Cloud Computing and firm performance: a SEM microdata analysis for Israeli firms

Raúl Katz, Juan Jung and Matan Goldman

Abstract

Purpose – *This paper aims to study the economic effects of Cloud Computing for a sample of Israeli firms. The authors propose a framework that considers how this technology affects firm performance also introducing the indirect economic effects that take place through cloud-complementary technologies such as Big Data and Machine Learning.*

Design/methodology/approach – *The model is estimated through structural equation modeling. The data set consists of the microdata of the survey of information and communication technologies uses and cyber protection in business conducted in Israel by the Central Bureau of Statistics.*

Findings – *The results point to Cloud Computing as a crucial technology to increase firm performance, presenting significant direct and indirect effects as the use of complementary technologies maximizes its impact. Firms that enjoy most direct economic gains from Cloud Computing appear to be the smaller ones, although larger enterprises seem more capable to assimilate complementary technologies, such as Big Data and Machine Learning. The total effects of cloud on firm performance are quite similar among manufacturing and service firms, although the composition of the different effects involved is different.*

Originality/value – *This paper is one of the very few analyses estimating the impact of Cloud Computing on firm performance based on country microdata and, to the best of the authors' knowledge, the first one that contemplates the indirect economic effects that take place through cloud-complementary technologies such as Big Data and Machine Learning.*

Keywords *Cloud Computing, Machine Learning, Big Data, Firm performance, Productivity*

Paper type *Research paper*

Raúl Katz is based at the Columbia Institute for Tele-Information, New York, New York, USA and Telecom Advisory Services, New York, USA.
Juan Jung is based at the ICADE, Faculty of Economics and Business Administration, Comillas Pontifical University, Madrid, Spain.
Matan Goldman is based at the Central Bureau of Statistics, Jerusalem, Israel.

1. Introduction

The development of digital technologies over the past decades has triggered deep transformations in the economy, particularly at the firm level through new processes, lower costs and operational optimization. These advances have created opportunities for substantial increases in firm performance, yielding as a result aggregate economic growth. This has been largely studied in the empirical literature over the past two decades for the internet and broadband connectivity, although the analysis of the economic effects derived from more advanced digital tools is still in its early days.

Among the recent digital advances, Cloud Computing has gained global recognition as a powerful tool for organizations seeking to remain competitive, achieving their strategic objectives and implementing large-scale transformations. Cloud Computing provides firms access to an environment for sharing and accessing computing resources like servers, storage areas and network service applications with high reliability and scalability (Park and Ryoo, 2013; Ebadi and Jafari Navimipour, 2019; Naseri and Jafari Navimipour, 2019; Khayer *et al.*, 2020; Vu *et al.*, 2020). By accessing to these resources, firms can benefit from advantages such as lower costs, flexibility and economies of scale.

Despite the increasing relevance of Cloud Computing for firm performance, empirical studies related to the economic impact of the technology at the firm level are still scarce.

Received 27 June 2023
Revised 10 August 2023
Accepted 29 January 2024

This article has been developed as part of a broader project funded by Amazon Web Services (AWS). The authors would like to thank Daniel Roash (Central Bureau of Statistics of Israel) for his cooperation and useful comments. This paper has also benefited from comments and suggestions provided by two anonymous referees.

The research evidence has been generated so far based on a sample of specific firms within a single country. That is the case of Loukis *et al.* (2019) for a sample of Dutch firms; Chou *et al.* (2017) for Taiwanese enterprises; Bolwin *et al.* (2022) for German firms; Garrison *et al.* (2015) for a group of Korean business; or Khayer *et al.* (2020) for a sample of Chinese firms. On a global scale, Chen *et al.* (2022) was also able to estimate the relationship between Cloud Computing and some firm-level performance metrics.

Despite those advances, there is still a lack of analysis regarding to the role of Cloud Computing within firm's digital transformation, particularly with respect to its complementarity with other technologies. This is extremely relevant because the use of other advanced technologies and use cases at the firm level can be enabled through cloud services. The indirect economic effects generated by Cloud Computing remain, to the best of our knowledge, unaddressed in the empirical research.

In this context, the purpose of this paper is to analyze how Cloud Computing directly affects firm performance, also assessing the indirect linkages that materialize through complementary technologies such as Big Data and Machine Learning. This is studied for a sample of Israeli firms.

The Israel case study is appealing for several reasons. First, Israel is a digitally advanced country where several firms are currently adopting cutting-edge technologies, thus, being accurate to measure the associated economic effects. The country is usually defined as a "startup nation," due to its high investment in resources and programs to encourage entrepreneurs and support them, especially in technologically advanced sectors [1]. Currently, Israel is home to both research and development centers for large companies along with innovation hubs. Second, the country is currently experiencing a momentum of cloud development, with significant investments involved [2]. Third, the availability of suitable micro data reported by the local central bureau of statistics (CBS), through the survey of information and communication technologies (ICT) uses and cyber protection in Business, makes this a valuable opportunity to explore the role of advanced technologies at the firm level.

Israel is no stranger to the recent advances in cloud development, with more than half of local firms adopting this technology according to the latest statistics available from the CBS. Despite this advance, there is still a notable divide in the country between digital-native companies and traditional enterprises in terms of their adoption and utilization of Cloud Computing. Digital natives are already leveraging advanced cloud services and solutions for innovation and rapid progress, while traditional firms primarily use cloud technology for basic purposes like collaboration tools and Software-as-a-Service (SaaS) solutions. However, this situation is expected to undergo a significant change. Major cloud service providers, known as *hyperscalers*, are investing in establishing cloud regions in Israel, with 11 availability zones either already open or in development by 2023. These investments are reducing key barriers to cloud adoption, such as data residency concerns and latency issues. For example, any Israeli company that could have been reluctant to allow their data to migrate to other countries may now feel more prone to acquire cloud services as the development of these infrastructures implies that data will remain locally. In addition, the local presence of these developments will be translated into faster and more reliable data transfers. Many of these investments have been motivated by the government's cloud migration initiative, known as Project Nimbus. In addition, cloud service providers are making substantial investments in developing local cloud talent, which is a significant obstacle for traditional companies in adopting cloud technology. The implementation and migration of technology solutions to the cloud is expected to enhance productivity for both startups and traditional organizations. However, the extent of the economic effects from Cloud Computing may be linked to the adoption of other complementary digital technologies. In addition, the degree of this impact may vary depending on company size and economic sector. These are the main gaps in the current research literature that this study aims to address.

The remainder of this paper is structured as follows. Section 2 presents a first descriptive perspective of the development of Cloud Computing in Israel. In Section 3, we provide a theoretical framework based on the research literature in the field. In Section 4, we develop a theoretical model suited for the data available, from where we derive the main empirical specification. In Section 5, we present the methodology and data for the empirical analysis. Section 6 provides the results of the econometric estimations conducted. Finally, Section 7 concludes, outlining policy implications.

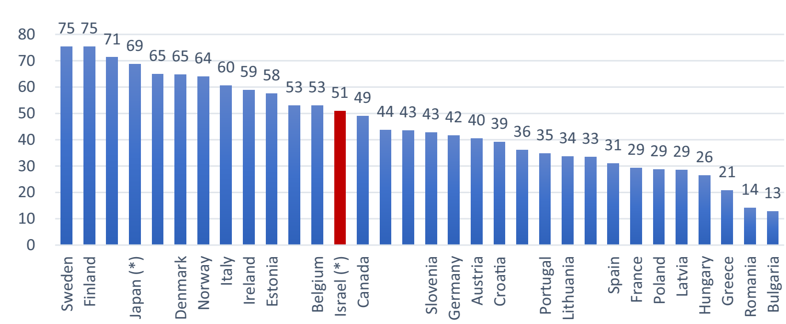
2. Cloud Computing in Israel

In recent years, Israel has made significant progress in adopting cloud technology. According to the CBS, approximately 50.85% of local companies purchased cloud services in 2020. When compared to other countries, Israel's level of cloud adoption is similar to that of Belgium and Canada, and higher than that of Germany or France. However, it still lags top-ranking countries such as Sweden and Finland, both of which have a 75% adoption rate, as shown in Figure 1.

Despite Israel's overall high adoption of Cloud Computing, the penetration rates vary across different sectors and types of businesses. The country has seen extensive cloud adoption among digital natives but relatively low adoption rates in the public sector, large enterprises and small and medium businesses, which can be referred to as traditional enterprises. This is particularly evident when it comes to core technologies and advanced applications. According to the CBS, 88.41% of information-intensive companies have embraced cloud services, whereas low-tech firms have only reached a 42.41% adoption rate. In terms of specific sectors, 85.31% of companies in the information and communication industry have migrated some or all of their systems to the cloud, while only 31.35% of businesses in the accommodation and food industry use cloud services.

Furthermore, while digital native companies have widely adopted and benefited from Cloud Computing, traditional companies mainly use it for basic purposes such as SaaS or CRM solutions, simple data analysis and collaboration tools. The CBS also reveals that 57.76% of cloud users in the information and communications sector rely on the cloud to run their company software, indicating advanced adoption. In contrast, this is the case for only 6.42% of cloud users in the transportation and storage sector.

Figure 1 Cloud penetration across Organisation for Economic Co-operation and Development (OECD) countries (2021); (firms purchasing cloud every 100 enterprises)



Notes: (*) 2020; (**) 2019
Source: CBS, OECD Statistics

In the upcoming years, the pace of cloud adoption in Israel is expected to increase even further. However, it is worth noting that the Israeli market is already quite vibrant. It is projected that the annual spending on cloud services in Israel will reach approximately US $2.14bn in 2023. Furthermore, the Israel cloud market has been experiencing an impressive annual growth rate of 34% (as shown in Figure 2).

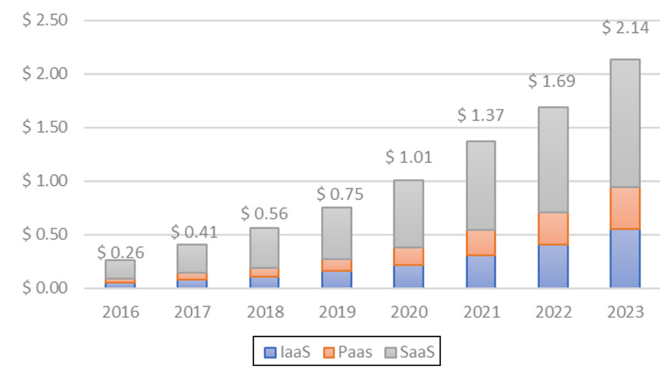
The largest market segment is SaaS with an estimated spending of US$1.20bn, in 2023, roughly 56% of the total cloud spend. When normalizing the 2021 cloud spending per capita for comparison purposes, Israel reaches US$146, slightly below the market leaders, the USA and the UK (see Figure 3).

3. Theoretical framework and hypotheses

3.1 Digitization and firm performance

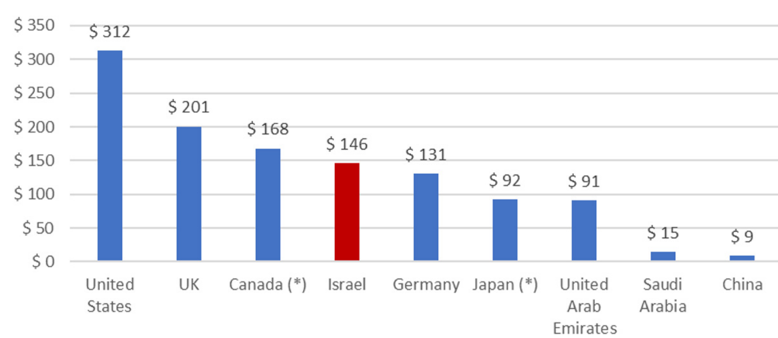
The development of digital technologies over the past decades has revolutionized the approach to business management. Firms have adapted their productive systems, routines

Figure 2 Israel: Cloud Computing market (2016–2023)



Notes: IaaS, PaaS and SaaS refer, respectively, to Infrastructure-as-a-Service, Platform-as-a-Service and Software-as-a-Service
Source: Statista; IDC; Gartner; author's analysis

Figure 3 Cloud spending per capita for selected countries in 2021 (US$)



Note: (*) 2020
Source: IDC, Statista, World Bank, author's analysis

and consumption patterns to a hyper-data-driven environment with new instruments for transmitting, storing, creating, sharing and exchanging data. These advances have created several potential paths by which digitization can boost company performance.

First, digitization has the potential to reduce the expenses of both external communication (with clients, suppliers, or other enterprises) and intra-firm communication (Jorgenson, 2001). An easier dissemination of information can improve communication channels and interactions to better search, share, store and analyze information and resources (Li *et al.*, 2019).

In second place, data analysis has been a major disruptor in recent years. It sets the way for a more in-depth examination of externally collected data (from clients or value-chain firms) as well as internal-process data. Digital tools allow firms to continuously generate, process and analyze significant volumes of useful information (Heredia *et al.*, 2022), thus, creating opportunities for organizations to reap the benefits from analyzing these massive influx of data (Benitez *et al.*, 2022) and improving firm performance (McAfee *et al.*, 2012). This is facilitated by the recent cost decreases associated with storing, processing and transmitting large amounts of data (Gu *et al.*, 2021).

Third, digital technologies can enable the development of new production processes and practices (Mack & Faggian, 2013; Zhai *et al.*, 2022), prompting important operational transformations within firms. In this respect, the so-called Industry 4.0 can be interpreted as an interdependent system of technologies operating at the firm level promoting internal optimization. These digital advances, when incorporated in the production processes, can generate competitive advantages in enterprises (Ribeiro-Navarrete *et al.*, 2021), making internal processes more flexible, rational and efficient.

Finally, decreased entry barriers allow development and access to new national and worldwide markets. From a market perspective, digitization can contribute to lower entry barriers, promote transparency and foster competition (Czernich *et al.*, 2011). Lower barriers induced by digital developments can help firms to enter new markets (Chege *et al.*, 2020), develop new networks and create new growth opportunities for companies.

Overall, the consequences of digitalization through these effects can benefit firms through product and process innovation, cost reductions and new sources of revenue. This is intended to result in increased productivity and the development of new business models.

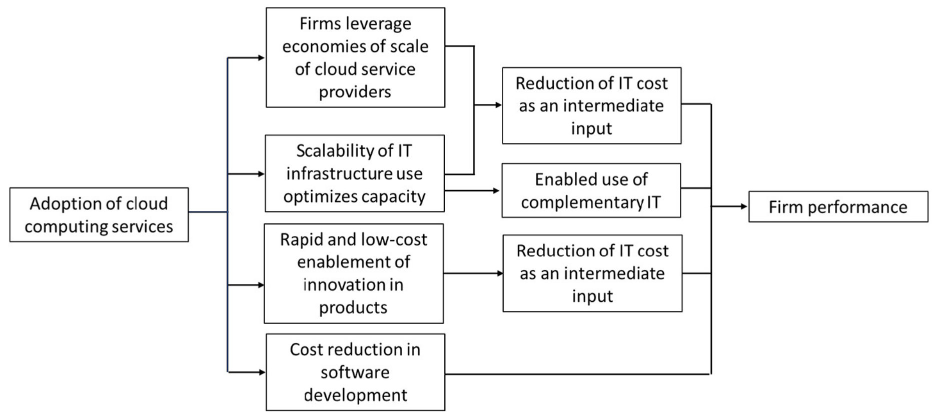
3.2 The role of Cloud Computing in firm's internal digitization

Cloud Computing also has an important contribution to the firm digitization process, through several internal effects that can be summarized as depicted in Figure 4.

The delivery of IT-based services has undergone a fundamental change thanks to Cloud Computing. One of its main advantages is that Cloud Computing offers a remote access environment for sharing and accessing computing resources like servers, storage areas and network service applications with high reliability and scalability (Park and Ryoo, 2013; Ebadi and Jafari Navimipour, 2019; Naseri and Jafari Navimipour, 2019; Khayer *et al.*, 2020; Vu *et al.*, 2020). Furthermore, cloud technology enables access to these computational resources via the internet at a minimal incremental cost. This eliminates the need for companies to invest significant time and resources in building their own infrastructure [3].

Therefore, companies adopting cloud services can benefit from advantages such as lower costs, flexibility and scalability. By relying in Cloud Computing, firms can also automatically scale storage and software use in response to load to save resources (Armbrust *et al.*, 2010). A reduction in resource spending has an impact on the firms' margins and consequently monetary value, which translates into economic contribution.

Figure 4 Microeconomic effects of Cloud Computing



Source: Prepared by the authors

An additional effect derived from the scalability of IT infrastructure provided by Cloud Computing is that it facilitates firms use of other technologies that are enabled by cloud, such as Big Data, Machine Learning or Internet of Things. These technologies are a key part of some of the economic impact generated by digitization, as they enable a fundamental transformation of business management practices.

The third effect refers to SaaS having a potential impact on firm-driven ICT-enabled innovation (e.g. product development) (Chou *et al.*, 2017; Kathuria *et al.*, 2018; Chen *et al.*, 2022), although the effect appears to be modest, according to some authors (Loukis *et al.*, 2019; PWC, 2021).

Finally, cloud services have an important economic contribution to software development. As stipulated by Byrne *et al.* (2018), when cloud vendors adopt technologies that enable them to develop products "higher up the stack" and offer services with greater abstractions, the work of software development is simplified, since firms can now focus only on code programming and its deployment, lowering development costs. This, in turn, leads again to higher margins and, potentially an increase in sales.

In sum, a combination of all these effects is expected to generate positive spillovers on firm performance.

3.3 Empirical evidence from the surveyed literature

Most empirical studies examining the economic impact of Cloud Computing have focused on firm-level analysis, often concentrating on specific economic sectors. These studies use diverse variables to measure firm performance, such as productivity, innovation or financial indicators.

Schniederjans and Hales (2016) conducted a study based on transaction cost economics, analyzing how Cloud Computing supports supply chain collaboration and positively influences firms' economic and environmental performance. They collected data from 247 IT and supply chain professionals through surveys and analyzed it using structural equation modeling (SEM). The findings showed that Cloud Computing can enhance collaboration among supply chain partners and lead to improved firm performance. Similarly, Loukis *et al.* (2019) surveyed 102 Dutch firms and concluded that both operational and innovative benefits of SaaS cloud technologies have a positive impact on business performance, resulting in improved operations and increased innovation rates. They also highlighted the role of a firm's absorptive capacity, which refers to its ability to recognize, acquire and incorporate valuable new knowledge from the external environment to drive innovation in processes, products and services. Coincidentally, Chou *et al.* (2017) analyzed data from 165 firms in various industries in Taiwan, including IT, travel, tourism, finance and banking, and found a positive association between cloud adoption and service innovation. Bolwin *et al.* (2022) conducted a large-scale survey of 1,504 companies in Germany to quantify the impact of AWS Cloud Computing on business performance. Extrapolating the survey results to the entire firm population, they estimated that 1.25 million German companies rely on the cloud, resulting in added value growth of 11.2bn euros using AWS technologies.

Other studies have focused on identifying the factors that enhance the impact of Cloud Computing at the firm level. Garrison *et al.* (2015) analyzed a survey of 302 Korean firms using SEM and found that managerial, technical and relational IT capabilities positively contribute to Cloud Computing's impact on firm performance, with managerial capability having the greatest influence.

As more comprehensive data sets became available, research on the microeconomic benefits of Cloud Computing expanded to emerging countries. For example, Kathuria *et al.* (2018) analyzed a survey of 147 Indian firms and found that firms can leverage Cloud Computing to enhance performance. They proposed a strategic value appropriation path for adopters to improve their business performance, emphasizing the importance of cloud technological and integration capability, cloud service portfolio capability and business flexibility. Similarly, Dalenogare *et al.* (2018) examined the impact of various digital services, including Cloud Computing, on firm performance metrics for Brazilian firms. They found a positive relationship between these services and performance. Khayer *et al.* (2020) discovered a positive impact of Cloud Computing on firm performance for a sample of Chinese firms during the period 2018–2019, emphasizing the relevance of external factors, such as end-user satisfaction, in contributing to firm performance.

On a global scale, Chen *et al.* (2022) estimated the relationship between Cloud Computing and firm-level performance metrics (e.g. return on assets and Tobin's Q) using difference-in-difference econometric techniques on a world sample of firms from 2010 to 2016. Their analysis revealed a positive correlation, indicating that firms adopting Cloud Computing experienced significantly improved profitability and market value. The authors also identified variations in the impact of Cloud Computing on performance based on industry type and firm size, with manufacturing firms showing greater profitability gains after adopting cloud services compared to service firms.

Despite the above-mentioned advances in the research literature, there is still a lack of analysis regarding to the role of Cloud Computing within firm digital adoption. A company's migration to the cloud is facilitated through the offering of multiple applications with varying level of complexity and substitution. At the more basic level, a cloud service provider offers on-demand infrastructure for computing power and storage, upon which a firm migrates its systems to the provider, thereby benefitting from economies of scale. Moving along the value of offerings, the cloud service provider might offer database management software, content delivery, analytics (which might include real time video and data streams analysis and using third party data), Machine Learning (including deep learning inference, identifying insights and relationship in text) and security applications. Some of these offerings can be conceptualized as being complementary technologies. A complementary technology refers to a set of technologies that work together to enhance or supplement the functionality of one another. In other words, these technologies are designed to work in tandem with each other, rather than as standalone solutions. The goal of complementary technology is to create a more comprehensive and effective solution that addresses a specific need or problem. These are unstudied angles of the link between Cloud Computing and firm performance that we aim to address in this research.

3.4 Hypotheses

Based in the theoretical framework and in the reviewed literature, we outline the following hypotheses regarding the links between Cloud Computing and firm performance for Israeli firms:

H1. Cloud Computing generates direct positive economic effects on firm performance.

H2. Cloud Computing enables the use of Machine Learning, generating indirect economic effects on firm performance.

H3. Cloud Computing enables the use of Big Data, generating indirect economic effects on firm performance.

H4. The effects from Cloud Computing on firm performance vary significantly depending on firm characteristics such as sector and size.

The proposed hypotheses add the Israeli case to the evidence generated in other contexts (*H1*), while at the same time, we advance a further step by addressing uncovered aspects such as the role of cloud in enabling infrastructure for the use of other digital technologies (*H2* and *H3*). This is a relevant topic, because if complementary technologies enhance the impact of cloud on a firm's performance, this may create incentives for enterprises to move up the stack of cloud service offerings to multiply its economic impact. Finally, we will intend to understand the heterogeneities in the effects of Cloud Computing on firm performance depending on firm characteristics (*H4*).

4. Model to formalize the role of digitalization for firm performance

In this section, we develop a model inspired in the theoretical framework. Despite enjoying from a rich data set as the one provided by the CBS, the empirical analysis still faces some data limitations that will require us to conduct some assumptions and rearrangements to deliver a feasible empirical specification.

We start with a production function where each firm *i* produces according to a Cobb-Douglas function with constant returns to scale on capital and labor:

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}$$

where $0<\alpha<1$. We assume that total factor productivity, denoted by A, is explained by some unobserved firm-level characteristics denoted by X, on the degree of firm digitalization and on human capital:

$$A_i = \Omega(X_i) e^{\theta DIGITAL_i + \lambda HK_i}$$

A first limitation we face that inhibits a direct estimate of the proposed production function is related to the absence of data regarding firm's capital stock. To overcome this setback, the production function can be derived with respect to K, yielding the marginal productivity of capital, which assuming that markets are competitive, should equal a firm's earnings (Romer, 2006). In other words, firms will acquire capital until its marginal productivity earns its price (Nicholson, 2005), which can be represented by the interest rate: [4]

$$\frac{\partial Y}{\partial K} = A\alpha K^{\alpha-1} L^{1-\alpha} = r$$

where we omit the subscripts *i* for the sake of simplicity. Re-arranging, demand for capital factor can be obtained:

$$K = \left(\frac{\alpha A L^{1-\alpha}}{r}\right)^{\frac{1}{1-\alpha}}$$

By inserting the above expression of capital in the production function, we can overcome the limitation of the lack of data regarding capital stock:

$$Y = A\left(\frac{\alpha A L^{1-\alpha}}{r}\right)^{\frac{\alpha}{1-\alpha}} L^{1-\alpha}$$

Meaning that the production function can be represented as follows:

$$Y = A^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} L$$

The above expression effectively proves that the production function can be estimated without capital stock data over the basis of some simple assumptions supported by the economic theory.

Another data limitation exists since the variable measuring output (revenues) in the data set entails some methodological problem. The reason is that the performance of most small startup firms in Israel is based on venture capital investment. Along those lines, revenue data provided in the data set does not consider venture capital money, which makes them to be misleading. To deal with this problem, we relied on average wage per employee as the variable to measure firm-performance, as it is expected to provide a more accurate reflection of it than revenues in this context [5].

Next, we will show how our empirical specification can be easily adapted to the use of wages as dependent variable. Mirroring the previous exercise for capital, the profit maximization condition will make firms to hire workers up to the point its marginal product equals its cost, represented by wages (Nicholson, 2005). The derivative of the output with respect to the labor factor will represent the marginal productivity of labor, which should equal to the wage:

$$\frac{\partial Y}{\partial L} = A^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} = w$$

Introducing the total factor productivity term in the previous equation, this will yield an expression for marginal productivity of labor that depends on firm characteristics, digitalization, human capital and interest rate:

$$w = \left(\Omega(X)e^{\theta DIGITAL+\lambda HK}\right)^{\frac{1}{1-\alpha}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}$$

Applying logarithms for linearization, and after some algebra:

$$\log(w) = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right) + \frac{1}{1-\alpha}\log\left(\Omega(X)\right) + \frac{\theta}{1-\alpha}DIGITAL + \frac{\lambda}{1-\alpha}HK$$

In our sample, the interest rate can be assumed constant, as all firms are expected to face a similar cost per unit of capital as they are all exposed to a same financial system for a single year. Renaming the parameters for simplicity, [6] we arrive to the empirical specification to be estimated:

$$\log(w) = \mu + Z(X) + \delta DIGITAL + \beta HK$$

At this point, we can measure firm performance through wages, as a proxy of marginal productivity of labor, while on the equation's right-hand side digitization is expected to contribute to explain the disparities in the outcome variable. Unobserved firm-level characteristics, denoted by *X*, will be approximated by the introduction of industry-level fixed effects and the number of employees, to account by differences in size.

5. Methodology and data set

In this section, we present the methodology and the data to be used for the empirical analysis. We start by presenting the SEM specification to be estimated, before describing the data set, including details on sample measures and the main descriptive statistics.

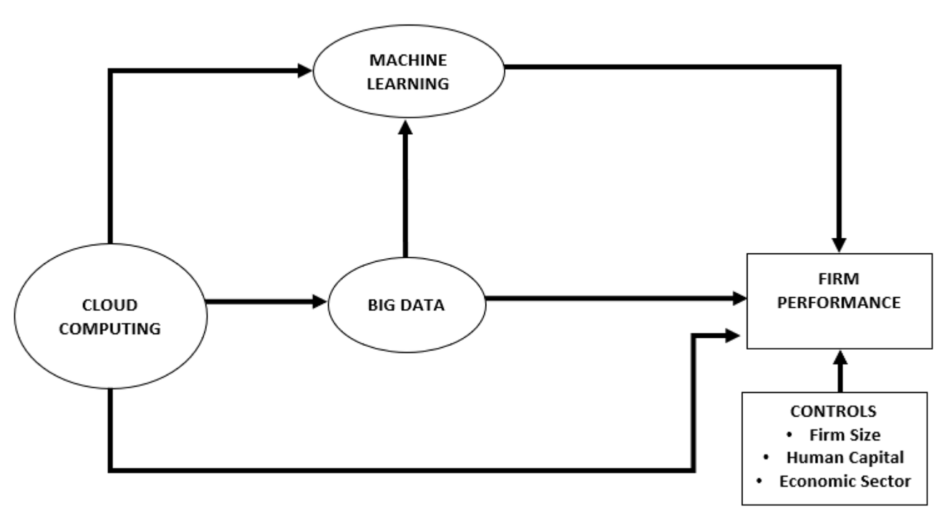
5.1 Proposed structural equation modeling specification

SEM is particularly useful for validating hypotheses using empirical data by examining the relationships and connections between multiple variables or constructs. These models allow for the examination of both direct and indirect effects, forming a network of interdependencies among the variables. This characteristic makes the SEM approach a suitable methodology to analyze the set of direct and indirect effects hypothesized in subsection 3.4. By conducting a comprehensive statistical analysis of the entire system, the model determines whether the observed data aligns with the proposed relationships (Pearl, 2012). Direct effects represent a straightforward relationship between two variables, where the first one influences the second variable directly. In contrast, indirect effects refer to an indirect pathway where one explanatory variable impacts another variable through the mediation of a third variable. Total effects encompass both direct and indirect effects, representing the overall influence between variables.

Figure 5 sketches the proposed a SEM specification derived from the theoretical framework that is consistent for the proposed empirical analysis regarding the role of Cloud Computing to enhance firm performance.

Accordingly, Cloud Computing is expected to have a positive and direct impact on firm performance (as denoted in *H1*). However, it is also expected to enable infrastructure for the use of other technologies such as Big Data and Machine Learning, which in turn, are assumed to influence output (these linkages were designed to test *H2* and *H3*). Cloud complementarities with these technologies have already been identified in the literature. For

Figure 5 Proposed SEM specification



Source: Prepared by the authors

instance, Zanoon *et al.* (2017) argue that Big Data and Cloud Computing constitute an integrated model in the world of distributed network technology, therefore being closely related. Something similar happens with Machine Learning. This has also been highlighted by Pop (2016), who argues that since Machine Learning is a resource-consuming task, Cloud Computing can provide valuable alternatives to speed-up the execution times. This will mean that Cloud Computing is expected to contribute to firm performance beyond the direct effect. In addition, Big Data is expected to contribute to accelerate the use of Machine Learning, by providing useful information for artificial intelligence (AI)-related decision-making processes. The complementarities between Big Data and AI have been highlighted in the research literature by Makridakis (2017), Yang (2022) and Brynjolfsson *et al.* (2018), among other authors. Finally, the hypothesis referred to heterogeneous effects depending on firm characteristics (*H4*) will be addressed by conducting multigroup moderations.

5.2 Data

Data is extracted from the survey of ICT uses and cyber protection in business conducted by the CBS during 2020. After data cleaning by removing outlier observations, our sample is composed of approximately 2,000 local firms from diverse economic sectors. About 34.99% of the surveyed firms belong to the manufacturing, mining, energy and water industries; 7.38% of the surveyed are construction; 17.34% of the surveyed are from trade sector (retail and wholesale); and 10.16% of the surveyed belong to the information and communication industry. Other industries represented in the sample include transportation and storage, postal and courier activities; accommodation and food service activities; real estate activities; professional, scientific and technical activities; and administrative and support service activities.

The variables to be used in the empirical analysis are described in Table 1. The dependent variable will be represented by the average wage per employee (in logarithms). We account for labor by the number of employees. While the data set does not report directly for human capital, we will proxy it with a binary indicator accounting for the presence of ICT experts within the firm.

Considering that the variables accounting for digital technologies present overlapping information, we built some constructs through factor analysis with the aim of reducing the dimension of the data set while keeping as much information as possible [7]. Each technology considered for the empirical analysis will be represented through a specific construct.

The Cloud Computing construct was measured with seven items referred to different uses of this technology at the firm level, as denoted in Table 1. The scale reliability proved to be very good (Cronbach's alpha = 0.859). This construct can be interpreted as a measure of the intensity in cloud use by the firm, where a higher value will reflect a deeper use of this technology at the firm-level.

The Big Data construct was measured through the five items related to the use of data analysis from diverse sources (sensors, products, website, mobile devices and social networks). The higher the value taken by this indicator, the more variety and intensity in the Big Data analysis. Reliability was very good (Cronbach's alpha = 0.836).

Finally, the Machine Learning construct is based on four indicators related to the use of certain AI technologies at the firm processes (automation, customization, logistics and quality controls). Reliability was slightly inferior to the previous constructs (Cronbach's alpha = 0.674), although it is still acceptable according to Hair et al (2006).

5.3 Descriptive statistics

In Table 2, we report the main descriptive statistics. Average annual wage is 136,899 shekels (in logs, 11.827), which is equivalent to approximately US$37,000 at current exchange rates. On average, firms have 336 employees, while 38.8% of them have hired an ICT expert.

Table 1 Variable description			
Variable		*Description*	*Values*
Log (wage)		Logarithm of average wage per employee	Local currency
Employees		Number of employees in the company	Quantity
ICT human capital		Binary variable that takes value of 1 if the company employs Information and Communications experts	1 = Yes, 0 = No
Cloud Computing	Cloud office	Use of cloud service in office software service	1 = Yes, 0 = No
	Cloud database	Use of cloud service in database basic accommodation	1 = Yes, 0 = No
	Cloud storage	Use of cloud service in file storage service	1 = Yes, 0 = No
	Cloud accounting	Use of cloud service in accounting software or funding	1 = Yes, 0 = No
	Cloud customer	Use of cloud service in customer contexts	1 = Yes, 0 = No
	Cloud power	Use of cloud service in computing power to run the company's software and processes	1 = Yes, 0 = No
	Cloud processes	Use of cloud services to run the company's software and processes	1 = Yes, 0 = No
Big Data	Big Data sensors	Use of Big Data coming from smart devices or sensors	1 = Yes, 0 = No
	Big Data products	Use of Big Data that comes from company products	1 = Yes, 0 = No
	Big Data website	Use of Big Data coming from the company's website or app	1 = Yes, 0 = No
	Big Data mobile	Use of Big Data from the use of mobile devices	1 = Yes, 0 = No
	Big Data social	Use of Big Data collected from social networks	1 = Yes, 0 = No
Machine Learning	ML automation	Use of artificial intelligence to make an automation of equipment and mechanism	1 = Yes, 0 = No
	ML products	Use of artificial intelligence to make the development and customization of products	1 = Yes, 0 = No
	ML logistics	Use of artificial intelligence for optimization and increased efficiency of using resources of transportation and distribution processes	1 = Yes, 0 = No
	ML quality	Use of artificial intelligence to make quality control and prevention and hazards	1 = Yes, 0 = No

Source: Prepared by the authors

Table 2 Descriptive statistics			
Variable		*Mean*	*SD*
Log (wage)		11.827	0.587
Employees		336.283	944.083
ICT human capital		0.388	0.487
Cloud Computing	Cloud office	0.374	0.484
	Cloud database	0.370	0.483
	Cloud storage	0.483	0.500
	Cloud accounting	0.270	0.444
	Cloud customer	0.235	0.424
	Cloud power	0.189	0.391
	Cloud processes	0.213	0.409
Big Data	Big Data sensors	0.062	0.242
	Big Data products	0.073	0.261
	Big Data website	0.082	0.275
	Big Data mobile	0.033	0.179
	Big Data social	0.038	0.192
Machine Learning	ML automation	0.032	0.176
	ML products	0.022	0.147
	ML logistics	0.028	0.165
	ML quality	0.015	0.120

Source: Prepared by the authors

As for the technological variables, naturally the averages are inversely proportional to the level of sophistication of the technology, with Cloud Computing being the more expanded, and Machine Learning the least. The most common use of cloud is for storage purposes (48.3%), followed by uses for office software and databases. As for Big Data, the most common use is based on data obtained from websites. Finally, the use of Machine Learning is more limited.

The correlations across the model variables are presented in the Table 3. We directly introduce the constructs in the corresponding matrix as we are interested in measuring their correlations. The correlation between constructs was found to be moderate in most cases.

Next, we conducted divergent validity checks by comparing this correlation index with the squared root of the average variance extracted (AVE) for each of them. The respective squared roots of AVE were above the correlation index, meaning that this correlation should not be a concern in our sample.

6. Econometric results

The SEM models are estimated through Maximum Likelihood approach with robust standard errors. We will start providing an estimate of the baseline model (that considers all firms available in the database) to test *H1, H2* and *H3*, while further checks will be based on multigroup moderation by firm size and economic industry (*H4*).

6.1 Baseline model

Results for the standardized effects of baseline model are presented in Table 4. The structural model yielded a good fit, as indicated by diverse statistics. The comparative fit index (CFI) has a value of 0.906, in line with the threshold defined by some authors (Kline, 2023). In addition, both the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) are well below the recommended threshold of 0.08 (Kline, 2023), indicating an adequate fit. The coefficient of determination (CD) also proved to be very good. The standardized regression weights of the construct items were all above 0.4 and significant at 1%, supporting the convergent validity of the scales.

First, we analyze the direct effects (Figure 6). Direct effects from Cloud Computing on firm performance are positive and statistically significant, verifying *H1*. Next, we test the direct effects from Cloud Computing on the other digital technologies. As expected, cloud technologies have an impact on Big Data and Machine Learning since it is an enabling infrastructure. Big Data also plays an important role in driving more intensive Machine Learning use. This means that Cloud Computing should present both direct and indirect effects on productivity, being these last ones those that materialize through Big Data and Machine Learning.

The direct link between Machine Learning and productivity presents a positive coefficient, significant at 5% level. Finally, the direct link between Big Data and productivity presents non-significant coefficient. This can be considered as unexpected, although a potential explanation can be based on Cappa et al (2021), who highlights the challenges of effectively managing large databases and emphasizes the importance of incorporating data variety (not only volume) to make a productive use of it. This suggests that if firms are not prepared to make a successful use of these technologies, improved performance may not be achieved.

Table 3 Correlation matrix (Cronbach's alpha in brackets)

	Log (wage)	*Employees*	*ICT human capital*	*Cloud Computing*	*Big Data*	*Machine Learning*
Employees	−0.051					
ICT human capital	0.324	0.230				
Cloud Computing	0.267	0.094	0.251	(0.859)		
Big Data	0.219	0.153	0.280	0.248	(0.836)	
Machine Learning	0.204	0.086	0.169	0.202	0.397	(0.674)

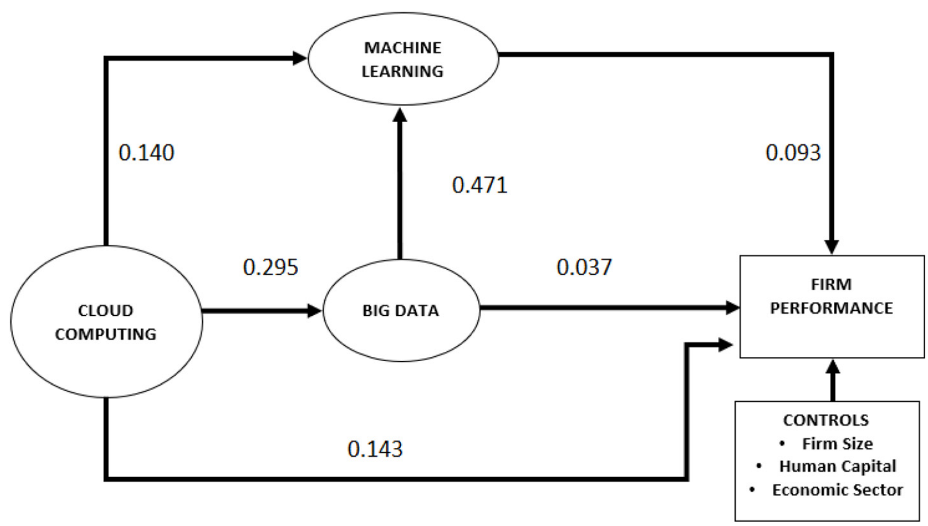
Source: Prepared by the authors

Table 4 Standardized effects from SEM model

	Direct effects					Indirect effects		Total effects				
Variables	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*	*Cloud Computing*	*Big Data*	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*
Big Data	0.295							0.295				
	(0.000)							(0.000)				
Machine Learning	0.140	0.471				0.139		0.279	0.471			
	(0.000)	(0.000)				(0.000)		(0.000)	(0.000)			
Log (wages)	0.143	0.037	0.093	0.176	−0.079	0.037	0.044	0.180	0.081	0.093	0.176	−0.079
	(0.000)	(0.202)	(0.011)	(0.000)	(0.002)	(0.000)	(0.014)	(0.000)	(0.001)	(0.011)	(0.000)	(0.002)
Model fit statistics												
Chi-squared MS	1,462.739											
Chi-squared BS	13,277.647											
CFI	0.906											
RMSEA	0.050											
SRMR	0.070											
CD	0.913											
Observations	1,983											

Notes: *p*-values from robust standard errors in brackets. Estimates include sector dummies as controls. MS and BS denote, respectively, model versus saturated and baseline versus saturated

Figure 6 Standardized direct effects



Source: Prepared by the authors

Other direct effects on productivity come from ICT human capital (positive) and size, as measured by number of employees (negative). While this last result may seem surprising (as one would expect larger firms to be more productive), in the next subsections we will find out that this is a particularity linked mainly to bigger firms and those belonging to the service sector, thus, not reflecting the overall sample. For instance, large retail stores and restaurant chains usually hire a big number of workers for low wages, something that can be reflected in this negative coefficient. In addition, there are several differences in productivity by economic sector, as the industry dummies are all statistically significant. The more productive sector appears to be information and communication, while at the other end, lower figures are found for accommodation and food service activities.

As for the indirect effects, all are positive and statistically significant. This indicates that Cloud Computing indirectly influences Machine Learning (through enhanced use of Big Data). This would mean a positive indirect effect of Cloud Computing on firm performance. Finally, Big Data also presents a positive indirect effect on firm performance, represented by the paths that take place through Machine Learning. In sum, despite not presenting a significant direct effect, Big Data is still a critical technology to deliver productivity gains. This evidence is enough to prove *H2* and *H3*.

Finally, total effects show the positive and significant contribution of the three technologies considered to drive firm performance. Comparatively, the technology that contributes the most to increase productivity is Cloud Computing, with significant direct and indirect roles. In second place comes Machine Learning, while Big Data comes in a close third place. The indirect effects of Cloud Computing on firm performance are relevant, as they represent more than 20% of the overall effect of this technology. This means that to maximize the economic gains from Cloud Computing it is important to complement the use of this technology with that of other technologies such as Big Data and Machine Learning.

6.2 Multigroup moderation

In this section we will carry out multigroup moderations to find out if the above-identified effects vary by firm size or by economic industry, as denoted in *H4*. First, we start by splitting the sample across firm groups determined by size: small firms (10–49 employees), medium firms (50–249 employees) and large firms (250+ employees). Results are presented in Table 5.

Direct effects from Cloud Computing on firm performance are larger in smaller firms. This result is consistent with the research by Chen *et al.* (2022), where small firms were found to accomplish higher improvement in profitability from cloud than big firms. The authors explain that smaller firms have less structural inertia than large companies, which is more beneficial for the efficient use of Cloud Computing services, as it enables them to attain more operational benefits from their implementation, thereby yielding higher profitability. In addition, the possibility of small firms with poor ICT capacity to gain access to sophisticated computational resources allows them to reduce operational costs and pay more attention to their core businesses, which can in turn result in higher competitive advantage and firm profitability. Specifically in the case of Israel, there are numerous small technology firms, such as high-tech startups, that as explained above should be capable of extracting high economic gains from cloud. However, the opposite seems to happen with other complementary technologies, in particular, with Machine Learning, that only presents a positive economic effect in larger firms. This can be associated to Machine Learning being a complex and sophisticated technology, where internal capabilities to make a successful use of it are quite crucial.

As for the indirect effects, Cloud Computing indirectly contributes to more use of Machine Learning across all firm sizes, although that effect only ends up increasing productivity in larger firms, as these are the most likely to use this technology to extract economic gains. Similarly, indirect effects from Big Data to firm performance are only positive and significant in the case of larger firms.

Total effects provide an important spillover on the overall Cloud Computing economic effects from larger firms, similar as that of the smaller ones. While smaller firms experience the largest direct effects from cloud on firm performance, they struggle to deliver when it comes to indirect effects, as these are materialized through more complex technologies such as Big Data and Machine Learning, where only larger firms seem to be currently delivering economic gains. This means that when we consider overall effects (direct + indirect) the impact seems to be quite similar in smaller than in larger firms (0.188 and 0.174, respectively), which suggests that policies to help smaller firms in using successfully sophisticated technologies are needed, for them to maximize economic gains from ICTs. Finally, there appears to be a middle-size trap, as medium firms seem to be less successful in extracting gains from Cloud Computing. However, they outperform the smaller ones when it comes to total effects from Big Data.

In Table 6, we conduct multigroup analysis by economic sector. For that purpose, we split the sample across two broad groups: Manufacturing and Services.

Manufacturing firms are those that belong to the following economic sectors: mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities; and construction. Service firms are those belonging to wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage, postal and courier activities; accommodation and food service activities; information and communication; real estate activities; professional, scientific and technical activities; administrative and support service activities.

Direct effects from Cloud Computing on firm performance appear to be similar for both groups of industries, although service firms seem to be more capable of extracting gains from Big Data, while the opposite happens with Machine Learning. Machine Learning seems to be an important tool for manufacturing firms, as the use of this technology seems to be much more benefited from Cloud Computing than in the case of services. Indirect effects seem to be similar among both groups of firms, although those related to Big Data

Table 5 Standardized effects from SEM model by size group

	Direct effects					*Indirect effects*		*Total effects*				
Variables	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*	*Cloud Computing*	*Big Data*	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*
10–49 employees												
Big Data	0.289							0.289				
	(0.000)							(0.000)				
Machine	0.138	0.381				0.110		0.248	0.381			
Learning	(0.016)	(0.013)				(0.043)		(0.000)	(0.013)			
Log (wages)	0.184	−0.013	0.032	0.152	0.122	0.004	0.012	0.188	−0.000	0.032	0.152	0.122
	(0.000)	(0.705)	(0.295)	(0.000)	(0.000)	(0.702)	(0.308)	(0.000)	(0.989)	(0.295)	(0.000)	(0.000)
50–249 employees												
Big Data	0.301							0.301				
	(0.000)							(0.000)				
Machine	0.136	0.486				0.146		0.282	0.486			
Learning	(0.099)	(0.007)				(0.021)		(0.004)	(0.007)			
Log (wages)	0.083	0.084	0.037	0.183	0.051	0.036	0.018	0.119	0.102	0.037	0.183	0.051
	(0.066)	(0.202)	(0.754)	(0.000)	(0.158)	(0.130)	(0.755)	(0.005)	(0.019)	(0.754)	(0.000)	(0.158)
250+ employees												
Big Data	0.328							0.328				
	(0.000)							(0.000)				
Machine	0.148	0.459				0.151		0.299	0.459			
Learning	(0.003)	(0.000)				(0.000)		(0.000)	(0.000)			
Log (wages)	0.110	0.075	0.130	0.170	−0.049	0.063	0.059	0.174	0.135	0.130	0.170	−0.049
	(0.001)	(0.121)	(0.046)	(0.000)	(0.142)	(0.000)	(0.031)	(0.000)	(0.001)	(0.046)	(0.000)	(0.142)

Notes: *p*-values from robust standard errors in brackets. Estimates include sector dummies as controls. MS and BS denote, respectively, model versus saturated and baseline versus saturated
Source: Prepared by the authors

Table 6 Standardized effects from SEM model by size group

	Direct effects					*Indirect effects*		*Total effects*				
Variables	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*	*Cloud Computing*	*Big Data*	*Cloud Computing*	*Big Data*	*Machine Learning*	*ICT human capital*	*Employees*
Manufacturing												
Big Data	0.302 (0.000)							0.302 (0.000)				
Machine Learning	0.172 (0.001)	0.427 (0.000)				0.129 (0.004)		0.301 (0.000)	0.427 (0.000)			
Log (wages)	0.202 (0.000)	0.021 (0.674)	0.148 (0.032)	0.197 (0.000)	0.053 (0.004)	0.051 (0.001)	0.063 (0.068)	0.253 (0.000)	0.084 (0.034)	0.148 (0.032)	0.197 (0.000)	0.053 (0.004)
Services												
Big Data	0.305 (0.000)							0.305 (0.000)				
Machine Learning	0.093 (0.046)	0.489 (0.000)				0.149 (0.000)		0.242 (0.000)	0.489 (0.000)			
Log (wages)	0.212 (0.000)	0.080 (0.061)	0.098 (0.059)	0.313 (0.000)	−0.222 (0.000)	0.048 (0.000)	0.048 (0.069)	0.261 (0.000)	0.128 (0.001)	0.098 (0.059)	0.313 (0.000)	−0.222 (0.000)

Notes: *p*-values from robust standard errors in brackets. Estimates include sector dummies as controls. MS and BS denote, respectively, model versus saturated and baseline versus saturated

Source: Prepared by the authors

appear to be slightly above in the manufacturing sector, because they took place through Machine Learning, a technology where these industries stand out.

Finally, the total effects of Cloud Computing on firm performance are quite similar among both firm groups, although the composition of the different effects involved seems to present differences: while both groups of firms seem to benefit from Big Data and Machine Learning, the relative importance of both technologies for firm performance is different. Overall effects from Machine Learning seem to be more relevant than Big Data for the case of manufacturing, while the opposite happens in the case of services.

All in all, the evidence provided by the multigroup moderation analysis verifies *H4* as important differences arise in the economic impact from cloud depending on firm characteristics.

7. Conclusions

The purpose of this paper was to analyze the economic effects of Cloud Computing for an extensive sample of Israeli firms. We first presented a Theoretical Framework that formalizes the topic and contextualizes Cloud Computing within the ongoing digital transformation process. In addition, we developed a model that considers how this technology affects firm performance, also introducing the indirect linkages that materialize through complementary technologies such as Big Data and Machine Learning.

The empirical analysis performed to test the study hypotheses was conducted through the SEM approach. Our results point to Cloud Computing being a crucial technology to increase firm performance, because of the significance of both direct and indirect effects. While Cloud Computing presents a strong direct impact on productivity (*H1*), additional economic effects take place through the use of other digital tools enabled by cloud provided infrastructure. In that sense, both Machine Learning and Big Data are benefited from cloud to deliver economic gains (verifying *H2* and *H3*).

We find that firms enjoying most economic gains from cloud direct effects are the smaller ones. However, larger enterprises are more capable of using the complementary technologies, resulting in a similar overall impact. With respect to economic sectors, the total effects of Cloud Computing on firm performance are quite similar among manufacturing and service firms, although the composition of the different effects involved is different: while both groups benefit from Big Data and Machine Learning, the relative impact of each technology to drive firm performance varies. Overall effects from Machine Learning seems to be more relevant than Big Data for the case of manufacturing, while the opposite happens in the case of services. This finding allowed us to prove *H4*.

All in all, our results provide robust evidence on the relevance of firm digitization in general, and of Cloud Computing in particular, to maximize firm performance. However, it is worth saying that our empirical research faced some limitations. First, our data set is limited to only one year period, which did not allow us to account for firm-level fixed effects. In addition, this data set does not include a measure of physical capital, while the revenue variable was found to be highly problematic, as explained above. These limitations made us to take some assumptions and rearrangements in the theoretical model before arriving to a feasible empirical specification.

Despite the limitations, these results can be interpreted as useful inputs for policymaking. In particularly, policies and regulations aimed to stimulate cloud investment can be desirable, as its economic effect seem to go much beyond the so-called "construction effect," triggered by Cloud Computing providers investment in infrastructure (data centers, software, etc.). While pro-cloud policies, such as Cloud First and data localization, are generally focused on accelerating the migration of government systems to the cloud, the policy impact on the private sector cloud adoption is a frequently unintended positive spillover. First, pro-cloud policies lead to investment and deployment of *hyperscalers*, which in turn provide the infrastructure needed to accommodate private sector systems. Second, the migration to government cloud systems triggers the development of a domestic source of human capital, such as systems integrators with expertise in the digital transformation linked to cloud implementation, which serve not only public organizations but also private enterprises. Third, in defining the government cloud model, which includes hosting arrangements, data classification and regulations, pro-cloud policies partly reduce the implementation risk incurred by private enterprises in migrating to the cloud. Government cloud policy has a positive signaling effect on the private sector by reducing implementation risk (through outlining cybersecurity processes) and providing an implementation framework that facilitates the transition of private enterprises to the cloud (for example, by addressing data hosting procedures). Finally, by allowing private enterprises to better interact with the government through the improvement of procurement and supply chain for government contracts, the migration to public cloud can streamline export documentation processing which in turn can facilitate foreign trade operations. In sum, the enactment and implementation of pro-cloud public policies has a derivative effect on private enterprises.

Moreover, public authorities should also encourage firms to adopt and use intensively complementary technologies such as Big Data and Machine Learning, as they proved to be critical to maximize the impact of cloud on firm performance. In general, policies having significant impact on Machine Learning applications adoption among enterprises range from promoting R&D with a focus on production-focused use case development and stimulating talent development in the production sector to facilitate technology assimilation. This should be fulfilled by structuring industry-university partnerships focused on building Machine Learning/AI training capacity within universities with derived effects in workforce development.

Notes

1. According to StartupBlink, occupies the third position in the world in terms of startup potential, with a score of 45.06, only behind the US and the UK. Israel's investment in R&D as a percentage of the GDP in 2022 is the largest in the world: 4.8%, twice that of the OECD average. As of December 2021, Israel had incubated sixteen "unicorns" with a total market capitalization of USD 136.50 billion (Source: TechAviv).
2. As part of Project Nimbus, a multi-year program to migrate government systems to the cloud, the Israeli government put in place the governance, processes, and foundations for cloud adoption at scale. This has triggered a dramatic increase in cloud infrastructure investment, and the buildup of consultancies focused on migrating enterprise systems to the cloud.
3. In the past, businesses had to build their own data centers, acquire the necessary hardware and software, and hire skilled personnel to manage them when Cloud Computing was not commercially available. This limited the benefits of this technology primarily to large companies.
4. It is assumed that the marginal productivity of capital is decreasing, something that is straightforward to verify as $\frac{\partial^2 Y}{\partial K^2} = A\alpha(\alpha - 1)K^{\alpha-2}L^{1-\alpha} < 0$.
5. The authors would like to thank CBS specialists for raising up this point.
6. $\mu = \frac{\alpha}{1-\alpha}\log\left(\frac{\alpha}{r}\right)$

   $Z(X) = \frac{1}{1-\alpha}\log(\Omega(X))$

   $\delta = \frac{\theta}{1-\alpha}$

   $\beta = \frac{\lambda}{1-\alpha}$
7. Constructs are latent (unobserved) variables deduced from the correlations between measured variables.

References

Armbrust, 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*, Vol. 53 No. 4, pp. 50-58.

Benitez, J., Arenas, A., Castillo, A. and Esteves, J. (2022), "Impact of digital leadership capability on innovation performance: the role of platform digitalization capability", *Information & Management*, Vol. 59 No. 2, p. 103590.

Bolwin, L., Ewald, J., Kempermann, H., Klink, H., Van Baal, D. and Zink, B. (2022), *The Importance of AWS for the German Economy*, Institut der deutschen Wirtschaft Köln Consult GmbH, Cologne.

Brynjolfsson, E., Rock, D. and Syverson, C. (2018), "Artificial intelligence and modern productivity paradox. a clash of expectations and statistics", *The Economics of Artificial Intelligence: An Agenda*, University of Chicago Press, USA, pp. 23-57.

Byrne, D., Corrado, C. and Sichel, D.E. (2018), "The rise of cloud computing: minding your P's, Q's and K's (no. w25188)", National Bureau of Economic Research.

Cappa, F., Oriani, R., Peruffo, E. and McCarthy, I. (2021), "Big data for creating and capturing value in the digitalized environment: unpacking the effects of volume, variety, and veracity on firm performance", *Journal of Product Innovation Management*, Vol. 38 No. 1, pp. 49-67.

Chege, S.M., Wang, D. and Suntu, S.L. (2020), "Impact of information technology innovation on firm performance in Kenya", *Information Technology for Development*, Vol. 26 No. 2, pp. 316-345.

Chen, X., Guo, M. and Shangguan, W. (2022), "Estimating the impact of cloud computing on firm performance: an empirical investigation of listed firms", *Information & Management*, Vol. 59 No. 3, p. 103603.

Chou, C.Y., Chen, J.S. and Liu, Y.P. (2017), "Inter-firm relational resources in cloud service adoption and their effect on service innovation", *The Service Industries Journal*, Vol. 37 No. 3-4, pp. 256-276.

Czernich, N., Falck, O., Kretschmer, T. and Woessmann, L. (2011), "Broadband infrastructure and economic growth", *The Economic Journal*, Vol. 121 No. 552, pp. 505-532.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F. and Frank, A.G. (2018), "The expected contribution of industry 4.0 technologies for industrial performance", *International Journal of Production Economics*, Vol. 204, pp. 383-394.

Ebadi, Y. and Jafari Navimipour, N. (2019), "An energy-aware method for data replication in the cloud environments using a tabu search and particle swarm optimization algorithm", *Concurrency and Computation: Practice and Experience*, Vol. 31 No. 1, p. e4757.

Garrison, G., Wakefield, R.L. and Kim, S. (2015), "he effects of IT capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations", *International Journal of Information Management*, Vol. 35 No. 4, pp. 377-393.

Gu, V.C., Zhou, B., Cao, Q. and Adams, J. (2021), "Exploring the relationship between supplier development, big data analytics capability, and firm performance", *Annals of Operations Research*, Vol. 302 No. 1, pp. 151-172.

Hair, J., Black, B., Babin, B. and Anderson, R. (2006), *Multivariate Data Analysis*, 6th edition Pearson Prentice Hall, NJ.

Heredia, J., Castillo-Vergara, M., Geldes, C., Gamarra, F.M.C., Flores, A. and Heredia, W. (2022), "How do digital capabilities affect firm performance? The mediating role of technological capabilities in the new normal", *Journal of Innovation & Knowledge*, Vol. 7 No. 2, p. 100171.

Jorgenson, D.W. (2001), "Information technology and the US economy", *American Economic Review*, Vol. 91 No. 1, pp. 1-32.

Kathuria, A., Mann, A., Khuntia, J., Saldanha, T.J. and Kauffman, R.J. (2018), "A strategic value appropriation path for cloud computing", *Journal of Management Information Systems*, Vol. 35 No. 3, pp. 740-775.

Khayer, A., Bao, Y. and Nguyen, B. (2020), "Understanding cloud computing success and its impact on firm performance: an integrated approach", *Industrial Management & Data Systems*, Vol. 120 No. 5, pp. 963-985.

Kline, R. (2023), *Principles and Practice of Structural Equation Modeling*, Guilford Publications, New York, NY.

Li, J., Chen, L., Yi, J., Mao, J. and Liao, J. (2019), "Ecosystem-specific advantages in international digital commerce", *Journal of International Business Studies*, Vol. 50 No. 9, pp. 1448-1463.

Loukis, E., Janssen, M. and Mintchev, I. (2019), "Determinants of software-as-a-service benefits and impact on firm performance", *Decision Support Systems*, Vol. 117, pp. 38-47.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D. (2012), "Big data: the management revolution", *Harvard Business Review*, Vol. 90 No. 10, pp. 60-68.

Mack, E. and Faggian, A. (2013), "Productivity and broadband: the human factor", *International Regional Science Review*, Vol. 36 No. 3, pp. 392-423.

Makridakis, S. (2017), "The forthcoming artificial intelligence (AI) revolution: its impact on society and firms", *Futures*, Vol. 90, pp. 46-60.

Naseri, A. and Jafari Navimipour, N. (2019), "A new agent-based method for QoS-aware cloud service composition using particle swarm optimization algorithm", *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10 No. 5, pp. 1851-1864.

Nicholson, W. (2005), *Microeconomic Theory: Basic Principles and Extensions*, Sixth Edition, McGraw-Hill.

Park, S.C. and Ryoo, S.Y. (2013), "An empirical investigation of end-users' switching toward cloud computing: a two factor theory perspective", *Computers in Human Behavior*, Vol. 29 No. 1, pp. 160-170.

Pearl, J. (2012), *The Causal Foundations of Structural Equation Modeling*, CA Univ Los Angeles Dept of Computer Science, Guilford Press, New York, NY, Chapter 5, pp. 68-91.

Pop, D. (2016), "Machine learning and cloud computing: survey of distributed and SaaS solutions", *arXiv*, preprint arXiv:1603.08767.

PwC (2021), *The Impact of Cloud Computing on the Indonesian Economy*, PricewaterhouseCoopers Consulting Indonesia.

Ribeiro-Navarrete, S., Botella-Carrubi, D., Palacios-Marqués, D. and Orero-Blat, M. (2021), "The effect of digitalization on business performance: an applied study of KIBS", *Journal of Business Research*, Vol. 126, pp. 319-326.

Romer, D. (2006), *Advanced Macroeconomics*, McGraw-Hill, Irwin, Boston, MA.

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*, Vol. 86, pp. 73-82.

Vu, K., Hartley, K. and Kankanhalli, A. (2020), "Predictors of cloud computing adoption: a cross-country study", *Telematics and Informatics*, Vol. 52, p. 101426.

Yang, C.H. (2022), "How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan", *Research Policy*, Vol. 51 No. 6, p. 104536.

Zhai, H., Yang, M. and Chan, K.C. (2022), "Does digital transformation enhance a firm's performance? Evidence from China", *Technology in Society*, Vol. 68, p. 101841.

Zanoon, N., Al-Haj, A. and Khwaldeh, S.M. (2017), "Cloud computing and big data is there a relation between the two: a study", *International Journal of Applied Engineering Research*, Vol. 12, pp. 6970-6982.

Further reading

Frontier Economics (2022), "The sky is the limit. How cloud computing is the key to better public services in Ireland", Technology Ireland.

Low, C., Chen, Y. and Wu, M. (2011), "Understanding the determinants of cloud computing adoption", *Industrial Management & Data Systems*, Vol. 111 No. 7, pp. 1006-1023.

Corresponding author

Juan Jung can be contacted at: jfjung@icade.comillas.edu