Evaluating the Impact of Robotic Process Automation on Earnings Management

# Abstract

This study examines the impact of Robotic Process Automation (RPA) on earnings management (EM) by analyzing 86 Taiwanese firms that adopted RPA, compared to a matched control group. Using the modified Jones model to assess discretionary accruals and proxies for real activities manipulation, we find a significant increase in both accrual-based and real activities EM strategies following RPA implementation. The results suggest that while RPA enhances operational efficiency and decision-making, it also creates additional opportunities for managers to engage in EM, likely due to the absence of robust control standards and risk management frameworks during initial adoption. These findings contribute to the growing literature on the influence of automation technologies on financial reporting, underscoring the need for stronger governance structures to mitigate the risk of EM in the digital era.

**JEL Classification: M41**

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

# **INTRODUCTION**

In the modern business landscape, disruptive technologies are reshaping industries at an unprecedented pace. Digital transformation is critical in driving value creation and enhancing competitive advantage. Technologies like enterprise resource planning (ERP) systems, artificial intelligence (AI), machine learning, blockchain, and robotic process automation (RPA) have significantly influenced finance and accounting functions, showcasing the rapid advancements in this field (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 indicated that following ERP implementation, real activities-based earnings management decreases, suggesting that ERP systems improve the quality of financial reporting by limiting opportunistic managerial actions. 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 decision-making capacities enabled by RPA might lead to a surge in EM, attributing it to the improvement of real-time information for the management to conduct EM. The surge might be 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.

This research 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: Section II presents the literature review and hypothesis development. Section III outlines the sample selection and research design, followed by Section IV, which discusses the univariate and multivariate results. Section V provides additional analyses, and the study concludes with Section VI.

# 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 an intra-company perspective, particularly within the accounting department, ERP systems streamline data collection and processing, providing enterprises with greater flexibility (Kanellou and Spathis 2013). Additionally, ERP systems facilitate tracking accounting transactions down to individual employees, including those on the assembly line or involved in barcode scanning. This capability has led to the automated generation of financial reports through predefined processes, replacing the manual compilation previously handled by accounting teams (Jędrzejka 2019). However, despite these advancements, ERP systems still require integration with other software applications, adding complexity and hindering the achievement of higher levels of automation in accounting (Hyvönen et al. 2008). As a result, businesses continue to handle many routine tasks manually, such as processing transactions, managing data, and facilitating interactions between digital systems. This persistent need for manual intervention underscores a gap between the potential of ERP systems and their current functionality, particularly in automating repetitive, low-value tasks across applications. This limitation can be effectively addressed by the next generation of automation: robotic process automation RPA.

## The New Automation Tool: RPA

RPA represents a cutting-edge technology designed to streamline the creation, deployment, and management of software robots. These software robots are designed to emulate human interactions with digital interfaces, enabling them to interpret on-screen data, perform keystrokes, navigate complex systems, and accurately recognize 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.

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 the limitations of ERP systems that were previously discussed, RPA emerges as an effective solution to overcome these limitations. 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 can be classified into two main types: accruals-based management (AM) and real earnings management (RM) (Healy and Wahlen 1999). 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 such as 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.

To the best of our knowledge, no empirical research directly links RPA with earnings management (EM). Therefore, we look to studies on ERP systems for insights, suggesting a potential relationship between RPA and EM. By analogy, the impact of ERP on EM may closely resemble the influence 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 emphasis on internal controls highlights the critical role of ERP systems in maintaining regulatory compliance and enhancing financial reporting integrity. This focus has driven many companies to implement ERPs as a means of achieving SOX compliance.

Given the mixed findings from prior studies on the relationship between ERP deployment and earnings management (EM), it is crucial to consider the regulatory context, including established internal control frameworks like COSO and COBIT, when assessing how ERP implementation affects EM and how RPA adoption might influence EM. This approach recognizes that a company’s decision to implement RPA may be driven by the benefits of automation tools or compliance requirements.

Eulerich et al. (2023) stated that a central governance framework for RPA is crucial to prevent unauthorized bot use and ensures compliance. However, enforcing these rules is challenging, as bots can be easily implemented without adhering to standards. Stringent governance practices are essential to mitigate risks and ensure operational integrity. Although risk management and control considerations for RPA partially overlap with those for ERP systems, existing frameworks like COSO (COSO 2013), COBIT (ISACA 2019), the ISO 27000 series (ISO 2013), and the NIST cybersecurity framework (NIST 2014) are deemed relevant but not fully adequate for RPA risk management (Hong et al. 2023). 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.

From the properties of these two automation technologies, 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. 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 both internal and external sources, which can support managerial decisions related to earnings management. By leveraging RPA, organizations can enhance their decision-making processes with timely and relevant data from various functions. Despite of the benefits that RPA offers, the frameworks for risk management and control specific to RPA appear underdeveloped. Considering this factor along with insights from previous research, we hypothesize that the positive 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. Therefore, we state our first hypothesis (H1) as:

**H1: The implementation of RPA is positively associated with earnings management through discretionary accruals.**

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### *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, provide advanced technical capabilities for collecting, analyzing, and reporting data critical to meeting the internal control requirements of SOX. As a result, many companies were motivated to adopt ERP systems specifically to comply with SOX regulations. Although SOX compliance prompted widespread ERP adoption, the benefits of these systems—such as improved data management and decision-making—had already attracted many businesses even before the mandate. 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. Moreover, ERP systems integrate various functional areas, improving communication, productivity, and efficiency, which strengthens the information environment and supports management's ability to conduct real activities manipulation (RM). For instance, leveraging data analytics to develop predictive models enables managers to engage in earnings management through RM before the period concludes, reducing the reliance on post-period accrual manipulation (Paredes and Wheatley 2017). Without an ERP system, managers may lack the insights needed to determine the level of RM required to meet earnings targets. However, real-time access to performance metrics provides managers with the tools to monitor progress and make more accurate forecasts, as demonstrated by Dorantes et al. (2013), ultimately encouraging and enabling 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 state our second hypothesis (H2) as:

**H2: 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 (TSE) or Taipei Exchange (TPEx), we aim to compile an exhaustive dataset on the RPA implementation. This strategy is enabled by the digital accessibility[[2]](#footnote-2) 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.[[3]](#footnote-3)

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 in 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.[[4]](#footnote-4) 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, companies in the financial industry (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 derived 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.[[5]](#footnote-5) 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.

## 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 more 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).[[6]](#footnote-6) 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 framework for AM and RM to address potential endogeneity issues[[7]](#footnote-7) between two approaches of EM that could lead to biased and inconsistent coefficient estimations through Ordinary Least Squares (OLS). We detect endogeneity issue between EM proxies considered endogenously related via Hausman auxiliary regression (Hill et al. 2018). Initially, we regress AM (RM) on the variables other than RM (AM) of each equation model to calculate the residuals of AM (RM). Subsequently, we add the residuals of RM (AM) into AM (RM) equations and run regression 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* serves as the indicator that differentiates the treatment group (with a value of 1) from the control group (with 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). Lastly, to control the effect of general economic changes over our sample, we include a fixed effect indicator, *YEAR*, following previous studies like Paredes and Wheatley (2017).

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. Panel A in Table 2 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.

Panel B in Table 2 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.

Panel A in Table 3 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. Panel B in Table 3 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 = 0.3957). For the EM proxies, there exists a significant gap (p = 0.0904) between two groups in terms of *ABSDA*, which shows that firms in control group are more likely to engage in AM compared to those in treatment group. On the contrary, it presents no significant difference for the RM measurements between two group. Panel C in Table 3 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 = 0.2855). Interestingly, it shows the significant gap (p = 0.0069) between the two groups for *ABSDA*, indicating that firms of treatment group become 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.

## Testing for Endogeneity between EM Proxies 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 in Table 4 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 variables other than RM (AM) in each equation to derive the predicted AM (RM). 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 are used in place of the actual values of the EM proxies.

## Within Treatment Group Analysis

Table 5 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, consistent with 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 *predictAM* 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.

## 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 *predictRM* coefficient (t = -1.790) in the AM equation and the negative significance of the *predictAM* 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 H1 and H2 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. 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.

# Additional Analyses

## Potential Self-selection bias for RPA implementation decision

Aside from coping with endogeneity issue between EM practices, we further investigate the potential self-selection bias arising from the managements’ decisions to adopt RPA technology via Heckman two-step procedures (Heckman 1979). We construct a probit regression model for RPA adoption, incorporating the determinants discussed in Dorantes et al. (2013), which identifies factors influencing a firm's decision to implement enterprise systems.[[8]](#footnote-8) The generated of inverse mills ratio (IMR)[[9]](#footnote-9) calculated from the first-step choice model will be added to the earnings management models for the Heckman second-step procedure. Table 6 presents the probit regression results and Table 7 shows the multivariate results and conclusion after adding inverse mills ratio remain unchanged. Additionally, the coefficient of IMR on RM equations are significant at 1% level, showing the importance of correcting self-selection bias with Heckman procedures.

## 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 of 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 more 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 8 presents 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. 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 7.

# 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. To address potential self-selection bias and endogeneity problem between EM proxies, we also adopt simultaneous equations for 2SLS and Heckman two-step procedures to mitigate these concerns. 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 both internal and external sources 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.

# Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT 4o by OpenAI  in order to  review and correct spelling and grammar issues, and to revise the writing (within 15 sentences) for improved clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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

NOTE: The definitions of all variables can be found in Appendix B.

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## 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 |

NOTE: \*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. The definitions of all variables can be found in Appendix B.

# Table 3 Mean Comparisons

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

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Pre-Implementation  (N=268) | | Post-Implementation  (N=248) | | Mean Difference  (t-Test) | |
|  | Mean | S.D. | Mean | S.D. | Difference | p-value |
| *ABSDA* | 0.0438 | 0.0436 | 0.0590 | 0.0527 | -0.0152 | 0.0004 |
| *ABPROD* | -0.0069 | 0.0966 | -0.0042 | 0.0973 | -0.0027 | 0.7480 |
| *ABEXP* | -0.0034 | 0.0740 | -0.0013 | 0.0647 | -0.0021 | 0.7315 |
| *RM* | -0.0108 | 0.1570 | -0.0054 | 0.1415 | -0.0054 | 0.6867 |
| *LEV* | 0.4424 | 0.1689 | 0.4777 | 0.1805 | -0.0353 | 0.0226 |
| *OCF* | 0.0679 | 0.0845 | 0.0827 | 0.1066 | -0.0148 | 0.0833 |
| *MTB* | 1.6579 | 1.3459 | 1.9609 | 1.5697 | -0.303 | 0.0194 |
| *MS* | 4.9856 | 9.0695 | 5.3980 | 9.2371 | -0.4124 | 0.6095 |
| *INST* | 0.4412 | 0.2340 | 0.4597 | 0.2525 | -0.0185 | 0.3896 |
| *CYCLE* | 101.2819 | 121.1574 | 107.2742 | 116.6800 | -5.9923 | 0.5674 |
| *NOA* | 0.5858 | 0.1962 | 0.5578 | 0.2217 | 0.0280 | 0.1308 |
| *ZSCORE* | 3.4622 | 2.6089 | 3.5806 | 2.6161 | -0.1184 | 0.6073 |
| *CL* | 0.2721 | 0.1488 | 0.2941 | 0.1676 | -0.0220 | 0.1168 |
| *ADJROA* | 0.0088 | 0.0676 | 0.0148 | 0.0738 | -0.0060 | 0.3382 |
| *SIZE* | 16.2458 | 1.8858 | 16.4086 | 1.8478 | -0.1628 | 0.3227 |
| *BIG4* | 1.9403 | 0.2374 | 1.9113 | 0.2849 | 0.0290 | 0.2115 |
| *RD* | 0.0490 | 0.0836 | 0.0486 | 0.0934 | 0.0004 | 0.9549 |
| *ADV* | 0.0629 | 0.0687 | 0.0718 | 0.0737 | -0.0089 | 0.1598 |

NOTE: The definitions of all variables can be found in Appendix B.

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

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Control Group  (N=268) | | RPA Adopters  (N=268) | | Mean Difference  (t-Test) | |
|  | Mean | S.D. | Mean | S.D. | Difference | p-value |
| *ABSDA* | 0.0508 | 0.0515 | 0.0438 | 0.0436 | 0.0070 | 0.0904 |
| *ABPROD* | -0.0102 | 0.1027 | -0.0069 | 0.0966 | -0.0033 | 0.6986 |
| *ABEXP* | -0.0006 | 0.0958 | -0.0034 | 0.0740 | 0.0028 | 0.7083 |
| *RM* | -0.0081 | 0.1725 | -0.0108 | 0.1570 | 0.0027 | 0.8541 |
| *LEV* | 0.4178 | 0.1831 | 0.4424 | 0.1689 | -0.0246 | 0.1066 |
| *OCF* | 0.0714 | 0.0996 | 0.0679 | 0.0845 | 0.0035 | 0.6670 |
| *MTB* | 2.0159 | 1.5124 | 1.6579 | 1.3459 | 0.3580 | 0.0040 |
| *MS* | 3.2605 | 6.9428 | 4.9856 | 9.0695 | -1.7251 | 0.0137 |
| *INST* | 0.4352 | 0.2213 | 0.4412 | 0.2340 | -0.0060 | 0.7607 |
| *CYCLE* | 230.9130 | 599.8826 | 101.2819 | 121.1574 | 129.6311 | 0.0006 |
| *NOA* | 0.6155 | 0.2317 | 0.5858 | 0.1962 | 0.0297 | 0.1095 |
| *ZSCORE* | 3.8896 | 3.0695 | 3.4622 | 2.6089 | 0.4274 | 0.0831 |
| *CL* | 0.2276 | 0.1490 | 0.2721 | 0.1488 | -0.0445 | 0.0006 |
| *ADJROA* | 0.0159 | 0.0858 | 0.0088 | 0.0676 | 0.0071 | 0.2872 |
| *SIZE* | 16.1130 | 1.7287 | 16.2458 | 1.8858 | -0.1328 | 0.3957 |
| *BIG4* | 1.9515 | 0.2152 | 1.9403 | 0.2374 | 0.0112 | 0.5676 |
| *RD* | 0.0418 | 0.0809 | 0.0490 | 0.0836 | -0.0072 | 0.3094 |
| *ADV* | 0.0691 | 0.0800 | 0.0629 | 0.0687 | 0.0062 | 0.3422 |

NOTE: The definitions of all variables can be found in Appendix B.

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

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Control Group  (N=248) | | RPA Adopters  (N=248) | | Mean Difference  (t-Test) | |
|  | Mean | S.D. | Mean | S.D. | Difference | p-value |
| *ABSDA* | 0.0471 | 0.0453 | 0.0590 | 0.0527 | -0.0119 | 0.0069 |
| *ABPROD* | -0.0003 | 0.1005 | -0.0042 | 0.0973 | 0.0039 | 0.6644 |
| *ABEXP* | 0.0020 | 0.0554 | -0.0013 | 0.0647 | 0.0033 | 0.5365 |
| *RM* | 0.0024 | 0.1334 | -0.0054 | 0.1415 | 0.0078 | 0.5231 |
| *LEV* | 0.4396 | 0.1806 | 0.4777 | 0.1805 | -0.0381 | 0.0193 |
| *OCF* | 0.0682 | 0.1101 | 0.0827 | 0.1066 | -0.0145 | 0.1358 |
| *MTB* | 1.8817 | 1.4081 | 1.9609 | 1.5697 | -0.0792 | 0.5546 |
| *MS* | 2.7790 | 5.4815 | 5.3980 | 9.2371 | -2.619 | 0.0001 |
| *INST* | 0.4543 | 0.2324 | 0.4597 | 0.2525 | -0.0054 | 0.8045 |
| *CYCLE* | 183.1106 | 540.7234 | 107.2742 | 116.6800 | 75.8364 | 0.0317 |
| *NOA* | 0.6026 | 0.2302 | 0.5578 | 0.2217 | 0.0448 | 0.0276 |
| *ZSCORE* | 3.5346 | 2.6626 | 3.5806 | 2.6161 | -0.046 | 0.8460 |
| *CL* | 0.2514 | 0.1721 | 0.2941 | 0.1676 | -0.0427 | 0.0054 |
| *ADJROA* | 0.0084 | 0.0824 | 0.0148 | 0.0738 | -0.0064 | 0.3620 |
| *SIZE* | 16.2376 | 1.7117 | 16.4086 | 1.8478 | -0.171 | 0.2855 |
| *BIG4* | 1.9153 | 0.2790 | 1.9113 | 0.2849 | 0.004 | 0.8735 |
| *RD* | 0.0601 | 0.1179 | 0.0486 | 0.0934 | 0.0115 | 0.2283 |
| *ADV* | 0.0787 | 0.0888 | 0.0718 | 0.0737 | 0.0069 | 0.3472 |

NOTE: The definitions of all variables can be found in Appendix B.

# Table 4 Hausman Auxiliary Regression tests for potential endogeneity between EM proxies

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Within Treatment-Group Analysis | | | | | Matched Results Analysis | | | |
|  | | *Dependent variable:* | | | | | | | |
|  | *ABSDA* | | *RM* | *ABEXP* | *ABPROD* | *ABSDA* | *RM* | *ABEXP* | *ABPROD* |
| *RMres* | 0.070\* | |  |  |  | 0.049\* |  |  |  |
|  | t = 1.852 | |  |  |  | t = 1.934 |  |  |  |
|  |  | |  |  |  |  |  |  |  |
| *RM* | -0.051 | |  |  |  | -0.042\* |  |  |  |
|  | t = -1.541 | |  |  |  | t = -1.787 |  |  |  |
|  |  | |  |  |  |  |  |  |  |
| *ABSDA* |  | | -9.268\*\*\* | -5.443\*\*\* | -3.913\*\* |  | -14.904\*\* | -8.857\*\* | -6.545 |
|  |  | | t = -3.546 | t = -5.395 | t = -2.040 |  | t = -2.332 | t = -2.509 | t = -1.568 |
|  |  | |  |  |  |  |  |  |  |
| *AMres* |  | | 9.390\*\*\* | 5.421\*\*\* | 4.043\*\* |  | 14.953\*\* | 8.751\*\* | 6.663 |
|  |  | | t = 3.591 | t = 5.371 | t = 2.101 |  | t = 2.341 | t = 2.480 | t = 1.597 |
|  |  | |  |  |  |  |  |  |  |
| *POST* | 0.012\*\* | | 0.138\*\*\* | 0.075\*\*\* | 0.065\*\*\* | -0.009\* | -0.113\* | -0.065\*\* | -0.05 |
|  | t = 2.328 | | t = 4.407 | t = 5.985 | t = 2.887 | 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* | -0.015 | | -0.210\*\* | -0.105\*\* | -0.109\* | 0.021 | 0.186 | 0.131\*\* | 0.054 |
|  | t = -0.701 | | t = -2.214 | t = -2.489 | t = -1.748 | t = 1.394 | t = 1.628 | t = 2.106 | t = 0.717 |
|  |  | |  |  |  |  |  |  |  |
| *OCF* | -0.03 | | -0.426\*\*\* | -0.150\*\*\* | -0.266\*\*\* | -0.100\*\*\* | -1.672\*\*\* | -0.839\*\*\* | -0.875\*\* |
|  | t = -0.701 | | t = -4.693 | t = -3.692 | t = -4.045 | t = -3.055 | t = -2.855 | t = -2.589 | t = -2.285 |
|  |  | |  |  |  |  |  |  |  |
| *MTB* | 0.006\*\*\* | | 0.057\*\*\* | 0.033\*\*\* | 0.023 | 0.004\*\* | 0.062\*\* | 0.036\*\* | 0.029 |
|  | t = 2.890 | | t = 2.841 | t = 4.175 | t = 1.594 | t = 2.121 | t = 2.050 | t = 2.157 | t = 1.452 |
|  |  | |  |  |  |  |  |  |  |
| *MS* | 0.00002 | | 0.002\*\* | 0.001\*\* | 0.001 | -0.0001 | -0.0004 | 0.0001 | -0.0004 |
|  | t = 0.060 | | t = 2.087 | t = 2.449 | t = 1.330 | t = -0.443 | t = -0.640 | t = 0.244 | t = -1.004 |
|  |  | |  |  |  |  |  |  |  |
| *INST* | 0.009 | | 0.095\*\* | 0.065\*\*\* | 0.033 | 0.0003 | 0.005 | 0.008 | -0.005 |
|  | t = 0.814 | | t = 2.214 | t = 3.343 | t = 1.161 | t = 0.040 | t = 0.208 | t = 0.694 | t = -0.336 |
|  |  | |  |  |  |  |  |  |  |
| *CYCLE* | -0.00002 | | -0.0002\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | -0.00001\*\* | -0.0001\*\* | -0.00004\* | -0.00004\* |
|  | t = -0.856 | | t = -5.043 | t = -3.597 | t = -4.950 | t = -2.046 | t = -2.249 | t = -1.947 | t = -1.827 |
|  |  | |  |  |  |  |  |  |  |
| *NOA* | 0.016 | | 0.227\*\*\* | 0.091\*\*\* | 0.144\*\*\* | 0.017\* | 0.266\*\*\* | 0.127\*\*\* | 0.140\*\* |
|  | t = 1.322 | | t = 4.695 | t = 4.409 | t = 4.050 | t = 1.873 | t = 3.061 | t = 2.639 | t = 2.461 |
|  |  | |  |  |  |  |  |  |  |
| *ZSCORE* | -0.002 | | -0.008 | -0.002 | -0.005 | -0.002\* | -0.027\*\* | -0.013\* | -0.015\* |
|  | t = -1.274 | | t = -1.025 | t = -0.789 | t = -0.958 | t = -1.749 | t = -2.139 | t = -1.924 | t = -1.849 |
|  |  | |  |  |  |  |  |  |  |
| *CL* | 0.054\*\*\* | | 0.562\*\*\* | 0.257\*\*\* | 0.317\*\*\* | 0.028\*\* | 0.460\*\*\* | 0.189\*\* | 0.281\*\*\* |
|  | t = 2.837 | | t = 3.375 | t = 3.816 | t = 2.690 | t = 1.975 | t = 2.902 | t = 2.181 | t = 2.718 |
|  |  | |  |  |  |  |  |  |  |
| *ADJROA* | -0.01 | | -0.762\*\*\* | -0.188\*\*\* | -0.580\*\*\* | 0.102\*\* | 1.126 | 0.873\*\* | 0.301 |
|  | t = -0.157 | | t = -6.237 | t = -3.494 | t = -6.727 | t = 2.553 | t = 1.547 | t = 2.213 | t = 0.629 |
|  |  | |  |  |  |  |  |  |  |
| *ADJROA\_sq* | 1.192\*\*\* | | 11.396\*\*\* | 6.751\*\*\* | 4.989\*\* | 0.889\*\*\* | 13.478\*\* | 7.982\*\* | 6.088 |
|  | t = 3.581 | | t = 3.609 | t = 5.548 | t = 2.153 | t = 4.874 | t = 2.221 | t = 2.343 | t = 1.550 |
|  |  | |  |  |  |  |  |  |  |
| *SIZE* | -0.005\*\* | | -0.055\*\*\* | -0.032\*\*\* | -0.024\*\* | -0.004\*\*\* | -0.064\*\* | -0.038\*\* | -0.028 |
|  | t = -2.550 | | t = -3.659 | t = -5.276 | t = -2.181 | t = -2.821 | t = -2.247 | t = -2.441 | t = -1.490 |
|  |  | |  |  |  |  |  |  |  |
| *BIG4* | 0.008 | |  |  |  | 0.003 |  |  |  |
|  | t = 1.101 | |  |  |  | t = 0.431 |  |  |  |
|  |  | |  |  |  |  |  |  |  |
| *ADV* |  | | -1.153\*\*\* | -0.637\*\*\* | -0.524\*\*\* |  | -0.969\*\*\* | -0.525\*\*\* | -0.472\*\*\* |
|  |  | | t = -10.035 | t = -10.873 | t = -7.603 |  | t = -12.688 | t = -10.661 | t = -11.016 |
|  |  | |  |  |  |  |  |  |  |
| *RD* |  | | -0.139 | -0.057 | -0.083 |  | -0.119\*\* | -0.067\* | -0.045 |
|  |  | | t = -1.511 | t = -1.115 | t = -1.603 |  | t = -1.962 | t = -1.679 | t = -1.370 |
| Constant | Included | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | Yes | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 516 | | 516 | 516 | 516 | 1,032 | 1,032 | 1,032 | 1,032 |
| Adjusted R2 | 0.172 | | 0.437 | 0.44 | 0.405 | 0.145 | 0.417 | 0.351 | 0.434 |
| F Statistic | 7.310\*\*\* | | 23.191\*\*\* | 23.512\*\*\* | 20.480\*\*\* | 10.223\*\*\* | 37.798\*\*\* | 28.922\*\*\* | 40.454\*\*\* |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in Appendix B. | | | | | | | | | |

# Table 5 Pre- vs. Post-Implementation for Within-Treatment Group and Matched Analysis

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Within Treatment-Group Analysis | | | | | Matched Results Analysis | | | |
|  | | *Dependent variable:* | | | | | | | |
|  | *ABSDA* | | *RM* | *ABEXP* | *ABPROD* | *ABSDA* | *RM* | *ABEXP* | *ABPROD* |
| *predictRM* | -0.051 | |  |  |  | -0.042\* |  |  |  |
|  | t = -1.553 | |  |  |  | t = -1.790 |  |  |  |
|  |  | |  |  |  |  |  |  |  |
| *predictAM* |  | | -9.263\*\*\* | -5.444\*\*\* | -3.908\*\* |  | -14.896\*\* | -8.875\*\* | -6.525 |
|  |  | | t = -3.523 | t = -5.408 | t = -2.021 |  | t = -2.327 | t = -2.524 | t = -1.555 |
|  |  | |  |  |  |  |  |  |  |
| *POST* | 0.012\*\* | | 0.138\*\*\* | 0.075\*\*\* | 0.065\*\*\* | -0.009\* | -0.113\* | -0.065\*\* | -0.05 |
|  | t = 2.306 | | t = 4.374 | t = 6.001 | t = 2.856 | 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\*\* | 0.12 |
|  |  | |  |  |  | t = 3.159 | t = 2.401 | t = 2.529 | t = 1.635 |
|  |  | |  |  |  |  |  |  |  |
| *LEV* | -0.015 | | -0.210\*\* | -0.106\*\* | -0.108\* | 0.021 | 0.187 | 0.131\*\* | 0.055 |
|  | t = -0.713 | | t = -2.195 | t = -2.496 | t = -1.722 | t = 1.393 | t = 1.628 | t = 2.107 | t = 0.718 |
|  |  | |  |  |  |  |  |  |  |
| *OCF* | -0.03 | | -0.425\*\*\* | -0.150\*\*\* | -0.265\*\*\* | -0.100\*\*\* | -1.671\*\*\* | -0.842\*\*\* | -0.873\*\* |
|  | t = -0.695 | | t = -4.649 | t = -3.702 | t = -3.998 | t = -3.051 | t = -2.849 | t = -2.604 | t = -2.268 |
|  |  | |  |  |  |  |  |  |  |
| *MTB* | 0.006\*\*\* | | 0.057\*\*\* | 0.033\*\*\* | 0.023 | 0.004\*\* | 0.062\*\* | 0.036\*\* | 0.028 |
|  | t = 2.902 | | t = 2.817 | t = 4.190 | t = 1.573 | t = 2.125 | t = 2.044 | t = 2.174 | t = 1.435 |
|  |  | |  |  |  |  |  |  |  |
| *MS* | 0.00001 | | 0.002\*\* | 0.001\*\* | 0.001 | -0.0001 | -0.0004 | 0.0001 | -0.0004 |
|  | t = 0.055 | | t = 2.070 | t = 2.461 | t = 1.294 | t = -0.446 | t = -0.651 | t = 0.268 | t = -1.042 |
|  |  | |  |  |  |  |  |  |  |
| *INST* | 0.01 | | 0.095\*\* | 0.065\*\*\* | 0.034 | 0.0003 | 0.005 | 0.008 | -0.005 |
|  | t = 0.826 | | t = 2.206 | t = 3.349 | t = 1.156 | t = 0.039 | t = 0.208 | t = 0.696 | t = -0.336 |
|  |  | |  |  |  |  |  |  |  |
| *CYCLE* | -0.00002 | | -0.0002\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | -0.00001\*\* | -0.0001\*\* | -0.00004\* | -0.00004\* |
|  | t = -0.854 | | t = -5.064 | t = -3.592 | t = -4.977 | t = -2.041 | t = -2.247 | t = -1.953 | t = -1.819 |
|  |  | |  |  |  |  |  |  |  |
| *NOA* | 0.017 | | 0.227\*\*\* | 0.091\*\*\* | 0.144\*\*\* | 0.017\* | 0.266\*\*\* | 0.127\*\*\* | 0.140\*\* |
|  | t = 1.339 | | t = 4.685 | t = 4.414 | t = 4.041 | t = 1.877 | t = 3.056 | t = 2.652 | t = 2.448 |
|  |  | |  |  |  |  |  |  |  |
| *ZSCORE* | -0.002 | | -0.008 | -0.002 | -0.005 | -0.002\* | -0.027\*\* | -0.013\* | -0.015\* |
|  | t = -1.270 | | t = -1.023 | t = -0.788 | t = -0.957 | t = -1.747 | t = -2.135 | t = -1.935 | t = -1.834 |
|  |  | |  |  |  |  |  |  |  |
| *CL* | 0.055\*\*\* | | 0.561\*\*\* | 0.257\*\*\* | 0.317\*\*\* | 0.028\*\* | 0.460\*\*\* | 0.189\*\* | 0.281\*\*\* |
|  | t = 2.861 | | t = 3.353 | t = 3.824 | t = 2.663 | t = 1.984 | t = 2.894 | t = 2.198 | t = 2.694 |
|  |  | |  |  |  |  |  |  |  |
| *ADJROA* | -0.011 | | -0.760\*\*\* | -0.189\*\*\* | -0.578\*\*\* | 0.102\*\* | 1.126 | 0.874\*\* | 0.3 |
|  | t = -0.166 | | t = -6.353 | t = -3.472 | t = -6.904 | t = 2.546 | t = 1.545 | t = 2.223 | t = 0.624 |
|  |  | |  |  |  |  |  |  |  |
| *ADJROA\_sq* | 1.191\*\*\* | | 11.385\*\*\* | 6.753\*\*\* | 4.978\*\* | 0.888\*\*\* | 13.468\*\* | 8.002\*\* | 6.065 |
|  | t = 3.603 | | t = 3.586 | t = 5.561 | t = 2.133 | t = 4.873 | t = 2.215 | t = 2.359 | t = 1.535 |
|  |  | |  |  |  |  |  |  |  |
| *SIZE* | -0.005\*\* | | -0.055\*\*\* | -0.032\*\*\* | -0.024\*\* | -0.004\*\*\* | -0.064\*\* | -0.038\*\* | -0.028 |
|  | t = -2.543 | | t = -3.629 | t = -5.297 | t = -2.154 | t = -2.817 | t = -2.241 | t = -2.457 | t = -1.474 |
|  |  | |  |  |  |  |  |  |  |
| *BIG4* | 0.007 | |  |  |  | 0.002 |  |  |  |
|  | t = 0.947 | |  |  |  | t = 0.395 |  |  |  |
|  |  | |  |  |  |  |  |  |  |
| *ADV* |  | | -1.147\*\*\* | -0.638\*\*\* | -0.517\*\*\* |  | -0.967\*\*\* | -0.529\*\*\* | -0.467\*\*\* |
|  |  | | t = -10.032 | t = -10.878 | t = -7.590 |  | t = -12.583 | t = -10.659 | t = -10.910 |
|  |  | |  |  |  |  |  |  |  |
| *RD* |  | | -0.138 | -0.057 | -0.081 |  | -0.119\*\* | -0.068\* | -0.045 |
|  |  | | t = -1.512 | t = -1.114 | t = -1.589 |  | t = -1.963 | t = -1.672 | t = -1.367 |
| Constant | Included | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | Yes | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 516 | | 516 | 516 | 516 | 1,032 | 1,032 | 1,032 | 1,032 |
| Adjusted R2 | 0.172 | | 0.437 | 0.441 | 0.403 | 0.146 | 0.417 | 0.348 | 0.431 |
| F Statistic | 7.692\*\*\* | | 24.480\*\*\* | 24.926\*\*\* | 21.430\*\*\* | 10.778\*\*\* | 39.793\*\*\* | 29.944\*\*\* | 42.151\*\*\* |
| F-test |  | |  |  |  | 0.155\*\* | 0.009\* | 0.089\*\*\* | 0.070\* |
|  | |  |  |  | t = 2.499 | t = 1.833 | t = 2.786 | t = 1.752 |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in Appendix B. | | | | | | | | | |

# Table 6 First-Stage of the Heckman Procedure

|  |  |
| --- | --- |
| **Estimation Results of Heckman First-Step Probit Model** | |
|  | |
|  | *Dependent variable:* |
|  |  |
|  | *RPAIMP* |
|  | |
| *LNAT* | 0.205\*\*\* |
|  | t = 8.696 |
|  |  |
| *LEV* | -0.099 |
|  | t = -0.745 |
|  |  |
| *CAPINT* | 0.204\*\*\* |
|  | t = 4.753 |
|  |  |
| *MB* | 0.005 |
|  | t = 0.415 |
|  |  |
| *LOSS* | 0.046 |
|  | t = 0.482 |
|  |  |
| *DIV* | 0.114 |
|  | t = 1.228 |
|  |  |
| *RDINT* | -0.393 |
|  | t = -0.573 |
|  |  |
| *ADVINT* | 0.983\*\*\* |
|  | t = 2.947 |
|  |  |
| *ANALYST* | -0.051\*\*\* |
|  | t = -2.761 |
|  |  |
|  | |
| Constant | Included |
| Year Effects | Yes |
| Pseudo R2 | 0.1259 |
| Observations | 9,121 |
|  | |

NOTE: \*, \*\*, \*\*\* p < 0.10, p < 0.05, and p < 0.01, respectively. Variable definition, sample description, and choice model of the first-stage probit regression can be found in Appendix C.

# Table 7 Second Step of the Heckman procedures: Pre- vs. Post-Implementation for Within-Treatment Group and Matched Analysis

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Within Treatment-Group Analysis | | | | | | Matched Results Analysis | | | |
|  | | | *Dependent variable:* | | | | | | | |
|  | *ABSDA* | | | *RM* | *ABEXP* | *ABPROD* | *ABSDA* | *RM* | *ABEXP* | *ABPROD* |
| *predictRM* | -0.051 | | |  |  |  | -0.042\* |  |  |  |
|  | t = -1.544 | | |  |  |  | t = -1.781 |  |  |  |
|  |  | | |  |  |  |  |  |  |  |
| *predictAM* |  | | | -9.086\*\*\* | -5.319\*\*\* | -3.846\*\* |  | -14.066\*\* | -8.274\*\* | -6.234 |
|  |  | | | t = -3.475 | t = -5.340 | t = -1.997 |  | t = -2.229 | t = -2.429 | t = -1.487 |
|  |  | | |  |  |  |  |  |  |  |
| *POST* | 0.012\*\* | | | 0.136\*\*\* | 0.073\*\*\* | 0.064\*\*\* | -0.009\* | -0.108\* | -0.062\* | -0.048 |
|  | t = 2.305 | | | t = 4.298 | t = 5.895 | t = 2.821 | t = -1.762 | t = -1.873 | t = -1.959 | t = -1.256 |
|  |  | | |  |  |  |  |  |  |  |
| *RPA* |  | | |  |  |  | -0.006 | -0.088\*\* | -0.047\*\* | -0.040\* |
|  |  | | |  |  |  | t = -1.503 | t = -2.532 | t = -2.524 | t = -1.740 |
|  |  | | |  |  |  |  |  |  |  |
| *POST＊RPA* |  | | |  |  |  | 0.018\*\*\* | 0.255\*\* | 0.145\*\* | 0.115 |
|  |  | | |  |  |  | t = 3.149 | t = 2.319 | t = 2.454 | t = 1.575 |
|  |  | | |  |  |  |  |  |  |  |
| *LEV* | -0.015 | | | -0.191\*\* | -0.092\*\* | -0.101 | 0.02 | 0.197\* | 0.139\*\* | 0.058 |
|  | t = -0.715 | | | t = -2.007 | t = -2.192 | t = -1.628 | t = 1.366 | t = 1.741 | t = 2.290 | t = 0.767 |
|  |  | | |  |  |  |  |  |  |  |
| *OCF* | -0.03 | | | -0.423\*\*\* | -0.149\*\*\* | -0.265\*\*\* | -0.100\*\*\* | -1.591\*\*\* | -0.784\*\* | -0.844\*\* |
|  | t = -0.693 | | | t = -4.669 | t = -3.749 | t = -3.999 | t = -3.052 | t = -2.756 | t = -2.509 | t = -2.200 |
|  |  | | |  |  |  |  |  |  |  |
| *MTB* | 0.006\*\*\* | | | 0.052\*\*\* | 0.030\*\*\* | 0.022 | 0.004\*\* | 0.053\* | 0.030\* | 0.025 |
|  | t = 2.831 | | | t = 2.619 | t = 3.822 | t = 1.483 | t = 2.119 | t = 1.788 | t = 1.857 | t = 1.288 |
|  |  | | |  |  |  |  |  |  |  |
| *MS* | 0 | | | 0.002\*\* | 0.001\*\*\* | 0.001 | -0.0001 | -0.0001 | 0.0003 | -0.0003 |
|  | t = 0.018 | | | t = 2.381 | t = 2.988 | t = 1.439 | t = -0.470 | t = -0.112 | t = 0.931 | t = -0.720 |
|  |  | | |  |  |  |  |  |  |  |
| *INST* | 0.009 | | | 0.097\*\* | 0.066\*\*\* | 0.034 | 0.0003 | 0.007 | 0.01 | -0.004 |
|  | t = 0.816 | | | t = 2.265 | t = 3.444 | t = 1.180 | t = 0.030 | t = 0.290 | t = 0.813 | t = -0.290 |
|  |  | | |  |  |  |  |  |  |  |
| *CYCLE* | -0.00002 | | | -0.0002\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | -0.00001\*\* | -0.0001\*\* | -0.00004\*\* | -0.00004\* |
|  | t = -0.839 | | | t = -5.223 | t = -3.979 | t = -5.026 | t = -2.038 | t = -2.284 | t = -2.025 | t = -1.821 |
|  |  | | |  |  |  |  |  |  |  |
| *NOA* | 0.017 | | | 0.229\*\*\* | 0.092\*\*\* | 0.145\*\*\* | 0.017\* | 0.256\*\*\* | 0.120\*\*\* | 0.136\*\* |
|  | t = 1.331 | | | t = 4.750 | t = 4.574 | t = 4.059 | t = 1.875 | t = 2.980 | t = 2.582 | t = 2.388 |
|  |  | | |  |  |  |  |  |  |  |
| *ZSCORE* | -0.002 | | | -0.006 | -0.001 | -0.005 | -0.002\* | -0.024\* | -0.011\* | -0.014\* |
|  | t = -1.273 | | | t = -0.855 | t = -0.485 | t = -0.880 | t = -1.766 | t = -1.952 | t = -1.707 | t = -1.725 |
|  |  | | |  |  |  |  |  |  |  |
| *CL* | 0.054\*\*\* | | | 0.576\*\*\* | 0.267\*\*\* | 0.322\*\*\* | 0.027\*\* | 0.461\*\*\* | 0.190\*\* | 0.281\*\*\* |
|  | t = 2.810 | | | t = 3.448 | t = 4.000 | t = 2.702 | t = 1.979 | t = 2.942 | t = 2.281 | t = 2.699 |
|  |  | | |  |  |  |  |  |  |  |
| *ADJROA* | -0.011 | | | -0.763\*\*\* | -0.191\*\*\* | -0.579\*\*\* | 0.102\*\* | 1.027 | 0.802\*\* | 0.265 |
|  | t = -0.171 | | | t = -6.489 | t = -3.548 | t = -6.989 | t = 2.539 | t = 1.429 | t = 2.104 | t = 0.553 |
|  |  | | |  |  |  |  |  |  |  |
| *ADJROA\_sq* | 1.193\*\*\* | | | 11.147\*\*\* | 6.585\*\*\* | 4.895\*\* | 0.890\*\*\* | 12.675\*\* | 7.428\*\* | 5.786 |
|  | t = 3.594 | | | t = 3.536 | t = 5.502 | t = 2.107 | t = 4.874 | t = 2.118 | t = 2.265 | t = 1.467 |
|  |  | | |  |  |  |  |  |  |  |
| *SIZE* | -0.005\*\* | | | -0.049\*\*\* | -0.027\*\*\* | -0.022\*\* | -0.004\*\*\* | -0.053\* | -0.031\*\* | -0.024 |
|  | t = -2.512 | | | t = -3.236 | t = -4.549 | t = -1.978 | t = -2.655 | t = -1.885 | t = -2.008 | t = -1.275 |
|  |  | | |  |  |  |  |  |  |  |
| *BIG4* | 0.007 | | |  |  |  | 0.002 |  |  |  |
|  | t = 0.942 | | |  |  |  | t = 0.390 |  |  |  |
|  |  | | |  |  |  |  |  |  |  |
| *ADV* |  | | | -1.117\*\*\* | -0.617\*\*\* | -0.507\*\*\* |  | -0.928\*\*\* | -0.501\*\*\* | -0.454\*\*\* |
|  |  | | | t = -9.901 | t = -10.771 | t = -7.450 |  | t = -12.750 | t = -10.897 | t = -10.888 |
|  |  | | |  |  |  |  |  |  |  |
| *RD* |  | | | -0.178\* | -0.085 | -0.095\* |  | -0.158\*\*\* | -0.096\*\* | -0.058\* |
|  |  | | | t = -1.923 | t = -1.611 | t = -1.864 |  | t = -2.665 | t = -2.449 | t = -1.774 |
|  |  | | |  |  |  |  |  |  |  |
| *IMR* | -0.001 | | | 0.049\*\* | 0.035\*\*\* | 0.017 | -0.001 | 0.062\*\*\* | 0.045\*\*\* | 0.022\*\* |
|  | t = -0.153 | | | t = 2.331 | t = 3.570 | t = 1.235 | t = -0.168 | t = 3.515 | t = 4.527 | t = 1.995 |
| Constant | Included | | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | Yes | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | 516 | | 516 | 516 | 516 | 1,032 | 1,032 | 1,032 | 1,032 |
| Adjusted R2 | 0.171 | | | 0.442 | 0.455 | 0.403 | 0.145 | 0.427 | 0.37 | 0.434 |
| F Statistic | 7.227\*\*\* | | | 23.681\*\*\* | 24.930\*\*\* | 20.353\*\*\* | 10.203\*\*\* | 39.344\*\*\* | 31.235\*\*\* | 40.479\*\*\* |
| F-test |  | | |  |  |  | 0.009\* | 0.147\*\* | 0.083\*\*\* | 0.067\* |
|  | | |  |  |  | t = 1.835 | t = 2.385 | t = 2.634 | t = 1.682 |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in Appendix B. | | | | | | | | | | |

# Table 8 Second Step of the Heckman procedures: Pre- vs. Post-Implementation for Within-Treatment Group and Matched Analysis by Using Alternative AM Proxy

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Within Treatment-Group Analysis | | | | | | Matched Results Analysis | | | |
|  | | | *Dependent variable:* | | | | | | | |
|  | *DAQ* | | | *RM* | *ABEXP* | *ABPROD* | *DAQ* | *RM* | *ABEXP* | *ABPROD* |
| *predictRM* | 0.092 | | |  |  |  | -0.082 |  |  |  |
|  | t = 1.059 | | |  |  |  | t = -1.406 |  |  |  |
| *predictAM* |  | | | -2.188\*\*\* | -1.273\*\*\* | -0.930\* |  | -0.833\*\* | -0.486\*\*\* | -0.365\* |
|  |  | | | t = -3.179 | t = -4.686 | t = -1.923 |  | t = -2.501 | t = -2.717 | t = -1.656 |
| *POST* | 0.049\* | | | 0.143\*\*\* | 0.078\*\*\* | 0.067\*\*\* | 0.041\* | 0.050\*\*\* | 0.031\*\*\* | 0.022\* |
|  | t = 1.903 | | | t = 3.861 | t = 5.200 | t = 2.597 | t = 1.798 | t = 2.835 | t = 3.302 | t = 1.897 |
| *RPA* |  | | |  |  |  | -0.006 | -0.021\*\* | -0.009 | -0.009 |
|  |  | | |  |  |  | t = -0.301 | t = -1.980 | t = -1.509 | t = -1.431 |
| *POST＊RPA* |  | | |  |  |  | 0.01 | 0.02 | 0.007 | 0.01 |
|  |  | | |  |  |  | t = 0.421 | t = 1.287 | t = 0.977 | t = 1.016 |
| *LEV* | -0.005 | | | 0.035 | 0.032 | -0.0001 | 0.049 | -0.029 | 0.004 | -0.041 |
|  | t = -0.073 | | | t = 0.531 | t = 1.033 | t = -0.002 | t = 1.099 | t = -0.692 | t = 0.192 | t = -1.618 |
| *OCF* | -0.433\*\*\* | | | -1.208\*\*\* | -0.598\*\*\* | -0.603\*\*\* | -0.532\*\*\* | -0.780\*\*\* | -0.291\*\*\* | -0.491\*\*\* |
|  | t = -3.543 | | | t = -3.876 | t = -4.761 | t = -2.748 | t = -5.455 | t = -4.322 | t = -2.979 | t = -4.095 |
| *MTB* | 0.003 | | | -0.014\*\* | -0.009\*\* | -0.006 | 0.006 | -0.004 | -0.004 | 0.0002 |
|  | t = 0.407 | | | t = -2.353 | t = -2.549 | t = -1.560 | t = 0.868 | t = -0.775 | t = -1.207 | t = 0.063 |
| *MS* | 0.006\*\*\* | | | 0.013\*\*\* | 0.008\*\*\* | 0.006\* | 0.008\*\*\* | 0.006\*\* | 0.004\*\*\* | 0.003 |
|  | t = 3.847 | | | t = 3.219 | t = 4.690 | t = 1.957 | t = 5.734 | t = 2.307 | t = 2.752 | t = 1.437 |
| *INST* | 0.027 | | | 0.032 | 0.024 | 0.011 | 0.004 | -0.009 | -0.001 | -0.009 |
|  | t = 0.485 | | | t = 0.758 | t = 1.290 | t = 0.396 | t = 0.123 | t = -0.403 | t = -0.104 | t = -0.668 |
| *CYCLE* | -0.00002 | | | -0.0003\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | 0.00002\*\* | 0.00001 | 0.00002\*\*\* | 0 |
|  | t = -0.508 | | | t = -5.343 | t = -5.305 | t = -4.568 | t = 2.356 | t = 1.389 | t = 3.036 | t = -0.003 |
| *NOA* | -0.06 | | | 0.004 | -0.036\*\* | 0.045 | -0.002 | 0.043\* | -0.003 | 0.040\*\* |
|  | t = -1.479 | | | t = 0.103 | t = -2.153 | t = 1.578 | t = -0.072 | t = 1.716 | t = -0.243 | t = 2.451 |
| *ZSCORE* | -0.009 | | | -0.002 | 0.001 | -0.002 | -0.008\*\* | -0.008\* | -0.002 | -0.007\*\* |
|  | t = -1.639 | | | t = -0.276 | t = 0.186 | t = -0.504 | t = -2.112 | t = -1.747 | t = -0.782 | t = -2.421 |
| *CL* | -0.072 | | | -0.055 | -0.096\*\*\* | 0.051 | -0.073 | 0.057 | -0.042\* | 0.099\*\*\* |
|  | t = -1.293 | | | t = -0.891 | t = -3.619 | t = 1.243 | t = -1.629 | t = 1.298 | t = -1.915 | t = 3.432 |
| *ADJROA* | 0.521\*\* | | | 0.046 | 0.281\*\* | -0.239 | 0.664\*\*\* | 0.019 | 0.195\* | -0.173 |
|  | t = 2.264 | | | t = 0.146 | t = 2.121 | t = -1.083 | t = 4.826 | t = 0.082 | t = 1.648 | t = -1.107 |
| *ADJROA\_sq* | 1.507\* | | | 3.356\*\*\* | 2.023\*\*\* | 1.577\* | 0.143 | -0.29 | -0.163 | -0.003 |
|  | t = 1.681 | | | t = 2.879 | t = 4.532 | t = 1.912 | t = 0.263 | t = -0.675 | t = -0.682 | t = -0.010 |
| *SIZE* | -0.029\*\* | | | -0.050\*\*\* | -0.027\*\*\* | -0.023\* | -0.040\*\*\* | -0.022 | -0.012\* | -0.01 |
|  | t = -2.216 | | | t = -2.824 | t = -3.825 | t = -1.861 | t = -3.937 | t = -1.637 | t = -1.645 | t = -1.180 |
| *BIG4* | 0.028\*\* | | |  |  |  | 0.039\*\*\* |  |  |  |
|  | t = 2.093 | | |  |  |  | t = 3.485 |  |  |  |
| *ADV* |  | | | -1.120\*\*\* | -0.615\*\*\* | -0.508\*\*\* |  | -0.977\*\*\* | -0.522\*\*\* | -0.477\*\*\* |
|  |  | | | t = -9.334 | t = -10.397 | t = -7.088 |  | t = -12.845 | t = -11.027 | t = -11.172 |
| *RD* |  | | | -0.466\*\*\* | -0.271\*\*\* | -0.193\*\*\* |  | -0.269\*\*\* | -0.180\*\*\* | -0.086\*\* |
|  |  | | | t = -4.215 | t = -5.417 | t = -2.630 |  | t = -3.903 | t = -4.363 | t = -1.967 |
| *IMR* | -0.017 | | | 0.051\*\* | 0.037\*\*\* | 0.015 | -0.017 | 0.064\*\*\* | 0.046\*\*\* | 0.021\* |
|  | t = -0.771 | | | t = 2.407 | t = 3.880 | t = 1.084 | t = -0.894 | t = 3.528 | t = 4.524 | t = 1.908 |
| Constant | Included | | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | | Yes | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | 492 | | 492 | 492 | 492 | 984 | 984 | 984 | 984 |
| Adjusted R2 | 0.085 | | | 0.471 | 0.5 | 0.419 | 0.121 | 0.454 | 0.404 | 0.451 |
| F Statistic | 3.669\*\*\* | | | 25.239\*\*\* | 28.266\*\*\* | 20.654\*\*\* | 8.135\*\*\* | 41.868\*\*\* | 34.371\*\*\* | 41.370\*\*\* |
| F-test |  | | |  |  |  | 0.050\*\* | 0.032\*\* | 0.016\*\* | 0.016\* |
|  | | |  |  |  | t = 2.338 | t = 2.528 | t = 2.504 | t = 1.933 |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in Appendix B. | | | | | | | | | | |

# Table 9 Comparison between automation technologies: Pre- vs. Post-Implementation for Within-Treatment Group and Matched Analysis

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Within Treatment-Group Analysis | | | | | | Matched Results Analysis | | | |
|  | | | | *Dependent variable:* | | | | | | | |
|  | | *ABSDA* | | | *RM* | *ABEXP* | *ABPROD* | *ABSDA* | *RM* | *ABEXP* | *ABPROD* |
| *predictRM* | | -0.050 | | |  |  |  | -0.041\* |  |  |  |
|  | | t = -1.482 | | |  |  |  | t = -1.722 |  |  |  |
|  | |  | | |  |  |  |  |  |  |  |
| *predictAM* | |  | | | -10.029\*\*\* | -5.725\*\*\* | -4.392\*\* |  | -15.679\* | -9.447\*\* | -6.886 |
|  |  | | | | t = -3.447 | t = -5.075 | t = -2.071 |  | t = -1.913 | t = -2.130 | t = -1.266 |
|  |  | | | |  |  |  |  |  |  |  |
| *POST* | 0.012\*\* | | | | 0.146\*\*\* | 0.079\*\*\* | 0.069\*\*\* | -0.009\* | -0.123\* | -0.072\* | -0.054 |
|  | t = 2.304 | | | | t = 4.154 | t = 5.672 | t = 2.740 | t = -1.759 | t = -1.671 | t = -1.790 | t = -1.115 |
|  |  | | | |  |  |  |  |  |  |  |
| *RPA* |  | | | |  |  |  | -0.006 | -0.098\*\* | -0.054\*\* | -0.044 |
|  |  | | | |  |  |  | t = -1.524 | t = -2.162 | t = -2.219 | t = -1.465 |
|  |  | | | |  |  |  |  |  |  |  |
| *POST＊RPA* |  | | | |  |  |  | 0.018\*\*\* | 0.281\*\* | 0.164\*\* | 0.126 |
|  |  | | | |  |  |  | t = 3.122 | t = 2.012 | t = 2.172 | t = 1.355 |
|  |  | | | |  |  |  |  |  |  |  |
| *AIPOST* | 0.09 | | | | 0.066\* | 0.046\*\*\* | 0.022 | 0.004 | 0.045 | 0.037 | 0.014 |
|  | t = 0.928 | | | | t = 1.736 | t = 3.064 | t = 0.818 | t = 0.546 | t = 0.794 | t = 1.220 | t = 0.362 |
|  |  | | | |  |  |  |  |  |  |  |
| *MLPOST* | -0.007 | | | | 0.001 | -0.064\*\*\* | 0.058 | -0.002 | -0.009 | -0.034 | 0.022 |
|  | t = -0.518 | | | | t = 0.020 | t = -3.726 | t = 0.911 | t = -0.181 | t = -0.146 | t = -1.406 | t = 0.486 |
|  |  | | | |  |  |  |  |  |  |  |
| *LEV* | -0.016 | | | | -0.210\*\* | -0.099\*\* | -0.114\* | 0.02 | 0.231 | 0.166\*\* | 0.069 |
|  | t = -0.730 | | | | t = -2.126 | t = -2.265 | t = -1.771 | t = 1.377 | t = 1.531 | t = 2.043 | t = 0.685 |
|  |  | | | |  |  |  |  |  |  |  |
| *OCF* | -0.028 | | | | -0.438\*\*\* | -0.144\*\*\* | -0.284\*\*\* | -0.098\*\*\* | -1.723\*\* | -0.878\*\* | -0.900\* |
|  | t = -0.636 | | | | t = -5.001 | t = -3.607 | t = -4.590 | t = -2.979 | t = -2.357 | t = -2.213 | t = -1.853 |
|  |  | | | |  |  |  |  |  |  |  |
| *MTB* | 0.006\*\*\* | | | | 0.061\*\*\* | 0.033\*\*\* | 0.027\* | 0.004\*\* | 0.062 | 0.036\* | 0.029 |
|  | t = 2.887 | | | | t = 2.714 | t = 3.731 | t = 1.666 | t = 2.146 | t = 1.558 | t = 1.677 | t = 1.101 |
|  |  | | | |  |  |  |  |  |  |  |
| *MS* | -0.0001 | | | | 0.002\*\* | 0.001\*\* | 0.001 | -0.0001 | -0.0002 | 0.0002 | -0.0003 |
|  | t = -0.208 | | | | t = 2.344 | t = 2.553 | t = 1.633 | t = -0.524 | t = -0.309 | t = 0.583 | t = -0.739 |
|  |  | | | |  |  |  |  |  |  |  |
| *INST* | 0.009 | | | | 0.102\*\* | 0.066\*\*\* | 0.039 | 0.0002 | 0.007 | 0.009 | -0.004 |
|  | t = 0.762 | | | | t = 2.420 | t = 3.461 | t = 1.376 | t = 0.018 | t = 0.293 | t = 0.789 | t = -0.275 |
|  |  | | | |  |  |  |  |  |  |  |
| *CYCLE* | -0.00002 | | | | -0.0003\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | -0.00001\*\* | -0.0001\*\* | -0.00005\* | -0.00005 |
|  | t = -1.255 | | | | t = -4.960 | t = -4.916 | t = -4.175 | t = -2.038 | t = -1.961 | t = -1.832 | t = -1.518 |
|  |  | | | |  |  |  |  |  |  |  |
| *NOA* | 0.018 | | | | 0.255\*\*\* | 0.106\*\*\* | 0.158\*\*\* | 0.018\* | 0.281\*\* | 0.138\*\* | 0.146\* |
|  | t = 1.488 | | | | t = 4.550 | t = 4.496 | t = 3.889 | t = 1.914 | t = 2.481 | t = 2.245 | t = 1.945 |
|  |  | | | |  |  |  |  |  |  |  |
| *ZSCORE* | -0.002 | | | | -0.009 | -0.002 | -0.006 | -0.002\* | -0.027\* | -0.014 | -0.015 |
|  | t = -1.297 | | | | t = -1.116 | t = -0.728 | t = -1.121 | t = -1.763 | t = -1.730 | t = -1.591 | t = -1.479 |
|  |  | | | |  |  |  |  |  |  |  |
| *CL* | 0.055\*\*\* | | | | 0.632\*\*\* | 0.290\*\*\* | 0.355\*\*\* | 0.027\*\* | 0.499\*\* | 0.216\*\* | 0.297\*\* |
|  | t = 2.834 | | | | t = 3.459 | t = 3.940 | t = 2.745 | t = 1.978 | t = 2.504 | t = 2.026 | t = 2.246 |
|  |  | | | |  |  |  |  |  |  |  |
| *ADJROA* | -0.013 | | | | -0.764\*\*\* | -0.190\*\*\* | -0.581\*\*\* | 0.102\*\* | 1.217 | 0.938\* | 0.343 |
|  | t = -0.197 | | | | t = -6.518 | t = -3.535 | t = -7.017 | t = 2.530 | t = 1.310 | t = 1.891 | t = 0.554 |
|  |  | | | |  |  |  |  |  |  |  |
| *ADJROA\_sq* | 1.177\*\*\* | | | | 12.078\*\*\* | 7.012\*\*\* | 5.411\*\* | 0.887\*\*\* | 14.122\* | 8.501\*\* | 6.355 |
|  | t = 3.501 | | | | t = 3.493 | t = 5.284 | t = 2.140 | t = 4.862 | t = 1.830 | t = 2.012 | t = 1.247 |
|  |  | | | |  |  |  |  |  |  |  |
| *SIZE* | -0.005\*\* | | | | -0.054\*\*\* | -0.030\*\*\* | -0.024\*\* | -0.004\*\*\* | -0.061 | -0.036\* | -0.027 |
|  | t = -2.501 | | | | t = -3.215 | t = -4.467 | t = -2.007 | t = -2.660 | t = -1.635 | t = -1.799 | t = -1.089 |
|  |  | | | |  |  |  |  |  |  |  |
| *BIG4* | 0.006 | | | |  |  |  | 0.002 |  |  |  |
|  | t = 0.834 | | | |  |  |  | t = 0.316 |  |  |  |
|  |  | | | |  |  |  |  |  |  |  |
| *ADV* |  | | | | -1.111\*\*\* | -0.614\*\*\* | -0.504\*\*\* |  | -0.923\*\*\* | -0.499\*\*\* | -0.451\*\*\* |
|  |  | | | | t = -9.931 | t = -10.749 | t = -7.493 |  | t = -12.787 | t = -10.878 | t = -10.931 |
|  |  | | | |  |  |  |  |  |  |  |
| *RD* |  | | | | -0.171\* | -0.085 | -0.089\* |  | -0.144\*\* | -0.091\*\* | -0.05 |
|  |  | | | | t = -1.895 | t = -1.624 | t = -1.777 |  | t = -2.423 | t = -2.305 | t = -1.519 |
|  |  | | | |  |  |  |  |  |  |  |
| *IMR* | -0.002 | | | | 0.054\*\*\* | 0.035\*\*\* | 0.021 | -0.001 | 0.062\*\*\* | 0.045\*\*\* | 0.022\*\* |
|  | t = -0.207 | | | | t = 2.607 | t = 3.586 | t = 1.611 | t = -0.168 | t = 3.535 | t = 4.466 | t = 2.069 |
| Constant | Included | | | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | Yes | | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | | 516 | | 516 | 516 | 516 | 1,032 | 1,032 | 1,032 | 1,032 |
| Adjusted R2 | 0.172 | | | | 0.454 | 0.460 | 0.420 | 0.144 | 0.436 | 0.378 | 0.440 |
| F Statistic | 6.611\*\*\* | | | | 22.439\*\*\* | 22.925\*\*\* | 19.658\*\*\* | 9.288\*\*\* | 37.215\*\*\* | 29.442\*\*\* | 37.870\*\*\* |
| F-test |  | | | |  |  |  | 0.009\* | 0.159\*\* | 0.092\*\* | 0.072 |
|  | | | |  |  |  | t = 1.804 | t = 2.051 | t = 2.323 | t = 1.427 |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in Appendix B. | | | | | | | | | | | |

# Table 10 Comparison between automation technologies: Pre- vs. Post-Implementation for Within-Treatment Group and Matched Analysis by Using Alternative AM Proxy

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Within Treatment-Group Analysis | | | | | | Matched Results Analysis | | | |
|  | | | *Dependent variable:* | | | | | | | |
|  | *DAQ* | | | *RM* | *ABEXP* | *ABPROD* | *DAQ* | *RM* | *ABEXP* | *ABPROD* |
| *predictRM* | 0.097 | | |  |  |  | -0.078 |  |  |  |
|  | t = 1.129 | | |  |  |  | t = -1.351 |  |  |  |
|  |  | | |  |  |  |  |  |  |  |
| *predictAM* |  | | | -2.310\*\*\* | -1.315\*\*\* | -1.012\*\* |  | -0.805\*\* | -0.484\*\* | -0.345 |
|  |  | | | t = -3.162 | t = -4.469 | t = -1.994 |  | t = -2.169 | t = -2.418 | t = -1.406 |
|  |  | | |  |  |  |  |  |  |  |
| *POST* | 0.050\* | | | 0.149\*\*\* | 0.081\*\*\* | 0.069\*\* | 0.041\* | 0.047\*\* | 0.031\*\*\* | 0.020 |
|  | t = 1.952 | | | t = 3.753 | t = 4.998 | t = 2.546 | t = 1.802 | t = 2.533 | t = 3.077 | t = 1.628 |
|  |  | | |  |  |  |  |  |  |  |
| *RPA* |  | | |  |  |  | -0.006 | -0.021\*\* | -0.009 | -0.009 |
|  |  | | |  |  |  | t = -0.346 | t = -1.960 | t = -1.516 | t = -1.390 |
|  |  | | |  |  |  |  |  |  |  |
| *POST＊RPA* |  | | |  |  |  | 0.008 | 0.02 | 0.007 | 0.011 |
|  |  | | |  |  |  | t = 0.345 | t = 1.358 | t = 1.001 | t = 1.093 |
|  |  | | |  |  |  |  |  |  |  |
| *AIPOST* | 0.039\*\* | | | 0.027 | 0.026\*\* | 0.003 | 0.043\*\*\* | -0.017 | 0.001 | -0.015 |
|  | t = 2.247 | | | t = 0.953 | t = 2.230 | t = 0.175 | t = 3.086 | t = -0.769 | t = 0.099 | t = -1.042 |
|  |  | | |  |  |  |  |  |  |  |
| *MLPOST* | -0.06 | | | 0.028 | -0.054\*\*\* | 0.074 | 0.002 | 0.04 | -0.006 | 0.046 |
|  | t = -1.544 | | | t = 0.399 | t = -3.341 | t = 1.221 | t = 0.070 | t = 0.694 | t = -0.330 | t = 1.082 |
|  |  | | |  |  |  |  |  |  |  |
| *LEV* | -0.007 | | | 0.04 | 0.034 | 0.004 | 0.05 | -0.032 | 0.006 | -0.045\* |
|  | t = -0.116 | | | t = 0.624 | t = 1.086 | t = 0.101 | t = 1.147 | t = -0.770 | t = 0.267 | t = -1.775 |
|  |  | | |  |  |  |  |  |  |  |
| *OCF* | -0.420\*\*\* | | | -1.263\*\*\* | -0.606\*\*\* | -0.650\*\*\* | -0.518\*\*\* | -0.769\*\*\* | -0.288\*\*\* | -0.486\*\*\* |
|  | t = -3.440 | | | t = -3.919 | t = -4.553 | t = -2.915 | t = -5.405 | t = -3.983 | t = -2.745 | t = -3.791 |
|  |  | | |  |  |  |  |  |  |  |
| *MTB* | 0.004 | | | -0.013\*\* | -0.008\*\* | -0.005 | 0.007 | -0.004 | -0.004 | -0.0001 |
|  | t = 0.503 | | | t = -2.216 | t = -2.489 | t = -1.427 | t = 1.059 | t = -0.808 | t = -1.156 | t = -0.029 |
|  |  | | |  |  |  |  |  |  |  |
| *MS* | 0.006\*\*\* | | | 0.014\*\*\* | 0.008\*\*\* | 0.006\*\* | 0.007\*\*\* | 0.006\*\* | 0.004\*\* | 0.002 |
|  | t = 3.788 | | | t = 3.312 | t = 4.572 | t = 2.131 | t = 5.681 | t = 2.088 | t = 2.508 | t = 1.304 |
|  |  | | |  |  |  |  |  |  |  |
| *INST* | 0.022 | | | 0.036 | 0.023 | 0.016 | 0.002 | -0.007 | -0.001 | -0.008 |
|  | t = 0.404 | | | t = 0.892 | t = 1.238 | t = 0.615 | t = 0.057 | t = -0.311 | t = -0.062 | t = -0.565 |
|  |  | | |  |  |  |  |  |  |  |
| *CYCLE* | -0.0001 | | | -0.0003\*\*\* | -0.0001\*\*\* | -0.0002\*\*\* | 0.00002\*\* | 0.00001 | 0.00002\*\*\* | 0 |
|  | t = -1.248 | | | t = -4.473 | t = -4.858 | t = -3.632 | t = 2.371 | t = 1.312 | t = 2.868 | t = 0.008 |
|  |  | | |  |  |  |  |  |  |  |
| *NOA* | -0.053 | | | 0.007 | -0.033\*\* | 0.046\* | 0.001 | 0.044\* | -0.003 | 0.041\*\* |
|  | t = -1.357 | | | t = 0.181 | t = -2.047 | t = 1.664 | t = 0.020 | t = 1.755 | t = -0.208 | t = 2.494 |
|  |  | | |  |  |  |  |  |  |  |
| *ZSCORE* | -0.009\* | | | -0.003 | 0.00003 | -0.003 | -0.009\*\* | -0.008 | -0.002 | -0.007\*\* |
|  | t = -1.712 | | | t = -0.450 | t = 0.009 | t = -0.666 | t = -2.168 | t = -1.641 | t = -0.742 | t = -2.291 |
|  |  | | |  |  |  |  |  |  |  |
| *CL* | -0.073 | | | -0.058 | -0.098\*\*\* | 0.05 | -0.073 | 0.06 | -0.042\* | 0.102\*\*\* |
|  | t = -1.312 | | | t = -0.938 | t = -3.691 | t = 1.206 | t = -1.630 | t = 1.350 | t = -1.886 | t = 3.459 |
|  |  | | |  |  |  |  |  |  |  |
| *ADJROA* | 0.525\*\* | | | 0.103 | 0.305\*\* | -0.205 | 0.659\*\*\* | 0.01 | 0.198 | -0.181 |
|  | t = 2.298 | | | t = 0.310 | t = 2.162 | t = -0.893 | t = 4.827 | t = 0.038 | t = 1.514 | t = -1.058 |
|  |  | | |  |  |  |  |  |  |  |
| *ADJROA\_sq* | 1.458\* | | | 3.394\*\*\* | 2.058\*\*\* | 1.584\* | 0.091 | -0.336 | -0.173 | -0.041 |
|  | t = 1.648 | | | t = 2.893 | t = 4.517 | t = 1.927 | t = 0.168 | t = -0.804 | t = -0.735 | t = -0.143 |
|  |  | | |  |  |  |  |  |  |  |
| *SIZE* | -0.029\*\* | | | -0.053\*\*\* | -0.028\*\*\* | -0.025\* | -0.041\*\*\* | -0.021 | -0.012 | -0.009 |
|  | t = -2.245 | | | t = -2.846 | t = -3.746 | t = -1.926 | t = -3.991 | t = -1.383 | t = -1.461 | t = -0.964 |
|  |  | | |  |  |  |  |  |  |  |
| *BIG4* | 0.026\* | | |  |  |  | 0.035\*\*\* |  |  |  |
|  | t = 1.917 | | |  |  |  | t = 3.136 |  |  |  |
|  |  | | |  |  |  |  |  |  |  |
| *ADV* |  | | | -1.117\*\*\* | -0.614\*\*\* | -0.507\*\*\* |  | -0.972\*\*\* | -0.520\*\*\* | -0.475\*\*\* |
|  |  | | | t = -9.429 | t = -10.412 | t = -7.196 |  | t = -12.877 | t = -11.007 | t = -11.219 |
|  |  | | |  |  |  |  |  |  |  |
| *RD* |  | | | -0.434\*\*\* | -0.266\*\*\* | -0.168\*\* |  | -0.247\*\*\* | -0.172\*\*\* | -0.071 |
|  |  | | | t = -3.967 | t = -5.279 | t = -2.339 |  | t = -3.523 | t = -4.104 | t = -1.629 |
|  |  | | |  |  |  |  |  |  |  |
| *IMR* | -0.02 | | | 0.056\*\*\* | 0.037\*\*\* | 0.02 | -0.017 | 0.064\*\*\* | 0.045\*\*\* | 0.022\*\* |
|  | t = -0.882 | | | t = 2.680 | t = 3.876 | t = 1.466 | t = -0.882 | t = 3.547 | t = 4.459 | t = 1.985 |
| Constant | Included | | | Included | Included | Included | Included | Included | Included | Included |
| Year Effects | Yes | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | | 492 | | 492 | 492 | 492 | 984 | 984 | 984 | 984 |
| Adjusted R2 | 0.084 | | | 0.481 | 0.502 | 0.436 | 0.124 | 0.462 | 0.411 | 0.458 |
| F Statistic | 3.355\*\*\* | | | 23.753\*\*\* | 25.780\*\*\* | 20.007\*\*\* | 7.605\*\*\* | 39.429\*\*\* | 32.164\*\*\* | 38.717\*\*\* |
| F-test |  | | |  |  |  | 0.048\*\* | 0.034\*\*\* | 0.017\*\*\* | 0.016\*\* |
|  | | |  |  |  | t = 2.242 | t = 2.638 | t = 2.644 | t = 1.980 |
| NOTE: \*, \*\*, \*\*\* 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 to robust standard errors, as proposed by White (1980), to account for potential heteroskedasticity. The definitions of all variables can be found in 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.

# 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 |
| *AMres* | Residuals value estimated by regressing AM on the variables other than RM in AM equation |
| *RMres* | Residuals value estimated by regressing RM on the variables other than AM in RM equations |
| *predictAM* | Fitted value estimated by regressing AM on the variables other than RM in AM equation |
| *predictRM* | Fitted value estimated by regressing RM on the variables other than AM in RM equations |
| *POST* | An indicator variable equal to 1 for the observation is during or post RPA-implementation period, 0 otherwise. (For each firm in control group, this indicator will be 1 during or post RPA-implementation period that corresponding to the treatment firm with which it is matched, 0 otherwise. |
| *AIPOST* | An indicator variable equal to 1 for the observation is during or post AI -implementation period, 0 otherwise. |
| *MLPOST* | An indicator variable equal to 1 for the observation is during or post ML -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 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 |
| *IMR* | The inverse mills ratio is estimated as q(z)/p(z), where z represents the fitted value of the probit regression function (refer to Appendix C). Here, q is the density function of the standard normal distribution, and p is the cumulative density function of the standard normal distribution. |

# Appendix C First-Step Choice Model of Heckman Procedures

To construct the first-step equation of the choice model for RPA adoption, we incorporate the determinants mentioned in Dorantes et al. (2013)’s study into our probit model, which discuss the factors influencing a firm's decision to implement enterprise systems. We compare RPA-adopted firms with all non-adopted firms within the same TSE code from 2017 to 2022:

where is an indicator variable equal to 1 for the observation of firm j that had implemented RPA in year t , 0 otherwise; represents the natural logarithm of total assets at beginning of the year t of firm j; is calculated as total liabilities divided by total assets at the beginning of the year t of firm j; is the capital intensity defined as net sales divided by total assets of the beginning year t of firm j; represents market-to-book value ratio at the beginning of the year t if firm j; is set to 1 if income from continuing operations at the beginning year t of firm j is negative; is set to 1 if firm j paid cash dividends in year t-1, 0 otherwise; is set to 1 if firm j made foreign transaction in year t-1 ; is set to 1 if firm j had merge and acquisition activity in year t-1; is defined as R&D intensity calculated from R&D expenses divided by total assets of the beginning year t of firm j; is defined as advertising intensity calculated from advertising expenses divided by total assets of the beginning year t of firm j; represents the natural logarithm of the number of analysts issuing financial forecasting in year t-1 for j firm plus 1.

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), etc. [↑](#footnote-ref-1)
2. Article 23 of the Regulations Governing Information to be Published in Annual Reports of Public Companies (Taiwan) 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-2)
3. 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-3)
4. The anecdotal evidence (news articles in Taiwanese Mandarin) also indicated that Taiwanese companies implemented RPA starting from 2017. [↑](#footnote-ref-4)
5. 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 from Paredes and Wheatley (2017), 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-5)
6. 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-6)
7. 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-7)
8. We suppose that implementing RPA might share similar determinants with implementing enterprise systems for their core objectives like improving operational efficiency and data accuracy as previous section mentioned. [↑](#footnote-ref-8)
9. See Appendix C for detailed calculation of Heckman first-step model [↑](#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)