ABSTRACT

This study examines stock market data to assess shareholders’ responses to 210 audit data analytics (ADA) announcements from the years 2006 to 2018. Because the benefits and costs of ADA are typically intangible, hidden, and long-term oriented, no studies have empirically validated ADA’s associated risks and returns. We analyze the abnormal return of each announcing firm’s stock within a 3-day period around the date when the firm made an announcement, capturing potential improvements shareholder value. We find that shareholders are favorable about the prospective returns of client firms who adopt ADA selectively, as those firms can easily coordinate and manage ADA implementation. Our findings may help researchers and practitioners understand complex ADA adoption and related issues, while also helping firms maximize the market impact of their ADA adoption strategies.

Key Words: Audit Data Analytics (ADA); market reaction; asset specificity; selective

Data Availability: Data are available from the public sources cited in the text.
Audit data analytics (ADA), the science of discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter (AICPA 2015), has been recognized by accounting professionals as increasingly valuable and able to enhance overall firm performance. The business analytics market is expected to grow from $130 billion in 2016 to more than $203 billion in 2020 (Press 2017). Acknowledged potential benefits of ADA adoption include reduced risks and costs, improved system quality and transparency, the ability to focus on core competencies, and access to new technologies. Thus, issues pertaining to the potential returns associated with ADA have become subjects of research, spawning several studies that explore the outcomes of ADA (Perols, Bowen, Zimmermann, and Samba 2017; Rose, Rose, Sanderson, and Thibodeau 2017; Li, Dai, Gershberg, and Vasarhelyi 2018).

Despite increased practitioner and researcher interest in understanding the performance effects of ADA adoption, no scholarly research has yet focused on shareholder value effects. Market measures such as stock market returns and Tobin’s q for emerging new technologies (e.g., IT investments, e-commerce, ERP, etc.) have proven to be more reliable measures of a firm’s future performance (since accounting-based measures do not attempt to measure the future) as they tend to be forward-looking, risk-adjusted, and less susceptible to accounting rule changes (Bharadwaj, Bharadwaj, and Konsynski 1999; Chatterjee, Richardson, and Zmud 2001; Dehning, Richardson, and Zmud 2003). Specifically, stock price changes are expected to reflect the discounted value of all future cash flows of a firm, and to represent the collective perceptions of a large group of shareholders, reflecting a more accurate valuation. Prior commentary papers only discuss related issues, such as the general benefits and hurdles of ADA adoption (e.g., Brown-
Liburd and Vasarhelyi 2015; Cao, Chychyla, and Stewart 2015), or the value of advanced ADA techniques using a design science research approach (Jans, Lybaert, and Vanhoof 2010; Perols 2011; Zhou and Kapoor 2011; Jans, Alles, and Vasarhelyi 2014; Perols et al. 2017) or by surveying audit practitioners (Li et al. 2018).

The goal of this study, therefore, is to assess the impact of ADA adoption on the shareholder value of a firm. In this study, an “event” is defined as the public announcement of an ADA adoption contract made by a firm traded on a major US stock exchange. The sample employed in this study consists of all 210 ADA adoptions publicly announced from 2006 to 2018. For these events, we analyze the abnormal return of each announcing firm’s stock within a 3-day time period around the event date (when the firm made an ADA announcement), capturing potential improvements in shareholder value. In addition to examining the market’s reaction to ADA adoptions in general, we specifically seek to answer the following: To what extent does the sophistication of the ADA functions (e.g., asset specificity) influence the market’s reaction to ADA announcements? How does the scope of adoption of ADA functions, either selective or total, affect the market’s perception of ADA announcements?

This study has implications for accounting and information systems (AIS) researchers. To our knowledge, we are the first to study all publicly available ADA announcements, covering the full scope of industries and ADA functions from 2006 to 2018. Prior studies often demonstrate or predict if and how ADA is or will be adopted by surveying practitioners or conducting literature reviews (e.g., Cao et al. 2015; Li et al. 2018). By extensively collecting and validating actual ADA announcements, this study demonstrates the expected outcomes of ADA and assesses ways to maximize returns. This might provide useful insights to not only researchers but also practitioners and regulators who are interested ADA adoption. Second, this study contributes to the literature
by studying market reaction (Chatterjee et al. 2001; Campbell, Gordon, Loeb, and Zhou 2003; Dehning et al. 2003; Dehning, Richardson, Urbaczewski, and Wells 2004; Ettredge and Richardson 2003; Chai, Kim, and Rao 2011; Goldstein, Chernobai, and Benaroch 2011, ) to specific characteristics that are publicly announced including the degree of ADA sophistication and the level of control retained by the client. Our findings suggest that shareholders are more favorable about the prospective returns of client firms which adopt ADA selectively due to easily coordinated and manage ADA implementation. This should help researchers understand complex ADA adoptions, and help firms maximize the market impact of their ADA adoption strategies.

The findings of this study can help practitioners understand what types of ADA adoption will likely enhance (or diminish) the market value of their firms in light of shareholders’ perceptions of the returns generated by these contracts. The findings can help practitioners avoid negative market reactions to ADA adoption that are perceived as risky (e.g., high sophistication and broad scope). Our findings may also have policy implications for the accounting profession. We show that disclosure of ADA announcements provides value-relevant, forward-looking information to the capital market. Such information is currently not available in traditional financial reports. Thus, by including non-financial information concerning management strategies, financial reports have the potential to decrease information asymmetry and increase users’ ability to assess the amount, timing, and certainty of cash flows.

This paper is structured into five sections, of which this introduction is the first. The second section reviews of existing research and develops research hypotheses. The third outlines the methods employed in this study. The fourth indicates the results of the statistical analysis of the ADA adoption announcement impact on firms’ stock prices. The final section includes a summary with conclusions and recommendations for future research.
II. INSTITUTIONAL BACKGROUND AND HYPOTHESES DEVELOPMENT

ADA Background

Audit data analytics (ADA), the science of discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter (AICPA 2015), has been recognized by accounting professionals as increasingly valuable and able to enhance overall firm performance. For example, by adopting a cloud-based risk management platform with dashboard and ADA functions from ACL, CHC Helicopter, one of the largest helicopter airline companies in the world, increased productivity by 15 percent (ACL 2013). KPMG also indicates that the increased revenue for fiscal year 2017 audit service by 3.1% due to its investment in KPMG Clara, an automated, agile, intelligent and scalable ADA platform (KPMG 2017). In 2012, predictive analytics algorithms allowed Walmart to reduce overstock, thereby increasing 10-15 percent in online sales (Grover, Chiang, Liang, and Zhang 2018). The global accounting software market size has been increasingly valued at $5.7 billion in 2017, and it is expected to reach $11.8 billion by 2026 (Transparency Market Research 2018).

ADA also plays a vital role in accounting practices. For example, Deloitte’s 2018 Global Chief Audit Executive Survey reports that 55 percent of respondents use basic ADA, and 21 respondents utilize advanced ADA such as statistical analysis, data mining, and predictive analytics in internal audit, which enhance business processes and improve firm performance (Deloitte 2018). Because of the ability to accurately identify risks, Ernst & Young notes that 90% of their 2018 audit engagements of US public companies used ADA, including risk assessments and tests of details, resulting in enhanced audit quality and firm performance (EY 2018). Overall, the use of ADA brings significant benefits and changes to not only the accounting profession, but also to firms’ market value.
Prior Research on ADA

AIS research has adopted the ADA phenomenon as an area of research interest since Stringer (1975) proposed statistical methods for analytical review. ADA enables population-level analysis without increasing firm costs. To mitigate sampling risks\(^1\), ADA examines the entire population of transactions in a timely fashion, effectively identifying anomalies (Cao et al. 2015; Earley 2015; Murphy and Tysiac 2015; Harris 2017) and reducing audit costs. Next, by automating the financial statement audit process (Krahel and Titera 2015) and identifying risky areas, firms save time and enhance efficiency (Cao et al. 2015; Appelbaum, Kogan, and Vasarhelyi 2018). For example, by utilizing ADA, firms can precisely set the expected value of account balances or transactions by accessing a variety of sources of information, such as customer satisfaction rates, and by deploying advanced analytical models such as machine learning and data mining (Appelbaum, Kogan, and Vasarhelyi 2017).

Indeed, ADA predicts and captures the causes of failures, barriers, and anomalies within business processes in order to minimize operational costs (Grover et al. 2018). For instance, ADA utilizes event log data containing individual transactions within a firm’s business processes to monitor process flows in detail and in real time (Caron, Vanthienen, and Baesens 2013; Maggi, Di Francescomarino, Dumas, and Ghidini 2014). Advanced ADA techniques such as data mining (Bhattacharyya, Jha, Tharakunnel, and Westland 2011; Jans et al. 2010; Jans, Van Der Werf, Lybaert, and Vanhoof 2011) and textual analysis (Holton 2009; Wang and Xu 2018) can analyze complex tasks by identifying the rarity of errors (Perols et al. 2017) and internal control deficiencies (Jans et al. 2014) and predicting fraud incidences (Schneider, Dai, Janvrin, Ajayi, and Raschke 2015).

\(^1\) Sampling techniques are often used as a test of controls and a test of details, but they have inherent limitations since a subset of the population cannot fully represent the entire population.
ADA enhances the value not only of products and services, but also of relationships with customers and suppliers, thereby reducing operating risks and enhancing competitive advantage. To maximize payoffs, ADA incorporates other innovative technologies, such as blockchain, radio-frequency identification (RFID), and GPS, which facilitates process automation and transparency, improving firm performance \(^2\). Real-time monitoring of information including proactive notification and alerts can prevent unfavorable and unexpected events and allow a firm to respond quickly and effectively to the unexpected (Wang, Kung, and Byrd 2018). Additionally, ADA allows a firm to develop real-time solutions for anomalies or unusual trends of the provided service or products, and to conduct advanced sentiment analyses and thereby enhance customer relationships (Hu, Bose, Koh, and Liu 2012). Third, ADA can link a firm’s internal systems with external entities such as customers and suppliers by facilitating the exchange of key performance indicators (KPIs) for a firm’s business processes. For instance, ADA allows retail firms such as Walmart to identify a product’s origin, time of delivery, and other significant information to identify possible operating inefficiencies (Yiannas 2018). Overall empirical and anecdotal evidence in this medium could positively influence shareholders’ perceptions about ADA.

Since ADA is considered an emerging accounting technology, prior studies adopt a limited scope of research approaches such as commentary papers discussing general benefits and hurdles of ADA adoption (e.g., Alles and Gray 2016), or demonstrations of the value of advanced ADA techniques utilizing a design science research approach (Jans et al. 2010; Perols 2011; Zhou and Kapoor 2011; Jans et al. 2014; Perols et al. 2017) or surveying audit practitioners (Li et al. 2018).

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\(^2\) ADA with blockchain technology, a decentralized digital ledger, which allows to record all transactions between a peer and a peer, is considered to enhance audit efficacy and effectiveness in that this technology automatically records and stores transactional information in real-time basis and this information is difficult to be tempered (Dai and Vasarhelyi 2017). With RFID and GPS technology, ADA enable auditors to trace inventory relevant transactions automatically and precisely (Krahel and Titera 2015; Yoon, Hoogduin, and Zhang 2015).
ADA can access and analyze a large volume and variety of data in a timely manner, allowing firms to acquire and share needed information concerning their customers, business, market, and other external circumstances, resulting in enhanced overall firm performance; however, we are currently unaware of any study that has identified common market-based success factors in an ADA context.

Research Objective

The purpose of this study is to investigate the impact of ADA adoption on the shareholder value of a firm. If an announced ADA adoption contains new information, it should cause financial markets to revalue the firm. In this event study, the stock market’s response to events with value-relevant information is examined. Stock price is an unbiased estimate of future return on ADA adoptions. The semi-strong form of the efficient market hypothesis asserts that a firm’s stock market price fully reflects all publicly available information (Fama, Fisher, Jensen, and Roll 1969). Consequently, if an event has information content, or is an information signal that alters shareholders’ beliefs (Watts and Zimmerman 1986; Ziebart 1990), an abnormal stock price return often will be observed.

The impact of announcements of IT projects on stock price is computed using event-study methods commonly employed in the accounting and finance literature, including AIS research studies involving IT infrastructure announcements (Chatterjee et al. 2001; Im, Dow, and Grover 2001), investments in innovative IT applications (Dehning et al. 2003; Yang, Lim, Oh, Animesh, and Pinsonneault 2012), and e-commerce-related investments (Subramani and Walden 2001). ADA adoption carries both costs and benefits like other IT investments, such as IT infrastructure announcements (Chatterjee et al. 2002; Im et al. 2001), investments in innovative IT applications (Dehning et al. 2003), e-commerce-related investments (Subramani and Walden 2001), and ERP (Ranganathan and Brown 2006). Evidence indicates that these activities create positive, significant
shareholder value for firms. Event studies afford researchers the opportunity to measure stock price changes that can serve as estimates for the effectiveness of the firm in foreseeing and rapidly adapting to its changing environment (Brynjolfsson and Yang 1996).

Also, like other IT investments, the costs and benefits of ADA adoption are mostly hidden and unobservable. Shareholder response to ADA adoption may serve as a long-term measure of the net benefit of ADA adoption, although we cannot measure the costs and benefits separately. Shareholders positively respond when they believe that the benefits are greater than the costs (or the net benefit is greater than zero); otherwise, share price suffers. Cumulative abnormal returns (CAR) around the ADA announcement date may therefore measure market perceptions of the net benefits of ADA adoption. The ADA announcements in our sample do not specify implementation timing, so the effect of ADA on business performance cannot be easily measured.3

In this study, we argue that if rational shareholders value both tangible and intangible aspects of ADA, a change in stock price should approximate the contribution of the ADA adoption to the firm’s value. For instance, when firms announce that they are implementing ADA, the announcement could implicitly signal that they would acquire future analytical capabilities for making sound audit judgments (Brown-Liburd, Issa, and Lombardi 2015) by enhancing monitoring capacities and understanding of business processes (PwC 2017). Therefore, we expect that firms that implement ADA experience appreciation in their market value and profitability, which could shape shareholders’ positive perception about ADA. In particular, we examine specific factors (e.g., the degree of ADA sophistication and control structure) associated with

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3 Similar to other AIS events (Chatterjee et al. 2002; Im et al. 2001; Dehning et al. 2003; Subramani and Walden 2001; Ranganathan and Brown 2006), we cannot specify when the ADA was completely implemented. However, following a recommendation from prior research (Yang et al. 2012), we have carefully re-validated ADA announcements with a related search for certain key words (e.g., launch, implement) to confirm that the announcements in our sample did relate to actual ADA implementation. More details are explained in the sample selection section.
successful ADA adoption – a topic that has drawn significant interest but has not yet been investigated empirically. In analyzing ADA adoption announcements, this study examines the market’s reaction to a firm’s selection of ADA, and managing the IT infrastructure efficiently. Subsequently, this study delineates a set of firm-level characteristics (e.g., industry type) and specifies how these factors influence the stock market reaction to ADA adoptions.

**Sophistication of ADA**

Asset specificity\(^4\) has been acknowledged as a critical dimension of IT, as most IT applications are proprietary by nature and are developed to satisfy a firm’s specific needs. As a key component of ADA is the set of techniques that transform data into value (Holsapple, Lee-Post, and Pakath 2014; Gandomi and Haider 2015), asset specificity is dependent on the degree of customization of the methods being considered. In addition, the client-vendor relationship and its risk vary based on the degree to which the IT resources exchanged (e.g., products or services) are asset-specific.

The adoption of a specific type of ADA profoundly shapes the nature of business processes and risks and often requires firms to modify their internal business routines. Thus, based on a taxonomical view articulated by Delen and Zolbanin (2018)\(^5\), this study classifies an ADA’s specificity as high (e.g., predictive and prescriptive analytics) or low (e.g., descriptive and diagnostic analytics):

- Descriptive analytics are most widely used for preliminary data processing and yield useful performance data, including descriptive statistics, routine tracking, reviewing, and monitoring business performance or activities, and visualization (Banerjee, Bandyopadhyay, and Acharya 2013; Souza 2014).
- As a natural extension of descriptive analytics, diagnostic analytics are often treated as exploratory data analysis to discover the root causes of issues. Such techniques include

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\(^4\) A resource is defined as *asset specific* if it cannot readily be redeployed by other firms (Williamson 1979, 1987).

\(^5\) According to Delen and Zolbanin (2018), analytics techniques can be used to answer questions such as what has happened (descriptive analytics), why it happened (diagnostic analytics), what will happen (predictive analytics), and what should be done about it (prescriptive analytics).
drill-down, identifying anomalies and fraud, and data discovery (Banerjee et al. 2013; Delen and Zolbanin 2018).

- Predictive analytics involves the assessment of algorithmic models that employs a prospective approach to specify the values between inputs and outputs and provide real-time insights, including predictive, preventive, probability, and forecast-related analytical techniques and data science such as machine learning algorithms and artificial intelligence (Appelbaum, Kogan, Vasarhelyi, and Yan 2017).

- Prescriptive analytics involves a set of advanced mathematical techniques, such as optimization and simulations, that computationally determine the optimal action or decision given a complex set of objectives, requirements, and constraints, with the goal of improving business performance (Banerjee et al. 2013).

Consistent with the notion with prior research (Oh, Kim, and Richardson 2006b; Kim and Lim 2011), we argue that an IT-induced agent risk arises when highly asset-specific IT resources have received a great deal of attention in practice and reduce firm value in the market. Firms that invest highly in asset-specific ADA are likely to create transaction difficulties and generate agency problems that could lead to cost overruns and, ultimately, project failure. For example, predictive analytics require more sophisticated techniques (e.g., machine learning algorithms), greater computational effort, and greater implementation effort, compared to descriptive analytics. Statistically descriptive analytics contain lower uncertainties than predictive analytics since unlike descriptive analytics prediction analytics are designed to find patterns in data that allow for predictions of new observations. Furthermore, when highly proprietary resources are managed by a vendor that does not meet its commitments, high asset-specificity ADA may make it more difficult and costly for the client firm to substitute another vendor. The substitution is likely to result in significant delays and a steep learning curve for the new vendor (Ryan and Harrison 2000). This suggests that a different degree of negative relationship exists between high- vs. low- asset specificity on ADA success leading to the following hypothesis.

**H1: Announcements of ADA involving low asset specificity IT (e.g., descriptive, diagnostic) will generate more positive returns than those involving high asset specificity IT (e.g., predictive and prescriptive analytics).**
Scope of ADA

Since IT investments often are subject to high uncertainty, firms can opt for either selective or enterprise-wide ADA implementation. Compared to the former, the latter often requires analytics-oriented culture in a firm, which is difficult to create or replicate, but might allow a firm to achieve ADA functions effectively (Teo, Nishant, and Koh 2016). Thus, an enterprise-wide ADA, subject to high uncertainty and irreversibility, might generate greater values (Fichman 2004) than a selective adoption of ADA. On the other hand, an enterprise-wide ADA implementation can be considered as too risky (Kumar 1996), so shareholders may perceive less competitive benefit from such an implementation. In practice, close to 85% of data analytics projects might fail (Asay 2017) partly because a firm adopts the project for a wide scope of business processes. As a result, Bean and Davenport (2019) suggest that firms should initiate specific projects and gradually move forward over a long-term company-wide transformation.

More selective IT adoption has reduced risks and increased cost savings (Clemons and Weber 1990), due to greater flexibility and control. For instance, Capital One Financial Corp. recognized cardholders’ specific concerns regarding fraudulent transactions, and decided to use a mapping visualization tool on a customer’s statement, thereby allowing customers to identify fraudulent activities (Wixom and Ross 2017). Also, firms have begun to utilize predictive speech and behavior analytics at specifically call centers to identify fraudulent or fake callers (Gandomi and Haider 2015), reducing hold times, increasing customer satisfaction, and enhancing firm performance. After identifying IT functions, firms are able to selectively adopt, and such selective ADA provides more flexibility.

In this study, the degree to which a firm adopts ADA (defined herein as the SELECTIVE of ADA) reflects the range of business units involved in internal IT infrastructure. While some
firms implement ADA at an enterprise level, others do so only for specific applications, departments (e.g., call centers), or business processes (e.g., customer service, purchasing). Firms that incorporate incremental and selective ADA adoption initiatives (e.g., implementing one or two specific IT applications in one or a few divisions) may be more successful than firms that adopt ADA enterprise-wide since the former approach does not require the same level of coordination. This leads to the following hypothesis.

**H2:** Announcements of ADA involving selective strategic adoption will generate more positive returns than those involving enterprise-wide strategic adoption.

### III. METHODS

**Sample Selection**

This paper examines changes in the market value of firms in response to ADA announcements. ADA announcements are identified using the LexisNexis Academic Universe database (General News Topics and Business News Topics) and Major Newspapers and Wire Services. The firms’ press releases which contained keywords from the two lists below are retrieved, with at least one keyword from both audit- or accounting- and analytic- relevant words each group contained in each qualifying press release:

- Audit- or accounting-relevant words include *audit* (Cao et al. 2015; Appelbaum et al. 2018), *internal control* (Grover et al. 2018), *fraud* (Schneider et al. 2015), and *Sarbanes-Oxley* (Gambetta, García-Benau, and Zorio-Grima 2016).
- Analytic relevant words include *analytics*, *data mining*, *text mining*, *visualization*, *pattern recognition*, *predictive*, *real-time*, *artificial intelligence* and their variations based on Appelbaum et al. (2018)’s list of ADA techniques.

These search terms provide an initial sample of 9,880 from January 1, 2006 to December 31, 2018.

Since this study specifically focuses on ADA adoptions, the timing and content of related press releases is of paramount importance and utility. Similar to other AIS events (Chatterjee et al.
2002; Im et al. 2001; Dehning et al. 2003; Subramani and Walden 2001; Ranganathan and Brown 2006), we cannot specify when the ADA was completely implemented. However, following a recommendation from prior research (Yang et al. 2012), we have carefully re-validated ADA announcements with a related search for certain key words (e.g., launch, implement) to confirm that the announcements in our sample did relate to actual ADA implementation. When it is uncertain if a client firm implemented ADA – for instance, press releases only contain vague action verbs such as select, adopt, or use – we manually read the release to determine its meaning. A subsequent review reveals 8,957 duplicate or irrelevant announcements⁶, which are eliminated from the sample, leaving 297 usable announcements.

Next, this study eliminates 80 firms whose information is unavailable on the University of Chicago’s Center for Research in Security Prices (CRSP) database or non-wire news stories. An additional seven firms are eliminated because data are unavailable from Compustat or Edgar. Table 1 shows the final sample: 210 publicly traded ADA announcing firms from 2006 to 2018.⁷

Panel B presents the distribution of our sample by 2-digit SIC code. The 210 ADA firm-years cover 9 industry groups. Among them, Financial has the most firm-year observations, followed by Business Services, Auto Repair, and Recreation.

[Insert Table 1: Sample Selection]

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⁶ Irrelevant announcements include those made by private firms or accompanied by other company news (e.g., lawsuits, strikes, earnings, dividends, mergers, acquisitions, joint ventures, alliances, or other events), which are eliminated from the sample.

⁷ The timeframe of 2006-2018 is selected for two reasons. First, while 2004 marks the first major modernized ADA (online, web, IT specific, and social media relevant) occurrence (Chen, Chiang, and Storey 2012), ADA announcements began to be released in considerable quantity through the wire services and news stories in 2006, so our sample begins there. Second, the most recent available financial data points from CRSP and Compustat are in 2018, thus providing our sample’s end year.
Measures

Two independent variables (LOWAS and SELECTIVE) were included in the ordinary least squares (OLS) regression analysis to explain the variations in the outcomes of the CAR. The LOWAS variable indicates with 1 if the announced ADA initiative is in low asset specificity, such as descriptive and diagnostic analytics, or with 0 if the initiative contains high asset specificity, such as predictive and prescriptive analytics. The SELECTIVE variable indicates with 1 if the ADA adoption is being selectively (e.g., one or two ADA functions/applications/features in one or a few divisions), or with 0 if the ADA adoption is being announced for the entire firm (e.g., comprehensive, enterprise-wide, or total ADA adoption). Two authors and one research assistant each read all of the articles selected for the final sample and performed individual coding based on a binary scheme. The percentages of agreement (the inter-rater reliability) among these three independent coders were 80% and 85% for the LOWAS and SELECTIVE variable respectively. These agreement scores are well above the recommended threshold of 70% (Cohen 1960). To cross-validate the results of coding procedures, disagreements were reconciled through discussions between three independent coders. Appendix B lists the coding rule for LOWAS and SELECTIVE and abbreviated ADA examples.

To evaluate shareholders’ perception of ADA announcements, two other variables (ITIND_{t-1} and SIZE_{t-1}) were included as control variables. The SIZE variable is the natural log of total market capitalization at the end of the quarter before the ADA announcement. We included IT-intensive industries (ITIND) as a dummy to control for potential industry effects by indicating 1 if the firm is a member of IT producing companies (three digit SIC codes 357 (Computers and Office Equipment), 366 (Communications Equipment), 367 (Electronic Components), and 737(Computer Services), or 0 otherwise (Chatterjee et al. 2001; Jorgenson and Vu 2005). Each
performance measure was winsorized at +/-1 standard deviations to control for any potential outliers. Appendix A provides detailed definitions of all of the variables included in our analyses.

**Market Model**

The event study methodology calculates an excess return, or abnormal return, for each firm on the event date relative to a market wide return. Intuitively, the market-adjusted return that is expected for a stock for a particular date depends on its estimated systemic risk and overall stock price movement. Because the entire stock market increases or decreases in value during any day, the market-adjusted event return measures how much one stock should have moved, given its estimated parameters. Simply put, the difference between the expected change and the actual change during the event period, called the abnormal return, is the return in excess of the normal return, given overall market movements.

Selection of the length of event period and estimation period is based on previous event studies and institutional factors. In initial testing, the three event windows are categorized based on the announcement day 0: (1) day -1 through day 0; (2) day -1 and day +1; (3) day 0 and day +1. All four windows provide similar results for the full sample standardized cumulative abnormal return (CAR); however, rather than report the results for all four windows, this study reports a two-day event window (-1, 0) that is commonly used in IT investment, accounting, and finance studies (Chatterjee et al. 2001; Campbell et al. 2003; Dehning et al. 2003; Dehning et al. 2004; Ettredge and Richardson 2003; Chai et al. 2011; Goldstein et al. 2011).

Cumulative abnormal returns (CAR) indicate the extent to which shareholders adjust their beliefs about a firm’s value due to recent events. Positive CARs are likely to occur when most shareholders perceive that the event will result in significant future cash flows. Conversely, negative CARs occur when shareholders hold pessimistic views regarding the impact of the event.
on future cash flows. With respect to the methods for computing the CARs, we follow the
conventional procedures employed in prior IT event studies (Dos Santos, Peffers, and Mauer 1993;
Im et al. 2001; Chatterjee et al. 2001; Dehning et al. 2003; Yang et al. 2012; Jeong, Lee, and Lim
2019).

\[ R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \]  

\( R_{it} \) = the daily return firm i at time t,
\( R_{mt} \) = the equally weighted market return from the CRSP index at time t,
\( \alpha \) & \( \beta \) = the market model parameters for firm i, and
\( \varepsilon_{it} \) = the disturbance term.

The market model is estimated using returns data from a 355-day trading interval starting
365 days prior to the ADA announcement and ending 10 days prior to the announcement. Using
the parameter values estimated from equation (1), abnormal returns (AR) are next constructed for
each firm (i) during the event window (t) as indicated in the following formula:

\[ AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) \]  

The average abnormal return (AAR\(_t\)) is defined as the sample mean:

\[ AAR_t = \frac{\sum_{i=1}^{N} AR_i}{N} \]  

where \( t \) is defined in trading days relative to the event date

Then, we computed the CARs by aggregating the average abnormal returns for the test period:

\[ CAR (t_1, t_2) = \frac{1}{N} \left( \sum_{i=1}^{N} \sum_{t_1}^{t_2} AR_{it} \right) \]  

where \( t_1 \) is the beginning trading day and \( t_2 \) is the ending trading day for the period.

In order to identify the statistical significance of CARs around the event date, we employ
the standardized abnormal return method and calculate Z-statistics. For each firm (i) the
standardized abnormal return (CAR) is accumulated and divided by the square root of the number
of days in the event window. The test statistic (z) for N firms is the sum of the standardized
cumulative abnormal return (CAR) divided by the square root of the number of firms, as determined below:

\[ Z = \frac{\sum \text{CAR}_i}{\sqrt{N}} \]

(5)

\( Z \) is \( N(0,1) \)

**Cross-Sectional Test**

We conduct a regression analysis as shown in Eq. (6) using CAR as the dependent variable, and the two variables corresponding to H1-H2 (plus an intercept term) as the independent variables. We also include two control variables, ITIND and SIZE to control for the possible effects of firm and industry characteristics on the outcomes:

\[ \text{CAR}_i = \beta_0 + \beta_1 \text{LOWAS}_i + \beta_2 \text{SELECTIVE}_i + \beta_3 \text{ITIND}_i + \beta_4 \text{SIZE}_i + \varepsilon_i \]

(6)

**IV. RESULTS**

Panel A of Table 2 displays that the mean values of CAR for the full sample and two sub-samples, LOWAS =1 (\( N = 147 \) obs.) and SELECTIVE =1 (\( N = 84 \) obs.). As shown in Col. (1), the mean CAR is only 0.1% for the 2-day event window (-1, 0); that is, shareholders do not react to all 210 ADA announcements. However, when the LOWAS subsample is employed in Col. (2), the mean values of CAR for (-1, 0) and (-1, 1) are positive and marginally significant (at one-tail test of \( p < 0.1 \)). The results of LOWAS suggest that shareholders of firms with low asset specificity positively value announcements of ADA adoption, suggesting they believe firms can extract value from low risk ADA implementations, such as descriptive and diagnostic ADA. In addition, as reported in Col. (3), we find that the mean values of CAR using the SELECTIVE subsample are significantly positive for all three windows. In other words, the findings of SELECTIVE strongly indicate that shareholders of firms positively value announcements of selective ADA adoption.
Overall results suggest that the market reacts to ADA investments when the announcements are less asset-specific or for more selective investments in ADA functions.

The mean values of CAR using the LOWAS and SELECTIVE subsamples are comparable to the mean values of CAR in prior studies such as Dehning et al. (2003) and Oh et al. (2006b). We find that the mean values of CAR lie in the range of 0.6% to 1.0% using the SELECTIVE sample and in the range of 0.1% to 0.3% using the LOWAS sample. Dehning et al. (2003) report that the mean values of CAR around the announcements of different types of IT investments are from 0.4% to 1.5% for three-day window. Oh et al. (2006b) document that, using two-day windows, the mean value of CAR around IT investments are from 0.11% to 0.26%. Additionally, Oh et al. (2006b) report that using the same four windows in Panel A of Table 2, CAR is from 0.23% to 0.54%.

We further investigate market reaction by estimating average abnormal returns using the LOWAS and SELECTIVE samples. Panel B of Table 2 shows the average abnormal returns around the event, starting from two days before to two days after ADA announcements. Using the LOWAS sample, we find that market reaction is significantly positive at days -2 ($p < 0.05$) and -1 ($p < 0.10$). Using the SELECTIVE sample, we find that shareholders react positively to the selective ADA announcements on the actual date of the announcement (0, 0), with an abnormal return of 0.62% ($p < 0.05$). The average abnormal returns for the day of -2 and -1 are also 0.64% and 0.78% respectively, which are significantly positive ($p < 0.01$, $p < 0.01$, respectively). Overall, our findings indicate that the market reacts positively when the ADA investments are less asset specific or selective.
Descriptive statistics for all variables are shown in Table 3. Panel A shows the descriptive statistics using our full sample. The mean value of CAR is 0.1%. About 70% of our total observations are classified into LOWAS, while 40% of our observations are classified into SELECTIVE. 36.7% of the observations are in IT industries. Panel B shows the descriptive statistics and differences in mean values of the variables in the LOWAS sample. The mean difference of ITIND is marginally significant ($p < 0.10$), which indicates that firms in IT industries are more likely to have less asset-specific ADA investments. Panel C shows the differences in mean values of the variables using the SELECTIVE sample. The results show that CAR is significantly higher ($p < 0.01$) when the ADA investment is selective. Also, firms in IT industries are more likely to have selective ADA investments. The mean value of SIZE is significantly larger for the SELECTIVE sample ($p < 0.10$), suggesting that larger firms are more likely to have selective ADA investments.

[Insert Table 3: Descriptive Statistics]

Panel D of Table 3 presents correlations among the variables. The dependent variable (CAR) is positively correlated with SELECTIVE ($p < 0.01$), while CAR is positively but not significantly correlated with LOWAS. LOWAS and SELECTIVE are positively correlated with ITIND. In particular, SELECTIVE is highly correlated with ITIND ($p < 0.01$). SIZE is also positively correlated with SELECTIVE ($p < 0.01$). However, none of the correlations are above 0.70, and the highest variance inflation factor (VIF) in our regression is only 1.63, which is well below the suggested multicollinearity threshold of 10 (Marquandt 1980; Gujarati 1995). Our examination of the standard errors and size of the coefficient also shows that they are not sensitive to the inclusion or exclusion of the highly correlated variables, indicating that multicollinearity is unlikely to be problematic (Hosmer and Lemeshow 1989).
Regression Results

Table 4 summarizes regression results for the overall model shown in Eq. (6). The result includes one control variable, size (SIZE), that equals the natural log of total market capitalization, at the end of the quarter before ADA announcement. The industry dummy variable (ITIND) controls for IT-intensive vs. non-IT-intensive industries. As shown in Col. (1) of Table 4, the model is effective in explaining the CARs, with significant model $F$-statistics and adjusted $R^2$ of about 6.4%. This low $R^2$ value is not unusual, as several studies in both IS and accounting/finance literature have reported similar values (Im et al. 2001; Chatterjee et al. 2001; Dehning et al. 2003).

Table 4 shows market reaction to ADA adoption in the sub-sample of ADA functions. First, we find a positive and significant coefficient on the variable representing LOWAS ($p < 0.05$), supporting H1. In other words, shareholders are more favorable about the prospective returns of client firms who adopt low asset specificity (e.g., descriptive and diagnostic) than those who adopt high asset-specificity (e.g., predictive and prescriptive analytics). The results suggest that low asset-specificity IT appears to carry lower risks and greater benefits due to reduced transaction difficulty and fewer routine modifications. Second, we find a positive and significant coefficient on the SELECTIVE variable, which indicates larger returns when ADA adoption is implemented selectively ($p < 0.01$), supporting H2. In other words, a smaller scope allows the client to easily coordinate and manage the ADA implementation. Given positive CARs on average, the expected coefficient of SIZE is negative. This is because larger firms have greater information sources, leading to smaller announcement surprises (Oh, Gallivan, and Kim 2006a).

[Insert Table 4: Regression Results]
Robustness Checks

To assess the robustness of our results, we used an alternative procedure and different methods for measuring our variables. Table 5 shows the regression results using a different approach to estimate CAR based on the market adjusted return (Kobelsky, Richardson, Smith, and Zmud 2008). Instead of estimating an individual firm’s normal return, we use the market portfolio return as a normal return. Thus, CAR is estimated by a firm’s return minus the market portfolio return. As presented in Col. (1) of Table 5, the results are qualitatively similar: Using CAR for (-1,0) window, we find that the coefficients of LOWAS and SELECTIVE are positively significant ($p < 0.01, p < 0.10$, respectively), supporting both H1 and H2.

[Insert Table 5: Regression Results Using CAR Estimated by Market Adjusted Return]

Selection of the length of event period and estimation period is based on previous event studies and institutional factors (Dos Santos et al. 1993, Im et al. 2001; Yang et al. 2012). For example, when the event announcement appears in the newspaper, it is unclear whether the market was informed before the close of the market on the prior trading day. Thus, if the announcement occurs after the close of the trading on the previous day, any immediate valuation effects will be reflected in the stock price on the day in which the announcement appears in press. However, if the information is released prior to the close of trading, any immediate valuation effect will be registered on the day before the announcement appear in print (McConnell and Muscarella 1985). We highlight our results by the shorter window (-1, 0)$^8$, because it is likely to more accurately reflect the information content of the ADA announcements itself. To check the robustness of the result to changes in the event windows, we also replicated our results for other multi-day event

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$^8$ We thank for the anonymous reviewer for suggesting the selection of the event period.
windows (e.g., (0, 1), (-1, 1), and (-2, 2)), and our major results (not tabled) are weaker, but similarly support H1 and H2.

The level of information asymmetry between managers and shareholders tends to vary by industry (Flannery 1986). Finance or service industries tend to provide less relevant information to shareholders via standard financial reporting systems, since these systems do not collect data on or reveal many factors that impact the value of these firms (Amir and Lev 1996). Thus, the announcement of forward-looking strategic information by firms (including peers in the same industry) in the finance or service industries has the potential to decrease information asymmetry and allow for proper market valuation. With this in mind, we rerun our model using more industry membership variables such as FIN and SERV. In this study, FIN is one when firm belongs to a financial industries defined as two-digit SIC (SIC codes are between 6000 and 6999), 0 otherwise (Chatterjee et al. 2001; Im et al. 2001). Also, we include SERV which is one when the firm is a member of the service industry (two digit SIC codes are between 70 and 89), 0 otherwise (Chatterjee et al. 2001; Im et al. 2001; Ranganathan and Brown 2006). The untabulated results are similar. The coefficients of LOWAS and SELECTIVE are significantly positive with CAR ($p < 0.1$, $p < 0.01$, respectively), supporting our H1 and H2; however, the coefficients of ITIND, FIN, and SERV are not significant.

V. DISCUSSION

We begin the study with one general research question: Does the stock market react favorably to ADA adoptions? The expectation of a positive reaction was based on the assumption that firms adopting ADA do so with the intent of streamlining data accessibility and organization and/or to derive deeper insights (e.g., identify operational inefficiencies, predict risks and future value, provide enhanced assurance). These actions are expected to impact abnormal returns
positively since the stock market monitors and responds systematically to various strategic actions, such as the implementation of various types of ADA and control structures. The study provides evidence that capital markets generally reward firms that adopt ADA. The results further demonstrate the impact of scope and sophistication of ADA functions in determining the success of ADA adoptions.

Like any other study using an event-study methodology, the results should be considered with the limitation of using market-based measures for assessing firm value. Stock market valuation reflects only shareholders’ collective perceptions of firm’s potential business gains from an initiative, which may not reflect actual, realized gains. The low $R^2$ suggests that several unknown, omitted factors might affect shareholder reactions to ADA events. Although our sample collection procedure is comprehensive, our data might explain ADA functions too narrowly. Because we collect ADA announcements data from all publicly available news on LexisNexis, the data do not reflect detailed information, such as the scale of a given ADA or the dollar amount of ADA investment. This limitation applies to all studies that rely on secondary data.

Accounting and IS researchers as well as professional managers can gain deeper insight into why and how the capital market responds to a host of AIS issues, such as investments in specific information technologies like ADA. Investigating the market’s reactions to IT and other technology-related issues is important to business managers since firm value is a key indicator of the effectiveness of strategically oriented accounting and IT-related initiatives. The study’s findings may also have policy implications for the accounting profession, as it shows that disclosure of ADA announcements provides value relevant, forward-looking information to the capital market. Such information is currently not available in traditional financial reports. Thus, by including non-financial information concerning management strategies, financial reports have
the potential to decrease information asymmetry and increase their usefulness in assessing the amount, timing, and certainty of cash flows.

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EY. 2018. Our commitment to audit quality: Information for audit committees, investors and other stakeholders.


Harris, S. B. 2017. Technology and the Audit of Today and Tomorrow.


Table 1: Sample Analysis

Panel A: Restrictions Leading to Final Sample

<table>
<thead>
<tr>
<th>Steps</th>
<th>Description</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Initial sample (via Lexis-Nexis) by using a set of keywords searches</td>
<td>9,880</td>
</tr>
<tr>
<td>Step 2</td>
<td>Less:</td>
<td>(8,952)</td>
</tr>
<tr>
<td></td>
<td>- articles that contain generic news on ADAs without mentioning firm-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>specific events</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- articles that contain either financial performance announcements (e.g.,</td>
<td></td>
</tr>
<tr>
<td></td>
<td>earnings, dividend payments) or management staff changes (hiring or</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retiring of executives)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- articles that contain events irrelevant to ADA businesses</td>
<td></td>
</tr>
<tr>
<td>Step 3</td>
<td>Less: duplicate announcements</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>Less: irrelevant announcements</td>
<td>(626)</td>
</tr>
<tr>
<td></td>
<td>Less: announcements missing CRSP data</td>
<td>(80)</td>
</tr>
<tr>
<td></td>
<td>Less: announcements missing COMPUSTAT data</td>
<td>(7)</td>
</tr>
<tr>
<td></td>
<td>Final sample Size</td>
<td>210</td>
</tr>
</tbody>
</table>

Panel B: Industry Composition

<table>
<thead>
<tr>
<th>2-Digit SIC Code</th>
<th>Industry</th>
<th>No.</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10–19</td>
<td>Mining, Oil and Gas, and Others</td>
<td>1</td>
<td>0.48</td>
</tr>
<tr>
<td>20–29</td>
<td>Food, Printing and Publishing, Chemicals, Petroleum and Coal</td>
<td>9</td>
<td>4.29</td>
</tr>
<tr>
<td>30–39</td>
<td>Metal, Machinery and Equipment</td>
<td>27</td>
<td>12.86</td>
</tr>
<tr>
<td>40–49</td>
<td>Transportation</td>
<td>10</td>
<td>4.76</td>
</tr>
<tr>
<td>50–59</td>
<td>Wholesale and Retail</td>
<td>21</td>
<td>10.00</td>
</tr>
<tr>
<td>60–69</td>
<td>Financial</td>
<td>70</td>
<td>33.33</td>
</tr>
<tr>
<td>70–79</td>
<td>Business Services, Auto Repair and Recreation</td>
<td>68</td>
<td>32.38</td>
</tr>
<tr>
<td>80–89</td>
<td>Health, Engineering and Management Service</td>
<td>2</td>
<td>0.95</td>
</tr>
<tr>
<td>99</td>
<td>Others</td>
<td>2</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>210</td>
<td>100</td>
</tr>
</tbody>
</table>
Table 2: The Average Standardized Cumulative Abnormal Returns (N = 210)

Panel A: CAR for Various Event Windows

<table>
<thead>
<tr>
<th>Window</th>
<th>Full Sample (N=210)</th>
<th>LOWAS (N=147)</th>
<th>SELECTIVE (N=84)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(-1, 0)</td>
<td>0.001</td>
<td>0.003*</td>
<td>0.008***</td>
</tr>
<tr>
<td>(-1, 1)</td>
<td>0.001</td>
<td>0.004*</td>
<td>0.010***</td>
</tr>
<tr>
<td>(0, 1)</td>
<td>0.000</td>
<td>0.002</td>
<td>0.006***</td>
</tr>
</tbody>
</table>

Panel B: Average Abnormal Return around Event Date

<table>
<thead>
<tr>
<th>Day</th>
<th>LOWAS</th>
<th>SELECTIVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>0.41%*</td>
<td>0.78%***</td>
</tr>
<tr>
<td>0</td>
<td>0.24%</td>
<td>0.62%**</td>
</tr>
<tr>
<td>1</td>
<td>0.10%</td>
<td>0.26%</td>
</tr>
</tbody>
</table>

*, **, *** represent statistical significance at p < 0.10, 0.05 and 0.01 level (two-tailed) respectively. + represents statistical significance at p < 0.10 level (one-tailed). See Appendix A for variable definitions.
Table 3: Descriptive Statistics

Panel A: Full Sample

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAR$_{-1,0}$</td>
<td>-0.071</td>
<td>0.096</td>
<td>0.001</td>
<td>0.026</td>
</tr>
<tr>
<td>LOWAS</td>
<td>0.000</td>
<td>1.000</td>
<td>0.700</td>
<td>0.459</td>
</tr>
<tr>
<td>SELECTIVE</td>
<td>0.000</td>
<td>1.000</td>
<td>0.400</td>
<td>0.491</td>
</tr>
<tr>
<td>ITIND</td>
<td>0.000</td>
<td>1.000</td>
<td>0.367</td>
<td>0.483</td>
</tr>
<tr>
<td>SIZE</td>
<td>3.452</td>
<td>13.537</td>
<td>8.707</td>
<td>2.195</td>
</tr>
</tbody>
</table>

Panel B: LOWAS

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LOWAS=1</td>
<td>LOWAS=0</td>
</tr>
<tr>
<td>CAR$_{-1,0}$</td>
<td>0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td>SELECTIVE</td>
<td>0.401</td>
<td>0.397</td>
</tr>
<tr>
<td>ITIND</td>
<td>0.408</td>
<td>0.270</td>
</tr>
<tr>
<td>SIZE</td>
<td>8.751</td>
<td>8.605</td>
</tr>
</tbody>
</table>

Panel C: SELECTIVE

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SELECTIVE=1</td>
<td>SELECTIVE=0</td>
</tr>
<tr>
<td>CAR$_{-1,0}$</td>
<td>0.008</td>
<td>-0.003</td>
</tr>
<tr>
<td>LOWAS</td>
<td>0.702</td>
<td>0.698</td>
</tr>
<tr>
<td>ITIND</td>
<td>0.726</td>
<td>0.127</td>
</tr>
<tr>
<td>SIZE</td>
<td>9.017</td>
<td>8.500</td>
</tr>
</tbody>
</table>

Panel D: Correlation Matrix (N = 210)

<table>
<thead>
<tr>
<th>CAR$_{-1,0}$</th>
<th>LOWAS</th>
<th>SELECTIVE</th>
<th>ITIND</th>
<th>SIZE</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAR$_{-1,0}$</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOWAS</td>
<td>0.104</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SELECTIVE</td>
<td>0.197***</td>
<td>0.004</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>ITIND</td>
<td>0.062</td>
<td>0.132*</td>
<td>0.609***</td>
<td>1</td>
</tr>
<tr>
<td>SIZE</td>
<td>-0.090</td>
<td>0.031</td>
<td>0.116*</td>
<td>0.096</td>
</tr>
</tbody>
</table>

*, **, *** represent statistical significance at p < 0.10, 0.05 and 0.01 level (two-tailed) respectively. See Appendix A for variable definitions.
Table 4: Results of Regression Analysis (N = 210)

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Exp. Sign</th>
<th>Coefficients</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td></td>
<td>0.006</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td>LOWAS</td>
<td>H1</td>
<td>+</td>
<td>0.009</td>
<td>2.08</td>
</tr>
<tr>
<td>SELECTIVE</td>
<td>H2</td>
<td>+</td>
<td>0.014</td>
<td>2.96</td>
</tr>
<tr>
<td>ITIND</td>
<td></td>
<td>?</td>
<td>-0.004</td>
<td>-0.86</td>
</tr>
<tr>
<td>SIZE</td>
<td>+/-</td>
<td>-0.002</td>
<td>-1.90</td>
<td>*</td>
</tr>
</tbody>
</table>

Year fixed effect: Included
F-value: 4.39***
Adjusted R-Square: 0.064

*, **, *** represent statistical significance at p < 0.10, 0.05 and 0.01 level (two-tailed) respectively. See Appendix A for variable definitions.
Table 5: Results of Regression Analysis Using CAR Estimated by Market Adjusted Return

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Exp. Sign</th>
<th>Coefficients</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td></td>
<td>0.004</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>LOWAS H1</td>
<td>+</td>
<td>0.007</td>
<td>1.75</td>
<td>*</td>
</tr>
<tr>
<td>SELECTIVE H2</td>
<td>+</td>
<td>0.013</td>
<td>2.84</td>
<td>***</td>
</tr>
<tr>
<td>ITIND</td>
<td>?</td>
<td>-0.002</td>
<td>-0.56</td>
<td></td>
</tr>
<tr>
<td>SIZE</td>
<td>+/-</td>
<td>-0.001</td>
<td>-1.58</td>
<td></td>
</tr>
</tbody>
</table>

Year fixed effect Included
F-value 3.90***
Adjusted R-Square 0.055

*, **, *** represent statistical significance at p < 0.10, 0.05 and 0.01 level (two-tailed) respectively. See Appendix A for variable definitions.
### Appendix A: Variable Descriptions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CAR(_i)</strong></td>
<td>The average standardized cumulative abnormal returns for firm (i) over days -1 and day 0. For more detailed discussion of analytical techniques employed in event studies, see Loderer and Mauer (1992) and McWilliams and Siegel (1997).</td>
</tr>
<tr>
<td><strong>LOWAS</strong></td>
<td>1 if the ADA resources are low in asset specificity (e.g., descriptive and diagnostic), 0 if the ADA resources are high in asset specificity (e.g., predictive and prescriptive analytics).</td>
</tr>
<tr>
<td><strong>SELECTIVE</strong></td>
<td>1 if the ADA adoption is being selectively (e.g., one or two ADA functions/applications/features in one or a few divisions), 0 if the ADA adoption is being announced for entire firm (e.g., comprehensive, enterprise-wide or total ADA adoption).</td>
</tr>
<tr>
<td><strong>ITIND</strong></td>
<td>1 if the firm is a member of IT producing industries (three digit SIC codes are 357 (Computers and Office Equipment), 366 (Communications Equipment), 367 (Electronic Components), and 737 (Computer Services), 0 otherwise (Chatterjee et al. 2001; Jorgenson and Vu 2005).</td>
</tr>
<tr>
<td><strong>SIZE</strong></td>
<td>equals the natural log of total market capitalization (Watts and Zimmerman 1986).</td>
</tr>
</tbody>
</table>
## Appendix B: ADA Examples and Coding

<table>
<thead>
<tr>
<th>Case (ADA announcements)</th>
<th>Coding</th>
<th>Abbreviated descriptions from LexisNexis</th>
</tr>
</thead>
<tbody>
<tr>
<td>7/8/2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SELECTIVE = 0</strong></td>
<td></td>
<td>CL Services Ltd. today announced at The Institute of Internal Auditor’s annual international conference that Siemens AG, one of the world’s largest companies, has selected <em>ACL technology to continuously monitor critical financial transactions that are at risk for fraud, error and abuse</em> in each of its 1,300-plus corporate entities in more than 190 countries. The ACL technology installation—across Siemens’ global corporate entities—represents the broadest implementation of <em>monitoring technology and enforces the clear mandate to strengthen controls within the entire purchase-to-pay process, from order entry to approval to payment</em>. Siemens selected ACL as the best-in-breed technology for audit analytics and transaction monitoring.</td>
</tr>
<tr>
<td><strong>LOWAS = 1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4/7/2014</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SELECTIVE = 1</strong></td>
<td></td>
<td>TSYS (NYSE: TSS) announced today an agreement with Oversight Systems to provide <em>an automated monitoring and analysis solution to help corporate purchasing professionals detect and eliminate fraud, policy misuse, and waste within their card programs</em>. …Oversight Insights On Demand -- Powered by TSYS is an innovative solution that will facilitate transparency, accountability and growth of card programs for corporate customers. The solution performs automated analysis, first <em>by reviewing 100 percent of the transactions, then delivering results through a management dashboard and analyst workbench with built-in workflow capabilities</em>.</td>
</tr>
<tr>
<td><strong>LOWAS = 1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10/28/2014</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SELECTIVE = 0</strong></td>
<td></td>
<td>Cognos(R) (NASDAQ: COGN) (TSX: CSN), the world leader in business intelligence and performance management solutions, today announced that Dorel Industries (TSX: DII.B, DII.A) has selected Cognos <em>to help optimize operational planning and reporting across all divisions</em>. Dorel will use Cognos 8 BI to report against key performance benchmarks, <em>analyze timely information to uncover root causes of issues, and track trends</em>, simplifying decision making. It is expected that Cognos 8 Controller will improve efficiencies in financial statement preparation, while also strengthening Dorel's internal control environment to optimize compliance with legislation, such as SOX,</td>
</tr>
<tr>
<td>LOWAS = 0</td>
<td>as well as other regulatory requirements worldwide. Finally, Dorel intends to use Cognos 8 Planning to develop consistent and accurate sales and operations plans and to allow for the preparation of up-to-date rolling forecasts in the most efficient manner possible.</td>
<td></td>
</tr>
</tbody>
</table>