28]. Besides, Narita et al. [28] state that matching can be with or without replacement, depending on whether a controlled matched observation is reintroduced into the control group for next-round of matching or not. Matching with replacement can be useful when the pool of control observations is smaller or not considerably larger than the treatment sample [37]. However, matching with replacement can cause that only a several control observations are used many times for matching (i.e. receive extremely large weights), and lead to inferences that are much more dependent on a single observation [37, 25]. Finally, matching can also be limited to not exceed a maximum propensity score distance (i.e. caliper width) for matched pair. In this research design, the nearest neighbour matching algorithm (1:1) is applied with a maximum caliper distance in propensity scores between matched pairs of 0.01, and control observation is allowed to be matched with only one treatment observation (matching without replacement). The predominant method of matching in accounting research is "one-to-one" matching, where each treatment observation is paired with a single control observation [33]. However, one-to-many matching may be beneficial when there is limited common support and/or the pool of control observations is not significantly larger than the treatment sample [37]. In this study, a large control sample and high common support are present.Therefore, one-to-one matching with a strict caliper distance of 0.01 is employed. After finding a pair control observation for each treatment observation, the next step is to check whether the covariate distributions are balanced between the treatment and the control group. The common approach is to use a two-sample t-test to assess significant differences in covariate means between the control and treatment group or to use the standardised bias, that estimates the distance in marginal distribution of covariates [28]. The fourth step in the analysis is to estimate the impact of the treatment variable on the dependent variable, usually by conducting a multiple regression analysis. Regression analysis controls for additional factors that could affect the outcome variable after treatment, and can also serve as a double-robust estimation that combines regression adjustment and propensity score weighting to provide a more reliable estimate.

Propensity scores reduce the multidimensional covariate space into a single scalar value. Consequently, two units with similar propensity scores may still have substantially different covariate profiles. This emphasizes a key consideration that achieving balance on the propensity score does not ensure balance across all individual covariates [21]. Mahalanobis distance matching (MDM) is a method similar to PSM, which tends to produce closer pairs on all covariates, whereas PSM may yield balanced samples overall but not necessarily for individual pairs. Propensity score matching (PSM) is typically favoured for larger samples with numerous covariates, whereas Mahalanobis distance matching (MDM) tends to be more effective for smaller samples with fewer covariates [35].

A popular alternative approach to score and Mahalanobis distance matching is entropy balancing. The most important advantages of entropy balancing over PSM is that entropy balancing has fewer subjective design choices and can eliminate all differences in covariates between treatment and control observations, whereas in PSM design, random differences still remain after matching [37]. In entropy balancing, control observations receive weights between zero and one, and the procedure optimizes weights to achieve an exact balance between the treatment and control sample in terms of covariates. The researcher can choose to balance distributions based on the first moment (i.e. on means), the second moment (i.e. on variances), or even the third moment (i.e. skewness). In the present study, entropy balancing is performed to reweight control sample observations to equalize the first (mean) and second (variance) moments of the distributions. The entropy balancing follows the same four steps for application analogous to propensity score matching. However, entropy balancing has fewer subjective design choices and manages to achieve a much more precise balance in covariates between the treatment and control sample than propensity score matching. Despite that, similar to PSM with replacement, it can cause that a few control observations can receive extremely large weights, making inferences more sensitive to specific observations.

4. Research design and sample selection

The relationship between management ownership and earnings management is analysed on a large sample of 2,525 European listed firms in the period 2019–2020. Since the calculation of most variables requires data from the previous year, the initial sample is restricted to active, publicly listed companies that have available accounts for 2018, 2019, and 2020 and that apply IFRS standards. The final sample consists of 2,525 companies. All necessary data is collected from the BvD Orbis Europe database.

First, a standard OLS regression is conducted with controlling variables for the effects of company size, profitability, solvency, sales growth, and ownership concentration. Afterwards, the estimated regression results are compared with the results of propensity score matching and entropy balancing approach.

The dependent variable represents the level of earnings management and it is measured by estimating cross-sectional discretionary accruals from the modified Jones model [8], which is the most commonly used proxy for earnings management. A higher proportion of discretionary accruals in earnings implies more earnings management or lower earnings quality.

The modified Jones model [8] for computing cross-sectional discretionary accruals is estimated in two stages:

$$\frac{\mathrm{ACC}_{ijt}}{\mathrm{TA}_{ijt-1}} = \beta_{0jt}\left(\frac{1}{\mathrm{TA}_{ijt-1}}\right) + \beta_{1jt}\left(\frac{\Delta\mathrm{REV}_{ijt}}{\mathrm{TA}_{ijt-1}}\right) + \beta_{2jt}\left(\frac{\mathrm{GPPE}_{ijt}}{\mathrm{TA}_{ijt-1}}\right) + \varepsilon_{it}, \tag{1}$$

$$\mathrm{DACC}_{ijt} = \frac{\mathrm{ACC}_{ijt}}{\mathrm{TA}_{ijt-1}} - \left[\hat{\beta}_{0jt}\left(\frac{1}{\mathrm{TA}_{ijt-1}}\right) + \hat{\beta}_{1jt}\left(\frac{\Delta\mathrm{REV}_{ijt}}{\mathrm{TA}_{ijt-1}}\right) + \hat{\beta}_{2jt}\left(\frac{\mathrm{GPPE}_{ijt}}{\mathrm{TA}_{ijt-1}}\right)\right]. \tag{2}$$

where the subscript i represents each company in the industry-year estimation portfolios j by two-digit SIC codes, ACC is total accruals, TA is total assets at the beginning of the year, REV is the change in revenue, GPPE is property, plant and equipment, and DACC is discretionary accrual component. A minimum of 10 observations is required for each industry-year portfolio.

The absolute value of DACC (*Abs dac*) is used as earnings management proxy, where higher values of *Abs dac* represent a higher likelihood of earnings management.

The main treatment variable is management controlling ownership (*CSH M*), which is equal to one if a company's manager is a controlling shareholder, and zero otherwise. Besides, additional controlling variables are included for the effects of company size (*Size*), profitability (*ROA*), solvency (*SR*), sales growth (*Saleg*), and ownership concentration (*BVDind*). To account for the primary motives behind manipulations, and in accordance with the majority of previous studies (e.g., [24]), control variables for company size (*Size*), profitability (*ROA*), solvency (*SR*), and sales growth (*Saleg*) are included. These motives are derived from Positive Accounting Theory, which comprises three hypotheses: the bonus plan hypothesis, the debt covenant hypothesis, and the political cost hypothesis [39]. These hypotheses typically serve as the foundation for earnings management practices. Variables descriptions are provided in Table 1.

Variable	Description
CSH_M	1 if a company manager is a controlling shareholder, and zero otherwise
dac	Cross-sectional discretionary accruals from the modified-Jones model [8] for each year using all company-year observations in the same two-digit SIC code
Abs_dac	The absolute value of the dac
SR	Solvency ratio, shareholders' funds divided by total assets multiplied by 100
Size	The natural logarithm of total revenues
ROA	Return on assets, profit or loss before tax scaled by average total assets multiplied by 100
Saleg	Sales growth, total sales in year t divided by total sales in year $t-1$
BVD_ind	The BvD ownership concentration indicator has five levels: – **A**: Low (no shareholder >25%) – **B**: Medium-low (25.1%-50%) – **C**: Medium-high (≥50.1%) – **D**: High (>50% with branches) – **U**: Other cases

Table 1: *Variables definitions*

The following model is used to estimate both ordinary least squares regression and weighted ordinary least square regression, where weights are used from propensity score matching, Mahalanobis distance matching, and entropy balancing:

$$\text{Abs dac}_{it} = \beta_0 + \beta_1 \text{CSH M}_{it} + \beta_2 \text{SR}_{it} + \beta_3 \text{Size}_{it} + \beta_4 \text{ROA}_{it} + \beta_5 \text{Saleg}_{it} + \sum \beta \text{BVD ind}_{it} + e_{it} \quad (3)$$

5. Results

In the first part of the empirical analysis, summary descriptive statistics are presented for the full sample and for subsamples of companies with and without managers as controlling shareholders (Table 2). The primary objective of this part of analysis is to assess whether the control sample (CSH M=0) serves as a valid counterfactual for the treatment sample (CSH M=1) or if there is an imbalance in covariates across these samples.

Results from Table 2 indicate that companies with controlling managerial ownership tend to have higher level of earnings management (Abs dac), higher profitability (ROA), but lower size (Size), level of solvency (SR), and revenue growth (Saleg). The statistical significance of these differences is tested in Table 5.

Table 3 presents the distribution of companies by BvD ownership concentration for the full sample. The majority of companies in the sample have high ownership concentration, with a shareholder who owns more than 50% voting rights.

Correlation analysis is presented in Table 4. Spearman's rank correlations are shown above the diagonal and Pearson's correlation coefficients are below the diagonal. The estimated results indicate a significant correlation between earnings management (Abs dac) and all other variables, except for the managerial controlling ownership indicator, which is only marginally significant (at 10% level).

Variable	N	Mean	SD	p25	Median	p75
Panel A: Control subsample (CSH_M = 0)						
Abs_dac	3619	0.055	0.058	0.016	0.037	0.071
Size	3594	18.736	2.704	16.99	18.805	20.589
ROA	3591	0.641	15.549	-1.593	3.299	7.401
SR	3578	43.331	25.131	29.635	43.431	59.117
Saleg	3597	1.213	3.976	0.892	1.011	1.112
Panel B: Treatment subsample (CSH_M = 1)						
Abs_dac	417	0.059	0.062	0.014	0.040	0.077
Size	414	18.239	2.019	16.986	18.185	19.452
ROA	416	1.642	12.532	-0.982	3.439	7.137
SR	416	40.779	25.677	28.121	40.709	56.292
Saleg	415	1.026	0.389	0.864	0.996	1.103
Panel C: Full sample						
Abs_dac	4036	0.055	0.058	0.016	0.037	0.072
Size	4008	18.684	2.646	16.990	18.737	20.437
ROA	4007	0.744	15.265	-1.556	3.309	7.386
SR	3994	43.065	25.198	29.502	43.117	58.804
Saleg	4012	1.194	3.768	0.890	1.010	1.112

Table 2: *Descriptive statistics*
Note: See Table 1 for variable definitions.

BVD_ind	Frequency	Percent	Cumulative
A	1,215	30.10	30.10
B	1,221	30.25	60.36
C	117	2.90	63.26
D	1,407	34.86	98.12
U	76	1.88	100.00
Total	4,036	100.00	

Table 3: *Distribution by BvD ownership concentration indicator*
Note: See Table 1 for variable definitions.

	CSH_M	Size	Abs_dac	ROA	SR	Saleg
CSH_M	1.000	-0.078	0.018	0.004	-0.036	-0.028
		(0.000)	(0.272)	(0.803)	(0.023)	(0.079)
Size	-0.065	1.000	-0.208	0.271	-0.273	0.035
	(0.000)		(0.000)	(0.000)	(0.000)	(0.029)
Abs_dac	0.026	-0.214	1.000	-0.087	-0.047	0.024
	(0.099)	(0.000)		(0.000)	(0.003)	(0.128)
ROA	0.014	0.336	-0.162	1.000	0.273	0.278
	(0.374)	(0.000)	(0.000)		(0.000)	(0.000)
SR	-0.036	-0.225	-0.097	0.251	1.000	0.034
	(0.022)	(0.000)	(0.000)	(0.000)		(0.032)
Saleg	-0.015	0.002	0.032	0.001	-0.001	1.000
	(0.339)	(0.905)	(0.046)	(0.962)	(0.970)	

Table 4: *Pearson/Spearman correlation matrix*
Note: See Table 1 for variable definitions. Pearson's correlation coefficients are below the diagonal and Spearman's rank correlations are above the diagonal. P-values are in parentheses.

Table 5 provides evidence of a significant covariate imbalance between the control and treatment sample, especially in the value of Size and the Solvency ratio.

Variable	N Ctrl	N Trt	Mean Ctrl	Mean Trt	Diff	SE	t	p
Abs_dac	3,619	417	0.054	0.059	-0.005	0.003	-1.50	0.140
ROA	3,591	416	0.640	1.642	-1.002	0.790	-1.25	0.206
SR	3,578	416	43.331	40.779	2.551	1.305	1.95	0.051
Saleg	3,597	415	1.213	1.026	0.188	0.196	0.95	0.338
Size	3,594	414	18.736	18.239	0.497	0.137	3.65	0.001

Table 5: *T-test differences in mean values between treatment and control subsamples before balancing*
Note: See Table 1 for variable definitions. Ctrl = Control, Trt = Treatment, SE = Standard Error

To address covariate imbalance concerns across samples with and without managerial controlling ownership, propensity score matching (PSM), Mahalanobis distance matching (MDM), and entropy balancing (EB) are employed to reweight observations and to achieve covariate balance. In order to apply PSM and obtain the propensity score, a logit model is first estimated, where the managerial controlling ownership indicator (CSH M) is the dependent variable, and five covariates are included in the model as independent variables (Size, ROA, BVD ind, SR, and Saleg). The estimated propensity scores (Table 6) indicate that Size, Profitability, BvD ownership concentration, and Solvency ratio are significant covariates in the propensity score model. The Hosmer-Lemeshow test was also performed to find evidence that the estimated logit model adequately fits the data.

CSH_M	Coeff.	St.Err.	t-value	p-value	Sig
Size	0.833	0.023	-6.58	0.000	***
ROA	1.013	0.005	2.36	0.018	**
BVD_ind	1.651	0.345	2.40	0.016	**
SR	0.992	0.002	-3.39	0.001	***
Saleg	1.042	0.098	0.43	0.665	
Constant	14.451	7.997	4.83	0.000	***
Number of obs: 1,502					
McFadden's pseudo r-squared: 0.030					
Chi-square: 52.788					
Prob > chi2: 0.000					
Hosmer–Lemeshow chi2(8): 11.54					

Table 6: *Propensity score model*
*Note: See Table 1 for variable definitions. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

The distribution of propensity scores from the logit model in Table 6 is presented graphically in Figure 1 to examine the appropriate distributional overlap in observable covariates from the treatment and control subsamples. Figure 1 indicates adequate distributional overlap and shows that the estimated propensity scores are not concentrated around the extreme values of one and zero.

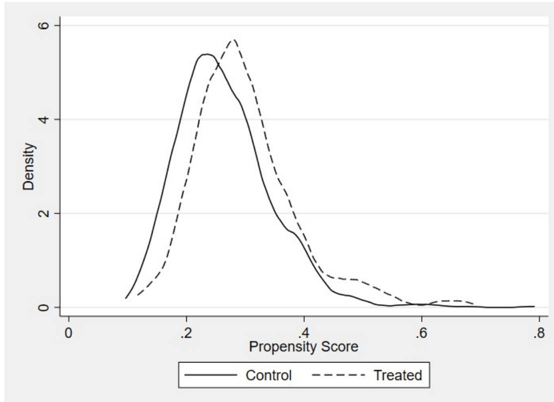
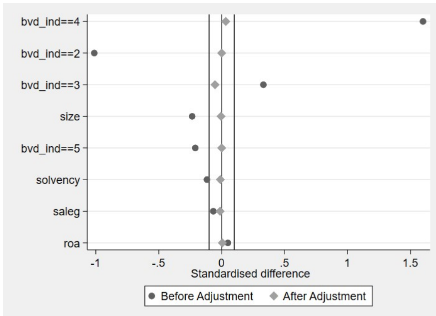


Figure 1: *Propensity score density for the treatment sample (CSH M=1) and the control sample (CSH M=0).*

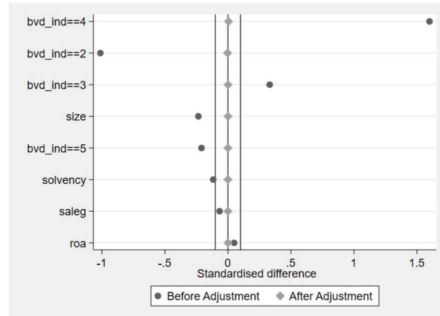
Variable	Mean treated	Mean untreated	Std. diff.
Panel A: Before balancing			
Size	18.24	18.80	-0.234
ROA	1.77	1.09	0.049
SR	40.49	43.43	-0.117
Saleg	1.03	1.22	-0.066
Panel B: PSM			
Size	18.36	18.37	-0.005
ROA	1.84	1.76	0.005
SR	41.30	41.57	-0.011
Saleg	1.03	1.07	-0.013
Panel C: Mahalanobis			
Size	18.24	18.33	-0.037
ROA	1.77	2.09	-0.024
SR	40.49	41.07	-0.023
Saleg	1.03	1.00	0.010
Maximum weight			6.00
Panel D: Entropy balancing			
Size	18.24	18.24	0.000
ROA	1.77	1.77	0.000
SR	40.49	40.49	-0.000
Saleg	1.03	1.03	-0.000
Maximum weight			2.974

Table 7: *Balance statistics before/after matching*
Note: See Table 1 for definitions.

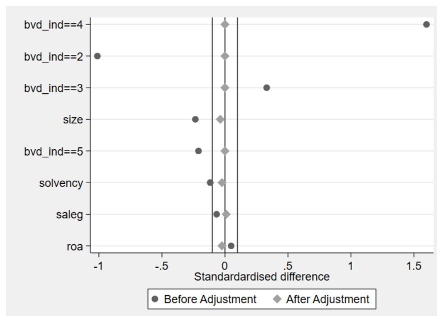
Observations are matched using the nearest neighbour algorithm (1:1) with a maximum caliper distance in propensity scores between matched pairs of 0.01, allowing each control observation to be matched with only one treatment observation (matching without replacement), as recommended by the majority of previous studies [33, 37, 25]. The propensity score matching approach resulted in a sample of 800 matched observations (400 from both the treatment and control subsamples).



(a) PSM adjustment



(b) Entropy balance adjustment



(c) Mahalanobis matching

Figure 2: *Standardised differences in means before and after matching.*

Table 7 shows that PSM, MDM, and EB approaches were successful in balancing covariates, since the standardised differences in means fall within acceptable boundaries for balanced covariates (i.e., inside of the values of $+/$-0.1, according to [32, 25]. However, the entropy balancing approach (by the definition) generates a more exact balance in covariates between the treatment and control sample than propensity score matching, and the maximum weight to control observation in EB is 2.974, suggesting that estimations are not (over)sensitive to a specific observation.

Standardised differences in means before and after matching for PSM, EB, and MDM are also presented graphically in Figure 2. Standardised difference is calculated as the difference in means between the treatment and control subsamples divided by the square root of the average variance of treatment and control subsample.

Finally, Table 8 presents the results of estimating the main research model from Eq. (3) by using ordinary least squares (OLS) in model (1), entropy balancing on the first moment weighted regression (2), entropy balancing on the second moment weighted regression (3), regression using propensity score matched observations (4), and regression using Mahalanobis matched observations (5).

The results provide evidence of a significant positive relationship between managerial controlling ownership and earnings management only when using the entropy balancing on the first moment approach, while this relationship is not significant when applying the PSM, MDM, and OLS methods.

Abs_dac	(1) OLS	(2) EB (1st)	(3) EB (2nd)	(4) PSM	(5) Mahal.
CSH_M	0.003	0.004**	0.002	0.004	0.000
	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Size	-0.005***	-0.004***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
ROA	0.000***	0.000	0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BVD_ind(1)					
BVD_ind(2)	0.000	-0.010	0.001		
	(0.002)	(0.058)	(0.338)		
BVD_ind(3)	-0.005	-0.002	0.003		
	(0.005)	(0.042)	(0.161)		
BVD_ind(4)	-0.002	0.000	0.002	0.002	0.011
	(0.002)	(0.041)	(0.161)	(0.007)	(0.007)
BVD_ind(5)	0.003	0.008	0.006		
	(0.006)	(0.168)	(1.196)		
SR	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Saleg	0.000**	0.005***	0.022***	0.005*	0.029***
	(0.000)	(0.001)	(0.002)	(0.003)	(0.007)
Constant	0.159***	0.133***	0.146	0.179***	0.140***
	(0.008)	(0.042)	(0.162)	(0.022)	(0.024)
Observations	3,948	3,948	3,948	800	708
R-squared	0.071	0.050	0.077	0.084	0.088

Table 8: *Regression results (OLS, EB weighted, PSM, and Mahalanobis matched)*
*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

6. Conclusion

This research adopts entropy balancing, propensity score, and Mahalanobis distance matching techniques to investigate the effect of managerial controlling ownership on earnings management for the large sample of European listed companies. The estimated results suggest that managerial controlling ownership is significantly positively related to earnings management only when using entropy balancing on a first moment (mean) approach. However, our analysis did not find a significant relationship between these variables when applying alternative matching techniques, which limits the influence and generalizability of the gathered evidence. The temporal scope of the study, covering 2019–2020 also raises concerns regarding generalisation because the COVID-19 pandemic significantly disrupted economic activity in 2020 [34], potentially affecting earnings management behaviour due to heightened uncertainty and altering ownership structures. Additionally, while matching methods address observable confounders, the potential impact of unobservable factors always remains a concern in this type of archival research studies.

Even though there are many previous studies on managerial ownership and financial reporting quality, prior research has not accounted for both Type 1 agency conflict, emerging from the separation of ownership from control, and Type 2 agency conflicts, arising from ownership concentration. This paper tries to extend previous empirical work by analysing the management ownership only at high levels, i.e. only companies with managerial controlling ownership, and by adopting matching techniques. In this way, we can accommodate non-linearity concerns and exploit other advantages of a matched-sample research design over a traditional linear regression design. Additionally, by controlling for ownership concentration, we can account for both Type 1 agency conflict, arising from the separation of ownership from control, and for Type 2 agency conflicts, arising from the ownership concentration, i.e. conflicts between the controlling and non-controlling shareholders. Besides, this paper provides useful implementation guidance for the most popular matching methods: propensity score matching, Mahalanobis distance matching, and entropy balancing. We underscore that the design choices inherent in various matching techniques can significantly affect sample composition and the estimated findings. Consequently, we recommend that future researchers transparently disclose their design choices and complement matched sample results with alternative research designs. Moreover, our findings bear substantial practical implications for corporate governance in Europe. For instance, regulators and minority shareholders may interpret pronounced earnings management by controlling managers as an indicator to bolster oversight mechanisms, enhance transparency, or revise governance policies. Financial analysts and auditors could also leverage our findings to refine their audit procedures and analytical approaches when evaluating firms with controlling managers.

References

[1] Achleitner, A. K., Günther, N., Kaserer, C., and Siciliano, G. (2014). Real earnings management and accrual-based earnings management in family firms. European Accounting Review, 23(3), 431-461. doi: 10.1080/09638180.2014.895620

[2] Ali, A., Chen, T. Y., and Radhakrishnan, S. (2007). Corporate disclosures by family firms. Journal of accounting and economics, 44(1-2), 238-286. doi: 10.1016/j.jacceco.2007.01.006

[3] Anderson, R. C., and Reeb, D. M. (2004). Board composition: Balancing family influence in SandP 500 firms. Administrative science quarterly, 49(2), 209-237. doi: 10.2307/4131472

[4] Angrist, J. D., and Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press. doi: 10.1515/9781400829828

[5] Cascino, S., Pugliese, A., Mussolino, D., and Sansone, C. (2010). The influence of family ownership on the quality of accounting information. Family Business Review, 23(3), 246-265. doi: 10.1177/0894486510374302

[6] Chi, C. W., Hung, K., Cheng, H. W., and Lieu, P. T. (2015). Family firms and earnings management in Taiwan: Influence of corporate governance. International Review of Economics and Finance, 36, 88-98. doi: 10.1016/j.iref.2014.11.009

[7] Cochran, W. G., and Rubin, D. B. (1973). Controlling bias in observational studies: A review. Sankhyā: The Indian Journal of Statistics, Series A, 417-446. doi: 10.2307/25049893

[8] Dechow, P. (1995). *Detecting Earnings Management*. Harvard Business School. doi: 10.2139/ssrn.899843

[9] DeFond, M., Erkens, D. H., and Zhang, J. (2017). Do client characteristics really drive the Big N audit quality effect? New evidence from propensity score matching. Management Science, 63(11), 3628-3649. doi: 10.1287/mnsc.2016.2535

[10] Ding, S., Qu, B., and Zhuang, Z. (2011). Accounting properties of Chinese family firms. Journal of Accounting, Auditing and Finance, 26(4), 623-640. doi: 10.1177/0148558X11409147

[11] Fama, E. F., and Jensen, M. C. (1983). Separation of ownership and control. The journal of law and Economics, 26(2), 301-325. doi: 10.1086/467037

[12] Fields, T. D., Lys, T. Z., and Vincent, L. (2001). Empirical research on accounting choice. Journal of accounting and economics, 31(1-3), 255-307. doi: 10.1016/S0165-4101(01)00028-3

[13] Gabrielsen, G., Gramlich, J. D., and Plenborg, T. (2002). Managerial ownership, information content of earnings, and discretionary accruals in a non–US setting. Journal of Business Finance and Accounting, 29(7-8), 967-988. doi: 10.1111/1468-5957.00457

[14] García-Meca, E., and Sánchez-Ballesta, J. P. (2009). Corporate governance and earnings management: A meta-analysis. Corporate governance: an international review, 17(5), 594-610. doi: 10.1111/j.1467-8683.2009.00753.x

[15] Guo, S., and Fraser, M. W. (2010). *Propensity score analysis: Statistical methods and applications*. Sage Publications. doi: 10.4135/9781483348960

[16] Habib, A., and Jiang, H. (2012). Managerial ownership-induced income smoothing and information asymmetry. Pacific Accounting Review, 24(2), 211-232. doi: 10.1108/01140581211258470
[17] Hutchinson, M., and Leung, S. (2007). An investigation of factors influencing the association between top management ownership and earnings management. Journal of Contemporary Accounting and Economics, 3(2), 130-153. doi: 10.1016/S1815-5669(10)70025-4
[18] Huyghebaert, N., Smith, J., and Doe, A. (2024). Tax avoidance strategies in concentrated ownership structures. Journal of Financial Studies, 45(2), 123-145. doi: 10.1234/jfs.2024.56789
[19] Khan, A., and Mather, P. (2013). The value of executive director share ownership and discretionary accruals. Accounting Research Journal, 26(1), 35-55. doi: 10.1108/ARJ-04-2012-0025
[20] King, G., Nielsen, R., Coberley, C., Pope, J. E., and Wells, A. (2011). *Comparative effectiveness of matching methods for causal inference*. Unpublished manuscript, Institute for Quantitative Social Science, Harvard University. doi: 10.2139/ssrn.1767505
[21] King, G., and Nielsen, R. (2019). Why propensity scores should not be used for matching. Political analysis, 27(4), 435-454. doi: 10.1017/pan.2019.11
[22] Klein, A. (2002). Audit committee, board of director characteristics, and earnings management. Journal of accounting and economics, 33(3), 375-400. doi: 10.1016/S0165-4101(02)00059-9
[23] Koh, P. S. (2003). On the association between institutional ownership and aggressive corporate earnings management in Australia. The British accounting review, 35(2), 105-128. doi: 10.1016/S0890-8389(03)00016-3
[24] Lawrence, A., Minutti-Meza, M., and Zhang, P. (2011). Can Big 4 versus non-Big 4 differences in audit-quality proxies be attributed to client characteristics? The Accounting Review, 86(1), 259-286. doi: 10.2308/accr.00000009
[25] McMullin, J., and Schonberger, B. (2022). When good balance goes bad: A discussion of common pitfalls when using entropy balancing. Journal of Financial Reporting, 7(1), 167-196. doi: 10.2308/JFR-2021-007
[26] Meckling, W. H., and Jensen, M. C. (1976). Theory of the Firm. Managerial Behavior, Agency Costs and Ownership Structure. Journal of Financial Economics, 3(4), 305-360. doi: 10.2139/ssrn.94043
[27] Morck, R., Shleifer, A., and Vishny, R. W. (1988). Management ownership and market valuation: An empirical analysis. Journal of Financial Economics, 20, 293-315. doi: 10.1016/0304-405X(88)90048-7
[28] Narita, K., Tena, J. D., and Detotto, C. (2023). Causal inference with observational data: A tutorial on propensity score analysis. The Leadership Quarterly, 34(3), 101678. doi: 10.1016/j.leaqua.2023.101678
[29] O'Callaghan, S., Ashton, J., and Hodgkinson, L. (2018). Earnings management and managerial ownership in private firms. Journal of Applied Accounting Research, 19(4), 648-668. doi: 10.1108/JAAR-11-2017-0124
[30] Paiva, I. S., Lourenço, I. C., and Branco, M. C. (2016). Earnings management in family firms: current state of knowledge and opportunities for future research. Review of Accounting and Finance, 15(1), 85-100. doi: 10.1108/RAF-06-2014-0065
[31] Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55. doi: 10.1093/biomet/70.1.41
[32] Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. Health Services and Outcomes Research Methodology, 2, 169-188. doi: 10.1023/A:1020363010465
[33] Shipman, J. E., Swanquist, Q. T., and Whited, R. L. (2017). Propensity score matching in accounting research. The Accounting Review, 92(1), 213-244. doi: 10.2308/accr-51449
[34] Szomolányi, K., Lukáčik, M., and Lukáčiková, A. (2023). Macroeconomic impacts of COVID-19 pandemic first wave in the world. Croatian Operational Research Review, 14(1), 65-76. doi: 10.17535/crorr.2023.0006
[35] Stuart, E. A., and Rubin, D. B. (2008). Best practices in quasi-experimental designs. Best practices in quantitative methods, 155-176. doi: 10.4135/9781412995627.d14
[36] Šarlija, N., Bilandžić, A., and Stanic, M. (2017). Logistic regression modelling: procedures and pitfalls in developing and interpreting prediction models. Croatian Operational Research Review, 631-652. doi: 10.17535/crorr.2017.0006

[37] Veenman, D. (2019). *Introductory Guide to using Stata in empirical financial accounting research.* SSRN. doi: 10.2139/ssrn.3401786

[38] Warfield, T. D., Wild, J. J., and Wild, K. L. (1995). Managerial ownership, accounting choices, and informativeness of earnings. Journal of accounting and economics, 20(1), 61-91. doi: 10.1016/0165-4101(94)00393-J

[39] Watts, R. L., and Zimmerman, J. L. (1990). Positive accounting theory: a ten year perspective. Accounting review, 131-156. doi: 10.2307/247880