



# Shareholder wealth implications of software firms' transition to cloud computing: a marketing perspective

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## Abstract

Moving into cloud computing represents a major marketing shift because it replaces on-premises offerings requiring large, up-front payments with hosted computing resources made available on-demand on a pay-per-use pricing scheme. However, little is known about the effect of this shift on cloud vendors' financial performance. This study draws on a longitudinal data set of 435 publicly listed business-to-business (B2B) firms within the computer software and services industries to investigate, from the vendors' perspective, the shareholder wealth effect of transitioning to the cloud. Using a value relevance model, we find that an unanticipated increase in the cloud ratio (i.e., the share of a firm's revenues from cloud computing) has a positive and significant effect on excess stock returns; and it has a negative and significant effect on idiosyncratic risk. Yet these effects vary across market structures and firms. In particular, unanticipated increases in market maturity intensify the positive effect of moving into the cloud on excess stock returns. Further, unexpected increases in advertising intensity strengthen the negative effect of shifting to the cloud on idiosyncratic risk.

**Keywords** Cloud ratio · Excess stock returns · Idiosyncratic risk · Market maturity · Advertising intensity

Over the past few years, the computer software and services industries have witnessed a rapid growth in cloud computing, with the global public cloud market expected to reach nearly \$364 billion by 2022, up from \$242 billion in 2019 (Gartner, 2020). Cloud computing is a technological innovation that grants customers on-demand access to hosted computing resources made available on a pay-per-use pricing model (Chen & Wu, 2013; Mell & Grance, 2011). Shifting to the cloud has dominated discussions among information technology (IT) firms because it involves substantial changes

to the components of a vendor's marketing mix (see Moorman et al., 2018).

First, moving to the cloud amounts to a paradigm shift in the nature of a vendor's offerings: from providing IT as a product to delivering computing functionality as a service (see Cusumano et al., 2015). In particular, cloud solutions are delivered in a hosted environment operated by the vendor—unlike the in-house IT infrastructure deployed internally by customers (Fazli et al., 2018; Ma & Seidmann, 2015). Hosting arrangements provide computing resources as on-demand services; they neither constitute a license purchase nor provide customers with contractual rights to take possession of the underlying IT assets (Chen & Wu, 2013). Second, transitioning to the cloud entails a fundamental shift in the vendor's pricing strategy. Specifically, cloud offerings are typically billed on a pay-per-use basis; hence, they disrupt software firms' revenue streams hitherto characterized by lump-sum, up-front licensing fees (Brenzitz et al., 2018; Burgelman & Schiffrin, 2014). Third, moving into the cloud entails a profound shift in the firm's distribution strategy. In fact, the Internet-based delivery model in cloud arrangements establishes a direct online channel that can bypass traditional third-party distributors (e.g., software resellers and integrators).

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In response to these extensive changes, there has been considerable variation in firms' reliance on cloud computing in their business models. For example, Oracle and [Sales force.com](https://www.pwc.com/gx/en/industries/technology/publications/global-100-software-leaders/25-fastest-growing-cloud-companies.html) generated, respectively, about 5% and 93% of their revenues in 2015 from selling cloud-based solutions. The implication is that there are different opinions, among managers and investors, regarding the effectiveness of shifting to the cloud, as noted by Exact Holding's chief executive officer, Erik Van Der Meijden:

After we had completed an internal restructuring and we had put [our] cloud solutions on a solid growth trajectory, I wanted to grow even faster in the cloud. Our shareholders were divided on that, and we had to temporize our transformation in order not to alienate investors and the stock market from us.<sup>1</sup>

We therefore need empirical research that documents (a) how moving into the cloud affects firm performance, and (b) how this effect varies across market structures and firms. Yet the literature on cloud computing is still relatively nascent, and largely focuses on the technological aspects of shifting to the cloud, leaving the research on the performance outcomes of cloud transition an underexploited area (Fazli et al., 2018).

Against this backdrop, the current study makes two key contributions. *First*, we investigate empirically the joint effects of unanticipated changes in the cloud ratio on a vendor's stock returns and stock risk. We define the *cloud ratio* as a firm's share of revenues that are generated by providing cloud-based solutions. We exploit unexpected changes in the cloud ratio to explore the value relevance of moving into the cloud. The reason is that, according to the efficient market hypothesis (Fama, 1970), the stock market reacts only to the release of unanticipated information that can change investors' expectations of future cash flows. Shareholders are likely to encounter cloud revenue surprises because, for example, prices in contract-based payment arrangements "are privately negotiated, opaque, and involve price discrimination" (Du et al., 2013, p. 625). Further, we use market-based measures as performance metrics because they are forward-looking and less easily manipulated by accounting practices (Edeling et al., 2020; Srinivasan & Hanssens, 2009).

*Second*, we develop a contingency framework that examines the moderating effects of unanticipated changes in market maturity and advertising intensity. Market maturity, or the extent of product commoditization and sluggish growth in a market, plays a leading role in shaping the dynamics

and outcomes of innovations (Cusumano et al., 2015; Utterback & Abernathy, 1975). Unanticipated changes in market maturity may happen in response to the emergence of a dominant design or a new technological trajectory (Sood & Tellis, 2005). Similarly, advertising is a chief contributor to how effectively innovations create value for customers and competitive advantage for firms (Srinivasan et al., 2009). Unanticipated changes in advertising intensity occur because, for instance, managers may unexpectedly use discretion in advertising expenditures to meet or beat analysts' earnings forecasts (Caylor, 2010; Mizik, 2010).

To test our conceptual framework, we assemble a longitudinal data set of 2,008 yearly observations pertaining to 435 publicly traded B2B firms within the computer software and services industries (primary Standard Industrial Classification [SIC] codes of 7370-7379) from 2005 to 2019. Using a stock return response model, we find that an unanticipated increase in the cloud ratio enhances shareholder wealth by increasing excess stock returns and by decreasing idiosyncratic risk.<sup>2</sup> To the best of our knowledge, the current study presents the first systematic empirical evidence on the long-term return and risk implications of shifting to the cloud from the cloud providers' perspective. As such, our study complements that of Son et al. (2014), which examines the effect of adopting cloud computing on short-term announcement abnormal returns from the cloud users' viewpoint.

We also find that unanticipated increases in market maturity and advertising intensity enhance the performance effects of shifting to the cloud. Specifically, unexpected increases in market maturity intensify the positive effect of shifting to the cloud on excess stock returns. Further, unanticipated increases in advertising intensity strengthen the negative effect of moving into the cloud on idiosyncratic risk. These findings highlight the importance of integrating an industry life cycle perspective into the performance analysis of cloud computing as a technological innovation with the potential to disrupt current IT delivery models and hence the marketplace's competitive dynamics (see Cusumano et al., 2015). Furthermore, the results indicate that the success of adopting a cloud-based business model depends heavily on vendors' investment in marketing—as is evident from the testimony of practitioners, who state that "marketing is a core competency (sometimes the only one) of every successful cloud business" (Bessemer Venture Partners, 2012, p. 17).

<sup>1</sup> <https://www.pwc.com/gx/en/industries/technology/publications/global-100-software-leaders/25-fastest-growing-cloud-companies.html>

<sup>2</sup> A stock return response model establishes whether the new information contained in a variable (as captured by its unexpected changes) is associated with long-term changes in stock prices (for applications, see, e.g., Bharadwaj et al., 2011; Frennea et al., 2019; Mishra & Modi, 2016)

The rest of this paper proceeds as follows. We start by developing our theory and hypotheses. Next, we describe the data, our measurement and operationalization of constructs, the model estimation procedures, and our results. We conclude by discussing our study's contributions, summarizing its limitations, and identifying directions for further research.

## Conceptual background and hypotheses

The global IT market size is projected to total \$4.2 trillion in 2021, an increase of 8.6% from 2020 (Gartner, 2021). An intriguing phenomenon is that, over the past several years, many software and IT service companies have been replacing their traditional, on-premises offerings with cloud-based solutions. The National Institute of Standards and Technology defines cloud computing as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction” (Mell & Grance, 2011, p. 2).

Cloud computing is a technological innovation that enables the on-demand use of IT as a utility. The underlying technology in cloud computing represents a significant advance in the state of the art over on-premises IT solutions. For example, the multi-tenancy hosted architecture of the cloud allows vendors to share pooled resources across multiple customers. It follows that cloud providers can orchestrate the required support services centrally with possibly fewer debugging efforts (August et al., 2014); hence, shifting to the cloud enables vendors to spread their costs across scaled operations. In contrast, on-premises offerings are installed and maintained locally on the customers' in-house IT infrastructure—which requires the vendor to deliver regular maintenance, bug-fixing patches, and upgrades separately for each customer.

A related advantage of cloud computing is that the vendor can, by automatically changing its active number of servers, allow customers to scale their computational capacity up or down in (nearly) real time without requiring that they make capacity pre-commitments (Fazli et al., 2018). A fully scalable architecture eliminates the need to respond manually to traffic spikes that would otherwise call for additional resources. This increased flexibility helps customers lower operational costs and enhance performance reliability by seamlessly matching capacity to fluctuating demand (Ma & Seidmann, 2015). In contrast, on-premises offerings require customers to build their service set-ups with ample capacity to hedge against the risk of network congestion. The downside of that approach is that often a large proportion

of in-house computing power then remains idle simply to ensure constant and “always on standby” service capacity, which increases the cost of keeping the IT infrastructure running (Ma & Seidmann, 2015).

According to Sood and Tellis (2005, p. 152), “understanding technological innovation is vital for marketers” because it “is perhaps the most powerful engine of growth.” However, “academic research on cloud computing is still relatively new and most of the work done on this topic focuses on technological issues of the cloud” (Fazli et al., 2018, p. 3). For example, Choudhary and Zhang (2015) examine cloud vendors' optimal software release time and patching strategy; and August et al. (2014) investigate the security implications of offering cloud solutions. It follows that researchers and practitioners need a better understanding of the performance effects of shifting to the cloud—a technological innovation capable of transforming vendors' business models.

In light of these considerations, this study has two objectives. *First*, we examine—from the vendors' perspective—the link between adopting a cloud-based business model and firm performance. Thus, we explore the effects of unanticipated changes in the cloud ratio on firm return and firm risk. Toward that end, we use stock return response modeling because (i) the stock market reacts only to the release of unanticipated information that can change investors' expectations of future cash flows (Fama, 1970); and (ii) marketing actions often incorporate information that takes a long time before being fully reflected in stock prices (Pauwels et al., 2004; Srinivasan et al., 2009). Using a value relevance model enables us to determine whether the new information contained in a firm's cloud ratio changes is associated with long-term changes in its stock price (see Sorescu et al., 2017).

As Sorescu and Spanjol (2008) point out, technological innovations can affect firm return and risk differently. Therefore, accounting for return and risk as separate dimensions of shareholder value yields a more granular insight into the performance implications of shifting to the cloud. Thus, we focus on excess stock returns as a measure of a firm return, thereby assessing the net value that the stock market bestows on a vendor's emphasis on cloud computing (see, e.g., Bharadwaj et al., 2011; Frennea et al., 2019; Mishra & Modi, 2016). Our proxy for firm risk is idiosyncratic risk, which captures the stock returns volatility that is unexplained by overall market movements. Idiosyncratic risk accounts for nearly 85% of the observed variation in stock prices (Goyal & Santa-Clara, 2003); hence, it is widely used as a measure of stock returns risk in the marketing literature (see, e.g., Frennea et al., 2019; Han et al., 2017).

*Second*, we develop a contingency framework that investigates the boundary conditions for the relationship between moving into the cloud and firm performance. Specifically,

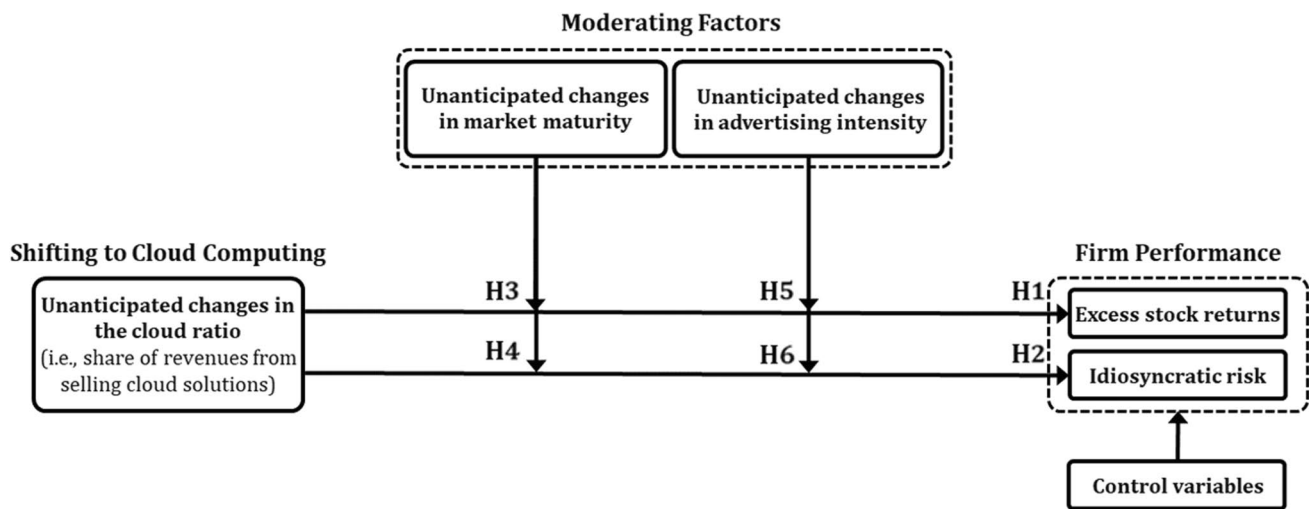


Fig. 1 Conceptual framework

competition dynamics determined by an industry's life cycle stage are likely to influence the effectiveness of providing on-demand, hosted cloud solutions that substitute traditional, on-premises offerings (see Cusumano et al., 2015; Macdonald et al., 2016; Suarez et al., 2013). Therefore, we explore the role of unanticipated changes in market maturity as a potential factor that moderates the linkage between shifting to the cloud and firm performance. Market maturity is the phase of an industry's life cycle characterized by high levels of technological standardization and slow demand growth (Cusumano et al., 2015). "When these limits are reached, the only possible way to maintain the pace of progress is through radical system redefinition—that is, a move to a new technological platform" (Sood & Tellis, 2005, p. 154). As such, the emergence of maturity in a market is likely to affect the performance potential of cloud computing as a technological disruption.

Further, we explore the role of unanticipated changes in advertising intensity as a potential factor that can determine the effectiveness of transitioning to the cloud. Advertising has become an increasingly important part of B2B marketing (Swani et al., 2020). Expenditures on advertising make up nearly 13.8% of the typical B2B communications budget (Gopalakrishna & Lilien, 2012).<sup>3</sup> Investing in advertising is of direct importance to cloud providers for several reasons. First, customers' frequently cited concerns about cloud computing (e.g., security risks, service availability) can adversely affect their adoption of cloud-based solutions. Advertising can reinforce a cloud vendor's value proposition

and provide a form of service quality assurance that mitigates customers' perceived risk of purchase (see Srinivasan et al., 2009). Second, vendors typically offer cloud solutions directly and online, rather than through independent distributors. Hence, they are less likely to benefit from the promotional activities performed by third-party distributors. Under such circumstances, a vendor's investment in advertising likely becomes an essential component of its cloud transition success. Fig. 1 depicts our conceptual framework.

In developing our theoretical framework, we draw on the innovation literature to identify the pathways by which moving into the cloud might affect firm performance (see, e.g., Dotzel & Shankar, 2019; Fang et al., 2011; Rubera & Kirca, 2012; Sood & Tellis, 2005; Sorescu & Spanjol, 2008). According to this literature, technological disruptions could affect firm performance via several mechanisms. For instance, offering new customer value through innovations generates demand from existing and new customers, thereby resulting in increased cash flows (Dotzel & Shankar, 2019). Similarly, delivering innovation-based value differentiates a firm in the market and magnifies customers' switching costs, leading to a more stable customer base that promises a smoother cash flow stream (Sorescu & Spanjol, 2008). Accordingly, it would be reasonable to examine how shifting to cloud computing as a technological disruption influences firm performance from the innovation viewpoint.

<sup>3</sup> Publicly-traded B2B firms that operate in the computer software and services industries invest, on average, about 3% of their revenues in advertising.

## Effects of unanticipated changes in the cloud ratio on excess stock returns

A firm's shift to cloud computing affects excess stock returns in several ways. First, cloud solutions generate greater value for customers (Son et al., 2014). For example, the hosted nature of cloud offerings relieves customers of the burdens associated with installing and maintaining expensive in-house IT infrastructure and of the need to deal with such time-consuming administrative functions as security management and capacity planning (Ma & Seidmann, 2015). Cloud users also have quicker access to product upgrades because the cloud's hosted aspect enables vendors to deploy product enhancements centrally, reducing not only the intervals between software releases but also the time-to-market of new functionalities (Breznitz et al., 2018; Son et al., 2014). Delivering added value to customers should enhance customer satisfaction and customer loyalty, which result in larger cash flows (Srivastava et al., 1998).

Second, transitioning to the cloud provides opportunities for the vendor to expand its customer base and thus to increase its cash flow. For instance, the pay-per-use pricing model enables cloud providers to attract financially constrained customers who would otherwise be excluded from the market (Breznitz et al., 2018). The reason is that the usage-based pricing model allows customers to convert their fixed IT-related expenses to costs that vary as a function of their usage rates—unlike perpetual licensing, which typically involves large up-front fees (Chen & Wu, 2013; Son et al., 2014). Along these same lines, the Web-based nature of cloud offerings allows vendors to expand their market to include almost any place with Internet access; hence, they can effectively reach geographically distant customers that have limited access to traditional distribution channels.

Third, moving into the cloud enables vendors to exploit economies of scale and a more efficient allocation of resources (Chen & Wu, 2013). In particular, the cloud's multi-tenancy hosted architecture allows vendors to share pooled resources across multiple customers. Hence, cloud providers can undertake support services centrally and may end up devoting less effort to debugging tasks (August et al., 2014). The presence of scale economies enables cloud vendors to concentrate on cost reduction and profit improvement. In contrast, because on-premises offerings are installed and maintained locally on the customer's in-house IT infrastructure, they require the vendor to deliver regular maintenance, bug fixing, and upgrades separately for each customer. The consequence is reduced operational efficiency, which impairs vendors' profitability.

Fourth, the hosted nature of cloud solutions implies that vendors usually have complete access to detailed real-time data on customers' usage behavior. Accessing such

information plays a central role in developing a customer-oriented marketing strategy (Kopalle et al., 2020)—as noted by Mark Garret, Adobe's former chief financial officer:

Because we are operating in the cloud, we have a better read on their needs—we know who signed up for Creative Cloud, which apps they have downloaded, and which features they are using. We are using predictive analytics and our own marketing tools to listen to our customers and strengthen our relationships with them.<sup>4</sup>

The ability to acquire and utilize customer usage data makes it possible for firms to be more precise in their processes of value creation and customer engagement (Kopalle et al., 2020). For example, leveraging usage history data helps cloud vendors identify unmet customer needs and thereby increase their cash flows by developing novel functionalities that satisfy those requirements (Liu et al., 2016).

Despite these benefits, several concerns may be raised about vendors' transition to the cloud. For instance, one could argue that users' sensitivity to security risks discourages them from adopting cloud-based solutions. Yet as Steve Daheb, senior vice president for Oracle Cloud, has stated, emerging technologies such as machine learning and artificial intelligence can be integrated within the cloud so that identifying potential threats and/or self-patching can be performed automatically—rendering the cloud more secure than in-house IT assets, specifically for customers with limited IT capabilities.<sup>5</sup> Another concern is that moving into the cloud makes a vendor's customer base more susceptible to competition because it lowers customers' switching costs by eliminating up-front investments in IT infrastructure. However, switching suppliers involves nontrivial expenditures on search, adaptation, and development (Burnham et al., 2003); hence, offering cloud-based solutions does not eliminate entirely the “lock-in” advantage. More importantly, vendors “tend to sign multi-year cloud contracts” (Yahoo! Finance 2015), which “not only give providers ... a steady, stable revenue source they can rely on, but they also disincentivize customers from shopping around with competitors” (Insider, 2020).<sup>6</sup>

Taken together, shifting to the cloud increases a vendor's cash flows by delivering superior value to customers, expanding its customer base, enhancing its operational efficiency, and generating customer intelligence. A larger

<sup>4</sup> <https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/reborn-in-the-cloud>

<sup>5</sup> <https://www.bloomberg.com/professional/blog/ai-will-lead-next-phase-cloud/>

<sup>6</sup> For example, companies such as Workday (2018) and ACI Worldwide, Inc (2018) indicate in their annual reports that their cloud contracts typically have a term of three years or longer and are often non-cancelable.



cash flow enhances shareholder wealth through increased firm value (Rao & Bharadwaj, 2008). As such, unanticipated changes in a firm's cloud ratio are likely to convey credible information to shareholders about its prospective performance. According to the efficient market hypothesis, investors incorporate this information into security prices when assessing the firm's future financial health. Formally:

- H1** An unanticipated increase in the cloud ratio has a positive effect on excess stock returns.

### Effects of unanticipated changes in the cloud ratio on idiosyncratic risk

An unanticipated increase in the cloud ratio reduces a vendor's idiosyncratic risk for several reasons. First, as discussed in the prior section, cloud-based solutions offer customers added value, in the form of cost reductions and/or productivity enhancements. Delivering superior value enhances customer satisfaction and engenders customer loyalty (Coulter and Coulter 2003; Mani et al. 2006). Loyal customers are less vulnerable to competition and hence provide vendors with a relatively smoother cash flow stream as they return to repurchase, cross-buy, or purchase add-ons (Bharadwaj et al., 2011). Second, cloud vendors' access to detailed, real-time information on customers' usage behavior enables them to forecast users' demand pattern more accurately and hence reduce the uncertainty associated with their future cash flows (see Kopalle et al., 2020). Third, unlike on-premises offerings with typically one-time payments, subscription-based cloud solutions generate recurring revenues that promise a more predictable cash flow stream (Breznitz et al., 2018). Fourth, cloud offerings are often delivered based on medium- to long-term contracts (see Yahoo! Finance 2015), a well-known safeguard against customer churn (see Bharadwaj et al., 1993).

Taken together, the combination of delivering added benefits, accessing information on customers' usage behavior, establishing a recurring subscription-based revenue model, and enforcing contractual commitment helps a cloud vendor build a more stable customer base that offers a smoother revenue stream (Srivastava et al., 1998). Accordingly, unanticipated changes in a firm's cloud ratio signal credible information to shareholders about the stability of its future cash flows. Based on the efficient market hypothesis, shareholders integrate this information into their valuation of the firm. Hence,

- H2** An unanticipated increase in the cloud ratio has a negative effect on idiosyncratic risk.

### Moderating effect of unanticipated changes in market maturity

An increase in market maturity is manifested by increased product commoditization and demand saturation (Cusumano et al., 2015). In that event, it becomes much more difficult to earn and sustain above-normal profits. We expect the effect of moving into the cloud on excess stock returns to be stronger in mature markets. The price sensitivity of customers in a market's mature phase makes cloud-based solutions more economically appealing to them (see Cusumano et al., 2015). For example, the hosted nature of cloud computing lowers customers' operating expenses as compared with running IT infrastructure in house (Ma & Seidmann, 2015). The cloud's usage-based pricing scheme likewise enables customers to eliminate those costs associated with unused IT resources that stem from demand uncertainties (Chen & Wu, 2013). Moreover, shifting to the cloud allows vendors to expand their customer base by reaching new customer segments—including small- and medium-sized businesses with limited purchasing power as well as remotely located businesses with limited access to traditional distributors. The additional revenues from these customers help cloud vendors cope with the declining demand characteristic of a mature market.

In sum, as price-based competition increases in mature markets, shifting to the cloud becomes an indispensable source of value creation and hence of revenue generation. Therefore, an unanticipated increase in market maturity provides new information to investors about the performance potentials of a move into cloud computing. Therefore,

- H3** An unanticipated increase in market maturity strengthens the positive effect of unanticipated cloud ratio increases on excess stock returns.

Similarly, we argue that an unanticipated increase in market maturity strengthens the negative effect of unexpected cloud ratio increases on a firm's idiosyncratic risk. The lack of technological differentiation in mature markets exacerbates the competition by increasing the substitutability of vendors' offerings (Sawhney et al., 2003; Suarez et al., 2013). Delivering added value to customers in the form of cost reductions and/or productivity gains differentiates a cloud provider in mature markets and encourages customers' repurchasing (see Ulaga & Reinartz, 2011). Further, cloud-based solutions often lock customers into long-term contracts (see Yahoo! Finance 2015). Contractual commitments prevent customers from switching to other suppliers, so cloud vendors can remove some of the market from the competitive arena to ensure earnings smoothing (see Bharadwaj et al., 1993). This effect becomes more prominent in

mature markets where customers often incur less costs to switch to other suppliers (see Cusumano et al., 2015). Therefore, an unanticipated increase in market maturity provides new information to investors about the performance implications of shifting to the cloud for a vendor's earnings stability. Accordingly,

- H4** An unanticipated increase in market maturity strengthens the negative effect of unanticipated cloud ratio increases on idiosyncratic risk.

### Moderating effect of unanticipated changes in advertising intensity

We expect an unanticipated increase in advertising intensity to strengthen the positive effect of unexpected cloud ratio increases on excess stock returns. Specifically, advertising accelerates the adoption rate of innovative offerings by boosting brand awareness (Joshi & Hanssens, 2010); and by reducing customers' perceived risk of purchase (Srinivasan et al., 2009). Leveraging these benefits is vital for cloud providers because they often provide cloud solutions directly and online, rather than through third-party distributors. Hence, cloud providers are less likely to benefit from promotional activities performed by independent distributors or sales representatives. Furthermore, customers' frequently cited concerns about shifting to the cloud (e.g., security risks, service availability) suggest that advertising can serve to mitigate their purchase risk through reinforcing a vendor's value proposition and providing a form of service quality assurance (see Tuli et al., 2012). In addition, the discretionary nature of advertising is such that it conveys credible signals to investors about a firm's potential for demand growth (Tuli et al., 2012). The competitive advantages derived from advertising investments make it easier for the firm to attract new customers and to nurture existing ones. Hence, an increase in advertising expenditures is indicative of a firm's potential to capitalize on the growth opportunities available from shifting to the cloud.

The preceding remarks lead us to conclude that an unanticipated increase in advertising intensity conveys new information to shareholders regarding a cloud provider's intention to build the market-based competencies necessary for competitive success in the cloud environment. It also transmits a positive signal to the stock market about the firm's confidence in the prospects of its cloud business. We again reference the efficient market hypothesis in positing that the disclosure of this new information affects investors' assessment of the firm's shift to cloud computing, which should strengthen the relationship between cloud transition and excess stock returns. Formally, we postulate:

- H5** An unanticipated increase in advertising intensity strengthens the positive effect of unanticipated cloud ratio increases on excess stock returns.

Similarly, we argue that an unanticipated increase in advertising intensity strengthens the negative effect of unexpected cloud ratio increases on idiosyncratic risk. A firm's advertising efforts create customer brand equity, an intangible market-based asset that enhances customer loyalty and retention (McAlister et al., 2007). Advertising also helps differentiate a firm's brand from those of competitors and hence makes it more costly for customers to switch their transactions to a different vendor (Anderson & Simester, 2013; Sridhar et al., 2016). Increased brand loyalty and differentiation function as hedging mechanisms (McAlister et al., 2007), enabling cloud vendors to build a more stable customer base that is less vulnerable to competition. Building on the efficient market hypothesis, we expect the disclosure of new information on a vendor's advertising intensity to influence the risk implications of the firm's transition to the cloud. Formally,

- H6** An unanticipated increase in advertising intensity strengthens the negative effect of unanticipated cloud ratio increases on idiosyncratic risk.

## Methodology

### Data and sample

To test our theoretical framework, we assemble a longitudinal data set from multiple sources. As the starting point for sample construction, we use the merged Center for Research in Security Prices (CRSP)-Compustat database to create a list of publicly traded firms operating in the computer software and services industries (primary SIC four-digit codes of 7370-7379). There are several reasons why these industries are a relevant context in which to study cloud computing. First, cloud solutions are increasingly replacing on-premises licensing, which has a strong effect on the revenue streams of traditional computer software and service providers (PwC, 2016). Second, computer software and service vendors typically disclose their revenues from cloud computing in their 10-K annual reports, which allows us to build the cloud ratio measure as a proxy for the degree of emphasis on cloud computing in a firm's business model.

We obtain accounting and stock returns data from, respectively, the merged CRSP-Compustat and the CRSP databases. To do so, we use PERMNOs as our firm identifier. Also, we use the Kantar Media's AdSpender database to collect the information on firms' advertising spending. We carefully match the company names from the merged

**Table 1** Sample distribution across the SIC four-digit industries

SIC Code	Industry Label	Number of Observations	Example Firms in the Sample
7370	Computer programming and data processing	801	21Vianet Group, Autodesk, Workday
7371	Computer programming services	26	Infosys, TSR
7372	Prepackaged software	731	Ansys, Check Point Software Technologies, Citrix Systems, NextGen Healthcare, <a href="https://www.salesforce.com">Salesforce.com</a> , SAP
7373	Computer integrated systems design	276	Streamline Health Solutions, Tyler Technologies
7374	Computer processing and data preparation and processing services	174	Fiserv, Innotrak

CRSP-Compustat database with those in the AdSpender dataset to retrieve the information on firms' advertising expenditures.

The merged CRSP-Compustat database includes 6,079 observations pertaining to 975 firms with SIC codes of 7370-7379, single class shares, and non-missing PERMNOs during the 2005-2019 time period. Given that our focus in this research is on B2B firms, we exclude from our sample those firms that sell business-to-consumer (B2C) offerings either solely or jointly with B2B solutions. This reduces the sample size to 4,707 observations for 753 firms. To compute the firms' cloud ratios, we draw on the information available in their 10-K annual reports. However, we exclude 383 observations pertaining to 142 firms from the sample because they do not provide enough information about whether or not they offer cloud-based solutions. This results in a sample of 4,324 observations for 691 firms that can be accurately classified as cloud vs. non-cloud providers.

Nonetheless, not all the firms that provide cloud-based solutions disclose information on their cloud revenues as a separate item in their income statements. Indeed, firms may bundle their cloud revenues with the revenues from non-cloud offerings; examples of the latter include perpetual licenses, post-contract customer support and maintenance services, and professional services (e.g., consulting services). For instance, in its 2020 annual report, NCR classifies cloud revenues as a part of the firm's "service revenue", which includes also "hardware and software maintenance revenue, implementation services revenue, ... as well as professional services revenue" (p. 34). The bundling of cloud- and non-cloud revenues prevents us from computing a firm's cloud ratio. Therefore, we exclude from our sample those observations that offer cloud-based solutions without separately disclosing their cloud revenues. This reduces the sample size to 2,725 observations from 515 firms.

Finally, data requirements for estimating autoregressive models to operationalize the continuous explanatory variables in our models as unanticipated changes in those variables (as detailed later) jointly with data availability on the control variables in our models reduce the final usable

sample size to 2,008 yearly observations from 435 firms over the 2005-2019 time period. Table 1 presents the sample distribution across the primary SIC four-digit industries.

## Measures

**Excess stock returns** Following Bharadwaj et al. (2011), we compute compounded monthly stock return as below:

$$SR_{ijt} = \prod_{k=1}^{12} (1 + Ret_{ijk}). \quad (1)$$

In Equation 1, and throughout the study, the subscripts  $i$ ,  $j$ ,  $t$ , and  $k$  respectively denote firm, 4-digit SIC industry, year, and month;  $SR_{ijt}$  is the compounded monthly stock return; and  $Ret_{ijk}$  reflects the holding-period return. To obtain excess stock returns, we subtract the returns on US Treasury bonds, which is also known as the risk-free rate of return, from the compounded monthly return.

**Idiosyncratic risk** To compute our measure of idiosyncratic risk, we use Carhart's (1997) four-factor model—which adds a "momentum" factor to the three-factor model of Fama and French (1993):

$$R_{ijtd} - R_{f,td} = \alpha_0 + \alpha_1 (R_{m,td} - R_{f,td}) + \alpha_2 (SMB_{td}) + \alpha_3 (HML_{td}) + \alpha_4 (UMD_{td}) + \varepsilon_{ijtd} \quad (2)$$

Here,  $R_{ijtd}$  denotes daily return on day  $d$ ;  $R_{f,td}$  is daily risk-free return;  $R_{m,td}$  denotes daily return on a value-weighted market portfolio;  $SMB_{td}$  is daily return on a portfolio of small stocks minus the return on a portfolio of large stocks;  $HML_{td}$  represents daily return on a portfolio of stocks with a high book-to-market ratio minus the return on a portfolio of stocks with a low book-to-market ratio;  $UMD_{td}$  is the momentum factor;  $\varepsilon_{ijtd}$  denotes the error term; and  $\alpha_0$ - $\alpha_4$  are the regression parameters. The standard deviation of the estimated residuals in Equation 2 captures the idiosyncratic variation in stock returns.



**Cloud ratio** Computer software and service providers typically break out cloud and non-cloud revenues in their 10-K annual reports. We use keywords such as “cloud”, “hosted” (vs. “in-house”), “on-demand” (vs. “on-premises” and “perpetual”), “Internet-based”, “Web-based”, “online”, “Software-as-a-Service”, “Platform-as-a-Service”, and “Infrastructure-as-a-Service” to identify cloud-based revenue sources in the firms’ annual reports. We compute a firm’s cloud ratio in a given year as the sum of its revenues from cloud computing divided by its total revenues. [Appendix A](#) gives some examples of how we construct the cloud ratio measure.

**Market maturity** We follow Suarez et al.’s (2013) approach to measure market maturity at the primary 4-digit SIC code level. In the growth stage of an industry’s life cycle, market density—that is, the number of firms operating in a market—continues to increase as new firms enter the market. Once the market enters its mature phase, however, density begins to decline because firms start to exit the market (Agarwal et al., 2002). We identify the onset of maturity as the peak of market density. Then, we compute market maturity as  $(-1/Density_{jt}) \times 100$  for the years before the onset of maturity and as  $(1/Density_{jt}) \times 100$  for the years thereafter, where  $Density_{jt}$  denotes the market density of 4-digit SIC industry  $j$  in year  $t$ . As such, market maturity takes negative (resp., positive) and increasing values before (resp., after) the onset of maturity.

**Advertising intensity** In line with prior research (e.g., Malshe & Agarwal, 2015), we measure advertising intensity as the ratio of advertising expenditures to total sales.

We use Kantar Media’s AdSpender database to obtain the information on firms’ advertising spending. Given that Kantar Media does not naturally cover all the firms in our sample, we follow Malshe and Agarwal (2015) and Malshe et al. (2020) to impute the missing advertising values.<sup>7</sup> Specifically, we compute the ratio of advertising to sales, general, and administrative (SG&A) expenses for each firm with available advertising spending in a given year in the AdSpender database; then, we obtain the annual average of the advertising-to-SG&A ratio at the 4-digit SIC code level. To estimate the missing value of advertising for a firm, we multiply the firm’s SG&A by the corresponding yearly average of advertising/SG&A ratio for its 4-digit SIC industry.

**Control variables** In our analysis, we control for several firm- and industry-specific factors that are likely to affect firm performance. In particular, the size of a firm is a key

determinant of its security returns (Fama & French, 1992); hence, we control for *firm size*, computed as the log-transform of total sales (Kalaianan et al., 2013). We also control for *market share*, or a firm’s sales divided by the overall sales of its 4-digit SIC industry. A larger market share is likely to improve a firm’s financial performance because it results in market-power advantages and enables the firm “to charge higher selling prices from customers and to negotiate lower purchase prices with suppliers” (Edeling & Himme, 2018, p. 3). In addition, we use *firm profitability*, or the ratio of earnings before interest and taxes (EBIT) to total sales, as a control (de Andrés et al., 2017). We also control for *R&D intensity*, or the ratio of R&D expenditures to total sales, as a proxy for the level of a firm’s emphasis on research and development activities.

We control for *accounts receivable intensity*, or the ratio of receivables to total sales, because it has been shown to affect both firm return and risk (Frennea et al., 2019). We include *financial leverage* as a control because it affects stock returns through equity risk (Ozdogli, 2012); leverage is measured as the ratio of long-term debt to EBIT (see, e.g., Bates et al., 2009). To account for the effect of acquisition investments on changes in cloud-based revenues, we control for *acquisitions expenditures*, normalized by total assets (Bates et al., 2009). We control for *financial slack* because it affects a firm’s ability to invest in growth opportunities (Fang et al., 2008). We operationalize financial slack as the ratio of working capital to total sales (Kim et al., 2018). We also control for *intangible intensity*, or 1 minus the ratio of net property, plant and equipment to total assets, because intangible assets are critical sources of competitiveness (Tuli et al., 2010). In addition, we include *the dividends payout ratio*, or the dividends-to-income ratio (He et al. 2020), as a control because changes in a firm’s dividends policy may incorporate information about its future earnings (Benartzi et al., 1997).

We also control for *competitive intensity*, which is operationalized as 1 minus the Herfindahl-Hirschman index (Lee et al., 2015). In addition, we use *market turbulence* as a control because moving into cloud services may become a more prominent source of revenue in volatile markets (see, e.g., Fang et al., 2008). We operationalize market turbulence as the coefficient of variation for the overall sales in a given 4-digit SIC industry over the preceding five years (Claussen et al., 2018). Finally, we include year dummies as controls to capture the effect of global shocks on firm performance. Table 2 summarizes our constructs’ definitions and how they are measured.

<sup>7</sup> The AdSpender database covers about 74% of the observations in our sample.

**Table 2** Constructs, definitions, and operationalizations

Constructs	Definitions	Operationalizations (References)
Excess stock returns	Stock returns beyond the risk-free rate	Compounded monthly return on a firm's stock less the return from investing in the US treasury bonds (Bharadwaj et al., 2011)
Idiosyncratic risk	Firm-specific stock returns volatility that is unexplained by overall market movements	The standard deviation of residuals obtained from Carhart's (1997) four-factor model (Frennea et al., 2019)
Cloud ratio	The extent to which a firm relies on cloud computing as a source of revenue	Share of a firm's revenue generated from selling cloud solutions
$R_m - R_f$	Excess market returns beyond the risk-free rate	Annual return on a value-weighted market portfolio, less the return on investing in the US treasury bonds (Fama & French, 1993)
SMB	Differences in returns on a portfolio of small versus large stocks	Annual return on the Fama and French's size portfolio (Fama & French, 1993)
HML	Differences in returns on a portfolio of stocks with high versus low book-to-market ratios	Annual return on the Fama and French's market-to-book portfolio (Fama & French, 1993)
UMD	Differences in returns on a portfolio of stocks with high versus low prior returns	Annual return on the Carhart's (1997) momentum portfolio
Market maturity	A stage of industry life cycle characterized by product standardization and sluggish market growth	Inverse of market density (i.e. the number of firms operating in the market) multiplied by either -100 (for the years prior to the onset of maturity) or 100 (for the years after the onset of maturity) (Suarez et al., 2013)
Advertising intensity	The level of a firm's emphasis on advertising	Advertising expenditures, divided by total sales (Malshe & Agarwal, 2015)
Firm size	Size of a firm	Log-transform of total sales (Kalaighnam et al., 2013)
Market share	Share of a firm in its market's overall sales	The ratio of a firm's sales to the overall sales of all the firms operating in the same industry (Malshe & Agarwal, 2015)
Firm profitability	Net income or loss of a firm	The ratio of EBIT to total sales (de Andrés et al., 2017)
R&D intensity	The level of a firm's emphasis on research and development activities	The ratio of R&D expenditures to total sales (Malshe & Agarwal, 2015)
Accounts receivable intensity	The level of a firm's emphasis on selling products and/or services on credit rather than for cash	Accounts receivable, normalized by total assets (Frennea et al., 2019)
Financial leverage	The extent to which a firm relies on borrowed capital	The ratio of long-term debt to EBIT (see, e.g., Bates et al., 2009)
Acquisitions expenditure	A firm's degree of emphasis on acquisition investments	Acquisition expenditures, normalized by total assets (Bates et al., 2009)
Financial slack	Surplus of financial resources in an organization for ongoing activities	The ratio of working capital to total assets (Kim et al., 2018)
Intangible intensity	A firm's degree of emphasis on intangible assets	1 <i>minus</i> the ratio of plant, property, and equipment to total assets (Tuli et al., 2010)
Dividends payout ratio	Share of earnings paid to stockholders	The dividends-to-income ratio (He et al 2020)
Competitive intensity	Degree of rivalry among firms operating in a market	1 <i>minus</i> the Herfindahl-Hirschman index (Lee et al., 2015)
Market turbulence	The degree of demand volatility in a market	Coefficient of variation for overall sales in a market over the preceding five years (Claussen et al., 2018)

## Operationalization

The stock market reacts only to the release of unexpected information with critical implications for future firm performance (Fama, 1970). We therefore use a stock return response model that explores whether the new information

contained in a construct is associated with long-term changes in a firm's stock price (see, e.g., Bharadwaj et al., 2011; Edeling et al., 2020; Frennea et al., 2019; Mishra & Modi, 2016). To capture the release of new information, we operationalize the continuous explanatory variables in our framework as unanticipated changes in those variables.

**Table 3** Descriptive statistics and correlations

Constructs	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Excess stock returns(%)	1.000																				
2. Idiosyncratic risk	-.360	1.000																			
3. U $\Delta$ Cloud ratio	.033	-.016	1.000																		
4. $R_m - R_f$	.377	-.155	.057	1.000																	
5. SMB	.122	.098	-.008	.255	1.000																
6. HML	-.065	-.024	-.032	.031	.315	1.000															
7. UMD	-.163	-.150	.020	-.456	-.486	-.131	1.000														
8. U $\Delta$ Market maturity	-.043	-.016	-.014	-.021	-.121	.146	.089	1.000													
9. U $\Delta$ Advertising intensity	-.038	.054	-.008	-.065	.035	.037	-.105	.065	1.000												
10. U $\Delta$ Firm size	.056	-.088	-.035	-.012	-.139	.012	.202	.029	-.094	1.000											
11. U $\Delta$ Market share	-.036	.011	-.008	-.097	.040	-.000	.045	.057	.006	.420	1.000										
12. U $\Delta$ Firm profitability	.227	-.023	-.079	.025	.056	-.009	-.042	-.014	-.074	.330	.052	1.000									
13. U $\Delta$ R&D intensity	-.175	.053	.054	-.037	-.034	.013	.032	.019	.025	-.256	-.068	-.583	1.000								
14. U $\Delta$ Accounts receivable intensity	.056	-.073	.018	.040	-.057	.002	.038	.052	-.008	-.034	-.023	-.073	.067	1.000							
15. U $\Delta$ Financial leverage	.007	-.022	.035	.017	.011	.025	.018	.018	.031	.032	.024	-.002	.000	.048	1.000						
16. U $\Delta$ Acquisitions expenditure	-.048	-.024	.033	-.066	-.076	-.018	.087	-.016	.050	.225	.157	-.038	.047	.133	.119	1.000					
17. U $\Delta$ Financial slack	.103	-.031	.059	.073	-.003	-.047	.037	-.037	-.048	-.165	-.082	-.007	.055	.132	.004	-.182	1.000				
18. U $\Delta$ Intangible intensity	.156	-.076	.031	.076	-.021	-.029	.028	-.011	-.045	.037	-.045	.123	-.082	.093	.006	.024	.275	1.000			
19. U $\Delta$ Dividends payout ratio	.012	-.018	.004	-.004	-.002	.013	.007	-.014	.013	.010	.012	.043	-.029	.010	.011	.036	.003	.000	1.000		
20. U $\Delta$ Competitive intensity	.065	-.062	.027	.093	-.130	-.079	.047	-.079	-.072	-.013	-.110	-.050	.032	.A24	.005	-.003	.002	.044	-.008	1.000	
21. U $\Delta$ Market turbulence	.058	-.058	.032	.200	-.261	.111	.216	.024	-.052	.034	-.154	-.018	.008	.074	-.023	-.024	.057	.058	.043	-.009	1.000
Mean	1.071	.020	-.000	.075	.004	-.022	-.013	.047	-.000	.005	-.000	.002	-.000	-.002	-.180	-.002	-.001	.002	.015	.003	-.001
SD	.458	.012	.008	.185	.068	.108	.268	.281	.002	.117	.001	.064	.018	.032	2.088	.048	.180	.015	.197	.011	.002

For each firm, we disentangle the time-based unexpected changes in a continuous variable by estimating a first-order autoregressive time-series model as follows (Bharadwaj et al., 2011; Mishra & Modi, 2016; Mizik & Jacobson, 2004):

$$X_{ijt} = \delta_{0i} + \delta_{1i}X_{ijt-1} + \xi_{X,ijt}; \quad (3)$$

where  $X_{ijt}$  is the variable of interest;  $\delta_{0i}$  is the firm-specific intercept;  $\delta_{1i}$  reflects the persistence of time series; and the predicted residuals (i.e.,  $\hat{\xi}_{X,ijt}$ ) reflect the unanticipated changes in variable  $X$  (i.e.,  $U\Delta X_{ijt}$ ). We provide the descriptive statistics and correlations for the variables in Table 3. To limit the influence of potential outliers in our estimations, we winsorize all the continuous variables at the 5% and 95% levels of their respective distributions.

## Estimation

We build our stock return response model on Carhart's (1997) four-factor model. Since a firm's stock price at a given point in time reflects all available information about the firm up to that time, adding unanticipated changes in the variables of interest allows us to capture the investors' reaction to the release of new information (Edeling et al., 2020). Therefore, to examine the effect of moving into the cloud on excess stock returns, we incorporate unanticipated changes in the continuous explanatory variables, along with year dummies, into Carhart's model:

$$\begin{aligned} SR_{ijt} - R_{f,t} = & \beta_0 + \beta_1(R_{m,t} - R_{f,t}) + \beta_2(SMB_t) + \beta_3(HML_t) + \beta_4(UMD_t) \\ & + \beta_5(U\Delta CR_{ijt}) + \beta_6(U\Delta MM_{jt}) + \beta_7(U\Delta ADI_{ijt}) \\ & + \beta_8(U\Delta CR_{ijt} \times U\Delta MM_{jt}) + \beta_9(U\Delta CR_{ijt} \times U\Delta ADI_{ijt}) \\ & + \mathbf{Z}_{ijt}\mathbf{B} + \mu_{ijt} \end{aligned} \quad (4)$$

Here,  $U\Delta CR_{ijt}$  denotes unanticipated changes in the cloud ratio;  $U\Delta MM_{jt}$  is unanticipated changes in market maturity;  $U\Delta ADI_{ijt}$  is unanticipated changes in advertising intensity;  $\mathbf{Z}_{ijt}$  represents the matrix of control variables, which consists of unexpected changes in firm size, market share, profitability, R&D intensity, accounts receivable intensity, financial leverage, acquisition expenditures, financial slack, intangible intensity, the dividends payout ratio, competitive intensity, and market turbulence as well as year dummies. The  $\mu_{ijt}$  term captures unobservable variables; and  $\beta_0$ - $\beta_9$  and the vector  $\mathbf{B}$  denote the regression coefficients to be estimated.

We similarly use the following model to examine how shifting to the cloud affects idiosyncratic risk:

$$\begin{aligned} IDR_{ijt} = & \theta_0 + \theta_1(U\Delta CR_{ijt}) + \theta_2(U\Delta MM_{jt}) + \theta_3(U\Delta ADI_{ijt}) \\ & + \theta_4(U\Delta CR_{ijt} \times U\Delta MM_{jt}) + \theta_5(U\Delta CR_{ijt} \times U\Delta ADI_{ijt}) \\ & + \mathbf{Z}_{ijt}\mathbf{\Theta} + v_{ijt}; \end{aligned} \quad (5)$$

where  $IDR_{ijt}$  represents idiosyncratic risk;  $v_{ijt}$  captures unobservable variables; and  $\theta_0$ - $\theta_5$  together with the vector  $\mathbf{\Theta}$  are the regression coefficients.

The models specified in Equations 4 and 5 are susceptible to two possible sources of endogeneity: (i) sample selection bias due to the exclusion of firms with missing or bundled cloud revenue data; and (ii) omitted variables. Following Han et al. (2017), we address these two issues as detailed below.

**Sample selection** Our focal independent variable is unanticipated changes in the cloud ratio. Therefore, our sample includes only firms with non-missing, identifiable cloud revenue data. However, the software industry also includes firms that bundle their cloud sales with other sources of revenues in their 10-k reports. Excluding such firms from our sample could lead to selection bias because disclosing cloud revenues may be a non-random strategic decision. To address sample selection, we use the approach proposed by Heckman (1979). A firm's choice to disclose ( $S_{ijt} = 1$ ) or to not disclose ( $S_{ijt} = 0$ ) cloud revenue data is a function of firm- and industry-level characteristics. Following Han et al. (2017), we use the proportion of peer firms (i.e., those firms operating in the same 4-digit SIC industry as a focal firm) with non-missing cloud revenue data as an exclusion restriction. We argue that our excluded variable satisfies both the instrument relevance criterion and the exclusion restriction. In fact, common industry norms in disclosing cloud revenues are likely to be related to a firm's decision to report its cloud sales. Yet it is unlikely that peer firms can collectively observe and/or act on the focal firm's omitted variables, suggesting that our excluded variable is uncorrelated with the omitted variables captured by the error terms in Equations 4 and 5 (see Srinivasan & Ramani, 2019). Therefore, we estimate the following probit model:

$$\Pr(S_{ijt} = 1) = \Phi[\pi_0 + \pi_1(PPF\_CR_{ijt}) + \pi_2(U\Delta MM_{jt}) + \pi_3(U\Delta ADI_{ijt}) + \mathbf{Z}_{ijt}\mathbf{\Pi}]; \quad (6)$$

where  $PPF\_CR_{ijt}$  denotes the proportion of peer firms that disclose data on their cloud revenues; and  $\pi_0$ - $\pi_3$  alongside the vector  $\mathbf{\Pi}$  are the regression coefficients to be estimated. We subsequently include the inverse Mills ratio obtained from Equation 6 into the final models to control for the selection bias.

**Control function approach** Even with the extensive list of covariates used in Equations 4 and 5, we are unable to account for all the variables that could affect both unanticipated changes in the cloud ratio and firm performance. It follows that, in our model specification, the presence of time-invariant unobservable variables (e.g., organizational culture) that could be correlated with unexpected cloud ratio changes may bias our estimates. To overcome this challenge,



we use a fixed-effects time-series panel model that removes time-invariant unobservable variables by applying a within-transformation to the data (see Bharadwaj et al., 2011; Srinivasan et al., 2009; Wooldridge, 2009).

Further, the error terms in Equations 4 and 5 include unobserved time-varying components that may affect both firm performance and the cloud ratio. For example, performance is driven by many other variables—such as organizational agility in responding to changing market conditions—that could also influence the shift to cloud computing. Similarly, unobserved time-varying factors such as investment opportunities are likely to affect a firm's allocation of resources to strategic initiatives (e.g., Chakravarty & Grewal, 2011). If so, then there may be an endogeneity concern as regards advertising intensity in our models. Accordingly, one must control for such unobservable variables in order to correct for biases that may arise from the non-random nature of cloud transition or advertising investment decisions. However, information on these potentially crucial variables is not available in our data. Hence, there may be an omitted variable bias in our models' estimates of the relationship between unanticipated cloud ratio changes and firm performance or the moderating effect of unexpected changes in advertising intensity (see Germann et al., 2015; Papies et al., 2017).

Following previous studies (e.g., Sridhar et al., 2016; Srinivasan et al., 2018), we use the control function approach to address these sources of endogeneity. In doing so, we employ the average of peer firms' cloud ratios and advertising intensities as our instrumental variables. Using the information available about peer firms to construct our instruments is in accord with previous research in marketing (e.g., Germann et al., 2015; Jindal & McAlister, 2015; Srinivasan et al., 2018). Our excluded variables meet both the instrument relevance criterion and the exclusion restriction.

In terms of the relevance criterion, we argue that an increase in the average of peer firms' cloud ratios could be indicative of an overall increase in the market demand for cloud solutions. It is therefore reasonable to assume that a vendor places more emphasis on cloud computing when the average of peer firms' cloud ratios increases. Hence, we expect that the average of peer firms' cloud ratios will be positively related to unanticipated changes in a firm's cloud ratio. Similarly, "firms are known to look to their peers to guide their marketing actions", suggesting a high correlation between a firm's and its peers' degree of emphasis on advertising in their promotion mix "because they are guided by similar norms" (Sridhar et al., 2016, p. 47). Therefore, we expect the average of peer firms' advertising intensities will be positively related to unanticipated changes in a focal firm's advertising intensity.

In terms of the exclusion restriction, we argue that a firm's omitted variables are difficult to observe and hence

to assess. Therefore, it is most unlikely that peer firms can collectively measure such variables and/or act on them strategically (Germann et al., 2015; Sridhar et al., 2016). Thus, we can reasonably expect that our excluded variables are uncorrelated with the omitted variables that are captured by the error terms in Equations 4 and 5.

The control function method relies on a two-step procedure to condition out the variation in unobservable factors correlated with the endogenous variables of interest (for details, see, e.g., Petrin & Train, 2010; Wooldridge, 2015). First, we perform auxiliary regressions of unexpected cloud ratio and advertising intensity changes on our instrumental variables together with other exogenous variables as regressors:

$$U\Delta CR_{ijt} = \gamma_0 + \gamma_1 (AVGPF\_CR_{ijt}) + \gamma_2 (AVGPF\_ADI_{ijt}) + \gamma_3 (U\Delta MM_{ijt}) + \gamma_4 (IMR_{ijt}) + \mathbf{Z}_{ijt}\boldsymbol{\Gamma} + \sigma_{ijt}; \quad (7)$$

$$U\Delta ADI_{ijt} = \tau_0 + \tau_1 (AVGPF\_CR_{ijt}) + \tau_2 (AVGPF\_ADI_{ijt}) + \tau_3 (U\Delta MM_{ijt}) + \tau_4 (IMR_{ijt}) + \mathbf{Z}_{ijt}\mathbf{T} + \rho_{ijt}; \quad (8)$$

where  $AVGPF\_CR_{ijt}$  represents the average of peer firms' cloud ratios;  $AVGPF\_ADI_{ijt}$  denotes the average of peer firms' advertising intensities;  $IMR_{ijt}$  is the inverse Mills ratio;  $\sigma_{ijt}$  and  $\rho_{ijt}$  are random error terms; and  $\gamma_0$ - $\gamma_4$ ,  $\tau_0$ - $\tau_4$ , and the vectors  $\boldsymbol{\Gamma}$  and  $\mathbf{T}$  are the regression parameters.

Second, the predicted residuals (i.e.,  $\hat{\sigma}_{ijt}$  and  $\hat{\rho}_{ijt}$ ) from these regressions are added to the final models to serve as the control functions that condition on the parts of unexpected cloud ratio and advertising intensity changes that depend on the error terms. After adding the predicted residuals, the remaining variations in unexpected cloud ratio and advertising intensity changes will be independent of the error terms. Equations 9 and 10 specify our final models:

$$SR_{ijt} - R_{f,t} = \lambda_0 + \lambda_1 (R_{m,t} - R_{f,t}) + \lambda_2 (SMB_t) + \lambda_3 (HML_t) + \lambda_4 (UMD_t) + \lambda_5 (U\Delta CR_{ijt}) + \lambda_6 (U\Delta MM_{ijt}) + \lambda_7 (U\Delta ADI_{ijt}) + \lambda_8 (U\Delta CR_{ijt} \times U\Delta MM_{ijt}) + \lambda_9 (U\Delta CR_{ijt} \times U\Delta ADI_{ijt}) + \lambda_{10} (IMR_{ijt}) + \lambda_{11} (\hat{\sigma}_{ijt}) + \lambda_{12} (\hat{\rho}_{ijt}) + \mathbf{Z}_{ijt}\boldsymbol{\Lambda} + \eta_{ijt}; \quad (9)$$

$$IDR_{ijt} = \phi_0 + \phi_1 (U\Delta CR_{ijt}) + \phi_2 (U\Delta MM_{ijt}) + \phi_3 (U\Delta ADI_{ijt}) + \phi_4 (U\Delta CR_{ijt} \times U\Delta MM_{ijt}) + \phi_5 (U\Delta CR_{ijt} \times U\Delta ADI_{ijt}) + \phi_6 (IMR_{ijt}) + \phi_7 (\hat{\sigma}_{ijt}) + \phi_8 (\hat{\rho}_{ijt}) + \mathbf{Z}_{ijt}\boldsymbol{\Phi} + \zeta_{ijt}; \quad (10)$$

where  $\eta_{ijt}$  and  $\zeta_{ijt}$  denote the random error terms; and  $\lambda_0$ - $\lambda_{12}$ ,  $\phi_0$ - $\phi_8$ , and the vectors  $\boldsymbol{\Lambda}$  and  $\boldsymbol{\Phi}$  are the regression parameters. Following Petrin and Train (2010) and Wooldridge (2015), we bootstrap the entire estimation procedure based on 1,000 replications to obtain valid standard errors for the estimated coefficients.

**Table 4** Auxiliary regressions

	Model 1: Selection Model		Model 2: Control Function		Model 3: Control Function	
	DV: Cloud Revenue Disclosure Dummy		DV: U $\Delta$ Cloud Ratio		DV: U $\Delta$ Advertising Intensity	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
<b>Excluded variables</b>						
Proportion of peer firms with non-missing cloud revenues	2.141 ***	(.993)	–	–	–	–
Average of peer firms' cloud ratios	–	–	.031 **	(.012)	.002 *	(.001)
Average of peer firms' advertising intensity	–	–	.073	(.200)	.033 ***	(.007)
<b>Control variables</b>						
R <sub>m</sub> -R <sub>f</sub>	.043	(.591)	.006	(.015)	-.001	(.000)
SMB	1.987	(1411)	-.020	(.028)	.003 **	(.001)
HML	-.970	(.938)	.012	(.015)	-.001 *	(.001)
UMD	-.174	(.393)	.002	(.010)	.000	(.000)
U $\Delta$ Market maturity	.318	(.213)	.000	(.001)	.001 ***	(.000)
U $\Delta$ Advertising intensity	-48.716	(33.495)	–	–	–	–
U $\Delta$ Firm size	-1.043 **	(.502)	.019	(.012)	-.003 ***	(.000)
U $\Delta$ Market share	33.614	(54322)	.002	(.117)	.186***	(.054)
U $\Delta$ Firm profitability	.287	(1.026)	-.011 ***	(.004)	-.000	(.001)
U $\Delta$ R&D intensity	2.367	(3.360)	.038	(.037)	.003	(.003)
U $\Delta$ Accounts receivable intensity	1.150	(1.483)	.017	(.015)	.003**	(.001)
U $\Delta$ Financial leverage	.005	(.019)	-.000 n	(.000)	.000 *	(.000)
U $\Delta$ Acquisitions expenditure	–	(.956)	.020	(.014)	-.001 *	(.001)
U $\Delta$ Financial slack	.244	(.318)	.013 ***	(.004)	-.000	(.000)
U $\Delta$ Intangible intensity	.330	(3.090)	.008	(.038)	-.000	(.003)
U $\Delta$ Dividends payout ratio	-.255	(.296)	-.000	(.000)	-.001 ***	(.000)
U $\Delta$ Competitive intensity	9.128**	(4.246)	-.020	(.053)	.020***	(.005)
U $\Delta$ Market turbulence	2.946	(2.921)	.097	(.107)	.016***	(.003)
Inverse Mills Ratio	–	–	.060	(.113)	.079***	(.006)
Intercept	1.297 *	(.671)	-.011	(.008)	-.002 ***	(.001)
Year dummies	Included		Included		Included	
Wald chi-square statistic	151.80***		–		–	
F-statistic	–		14.90***		12.55***	
Number of observations	3,416		2,008		2,008	

\*Significant at 10% level, two-sided

\*\*Significant at 5% level, two-sided

\*\*\*Significant at 1% level, two-sided

## Estimation results

We present the estimation results for the auxiliary models (i.e., Equations 6–8) in Table 4. As Model 1 shows, the proportion of peer firms with non-missing cloud revenues is a significant predictor of the selection probability ( $\pi = 2.441$ ,  $p < .01$ ). In Model 2, the average of peer firms' cloud ratios has a positive and significant effect on unanticipated changes in a firm's cloud ratio ( $\gamma = .031$ ,  $p < .05$ ). In Model 3, the effect of average of peer firms' advertising intensities on unanticipated changes in a firm's advertising intensity is

positive and significant ( $\tau = .033$ ,  $p < .01$ ). In addition, the  $F$ -statistics in Models 2 and 3 are, respectively, 14.90 ( $p < .01$ ) and 12.55 ( $p < .01$ ), which are above the recommended threshold of 10 (Staiger and Stock 1997). These findings constitute strong evidence for the validity of our instrumental variables.

**Table 5** Effect of shifting to cloud computing on firm performance

	Model 1		Model 2		Model 3		Model 4				
	DV: Excess Stock Returns		DV: Idiosyncratic Risk		DV: Excess Stock Returns		DV: Idiosyncratic Risk				
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)			
<b>Main effects</b>											
UΔCloud ratio	H <sub>1</sub>	20.208 **	(8.656)	H <sub>2</sub>	-.338 **	(.165)	25.218 **	(12.189)	-.393 **	(.192)	
<b>Moderating effects</b>											
UΔCloud ratio × UΔMarket maturity		-	-		H <sub>3</sub>		9.768 **	(470)	H <sub>4</sub>	-.028	(.059)
UΔCloud ratio × UΔAdvertising intensity		-	-		H <sub>5</sub>		-348.473	(753.238)	H <sub>6</sub>	21.416 **	(8.770)
<b>Control variables</b>											
R <sub>m</sub> -R <sub>f</sub>		.243 *	(.134)		-	-	231	(.154)		-	-
SMB		-.019	(371)		-	-	.042	(520)		-	-
HML		-.368 *	(.202)		-	-	-.526 *	(277)		-	-
UMD		.044	(.092)		-	-	.049	(.092)		-	-
UΔMarket maturity		.051	(.053)		.000	(.001)	.171 **	(.076)		.000	(.001)
UΔAdvertising intensity		-33.518	(33.406)		-.634	(.780)	-70338	(43.190)		-.634	(595)
UΔFirm size		.330 **	(.165)		-	(.004)	.319 *	(.186)		-.008 **	(.004)
UΔMarket share		-17.341	(15.515)		-.274	(.282)	-7.607	(14.670)		-.284	(.280)
UΔFirm profitability		1.396 ***	(.275)		-.002	(.005)	1571 ***	(.325)		-.002	(.005)
UΔR&D intensity		-1.079	(.851)		-.005	(.014)	-.859	(.945)		-.003	(.018)
UΔAccounts receivable intensity		.921 "	(.368)		-.019 ***	(.007)	1.467 ***	(517)		-.019 ***	(.006)
UΔFinancial leverage		.005	(.005)		.000	(.000)	.004	(.007)		.000	(.000)
UΔAcquisitions expenditure		-.517 *	(.280)		-.004	(.004)	-.639 *	(361)		-.004	(.005)
UΔFinancial slack		.010	(.070)		-.000	(.001)	.079	(.091)		-.000	(.002)
UΔIntangible intensity		1.980 **	(.888)		-.025	(.016)	-.083	(.234)		-.025	(.017)

Table 5 (continued)

	Model 1		Model 2		Model 3		Model 4	
	DV: Excess Stock Returns		DV: Idiosyncratic Risk		DV: Excess Stock Returns		DV: Idiosyncratic Risk	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
UΔDividends payout ratio	.052	(.060)	.001	(.001)	-.011	(.076)	.001	(.001)
UΔCompetitive intensity	1.860	(1.263)	-.015	(.024)	2.753 *	(1.432)	-.015	(.030)
UΔMarket turbulence	.124	(.894)	.008	(.022)	.861	(.695)	.008	(.017)
Inverse Mills Ratio	1.931	(3.026)	.056	(.073)	5.803 *	(3.489)	.056	(.060)
Control function (UΔCloud ratio)	-20.759 *	(10.083)	.345 *	(.194)	-26.349 *	(14.028)	.396	(.221)
Control function (UΔAdvertising intensity)	42.187	(38.868)	.628	(.898)	90.139 *	(49310)	.619 *	(.711)
Intercept	.707 ***	(.139)	.030 ***	(.002)	576 ***	(.164)	.030	(.003)
Year dummies	Included		Included		Included		Included	
Number of observations	2,008		2,008		2,008		2,008	
Wald chi-square statistic	2,750.63 ***		1,362.35 ***		2,529.25 ***		1,072.75 ***	
R <sup>2</sup>	.320		.262		.335		.264	

\*Significant at 10% level, two-sided

\*\*Significant at 5% level, two-sided

\*\*\*Significant at 1% level, two-sided



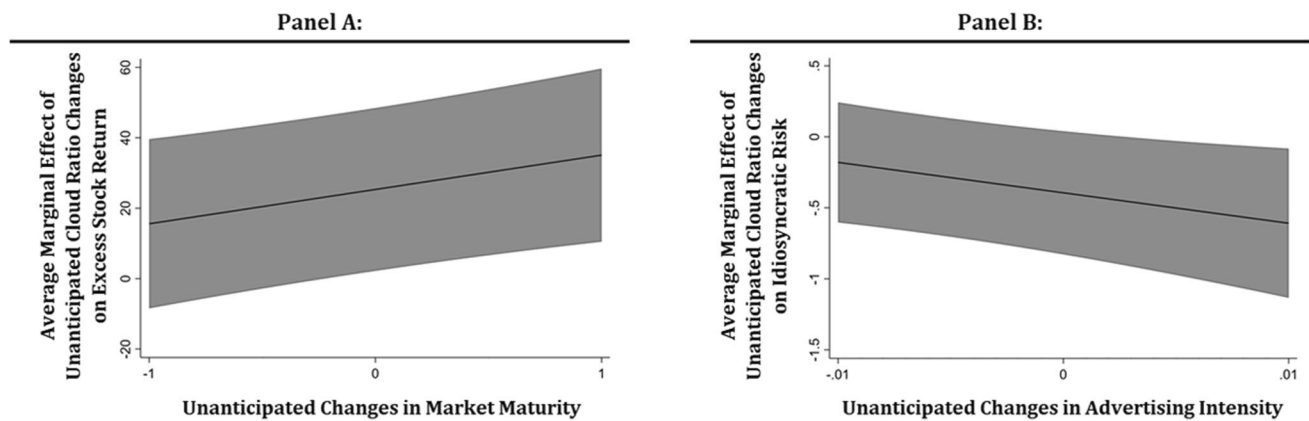


Fig. 2 Moderating effects of unexpected changes in market maturity and advertising intensity

## Hypotheses tests

We report the estimation results for Equations 9 and 10 in Table 5. In Model 1, the coefficient for unexpected cloud ratio changes is positive and significant ( $\lambda = 20.208$ ,  $p < .05$ ). We thus find evidence for a positive effect of an unanticipated increase in the cloud ratio on excess stock returns, which supports H1. In Model 2, unanticipated increases in the cloud ratio have a negative and significant effect on idiosyncratic risk ( $\varphi = -.338$ ,  $p < .05$ ), which supports H2.

In Model 3, after adding the interaction terms, the effect of unexpected cloud ratio changes on excess stock returns remains positive and significant ( $\lambda = 25.218$ ,  $p < .05$ ). Furthermore, we find that unexpected changes in market maturity positively moderate the effect of unexpected cloud ratio changes on excess stock returns ( $\lambda = 9.768$ ,  $p < .05$ ), in support of H3. However, the moderating effect of unanticipated changes in advertising intensity on the link between unexpected cloud ratio changes and excess stock returns is insignificant ( $\varphi = -.348.473$ , *n.s.*); we thus fail to find support for H5. This is likely because unexpected changes in advertising intensity can have dual opposing effects that offset each other in the cloud environment. On the one hand, advertising expenditures provide credible signals to investors about the potential for demand growth. On the other hand, adopting a subscription-based business model may, at least initially, result in slow cash inflow (see Breznitz et al., 2018). Therefore, given the capital-intensive nature of advertising investments, an unexpected increase in advertising spending may concern investors about a cloud vendor's short-term profitability.

In Model 4, after including the interaction terms, the effect of unanticipated cloud ratio changes on idiosyncratic risk remains negative and significant ( $\varphi = -.393$ ,  $p < .05$ ). However, the moderating effect of unanticipated changes in market maturity on the relationship between unexpected cloud ratio changes and idiosyncratic risk is insignificant ( $\varphi$

$= -.028$ , *n.s.*); we thus fail to find support for H4. This is likely because switching suppliers in the maturity phase of technology- and capital-intensive markets may still involve nontrivial expenditures on search, integration, and adaptation (see Burnham et al., 2003). This can, at least partially, substitute the “lock-in” advantage available from moving into the cloud and hence lessen the competitiveness of cloud vendors. Finally, unanticipated changes in advertising intensity negatively moderate the effect of unexpected cloud ratio changes on idiosyncratic risk ( $\varphi = -21.416$ ,  $p < .05$ ), in support of H6. We plot these moderating effects in Fig. 2.

## Sensitivity analyses

**Alternative source of advertising spending data** In our main analyses, we used the Kantar Media's AdSpender database to retrieve the information on firms' advertising expenditures. As an alternative data source, we use the merged CRSP-Compustat database to obtain the information on firms' advertising spending. As shown in Table 6, Models 1 and 2, our findings are not sensitive to using this alternative source of advertising spending data.

**Data requirement for calculating idiosyncratic risk** To operationalize the idiosyncratic risk measure, we estimate Equation 2 after restricting our sample to firms with at least 250 daily stock return observations in a given year. The results in Model 3 of Table 6 indicate that our findings are robust to imposing this constraint on our sample.<sup>8</sup>

<sup>8</sup> We found similar results after limiting our sample to firms with at least 30, 60, or 120 daily stock return observations in a given year. The results are available upon request.

**Table 6** Sensitivity analyses

	Using an Alternative Source of Advertising Spending Data				Data Requirement for Measuring Firm Risk	
	Model 1		Model 2		Model 3	
	DV: Excess Stock Returns		DV: Idiosyncratic Risk		DV: Idiosyncratic Risk	
	Estimate	(SE)	Estimate	(SE)	Estimate	(SE)
<b>Main effects</b>						
UΔCloud ratio	27.214 **	(11.979)	-.761 ***	(.176)	-.436**	(.218)
<b>Moderating effects</b>						
UΔCloud ratio × UΔMarket maturity	8.251 *	(4.745)	-.135	(.093)	-.029	(.056)
UΔCloud ratio × UΔAdvertising intensity	549.203	(399.537)	-9.378 ***	(3.527)	-22.754***	(7.964)
<b>Control variables</b>						
R <sub>m</sub> -R <sub>f</sub>	.249	(.152)	—	—	—	—
SMB	-.195	(.452)	—	—	—	—
HML	-.488 **	(.245)	—	—	—	—
UMD	.034	(.097)	—	—	—	—
UΔMarket maturity	.181**	(.074)	-.002	(.002)	.000	(.001)
UΔAdvertising intensity	-.565	(12.811)	.321	(.263)	-.370	(.703)
UΔFirm size	.495 ***	(.139)	-.007 **	(.003)	-.007 *	(.004)
UΔMarket share	-16.582	(16.596)	-.729 **	(.305)	-.434	(.325)
UΔFirm profitability	1.454 ***	(.333)	.001	(.007)	-.001	(.006)
UΔR&D intensity	-1.037	(.853)	-.014	(.017)	-.004	(.018)
UΔAccounts receivable intensity	1.044***	p73)	-.022.***	(.006)	-.018 ***	(.007)
UΔFinancial leverage	.004	(.006)	.000	(.000)	.000	(.000)
UΔAcquisitions expenditure	-.562 **	(.270)	.005	(.006)	-.002	(.005)
UΔFinancial slack	.087	(.106)	.001	(.002)	-.001	(.002)
UΔIntangible intensity	-.066	(.265)	-.033 *	(.018)	-.023 *	(.014)
UΔDividends payout ratio	.024	(.080)	.001	(.001)	.001	(.001)
UΔCompetitive intensity	2.320	(1.756)	-.033	(.028)	-.022	(.036)
UΔMarket turbulence	.080	(.905)	.003	(.021)	-.008	(.017)
Inverse Mills Ratio	.321	(2.611)	.026	(.047)	.031	(.069)
Control function (UΔCloud ratio)	-28.128 **	(13.424)	.806 ***	(.194)	.436 *	(.243)
Control function (UΔAdvertising intensity)	3.512	(15.641)	-.428	(.297)	.314	(.837)
Intercept	.617 ***	(.131)	.033 ***	(.004)	.030 ***	(.002)
Year dummies	Included		Included		Included	
Number of observations	1,913		1,913		1,834	
Wald chi-square statistic	3,118.44 ***		832.86 ***		1,211.77 **	
R <sup>2</sup>	.337		.292		.287	

\*Significant at 10% level, two-sided

\*\*Significant at 5% level, two-sided

\*\*\*Significant at 1% level, two-sided

## General discussion

The invention of cloud computing as a disruptive technological paradigm for delivering IT products and services has shaken the software industry to its core. Pivoting to the cloud—in light of its profound effects on a vendor's mix of marketing elements—has dominated discussions among marketing managers at software firms (see Moorman et al.,

2018). Yet the literature on the performance implications of moving into the cloud is sparse, leaving academics and practitioners with a limited understanding of the financial outcomes of adopting a cloud-based business model (Fazli et al., 2018). In addressing this gap, our study fulfills two objectives.

First, we document empirically the shareholder wealth implications of transitioning to the cloud from the vendors'

perspective. Our results establish that an unanticipated increase in the cloud ratio enhances a firm's excess stock returns and reduces its idiosyncratic risk. By focusing on the shareholder value implications of moving into the cloud, our study responds to the growing body of marketing-finance interface research that calls for examining the value relevance of marketing-related innovations (e.g., Dotzel et al., 2013; Dotzel & Shankar, 2019; Geyskens et al., 2002; Sood & Tellis, 2009).

Second, we highlight the roles of market maturity and advertising intensity as key determinants of the effectiveness of moving into the cloud. Our findings reveal that the effect of shifting to the cloud on firm return becomes stronger in the presence of unexpected increases in market maturity. Further, an unexpected increase in advertising intensity enhances the negative relationship between moving into the cloud and idiosyncratic risk.

## Theoretical contributions

Our research bears a number of important theoretical implications. To the best of our knowledge, this is the first large-scale empirical study to investigate, from the vendors' standpoint, the long-term return and risk implications of moving into the cloud. As such, our study complements that of Son et al. (2014) in three important ways.

First, Son et al. (2014) explore the effect of adopting cloud-based solutions from the users' perspective. In contrast, our study examines the performance implications of shifting to the cloud from the vendors' point of view. This is of direct importance to cloud providers because they are under intense pressure to determine how well they are operating in the cloud environment (McKinsey & Co., 2015). Second, technological innovations such as cloud computing can affect firm return and firm risk differently (see Sorescu & Spanjol, 2008). Therefore, developing a more granular insight into the performance implications of shifting to the cloud requires accounting for return and risk as separate dimensions of shareholder value. Although Son et al. (2014) examine the effect of adopting cloud computing on users' abnormal returns, they do not account for the potential risk implications of this shift. In this study, we use stock return response modeling to investigate the joint effects of moving to the cloud on a vendor's firm return and firm risk. Third, Son et al. (2014) explore how announcing the adoption of cloud computing affects customers' short-term abnormal stock returns. In the current study, we use the stock return response model approach to examine the long-term performance implications of vendors' transition to the cloud. This is of direct interest to cloud vendors and their shareholders because "it is well known that the economic return to a

marketing activity, such as a new product introduction, is obtained over the long run" (Srinivasan et al., 2009, p. 30).

Furthermore, by examining the moderating role of market maturity in determining the effectiveness of shifting to the cloud, we complement previous studies in the innovation literature that underscore how an industry's life cycle affects the evolution of technological innovations (e.g., Cusumano et al., 2015; Sood & Tellis, 2005). In addition, our investigation into the role of advertising intensity in moderating the relationship between cloud transition and shareholder wealth contributes to the nascent literature on the performance effects of value creation and appropriation investments (e.g., Frennea et al., 2019; Srinivasan et al., 2009).

## Managerial implications

Our findings have critical implications for managerial practice. Despite software firms' increasing interest in cloud computing, there remains considerable skepticism among senior managers about the financial outcomes of transitioning to the cloud (PwC, 2017). Our study offers corporate executives a fresh perspective on the performance implications of moving into cloud computing. We show that shifting to the cloud can contribute to shareholder wealth by increasing excess stock returns. For an average firm in our sample, a 1 percentage point unexpected increase in the cloud ratio boosts excess stock returns by about .2 percentage point, which corresponds to an increase of \$384 million in the firm's market capitalization. This finding should give top management the confidence to depart from traditional on-premises licensing schemes and to embrace cloud-based business models. It also has practical importance for the investment community because unexpected cloud ratio increases can convey credible signals about a firm's future financial health and hence must be integrated into portfolio composition analyses.

Our results also suggest that moving into the cloud increases shareholder wealth by reducing idiosyncratic risk. For an average firm in the sample, a 1 percentage point unexpected increase in the cloud ratio reduces idiosyncratic risk by about .004, which is equivalent to a 25% decrease in the firm's idiosyncratic risk. This finding is of direct relevance to managers because risk is a fundamental dimension of firms' financial performance (Han et al., 2017). An increase in risk makes bondholders and creditors more averse to uncertain payoffs and thereby exacerbates a firm's cost of raising external capital (Panousi & Papanikolaou, 2012). Risk has a similarly adverse effect on a firm's ability to invest in R&D and capital expenditures because uncertain cash flows increase the likelihood of a cash shortfall (Minton & Schrand, 1999).

In addition, we find that the relationship between moving to the cloud and shareholder wealth is contingent on industry- and firm-level factors. In particular, the effect of unexpected cloud ratio changes on firm return becomes stronger in the presence of unanticipated increases in market maturity. Our results establish that moving from the lowest to the highest quartile of unanticipated changes in market maturity amplifies the positive effect of unexpected cloud ratio increases on excess stock returns by approximately 4.9%. Hence, managers should be aware that the life cycle stage of an industry in which a firm operates bears implications for investing in the cloud as an IT delivery model. For example, the intense price-based competition that prevails in the mature phase of an industry's life cycle provides a highly suitable environment for the shift to cloud computing.

Moreover, an unexpected increase in advertising intensity strengthens the linkage between moving to the cloud and firm risk. Moving from the lowest to the highest quartile of unanticipated changes in advertising intensity increases the negative effect of unexpected cloud ratio increases on idiosyncratic risk by about 4.7%. This finding should interest marketing managers, who are under constant pressure "to demonstrate the contribution of advertising to financial performance" (Srinivasan et al., 2009, p. 24). It also illustrates that the stock market bestows higher values on shifting to the cloud when that strategy is backed by substantial advertising investments. Therefore, software firms should involve marketing managers in both the formulation and implementation of their shift to cloud computing so as to ensure that their business model objectives and marketing efforts are well aligned and integrated.

### Limitations and opportunities for further research

Our study has limitations that translate into avenues for future research. First, this work is a crucial first step toward understanding the role of moving to the cloud in the context of firms' marketing strategies. Motivated by data availability, we have focused on cloud computing in general. Yet our findings could be enriched by examinations of how different types of cloud solutions affect firm performance. Similarly, data availability limited us to using a firm's overall advertising spending when measuring its advertising intensity. Future studies are encouraged to expand our findings by distinguishing between cloud- vs. non-cloud-based advertising expenditures.<sup>9</sup> Second, we followed previous empirical research in the marketing-finance interface literature by including only publicly traded software firms in our sample. Although our theory is applicable to a broad range of firms, future research could examine the generalizability of our findings by using a sample that includes private firms.

Third, our study focuses on the shareholder wealth implications of moving into the cloud from the vendors' perspective; however, it would be also instructive to examine how the stock market evaluates the migration of customers to cloud computing. The anecdotal evidence shows the rapidly rising rate of cloud adoption. In a survey conducted by International Data Group, Inc (2018), 73% of the respondents reported that they already have at least one application—or a part of their computing infrastructure—in the cloud. With regard to this topic, Son et al. (2014) examine how announcing the adoption of cloud computing affects customers' abnormal stock returns. Scholars could profit from adopting our value relevance approach to explore the long-term return and risk implications of this shift from the users' viewpoint.

Fourth, our sample ends in 2019, which is prior to the COVID-19 outbreak. However, as noted by PwC, "a confluence of existing factors driving cloud transition has been further accelerated by the COVID-19 crisis: Cloud spending rose 37% to \$29 billion during the first quarter of 2020. This trend is likely to persist, as the exodus to virtual work underscores the urgency for scalable, secure, reliable, cost-effective off-premises technology services".<sup>10</sup> Future studies can build on our findings to explore the performance implications of shifting to the cloud during and post the COVID-19 pandemic.<sup>11</sup>

Fifth, in order to ensure the consistency and integrity of our conceptual and empirical frameworks, we focus our analyses on B2B cloud providers. Although we expect our empirical results to be generalizable to the B2C context, future studies can expand our findings by examining the performance implications of shifting to the cloud in the B2C setting. Sixth, our findings highlight the importance of advertising investments as a key marketing promotional activity in the B2B cloud environment. "The massive budgets allocated towards marketing, and advertising in particular, suggests that B2B managers consider advertising a smart investment" (Swani et al., 2020, p. 582). Another important future extension is to investigate the moderating role of direct selling investments as a type of relationship marketing activity in the B2B cloud selling process.<sup>12</sup>

<sup>9</sup> We thank an anonymous reviewer for raising this point.

<sup>10</sup> <https://www.pwc.com/us/en/industries/tmt/library/covid19-cloud-infrastructure.html>

<sup>11</sup> We thank an anonymous reviewer for raising this point.

<sup>12</sup> We thank an anonymous reviewer for raising this point.



## Appendix A Examples of calculating the cloud ratio

Company	For the Fiscal Year Ended	Revenue Source	Description	Cloud versus Non-cloud Revenue
Oracle	May 31, 2015	New software licenses	... new software licenses revenues earned from granting licenses to use our software products ... New software licenses revenues primarily represent fees earned from granting customers licenses to use our database, middleware and application software and exclude cloud SaaS and PaaS revenues	Non-cloud revenue
		Cloud software as a service and platform as a service	cloud SaaS and PaaS revenues generated from fees for granting customers access to a broad range of our software and related support offerings on a subscription basis in a secure, standards-based <i>cloud computing</i> environment ...	Cloud revenue
		Cloud infrastructure as a service	... cloud IaaS revenues generated from fees for deployment and management offerings for our software and hardware and related IT infrastructure generally on a subscription basis ...	Cloud revenue
		Software license updates and product support	... license updates and product support revenues ...	Non-cloud revenue
		Hardware systems products	... the sale of hardware systems products including Oracle Engineered Systems, computer servers, storage products, networking and data center fabric products, and industry specific hardware ...	Non-cloud revenue
		Hardware systems support	Our hardware systems support offerings generally provide customers with software updates for the software components that are essential to the functionality of our hardware products and can also include product repairs, maintenance services and technical support services	Non-cloud revenue
		Services revenues	... software and hardware related services including consulting, advanced customer support and education revenues ...	Non-cloud revenue

Interactive Intelligence	December 31, 2015	Support fees	... annual support fees from on-premises license agreements ...	Non-cloud revenue
		Cloud subscriptions	... fees from the Company's <i>cloud offerings</i> ...	Cloud revenue
		License and hardware	License and hardware revenues are generated from licensing the right to use its software products on-premises and, in certain instances, selling hardware as a component of the product offering.	Non-cloud revenue
Salesforce.com	January 31, 2015	Services	Services revenues are generated primarily from professional services and educational services fees.	Non-cloud revenue
		Subscription and support	... subscription fees from customers accessing our enterprise <i>cloud computing</i> services and from customers paying for additional support beyond the standard support that is included in the basic subscription fees ...	Cloud revenue
		Professional services and other	... related professional services such as process mapping, project management, implementation services and other revenue. "Other revenue" consists primarily of training fees ...	Non-cloud revenue
Company	Revenue Source *	Revenue * (in million dollars)	Sum of Cloud Revenues (in million dollars)	Total Revenues (in million dollars)
Oracle	New software licenses	8,535.0000	1,485.0000 + \$608.0000 = 2,093.0000	8,535.0000 + 1,485.0000 + 608.0000 + 18,847.0000 + 2,825.0000 + 2,380.0000 + 3,546.0000 = 38,226.0000
	Cloud software as a service and platform as a service	1,485.0000		2,093.0000 / 38,226.0000 = .0547
	Cloud infrastructure as a service	608.0000		
	Software license updates and product support	18,847.0000		
	Hardware systems products	2,825.0000		
	Hardware systems support	2,380.0000		

\*\* As reposted in Form 10-k

**Conflict of interest** The authors declare that they have no conflict of interest.

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