Green Cloud? An Empirical Analysis of Cloud Computing and Energy Efficiency

Jiyong Park*, Kunsoo Han†, and Byungtae Lee‡

Abstract

The rapid, widespread adoption of cloud computing over the past decade has sparked debates on its environmental impacts. Given that cloud computing alters the dynamics of energy consumption between service providers and users, a complete understanding of the environmental impacts of cloud computing requires an investigation of its impact on the user side, which can be weighed against its impact on the vendor side. Drawing upon production theory and using a stochastic frontier analysis, this study examines the impact of cloud computing on users' energy efficiency. To this end, we develop a novel industry-level measure of cloud computing based on cloud-based information technology (IT) services. Using US economy-wide data from 57 industries during 1997–2017, our findings suggest that cloud-based IT services improve users' energy efficiency. This effect is found to be significant only after 2006, when cloud computing started to be commercialized, and becomes even stronger after 2010. Moreover, we find heterogeneous impacts of cloud computing, depending on the cloud service models, energy types, and internal IT hardware intensity, which jointly assist in teasing out the underlying mechanisms. Although Software-as-a-Service (SaaS) is significantly associated with both electric and non-electric energy efficiency improvement across all industries, Infrastructure-as-a-Service (IaaS) is positively associated only with electric energy efficiency for industries with high IT hardware intensity. To illuminate the mechanisms more clearly, we conduct a firm-level survey analysis, which demonstrates that SaaS confers operational benefits by facilitating energy-efficient production, whereas the primary role of IaaS is to mitigate the energy consumption of internal IT equipment and infrastructure. According to our industry-level analysis, the total user-side energy cost savings from cloud computing in the overall US economy are estimated to be 2.8 to 12.6 billion US dollars in 2017 alone, equivalent to a reduction in electricity use by 31.8 to 143.8 billion kilowatt-hours. This estimate exceeds the total energy expenditure in the cloud service vendor industries and is comparable to the total electricity consumption in US data centers.

Keywords: Cloud computing; Software-as-a-Service; Infrastructure-as-a-Service; IT outsourcing; Energy efficiency; Green IT; Green IS; Sustainability; Stochastic frontier analysis

* Bryan School of Business and Economics, University of North Carolina at Greensboro, 516 Stirling Street Greensboro, North Carolina 27412, USA (email: jiyong.park@uncg.edu)
† Desautels Faculty of Management, McGill University, 845 Sherbrooke St W, Montreal, Quebec H3A 1G5, Canada (email: kunsoo.han@mcgill.ca)
‡ College of Business, Korea Advanced Institute of Science and Technology, 85 Hoegiro Dongdaemoon-gu, Seoul, Korea (email: btlee@kaist.ac.kr)

Introduction

Cloud computing—providing information technology (IT) services over a network—has been widely adopted by businesses across industries due to such benefits as flexibility, scalability, always-on availability, and pay-as-you-go pricing (Marston et al. 2011). A cloud service vendor provides users with on-demand access not only to various computing resources in the cloud (e.g., storage, networking, servers), but also to software and applications through the Internet. The former service model is commonly known as Infrastructure-as-a-Service (IaaS) (e.g., Amazon Web Services EC2, Google Compute Engine), while the latter is typically called Software-as-a-Service (SaaS) (e.g., Salesforce, Google Workspace, Microsoft Office 365). Gartner (2021) predicts that public cloud spending will exceed 45% of all enterprise IT spending, up from less than 17% in 2021. According to an IT trend report by the Society for Information Management (2020), cloud computing was the top organizational investment in 2020 for the first time since 2010. The rapid, widespread adoption of cloud computing over the past decade has sparked debates on its environmental impacts among practitioners and academics alike. In particular, sustainability has been identified as one of major driving forces that may reshape the relationship between cloud service providers and users; as Gartner (2021) puts it, "New sustainability requirements will be mandated over the next few years and the choice of cloud services providers may hinge on the provider's 'green' initiatives."

On one hand, there has been a pervasive view that cloud computing is one of the main culprits of global energy consumption and environmental degradation. For example, the large volume of electricity consumed to support cloud services has often been described as a "dirty secret" of cloud computing (e.g., *Fortune* 2019). According to a study conducted by the Lawrence Berkeley National Laboratory (Shehabi et al. 2016), US data centers consumed approximately 70 billion kilowatt-hours of electricity in 2014, representing 2% of the country's total electricity consumption. These numbers are expected to grow rapidly as the demand for cloud-based IT and data services increases (Jones 2018; Mastelic et al. 2014). In addition to data center operations, data transfer from data centers to users may also consume a significant amount of energy (Baliga et al. 2011).

On the other hand, some practitioners and scholars suggest that cloud computing can lead to net energy savings for the overall economy if we factor in the user-side benefits. For example, organizations can replace an energy-inefficient internal IT infrastructure with cloud-based IT services accessible on demand over a network, which allows them to optimize IT resource utilization and enhance energy efficiency. Capitalizing on economies of scale, cloud computing can save a substantial amount of energy through virtualization, which allows a number of different applications/instances that typically have a large amount of unused capacity in the absence of cloud computing to be consolidated onto a single server (Bose and Luo 2011). A simulation study argues that if all US businesses moved their applications to the cloud (i.e., cloud service providers' servers), they could reduce their computing energy footprint by 87% (Masanet et al. 2013). Moreover, on-demand cloud services provide low-cost access to scalable, high-powered software running on the cloud that can confer greater operational and sustainability benefits in ways to reduce wasted resources, including energy (Battleson et al. 2016), which could not be achieved through in-house development or traditional software licensing.

Despite ongoing debates over the environmental impacts of cloud computing, a comprehensive assessment of the impacts from the perspectives of both service providers (vendors) and users (clients) has been elusive, mainly due to a lack of the necessary data. Mytton (2020) highlights the challenge in evaluating the environmental impacts of cloud computing, as it may alter the energy consumption dynamics between users and service providers. In this regard, a complete understanding of the environmental implications of cloud computing requires an investigation of its impact on *the user side*, which can be weighed against its *vendor-side* effect. Although prior literature has examined how the energy consumption on the vendor side adversely affects the environment and how the energy efficiency of cloud computing facilities can be improved (e.g., hyperscale data centers) (Jones 2018; Mastelic et al. 2014), little attention has been devoted to the broader impacts of cloud computing on the user side (Marston et al. 2011). Drawing upon production theory, this study aims to fill the current void by empirically examining the *user-side* effect of cloud computing on energy efficiency improvement, which allows us to assess the economy-wide impact of cloud computing on energy use. Moreover, cloud computing has transformed the way various IT resources (i.e., hardware/infrastructure and software) are procured. Given that hardware and software may have different implications for energy consumption and environmental sustainability due to first- and second-order effects (Horner et al. 2016), we also scrutinize the differential roles of cloud service models provisioning hardware/infrastructure (i.e., IaaS) and software (i.e., SaaS) in shaping energy efficiency, which helps us tease out the underlying mechanisms and thus offer novel theoretical and managerial implications.

For the empirical analysis, we develop a novel industry-level measure of cloud computing that captures purchased cloud-based IT services by combining industry-level product sales data from the US Economic Census and inter-industry purchase flows from input-output use tables. This approach allows us to distinguish different types of cloud services (SaaS and IaaS), based on the types of IT services purchased by an industry. In addition, a stochastic frontier analysis is employed to estimate an energy frontier—the minimum level of energy consumption needed to produce a given output with extant production inputs—which is used to measure an industry's energy efficiency as a deviation from the energy frontier. Then, we examine whether and how cloud-based IT services influence users' energy efficiency. We further delve into the differential effects involving two types of cloud computing services.

Using data from 57 US private industries over the period 1997–2017, we find that cloud-based IT services improve client industries' energy efficiency. In contrast, no significant effect has been found for non-cloud IT services such as computer systems design, which typically relies on clients' own IT infrastructure. While cloud-based IT services have no significant impact on energy efficiency prior to 2006, its impact becomes statistically significant after 2006, when the first commercial cloud services (i.e., Amazon Web Services; AWS) were launched; its impact becomes even larger after 2010, when the prices of cloud services substantially declined due to increased competition. Moreover, we find heterogeneous impacts of cloud computing on energy efficiency, depending on the cloud service models, energy types, and internal IT hardware intensity, which jointly assist in teasing out the underlying mechanisms. Although

SaaS is significantly associated with energy efficiency improvement across all industries, the impact of IaaS varies, depending on the internal IT intensity and energy type. Specifically, the positive contribution of IaaS to energy efficiency is stronger in industries that make more intensive use of IT hardware. In addition, while the main effects of SaaS on energy efficiency are significant for both electric and non-electric energy efficiency, IaaS only improves electric energy efficiency for industries with high IT hardware intensity.

To illuminate the underlying mechanisms more clearly, we conduct a firm-level analysis using survey data from 187 firms. The results corroborate our industry-level findings and validate the underlying mechanisms at a more granular level. Specifically, while both SaaS and IaaS are positively associated with energy efficiency, the effects of SaaS and IaaS are mainly mediated by operational benefits and a reduction in the energy consumption of internal IT, respectively. Taken together, the findings from industry- and firm-level analyses highlight the intricate way that cloud computing leads to energy efficiency improvement: while SaaS facilitates energy-efficient production by mainly helping to optimize operations and redesign production processes (which consume both electric and non-electric energy), the primary role of IaaS is to mitigate the adverse impacts of internal IT equipment and infrastructure (which rely on electric energy) on energy efficiency.

According to the back-of-the-envelope calculation based on our industry-level estimates, the total energy cost savings from cloud computing on the user side in the US economy are estimated to be 2.8 to 12.6 billion US dollars in 2017 (based on the 95% confidence interval). This estimate is equivalent to a reduction in electricity use by 31.8 to 143.8 billion kilowatt-hours, which represents approximately 0.9% to 3.9% of total electricity use in the US. The estimated energy savings exceed the total energy consumption by cloud service vendor industries and is comparable to the total electricity consumption by US data centers estimated by the Lawrence Berkeley National Laboratory (70 billion kilowatt-hours in 2014; Shehabi et al. 2016). Our estimates highlight the notion that the cloud computing's energy efficiency benefits on the user side far outweigh its vendor-side adverse effects in the overall economy.

From the business perspective, this research presents the first empirical evidence of the user-side effect of cloud computing on energy efficiency, which is imperative for a comprehensive assessment of the economy-wide impact of cloud computing on energy use. Going beyond the business value of IT, this study advances the body of knowledge in the information systems (IS) literature by shedding new light on the "green" value of cloud computing and uncovering the way cloud computing confers sustainability benefits to business users and the economy as a whole. This study also provides meaningful policy and managerial implications, informing ongoing dialogues on cloud computing and environmental sustainability.

Related Literature and Theoretical Framework

Cloud Computing

Cloud computing is generally defined as an "information technology service model where computing services (both hardware and software; HW and SW hereafter) are delivered on-demand to customers over a network in a self-service fashion, independent of device and location" (Marston et al. 2011, p. 177). The National Institute of Standards and Technology suggests five essential characteristics of cloud computing—on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service—and three service models—*Software-as-a-Service (SaaS)*, *Platform-as-a-Service (PaaS)*, and *Infrastructure-as-a-Service (IaaS)* (Mell and Grance 2011). SaaS allows users to access SW and applications run on the cloud, eliminating the need to install and run applications on their own machines. Examples range from enterprise systems such as Salesforce, Workday, and NetSuite to personal applications such as Gmail and Microsoft Office 365. PaaS provides a platform on which applications can be developed without considering the underlying technical layers such as the server uptime, virtualization parameters, and network security (e.g., Microsoft Azure, Salesforce Platform, Google Cloud Platform). IaaS provides users with on-demand access to storage, networking, servers, and other computing resources over a network (e.g., Amazon EC2, Google Compute Engine, and Alibaba Cloud).

On-demand IT services with scalability and the pay-as-you-go pricing model make it attractive for firms to source more IT services from the cloud and use computing resources as a utility (Brynjolfsson et al. 2010). While a few studies have examined the economic impacts of cloud computing (Jin and McElheran 2019; Wauters et al. 2016) and its operational benefits (Loukis et al. 2019; Rodrigues et al. 2021), its environmental impacts on users have only been discussed conceptually (Iyer and Henderson 2010) with little empirical evidence. By reviewing 236 scholarly journal articles on cloud computing published between 2009 and 2014, Bayramusta and Nasir (2016) highlight that the energy consumption dimension of cloud computing is the least attention-grabbing theme in the literature, accounting for only four percent of publications; even those studies examine the energy use of cloud systems on the vendor side only. Using survey data with a focus on supply chain management, Schniederjans and Hales (2016) present evidence of a positive relationship between the use of cloud computing and perceived environmental performance such as reducing solid waste, resource consumption, and hazardous material consumption; however, the authors neither quantify the impact of cloud computing on actual energy consumption/efficiency in the overall economy nor disentangle the roles of different types of cloud services (e.g., SaaS vs. IaaS).

Given that cloud computing alters the energy consumption dynamics between users (clients) and service providers (vendors) (Mytton 2020), there is a critical need for a comprehensive empirical assessment of the environmental impacts of cloud computing, considering both clients and vendors. Hence, the current study aims to fill this important gap in the literature and advance our understanding of whether and how cloud computing confers environmental benefits to its users, based on a novel measure of cloud computing and industry-level data that cover the entire US economy. Doing so will allow us to assess the economy-wide net effect of cloud computing on energy use.

Cloud Computing and Energy Efficiency from the User Perspective

The environmental effects of IT can be classified into first-order effects—direct effects from the physical existence of IT that increase energy consumption—and second-order effects—indirect, energy-saving effects from the ongoing use and application of IT (Hilty et al. 2006; Horner et al. 2016).[4] In the IS literature, mitigating the first-order effects is often termed as "green IT," and facilitating the second-order effects is referred to as "green IS" (Malhotra et al. 2013). Against this backdrop, we posit that cloud computing services can improve users' energy efficiency through two mechanisms: (i) by *mitigating the energy consumption of IT infrastructure and equipment*, and (ii) by *facilitating energy-efficient production and operations*.

Mitigating the energy consumption of IT infrastructure and equipment: Given that the US is home to three million data centers (*Fortune* 2019), IT equipment and infrastructure have been blamed for their intensive energy consumption (Murugesan 2008). An annual report by Greenpeace (2017) highlights the importance of the IT sector in global energy demand, stating that "the IT sector was estimated to already consume over 7% of global electricity demand in 2012… and [will] continue to grow at least 7% annually through 2030, double the average rate of electricity growth globally" (p. 15). The Lawrence Berkeley National Laboratory also estimates the electricity consumption of US data centers as being approximately 2% of the country's total electricity use (Shehabi et al. 2016).

In this regard, IaaS allows its users to optimize IT resource utilization and minimize the cost of their own energy-intensive IT infrastructure by providing on-demand access to computing resources (e.g., processors, networks, servers, storage) over a network (Armbrust et al. 2010; Bose and Luo 2011). A report by Deloitte and the European Commission suggests that the largest economic benefit of cloud computing is direct cost savings such as those from reduced IT infrastructure investment and maintenance, which account for 20-50% of total IT costs (Wauters et al. 2016). Given that energy-related costs account for 42% of server operations costs—direct power consumption (19%) and cooling infrastructure (23%) (Jing et al. 2013), cloud service users can reduce their energy costs by migrating their own servers and data centers to

[4] Third-order effects refer to the structural and behavioral effects of digital technologies in the long run on transforming economic and industrial structures and altering consumer behaviors, thereby broadly affecting the environment, which we do not consider, as this is beyond the scope of our study.

the cloud without needing to power and cool them. In addition, SaaS can reduce the energy consumption required to run and support SW applications on the user side. For instance, the power consumption needed to run Excel 365 (a cloud-based version of Microsoft Excel) on user devices is estimated as being 15.7% (tablet) to 27.3% (laptop) lower than that needed to run the on-premises Excel 2010 (Williams and Tang 2013).

Moreover, cloud computing services allow users to respond to uncertain demand and meet excess requirements without incurring the costs of purchasing and running internal IT infrastructures, which are highly underutilized during low-demand periods (Marston et al. 2011). This cloud-driven flexibility and agility can reduce wasted resources and increase the utilization rate of IT resources, leading to energy savings. For example, after making its service available via Facebook in 2008, a US-based online video service, Animoto, experienced a demand surge of 750,000 new users in three days, a phenomenon known as the "Slashdot effect" (Klems et al. 2009), resulting in a dramatic increase in Amazon EC2 usage, from 50-100 instances to 3,400 instances (*AWS* 2008). Had Animoto relied on its internal IT infrastructure, it would have needed to purchase many additional servers, incurring huge fixed costs; however, it still would not have been able to scale up quickly enough, resulting in severely disrupted operations and the loss of tremendous sales opportunities. Recently, cloud service providers have introduced autoscaling, which allows users to scale their computational capacity automatically in real-time without having to make capacity pre-commitments, thereby helping them avoid extra costs from overinvestment (Fazli et al. 2018).

Facilitating energy-efficient production and operations: Cloud-based SW and applications can help improve operational efficiency and reduce resource waste in production, thereby enhancing energy efficiency. Loukis et al. (2019) suggest that the operational benefits of SaaS can drive firm performance. Using a manager survey, Rodrigues et al. (2021) find that the business value of the operational benefits, cost efficiency, and quality of process and products/services mediates the effect of SaaS on firm performance. Indeed, interviews with senior executives responsible for making decisions on cloud computing investment indicate that cloud computing has transformed firms' business processes and has significantly enhanced efficiencies in terms of cost and time to serve customers (Battleson et al. 2016). According to a survey of product development professionals, cloud-based system users reported higher levels of success (e.g., meeting cost targets, being more innovative, and delivering on time) than users of server-based SW or those with no formal systems (Engineering.com 2018).

It is noteworthy that the operational benefits from IT services may not be exclusive to cloud computing. For instance, Han and Mithas (2013) demonstrate that IT outsourcing can save non-IT operating costs by increasing operational efficiencies and allowing the reallocation of internal IT resources. Chou and Chang (2008) suggest that enterprise resource planning (ERP) systems can confer benefits through improved coordination and task efficiency. However, by virtue of subscription-based (or pay-as-you-go) pricing, always-on accessibility, scalability, modularity, and its broader community of users, we argue that cloud-based SaaS plays a more prominent role in conferring operational benefits, thereby reducing waste and energy costs and ultimately enhancing energy efficiency to a greater extent than traditional SW and other IT service outsourcing.

First, SaaS provides low-cost access to expensive, high-powered SW running on the cloud, with a great potential for efficiency gains, which might be unobtainable through in-house development or traditional SW licensing. A case in point is Emerson, a climate system manufacturer (heating, ventilation, air conditioning, and refrigeration). Although Emerson's supermarket customers may not be able to afford large upfront investments for standalone analytics SW, they could use Emerson's products equipped with cloud-enabled big data analytics applications that enable remote diagnosis, maintenance, and repairs. As a result, the customers were able to achieve energy cost savings of more than 10% (*KPMG* 2014).

Second, SaaS allows users not only to access their work anywhere and anytime, but also to add new applications, services, or SW features on the fly, which helps reduce or remove any unnecessary energy use caused by traveling or occupying fixed spaces. According to an industry survey (*Business Advantage* 2017), higher mobility and access from anywhere was the primary reason for choosing cloud-based computeraided design (CAD) programs, followed by the ease of software updates, improved collaboration, better scalability of computing power, storage, and memory, and the ability to pay only for what is used.

Third, SaaS provides a cost-effective and standardized way to rapidly deploy and scale up IT solutions, thereby reducing operating costs and improving efficiency. Iyer and Henderson (2012) illustrate an experience related to implementing a cloud-based human resources management solution, Workday: "Fairchild Semiconductors switched from an on-premises provider of enterprise SW to a cloud service provider, helping it simplify and standardize core human resources business processes for more than 10,000 employees and managers globally… Paul Lones of Fairchild Semiconductor… estimates that the cost to implement and run Workday was about 15% less than buying, installing and maintaining the traditional ERP software. In addition, he estimates that implementing an SaaS solution required about 50% to 70% less time" (p. 55). Another case in point is Volkswagen's development of an industrial cloud on AWS. In their global plants, a large volume of data from several hundred thousand machines and plant items are recorded by sensors and analyzed by standardized apps on their cloud platform; these actions are mainly carried out for the predictive maintenance of machines and the reduction of reworking on vehicles. The company expects implementation of the industrial cloud to save approximately 200 million euros up to the end of 2025 (Volkswagen Newsroom 2020).

Finally, SaaS provides a higher quality alternative to on-premises SW with up-to-date features, which leads to a greater potential for enhancing operational efficiency and reducing waste. Choudhary (2007) argues that the subscription-based licensing model of SaaS gives vendors more incentives to invest in product development than traditional perpetual licensing, leading to higher SW quality. In addition, the modularity of cloud services makes SW updates and maintenance easier (Hardy 2018). Also, collective problem solving from a community of users (typically broader than traditional IT outsourcing clients) is another benefit of cloud computing that can lead to higher quality services; as Iyer and Henderson (2012) put it, "Cloud technology allows multiple users to share data and processes owned by a vendor. The vendors can choose to allow their partners to modify and enhance this shared asset, while allowing all users to enjoy the benefits of continuous improvement" (p. 53).

In addition to SaaS, IaaS provides scalability and flexibility, which allows users to free up and reallocate internal resources to more urgent and mission-critical activities, leading to higher efficiency in production and operations. For example, the ride-sharing company, Uber, highlights the importance of its hybrid cloud model in not only ensuring constant uptime, but also facilitating product development and deployment processes (*ZDNet* 2019). Table 1 summarizes the theoretical propositions based on the two mechanisms with anecdotal evidence, which will guide our empirical analyses.

[Table 1 about here]

Data

We use the economy-wide panel data of US private industries over the period 1997–2017, obtained from the Multifactor Productivity (MFP) database of the US Bureau of Labor Statistics (BLS). The MFP database provides the annual output, capital stock, labor costs, and intermediate input costs at the three-digit North American Industry Classification System (NAICS) industry level. We exclude one industry that does not utilize any IT services at measurable levels—water transportation (NAICS 483) (see Table A1 in Online Appendix A for a list of 57 industries). Table 2 summarizes the variables used in our analysis (see Table A2 for the correlations).

[Table 2 about here]

For capital inputs, we use data on "productive capital stocks" in 2012 constant dollars, which measure the income-producing capacity of the existing stock during a given period (Stiroh 2002). We measure HW capital as the productive capital stock of "computers" and "communication equipment" in the "information capital" category, and SW capital as the productive capital stock of "software" in the "intellectual property capital" category. We calculate IT capital by adding HW and SW capital, and non-IT capital by subtracting IT capital from the total capital. Non-IT capital includes non-IT equipment (i.e., industrial and transportation equipment), structures (including land), and intellectual property products, excluding SW. Further, labor input is measured as labor compensation.

The MFP database provides information on intermediate inputs purchased from both domestic and offshore suppliers in three categories: energy, materials, and purchased services. We measure an industry's energy consumption by the cost of energy input. Other intermediate inputs are calculated by subtracting the energy cost from the costs of the total intermediate inputs, which include materials and purchased services. It is common in the business and economics literature to use energy expenditure to measure energy use in production (e.g., energy intensity is measured by the energy expenditure over the output in Bloom et al. 2010 and Lyubich et al. 2018). In addition, it is worth noting that detailed products may be assigned to different categories, depending on the industry (Strassner et al. 2005). For instance, while a petroleum-derived product is categorized as an energy input in most industries, it is categorized as a material input in the petroleum-refining and chemical-manufacturing industries. Hence, our measure of energy consumption only captures the energy *consumed* by industries to operate and support their production processes. In converting the nominal costs of intermediate inputs into real values (2012 constant dollars), we multiply nominal values from the base year 2012 by the chain-type quantity indices of each intermediate input. Thus, our measure of energy consumption is proportional to the quantities of energy consumed, with energy prices held constant at the 2012 level. To further control for substitution between production factors due to relative price changes, we also consider the price index of each factor (base year 2012). Note that the industry-level energy price index reflects the composition of energy sources.

Measurement of Cloud Computing

Given that cloud computing is considered as part of IT service outsourcing (Choudhary and Vithayathil 2013), we define an industry's use of cloud computing as cloud-based IT services purchased as an intermediate production input. To the best of our knowledge, there is no existing measure of cloud computing at the aggregate level, which makes it difficult to study the economy-wide impacts of cloud computing. While some studies rely on survey-based subjective measures (e.g., Loukis et al. 2019; Schniederjans and Hales 2016), they have a limitation in evaluating the economy-wide implications of cloud computing. Other studies measure cloud computing via overall IT service expenditures (e.g., Jin and McElheran 2017), but doing so is likely to overestimate the use of cloud computing, as it captures both cloud- and non-cloud-based IT services. Thus, we develop a novel industry-level measure of cloud-based IT services by combining industry-level product/service sales data (which provide a detailed description of the products/services that each industry sells) with inter-industry purchase flows.

First, we define product/service types corresponding to IT service outsourcing, based on the North American Product Classification System (NAPCS). Prior studies have defined an industry's IT outsourcing as the purchased services from two IT service industries (Han et al. 2011; Qu et al. 2011): *data processing, hosting, and related services* (NAICS 5182) and *computer systems design and related services* (NAICS 5415). Using industry-level product/service sales data obtained from the US Economic Census, we define IT services as product/service types that account for more than 1% of sales in the two IT service industries. Table 3 shows the list of product/service types corresponding to IT services.

[Table 3 about here]

Second, we distinguish cloud-based from non-cloud IT services. Among the IT services reported in Table 3, we consider application service provisioning (ASP) as SaaS, given that "the SaaS model can be viewed as an evolution of the ASP model" (Loukis et al. 2019, p. 38). By contrast, IT infrastructure provisioning services for website hosting, content streaming, data storage, etc. are considered as IaaS (see Table A3 for detailed descriptions of cloud computing services).[5] Our measures of SaaS and IaaS are

[5] As shown in Table 3, cloud-based IT services are provided by the data processing and hosting service industry (NAICS 5182; 42.6% of sales), the motion picture, video, and sound recording industries (NAICS 512; 2.1%), the computer systems design service industry (NAICS 5415, 2.0%), other information services (NAICS 519; 0.5%), and software publishers (NAICS 5112; 0.4%). Although business process management and data management services account for a large portion of sales in the data processing and hosting industries (NACIS 5182), we do not consider them as cloud computing because these services cover more comprehensive services, including application and systems design, as well as technical and management consulting.

consistent with commonly accepted definitions (Mell and Grance 2011).[6] It is noteworthy that cloud-based IT services have been available even before the advent of major cloud computing services (e.g., AWS). A case in point is ASP, which has been rapidly replaced by SaaS. Although the ASP model provides computer-based services to clients over a network similar to SaaS, ASP provides monolithic enterprise applications and does not typically provide shared services to multiple clients. However, in the SaaS model, a single instance of an SW application and the supporting infrastructure serve multiple users (Ju et al. 2010). Also, Ju et al. (2010) state that "most ASP-supported applications were immense client-server programs with simple HTML Web interfaces, [but] SaaS solutions today are designed specifically for the Web environment, which improves usability and manageability" (p. 385).

Finally, we calculate an industry's purchased cloud-based IT services by combining the product/service sales data with the inter-industry purchase flows from input-output tables, which show the output produced by one industry and the intermediate inputs purchased by another industry for each pair of industries (Han et al. 2011). Employing input-output use tables provided by BLS,[7] we compute industry *i*'s cloud-based IT services in year *t* by summing up the intermediate inputs purchased from each "supplier" industry *j* weighted by the sales share of cloud computing in industry *j*:

$$\mathrm{Cloud}_{\mathrm{it}} = \sum_j (\text{sales share of cloud} - \text{based IT services in industry } j \text{ in year } t) \times$$
$$(\text{intermediate inputs purchased by industry } i \text{ from industry } j \text{ in year } t).$$

Because the Economic Census is conducted every five years, the sales share of cloud-based IT services is linearly interpolated during 1997–2017, based on the 2002, 2007, and 2012 Economic Census data that were available at the time of our analysis.

[6] PaaS is another type of cloud service, though there is no product/service type corresponding to PaaS, according to the current structure of NAPCS. We conjecture that PaaS may be distributed across types of IT infrastructure provisioning services (IaaS), as Armbrust et al. (2010) put it, "the line between 'low-level' infrastructure and a higher-level 'platform' is not crisp. We believe the two are more alike than different" (p. 50).

[7] The raw data of BLS' input-output tables come from the Bureau of Economic Analysis (BEA). In this study, we use BLS' input-output tables instead of those from BEA because BLS' input-output tables provide more granular data at the four-digit NAICS level. Thus, to be more precise, we calculate the cloud computing purchases at the four-digit industry level and then aggregate them at the three-digit industry level, which correspond to the production account data (from BLS MFP).

Figure 1 presents the trends of cloud-based IT services in US industries over the period 1997–2017 (see Figures A1 and A2 in Online Appendix A for trends in IT services by type). This trend illustrates that the use of cloud computing has consistently increased in US industries during the last two decades, and its growth has accelerated since 2010. Cloud-based IT services have increased from 3.6 billion USD in 1997 to 20.0 billion USD in 2009, and to 45.8 and 54.8 billion USD in 2016 and 2017 in the overall US economy.[8] As shown in Figure A3, the industries that rely heavily on cloud services include the administrative and support service industry (NAICS 561), financial institutions (NAICS 521, 522), the broadcasting and telecommunications industry (NAICS 515, 517), and the legal service industry (NACIS 5411).

Our estimate of cloud-based IT services is comparable to the cloud computing market revenue in the US estimated by Statista (47.3 and 53.2 billion USD in 2016 and 2017).[9] Moreover, our measures of SaaS and IaaS are comparable to the SaaS and IaaS market revenues in the US estimated by Gartner and IDC.[10] For comparison, we also present trends in the net sales of AWS, the global market leader of public cloud services.[11] The net sales of AWS have also increased, especially since 2010, reaching 17.5 billion USD in 2017, which accounts for 31.9 % of our estimate. Given that AWS' public cloud market share was estimated at approximately 34% to 52% in 2017, our measure of cloud-based IT services appears to represent the total market size of cloud computing in the US quite well, thereby adding to the validity of the measure.[12]

[Figure 1 about here]

---

[8] All monetary values based on our measure of cloud computing are based on constant 2012 USD.
[9] Source: https://www.statista.com/forecasts/963837/cloud-services-revenue-in-united-states
[10] We use the worldwide cloud IT infrastructure spending forecast by IDC (https://www.statista.com/statistics/503686/worldwide-cloud-it-infrastructure-market-spending/) and the worldwide public cloud service revenue forecast for SaaS (Cloud Application Services) and IaaS/PaaS (Cloud Application/System Infrastructure Services) by Gartner (https://www.gartner.com/en/newsroom/press-releases/2017-10-12-gartner-forecasts-worldwide-public-cloud-services-revenue-to-reach-260-billionin-2017), although detailed statistics by country are not available. To infer the cloud market size in the US, we use Statista's estimations on public cloud revenues by country—the US accounts for 50.6% of global public cloud revenues, followed by China (8.5%), the United Kingdom (4.4%), and Germany (4.1%) (https://www.statista.com/outlook/16000/100/public-cloud).
[11] Net sales of Amazon are obtained from its annual reports. Amazon began to report AWS as a separate segment since its 2015 annual report. Until then, AWS sales were included in sales from non-retail activities in the North American segment ("North America - Others"). In 2013 and 2014, when both "AWS" and "North America - Others" statistics are available, AWS sales account for approximately 85% of non-retail sales in North America.
[12] For example, see reports by the Synergy Research Group (https://www.srgresearch.com/articles/leading-cloud-providers-continue-run-away-market) and Gartner (https://www.gartner.com/en/newsroom/press-releases/2018-08-01-gartner-says-worldwide-iaas-public-cloud-services-market-grew-30-percent-in-2017).

Methodology

Two-Stage Stochastic Frontier Analysis

Prior studies have estimated energy efficiency as a ratio of the optimal-to-actual energy input from the total factor productivity framework (see Filippini and Hunt 2015 for a review on energy efficiency). Thus, we adopt the neoclassical production theory to measure energy efficiency in production. In the production theory, energy inefficiency is defined as a deviation from the best practice, or the energy frontier, which represents the minimum level of energy consumption required to produce a given output using extant production inputs (see Online Appendix C for the theoretical background).

For our empirical analysis, we employ a two-stage stochastic frontier analysis (SFA), which has the primary advantage of isolating efficient energy use from the technological change that shapes and shifts the energy frontier. For such a reason, SFA has been widely employed to examine the impacts of IT on productivity and various types of efficiency (Chang and Gurbaxani 2013; Lee and Barua 1999; Pang et al. 2014; Shao and Lin 2001). Figure 2 depicts the two-stage stochastic frontier approach where each dot represents an industry-year observation. In the first-stage estimation, we derive an energy frontier using SFA. By capturing how far the actual energy consumption is from the given energy frontier, we measure energy inefficiency at the industry-year level, from which we derive energy efficiency. In the second stage, we regress the estimated energy efficiency on the production factors, including cloud-based IT services, to examine the factors' contribution to energy efficiency.

[Figure 2 about here]

First Stage: Estimating Energy Efficiency

In general, a production technology can be defined as

$$T = \{(X, E, Y) : (X, E) \text{ can produce } Y\},$$

where Y is the industry output, and X and E are the production inputs (e.g., capital, labor) and the energy input, respectively. The production technology T consists of all feasible input-output vectors for the given technology. Consistent with prior work (Lin and Du 2014), we define the Shephard energy distance function (EDF) (Shephard 1970) as follows:

$$EDF(X, E, Y) = sup\left\{\alpha : \left(X, \frac{E}{\alpha}, Y\right) \in T\right\},$$

where $EDF(X, E, Y)$ is the ratio of the actual energy consumption to the energy frontier, which reflects the extent to which energy consumption decreases with the extant inputs and output being maintained. If $EDF(X, E, Y)$ equals 1, an industry's technology is on an energy frontier where the industry consumes the minimum level of energy for the given inputs and output; industries on the energy frontier are considered as energy-efficient, given the extant production technology. When it is greater than 1, an industry is considered as energy-inefficient and can reduce energy proportionally by $EDF - 1$.

Among others, the Cobb-Douglas production function has been used most widely in the IT productivity literature (Brynjolfsson and Hitt 1996; Dewan and Kraemer 2000; Tambe and Hitt 2012). It has been extended to include intermediate inputs as production inputs in addition to capital and labor (Han et al. 2011). In the literature, the "embodied energy" required to produce goods and services (measured using input-output data) is found to play a significant role in productivity (Costanza 1980), and energy has been included in a production function as an input alongside with other intermediate inputs (materials and purchased services) (Bloom et al. 2010; Boyd and Curtis 2014). Following the prior literature, we consider the following extended Cobb-Douglas production function:

$$Y = A \times K^{c_1} L^{c_2} M^{c_3} E^{c_4},$$

where A is a parameter capturing total-factor productivity (TFP), and Y, K, L, M, and E are the output, capital, labor, other intermediate inputs (materials and purchased services), and energy, respectively.

In the energy literature, a cost function-based energy demand model has been adopted to explicitly take the energy price effects into account, which is not possible in a production function (Fisher-Vanden et al. 2004; Hang and Tu 2007; Wurlod and Noailly 2018). From the extended Cobb-Douglas production function, we can obtain the following total-cost function:

$$C(P_K, P_L, P_M, P_E, Y) = \delta \left(\frac{Y}{A}\right)^k P_K^{c'_1} P_L^{c'_2} P_M^{c'_3} P_E^{c'_4},$$

where δ is a constant, P_i is the price for each factor i and its multiplier c'_i is $\frac{c_i}{c_1+c_2+c_3+c_4}$, and k is $\frac{1}{c_1+c_2+c_3+c_4}$. By applying Shephard's Lemma, we can derive the cost-minimizing energy demand function to determine the energy frontier as

$$E_{frontier} = \frac{\partial C(P_K, P_L, P_M, P_E, Y)}{\partial P_E} = \delta c'_4 \left(\frac{Y}{A}\right)^k P_K^{c'_1} P_L^{c'_2} P_M^{c'_3} P_E^{c'_4 - 1},$$

where $E_{frontier}$ is the optimal level of energy required to produce the same level of output with the minimum costs.

To capture the energy inefficiency, we incorporate a multiplicative energy distance function with a random error into the energy demand function, E_{it}, for industry *i* at time *t*:

$$E_{it} = E_{frontier} \times EDF_{it}(X_{it}, E_{it}, Y_{it}) \times exp(v_{it}), \tag{1}$$

where $EDF_{it}(X_{it}, E_{it}, Y_{it})$ is defined in the same way as above, and v_{it} is an idiosyncratic random error. Taking the natural logarithm of the energy demand equation, we can obtain the following stochastic energy frontier model:

$$ln(E_{it}) = \beta_i + k \ln Y_{it} - k\, ln\, A_{it} + c'_1\, ln\, P_K + c'_2\, ln\, P_L + c'_3\, ln\, P_M + (c'_4 - 1)\, ln\, P_E + u_{it} + v_{it} \quad (2),$$

where β_i captures industry-level heterogeneity in the output elasticity of energy ($\ln \delta c'_4$), and $u_{it} \equiv ln\, EDF_{it}(X_{it}, E_{it}, Y_{it})$ is a non-negative random variable associated with time-varying energy inefficiency that follows an exponential distribution.

We model TFP ($ln\, A_{it}$) as a function of the IT and R&D shares of the total capital (i.e., IT intensity and R&D intensity), as well as the material and purchased service intensities—the other two categories of intermediate inputs in addition to energy. In the productivity literature, IT intensity has been identified as one of the main determinants of TFP (Gu and Wang 2004; Jorgenson et al. 2011; Seo and Lee 2006). R&D intensity has also been shown to influence TFP (Isaksson 2007). In addition, we further consider intermediate input intensities that are related to TFP growth (Baptist and Hepburn 2013). Specifically, we include material and purchased service intensities because they play a critical role in energy use and carbon emission (hence, the energy frontier) (Allwood et al. 2011).

By defining the TFP as an additive form, we obtain the estimation-friendly energy demand function as a form of the cost frontier (Kumbhakar and Lovell 2000):

$$ln(E_{it}) \ = \beta_i + \beta_1 Y_{it} + \beta_2\, ln(\text{IT share of total capital})_{it} + \beta_3\, ln(\text{R\&D share of total capital})_{it} + \beta_4\, ln(\text{Materials share of total cost})_{it} + \beta_5\, ln(\text{Purchased services share of total cost})_{it} + \beta_6\, ln\, P_K + \beta_7\, ln\, P_L + \beta_8\, ln\, P_{Materials} + \beta_9\, ln\, P_{Purchased\ Services} + \beta_{10}\, ln\, P_E + \tau_t + u_{it} + v_{it}, \qquad (3)$$

where the multipliers of the terms are replaced with estimated coefficients, and the prices of other intermediate inputs are decomposed into those of materials and purchased services. To capture industry-level heterogeneity in the production processes and output elasticity of energy, we employ a fixed-effects stochastic frontier model, which Greene (2005a, 2005b) calls the “true” fixed-effects model. This fixed-effects stochastic frontier model allows us to isolate the time-varying inefficiency term after netting out the industry-specific heterogeneity in energy use. We also include year dummies (τ_t) to control for common year-specific shocks (Filippini and Hunt 2015).

From the first-stage estimation based on Equation (3), the energy efficiency (*EE*), which ranges from 0 to 1, can be measured as

$$EE_{it} \equiv \frac{1}{EDF_{it}(X_{it}, E_{it}, Y_{it})} = \frac{\mathbb{E}[E_{it}^* \mid 0, v_{it}, X_{it}, Y_{it}]}{\mathbb{E}[E_{it} \mid u_{it}, v_{it}, X_{it}, Y_{it}]} = exp(-\mathbb{E}[u_{it} \mid v_{it}]),$$

where $\mathbb{E}[*]$ is an expected value, and E_{it}^* is the minimum level of energy consumed to produce Y_{it}, given the production inputs (X_{it}) (Battese and Coelli 1988; Lin and Du 2014). If u_{it} is equal to 0 (i.e., *EE* = 1), an industry’s technology is on the frontier, and the industry consumes the minimum energy level for a given level of inputs and output. On the other hand, if u_{it} is greater than 0 (i.e., EE < 1), it indicates that an industry's production lies above the energy frontier, which means that the industry is energy-inefficient.

Second Stage: Estimating Factor Contribution to Energy Efficiency

In the second stage, we model energy efficiency as a function of IT capital and cloud-based IT services. Additionally, we include non-IT capital and other intermediate inputs (including non-cloud IT services) to control for capital deepening and production dependence on intermediate inputs, which might influence energy efficiency. Given that energy efficiency ranges from 0 to 1, we normalize the production factors by dividing each by labor compensation, as in Chang and Gurbaxani (2013).

Specifically, we estimate the following energy efficiency equation:

$$EE_{it} = \alpha_i + \alpha_1 EE_{it-1} + \alpha_2 \ln\left(\frac{IT_{it}}{L_{it}}\right) + \alpha_3 \ln\left(\frac{Non{-}IT_{it}}{L_{it}}\right) + \alpha_4 \ln\left(\frac{M_{it}}{L_{it}}\right) + \alpha_5 \ln\left(\frac{Cloud_{it}}{L_{it}}\right) + \alpha_6 \ln\left(\frac{Non{-}Cloud_{it}}{L_{it}}\right) + \theta_t + \varepsilon_{it}, \tag{4}$$

where EE_{it} is the energy efficiency estimated in the first stage, and ε_{it} is a random error for industry *i* at time *t*. We consider industry fixed effects (α_i) and year dummies (θ_t) to control for industry-level heterogeneity and common shocks (e.g., changes in global energy prices and nationwide environmental policies). We are primarily interested in α_5, which represents the percentage point change in energy efficiency associated with a 1% increase in the intensity of cloud-based IT services.[13]

To account for the potential endogeneity of production factors and the dynamic nature of efficiency, we employ a system generalized method of moments (GMM) model to estimate Equation (4) (Arellano and Bond 1991; Blundell and Bond 1998). The system GMM model estimates a system of two equations—the original equation and the first-differenced one—using lagged values in the first differences and levels as internal instrumental variables (IVs), respectively. The system GMM model has been used as an effective

[13] Because energy efficiency measure is normalized between 0 to 1, the unit of energy efficiency is a percentage.

way to account for the endogeneity of IT investment in the IT productivity literature (Chang and Gurbaxani 2013; Chung et al. 2019; Tambe and Hitt 2012). At the same time, the system GMM model can also consider the dynamic nature of efficiency by accounting for a lagged efficiency level (EE_{it-1}). Given that successful performance in the past may be a result of superior capabilities or know-how and structural changes with respect to energy utilization, it is reasonable to assume that the current level of energy efficiency is correlated with its past level (Chang and Gurbaxani 2013).

We employ the one-step system GMM with robust standard errors. In doing so, we assume that all production factors are endogenous and restrict the number of lags to two in order to avoid overidentification. In our empirical analyses, we test the validity of the internal instruments of the system GMM by conducting statistical tests for instrument validity (Hansen test of overidentification restrictions) and second-order serial correlation (Arellano-Bond test for AR(2) in the first differences). Across all estimations, the test results indicate that the instruments are orthogonal to the error terms, and there is no second-order serial correlation, which supports the validity of the system GMM results.

Results

Impacts of Cloud Computing on Energy Efficiency

In the first stage, we estimate the energy frontier model and then measure the energy efficiency (see Online Appendix B for the result of the first-stage estimations). In the second stage, we regress the estimated energy efficiency on the production factor intensities. Table 4 presents the results from the system GMM model. In Column 1, our findings demonstrate that cloud-based IT services have significantly contributed to energy efficiency improvement, moving the industries closer to the energy frontier. The results remain unchanged after controlling for non-cloud IT services (Column 2). Our estimates suggest that doubling the cloud computing services (a 100% increase) leads to a 1.5 to 2.0 percentage point increase in energy efficiency. To delve deeper into the distinct roles of different cloud computing types, we separate cloud-based IT services into SaaS and IaaS. The results show that the contribution of cloud computing to energy efficiency is driven mainly by SaaS rather than IaaS (Column 3); moreover, the results are virtually identical after further separating IT into HW and SW (Column 4).

[Table 4 about here]

Time-Split Analysis of Cloud Computing and Energy Efficiency

We examine whether the magnitude of the effect has changed over time as cloud services have advanced and penetrated into the broader economy, based on two notable milestones related to cloud computing: (i) the year 2006 as the beginning of the cloud computing era and (ii) the year 2010 as the start of the rapid growth period with intensified competition.

Although the underlying concepts of cloud computing might trace back to the 1960s, only after 2000 has it emerged as a commercial reality (Qian et al. 2009). In particular, commercial cloud computing services were first introduced by AWS in 2006. AWS delivered the first storage service (Amazon S3) in the spring of 2006 and provided computing capacity (Amazon EC2) in the fall of that year. To further justify the choice of 2006 as the beginning of the cloud computing era, we look into the Google search volume of cloud computing-related terms. From the upper panel of Figure A4 in Online Appendix A, two noteworthy patterns are observed: (i) the terms “Amazon EC2” and “Amazon S3” were first mentioned in 2006 and (ii) the search volumes of “cloud computing” started to soar in 2007. Thus, it is reasonable to assume that cloud computing services began to be commercialized in 2006. This time-split approach is consistent with prior literature; for example, Ewens et al. (2018) separate the period into before and after 2006 when investigating how cloud computing reduces costs for startup firms, and thus how it influences venture capital investments.

In Figure A4, the Google search volume of “cloud computing” peaked in 2010, which coincides with the time when the deployment of cloud computing in US industries accelerated (see Figure 1). This may be because several other major cloud services have launched since 2010. For instance, Microsoft Azure and Google Cloud, which follow AWS in the public cloud services market, made their services generally available in the spring of 2010 and the fall of 2011, respectively. The rapid deployment of cloud services was driven partially by a sharp decline in prices due to increased competition. Furthermore, advanced features have been continually added to cloud computing services such as autoscaling (Fazli et al. 2018) and predictive scaling powered by machine learning (*AWS* 2018). Because such wide deployment and advanced features of cloud computing may have helped increase its users' energy efficiency, we further compare the effect of cloud computing before and after 2010, as in Jin and McElheran (2017).

The results in Columns 5 to 10 of Table 4 confirm our conjecture. In Columns 5 and 6, cloud-based IT services (both SaaS and IaaS) have a positive yet insignificant association with energy efficiency during 1997–2005, whereas their coefficients (particularly SaaS) increase in magnitude and become statistically significant after 2006 (Columns 7 and 8). We also find that the effect of cloud computing becomes even more salient after 2010. During 2010–2017, the coefficient of cloud-based IT services is 0.038, meaning that a 100% increase (doubling) in cloud services leads to an *increase* in energy efficiency by 3.8 percentage points.

To investigate long-run cross-sectional effects, we estimate a static model of energy efficiency (i.e., Equation 4 without a lagged term) year by year, an approach used by Dewan and Kraemer (2000). To account for correlations in error terms across years, we estimate them using seemingly unrelated regression (SUR). Figure 3 shows the regression coefficients of cloud computing by year. In keeping with our arguments on the advent and proliferation of cloud computing, the coefficient of cloud services is positive and significant only from 2006 at the 5% level. Although this effect disappears during the financial crisis (2007-2009), it becomes significant again from 2010 on.

[Figure 3 about here]

Taken together, the results of the time-split analysis support our argument that the rapid migration of IT services to the cloud has contributed to energy efficiency improvement in US industries.

Robustness Checks

To lend further credence to our findings, we conduct a series of robustness checks. We briefly discuss them as summarized in Table 5, and detailed descriptions and results are reported in Online Appendix C.

First, we test the sensitivity of our results to the modeling choices in the system GMM model. Following recommendations by Cheng and Bang (2021), who critically review the use of the Arellano–Bond GMM in IS research, we re-estimate the system GMM model with different sets of IVs (Table C1) and also replicate the estimations using a difference GMM model (Table C2). In addition, we present the results using alternative panel models, including (i) the fixed-effects model with robust standard errors clustered by industry, (ii) feasible generalized least squares (FGLS), and (iii) ordinary least squares with panel-corrected standard errors (OLS-PCSE) (Table C3). All estimation results of the alternative models are consistent with our main findings from the system GMM model.

Second, we employ a difference-in-differences (DID)-style model by exploiting two sources of variation: (i) temporal variation before and after the launch of the first commercial cloud services in 2006 and (ii) cross-sectional variation across industries based on the intensity of cloud-based IT services in the pre-cloud computing era (before 2006). The rationale is that industries that heavily utilized cloud-based IT services (such as ASP and IT infrastructure provisioning services) in the pre-cloud computing era would have adopted cloud services more aggressively after 2006 when the launch of AWS played a role as an exogeneous shock. Table C4 demonstrates that the industries with a higher proportion of IT outsourcing spending in cloud-based IT services before 2006 experienced a significantly greater increase in energy efficiency in the post-cloud computing era (after 2006). As a falsification test, alternative treatments based on the intensity of internal IT capital and general IT outsourcing prior to 2006 yield no significant impact on energy efficiency. These findings support our argument: cloud-based IT services that rapidly migrated to cloud environments after 2006 are indeed one of the main drivers of energy efficiency improvement in US industries. Third, we further address the endogeneity of cloud computing investment by using an industry's prior IT investment and customer (downstream) industries' use of cloud services as IVs. Table C5 shows that the results from IV-based three-stage least squares corroborate our main findings.

Fourth, we address potential measurement errors regarding cloud computing. Table C6 shows that the results remain consistent across alternative interpolation methods for measuring cloud-based IT services. In addition, in Online Appendix D, we discuss why a measurement error in cloud services is unlikely to alter our findings. Moreover, in Online Appendix E, we also provide an in-depth theoretical discussion regarding a measurement error in energy efficiency and an additional sensitivity test to demonstrate that the unmeasured portion of energy consumption unrelated to cloud computing is not likely to affect our estimate. Finally, Table C7 confirms that our results are robust to using alternative measures of factor intensity and to excluding a few influential industries that might drive the results.

The aforementioned robustness checks yield results that are consistent with the main findings, thereby strengthening the credence and validity of our findings (see Online Appendix C for details).

[Table 5 about here]

Investigation of Underlying Mechanisms

As summarized in Table 1, both types of cloud services (IaaS and SaaS) have the potential to contribute to energy efficiency through the two distinct mechanisms. Although it is challenging to disentangle the mechanisms, we attempt to tease them out by empirically investigating (i) how the impact of cloud computing varies by the intensity of the internal HW that encompasses IT infrastructure and equipment, and (ii) how this impact varies across different energy types (i.e., electric vs. non-electric energy). Moreover, we conduct a firm-level survey analysis that allows us to directly investigate the underlying mechanisms by measuring factors that could mediate the relationship between cloud computing and energy efficiency.

Interaction between IT Intensity and Cloud Computing

Given that internal HW constitutes a major portion of IT equipment and infrastructure, we examine how IT intensity (HW intensity in particular) moderates the relationship between cloud computing and energy efficiency. To this end, we first include an additional interaction term involving IT intensity and cloud-based IT services.[14] In Column 1 of Table 6, no significant relationship between internal IT intensity and cloud-based IT services is found. Given that SaaS and IaaS play distinct roles in improving energy efficiency as we demonstrated, we interact SaaS and IaaS separately with IT intensity. Interestingly, in Column 2, IT intensity positively moderates the effect of IaaS on energy efficiency at the 10% level, but not for SaaS. Finally, we further split IT intensity into HW and SW intensity. In Column 3, we find that the interaction of HW intensity with IaaS is positive and significant, but its interaction with SaaS is not significant. In contrast, SW intensity does not play any moderating role in the relationship between cloud-based IT services and energy efficiency. These findings validate our conjecture that IaaS mainly affects energy efficiency by mitigating energy consumption of IT equipment and infrastructure. In Column 4, we also interact HW and SW with non-cloud IT services but find no significant interaction effects; however, the interaction between HW and IaaS remains significant after controlling for non-cloud IT services. In Column 5, we use the HW percentage of the total IT capital as an alternative measure of HW intensity and obtain a similar result.

[Table 6 about here]

Distinguishing Electric and Non-Electric Energy Efficiency

Given that energy inputs include both electric and non-electric energy (i.e., fuels), we separate the two types of energy to further illuminate the underlying mechanisms. Specifically, while the first mechanism (i.e.,

---

[14] For ease of interpretation, we mean-center the variables involving the interaction term so that the main terms can be interpreted as the average effect.

mitigating the energy consumption of IT infrastructure and equipment) is expected to mainly apply to electric energy, the second mechanism (i.e., facilitating energy-efficient production and operations) would concern not only electric energy, but also non-electric energy used in production processes.

We first measure electric energy use as an intermediate input purchased from the industry of electric power generation, transmission, and distribution (NAICS 2211). Then, we calculate non-electric energy by subtracting electric energy from the total energy input. We estimate electric and non-electric energy efficiencies separately in the first stage of our energy frontier model, which are subsequently included as dependent variables in the second stage. As reported in Table 7, the results reveal the nuanced roles of different cloud computing types in improving energy efficiency. Whereas the main effect of SaaS on energy efficiency is significant for both types of energy, IaaS only improves electric energy efficiency (but not non-electric energy efficiency) for industries with high HW intensity.

Taken together, the interaction between internal HW intensity and cloud-based IT services (Table 6) and the breakdown of different energy types (Table 7) indicate that SaaS can facilitate energy-efficient production by helping to optimize operations and redesign production processes that consume electric and non-electric energy, thereby enhancing the efficiency of both energy types. On the other hand, IaaS seems to play a primary role in optimizing the utilization of IT equipment and infrastructure—which have been blamed as a major "electricity hog"—and in mitigating the adverse impacts of internal HW on electric energy efficiency.

[Table 7 about here]

Firm-Level Survey Analysis

While our industry-level analysis allows us to estimate the economy-wide effect of cloud-based IT services on energy efficiency, it has a limitation in directly testing the underlying mechanisms through which cloud computing improves energy efficiency. Thus, we conduct a survey analysis by collecting data from business managers to further validate the effects of cloud services on energy efficiency at the firm level. Moreover, the survey method allows us to test the underlying mechanisms more directly by considering factors that could mediate the relationship between cloud computing and energy efficiency.

In partnership with a professional market research firm in the US, we collected data from managers at 201 firms, 187 of which are included in the final analysis after excluding unreliable responses. The sample covers a wide range of organizational sizes and industries. In particular, our sample represents 46 out of 57 industries included in the industry-level analysis. No respondents reported "no use of cloud computing services," implying the pervasiveness of cloud computing services across the overall economy. The wide coverage of our sample helps us generalize the results of the survey analysis. In addition, the majority of respondents work in IT-related functions and are top or senior managers, ensuring that our survey participants are knowledgeable about their firm's IT and cloud computing investments, as well as their organizational and environmental performance.

By adapting survey instruments from Khuntia et al. (2018) and Loukis et al. (2019), we measure variables, including the cloud computing expenditure, relative importance of IaaS (as a percentage of the cloud computing budget allocated to IaaS), and performance in terms of energy efficiency. Further, we measure two mediating factors that correspond to the underlying mechanisms we propose in this study: (i) energy reduction in IT equipment and infrastructure and (ii) operational benefits in terms of cost reduction and the improved quality regarding the electronic support of a company's operations and business processes (Loukis et al. 2019). See Online Appendix F for details about the methodology of the survey analysis.

Table 8 reports the estimation results of the causal mediation analysis (Imai et al. 2010). Columns 1 to 4 show the effect of cloud computing on each mediator, and Columns 5 to 10 present the effects of cloud computing on energy efficiency while accounting for mediating factors. In Columns 1 and 3, we find that cloud computing expenditure is positively associated with both energy reduction in IT equipment/infrastructure and operational benefits. To estimate the distinct effects of different types of cloud services, we additionally consider the interaction term involving cloud computing expenditure and the relative importance of IaaS, which represents the effect of IaaS. Given that the relative importance of IaaS is normalized between 0 and 1 as a percentage measure, the coefficient of the main term of cloud computing can be interpreted as the effect of cloud services when IaaS is rarely deployed, which reflects the effect of SaaS. In Columns 2 and 4, the results demonstrate that the main term of cloud computing (reflecting the use of SaaS) has a significant effect on operational benefits only. In contrast, the interaction term (reflecting the use of IaaS) is positively associated with both energy reduction in IT equipment/infrastructure and operational benefits, though the former effect is much stronger than the latter.

In Columns 5 and 6, we find that cloud computing expenditure is positively associated with energy efficiency for both types of cloud services, as the coefficients of both main and interaction terms are positive and significant. More importantly, Columns 7–10 show that these effects are partially mediated. Specifically, we find that 40.7% and 26.0% of the effect of cloud computing services on energy efficiency is mediated by energy reduction in IT and operational benefits, respectively (Columns 7 and 9). However, the two mediating factors play distinct roles in different types of cloud services. In Column 8, energy reduction in IT equipment and infrastructure mediates 61.4% of the effect of the interaction term (i.e., IaaS effect) on energy efficiency, whereas a very small portion (3.2%) of the effect of the main term (i.e., SaaS effect) is mediated by this factor. On the other hand, operational benefits mediate 32.6% and 14.4% of the effects of the main (SaaS effect) and interaction (IaaS effect) terms on energy efficiency, respectively (Column 10). The results remain consistent after controlling for general IT expenditure and top management commitment to energy efficiency (see Table F7 in Online Appendix F).

Taken together, the results from the firm-level survey analysis corroborate our industry-level findings and further validate our theoretical expositions on the underlying mechanisms. In sum, non-IaaS cloud services—reflecting SaaS—improve a company's energy efficiency through operational benefits. In contrast, the use of IaaS improves energy efficiency mainly by reducing energy consumption in IT equipment and infrastructure, while also contributing, albeit to a lesser extent, to energy efficiency by conferring operational benefits.

[Table 8 about here]

Discussion and Conclusions

User-Side Energy Savings vs. Vendor-Side Energy Consumption

To assess the economic significance regarding the impact of cloud computing on energy consumption, we perform a back-of-the-envelope calculation to estimate the amount of energy savings led by the use of cloud computing across US industries. In Equation 1, the actual level of energy consumption (E) is calculated as a hypothetical energy frontier ($E_{frontier}$) divided by energy efficiency (EE). To estimate the contribution of cloud computing to energy consumption, we decompose the energy efficiency into the change in energy consumption due to cloud computing services from the previous year (ΔEE_{cloud}) and the remainder (EE'):

$$E = \frac{\mathbb{E}[E_{frontier}]}{EE} = \frac{\mathbb{E}[E_{frontier}]}{EE' + \Delta EE_{cloud}}.$$

Then, the change in energy consumption due to cloud computing (ΔE_{cloud}), all else being equal, can be calculated as:

$$\Delta E_{cloud} = \frac{\mathbb{E}[E_{frontier}]}{EE' + \Delta EE_{cloud}} - \frac{\mathbb{E}[E_{frontier}]}{EE'} = E \times \frac{\Delta EE_{cloud}}{\Delta EE_{cloud} - EE}.$$

According to our energy efficiency equation (Equation 4), we calculate year-by-year efficiency changes due to cloud computing (ΔEE_{cloud}) by multiplying the coefficient of cloud-based IT services (based on the year-by-year estimates in Figure 3) with the change in the average cloud computing intensity across all industries. Based on this calculation, the user-side energy cost savings due to cloud computing are estimated to be approximately 2.8 to 12.6 billion US dollars in 2017 alone, based on the 95% confidence interval. Also, the cumulative energy savings from 2010 to 2017 are estimated to range between 13.2 and 52.6 billion US dollars.

To weigh these user-side energy savings against vendor-side energy consumption, we estimate the energy consumption by cloud computing vendor industries. Assuming that an industry's energy consumption to produce a product/service is proportional to its sales, we calculate a vendor industry's portion of the energy consumption needed for cloud service provisioning by multiplying its sales share of cloud-based IT services by the industry's total energy costs. According to our estimates, the total user-side energy savings in US industries in 2017 (US$ 2.8 to 12.6 billion) and during 2010–2017 (US$ 13.2 to 52.6 billion) are greater than the total energy costs incurred by cloud computing vendor industries during the same periods (US$ 382 million in 2017 and US$ 3.5 billion during 2010–2017). It is noteworthy, however, that our data from US industries have some limitations in measuring the energy consumption by cloud service vendors for two reasons. First, our data can only capture the energy consumption within the US, while not accounting for the offshore portion of energy consumption (e.g., energy consumption by offshore captive data centers). Second, although we assume that an industry's energy consumption to produce a product/service is proportional to its sales, the energy intensity needed to offer cloud services could differ from that to offer other services or products.

Therefore, we next compare our estimate of energy cost savings from the use of cloud computing to the total electricity consumption by US data centers, estimated by the Lawrence Berkeley National Laboratory (Shehabi et al. 2016). We convert the monetary energy expenditure into electricity use based on the average electricity price in industrial and commercial sectors, obtained from the US Energy Information Administration (EIA). The user-side energy savings from cloud computing in 2017 are equivalent to a reduction in electricity use by 31.8 to 143.8 billion kilowatt-hours, based on the 95% confidence interval, which represents approximately 0.9% to 3.9% of the total electricity use in the US economy.[15] This estimate appears to exceed (or at least be comparable to) the total electricity consumption by US data centers in 2014 (70 billion kilowatt-hours) (Shehabi et al. 2016).

Taken together, our analysis demonstrates that the energy consumption by cloud service vendors—an oft-cited culprit for the energy footprint of the IT industry—is more than offset by the reduced energy

[15] According to EIA, total electricity use in all sectors was 3,723,356 million kilowatt hours in 2017, and the average electricity price in the industrial and commercial sectors in 2017 were 6.88 and 10.66 cents per kilowatt-hour, respectively.

consumption by cloud computing users. Further, given that firms will utilize more cloud-based IT services particularly in the post-pandemic era, and that cloud service vendors have invested in energy efficiency technologies (Masanet et al. 2020) and transitioned to more efficient hyperscale data centers (Jones 2018),[16] we expect that the economy-wide energy saving effects of cloud computing will become stronger over time, thereby helping to usher in an era of sustainable growth.

Theoretical Contributions

Our study makes several important scholarly contributions. First, we contribute to the literature on the value and impacts of IT, wherein an abundance of evidence exists regarding the positive impacts of IT capital and IT outsourcing on economic performance (Melville et al. 2004), technical efficiency (Chang and Gurbaxani 2013), and cost savings (Han and Mithas 2013). However, few empirical works have been conducted to examine the environmental effects of IT in general and cloud computing in particular, despite calls for research on the impacts of IT on environmental performance (Dedrick 2010; Gholami et al. 2016; Malhotra et al. 2013; Melville 2010). By examining the impact of cloud computing on energy efficiency, our study broadens the scope of this research stream into the "green" value of IT investments, especially related to cloud computing, which constitutes an increasing portion of IT investments. Moreover, our theoretical framework and firm-level survey analysis help address the "how" question by illuminating the mechanisms through which cloud computing drives energy efficiency. Although the first-order effect (increasing energy consumption due to the physical presence of IT) and second-order effect (reducing energy consumption due to the ongoing use and application of IT) of IT have been discussed conceptually

[16] A report by the Lawrence Berkeley National Laboratory estimates that if 80% of servers in small US data centers were moved over to hyperscale facilities, it would result in a 25% drop in energy use for US data centers (Shehabi et al. 2016). Additionally, some case studies highlight how cloud-based solutions and virtualization could help achieve energy savings in the economy by utilizing a smaller number of cloud servers with high utilization and efficiency, as well as advanced, continuously optimized, and highly efficient cooling systems (Google 2012; Masanet et al. 2013; Microsoft 2010; Williams and Tang 2013).

(Horner et al. 2016), this study is the first to disentangle these two effects within the context of cloud computing.

Second, we contribute to the nascent literature on cloud computing by taking a perspective involving both clients and vendors. Our approach is similar to the IT outsourcing literature that has considered service venders, clients, and their relationship in reaping the value of IT outsourcing (e.g., Goo et al. 2009; Levina and Ross 2003). Given that "corporate users of cloud computing have an active role to play in ensuring that cloud computing ends up delivering on its promise of revolutionizing corporate computing" (Marston et al. 2011, p. 183), there has been a call for research on cloud computing from the corporate users' perspective. However, little empirical work has been conducted regarding the user-side impact of cloud computing on energy use, and our study fills this void. The paucity of empirical research can be attributed to the lack of a proper measure concerning the use of cloud computing. In this regard, our industry-level measure and firm-level survey instrument for the use of cloud computing can be useful for future researchers studying the value and impacts of cloud computing. Further, our proposed approach to categorizing industry-level IT services into distinct types of outsourced IT services (cloud-based IT services vs. non-cloud IT services), as well as different cloud computing types (SaaS vs. IaaS), highlights the importance of considering such differences when studying the impacts of IT outsourcing and cloud computing.

Finally, our study is one of the first attempts in the IS literature to measure energy efficiency based on a panel stochastic frontier model that can account for heterogeneity in energy efficiency across industries and over time, while accounting for TFP and factor prices. Due to its solid theoretical foundation, the stochastic frontier approach has been widely applied to various contexts related to IT productivity and technical efficiency in the literature. We believe that our SFA-based two-stage approach can be used to examine diverse aspects of the relationship between IT and energy efficiency at various levels (e.g., plant-, firm-, and country-levels).

Practical Implications

This study provides meaningful practical implications not only for corporate users of cloud computing, but also for cloud service vendors and policymakers. From the user's perspective, our findings can assist business managers in gauging the environmental impacts of cloud computing investments and formulating their IT strategies accordingly. Although previous studies have focused on the direct economic benefits of IT outsourcing, such as productivity gains (Chang and Gurbaxani 2012; Han et al. 2011) and cost reductions (Han and Mithas 2013), we suggest that the energy efficiency gains from using cloud computing be taken seriously, especially under the current social and regulatory pressures. In particular, firms can benefit generally from SaaS investments in terms of energy efficiency, though firms heavily relying on HW investments need to invest more in IaaS by migrating their energy-inefficient IT infrastructure into the cloud: the potential efficiency gains from doing so would be much greater than those in less HW-intensive industries.

Our findings also have implications for cloud service vendors that have faced public scrutiny and criticism related to the environmental sustainability of cloud computing. For instance, Greenpeace (2017) annually publishes a "Clean Energy Index" for major IT companies, including Amazon and Google, and its criteria are primarily related to vendor-side practices for reducing energy consumption (e.g., renewable energy commitment, energy efficiency of data centers, and the pollution mitigation of operations). Our findings can help IT managers and related stakeholders deal with societal concerns regarding environmental sustainability by allowing them to evaluate the environmental impacts of cloud computing from a holistic perspective, encompassing both the vendors and clients of cloud computing. While cloud service vendors need to keep improving the energy efficiency in data centers and related infrastructure that support cloud computing services, they must also devise strategies to leverage the energy saving benefits delivered to their users.

Moreover, our study can inform policymakers by providing novel evidence on the economy-wide energy-saving capacity of cloud computing on the user side. Given that the public discourse to date has focused on the negative environmental impact of cloud computing on the vendor side, our findings regarding its positive user-side environmental impacts can inform the sustainability debate of cloud computing: it is imperative to carefully consider the positive, indirect user-side effects and differentiate them from the negative, direct vendor-side environmental effects of cloud computing. Also, our empirical approach provides guidance for assessing the economy-wide net effect of cloud computing on energy use.

Limitations and Future Research

This study is not without limitations, which point to avenues for future research. First, in addition to what we account for in this paper (i.e., operational benefits from cloud computing, SaaS in particular), there may be unobserved systematic differences in the production processes between firms that invest in cloud computing and those that do not. However, not all unobserved production heterogeneities would confound our estimation results; they would influence the relationship between cloud computing investment and energy efficiency in different ways, depending on their complementarity to cloud computing. On one hand, there could be organizational complements to cloud computing, which tend to be adopted in concert with the use of cloud services (Brynjolfsson and Milgrom 2013), as in the case of traditional IT investments (e.g., Bresnahan et al. 2002). For example, IT-related business and management practices that were found to play a significant role in realizing the value of IT investment (Aral et al. 2012; Saunders and Brynjolfsson 2016) could also interplay with cloud computing and energy efficiency, as management practices are often associated with energy efficiency (e.g., Martin et al. 2012). Although such complementary factors may lead to heterogeneity in the effectiveness of cloud computing, they would not invalidate the overall contribution of cloud computing to energy efficiency that we found in this study. Given that our results represent the *average* effect of cloud computing on energy efficiency, future research should examine the role of organizational complements to understand organization-level heterogeneity in reaping energy efficiency benefits from cloud computing investment.

On the other hand, some organizational practices and process innovations are not complementary to cloud computing, but might coincide with replacing outdated IT systems with cloud-based IT services. For example, digital transformation initiatives might involve not only streamlining business processes and workflows that could potentially improve energy efficiency, but also replacing outdated IT with state-of-the-art cloud services. Although we account for time-invariant heterogeneity across industries using fixed effects and address omitted variable bias using several econometric techniques as well as a range of robustness tests, we cannot completely rule out the effect of unobserved confounders, which we leave for future research.

Second, while our findings demonstrate the overall contribution of cloud computing and the distinct roles of different types of cloud services in enhancing energy efficiency, we cannot tease out the impacts of different design features and functionalities of cloud computing. In particular, recent technical advances may open up additional opportunities for greater energy efficiency gains through cloud computing. For example, advanced analytics and machine learning applications can be more effective in improving energy efficiency, compared to legacy systems. Although such advanced functionalities could be either "rented" via cloud computing or purchased through traditional SW licensing, they are more likely provisioned via cloud computing because it can offer access to advanced service features on demand without large upfront investments for on-premises SW. In this case, firms' improved ability to access such advanced applications would partially explain the greater energy efficiency impact of cloud computing after 2010. Moreover, machine learning and artificial intelligence have empowered cloud computing, which can further enhance the energy efficiency of client organizations. A case in point is AWS' machine learning-powered predictive autoscaling, which provides its users with more opportunities to optimize their cloud computing usage (*AWS* 2018). Drawing upon our findings concerning the differential effects of distinct cloud computing types on energy efficiency and its increasing effects over the years, future research can examine how to design and evaluate unique features and functionalities of cloud-based IT services, vis-à-vis traditional on-premises SW, to improve users' energy efficiency.

Third, environmental issues are systematically interconnected, and there have been concerns about the rebound effect (Dimitropoulos 2007), which implies that improved energy efficiency may unexpectedly increase energy consumption in the long term. A case in point involves autoscaling in cloud computing. While the cloud's autoscaling feature could improve a user's energy efficiency in the short run (as we found in this study), it may also alter the nature of competition and influence entrepreneurial market entry by reducing the operating costs for new entrants (Fazli et al. 2018), which could change the total energy demand by incumbents and entrants in the long run. In addition, given the global distribution of data centers that support cloud services, cloud computing may shift the energy consumption of companies overseas. Thus, future research should consider the rebound effects and global dynamics of energy consumption in relation to cloud computing to advance our understanding of the longer-term, global environmental impact of cloud computing.

Finally, the current structure of NAPCS does not explicitly consider a range of cloud computing services. Although our measure of purchased cloud services based on the product/service types of NAPCS is a reasonable proxy for cloud computing investment, researchers and policymakers must incorporate cloud computing into national accounts (see Baer et al. 2020), given the increasing significance of cloud computing in the overall economy.

Concluding Remarks

This study investigated whether and how the use of cloud computing services influences energy efficiency. By using two datasets at the industry and firm levels, we provided what we believe to be the first evidence that the use of cloud computing increases users' energy efficiency by allowing them to utilize production inputs in a more energy-efficient manner. Moreover, additional analyses revealed that SaaS confers operational benefits to business users by facilitating energy-efficient production across all industries, whereas IaaS helps its users enhance energy efficiency, especially in HW-intensive industries, by mitigating energy consumption of internal IT equipment and infrastructure. Overall, our findings underscore the “green” value of cloud computing from the business perspective. We hope that our theoretical perspective and empirical approach can provide guidance to IT managers and policymakers regarding how to devise IT strategies and policies to reconcile their economic and environmental goals, and can spur future research on the role of IT and IS in environmental sustainability, especially in the era of cloud computing.

References

Allwood, J. M., Ashby, M. F., Gutowski, T. G., and Worrell, E. 2011. “Material Efficiency: A White Paper,” *Resources, Conservation and Recycling* (55:3), pp. 362–381.

Aral, S., Brynjolfsson, E., and Wu, L. 2012. “Three-Way Complementarities: Performance Pay, Human Resource Analytics, and Information Technology,” *Management Science* (58:5), pp. 913–931.

Arellano, M., and Bond, S. 1991. “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies* (58:2), pp. 277–297.

Armbrust, M., Stoica, I., Zaharia, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I., and Zaharia, M. 2010. “A View of Cloud Computing,” *Communications of the ACM* (53:4), p. 50.

AWS. 2008. “Animoto – Scaling Through Viral Growth,” *Amazon Web Services*. https://aws.amazon.com/blogs/aws/animoto-scali (accessed on April 3, 2022).

AWS. 2018. “Predictive Scaling for EC2, Powered by Machine Learning,” *Amazon Web Services*. https://aws.amazon.com/blogs/aws/new-predictive-scaling-for-ec2-powered-by-machine-learning (accessed on April 3, 2022).

Baer, A., Lee, K., and Tebrake, J. 2020. “Accounting for Cloud Computing in the National Accounts,” *IMF Working Papers* (20:127).

Baliga, J., Ayre, R. W. A., Hinton, K., and Tucker, R. S. 2011. “Green Cloud Computing: Balancing Energy in Processing, Storage, and Transport,” *Proceedings of the IEEE* (99:1), pp. 149–167.

Baptist, S., and Hepburn, C. 2013. “Intermediate Inputs and Economic Productivity,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* (371), p. 20110565.

Battese, G. E., and Coelli, T. J. 1988. “Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data,” *Journal of Econometrics* (38:3), pp. 387–399.

Battleson, D. A., West, B. C., Kim, J., Ramesh, B., and Robinson, P. S. 2016. “Achieving Dynamic Capabilities with Cloud Computing: An Empirical Investigation,” *European Journal of Information Systems* (25:3), pp. 209–230.

Bayramusta, M., and Nasir, V. A. 2016. “A Fad or Future of IT?: A Comprehensive Literature Review on the Cloud Computing Research,” *International Journal of Information Management* (36:4), pp. 635–644.

Bloom, N., Genakos, C., Martin, R., and Sadun, R. 2010. “Modern Management: Good for the Environment or Just Hot Air?,” *The Economic Journal* (120:544), pp. 551–572.

Blundell, R., and Bond, S. 1998. “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models,” *Journal of Econometrics* (87:1), pp. 115–143.

Bose, R., and Luo, X. 2011. “Integrative Framework for Assessing Firms’ Potential to Undertake Green IT Initiatives via Virtualization - A Theoretical Perspective,” *Journal of Strategic Information Systems* (20:1), pp. 38–54.

Boyd, G. A., and Curtis, E. M. 2014. “Evidence of an ‘Energy-Management Gap’ in U.S. Manufacturing: Spillovers from Firm Management Practices to Energy Efficiency,” *Journal of Environmental Economics and Management* (68:3), Elsevier, pp. 463–479.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. 2002. “Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence,” *Quarterly Journal of Economics* (117:1), pp. 339–376.

Brynjolfsson, E., and Hitt, L. 1996. “Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending,” *Management Science* (42:4), pp. 541–558.

Brynjolfsson, E., Hofmann, P., and Jordan, J. 2010. “Cloud Computing and Electricity: Beyond the Utility Model,” *Communications of the ACM* (53:5), pp. 32–34.

Brynjolfsson, E., and Milgrom, P. 2013. “Complementarity in Organizations,” in *The Handbook of Organizational Economics.* R. Gibbons and J. Roberts (eds.), Princeton: Princeton University Press, pp. 11–55.

Business Advantage. 2017. *CAD in the Cloud - Market Trends 2017 Report*, Business Advantage.

Chang, Y. B., and Gurbaxani, V. 2012. “Information Technology Outsourcing, Knowledge Transfer, and Firm Productivity: An Empirical Analysis,” *MIS Quarterly* (36:4), pp. 1043–1063.

Chang, Y. B., and Gurbaxani, V. 2013. “An Empirical Analysis of Technical Efficiency: The Role of IT Intensity and Competition,” *Information Systems Research* (24:3), pp. 561–578.

Cheng, N., and Bang, Y. 2021. “A Comment on the Practice of the Arellano-Bond/Blundell-Bond Generalized Method of Moments Estimator in IS Research,” *Communications of the Association for Information Systems* (48:Article 38).

Chou, S.-W., and Chang, Y.-C. 2008. “The Implementation Factors That Influence the ERP (Enterprise Resource Planning) Benefits,” *Decision Support Systems* (46:1), pp. 149–157.

Choudhary, V. 2007. “Comparison of Software Quality Under Perpetual Licensing and Software as a Service,” *Journal of Management Information Systems* (24:2), pp. 141–165.

Choudhary, V., and Vithayathil, J. 2013. “The Impact of Cloud Computing: Should the IT Department Be Organized as a Cost Center or a Profit Center?,” *Journal of Management Information Systems* (30:2), pp. 67–100.

Chung, S., Animesh, A., Han, K., and Pinsonneault, A. 2019. “Software Patents and Firm Value: A Real Options Perspective on the Role of Innovation Orientation and Environmental Uncertainty,” *Information Systems Research* (30:3), pp. 1073–1097.

Costanza, R. 1980. “Embodied Energy and Economic Valuation,” *Science* (210:4475), pp. 1219–1224.

Dedrick, J. 2010. “Green IS: Concepts and Issues for Information Systems Research,” *Communications of the Association for Information Systems* (27:11), pp. 173–183.

Dewan, S., and Kraemer, K. L. 2000. “Information Technology and Productivity: Evidence from Country-Level Data,” *Management Science* (46:4), pp. 548–562.

Dimitropoulos, J. 2007. “Energy Productivity Improvements and the Rebound Effect: An Overview of the State of Knowledge,” *Energy Policy* (35:12), pp. 6354–6363.

Engineering.com. 2018. “Research Report : Identifying the Core Issues That Frustrate Product Development Teams,” *Engineering.com*.

Ewens, M., Nanda, R., and Rhodes-Kropf, M. 2018. “Cost of Experimentation and the Evolution of Venture Capital,” *Journal of Financial Economics* (128:3), pp. 422–442.

Fazli, A., Sayedi, A., and Shulman, J. D. 2018. “The Effects of Autoscaling in Cloud Computing,” *Management Science* (64:11), pp. 5149–5163.

Filippini, M., and Hunt, L. C. 2015. “Measurement of Energy Efficiency Based on Economic Foundations,” *Energy Economics* (52), pp. S5–S16.

Fisher-Vanden, K., Jefferson, G. H., Liu, H., and Tao, Q. 2004. “What Is Driving China’s Decline in Energy Intensity?,” *Resource and Energy Economics* (26:1), pp. 77–97.

Fortune. 2019. “The Internet Cloud Has a Dirty Secret.,” https://fortune.com/2019/09/18/internet-cloud-server-data-center-energy-consumption-renewable-coal (accessed on April 3, 2022).

Gartner. 2021. “Gartner Says Four Trends Are Shaping the Future of Public Cloud,” *Gartner*. https://www.gartner.com/en/newsroom/press-releases/2021-08-02-gartner-says-four-trends-are-shaping-the-future-of-public-cloud (accessed on April 3, 2022).

Gholami, R., Watson, R. T., Hasan, H., Molla, A., and Bjørn-andersen, N. 2016. “Information Systems Solutions for Environmental Sustainability: How Can We Do More?,” *Journal of the Association for Information Systems* (17:8), pp. 521–536.

Goo, Kishore, Rao, and Nam. 2009. “The Role of Service Level Agreements in Relational Management of Information Technology Outsourcing: An Empirical Study,” *MIS Quarterly* (33:1), p. 119.

Google. 2012. *Google Apps: Energy Efficiency in the Cloud*, Google.

Greene, W. 2005a. “Fixed and Random Effects in Stochastic Frontier Models,” *Journal of Productivity Analysis* (23:1), pp. 7–32.

Greene, W. 2005b. “Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model,” *Journal of Econometrics* (126:2), pp. 269–303.

Greenpeace. 2017. *Clicking Clean: Who Is Winning the Race to Build a Green Internet*, Washington D.C.: Greenpeace.

Gu, W., and Wang, W. 2004. “Information Technology and Productivity Growth: Evidence from Canadian Industries,” in *Economic Growth in Canada and the United States in the Information Age,* pp. 57–82.

Han, K., Kauffman, R., and Nault, B. 2011. "Returns to Information Technology Outsourcing," *Information Systems Research* (22:4), pp. 824–840.
Han, K., and Mithas, S. 2013. "Information Technology Outsourcing and Non-IT Operating Costs: An Empirical Investigation," *MIS Quarterly* (37:1), pp. 315–331.
Hang, L., and Tu, M. 2007. "The Impacts of Energy Prices on Energy Intensity: Evidence from China," *Energy Policy* (35:5), pp. 2978–2988.
Hardy, Q. 2018. "How Cloud Computing Is Changing Management," *Harvard Business Review*.
Hilty, L. M., Arnfalk, P., Erdmann, L., Goodman, J., Lehmann, M., and Wäger, P. a. 2006. "The Relevance of Information and Communication Technologies for Environmental Sustainability – A Prospective Simulation Study," *Environmental Modelling & Software* (21:11), pp. 1618–1629.
Horner, N. C., Shehabi, A., and Azevedo, I. L. 2016. "Known Unknowns: Indirect Energy Effects of Information and Communication Technology," *Environmental Research Letters* (11:10), IOP Publishing, p. 103001.
Imai, K., Keele, L., and Yamamoto, T. 2010. "Identification, Inference and Sensitivity Analysis for Causal Mediation Effects," *Statistical Science* (25:1), pp. 51–71.
Isaksson, A. 2007. "Determinants of Total Factor Productivity: A Literature Review," *UNIDO Working Paper*, United Nations Industrial Development Organization.
Iyer, B., and Henderson, J. C. 2010. "Preparing for the Future: Understanding the Seven Capabilities of Cloud Computing," *MIS Quarterly Executive* (9:2), pp. 117–131.
Iyer, B., and Henderson, J. C. 2012. "Business Value from Clouds: Learning from Users," *MIS Quarterly Executive* (11:1), pp. 52–60.
Jin, W., and McElheran, K. 2019. "Economies Before Scale: Survival and Performance of Young Plants in the Age of Cloud Computing," *Rotman School of Management Working Paper No. 3112901*.
Jing, S.-Y., Ali, S., She, K., and Zhong, Y. 2013. "State-of-the-Art Research Study for Green Cloud Computing," *Journal of Supercomputing* (65:1), pp. 445–468.
Jones, N. 2018. "How to Stop Data Centres from Gobbling up the World's Electricity," *Nature* (561:7722), pp. 163–166.
Jorgenson, D. W., Ho, M. S., and Samuels, J. D. 2011. "Information Technology and U.S. Productivity Growth: Evidence from a Prototype Industry Production Account," *Journal of Productivity Analysis* (36:2), pp. 159–175.
Ju, J., Wang, Y., Fu, J., Wu, J., and Lin, Z. 2010. "Research on Key Technology in SaaS," in *2010 International Conference on Intelligent Computing and Cognitive Informatics*, IEEE, June, pp. 384–387.
Khuntia, J., Saldanha, T. J. V., Mithas, S., and Sambamurthy, V. 2018. "Information Technology and Sustainability: Evidence from an Emerging Economy," *Production and Operations Management* (27:4), pp. 756–773.
Klems, M., Nimis, J., and Tai, S. 2009. "Do Clouds Compute? A Framework for Estimating the Value of Cloud Computing," in *Part of the Lecture Notes in Business Information Processing book series (LNBIP, volume 22)*, Berlin: Springer, pp. 110–123.
KPMG. 2014. *2014 Cloud Survey Report: Elevating Business in the Cloud KPMG*.
Kumbhakar, S., and Lovell, K. 2000. *Stochastic Frontier Analysis*, Cambridge: Cambridge University Press.
Lee, B., and Barua, A. 1999. "An Integrated Assessment of Productivity and Efficiency Impacts of Information Technology Investments: Old Data, New Analysis and Evidence," *Journal of Productivity Analysis* (12:1), pp. 21–43.
Levina, and Ross. 2003. "From the Vendor's Perspective: Exploring the Value Proposition in Information Technology Outsourcing," *MIS Quarterly* (27:3), p. 331.
Lin, B., and Du, K. 2014. "Measuring Energy Efficiency under Heterogeneous Technologies Using a Latent Class Stochastic Frontier Approach: An Application to Chinese Energy Economy," *Energy* (76), pp. 884–890.
Loukis, E., Janssen, M., and Mintchev, I. 2019. "Determinants of Software-as-a-Service Benefits and Impact on Firm Performance," *Decision Support Systems* (117), Elsevier, pp. 38–47.
Lyubich, E., Shapiro, J. S., and Walker, R. 2018. "Regulating Mismeasured Pollution: Implications of Firm Heterogeneity for Environmental Policy," *AEA Papers and Proceedings* (108:2), pp. 136–142.
Malhotra, A., Melville, N. P., and Watson, R. T. 2013. "Spurring Impactful Research on Information Systems for Environmental Sustainability," *MIS Quarterly* (37:4), pp. 1265–1274.
Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., and Ghalsasi, A. 2011. "Cloud Computing — The Business Perspective," *Decision Support Systems* (51:1), pp. 176–189.
Martin, R., Muûls, M., de Preux, L. B., and Wagner, U. J. 2012. "Anatomy of a Paradox: Management Practices, Organizational Structure and Energy Efficiency," *Journal of Environmental Economics and Management* (63:2), pp. 208–223.

Masanet, E., Shehabi, A., Ramakrishnan, L., Liang, J., Ma, X., Walker, B., Hendrix, V., and Mantha, P. 2013. *The Energy Efficiency Potential of Cloud-Based Software: A U.S. Case Study*, Berkeley, California: Lawrence Berkeley National Laboratory.

Masanet, E., Shehabi, A., Lei, N., Smith, S. and Koomey, J. 2020. "Recalibrating Global Data Center Energy-Use Estimates," *Science* (367:6481), pp.984-986.

Mastelic, T., Oleksiak, A., Claussen, H., Brandic, I., Pierson, J.-M., and Vasilakos, A. V. 2014. "Cloud Computing: Survey on Energy Efficiency," *ACM Computing Surveys* (47:2), pp. 1–36.

Mell, P., and Grance, T. 2011. *The NIST Definition of Cloud Computing*, Gaithersburg, MD: National Institute of Standards and Technology.

Melville, N. P. 2010. "Information Systems Innovation for Environmental Sustainability," *MIS Quarterly* (34:1), pp. 1–21.

Melville, N. P., Kraemer, K., and Gurbaxani, V. 2004. "Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (28:2), pp. 283–322.

Microsoft. 2010. *Cloud Computing and Sustainability: The Environmental Benefits of Moving to the Cloud*, Accenture, WSP Environment & Energy, Microsoft.

Murugesan, S. 2008. "Harnessing Green IT: Principles and Practices," *IT Professional* (10:1), pp. 24–33.

Mytton, D. 2020. "Hiding Greenhouse Gas Emissions in the Cloud," *Nature Climate Change* (10:8), pp. 701–701.

Pang, M.-S., Tafti, A., and Krishnan, M. S. 2014. "Information Technology and Administrative Efficiency in U.S. State Governments: A Stochastic Frontier Approach," *MIS Quarterly* (38:4), pp. 1079–1101.

Qian, L., Luo, Z., Du, Y., and Guo, L. 2009. "Cloud Computing: An Overview," in *Cloud Computing. CloudCom 2009. Lecture Notes in Computer Science, vol 5931*, Berlin, Heidelberg: Springer, pp. 626–631.

Qu, W. G., Pinsoneault, A., and Oh, W. 2011. "Influence of Industry Characteristics on Information Technology Outsourcing," *Journal of Management Information Systems* (27:4), pp. 99–128.

Rodrigues, J., Ruivo, P., and Oliveira, T. 2021. "Mediation Role of Business Value and Strategy in Firm Performance of Organizations Using Software-as-a-Service Enterprise Applications," *Information & Management* (58:1), Elsevier, p. 103289.

Saunders, A., and Brynjolfsson, E. 2016. "Valuing Information Technology Related Intangible Assets," *MIS Quarterly* (40:1), pp. 83–110.

Schniederjans, D. G., and Hales, D. N. 2016. "Cloud Computing and Its Impact on Economic and Environmental Performance: A Transaction Cost Economics Perspective," *Decision Support Systems* (86), pp. 73–82.

Seo, H.-J., and Lee, Y. S. 2006. "Contribution of Information and Communication Technology to Total Factor Productivity and Externalities Effects," *Information Technology for Development* (12:2), pp. 159–173.

Shao, B. B. M., and Lin, W. T. 2001. "Measuring the Value of Information Technology in Technical Efficiency with Stochastic Production Frontiers," *Information and Software Technology* (43:7), pp. 447–456.

Shehabi, A., Smith, S. J., Sartor, D. A., Brown, R. E., Herrlin, M., Koomey, J. G., Masanet, E. R., Horner, N., Azevedo, I. L., and Lintner, W. 2016. *United States Data Center Energy Usage Report*, Berkeley, California: Lawrence Berkeley National Laboratory.

Shephard, R. 1970. *Theory of Cost and Production Functions*, Princeton: Princeton University Press.

Society for Information Management. 2020. "2020 SIM IT Trends," Mount Laurel, NJ.

Stiroh, K. J. 2002. "Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?," *American Economic Review* (92:5), pp. 1559–1576.

Strassner, E. H., Medeiros, G. W., and Smith, G. M. 2005. *Annual Industry Account: Introducing KLEMS Input Estimates for 1997 – 2003 Survey of Current Business*, U.S. Department of Commerce.

Tambe, P., and Hitt, L. M. 2012. "The Productivity of Information Technology Investments: New Evidence from IT Labor Data," *Information Systems Research* (23:3-part 1), pp. 599–617.

Volkswagen Newsroom. 2020. "Volkswagen Steps up Development of Industrial Cloud," *Volkswagen Newsroom*.

Wauters, P., Peijl, S. Van Der, Cilli, V., Bolchi, M., Janowski, P., Moeremans, M., Taylor, G., Graham, H. G., and Cocoru, D. 2016. *Measuring the Economic Impact of Cloud Computing in Europe*, European Commission / Deloitte.

Williams, D. R., and Tang, Y. 2013. "Impact of Office Productivity Cloud Computing on Energy Consumption and Greenhouse Gas Emissions," *Environmental Science & Technology* (47:9), pp. 4333–4340.

Wurlod, J.-D., and Noailly, J. 2018. "The Impact of Green Innovation on Energy Intensity: An Empirical Analysis for 14 Industrial Sectors in OECD Countries," *Energy Economics* (71), pp. 47–61.

ZDNet. 2019. "Uber vs. Lyft: How the Rivals Approach Cloud, AI, and Machine Learning," *ZDNet*. https://www.zdnet.com/article/uber-vs-lyft-how-the-rivals-approach-cloud-ai-machine-learning/ (accessed on April 3, 2022).

Table 1: Theoretical Framework on Cloud Computing and Energy Efficiency

Potential Mechanism	Software-as-a-Service (SaaS): Mitigating the energy consumption of IT infrastructure and equipment	Software-as-a-Service (SaaS): Facilitating energy-efficient production and operations	Infrastructure-as-a-Service (IaaS): Mitigating the energy consumption of IT infrastructure and equipment	Infrastructure-as-a-Service (IaaS): Facilitating energy-efficient production and operations
	(1)	(2)	(3)	(4)
Theoretical Proposition	SaaS running on cloud infrastructure can reduce the energy consumption required to run and support software applications.	SaaS can help redesign the production process to enhance operational efficiency and reduce energy waste by leveraging scalable applications delivered over the Internet on an on-demand basis.	IaaS can substitute cloud-based IT services for an energy-inefficient internal IT infrastructure.	Scalable, on-demand IT resources can increase scalability and flexibility, which can free up and reallocate internal resources to more urgent activities, leading to a higher level of overall efficiency in production and operations.
Anecdotal Evidence	• On user devices, the power consumption to run Excel 365 on the cloud, one of the most widely used analytics tools, is estimated to be 15.7% (tablet) to 27.3% (laptop) lower than that to run the on-premises Excel 2010 (Williams and Tang 2013).	• The Volkswagen Group is integrating its global plants into the industrial cloud. The main foci include the predictive maintenance of machines using plant data and the reduction of reworking on vehicles, which further improves the efficiency of manufacturing and logistics processes (Volkswagen Newsroom 2020). • Supermarket customers of Emerson, a climate system manufacturing company, use Emerson's products equipped with cloud-enabled big data analytics applications that offer remote diagnosis, maintenance, and repairs, leading to significant savings of energy costs by more than 10% (KPMG 2014). • According to a survey of product development professionals, cloud-based system users reported higher levels of success (meeting cost targets, innovation, and delivery on time) than users of server-based software or users with no formal systems (Engineering.com 2018).	• At data centers, expenses related to server operations account for 53% of the total budget, and energy-related costs account for 42% of the server operations costs, including both direct power consumption (19%) and cooling infrastructure (23%) (Jing et al. 2013). Thus, migrating internal IT infrastructure into the cloud can lower users' energy costs. • When Animoto, a New York-based online video service, made its service available via Facebook in 2008, the company experienced a demand surge of 750,000 new users in three days. The company coped with the surge demand by immediately increasing Amazon EC2 usage from 50-100 to 3,400 instances, rather than equipping itself with additional in-house servers and incurring huge fixed costs and energy consumption (AWS 2008).	• The ride-sharing company, Uber, leverages its hybrid cloud model not only to ensure constant uptime, but also to facilitate product development and deployment. The company said, "We have developed our infrastructure to be highly automated, enabling us to improve our platform and add new features with rapid velocity. We built our platform to handle spikes in usage, such as those we experience during holidays… (This platform) allows us to quickly and efficiently scale up our services to meet spikes in usage without upfront infrastructure costs, allowing us to maintain our focus on building great products" (ZDNet 2019).

Table 2: Summary Statistics (*N* = 1,197 for 57 Industries during 1997 – 2017)

Variable	Mean	Std. Dev.	1st Quartile	3rd Quartile	Description
Output	346,504.90	329,884.40	96,833.41	501,977.50	Sectoral output by industry
IT capital	20,236.90	45,854.51	1,910	17,132	Sum of HW and SW capital
HW capital	11,105.21	37,341.60	936	8,945	Productive capital stock of computers and communication equipment by industry
SW capital	9,131.69	16,004.80	728	7,963	Productive capital stock of software by industry
Non-IT capital	455,264.20	624,607.60	121,529	465,749	Productive capital stock of total capital, excluding IT capital, by industry
R&D capital	29,213.25	79,655.69	789	21,875	Productive capital stock of research and development by industry
Labor	118,892.60	140,598.20	28,457.99	146,069.7	Labor cost by industry
Energy input	12,276.86	23,935.12	1,749.99	11,772.81	Energy input by industry
Electric energy	4,230.65	23,935.12	619.42	3,905.40	Purchased intermediate input from electric power generation, transmission, and distribution industries (NAICS 2211) by industry
Non-electric energy	8,073.06	7,915.76	727.26	5927.07	Energy input, excluding electric energy, by industry
Other intermediate inputs	151,496.40	157,244	42,967.70	196,421.50	Intermediate inputs, excluding energy, cloud computing, and non-cloud IT services, by industry
Cloud-based IT services	361.83	702.01	30.74	346.03	Sum of SaaS and IaaS
Software-as-a-Service (SaaS)	177.21	370.31	8.07	156.59	Purchased services of application provisioning, defined in Table 3
Infrastructure-as-a-Service (IaaS)	184.62	337.46	19.17	173.53	Purchased services of IT infrastructure provisioning, defined in Table 3
Non-cloud IT services	3,225.72	4,624.51	423.03	3,992.92	Purchased IT services other than cloud computing
Price index of capital input	93.29	28.98	77.59	106.48	Price index of capital input (Base year = 2012)
Price index of labor input	87.78	16.54	75.68	100	Price index of labor input (Base year = 2012)
Price index of energy input	78.35	22.44	58.49	99.23	Price index of energy input among intermediate inputs (Base year = 2012)
Price index of material input	87.27	16.30	76.40	100	Price index of material input among intermediate inputs (Base year = 2012)
Price index of purchased services	91.10	11.21	81.85	100	Price index of purchased services among intermediate inputs (Base year = 2012)

Notes: All variables, except the price indices, are in millions of constant 2012 US dollars.

Table 3: Product Types of IT Services and Cloud Computing

Category			Sales Percentage (%): Data processing, hosting, and related services (NAICS 5182)			Computer systems design and related services (NAICS 5415)		
			2002	2007	2012	2002	2007	2012
Cloud-Based IT Services	Software-as-a-Service (SaaS)	Application service provisioning	10.5	17.4	22.5	0.3	0.7	1.2
	Infrastructure-as-a-Service (IaaS)	Website hosting services	5.2	6.8	11.2	0.2	0.3	0.4
		Video and audio streaming infrastructure provisioning services	0.3	1.3	3.8	0	0	0.1
		Data storage infrastructure provisioning services	2	2.1	1.5	0.4	0.2	0.3
		IT infrastructure collocation services	6.6	1.1	1.4	0	0	0
		Other IT infrastructure provisioning services	1.3	5.1	2.2	0	0	0
		Total Cloud Services (%)	25.9	33.8	42.6	0.9	1.2	2
Non-Cloud IT Services	Business process management services		24	32	17	0.4	1.2	1.6
	Data management services		11.8	11.7	14.1	0.3	0.5	0
	Computer systems design, development, and integration services		1.1	0.8	0.4	30.6	36.3	25.3
	Custom application design and development services		4.1	2.6	2.8	28.6	25.8	35
	Network design and development services		1.1	0.4	0.2	3.5	3.5	1.3
	IT infrastructure and network management services		8.7	1.8	2	9.7	6	5.4
	Information and document transformation services		5.5	3.3	1.3	0	0	0
	IT technical consulting services		3.3	1.5	2.2	10.5	4.8	10.1
	IT technical support services		8.3	6.2	9.3	7.4	10.1	11.4
	Temporary staffing - IT staff		0.3	0	0	1.5	1	1
		Total Non-Cloud IT Services (%)	68.2	60.3	49.3	92.5	89.2	91.1
		Total IT Services (%)	94.1	94.1	91.9	93.4	90.4	93.1
		Total Non-IT Services (%)	5.9	5.9	8.1	6.4	9.6	6.9

Notes: Product types are based on the North American Product Classification System (NAPCS). The sales percentages for each product are obtained from the 2002, 2007, and 2012 Economic Census of the US Census Bureau. See Table A3 in Online Appendix A for detailed descriptions of cloud computing products. See Figures A1 and A2 for trends in cloud computing and non-cloud IT services by product type.

Table 4: Estimation Results of Cloud Computing and Energy Efficiency

Dependent variable: Energy efficiency	System GMM									
	Full Sample				Time-Split Analysis					
					1997–2005		2006–2017		2010–2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged efficiency	0.722***	0.715***	0.713***	0.710***	0.639***	0.610***	0.723***	0.722***	0.748***	0.763***
	(0.051)	(0.052)	(0.048)	(0.048)	(0.097)	(0.091)	(0.046)	(0.039)	(0.071)	(0.056)
IT intensity	-0.009	-0.010**	-0.010**		-0.007		-0.012*		-0.021**	
	(0.006)	(0.004)	(0.004)		(0.010)		(0.007)		(0.010)	
HW intensity				-0.009		-0.024*		-0.010		-0.009
				(0.005)		(0.014)		(0.006)		(0.007)
SW intensity				0.000		0.013		-0.001		-0.006
				(0.004)		(0.012)		(0.005)		(0.007)
Non-IT intensity	0.012*	0.015**	0.016***	0.016***	0.018*	0.021*	0.017**	0.019***	0.023**	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.011)	(0.007)	(0.006)	(0.010)	(0.007)
Other intermediate inputs intensity	-0.021**	-0.021**	-0.022***	-0.023***	-0.021**	-0.027**	-0.028***	-0.028***	-0.029*	-0.028*
	(0.010)	(0.009)	(0.008)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.016)	(0.015)
Cloud-based IT services intensity	0.015***	0.020***			0.016		0.031***		0.038***	
	(0.005)	(0.007)			(0.011)		(0.009)		(0.013)	
SaaS intensity			0.023**	0.019**		0.012		0.028*		0.045**
			(0.009)	(0.009)		(0.012)		(0.014)		(0.020)
IaaS intensity			-0.000	0.001		-0.006		0.006		-0.004
			(0.009)	(0.010)		(0.013)		(0.011)		(0.014)
Non-cloud IT services intensity		-0.012	-0.011	-0.010	-0.005	0.003	-0.028***	-0.025***	-0.031***	-0.028***
		(0.009)	(0.008)	(0.008)	(0.013)	(0.011)	(0.010)	(0.008)	(0.011)	(0.010)
Arellano-Bond test for AR(2)	0.833	0.822	0.837	0.833	0.601	0.593	0.398	0.394	0.828	0.830
Instrument validity test	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Observations	1,140	1,140	1,140	1,140	456	456	684	684	456	456

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Summary of Robustness Checks

Concern	Test	Location
Sensitivity of system GMM estimations	• Replicate the system GMM estimations with different numbers of instrument variables.	Table C1
	• Estimate the difference GMM model using one-step and two-step estimations.	Table C2
	• Estimate alternative panel models, including the fixed-effects model, FGLS, and OLS-PCSE.	Table C3
Endogeneity of cloud computing investment	• Estimate the DID model by constructing the treatment group with the industries in the top quartile of the percentage of IT outsourcing invested in cloud-based IT services in the pre-cloud computing era (before 2006).	Table C4
	• Estimate the 3SLS model in which an industry's use of cloud services is assumed to be endogenously determined by prior IT investments and downstream customer industries' cloud computing investments.	Table C5
Measurement errors in cloud computing and energy efficiency	• Replicate the system GMM estimations with alternative measures of cloud computing constructed by different interpolation assumptions.	Table C6
	• Replicate the system GMM estimations using a hypothetical measure of cloud computing with simulated measurement errors added.	Figure D1
	• Replicate the system GMM estimations for energy efficiency adjusted by energy use uncorrelated with cloud computing.	Table E1
Model misspecifications	• Replicate the system GMM estimations with an alternative intensity measure by output instead of labor.	Table C7, Columns 1-5
	• Replicate the system GMM estimations after excluding IT service industries.	Table C7, Columns 6-10

Notes: All results of the robustness checks can be found in Online Appendices C, D, and E.

Table 6: Interactions between Internal IT Capital and Cloud Computing

Dependent variable: Energy efficiency	System GMM				
	(1)	(2)	(3)	(4)	(5)
Lagged efficiency	0.714***	0.715***	0.701***	0.699***	0.700***
	(0.050)	(0.045)	(0.047)	(0.047)	(0.049)
IT intensity	-0.010**	-0.010**			
	(0.004)	(0.004)			
HW intensity			-0.011	-0.011*	-0.008
			(0.007)	(0.006)	(0.006)
SW intensity			0.001	0.004	-0.001
			(0.005)	(0.005)	(0.004)
Non-IT intensity	0.015**	0.015**	0.013**	0.014**	0.013***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Other intermediate inputs intensity	-0.021**	-0.021**	-0.021***	-0.020**	-0.021***
	(0.009)	(0.0099)	(0.008)	(0.009)	(0.008)
Cloud-based IT services intensity	0.020***				
	(0.007)				
SaaS intensity		0.022***	0.019***	0.021***	0.021***
		(0.008)	(0.007)	(0.008)	(0.008)
IaaS intensity		-0.000	-0.006	-0.008	-0.009
		(0.009)	(0.008)	(0.009)	(0.009)
Non-cloud IT services intensity	-0.013	-0.011	-0.009	-0.006	-0.009
	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
Cloud-based IT services × IT intensity	0.000				
	(0.003)				
SaaS × IT intensity		-0.005			
		(0.004)			
IaaS × IT intensity		0.006*			
		(0.004)			
SaaS × HW intensity			-0.006	-0.006	
			(0.005)	(0.006)	
SaaS × SW intensity			0.001	-0.001	
			(0.004)	(0.004)	
IaaS × HW intensity			0.015***	0.017**	
			(0.006)	(0.007)	
IaaS × SW intensity			-0.010	0.001	
			(0.007)	(0.008)	
Non-cloud IT services × HW intensity				-0.005	
				(0.008)	
Non-cloud IT services × SW intensity				-0.009	
				(0.010)	
SaaS × HW percentage of IT					-0.018
					(0.018)
IaaS × HW percentage of IT					0.067**
					(0.027)
Arellano-Bond test for AR(2)	0.821	0.835	0.813	0.807	0.821
Instrument validity test	1.000	1.000	1.000	1.000	1.000
Observations	1,140	1,140	1,140	1,140	1,140

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Distinct Effects on Electric and Non-Electric Energy Efficiency

	System GMM							
Dependent variable:	Electric Energy Efficiency				Non-Electric Energy Efficiency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged efficiency	0.721***	0.712***	0.680***	0.688***	0.753***	0.757***	0.749***	0.753***
	(0.038)	(0.038)	(0.044)	(0.042)	(0.049)	(0.046)	(0.045)	(0.046)
IT intensity	-0.004	-0.005			-0.017**	-0.017**		
	(0.004)	(0.005)			(0.008)	(0.007)		
HW intensity			-0.016**	-0.011*			-0.010	-0.005
			(0.007)	(0.006)			(0.011)	(0.009)
SW intensity			0.012**	0.007			-0.008	-0.011
			(0.005)	(0.005)			(0.009)	(0.009)
Non-IT intensity	0.008**	0.010***	0.009**	0.009**	0.013	0.015	0.014*	0.013
	(0.004)	(0.004)	(0.004)	(0.004)	(0.012)	(0.010)	(0.009)	(0.009)
Other intermediate inputs intensity	-0.008	-0.011***	-0.012***	-0.011***	-0.031*	-0.032**	-0.027**	-0.028**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.016)	(0.013)	(0.014)	(0.013)
Cloud-based IT services intensity	0.011*				0.017			
	(0.006)				(0.012)			
SaaS intensity		0.017**	0.010*	0.014**		0.020**	0.018	0.020*
		(0.008)	(0.006)	(0.007)		(0.009)	(0.012)	(0.011)
IaaS intensity		-0.002	-0.008	-0.012		0.001	0.005	0.002
		(0.008)	(0.007)	(0.008)		(0.011)	(0.014)	(0.014)
Non-cloud IT services intensity	-0.010	-0.012*	-0.011*	-0.011*	-0.001	-0.004	-0.006	-0.003
	(0.007)	(0.007)	(0.006)	(0.006)	(0.015)	(0.013)	(0.012)	(0.012)
SaaS × HW intensity			-0.014***				0.006	
			(0.005)				(0.006)	
SaaS × SW intensity			0.003				-0.008	
			(0.004)				(0.007)	
IaaS × HW intensity			0.026***				-0.007	
			(0.008)				(0.010)	
IaaS × SW intensity			-0.014				0.016	
			(0.009)				(0.011)	
SaaS × HW percentage of IT				-0.039*				0.029
				(0.020)				(0.028)
IaaS × HW percentage of IT				0.105***				-0.047
				(0.037)				(0.047)
Arellano-Bond test for AR(2)	0.133	0.131	0.116	0.119	0.520	0.523	0.517	0.519
Instrument validity test	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Observations	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Estimation Results of Survey Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Effect of Cloud Computing on Mediator				Effect of Cloud Computing on Energy Efficiency					
Dependent variable:	Energy Reduction in IT Equipment/Infrastructure		Operational Benefits of Cloud Computing		Energy Efficiency					
Mediating variable:							Energy Reduction in IT Equipment/Infrastructure		Operational Benefits of Cloud Computing	
Cloud Computing Expenditure	0.475***	0.023	0.272***	0.167**	1.210***	0.500**	0.719***	0.478***	0.894***	0.336
	(0.114)	(0.151)	(0.061)	(0.079)	(0.153)	(0.226)	(0.132)	(0.177)	(0.165)	(0.211)
Cloud Computing Expenditure × Relative Importance of IaaS		0.617***		0.143***		0.968***		0.375**		0.827***
		(0.126)		(0.052)		(0.195)		(0.150)		(0.180)
Energy Reduction in IT Equipment/Infrastructure							1.033***	0.961***		
							(0.097)	(0.099)		
Operational Benefits of Cloud Computing									1.161***	0.985***
									(0.261)	(0.255)
Mediation Effect with 95% Confidence Interval (Imai et al. 2010)										
Percentage of the Main Effect *(Reflecting the Effect of SaaS)*, Mediated by Each Mediator							40.7% (32.3%, 55.4%)	3.2% (1.6%, 19.9%)	26.0% (21.2%, 35.2%)	**32.6% (16.7%, 124.9%)**
Percentage of the Interaction Effect *(Reflecting the Effect of IaaS)*, Mediated by Each Mediator								**61.4% (44.4%, 98.2%)**		14.4% (10.2%, 22.9%)
Control Variable	Firm Size									
R-squared	0.135	0.237	0.215	0.239	0.338	0.423	0.649	0.660	0.420	0.481
Observations	187	187	187	187	187	187	187	187	187	187

Notes: Robust standard errors are in parentheses. For brevity, we omit firm size dummies. * p<0.1, ** p<0.05, *** p<0.01.

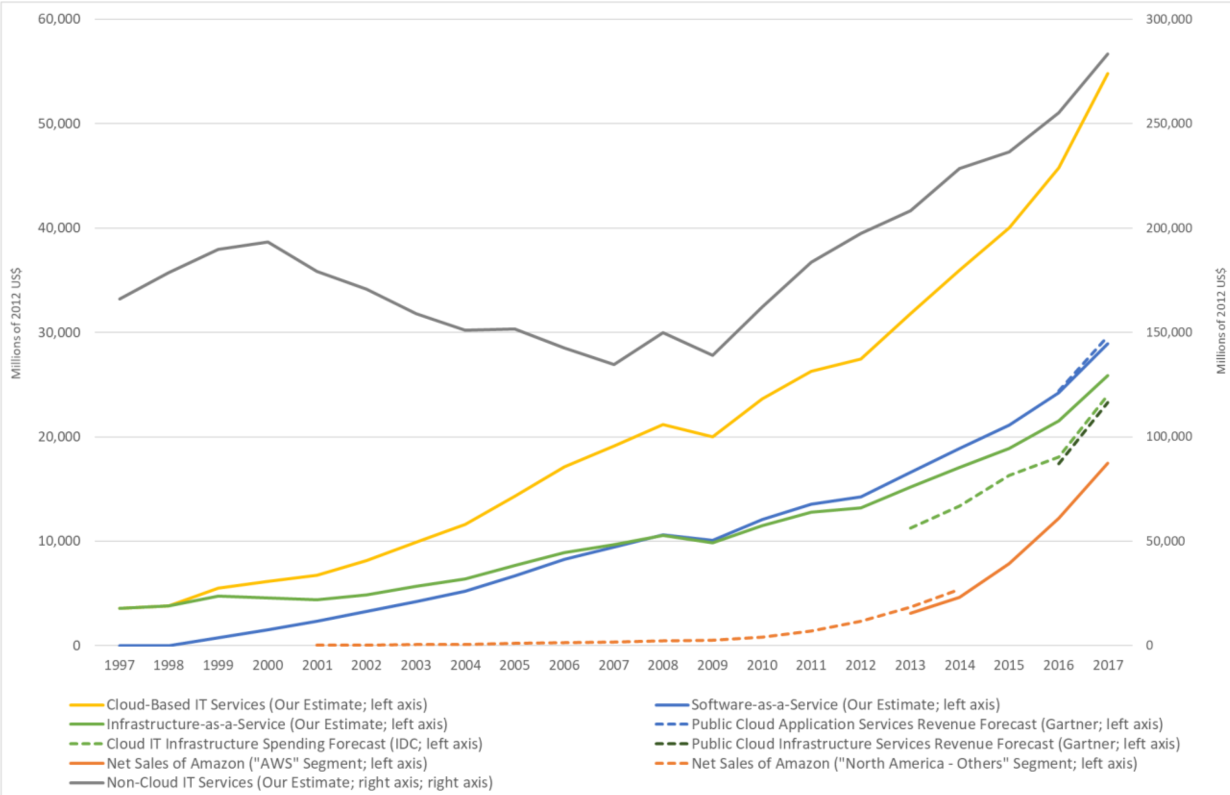

Figure 1: Trends in Cloud-Based IT Services in US Private Industries

Notes: Net sales of Amazon are obtained from its annual reports. Amazon began to report Amazon Web Service ("AWS") as a separate segment since its 2015 annual report. Until then, AWS sales were included in sales from non-retail activities in the North American segment ("North America - Others"). In 2013 and 2014, when both "AWS" and "North America - Others" statistics are available, AWS sales account for approximately 85% of non-retail sales in North America.

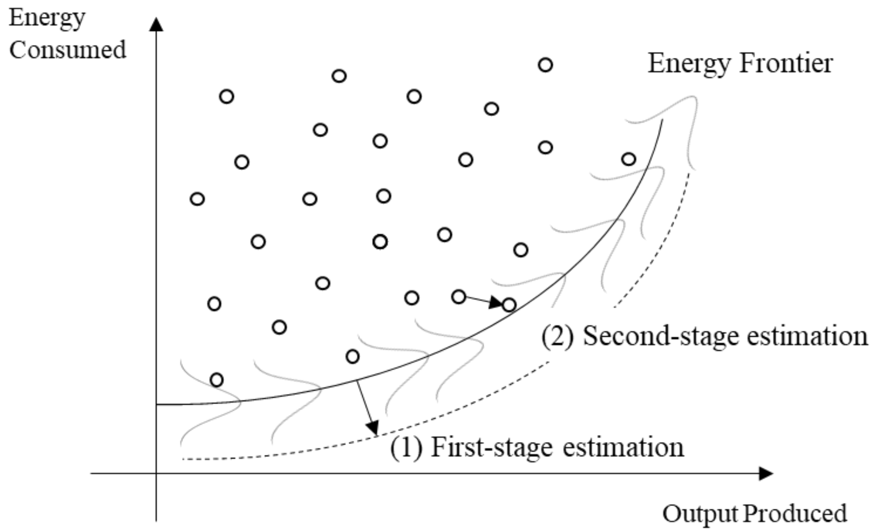

Figure 2: Stochastic Energy Frontier

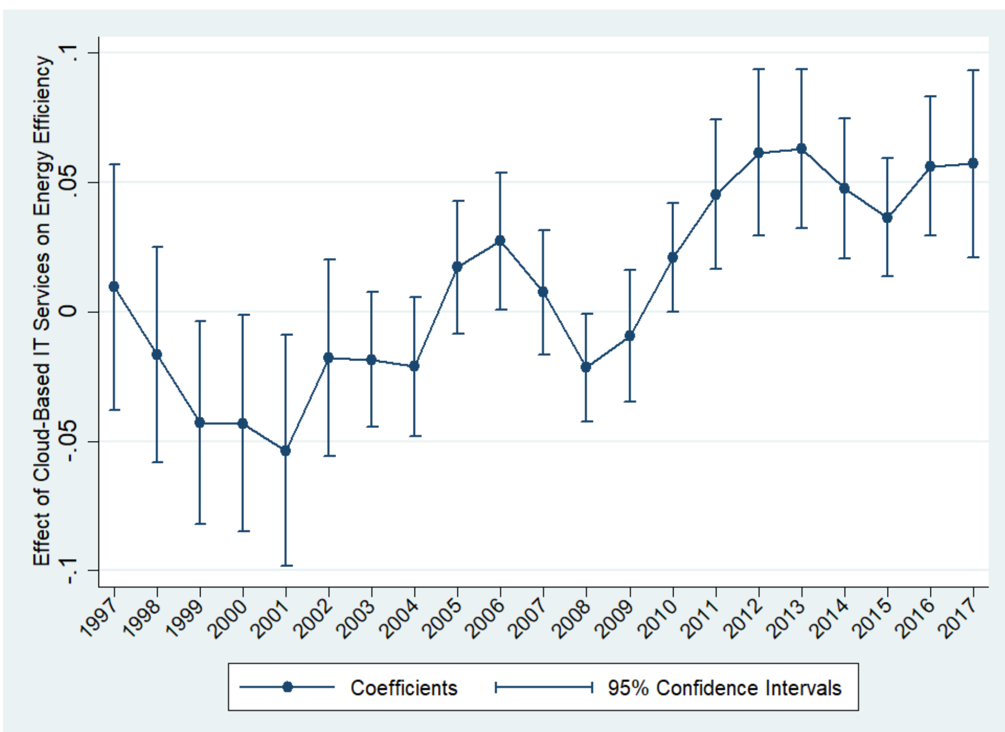

Figure 3: Year-by-Year Effects of Cloud-Based IT Services on Energy Efficiency

Notes: Coefficients are estimated year by year using seemingly unrelated regressions (SUR).

Online Appendices for

"Green Cloud? An Empirical Analysis of Cloud Computing and Energy Efficiency"

Online Appendix A: Supplementary Tables and Figures

Table A1: U.S. Private Industries

2007 NAICS Code	Industry Title	Mean of Energy Efficiency	Std. Dev. of Energy Efficiency
11	**Agriculture, Forestry, Fishing and Hunting**		
113, 114, 115	Forestry, fishing, and related activities	0.857	0.051
21	**Mining, Quarrying, and Oil and Gas Extraction**		
211	Oil and gas extraction	0.823	0.092
212	Mining, except oil and gas	0.818	0.086
213	Support activities for mining	0.771	0.158
22	**Utilities**	0.837	0.082
23	**Construction**	0.842	0.070
31-33	**Manufacturing**		
311, 312	Food, beverage, and tobacco products	0.833	0.088
313, 314	Textile mills and textile product mills	0.847	0.063
315, 316	Apparel and leather and allied products	0.771	0.126
321	Wood products	0.854	0.056
322	Paper products	0.829	0.091
323	Printing and related support activities	0.835	0.085
324	Petroleum and coal products	0.606	0.250
325	Chemical products	0.851	0.060
326	Plastics and rubber products	0.846	0.078
327	Nonmetallic mineral products	0.838	0.078
331	Primary metals	0.787	0.140
332	Fabricated metal products	0.851	0.079
333	Machinery	0.839	0.095
334	Computer and electronic products	0.720	0.209
335	Electrical equipment, appliances, and components	0.843	0.089
336	Transportation equipment	0.812	0.122
337	Furniture and related products	0.860	0.057
339	Miscellaneous manufacturing	0.861	0.047
42	**Wholesale Trade**	0.868	0.028
44-45	**Retail Trade**	0.865	0.036
48-49	**Transportation and Warehousing**		
481	Air transportation	0.835	0.087
482	Railroad transportation	0.827	0.112
484	Truck transportation	0.676	0.213
485	Transit and ground passenger transportation	0.780	0.174
486	Pipeline transportation	0.769	0.174
487, 488, 492	Other transportation and support activities	0.806	0.124
493	Warehousing and storage	0.859	0.045
51	**Information**		
511	Publishing industries (including software)	0.806	0.122
512	Motion picture and sound recording industries	0.735	0.237
515, 517	Broadcasting and telecommunications	0.752	0.212
518, 519	Information and data processing services	0.852	0.062
52	**Finance and Insurance**		
521, 522	Federal Reserve banks, credit intermediation, and related activities	0.835	0.091
523, 525	Securities, commodity contracts, fund, trusts and other financial investments and vehicles and related activities	0.761	0.174
524	Insurance carriers and related activities	0.833	0.091
53	**Real Estate and Rental and Leasing**		
531	Real estate	0.857	0.055
532, 533	Rental and leasing services and lessors of intangible assets	0.857	0.057
54	**Professional, Scientific and Technical Services**		
5411	Legal services	0.830	0.092
5415	Computer systems design and related services	0.823	0.101
541 ex. 5411, 5415	Miscellaneous professional, scientific, and technical services	0.833	0.081
55	**Management of Companies and Enterprises**	0.845	0.074
56	**Administrative and Support and Waste Management and Remediation Services**		
561	Administrative and support services	0.716	0.206
562	Waste management and remediation services	0.709	0.260
61	**Educational Services**	0.839	0.073
62	**Health Care and Social Assistance**		
621	Ambulatory health care services	0.808	0.105
622-623	Hospitals and nursing and residential care facilities	0.842	0.088
624	Social assistance	0.840	0.089
71	**Arts, Entertainment, and Recreation**		
711, 712	Performing arts, spectator sports, museums, and related activities	0.837	0.106
713	Amusements, gambling, and recreation industries	0.797	0.142
72	**Accommodation and Food Services**		
721	Accommodation	0.866	0.031
722	Food services and drinking places	0.869	0.024
81	**Other Services, except Government**	0.861	0.041

Table A2: Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Output	1.000									
(2)	IT capital	0.321	1.000								
(3)	HW capital	0.203	0.946	1.000							
(4)	SW capital	0.446	0.657	0.378	1.000						
(5)	Non-IT capital	0.533	0.250	0.233	0.173	1.000					
(6)	R&D capital	0.215	0.125	0.058	0.225	0.122	1.000				
(7)	Labor	0.807	0.316	0.150	0.555	0.260	0.074	1.000			
(8)	Energy input	0.366	-0.015	-0.011	-0.019	0.617	0.005	0.150	1.000		
(9)	Electric energy	0.556	0.043	0.034	0.045	0.730	0.048	0.252	0.534	1.000	
(10)	Non-electric energy	0.209	-0.035	-0.026	-0.039	0.432	-0.013	0.075	0.947	0.234	1.000
(11)	Other intermediate inputs	0.897	0.179	0.122	0.230	0.398	0.266	0.556	0.273	0.517	0.116
(12)	Cloud-based IT services intensity	0.498	0.579	0.417	0.686	0.233	0.038	0.563	0.047	0.155	-0.006
(13)	SaaS	0.488	0.531	0.359	0.682	0.218	0.042	0.544	0.047	0.154	-0.006
(14)	IaaS	0.501	0.622	0.473	0.679	0.246	0.033	0.574	0.046	0.155	-0.006
(15)	Non-cloud IT services	0.574	0.558	0.402	0.662	0.284	0.057	0.658	0.084	0.250	0.001
(16)	Price index of capital input	0.078	0.080	0.060	0.089	-0.049	0.012	0.132	-0.007	-0.063	0.016
(17)	Price index of labor input	0.119	0.183	0.140	0.199	0.080	0.073	0.028	0.011	0.020	0.005
(18)	Price index of energy input	0.102	0.165	0.120	0.192	0.120	0.106	0.008	-0.009	0.143	-0.064
(19)	Price index of material input	0.050	0.233	0.171	0.270	0.083	-0.010	0.181	-0.058	-0.032	-0.055
(20)	Price index of purchased services	0.114	0.218	0.156	0.261	0.045	0.057	0.103	-0.017	0.031	-0.031

Table A2 (Continued): Correlation Matrix

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	Output										
(2)	IT capital										
(3)	HW capital										
(4)	SW capital										
(5)	Non-IT capital										
(6)	R&D capital										
(7)	Labor										
(8)	Energy input										
(9)	Electric energy										
(10)	Non-electric energy										
(11)	Other intermediate inputs	1.000									
(12)	Cloud-based IT services intensity	0.328	1.000								
(13)	SaaS	0.326	0.993	1.000							
(14)	IaaS	0.324	0.991	0.968	1.000						
(15)	Non-cloud IT services	0.369	0.709	0.673	0.735	1.000					
(16)	Price index of capital input	0.040	0.111	0.107	0.114	0.013	1.000				
(17)	Price index of labor input	0.103	0.290	0.318	0.254	0.052	0.338	1.000			
(18)	Price index of energy input	0.099	0.232	0.257	0.201	0.026	0.245	0.728	1.000		
(19)	Price index of material input	-0.072	0.257	0.257	0.253	0.207	0.229	0.481	0.560	1.000	
(20)	Price index of purchased services	0.057	0.335	0.361	0.301	0.132	0.373	0.832	0.786	0.678	1.000

Table A3: Descriptions on Product Types Classified as Cloud-Based IT Services

Category	Description	Illustrative Example
Software-as-a-Service (SaaS)		
Application service provisioning	Providing leased software applications from a centralized, hosted, and managed computing environment (including cloud), customized to the needs of individual clients or for multi-tenant access. This category includes a subcategory of “software as a service, on cloud.”[17]	• application service provisioning with integration services • software services, on cloud or on demand, including antivirus software, customer relationship application software, healthcare application software, office software, online accounting software, and so on.
Infrastructure-as-a-Service (IaaS)		
Website hosting services	Providing the infrastructure to host a customer’s website and related files in a location that provides fast, reliable connection to the Internet.	• access to hosting applications for website hosting • access to databases for website hosting • e-commerce website hosting services • email hosting services
Video and audio streaming infrastructure provisioning services	Sending audio and video data over the Internet or providing services associated with the storage, production (including encoding), and support of video and audio streaming over the Internet.	• services of streamed video data sent over the Internet • services of streamed audio data sent over the Internet
Data storage infrastructure provisioning services	Managing or administrating the storage and back-up management of data such as remote back-up services, storage, or hierarchical storage management (migration).	• cloud storage services • data migration services • remote back-up services
IT infrastructure collocation services	Providing rack space within a secured facility for the placement of servers and enterprise platforms. Includes the provision of space for the client’s hardware and software, connection to the Internet or other communication networks, and routine monitoring of servers.	• carrier hotel services • co-location center
Other IT infrastructure provisioning services	Providing other IT hosting or infrastructure provisioning services such as hosting client's application, processing client's data, and computer time share.	• computer time share services • rental or leasing of CPU-time to third parties • services of processing client's data

Note: Product types are based on the North American Product Classification System (NAPCS).

[17] Source: North American Product Classification System (NAPCS) Canada 2017 (https://bit.ly/34IObnC)

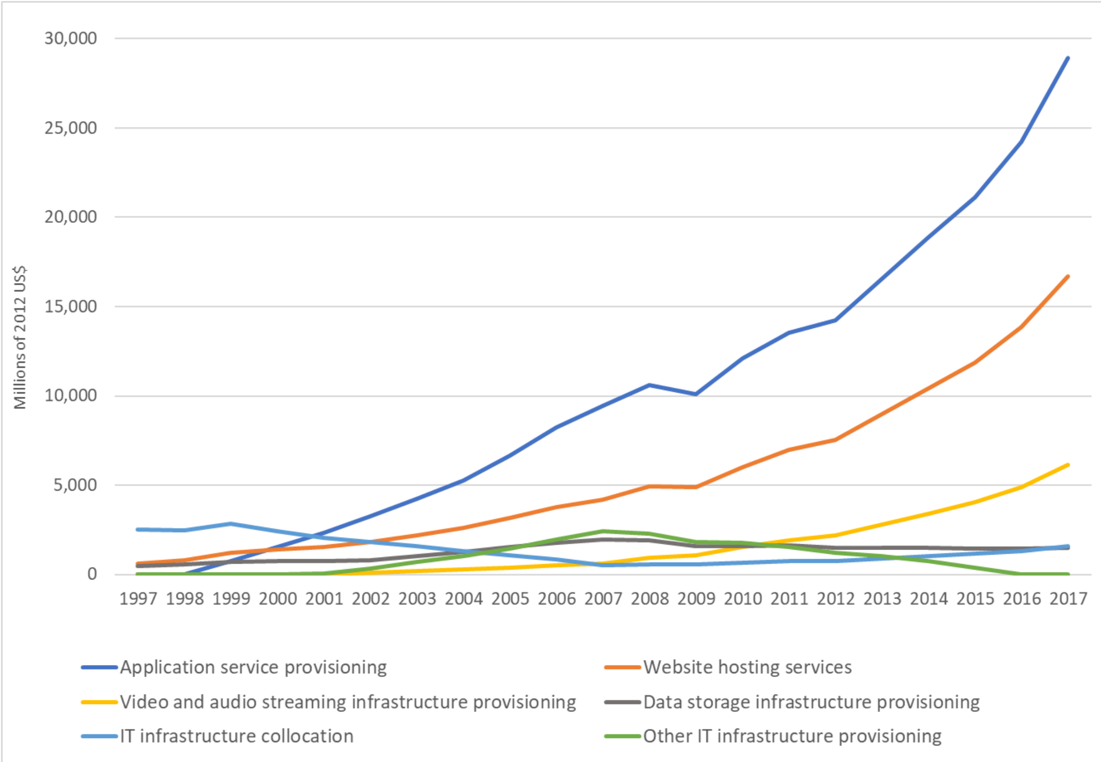

Figure A1: Trends in Cloud-Based IT Services by Type

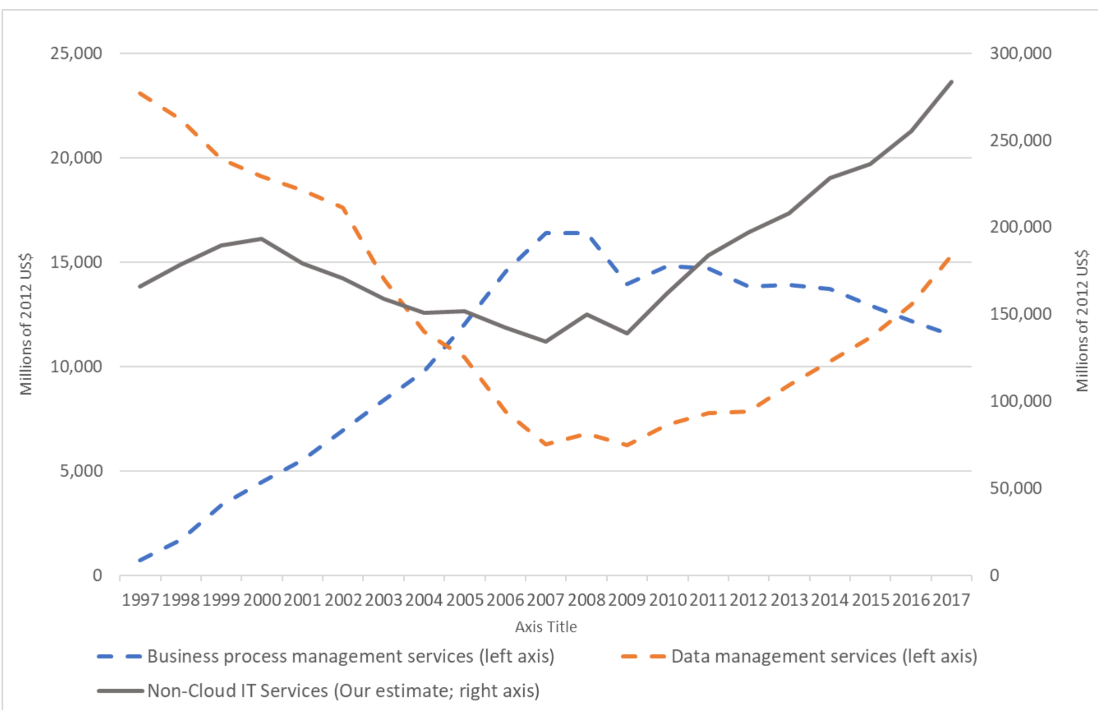

Figure A2: Trends in Non-Cloud IT Services by Type

Figure A3: Cloud-Based IT Services per Output in U.S. Industries (2017)

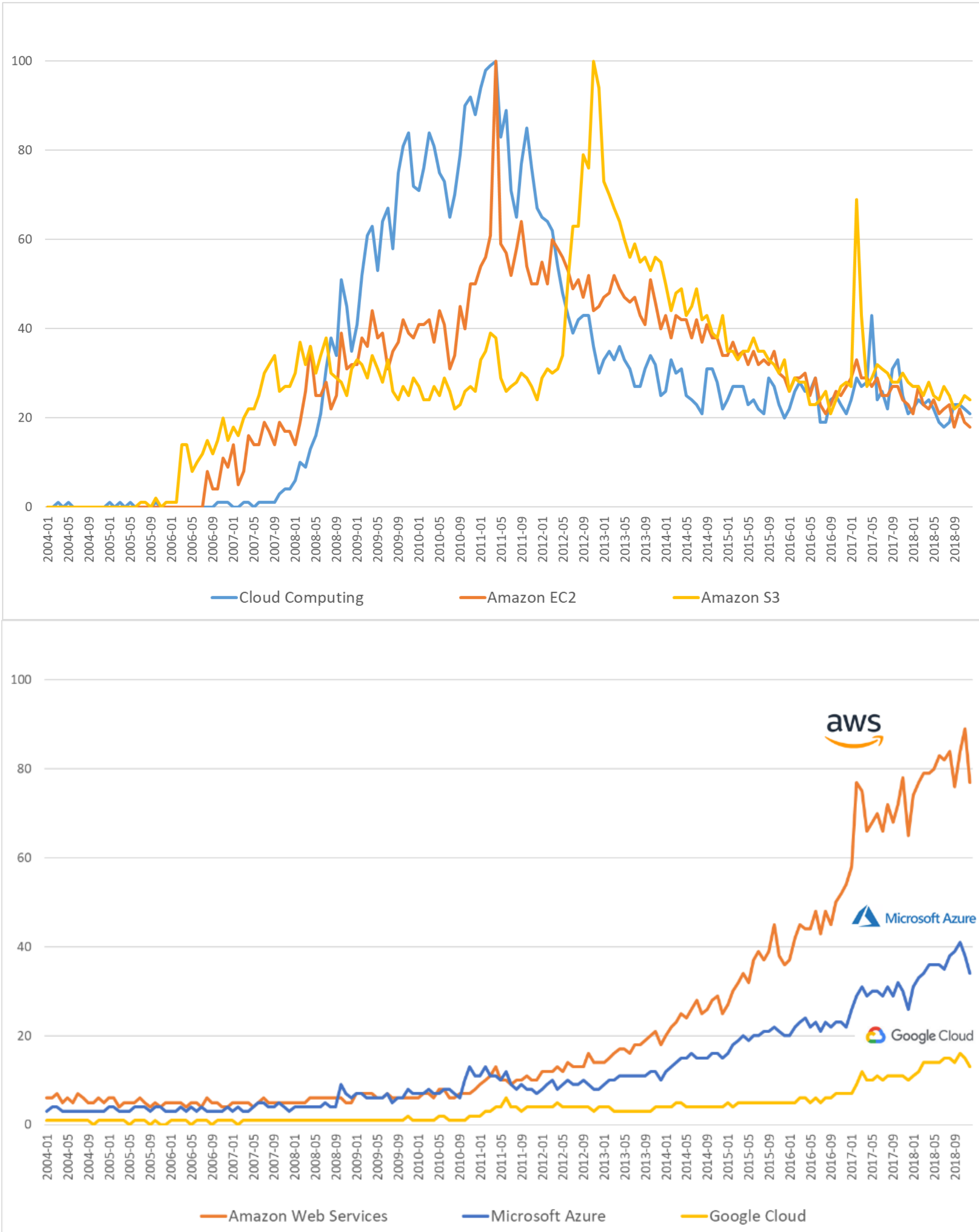

Figure A4: Google Search Volume of Cloud Computing-Related Terms

Online Appendix B: Measuring Energy Efficiency from Energy Frontier

Theoretical Background on Energy Efficiency in Production Theory

Broadly speaking, a production process is considered more energy efficient if it delivers more output for the same energy input or the same amount of output for less energy input (see Filippini and Hunt 2015 for a discussion on energy efficiency). Given that there is no unequivocal measure of energy efficiency, some studies measure energy efficiency simply as energy intensity or energy consumed per output, but this does not account for the roles of other production factors; hence, it is not in keeping with production theory (Boyd 2008). To address this issue, recent empirical studies estimate energy efficiency as a ratio of the optimal-to-actual energy input from the total factor productivity framework (Filippini and Hunt 2011, 2015; Lin and Wang 2014; Rahman and Hasan 2014; Zhou et al. 2012). We adopt this approach and present a brief discussion of energy efficiency from the perspective of neoclassical production theory.

Based on an output distance function, Fare et al. (1994) distinguish between technological progress and the efficiency gains that drive productivity growth. Extending the concept of productivity into energy consumption, in this section, we decompose the change in energy consumption into eco-friendly *technological change*, which is an energy frontier shifting effect, and *energy efficiency change*, which is a catching-up effect to the given best-practice frontier (most efficient level) (Wei et al. 2007).

Building on a neoclassic production framework, production technology can be defined as follows.

$$T_{it} = \{(X_{it}, E_{it}, Y_{it}): (X_{it}, E_{it})\ can\ produce\ Y_{it}\}$$

where Y_{it} is gross output and X_{it} and E_{it} are production inputs (e.g., capital and labor) and energy input for industry *i* at time *t*, respectively. The production technology T_{it} consists of all feasible input-output vectors for the given technology.

Following Lin and Du (2014) and Zhou et al. (2012), we define the Shephard energy distance function (EDF) (Shephard 1970) as follows:

$$EDF_{it}(X_{it}, E_{it}, Y_{it}) = sup\left\{\alpha: \left(X_{it}, \frac{E_{it}}{\alpha}, Y_{it}\right) \in T_{it}\right\}$$

where α is the ratio of actual energy consumption to the energy frontier, which reflects the extent to which energy consumption decreases as the extant inputs and output are maintained. If α equals 1, an industry's technology is on the energy frontier; that is, the industry consumes the minimum level of energy with the extant inputs and output given, and it is considered energy efficient. When α is greater than 1, an industry is considered energy-inefficient and can reduce energy proportionally by the difference between α and 1.

Then, the change in energy consumption can be decomposed into technological change (in terms of energy usage) and efficiency change, as follows:

$$\frac{EDF_{it}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})}{EDF_{it}(X_{it}, E_{it}, Y_{it})} = \frac{EDF_{it}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})}{EDF_{i,t+1}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})} \times \frac{EDF_{i,t+1}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})}{EDF_{it}(X_{it}, E_{it}, Y_{it})}.$$

Note that we use the energy frontier at time *t* as a benchmark to measure the change in energy demand between periods *t and t + 1*, as suggested by Chang and Gurbaxani (2013). Figure B1 illustrates the decomposition of the change in the energy demand. Points *e* and *b* represent the actual inputs, energy consumption, and output at times *t* and *t + 1*, respectively. The first term on the right-hand side indicates the change in energy frontiers, that is, the extent of technological change by comparing the energy distance function in periods *t* and *t* + 1 for the same set of inputs, energy demand, and output. When there is no technological change in terms of energy usage, the distance from the energy frontier is the same in both periods, and the ratio is 1. In the presence of technological progress, the minimum potential energy consumption with the extant technology is lower at time *t* + 1 than at *t*. In Figure B1, technological progress (if any) can be represented as $\frac{EDF_{it}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})}{EDF_{i,t+1}(X_{i,t+1}, E_{i,t+1}, Y_{i,t+1})} = \frac{ob/oc}{ob/oa} = \frac{oa}{oc}$, which is smaller than 1.

The second term on the right-hand side captures the change in energy efficiency between the two periods. As a firm uses (X_{it}, E_{it}) and $(X_{i,t+1}, E_{i,t+1})$ to produce Y_{it} and $Y_{i,t+1}$, respectively, using the extant technology, the ratio of the energy distance function in the numerator to that in the denominator reflects the change in energy efficiency between the two periods. In Figure B1, the change in energy efficiency can be represented as $\frac{EDF_{i,t+1}(X_{i,t+1},E_{i,t+1},Y_{i,t+1})}{EDF_{it}(X_{it},E_{it},Y_{it})} = \frac{ob/oa}{oe/od}$. If $\frac{ob}{oa}$ is smaller than $\frac{oe}{od}$, the production at time t + 1 is more energy-efficient than that at time t, in that the former is closer to the best practice on the energy frontier at the same level of inputs and output; otherwise, it is more energy-inefficient.

Estimation Results of the Energy Frontier Model

Table B1 reports the results of the first-stage estimations of the energy frontier (Equation 3 in the main manuscript). For comparison, we first estimate the energy frontier equation by considering only the output and prices of the production factors in Column 1. As expected, the more output an industry produces, the more energy it uses. In Columns 2 and 3, the model fit improves after controlling for industry- and year-specific effects, as both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are reduced. Moreover, the ratio of the variance of the inefficiency term (σ_u) to that of the stochastic term (σ_v) increases when the fixed effects are included. This finding implies that controlling for fixed effects in estimating an energy frontier allows us to better isolate efficiency change from the variation in energy use, which further justifies our use of fixed-effects stochastic frontier analysis (SFA). In Column 5, we estimate the full model, including the TFP function. AIC and BIC have further improved, confirming that our energy frontier model captures the industrial usage of energy well and, therefore, estimates the energy frontier more effectively. The results suggest that holding the level of output and other inputs constant, IT intensity decreases energy consumption by shifting the energy frontier down, whereas R&D intensity does not. Conversely, material and service outsourcing intensities appear to increase at the minimum level of energy consumption (e.g., the energy frontier). Based on the results in Column 5, we measure an industry's energy efficiency as optimal-to-actual energy consumption (i.e., a deviation from the energy frontier), which is subsequently included as a dependent variable in the second-stage estimation.

References

Boyd, G. A. 2008. "Estimating Plant Level Energy Efficiency with a Stochastic Frontier," *Energy Journal* (29:2), pp. 23–43.

Chang, Y. B., and Gurbaxani, V. 2013. "An Empirical Analysis of Technical Efficiency: The Role of IT Intensity and Competition," *Information Systems Research* (24:3), pp. 561–578.

Fare, B. R., Grosskopf, S., and Norris, M. 1994. "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review* (84:1), pp. 66–83.

Filippini, M., and Hunt, L. C. 2011. "Energy Demand and Energy Efficiency in the OECD Countries : A Stochastic Demand Frontier Approach Stochastic Demand Frontier Approach," *Energy Journal* (32:2), pp. 59–80.

Filippini, M., and Hunt, L. C. 2015. "Measurement of Energy Efficiency Based on Economic Foundations," *Energy Economics* (52), pp. S5–S16.

Lin, B., and Du, K. 2014. "Measuring Energy Efficiency under Heterogeneous Technologies Using a Latent Class Stochastic Frontier Approach: An Application to Chinese Energy Economy," *Energy* (76), pp. 884–890.

Lin, B., and Wang, X. 2014. "Exploring Energy Efficiency in China′s Iron and Steel Industry: A Stochastic Frontier Approach," *Energy Policy* (72), pp. 87–96.

Rahman, S., and Hasan, M. K. 2014. "Energy Productivity and Efficiency of Wheat Farming in Bangladesh," *Energy* (66), pp. 107–114.

Shephard, R. 1970. *Theory of Cost and Production Functions*, Princeton: Princeton University Press.

Wei, Y.-M., Liao, H., and Fan, Y. 2007. "An Empirical Analysis of Energy Efficiency in China's Iron and Steel Sector," *Energy* (32), pp. 2262–2270.

Zhou, P., Ang, B. W., and Zhou, D. Q. 2012. "Measuring Economy-Wide Energy Efficiency Performance: A Parametric Frontier Approach," *Applied Energy* (90:1), pp. 196–200.

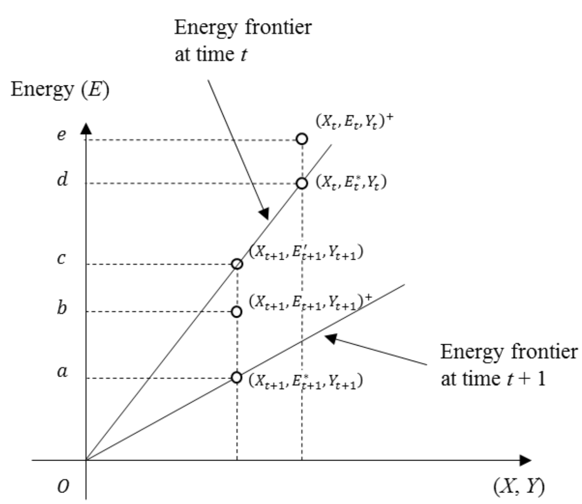

Figure B1: Decomposition of Change in Energy Consumption

Notes: Superscript '+' means actual inputs, energy, and output, and superscript '*' means the best practices with minimal energy consumption, required to convert the inputs to output. This figure is adapted from Chang and Gurbaxani (2013).

Table B1: First-Stage Results from the Stochastic Frontier Analysis

Dependent variable: ln(Energy input)	Energy Frontier Model				
	(1)	(2)	(3)	(4)	(5)
ln(Output)	0.750***	0.754***	1.311***	1.434***	1.014***
	(0.032)	(0.032)	(0.065)	(0.057)	(0.053)
IT share of total capital					-1.765***
					(0.345)
R&D share of total capital					-0.396
					(0.359)
Material share of total costs					2.576***
					(0.306)
Purchased services share of total costs					4.932***
					(0.244)
ln(Price index of capital input)	-0.271***	-0.241**	0.005	-0.038	-0.044
	(0.096)	(0.099)	(0.040)	(0.036)	(0.029)
ln(Price index of labor input)	0.749***	0.986***	-1.016***	-0.848***	-0.164*
	(0.273)	(0.282)	(0.112)	(0.114)	(0.095)
ln(Price index of material input)	-0.275	-0.446**	0.314***	0.225**	0.198**
	(0.198)	(0.198)	(0.092)	(0.091)	(0.078)
ln(Price index of purchased services)	0.902*	1.209	0.109	1.876***	1.555***
	(0.547)	(0.768)	(0.201)	(0.276)	(0.225)
ln(Price index of energy input)	-1.170***	-2.027***	-0.005	-0.044	-0.156*
	(0.160)	(0.209)	(0.065)	(0.106)	(0.087)
Variance ratio $\left(=\frac{\sigma_u}{\sigma_v}\right)$	0.278	0.395***	1.286***	1.067***	1.345***
	(0.256)	(0.137)	(0.033)	(0.028)	(0.033)
Akaike information criterion (AIC)	3,629.41	3,608.08	936.02	744.89	331.33
Bayesian information criterion (BIC)	3,675.20	3,755.62	1,266.71	1,177.33	784.12
Industry fixed effects	No	No	Yes	Yes	Yes
Year fixed effects	No	Yes	No	Yes	Yes
Observations	1,197	1,197	1,197	1,197	1,197

Notes: Standard errors are in parentheses. The variance ratio is the ratio of the standard deviation of the inefficiency term (σ_v) to the standard deviation of the stochastic term (σ_u); * p<0.1, ** p<0.05, *** p<0.01.

Online Appendix C: Robustness Checks

To further lend credence to our findings on the role of cloud-based IT services in enhancing energy efficiency, we conduct a series of robustness checks, as detailed in this section.

Sensitivity to Instruments in the System GMM

To ensure the robustness of our findings based on the system generalized method of moments (GMM) models, we follow the recommendations of Cheng and Bang (2021), who critically review the use of Arellano–Bond GMM estimators (including difference or system GMM models) in information systems (IS) research. By reviewing empirical papers published in premier IS journals from 2014 to 2019, the authors note that Arellano–Bond GMM models have become increasingly popular in IS research. However, using simulated and real-world data, the authors demonstrate that the Arellano–Bond GMM models could be sensitive to model assumptions and estimation techniques, and thus recommend researchers to test the sensitivity of estimation results to alternative modeling choices and alternative panel models such as the fixed-effects model. Following their recommendations, we consider alternative model specifications of the Arellano–Bond GMM model, including (i) different sets of instrumental variables (IVs) and (ii) a difference GMM model. In addition, we replicate our energy efficiency model (Equation 4 in the main manuscript) using alternative estimation methods for panel data.

First, we check the sensitivity of the system GMM estimations to the number of IVs, given that instrument proliferation, possibly resulting from a long panel, may weaken the Hansen test's ability to detect the problem of overidentification (Roodman 2009a, 2009b). The results of the sensitivity tests for different sets of IVs are listed in Table C1. In Columns 1 to 5, we use standard IVs in the system GMM estimations—lagged variables in levels and first differences —and restrict the length of the lags between one and five. In Columns 6 to 8, we also replace standard IVs with their principal components, with eigenvalues of at least 1, to reduce the number of IVs in a minimally arbitrary way, as prior studies highlight the relevance of factor IVs even when the number of IVs exceeds the sample size (Bai and Ng 2010; Kapetanios and Marcellino 2010). Furthermore, in Columns 9 to 11, we employ more conservative sets of IVs by collapsing standard IVs to one dimension and generating a one-moment condition. Roodman (2009b) suggests that collapsed IVs provide “the basis for some minimally arbitrary robustness and specification tests for difference and system GMM” (p. 149). In all cases, we obtain consistently significant and positive coefficients for Software-as-a-Service (SaaS) on energy efficiency, but not for Infrastructure-as-a-Service (IaaS), which is consistent with our main findings. These results indicate that our system-GMM models produce valid estimates that are not driven by instrument proliferation.

Second, we replicate the results in Table 4 (based on the system GMM model) using the difference GMM model. The results are reported in Table C2. Assuming that the error terms are serially uncorrelated, the difference GMM model takes the first difference in the original specification to eliminate industry-specific heterogeneity (fixed effects) and uses lagged values of endogenous variables as internal IVs for the first difference equation (Arellano and Bond 1991). However, lagged levels may not be good IVs for the first differences when the underlying variables persist over time (Arellano and Bover 1995; Blundell and Bond 1998). On the other hand, the system GMM estimates a two-equation system of regressions in levels and first differences that use lagged values in first differences and levels as IVs, respectively. Thus, we believe that the system GMM model has a substantial benefit over the difference GMM when estimating such a persistent series as energy efficiency (Blundell and Bond 1998). Nevertheless, as shown in Table C2, the estimation results using the difference GMM model are identical to those in Table 4, based on the system GMM model.

Finally, although our system GMM model has advantages in accounting for the dynamic characteristics of energy efficiency, industry-level heterogeneity, and endogeneity of production inputs, we further test whether our findings are robust to alternative panel models. Table C3 reports the estimation results using three panel models: (i) a fixed-effects model with robust standard errors clustered at the industry level (Columns 1–3), (ii) feasible generalized least squares (FGLS) (Columns 4–6), and (iii) ordinary least squares with panel-corrected standard errors (OLS-PCSE) (Columns 7–9). Given that observations for the same industry for 21 years might not be independent, clustered standard errors allow for correlations in errors across different years within an industry. In addition, the FGLS and OLS-PCSE models are widely used to estimate cross-sectional and time-series data to account for correlation structures other than independent ones (e.g., Han et al. 2011; Ren and Dewan 2015). In estimating FGLS and OLS-PCSE with industry and year fixed effects, we consider the heteroscedastic error structure with panel-specific first-order autocorrelation (AR1). In Table C3, the results from the alternative panel models confirm that our main findings remain unchanged, as the coefficient of SaaS is positively significant after 2006 and its magnitude is even larger after 2010.

Taken together, our findings on the contribution of cloud-based IT services (SaaS, in particular) to energy efficiency are not likely to be driven by any modeling choices in the system GMM model.

Endogeneity of Cloud Computing Investment

As discussed above, in our main analysis, we employ a structural model based on the system GMM to account for the endogeneity of production inputs, as commonly adopted in the IT productivity literature (e.g., Chang and Gurbaxani 2013; Chung et al. 2019; Tambe and Hitt 2012). We further address the endogeneity of cloud computing investment using alternative approaches using (i) a difference-in-differences (DID)-style model and (ii) an IV-based three-stage least squares (3SLS) model.

First, we employ a DID-style model. Conceptually, an ideal DID model quantifies the net effect of the treatment as the difference in the change in an outcome of interest after the treatment (e.g., the adoption of cloud computing) is applied, compared to the change in the control group unaffected by the treatment. In our context, we consider the pre- and post-cloud computing era based on the launch of the first commercial cloud service, Amazon Web Services (AWS), in 2006. However, it is challenging to distinguish between the treatment and control groups in our context because we do not have any information about the timing of cloud service adoption in U.S. industries. In such cases, prior studies have defined the treatment group as subjects falling in the top quartile of the variable of interest in the pretreatment period. A case in point is recent studies that examine the impacts of COVID-19 on organizational performance. First, no individuals or organizations have avoided the reach of the pandemic in 2020, which makes the whole year the post-period, similar to our context. Second, these studies adapted the classic DID approach by constituting treatment and control groups based on subjects' pre-pandemic characteristics of interest and comparing the outcomes between the two groups before and after the COVID-19 outbreak. For instance, in examining the impact of COVID-19 on firm performance depending on firms' work-from-home (WFH) feasibility, Bai et al. (2021) define a "treatment" indicator that takes a value of one if a firm's average WFH score in the pre-COVID-19 period falls into the top quartile. Albuquerque et al. (2020) define a treatment group based on the top quartile of firms' environmental and social performance ratings before the COVID-19 outbreak.

Following these studies, we design a DID-style model by exploiting two sources of variation: (i) temporal variation before and after the launch of AWS in 2006 and (ii) cross-sectional variation across industries based on the percentage of IT outsourcing invested in cloud-based IT services in the pre-cloud computing era (before 2006), which are likely to have moved to the cloud after 2006. Specifically, we define the treatment group as the industries in the top quartile (before 2006) of the percentage of IT outsourcing invested in cloud-based IT services. This modeling approach relies on the assumption that industries that utilized IT outsourcing mainly for cloud-based IT services, such as application service provisioning and IT infrastructure provisioning services, in the pre-cloud computing era, would adopt more cloud services after 2006. For a falsification test, we also define alternative treatment groups based on the top quartile of investments in internal IT capital and total IT services outsourcing, scaled by output, before 2006.

We estimate the following DID specification for industry *i* at time *t* by considering alternative and focal treatments hierarchically:

$$EE_{it} = EE_{it-1} + After2006_t + Treatment_i + After2006_t \times Treatment_i + \tau_i + \theta_t + \varepsilon_{it}.$$

Table C4 presents the estimation results for the DID-style model. The results in Columns 1 and 2 suggest that industries that invested more intensively in internal IT capital and general IT outsourcing before 2006 do not experience an increase in energy efficiency after 2006. Instead, as shown in Columns 3 and 4, the IT outsourcing structure plays a key role in driving the increase in energy efficiency after 2006. Specifically, the industries that utilized IT outsourcing mainly for cloud-based IT services before 2006 experience a significantly larger increase in energy efficiency after 2006 (Column 3) and after 2010 (Column 4) compared to the control group. This is also supported by the model-free trend in energy efficiency over time, as shown in Figure C1. In Figure C1, one might be concerned about the parallel trend assumption, particularly during the period 1997–2001. Columns 5 to 8 replicate the DID estimations by restricting the sample period to 2002–2017, which confirms that the results remain unchanged. Overall, these findings assist in ruling out an alternative explanation that production heterogeneity based on different levels of digitalization (as reflected by intensities of IT capital and general IT outsourcing) might coincide with the positive relationship between the use of cloud computing and energy efficiency. Rather, the results support our argument that cloud-based IT services, such as application service provisioning and IT infrastructure provisioning services, that rapidly migrated to cloud environments after 2006, are indeed the main drivers of energy efficiency in U.S. industries.

Second, we explicitly assume that the use of cloud-based IT services is endogenously determined by its own IT investment, as well as the supply chain partners' use of cloud services. Specifically, the levels of cloud services—SaaS and IaaS—are modeled as a function of the one-year lagged levels of IT capital—hardware (HW) and software (SW)—and customer (downstream) industries' use of cloud services. This approach is largely consistent with Chang and Gurbaxani's (2013) model, which addresses the endogeneity of IT investment in examining its impact on technical efficiency.

Given that interorganizational systems (IOSs) enable information sharing between upstream suppliers and downstream customers, IOSs require IT investment, including cloud computing by both parties (Cheng and Nault 2007, 2012). Recently, organizations have rapidly adopted cloud computing to support their supply chain operations (Wu et al. 2013). Manuel Maqueira et al. (2019) suggest that cloud computing assimilation is positively associated with supply chain integration. Based on a survey of high-tech firms, Low et al. (2011) show that trading partner pressure significantly affects the adoption of cloud computing. A case in point is Volkswagen's implementation of its own global cloud systems built on AWS. The company highlights that "the solutions and applications currently being developed by Volkswagen are also to be made available to other companies within an open ecosystem; development work on these applications will then continue together with the other companies" (Volkswagen Newsroom 2020). Therefore, we can logically infer a positive correlation between the use of cloud computing in a focal industry and that of its supplier chain partners.

It is noteworthy that although the use of cloud computing from upstream supplier industries and downstream customer industries may satisfy the relevance condition of IVs, the former is likely to violate the exclusion restriction condition. Specifically, cloud computing investment made by upstream suppliers might directly influence the downstream industry's energy efficiency, possibly due to supplier IT spillovers as an unmeasured increase in the quality of traded intermediate inputs (Ba and Nault 2017; Cheng and Nault 2007). On the other hand, customer IT spillovers result mainly from improved channel coordination and information sharing, rather than from the direct inflow of goods and services (Cheng and Nault 2012). Taken together, we expect the *use of cloud services by customer industries* to be positively correlated with the use of cloud services by the focal industry, and we do not have a strong reason to believe that *the cloud services of downstream customers* directly influence energy use and efficiency in an upstream industry after controlling for output (thereby, IT spillovers related to productivity) and production factors. Thus, we instrument the focal industry's use of cloud services with the *customer (downstream) industries' use of cloud computing*.

Following Cheng and Nault (2012), we measure the customer-side (downstream) use of cloud services by summing up all customer industries' cloud-based IT services weighted by the percentage of the focal industry's output, which is used as intermediate inputs for each customer industry based on input-output use tables. We also normalize the customer industries' use of cloud services by the focal industry's labor compensation to be consistent with other production inputs. In Table C5, we estimate the endogenous demand function of cloud-based IT services, determined by prior IT investments and customer industries' use of cloud services, simultaneously with our main energy efficiency function (Equation 4 in the main manuscript), using 3SLS. The 3SLS model combines two-stage least squares (2SLS) with seemingly unrelated regressions, which is widely adopted when dealing with endogeneity and contemporaneous cross-equation correlations between error terms (Kuruzovich et al. 2008). In Column 1, an industry's cloud service intensity is positively associated with lagged IT intensity and lagged customer industries' cloud-based IT service intensity. In Columns 2 and 3, SaaS and IaaS investments seem to be driven mainly by prior SW and HW investments as well as customers' SaaS and IaaS investments, respectively. Importantly, Columns 4–8 show the estimation results for our main energy efficiency function after accounting for the endogeneity of cloud computing investment. The 3SLS estimations yield results qualitatively similar to the main results reported in Table 4, substantiating the robustness of our findings.

Taken together, we believe that the series of additional analyses based on the DID and IV estimations that corroborate our main findings can significantly alleviate concerns about the endogeneity of cloud computing investment.

Measurement Errors in Cloud Computing and Energy Efficiency

Although our classification between cloud-based and non-cloud IT services reported in Table 3 is based on a close examination of the definitions of the detailed product/service categories, one might be concerned about a possible measurement error associated with cloud-based IT services. Similar to cloud-based IT services as the main independent variable, our main dependent variable, energy efficiency, might also be vulnerable to the stochastic energy frontier modeling. Thus, we test and discuss the sensitivity of our estimate to the measurement errors.

First, we consider alternative assumptions for measuring industry-level cloud-based IT services. Note that we measure an industry's cloud-based IT services by summing up the cloud services purchased from each "supplier" industry, which are calculated by multiplying intermediate inputs from a supplier industry (obtained from input-output tables) with the percentage of cloud services in the supplier industry's sales (obtained from Economic Census). While the intermediate inputs (the first component) are available annually, the sales percentage of cloud services (the second component) is available in 2002, 2007, and 2012, and thus needs to be interpolated over 1997–2017, which might be subject to an assumption of trends over the years.

To check whether our results are sensitive to interpolation methods, we employ several alternative approaches to interpolate the percentage of cloud services in the industry's sales, including (i) linear interpolation (our main specification), (ii) cubic spline interpolation, (iii) interpolation proportional to the IT share of total capital, and (iv) interpolation proportional to the AWS's sales share of Amazon's total sales. As illustrated in Figure C2, all alternative measures of cloud computing (SaaS and IaaS) follow a similar trend over the years, although the cloud computing measurement based on the growth trend of AWS, the global and North American market leaders of public cloud services, may reflect the recent rapid growth of the cloud services market. In Table C6, the results remain consistent across the alternative interpolation methods for measuring industry-level cloud-based IT services.

Second, given that not all measurement errors in our cloud computing measure are observable, we further discuss how such a measurement error is unlikely to alter our estimations. See Online Appendix D for a detailed theoretical discussion on the impact of potential measurement errors.

Finally, we provide an in-depth theoretical discussion and an additional sensitivity test to assess how the unmeasured portion of energy consumption that is unrelated to cloud computing affects our estimate. Further details are provided in Online Appendix E.

Alternative Model Specifications

We further test the sensitivity of the results to an alternative measure of factor intensity and exclusion of some influential industries that could drive the main results. In the main analysis, we employed an intensity measure with labor as the denominator to avoid econometric concerns. However, the results are virtually identical when we use an alternative intensity measure with output as the denominator (see Table C7, Columns 1 to 5). Regarding influential sectors, IT service industries are both cloud computing clients and vendors and inherently have a greater amount of IT capital (e.g., data centers), which may change the way cloud computing influences output and energy consumption from other sectors. Therefore, we re-estimate our models by excluding IT services industries from the sample: the information and data processing services industry (NAICS 518, 519), and the computer systems design and related services industry (NAICS 5415). As shown in Table C7, Columns 6–10, we obtain results similar to the main findings reported in Table 4.

References

Albuquerque, R., Koskinen, Y., Yang, S., and Zhang, C. 2020. "Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash," *Review of Corporate Finance Studies* (9:3), pp. 593–621.

Arellano, M., and Bond, S. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* (58:2), pp. 277–297.

Arellano, M., and Bover, O. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics* (68:1), pp. 29–51.

Ba, S., and Nault, B. R. 2017. "Emergent Themes in the Interface Between Economics of Information Systems and Management of Technology," *Production and Operations Management* (26:4), pp. 652–666.

Bai, J. (Jianqiu), Brynjolfsson, E., Jin, W., Steffen, S., and Wan, C. 2021. "Digital Resilience: How Work-From-Home Feasibility Affects Firm Performance," *National Bureau of Economic Research Working Paper 28588*.

Bai, J., and Ng, S. 2010. "Instrumental Variable Estimation in a Data Rich Environment," *Econometric Theory* (26:6), pp. 1577–1606.

Blundell, R., and Bond, S. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* (87:1), pp. 115–143.

Chang, Y. B., and Gurbaxani, V. 2013. "An Empirical Analysis of Technical Efficiency: The Role of IT Intensity and Competition," *Information Systems Research* (24:3), pp. 561–578.

Cheng, N., and Bang, Y. 2021. “A Comment on the Practice of the Arellano-Bond/Blundell-Bond Generalized Method of Moments Estimator in IS Research,” *Communications of the Association for Information Systems* (forthcoming).

Cheng, Z. (June), and Nault, B. R. 2007. “Industry Level Supplier-Driven IT Spillovers,” *Management Science* (53:8), pp. 1199–1216.

Cheng, Z. (June), and Nault, B. R. 2012. “Relative Industry Concentration and Customer-Driven IT Spillovers,” *Information Systems Research* (23:2), pp. 340–355.

Chung, S., Animesh, A., Han, K., and Pinsonneault, A. 2019. “Software Patents and Firm Value: A Real Options Perspective on the Role of Innovation Orientation and Environmental Uncertainty,” *Information Systems Research* (30:3), pp. 1073–1097.

Han, K., Kauffman, R., and Nault, B. 2011. “Returns to Information Technology Outsourcing,” *Information Systems Research* (22:4), pp. 824–840.

Kapetanios, G., and Marcellino, M. 2010. “Factor-GMM Estimation with Large Sets of Possibly Weak Instruments,” *Computational Statistics & Data Analysis* (54:11), pp. 2655–2675.

Kuruzovich, J., Viswanathan, S., Agarwal, R., Gosain, S., and Weitzman, S. 2008. “Marketspace or Marketplace? Online Information Search and Channel Outcomes in Auto Retailing,” *Information Systems Research* (19:2), pp. 182–201.

Low, C., Chen, Y., and Wu, M. 2011. “Understanding the Determinants of Cloud Computing Adoption,” *Industrial Management & Data Systems* (111:7), pp. 1006–1023.

Manuel Maqueira, J., Moyano-Fuentes, J., and Bruque, S. 2019. “Drivers and Consequences of an Innovative Technology Assimilation in the Supply Chain: Cloud Computing and Supply Chain Integration,” *International Journal of Production Research* (57:7), pp. 2083–2103.

Ren, F., and Dewan, S. 2015. “Industry-Level Analysis of Information Technology Return and Risk: What Explains the Variation?,” *Journal of Management Information Systems* (32:2), pp. 71–103.

Roodman, D. 2009a. “A Note on the Theme of Too Many Instruments,” *Oxford Bulletin of Economics and Statistics* (71:1), pp. 135–158.

Roodman, D. 2009b. “How to Do Xtabond2: An Introduction to Difference and System GMM in Stata,” *Stata Journal* (9:1), pp. 86–136.

Tambe, P., and Hitt, L. M. 2012. “The Productivity of Information Technology Investments: New Evidence from IT Labor Data,” *Information Systems Research* (23:3-part 1), pp. 599–617.

Volkswagen Newsroom. 2020. “Volkswagen Steps up Development of Industrial Cloud,” *Volkswagen Newsroom*.

Wu, Y., Cegielski, C. G., Hazen, B. T., and Hall, D. J. 2013. “Cloud Computing in Support of Supply Chain Information System Infrastructure: Understanding When to Go to the Cloud,” *Journal of Supply Chain Management* (49:3), pp. 25–41.

Table C1: Sensitivity Analysis to Instruments in the System GMM Models

Dependent variable: Energy efficiency	System GMM										
	Standard Instruments					Principal Components-based Instruments			Collapsed Instruments		
Length of lags as instruments:	One	Two	Three	Four	Five	Three	Four	Five	Three	Four	Five
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lagged efficiency	0.717***	0.713***	0.719***	0.717***	0.717***	0.616***	0.623***	0.616***	0.779***	0.742***	0.725***
	(0.052)	(0.048)	(0.041)	(0.039)	(0.038)	(0.083)	(0.083)	(0.084)	(0.081)	(0.082)	(0.073)
IT intensity	-0.011**	-0.010**	-0.006**	-0.005*	-0.005**	-0.012	-0.017	-0.018	-0.014	-0.017	-0.020
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.013)	(0.012)	(0.012)	(0.018)	(0.018)	(0.017)
Non-IT intensity	0.019***	0.016***	0.011***	0.008**	0.008***	0.012	0.013	0.013	0.029	0.034	0.035
	(0.006)	(0.006)	(0.004)	(0.003)	(0.003)	(0.012)	(0.013)	(0.013)	(0.022)	(0.023)	(0.022)
Other intermediate inputs intensity	-0.024***	-0.022***	-0.016**	-0.013*	-0.015**	-0.047**	-0.046**	-0.047**	-0.049	-0.048	-0.050
	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.020)	(0.019)	(0.020)	(0.032)	(0.032)	(0.031)
SaaS intensity	0.023***	0.023**	0.020**	0.018*	0.017**	0.075**	0.066**	0.065**	0.020*	0.020*	0.018*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.034)	(0.031)	(0.031)	(0.011)	(0.011)	(0.011)
IaaS intensity	0.006	-0.000	-0.002	-0.002	-0.003	-0.031	-0.024	-0.022	-0.020	-0.026	-0.022
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.036)	(0.032)	(0.032)	(0.018)	(0.019)	(0.019)
Non-cloud IT services intensity	-0.017*	-0.011	-0.011*	-0.009	-0.007	-0.031	-0.029	-0.029	0.033	0.047*	0.043*
	(0.010)	(0.008)	(0.007)	(0.006)	(0.005)	(0.021)	(0.018)	(0.018)	(0.027)	(0.026)	(0.024)
Number of instruments	286	412	531	643	748	110	123	123	48	55	62
Arellano-Bond test for AR(2)	0.838	0.837	0.833	0.831	0.832	0.876	0.862	0.858	0.856	0.872	0.865
Instrument validity test	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.073	0.114	0.407
Observations	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table C2: Estimation Results of Difference GMM Models

Dependent variable: Energy efficiency	Difference GMM									
	Full Sample				Time-Split Analysis					
					1997-2005		2006-2017		2010-2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged efficiency	0.632***	0.628***	0.630***	0.623***	0.570***	0.496***	0.569***	0.553***	0.505***	0.460***
	(0.082)	(0.078)	(0.073)	(0.072)	(0.123)	(0.116)	(0.060)	(0.057)	(0.062)	(0.056)
IT intensity	0.027	-0.012	-0.030		0.034		-0.114*		-0.027	
	(0.026)	(0.028)	(0.028)		(0.042)		(0.060)		(0.062)	
HW intensity				-0.026		0.003		-0.096***		-0.080
				(0.026)		(0.067)		(0.036)		(0.052)
SW intensity				0.002		0.047		-0.041		0.009
				(0.017)		(0.033)		(0.042)		(0.046)
Non-IT intensity	0.011	0.029	0.017	0.037	0.115	-0.013	0.042	0.071	-0.048	-0.022
	(0.058)	(0.057)	(0.058)	(0.056)	(0.177)	(0.147)	(0.103)	(0.081)	(0.138)	(0.131)
Other intermediate inputs intensity	0.020	0.007	0.013	0.002	0.073	0.023	0.041	0.076	-0.007	0.042
	(0.050)	(0.049)	(0.051)	(0.046)	(0.115)	(0.094)	(0.086)	(0.073)	(0.094)	(0.097)
Cloud-based IT services intensity	0.007	-0.004			-0.025		0.096**		0.136***	
	(0.044)	(0.037)			(0.094)		(0.046)		(0.049)	
SaaS intensity			0.027**	0.020*		0.005		0.232***		0.318***
			(0.011)	(0.010)		(0.013)		(0.088)		(0.113)
IaaS intensity			-0.014	-0.002		0.093		-0.103*		-0.148*
			(0.035)	(0.034)		(0.062)		(0.062)		(0.078)
Non-cloud IT services intensity		0.004	-0.009	-0.008	-0.030	-0.068	-0.130***	-0.168***	-0.107*	-0.152**
		(0.034)	(0.034)	(0.036)	(0.067)	(0.078)	(0.048)	(0.044)	(0.061)	(0.064)
Arellano-Bond test for AR(2)	0.846	0.812	0.834	0.830	0.642	0.664	0.557	0.633	0.892	0.918
Instrument validity test	1.000	1.000	1.000	1.000	0.803	0.999	1.000	1.000	0.998	1.000
Observations	1083	1083	1083	1083	399	399	684	684	456	456

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table C3: Estimation Results of Alternative Panel Models

Dependent variable: Energy efficiency	Fixed Effects Model with Clustered Standard Errors			FGLS with Heteroscedastic and Panel-Specific AR1 Errors			OLS-PCSE with Heteroscedastic and Panel-Specific AR1 Errors		
	1997-2005	2006-2017	2010-2017	1997-2005	2006-2017	2010-2017	1997-2005	2006-2017	2010-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged efficiency	0.484***	0.617***	0.534***	0.508***	0.587***	0.448***	0.431***	0.581***	0.535***
	(0.093)	(0.034)	(0.050)	(0.039)	(0.028)	(0.032)	(0.062)	(0.050)	(0.071)
HW intensity	0.000	-0.039*	-0.074**	0.034	-0.023**	-0.056***	0.017	-0.042***	-0.079***
	(0.056)	(0.021)	(0.032)	(0.025)	(0.010)	(0.013)	(0.040)	(0.016)	(0.021)
SW intensity	0.035	-0.011	0.028	0.015	-0.012	0.029**	0.037*	-0.009	0.047**
	(0.026)	(0.016)	(0.026)	(0.014)	(0.009)	(0.013)	(0.020)	(0.015)	(0.021)
Non-IT intensity	-0.020	0.025	-0.009	-0.021	-0.009	-0.039	0.018	0.022	-0.017
	(0.079)	(0.059)	(0.110)	(0.041)	(0.020)	(0.024)	(0.054)	(0.033)	(0.044)
Other intermediate inputs intensity	0.042	0.029	-0.023	0.062***	0.028*	0.001	0.076**	0.046*	-0.005
	(0.060)	(0.038)	(0.058)	(0.024)	(0.016)	(0.019)	(0.039)	(0.027)	(0.039)
SaaS intensity	0.007	0.097***	0.256***	0.010	0.121***	0.234***	0.005	0.117***	0.267***
	(0.012)	(0.029)	(0.057)	(0.007)	(0.028)	(0.043)	(0.010)	(0.036)	(0.064)
IaaS intensity	0.062	-0.041*	-0.151***	0.053**	-0.047**	-0.139***	0.047	-0.056**	-0.164***
	(0.040)	(0.023)	(0.041)	(0.021)	(0.021)	(0.036)	(0.031)	(0.027)	(0.049)
Non-cloud IT services intensity	-0.057	-0.077**	-0.069	-0.064***	-0.079***	-0.053***	-0.078**	-0.098***	-0.079**
	(0.060)	(0.030)	(0.045)	(0.020)	(0.014)	(0.017)	(0.038)	(0.023)	(0.033)
Within R-squared	0.350	0.425	0.361						
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	456	684	456	456	684	456	456	684	456

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. * p<0.1, ** p<0.05, *** p<0.01.

Table C4: Estimation Results of the DID-Style Model

Dependent variable: Energy efficiency	Fixed Effects Model with Clustered Standard Errors							
	1997–2017				2002–2017			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged efficiency	0.685***	0.682***	0.674***	0.674***	0.654***	0.657***	0.646***	0.637***
	(0.046)	(0.046)	(0.048)	(0.048)	(0.041)	(0.041)	(0.040)	(0.041)
Treatment (industries with higher IT capital intensity before 2006) x After 2006	0.003	-0.006	-0.005		0.002	0.016	0.016	
	(0.016)	(0.014)	(0.012)		(0.018)	(0.021)	(0.017)	
Treatment (industries with higher high IT outsourcing intensity before 2006) x After 2006		0.014	0.025*			-0.021	-0.010	
		(0.014)	(0.014)			(0.019)	(0.018)	
Treatment (industries with higher percentage of IT outsourcing for cloud-based IT services before 2006) x After 2006			0.040***				0.044**	
			(0.013)				(0.018)	
Treatment (industries with higher IT capital intensity before 2006) x After 2010				-0.004				0.007
				(0.010)				(0.011)
Treatment (industries with higher high IT outsourcing intensity before 2006) x After 2010				0.014				-0.009
				(0.011)				(0.0011)
Treatment (industries with higher percentage of IT outsourcing for cloud-based IT services before 2006) x After 2010				0.041***				0.039***
				(0.012)				(0.014)
Within R-squared	0.514	0.514	0.519	0.519	0.449	0.450	0.457	0.459
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,140	1,140	1,140	1,140	855	855	855	855

Notes: Robust standard errors clustered at the industry level are in parentheses. All intensity variables are log-transformed. Treatment and after-period indicators are absorbed by industry and year fixed effects, respectively. * p<0.1, ** p<0.05, *** p<0.01.

Table C5: Estimation Results of the 3SLS Model

	Full Sample				Full Sample		1997-2005	2006-2017	2010-2017
Dependent variable:	Cloud-based IT services intensity	SaaS intensity	IaaS intensity	*Dependent variable:*	Energy efficiency				
	(1)	(2)	(3)		(4)	(5)	(6)	(7)	(8)
Lagged IT intensity	0.180***			Lagged efficiency	0.681***	0.683***	0.486***	0.618***	0.529***
	(0.036)				(0.022)	(0.022)	(0.044)	(0.054)	(0.062)
Lagged HW intensity		0.091*	0.110***	IT intensity	-0.007				
		(0.051)	(0.040)		(0.011)				
Lagged SW intensity		0.092**	0.018	HW intensity		-0.004	0.006	-0.078*	-0.063
		(0.041)	(0.033)			(0.011)	(0.037)	(0.042)	(0.056)
Lagged customer industries′ Cloud-based IT services intensity	0.237***			SW intensity		-0.006	0.029	0.045	0.069*
	(0.041)					(0.010)	(0.025)	(0.042)	(0.038)
Lagged customer industries′ SaaS intensity		0.477***	-0.109***	Non-IT intensity	0.018	0.004	-0.031	0.033	-0.020
		(0.051)	(0.041)		(0.021)	(0.022)	(0.065)	(0.067)	(0.062)
Lagged customer industries′ IaaS intensity		-0.184***	0.438***	Other intermediate inputs intensity	-0.018	-0.018	0.042	0.032	-0.027
		(0.065)	(0.052)		(0.019)	(0.016)	(0.039)	(0.071)	(0.049)
				Cloud-based IT services intensity	0.046				
					(0.045)				
				SaaS intensity		0.050**	0.024	1.614***	1.086**
						(0.021)	(0.030)	(0.391)	(0.492)
				IaaS intensity		0.026	0.090*	-0.748***	-0.578**
						(0.031)	(0.053)	(0.226)	(0.238)
				Non-cloud IT services intensity	-0.004	-0.007	-0.058	-0.086	-0.066
					(0.023)	(0.021)	(0.040)	(0.163)	(0.245)
Industry fixed effects	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes
Observations	1,120	1,120	1,120		1,120	1,120	448	672	448

Notes: Standard errors are in parentheses. All intensity variables are log-transformed. One industry (NAICS 622 – hospitals) that does not have downstream customer industries is excluded from the 3SLS model. Columns (1) and (4) are estimated simultaneously, and columns (2), (3), and (5) are estimated simultaneously; The full results of 3SLS for the time-split analysis (Columns 6 to 8) are available upon request. * p<0.1, ** p<0.05, *** p<0.01.

Table C6: Sensitivity Tests for the Measurement of Cloud Computing

	System GMM											
Dependent variable: Energy efficiency	Linear Interpolation (Main Specification)			Cubic Spline Interpolation			Interpolation by IT Share of Total Capital			Interpolation by AWS Sales Share of Amazon's Total Sales		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IT intensity	-0.010**	-0.010**		-0.010**	-0.010**		-0.010**	-0.010**		-0.010**	-0.009**	
	(0.004)	(0.004)		(0.004)	(0.004)		(0.004)	(0.004)		(0.005)	(0.004)	
HW intensity			-0.011			-0.011			-0.009			-0.009
			(0.007)			(0.007)			(0.007)			(0.006)
SW intensity			0.001			0.001			-0.000			0.001
			(0.005)			(0.005)			(0.005)			(0.005)
Cloud-based IT services intensity	0.020***			0.021***			0.021***			0.018***		
	(0.007)			(0.007)			(0.007)			(0.007)		
SaaS intensity		0.023**	0.019***		0.026***	0.023***		0.030***	0.029***		0.013**	0.012**
		(0.009)	(0.007)		(0.009)	(0.007)		(0.009)	(0.010)		(0.005)	(0.006)
IaaS intensity		-0.000	-0.006		-0.002	-0.009		-0.005	-0.014		0.007	-0.003
		(0.009)	(0.008)		(0.009)	(0.008)		(0.009)	(0.009)		(0.007)	(0.007)
SaaS × HW intensity			-0.006			-0.005			-0.008			-0.001
			(0.005)			(0.005)			(0.005)			(0.003)
SaaS × SW intensity			0.001			0.001			0.003			-0.000
			(0.004)			(0.004)			(0.007)			(0.003)
IaaS × HW intensity			0.015***			0.015***			0.018***			0.010**
			(0.006)			(0.006)			(0.007)			(0.005)
IaaS × SW intensity			-0.010			-0.010			-0.012			-0.011
			(0.007)			(0.007)			(0.010)			(0.007)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Arellano-Bond test for AR(2)	0.822	0.837	0.813	0.822	0.824	0.789	0.809	0.785	0.729	0.824	0.859	0.843
Instrument validity test	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Observations	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140	1,140

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

Table C7: Sensitivity Analysis to Alternative Model Specifications

Dependent variable: Energy efficiency	System GMM									
	Alternative Intensity Measures					Exclusion of IT Services Industries				
	Full sample		1997-2005	2006-2017	2010-2017	Full sample		1997-2005	2006-2017	2010-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged efficiency	0.721***	0.717***	0.625***	0.739***	0.770***	0.710***	0.709***	0.616***	0.717***	0.741***
	(0.048)	(0.044)	(0.086)	(0.036)	(0.052)	(0.054)	(0.048)	(0.088)	(0.039)	(0.055)
IT intensity	-0.010**					-0.013**				
	(0.005)					(0.005)				
HW intensity		-0.008*	-0.024*	-0.007	-0.005		-0.008	-0.025*	-0.011	-0.009
		(0.005)	(0.013)	(0.006)	(0.007)		(0.005)	(0.014)	(0.007)	(0.008)
SW intensity		0.001	0.013	-0.000	-0.006		-0.002	0.013	-0.003	-0.008
		(0.004)	(0.011)	(0.005)	(0.007)		(0.004)	(0.012)	(0.005)	(0.007)
Non-IT intensity	0.015**	0.014***	0.020*	0.014**	0.017**	0.018***	0.018***	0.024*	0.021***	0.024***
	(0.006)	(0.005)	(0.011)	(0.007)	(0.008)	(0.007)	(0.006)	(0.012)	(0.006)	(0.007)
Other intermediate inputs intensity	-0.030	-0.027	-0.032	-0.038*	-0.042**	-0.024***	-0.024***	-0.030**	-0.030***	-0.031**
	(0.020)	(0.017)	(0.027)	(0.019)	(0.021)	(0.008)	(0.008)	(0.012)	(0.009)	(0.013)
Cloud-based IT services intensity	0.022**					0.021***				
	(0.010)					(0.007)				
SaaS intensity		0.020**	0.014	0.027	0.054**		0.018**	0.012	0.025*	0.040**
		(0.008)	(0.011)	(0.018)	(0.027)		(0.009)	(0.012)	(0.013)	(0.017)
IaaS intensity		0.001	-0.005	0.007	-0.013		0.002	-0.004	0.010	0.003
		(0.010)	(0.014)	(0.012)	(0.019)		(0.010)	(0.012)	(0.010)	(0.012)
Non-cloud IT services intensity	-0.011	-0.009	0.004	-0.026***	-0.028***	-0.015	-0.011	0.002	-0.027***	-0.031***
	(0.011)	(0.009)	(0.014)	(0.009)	(0.009)	(0.009)	(0.008)	(0.011)	(0.008)	(0.010)
Arellano-Bond test for AR(2)	0.830	0.838	0.595	0.400	0.825	0.778	0.789	0.582	0.386	0.844
Instrument validity test	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Observations	1,140	1,140	456	684	456	1,100	1,100	440	660	440

Notes: Robust standard errors are in parentheses. All intensity variables are log-transformed. We report the p-values of the test statistics for serial correlation (Arellano-Bond test) and instrument validity (Hansen test of overidentification restrictions), respectively. Year dummy variables are suppressed for brevity. * p<0.1, ** p<0.05, *** p<0.01.

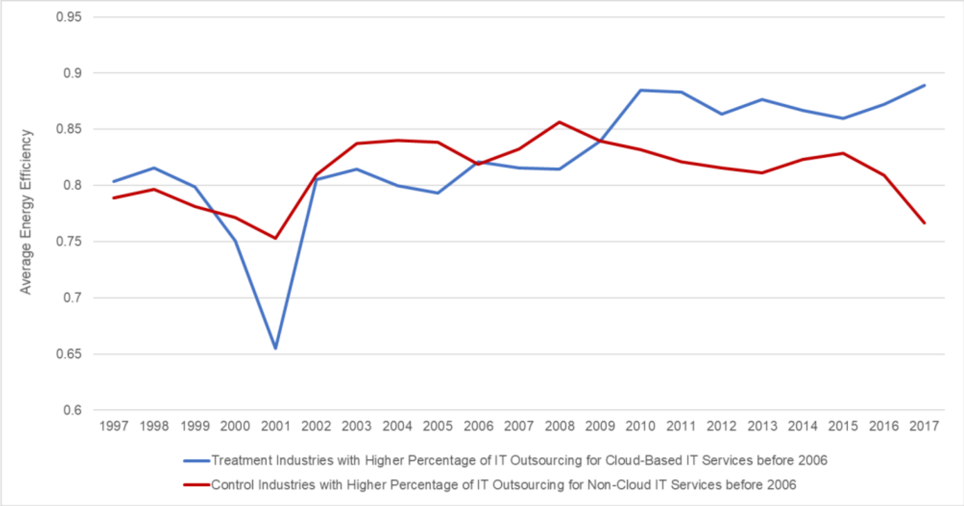

Figure C1: Trends in Energy Efficiency by IT Outsourcing Composition in the Pre-Cloud Computing Era (Before 2006)

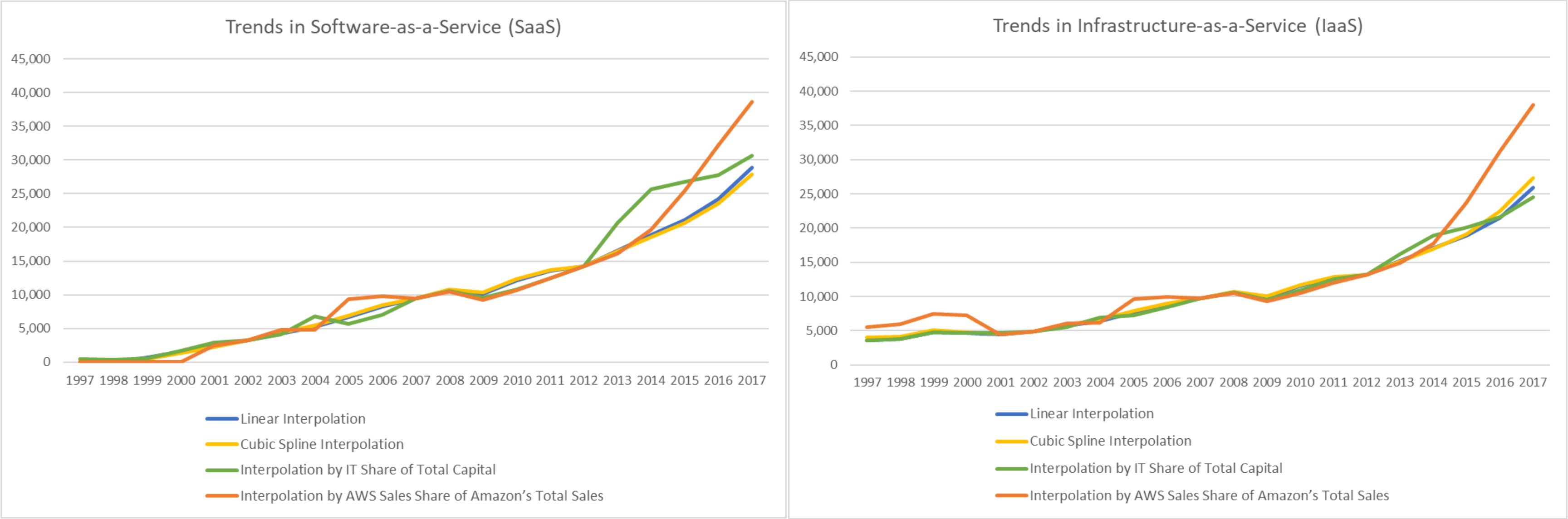

Figure C2: Trends in Cloud Computing in U.S. Industries by Alternative Measurement

Online Appendix D: Discussion on Measurement Error in Cloud Computing

One of the objectives of this study is to propose a novel approach to measure industry-level cloud computing services by combining industrial product sales with inter-industry purchase flows. Nonetheless, our proposed measures, based on industrial annual accounts published by federal agencies, are not free from measurement errors. By definition, we cannot observe measurement errors in our cloud computing estimates. In this section, we discuss how such a measurement error could affect our estimations of the impact of cloud computing on energy efficiency.

Consider a simple "true" model with one independent variable:

$$y = \beta x + \varepsilon \tag{a}$$

where y is the main dependent variable (energy efficiency), x is the explanatory variable of interest (cloud computing), and ε is a random error. Suppose we have data on a constructed variable of cloud computing ($\tilde{x}$) with an additive measurement error:

$$\tilde{x} = x + u. \tag{b}$$

For simplicity, we assume that the measurement error (u) has a mean of zero and is uncorrelated with the dependent variable (y) and the random error (ε).

By substituting (b) into (a), the following equation is obtained:

$$y = \beta(\tilde{x} - u) + \varepsilon = \beta\tilde{x} + (\varepsilon - u).$$

Then OLS estimator will be:

$$\tilde{\beta} = \frac{cov(\tilde{x}, y)}{var(\tilde{x})} = \frac{cov(x+u, \beta x+\varepsilon)}{var(x+u)}.$$

Based on this estimator, we consider two cases. First, if the measurement error is uncorrelated with the true explanatory variable ($\sigma_{xu} = 0$), then the OLS estimator is

$$plim(\tilde{\beta}) = \frac{\beta\sigma_x^2}{\sigma_x^2+\sigma_u^2} = \left(\frac{\sigma_x^2}{\sigma_x^2+\sigma_u^2}\right)\beta.$$

Given that $0 < \frac{\sigma_x^2}{\sigma_x^2+\sigma_u^2} < 1$, the estimated coefficient $\tilde{\beta}$ is biased toward zero, which is known as the attenuation bias.

Second, if the measurement error is correlated with the true explanatory variable ($\sigma_{\mathrm{xu}} \neq 0$), then the OLS estimator is

$$plim(\tilde{\beta}) = \frac{\beta(\sigma_x^2+\sigma_{\mathrm{xu}})}{\sigma_x^2+\sigma_u^2+2\sigma_{\mathrm{xu}}} = \left(1 - \frac{\sigma_u^2+\sigma_{\mathrm{xu}}}{\sigma_x^2+\sigma_u^2+2\sigma_{\mathrm{xu}}}\right)\beta = (1 - b_{u\tilde{x}})\beta,$$

where $b_{u\tilde{x}} \equiv \frac{\sigma_u^2+\sigma_{\mathrm{xu}}}{\sigma_x^2+\sigma_u^2+2\sigma_{\mathrm{xu}}}$. Note that the numerator in $b_{u\tilde{x}}$ is the covariance between $\tilde{x}$ and u, and the denominator is the variance of $\tilde{x}$. Thus, $b_{u\tilde{x}}$ is equivalent to the coefficient of regression of u on $\tilde{x}$. The possible measurement errors are as follows:

- $b_{u\tilde{x}}$ will be zero when there is no measurement error.
- If $0 < b_{u\tilde{x}} \leq 1$, coefficient $\tilde{\beta}$ will be biased toward zero, as in the attenuation bias.
- If $b_{u\tilde{x}} < 0$, the measurement error imparts an upward bias to the estimations of cloud computing effects.
- If $b_{u\tilde{x}} > 1$, the sign of $1 - b_{u\tilde{x}}$ is negative; thus, the sign of the estimated $\tilde{\beta}$ is reversed. This case, which is what Bound and Krueger (1991) call the "mean reverting" measurement error, should be of concern when interpreting the estimates of the observed variable.

Thus, we argue that the measurement error in our cloud computing measure does not alter our main results. First, any random measurement error that is independent of the true measure of cloud computing does not influence our main findings because it biases our estimates toward zero. Therefore, our results should be interpreted as conservative.

However, a systematic measurement error in our cloud computing measure may be a concern because it may lead to a biased estimate. To clarify the discussion on the measurement error that is correlated with the true measure of cloud computing, let us assume that the "true" measure of cloud computing (x) is proportional to our measure ($\tilde{x}$) as follows:

$$x = \lambda\tilde{x}.$$

where a λ below 1 indicates that all IT services included in our classification (as in Table 3) may not always be delivered to the cloud, and a λ greater than 1 implies that our measure of cloud computing underestimates the actual utilization of cloud computing. From Equation (b), we can obtain $u = \tilde{x} - x = (1 - \lambda)\tilde{x}$, and accordingly, $\mathrm{E}(b_{u\tilde{x}}) = 1 - \lambda$. Thus, if $0 < \lambda < 1$, our estimates are likely to be biased toward zero, whereas if $\lambda > 1$, our results tend to be overestimated.

To test the sensitivity of our estimations to the degree of such a systematic error, we employ a simulation approach to estimate the empirical model (Equation 4 in the main manuscript) with a hypothetical measure of cloud computing, calculated by multiplying γ by our measure of cloud computing. This approach is consistent with a simulation-extrapolation (SIMEX) approach to address measurement error (Cook and Stefanski 1994), which adds a simulated measurement error with increasing variance to the original data, estimates statistical models with simulated error-prone datasets, and identifies a trend in the model estimates. Figure D1 shows the coefficients and confidence intervals of cloud computing in the second-stage estimations for different λ values; note that $\lambda = 1$ corresponds to the main estimation results reported in Table 4. The results suggest that the regression coefficients of cloud computing on energy efficiency are stable and consistently significant over a wide range of λ. The robustness of our estimates to measurement errors may result from the fact that our system GMM model, which utilizes instrument variables, can mitigate the effect of a measurement error (Greene 2011).

Taken together, we believe that a measurement error in our proposed measure of cloud-based IT services is unlikely to alter our findings regarding the impact of cloud computing on energy efficiency.

References

Bound, J., and Krueger, A. B. 1991. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?," *Journal of Labor Economics* (9:1), pp. 1–24.

Cook, J. R., and Stefanski, L. A. 1994. "Simulation-Extrapolation Estimation in Parametric Measurement Error Models," *Journal of the American Statistical Association* (89:428), pp. 1314–1328.

Greene, W. H. 2011. *Econometric Analysis* (7th ed.), New Jersey: Prentice Hall.

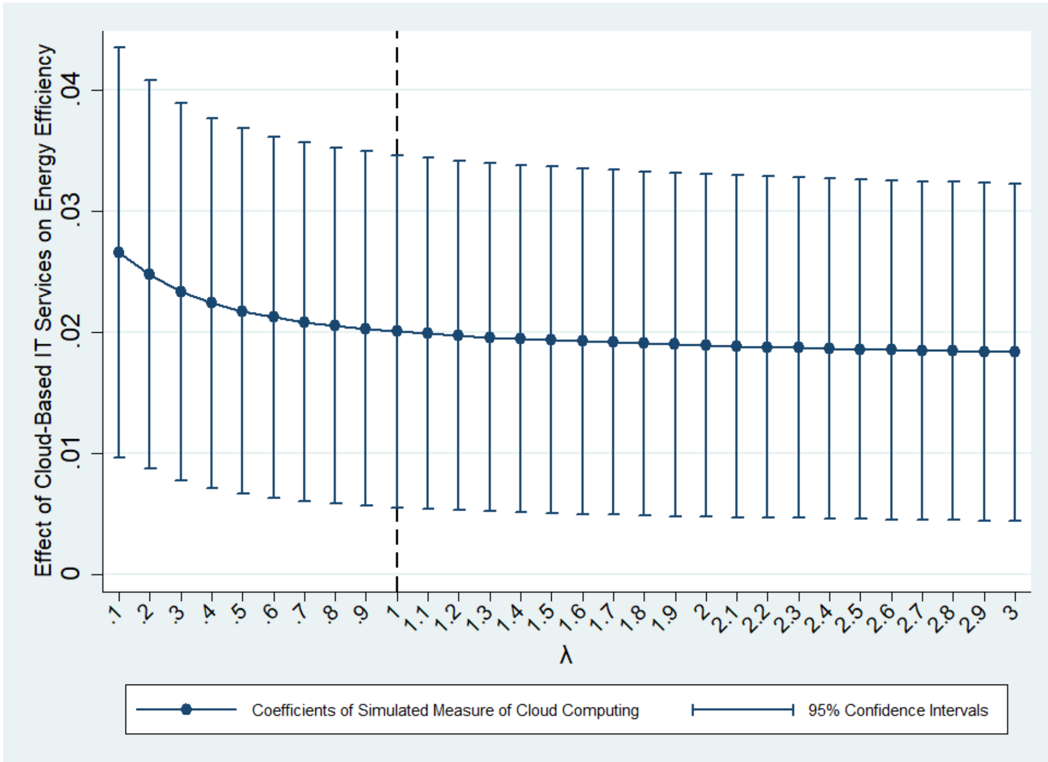

Figure D1: Estimation Results with Simulated Measure of Cloud Computing

Notes: The dashed line ($\lambda = 1$) indicates the original measure of cloud computing.

Online Appendix E: Discussion on Measurement Error in Energy Efficiency

Industrial energy use involves a range of production processes and activities to produce goods and provide services. Unfortunately, we cannot observe and decompose energy consumption by end-use, some of which might be unrelated to the use of cloud services. Thus, we explicitly discuss how such a measurement error in energy use could affect our estimates of the relationship between cloud computing and energy efficiency.

Consider an extension of our stochastic frontier model (Equation 2 in the main manuscript).

$$ln\left(E_{it}^{CC}\right) = \beta_i + k \ln Y_{it} - k\, ln\, A_{it} + c'_1\, ln\, P_K + c'_2\, ln\, P_L + c'_3\, ln\, P_M + (c'_4 - 1)\, ln\, P_E + u_{it}^{CC} + v_{it}^{CC} \tag{E1}$$

where E_{it}^{CC} is an energy input that is potentially related to cloud computing for industry *i* in year *t*, and all other variables are defined in the same manner as in Equation 2. u_{it}^{CC} is a nonnegative random variable that represents cloud computing-related energy inefficiency, which is separated from a random error, v_{it}^{CC}.

Suppose the portion (γ_{it}) of the total energy use (E_{it}) is unrelated to cloud computing ($0 < \gamma_{it} < 1$):

$$E_{it}^{CC} = E_{it}(1 - \gamma_{it}). \tag{E2}$$

By substituting (E2) into (E1), the following equation is obtained:

$$ln\left(E_{it}^{CC}\right) = ln(E_{it}(1 - \gamma_{it})) = ln(E_{it}) + ln(1 - \gamma_{it})$$

$$ln(E_{it}) = \beta_i + k \ln Y_{it} - k\, ln\, A_{it} + c'_1\, ln\, P_K + c'_2\, ln\, P_L + c'_3\, ln\, P_M + (c'_4 - 1)\, ln\, P_E + u_{it}^{CC} + v_{it}^{CC} + [-\, ln(1 - \gamma_{it})] \tag{E3}$$

where $[-\, ln(1 - \gamma_{it})]$ is larger than or equal to zero and monotonically increases with γ_{it}. Therefore, this component can be interpreted as the unobserved influence of energy use, which is unrelated to cloud computing.

If $[-\, ln(1 - \gamma_{it})]$ is independent of the cloud computing-related inefficiency term (u_{it}^{CC}) and the random error (v_{it}^{CC}), and the influence of energy use unrelated to cloud computing is captured as an inefficiency, then we can compute the overall energy efficiency (EE_{it}) and cloud computing-related energy efficiency (EE_{it}^{CC}) as

$$EE_{it} = exp\left(-\mathbb{E}\left[u_{it}^{CC} - ln(1-\gamma_{it}) \mid v_{it}^{CC}\right]\right) = exp\left(-\mathbb{E}\left[u_{it}^{CC} \mid v_{it}^{CC}\right] + ln(1-\gamma_{it})\right) = EE_{it}^{CC}(1-\gamma_{it}) \tag{E4}$$

In the second stage, we estimate Equation (E6), where Equation (E5) is intended.

$$EE_{it}^{CC} = \alpha_i + \alpha_1 EE_{it-1} + \alpha_2 \, ln\left(\frac{IT_{it}}{L_{it}}\right) + \alpha_3 \, ln\left(\frac{Non\text{-}IT_{it}}{L_{it}}\right) + \alpha_4 \, ln\left(\frac{M_{it}}{L_{it}}\right) + \alpha_5 \, ln\left(\frac{Cloud_{it}}{L_{it}}\right) + \alpha_6 \, ln\left(\frac{Non\text{-}Cloud_{it}}{L_{it}}\right) + \theta_t + \varepsilon_{it} \tag{E5}$$

$$EE_{it} = \alpha'_i + \alpha'_1 EE_{it-1} + \alpha'_2 \, ln\left(\frac{IT_{it}}{L_{it}}\right) + \alpha'_3 \, ln\left(\frac{Non\text{-}IT_{it}}{L_{it}}\right) + \alpha'_4 \, ln\left(\frac{M_{it}}{L_{it}}\right) + \alpha'_5 \, ln\left(\frac{Cloud_{it}}{L_{it}}\right) + \alpha'_6 \, ln\left(\frac{Non\text{-}Cloud_{it}}{L_{it}}\right) + \theta_t + (1-\gamma_{it})\varepsilon_{it} \tag{E6}$$

where $\alpha' \equiv \alpha(1-\gamma_{it})$. Given $0 < \gamma_{it} < 1$, this case will lead to an attenuation bias toward zero (while the sign remains unchanged), and our estimate would be underestimated and therefore conservative.

If $[-\, ln(1-\gamma_{it})]$ is correlated with the cloud computing-related inefficiency term (u_{it}^{CC}) and random error (v_{it}^{CC}), it is difficult to trace the consequences analytically. Thus, we adopt an alternative approach to empirically test how the influence of energy use unrelated to cloud computing affects the measurement of energy efficiency and, in turn, our second-stage estimation to identify the relationship between cloud computing use and the measured energy efficiency. Given that cloud-unrelated energy use is unobservable by nature, we borrow the empirical approach used by Hitt (1999) to remove the shared variance of the two variables. Specifically, we regress the logarithm of energy use on the logarithm of cloud computing during the sample period. We then consider the residual of this regression to be proportional to the energy use uncorrelated to cloud computing after netting out the variance shared by the purchased services for cloud computing. In the first-stage estimation of the energy stochastic frontier model, we explicitly model the variance of the inefficiency term and idiosyncratic random error as a function of the residual (as a proxy for energy use unexplained by cloud computing), which is subsequently included as the dependent variable in the second-stage estimations. In doing so, we use Stata's fpanel package to estimate panel stochastic frontier models (Belotti et al. 2013).

For comparison, Column 1 of Table E1 replicates Column 5 of Table B1. In Columns 2 and 3, we find that the cloud-uncorrelated component of energy consumption (i.e., the residual) is positively associated with the variance of the inefficiency term but not the variance of the random error. The correlation between the energy efficiency measured in Column 1 (our main specification) and the energy efficiency measured in Column 3 is 0.895. For the second-stage estimations, Columns 4 and 5 of Table E1 demonstrate that the coefficient of cloud computing (SaaS, in particular) is comparable to the main analysis, even after incorporating cloud-uncorrelated energy use in energy efficiency. These results imply that our main finding on the contribution of cloud computing to energy efficiency does not seem to be driven by unobserved energy use that is unrelated to the use of cloud computing.

Taken together, our theoretical discussion and sensitivity analysis imply that unobserved energy use that is unrelated to the use of cloud computing (if any) may have a negligible impact on our estimations.

References

Belotti, F., Daidone, S., Ilardi, G., and Atella, V. 2013. "Stochastic Frontier Analysis Using Stata," *Stata Journal* (13:4), pp. 719–758.

Hitt, L. M. 1999. "Information Technology and Firm Boundaries: Evidence from Panel Data," *Information Systems Research* (10:2), pp. 134–149.

Table E1: Accounting for Cloud-Unrelated Energy

Dependent variable: ln(Energy input)	First-Stage Energy Frontier Model			*Dependent variable: Energy efficiency, based on Column 3*	Second-Stage Energy Efficiency Function	
	(1)	(2)	(3)		(4)	(5)
ln(Output)	1.014***	1.005***	0.953***	Lagged efficiency	0.734***	0.736***
	(0.053)	(0.054)	(0.049)		(0.052)	(0.048)
IT share of total capital	-1.765***	-1.761***	-1.400***	IT intensity	-0.006	
	(0.345)	(0.353)	(0.320)		(0.004)	
R&D share of total capital	-0.396	-0.449	-0.013	HW intensity		-0.006
	(0.359)	(0.360)	(0.295)			(0.005)
Material share of total costs	2.576***	2.429***	2.821***	SW intensity		0.002
	(0.306)	(0.325)	(0.280)			(0.004)
Services share of total costs	4.932***	4.865***	5.073***	Non-IT intensity	0.011	0.010
	(0.244)	(0.250)	(0.228)		(0.007)	(0.006)
ln(Price index of capital input)	-0.044	-0.046	-0.028	Other intermediate inputs intensity	-0.021**	-0.020**
	(0.029)	(0.029)	(0.030)		(0.009)	(0.009)
ln(Price index of labor input)	-0.164*	-0.171*	-0.132	Cloud-based IT services intensity	0.024***	
	(0.095)	(0.095)	(0.088)		(0.008)	
ln(Price index of material input)	0.198**	0.175**	0.331***	SaaS intensity		0.019**
	(0.078)	(0.079)	(0.077)			(0.009)
ln(Price index of purchased services)	1.555***	1.567***	1.287***	IaaS intensity		0.001
	(0.225)	(0.225)	(0.225)			(0.009)
ln(Price index of energy input)	-0.156*	-0.138	-0.259***	Non-cloud IT services intensity	-0.011	-0.008
	(0.087)	(0.086)	(0.093)		(0.009)	(0.007)
Dependent variable: Variance of random error (σ_v)						
Residual of the regression of cloud computing on energy (A proxy of cloud-unrelated energy)		-0.112				
		(0.094)				
Dependent variable: Variance of inefficiency term (σ_u)						
Residual of the regression of cloud computing on energy (A proxy of cloud-unrelated energy)			0.794***			
			(0.098)			
Variance ratio $\left(=\frac{\sigma_u}{\sigma_v}\right)$	1.345***	1.422	1.138		-	-
	(0.033)					
Akaike information criterion (AIC)	331.33	331.57	248.10		-	-
Bayesian information criterion (BIC)	784.12	789.45	705.98		-	-
Industry fixed effects	Yes	Yes	Yes		Yes	Yes
Year fixed effects	Yes	Yes	Yes		Yes	Yes
Observations	1,197	1,197	1,197		1138	1138

Notes: Standard errors are in parentheses. The variance ratio is the ratio of the standard deviation of the inefficiency term (σ_v) to the standard deviation of the stochastic term (σ_u); * p<0.1, ** p<0.05, *** p<0.01.

Online Appendix F: Description of Firm-Level Survey Analysis

Although our industry-level econometric analysis allows us to estimate the economy-wide effect of cloud-based IT services on energy efficiency, it has a limitation in directly testing the underlying mechanisms through which cloud computing improves energy efficiency. Thus, we conduct an additional survey analysis by collecting firm-level data from business managers to further validate the effects of a company's use of cloud services on its energy efficiency at a more granular level. Moreover, the survey method allows us to test the underlying mechanisms in a clearer manner by measuring factors that could mediate the relationship between cloud computing and energy efficiency.

Data Collection

We recruited a survey panel in partnership with a professional market research firm in the U.S.[18] The survey was conducted online with anonymity to avoid response bias. To ensure that respondents had sufficient knowledge of the subject of interest, they were presented with screening questions on their knowledge of (i) general business activities and operations, (ii) IT usage and expenditure, (iii) cloud computing usage and expenditure, (iv) organizational performance (i.e., profit), and (v) environmental performance (i.e., energy consumption). Only respondents with moderate or higher levels of knowledge on all of those subjects could proceed with the survey. We collected 201 complete responses from business managers in the U.S. After excluding unreliable responses that reported the same option across all questions or expressed low levels of confidence in their answers (below 6 on the 10-point scale), our final survey sample includes 187 responses from the same number of firms.

The profiles of the survey sample are presented in Tables F1–F3. The sample covers a wide range of organizational sizes (Table F1) and industries (Table F3). In particular, out of 57 industries used in the

[18] The survey was conducted under the IRB exemption by the authors' institutions.

industry-level analysis, which covers the entire private nonfarm sector of the U.S. economy, business managers from 46 industries participated in the survey. No respondents reported "no use of cloud computing services," implying the pervasiveness of cloud computing services across the overall economy. Such a wide coverage allows us to generalize the results of the survey analysis. In addition, most respondents work in IT-related functions (Table F1) as top or senior managers (Table F2), ensuring that our survey participants are knowledgeable about their firm's IT and cloud computing investments as well as organizational and environmental performance.

Measurement

Table F4 presents the variables included in the survey and the corresponding questions used in the survey. Table F5 reports the summary statistics of these variables. Our measurement builds on Khuntia et al. (2018), who examine the effects of "green IT" expenditure on profit and energy reduction in IT equipment. We adapt their operationalization of the green IT budget to measure the general IT and cloud computing budgets. Additionally, we measure the relative importance of Infrastructure-as-a-Service (IaaS), compared to Software-as-a-Service (SaaS), as the percentage of cloud computing budget allocated to IaaS. The relative importance of IaaS in cloud computing investment is normalized between 0 and 1 as a percentage measure, based on mid-points of the survey responses. Following Khuntia et al. (2018), our variables are measured on the 5-point Likert scale (from 1 to 5), but a zero value is also allowed to indicate no use of IT/cloud computing or no effect.

As there is no unequivocal measure of energy efficiency (Filippini and Hunt 2015), managers from various industries may have different definitions and perceptions of energy efficiency. Thus, instead of measuring energy efficiency directly, we measure the effects of cloud computing using two variables: (i) an increase in profit and (ii) a reduction in energy consumption. We adapt the performance measures used by Khuntia et al. (2018) for these variables. By combining these variables, we measure the percentage change in energy efficiency, defined as profit per energy consumed, by summing the percentage increase in profit and percentage reduction in energy consumption, which is consistent with the following decomposition:

$$\Delta\, ln(Energy\ Efficiency) = \Delta\, ln\left(\frac{Profit}{Energy\ Consumption}\right) = \Delta\, ln(Profit) - \Delta\, ln(Energy\ Consumption).$$

To elucidate the underlying mechanisms through which the use of cloud computing services influences energy efficiency, we consider two mediating factors corresponding to our theoretical arguments in this study (see Table 1 in the main manuscript): (i) energy reduction in IT equipment and infrastructure, and (ii) operational benefits of cloud computing. The measure of energy reduction in IT equipment and infrastructure is directly adapted from Khuntia et al. (2018). To measure the operational benefits of cloud computing, we adapt Loukis et al.'s (2019) operationalization and measure the benefits of cloud computing services as “a reduction of costs and the improvement of the quality of the support of a company’s operations and business processes” (p. 38).

Empirical Model

To examine the effect of cloud computing services on energy efficiency, we regress the energy efficiency on the cloud computing budget using OLS with robust standard errors. We also consider the interaction term between the cloud computing budget and the relative importance of IaaS (the percentage of cloud computing budget allocated to IaaS) to isolate the effect of IaaS from that of other types of cloud services. Given that the relative importance of IaaS ranges between 0 and 1 as a percentage measure, the coefficient of the main term of the cloud computing budget can be interpreted as the effect of cloud services when IaaS is rarely deployed, which largely reflects the effect of SaaS. In addition, we control for the number of employees to account for differences in firm size, which might influence the usage of cloud computing.

Employing a causal mediation analysis (Imai et al. 2010), we statistically test the mediation effect by estimating the effects of the treatment variable (i.e., cloud computing) on the mediator (i.e., energy reduction in IT equipment/infrastructure, operational benefits) as well as the focal outcome variable (i.e., energy efficiency). Using the *mediation* package Stata (Hicks and Tingley 2011), we estimate the extent to which the effects of the main term of cloud computing (reflecting SaaS) and the interaction term of cloud computing and relative importance of IaaS (reflecting IaaS) are mediated by each mediator with a 95% confidence interval.

Results

Table F6 reports the results of the survey analysis. Columns 1 to 4 show the effect of cloud computing on each mediator, and Columns 5–10 present the effects of cloud computing on energy efficiency while accounting for mediating factors. Columns 1 and 3 show that cloud computing expenditure is positively associated with both energy reduction in IT equipment/infrastructure and operational benefits. To estimate the distinct effects of different types of cloud services, we additionally consider the interaction term involving cloud computing expenditure and relative importance of IaaS. As shown in Columns 2 and 4, while the interaction term (reflecting the use of IaaS) is positively and significantly associated with both energy reduction in IT equipment/infrastructure and operational benefits, the former is much greater. In contrast, the main term for cloud computing (reflecting the use of SaaS) has a significant effect only on operational benefits.

In Columns 5 and 6, we find that cloud computing expenditure is positively associated with energy efficiency, and both types of cloud services play a role in improving it, as the coefficients of the main and interaction terms are positive and significant. Importantly, Columns 7–10 show that these effects are partially mediated by each mediator. Specifically, we find that 40.7% and 26.0% of the effect of cloud computing services on energy efficiency is mediated by energy reduction in IT and operational benefits, respectively (Columns 7 and 9). However, the two mediating factors play distinct roles in different types of cloud services. In Column 8, when energy reduction in IT is considered, 61.4% of the effect of the interaction term (i.e., IaaS effect) on energy efficiency is mediated by energy reduction in IT equipment and infrastructure, whereas a very small portion (3.2%) of the effect of the main term (i.e., SaaS effect) is mediated by this factor. On the other hand, when the operational benefits of cloud computing are considered, 32.6% and 14.4% of the effects of the main (SaaS effect) and interaction (IaaS effect) terms on energy efficiency are mediated by the operational benefits, respectively (Column 10).

We conduct several robustness checks, as listed in Table F7. First, because our measure of energy efficiency is the ratio of profit to energy consumption, the positive relationship between cloud computing and energy efficiency can be derived either by an increase in profit, a decrease in energy consumption, or both. Thus, in Columns 1 and 2 of Table F7, we separately estimate the effects of cloud computing expenditure on profit and energy consumption. The results confirm that cloud computing not only increases profit but also reduces energy consumption, thereby enhancing energy efficiency. Second, one might be concerned that the use of cloud computing coincides with general IT expenditures, which may confound the estimation results. Thus, in Columns 3 to 6, we control for IT expenditure. While IT expenditure is also positively associated with energy efficiency, cloud computing services seem to have a greater effect on improvement in energy efficiency. Finally, as top management commitment plays a significant role in environmental performance (e.g., Colwell and Joshi 2013), we also control for whether the leadership team and top executives (e.g., CEO and CIO) made an explicit commitment to energy efficiency and find that the effects of cloud computing remain consistent.

In summary, the findings from the survey data of business managers are two-fold. First, general cloud services other than IaaS, which reflect SaaS, improve a company’s energy efficiency through operational benefits. Second, the use of IaaS appears to improve a company’s energy efficiency mainly by reducing energy consumption in IT equipment and IT infrastructure, while it also contributes, to a lesser extent, to energy efficiency by conferring operational benefits. These firm-level findings corroborate our industry-level findings and further substantitate the underlying mechanisms through which the use of cloud computing improves a firm’s energy efficiency.

References

Colwell, S. R., and Joshi, A. W. 2013. "Corporate Ecological Responsiveness: Antecedent Effects of Institutional Pressure and Top Management Commitment and Their Impact on Organizational Performance," *Business Strategy and the Environment* (22:2), pp. 73–91.

Filippini, M., and Hunt, L. C. 2015. "Measurement of Energy Efficiency Based on Economic Foundations," *Energy Economics* (52), pp. S5–S16.

Hicks, R., and Tingley, D. 2011. "Causal Mediation Analysis," *Stata Journal* (11:4), pp. 1–15.

Imai, K., Keele, L., and Yamamoto, T. 2010. "Identification, Inference and Sensitivity Analysis for Causal Mediation Effects," *Statistical Science* (25:1), pp. 51–71.

Khuntia, J., Saldanha, T. J. V., Mithas, S., and Sambamurthy, V. 2018. "Information Technology and Sustainability: Evidence from an Emerging Economy," *Production and Operations Management* (27:4), pp. 756–773.

Loukis, E., Janssen, M., and Mintchev, I. 2019. "Determinants of Software-as-a-Service Benefits and Impact on Firm Performance," *Decision Support Systems* (117), pp. 38–47.

Table F1: Profile of Survey Sample: Number of Employees and Functional Area

Number of Employees	Number of Participants	Functional Area	Number of Participants
20 or less	12	Information Technology	117
21 – 100	32	General Operations	25
101 – 500	54	Finance/Accounting	16
501 – 1000	63	Human Resources	13
more than 1000	26	Marketing/Sales	9
		Production/Supply Chain Management	4
		Other	3
Total	187	Total	187

Table F2: Profile of Survey Sample: Tenure and Position

Tenure	Number of Participants	Position	Number of Participants
less than 1 year	1	Owner/CEO/President	63
1 year – 3 years	25	Director	41
3 – 10 years	112	Senior Manager	41
over 10 years	49	Middle Manager	26
		Junior Manager	1
		Information Technology Specialist	12
		Other	3
Total	187	Total	187

Table F3: Industry Profile of Survey Sample

2007 NAICS Code	Industry Title	Number of Participants
113, 114, 115	Forestry, fishing, and related activities	5
211	Oil and gas extraction	6
212	Mining, except oil and gas	3
213	Support activities for mining	2
22	Utilities	10
23	Construction	8
311, 312	Food, beverage, and tobacco products	6
313, 314	Textile mills and textile product mills	1
315, 316	Apparel and leather and allied products	3
321	Wood products	2
323	Printing and related support activities	2
324	Petroleum and coal products	1
325	Chemical products	3
326	Plastics and rubber products	1
327	Nonmetallic mineral products	1
331	Primary metals	2
333	Machinery	3
334	Computer and electronic products	15
335	Electrical equipment, appliances, and components	3
336	Transportation equipment	2
337	Furniture and related products	1
42	Wholesale trade	6
44-45	Retail trade	17
482	Railroad transportation	1
485	Transit and ground passenger transportation	1
493	Warehousing and storage	1
511	Publishing industries (including software)	3
515, 517	Broadcasting and telecommunications	1
518, 519	Information and data processing services	25
521, 522	Federal Reserve banks, credit intermediation, and related activities	3
523, 525	Securities, commodity contracts, fund, trusts and other financial investments and vehicles and related activities	7
524	Insurance carriers and related activities	2
531	Real estate	3
5411	Legal services	2
5415	Computer systems design and related services	9
541 ex. 5411, 5415	Miscellaneous professional, scientific, and technical services	2
55	Management of companies and enterprises	1
61	Educational services	3
621	Ambulatory health care services	1
622-623	Hospitals and nursing and residential care facilities	2
624	Social assistance	1
711, 712	Performing arts, spectator sports, museums, and related activities	1
713	Amusements, gambling, and recreation industries	1
721	Accommodation	1
722	Food services and drinking places	5
81	Other services, except government	6
	Not Specified	2
	Total	187

Notes: Out of the 57 industries used in industry-level analysis that cover the entire private nonfarm sector of the U.S. economy, business managers from 46 industries participated in the survey.

Table F4. Variables and Measurement

Variable	Question	Reference
IT Expenditure	• What percentage of the total expenditures is allocated to IT in your company? 0 = no use of IT, 1 = 1 – 5%, 2 = 5 – 10%, 3 = 10 – 15%, 4 = 15 – 20%, 5 = more than 20%	Adapted from Khuntia et al. (2018)
Cloud Computing Expenditure	• What percentage of the IT budget is allocated to cloud computing in your company? 0 = no use of cloud computing, 1 = 1 – 5%, 2 = 5 – 10%, 3 = 10 – 15%, 4 = 15 – 20%, 5 = more than 20%	Adapted from Khuntia et al. (2018)
Relative Importance of IaaS	• What percentage of the cloud computing budget is allocated to Infrastructure-as-a-Service (IaaS) in your company, compared to Software-as-a-Services (SaaS)? 0 = no use of IaaS, 1 = 1 – 15%, 2 = 15 – 30%, 3 = 30 – 45%, 4 = 45 – 60%, 5 = more than 60%	Adapted from Khuntia et al. (2018)
Increase in Profit by Cloud Computing	• What is the effect of cloud computing on your company′s profit (increase in profit due to the use of cloud computing)? 0 = no increase, 1 = 1 – 5%, 2 = 5 – 10%, 3 = 10 – 15%, 4 = 15 – 20%, 5 = more than 20%	Adapted from Khuntia et al. (2018)
Reduction in Energy Consumption by Cloud Computing	• What is the effect of cloud computing on your company′s energy consumption (reduction in energy consumption due to the use of cloud computing)? 0 = no reduction, 1 = 1 – 5%, 2 = 5 – 10%, 3 = 10 – 15%, 4 = 15 – 20%, 5 = more than 20%	Adapted from Khuntia et al. (2018)
Energy Reduction in IT Equipment/Infrastructure	• How much has your company reduced energy consumption on IT equipment and IT infrastructure in last financial year? 0 = no reduction, 1 = 1 – 5%, 2 = 5 – 10%, 3 = 10 – 15%, 4 = 15 – 20%, 5 = more than 20%	Adapted from Khuntia et al. (2018)
Operational Benefits of Cloud Computing	• To what extent has your company′s use of cloud computing provided the following benefits? (1: very little – 5: very much) a. Reduction of the cost of the electronic support of your activities and operations/processes b. Improvement of the quality of the electronic support of your activities and operations/processes (e.g., provision of more capabilities/functionalities, higher availability) c. Use and exploitation of new technologies to support your activities and operations/processes without the need for additional investments	Adapted from Loukis et al. (2019)
Top Management Commitment to Energy Efficiency	• Have the leadership team/top executives (e.g., CEO, CIO) made an ″explicit & vigorous commitment to energy efficiency″ in your company? 1 = Yes, 2 = Maybe, 3 = No	Adapted from Khuntia et al. (2018)

Notes: Although the 5-point scales from 1 to 5 are used, we allow a zero value for the case of no use or no effect.

Table F5: Summary Statistics for Survey Analysis (*N* = 187)

Variable	Mean	Std. Dev.	Description
IT Expenditure	3.840	1.035	Percentage of total expenditures allocated to IT budget
Cloud Computing Expenditure	3.652	1.079	Percentage of IT budget allocated to cloud computing
Relative Importance of IaaS	0.433	0.226	Percentage of cloud computing budget allocated to Infrastructure-as-a-Service (IaaS). We compute the percentage by taking the mid-point of survey responses (e.g., "15 – 30%" is translated to 0.225).
Increase in Profit by Cloud Computing	3.401	1.342	Percentage increase in profit due to the use of cloud computing
Reduction in Energy Consumption by Cloud Computing	2.989	1.524	Percentage decrease in energy consumption due to the use of cloud computing
Energy Efficiency	6.390	2.517	Percentage change in energy efficiency (profit per energy), calculated by summing the percentage increase in profit and the percentage decrease in energy consumption
Energy Reduction in IT Equipment/Infrastructure	3.075	1.461	Reduction in energy consumption on IT equipment and IT infrastructure in last financial year
Operational Benefits of Cloud Computing	4.105	0.701	Benefits of cloud computing use in the electronic support of activities and operations/processes, which is measured as the average of three survey items for operational benefits of cloud computing
Top Management Commitment to Energy Efficiency	0.754	0.432	Binary variable of whether top management made explicit commitment to energy efficiency (Yes = 1 / No, Maybe = 0)

Notes: See Table F4 for the survey instrument to measure the variables.

Table F6: Estimation Results of Survey Analysis

	Effect of Cloud Computing on Mediator				Effect of Cloud Computing on Energy Efficiency					
Dependent variable:	Energy Reduction in IT Equipment/Infrastructure		Operational Benefits of Cloud Computing		Energy Efficiency					
Moderating variable:							Energy Reduction in IT Equipment/Infrastructure		Operational Benefits of Cloud Computing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cloud Computing Expenditure	0.475***	0.023	0.272***	0.167**	1.210***	0.500**	0.719***	0.478***	0.894***	0.336
	(0.114)	(0.151)	(0.061)	(0.079)	(0.153)	(0.226)	(0.132)	(0.177)	(0.165)	(0.211)
Cloud Computing Expenditure × Relative Importance of IaaS		0.617***		0.143***		0.968***		0.375**		0.827***
		(0.126)		(0.052)		(0.195)		(0.150)		(0.180)
Energy Reduction in IT Equipment/Infrastructure							1.033***	0.961***		
							(0.097)	(0.099)		
Operational Benefits of Cloud Computing									1.161***	0.985***
									(0.261)	(0.255)
Mediation Effect with 95% Confidence Interval (Imai et al. 2010)										
Percentage of the Main Effect *(Reflecting the Effect of SaaS)*, Mediated by Each Mediator							40.7% (32.3%, 55.4%)	3.2% (1.6%, 19.9%)	26.0% (21.2%, 35.2%)	**32.6% (16.7%, 124.9%)**
Percentage of the Interaction Effect *(Reflecting the Effect of IaaS)*, Mediated by Each Mediator								**61.4% (44.4%, 98.2%)**		14.4% (10.2%, 22.9%)
Control Variable	Firm Size									
R-squared	0.135	0.237	0.215	0.239	0.338	0.423	0.649	0.660	0.420	0.481
Observations	187	187	187	187	187	187	187	187	187	187

Notes: Robust standard errors are in parentheses. For brevity, we omit firm size dummies. * p<0.1, ** p<0.05, *** p<0.01.

Table F7: Robustness Checks for Survey Analysis

	Decomposition of Economic and Environmental Performance		Controlling for General IT Expenditure				Controlling for Top Management Commitment			
Dependent variable:	Increase in Profit	Reduction in Energy Consumption	Energy Efficiency				Energy Efficiency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cloud Computing Expenditure	0.714***	0.496***	0.962***	0.389*	0.460**	0.262	1.164***	0.494**	0.476***	0.339
	(0.082)	(0.095)	(0.173)	(0.221)	(0.182)	(0.207)	(0.150)	(0.219)	(0.175)	(0.210)
Cloud Computing Expenditure × Relative Importance of IaaS				0.874***	0.366**	0.766***		0.931***	0.362**	0.822***
				(0.191)	(0.150)	(0.179)		(0.191)	(0.149)	(0.179)
Energy Reduction in IT Equipment/Infrastructure					0.950***				0.953***	
					(0.105)				(0.099)	
Operational Benefits of Cloud Computing						0.921***				0.959***
						(0.264)				(0.280)
IT Expenditure			0.554***	0.402***	0.066	0.303**				
			(0.172)	(0.152)	(0.139)	(0.148)				
Top Management Commitment to Energy Efficiency							0.745*	0.539	0.265	0.134
							(0.420)	(0.401)	(0.298)	(0.425)
Control Variable	Firm Size									
R-squared	0.364	0.199	0.376	0.442	0.661	0.491	0.354	0.431	0.662	0.481
Observations	187	187	187	187	187	187	187	187	187	187

Notes: Robust standard errors are in parentheses. For brevity, we omit firm size dummies. * p<0.1, ** p<0.05, *** p<0.01.