Evaluating the Impact of Robotic Process Automation on Earnings Management

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# Abstract

This study explores the influence of Robotic Process Automation (RPA) on earnings management (EM) by analyzing 86 Taiwanese firms that adopted RPA, compared to a control group. Using the modified Jones model to assess discretionary accruals and proxies for real activities manipulation, we observe a significant rise in both accrual-based and real activities manipulation EM strategies following RPA implementation. The findings indicate that although RPA improves operational efficiency and decision-making capabilities, it also provides managers with increased opportunities to engage in EM. This tendency may be attributed to the initial lack of comprehensive control standards and risk management frameworks for RPA. These insights add to the growing body of research on the effects of automation technologies on financial reporting practices, highlighting the necessity for effective governance structures to curb the potential for EM in the era of digital transformation.

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**Keywords**: robotic process automation, RPA, earnings management, discretionary accruals, real activities management

# **INTRODUCTION**

In today’s business world, disruptive technologies have significantly reshaped various sectors. The advent of digital transformation has been instrumental in driving value creation and competitive advantage. Technologies such as enterprise resource planning systems (ERP) 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 ERPs. 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 technology. 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 in the post-implementation period (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) extended 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 suggested 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 (e.g., Fernandez and Aman 2018; Cooper et al. 2019; Jędrzejka 2019), 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), empirical studies are conspicuously sparse.

In this study, we explore the nuanced relationship between RPA adoption and earnings management (EM), including accruals-based earnings management (AM) and real activities manipulation (RM). Our investigation employs a comparative regression analysis of 86 firms that implemented RPA against a control group in Taiwan from 2017 to 2022. This analysis aims to reveal the influence of RPA technology on earnings management (EM). Our findings suggest that the sophisticated control and decision-making capacities enabled by RPA might lead to a surge in EM. The surge is probably attributed to a delay in the development of comprehensive control standards and risk management frameworks (Hong et al. 2023), which struggles to keep up with the swift pace of technological adoption.  
 After reviewing the ERP studies on EM to assess relation between RPA and EM, it is worth noted that the application scope of ERP and RPA within a company might differ. ERP systems are implemented company-wide, providing an integrated platform for managing business processes and data across the entire organization. On the other hand, RPA can be applied more selectively to specific functions due to its agility. While ERP systems can store vast amounts of data, some crucial figures may still require processing via retrieval and calculation, which can be accelerated by RPA. Additionally, RPA offers the advantage of integrating processed data with external sources, such as web pages. This capability enables real-time information extraction, which can support managerial decisions related to earnings management. This is particularly valuable in situations where the control framework for RPA is still under development. By leveraging RPA, organizations can enhance their decision-making processes with timely and relevant data from various functions.

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,[[1]](#footnote-1) 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 comprises literature reviews and the development of hypotheses. The third part involves sample selection and research design. The fourth section encompasses univariate and multivariate results, while the fifth section includes additional analyses. The final section presents the conclusion of this study.

# LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

## First Wave of Automation in Accounting: ERP Systems

　　The introduction of ERP systems, as one of the automation technologies 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 systems 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, Chen 2001; Yen et al. 2002). From the inter-company perspective, ERP systems 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). In addition, 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). Despite advancements in ERP systems, they still need to be integrated with other software applications, making them more complex to utilize and manage, making it difficult to achieve higher levels of automation in accounting (Hyvönen et al. 2008). Moreover, businesses still need to manually handle many routine tasks such as processing transactions, managing data, and facilitating interactions between different digital systems. This remaining need for manual intervention indicates that there’s still a gap between the potential of ERP systems and their current functionality, especially in automating mundane, low-value tasks across different applications.

## The New Automation Tool: 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, possessing the capability to comprehend visual data on screens, execute precise keystrokes, navigate through various systems, and accurately identify and extract information.[[2]](#footnote-2) 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.

RPA has exerted significant influence both across industries and within individual organizations. At the macro level, the advent of RPA has notably impacted various sectors, with the banking, investment funds, Business Process Outsourcing (BPO), and Shared Services Centers (SSC) industries experiencing profound changes (Sobczak 2022). Zooming in on the intra-company perspective, extensive research has delved into the application of RPA within accounting functions (Jędrzejka, Cooper et al. 2019; Tiron‐Tudor et al. 2024). The processes in these domains are suitable for automation due to the high degree of accuracy and consistency required in recording operations, alongside the manual handling of repetitive transactions. Traditionally, accounting staff have had to gather information from diverse and fragmented systems, process data for verification and approval, and finally input these into an accounting system—a process fraught with time-consuming and error-prone manual tasks like data entry and report generation. The introduction of RPA offers a remedy to these inefficiencies by taking over such tasks, thereby saving time and reducing the incidence of errors (Tucker 2017; Chui et al. 2016). Moreover, accounting processes, governed by well-defined rules and procedures, lend themselves to automation, enabling more efficient tracking, approval, and document management. The enhanced detail in audit logs from automated processes surpasses what is typically achievable through manual handling. Importantly, as accounting standards and regulations evolve, RPA systems can be swiftly retrained to comply with new legal requirements, showcasing adaptability that is particularly beneficial in environments characterized by frequent legislative changes (Primer 2015). Additionally, the presence of legacy systems within organizations, which may not support traditional automation approaches, further underscores the value of RPA in modernizing accounting practices without the need for extensive system overhauls (Van der Aalst et al. 2018;2019).

Given the backdrop of ERP systems’ limitations previously discussed, RPA emerges as an effective solution to overcome the limitations of ERP systems. Distinct from traditional automation approaches that demand extensive programming, creation of bespoke software, or rigorous efforts towards integration—often to ensure compatibility and communication between disparate applications—RPA presents a streamlined, non-intrusive alternative. It adeptly automates repetitive tasks by imitating human actions with existing user interfaces, obviating the need for the direct integration of applications (Cohen et al. 2019; Jędrzejka 2019). This adaptability enables RPA to facilitate automation across a wide array of organizational functions without necessitating modifications to the current software ecosystem (Kaya et al. 2019). Therefore, RPA not only circumvents the complexities inherent in ERP systems but also significantly diminishes reliance on manual processes, closing the gap between expected and actual functionalities, and elevating operational efficiency.

## Earnings Management with Automation Tools

EM, according to Healy and Wahlen (1999), can be divided into two main types: accruals-based management (AM) and real earnings management (RM). Both AM and RM are tactics used by company managers to influence the reported earnings of a company to meet specific benchmarks. AM involves altering financial statements through accounting choices that don’t accurately reflect the outcome of the company’s actual economic activities. This can include manipulating revenues, expenses, depreciation methods, and estimations of bad debts, among others. RM, on the other hand, deviates from the usual business operations and includes practices like prematurely recognizing sales by altering credit terms, delaying research and development (R&D) or advertising expenses, and reducing the reported cost of sales by producing more goods than needed (Roychowdhury 2006).

As for the two automation tools, both ERP and RPA technologies are united by their core objective to elevate operational efficiency and data accuracy within organizations, facets critically relevant to the quality of financial reporting. While ERP systems ensure data consistency and aid in decision-making through the comprehensive integration and automation of core business processes, RPA complements these efforts by automating rule-based, repetitive tasks, minimizing errors, and freeing human resources for more strategic roles (Shehab et al. 2004; Jędrzejka 2019). Namely, RPA serves as an auxiliary role to ERP, concentrating on automating specific tasks that, although not the primary focus of ERP systems, are still essential for the seamless operation of business workflows.

Given no empirical research directly linking RPA with EM, to our best knowledge, we turn to studies on ERP systems for insights, suggesting a potential relation between RPA and EM and drawing an analogy that the influence of ERP on EM may closely mirror that of RPA on EM.

### *Accrual-based Earnings Management with Automation Tools*

Research on the impact of ERP systems on AM has yielded inconclusive and varied findings. Brazel and Dang (2008) initiated this discourse by highlighting the dual-faceted impact of ERP systems on earnings management via accruals. Their arguments are centered around two key elements: the motivations behind management decisions and the efficiency of internal control systems. ERP systems enhance managerial decision-making by providing precise, real-time information across an organization, aiding in financial reporting and operational data analysis, such as customer relationships and related accruals information (Poston and Grabski 2001; Davenport 1998; Hitt et al. 2002). These systems facilitate the monitoring of firm performance and offer insights into the financial condition, streamlining accounting processes (Oliver 1999; Davenport 2000). For the viewpoint from internal control, research by Hunton et al. (2003) and Brazel and Agoglia (2007) indicates that ERP implementations may compromise the effectiveness of auditor risk assessments and testing quality. Concerns also extend to the competency of IT auditors in evaluating ERP systems (Bagranoff and Vendrzyk 2000; Janvrin et al. 2008). Furthermore, Wright and Wright (2002) found that a significant portion of IT audit specialists reported inadequate internal controls within ERP systems, necessitating additional measures to uphold governance standards (Moore and Warrick 1998), with such deficiencies often cited in SEC filings as sources of material weaknesses (Doogar et al. 2010).

Contrary to Brazel and Dang (2008) ‘s findings, subsequent research by Morris and Laksmana (2010) presents another point of view. They report a reduction in absolute total discretionary accruals specially driven by short-term accruals in post-ERP implementation periods. Leveraging agency theory, they posit that ERP systems mitigate earnings management by enhancing transparency across organizational levels, making it harder for managers to make undetected adjustments. Studies like Brazel and Dang (2008) focus on total discretionary accruals to assess earnings management, predominantly at the top management level. Extending this, their approach examines both short-term and long-term accruals to address information asymmetries at lower management levels. Prior research (e.g. Somers et al. 2003; Hunton et al. 2003) supports the notion that increased transparency curtails earnings management activities, with ERP systems facilitating greater visibility and thus reducing opportunities for such activities across all levels of management. Additionally, they suggest that 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.

The mixed outcomes in previous studies might stem from differences in the time frames of the sample period analyzing the impact ERP systems on AM. Brazel and Dang (2008) examined data from 1993 to 1999, whereas Morris and Laksmana (2010) looked at ERP implementations between 1994 and 2003, extending to the early years following Sarbanes-Oxley Act (SOX) and may be influenced by the increased emphasis in internal controls that resulted from the SOX, which is supported by Kumar et al. (2008) who mentioned that the SOX motivated companies to adopt ERP systems, as these systems assist in creating and overseeing robust internal controls. Before the SOX, ERP systems offered certain advantages, but they were not as powerful or effective as the more sophisticated solutions that emerged after the SOX was more fully implemented (Paredes and Wheatley 2017).

Companies invest in ERP systems primarily for cost reduction and productivity gains (Shehab et al. 2004). The passage of the SOX significantly altered financial reporting standards, compelling many firms to adopt ERP systems to comply with new regulatory demands. These systems are crucial for collecting, analyzing, and reporting financial data and for enforcing internal controls required by the SOX. Among the SOX’s provisions, Section 404 is particularly influential on IT governance, mandating that companies assess and report on the effectiveness of their internal control over financial reporting. This section requires senior executives to confirm the adequacy of the internal control structure, including IT controls, which has led many to adopt frameworks like COSO for evaluating these controls. Section 404’s focus on internal controls underscores the role of ERPs in ensuring regulatory compliance and enhancing financial reporting integrity, encouraging a number of companies implemented ERPs to achieve the SOX compliance.

Considering the mixed results from prior studies on the link between ERP deployment and AM, it’s essential to factor in the regulatory context, including established internal control frameworks like COSO and COBIT, when extrapolating the impact of ERP implementation on AM to assess how adopting RPA might influence AM. This consideration acknowledges the motivations behind a company’s decision to implement RPA, whether driven by the benefits of automation tools or compliance requirements.

The risk management and control considerations for RPA partially overlap with those for ERP systems (Hong et al. 2023). However, existing frameworks like COSO (2013), COBIT (ISACA 2019), the ISO 27000 series (International Organization for Standardization 2013), and the NIST cybersecurity framework (2014) are deemed relevant but not fully adequate for RPA risk management. This inadequacy stems from two main reasons highlighted by interviewees in the study. Firstly, RPA processes are highly customized, making the application of broad, abstract frameworks challenging for specific RPA scenarios. Secondly, these frameworks typically address singular types of risk (such as financial reporting or cybersecurity), whereas managing RPA risks requires a comprehensive approach that encompasses multiple risk categories. Consequently, there’s no singular framework that effectively covers all aspects of RPA risk management as of now.

Despite the benefits that RPA offers businesses, particularly in streamlining accounting processes related to financial reporting, the frameworks for risk management and control specific to RPA appear underdeveloped. Considering this factor along with insights from previous research, we suggest that the relationship between RPA implementation and AM might mirror the findings of Brazel and Dang (2008). This resemblance is due to the absence of a comprehensive control framework, potentially allowing firms to exploit automation tools for engaging in AM practices. Then, we propose the hypothesis that:

**Hypothesis 1: The implementation of RPA is positively 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). Paredes and Wheatley (2017) found that firms are less likely to engage in RM in post-ERP implementation period, suggesting that the integration of intra-company systems, alongside ERP monitoring, might restrict managers’ control over real activities like adjusting production or discretionary spending.

From the viewpoint of monitoring, Masli et al. (2010) investigated the impact of new internal control monitoring systems on firms and discovered a correlation with a reduced likelihood of material weaknesses. Additionally, Morris (2011) observed that firms implementing ERP systems were less prone to reporting internal control weaknesses (ICW) compared to a matched control sample of non-ERP-implementing firms. These studies collectively suggest that both internal control monitoring systems and ERP implementations contribute to strengthening internal controls and reducing the occurrence of material weaknesses or ICWs within organizations. Moreover, Lenard et al. (2016) found that companies disclosing internal control weaknesses were more likely to engage in real activities manipulation by using the sample period after the SOX. Based on the perspective of the stronger function of the monitoring, the integration of ERP systems appears to reduce the likelihood of RM within a firm.

However, Morris (2011) referenced Brazel and Dang (2008) to highlight that their research centers on ERP implementations during the early stages of ERP adoption, prior to the SOX. Similar to the hypothesis development of the relation between the implementation of automation tools and AM, increasing control from the requirement of the regulation after the SOX might give different situation for the management to apply the automation technologies. Newer generations of ERP systems, introduced after 2002, offer advanced technical capabilities for collecting, analyzing, and reporting data essential for fulfilling the internal control mandates of the SOX. Consequently, many companies were motivated to adopt ERP systems with the aim of achieving compliance with the SOX regulations. The motivations driving management to adopt ERP systems likely shifted following the enactment of the SOX. ERP systems significantly enhance both assessment and planning processes, providing companies with reliable, transparent, real-time data access that enables better and faster decision-making. Managers anticipate improved data access post-implementation, leading to more accurate forecasting. Additionally, the integration of various functional areas enhances communication, productivity, and efficiency. This improved information environment facilitates management’s ability to engage in RM. For example, utilizing data analytics to construct predictive models enables managers to engage in earnings management through RM before period ends, thus avoiding post-ending accruals manipulation (Paredes and Wheatley 2017). Absent an ERP, managers may lack insight into the extent of RM necessary to meet earnings targets. Real-time information, however, provides managers with direct access to performance measures, aiding in progress monitoring. Coupled with more accurate forecasting, as demonstrated by Dorantes et al. (2013), this encourages or facilitates managers’ ability to engage in RM.

In line with the hypothesis development concerning the association between RPA implementation and AM, we propose that the connection between RPA implementation and RM could resemble the scenario outlined by Brazel and Dang (2008). This similarity arises from the lack of a comprehensive control framework, which could potentially enable firms to utilize automation tools to carry out RM practices, and we form our second hypothesis:

**Hypothesis 2: The implementation of RPA is positively associated with earnings management through real activities manipulation.**

# 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.

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[[3]](#footnote-3) 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 analyze these documents containing searched keyword to verify whether the firm may have been RPA adopted.[[4]](#footnote-4)

Our methodology assumes continuity in RPA initiatives; if a firm reported RPA adoption in one year, we mark 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.[[5]](#footnote-5) 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.[[6]](#footnote-6) 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 more details).[[7]](#footnote-7) These proxies 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 (Cohen and Zarowin 2010).

## 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[[8]](#footnote-8) 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) and remaining exogenous (control) variables in AM (RM) equation respectively 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), Zang (2011), and 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 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 to capture the effects of various firm-specific and market factors in both equations. These control variables 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 variable 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 firms do not appear to take RM initiatives like overproduction and reduction of discretionary expenses in general. The 25th percentile of ZSCORE (1.93) exceeds 1.8 (Eidleman 1995), 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 results for the comparison of RPA adopters with pre- versus post- implementation periods. As for the measurements of EM, the mean of 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. 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 displays 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 the 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 the 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 from the previous section, 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. This indicates that the Two-Stage Least Squares (2SLS) method is more suitable than Ordinary Least Squares (OLS). Followings are the results from Hausman auxiliary regression test. In the RPA adopter group, testing result reveals that the residual coefficient of RM in the AM equation is 0.07 with a t-value of 1.852. Additionally, the residuals of AM in the RM, ABEXP, and ABPROD equations have coefficients of 9.390, 5.421, and 4.4043, respectively, with corresponding t-values of 3.591, 5.371, and 2.101. In regression analysis considering both RPA adopter and control groups, the residual coefficient of RM in the AM equation is 0.049 with a t-value of 1.934. Moreover, the residuals of AM in the RM and ABEXP equations have coefficients of 14.953 and 8.751, respectively, with t-values of 2.341 and 2.480. Consequently, the following 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. Despite the ABPROD equation for comparison with the control group, all the other models show the endogeneity problem between AM and proxies of RM. 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.

## Within Treatment Group Analysis

Table 4 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 ABSDA, 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 our Hypotheses 1 and 2.

Regarding the potential complementary or substitutive effects between the two EM approaches, the coefficients for ABSDA 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 (t = 3.603) 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 (t = -1.722, -2.496, and -2.195) ,CYCLE (t = -4.977, -2.496, and -3.592), ADV (t = -7.590, -10.878 and -10.032), and SIZE (t = -2.154, -5.297, and -3.629) in the ABPROD, ABEXP, and RM equations.

In summary, our findings support 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 4 Here]*

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

Table 5 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 coefficients 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 are aligned with 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 RM coefficient (t = -1.790) in the AM equation and the negative significance of the ABSDA 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 (t = -3.051), CYCLE (t = -2.041), ZSCORE (t = -1.747), and SIZE (t = -2.817) 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, stronger financial health, and more intensive advertising expenses are less likely to engage in RM activities, with the negative and significant coefficients of OCF (t = -2.268, -2.604, and -2.849), CYCLE (t = -1.819, -1.953, and -2.247), ZSCORE (t = -1.834, -1.935, and -2.135), and ADV (t = -10.910, -10.659, and -12.583) in ABPROD, ABEXP, and RM equations respectively. While higher net operating assets and higher ratio of current liabilities minus short-term debts, the more likely firms partake RM activities since the coefficients of CL (t = 2.694, 2.198, and 2.894) and NOA (t = 2.448, 2.652, and 3.056) are positive and significant in ABPROD, ABEXP, and RM equations respectively.

Both Hypothesis 1 and Hypothesis 2 are supported by the analysis, 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.

Nevertheless, our multivariate results, either from within-group design or from that of both RPA adopter group and control group, are diverse from the findings by Ashraf (2024) who extends the discussion to automation technologies at large, documenting an improvement in financial reporting quality through a reduction in internal control weaknesses[[9]](#footnote-9). The difference in conclusion might arise from the concern mentioned in his study. It is that Ashraf (2024) does not differentiate the impacts of various automation technologies, including machine learning, artificial intelligence, and RPA, which may not be able to contribute to the specific type of technology improving financial reporting quality.

*[Insert Table 5 Here]*

## Additional Analysis: Alternative Measure for AM Proxy

Dechow and Dichev (2002) propose a model (DD model) to evaluate accruals quality (AQ) by analyzing how well current accruals reflect the operating cash flows in the current period, the preceding period, and the future period. They excluded non-current accruals due to the significant delays between these accruals and their corresponding cash flows. The unexplained portion of current accruals, after adjusting for cash flows from operations, is captured in the residuals of DD model. The standard deviation of these residuals serves as a proxy for AQ. Essentially, a higher variability in residuals indicates poorer AQ. McNichols (2002) extends the DD model by including growth in revenue to better capture performance indicators, and by adding property, plant, and equipment (PPE) to the equation.   
 Francis et al. (2005) suggest that accruals quality (AQ) consists of two distinct parts: innate AQ, which stems from the underlying economic factors like the operating environment and business model; and discretionary AQ (DAQ), which arises from the decisions management makes regarding accounting practices and estimates. The latter is our main interest for the alternative metric for accruals quality.   
 To calculate DAQ (see Appendix A for details), an alternative proxy for accrual earnings management, a firm must have comprehensive financial data spanning from 2012 to 2023. This data is necessary to fulfill the firm-year observation periods for DAQ calculation from 2017 to 2022. Due to incomplete data, four pairs of firms were excluded from the previous analysis of 172 sample firms, ending up with 82 treatment firms and 82 control firms.  
 We replaced the proxy of AM with DAQ and reran the regression models. Table 6 and Table 7 present the multivariate results of the second stage for the within-treatment group analysis and the matched results analysis, respectively. The coefficients of the primary variables of interest, POST, remain positively significant across both the AM and RM equations in the within-treatment group analysis in Table 4. For the matched results analysis, the linear hypothesis test on the joint coefficients of POST and POST＊RPA () remains positively significant across both the AM and RM equations, consistent with the findings reported in Table 5.

*[Insert Table 6 Here]*

*[Insert Table 7 Here]*

# CONCLUSIONS

The advent of 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. Additionally, the regression models are also robust after utilizing discretionary component of accruals quality as another AM proxy, consistent with our hypothesis. 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.   
 Our studies reference ERP studies on EM to discuss the relationship between RPA adoption and EM. ERP systems provide a comprehensive, company-wide platform for managing business processes and data, while RPA is more agile and can be applied to specific functions. Although ERP systems can store large amounts of data, RPA is essential for efficiently processing key figures through retrieval and calculation. Furthermore, RPA can integrate this processed data with external sources, like web pages, to extract real-time information. This capability is particularly beneficial for managerial decisions related to earnings management, especially when the RPA control framework is still being developed, as it enhances decision-making with timely and relevant data.

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.[[10]](#footnote-10) 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 the content unrelated to RPA after manual examine each annual report | (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 | Max | P25 | P75 |
| POST | 1,032 | 0.4806 | 0 | 0.4999 | 0 | 0 | 1 | 1 |
| RPA | 1,032 | 0.5 | 0 | 0.5002 | 0 | 0 | 1 | 1 |
| 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) | (19) | (20) |
| (1) POST | 1 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (2) RPA | 0 | 1 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (3) ABSDA | 0.072\* | 0.024 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (4) ABPROD | 0.02 | -0.009 | 0.035 | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (5) ABEXP | -0.041 | -0.085\*\* | -0.062\* | 0.468\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (6) RM | -0.01 | -0.044 | 0.006 | 0.912\*\*\* | 0.752\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (7) LEV | 0.077\* | 0.091\*\* | 0.097\*\* | 0.217\*\*\* | 0.046 | 0.187\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| (8) OCF | 0.029 | 0.015 | -0.031 | -0.393\*\*\* | 0.050 | -0.258\*\*\* | -0.113\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |  |
| (9) MTB | 0.067\* | -0.083\*\* | 0.143\*\*\* | -0.229\*\*\* | -0.061 | -0.172\*\*\* | 0.033 | 0.352\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |  |  |
| (10) MS | 0.04 | 0.095\*\* | -0.037 | 0.021 | 0.032 | 0.033 | 0.357\*\*\* | 0.083\*\* | -0.074\* | 1.000 |  |  |  |  |  |  |  |  |  |  |
| (11) INST | 0.033 | 0.01 | -0.036 | -0.078\* | 0.059 | -0.024 | 0.189\*\*\* | 0.153\*\*\* | 0.088\*\* | 0.463\*\*\* | 1.000 |  |  |  |  |  |  |  |  |  |
| (12) CYCLE | -0.041 | -0.017 | -0.038 | -0.043 | -0.074\* | -0.049 | -0.125\*\*\* | -0.155\*\*\* | -0.063\* | -0.288\*\*\* | -0.246\*\*\* | 1.000 |  |  |  |  |  |  |  |  |
| (13) NOA | -0.045 | -0.069\* | -0.052 | 0.105\*\*\* | 0.026 | 0.098\*\* | -0.048 | -0.255\*\*\* | -0.216\*\*\* | 0.005 | -0.021 | 0.379\*\*\* | 1.000 |  |  |  |  |  |  |  |
| (14) ZSCORE | -0.004 | -0.023 | 0.069\* | -0.344\*\*\* | -0.025 | -0.255\*\*\* | -0.593\*\*\* | 0.414\*\*\* | 0.552\*\*\* | -0.159\*\*\* | -0.055 | -0.048 | -0.210\*\*\* | 1.000 |  |  |  |  |  |  |
| (15) CL | 0.046 | 0.166\*\*\* | 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 |  |  |  |  |  |
| (16) ADJROA | -0.006 | -0.046 | 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 |  |  |  |  |
| (17) SIZE | 0.059 | 0.032 | -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 |  |  |  |
| (18) BIG4 | -0.064\* | -0.015 | -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 |  |  |
| (19) RD | -0.008 | 0.009 | -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 |  |
| (20) ADV | 0.056 | 0.018 | 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 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | *Dependent Variable* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RM | -0.051 |  |  |  |
|  | t = -1.553 |  |  |  |
|  |  |  |  |  |
| ABSDA |  | -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 | Included | Included | Included | Included |
| 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 5 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters and Control Sample

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | | | | |
|  | *Dependent Variable* | | | |
|  |  | | | |
|  | ABSDA | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RM | -0.042\* |  |  |  |
|  | t = -1.790 |  |  |  |
|  |  |  |  |  |
| ABSDA |  | -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 | Included | Included | Included | Included |
| 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.

# Table 6 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters Sample for Alternative AM Proxy Analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | DAQ | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RM | 0.089 |  |  |  |
|  | t = 1.037 |  |  |  |
|  |  |  |  |  |
| DAQ |  | -2.242\*\*\* | -1.312\*\*\* | -0.946\* |
|  |  | t = -3.246 | t = -4.818 | t = -1.949 |
|  |  |  |  |  |
| POST | 0.049\* | 0.147\*\*\* | 0.080\*\*\* | 0.068\*\*\* |
|  | t = 1.891 | t = 3.965 | t = 5.389 | t = 2.636 |
|  |  |  |  |  |
| LEV | 0.002 | 0.018 | 0.020 | -0.005 |
|  | t = 0.038 | t = 0.271 | t = 0.633 | t = -0.128 |
|  |  |  |  |  |
| OCF | -0.433\*\*\* | -1.232\*\*\* | -0.615\*\*\* | -0.610\*\*\* |
|  | t = -3.544 | t = -3.932 | t = -4.857 | t = -2.769 |
|  |  |  |  |  |
| MTB | 0.002 | -0.011\* | -0.006\* | -0.005 |
|  | t = 0.290 | t = -1.830 | t = -1.876 | t = -1.326 |
|  |  |  |  |  |
| MS | 0.006\*\*\* | 0.013\*\*\* | 0.008\*\*\* | 0.006\* |
|  | t = 4.034 | t = 3.214 | t = 4.692 | t = 1.954 |
|  |  |  |  |  |
| INST | 0.030 | 0.029 | 0.022 | 0.010 |
|  | t = 0.540 | t = 0.682 | t = 1.161 | t = 0.364 |
|  |  |  |  |  |
| CYCLE | -0.00003 | -0.0003\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* |
|  | t = -0.574 | t = -5.270 | t = -5.032 | t = -4.555 |
|  |  |  |  |  |
| NOA | -0.058 | -0.002 | -0.041\*\* | 0.043 |
|  | t = -1.446 | t = -0.055 | t = -2.403 | t = 1.512 |
|  |  |  |  |  |
| ZSCORE | -0.009 | -0.003 | -0.001 | -0.003 |
|  | t = -1.602 | t = -0.478 | t = -0.167 | t = -0.590 |
|  |  |  |  |  |
| CL | -0.064 | -0.085 | -0.118\*\*\* | 0.042 |
|  | t = -1.142 | t = -1.336 | t = -4.279 | t = 1.013 |
|  |  |  |  |  |
| ADJROA | 0.526\*\* | 0.069 | 0.298\*\* | -0.232 |
|  | t = 2.282 | t = 0.217 | t = 2.229 | t = -1.045 |
|  |  |  |  |  |
| ADJROA\_sq | 1.484\* | 3.470\*\*\* | 2.105\*\*\* | 1.611\* |
|  | t = 1.656 | t = 2.971 | t = 4.664 | t = 1.950 |
|  |  |  |  |  |
| SIZE | -0.027\*\* | -0.056\*\*\* | -0.032\*\*\* | -0.025\*\* |
|  | t = -2.086 | t = -3.178 | t = -4.505 | t = -2.000 |
|  |  |  |  |  |
| BIG4 | 0.029\*\* |  |  |  |
|  | t = 2.143 |  |  |  |
|  |  |  |  |  |
| ADV |  | -1.149\*\*\* | -0.637\*\*\* | -0.517\*\*\* |
|  |  | t = -9.472 | t = -10.516 | t = -7.226 |
|  |  |  |  |  |
| RD |  | -0.426\*\*\* | -0.243\*\*\* | -0.181\*\* |
|  |  | t = -3.831 | t = -4.828 | t = -2.451 |
|  |  |  |  |  |
| YEAR | -0.008 | -0.021\*\*\* | -0.012\*\*\* | -0.010\*\* |
|  | t = -1.185 | t = -3.321 | t = -4.674 | t = -2.141 |
|  | | | | |
| Constant | Included | Included | Included | Included |
| Observations | 492 | 492 | 492 | 492 |
| R2 | 0.116 | 0.483 | 0.502 | 0.439 |
| Adjusted R2 | 0.086 | 0.465 | 0.484 | 0.419 |
| F Statistic | 3.887\*\*\* | 26.088\*\*\* | 28.123\*\*\* | 21.790\*\*\* |
|  | | | | |
| \*, \*\*, \*\*\* 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 Second Stage Equations: Pre- vs. Post-Implementation for RPA Adopters and Control Sample for Alternative AM Proxy Analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | | | |
|  | | | | |
|  | *Dependent variable:* | | | |
|  |  | | | |
|  | DAQ | RM | ABEXP | ABPROD |
|  | (1) | (2) | (3) | (4) |
|  | | | | |
| RM | -0.088 |  |  |  |
|  | t = -1.541 |  |  |  |
|  |  |  |  |  |
| DAQ |  | -0.883\*\*\* | -0.521\*\*\* | -0.382\* |
|  |  | t = -2.616 | t = -2.827 | t = -1.729 |
|  |  |  |  |  |
| POST | 0.040\* | 0.055\*\*\* | 0.035\*\*\* | 0.023\*\* |
|  | t = 1.752 | t = 3.065 | t = 3.555 | t = 2.027 |
|  |  |  |  |  |
| RPA | -0.006 | -0.021\* | -0.009 | -0.009 |
|  | t = -0.318 | t = -1.955 | t = -1.478 | t = -1.425 |
|  |  |  |  |  |
| POST＊RPA | 0.011 | 0.019 | 0.007 | 0.010 |
|  | t = 0.445 | t = 1.217 | t = 0.878 | t = 0.984 |
|  |  |  |  |  |
| LEV | 0.057 | -0.054 | -0.014 | -0.049\* |
|  | t = 1.337 | t = -1.280 | t = -0.641 | t = -1.920 |
|  |  |  |  |  |
| OCF | -0.532\*\*\* | -0.809\*\*\* | -0.312\*\*\* | -0.501\*\*\* |
|  | t = -5.461 | t = -4.396 | t = -3.072 | t = -4.157 |
|  |  |  |  |  |
| MTB | 0.004 | 0.001 | -0.0001 | 0.002 |
|  | t = 0.718 | t = 0.210 | t = -0.045 | t = 0.583 |
|  |  |  |  |  |
| MS | 0.008\*\*\* | 0.006\*\* | 0.004\*\*\* | 0.003 |
|  | t = 5.923 | t = 2.284 | t = 2.676 | t = 1.441 |
|  |  |  |  |  |
| INST | 0.006 | -0.013 | -0.004 | -0.011 |
|  | t = 0.177 | t = -0.545 | t = -0.311 | t = -0.745 |
|  |  |  |  |  |
| CYCLE | 0.00002\*\* | 0.00002\* | 0.00002\*\*\* | 0.00000 |
|  | t = 2.256 | t = 1.859 | t = 3.546 | t = 0.291 |
|  |  |  |  |  |
| NOA | -0.002 | 0.043\* | -0.004 | 0.040\*\* |
|  | t = -0.049 | t = 1.657 | t = -0.276 | t = 2.425 |
|  |  |  |  |  |
| ZSCORE | -0.008\*\* | -0.010\*\* | -0.003 | -0.007\*\*\* |
|  | t = -2.073 | t = -2.109 | t = -1.290 | t = -2.602 |
|  |  |  |  |  |
| CL | -0.067 | 0.032 | -0.060\*\*\* | 0.090\*\*\* |
|  | t = -1.512 | t = 0.707 | t = -2.590 | t = 3.092 |
|  |  |  |  |  |
| ADJROA | 0.665\*\*\* | 0.056 | 0.222\* | -0.160 |
|  | t = 4.847 | t = 0.239 | t = 1.828 | t = -1.026 |
|  |  |  |  |  |
| ADJROA\_sq | 0.116 | -0.251 | -0.136 | 0.010 |
|  | t = 0.214 | t = -0.580 | t = -0.540 | t = 0.033 |
|  |  |  |  |  |
| SIZE | -0.039\*\*\* | -0.030\*\* | -0.018\*\* | -0.013 |
|  | t = -3.727 | t = -2.313 | t = -2.534 | t = -1.526 |
|  |  |  |  |  |
| BIG4 | 0.040\*\*\* |  |  |  |
|  | t = 3.554 |  |  |  |
|  |  |  |  |  |
| ADV |  | -1.017\*\*\* | -0.550\*\*\* | -0.490\*\*\* |
|  |  | t = -12.697 | t = -10.813 | t = -11.202 |
|  |  |  |  |  |
| RD |  | -0.226\*\*\* | -0.149\*\*\* | -0.072\* |
|  |  | t = -3.186 | t = -3.422 | t = -1.645 |
|  |  |  |  |  |
| YEAR | -0.007 | -0.008\*\* | -0.006\*\*\* | -0.003 |
|  | t = -1.550 | t = -2.159 | t = -3.093 | t = -1.029 |
|  | | | | |
| Constant | Included | Included | Included | Included |
| Observations | 984 | 984 | 984 | 984 |
| R2 | 0.138 | 0.455 | 0.394 | 0.459 |
| Adjusted R2 | 0.122 | 0.444 | 0.382 | 0.449 |
| F Statistic | 8.566\*\*\* | 42.336\*\*\* | 33.035\*\*\* | 43.120\*\*\* |
| F-test: | 0.050\*\*  t = 2.314 | 0.074\*\*\*  t = 3.323 | 0.041\*\*\*  t = 3.655 | 0.033\*\*  t = 2.231 |
|  | | | | |
| \*, \*\*, \*\*\* 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
     1. Absolute value of discretionary accruals (ABSDA)  
        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. Alternative AM proxy: discretionary component of accruals quality (DAQ)
        1. First step: accruals quality calculation  
            We adopt modified DD model (MDD model) from McNichols (2002) to calculate AQ proxy following below equation:   
              
           where represents the change in working capital of firm j from year t-1 to year t; ; , , represent operating cash flow of firm j in year t-1, t, t+1 respectively. is the difference of net sales for firm j between year t-1 and year t. is gross property, plant, and equipment. , *,* , and represent current assets, current liabilities, cash and cash equivalents and short-term debts for firm j in year t respectively. All continuous variables are scaled by average total assets from year t-1 to year t.  
            We follow prior literature (e.g. Francis et al. 2005; Gray et al. 2009) to estimate MDD model cross-sectionally for each industry by TSE industry code with at least 15 firms in year t. A firm-year specific accruals quality metric hereafter is calculated as the standard deviation of the residuals for firm j from the MDD model over year t-4 through year t.
        2. Second step: discretionary component of accruals quality calculation  
            To distinguish two components of AQ, we follow Francis et al. (2015) via using five innate factors influencing AQ to run the annual equations below:   
           where is the standard deviation of firm j’s cash flows from operation over past five years; is the standard deviation of firm j’s net sales over past five years; is calculated as natural logarithm of sum of days accounts receivable and days inventory plus 1 at the end of year t for firm j. represents the number of years over past five years, where firm j reported negative income from continuing operation at the end of year t. indicates the industry dummy variable for TSE industry code to control industry effect (Le et al. 2021). is the residual value from the above equation, representing the estimate of the discretionary component of firm j’s AQ.
  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.

* 1. Discretionary component of accruals quality (DAQ)

# 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 |
| DAQ | Discretionary component of accruals quality (Francis et al. 2005; Gray et al. 2009; Le et al. 2021). |
| RM | Aggregation of ABPROD and ABEXP |
| 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 |
| LEV | Total liabilities divided by total assets at the end of the year |
| OCF | Operating cash flows at the end of the year scaled by lagged total assets |
| MTB | Market-to-book value ratio at the end of the year |
| MS | The market share based on net sales of the firm among industry-year observations at the end of the year |
| INST | The percentage of institutional investors at the beginning of the year |
| CYCLE | Net operating cycle at the beginning of the year. Calculated as the sum of inventory period and accounts receivable period deducted by accounts payable period |
| NOA | Net operating asset at the end of the year 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 at the end of the year, 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 at the end of the year 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 at the end of the year 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 at the end of the year, calculated as R&D expenses divided by net sales |
| ADV | Advertising intensity at the end of the year, calculated as advertising expenses divided by net sales |
| YEAR | Trend variable |

1. For instance, Committee of Sponsoring Organizations of the Treadway Commission (COSO), Control Objectives for Information and Related Technologies (COBIT), International Organization for Standardization (ISO), [↑](#footnote-ref-1)
2. UiPath. What is robotic process automation? Available at: https://www.uipath.com/rpa/robotic-process-automation/. Accessed March 9, 2024. [↑](#footnote-ref-2)
3. Article 23 of the Regulations Governing Information to be Published in Annual Reports of Public Companies mandates that public companies must upload an electronic file containing their annual report to the information disclosure website designated by the Financial Supervisory Commission (FSC). [↑](#footnote-ref-3)
4. The content related to the adoption of RPA in the document via analyzing reports individually includes RPA implementation, RPA education and training, RPA management measures, and the applications of RPA within the company, ensuring that the firm had implemented RPA. [↑](#footnote-ref-4)
5. The anecdotal evidence (news articles in Taiwanese Mandarin) also indicated that Taiwanese companies implemented RPA starting from 2017. [↑](#footnote-ref-5)
6. We encounter duplicate matching while the beginning implementation year of RPA adopters. In contrast to the high standard deviation of assets observed in the USA-based sample studied by Paredes and Wheatley, Taiwanese firms exhibit different asset characteristics. To address the challenge of duplicate matching stemming from these disparities, we adjust our matching approach. Instead of relying on total assets at the beginning of the implementation year, we calculate the average logarithm total assets of each firm over the sample period. This modification ensures that each treatment firm is matched with a control firm to avoid the situation that different treatment firms with different beginning implementation year to match same control firm. [↑](#footnote-ref-6)
7. As the concerns Zang (2011) mentioned, another proxy abnormal cash flow delineated by Roychowdhury (2006) is about its ambiguous net effect and manipulation directions. As a result, we also exclude this proxy as a RM measurement in our research. [↑](#footnote-ref-7)
8. From Zang's (2012) study, we know that the choice between AM and RM depends on their relative costs; higher costs in one type of earnings management lead to increased use of the other. Additionally, Hamza (2019) pointed out the endogeneity problem since total earnings management includes both types of manipulation and their disturbance terms. Thus, both types of manipulation are part of a joint decision to manage earnings, with one approach of EM being endogenously related to the other. [↑](#footnote-ref-8)
9. Chan et al. (2008) found a negative relationship between AM and internal control weaknesses (ICWs). Lenard et al. (2018) also provided evidence that firms with fewer ICWs are less likely to engage in RM. Therefore, the relationship between ICWs and EM is generally negative, regardless of the type of EM. Ashraf (2024) indicated that improved internal controls with various automation technologies. However, our results suggest that RPA may increase EM, implying that RPA might be positively associated with ICWs. Given this, it can be inferred that other automation technologies might have a negative relationship with EM. [↑](#footnote-ref-9)
10. As Paredes and Wheatley (2017) have indicated, one limitation of this approach is the potential for self-selection bias. This bias arises because the decision to disclose ERP adoption in a firm's annual report may not be deemed materially significant enough for inclusion. This same limitation applies when discussing the adoption of RPA, suggesting that not all relevant adoptions are reported, thereby skewing the data towards those firms that do choose to disclose this information. [↑](#footnote-ref-10)