Artificial intelligence focus and firm performance

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Abstract
Artificial Intelligence is poised to transform all facets of marketing. In this study, we examine the link between firms’ focus on AI in their 10-K reports and their gross and net operating efficiency. 10-K reports are a salient source of insight into an array of issues in accounting and finance research, yet remain relatively overlooked in marketing. Drawing upon economic and marketing theory, we develop a guiding framework to show how firms’ AI focus could be related to gross and net operating efficiency. We then use a system of simultaneous equations to empirically test the relationship between AI focus and operating efficiency. Our findings confirm that US-listed firms are in a state of impending transformation with regards to AI. We show how AI focus is associated with improvements in net profitability, net operating efficiency and return on marketing-related investment while reducing adspend and creating jobs.

Keywords Firm performance · Firm efficiency · Artificial intelligence · Marketing metrics

Introduction
The literature that seeks to understand the impact of marketing and sales activities on firm performance is vast, highlighting the complexities associated with measuring marketing’s return on investment (Edeling et al., In Press; Feng et al., 2015; Mintz et al., 2021). Further contributing to this challenge, the emergence of new technologies is creating a revolution in marketing—rendering much of the discipline’s extant thinking and practice increasingly obsolete (Rust, 2020). Artificial intelligence (AI, hereafter) is one such technology, poised to transform all facets of marketing through the augmentation and amplification of human intelligence (Davenport et al., 2020; Rust, 2020). Forecasts suggest AI will deliver an economic output of approximately $13 trillion by 2030 and create between $1.4 and $2.6 trillion of value in marketing (Chui et al., 2018). This will facilitate the processing of large scale and unstructured data in real-time, and by generating predictive insights that enhance marketing decision making (Albrecht et al., 2021).

Albeit of unparalleled significance to the competitiveness of firms in the future, AI adoption represents a substantial and costly challenge for firms, one where the impact of efforts is equivocal (Haenlein & Kaplan, 2021; Lui et al., In Press). Indeed, overall adoption of AI among businesses remains low, due in part to a lack of expertise, inadequate technological infrastructure, high levels of perceived complexity and dubious outcomes (Balakrishnan & Dwivedi, 2021; Lui et al., In Press). It is unclear whether the benefits of AI investment outweigh the costs (Bock et al., 2020; Makarius et al., 2020). Firm efficiency is central to determining AI cost–benefit, as efficiency today will influence performance tomorrow. Therefore, the current study examines how firms’ AI focus is related to their gross and net operating efficiency, since firms’ operating efficiency ultimately determines their survival and growth. Thus, building on prior marketing literature and economic theory, we develop a guiding framework to demonstrate how AI could affect firms’ operating efficiency. We then use a system of simultaneous equations to test the empirical relationship between AI focus and operating efficiency. Our study provides timely and nuanced empirical insight into the implications of firms’ strategic focus on AI.
AI and marketing

AI refers to the ability of “machines to mimic intelligent human behaviour” (Syam & Sharma, 2018, p. 136), encompassing the subdomains of machine learning, neural networks and deep learning (Shrestha et al., 2021; Sze et al., 2017). Internet Appendix I provides a comprehensive synopsis of developments in the AI domain, between 2016 and 2022. AI technology is advancing rapidly, and marketing applications, accordingly, are expanding. These include social media mining (Kietzmann et al., 2018), real-time price optimization (Davenport et al., 2020), sentiment analysis (Ma & Sun, 2020), customer churn analysis (Loureiro et al., 2020) and talent acquisition (Makarius et al., 2020; Raisch & Krakowski, 2021). The potential implications of AI applications in marketing are considerable. They span the areas of merchandising (Pillai et al., 2020), supply chain management (Toorajipour et al., 2021), customer management (Ma & Sun, 2020; Pillai et al., 2020) and market research (Huang & Rust, 2021a, b; Lee et al. 2020).

Meanwhile, AI’s touted benefits include greater efficiency in lead generation (Syam & Sharma, 2018), enhanced resilience (Bag et al., 2021), swifter decision making (Duan et al., 2019; Shrestha et al., 2021), greater creativity (Mikalef & Gupta, 2021) and superior performance (Lin et al., 2020; Ma & Sun, 2020). As such AI has become increasingly important for businesses and its impact on marketing will, undisputedly, be profound (Davenport et al., 2020). However, studies that explicitly examine the impact of AI focus on either firm efficiency or performance for a large sample are absent. Prior literature has indicated that AI has a positive effect on firms’ performance (Ma & Sun, 2020). However, our focus is firms’ operating efficiency because firms achieve higher performance only if they are efficient. In other words, firms’ operating efficiency is the channel via which firms achieve higher stock returns. Our study empirically tests the mechanism by which AI is positively related to stock returns.

Guiding framework and hypotheses

Our guiding framework draws on both economic and marketing theory. In economics, Zeira (1998) and Mundlak (1988) show that the production of new technology is determined using a set of existing technologies that firms utilize to produce goods and services. The existing technology helps firms produce output and sell it profitably, allowing them to re-invest in new technology. For example, a firm might use technology to collect and analyze customer buying patterns and then try to sell new products to these customers. Further, firms could invest these profits in acquiring better analytical capabilities (including AI), which would enable them to predict customers’ future needs/purchases better and thereby realize additional profits.

Similarly, Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018), show how AI improves firm productivity and creates jobs. We draw on Acemoglu and Restrepo’s model (2018) to detail precisely how AI can increase productivity and employment growth. Zeira (1998) and Mundlak (1988) have implicitly shown that technology is a function of firms’ output among other intermediate technologies. Thus, we argue that AI focus will depend on firm output – and the corollary: AI will improve firm output and employee growth. Since employee growth can increase costs, it is crucial to test whether AI focus improves efficiency, which considers outputs and inputs.

We also draw on the literature in marketing linking AI to sales and marketing expenditure. Singh et al. (2019) and Syam and Sharma (2018) expect AI to alter all sales process stages: from prospecting, pre-approach and presentation, to follow-up. AI can provide real-time feedback to salespeople, monitor tele-conversations in real-time and even infer from a customer’s tone that an unmentioned issue remains (Barro & Davenport, 2019). Bock et al. (2020) find that AI can create value in services by identifying service failures before customers are aware of their existence and aiding in service recovery by identifying alternative solutions that resolve failures. Moreover, AI generates and assesses the promise of sales leads (Davenport et al., 2020), augmenting and elevating firm sales capabilities, to positively impact future sales (Grewal et al., 2017; Huang & Rust, 2018; Syam & Sharma, 2018). Albrecht et al. (2021) establish that machine learning methods yield the most accurate forecasts, while Ma and Sun (2020) find that AI generates accurate predictions that assist marketing decisions and in turn improve all aspects of business performance. Thus, we expect that AI focus will improve marketing inputs and outputs.

We show the simultaneous relationships between AI focus and firm efficiency using a guiding framework. This framework outlines how we expect AI focus to influence firms’ operating efficiency. It is the foundation of our research design and reflects the empirical analysis, which employs a system of ten equations. The framework demonstrates the mechanism via which AI influences firms’ operating efficiency. Since the customer base is the most important asset of a firm (Gupta & Lehmann, 2003; Pitt et al., 2000), we expect firms that adopt AI to enhance target marketing. Hence AI will directly impact adspend. As an emerging technology, firms require labor to use and manage AI (Acemoglu & Restrepo, 2018; Gries & Naudé, 2021). Thus, the
first two variables in our guiding framework are adspend and number of employees. The next variable in our framework is sales, because AI will affect sales via adspend and labor among other firm-specific characteristics. Subsequently, we use sales per employee to show how AI is related to gross operating efficiency via sales. Finally, we have three net efficiency variables to show how we expect AI will relate to net operating efficiency via gross operating efficiency; return on sales, return on investment, and net operating efficiency.

The framework shows how AI focus is negatively related to adspend per $ of asset (Davenport et al., 2020; Kietzmann et al., 2018) and positively related to number of employees (Acemoglu & Restrepo, 2018). Next, we show how AI focus, adspend per $ of asset and number of employees are related to sales per $ of asset. We do not conject the sign of the relationship between AI focus and sales per $ of asset because the sign of the relationship will depend on the relative strength of the correlation between AI focus and adspend per $ of asset; AI focus and number of employees. Next, we show how sales per $ of asset is related to sales per employee.

Sales per employee is our measure of gross operating efficiency. Prior literature shows a positive relationship between AI focus and sales and AI focus and number of employees. Yet, reskilling employees and reconfiguring marketing positions to support the automation of marketing and selling capabilities is costly (Barro & Davenport, 2019). Therefore, it is important to know if AI focus is positively or negatively related to sales per employee. We hypothesize that AI focus is negatively related to sales per employee because our guiding framework does not predict the sign of the relationship between AI focus and sales. Further, our guiding framework posits a positive relationship between AI focus and number of employees. Hiring more employees comes with additional costs, thus we expect the relationship between AI focus and sales per employee to be negative.

**H1** Increase in AI focus will be negatively associated with gross operating efficiency (sales per employee)

Next, we show how AI focus and sales per employee is related to net income\(^1\) per $ of sales, net income per $ of marketing expenditure\(^2\) and net income per employee. Vast and ongoing improvements in machine learning translation have amplified the reach and volume of trade for firms (Agrawal et al., 2019; Brynjolfsson & McAfee, 2017). AI will enable improvements in sales management tasks including scheduling, planning and matching stock with segmentation (Grewal et al., 2017; Huang & Rust, 2018; Syam & Sharma, 2018). Furthermore, AI enables the forecasting of future purchases with a high degree of accuracy and specificity, designing optimal presentation approaches and audio-visual analysis of sales-person-customer communications to enhance sales (Grewal et al., 2017; Huang & Rust, 2018; Syam & Sharma, 2018). Thus we posit:

**H2** Increase in AI focus will be positively associated with return on sales (net income per $ of sales)

The last three propositions measure net operating efficiency. We expect that AI will be positively related to these three measures by reducing production cost significantly. However, we do not conject the sign of the relationship between AI focus and return on marketing investment, because our AI Focus is a general measure. Rather, we have a positive sign in the main analysis and a negative sign in the weighted industry analysis, since general AI focus may not be positively related to return on marketing investment. Prior literature shows AI focus could reduce costs (Huang & Rust, 2021a; Stahl et al., 2021). AI enables a superior approach to target marketing and could enhance marketing communication through tailoring of personalized information based on customer insights and analyses (Kaplan & Haenlein, 2019). In this way marketing communications can potentially provide more relevant messages to the appropriate audience at a time and in a place where they are most receptive. These insights are not restricted to consumers, they also can enhance a firm’s approach to potential employees, ensuring that the firm attracts superior talent that will build firm value. Machine learning, one facet of AI, identifies probabilistic matches within data sets. According to Davenport and Ronanki (2018: 111), the application of this technology by GE to integrate supplier data enabled it to save `$80 million in its first year by eliminating redundancies and negotiating contracts that were previously managed at the business unit level’. Applications of AI will optimize internal business operations, improving firm revenue and ultimately profitability. However, whether AI focus will reduce or increase firm costs divides the extant literature (Huang & Rust, 2021a; Stahl et al., 2021). Aside from the costs involved in acquiring AI technologies, an AI focus requires reskilling employees and reconfiguring marketing positions to support the automation of marketing and selling capabilities. Indeed, AI focus could come at a considerable cost. Thus:

**H3** Increase in AI focus will be associated with return on marketing-related investment (net income per $ of marketing investment)
The digital revolution has significantly lowered the cost and accessibility of information. Intelligent systems have the potential to process and derive valuable information from complex data sets otherwise unfeasible or impossible to compute with human intellect (Kietzmann et al., 2018; Martínez-López & Casillas, 2013). Automating marketing tasks including segmentation, targeted marketing communications and aspects of marketing planning will optimize external processes, reducing marketing costs and concurrently the number of employees required (Davenport & Ronanki, 2018; Kaplan & Haenlein, 2019). Managerial capabilities that will be of the greatest value are those that involve creativity, determining how best to apply AI and discerning which predictions to appropriate (Agrawal et al., 2019; Syam & Sharma, 2018). Li et al. (2007), for example, present a system that assists in marketing planning in a B2B context. In facilitating the decision making, the intelligent agent technology enhances the negotiation and supplier evaluation efficiency `by saving time and cost´(Li et al., 2007, p. 877). Automating prediction enhances decision making effectiveness in critical situations (Agrawal et al., 2019). Improvements in the accuracy of information inputs will enhance marketing decisions. AI facilitates the automation of repetitive mental tasks which will enable marketing employees to focus on identifying creative opportunities that enhance firms’ advertising or broader marketing strategy (Davenport & Ronanki, 2018; Huang & Rust, 2020; Makridakis, 2017). Automation extends to other expert systems (Davenport & Ronanki, 2018), for instance, Du Pont utilized such systems to correct errors in equipment and save $50 million (Winters, 1991) and more recently Google’s DeepMind unit optimized the use of air conditioners in its data centres, reducing energy consumption by 40% (Agrawal et al., 2019; Evans & Gao, 2019; Shead, 2018). It is reasonable that such gains can be extended to other facets of business operations and transferred specifically to the marketing department. Through real time analysis, that draws on evolving data, AI supports adaptive marketing. It allows for continuous revisions to product information and price offers in “real-time” (Agrawal et al., 2016; Agrawal et al., 2019; Kumar et al., 2016, p. 25). Therefore, we expect:

**H4** Increase in AI focus will be positively associated with net operating efficiency (net profit per employee)

Higher operating efficiencies will encourage firms to implement more AI—as the framework depicts (Fig. 1).

### Research approach

#### Data

Data was collected from two different sources: EDGAR and COMPUSTAT. To measure AI focus in firms, we downloaded all the 10-K filings, excluding amended documents, from the SEC’s Electronic Data Gathering, Analysis, and Retrieval (EDGAR) website (www.sec.gov) filed for the period 2005–2019. We use 10-K filings to measure AI focus because the 10-K is an annual filing that publicly traded companies in the US are legally required to send to the SEC. 10-Ks offer a comprehensive summary of a company’s financial performance. The 10-K includes information on the firms’ history, organizational structure, executive compensation, equity, subsidiaries, and other pertinent facts. If firms are innovative and focusing on AI, this should be reflected in their official written documents, in order to impress investors, the market, and other salient stakeholders. Thus, through textual analysis of their 10-K reports, it is structurally possible to examine the strategic and operational intent of the focal firms (Hanley & Hoberg, 2010; Li, 2008; Loughran & McDonald, 2011; Tetlock, 2007; Tetlock et al., 2008). Moreover, recent research using textual analysis confirms the credibility of information provided in these reports (Balakrishnan et al., 2010; Bodnaruk et al., 2015; Buehlmaier & Whited, 2018; Hoberg & Maksimovic, 2015).
We constructed the AI focus variable by searching for 122 AI-related words (reported in Internet Appendix III). Researchers can generate items/terms using either a deductive and/or an inductive approach (Schwab et al., 1980). We followed an inductive approach initially (phase 1) and then validated it deductively (phase 2). An inductive approach involves identifying constructs based on qualitative insights gleaned from respondents (Hinkin, 1995). This approach is often used when there is a limited theory or knowledge concerning a topic. We drew on the collective wisdom of a group of highly qualified AI experts – as described in Internet Appendix IV. We searched for the frequency of these terms in all the 10-Ks filed for the entire sample period and scaled it by the total number of words in the annual report.3

More specifically,

\[
\text{AI Focus}_{it} = \frac{\text{No. of Words Related to AI}_{it}}{\text{No. of Words in the Annual Report}_{it}} \times 100
\]

Since our AI Focus measure is annual, we used annual data in our analysis. We collected data on firm characteristics from COMPUSTAT. To measure AI, in accordance with Bodnaruk et al. (2015), we first cleaned the data to separate all the text from the annual reports. Then, we computed the frequency of AI-related words and the total number of words and computed our AI focus measure as shown above. Recent research in marketing has followed a similar approach (Mishra et al., 2020). The final sample comprised 19,000 firm-year observations. We provide the variables used in this paper in Internet Appendix II.

Empirical research design

Our guiding framework reflects the simultaneous relationships between AI focus and four firm efficiency measures. Therefore, we employ a simultaneous equation framework for our empirical analysis. We examine the relationships between AI focus in firms’ 10-K (annual) reports and four efficiency measures. Prior research (Boubakri & Cosset, 1998), which compares private and public firms, motivates our choice of firm efficiency measures. The measures of firms’ efficiency include net income per $ of sales (NI/Sales: return on sales), net income per $ of marketing expenditure (NI/30% of SGA: return on marketing expenditure), sales per employee, (Sales/Emp: gross operating efficiency) and net income per employee (NI/Emp: net operating efficiency). The relationship between measures of firms’ efficiency and AI focus might be endogenous, thereby raising doubts about causality.

Endogeneity is an increasing concern for researchers seeking to draw causal inferences from the analysis of non-experimental data (Lehmann et al., 2011). Endogeneity concerns arise where an explanatory or independent variable correlates with the error term, thus rendering the coefficient of interest inconsistent. Rutz and Watson (2019) consider endogeneity in marketing research and how it can be addressed, including by employing simultaneous models. Hence, from an econometric perspective, to study the relationship between any two of these variables, one would need to formulate a system of simultaneous equations that specifies the relationships among the variables. Accordingly, we specify a system of simultaneous equations.

In accordance with our guiding framework, we set up the following system of ten equations. The guiding framework shows a sequence of how AI focus could be related to firm efficiency. To examine the direct relationship between AI focus, different firm specific measures and efficiencies, we include AI focus in all equations. In the equations below we highlight the most important variables. Our first equation shows adspend is a function of AI focus and other control variables. We use a set of control variables (Z) in all equations. Not all control variables are included in all the models. This is to ensure that our system of equations is identified without omitting relevant variables. Any control variable(s) not included in the equations have a negative sign and a superscript of Z for ease of understanding. In the first equation we do not include HHI since we already include Risk in our framework (the variable Risk captures HHI to some extent). In the below equations we have used the term “AI” rather than “AI Focus”.

\[
\left( \frac{\text{ADV}}{\text{Asset}} \right)_{it} = f_1\left( \text{AI}_{it}, Z_{it}^{HHI}, \epsilon_{1it} \right)
\]

\[Z = \text{Size, Growth, Lev, Liquidity, Tangible, Intangible, Risk, competition, Ind, Year}\]

The second equation shows number of employees in a firm is a function of AI focus.

\[
\text{Ln}(\text{emp})_{it} = f_2\left( \text{AI}_{it}, Z_{it}, \epsilon_{2it} \right)
\]

The third equation shows sales is a function of adspend, number of employees and AI focus.

\[
\left( \frac{\text{Sales}}{\text{Asset}} \right)_{it} = f_3\left( \left( \frac{\text{ADV}}{\text{Asset}} \right)_{it}, \ln(\text{emp})_{it}, \text{AI}_{it} Z_{it}, \epsilon_{3it} \right)
\]

The fourth equation shows sales per employee or gross operating efficiency is a function of sales per $ of asset and AI focus.

\[
\left( \frac{\text{Sales}}{\text{Emp}} \right)_{it} = f_4\left( \left( \frac{\text{Sales}}{\text{Asset}} \right)_{it}, \text{AI}_{it}, Z_{it}, \epsilon_{4it} \right)
\]

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3 We use BUTTER (https://www.butter.tools/) software for this computation.

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The fifth equation shows return on marketing investment is a function of sales per employee and AI focus.

\[
\left( \frac{NI}{30\% \ of \ SGA} \right)_{it} = f_5 \left( \frac{Sales}{Emp} \right)_{it}, AI_{it}, Z_{it}, \epsilon_{it} \tag{5}
\]

The sixth equation shows return on sales is a function of sales per employee and AI focus.

\[
\frac{NI}{Sales}_{it} = f_6 \left( \frac{Sales}{Emp} \right)_{it}, AI_{it}, Z_{it}, \epsilon_{it} \tag{6}
\]

The seventh equation shows net profit per employee is a function of sales per employee and AI focus.

\[
\frac{NI}{Emp}_{it} = f_7 \left( \frac{Sales}{Emp} \right)_{it}, AI_{it}, Z_{it}, \epsilon_{it} \tag{7}
\]

The eighth, ninth and tenth equations show AI focus is a function of return on marketing investment, return on sales and net profit per employee. However, these variables are similar proxies of firm efficiency. Thus, we did not include these in one equation.

\[
AI_{it} = f_2 \left( \frac{NI}{30\% \ of \ SGA} \right)_{it}, Z^{-Lev, Risk}_it, \epsilon_{it} \tag{8}
\]

\[
AI_{it} = f_2 \left( \frac{NI}{Sales} \right)_{it}, Z^{-Lev, Risk}_it, \epsilon_{it} \tag{9}
\]

\[
AI_{it} = f_2 \left( \frac{NI}{Emp} \right)_{it}, Z^{-Lev, Risk}_it, \epsilon_{it} \tag{10}
\]

The guiding framework outlines the system of equations are grounded in economic theories of AI. For example, drawing on Acemoglu and Restrepo (2018), number of employees can be affected by AI focus. Similarly, turning to the marketing literature (Bock et al., 2020; Ma & Sun, 2020; Syam & Sharma, 2018) adspend can be affected by AI focus. Sales per dollar of asset can be affected by adspend per dollar of asset, number of employees, size (natural logarithm of total assets) of firm, growth opportunities (the ratio of the market value of equity to book value of equity), leverage (sum of short term and long-term debt scaled by total asset), tangible investment (gross property plant and equipment scaled by total assets), intangible investment (sum of 30% of SGA), research and development expenses and other intangibles, scaled by total assets (Peters & Taylor, 2017; Ptkok et al., 2018), risk (rolling standard deviation of earnings per share over the last four years), liquidity (cash in the business scaled by total assets) and industry competition (Herfindahl Index (HHI). Internet Appendix II defines all variables used in the analysis and to set up the other system similarly.

To estimate the system of equations, identification of the system is necessary. Identification means the quantity of information is substantial enough to estimate the parameters of the framework given the specified functional form. For identification there must be at least as many noncollinear exogenous variables in the remaining system as there are endogenous right-hand-side variables in an equation. This condition must hold for each equation in the system. For example, if the number of right-hand-side endogenous variables in an equation is m, if the number of exogenous variables in the same equation is k, and the total number of exogenous variables in all the structural equations plus any additional instrumental variables is K, the parameters of the system can be estimated if m < (K − k). For example, in equation one, there are two m variables (AI and ADV/Asset), 32 (7 control variables + 11 industry level indicator variables + 14-year level indicator variables) k variables and 40 K variables (8 control variables + 11 industry level indicator variables + 14-year level indicator variables + 7 lag dependent variables). Therefore, 2 < (40 − 32) and we can estimate the parameters of the system.

The error terms, \( \epsilon_{it} \), are associated with exogenous noise and the unobservable features of management ability that explain cross-sectional variation in firms’ efficiency and AI focus. We estimate the system using three-stage least squares (3SLS) with instrumental variables to allow for the fact that regressors in one or more equation are correlated with the error terms. We use lag values of AI focus, adspend per $ of asset, natural log of employees, sales per $ of asset, sales per employee, net income per $ of sales, net income per marketing investment, net income per employee. Prior literature has used lag values of the endogenous variable as an instrument in a simultaneous equation framework (Bhagat & Bolton 2008).

**Results**

**Validation of AI variable**

Before employing the AI focus measure in the empirical analysis, it is important to establish its validity. In this regard, we consider two variables: research and development expenses (R&D), and selling and general administrative expense (SGA). If firms invest in AI, this should be accounted for under R&D expenses. Firms with a greater AI focus are likely to be more innovative. However, it is also possible that instead of developing their own AI, firms may resource it from other vendors, in which case it should be accounted for under SGA. To demonstrate this, we divide

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4 30% of SGA is calculated after subtracting R&D from SGA.
our sample into five quintiles based on the magnitude of AI focus. Then for each quintile, we calculate the mean of R&D and SGA, both scaled by the firm’s total assets. Firms in higher quintiles of AI focus should have higher values of R&D and SGA. Consistent with our expectations, we find firms in the lowest quintile have low R&D and SGA expenses compared to firms in the highest quintile of AI focus. Further, we compare quintile 1 vs. 2, 3, 4, and 5, quintile 2 vs. 3, 4, and 5, quintile 3 vs. 4 and 5, and quintile 4 vs. 5. Table 1 confirms the results of the validation test. The difference in mean t-test and associated p-values are shown in the table. The p-values are statistically significant at 1% in most cases, suggesting that firms in higher quintiles have higher R&D and SGA expenses than firms in lower quintiles.

As our AI focus variable is an aggregation of 122 AI terms, it is important to understand which variables are most significant in driving the difference in R&D and SGA expenses for low and high values of AI. To understand this point, we bootstrap the above exercise for all the individual AI focus terms. We could compute mean difference in R&D (SGA) expenses for quintile one and five for 66 (68) AI terms. For the other 56 (54) terms it was not possible to compute the mean difference because the variation of AI terms across our sample was minimal. The mean difference in R&D (SGA) expenses is not significant for 8 (18) AI terms. This univariate analysis suggests about 42% (29%) of all AI terms are driving the difference in R&D (SGA) for low and high values of AI. Due to space constraints, Internet Appendix V presents the results.

**Descriptive statistics**

Having validated our AI focus variable, we consider the distribution of AI focus across twelve Fama French industries. Table 2 presents the descriptive statistics of AI by industry.

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### Table 1 Validation of AI focus

| Quintile | R&D/Asset | p-value | SGA/Asset | p-value |
|----------|-----------|---------|-----------|---------|
| Quintile 1 | 0.060 | 0.276 |
| Quintile 2 | 0.058 | 0.322 |
| Quintile 3 | 0.056 | 0.340 |
| Quintile 4 | 0.067 | 0.371 |
| Quintile 5 | 0.087 | 0.403 |

**Difference in mean t-test between Quintiles**

| Quintile | R&D/Asset | p-value | SGA/Asset | p-value |
|----------|-----------|---------|-----------|---------|
| 1 and 2 | 1.276 | 0.899 | -4.072 | 0.000 |
| 1 and 3 | 3.580 | 0.898 | -5.571 | 0.000 |
| 1 and 4 | -2.198 | 0.014 | -7.862 | 0.000 |
| 1 and 5 | -7.992 | 0.000 | -10.525 | 0.000 |
| 2 and 3 | 0.800 | 0.788 | -1.516 | 0.066 |
| 2 and 4 | -2.697 | 0.004 | -3.911 | 0.000 |
| 2 and 5 | -8.552 | 0.000 | -6.476 | 0.000 |
| 3 and 4 | -3.660 | 0.000 | -2.423 | 0.000 |
| 3 and 5 | -9.793 | 0.000 | -4.946 | 0.000 |
| 4 and 5 | -5.016 | 0.000 | -2.206 | 0.013 |

### Table 2 AI focus by industry

| Industry | N | P25 | Mean | Median | P75 | SD | t-test |
|----------|----|-----|------|--------|-----|----|--------|
| Consumer Non-Durables | 796 | 0.0022 | 0.0065 | 0.0038 | 0.0075 | 0.0086 | -13.119*** |
| Consumer Durable | 605 | 0.0023 | 0.0101 | 0.0046 | 0.0098 | 0.0192 | -8.096*** |
| Manufacturing | 2254 | 0.0028 | 0.0111 | 0.0052 | 0.0104 | 0.0206 | -13.042*** |
| Oil, Gas, and Coal | 1445 | 0.0026 | 0.0115 | 0.0048 | 0.0083 | 0.0257 | -9.948*** |
| Chemicals and Allied | 597 | 0.0022 | 0.0064 | 0.0041 | 0.0078 | 0.0065 | -11.430*** |
| Business Equipment | 5630 | 0.0043 | 0.0196 | 0.0092 | 0.0211 | 0.0280 | -10.590*** |
| Telephone and Television | 492 | 0.0019 | 0.0061 | 0.0033 | 0.0070 | 0.0106 | -19.901*** |
| Utilities | 1206 | 0.0009 | 0.0035 | 0.0020 | 0.0043 | 0.0047 | -15.682*** |
| Wholesale, Retail | 1543 | 0.0026 | 0.0081 | 0.0047 | 0.0087 | 0.0123 | -19.908*** |
| Healthcare, Medical | 2705 | 0.0021 | 0.0084 | 0.0041 | 0.0088 | 0.0124 | -27.664*** |
| Finance | 8032 | 0.0035 | 0.0100 | 0.0065 | 0.0126 | 0.0113 | -17.377*** |
| Mines, Constructions | 2716 | 0.0025 | 0.0096 | 0.0049 | 0.0101 | 0.0149 | -19.908*** |

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5 We thank an anonymous referee for pointing this out.
The mean (median) of Sales/Asset, NI/Sales, NI/30% of SGA, ADV/Asset, Ln(Emp), Sales/Emp (Gross Operating Efficiency) and NI/Emp (Net Operating Efficiency) are $0.715 ($0.518), -$0.724 ($0.058), $0.878 ($0.894), $0.008 ($0.000), 1.324 (0.849), 524.61 (281.084) and -23.145 (15.681) respectively. Similarly, the mean (median) of AI is 0.001 (0.006). The mean (median) of Size, Lev, Growth, Liquidity, Tangible Investments, Intangible Investments, Risk, HHI are 6.92 (7.183), 0.738 (0.183), 6.414 (1.945), 0.127 (0.059), 0.452 (0.295), 0.128 (0.043), 1.261 (0.586) and 0.182 (0.065) respectively. Table 5 presents the correlation between AI focus and different efficiency measures.

In most cases, the correlation coefficients are significant. We see a positive correlation between AI focus and Sales/Asset, NI/Sales and NI/Emp. However, the correlation is negative between AI and NI/30% of SGA, Ln(Emp), Adv/Asset and Sales/Emp. The sign of the correlation between AI and different efficiency measures is as expected, except for NI/30% of SGA and Ln(Emp). This could be because we are only looking at the pairwise correlation without controlling for other variables. Next, Table 6 displays the difference in
mean of all efficiency measures across different quintiles of AI focus. This test aims to present initial evidence that firms in the highest quintile of AI are more efficient than firms that are in the lowest quintile.

The last column shows the p-values for the difference in mean for quintiles one and five. We find the difference mean between low AI focus and high AI focus firms are not significant for Sales/Asset and NI/30% of SGA. In contrast to our expectations, firms in the lowest quintile of AI have higher numbers of employees than firms in the highest quintile. However, for the rest of the measures, firms in the lowest quintile of AI have lower efficiency than firms in the highest quintile.

**Main results**

Tables 7 and 8 show the results for our system of equations. The endogenous variables in this system are AI focus, Sales/Asset, ADV/Asset, Sales/Emp, NI/30% of SGA, NI/Sales and NI/Emp. Table 7 displays the models where the dependent variables are ADV/Asset, Ln(Emp), Sales/Asset, Sales/Emp and NI/30% of SGA. We find AI focus has a negative and significant relationship with ADV/Asset and has a positive and significant relation with Ln(Emp). We find both Ln(Emp) and ADV/Asset has a positive and significant relationship with Sales/Asset. However, AI focus is not significant in the Sales/Asset model. Our guiding framework shows that the relationship between AI focus and Sales/Asset can go either way since this is just gross performance. Similarly, AI focus has a negative and significant relationship with Sales/Emp, a measure of gross efficiency. However, AI focus has a positive and significant relationship with NI/30% of SGA, return on marketing investment (Davenport & Ronanki, 2018). Consistent with contemporary marketing practice, marketing-related investment is measured by 30% of SGA (Peters & Taylor, 2017; Ptok et al., 2018).

Table 8 shows the framework where the dependent variables are NI/Sales, NI/Emp and AI focus. AI focus has a positive and significant relationship with both NI/Sales, NI/Emp. Similarly, all net efficiency measures such as NI/Sales, NI/Emp and NI/30% of SGA has a positive and significant relationship with AI focus. Both AI and Sales/Emp

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7 We multiplied the AI focus by 1000 before running the analysis since the AI focus variable is small compared with the other performance variables.

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8 Ptok et al. (2018) suggests that a small portion of SGA expense can be used as marketing investment. Peters and Taylor (2017) suggests that 30% of SGA (after subtracting R&D from SGA) can be used as marketing investment. We have provided the detail measure of 30% of SGA in the variable appendix.
positively affect net operating efficiency (Huang & Rust, 2018; Syam & Sharma, 2018).

The coefficient on size is mostly positive except in Sales/Asset and AI focus models. The coefficient on growth is positive and significant in ADV/Asset and AI focus models but negative and significant in the Sales/Emp model. Thus, suggesting higher growth opportunity reduces gross operating efficiency. For other models it is not significant. The coefficient for leverage is positive and significant for Ln(Emp) and NI/Sales model. It is negative and significant for Sales/Asset, Sales/Emp, Ln(Emp) and AI focus models. The coefficient on intangible investments is positive and significant for ADV/Asset, Ln(Emp), Sales/Asset and AI focus models. For other models it is negative and significant. Risk is positive and significant for Sales/Asset and Sales/Emp models. In other models it is negative and significant. Finally, HHI, industry competition is positive and significant for all models.

### Table 7: Relationship between AI focus and firms’ operating efficiency

| Variables   | (1) ADV/Asset | (2) Ln(Emp) | (3) Sales/Asset | (4) Sales/Emp | (5) NI/30% of SGA |
|-------------|---------------|-------------|----------------|---------------|------------------|
| Ln(Emp)     | 0.298***      | 0.015***    | -0.282         | -1.569***     | 10.337***        |
|             | (0.006)       | (0.004)     | (0.210)        | (0.210)       | (1.501)          |
| ADV/Asset   | 0.617***      | 0.519***    | -0.197***      | 40.924***     | 0.323***         |
|             | (0.189)       | (0.004)     | (2.338)        | (0.022)       |                  |
| AI          | -0.019*       | 0.015***    | -0.282         | -1.569***     | 10.337***        |
|             | (0.010)       | (0.003)     | (0.223)        | (0.210)       | (1.501)          |
| Size        | 0.001***      | 0.519***    | -0.197***      | 40.924***     | 0.323***         |
|             | (0.000)       | (0.003)     | (0.004)        | (2.338)       | (0.022)          |
| Growth      | 0.000***      | 0.001       | 0.001          | 1.432**       | 0.005            |
|             | (0.000)       | (0.001)     | (0.001)        | (0.607)       | (0.006)          |
| Lev         | 0.000***      | -0.003      | 0.002          | -1.388        | -0.001           |
|             | (0.000)       | (0.002)     | (0.002)        | (1.873)       | (0.013)          |
| Liquidity   | 0.013***      | -0.081*     | -0.469***      | 62.125*       | 1.467***         |
|             | (0.002)       | (0.042)     | (0.355)        | (32.523)      | (0.308)          |
| Tangible    | -0.001        | 0.268***    | -0.033***      | -48.142***    | -0.010           |
|             | (0.001)       | (0.017)     | (0.014)        | (12.767)      | (0.121)          |
| Intangible  | 0.025***      | 0.946***    | 0.441***       | -157.499***   | -3.060***        |
|             | (0.001)       | (0.031)     | (0.027)        | (23.994)      | (0.223)          |
| Risk        | -0.001***     | -0.024***   | 0.010***       | 28.912***     | -0.156***        |
|             | (0.000)       | (0.003)     | (0.002)        | (2.206)       | (0.016)          |
| HHI         | 0.100***      | 0.119***    | 57.664***      | 0.384**       |
|             | (0.023)       | (0.019)     | (17.610)       | (0.167)       |
| Sales/Asset | 141.417***    | 0.001***    |
|             | (4.450)       | (0.000)     |
| Sales/Emp   | -1.858***     | 1.938***    | -169.540***    | -0.593*       |
|             | (0.049)       | (0.042)     | (37.966)       | (0.355)       |
| Constant    | 26,908.13     | 2067.69     | 2196.24        | 196.56        |
|             | (0.000)       | (0.000)     | (0.000)        | (0.000)       |
| Observations| 15,553        | 15,553      | 15,553         | 15,553        |
| R-squared   | 0.119         | 0.739       | 0.377          | 0.285         |

Standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1
Following prior literature (Bhagat & Bolton, 2008; Fair, 1970; Sargan, 1988), we use the lagged values of the endogenous variables as instruments. We include at least as many instruments as we have endogenous variables. Although the asymptotic efficiency of the estimation improves as the number of instruments increases, so too does the finite-sample bias (Johnston & DiNardo, 1997). Further, it is crucial to choose suitable instruments. Selecting “weak instruments” can lead to problems of inference in the estimation. An instrument is “weak” if the correlation between the instruments and the endogenous variable is small. We use Stock et al. (2005) test for weak instruments – which evaluates the strength of the first-stage regression by considering the F-statistic of the reduced form first stage regression of excluded instruments. High F-statistics and low p-values suggest robust instruments (this test was derived from the Cragg and Donald 1993 test). The Cragg-Donald F-statistics are statistically significant, for all our simultaneous equations models, suggesting that the instruments are not weak.

### Table 8 Relationship between AI focus and firms’ operating efficiency

| Variables     | (6) NI/Sales | (7) NI/Emp | (8) AI | (9) AI | (10) AI |
|---------------|--------------|------------|--------|--------|--------|
| AI            | 9.800***     | 5.948***   |        |        |        |
| Size          | 0.159***     | 15.480***  | -0.802*** | -0.634*** | -0.637*** |
| Growth        | -0.001       | 0.017      | 0.049** | 0.049** | 0.048** |
| Lev           | -0.001       | 0.023      |        |        |        |
| Liquidity     | -3.177***    | -120.501***| -1.750 | -2.237* | -3.622*** |
| Tangible      | 0.281***     | -15.226*** | -3.098*** | -3.436*** | -3.339*** |
| Intangible    | -4.616***    | -199.587***| 4.755*** | 3.721*** | 2.627*** |
| Risk          | -0.073***    | -3.377***  |        |        |        |
| HHI           | 0.433***     | 38.733***  | 6.800*** | 7.233*** | 7.329*** |
| Sales/Emp     | 0.001***     | 0.055***   |        |        |        |
| NI/Emp        |              | 0.013***   |        |        |        |
| NI/Sales      |              |            | 0.354*** |        | 0.174*** |
| NI/30% of SGA |              |            |        |        |        |
| Constant      | -0.683***    | -62.426*** | 9.185*** | 8.648*** | 8.523*** |
| Industry and Year Effect | Included | Included | Included | Included | Included |
| Weak Instrument Test (Cragg Donald F-stat) (p-value) | 652.77 (0.000) | 193.63 (0.000) | 731.18 (0.000) | 731.18 (0.000) | 731.18 (0.000) |
| Observations  | 15.553       | 15.553     | 15.553 | 15.553 | 15.553 |
| R-squared     | 0.179        | 0.172      | 0.056  | 0.068  | 0.067  |

**Test of weak instruments**

Following prior literature (Bhagat & Bolton, 2008; Fair, 1970; Sargan, 1988), we use the lagged values of the endogenous variables as instruments. We include at least as many instruments as we have endogenous variables. Although the asymptotic efficiency of the estimation improves as the number of instruments increases, so too does the finite-sample bias (Johnston & DiNardo, 1997). Further, it is crucial to choose suitable instruments. Selecting “weak instruments” can lead to problems of inference in the estimation. An instrument is “weak” if the correlation between the instruments and the endogenous variable is small. We use Stock et al. (2005) test for weak instruments – which evaluates the strength of the first-stage regression by considering the F-statistic of the reduced form first stage regression of excluded instruments. High F-statistics and low p-values suggest robust instruments (this test was derived from the Cragg and Donald 1993 test). The Cragg-Donald F-statistics are statistically significant, for all our simultaneous equations models, suggesting that the instruments are not weak.

**Possible self selection bias in sample**

One of the requirements of the 3SLS regression is that the instrumental variables are uncorrelated with the error terms of each single equation. Schmidt (1990) points out that 3SLS
estimator is only consistent if all error terms and all instruments are uncorrelated. However, on occasion this may be unavoidable. Thus, there could be confounding variables that may affect both the instruments and the dependent variables. Further, firms may strategically choose a level of AI focus to maximize their efficiency. These firms, which explicitly focus more on AI, could display different inherent characteristics to firms that are less focused on AI. Accordingly, this could create a self-selection bias in our sample—suggesting that firms with higher focus on AI tend to outperform firms that are less focused on AI. In this case, our results may not be completely attributable to AI focus. To address this concern, we adopt a propensity score matching approach to identify a sample of control firms that differ in their levels of focus on AI, but do not differ on other observable characteristics. We create a matched sample based on AI focus because that is our main variable of interest. The consequence of creating a matched sample, the similarity between treatment and control groups, is that any baseline differences in the dependent variable of interest between the treatment and control groups will be minimized to a larger extent. In other words, it eliminates the problem that unobserved confounders might be driving any correlation between the independent and the dependent variables. To generate a propensity score matched sample we estimate the following regression:

\[ \text{High}_{it} = a_{1} + a_{2}\text{Size}_{it} + a_{3}\text{Lev}_{it} \\
+ a_{4}\text{MTB}_{it} + a_{5}\text{Liquid}_{it} + a_{6}\text{Tangible}_{it} \\
+ a_{7}\text{Intangible}_{it} + a_{8}\text{Risk}_{it} + a_{9}\text{Competition}_{it} \\
+ \sum_{k} \delta_{k}\text{Year}_{it} + \sum_{m} \kappa_{m}\text{Indus}_{it} + \epsilon_{it} \]  

(11)

In the equation above, \( \text{High}_{it} \) is a dummy variable equal to 1 if the firm has a higher value of AI focus than the median of the distribution for the sample and 0 otherwise. We select the above median value of AI focus to denote treatment firms because very few industries in our sample (see Table 2) have AI focus values that are higher than the median. Only firms in business equipment and finance industries have a higher AI value than the sample median. By choosing the median cut off, we are categorizing firms that have high AI focus and low AI focus. Firms that have higher AI focus values than the sample median are our treatment firms and firms that have AI focus values below the sample median are the control firms. Prior research has also used the industry median as a cut off to generate a matched sample (Balachandran & Duong, 2019). We use previously defined control variables in our model. To create a matched sample that is very close in different firm characteristics, we also include year and industry fixed effects in the model. We formed our matched sample based on the propensity score generated by the equation above. For each firm with a higher than median AI focus value, we identify one control firm with the closest propensity score within a calliper of 0.001 from the sample that has a lower than median AI focus value. We use this approach following prior research (Rosenbaum & Rubin, 1983).

Before we estimate our first stage model, we show the mean difference of firm characteristics for firms that have high and low AI focus. This is to show that firm

| Variable | Treatment | Control | p-value of t-test of mean difference between treatment and control sample |
|----------|-----------|---------|-----------------------------------------------------------------------|
| Size     | 6.607     | 7.199   | 0.000                                                                |
| Growth   | 5.506     | 7.225   | 0.000                                                                |
| Leverage | 0.736     | 0.736   | 0.931                                                                |
| Liquidity| 0.135     | 0.120   | 0.000                                                                |
| Tangible | 0.393     | 0.498   | 0.000                                                                |
| Intangible| 0.142   | 0.116   | 0.000                                                                |
| Risk     | 1.003     | 1.501   | 0.000                                                                |
| HHI      | 0.185     | 0.177   | 0.000                                                                |
| AI       | 0.020     | 0.003   | 0.000                                                                |

We find similar results when we use Balachandran and Duong (2019) approach of splitting the sample based on industry median.
characteristics are significantly different for firms that have high and low AI focus. We outline this test in Table 9. We find that firm characteristics are significantly different for firms that have high AI focus. We show the results for the first stage probit regression (Eq. 11) in Table 10. We find size and tangible investment risk has a negative effect on the probability that a firm has a high AI focus. This suggests smaller firms, in our sample, focus more on AI than larger firms. Having said that the mean asset in our sample is $1.01 billion. Similarly, firms with high tangible investment tend to have lower AI focus. Firms that are riskier tend to have less AI focus. On the other hand, firms that have high growth opportunities and operate in highly competitive industries tend to have a high AI focus.

In our matched sample we have 15,390 observations where 7,695 observations belong to the treatment sample and 7,695 to the control sample. To establish that our treatment firms and control firms are similar in other characteristics except for AI focus, we provide a t-test of mean difference of the observable characteristics for the treatment and control sample in Table 11. The mean values of the control variables for the treatment and control sample are similar. In Table 12, we present the industry distribution of firms that are in the treatment and control samples. Since we included industry fixed effect in the first stage regression, the industry distribution across the treatment and control sample is very similar. There are 1801 firms in the treatment sample and 2251 firms in the control sample.

Next, we estimate our baseline simultaneous equation model for the propensity score matched sample. We present the results in Tables 13 and 14. Our results are consistent with our main baseline results shown in Tables 7 and 8, with a few exceptions. We find the relationship between AI focus and Sales/Asset is negative and weakly significant. This follows from our guiding framework where we did not predict the sign of the relation between AI focus and Sales/Asset. The sign and significance of all the control variables are comparable to our main baseline model.

### Industry weighted measure of AI focus

Next, we estimate our baseline simultaneous equation model using an industry weighted measure of AI focus. Our main variable of interest is AI focus, which is constructed by counting the frequency of 122 AI related keywords and phrases in firms’ 10-K filings. It is possible that some of the key words, such as “Python”, “Automation” and the like, are too broad. Therefore, to assign appropriate weight to each of the keywords based on what we observe in that industry year, first we individually search for these 122 key words and phrases in the 10-Ks. Appendix VI outlines the most frequently used AI focus keywords by industry and year. The keywords vary across different industries. However, a few keywords are shared between the different industries. For example, “SAS”, “Automation”, “Data acquisition”, “Data processing” are common in multiple industries. Appendix VII outlines the percentage of the 122 AI terms used in the 10-Ks. These range from 8 to 48%. In most industries, the percentage of AI terms used are quite low, which biases against finding any results in our empirical analysis. However, we have found consistent and significant results, which suggest that AI focus really does matter for firms.

Next, we compute a weighted measure of AI focus (WAI) by assigning weights to different AI terms depending on how frequently they are used in a specific industry and year. First, we compute the sum of all keywords by industry year. Then,

### Table 11 Firm characteristics after matching

| Variable | Treatment | Control | p-value of t-test of mean difference between treatment and control sample |
|----------|-----------|---------|---------------------------------------------------------------|
| Size     | 6.532     | 6.503   | 0.483                                                        |
| Growth   | 4.439     | 4.476   | 0.782                                                        |
| Leverage | 0.610     | 0.623   | 0.791                                                        |
| Liquidity| 0.157     | 0.156   | 0.787                                                        |
| Tangible | 0.418     | 0.426   | 0.311                                                        |
| Intangible| 0.159    | 0.159   | 0.968                                                        |
| Risk     | 1.211     | 1.227   | 0.619                                                        |
| HHI      | 0.224     | 0.227   | 0.570                                                        |
| AI       | 0.012     | 0.003   | 0.000                                                        |

### Table 12 Industry distribution of the matched sample

| Fama French industries | Number of observations in treatment sample | Number of observations in control sample |
|------------------------|-------------------------------------------|------------------------------------------|
| Consumer Non-Durable   | 229                                       | 240                                      |
| Consumer Durable       | 225                                       | 235                                      |
| Manufacturing          | 920                                       | 945                                      |
| Oil, Gas and Coal      | 511                                       | 502                                      |
| Chemicals and Allied   | 180                                       | 199                                      |
| Business Equipment     | 1,897                                     | 1,909                                    |
| Telephone and Televisio| 115                                       | 106                                      |
| Utilities              | 62                                        | 67                                       |
| Wholesale, Retail      | 559                                       | 535                                      |
| Healthcare, Medical    | 920                                       | 904                                      |
| Finance                | 1,057                                     | 1,033                                    |
| Mines, Constructions   | 1,020                                     | 1,020                                    |

10 We thank an anonymous referee for pointing this out and for suggesting that we weight the firm level AI focus measure.
we compute the weight for each keyword in a given industry \( j \) and year as \( W_{jp} = \frac{w_{jp}}{\sum_{p=1}^{122} w_{jp}} \). To compute a weighted AI focus measure for a firm year we multiply this weight, \( W_{jp} \), with the total number of occurrences of word \( p \) and sum it across all words. This is denoted as \( WAI_{it} = \sum_{p=1}^{122} W_{jp} \times AI_{ip} \). Table 15 presents the descriptive statistics of WAI by industry. The mean WAI is highest for Business Equipment and lowest for Telephone and Telecommunication industries.

We then estimate our baseline system of equations model using the WAI variable. Tables 16 and 17 present the results. Our results are in line with our baseline results shown in Tables 7 and 8, with one exception. We find the coefficient on WAI focus is negative and significant for the NI/30% of SGA model. Similarly, the coefficient on NI/30% of SGA is negative and significant in the WAI model. This suggests AI focus is negatively correlated with return on marketing investment. If we observe the most frequently used keywords in different industries, they indicate firms use AI to improve production efficiencies. None of the most frequently used keywords indicate the use of AI in marketing, which could be one reason why we see a negative relationship between WAI focus and return on marketing investment.

**Industry adjusted measure of AI focus**

As an alternative measure of AI focus, we employ an industry adjusted measure of AI focus. We have used industry fixed

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**Table 13** Relationship between AI focus and firms’ operating efficiency for a propensity score matched sample

| Variables | (1) | (2) | (3) | (4) | (5) |
|-----------|-----|-----|-----|-----|-----|
| Ln(Emp)   | 0.298*** (0.007) | | | | |
| ADV/Asset | 0.852*** (0.196) | | | | |
| AI        | -0.019* (0.010)  | 0.014*** (0.003) | -0.400* (0.231) | -1.473*** (0.213) | 8.967*** (1.564) |
| Size      | 0.001*** (0.000) | 0.525*** (0.003) | -0.202*** (0.004) | 39.027*** (2.418) | 0.310*** (0.023) |
| Growth    | 0.001*** (0.000) | 0.001 | 0.001 | -1.769*** (0.638) | 0.009 (0.006) |
| Lev       | 0.001* (0.000) | -0.005* (0.003) | 0.001 | -0.537 | -0.003 (1.906) |
| Liquidity | 0.013*** (0.002) | -0.084* (0.044) | -0.500*** (0.036) | 71.388** (32.902) | 1.476*** (0.313) |
| Tangible  | -0.000 (0.001) | 0.306*** (0.017) | -0.036** (0.015) | -71.314*** (13.100) | 0.097 (0.125) |
| Intangible| 0.025*** (0.001) | 0.955*** (0.033) | 0.393*** (0.028) | -162.963*** (24.875) | -3.191*** (0.233) |
| Risk      | -0.000*** (0.000) | -0.024*** (0.003) | 0.014*** (0.003) | 28.223*** (2.475) | -0.150*** (0.018) |
| HHI       | 0.089*** (0.024) | 0.129*** (0.020) | 82.110*** (18.131) | 0.328* (0.173) |
| Sales/Asset| 145.455*** (4.442) | | | | |
| Sales/Emp | 0.001*** (0.000) | | | | |
| Constant  | 0.021*** (0.002) | -1.921*** (0.050) | 1.970*** (0.044) | -177.110*** (38.449) | -0.538 (0.362) |
| Industry and Year Effect Included | Included | Included | Included | Included | Included |
| Weak Instrument Test (Cragg Donald F-stat) (p-value) | 2004.65 (0.000) | 25,178.60 (0.000) | 2037.27 (0.000) | 1947.66 (0.000) | 198.75 (0.000) |
| Observations | 14,459 | 14,459 | 14,459 | 14,459 | 14,459 |
| R-squared | 0.120 | 0.738 | 0.380 | 0.284 | 0.088 |
### Table 14: Relationship between AI focus and firms' operating efficiency for a propensity score matched sample

| Variables | (6) | (7) | (8) | (9) | (10) |
|-----------|-----|-----|-----|-----|-----|
| AI | 8.406*** (0.702) | 5.364*** (0.226) | -0.541*** (0.092) | -0.381*** (0.091) | -0.381*** (0.091) |
| Size | 0.145*** (0.016) | 15.466*** (1.034) | -0.381*** (0.091) | -0.381*** (0.091) | -0.381*** (0.091) |
| Growth | 0.005 (0.004) | 0.029 (0.278) | 0.010 (0.025) | 0.008 (0.025) | 0.008 (0.025) |
| Lev | -0.001 (0.006) | -0.022 (0.202) | -0.132 (1.274) | -1.816 (1.268) | -3.092*** (1.268) |
| Liquidity | -3.345*** (0.226) | -128.152*** (14.310) | -1.312 (1.274) | -1.816 (1.268) | -3.092*** (1.268) |
| Tangible | 0.258*** (0.090) | -7.118 (5.692) | -2.307*** (0.507) | -2.520*** (0.504) | -2.454*** (0.504) |
| Intangible | -4.857*** (0.167) | -209.470*** (10.518) | 4.689*** (0.935) | 3.658*** (0.930) | 2.577*** (0.931) |
| Risk | -0.064*** (0.008) | -3.174*** (0.264) | 0.012*** (0.001) | 0.317*** (0.000) | 0.143*** (0.000) |
| HHI | 0.415*** (0.124) | 32.307*** (7.872) | 6.003*** (0.702) | 6.345*** (0.698) | 6.436*** (0.698) |
| Sales/Emp | 0.000*** (0.000) | 0.057*** (0.001) | 0.317*** (0.000) | 0.317*** (0.000) | 0.317*** (0.000) |
| Constant | -0.522** (0.261) | -63.664*** (16.523) | 7.421*** (1.471) | 6.851*** (1.464) | 6.771*** (1.465) |
| Industry and Year Effect | Included | Included | Included | Included | Included |
| Weak Instrument Test | 626.64 (0.000) | 190.47 (0.000) | 666.73 (0.000) | 666.73 (0.000) | 666.73 (0.000) |
| Observations | 14,459 | 14,459 | 14,459 | 14,459 | 14,459 |
| R-squared | 0.186 | 0.177 | 0.053 | 0.063 | 0.062 |

### Table 15: Descriptive statistics of industry weighted AI focus (WAI) by industry

| Industry Type | N | P25 | Mean | Median | P75 | SD |
|---------------|---|-----|------|-------|-----|----|
| Consumer Non-Durables | 728 | 0.173 | 1.244 | 0.444 | 1.270 | 2.389 |
| Consumer Durable | 601 | 0.242 | 1.441 | 0.651 | 1.565 | 2.397 |
| Manufacturing | 2220 | 0.327 | 1.521 | 0.708 | 1.575 | 2.509 |
| Oil, Gas, and Coal | 1439 | 0.371 | 1.639 | 0.885 | 1.541 | 2.673 |
| Chemicals and Allied | 586 | 0.389 | 1.312 | 0.823 | 2.000 | 1.484 |
| Business Equipment | 5579 | 0.313 | 1.658 | 0.700 | 1.739 | 2.589 |
| Telephone and Television | 475 | 0.192 | 0.932 | 0.459 | 1.015 | 1.330 |
| Utilities | 1183 | 0.295 | 0.974 | 0.608 | 0.882 | 1.425 |
| Wholesale, Retail | 1483 | 0.225 | 1.125 | 0.464 | 1.079 | 1.978 |
| Healthcare, Medical | 2630 | 0.154 | 0.858 | 0.316 | 0.692 | 1.898 |
| Finance | 7915 | 1.352 | 3.216 | 2.613 | 4.277 | 3.127 |
| Mines, Constructions | 2664 | 0.201 | 1.014 | 0.468 | 0.997 | 1.795 |
effect in our analysis. However, industry fixed effect only captures time invariant unobservable industry specific characteristics. It does not capture time varying changes across industries. AI focus across industries can vary significantly over time. For example, technology industries are likely to focus more on AI than utilities. All models apply an industry fixed effect to capture time-invariant, unobservable systematic factors. It is possible that over time the focus of AI changes across industries. Thus, the time varying AI focus of specific industries could have a dominant effect on the results. Our industry adjusted AI focus measures the AI focus of firms relative to their industry peers over time – to rule out that our results are driven by time-varying industry AI focus. To this effect, we use simultaneous equations to examine the relation between industry-adjusted AI focus and firm efficiency measures. Our results are consistent with our baseline model results which Tables 7 and 8 present. However, due to space constraints we do not report the results in the paper.

Table 16  Relationship between AI focus and firms’ operating efficiency using industry weighted AI measure

| Variables | (1) ADV/Asset | (2) Ln(Emp) | (3) Sales/Asset | (4) Sales/Emp | (5) NI/30% of SGA |
|-----------|--------------|-------------|----------------|---------------|-------------------|
| Ln(Emp)   | 0.294***     | (0.006)     |                 |               |                   |
| ADV/Asset | 0.758***     | (0.190)     |                 |               |                   |
| WAI       | -0.001       | 0.019***    | 0.001           | -0.028***     | -0.032***         |
|           | (0.000)      | (0.003)     | (0.002)         | (0.002)       | (0.014)           |
| Size      | 0.001***     | 0.517***    | -0.196***       | 42.292***     | 0.294***          |
|           | (0.000)      | (0.003)     | (0.004)         | (2.386)       | (0.022)           |
| Growth    | 0.000***     | 0.001       | -0.001          | -1.391**      | 0.007             |
|           | (0.000)      | (0.001)     | (0.001)         | (0.619)       | (0.006)           |
| Lev       | 0.000***     | -0.003      | 0.001           | -0.949        | 0.038***          |
|           | (0.000)      | (0.002)     | (0.002)         | (1.876)       | (0.012)           |
| Liquidity | 0.013***     | -0.098**    | -0.443***       | 57.193*       | 1.214***          |
|           | (0.002)      | (0.043)     | (0.036)         | (33.154)      | (0.312)           |
| Tangible  | -0.001       | 0.270***    | -0.034***       | -56.267***    | -0.103            |
|           | (0.001)      | (0.017)     | (0.014)         | (13.085)      | (0.123)           |
| Intangible| 0.024***     | 0.948***    | 0.435***        | -163.893***   | -3.194***         |
|           | (0.001)      | (0.032)     | (0.027)         | (24.614)      | (0.226)           |
| Risk      | -0.000***    | -0.024***   | 0.013***        | 30.406***     | -0.061***         |
|           | (0.000)      | (0.003)     | (0.002)         | (2.257)       | (0.014)           |
| HHI       | 0.069***     | 0.116***    | 0.435***        | 104.106***    | 0.498***          |
|           | (0.024)      | (0.020)     | (0.027)         | (18.415)      | (0.171)           |
| Sales/Asset| 137.456***   | (4.240)     |                 |               |                   |
| Sales/Emp |                 |             |                 |               | 0.001***          |
|           |             |             |                 |               | (0.000)           |
| Constant  | 0.022***     | -1.880***   | 1.905***        | -151.070***   | -0.452            |
|           | (0.002)      | (0.051)     | (0.044)         | (39.484)      | (0.368)           |
| Industry and Year Effect | Included | Included | Included | Included | Included |
| Weak Instrument Test (Cragg Donald F-stat) (p-value) | 2159.39 | 32,078.61 | 2157.44 | 2190.55 | 199.06 |
| Observations | 15,003 | 15,003 | 15,003 | 15,003 | 15,003 |
| R-squared | 0.118 | 0.739 | 0.374 | 0.281 | 0.089 |

Std error values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.001
Discussion

Our findings confirm that US-listed firms are in a state of transition/impending transformation (Davenport et al., 2020) with regard to their focus on AI. We show how AI focus in business is associated with improvements in net profitability, net operating efficiency and return on marketing-related investment, while reducing adspend and creating jobs. Our findings are consistent with prior economic (Acemoglu & Restrepo, 2019) and marketing theory (Albrecht et al., 2021; Davenport et al., 2020; Ma & Sun, 2020), which contend that AI can increase productivity, whether through automation and/or job creation. The first implication is that revenues can increase through improved marketing (e.g., dynamic pricing, tailored promotions, product recommendations, enhanced customer engagement). The second implication is that if the use of AI leads to increased automation, there may be cost savings. Costs may decline due to automation, improved customer service or more structured market transactions (Perez-Vega et al., 2021). However, if AI leads to job creation, then there may be short-term increases in costs.

We find that a focus on AI reduces adspend, suggesting more automated promotions and more targeted marketing (Columbus, 2019; Parekh, 2018). The relationship between

| Table 17 Relationship between AI focus and firms' operating efficiency using industry weighted AI measure |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Variables                   | (6) NI/Sales                | (7) NI/Emp                  | (8) WAI                      | (9) WAI                      | (10) WAI                     |
| WAI                         | 0.080*** (0.006)            | 0.038*** (0.004)            | 63.234*** (9.610)            | 6.584*** (0.961)             | 7.343*** (0.961)             |
| Size                        | 0.131*** (0.016)            | 14.548*** (1.021)           | 3.348 (9.261)                | 0.334 (0.256)                | 0.338 (0.256)                |
| Growth                      | 0.000 (0.004)               | 0.030 (0.271)               | 3.348 (2.561)                | 0.334 (0.256)                | 0.338 (0.256)                |
| Lev                         | -0.016*** (0.005)           | -1.036*** (0.344)           | -105.226 (13.696)            | -7.208 (13.696)              | -13.899 (13.696)             |
| Liquidity                   | -3.034*** (0.223)           | -119.556*** (14.472)        | 53.720 (5.369)               | 5.371 (5.369)                | 19.621** (5.371)             |
| Tangible                    | 0.250*** (0.088)            | -18.072*** (5.683)          | -474.191*** (53.720)         | -48.803*** (5.369)           | -48.426*** (5.369)           |
| Intangible                  | -4.645*** (0.160)           | -196.318*** (10.418)        | 310.810*** (98.105)          | 35.530*** (9.806)            | 19.621** (9.808)             |
| Risk                        | -0.003 (0.006)              | -1.148*** (0.416)           | 7.889 (2.561)                | 7.440 (2.561)                | 7.440 (2.561)                |
| HHI                         | 0.395*** (0.121)            | 36.180*** (7.889)           | 1.693.026*** (74.434)        | 169.666*** (7.440)           | 171.729*** (7.440)           |
| Sales/Emp                   | 0.000*** (0.000)            | 0.054*** (0.002)            | 0.393*** (0.000)             | 2.638*** (0.000)             | -1.108*** (0.001)            |
| NI/Emp                      |                            |                             |                              |                             |
| NI/Sales                    |                            |                             |                              |                             |
| NI/30% of SGA               |                            |                             |                              |                             |
| Constant                    | -0.674** (0.263)            | -56.984*** (17.065)         | 100.974 (161.562)            | 9.676 (16.149)               | 7.491 (16.152)               |
| Industry and Year Effect    |                            |                             |                              |                             |
| Weak Instrument Test        | 634.24 (0.000)              | 192.07 (0.000)              | 933.31 (0.000)               | 933.31 (0.000)               | 933.31 (0.000)               |
| Industry and Year Effect    |                            |                             |                              |                             |
| Observations                | 15.003                      | 15.003                      | 15.003                       | 15.003                       | 15.003                       |
| R-squared                   | 0.177                       | 0.169                       | 0.061                        | 0.062                        | 0.061                        |
ADV/Asset and Sales/Asset is consistent with prior literature (Kietzmann et al., 2018; Perez-Vega et al., 2021; Pillai et al., 2020). These results suggest higher AI focus has a negative correlation with adspend because an increase in the use of AI in marketing reduces future advertising spending due to better target marketing, segmentation, analytics (related to marketing strategy), messaging and personalization (Colombus, 2019; Tong et al., 2020). AI can also further reduce advertising expenditure through programmatic buying of digital ads (Parekh, 2018), thus decreasing adspend. Higher AI focus is positively correlated with the number of employees in firms. This result confirms our theoretical framework, in that AI creates jobs and increases employee numbers (Huang & Rust, 2018; Tschang & Almirall, 2021).

We find a reduction in gross operating efficiency and an increase in net operating efficiency, suggesting that costs are increasing at a slower rate than revenue due to automation. We also find that AI focus can boost employment. This can potentially increase costs for the firms in terms of wages and salaries. This is consistent with (Acemoglu & Restrepo, 2018) theoretical results. For example, it is possible that the firm can use chatbots (automation) to reduce adspend and increase personalization but will need to hire skilled employees who can design and manage the chatbots (i.e., creation of new jobs), and hence their headcount will increase. Our findings are also consistent with Vlačić et al. (2021) and Guha et al. (2021). Indeed, IBM CEO Ginni Rometty contends that AI is not a case of man “versus” machine, but rather man “plus” machines (Carpenter, 2015; Davenport et al., 2020).

The findings are also consistent with Davenport et al. (2020), Syam and Sharma (2018) and Pillai et al. (2020), who contend that AI will have a positive impact on sales processes across various industries. Similarly, Tschang and Almirall (2021) contend that AI will not eliminate jobs—but will help workers perform better. They predict that new jobs will be created and demand for uniquely human skills will continue to grow. It is important to mention that our findings do not contradict Huang and Rust (2018), who develop a theory of AI job replacement in the context of services. This is because Huang and Rust (2018) only consider job replacement in services, whereas our employment measure is much broader.

**Theoretical contributions**

Our study makes several theoretical contributions. While many posit that AI will improve firm performance (Lin et al., 2020; Ma & Sun, 2020; Mishra & Pani, 2020), enhancing firm efficiencies and transforming marketing strategies (Albrecht et al., 2021; Davenport et al., 2020; Haenlein & Kaplan, 2021; Rust, 2020), as far as we know, this is the first attempt to map a guiding framework of AI with empirical analyses for a large sample. We developed and employed a novel quantitative measure of AI focus from listed US firms’ annual 10-K reports. Our study is also the first to empirically examine the role of AI focus on firm performance using 15 years of 10-K data for some 4,052 firms. We find that a focus on AI has a positive correlation with sales, return on sales, return on marketing-related investment and net operating efficiency.

Similarly, we find that AI reduces adspend and creates jobs. This is a significant contribution because as more and more firms embrace AI in different aspects of their operations, it is essential to empirically determine whether (and how) the use of AI affects firm performance. Our research compliments Acemoglu and Restrepo (2018) theoretical framework. Our findings are sufficiently robust and underscore the importance of the AI-productivity link and how the relationship with costs can be either positive or negative depending on the scenario. Our research complements the theoretical relationship between AI and firm performance (Davenport et al., 2020). Demonstrating how the findings are consistent when implemented for a matched sample of firms represents another distinct contribution. The firms are similar in all other characteristics, differing only in their use of AI.

**Limitations and future research**

Our results should be interpreted cautiously as our conclusions are based on firms’ use of 122 AI related keywords in their 10-K reports. First, although we have a large sample, it is possible we have ‘missed’ some firms who have an AI focus but have not explicitly mentioned it in the 10-Ks. Alternatively, they may have mentioned terms not on our list in their 10-K reports. We did not include any other verbal or written articulations of AI by the firms concerned. We did not access any promotional materials of these firms, nor any internal documents that might express or expound views on, or stances towards AI.

Third, although we use an industry adjusted measure of AI focus to address time-varying changes across industries, we did not conduct an industry-specific analysis or make comparisons between firms in different industries. Fourth, although we track the use of 122 AI terms, we have not differentiated between terms or categorized terms into broader themes (e.g., automation, customization, job creation). Finally, our ‘dictionary’ of 122 AI terms may not be exhaustive—we may have overlooked some salient terminology given the rapid increase in AI methods and processes over the years. We chose 10-K filings to search for these terms.
because this is the most common and comprehensive reporting format for US public firms. Prior literature has highlighted the importance of the management and discussion section of the annual 10-K report and its link to firm value. Further, since 10-K filings are a mandatory requirement by the Securities Exchange Commission, the information provided in 10-K is more likely to be truthful and reliable (with less PR ‘spin’ and/or hyperbole).

Multiple directions for future research flow from this work. First, future research could develop a more comprehensive construct of AI focus. Our AI focus measure is quite general. Prior literature has used qualitative measures of AI to examine its impact. Our measure could be further strengthened by expanding and enriching the dictionary of terms. Second, future research could develop a marketing specific construct of AI focus. Focusing on fewer, exclusively marketing-oriented keywords and then examining their relationship with adspend and marketing investment would be valuable.

Third, future research could test theoretically meaningful moderators. For example, differentiating between automation and innovative AI terms and examining their respective effects on performance. Fourth, future research could broaden the scope of variables and test their interactions. For example, examining the impact of AI focus on firm performance in small to medium enterprises or testing the process models in comparable and disparate countries may prove fruitful. The prevalence of articulation of AI might be higher for some industries than in others, as we evidence from the descriptive statistics in the case of business equipment and financial services industries. Indeed, Davenport et al. (2020) contend that the impact of AI on marketing is highest in industries such as consumer packaged goods, retail, banking and travel. Therefore, future research could also pursue industry-level comparisons in the form of case studies.

Fifth, examining novel and untested outcomes represents another potential avenue for future research. We did not find a significant negative relationship between AI and adspend when we used the weighted AI measure. Therefore, future research could investigate this result further by examining the role of marketing related AI on marketing related expenditure. Our results are inconclusive for return on marketing investment. For general AI focus, we find there is a positive correlation between AI and return on marketing investment but for an industry weighted measure of AI focus we find the opposite. Future research can investigate the relationship between AI focus and return on marketing investment by focusing on marketing related AI keywords.

We find that AI focus is negatively related to gross operating efficiency and positively related to net operating efficiency. This suggests costs reduced in other areas of the production process, although cost in terms of employee salary and wages have gone up. Thus, future research that investigates the specific areas where AI has reduced costs is also important. Not all firms have a positive view with regards to AI. Some firms consider AI to be a major risk or even a threat. In such cases, it would be valuable to examine the positive and negative role of AI by analyzing the text surrounding AI terms in the 10-K reports.

Finally, we believe that this study has further demonstrated the richness of 10-K reports and what they offer to finance scholars and marketers and their colleagues in strategy, management and operations. While 10-K reports are essentially technical in nature, they communicate salient messages to stakeholders and the investment community. Automated text analysis tools such as LIWC (e.g., Chung & Pennebaker, 2012; Cohn et al., 2004) would be helpful in future (longitudinal) 10-K analyses.

**Conclusion**

We have shown how AI focus is correlated with firms’ efficiency measures. Using text analyses, we searched for terms associated with AI in all listed US-based firms’ annual 10-K reports for the period 2005–2019. We demonstrate how AI focus can reduce costs by reducing adspend and increasing cost by increasing headcount/wage growth. This is because there are two broad aspects to AI; one focused on automation and the other on new jobs. If automation is used it may reduce costs, but if new jobs are created, then it can increase costs for the firm in the short term due to an increase in salaries and wages. Further, we find that AI focus is negatively correlated with gross operating efficiency (sales per employee), suggesting that AI focus increases the number of employees more than it increases sales. Although cost has increased in terms of salaries and wages, AI focus has a positive correlation with net efficiency measures such as return on sales (net income per $ of sales), return on marketing investment (net income per $ of marketing investment) and net profit per employee. This suggests costs are reduced in other areas of the production process.

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Declarations

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

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