Evaluating the Impact of Robotic Process Automation on   
Earnings and Real Activities Management

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# Abstract

**JEL Classification: M**

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# **INTRODUCTION**

In today's business world, disruptive technologies have significantly reshaped various sectors, particularly in finance and accounting. The advent of digital transformation has been instrumental in driving value creation and competitive advantage. Technologies such as artificial intelligence, machine learning, cloud computing, blockchain, and robotic process automation (RPA) have particularly impacted the finance and accounting functions, reflecting the rapid evolution in this domain (Moll and Yigitbasioglu 2019).

A pivotal example of such technological influence is the introduction of enterprise resource planning systems (ERP). ERPs have revolutionized financial operations, enhancing cross-functional integration, centralizing control, and advancing automation. (Scapens and Jazayeri 2003; Nicolaou and Bhattacharya 2008; Kanellou and Spathis 2013). This transformation has led to more efficient financial reporting and transparency, where accounting transactions are easily traceable and financial reports are generated automatically, marking a shift from manual to automated processes (Kuhn and Sutton 2010).

Empirical evidence supports the positive impact of such technologies. The integration of ERP systems has been extensively analyzed, showcasing its diverse impacts on organizations. The immediate value of these systems is evident through positive market responses post-implementation (Hayes et al. 2001). Furthermore, ERP adoption is positively correlated with enhanced financial performance, indicating its significant economic benefits (Hitt et al. 2014). In terms of operational efficiency, ERP systems have been shown to significantly improve business process effectiveness (Hunton et al. 2003). The strategic implications of ERP on corporate finances, especially in areas like earnings management, have been thoroughly examined, presenting a comprehensive view of its influence beyond traditional performance measures (Morris and Laksmana 2010). Additionally, Paredes and Wheatley (2017) extend this examination by investigating how the increase in managers' access to accounting data via ERP systems influences managerial behavior, particularly regarding real activities manipulation. Their findings suggest that after the implementation of ERP, earnings management through real activities declines, indicating that ERP implementations enhance the quality of financial reporting by constraining opportunistic managerial behavior. This underscores the multifaceted benefits of ERP systems, not only in improving operational performance but also in promoting more transparent and reliable financial reporting practices.

Despite extensive research on ERP systems, RPA in accounting is a nascent field. Current literature predominantly explores theoretical aspects and potential impacts of RPA on accounting and auditing, primarily utilizing secondary data to understand its role in the digitization of accounting and interaction with related technologies (Tiron-Tudor et al. 2024). Although recent studies have ventured into qualitative analyses, examining motivations for RPA adoption and its broader implications for the accounting profession (Fernandez and Aman 2018; Moffitt et al. 2018; Asatiani et al. 2020; Stravinskienė and Serafinas 2021), studies employing quantitative methodologies are conspicuously sparse.

In this study, we explore the nuanced relationship between RPA adoption and earnings management (EM) across firms, including accruals-based earnings management (AM) and real activities manipulation (RM). Through a comparative analysis involving 86 firms utilizing RPA against a control group of 86 firms without such implementations from 2017 to 2022, our investigation aims to reveal how RPA technology influence EM. Our findings suggest that the sophisticated control and decision-making capacities enabled by RPA might lead to a surge in EM. This phenomenon is probably attributed to a delay in the development of comprehensive control standards and risk management frameworks, which struggles to keep up with the swift pace of technological adoption.

This investigation is not only of academic interest but also holds significant practical implications for a range of stakeholders, including corporations themselves, regulatory bodies, standard setters, and audit firms. For corporations, the insights derived could guide the formulation of more effective control and risk management frameworks in the wake of RPA integration. Regulatory authorities might leverage the findings to refine policies that enhance transparency and accountability in the digital age. Additionally, for the audit practice, this study illuminates the evolving challenges and opportunities in identifying and mitigating earnings management in an era increasingly dominated by RPA technology.

The remaining sections of this study as follows: The second section is literature reviews and development of hypotheses; the third part is sample selection and research design; the fourth section is the univariate and multivariate results, the fifth section is additional analyses; and the last section is the conclusion of this study.

# LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

## Automation Tools: from ERP to RPA

　　Before RPA, the introduction of ERP system, as one of the automation technologies as mentioned by Jędrzejka (2019), has brought about the integration of various functions across the organization, centralized system control, and enhanced automation, leading to significant gains in efficiency (Scapen 2003; Nicolaou and Bhattacharya 2008; Kanellou and Spathis 2013). ERP system is a unified business management framework consisting of interconnected software modules that, when effectively applied, streamline and consolidate all organizational operations. These modules typically feature robust business applications and utilities for managing financials, sales, distribution, inventory, human resources, production scheduling, computer-aided manufacturing, supply chain logistics, and customer data (Boykin, 2001; Chen, 2001; Yen et al., 2002). From the inter-company perspective, ERPs were initially implemented in industries requiring substantial capital investment, such as manufacturing, construction, aerospace, and defense. Over time, their usage has expanded to encompass a wider range of sectors, including finance, healthcare, hospitality, education, insurance, retail, and telecommunications (Shehab et al. 2004). From the viewpoint of intra-company functionalities, especially for the accounting department, ERP systems facilitate the easier and quicker gathering and processing of data, thereby offering enterprises a greater degree of flexibility (Kanellou and Spathis 2013). Additionally, ERPs enabled the tracking of accounting transactions to specific employees, such as those working on an assembly line or involved in barcode scanning. This advancement led to the automated generation of financial reports through predefined processes, moving away from the manual compilation by accounting teams (Jędrzejka 2019).

## What is RPA?

Robotic Process Automation (RPA) represents a cutting-edge software technology designed to streamline the creation, deployment, and management of software robots. These robots are programmed to mimic human interactions with digital interfaces and systems, enabling them to perform a myriad of tasks with precision and efficiency. According to UiPath, a leader in the RPA industry, these software robots possess the capability to comprehend visual data on screens, execute precise keystrokes, navigate through various systems, and accurately identify and extract information. Notably, RPA robots accomplish these tasks with greater speed and consistency than human counterparts, all the while eliminating the need for breaks or downtime. This technology heralds a new era in how businesses approach routine and complex tasks, offering scalable solutions that enhance productivity and operational efficiency.  
 The finance and accounting sector, as outlined by Jędrzejka (2019) and supported by Fernandez and Aman (2018), has been the primary adopter of RPA technologies. This sector has utilized RPA to automate tasks such as transaction processing, audit preparation, and financial reporting, driven by the sector's need for precision and the high volume of repetitive transactions. The accounting department, in particular, benefits from RPA's ability to execute tasks with high accuracy and efficiency, addressing the industry's challenge of managing routine, error-prone tasks.

RPA's benefits, particularly in finance and accounting, are manifold. Jędrzejka (2019) and Le Clair (2017) highlight RPA's potential to reduce operational costs, enhance process execution efficiency, and improve accuracy. RPA's ability to operate continuously, its scalability, and ease of implementation make it a valuable tool for the sector. These benefits directly address the needs of the accounting department, emphasizing RPA's role in transforming the industry by making operations more efficient and reducing the likelihood of errors in financial reporting.

## Earnings Management with Automation Tools

EM, according to Healy and Wahlen (1999), can be divided into two main types: accruals-based management and real earnings management. AM allows managers to influence reported earnings through the accounting discretion under accounting standards. flexibility. On the other hand, RM involves managerial actions that alter the timing or structure of real business operations.

Exploring the RPA and EM relationship opens a novel research avenue. With scant direct empirical evidence linking RPA, especially to EM, we're charting new territory rather than facing a traditional limitation. RPA's role in boosting operational efficiency and data accuracy in finance mirrors the documented benefits of ERP. Although prior studies have shed light on ERP's effects on EM, RPA's specific impact awaits thorough exploration. Viewing RPA as an ERP extension, especially in tasks challenging for ERP, frames this gap as an alternative research path. This stance enables leveraging ERP studies as a base, while considering RPA's unique potential in EM. The subsequent sections will detail prior ERP and both types of EM research and propose hypotheses connecting RPA to earnings management. This approach not only bridges the current knowledge gap but also sets the stage for future work, aiming to broaden our grasp of automation's role in financial practices.

### Accrual-based earnings management with automation tools

The integration of technological advancements in accounting and financial reporting processes, particularly through ERP systems, has been a subject of academic interest and debate for several decades. This interest has been partly driven by the evolving nature of internal controls and the potential of these technologies to influence earnings management practices. The advent of RPA, despite being a relatively newer field of study, necessitates a nuanced understanding of its implications on financial reporting quality and earnings management, drawing parallels and distinctions from ERP implementations.

Brazel and Dang (2008) initiated this discourse by highlighting the dual-faceted impact of ERP systems on earnings management via accruals. They argue that while ERPs can enhance the financial reporting process and managerial decision-making through accurate and timely information provision (Poston and Grabski 2001), they also afford management greater discretion over financial information, potentially exacerbating earnings management practices. This is grounded in the belief that enhanced internal information asymmetry and managerial access to financial data could embolden discretional accruals to meet market expectations (Graham et al. 2006).

Contrary to Brazel and Dang's findings, subsequent research by Morris and Laksmana (2010) presents a more nuanced view. They report a reduction in accrual-based earnings management in post-ERP implementation periods, attributed to improved internal controls and audit quality, potentially as a response to regulatory changes such as the Sarbanes-Oxley Act. Morris (2011) further reinforced this perspective by suggesting that the structured nature of ERP systems, coupled with stringent compliance requirements, bolsters the effectiveness of internal controls over financial reporting.

Drawing parallels to ERP, the research by Ashraf (2024) extends the discussion to automation technologies at large, documenting an improvement in financial reporting quality through a reduction in internal control weaknesses. However, the inability in that research to differentiate the impacts of various automation technologies, including machine learnings, artificial intelligence, and RPA, underscores a gap in the literature. Specific for the RPA, this gap is critically discussed by Hong et al. (2023), who elucidate the distinct risks and control challenges posed by RPA, emphasizing its potential operational and managerial separation from traditional IT governance frameworks.

Given the aforementioned discourse, it is evident that RPA embodies a complementary yet distinct role in financial reporting and internal control landscapes. While ERP systems have been extensively studied for their impact on earnings management, the unique characteristics and deployment contexts of RPA necessitate a separate inquiry. Particularly, the decentralized management and highly customized nature of RPA solutions present both opportunities and challenges for earnings management practices. (Hong et al. 2023) Therefore, considering the mixed outcomes from ERP-related studies and the nascent but insightful research on RPA, we propose the following hypothesis:

**Hypothesis 1: Implementation of RPA will not be associated with earnings management through discretionary accruals.**

### Real activities manipulation with automation tools

Drawing from the interplay between RPA implementation and EM, particularly through accruals as discussed in the provided literature, we extend the investigation to another form of EM—real activities manipulation (RM). Given the findings of Paredes and Wheatley (2017) that firms are less likely to engage in RM post-ERP implementation, we consider the potential parallel effects of RPA on RM. This parallel is further supported by the role of internal controls, as Lenard et al. (2016) find a positive association between firms with internal control weaknesses (ICWs) and engagement in RM. Morris (2011) contributes to this narrative by demonstrating an improvement in internal controls post-ERP implementation, suggesting a potential reduction in RM as well (Morris and Laksmana 2010).

However, while ERP's impact on internal controls and subsequent influence on RM has been documented, the literature on RPA's effects on RM remains sparse and undiscovered. RPA, like ERP in its technological advancement and impact on financial reporting, lacks a standardized control framework as mentioned by Hong et al. (2023), which could affect its association with RM. Studies before regulatory changes like the Sarbanes-Oxley Act (SOX) observed varied results regarding AM in the previous section, leading to reconsiderations in the post-SOX era that might also apply to RPA implementation effects on RM.

Given the mixed results regarding the relationship between automation technologies and EM, and in alignment with the complexities discussed in both the attachment and the referenced studies (Paredes and Wheatley 2017; Lenard et al. 2016; Morris 2011; Hong et al. 2023), we form the hypothesis:

**Hypothesis 2: Implementation of RPA will not be associated with earnings management through real activities manipulation.**

In developing these hypotheses, it is crucial to acknowledge the complementary roles of ERP and RPA within the broader context of technological integration in financial reporting processes. While ERP systems have paved the way for standardized, integrated information systems, RPA offers a layer of agility and customization, addressing specific operational efficiencies outside the traditional scope of ERP systems (Hong et al. 2023). The interaction between these technologies, coupled with regulatory and governance frameworks, forms the bedrock of our understanding of how automation potentially influences earnings management practices.

# SAMPLE SELECTION & RESEARCH DESIGN

## Main Interest: RPA implementation Indicator

Our study specifically targets the domain of RPA technology adoption. The approach mirrors the document analysis strategy utilized by Paredes and Wheatley (2017) in their examination of ERP implementations through 10-K SEC filings. ~~Their meticulous analysis, which highlights the insights that can be garnered from corporate disclosures despite potential biases, serves as a methodological benchmark for our work.~~

Employing a systematic keyword search strategy within the digital annual reports of firms listed on Taiwan Stock Exchange Corporation (TWSE) or Taipei Exchange (TPEx), we aim to compile an exhaustive dataset on the RPA implementation. This strategy is enabled by the digital accessibility and legal requirement for these firms to submit their annual reports electronically, which facilitates a more efficient and accurate data extraction process. The search terms included “Robotic Process Automation,” “RPA,” and the full term in Taiwanese Mandarin ensuring that our identification of relevant disclosures was as precise as possible. We analyzed these documents containing searched keyword to verify whether the firm may have been RPA adopted or not.

In addition, our methodology assumes continuity in RPA initiatives; if a firm reported RPA adoption in one year, we marked it as continuing its RPA engagement in the following years within the sample period, even if the subsequent report did not explicitly mention RPA. This approach acknowledges the ongoing impact of RPA projects, if once a firm embarks on RPA, the effects and implementations are sustained over time. This assumption allows for a deeper analysis of the influence and permanence of RPA technology within firms.

## Sample

In our study, we meticulously outlined the selection and classification of sample firms that have adopted RPA between 2017 and 2022, as detailed in Panel A to C of Table 1. The choice of initiating the sample period in 2017 stems from the absence of any annual reports disclosing RPA implementation before that year.[[1]](#footnote-1) Panel A in Table 1 elucidates the selection steps, beginning with an analysis of text from annual reports, ensuring that each company has complete data for variables calculation during the specified period and belonged to an industry with at least 15 firm-year observations for EM proxies’ calculation (Roychowdhury 2006, Zang 2011), resulting in 86 unique firms. Notably, financial institutions coded with M2800 were excluded, despite their potential prevalence in our sample. Panel B in Table 1 further categorizes these firms by industry, revealing a diverse representation across 21 different sectors according to the TSE industry codes. Lastly, Panel C in Table 1 delves into the implementation timeline, offering a year-by-year breakdown of RPA adoption among these firms from 2017 to 2022, thereby providing a comprehensive overview of our sample selection methodology and the industry-wide spread of RPA utilization. All financial data needed to the empirical models are from Taiwan Economic Journal (TEJ) database.

Similar to the studies from Morris and Laksmana (2010) and Paredes and Wheatley (2017), we match another 86 comparable individual firms without RPA implementation as a control group. We utilized Mahalanobis distance to identify the nearest match for each of our sample firms based on the pairing criteria of the same industry code and closest average natural logarithm of total assets during sample periods from 2017 to 2022. We initiate a new search to determine if the control firms might be using RPA after the initial pairing. Should we find indications that RPA could be in use at these firms, we exclude such control firms and repeat the matching process. This step is reiterated until we identify a set of control firms for which there is no news related to RPA adoption. After two iterations of the matching process, three and then two firms were identified and replaced.

*[Insert Table 1 Here]*

## Proxies for Accrual-based Earnings Management & Real Activities Manipulation

In the analysis of AM, the absolute value of discretionary accruals is employed as a proxy, reflecting the dual potential for managers to manipulate earnings both upwards and downwards. This choice is supported by seminal studies (e.g., Jones 1991; Becker et al. 2010), emphasizing the significance of capturing the full spectrum of AM activities. The estimation of these discretionary accruals is conducted using modified Jones model. The differences are considered to represent the discretionary component of accruals (see Appendix A for details), thereby serving as an indicator of AM. This methodology underscores the nuanced understanding that earnings manipulation can involve both overstatements and understatements, aiming to provide a comprehensive measure of such practices.

Drawing upon established research, this study employs proxies for RM as Zang (2011). These proxies—abnormal production costs (ABPROD) and abnormal discretionary expenses (ABEXP)—serve as indicators of managerial strategies aimed at influencing financial reports to meet earnings expectations (see Appendix A for details). These measurements capture some key manipulative tactics, including overproduction, and discretionary spending cuts, as mechanisms for short-term earnings enhancement at potential long-term detriment. We also derive a comprehensive measure for abnormal RM activities by aggregating the individual proxies of ABPROD and ABEXP, enabling the detection of the overall level of RM activities, as outlined by Cohen and Zarowin (2010).  
  
As the concerns Zang (2011) mentioned, another proxy abnormal cash flows delineated by Roychowdhury (2006) is about its ambiguous net effect and manipulation directions. As a results, we also exclude this proxy as a RM measurement in our research.

## Empirical Models

Building on the methodologies of previous studies such as Zang (2011) and Chen et al. (2012), we apply simultaneous equations for AM and RM to address potential endogeneity issues that could lead to biased and inconsistent coefficient estimations through Ordinary Least Squares (OLS). We detect endogeneity issue between EM proxies via Hausman auxiliary regression (Hill et al. 2018). Initially, we regress AM and RM on the exogenous (control) variables of each equation model to calculate the residuals of AM and RM. Subsequently, we regress AM (RM) on RM (AM) along with the residuals of RM (AM) to assess whether the coefficient of the residuals equals zero. A non-zero coefficient of the residuals allows us to reject the null hypothesis that RM (AM) is exogenous in the equation, indicating a correlation between the error term and RM (AM). This finding prompts the selection of the Two-Stage Least Squares (2SLS) method to mitigate endogeneity bias inherent in OLS.

Following Cohen and Zarowin (2010) and Zang (2011), as well as Chen et al. (2012), we consider common control variables for both equations, alongside variables specific to AM and RM. This approach is to construct simultaneous equations that accurately capture the relationship between EM and RPA implementation, ensuring a comprehensive analysis that accounts for both shared and unique factors influencing the two types of earnings management.

Below first stage simultaneous equations aim to test for the within RPA adopter group:

Below first stage simultaneous equations are for both RPA adopter group and control group:

Below Hausman test auxiliary equations aim to test for the within RPA adopter group:

Below Hausman test auxiliary equations are for both RPA adopter group and control group:

Below second stage simultaneous equations aim to test for the within RPA adopter group:

Below second stage simultaneous equations are for both RPA adopter group and control group:

where RMPROXIES are *ABEXP*, *ABPROD*, and *RM*

In our study, we focus on main variables of interest, where *POST* serves as an indicator, assigned a value of 1 for firm-year observations during and after RPA implementation. *RPA* acts as an indicator distinguishing the treatment group (assigned a value of 1) from the control group (assigned a value of 0).

We include a set of shared control variables (CVs) to capture the effects of various firm-specific and market factors in both equations. These CVs consist of leverage (*LEV*) and the market-to-book ratio (*MTB*) to assess the financial structure, operating cash flows (*OCF*) to evaluate the firm's liquidity impact on EM, and firm size (*SIZE*) to examine size effects on EM practices, following Becker et al. (2010) and Roychowdhury (2006).

To explore the costs associated with AM and RM mentioned in study of Zang (2011), we incorporate industry-year market share (*MS*), the percentage of institutional investors (*INST*), Altman’s Z-score (*ZSCORE*), net operating cycle (*CYCLE*), and net operating assets (*NOA*). We opt for industry-adjusted ROA (*ADJROA*), following Kim et al. (2012), and include the square of ADJROA, as considered by Kothari et al. (2005), to account for the non-linear relationship between a firm’s performance and its abnormal accruals. Additionally, we include a measure of short-term credit risk (*CL*), following the study by Roychowdhury (2006).

Specific variables tailored to each equation include the big four audit firm indicator (*BIG4*) for the AM equation, in line with Chen et al. (2012). For the RM equation, we incorporate R&D intensity (*RD*) and advertising intensity (*ADV*) as measures of a company’s commitment to innovation and marketing promotion, as discussed in the literature (Chouaibi et al. 2019; Tanveer et al. 2022). Through this comprehensive set of control variables (exogeneity variables), our analysis aims to provide a nuanced understanding of how RPA implementation might influence EM, considering a broad array of factors that could affect this relationship (see Appendix B for detailed variables definition).

# RESULTS

## Descriptive statistics

Table 2 shows the overall sample univariate statistics results of both treatment and control sample. Table 2 panel A presents the descriptive statistics for the selected variables. All continuous variables are winsorized at the top and bottom 1% of their distribution. The mean value of ABSDA is about 5%. The mean value of ABPROD, ABEXP, and RM are -0.00552, -0.00087, and -0.0563 respectively, showing that in general, firms do not appear to take RM initiatives like overproduction and reduction of discretionary expenses. The 25 percentile of ZSCORE (1.93) is larger than 1.81, meaning that most of the observations are not in the distress zone for higher likelihood to go bankruptcy. Mean value of BIG4 is larger than 90%, showing that most of our sample firms are audited by big four audit firms.

Table 2 panel B shows the spearman correlation matrix of the selected variables. For the correlation between AM and RM proxies, only ABEXP is negatively correlated with ABSDA (P<0.1), suggesting a substitutive effect between the abnormal discretionary expenses and discretionary accruals. Focus the correlation of control variables on ABSDA and RM, we find that LEV and CL are all significantly and positively associated with both EM proxies, showing that firms with higher leverage and higher percentage of current liabilities excluding short-term debts divided by total assets are more probably to engage EM regardless of which type of EM. As for the market-to-book value ratio (MTB) and ZSCORE, on the contrary, are significantly and positively (negatively) related to ABSDA (RM), showing that firms with higher market-to-book value ratio or with stronger financial health will take AM as the EM approach instead of RM.

*[Insert Table 2 Here]*

Table 3 panel A presents the statistics results for the comparison of RPA adopters with pre-versus post implementation periods. As for the measurements of EM, mean ABSDA is significantly different after the implementation at 1% significant level, showing the potential evidence that RPA indeed affect EM, especially on AM. Nevertheless, there seems to be no difference between the pre and post periods of RPA implementation on RM. Table 3 panel B shows the comparison between treatment group and control group given the pre-implementation of RPA periods. We can see that there is no difference between control group and RPA adopter group on mean difference of SIZE. (P=0.5812) For the EM proxies, there exists a significant gap (P<0.01) between two groups in terms of ABEXP, which shows that firms in control group are more likely to engage in RM through discretionary expenses compared to those in treatment group. On the contrary, it presents no significant difference for the AM measurements between two group. Table 3 panel C, on the other hand, display the comparison of selected variables between treatment and control groups after RPA adoption. Again, there is no difference between control group and RPA adopter group on mean difference of SIZE. (P=0.3491) Interestingly, it shows the significant gap between two groups for ABSDA. The firms of treatment group are more likely to engage in AM in the post implementation period. However, there are no differences between two groups in terms of all RM proxies after the RPA implementation.

*[Insert Table 3 Here]*

## Testing for endogeneity and 2SLS

Based on the testing procedure outlined in Section 3.5, we have determined that the coefficients of the residuals in AM (RM) are significantly different from zero. This finding holds true not only across all equations tested within the implementers' regression models but also when compared with the control group, which is presented by Table 6 and Table 7 since the coefficient of AMres and RMres are significant. This indicates that the Two-Stage Least Squares (2SLS) method is more suitable than Ordinary Least Squares (OLS). Consequently, the upcoming multivariate analysis section will employ 2SLS for regression analyses. We regress AM (RM) against all control variables to derive the predicted AM (RM), which represents the fitted value from the first stage equation. Table 4 and Table 5 presents the multivariate results of first stage equations. Table 6 and Table 7 show the results of the endogeneity tests for all models via Hausman test auxiliary regression. Despite the ABPROD equation for comparison with the control group, all the other models show the endogeneity problem between AM and RM since the significant coefficients of AMres and RMres. As a result, fitted values predicted from the first stage equations are used in place of the actual values of the EM proxies in the second stage.

*[Insert Table 4 Here]*

*[Insert Table 5 Here]*

*[Insert Table 6 Here]*

*[Insert Table 7 Here]*

## Within treatment group analysis

Table 8 presents the multivariate results of the second stage for both equations across four models, examining implementer firms in the pre- versus post-RPA adoption period. The main variable of interest, POST, is positively significant at the 5% level in AM models, indicating that firms' engagement in AM increases following RPA adoption, rejecting our hypothesis. Similarly, in all RM proxy models that utilize AMhat, the coefficients of POST are consistently positive and significant in ABPROD, ABEXP, and RM models at 1% significant level. This suggests that firms' engagement in RM also increases post-RPA adoption, which shows the supportive evidence to reject our hypothesis.

Regarding the potential complementary or substitutive effects between the two EM approaches, the coefficients for AMhat are significantly negative across the ABPROD, ABEXP, and RM equations at 1% significant level. This indicates a substitutive effect between AM and RM, suggesting that firms are less likely to adopt both EM initiatives simultaneously, aligning with prior research (Zang 2011; Cohen and Zarowin 2010).

In the AM equation's control variables, we observe that larger firms are less likely to manipulate accruals, as evidenced by the negative coefficients of SIZE at 5% significance level. The positive coefficient of ADJROA squared (P<0.01) indicates a nonlinear relationship between firm performance and abnormal accruals, implying that firms engage in AM when ADJROA is either very high or very low. Furthermore, the positive coefficient of MTB and CL, significant at the 1% and 10% level, suggests that firms with higher market-to-book ratio or higher ratio of current liabilities to total assets are more likely to engage in AM.

For the control variables in the RM proxy equations, firms with higher NOA and CL are generally more inclined to engage in RM, as shown by the positive significance of NOA and CL coefficients in ABPROD, ABEXP, and RM equations at 1% significant level. Conversely, firms with higher leverage, lower net operating cycle, higher advertising intensity, and larger size tend to be less inclined towards the RM approach in EM, as indicated by the negative coefficients of LEV (P<0.1, <0.05, and <0.05) ,CYCLE (all P<0.01), ADV (all P<0.01), and SIZE (P<0.05, <0.01, and <0.01) in the ABPROD, ABEXP, and RM equations.

In summary, our findings reject both hypotheses, demonstrating an increase in earnings management through either approach in terms of post-RPA adoption. This is supported by the multivariate results from the analysis of implementer firms during the pre- versus post-RPA adoption periods in our sample.

*[Insert Table 8 Here]*

## Matched Result Analyses with RPA Adopted and RPA Non-Adopted Sample

Table 9 presents the multivariate results of the second stage for both equations across four models, comparing RPA non-adopted firms with RPA-adopted firms in the pre- versus post-implementation period. The coefficients of our main variable of interest, the interaction term between POST and RPA, are positively significant at the 1%, 5%, and 5% levels in the AM, ABEXP, and RM equations, respectively. Additionally, the linear hypothesis test on joint coefficient of POST and POST\_RPA are positively significant across AM, ABPROD, ABEXP, and RM equations at 5%, 1%, 5% and 10% significant level. The evidence suggests that a firm adopting RPA software is more likely to employ either AM or RM as a means of EM after the implementation year, compared to a similar industry and firm size sample. These findings reject our Hypotheses 1 and 2.

The regression analysis also reveals a substitutive relationship between AM and RM, as indicated by the negative significance of the RMhat coefficient (P<0.1) in the AM equation and the negative significance of the AMhat coefficients in both ABEXP and RM equations at 5% significant level. This supports the conclusions of previous studies by Zang (2011) and Cohen and Zarowin (2010).

In the control variables of the AM equation, we find that firms with higher operating cash flows, longer net operating cycle, higher Z-score, and larger sizes are less likely to engage in AM, as shown by the negative significance of the OCF (P<0.1), CYCLE(P<0.05), ZSCORE(P<0.01), and SIZE (P<0.01) coefficients. Conversely, characteristics such as higher market-to-book ratio, higher net operating assets, higher portion of current liabilities excluding short-term debts are associated with a greater propensity to engage in AM, as evidenced by the positive and significant coefficients of MTB, NOA, and CL at 5%, 10%, and 5% significant level respectively.

Regarding the control variables in the RM equations, the most prevalent characteristics across all three RM proxies models indicate that firms with higher operating cash flows, longer net operating cycle, higher net operating assets, stronger financial health, and more intensive advertising expenses are less likely to engage in RM activities, with the negative and significant coefficients of OCF (P<0.05, <0.01, and <0.01), CYCLE (P<0.1, <0.1, and <0.05), NOA (P<0.05, <0.01, and <0.01), ZSCORE (P<0.1, <0.1, and <0.05), and ADV (all P<0.01) in ABPROD, ABEXP, and RM equations respectively. While higher ratio of current liabilities minus short-term debts, the more likely firms partake RM activities since the coefficients of CL are positive and significant at 10%, 5%, and 1% in ABPROD, ABEXP, and RM equations respectively.

In conclusion, our analysis rejects both hypotheses, indicating an increase in earnings management, whether through AM or RM, following RPA adoption. This conclusion is bolstered by the multivariate results from our sample of implementer firms during the pre- versus post-RPA adoption periods, considering a control group for comparison.

*[Insert Table 9 Here]*

# CONCLUSIONS

The advent of Robotic Process Automation (RPA) heralds a new era in the technological evolution of finance and accounting. Despite the proliferation of empirical research on ERP technologies, the empirical examination of RPA, particularly in its relation to earnings management, remains largely unexplored. This study positions RPA as an innovative extension of ERP, venturing into novel empirical terrain to explore its potential implications on earnings management practices, thereby filling a significant gap in the existing literature.

The study explores the relationship between Robotic Process Automation (RPA) implementation and earnings management (EM) by comparing 86 firms with RPA to an equal number of control firms without RPA, spanning from 2017 to 2022. The data were sourced from digital annual reports. Earnings management is assessed through discretionary accruals, as defined by the modified Jones model, while real activities manipulation (RM) is indicated by deviations in normal levels of production costs and discretionary expenses.

Our regression analysis reveals that firms with RPA are more inclined towards earnings management in post-implementation period. This finding aligns with theories proposed by Brazel and Dang (2008) and further mentioned by Hong et al. (2023), suggesting that the increased control and decision-making flexibility afforded by enhanced information systems lead to more EM activities. This tendency occurs despite the improved information set because control standards and risk management protocols may still be underdeveloped. Incorporating the control group into a multivariate analysis supports this conclusion, indicating a broader applicability and robustness of the findings. Our results underscore the need for enhanced control standards and risk management practices in the context of RPA adoption to mitigate the potential for earnings management.

This study's potential contributions extend to various stakeholders, including firms, government regulators, and audit firms, emphasizing the multifaceted impact of RPA on earnings management practices. For firms, the findings highlight the importance of developing robust control standards and risk management practices when implementing RPA, to leverage the benefits of automation while mitigating risks associated with earnings management. Government regulators may find these insights valuable for shaping policies and guidelines aimed at ensuring corporate transparency and accountability, particularly in the context of rapidly evolving digital transformation. For audit firms, understanding the nuanced effects of RPA on earnings management can enhance audit quality and effectiveness, enabling auditors to tailor their approaches to better detect and address potential earnings management in the era of automation. Collectively, the study sheds light on the critical balance between technological advancement and ethical financial reporting, offering a roadmap for stakeholders to navigate the complexities introduced by RPA.

The limitations of this study are primarily twofold. First, the absence of specific contract details compelled us to depend on annual reports for data on RPA implementation. This method may introduce discrepancies when contrasted with direct contract information, as annual reports may not capture the complete spectrum of RPA engagements. Second, given the novelty of RPA, especially within the Taiwanese context, the study is constrained by a limited temporal scope. This emerging technology's relatively recent introduction means that the available data span a short period, potentially limiting the depth of our analysis and the generalizability of our findings across different temporal contexts.

For subsequent research endeavors that aim to investigate the intersection of RPA with accounting or auditing, focusing on the potential weaknesses in internal controls related to EM could provide valuable insights, a topic not directly addressed in this study. Furthermore, given the constraints posed by the limited data availability due to the nascent stages of RPA development, future studies are encouraged to undertake a more detailed examination of RPA implementation levels. Drawing inspiration from the methodology of Brazel and Dang (2008) in their ERP research, which gauges the extent of ERP integration through the count of system modules, the depth of a company's RPA utilization could similarly be evaluated based on the quantity of both attended and unattended licenses, offering a direct measure of RPA's operational engagement.

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# Table 1 Sample Firms Descriptions

**Panel A: Selection Procedure**

|  |  |
| --- | --- |
| Unique firms with searched keyword in annual reports within the sample period | 128 |
| Less: |  |
| Remove RPA not the abbreviation for robotic process automation | (9) |
| Financial institutions (TSE code: M2800) | (21) |
| Missing value for variables calculation OR  Not satisfied with minimum industry-year observations for calculation of EM proxies | (12) |
| Total | 86 |

**Panel B Distribution of RPA Adoptions by Industry**

|  |  |  |
| --- | --- | --- |
| TSE Code | Industry Name | Number of Firms |
| M1300 | Plastics | 3 |
| M1400 | Textiles | 9 |
| M1500 | Electric machinery | 5 |
| M1721 | Chemical | 2 |
| M1722 | Biotechnology and medical care | 3 |
| M2200 | Automobile | 1 |
| M2324 | Semiconductor | 6 |
| M2325 | Computer and peripheral equipment | 8 |
| M2326 | Optoelectronic | 7 |
| M2327 | Communications and internet | 7 |
| M2328 | Electronic parts/components | 7 |
| M2329 | Electronic products distribution | 2 |
| M2330 | Information service | 10 |
| M2331 | other electronic | 2 |
| M2500 | Building material and construction | 1 |
| M2600 | Shipping and transportation | 4 |
| M2700 | Tourism and hospitality | 2 |
| M2900 | Trading and consumers' goods industry | 1 |
| M3700 | Sports and leisure | 2 |
| M3800 | Household | 1 |
| M9900 | Others | 3 |
| Total | | 86 |

**Panel C Distribution of RPA Adoptions by Year**

|  |  |
| --- | --- |
| Adoption Year | Number of Firms |
| 2017 | 1 |
| 2018 | 14 |
| 2019 | 12 |
| 2020 | 22 |
| 2021 | 21 |
| 2022 | 16 |
| Total | 86 |

# Table 2 Descriptive Statistics and Correlation Matrix

## Panel A: Descriptive Statistics for Both RPA Adopters and Control Group

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | N | Mean | Median | S.D. | Min | P25 | P75 | Max |
| ABSDA | 1,032 | 0.0501 | 0.0360 | 0.0486 | 0.0007 | 0.2380 | 0.0154 | 0.0684 |
| ABPROD | 1,032 | -0.0055 | -0.0001 | 0.0993 | -0.3625 | 0.2359 | -0.0506 | 0.0521 |
| ABEXP | 1,032 | -0.0009 | 0.0103 | 0.0744 | -0.3994 | 0.1276 | -0.0234 | 0.0389 |
| RM | 1,032 | -0.0056 | 0.0101 | 0.1522 | -0.6393 | 0.3171 | -0.0627 | 0.0790 |
| LEV | 1,032 | 0.4438 | 0.4401 | 0.1793 | 0.0980 | 0.8888 | 0.3042 | 0.5567 |
| OCF | 1,032 | 0.0724 | 0.0637 | 0.1004 | -0.1858 | 0.4156 | 0.0133 | 0.1293 |
| MTB | 1,032 | 1.8775 | 1.4658 | 1.4649 | 0.3915 | 8.3286 | 0.9324 | 2.2643 |
| MS | 1,032 | 4.1065 | 0.9108 | 7.9144 | 0.0153 | 40.6648 | 0.1726 | 4.0773 |
| INST | 1,032 | 0.4472 | 0.4270 | 0.2349 | 0.0307 | 0.9207 | 0.2488 | 0.6394 |
| CYCLE | 1,032 | 156.0500 | 89.3900 | 416.2791 | -237.4192 | 3517.9040 | 47.0300 | 137.9200 |
| NOA | 1,032 | 0.5908 | 0.6103 | 0.2209 | 0.0147 | 1.0877 | 0.4342 | 0.7468 |
| ZSCORE | 1,032 | 3.6191 | 2.8691 | 2.7510 | 0.0341 | 14.5969 | 1.9316 | 4.2370 |
| CL | 1,032 | 0.2609 | 0.2238 | 0.1610 | 0.0290 | 0.7570 | 0.1385 | 0.3413 |
| ADJROA | 1,032 | 0.0120 | 0.0038 | 0.0777 | -0.2116 | 0.2804 | -0.0224 | 0.0431 |
| SIZE | 1,032 | 16.2485 | 15.8113 | 1.7960 | 13.2138 | 20.2936 | 14.7886 | 17.6342 |
| BIG4 | 1,032 | 0.9302 | 1.0000 | 0.2549 | 0.0000 | 1.0000 | 1.0000 | 1.0000 |
| RD | 1,032 | 0.0497 | 0.0197 | 0.0947 | 0.0000 | 0.6261 | 0.0019 | 0.0511 |
| ADV | 1,032 | 0.0704 | 0.0403 | 0.0781 | 0.0000 | 0.3639 | 0.0238 | 0.0880 |

## Panel B Spearman Correlation Matrix

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
| (1) ABSDA | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (2) ABPROD | 0.035 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (3) ABEXP | -0.062\* | 0.468\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (4) RM | 0.006 | 0.912\* \* \* | 0.752\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (5) LEV | 0.097\* \* | 0.217\* \* \* | 0.046 | 0.187\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (6) OCF | -0.031 | -0.393\* \* \* | 0.050 | -0.258\* \* \* | -0.113\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |
| (7) MTB | 0.143\* \* \* | -0.229\* \* \* | -0.061 | -0.172\* \* \* | 0.033 | 0.352\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |
| (8) MS | -0.037 | 0.021 | 0.032 | 0.033 | 0.357\* \* \* | 0.083\* \* | -0.074\* | 1.000 |  |  |  |  |  |  |  |  |  |  |
| (9) INST | -0.036 | -0.078\* | 0.059 | -0.024 | 0.189\* \* \* | 0.153\* \* \* | 0.088\* \* | 0.463\* \* \* | 1.000 |  |  |  |  |  |  |  |  |  |
| (10) CYCLE | -0.038 | -0.043 | -0.074\* | -0.049 | -0.125\* \* \* | -0.155\* \* \* | -0.063\* | -0.288\* \* \* | -0.246\* \* \* | 1.000 |  |  |  |  |  |  |  |  |
| (11) NOA | -0.052 | 0.105\* \* \* | 0.026 | 0.098\* \* | -0.048 | -0.255\* \* \* | -0.216\* \* \* | 0.005 | -0.021 | 0.379\* \* \* | 1.000 |  |  |  |  |  |  |  |
| (12) ZSCORE | 0.069\* | -0.344\* \* \* | -0.025 | -0.255\* \* \* | -0.593\* \* \* | 0.414\* \* \* | 0.552\* \* \* | -0.159\* \* \* | -0.055 | -0.048 | -0.210\* \* \* | 1.000 |  |  |  |  |  |  |
| (13) CL | 0.146\* \* \* | 0.068\* | -0.035 | 0.030 | 0.543\* \* \* | 0.110\* \* \* | 0.184\* \* \* | 0.269\* \* \* | 0.106\* \* \* | -0.243\* \* \* | -0.449\* \* \* | -0.047 | 1.000 |  |  |  |  |  |
| (14) ADJROA | 0.058 | -0.424\* \* \* | -0.019 | -0.306\* \* \* | -0.167\* \* \* | 0.558\* \* \* | 0.358\* \* \* | 0.102\* \* \* | 0.138\* \* \* | -0.083\* \* | -0.071\* | 0.566\* \* \* | 0.156\* \* \* | 1.000 |  |  |  |  |
| (15) SIZE | -0.080\* | 0.018 | 0.075\* | 0.046 | 0.379\* \* \* | 0.097\* \* | -0.174\* \* \* | 0.703\* \* \* | 0.597\* \* \* | -0.185\* \* \* | 0.125\* \* \* | -0.303\* \* \* | 0.155\* \* \* | 0.134\* \* \* | 1.000 |  |  |  |
| (16) BIG4 | -0.007 | -0.036 | -0.024 | -0.022 | 0.013 | 0.050 | -0.010 | 0.069\* | 0.112\* \* \* | -0.010 | -0.028 | 0.074\* | 0.084\* \* | 0.101\* \* | 0.212\* \* \* | 1.000 |  |  |
| (17) RD | -0.010 | -0.114\* \* \* | -0.164\* \* \* | -0.165\* \* \* | -0.368\* \* \* | 0.053 | 0.160\* \* \* | -0.397\* \* \* | -0.252\* \* \* | 0.109\* \* \* | -0.200\* \* \* | 0.246\* \* \* | -0.067\* | -0.064\* | -0.270\* \* \* | 0.002 | 1.000 |  |
| (18) ADV | 0.032 | -0.263\* \* \* | -0.478\* \* \* | -0.386\* \* \* | -0.157\* \* \* | -0.154\* \* \* | 0.073\* | -0.065\* | -0.104\* \* \* | 0.167\* \* \* | -0.003 | 0.054 | -0.101\* \* | -0.140\* \* \* | -0.270\* \* \* | -0.098\* \* | 0.144\* \* \* | 1.000 |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively.

# Table 3 Mean Comparisons

## Panel A The Comparison between Pre- and Post-Implementation for RPA Adopters

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Pre-Implementation | | Post-Implementation | | Wilcox Test |
|  | Mean | S.D. | Mean | S.D. | p-value |
| ABSDA | 0.0438 | 0.0436 | 0.0590 | 0.0527 | 0.0003 |
| ABPROD | -0.0069 | 0.0966 | -0.0042 | 0.0973 | 0.8707 |
| ABEXP | -0.0034 | 0.0740 | -0.0013 | 0.0647 | 0.7425 |
| RM | -0.0108 | 0.1570 | -0.0054 | 0.1415 | 0.9797 |
| LEV | 0.4424 | 0.1689 | 0.4777 | 0.1805 | 0.0190 |
| OCF | 0.0679 | 0.0845 | 0.0827 | 0.1066 | 0.1560 |
| MTB | 1.6579 | 1.3459 | 1.9609 | 1.5697 | 0.0013 |
| MS | 4.9856 | 9.0695 | 5.3980 | 9.2371 | 0.3011 |
| INST | 0.4412 | 0.2340 | 0.4597 | 0.2525 | 0.5591 |
| CYCLE | 101.2819 | 121.1574 | 107.2742 | 116.6800 | 0.7760 |
| NOA | 0.5858 | 0.1962 | 0.5578 | 0.2217 | 0.2158 |
| ZSCORE | 3.4622 | 2.6089 | 3.5806 | 2.6161 | 0.4402 |
| CL | 0.2721 | 0.1488 | 0.2941 | 0.1676 | 0.2901 |
| ADJROA | 0.0088 | 0.0676 | 0.0148 | 0.0738 | 0.3429 |
| SIZE | 16.2458 | 1.8858 | 16.4086 | 1.8478 | 0.1453 |
| BIG4 | 1.9403 | 0.2374 | 1.9113 | 0.2849 | 0.2079 |
| RD | 0.0490 | 0.0836 | 0.0486 | 0.0934 | 0.0975 |
| ADV | 0.0629 | 0.0687 | 0.0718 | 0.0737 | 0.1009 |

## Panel B Comparisons between RPA Adopters and Control Group in the Pre-Implementation Period

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Control Group | | RPA Adopters | | Wilcox Test |
|  | Mean | S.D. | Mean | S.D. | p-value |
| ABSDA | 0.0508 | 0.0515 | 0.0438 | 0.0436 | 0.1604 |
| ABPROD | -0.0102 | 0.1027 | -0.0069 | 0.0966 | 0.7012 |
| ABEXP | -0.0006 | 0.0958 | -0.0034 | 0.0740 | 0.0027 |
| RM | -0.0081 | 0.1725 | -0.0108 | 0.1570 | 0.2759 |
| LEV | 0.4178 | 0.1831 | 0.4424 | 0.1689 | 0.0819 |
| OCF | 0.0714 | 0.0996 | 0.0679 | 0.0845 | 0.7094 |
| MTB | 2.0159 | 1.5124 | 1.6579 | 1.3459 | 0.0008 |
| MS | 3.2605 | 6.9428 | 4.9856 | 9.0695 | 0.0567 |
| INST | 0.4352 | 0.2213 | 0.4412 | 0.2340 | 0.7436 |
| CYCLE | 230.9130 | 599.8826 | 101.2819 | 121.1574 | 0.2782 |
| NOA | 0.6155 | 0.2317 | 0.5858 | 0.1962 | 0.1587 |
| ZSCORE | 3.8896 | 3.0695 | 3.4622 | 2.6089 | 0.1753 |
| CL | 0.2276 | 0.1490 | 0.2721 | 0.1488 | 0.00003 |
| ADJROA | 0.0159 | 0.0858 | 0.0088 | 0.0676 | 0.0312 |
| SIZE | 16.1130 | 1.7287 | 16.2458 | 1.8858 | 0.5812 |
| BIG4 | 1.9515 | 0.2152 | 1.9403 | 0.2374 | 0.5671 |
| RD | 0.0418 | 0.0809 | 0.0490 | 0.0836 | 0.1323 |
| ADV | 0.0691 | 0.0800 | 0.0629 | 0.0687 | 0.9231 |

## Panel C Comparisons between RPA Adopters and Control Group in the Post-Implementation Period

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Control Group | | RPA Adopters | | Wilcox Test |
|  | Mean | S.D. | Mean | S.D. | p-value |
| ABSDA | 0.0471 | 0.0453 | 0.0590 | 0.0527 | 0.0081 |
| ABPROD | -0.0003 | 0.1005 | -0.0042 | 0.0973 | 0.4330 |
| ABEXP | 0.0020 | 0.0554 | -0.0013 | 0.0647 | 0.4262 |
| RM | 0.0024 | 0.1334 | -0.0054 | 0.1415 | 0.3936 |
| LEV | 0.4396 | 0.1806 | 0.4777 | 0.1805 | 0.0119 |
| OCF | 0.0682 | 0.1101 | 0.0827 | 0.1066 | 0.2908 |
| MTB | 1.8817 | 1.4081 | 1.9609 | 1.5697 | 0.8790 |
| MS | 2.7790 | 5.4815 | 5.3980 | 9.2371 | 0.0121 |
| INST | 0.4543 | 0.2324 | 0.4597 | 0.2525 | 0.8726 |
| CYCLE | 183.1106 | 540.7234 | 107.2742 | 116.6800 | 0.6648 |
| NOA | 0.6026 | 0.2302 | 0.5578 | 0.2217 | 0.0795 |
| ZSCORE | 3.5346 | 2.6626 | 3.5806 | 2.6161 | 0.7000 |
| CL | 0.2514 | 0.1721 | 0.2941 | 0.1676 | 0.0007 |
| ADJROA | 0.0084 | 0.0824 | 0.0148 | 0.0738 | 0.9356 |
| SIZE | 16.2376 | 1.7117 | 16.4086 | 1.8478 | 0.3491 |
| BIG4 | 1.9153 | 0.2790 | 1.9113 | 0.2849 | 0.8733 |
| RD | 0.0601 | 0.1179 | 0.0486 | 0.0934 | 0.1924 |
| ADV | 0.0787 | 0.0888 | 0.0718 | 0.0737 | 0.5000 |

# Table 4 First Stage Equations: Pre- vs. Post-Implementation for RPA Adopters Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| POST | 0.011\*\* | 0.040\*\*\* | 0.017\*\* | 0.023\*\* |
|  | t = 2.155 | t = 2.893 | t = 2.573 | t = 2.556 |
|  |  |  |  |  |
| LEV | -0.022 | 0.007 | 0.022 | -0.017 |
|  | t = -1.084 | t = 0.107 | t = 0.715 | t = -0.453 |
|  |  |  |  |  |
| OCF | -0.022 | -0.226\*\*\* | -0.034 | -0.182\*\*\* |
|  | t = -0.504 | t = -3.043 | t = -0.974 | t = -3.432 |
|  |  |  |  |  |
| MTB | 0.007\*\*\* | -0.011\*\* | -0.007\*\* | -0.005 |
|  | t = 3.878 | t = -2.092 | t = -2.125 | t = -1.460 |
|  |  |  |  |  |
| MS | 0.0002 | -0.0001 | -0.00001 | -0.0001 |
|  | t = 0.863 | t = -0.105 | t = -0.031 | t = -0.139 |
|  |  |  |  |  |
| INST | 0.009 | -0.001 | 0.008 | -0.007 |
|  | t = 0.812 | t = -0.033 | t = 0.509 | t = -0.345 |
|  |  |  |  |  |
| CYCLE | -0.00000 | -0.0002\*\*\* | -0.00005\*\* | -0.0001\*\*\* |
|  | t = -0.213 | t = -4.409 | t = -2.526 | t = -4.702 |
|  |  |  |  |  |
| NOA | 0.011 | 0.109\*\*\* | 0.021 | 0.094\*\*\* |
|  | t = 0.933 | t = 3.523 | t = 1.461 | t = 4.132 |
|  |  |  |  |  |
| ZSCORE | -0.002\* | 0.014\*\*\* | 0.010\*\*\* | 0.004 |
|  | t = -1.671 | t = 3.479 | t = 5.422 | t = 1.449 |
|  |  |  |  |  |
| CL | 0.052\*\*\* | 0.051 | -0.043 | 0.101\*\*\* |
|  | t = 2.703 | t = 0.842 | t = -1.605 | t = 2.648 |
|  |  |  |  |  |
| ADJROA | 0.019 | -0.910\*\*\* | -0.277\*\*\* | -0.641\*\*\* |
|  | t = 0.280 | t = -7.643 | t = -5.216 | t = -7.729 |
|  |  |  |  |  |
| ADJROA\_sq | 1.211\*\*\* | 0.233 | 0.199 | 0.273 |
|  | t = 3.713 | t = 0.343 | t = 0.751 | t = 0.553 |
|  |  |  |  |  |
| SIZE | -0.006\*\*\* | -0.003 | -0.001 | -0.002 |
|  | t = -2.991 | t = -0.631 | t = -0.454 | t = -0.641 |
|  |  |  |  |  |
| BIG4 | 0.007 |  |  |  |
|  | t = 0.897 |  |  |  |
|  |  |  |  |  |
| ADV |  | -1.138\*\*\* | -0.633\*\*\* | -0.514\*\*\* |
|  |  | t = -9.836 | t = -10.814 | t = -7.416 |
|  |  |  |  |  |
| RD |  | -0.143 | -0.060 | -0.083 |
|  |  | t = -1.559 | t = -1.173 | t = -1.617 |
|  |  |  |  |  |
| YEAR | 0.001 | -0.004 | -0.002 | -0.002 |
|  | t = 0.706 | t = -1.093 | t = -1.203 | t = -0.950 |
|  |  |  |  |  |
| Constant | -2.121 | 8.715 | 4.359 | 4.979 |
|  | t = -0.673 | t = 1.100 | t = 1.212 | t = 0.953 |
|  |  |  |  |  |
|  | | | | |
| Observations | 516 | 516 | 516 | 516 |
| R2 | 0.192 | 0.444 | 0.442 | 0.418 |
| Adjusted R2 | 0.168 | 0.426 | 0.424 | 0.399 |
| F Statistic | 7.928\*\*\* | 24.916\*\*\* | 24.698\*\*\* | 22.376\*\*\* |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 5 First Stage Equations: Pre- vs. Post-Implementation for RPA Adopters and Control Sample | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| POST | -0.009\* | 0.020 | 0.014\*\* | 0.008 |
|  | t = -1.715 | t = 1.605 | t = 2.020 | t = 1.088 |
|  |  |  |  |  |
| RPA | -0.005 | -0.016 | -0.005 | -0.008 |
|  | t = -1.338 | t = -1.487 | t = -0.785 | t = -1.193 |
|  |  |  |  |  |
| POST\_RPA | 0.017\*\*\* | 0.012 | 0.002 | 0.008 |
|  | t = 3.043 | t = 0.822 | t = 0.232 | t = 0.811 |
|  |  |  |  |  |
| LEV | 0.018 | -0.077\* | -0.026 | -0.061\*\*\* |
|  | t = 1.204 | t = -1.946 | t = -1.253 | t = -2.608 |
|  |  |  |  |  |
| OCF | -0.091\*\*\* | -0.312\*\*\* | -0.032 | -0.277\*\*\* |
|  | t = -2.773 | t = -5.011 | t = -0.912 | t = -6.801 |
|  |  |  |  |  |
| MTB | 0.005\*\*\* | -0.008\* | -0.005\* | -0.002 |
|  | t = 2.746 | t = -1.715 | t = -1.866 | t = -0.721 |
|  |  |  |  |  |
| MS | 0.00004 | -0.001 | -0.0002 | -0.001\* |
|  | t = 0.171 | t = -1.644 | t = -0.572 | t = -1.807 |
|  |  |  |  |  |
| INST | 0.0003 | 0.002 | 0.007 | -0.006 |
|  | t = 0.031 | t = 0.088 | t = 0.556 | t = -0.423 |
|  |  |  |  |  |
| CYCLE | -0.00001\* | 0.00000 | 0.00001\*\* | -0.00001 |
|  | t = -1.739 | t = 0.194 | t = 2.314 | t = -1.414 |
|  |  |  |  |  |
| NOA | 0.013 | 0.076\*\*\* | 0.014 | 0.056\*\*\* |
|  | t = 1.392 | t = 3.014 | t = 0.973 | t = 3.495 |
|  |  |  |  |  |
| ZSCORE | -0.002\* | 0.001 | 0.003\* | -0.003 |
|  | t = -1.817 | t = 0.355 | t = 1.784 | t = -1.428 |
|  |  |  |  |  |
| CL | 0.023\* | 0.110\*\*\* | -0.019 | 0.128\*\*\* |
|  | t = 1.679 | t = 2.707 | t = -0.942 | t = 4.929 |
|  |  |  |  |  |
| ADJROA | 0.115\*\*\* | -0.591\*\*\* | -0.149\*\*\* | -0.452\*\*\* |
|  | t = 2.853 | t = -6.619 | t = -2.855 | t = -8.046 |
|  |  |  |  |  |
| ADJROA\_sq | 0.945\*\*\* | -0.568 | -0.361 | -0.083 |
|  | t = 5.452 | t = -1.376 | t = -1.526 | t = -0.296 |
|  |  |  |  |  |
| SIZE | -0.005\*\*\* | 0.003 | 0.001 | 0.002 |
|  | t = -3.282 | t = 0.690 | t = 0.668 | t = 0.648 |
|  |  |  |  |  |
| BIG4 | 0.002 |  |  |  |
|  | t = 0.336 |  |  |  |
|  |  |  |  |  |
| ADV |  | -0.964\*\*\* | -0.528\*\*\* | -0.466\*\*\* |
|  |  | t = -12.577 | t = -10.661 | t = -10.855 |
|  |  |  |  |  |
| RD |  | -0.118\*\* | -0.067\* | -0.044 |
|  |  | t = -1.975 | t = -1.682 | t = -1.360 |
|  |  |  |  |  |
| YEAR | 0.002\*\* | -0.002 | -0.002 | -0.0002 |
|  | t = 2.089 | t = -0.724 | t = -1.413 | t = -0.092 |
|  |  |  |  |  |
| Constant | -4.776\*\* | 4.311 | 4.203 | 0.355 |
|  | t = -2.046 | t = 0.729 | t = 1.422 | t = 0.095 |
|  |  |  |  |  |
|  | | | | |
| Observations | 1,032 | 1,032 | 1,032 | 1,032 |
| R2 | 0.157 | 0.425 | 0.356 | 0.441 |
| Adjusted R2 | 0.143 | 0.415 | 0.345 | 0.431 |
| F Statistic | 11.122\*\*\* | 41.648\*\*\* | 31.166\*\*\* | 44.347\*\*\* |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

# Table 6 Endogeneity Test: Pre- vs. Post-Implementation for RPA Adopters Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RMres | 0.070\* |  |  |  |
|  | t = 1.852 |  |  |  |
|  |  |  |  |  |
| RM | -0.051 |  |  |  |
|  | t = -1.541 |  |  |  |
|  |  |  |  |  |
| ABSDA |  | -9.268\*\*\* | -5.443\*\*\* | -3.913\*\* |
|  |  | t = -3.546 | t = -5.395 | t = -2.040 |
|  |  |  |  |  |
| AMres |  | 9.390\*\*\* | 5.421\*\*\* | 4.043\*\* |
|  |  | t = 3.591 | t = 5.371 | t = 2.101 |
|  |  |  |  |  |
| POST | 0.012\*\* | 0.138\*\*\* | 0.075\*\*\* | 0.065\*\*\* |
|  | t = 2.328 | t = 4.407 | t = 5.985 | t = 2.887 |
|  |  |  |  |  |
| LEV | -0.015 | -0.210\*\* | -0.105\*\* | -0.109\* |
|  | t = -0.701 | t = -2.214 | t = -2.489 | t = -1.748 |
|  |  |  |  |  |
| OCF | -0.030 | -0.426\*\*\* | -0.150\*\*\* | -0.266\*\*\* |
|  | t = -0.701 | t = -4.693 | t = -3.692 | t = -4.045 |
|  |  |  |  |  |
| MTB | 0.006\*\*\* | 0.057\*\*\* | 0.033\*\*\* | 0.023 |
|  | t = 2.890 | t = 2.841 | t = 4.175 | t = 1.594 |
|  |  |  |  |  |
| MS | 0.00002 | 0.002\*\* | 0.001\*\* | 0.001 |
|  | t = 0.060 | t = 2.087 | t = 2.449 | t = 1.330 |
|  |  |  |  |  |
| INST | 0.009 | 0.095\*\* | 0.065\*\*\* | 0.033 |
|  | t = 0.814 | t = 2.214 | t = 3.343 | t = 1.161 |
|  |  |  |  |  |
| CYCLE | -0.00002 | -0.0002\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* |
|  | t = -0.856 | t = -5.043 | t = -3.597 | t = -4.950 |
|  |  |  |  |  |
| NOA | 0.016 | 0.227\*\*\* | 0.091\*\*\* | 0.144\*\*\* |
|  | t = 1.322 | t = 4.695 | t = 4.409 | t = 4.050 |
|  |  |  |  |  |
| ZSCORE | -0.002 | -0.008 | -0.002 | -0.005 |
|  | t = -1.274 | t = -1.025 | t = -0.789 | t = -0.958 |
|  |  |  |  |  |
| CL | 0.054\*\*\* | 0.562\*\*\* | 0.257\*\*\* | 0.317\*\*\* |
|  | t = 2.837 | t = 3.375 | t = 3.816 | t = 2.690 |
|  |  |  |  |  |
| ADJROA | -0.010 | -0.762\*\*\* | -0.188\*\*\* | -0.580\*\*\* |
|  | t = -0.157 | t = -6.237 | t = -3.494 | t = -6.727 |
|  |  |  |  |  |
| ADJROA\_sq | 1.192\*\*\* | 11.396\*\*\* | 6.751\*\*\* | 4.989\*\* |
|  | t = 3.581 | t = 3.609 | t = 5.548 | t = 2.153 |
|  |  |  |  |  |
| SIZE | -0.005\*\* | -0.055\*\*\* | -0.032\*\*\* | -0.024\*\* |
|  | t = -2.550 | t = -3.659 | t = -5.276 | t = -2.181 |
|  |  |  |  |  |
| BIG4 | 0.008 |  |  |  |
|  | t = 1.101 |  |  |  |
|  |  |  |  |  |
| ADV |  | -1.153\*\*\* | -0.637\*\*\* | -0.524\*\*\* |
|  |  | t = -10.035 | t = -10.873 | t = -7.603 |
|  |  |  |  |  |
| RD |  | -0.139 | -0.057 | -0.083 |
|  |  | t = -1.511 | t = -1.115 | t = -1.603 |
|  |  |  |  |  |
| YEAR | 0.001 | 0.006 | 0.004\* | 0.002 |
|  | t = 0.715 | t = 1.241 | t = 1.826 | t = 0.578 |
|  |  |  |  |  |
| Constant | -2.147 | -11.507 | -7.560\* | -3.523 |
|  | t = -0.687 | t = -1.158 | t = -1.715 | t = -0.524 |
|  |  |  |  |  |
|  | | | | |
| Observations | 516 | 516 | 516 | 516 |
| R2 | 0.200 | 0.456 | 0.460 | 0.426 |
| Adjusted R2 | 0.172 | 0.437 | 0.440 | 0.405 |
| F Statistic | 7.310\*\*\* | 23.191\*\*\* | 23.512\*\*\* | 20.480\*\*\* |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 7: Endogeneity Test: Pre- vs. Post-Implementation for RPA Adopters and Control Sample | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RMres | 0.049\* |  |  |  |
|  | t = 1.934 |  |  |  |
|  |  |  |  |  |
| RM | -0.042\* |  |  |  |
|  | t = -1.787 |  |  |  |
|  |  |  |  |  |
| ABSDA |  | -14.904\*\* | -8.857\*\* | -6.545 |
|  |  | t = -2.332 | t = -2.509 | t = -1.568 |
|  |  |  |  |  |
| AMres |  | 14.953\*\* | 8.751\*\* | 6.663 |
|  |  | t = 2.341 | t = 2.480 | t = 1.597 |
|  |  |  |  |  |
| POST | -0.009\* | -0.113\* | -0.065\*\* | -0.050 |
|  | t = -1.762 | t = -1.930 | t = -1.994 | t = -1.306 |
|  |  |  |  |  |
| RPA | -0.006 | -0.093\*\*\* | -0.050\*\*\* | -0.041\* |
|  | t = -1.501 | t = -2.620 | t = -2.588 | t = -1.816 |
|  |  |  |  |  |
| POST\_RPA | 0.018\*\*\* | 0.268\*\* | 0.154\*\* | 0.120\* |
|  | t = 3.160 | t = 2.406 | t = 2.511 | t = 1.649 |
|  |  |  |  |  |
| LEV | 0.021 | 0.186 | 0.131\*\* | 0.054 |
|  | t = 1.394 | t = 1.628 | t = 2.106 | t = 0.717 |
|  |  |  |  |  |
| OCF | -0.100\*\*\* | -1.672\*\*\* | -0.839\*\*\* | -0.875\*\* |
|  | t = -3.055 | t = -2.855 | t = -2.589 | t = -2.285 |
|  |  |  |  |  |
| MTB | 0.004\*\* | 0.062\*\* | 0.036\*\* | 0.029 |
|  | t = 2.121 | t = 2.050 | t = 2.157 | t = 1.452 |
|  |  |  |  |  |
| MS | -0.0001 | -0.0004 | 0.0001 | -0.0004 |
|  | t = -0.443 | t = -0.640 | t = 0.244 | t = -1.004 |
|  |  |  |  |  |
| INST | 0.0003 | 0.005 | 0.008 | -0.005 |
|  | t = 0.040 | t = 0.208 | t = 0.694 | t = -0.336 |
|  |  |  |  |  |
| CYCLE | -0.00001\*\* | -0.0001\*\* | -0.00004\* | -0.00004\* |
|  | t = -2.046 | t = -2.249 | t = -1.947 | t = -1.827 |
|  |  |  |  |  |
| NOA | 0.017\* | 0.266\*\*\* | 0.127\*\*\* | 0.140\*\* |
|  | t = 1.873 | t = 3.061 | t = 2.639 | t = 2.461 |
|  |  |  |  |  |
| ZSCORE | -0.002\* | -0.027\*\* | -0.013\* | -0.015\* |
|  | t = -1.749 | t = -2.139 | t = -1.924 | t = -1.849 |
|  |  |  |  |  |
| CL | 0.028\*\* | 0.460\*\*\* | 0.189\*\* | 0.281\*\*\* |
|  | t = 1.975 | t = 2.902 | t = 2.181 | t = 2.718 |
|  |  |  |  |  |
| ADJROA | 0.102\*\* | 1.126 | 0.873\*\* | 0.301 |
|  | t = 2.553 | t = 1.547 | t = 2.213 | t = 0.629 |
|  |  |  |  |  |
| ADJROA\_sq | 0.889\*\*\* | 13.478\*\* | 7.982\*\* | 6.088 |
|  | t = 4.874 | t = 2.221 | t = 2.343 | t = 1.550 |
|  |  |  |  |  |
| SIZE | -0.004\*\*\* | -0.064\*\* | -0.038\*\* | -0.028 |
|  | t = -2.821 | t = -2.247 | t = -2.441 | t = -1.490 |
|  |  |  |  |  |
| BIG4 | 0.003 |  |  |  |
|  | t = 0.431 |  |  |  |
|  |  |  |  |  |
| ADV |  | -0.969\*\*\* | -0.525\*\*\* | -0.472\*\*\* |
|  |  | t = -12.688 | t = -10.661 | t = -11.016 |
|  |  |  |  |  |
| RD |  | -0.119\*\* | -0.067\* | -0.045 |
|  |  | t = -1.962 | t = -1.679 | t = -1.370 |
|  |  |  |  |  |
| YEAR | 0.002\*\* | 0.034\*\* | 0.019\*\* | 0.016 |
|  | t = 2.141 | t = 2.139 | t = 2.206 | t = 1.520 |
|  |  |  |  |  |
| Constant | -4.895\*\* | -67.305\*\* | -38.397\*\* | -31.067 |
|  | t = -2.103 | t = -2.133 | t = -2.198 | t = -1.518 |
|  |  |  |  |  |
|  | | | | |
| Observations | 1,032 | 1,032 | 1,032 | 1,032 |
| R2 | 0.161 | 0.428 | 0.364 | 0.445 |
| Adjusted R2 | 0.145 | 0.417 | 0.351 | 0.434 |
| F Statistic | 10.223\*\*\* | 37.798\*\*\* | 28.922\*\*\* | 40.454\*\*\* |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

# Table 8 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RMhat | -0.051 |  |  |  |
|  | t = -1.553 |  |  |  |
|  |  |  |  |  |
| AMhat |  | -9.263\*\*\* | -5.444\*\*\* | -3.908\*\* |
|  |  | t = -3.523 | t = -5.408 | t = -2.021 |
|  |  |  |  |  |
| POST | 0.012\*\* | 0.138\*\*\* | 0.075\*\*\* | 0.065\*\*\* |
|  | t = 2.306 | t = 4.374 | t = 6.001 | t = 2.856 |
|  |  |  |  |  |
| LEV | -0.015 | -0.210\*\* | -0.106\*\* | -0.108\* |
|  | t = -0.713 | t = -2.195 | t = -2.496 | t = -1.722 |
|  |  |  |  |  |
| OCF | -0.030 | -0.425\*\*\* | -0.150\*\*\* | -0.265\*\*\* |
|  | t = -0.695 | t = -4.649 | t = -3.702 | t = -3.998 |
|  |  |  |  |  |
| MTB | 0.006\*\*\* | 0.057\*\*\* | 0.033\*\*\* | 0.023 |
|  | t = 2.902 | t = 2.817 | t = 4.190 | t = 1.573 |
|  |  |  |  |  |
| MS | 0.00001 | 0.002\*\* | 0.001\*\* | 0.001 |
|  | t = 0.055 | t = 2.070 | t = 2.461 | t = 1.294 |
|  |  |  |  |  |
| INST | 0.010 | 0.095\*\* | 0.065\*\*\* | 0.034 |
|  | t = 0.826 | t = 2.206 | t = 3.349 | t = 1.156 |
|  |  |  |  |  |
| CYCLE | -0.00002 | -0.0002\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* |
|  | t = -0.854 | t = -5.064 | t = -3.592 | t = -4.977 |
|  |  |  |  |  |
| NOA | 0.017 | 0.227\*\*\* | 0.091\*\*\* | 0.144\*\*\* |
|  | t = 1.339 | t = 4.685 | t = 4.414 | t = 4.041 |
|  |  |  |  |  |
| ZSCORE | -0.002 | -0.008 | -0.002 | -0.005 |
|  | t = -1.270 | t = -1.023 | t = -0.788 | t = -0.957 |
|  |  |  |  |  |
| CL | 0.055\*\*\* | 0.561\*\*\* | 0.257\*\*\* | 0.317\*\*\* |
|  | t = 2.861 | t = 3.353 | t = 3.824 | t = 2.663 |
|  |  |  |  |  |
| ADJROA | -0.011 | -0.760\*\*\* | -0.189\*\*\* | -0.578\*\*\* |
|  | t = -0.166 | t = -6.353 | t = -3.472 | t = -6.904 |
|  |  |  |  |  |
| ADJROA\_sq | 1.191\*\*\* | 11.385\*\*\* | 6.753\*\*\* | 4.978\*\* |
|  | t = 3.603 | t = 3.586 | t = 5.561 | t = 2.133 |
|  |  |  |  |  |
| SIZE | -0.005\*\* | -0.055\*\*\* | -0.032\*\*\* | -0.024\*\* |
|  | t = -2.543 | t = -3.629 | t = -5.297 | t = -2.154 |
|  |  |  |  |  |
| BIG4 | 0.007 |  |  |  |
|  | t = 0.947 |  |  |  |
|  |  |  |  |  |
| ADV |  | -1.147\*\*\* | -0.638\*\*\* | -0.517\*\*\* |
|  |  | t = -10.032 | t = -10.878 | t = -7.590 |
|  |  |  |  |  |
| RD |  | -0.138 | -0.057 | -0.081 |
|  |  | t = -1.512 | t = -1.114 | t = -1.589 |
|  |  |  |  |  |
| YEAR | 0.001 | 0.006 | 0.004\* | 0.002 |
|  | t = 0.716 | t = 1.238 | t = 1.827 | t = 0.578 |
|  |  |  |  |  |
| Constant | -2.160 | -11.552 | -7.552\* | -3.571 |
|  | t = -0.688 | t = -1.156 | t = -1.715 | t = -0.526 |
|  |  |  |  |  |
|  | | | | |
| Observations | 516 | 516 | 516 | 516 |
| R2 | 0.198 | 0.455 | 0.460 | 0.422 |
| Adjusted R2 | 0.172 | 0.437 | 0.441 | 0.403 |
| F Statistic | 7.692\*\*\* | 24.480\*\*\* | 24.926\*\*\* | 21.430\*\*\* |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

# Table 9 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters and Control Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RMhat | -0.042\* |  |  |  |
|  | t = -1.790 |  |  |  |
|  |  |  |  |  |
| AMhat |  | -14.896\*\* | -8.875\*\* | -6.525 |
|  |  | t = -2.327 | t = -2.524 | t = -1.555 |
|  |  |  |  |  |
| POST | -0.009\* | -0.113\* | -0.065\*\* | -0.050 |
|  | t = -1.766 | t = -1.927 | t = -2.004 | t = -1.298 |
|  |  |  |  |  |
| RPA | -0.006 | -0.093\*\*\* | -0.050\*\*\* | -0.041\* |
|  | t = -1.503 | t = -2.615 | t = -2.604 | t = -1.802 |
|  |  |  |  |  |
| POST＊RPA | 0.018\*\*\* | 0.268\*\* | 0.154\*\* | 0.120 |
|  | t = 3.159 | t = 2.401 | t = 2.529 | t = 1.635 |
|  |  |  |  |  |
| LEV | 0.021 | 0.187 | 0.131\*\* | 0.055 |
|  | t = 1.393 | t = 1.628 | t = 2.107 | t = 0.718 |
|  |  |  |  |  |
| OCF | -0.100\*\*\* | -1.671\*\*\* | -0.842\*\*\* | -0.873\*\* |
|  | t = -3.051 | t = -2.849 | t = -2.604 | t = -2.268 |
|  |  |  |  |  |
| MTB | 0.004\*\* | 0.062\*\* | 0.036\*\* | 0.028 |
|  | t = 2.125 | t = 2.044 | t = 2.174 | t = 1.435 |
|  |  |  |  |  |
| MS | -0.0001 | -0.0004 | 0.0001 | -0.0004 |
|  | t = -0.446 | t = -0.651 | t = 0.268 | t = -1.042 |
|  |  |  |  |  |
| INST | 0.0003 | 0.005 | 0.008 | -0.005 |
|  | t = 0.039 | t = 0.208 | t = 0.696 | t = -0.336 |
|  |  |  |  |  |
| CYCLE | -0.00001\*\* | -0.0001\*\* | -0.00004\* | -0.00004\* |
|  | t = -2.041 | t = -2.247 | t = -1.953 | t = -1.819 |
|  |  |  |  |  |
| NOA | 0.017\* | 0.266\*\*\* | 0.127\*\*\* | 0.140\*\* |
|  | t = 1.877 | t = 3.056 | t = 2.652 | t = 2.448 |
|  |  |  |  |  |
| ZSCORE | -0.002\* | -0.027\*\* | -0.013\* | -0.015\* |
|  | t = -1.747 | t = -2.135 | t = -1.935 | t = -1.834 |
|  |  |  |  |  |
| CL | 0.028\*\* | 0.460\*\*\* | 0.189\*\* | 0.281\*\*\* |
|  | t = 1.984 | t = 2.894 | t = 2.198 | t = 2.694 |
|  |  |  |  |  |
| ADJROA | 0.102\*\* | 1.126 | 0.874\*\* | 0.300 |
|  | t = 2.546 | t = 1.545 | t = 2.223 | t = 0.624 |
|  |  |  |  |  |
| ADJROA\_sq | 0.888\*\*\* | 13.468\*\* | 8.002\*\* | 6.065 |
|  | t = 4.873 | t = 2.215 | t = 2.359 | t = 1.535 |
|  |  |  |  |  |
| SIZE | -0.004\*\*\* | -0.064\*\* | -0.038\*\* | -0.028 |
|  | t = -2.817 | t = -2.241 | t = -2.457 | t = -1.474 |
|  |  |  |  |  |
| BIG4 | 0.002 |  |  |  |
|  | t = 0.395 |  |  |  |
|  |  |  |  |  |
| ADV |  | -0.967\*\*\* | -0.529\*\*\* | -0.467\*\*\* |
|  |  | t = -12.583 | t = -10.659 | t = -10.910 |
|  |  |  |  |  |
| RD |  | -0.119\*\* | -0.068\* | -0.045 |
|  |  | t = -1.963 | t = -1.672 | t = -1.367 |
|  |  |  |  |  |
| YEAR | 0.002\*\* | 0.034\*\* | 0.019\*\* | 0.016 |
|  | t = 2.144 | t = 2.136 | t = 2.216 | t = 1.509 |
|  |  |  |  |  |
| Constant | -4.898\*\* | -67.279\*\* | -38.453\*\* | -31.005 |
|  | t = -2.106 | t = -2.130 | t = -2.208 | t = -1.507 |
|  |  |  |  |  |
|  | | | | |
| Observations | 1,032 | 1,032 | 1,032 | 1,032 |
| R2 | 0.161 | 0.428 | 0.360 | 0.442 |
| Adjusted R2 | 0.146 | 0.417 | 0.348 | 0.431 |
| F Statistic | 10.778\*\*\* | 39.793\*\*\* | 29.944\*\*\* | 42.151\*\*\* |
| F-test: | 0.155\*\*  t = 2.499 | 0.009\*  t = 1.833 | 0.089\*\*\*  t = 2.786 | 0.070\*  t = 1.752 |
|  | | | | |

\*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. All standard errors and significance levels reported in the regression results have been adjusted using the HC0 method, as proposed by White, to account for potential heteroskedasticity. The definition of all the variables above can see appendix B.

# Appendix A EM proxies’ calculations

Consistent with the prior literatures, we run the following prediction model for each year within each TSE industry code at minimum of 15 observations (Zang 2011; Brazel and Dang 2008; Paredes and Wheatley 2017).

* 1. Accrual-based earnings management proxy  
     We use the modified Jones model to calculate the accrual-based earnings management proxy. As modified Jones model, this model is a firm-specific measure based on cross-sectional estimation. According to this model, total accruals are affected by the change in sales, level of property, plant, and equipment:   
     where TA is net income from continuing operations minus operating cash flows; A is total assets; S is net sales; PPE is gross property, plant, and equipment.
  2. Real activities manipulation proxies
     1. Abnormal Production Costs (ABPROD)  
        One of the measurements of real activities manipulation as mentioned from prior studies is abnormal production costs.

where production costs (PROD) are the sum of cost of goods sold and change in inventory; A is total assets; S is net sales.

* + 1. Abnormal Discretionary Expenses (ABEXP)  
       The other measurement of real activities manipulation as mentioned from prior studies is abnormal discretionary expenses.

where discretionary expenses (EXP) are the operating expenses; A is total assets; S is net sales. Operating expenses is defined as expenses incurred by a business from its operating activities in TEJ database, which is the sum of selling expenses, administrative expenses, R&D expenses, other expenses, and expected credit losses (loss) benefit- operating expenses.

# Appendix B Variables Definition

|  |  |
| --- | --- |
| Variables | Definition |
| ABSDA | Absolute value of discretionary accruals calculated from modified Jones model |
| ABPROD | Absolute value of the difference between actual production costs and estimated normal production costs level, where production costs is defined as sum of cost of goods sold and change in inventory |
| ABEXP | Absolute value of the difference between actual discretionary expenses and estimated normal discretionary expenses level multiplied by minus one so that interpretation direction of the coefficient is consistent with ABSDA |
| RM | Aggregation of ABPROD and ABEXP |
| AMhat | Fitted value from the first-stage regression model regressing ABSDA on control variables |
| RMhat | Fitted value from the first-stage regression model regressing RM on control variables |
| AMres | Residuals from the first-stage regression model regressing ABSDA on control variables |
| RMres | Residuals from the first-stage regression model regressing RM on control variables |
| POST | An indicator variable equal to 1 for the observation is during or post RPA-implementation period, 0 otherwise. |
| RPA | An indicator variable equal to 1 for the RPA adopted firms, 0 for the control firms |
| POST\_RPA | Interaction term of RPA and POST |
| LEV | Total liabilities divided by total assets |
| OCF | Operating cash flows scaled by lagged total assets |
| MTB | Market-to-book value ratio |
| MS | The market share based on net sales of the firm among industry-year observations |
| INST | The percentage of institutional investors at the beginning of the period |
| CYCLE | Net operating cycle at the beginning of the period. Calculated as the sum of inventory period and accounts receivable period deducted by accounts payable period |
| NOA | Net operating asset divided by lagged total assets; net operating asset is calculated as (TA-C)-(TL-STD-LTD) where TA is total assets, C is cash and cash equivalents, TL is total liabilities, STD and LTD are short-term and long-term debts respectively (Papanastasopoulos et al. 2011). |
| ZSCORE | Altman's z-score, calculated as 1.2\*A1+1.4\*A2+3.3\*A3+0.6\*A4+A5 where A1 equals to working capital divided by total assets, A2 equals to retained earnings divided by total assets, A3 equals to earnings before interests and taxes divided by total assets, A4 equals to market value divided by total liabilities, and A5 equals to net sales divided by total assets |
| CL | Current liabilities excluding short-term debts divided by lagged total assets |
| ADJROA | Industry median-adjusted ROA, which is calculated as ROA minus industry-year median, and ROA is calculated as income from continuing operation divided by lagged total assets |
| ADJROA\_sq | Square of ADJROA |
| SIZE | Natural logarithm of market value of equity |
| BIG4 | An indicator variable with a value equal to 1 if the firm is audited by a big four accounting firm (Deloitte, KPMG, PwC, or EY) in Taiwan, and 0 otherwise. |
| RD | R&D intensity, calculated as R&D expenses divided by net sales |
| ADV | Advertising intensity, calculated as advertising expenses divided by net sales |
| YEAR | Trend variable |

1. The anecdotal evidence (news articles in Taiwanese Mandarin) also indicated that Taiwanese companies implemented RPA starting from 2017. [↑](#footnote-ref-1)