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FIRM PRODUCTIVITY AND LEARNING IN THE DIGITAL ECONOMY: EVIDENCE FROM CLOUD COMPUTING

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ABSTRACT

Computing technologies have become critical inputs to production in the modern firm. However, there is little large-scale evidence on how efficiently firms use these technologies. In this paper, we study firm productivity and learning in cloud computing by leveraging CPU utilization data from over one billion virtual machines used by nearly 100,000 firms. We find large and persistent heterogeneity in compute productivity both across and within firms, similar to canonical results in the literature. More productive firms respond better to demand fluctuations, show higher attentiveness to resource utilization, and use a wider variety of specialized machines. Notably, productivity is dynamic as firms learn to be more productive over time. New cloud adopters improve their productivity by 33% in their first year and reach the productivity level of experienced firms within four years. In our counterfactual calculations, we estimate that raising all firms to the 80th percentile of productivity would reduce aggregate electricity usage by 17%.

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1 Introduction

Firm productivity has long been a central focus in economic research, with an extensive literature investigating its dispersion, persistence, and underlying drivers (Syverson, 2004; Foster et al., 2008). Production is a dynamic process, often requiring firms to adapt to new technologies. A recent example is the digital revolution, which has transformed production across all sectors (Agrawal et al., 2018; Goldfarb and Tucker, 2019). With the acceleration of digitization and the emergence of AI, firms are increasingly integrating digital technologies into production, relying heavily on computation and data (Brynjolfsson and McElheran, 2016; McElheran et al., 2024).

While an extensive literature explores the rise of the digital economy and the impact of IT on firm productivity (Brynjolfsson and Hitt, 2003; Bartel et al., 2007; Bloom et al., 2012), there is a notable gap in our understanding of how productively firms use these new technologies. Studies of technology adoption often view IT as a complementary technology, helping firms improve existing modes of production (Brynjolfsson and Milgrom, 2013). However, the rise of the digital economy emphasizes the importance of treating IT as a mode of production itself, making IT productivity an object of interest in its own right.

A key reason for the limited evidence on emerging inputs is the prevalence of total factor productivity (TFP) in empirical and methodological studies of productivity. Most studies focus on manufacturing sectors and use TFP as the main productivity metric (Bartelsman and Doms, 2000; Syverson, 2011). However, TFP is inherently a "residual" measure, in that it quantifies output unexplained by observed inputs (Solow, 1957). The black-box nature of TFP limits insight into the mechanisms underlying firm productivity, which are particularly important when studying emerging technologies.

In this paper, we study firm productivity in the digital economy using data from a global cloud computing provider. Our analysis draws on high-frequency utilization data from over one billion virtual machines (VMs) used by nearly 100,000 firms across various industries and countries. Using this dataset, we construct firm- and division-level compute productivity measures that quantify the extent to which organizations could perform the same computing tasks with fewer compute inputs. We use our measures to analyze dispersion in compute productivity both across and within firms, as well as the process by which firms learn to use computing more productively.

Our compute productivity measure offers unique advantages that can advance our understanding of firms and firm productivity beyond digital technologies. First, as a largely uniform input used across all industries, it facilitates analysis and comparison of a uniquely wide breadth of firms. Second, it enables high-frequency tracking of "machine-level" production, offering detailed insights into the mechanisms driving productivity dispersion and learning. Third, it permits productivity estimation for individual divisions within firms, improving our understanding of intra-firm productivity dynamics. Lastly, as a quantity-based measure attributable to a specific aspect of production, it allows for precise quantification of economic resources such as compute hardware and electricity.

We begin our paper by providing background information on productivity in computing. In computing, the productivity of resources, such as server hardware, is commonly measured by their utilization rate. Achieving high utilization has been a persistent challenge for firms, both historically in on-premise computing and in the current cloud era (Whitney et al., 2014). While on-premise computing requires firms to make periodic capital investments, cloud computing lets firms rent compute resources on demand, eliminating the need to maintain excess capacity. To take advantage of this flexibility, firms must monitor usage and efficiently deploy compute resources to match varying workloads. Existing evidence highlights the difficulty of this task: firm surveys and utilization studies detail persistent self-reported compute underutilization on the cloud, which industry sources attribute to organizational frictions and the new skills required to efficiently deploy the right type and size of compute resources (Cortez et al., 2017; Tirmazi et al., 2020; Everman et al., 2022; Flexera, 2023).

In cloud computing, virtual machines (VMs) function as the fundamental unit of production for firms. Firms typically deploy many VMs simultaneously to meet their computing needs. This process can be managed manually or automatically through a variety of tools that dynamically adjust compute resources within seconds to accommodate variations in workload. Pricing in cloud computing mainly follows a linear model, where firms pay a fixed per-minute price for each deployed VM. This price scales with the VM's capacity and is paid regardless of how much the firm actually uses the VM.

With these characteristics, cloud computing represents an input with truly marginal cost, enabling firms to scale flexibly with negligible adjustment costs (Pindyck, 1986; Asker et al., 2014). Further, the global scale and uniformity of cloud computing make it largely free of external factors that could impact firms' productivity (Syverson, 2011). These elements make cloud computing an ideal setting to study firms' productivity in using a new technology.

Our empirical analysis relies on a firm-level compute productivity measure constructed using VM-level utilization data collected at 5-minute intervals. In the context of production theory, this measure quantifies a firm's resource usage relative to that of a cost-minimizing firm with the same compute output and choice set of VMs. At a high level, our measure tracks how efficiently firms use computing resources, similar to other factor productivity measures such as labor productivity (Baily et al., 2001; Bandiera et al., 2009). Following industry practice, we construct our measure using CPU utilization, which measures how many computations a machine makes as a percentage of its capacity.

Our measure incorporates two sources of inefficient usage: idle and overprovisioned VMs. We define a VM as *idle* if the firm never uses it and *overprovisioned* if its peak compute load would fit within the capacity of a smaller but readily substitutable VM. The underlying idea is that firms could eliminate idle VMs or downsize overprovisioned ones without impacting their computing output, thus saving resources and money. Importantly, these measures are defined using peak utilization over a seven-day period, ensuring that low average utilization due to volatile demand is not interpreted as inefficiency. By aggregating both sources of VM-level inefficiency, we obtain monthly firm- and division-level compute productivity estimates.

Using this measure, we first document new empirical facts about productivity in computing. Our findings reveal significant dispersion in compute productivity across firms that is persistent in short (1-month) and long-term (5-year) horizons. Controlling for industry and month, we find that firms at the 90th percentile of the distribution are 3.5 times more efficient than those at the 10th percentile. There is also substantial within-firm productivity dispersion: 44.3% of the cross-division variance in productivity is within the firm. The levels of dispersion and persistence in compute productivity are comparable to findings in other productivity studies (Syverson, 2011; Cunningham et al., 2023) and are not simply explained by observables such as industry, firm size, and VM characteristics.

Using our data, we go beyond dispersion and ask what makes firms more productive in computing. Even though the scale of our study precludes us from observing data on managerial practices, we analyze patterns in firms' VM deployment behavior that are indicative of heterogeneity in firms' practices. Our analysis establishes three key patterns that differentiate more from less productive firms. First, more productive firms (above industry-level median productivity) better adjust to demand fluctuations, reducing their provisioned VMs by 75.2% more than low-productivity firms on weekends, during which compute demand declines substantially. Second, more productive firms have better monitoring capabilities: when resources remain idle, they are more than twice as likely to detect and shut down idle VMs than less productive firms. Finally, more productive firms demonstrate greater expertise in VM selection; they employ more specialized machines and are less likely to put all of their jobs on a single VM type.

We next shift our focus to productivity dynamics. Learning is a natural focus in this context, given that cloud computing is a recent and rapidly evolving technology. Our analysis asks whether firms improve their productivity as they accumulate experience with cloud computing. To study this, we analyze the productivity trajectories of firms over time, considering both short- and long-term learning.

We find that new adopters improve their cloud productivity consistently and substantially over time. Firms with one year of experience are 32.6% more productive than their initial productivity on average. The rate of improvement slows after the initial year, with firms exhibiting 44.0% higher productivity by the end of their fourth year and making no improvements thereafter. The extended time to reach steady-state productivity is longer than that estimated in previous learning-by-doing studies (Benkard, 2000; Levitt et al., 2013), perhaps reflecting the need for investment in complementary technologies and practices, as is widely documented in the literature (Bresnahan et al., 2002; Tambe et al., 2012).

Our learning analysis reveals significant heterogeneity in learning rates across firms. Firms that are less productive at the time of adoption learn significantly faster but still do not catch up to those that were more productive initially within one year. The heterogeneity in learning reduces productivity dispersion fourfold over the first year of adoption, yet even after the first year, dispersion remains notably higher than the overall dispersion in the economy. These results highlight that the maturity of the production technology is an important determinant of the level and dynamics of productivity dispersion.

Next, we explore the detailed mechanisms behind *how* firms learns. We decompose firms' productivity growth into (i) within-division learning, (ii) across-division reallocation, and (iii) division entry and exit to determine whether learning results from reallocating resources or improvements within divisions. We find that firm-level learning masks substantial within-firm productivity dynamics. First, we observe significant productivity growth at the division level, persisting even beyond the firm's fourth year on the cloud, suggesting that individual divisions continue to improve their productivity even when firm-level learning plateaus. The flattening in firms' productivity comes from firms deploying new divisions to the cloud, which themselves start relatively unproductive and need to learn to use the cloud. Therefore, while firms do have less productive divisions exiting the cloud, our results demonstrate that learning at the firm level does not come from reallocation. When we study how divisions improve their productivity, we see that they try many new VM types that they are initially less productive at using, but discard the less productive machines and get substantially more productive with the machines they retain, suggesting that learning is at least in part driven by experimentation.

In our final analysis, we conduct simple counterfactual calculations to quantify the aggregate impact of compute productivity dispersion on economic resources. In particular, we calculate compute and electricity savings if all firms were to reach a benchmark productivity level. To perform this analysis, we first estimate the relationship between electricity consumption and CPU utilization using a separate dataset. We find that improving compute productivity has an outside impact on resource utilization: idle machines still consume 50% of their full-load electricity, and one percentage point (pp) increase in utilization leads to a 0.5 pp increase in electricity consumption.

We find significant aggregate implications of productivity dispersion in computing. If the productivity of all firms below the 80th percentile rose to that level, firms would reduce total compute resource usage by 21.0% and electricity consumption by 16.5%. The difference between these two figures underscores a nonlinear relationship between productivity distribution and underlying resource usage, highlighting the importance of accounting for the machine-level "production function" in estimating the economic impact of productivity dispersion.

We take steps to ensure our method accurately captures compute productivity without picking up potential confounding factors. First, we intentionally estimate a conservative measure by considering peak CPU utilization over seven days and excluding potentially complex VM provisioning optimizations, like consolidating multiple jobs onto fewer VMs. While these choices may overestimate productivity, they ensure our measures reflect genuine inefficiency. Second, we show that our results remain similar when controlling for a rich set of VM characteristics and that dispersion in compute productivity is not simply explained by firm-level observables. Third, we extensively review industry literature to demonstrate that our measure closely aligns with how firms measure inefficiency in practice and how productivity is measured in the operating systems literature (Islam et al., 2012; Folkerts et al., 2013). Fourth, we estimate compute productivity with publicly available data from various cloud providers and find a similar dispersion level. Fifth, we analyze other utilization metrics in computing (memory and networking) and find similar results.

We nevertheless acknowledge some limitations of our study. First, our approach does not capture all forms of compute inefficiency, such as inefficiently written code or inefficiently run data centers. While important, such inefficiencies are fundamentally different, as they pertain to changing the production process rather than resource deployment. Second, our dataset is limited to compute inputs, as we do not observe other firm inputs or outputs. We believe this is a worthwhile tradeoff given the extensive research on IT's impact on various firm-level measures (spending, capital, labor, and revenue), while micro-analysis of IT usage remains scarce.

Contribution to the Literature. First and foremost, this paper contributes to the large literature on firm productivity (e.g., Syverson, 2004; Bloom and Van Reenen, 2007; Hsieh and

Klenow, 2009; Syverson, 2011). While many papers in this literature use plant-level TFP of manufacturing firms as their primary productivity measure, several define productivity measures based on efficient utilization of inputs, as we do (Hubbard, 2003; Braguinsky et al., 2015; Butters, 2020). This literature has documented large dispersion in firm productivity and analyzed the drivers of productivity differences. Our paper extends this literature by studying firm productivity in computing, an increasingly important input for modern firms. We document several empirical facts about compute productivity that parallel findings in the productivity literature, quantify the link between productivity and resource usage, and analyze productivity dynamics at an extremely granular level.

Our paper also contributes to the literature studying the effect of IT on firm outcomes, including productivity, profit, and firm growth (Brynjolfsson and Hitt, 2003; Bartel et al., 2007; Bloom et al., 2012; Brynjolfsson and McElheran, 2016; Brynjolfsson et al., 2023).[1] While this literature emphasizes the heterogeneity of IT's impact on different firm outcomes and the need for complementary investments to use IT effectively (Bresnahan et al., 2002), our paper directly measures how efficiently firms use a transformative digital technology at a large scale. As such, we provide more detailed evidence on firms' use of an IT technology and complement the canonical findings in this literature.

By demonstrating firm learning in cloud computing, our paper contributes to the empirical literature on learning-by-doing (Benkard, 2000; Thornton and Thompson, 2001; Kellogg, 2011; Levitt et al., 2013; Hendel and Spiegel, 2014; Tadelis et al., 2023). Much of this literature analyzes a single firm or a small number of firms in a narrow industry, showing that productivity improves with firm experience. Our study differs by focusing on learning in a widely adopted and rapidly evolving technology. We find a longer period to reach a steady-state productivity level than much of the existing literature, which we attribute to the general-purpose nature of cloud technology and within-firm learning dynamics.

Finally, we contribute to the recent but growing literature on the economics of cloud computing by quantifying productivity dispersion and learning on the cloud (Jin and McElheran, 2017; Jin, 2022; DeStefano et al., 2023; Demirer et al., 2024; Lu et al., 2024).

2 The Role of Computing in Firm Production

This section provides an overview of firms' use of computing technologies, with a focus on cloud computing. Additional details on cloud computing are provided in Appendix A.

[1] Other papers in this literature have focused on case studies, focusing on the mechanisms of IT's effect on firms (Baker and Hubbard, 2004; Miller and Tucker, 2011).

2.1 Background on Computing

Computing has become a fundamental input for firms across all industries. Together with storage and networking, computing forms an essential component of firms' IT infrastructure. One can categorize firms' use of computing into production, development, and administrative purposes. In production, firms rely extensively on computing (i.e., servers, data centers) to deliver digital services such as streaming, online banking, mobile applications, and websites (Greenstein, 2020). Additionally, compute is a complementary input in producing non-digital services, facilitating functions such as payment processing, customer relationship management, inventory management, logistics optimization, and predictive analytics (Zolas et al., 2021).

Computing is also widely used for product development. Firms that produce software applications rely on computing throughout the product development cycle. In the non-digital context, with the rise of computer-aided design (CAD), manufacturing firms use computing to design and test products before physical prototyping and production (Leigh et al., 2020). Finally, firms also employ computing technology for various administrative functions, such as human resources, finance, sales, and internal communications.

2.2 Background on Cloud Computing

Traditionally, computing is done on servers purchased and maintained by individual firms, known as "on-premise" or "on-prem" computing. More recently, however, advancements in server technology and broadband connectivity have given rise to cloud computing, which allows firms to access IT services remotely over the Internet. In cloud computing, the physical resources are owned and maintained by cloud providers, and firms have on-demand access to these resources via a rental market. Cloud computing is one of the most rapidly adopted technologies by firms in recent years, with nearly 80% of firms using at least one IT function on the cloud as of 2018 (Kalyani et al., 2021; Zolas et al., 2021).

The services offered by cloud platforms fall into three categories: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). From SaaS to IaaS, each type progressively increases the user's responsibility for managing the underlying infrastructure. SaaS products (e.g., Microsoft Office 365, Dropbox) offer ready-to-use applications, while PaaS products (e.g., Salesforce Platform) provide a user-friendly development environment that simplifies infrastructure management.

IaaS, the focus of our paper, refers to fundamental components of IT infrastructure like computing, storage, and networking, which are directly managed by cloud users. This allows users to maintain granular control over their IT environments, customizing them

Figure 1: Sample of VM Choices on Amazon Web Services

Instance name	On-Demand hourly rate	vCPU	Memory	Storage	Network performance
t4g.nano	$0.0042	2	0.5 GiB	EBS Only	Up to 5 Gigabit
t4g.micro	$0.0084	2	1 GiB	EBS Only	Up to 5 Gigabit
t4g.small	$0.0168	2	2 GiB	EBS Only	Up to 5 Gigabit
t4g.medium	$0.0336	2	4 GiB	EBS Only	Up to 5 Gigabit
t4g.large	$0.0672	2	8 GiB	EBS Only	Up to 5 Gigabit
t4g.xlarge	$0.1344	4	16 GiB	EBS Only	Up to 5 Gigabit

Notes: This figure presents a sample of VM choices from one family of VMs available on Amazon Web Services (AWS). The table outlines various VM classes along with their associated on-demand hourly rates, virtual CPUs (vCPUs), memory, storage, and network characteristics.

to meet specific needs and requirements. In this way, IaaS serves as a modern alternative to on-prem IT, offering similar levels of control with the added benefits of scalability and reduced physical infrastructure costs (Jin and McElheran, 2017).[2]

2.2.1 Virtual Machines

VMs, the unit of production in cloud computing, are the primary compute resources that firms use when running workloads in the cloud. VMs enable a single server to run multiple isolated operating systems or applications, each with its own dedicated CPU, memory, and storage. This technology, known as virtualization, allows cloud providers to partition the same physical machine into separate resources and allocate them to different firms independently. VMs are the most widely used IaaS products and are offered by all major cloud platforms.[3]

Firms typically use tens or even hundreds of VMs simultaneously to support their operations. For instance, a medium-sized firm might maintain a cluster of 50-100 VMs distributed across various functions: web servers, application servers, databases, and development environments. Firms can deploy VMs either manually through cloud providers' websites, or automatically using scripts or specific tools without direct human intervention. The automated approach allows firms to pre-define VM configurations and rules, which provision VMs in response to changing demand. Once requested, VMs are typically

[2]IaaS accounts for a large share of cloud computing revenue—over 20% of the 2022 total of $545.8 billion. IDC— Worldwide Public Cloud Services Revenues. All web links in the paper were accessed on Sept 3, 2024.

[3]Cloud providers also offer more sophisticated products like "serverless" computing, which charges users only for the resources they utilize, and "container" services, which allow for isolated application development. These products are less widely adopted as they require specialized knowledge and specific contexts. Thus, they are not suitable for all types of applications. Appendix A.3.1 provides an overview of these products.

deployed within seconds (Nguyen and Lebre, 2017; Tirmazi et al., 2020).[4]

When selecting a VM in the cloud, firms can choose between many configurations of CPU, memory, storage, and networking designed for different use cases. For example, Amazon Web Services (AWS) offers a menu of VM options even within a single VM class, as shown in Figure 1. In choosing VM types, firms must consider factors such as price, memory, and storage, and evaluate them against their need. Firms face a vast menu of configurations; AWS advertises over 750 different types of VMs on its EC2 public cloud.[5]

The pricing of VMs depends on several factors, including hardware model, operating system, and geographic region (Hummel and Schwarz, 2022). More powerful VMs with more advanced hardware specifications generally cost more. However, for a given VM, firms are usually charged a fixed rate per unit of time regardless of the purpose or actual utilization of the VM.[6] Within a VM type, computing capacity is determined by the number of cores—independent processing units that execute tasks simultaneously. The product of the number of cores and the duration of the VM's use gives *core-hours*, the unit of computation resource we use throughout the paper.

2.3 The Economics of Cloud versus On-Premise Computing

The advent of cloud computing has dramatically shifted the economics of IT, eliminating the fixed costs of acquiring and maintaining compute hardware (Etro, 2015). Traditional on-prem IT involves hosting physical servers in data centers located within an organization's facilities. In this paradigm, computing capacity is a capital expenditure: firms make periodic investments under uncertainty and own servers that depreciate over time (Pindyck, 1986). This leads to a classical peak-load problem: firms must invest in enough capacity to handle peak loads, which leads to underutilization during off-peak periods (Brown and Johnson, 1969; Carlton, 1977). Indeed, Whitney et al. (2014) estimate that utilization rates of on-prem servers are as low as 12%. As a result, firms face a tradeoff between the costs of maintaining excess capacity and the risks of insufficient capacity to meet demand.

Cloud computing flips this paradigm by shifting computing from a capital expenditure to a variable cost. Firms using the cloud no longer need to worry about capacity planning or

[4] We provide more details on VMs and VM deployment in Appendix A.1. For technically oriented readers, Appendix A.2 describes VM use for two real-world applications in web development and machine learning.
[5] AWS EC2— Overview.
[6] Cloud providers offer discounts if firms commit to using cloud services over a specific period of time (typically one year or three years). These discounts are called "reserved instance" or "committed use" discounts, depending on the provider. These discounts are applied to the list price and are the same across customers except for very large ones. For more details, see Appendix A.3.3.

resource constraints, as capacity is always available on demand.[7] This allows firms to scale their compute resources based on varying requirements. Thus, firms can accommodate sudden spikes in traffic, handle increased workloads during peak periods, and scale down when resources are no longer needed, all without the need to invest in and maintain hardware.

In summary, linear pricing, instant scalability, and minimal transaction costs make computing a truly variable input, largely free from adjustment costs or dynamic frictions (Asker et al., 2014). Furthermore, all firms have access to the same technology and pricing structure in the cloud regardless of their location or industry. This makes cloud computing an ideal setting for studying firms' ability to use and learn new technologies, as we can abstract away from many of the frictions associated with dynamic inputs and rule out external factors that directly affect productivity (Syverson, 2011; Restuccia and Rogerson, 2017).

2.4 Drivers of Productivity in Cloud Computing

While cloud computing brings numerous benefits, it also introduces new challenges that firms must manage for efficient use. Industry sources and economic theory highlight two primary challenges: organizational monitoring frictions and the new skills required for cloud computing.

First, cloud computing can exacerbate latent monitoring problems within firms. Real-time monitoring of compute usage is far more important in the cloud than in on-prem computing due to positive marginal cost. Engineers who provision VMs may not naturally have an incentive to be cost-conscious, creating principal-agent problems for the firm (Holmström, 1979; Grossman and Hart, 1992). Organizational inertia can make it hard to fix this monitoring problem quickly—as firms transition to cloud computing, efficiency requires new management practices and complementary investment, referred to as "digital capital" by Tambe et al. (2020). These changes may be difficult or take time to implement, as the previous literature on IT adoption has found (Bresnahan et al., 2002; Garicano, 2010; Bloom et al., 2012).[8] For example, 81% of respondents in an industry survey say that "their development teams are embracing the cloud and other technologies faster than the rest

[7] In practice, firms initially request a quota, and the capacity is available up to this quota. Except for a few specialized VMs, firms can choose a high enough quota for their computing needs. Cloud providers can offer enough on-demand capacity using spot instances, in which VMs are available at a significant discount but can be reclaimed with short notice. Spot instances account for a small share of the IaaS market, and we exclude them from our sample. For details, see Appendix A.3.2.

[8] These challenges were also observed in the previous major shift in computing, the transition from mainframe to client/server architectures, as documented by Bresnahan et al. (1996).

of the organization can adopt and manage them" (Couchbase, 2022).[9] Another example is "shadow IT," the widespread practice of different units of the firm using IT resources without the oversight or knowledge of the IT department.[10]

Second, like many emerging technologies, cloud computing requires new skills (Griliches, 1969; Caselli and Coleman, 2001; Bartel et al., 2007). Chief among these is choosing a VM and using various tools available in the cloud. This requires adaptation and learning on the part of employees of firms that shift to the cloud. Indeed, one industry report says that finding the best match for a workload in a cloud provider's inventory is "easier said than done," with many teams "simply choos[ing] instances they know and have used before," which tends to "underutiliz[e] other resources that they have paid for" (CAST AI, 2024).[11]

The challenge of optimizing cloud spending has led to the development of a plethora of tools to help firms become more efficient. First, cloud platforms themselves offer customers various ways to view and manage their usage and costs, often proposing steps to eliminate underutilized VMs.[12] Autoscaling and load balancing are the most important first-party efficiency tools, allowing customers to set rules for shutting off underutilized VMs and deploying new VMs during high-demand periods.[13] For example, an online retailer may use autoscaling to scale up compute capacity during promotions and scale down afterward. We provide an overview of first-party tools in Appendix A.1.2 and Table OA-3.

There are also several third-party tools to help firms optimize their cloud costs. This includes a large and fast-growing market of cloud optimization consultants who analyze firms' cloud usage and recommend ways in which firms can become more efficient. These consultants engage more deeply with the firm and provide more tailored recommendations than first-party tools do. This market was worth $17.6 billion in 2022 and is projected to reach over $80 billion by 2030.[14] There are also open-source best practices collected in a framework called FinOps, short for Financial Operations, to help firms manage their cloud resources efficiently.

These tools underscore that while the cloud provides flexibility to firms, it brings its

[9] According to an employee of a cloud optimization startup we interviewed, it is challenging to get engineers to take action because there is a lack of incentive for full engagement, and large companies, in particular, are subject to operational inertia that hinder full internalization of organizational objectives.

[10] Wikipedia — Shadow IT; IBM — What is Shadow IT?; Cisco — What is Shadow IT?

[11] Another report states that many firms either "do not have the skills they need to manage their database infrastructure in-house, or they are using resources that could create greater value if used elsewhere in the business" (Couchbase, 2022)

[12] AWS— Cost Optimization; Azure— Deployment Optimizer; Google Cloud—Cost Management.

[13] See Figure OA-9 for an illustration of a load balancer.

[14] Yahoo Finance— Global Cloud Computing Report. For an example of the tool provided by one of these startups, see Figure OA-8.

own set of impediments to achieving full efficiency. Such challenges are nontrivial but tractable, as there are many tools that can help firms improve their productivity. The potential cost savings from such productivity improvements are not negligible for firms: IT's cost share is large and rapidly increasing across many sectors, accounting for 11.8% of costs in the software industry and 5% in the services industry (Demirer et al., 2024).[15] Furthermore, improving VM provisioning is likely more cost-effective than other potential methods as it does not require changes in code or additional IT infrastructure investments.

3 Data and Summary Statistics

This section introduces the datasets used in our analysis and presents summary statistics. We provide a more detailed description of the data in Appendix B.

3.1 CPU Utilization Data

Our primary dataset includes detailed CPU utilization information of a large random sample of VMs from a global cloud provider.[16] CPU utilization measures the percentage of a computer's processing capacity in use relative to its maximum capacity, and is a critical metric in assessing a computer's efficiency (Mason et al., 2018). Computing systems typically record CPU utilization at 5 or 10-minute intervals. To make these data more manageable, we aggregate it to the VM-day level, recording the CDF of CPU utilization every day while the VM is active. We then impose sample restrictions to remove very short VMs, as detailed in Appendix B.5.[17]

The CPU utilization data are available intermittently between 2017 and 2023, with varying durations each year. The 2017 data cover approximately 60 days, while in 2018 and 2019, the collection period was about 30 days each year. No data are available for 2020 and 2021, but we have a consecutive 12 months of data across 2022 and 2023.[18] Although the intermittency of the data may limit some analyses, it still allows us to estimate both short-term and long-term productivity dynamics over a six-year period.

For each VM in our data, we observe its duration, the anonymized firm ID using the VM, and the anonymized division or unit ID for multi-division firms. A "division" or

[15] We estimate the overall cost savings to firms from improving productivity to a baseline level in Section 8.
[16] The dataset is sampled to reduce its size, remove firms with very low cloud usage, and minimize the inclusion of confidential information about the provider. See Appendix B.4 for details on the sampling procedure.
[17] Additionally, we have memory and network utilization data for a one-month period. Memory utilization indicates the share of available RAM a system uses, while network utilization measures the data transfer usage relative to the total bandwidth. We analyze these data as a robustness check in Appendix E.
[18] The company stored these data intermittently for independent reasons and made them available to us for research.

"unit" collects all users that share an administrative structure for oversight of the VMs and a payment and billing account with the cloud provider. These units may correspond to product teams or functional divisions within the company, though no further information is available. As such, we will refer to these as "units" in the rest of the paper.

We also observe various attributes of the VMs, including their type, a machine series ID that provides information on the hardware manufacturer and series, operating system, memory, and number of cores. Based on this information, VMs are categorized into *type* (broad categories of workloads the VM is optimized for, like compute- or memory-intensive), *series* (groupings based on performance, hardware, or use cases), and *configuration* (the combination of memory, cores, operating system, VM series, and data center).[19] Our data also specify the region of the data center hosting the VM (EU, US, and others) and an anonymized data center ID.

3.2 Firm and Firm-Unit Level Data

Although our CPU utilization data are an unbalanced panel, we have a balanced monthly panel at the firm and unit levels. These data cover the period from 2017 to mid-2023 and include each firm's and unit's normalized monthly total computation in core-hours. With these data, which include the date each unit joined the cloud, we can track firms' entry/exit into or out of the cloud and changes in compute usage over time.[20] In addition, we observe the firm region (EU, US, or other), whether the firm is multinational, industry (2-digit SIC), and quartiles of a size measure, which proxies the number of employees. At the unit level, we observe industry and usage regions.

3.3 Publicly Available Cloud Data

We supplement our main dataset with publicly available CPU utilization data from Google Cloud and Microsoft Azure. These datasets provide additional information not available in our main dataset and allow us to validate our findings in other cloud computing environments. One of these datasets is the 2019 Power Traces from Google Cloud, which records 5-minute electricity consumption and CPU utilization of VMs in a data center. We use this dataset to estimate the relationship between CPU utilization and electricity consumption, quantifying the electricity usage of inefficient VMs. Further details of these datasets can be found in Appendix B.6.

[19] Appendix B.2 contains more details on each of these categories. See Tables OA-1 and OA-2 for examples of VM series offered by different cloud providers and their features.

[20] We observe data from one cloud provider only, and therefore cannot tell if a firm used a different cloud provider beforehand. As such, our measure of cloud experience is a lower bound on firms' actual experience.

Table 1: Distribution of Industries, Firm Regions, and VM Statistics in Mid-Sample (2020)

	Share (%)	Multi-unit (%)	Average Cloud Experience (Years)
	(1)	(2)	(3)
	Panel A. Industry Category (1-digit SIC)		
Services	36.20	26.72	1.97
IT/Software	23.15	43.06	2.73
Retail Trade	12.29	32.28	2.00
Manufacturing	9.11	43.27	2.24
Public Administration	7.48	47.20	2.52
Transportation and Communications	6.10	44.11	2.38
Finance, Insurance, and Real Estate	4.54	48.33	2.25
Other	1.12	32.62	1.96
	Panel B. Firm Region		
Other	41.12	29.54	1.90
US	31.22	26.24	1.97
EU	21.43	29.77	1.93
Multinational	6.22	59.81	2.65
	Panel C. VM Statistics		
	Mean	SD	Mode
Duration (days)	2.52	13.75	1
Number of cores	7.88	12.04	4
Share downsizable	0.72	0.45	1

Notes: This table reports summary statistics for industries, regions, and VMs in our sample for June 2020, the midpoint of our sample. Industries are classified by SIC codes, with the exception of software firms, which are carved out of the services industry. Column (1) reports the unweighted shares based on the number of firms. Column (2) reports the share of firms with multiple units, and Column (3) reports the average number of years since the firm first used the cloud. Panel C provides unweighted summary statistics for VMs created during a week in 2022, including their duration, number of cores, and share of downsizable VMs.

3.4 Summary Statistics

Table 1 presents summary statistics from our data as observed in 2020, the midpoint of our sample. Panel A shows industry categories based on 1-digit SIC codes, highlighting the predominant sectors such as services and IT/software, which account for 36.20% and 23.15% of firms in our sample, respectively. Although smaller in share, we observe non-digital industries such as manufacturing and transportation. Column (2) shows the share of firms at which multiple units use cloud computing. This percentage ranges from 26.72% to 48.33% across industries, indicating that we observe the productivity of multiple units in many firms. Column (3) shows firms' average experience in cloud computing, measured in years. Since cloud computing is a recent technology, the average experience is only a few years, with little variation across industries.

Panel B shows the geographical distribution of firms, with 31.22% located in the US, 21.43% in the EU, and 6.22% classified as multinational. As expected, multinational firms are more likely to be multi-unit and, on average, have 0.7 years more cloud computing experience than domestic firms. Panel C presents summary statistics at the VM level. The average lifespan of a VM is 2.52 days, but there is significant heterogeneity. Similarly, we observe large variations in the number of cores, reflecting that firms use VMs with varying capacities. Finally, 72% of the VMs in the data are downsizable, meaning that in most cases, firms can choose smaller-capacity VMs if they overprovision.

4 Productivity in Computing

This section details our approach to measuring compute productivity. Our goal is to quantify how efficiently firms use computation in order to study productivity and learning in the context of an emerging technology. As such, instead of focusing on the production function as a whole, we analyze one input in minute detail, measuring firms' compute productivity at the machine level using high-frequency data. Nonetheless, we demonstrate conditions under which our measure could be incorporated into a full production function in Appendix C.2.

In developing our measure, we ask the following question: how would a perfectly cost-minimizing firm that needs to produce the same compute output and faces the same menu of VM choices deploy compute resources in the cloud?[21] The share of resources this cost-minimizing firm uses relative to the actual firm's usage defines compute productivity. Importantly, this method goes beyond simply using the utilization rate as an efficiency measure, instead considering the environment the firm faces when deploying compute inputs.

In what follows, we first describe how we measure compute productivity. We then argue that our method is consistent with industry practice and has first-order importance to understanding productivity in computing. Finally, we discuss the strengths and weaknesses of compute productivity relative to TFP. A more formal description of our measure is in Appendix C.1.

[21] Our cost minimization framework is distinct from yet similar to the traditional cost-minimization assumption in neoclassical production theory. Instead of firms taking input prices as given and minimizing costs to produce an output level, in our framework, they take a menu of VMs as given and find the VM that minimizes the resource cost of producing a given compute output.

Table 2: Example CPU Usage for a Hypothetical Firm

Job	Capacity	Duration	Actual Input Use	Peak Util.	Peak Load	Efficient Usage	Efficient Input Use	Efficiency
	[a]	[b]	[c] = [a] × [b]	[d]	[e] = [a] × [d]		[f]	[g] = [f] ÷ [c]
Job 1	2-core	10h	20 ch	0%	0 cores	**Eliminate**	0 ch	0%
Job 2	4-core	5h	20 ch	25%	1 core	**Downsize**	10 ch	50%
Job 3	8-core	10h	80 ch	75%	6 cores	**Maintain**	80 ch	100%
Total			**120 ch**				**90 ch**	**75%**

Notes: Table 2 presents a breakdown of CPU usage for three different jobs within a hypothetical firm. Job 1, with a 2-core capacity and minimal utilization, suggests idleness (0% peak utilization), leading to the recommendation to eliminate this job. Job 2, with a 4-core capacity used at 25% peak utilization, indicates overprovisioning, and the advice is to downsize. In contrast, Job 3 shows optimal use of an 8-core capacity at 75% peak utilization, which is maintained as efficiently used. The total CPU input across all jobs accumulates to 120 core-hours with an actual efficient use of 90 core-hours, reflecting an overall efficiency of 75%.

4.1 Measuring Compute Productivity

To illustrate our measure, consider the usage pattern of a hypothetical firm documented in Table 2. Suppose there are three sizes of VMs available for the firm's use case: 2-core, 4-core, and 8-core. The firm runs three jobs: Job 1 on a 2-core machine, Job 2 on a 4-core machine, and Job 3 on an 8-core machine. Jobs 1 and 3 last 10 hours, and Job 2 lasts 5 hours. Therefore, the total computing resource the firm pays for—the firm's total input use—is $2 \times 10 + 4 \times 5 + 8 \times 10 = 120$ core-hours.

Now suppose that we observe the following utilization patterns. On Job 1, the firm did not actually utilize the machine at all; the peak load for Job 1 was 0 cores. On Job 2, the firm did use the machine, but at most 25% of the computing capacity was used at any given moment. Therefore, the peak load of Job 2 was $25\% \times 4 = 1$ core. Finally, on Job 3, the peak utilization was 75%, meaning the peak load of the job was $75\% \times 8 = 6$ cores. These loads define the cores that were needed to perform the observed workloads and can be used to determine computing efficiency.

What would a perfectly cost-minimizing firm have done if it had the same computing needs and faced the same set of VMs? First, it would eliminate Job 1, which does not result in any computing output for the firm. By doing so, the firm can avoid paying for 20 core-hours of input. Second, given that Job 2 only requires a capacity of 1 core at peak, the firm would downsize it to a 2-core machine, reducing the input usage from 20 core-hours to 10 core-hours. Finally, since Job 3 requires a peak capacity of 6 cores, it cannot be downsized (the next smallest available machine is 4 cores); the cost-minimizing firm would provision the same 8-core machine for the job and use the same 80 core-hours of input. Overall, therefore, a cost-minimizing firm would have only used 90 core-hours, while this firm actually used 120 core-hours. As such, we conclude that this firm could have used 75% as much input as it actually did to get the same output.

Our measure of compute productivity generalizes the logic of this example. We assign each job j run by firm i on day t a productivity $\omega_{ijt} \in [0, 1]$, where, at a high level,

$$\omega_{ijt} = \frac{\text{Minimum number of core-hours needed for job}}{\text{Actual core-hours used for job}}.$$

This formula essentially measures (the inverse of) the share of resources that are wasted when running job j. To determine the minimum number of core-hours needed for job j, we use its peak utilization over a seven-day period.[22] The focus on peak utilization ensures our measures remain robust to various concerns that might explain low utilization. For instance, our approach does not mark as inefficient low average utilization due to fluctuating demand, nor does it credit potential short-term efficiency gains from briefly turning a VM off and on. We take peak utilization to be the 95th percentile CPU utilization over a seven-day period, following the recommendations made by cloud providers, as well as in the computing literature (Reiss et al., 2012; Cortez et al., 2017).[23]

Our method identifies two distinct sources of inefficient VMs: idleness and overprovisioning. Job j is *idle* if the peak CPU utilization for the job is under 10% of the capacity of the VM the firm chose. This amount of utilization is explained by the CPU's background processes rather than any actual CPU usage by the user (Breitgand et al., 2014). Because an idle job does not have any output, the minimum number of core-hours needed for the job is zero, hence $\omega_{ijt} = 0$.

Job j is *overprovisioned* if it is not idle, but would have only reached a peak utilization of 90% or less on a VM that has fewer cores but is otherwise similar. In this case, the minimum number of cores to run the job is that of the smallest such VM that fits the job's peak load. If such a smaller substitute exists—that is, if there exists a configuration with fewer cores but the same machine type, memory, data center, and operating system—we call the VM *downsizable*.[24] Typically, cores scale in powers of two, so an overprovisioned VM will often be resized to a VM with half the number of cores, in which case $\omega_{ijt} = 0.5$.[25]

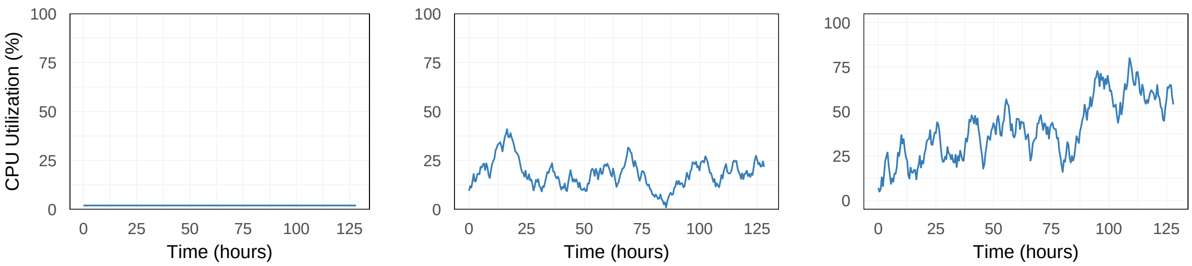
[22]For VMs shorter than seven days, we use the peak utilization over the life of the VM.

[23]This measurement is less sensitive to measurement errors or spikes stemming from random events like software updates than the maximum CPU utilization.

[24]We focus on these characteristics because VMs that share these characteristics are readily substitutable. We discuss this further and demonstrate that our analyses are robust to alternative definitions in Appendix E.5.

[25]We treat a VM-day as idle or overprovisioned if it is a part of any seven-day streak with a sufficiently low peak utilization. In addition, in some cases, it is possible to downsize to a quarter of the number of cores, i.e., if the peak utilization is 20% and a VM with one-fourth of the number of cores is available. In this case $\omega_{ijt} = 0.25$. Although we omit this category from this section for brevity, as it is rarely observed in the data, we include it in our productivity calculations. See Appendix D.1 for the details of the productivity

Figure 2: CPU Usage Patterns



(a) Idle VM **(b)** Overprovisioned VM **(c)** Properly Provisioned VM

Notes: This figure illustrates the CPU usage patterns of three different types of VM usage. Panel (a) shows the CPU utilization of an idle VM, maintaining a constant utilization near 0% throughout the duration. Panel (b) shows an overprovisioned VM where the peak utilization only reaches about 40%. Panel (c) shows a properly provisioned VM with peak utilization above 75%.

Finally, if a job is neither idle nor overprovisioned, it is *properly provisioned*. In this case, $\omega_{ijt} = 1$.

Figure 2 is another illustration of our measure. Each panel displays the CPU utilization of a job over time. Panel (a) is an idle job. The firm uses over 125 hours of compute resources even though it actually did not utilize the VM it provisioned. This idle VM cannot be reallocated to another firm by the cloud provider and still consumes around 50% of the electricity of a fully utilized machine (Kansal et al., 2010).[26] Panel (b) is a potentially overprovisioned job. Although the VM was continuously used for the job, it could have also fit on a substitute VM with half the number of cores. If such a VM exists, this job would be marked as overprovisioned and have a productivity of 0.5. Finally, panel (c) reflects a properly provisioned job. Although not all of the capacity of the VM is used—indeed, most of the time, the job would have fit on a smaller VM—the peak CPU utilization on the chosen VM is around 75%, which means the peak load of the job would not be able to fit on a smaller VM.

As in the example in Table 2, we can aggregate the VM-level productivity to a firm-level productivity by taking a weighted average across VMs, weighted by the core-hours of each VM. The overall productivity level in month m for firm i with VMs J_{im} is:

$$\omega_{im} = \frac{\sum_{j \in J_{im}} \sum_t \omega_{ijt} ch_{ijt}}{\sum_{j \in J_{im}} \sum_t ch_{ijt}} \tag{1}$$

calculation procedure.

[26]Cloud providers have service-level agreements (SLAs) with their clients, committing to maintain VM availability with extremely high probability (e.g., 99.99%, commonly referred to as "four 9s"). Redmond Channel Partner—Microsoft Promises To Raise Azure AD Uptime to 99.99 Percent. Therefore, reallocating idle VMs could risk violating these SLAs and pose monetary and reputational risks (Perez-Salazar et al., 2022).

where ch_{ijt} is the core-hours of VM j on day t. As the ratio between the actual and cost-minimizing resource usage, ω_{im} represents a direct measure of firm i's compute output divided by firm i's compute input. Using the same procedure, we also estimate firm-level productivity over our entire sample period, unit-month level productivity for a within-firm analysis, and idleness and overprovisioning productivity to decompose total compute productivity, as described in Appendix D.1.[27]

While our measure represents a physical measure of productivity, it may also be desirable to control for job characteristics, such as time and VM type. To do so, we estimate the following fixed-effect regressions:

$$\omega_{ijt} = \omega_{im} + Z'_{jt}\beta + \epsilon_{ijt}, \tag{2}$$

where Z_{jt} includes job- and time-specific factors such as the type of the machine and the day of the week (utilization could be lower on weekends). The resulting firm-month fixed effect ω_{im} is our estimate of firm i's productivity in month m, controlling for the factors in Z_{jt}. We weight observations by the number of core-hours of each VM on each day; therefore, if Z_{jt} were not included, the resulting estimates of ω_{im} would be numerically equivalent to the core-hour-weighted average given in equation (1). Our baseline results use the specification without controls, as the choice of VM may itself reflect firm productivity. However, we report our main results with various controls in the Appendix.

In measuring compute productivity, we use the hypothetical cost-minimizing firm that can always match its VMs to its computing needs as a benchmark. However, our measure does not require an assumption that firms can perfectly predict their compute demand. As discussed in Section 2, many tools in cloud computing allow firms to automatically scale their capacity up and down instantly in response to demand changes. These tools decouple the relationship between demand forecasting and provisioning, meaning that firms do not need to predict demand perfectly to provision VMs efficiently. Failing to take advantage of these tools should be viewed as an inefficiency in and of itself, which is captured by our measure.

While our measure of compute productivity is novel to the economics literature, it is in line with measures used in industry and bears similarity to previously developed resource utilization-based productivity measures in economics. First, cloud providers' definitions of efficiency are similar to our own; for example, Microsoft Azure's API generates a "resize" recommendation if the 95th percentile CPU of a job would be under 80% on a less

[27] In these fixed effect regressions, we can only compare the fixed effects of firms within a connected set (Abowd et al., 1999; Metcalfe et al., 2023). We find that across these specifications, there is either one connected set or that the largest connected set covers more than 99% of the firms.

expensive VM, nearly identical to our definition of overprovisioning.[28] Second, the cloud optimization startups described in Section 2 also focus on idleness and overprovisioning; one such startup states that the "best practices for optimizing cloud costs" are to "identify underutilized resources, detect idle resources, [and] rightsize cloud resources."[29] Third, similar metrics have also been used to measure productivity in the operating systems and IT literature (Folkerts et al., 2013). Finally, the idea behind our measure—that the extent to which firms utilize their inputs is a dimension of firms' productivity—has been used to study productivity in several other contexts in economics (Hubbard, 2003; Braguinsky et al., 2015; Butters, 2020, for example).[30]

Nevertheless, there are three caveats to point out about our measure. First, it does not capture other computing inefficiencies like poorly written code that consumes excess compute, meaning some jobs we deemed properly provisioned would actually be overprovisioned if the code were optimized. Therefore, our measure should be viewed as a productivity measure due to provisioning decisions, conditional on code efficiency and all other factors. To the extent that provisioning and coding skills are positively correlated, then we will understate the degree of productivity dispersion and the amount of learning. Second, we focus on CPU utilization and do not capture other dimensions of VM utilization (memory and network) since CPU utilization is the most commonly used measure in the industry. However, we perform robustness checks with the limited data on memory and network utilization in Appendix E.1. Finally, we do not account for more elaborate efficiency improvements, such as consolidating multiple VMs with 70% peak CPU usage into a smaller number of more fully utilized VMs. While theoretically possible, such improvements may not be practical and would require additional assumptions.

4.2 Comparison of Compute Productivity with TFP

As the productivity literature has overwhelmingly focused on TFP, it is important to discuss the relative strengths and weaknesses of compute productivity. TFP is defined as the residual in the production function after accounting for the contributions of measured inputs. Therefore, as the "unexplained" part of the output, it can correspond to various unobserved factors such as technology and management, offering limited insight into

[28] Azure— How-to Guides. AWS and Google Cloud Platform have their own similar definitions of idleness and overprovisioning. AWS— API Reference; Google Cloud— Reduce Overprovisioned Instances; Google Cloud— Identify Idle Instances.

[29] CASTAI— Cloud Cost Optimization.

[30] The key difference between our measure and those previously developed in the literature is that these papers tend to consider capacity as fixed in the short run and load as variable, while in our context, we think of load as fixed and the provisioned computing capacity as variable. Nevertheless, the common source of inefficiency is a mismatch between load and capacity.

specific mechanisms (Solow, 1957). Moreover, TFP estimation faces well-documented measurement challenges, including conflation of physical productivity with output prices due to using revenue data (Foster et al., 2008), reliance on input aggregation (Orr, 2022), measurement errors (Collard-Wexler and De Loecker, 2016), and lack of high-frequency data.

While narrower in scope compared to TFP, our productivity measure is attributable to a single input with a clear interpretation. It is a physical productivity measure directly linked to the actual resources used in production, such as compute resources and electricity. Additionally, by observing productivity at the minimal unit of production (VM), we can study the precise mechanisms underlying inefficiencies. These advantages make it possible to study aspects of productivity that are hard to analyze using TFP, thereby complementing existing evidence on firm productivity.

5 Empirical Facts on Compute Productivity

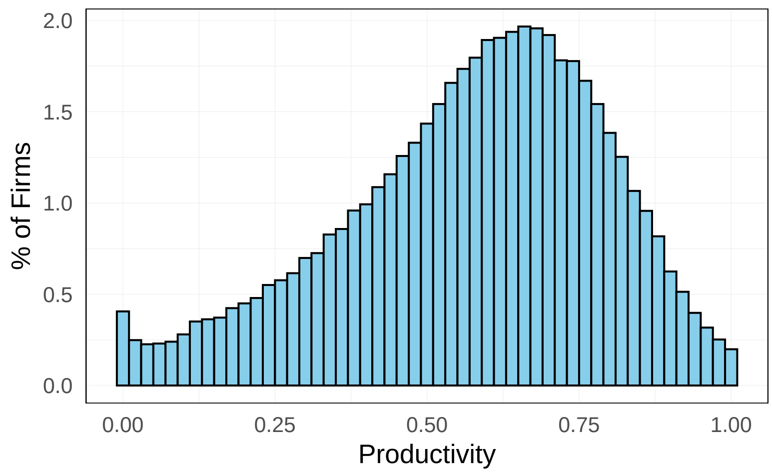
This section begins by presenting our findings on the dispersion and persistence of compute productivity. We then analyze within-firm productivity dispersion and examine how productivity varies with firm characteristics, such as size and region.

5.1 Dispersion and Persistence of Compute Productivity

Our compute productivity estimates show significant productivity variation across firms. In Figure 3, we plot the distribution of compute productivity at the firm level, and Panel A of Table 3 reports several dispersion statistics both without controls and controlling for industry, time, and industry-by-time.[31] The productivity estimates range from 0 to 1, where 0 indicates consistently idle VMs, and 1 represents optimal VM provisioning without idleness or overprovisioning. We observe that the productivity distribution is approximately normal-shaped, with a median of 0.62 and a mean of 0.60, suggesting that firms utilize only 60% of their provisioned resources productively on average. However, there is substantial dispersion around this mean. While firms in the right tail fully utilize their VMs, others in the left tail leave all of their VMs idle. Overall, controlling for industry and time, we observe a 90th to 10th percentile ratio of 3.53, indicating that some firms are more capable of using compute resources efficiently than others.

[31] Our industry classification uses 2-digit SIC codes, broader than the 4- or 6-digit codes common in the literature. Unlike full production functions, which vary greatly even within narrow industries, compute input is relatively homogeneous. Thus, 2-digit classifications are likely to capture potential heterogeneity in use cases.

Figure 3: Dispersion of Firm Compute Productivity



Notes: This figure shows the distribution of firm-level compute productivity, estimated using Equation (1). The x-axis represents productivity levels ranging from 0 to 1, while the y-axis shows the percentage of firms. Each observation corresponds to a firm, and the histogram bars reflect the unweighted distribution of firms across different productivity intervals. Productivity dispersion by industry is reported in Figure OA-3.

Next, we analyze within-firm productivity dispersion in Table 3. We find that different units in the same firm can exhibit significantly different compute productivity: 44.28% of productivity dispersion across units in our sample is within-firm. We further decompose this within-firm heterogeneity into within- and between-region components by analyzing multinational firms that own units in different geographies and find that region explains 18.22% of within-firm variation. Although this percentage is small, it still shows that the geographic location of a unit, even within the same firm, accounts for a non-negligible share of productivity differences. These regional differences could be driven by human capital heterogeneity, the timing of the cloud adoption, or organizational differences, as documented in Bloom et al. (2012). The large within-firm productivity dispersion emphasizes the importance of within-firm productivity dynamics, which we will revisit in Section 7.

We next examine the persistence of productivity over time. Panel B of Table 3 reports AR(1) coefficients estimated for 1-month, 1-year, and 5-year horizons. Productivity is extremely persistent in the short run: AR(1) coefficients are 0.93 and 0.64 for 1-month and 1-year horizons, respectively. While this persistence declines over longer horizons, it remains large, with a 5-year AR(1) coefficient of 0.32. Moreover, the different components of productivity—idleness and overprovisioning—are also persistent, although overprovisioning exhibits less persistence than idleness, especially in the long run. One interpretation of this result is that monitoring frictions are more persistent than skill de-

Table 3: Dispersion and Persistence of Compute Productivity

	No Control (1)	Industry (2)	Time (3)	Industry/Time (4)
	Panel A. Dispersion			
Dispersion:				
Mean	0.60	-	-	-
Median	0.62	-	-	-
10-90th perc ratio	3.51	3.49	3.53	3.53
Inter Quartile Range	1.72	1.72	1.73	1.73
R^2	-	0.009	0.002	0.012
Within-Firm Decomp. (%):				
Between-firm	33.08	32.33	44.28	43.57
Within-firm	66.92	67.67	55.72	56.43
Within-Firm-Between-Region Decomp. (%):				
Between-region	5.88	-	18.22	-
Within-region	94.12	-	81.78	-
	Panel B. Persistence (AR(1) Coefficients)			
1-month persistence:				
Productivity	0.93	0.93	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)
Idleness Productivity	0.93	0.93	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning Productivity	0.91	0.92	0.91	0.91
	(0.00)	(0.00)	(0.00)	(0.00)
1-year persistence:				
Productivity	0.64	0.63	0.64	0.63
	(0.00)	(0.00)	(0.00)	(0.00)
Idleness Productivity	0.66	0.64	0.66	0.64
	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning Productivity	0.60	0.59	0.56	0.56
	(0.00)	(0.00)	(0.00)	(0.00)
5-years persistence:				
Productivity	0.32	0.30	0.32	0.30
	(0.01)	(0.01)	(0.01)	(0.01)
Idleness Productivity	0.33	0.31	0.33	0.31
	(0.01)	(0.01)	(0.01)	(0.01)
Overprovisioning Productivity	0.10	0.10	0.10	0.10
	(0.01)	(0.01)	(0.01)	(0.01)

Notes: This table reports the dispersion and persistence of productivity measures with different sets of controls. Panel A presents statistics on the distribution of productivity, as well as the composition of productivity dispersion. Panel B shows the persistence of productivity measures with 1-month, 1-year, and 5-year AR(1) coefficients, with standard errors clustered at the firm level in parentheses. Productivity measures are obtained using Equation (1) separately for overall productivity, idleness, and overprovisioning productivity. Further details of the estimation and a visualization of persistence are provided in Appendix D.2 and in Figure OA-5.

velopment within firms, as idleness is more likely to be driven by such frictions than overprovisioning.

It is important to examine whether simple observable factors can explain this dispersion and persistence in compute productivity. The R^2 estimates in Panel A suggest that this is not the case: observables explain at most 1.2% of variation in firm productivity, and the magnitudes of dispersion and persistence are similar in different specifications. These results point to the role of unobserved heterogeneity in compute productivity, mirroring common findings in the productivity literature (Fox and Smeets, 2011; Metcalfe et al., 2023).[32]

5.2 Productivity Differences by Firm Characteristics

This section examines the relationship between compute productivity and key firm characteristics, focusing on firm size and geographical location. The drivers of compute productivity described in Section 2 suggest no clear ex-ante relationship between firm size and compute productivity. While larger firms may benefit from greater resources for complementary investments and skill development, they might also face more organizational frictions. Our findings, presented in Table 4, confirm this intuition: we find no consistent relationship between firm size and compute productivity. While the firms in the 2nd and 3rd quartiles of the size distribution are 1.0% to 2.8% more productive than the 1st quartile firms, the largest firms are 3.8% less productive than the smallest firms. However, when examining the components of productivity, we observe that firms in the largest quartile exhibit 6.0% lower idleness productivity but 7.5% higher overprovisioning productivity relative to those in the smallest quartile. This pattern may reflect greater organizational frictions and monitoring challenges in larger firms, potentially resulting in more idle machines, while their IT capabilities lead to higher overprovisioning productivity.

In Panel B, we report the productivity differences between US and EU firms. The results reveal that US firms consistently outperform EU firms, demonstrating a 3.3% to 5.2% higher compute productivity across all categories. This finding is consistent with Bloom et al. (2012), who find that American firms are better at utilizing IT. Bloom et al. (2012) attribute this difference to differences in organizational structure between US and EU firms, which supports our result that the gap between US and EU firms is wider in idleness than overprovisioning.

[32] Murciano-Goroff et al. (2024) find similar evidence in the digital economy by showing that observable characteristics explain little variation in firms' propensity to use software with known vulnerabilities.

Table 4: Productivity Differences Across Firm Characteristics

	Overall Prod. (1)	Idleness Prod. (2)	Overprov Prod. (3)
	Panel A: Firm Size (% difference relative to 1st quartile)		
2^{nd} quartile	0.010	-0.009	0.061
	(0.003)	(0.002)	(0.005)
3^{rd} quartile	0.028	-0.007	0.127
	(0.003)	(0.002)	(0.004)
4^{th} quartile	-0.038	-0.060	0.075
	(0.003)	(0.002)	(0.004)
	Panel B: Region (% difference relative to EU)		
US firms	0.052	0.048	0.033
	(0.004)	(0.003)	(0.002)
Industry FE	X	X	X
Time FE	X	X	X

Notes: This table reports the productivity differences across firm characteristics. Panel A presents the average productivity estimates for firms in different size quartiles relative to the 1st quartile, expressed in percentage terms. Panel B shows the differences between US firms and EU firms. Columns (1-3) report the results for overall productivity, idleness productivity, and overprovisioning productivity, respectively. The estimates are obtained from firm-month level regressions, where the outcome variable is the level of productivity specified in columns, with the control variables specified in the bottom panel table. The construction of firm-month level productivity estimates is described in Section 4 and Appendix D.1. Standard errors are calculated using the delta method, clustered at the firm level, and reported in parentheses.

5.3 Comparison to the Literature

Numerous studies have documented large productivity dispersion across firms, primarily relying on TFP from manufacturing industries. We should expect compute productivity dispersion to be directionally ambiguous relative to canonical results in the literature; while focusing on a single and uniform input could reduce dispersion, the evolving nature of computing technology could lead to larger dispersion. Syverson (2004) reports an average 90-10th percentile ratio of 2.45 in the US manufacturing sector, slightly smaller than our finding. Other estimates include an interquartile range of 1.76 in US retail (Foster et al., 2006) and a 90-10 ratio of 5 in Chinese and Indian manufacturing industries (Hsieh and Klenow, 2009). There are also estimates of productivity dispersion focusing on a specific input like us. Fox and Smeets (2011) study labor productivity using Danish employer-employee data and finds a 90-10 ratio of 3.36, while Davis et al. (2008) report a 90-10 ratio of 7.3 in electricity productivity in the US Census.

Regarding within-firm heterogeneity, while limited evidence is available in the literature for comparison, some recent papers have explored within-firm dispersion in various outcomes, with similar results to our findings. For instance, Kehrig and Vincent (2019) find that within-firm dispersion accounts for 60% of the variation in the marginal product of capital, and Orr (2022) reports that close to 40% of variance of product-specific productivity among multi-product firms is explained by within-firm heterogeneity.

Overall, our findings on dispersion and persistence of compute productivity are remarkably consistent with the large body of evidence of productivity differences in the literature, despite differences in measurement approaches and our focus on the digital economy. In this way, our results complement the prior literature by showing that persistent productivity differences continue to exist in the digital economy and with emerging inputs.

5.4 Robustness Checks and Ruling Out Alternative Explanations

Several alternative explanations could generate the dispersion in compute productivity we observe. The most important ones are demand volatility and risk aversion: seemingly inefficient firms may purposefully maintain idle and overprovisioned VMs because they are worried about rare demand spikes that do not materialize. As discussed in Section 4.1, this is solvable using universally available tools such as autoscaling and, therefore, should be viewed as its own form of inefficiency. Nevertheless, we conduct two exercises to show that this concern does not explain our results. First, in Appendix E.4, we estimate various measures of firm compute demand volatility and show that they explain less than 1% of productivity variance. Second, we calculate the probability of firms being capacity-constrained by their chosen VM (similar to a stockout) and show that high-productivity firms do not experience higher stockout rates than low-productivity firms.

A second explanation for productivity dispersion is that firms use computing for different purposes, which could inherently have different productivity patterns. While we have shown that industry has little explanatory power, we go further and control for specific use cases using VM characteristics, such as memory and machine type, as they are informative about the type of jobs firms run in the cloud. The results in Appendix E.3 suggest that while these factors have some explanatory power for productivity differences, they account for only a small fraction of the overall variation.[33]

Our other robustness checks, described and reported in Appendices E and H, confirm our results' robustness and external validity. First, we repeat our analysis with alternative downsizability and peak utilization definitions and find that the results are robust to these

[33] As reported in Figure OA-1, machine type and memory explain 4.1% and 6.8% of the variation, respectively. Even controlling for the precise configuration of a VM explains only 23.9% of the observed variation in productivity. This suggests that approximately three-quarters of the variation in productivity occurs among firms that use identical VMs.

choices. Second, we find that firms with below-median productivity are 60.0% likelier to exit the cloud than those above the median, again similar to other results in the productivity literature (Foster et al., 2016). Third, we extend our analysis to other dimensions of VM utilization, including memory and network, and find that these dimensions positively correlate with CPU utilization, indicating that VMs identified as CPU-inefficient are likely inefficient in memory and network utilization as well. Fourth, we show that idleness and overprovisioning productivity, which are potentially generated by different mechanisms, are positively correlated. Finally, we analyze dispersion in compute productivity using publicly available datasets from Google Cloud and Microsoft Azure and find comparable magnitudes of dispersion.[34]

Beyond these empirical tests, many of our results suggest simple mechanical relationships do not drive productivity differences. The empirical patterns of compute productivity align closely with established findings of the productivity literature, reinforcing the validity of our results. Moreover, we showed that productivity dispersion exists within firms and even within units—to the extent that jobs in the same unit within the same firm tend to have similar use cases; this demonstrates that the use case itself does not drive the observed dispersion. Finally, as we will document in Section 7, there is significant short- and long-term learning at both firm and unit levels, indicating firm productivity is not solely determined by time-invariant firm characteristics.

6 Mechanisms: What Do More Productive Firms Do?

We have now seen that firms differ dramatically in the efficiency with which they use computing, that these differences are persistent, and that they are not explained by observables. The industry sources and economic literature reviewed in Section 2.4 point to two primary factors that could be driving these productivity differences: organizational factors such as monitoring capabilities and employee skill heterogeneity. As we do not have specific data on managerial practices or organizational structure within firms, and the scale of our study precludes collecting that information using surveys, we cannot directly test the extent to which these factors explain productivity differences in our context. However, these factors each predict specific patterns that should distinguish the VM provisioning behavior of more and less productive firms. We can, therefore, use our data to evaluate some implications of each mechanism.

[34] Another potential concern is that we have a selected sample of firms, specifically the customers of our data provider. However, the relevant population for this study is the firms that use cloud computing. Conditional on this sample, our understanding of the cloud industry suggests minimal selection bias, as cloud providers offer similar services. Our analysis of public datasets in Appendix E.8 also confirms this intuition.

In this section, we examine the association between productivity and three such patterns: responsiveness to demand changes, attentiveness to idle resources, and usage of a wider variety of VM types. First, firms that take advantage of cloud capabilities should be more effective at adapting to changes in demand. We study provisioning decisions on weekends, when firms face a sizable drop in demand for computing, and test whether more productive firms are better at dealing with these short-term fluctuations. Second, when there are mistakes and resources are left idle, firms that are better at monitoring should be better able to shut down these idle resources faster. Finally, more knowledgeable employees are likely better at matching the machine to the job, using a wider variety of more specialized machines, and less likely to put all jobs on one VM type.

To study these factors, we perform the following out-of-sample exercise. We first classify firms as "high" or "low" productivity based on their productivity in 2022 relative to their industry's median productivity. We then analyze the differences in the VM provisioning behavior between these groups in 2023. In a similar manner to difference-in-differences, our analyses compare high- and low-productivity firms in certain circumstances relative to a within-group baseline, which avoids our results being mechanically driven by serial correlation in productivity.

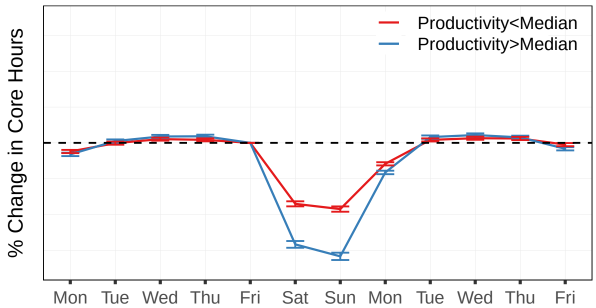
6.1 Responsiveness to Demand Changes

To analyze the differences in responses to demand changes between high and low-productivity firms, we employ an event study approach and estimate the following specification:

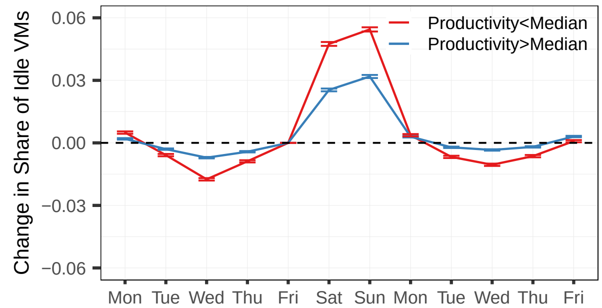
$$y_{it} = \sum_{k=-4}^{7} \beta_k^H D_{i,t-k}^H + \sum_{k=-4}^{7} \beta_k^L D_{i,t-k}^L + \alpha_i + \gamma_t + \epsilon_{it}. \tag{3}$$

This specification allows us to compare how high- and low-productivity firms adjust their compute resources over the course of a two-week period while controlling for firm- and time-specific factors. In this equation, y_{it} represents the outcome variable for firm i on day t. $D_{i,t-k}^H$ and $D_{i,t-k}^L$ are indicator variables for high- and low-productivity firms, respectively, where k represents each day relative to the first Friday in a two-week cycle. We include firm fixed effects (α_i) to account for time-invariant firm characteristics and time-fixed effects (γ_t) for every two weeks to control for overall time trends or seasonality. The coefficients of interest are β_k^H and β_k^L, representing the change in the outcome variable relative to the first Friday in the two-week cycle for high- and low-productivity firms, respectively. We estimate this regression for two main outcome variables: the logarithm of total provisioned resources and the share of idle VMs.

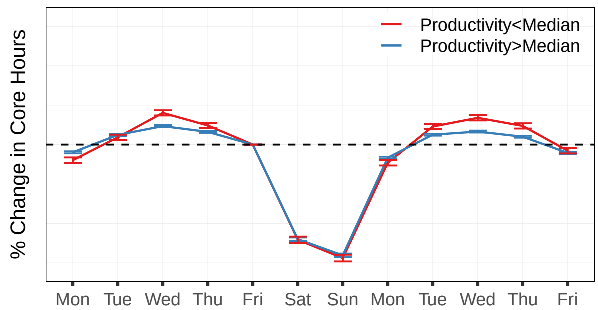
Figure 4: Firm Responses to Weekend Demand by Productivity Level



(a) Change in Provisioned Resources



(b) Share of Idle Machines



(c) Change in Load

Notes: These figures show coefficient estimates from Equation (3) with three outcome variables listed in the text, reporting the percentage changes in provisioned resources, the share of idle VMs, and compute load for firms above and below the median productivity level. The productivity levels are estimated using the 2022 sample, whereas the regressions are estimated using the 2023 sample. The estimates are calculated using firm-day level data, constructed using an analog of Equation (1) for daily frequency controlling for firm-fixed effects and week-fixed effects. Error bars represent 95% confidence intervals clustered at the firm level. The y-axes of Panels (a) and (c) are obfuscated for confidentiality reasons.

Panels (a) and (b) of Figure 4 plot the coefficients separately for high-productivity and low-productivity firms. Both groups use fewer resources and are likelier to leave VMs idle on weekends. However, high-productivity firms reduce computing resources by 75.2% more than low-productivity firms, resulting in significantly lower computing resource usage. Additionally, high-productivity firms utilize their provisioned resources more effectively: they are 2.6 pp more likely to leave VMs idle on weekends compared to weekdays, while low-productivity firms have a 4.7 pp increase in idle VMs.

One might be concerned that low- and high-productivity firms systematically differ in how much they require computing on weekends, which could be driving these results. To investigate this, we run the same regression using the logarithm of total load (i.e., total compute output) as the dependent variable, the results of which are plotted in panel (c) of

Figure 4.[35] We find that compute load is extremely flat on weekdays in both groups and, as expected, drops substantially on weekends. Notably, these trends are almost identical between the two groups, demonstrating that differences in compute demand changes on weekends between high- and low-productivity firms are not driving the results of panels (a) and (b).[36]

This analysis demonstrates that a firm's ability to adapt to demand fluctuations significantly influences its productivity.[37] Our findings not only inform our analysis of compute productivity but also, to the best of our knowledge, provide the first large-scale evidence that firms vary in their capacity to adjust to high-frequency demand fluctuations. Responsiveness to shocks is a fundamental component of an economy's dynamic efficiency, as has been analyzed in the context of low-frequency, market-level shocks (Pozzi and Schivardi, 2016; Berger and Vavra, 2019; Cooper et al., 2024). Our research adds a new dimension to this understanding by examining how firms leverage specific technologies to respond to changing market environments.

6.2 Attentiveness to Idle Resources

The second factor we investigate is the timeliness with which low- and high-productivity firms detect and shut down idle resources. Idle resources in the cloud are a relatively common and well-documented phenomenon that can occur when firms deploy resources but do not shut them off after they are no longer being used.[38] Given that firms often run hundreds of VMs at once, it is not trivial to identify and stop idle resources, and firms with better monitoring structures in place should be better positioned to do so.

To test this, we estimate the speed at which low- and high-productivity firms shut down idle machines. We first identify all VMs that are idle for at least one consecutive day at the end of their lives. We then estimate, separately for low- and high-productivity firms, the probability that a VM that has remained idle for a given number of days is shut down on the following day. Put another way, we compute the hazard rate of shutting down an

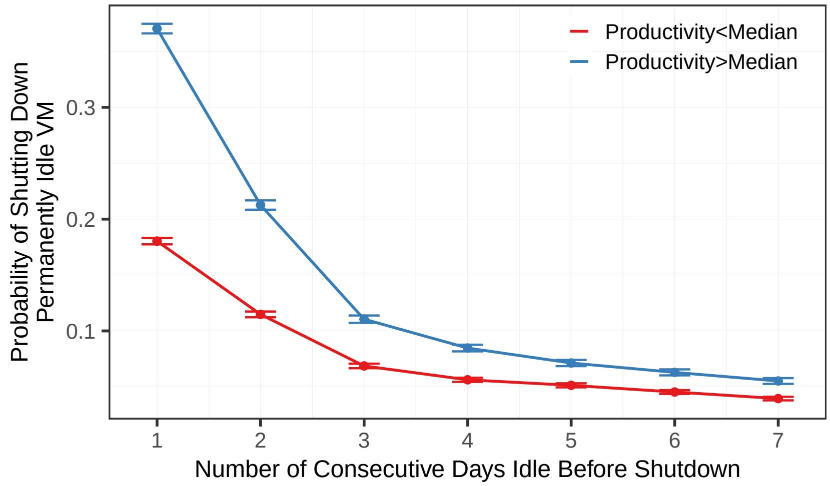
[35] Load is computed at the VM-day level by multiplying the average CPU utilization of the VM on a given day with the number of core-hours of the VM on that day. Summing across all of a firm's active VMs gives the total compute load of the firm on that day.

[36] We interpret load as being primarily by demand. However, one concern with our interpretation could be that not all load changes are demand-driven, as firms might use compute resources for other purposes, such as product development. To address this concern, we repeat this exercise by focusing on software firms whose compute loads are more likely to be driven by customer demand and find similar results.

[37] An alternative interpretation of these results is that more productive firms are better at predicting load changes on weekends. We view this as less likely, considering that the drop in load on weekends is very consistent, and the occurrence of the weekend in the first place is a predictable and non-stochastic event.

[38] One industry survey found that nearly half of cloud spend is on idle or unused resources (StormForge, 2021).

Figure 5: Shutdown Probabilities of Permanently Idle VMs by Productivity Level



Notes: This figure displays the probability that a VM that is idle for multiple days at the end of its life is shut down after each given number of days, conditional on being idle for at least that many days. The red line represents less productive firms, while the blue line represents more productive firms. The productivity levels are estimated using 2022 data, while the probabilities are estimated using 2023 data. The crossbars are 95% confidence intervals, with standard errors clustered by firm. Only includes VMs that last longer than one day and that end before the end of our sample period.

idle VM separately for the two groups.[39] If more productive firms are better at monitoring and identifying idle resources, then they should shut down idle VMs faster, resulting in higher hazard rates. The results are displayed in Figure 5.

Overall, we find that high-productivity firms demonstrate a significantly higher likelihood of shutting down idle VMs. High-productivity firms have a 37.0% probability of shutting down a VM on the day it becomes idle, compared to 18.0% for low-productivity firms. Even if the VM is not shut down on the first day it becomes idle, high-productivity firms are more likely to detect it and shut it down on any given day within the next week, if it gets to that day. Because we condition on resources being idle, we abstract away from skill differences that cause idle resources in the first place; this analysis, therefore, speaks more directly to differences in monitoring capabilities across firms.

6.3 Usage of a Variety of VM Types

Firms have access to various types of VMs, each specialized for different workloads. Unlike the quantity of provisioned resources, which can be automated by tools like autoscaling, the choice of VM is most often manually and actively chosen by cloud users themselves. As such, firms with employees who are more knowledgeable about the various VM types

[39] While the base rate of idle resources is higher for less productive firms by construction, conditioning on a resource being idle eliminates this mechanical correlation from our analysis.

Table 5: Usage Patterns by Productivity Level

Dependent variable	prod >median	% of mean	prod >median	% of mean
HHI of usage across VM series	-0.094	-15.8	-0.067	-11.2
	(0.002)		(0.002)	
1(all usage on one VM series)	-0.118	-54.3	-0.092	-42.5
	(0.002)		(0.002)	
Number of VM series used	1.260	28.5	0.764	17.3
	(0.029)		(0.026)	
Cohort quarter/firm size FE			X	X
Industry/region FE			X	X

Notes: All rows display the coefficient of a regression of the dependent variable on an indicator for whether the firm is more productive than the median firm, along with the ratio between the coefficient and the mean of the dependent variable. The left set of columns includes the raw difference between the groups, while the right set controls for cloud adoption quarter fixed effects, industry (2-digit SIC code) fixed effects, region fixed effects, and firm size quartile fixed effects. Productivity levels are estimated using the 2022 sample, while the regressions are estimated using the 2023 sample. Standard errors clustered at the firm level are in parentheses.

in the cloud would be expected to use a wider variety of VM types.

With this idea in mind, we investigate the machine choices of high and low-productivity firms and test whether more productive firms tend to use a wider array of more specialized VM series. To do so, we estimate the following at the firm level:

$$y_i = \beta D_i^H + Z_i' \gamma + \epsilon_i \tag{4}$$

The outcome variables, y_i, include measures of dispersion of firms' usage on different machine series, including a machine series HHI (the sum of the squared usage shares of each machine series for each firm), an indicator for whether the firm only uses one machine series, and the number of machine series the firm uses. The coefficient of interest, β, multiplies an indicator for whether the firm's productivity is higher than the median productivity in its industry. Finally, Z_i includes firm-level controls such as firm size, industry, region, and cohort quarter fixed effects.

Table 5 displays the results. We consistently find that more productive firms tend to spread out their usage across a wider array of VM series. This is true both unconditionally and controlling for firm-level covariates. For example, we find that high-productivity firms have a VM series HHI that is 0.067 lower than low-productivity firms—more than 11% of the mean VM series HHI across firms. They also use more VM series and are drastically less likely to put all their usage on one VM series. These results suggest important differences in the sophistication between high- and low-productivity firms; high-productivity firms are more aware of the full menu of VMs offered by cloud providers and are better able to take advantage of specialized VM series on different jobs.

In summary, this section documents differences in the way firms with different productivity levels behave. More productive firms utilize fewer resources per unit of computing output both in a steady state and in response to changes in demand, are better able to monitor and shut down idle resources, and use a wider array of more specialized machines. These results are suggestive of deeper differences that are not necessarily tied to a specific external factor or mechanism, but rather seem to be internal to the firm. In this sense, they may be interpreted through the lens of X-(in)efficiency (Leibenstein, 1966; Perelman, 2011): some firms seem to be better at navigating various frictions to reduce their costs. It is natural to think that the nature of these factors may be different in the context of new technologies: firms can monitor and improve their performance or implement changes that might be easier organizationally when adopting a new technology. We analyze the extent to which this is the case in the next section.

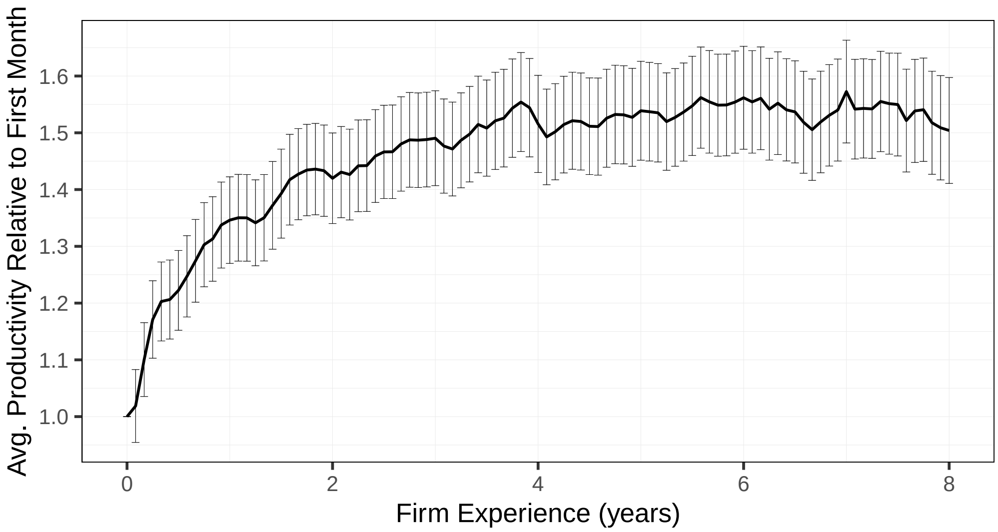
7 Learning: How Firm Productivity Changes Over Time

In this section, we investigate the role of learning: firms becoming more productive as they use the cloud more. There is reason to believe that learning could explain productivity dispersion *ex-ante*. Cloud computing is a relatively new technology, and learning processes can take time to diffuse with new technologies (Arrow, 1962; Rosen, 1972; Chari and Hopenhayn, 1991). However, it is unclear *ex-ante* how quickly firms learn and what they do to improve their productivity. Do they shift resources to more productive units? Do they experiment with different machines and find the best fit for their applications? Or do they simply become more efficient with their existing products?

To answer these questions, we present two sets of results. First, we document that firms indeed learn to be more productive over time—there is a strong relationship between a firm's overall productivity and its experience using the cloud. This relationship holds both cross-sectionally (at a given point in time, more experienced firms are more productive) and over time (cohorts of firms that adopt the cloud at the same time get better over time).

Second, we demonstrate *how* firms learn. We decompose firms' productivity growth and find that just about all firm productivity growth is from units within the firm getting more productive, with no contribution from allocative efficiency. We further decompose this within-unit productivity growth to see how units become more productive through their VM choices. While much of the within-unit productivity growth occurs within

Figure 6: Productivity Against Firm Experience in July-September 2022



Notes: This figure illustrates the average productivity level as a function of firm experience, measured in years since the firm first began using cloud services. The productivity level in the initial month (month 0) is normalized to 1. The crossbars indicate the 95% confidence intervals. The analysis is based on data from July-September 2022.

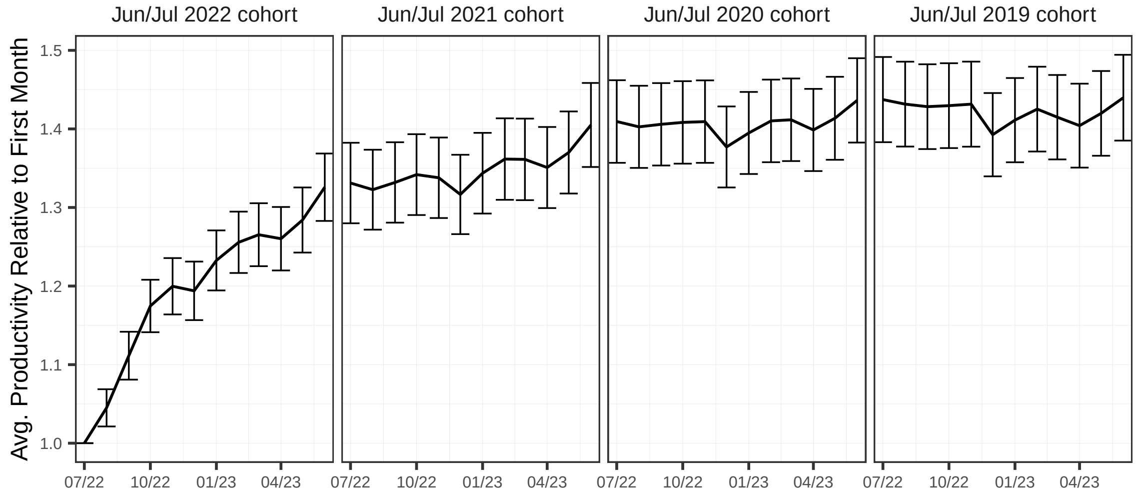
the same type of VM, suggesting that firms get better at provisioning the kind of VM they originally choose, we find that even experienced units are trying new kinds of VMs, ramping up the usage of those that perform well, and stopping to use those that perform poorly, suggesting that experimentation also plays a role in explaining how firms learn.

7.1 Learning at the Firm Level

At any given point in time, more experienced firms are substantially more productive than less experienced firms. Figure 6 plots the length of time each firm has used the cloud as of one quarter, July through September 2022, against productivity in that quarter. The average productivity of firms in their first month of usage is normalized to 1. The difference between new firms and firms with one year of experience is stark: one-year-old firms are 34.6% more productive than firms that are new to the cloud. Experience is still positively correlated with productivity after the first year, but the relationship is weaker. Four-year-old firms are 51.6% more productive than brand-new firms, and receive fairly minimal productivity gains after that.

While suggestive, this cross-sectional relationship between experience and productivity does not itself establish the existence of learning. We might be worried about two forms of selection. First, there might be selection based on cloud adoption: firms that adopted the cloud earlier did so because they knew they would be more productive. Second, there

Figure 7: Productivity by Cohorts Over Time



Notes: This figure displays productivity estimates for different cohorts during the period between July 2022 and June 2023. It reports estimates for four distinct cohorts, each cohort reflecting productivity relative to their experience levels: 0-1, 1-2, 2-3, and 3-4 years. The average productivity for the June-July 2022 cohort in July 2022 is normalized to 1. To be included in the analysis, a firm must have had nonzero usage every month from July 2022 to June 2023. Error bars indicate the 95% confidence intervals, with standard errors clustered by firm.

might be survivorship bias: if less productive firms tend to exit, then the experienced firms will tend to be more productive on average, regardless of whether learning occurs.

To control for both forms of selection, we focus on the productivity growth of individual cohorts over time, conditional on survival to the end of our sample. Figure 7 plots the productivity over the second half of 2022 and the first half of 2023 for four cohorts of firms: those that adopted the cloud in June-July 2022, 2021, 2020, and 2019. We find that firms' productivity dynamics over time exhibit extremely similar patterns to the cross-sectional pattern discussed above.[40] Firms that started in the middle of 2022 had their productivity increase by 32.6% in their first year of usage. Their productivity at the end of their first year was similar to the productivity of the 2021 cohort at the beginning of their second year, suggesting that productivity dynamics are not driven by differences in cohort adoption.

Over the next several years, the pace of learning slows down substantially. Nevertheless, the cohorts still exhibit similar learning dynamics, as the productivity of each cohort at the end of the year is nearly identical to the productivity of the cohort from the year prior at the start of the year. Learning eventually plateaus at around 40-45% more productive

[40]Figure 7 still incorporates some cross-sectional variation in productivity across different cohorts. Using our data from 2017-2019, we are able to characterize learning for the cohort of firms that started using the cloud in 2017 over six years in a way that only uses within-firm variation over time. The sparsity of our data limits this analysis, as we can observe firm productivity only intermittently. Nevertheless, we still find clear evidence of learning among this cohort of firms in the long run. See Figure OA-7 in Appendix C.

Table 6: Learning by Initial Productivity Quintile

	Productivity Quintile in 2022Q3						
Quarter	1	2	3	4	5	Full Sample	90-10 ratio
2022Q3	0.09	0.55	0.99	1.39	1.98	1.00	35.7
2022Q4	0.40	0.83	1.13	1.46	1.86	1.14	10.7
2023Q1	0.55	0.94	1.20	1.50	1.77	1.19	8.5
2023Q2	0.65	1.00	1.23	1.50	1.72	1.22	8.2

Notes: This table reports the average productivity values for each quintile and the full sample at quarterly intervals. The "Full Sample" column represents the average across all quintiles for each quarter. The average productivity for the full sample in 2022Q3 is normalized to 1.

than the first month; the average productivity of the 2019 cohort at the end of the fourth year is 44.0%. The flat productivity level of older cohorts also suggests that learning is not driven by aggregate productivity trends in the cloud industry; if this were the case, then older cohorts would be getting more productive, too.

We find that firms achieve steady-state productivity after four years, longer than many studies of learning-by-doing. For example, Levitt et al. (2013) study a car manufacturing plant whose productivity in producing a new model plateaued after eight weeks; Kellogg (2011) found that cost reductions of pairs of oil producers and drillers flattened out after 20 weeks; and Thompson (2012) reviews evidence that the productivity of new shipyards in World War II converged within roughly two years. This difference could be attributed to the nature of the technology learned by the firm. Cloud computing can be viewed a general-purpose technology, affecting many parts of the firm at once and requiring organizational changes to be used fully efficiently (Bresnahan and Trajtenberg, 1995; Brynjolfsson et al., 2024). With this interpretation, the results suggest that firms take longer to implement these changes than to adopt incremental improvements in production technology.

We can analyze the learning of different groups of firms based on their initial productivity to investigate the extent to which aggregate learning comes from more or less initially productive firms. Table 6 breaks out the June-July 2022 cohort's productivity in each quarter by the productivity quintile in the first quarter, along with the overall average productivity and the ratio between the 90th and 10th percentile productivity in each quarter. Table 6 demonstrates that learning is primarily driven by the bottom of the distribution improving their productivity relative to the top. Indeed, while the top quintiles are substantially more productive than the bottom quintiles initially, productivity is relatively flat for the top two quintiles (after an initial drop-off for the top quintile, which could be attributed to mean reversion after a favorable initial draw) but increases significantly for the less initially productive firms. The sizable heterogeneity in the length of time firms require to be more productive reinforces the importance of large-scale evidence on learning-by-doing.

Table 6 also demonstrates interesting patterns related to productivity dispersion. Productivity dispersion starts extremely high, with a 90-10 ratio of 35.7, but substantially declines over the first year, ending at 8.2. However, even after one year, the 90-10 ratio is significantly higher than 3.5, the value in the full sample. In addition to demonstrating that learning tends to reduce productivity dispersion, these results highlight that the maturity of the production technology is an important determinant of productivity dispersion.

While the results of this subsection establish that new firms increase their productivity over time, they do not reveal the specific mechanisms behind learning. In the next two subsections, we investigate how firms learn.

7.2 Decomposing Within-Firm Learning

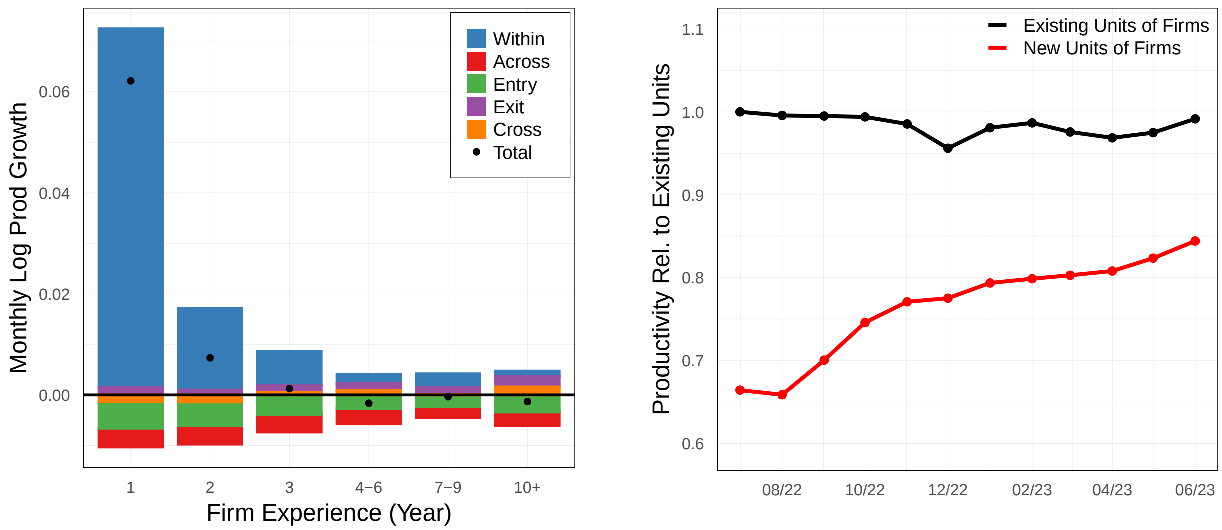
We begin by studying whether learning happens across or within units. On one hand, learning might be driven by firms devoting more resources to more productive units (across-unit learning); on the other, units themselves might be getting more productive (within-unit learning). To quantify these mechanisms, we decompose firm-level monthly productivity growth using the method outlined in Foster et al. (2001). Firm i has a set of units K_{im} in month m; each unit $k \in K_{im}$ has monthly productivity ω_{ikm}. We can write firm i's productivity in month m as the core-hour weighted average productivity of each of its units; that is, letting s_{ikm} be the core-hour share of unit k in month m,

$$\omega_{im} = \sum_{k \in K_{im}} s_{ikm} \omega_{ikm}.$$

We are interested in decomposing $\Delta\omega_{im} = \omega_{im} - \omega_{i(m-1)}$, the change in productivity for firm i from month $m-1$ to month m. For ease of notation, label $m = 1$. Let $S_{i1} = K_{i0} \cap K_{i1}$ be the set of units in the firm that used the cloud in both month 0 and month 1; $X_{i1} = K_{i0} \setminus K_{i1}$ the set of units that stopped using the cloud in month 0; and $E_{i1} = K_{i1} \setminus K_{i0}$ the set of units that started using the cloud in month 1. We can decompose $\Delta\omega_{i1}$ as follows:

$$\begin{aligned}\Delta\omega_{i1} = & \overbrace{\sum_{k \in S_{i1}} s_{ik0}(\omega_{ik1} - \omega_{ik0})}^{=\text{Within}} + \overbrace{\sum_{k \in S_{i1}} (s_{ik1} - s_{ik0})(\omega_{ik0} - \omega_{i0})}^{=\text{Across}} + \overbrace{\sum_{k \in S_{i1}} (s_{ik1} - s_{ik0})(\omega_{ik1} - \omega_{ik0})}^{=\text{Cross}} \\ & + \underbrace{\sum_{k \in E_{i1}} s_{ik1}(\omega_{ik1} - \omega_{i0})}_{=\text{Entry}} + \underbrace{\sum_{k \in X_{i1}} s_{ik0}(\omega_{i0} - \omega_{ik0})}_{=\text{Exit}}.\end{aligned} \tag{5}$$

Figure 8: Decomposition of Firm Learning Within and Across Units



(a) Within-firm Learning Decomposition **(b)** New vs. Existing Unit Productivity

Notes: Panel (a) presents the decomposition of monthly log productivity growth by firms' years of experience in cloud computing, displaying the five components of equation (5): within-firm, across-firm, entry, exit, and cross. The x-axis represents the firm's cloud experience in years, while the y-axis shows the monthly log productivity growth. The black dots indicate the average month-to-month productivity growth at the firm-level, whereas each bar represents a component of the decomposition. Panel (b) plots the average productivity of the unit(s) that joined in June-July 2022 against the average productivity of the older units in the same firm. The productivity of existing units in July 2022 is normalized to 1. The details of the estimation procedure are provided in Appendix D.4.

The first term of the decomposition, Within, reflects the productivity growth coming from within-unit learning. The second term, Across, reflects the productivity growth from the reallocation of resources across units. It would be positive if growing units were more productive than the firm's average productivity, $\omega_{ik0} > \omega_{i0}$. The third term, Cross, represents the correlation between within-firm productivity growth and within-firm resource share growth. The fourth term, Entry, represents the contribution of units that are new to the cloud and would be positive if entering units were more productive than the firm average. Finally, Exit reflects the contribution of units that stop using the cloud and would be positive if exiting units are less productive than average.

Fixing two months, we take this decomposition for each firm and then average the terms across firms, separated by the experience group of each firm. Figure 8(a) plots these average decomposition terms by firms' years of experience in cloud computing. The black dots represent the overall average monthly productivity growth for firms of each experience group. From this, we see that the flattening-out of firm productivity over time masks substantial dynamics in firm productivity. In the first year, the within component is positive, and the across component is negative, suggesting that units within firms themselves learn rather than firms learning how better to allocate resources across units. The negative across term is likely due to newer units having greater month-to-month usage growth while being less productive. The entry term remains negative regardless of how experienced the firm is, meaning that units that join the cloud tend to be less productive than the firm. This suggests that firms cannot fully transmit whatever one unit learns about using the cloud to other units. Finally, the exit term is positive but small—relatively few units stop using the cloud, but those that do tend to be less productive than the firm as a whole.

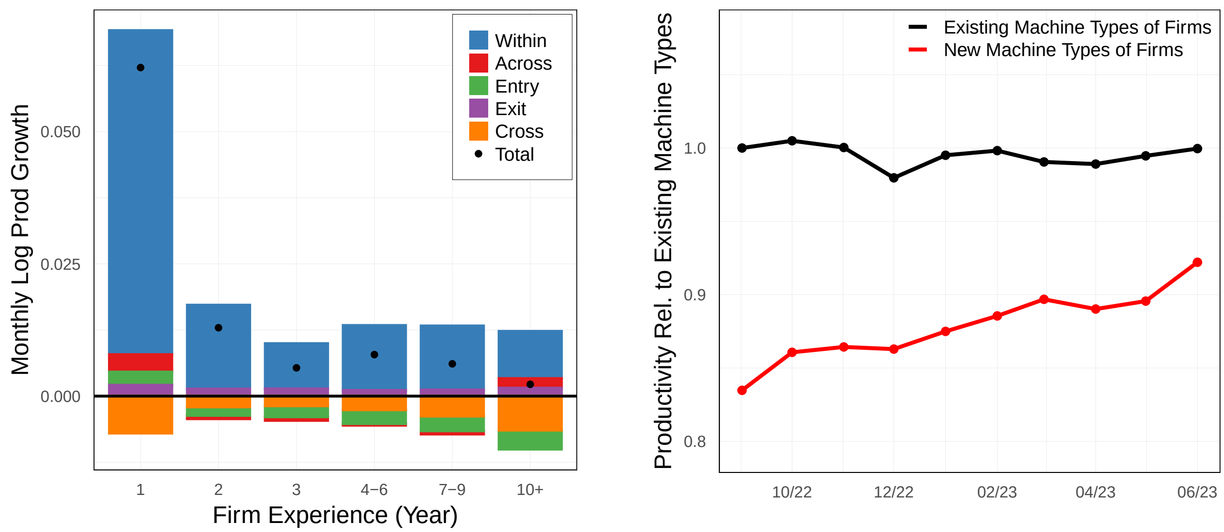
Other patterns in the data confirm that much of the firm-level learning happens within units. In Figure 8(b), we plot the productivity of new units in the firm relative to existing units, normalizing the productivity of existing units in July 2022 to one. New units start out with 34.3% lower productivity than other units in the same firm but close roughly two-thirds of that gap in their first year. This is similar in magnitude to the overall pace of firm-level learning shown in Figures 6 and 7, suggesting that new units of experienced firms do not seem to learn any differently than new firms. In Figure OA-2 reported in the Appendix, we examine within-firm knowledge transfer more closely by looking at whether new units at experienced firms learn differently depending on the firm's productivity. We find that new units at more productive firms tend to be more productive overall but that the rate of productivity growth is invariant to the firm's productivity level. Therefore, our analysis suggests limited evidence for within-firm learning transfer.

7.3 How Units Learn at the Machine Level

We further decompose learning within units to see how units become more productive at the machine level. We take a similar approach to the last subsection, utilizing the decomposition of productivity growth from Foster et al. (2001) shown in Equation (5). Instead of decomposing firm productivity growth into within- and across-unit components, we decompose unit productivity growth into within- and across-machine series terms. This helps us learn about changing machine usage patterns as units become more productive.

Figure 9(a) displays the results of this decomposition. Units are broken out by the firm's cloud experience. The black dots reflects the total within-unit component and, therefore, will be equal to the "within" term of Figure 8(a). It reveals that units' machine choices are not static; even more experienced firms try new machines and get more productive with the machine series they provision. The entry term is negative, reflecting the fact that units are less productive when they try machines for the first time. Units discard the less

Figure 9: Decomposition of Within-Unit Learning Within and Across Machine Series



(a) Within-unit Learning Decomposition **(b)** New vs. Existing VM Productivity

Notes: Panel (a) presents the decomposition of monthly log unit-level productivity growth, displaying the five components of equation (5): within-firm, across-firm, entry, exit, and cross. The x-axis represents the firm's cloud experience in years, while the y-axis shows the monthly log productivity growth of the unit. The black dots indicate the average month-to-month productivity growth at the unit level, whereas each bar represents a component of the decomposition. Panel (b) plots the average productivity of the machine series that firms start using in August-September 2022 against the average productivity of the older machine in the same firm. The productivity of existing VMs in September 2022 is normalized to 1.

productive machines (the exit term is positive) and get more productive with the machines they retain (the within term is positive). Meanwhile, the cross term is negative, reflecting that as firms add new machines, the share of their existing machines with increasing productivity declines, leading to a negative correlation between productivity and share changes.

Figure 9(b) provides deeper insight into the within-unit component by comparing the productivity levels of machines that unit firms have experience with versus new machines they adopt. The data reveals that firms are about 16.5% less productive with newly adopted machines compared to their existing ones. This productivity gap is notably smaller than the 34.3% difference observed between new and old units, indicating that units can leverage some of their existing expertise when adopting new machines, but there is still a learning curve at the machine level.

Overall, the patterns in within-unit usage demonstrated by Figure 9 reveal a dynamic picture of experimentation-driven learning. Aggregate productivity gains are a compositional effect of productivity declines due to experimentation with new machines, and productivity increases from learning to use the new machines efficiently and stopping the use of the less productive ones that were tried. With these results, we provide empirical evidence for the mechanisms by which productivity growth and learning take place within firms, mirroring the experimentation-driven productivity dispersion observed by Foster et al. (2019) in the context of innovative industries.

8 Counterfactual Resource Calculations: Electricity and VM

This section quantifies the aggregate implications of productivity dispersion using back-of-the-envelope calculations. Specifically, we estimate the amount of compute resources (core-hours) and electricity that would be saved if all firms reached a benchmark productivity level. We focus on electricity because electricity consumption of computing is a key policy concern: data centers are projected to consume 9% of U.S. electricity by 2030 (Aljbour et al., 2024). We note that this counterfactual analysis is a partial equilibrium exercise and does not consider several important factors, such as resource constraints of the cloud provider, price changes, or firms' responses to productivity changes. We view this section as a quantification exercise to understand the importance of productivity dispersion in computing rather than a full modeling of the cloud market.

8.1 Estimating the Electricity Consumption and Utilization

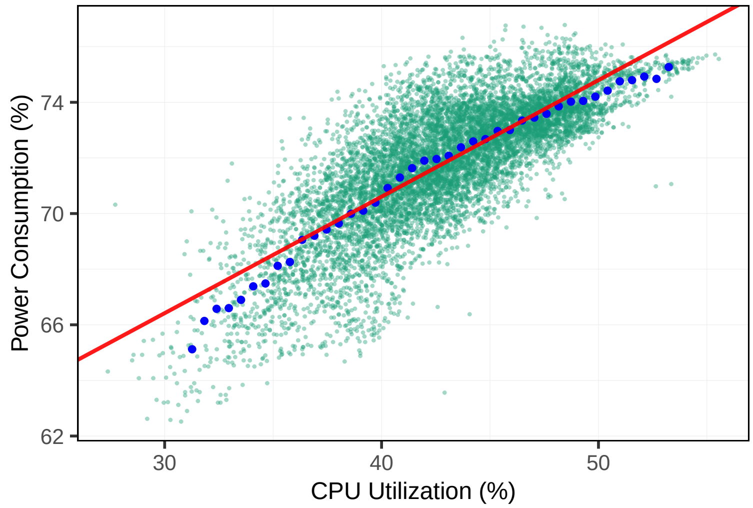
One unique aspect of computing hardware is that it consumes a significant amount of electricity even when idle because it needs to maintain essential functions such as operating systems, network connections, and cooling systems (Meisner et al., 2009; Duan et al., 2015).[41] Therefore, understanding the relationship between utilization and electricity consumption is crucial for calculating the overall resource impact of productivity dispersion, as different types of computing inefficiencies (idleness and overprovisioning) result in different levels of inefficient electricity use.

We estimate the relationship between CPU utilization and electricity consumption using a dataset from Google Cloud. The dataset includes 5-minute normalized power consumption readings of 57 power domains and the CPU utilization of all VMs connected to these power domains. To analyze these data, we aggregate the utilization of VMs to average utilization for each power domain. This aggregation results in panel data on power usage and CPU utilization at 5-minute intervals for one month in 2019.[42] With these data,

[41] Additionally, peripheral components like hard drives and power supplies continue to draw power, and the servers must remain in a ready state for quick activation.

[42] This analysis measures power consumption at the power domain level, not at the VM level, which is the level of analysis in our study. However, the aggregate changes we will later analyze should be well-approximated by changes at the power domain level. Moreover, the experimental literature using single servers is consistent

Figure 10: Relationship Between Power and CPU Utilization



Notes: This figure shows the estimated relationship between CPU utilization and power consumption for VMs. The scatter plot shows individual data points representing power consumption (%) as a function of CPU utilization (%) in 5-minute intervals. Blue points show binned scatter points, and the red line shows the regression line.

we model electricity usage as a function of CPU utilization, a common approach in the literature due to the CPU's direct impact on power usage (Möbius et al., 2013). The details of this estimation procedure can be found in Appendix D.5.

Figure 10 displays the results from the regression of electricity usage on utilization along with a binscatter plot. The results reveal several noteworthy findings. First, the range of CPU utilization at the power domain level is limited, with the average utilization rarely exceeding 50% or dropping below 30%. Second, the regression line has a slope of 0.5, indicating that every percentage point (pp) increase in utilization leads to a 0.5 pp increase in power consumption.[43] Finally, by extrapolating the regression line to 0% utilization, we estimate that idle VMs consume approximately 50% of their maximum power. Based on these findings, we propose the following relationship between power and utilization:

$$\mathbb{E}[p_{vt}] = (0.5 + 0.5u_{vt})k_v^{max}, \tag{6}$$

where k_v^{max} denotes the power consumption when VM v is utilized at 100% and u_{vt} denotes the CPU utilization of VM v at time t. Following the computing literature (Bertran et al., 2010), we further assume that power consumption increases linearly with the number of

with our results (Kansal et al., 2010; Waßmann et al., 2013). See Appendix D.5.2 for a review of this literature.

[43] Although the relationship becomes nonlinear at the boundary of the utilization support, it is not precisely estimated due to a lack of data. Additionally, the line has to cross (1,1) by construction, supporting the linearity assumption.

cores, meaning that $k_v^{max} = kc_v$, where c_v represents the number of cores of machine v and k is an arbitrary constant.

8.2 Estimating Compute and Electricity Savings Savings

This section provides an overview of the calculation of counterfactual compute resources and electricity, while Appendix D.6 provides the details. We calculate the potential core-hour savings if all firms below a benchmark productivity level $\bar{\omega}_{it}$ reached that level. More formally, we write the counterfactual productivity (ω_{it}^c) as:

$$\omega_{it}^c = \bar{\omega}_{it} \cdot \mathbf{1}(\omega_{it} < \bar{\omega}_{it}) + \omega_{it} \cdot 1(\omega_{it} \geq \bar{\omega}_{it}). \tag{7}$$

Calculating counterfactual core-hours consumed is straightforward, as it is independent of how firms improve productivity. In particular, core-hour changes resulting from increased productivity would remain the same regardless of whether a firm reduces idleness or addresses overprovisioning. Therefore, we simply calculate each firm's unused core-hours at the benchmark productivity level and then aggregate these savings at the economy level.

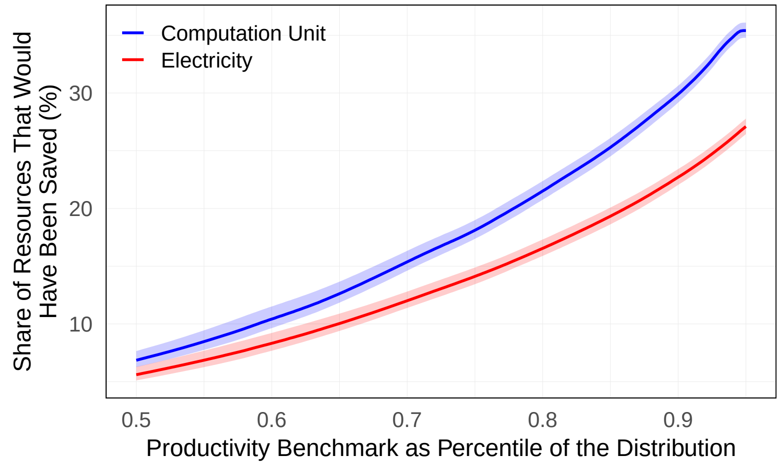
The second counterfactual calculates electricity savings due to improved firm productivity using the estimated relationship between electricity consumption and VM utilization in Equation (6). Unlike the core-hour calculation, this analysis requires assumptions about firms' productivity improvement method as the relationship between electricity consumption and utilization is not perfectly proportional. In other words, reducing idleness versus overprovisioning affects electricity consumption differently.[44] Therefore, we must take a stance on how firms reach the benchmark productivity level.

We assume that core-hour savings from each mechanism are proportional to the potential productivity improvement from each mechanism. For example, if a firm has 50% of its VMs idle and 30% overprovisioned, the ratio of eliminated idle VMs to eliminated overprovisioned VMs to achieve the benchmark productivity will be 5/3. Under these assumptions and using the calculations detailed in Appendix D.7, we can estimate the total electricity savings if all firms reach a given productivity level.

Figure 11 presents our calculations, with the x-axis showing benchmark productivity levels from the 50th to 100th percentile of firm-level productivity and the y-axis indicating

[44] To see this, assume a firm has one idle VM and one overprovisioned VM, both with two cores, and that maximum electricity consumption is two units per VM. The productivity of this firm is 25%, and its total electricity consumption is 1 + 1.5 = 2.5 units. Suppose the benchmark productivity is 50%. The firm can achieve this productivity level either by eliminating the idle VM or rightsizing the overprovisioned VM. Eliminating the idle VM would save 1 unit of electricity, while rightsizing the overprovisioned VM would save 0.5 units of electricity.

Figure 11: Resource Savings Under Counterfactual Productivity Increase



Notes: This figure illustrates the potential resource savings in computation units and power consumption under a counterfactual increase in productivity. The x-axis represents the productivity benchmark as a percentile of the distribution, while the y-axis shows the percentage of resources that would have been saved. The blue line shows the percent change in core-hours, and the red line shows the percent change in power consumption. Shaded regions surrounding each line represent the 95% confidence intervals obtained using a bootstrap procedure.

the percent of resource savings. First, even simply elevating all firms to the median level of productivity leads to a 6.9% decline in compute resources and a 5.6% decline in electricity. These savings increase to 21.0% and 16.5%, respectively, at the 80th percentile of productivity.

The results reveal a nonlinear relationship between productivity changes and resource savings, with compute resource savings consistently exceeding electricity savings. This disparity arises because idle jobs consume all of the core-hours but only part of the electricity of a fully utilized VM. Further, the gap between compute and electricity savings widens as the benchmark productivity rises, reflecting differing elasticities of these resources with respect to productivity. These findings underscore the importance of linking productivity measures to real-world resource use and estimating a "machine-level" production function to understand the implications of productivity dispersion fully.

In summary, in addition to showing that firm-level compute productivity dispersion has significant aggregate implications on resource usage, these results also demonstrate that compute productivity improvements would result in sizable cost savings for firms. Multiplying the 21% core-hour savings by the industry-level cost shares given in Section 2.4 suggests that elevating all firms to the 80th productivity percentile reduces total production costs by 2.4% for software firms and 1.0% for services firms. The cost savings are even higher for low-productivity firms with larger potential efficiency improvements, and are likely to increase as cloud computing becomes more ubiquitous across the economy.

9 Concluding Remarks

A robust finding from firm studies is the high degree of dispersion in various firm outcomes, including productivity, markups, and labor shares (Syverson, 2011; Van Reenen, 2018; Autor et al., 2020). In this paper, we show that similar differences exist in how productively firms use emerging technologies by analyzing evidence from cloud computing. We also document significant firm learning over both the short and long terms.

Our study uses CPU utilization data from over 1 billion VMs employed by nearly 100,000 firms. We develop a novel compute productivity measure and show substantial dispersion in productivity across and within firms. To better understand this dispersion, we study the specific practices that separate high- from low-productivity firms, finding that more productive firms are better at handling compute demand fluctuations, are more attentive to idle resources, and use a wider variety of more specialized compute inputs. Finally, we study learning in the cloud and find that new firms improve substantially in their first year on the cloud and attain a stable productivity level within four years.

Our results have several implications for the broader productivity literature. First, although our productivity measure is derived from far more granular and specific data than is typical, our estimates of productivity dispersion and persistence corroborate the general magnitudes seen in other studies. However, we find that productivity dispersion is dynamic in the context of a new technology—initial dispersion is extremely high, but shrinks over time due to heterogeneous learning rates across firms. Second, we highlight that organizational frictions such as imperfect monitoring can drive this dispersion, emphasizing the importance of accounting for such frictions in models of firm behavior. Finally, our learning results demonstrate that within-firm productivity growth plays an important role in the evolution of aggregate productivity and its dispersion in industries adopting a new technology, suggesting that efficiency gains from innovation can take time to propagate throughout the economy even after widespread adoption.

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Firm Productivity and Learning in the Digital Economy: Evidence from Cloud Computing

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Appendix - For Online Publication

Contents

A Institutional Details

A.1 Details of VM Deployment

In this section, we provide more details about VMs.

A.1.1 VM Creation and Selection

All cloud providers offer a browser-based platform with step-by-step instructions for generating a VM. These instructions are typically designed for first-time VM creation and may not be relevant for firms' daily operations. In this section, we outline the VM selection steps to explain the various steps involved. In the next subsection, we provide an overview of the tools commonly used by firms for VM management and operations.

Account Creation: Before deploying VMs, user accounts or service accounts need to be created and configured. This involves setting up the necessary permissions and roles to ensure that users or services have the appropriate access levels to manage and interact with the VMs.

Resource Allocation: During deployment, specific amounts of CPU, memory, and storage must be chosen for the VM.

Network Configuration: VMs need to be connected to the appropriate virtual networks. This involves assigning IP addresses, configuring network interfaces, and setting up necessary VLANs (virtual local access networks).

Storage Provisioning: VMs require storage for the operating system, applications, and data. This can involve allocating space on local disks or choosing a storage system linked to the VM.

Security Settings: Security configurations need to be applied during deployment. This includes setting up firewalls, defining access controls, and implementing any required encryption.

Region Choice: The user selects the geographic region of the data center for the VM. This choice can impact performance due to latency and varying redundancy policies.

These steps are required when creating a VM for the first time. In practice, developers can use VM images, which are templates that store information such as the OS, security settings, and pre-installed software, allowing users to create VMs without redefining these parameters. Organizations often maintain a library of standardized images for various purposes, streamlining the VM deployment process.

A.1.2 Available Tools For Flexible VM Deployment

As we argue in Section 2.4, there are many available tools in cloud computing that can reduce potential frictions firms might face when deploying VMs. In this section, we list some of these tools and provide a brief description.

Cloning a VM: Cloning technology allows users to create new VMs from the running state of an existing VM. The cloned VM is identical to the source VM and can be created quickly from a specific point in time. This method makes it efficient to deploy large-scale applications and enables the creation of numerous VMs on a single host. All major cloud providers offer some form of cloning capability.

Auto Shutdown: In cloud computing, users have the capability to schedule or automatically shut down VMs to help manage costs and optimize resource usage. This functionality allows users to define specific times for VMs to stop and start, eliminating the need for constant monitoring.

Live Migration: Live migration allows users to move running VMs from one physical host to another without downtime. With this technology, applications can continue to operate during maintenance, load balancing, or hardware upgrades.

Automatic Redundancy and Fault Tolerance: Cloud providers offer built-in automatic redundancy and fault tolerance to ensure high availability and reliability of services. These features include distributing data and workloads across multiple servers, data centers, or geographic regions to prevent single points of failure. In case of hardware or software failures, automatic failover mechanisms can redirect traffic to healthy instances, minimizing downtime and maintaining service continuity.

Autoscaling: In cloud computing, autoscaling refers to the automatic adjustment of compute resources based on the current demand. This capability allows cloud environments to dynamically allocate or deallocate resources such as CPU, memory, and storage to applications or services as needed. When demand increases, autoscaling provisions additional instances to handle the load, ensuring that applications can maintain performance levels. Conversely, when demand decreases, it reduces the number of active instances, scaling down the resources in use.

The process of autoscaling involves automatic monitoring of the performance metrics and resource utilization of applications. Firms can set autoscaling rules and policies based on their specific requirements, such as thresholds for CPU usage, memory consumption, or network traffic. For example, if CPU utilization exceeds a certain threshold, the autoscaling mechanism adds more instances to distribute the load. Similarly, if resource usage falls below a specified level, it scales back the instances. These rules can be configured through cloud provider dashboards or APIs.

Load Balancers: Load balancers distribute incoming network traffic across multiple VMs. By evenly distributing the load, load balancers ensure that no single server hits capacity, which helps maintain application performance and reliability. They achieve this by constantly monitoring the health of instances and redirecting traffic away from failing or underperforming. Load balancers also complement autoscaling by working together to optimize resource utilization and application performance. While autoscaling dynamically adjusts the number of active VMs based on demand, load balancers distribute the incoming traffic among these VMs.

Cost Monitoring Tools: Cloud providers offer a range of tools to help users monitor and manage their resource utilization and costs. For example, AWS CloudWatch provides monitoring for resources and applications across AWS environments. It includes visualization tools, automated alarms, and integration with other AWS services to help identify and manage idle resources. Similarly, Google Cloud Operations offers integrated monitoring, logging, and tracing for applications and systems on Google Cloud. These tools may also include the observability of metrics specific to detecting and managing idle resources.

A.2 Details of VM Deployment: Two Examples

In this section, we provide two examples of deploying IT resources in cloud computing to help readers understand their use cases. While this section is quite technical, it offers important insights about the day-to-day work of software developers in cloud environments.

A.2.1 "Create, Read, Update, Delete" Application

The first toy example we consider is the deployment of a simple CRUD (Create, Read, Update, Delete) application. This refers to a general class of applications that provide a user interface for the typical operations involved in persistent storage. A common example of this application is a blog or message board. In this example, "Create" corresponds to a user making a new post or comment, "Read" corresponds to the functionality of listing all posts and comments corresponding to some filter, "Update" corresponds to editing posts or profile information, and "Delete" corresponds to the deletion of posts or comments. The basic components of the architecture of this application includes a web server, which is accessible by users on the public internet, and a database server, which is typically only accessible by the web server itself. The web server's responsibilities include authenticating users, producing HTML that provides the information and features available to the user, and issuing control commands and queries to the database based on the user's request.

We describe specific deployment scenarios of this application type on the Microsoft

Azure cloud. For the first example, we consider hosting this application only in a single region, with a fixed resource footprint, and with manual processes to deploy resources. To complete this deployment we:

1. Create a Resource Group (RG), a logical group which will contain all of the resources for this deployment.

2. Create a Virtual Network (VNet) and create a subnet within this VNet.

3. Select and provision an appropriate VM to run the web application based on our application's requirements, budget, and account quota. Additionally, we must:

   (a) Select the proper region and operating system for the application.

   (b) Add the VM's network interface to the appropriate subnet within the VNet.

   (c) Create a Network Security Group (NSG) and add rules that restrict the incoming traffic to SSH/RDP and HTTPS traffic from internet IP Addresses.

   (d) Give the VM a static IP address. It is also possible to give it a human-readable alias using Azure DNS.

4. Create an Azure Database for PostgreSQL to serve as the persistent storage back-end for the application.

   (a) Similar to the web server VM, we must choose an appropriate virtual core count, virtual memory amount, storage size, storage scale rule, and storage performance tier based on our requirements and budget.

   (b) We will place the database in the same region as our web server.

   (c) We will disallow public IP access to the database and integrate it into the existing VNet and the same or new subnet.

At this point our resources are established and we can install the application onto the web server and complete the connection between the application and the database to be able to service user requests using the persistent storage. We can monitor the health and utilization of the instances using Azure Monitor.

The above architecture leans towards using IaaS solutions (Infrastructure as a Service) and is not capable of scaling horizontally. It is a simple deployment method that can be hard to maintain, and the architecture will likely be insufficient to handle dynamic loads. Since we can only control the size of a single instance for the web server and database, respectively, it will be challenging to avoid being under or over-provisioned, and we will incur downtime in the application if we need to scale instances up or down. A common way to handle this is by using IaaS offerings for the web server, such as a Virtual Machine Scale Set (VMSS) and Load Balancer (LB). The VMSS is a collection of identical VMs in a single region. With this deployment method, we can define conditions on the pool of VMs that will trigger custom scale-up and scale-down actions. These rules or conditions are defined by statistics on the time series of instance-level counters such as CPU, Network, and Disk Utilization. The LB can be configured with a front-end IP address to accept user traffic and then given the VMSS as a back-end pool to distribute requests over. This architecture allows us to scale horizontally instead of vertically, increasing our ability to handle dynamic loads, making us less likely to be under or over-provisioned at any given time, and decreasing our application's expected downtime. In this design, it is possible to use reserved instance purchases to reduce costs on the compute hosting the application. We can monitor request traffic, instance utilization, and allocation rates to develop an estimate of a lower bound on the capacity we require to host the application.

Scaling the database using only IaaS offerings would require a lot of engineering effort, and on modern cloud platforms, it is much more common to use a managed database service. In the above example, we could use Azure SQL Server, or if we switch away from a relational database, we could consider Cosmos DB. The choice of which type of database to use is technical and heavily depends on the data model and transaction requirements of the application. Generally, Cosmos DB offers more scaling options but is a non-relational/NoSQL database. Fortunately, both options allow for horizontal scaling for read replicas. This means that we can apply similar scaling procedures to service the read requests from the web application servers.

A.2.2 Data Analytics and Machine Learning

Another common use of modern public cloud infrastructure is building pipelines for data analytics and machine learning use cases. Since many of these use cases can be implemented purely as PaaS services, we will focus on a sample architecture that favors IaaS resources for batch training of a custom machine learning model or a numerical simulation. In these settings, it is common to have a highly parallelizable workload that consists of iterating over a set of parameters or hyperparameters for an underlying model or simulation, where for each parameter setting, we wish to construct the model or simulation according to the specified parameters, and then train the model or execute the simulation and store the relevant results from the process. We could implement a system like this using Azure Blob Storage or Azure Data Lake Storage (ADLS) to store the model or simulation parameter configurations and training/simulation results, Azure Batch to acquire the required capacity and allocate jobs to nodes, and then either a single dedicated VM or cluster of dedicated VMs that orchestrate the Azure Batch node pool and collate results from the storage. The exact steps to provision these resources and develop the code to orchestrate and execute the jobs is involved, but we can describe an outline of the process and architecture:

1. Provision a storage account and create a container that will store model/simulation result blobs and another to store blobs defining the model/simulation parameters.[45]

2. Provision an Azure Container Registry, construct a Docker image, which defines the functionality of the model or simulation given the parameter data, and write that Docker image into the container registry.[46]

3. Given an estimate of model training time and the desired parameters to iterate over, estimate the number of worker nodes needed to complete the entire batch job in a reasonable time period.

4. From the orchestration nodes, construct the parameter data structures, write them to storage, and then define jobs using the Azure Batch API, which points to the parameters in storage and the image stored in the container registry.

5. Start the job and monitor the job status for task-level failures from the orchestration nodes.

6. Detect when the job completes and collate the results to do model parameter selection or generate simulation reports on the orchestration nodes.

This architecture still leverages some PaaS services to manage persistent storage and container images. Azure Batch is capable of acquiring very large amounts of capacity (tens of thousands of instances) relatively quickly and efficiently, allocating work to the acquired nodes.

All of the examples listed above comprise only a small fraction of all of the use cases of modern public clouds like Azure. However, even among this small sample, we see significant variability in terms of the PaaS services coupled with our deployed VMs and the potential utilization patterns of the deployed VMs themselves. The latter utilization

[45] A blob, short for Binary Large OBject, is a collection of binary data stored as a single entity in a database management system. In the context of cloud storage, blobs are used to store large amounts of unstructured data such as text, images, videos, or, in this case, model/simulation results and parameters.

[46] Docker is a platform that uses OS-level virtualization to deliver software in packages called containers. These containers are lightweight, standalone, and executable packages of software that include everything needed to run an application: code, runtime, system tools, system libraries, and settings.

variability by use case is relevant to the VM counter data examined in this paper. For example, in the CRUD application case, we are subject to an uncontrollable and variable amount of user requests in the future and must design our architecture to handle both the expected and unexpected variability in this load. In the model training pipeline, we can learn more about the workload ahead of time. Instead, we need to focus on ensuring that the worker pool is sized correctly and that we efficiently pack jobs onto the nodes.

A.3 Details on Cloud Computing

A.3.1 Non-IaaS Cloud Computing

As we mention in the text, there are three types of cloud products: SaaS, PaaS, and IaaS. SaaS is fundamentally different from PaaS and IaaS because it has broader coverage (including email, office products, etc.) and is more consumer-facing than purely business-to-business products. Therefore, we restrict our discussion to PaaS and IaaS in this section. While this paper primarily focuses on IaaS and VMs, which are more common than PaaS, PaaS could be a substitute for IaaS in some cases.

Non-IaaS cloud computing encompasses a range of services that abstract and automate the underlying infrastructure, allowing users to focus more on application development and deployment rather than managing physical or virtual hardware. These services include containers and container orchestration, serverless computing, and Code as a Service. Containers package applications with their dependencies, ensuring consistent and reliable performance across different environments, while container orchestration tools manage the deployment, scaling, and operation of these containers. Serverless computing, also known as Function as a Service (FaaS), enables developers to run code without provisioning or managing servers, as the cloud provider handles the infrastructure, scaling, and execution of code in response to events. PaaS offers a managed platform that includes the operating system, development frameworks, and other tools needed to build and deploy applications, abstracting the underlying infrastructure to allow for faster and easier application development.

Despite the convenience of non-IaaS services, IaaS remains more common because it provides a high degree of flexibility and control, allowing users to tailor the infrastructure to their specific needs. This level of control is important for complex, custom applications and enterprise environments that require precise configurations and optimizations. Additionally, IaaS can accommodate a wide range of workloads, from legacy applications to modern microservices, making it more versatile than PaaS services.

A.3.2 Resource Availability in Cloud Computing

In cloud computing, firms typically request a quota that specifies the maximum capacity they may need at any given time. Once this quota is established, users can access the resources up to that limit whenever they require them. Except for a few specialized VMs, firms can adjust or increase their quota anytime. Even though the quota cannot guarantee the immediate availability of resources, the high reliability of cloud services ensures that firms rarely face situations where their resource requests cannot be fulfilled.

Cloud computing providers ensure sufficient capacity by making significant investments in their data centers. While predicting the needs of individual firms can be challenging, cloud providers can more accurately forecast aggregate demand across all users. By leveraging the law of large numbers along with the relative lack of variation in firms' workloads, they can predict overall load requirements more effectively and invest accordingly to maintain sufficient infrastructure.

However, aggregate demand is still volatile, and cloud providers need to make short-term adjustments to the available capacity. Cloud providers use a mechanism known as spot instances to manage this volatility. Spot instances allow providers to rent out unused capacity at steep discounts, offering a cost-effective option for firms with workloads that are less sensitive to interruptions. However, these instances come with the caveat that the cloud provider can reclaim the resources at any time. Essentially, cloud providers overinvest in infrastructure to ensure they can meet peak demand and then monetize the excess capacity through the spot market.

A.3.3 Pricing in Cloud Computing

Cloud computing pricing is primarily designed to be on-demand, allowing users to pay only for the resources they provision. This flexible pricing model is generally linear, meaning that costs scale directly with usage—whether it's computing power, storage, or bandwidth. Users are billed based on the amount of resources used over a given period, making it straightforward to predict and manage costs for various workloads.

However, beyond this simple linear model, cloud providers offer more elaborate pricing mechanisms to cater to different needs and usage patterns. For instance, reserved instances allow users to commit to a certain level of resource usage over a longer term in exchange for a lower rate, which can be beneficial for predictable, steady workloads. Additionally, spot instances are available at a significantly reduced cost but come with the trade-off that the cloud provider can reclaim the resources with little notice, making them ideal for non-critical or flexible tasks. Despite these varied pricing strategies, cloud costs can still be thought of as variable costs for firms, as they are still directly tied to the level of resource consumption.

B Data Appendix

B.1 CPU Utilization Data

CPU utilization is a fundamental metric in computing that quantifies the workload on a computer's central processing unit. It is typically expressed as a percentage, representing the proportion of time the CPU spends executing non-idle tasks relative to its total available processing time (Gregg, 2014).

The most common method for measuring CPU utilization relies on system counters provided by the operating system. These counters continuously track the CPU's state, recording the time spent in various modes such as user mode (executing application code), system mode (executing kernel-level operations), and idle mode. By sampling these counters at regular intervals, typically every few milliseconds, the operating system can calculate the percentage of time the CPU spends in non-idle states (Gregg, 2014). This data is then aggregated over longer periods (e.g., seconds or minutes) to provide a meaningful representation of CPU usage.

The raw data we have access to are aggregations of counter readings at the 5-minute level, taking the maximum utilization reading in each 5-minute interval. Therefore, for each VM, at a 5-minute interval, we have the maximum CPU utilization. Since we have data on more than 1 billion VMs, the data at this granularity are not manageable, and we further aggregate this data to the VM-day level by calculating the inverse CDF of max CPU utilization in 5% intervals. In particular, for each 5% increment, we calculate the number of counters under 5, 10, . . ., 95% utilization. We also record the maximum CPU utilization and the total number of hours the VM is running during that day. This sample forms the primary dataset for all analyses conducted in the paper.

B.2 Virtual Machine Data

Together with the information on CPU utilization of VMs, we also collect information on the important characteristics of VMs to understand their usage patterns and performance. Our data includes the data center of the VM, which is anonymized for privacy and security reasons. However, we observe the geographical region of the data center, categorized into US, EU, and Other. This helps identify the geographical location of the firm and whether firms and units run jobs outside of their domestic country. We also observed the series to which each VM belongs. Cloud providers group VMs of similar sizes, hardware, and features into the same families, typically referred to as machine series or instance types, depending on the cloud provider.[47] This variable is anonymized, and we only observe a unique identifier for confidentiality reasons.

Another important piece of information is the VM type, which categorizes VMs based on their primary purpose, such as general-purpose, compute-optimized, memory-optimized, and storage-optimized. We observe the actual values of these variables, allowing us to analyze the types of VMs used by each firm. In addition, we observe other key VM characteristics, including their operating system (Linux or Windows), memory, and number of cores.

These VM characteristics include the following set of VM groupings, which we use throughout the text.

1. The *VM type*, as described above, categorizes VMs based on their primary purpose. It takes the values of general purpose, compute optimized, memory optimized, storage optimized, HPC (high-performance computing), or GPU (graphics processing unit).

2. The *VM series* is a more granular indicator of the architecture of the VM. Each VM series is defined by a combination of hardware such as processing chip, software components, and certain proportions or features such as the menu of available memory per CPU combinations. Generally speaking, VMs that are in the same VM series will only differ according to the data center they are physically located in, size attributes such as cores or memory, and their operating system; the VM series defines all other attributes of the VM.

3. The *VM configuration* is a unique combination of a VM series, data center, operating system, number of cores, and amount of memory. This variable represents the exact hardware and software that the VM user chooses, and is the most granular variable that classifies a VM.

B.3 Firm and Unit Level Data

There are two ID variables associated with the creator of each VM in our CPU utilization data. Each VM is associated with a unit ID. The unit ID collects all users that share a system administrative structure for oversight of the VMs and a payment/billing contract with the cloud provider. Each unit ID is then associated with a higher-level firm ID. All unit IDs whose users are part of the same directory will be part of the same firm ID.

Although our CPU utilization data are intermittent throughout 2017-2023, we have unit-month and firm-month level panel datasets that cover the entire sample period from

[47] For examples of machine series from top providers, see these links: Google Cloud— Machine Families, AWS EC2— Instance Types

2017 until mid-2023. These panel datasets contain normalized statistics on the cloud usage of each unit and firm in each month, including the number of VMs deployed, the number of active VM days, a measure of cloud spend, and the total number of hours and core-hours across all VMs on the cloud. The datasets also include whether the firm used any reserved instances and the share of the firm's total usage of PaaS products.

In addition to these panels, we also have datasets with information about each unit and firm in our sample. We observe the industry of each firm, which we then map to 2-digit SIC codes. Each firm is also associated with potentially multiple billing addresses; while we do not observe the billing addresses themselves, we observe indicators for whether the firm is associated with billing addresses in the US, EU, or another region of the world, as well as an indicator for whether the firm is multinational (has billing addresses in multiple countries). We also construct a "usage region" for each firm and unit based on the locations of the data centers in which the firm or unit had the most compute usage. Since network latency increases with the geographic distance between the user and the data center, cloud users are more likely to choose data centers in the same region, making the region that the firm or unit had the most usage a useful proxy for the operational location of the firm or unit. Finally, our data also includes quartiles of an independent measure of firm size for each firm that proxies the number of employees of the firm. The quartiles are calculated separately for every region-industry-year.

B.4 Sampling Details

In addition to aggregating our data to the VM-day level used in this paper, we take multiple other steps to reduce the data to a manageable size and to fully obfuscate firm identities. With our VM-day dataset, we perform three such sampling steps. First, we filter out the firms that fall below fixed thresholds for total usage and consistency of usage. Second, we thin the right tail of the distribution by sampling the top few percentiles of firms (measured by total usage) at an undisclosed sample rate. This sampling allows us to maintain a sample that is representative of a wide array of firms while also reducing the size of the data further and eliminating the possibility of identifying large firms through the combination of our data with public information and from producing sensitive aggregate statistics about the cloud platform itself. Finally, we sample VM-day observations at a fixed undisclosed rate within the firm that is between 70% and 100%.

B.5 Cleaning Steps for VM-day Data

In addition to the initial cleaning and sampling steps applied to the raw data, we implement additional filtering steps to the VM data to remove firms with low usage and short-duration VMs.

First, we remove VMs with a duration of less than 20 minutes. These VMs are likely used by firms to initiate another job, such as testing configurations or starting batch processing jobs. They may also be part of a scale set that has been activated only briefly to handle temporary spikes in demand. These short-duration VMs account for a negligible share of total core-hours. Additionally, we exclude a very small number of VMs (less than 0.01%) associated with operating systems other than Linux and Windows or that are missing information such as memory or VM configuration.

At the firm level, we remove firms that are inactive for more than 80% of the months and those with less than 1,000 hours, 500 core-hours, or 200 VM-days of usage. This step ensures that each firm has a sufficient sample size to estimate its productivity accurately. These cleaning steps affect only a negligible fraction of firms, accounting for less than 1% of those in the raw data.

B.6 Public Cloud and Compute Data

There are a number of publicly available *traces* detailing utilization information pertaining to both cloud and cluster environments. A trace is a dataset containing detailed information about the utilization and performance of compute resources. These traces often provide data on users and compute hardware as well.

Traces are collected from real-world compute environments. Providers of these compute resources make their traces publicly available for research, analysis, and educational purposes. Below, we describe three usage traces. The first dataset we describe was released by Google Cloud (GC) and is a trace of a high-performance computing cluster. The second dataset is a public *power* trace provided by GC (Google, 2019) that corresponds to the public GC cluster trace. The third was released by Microsoft Azure (Azure) and is a trace of a cloud computing environment.

As in the main text, the key variables in these datasets pertain to both resources provisioned and utilized. Each of the datasets described in this section is a trace of cluster information about users' resources, compute activity and the networks within which their VMs run workloads.

B.6.1 Google Cloud Platform Cluster Trace

The contents of this trace allow for the close study of job scheduling and cluster management (Verma et al., 2015; Tirmazi et al., 2020). However, our main interest in these data is to use the information provided on resource utilization to measure the compute productivity of users.

The GC trace was sampled in May 2019 and pertains to eight clusters utilizing Google's *Borg* cluster manager. These clusters are located in data centers in New York and Chicago in North America, Helsinki and Brussels in Europe, and Singapore in Asia. The users of the clusters traced in these data are Google engineers and services.

The unit of observation in the usage component of the trace data is a *task*. Tasks are processes that originate from programs running as part of jobs submitted to the cluster manager by users. The tasks detailed in this trace are either the result of jobs run by Google engineers, or they are run within reserved resources available to Google services used by internal or external users (Wilkes et al., 2020). Tasks are executed either within resource allocations (similar to a VM) or directly on machines. The data also contains task-related event information. For example, task-related events include when the task is submitted to the scheduler, when the task completes, as well as auxiliary events that occur during the task's runtime or if it fails. Observations are recorded every five minutes. Hence, these data are an unbalanced panel of usage and event information of processes executed on the a cluster.

On the user end, these data contain original resource requests and usage, and user-configured constraints on the requested resources. The resources users can request are memory (RAM) and CPU cores. Requested and used memory is measured in bytes and then reported after being normalized by a constant factor. CPU requests are measured in internal "Google Compute Units" (GCUs), which are similar to CPU cores but enable the comparison of compute hardware across machines (Wilkes et al., 2020). Similar to memory, the GCU measurements are reported after being normalized by a constant factor. CPU usage (i.e., GCU usage) is measured in CPU-seconds and reported after being normalized. The data also contains information about machine attributes, machine availability, obfuscated user and job identifiers, and variables that track events, missing data, and reasons for task failures.

B.6.2 Google Cloud Platform Power Trace

The content of this trace complements the trace above in that it provides information on the power consumption of the machines from the GC cluster trace during the same sampling period, May 2019. This enables us to measure the relationship between CPU utilization and power consumption.

A typical data center draws power from its local grid. These facilities also maintain a set of large generators that ensure continuous operations during power outages or other disruptions to the primary grid power supply. Once power is drawn into the data center, it is transformed down into a power distribution unit (PDU). PDUs are the main distributor of power to both IT and non-IT resources in a data center. They manage the flow of power to equipment and monitor environmental factors like temperature and humidity. PDUs often also provide a layer of redundancy in order to increase uptime and reliability. On the data center floor, PDUs manage power supplied to clusters and their supporting IT equipment, as well non-IT equipment such as cooling resources (Radovanovic et al., 2022).

Modern cluster computing produces large amounts of heat. Therefore, measuring power consumption requires accounting for the composite power supply to both IT (e.g., servers) and non-IT (e.g., coolers) resources on the data center floor (Singh et al., 2015; Athavale et al., 2018). The power trace provided by GC incorporates both IT and non-IT power demands. This dataset includes power utilization levels of 55 PDUs, which manage the power supply to each of the clusters in the GC cluster trace. The power for each cluster is managed by multiple PDUs. The data include two key variables: total power utilization and production power utilization.

Total power utilization, measured in 5-minute intervals, indicates the percentage of available power capacity consumed through a PDU for all IT and non-IT equipment, including coolers. Similarly, production power utilization is an estimated measure provided by GC that details the power consumption attributable to production workloads, including power consumed by non-IT equipment.

B.6.3 Microsoft Azure Trace

Azure publicly provides a number of cloud traces. We focus on a 2019 trace containing a representative subset of Azure VM workloads (Microsoft Azure, 2019). An analysis of the previous version of trace can be found in Diaconu et al. (2013).

The dataset covers 30 consecutive days and includes over two million VMs. The dataset comprises unbalanced panel data with 5-minute VM CPU utilization readings. Nearly 1.25 billion VM CPU utilization readings are recorded from over five thousand subscriptions. This trace includes the following key variables: sanitized user, VM, and deployment IDs; timestamp in seconds (recorded every 5 minutes); indicators for when VMs were created and deleted; count of VMs created; deployment size; maximum, minimum, average, and 95th percentile of CPU utilization; VM virtual core count; and VM memory utilization in

GBs.

C Productivity Measurement Details

C.1 Details of Measuring Cloud Productivity

As in the main text, index firms by i, jobs by j, and days by t. Firm i assigns job j, which runs for h_{ijt} hours on day t, to VM v_{ij}. Each VM v is defined by a tuple $(c(v), x(v))$, where $c(v) \in C \subset \mathbb{N}$ is the number of cores of VM v and $x(v) \in X$ are the VM's characteristics, which includes the VM's machine type, memory, data center, and operating system.

On day t, we observe n_{ijt} snapshots of CPU utilization $\{u_{ijst}\}_{s=1}^{n_{ijt}}$. By multiplying the utilization with the capacity of the chosen machine, we get n_{ijt} snapshots of the load of each job: $\{\ell_{ijst}\}_{s=1}^{n_{ijt}}$, where $\ell_{ijst} := u_{ijst}c(v_{ij})$. We assume that the load for each job is exogenous — that is, we take it as given that each firm must use the exact same amount of computing power that we observe them using in the data.

On each day, there is a set of VMs available for the firm to choose from. Let V_t be the set of VMs available on day t, and $V_t(x) = \{v \in V_t : x(v) = x\}$ be the set of VMs available on day t that have characteristics x. We also define the outside option "VM" v_0 as the 0-core VM that represents not running a job. Similar to the load, we assume that the characteristics v_t of a VM are exogenous, and we take it as given that the firm chose these correctly. Therefore, we infer the choice set of firm i for job j on day t to be $V_{ijt} = V_t(x(v_{ij})) \cup \{v_0\}$.

We compare the firm's provisioning decision v_{ijt} with the decision of a hypothetical cost-minimizing firm v^*_{ijt}. To do so, we need to model the optimal provisioning process. For our baseline analysis, we assume the following:

Assumption 1. *The cost-minimizing firm provisions based solely on the peak load of the VM, which we take to be the 95th percentile load over the period in which the VM is being provisioned.*

Assumption 2. *If a VM has a peak utilization of under 10% over a given time period, then the firm does not receive any benefit from that job over that time period.*

Assumption 3. *The cost-minimizing firm will downsize a machine only if the peak utilization on that machine would be less than 90%.*

Assumption 4. *After the initial provisioning decision, it is only worthwhile for a firm to change its provisioning decision if a VM will be improperly provisioned over a seven-day period or longer.*

As discussed in the main text, Assumption 1 is relatively standard, both in industry and literature definitions of improper provisioning. Assumption 2 is justified by a 10% peak CPU utilization being explainable by background processes of the CPU and not by any foreground processes run by the user. Assumption 3 comports with the rightsizing recommendations given by cloud providers to their clients. Finally, Assumption 4 is justified by firms facing sufficiently high switching costs from reconfiguring a job to a new type of VM.[48]

Let $\mathcal{T}_t^k = \{t, t+1, \ldots, t+k-1\}$ be defined as the set of k consecutive days starting with day t. Let $\bar{\ell}_{ij}(\mathcal{T}_t^k)$ be the peak utilization over $\mathcal{T}_t^k$:

$$\bar{\ell}_{ij}(\mathcal{T}_t^k) = \max\left\{\ell : \frac{\sum_{r=t}^{t+k-1}\sum_{s=1}^{n_{ijr}} \mathbf{1}(\ell > \ell_{ijsr})}{\sum_{r=t}^{t+k-1} n_{ijr}} \leq 0.95\right\} \tag{8}$$

Define the peak utilization $\bar{u}_{ij}(\mathcal{T}_t^k)$ analogously. Let T be the length of job j in days and, for ease of exposition, relabel the days so that job j lasts from day 1 to day T.

First suppose $T \geq 7$. Given our assumption, the cost-minimizing firm's decision on each day $t = 1, \ldots, T$ solves:

$$\begin{aligned} v^*_{ijt} &= \arg\min_{v \in V_{ij}} c(v) \\ \text{s.t.} \quad \min_{r \in \{\max\{1,t-6\},\ldots,\min\{t,T-6\}\}} & \bar{\ell}_{ij}(\mathcal{T}^7_{t-r})\mathbf{1}(\bar{u}_{ij}(\mathcal{T}^7_{t-r}) \leq 0.1) \leq c(v) - 0.1 \cdot \mathbf{1}(v \neq v_{ij}) \end{aligned} \tag{9}$$

It is easiest to interpret the constraint of (9) in words. The left-hand side of the constraint searches over all of the sets of seven consecutive days that include day t. If day t is part of a seven-day stretch in which the peak utilization is under 0.1, then it is idle, the left-hand side of the constraint will evaluate to zero, and any VM will cover the load over those seven days. In this case, the cost-minimizing firm will choose to deprovision the job, i.e., select $v^*_{ijt} = v_0$ for those seven days. Otherwise, firm i will take the smallest VM that will cover the peak utilization of job j over a seven-day stretch that includes day t. This will always include as a possibility the actual VM that the firm chose, v_{ij}, but could include a smaller VM if the VM is downsizable (there exists a smaller VM with the same characteristics) and the peak load over the seven-day period is small enough to be covered by this smaller VM with at most a peak utilization of 90%. If this indeed is the case, then $v^*_{ijt} \neq v_{ij}$ and we say that job j is overprovisioned over those seven days. In practice, because the number of cores in a given VM nearly always scales by powers of two, a VM will be overprovisioned if a smaller VM exists and its 95th percentile CPU utilization over a seven-day period is under 45%.

[48]In practice, some major cloud providers have processes to reprovision running jobs to VMs of different sizes without any interruption in service. For example, see Amazon Web Services, "Resizing clusters," available at https://docs.aws.amazon.com/redshift/latest/mgmt/rs-resize-tutorial.html, accessed on June 5, 2024. Thus, we view this assumption as conservative.

For VMs that are shorter than seven days — $T < 7$ — we evaluate only the initial provisioning decision and do so over the entire length of the VM. That is, the cost-minimizing firm's provisioning decision solves

$$v^*_{ijt} = \arg\min_{v \in V_{ijt}} c(v) \text{ s.t. } \bar{\ell}_{ij}(\mathcal{T}_1^T)\mathbf{1}(\bar{u}_{ij}(\mathcal{T}_1^T) \leq 0.1) \leq c(v) - 0.1 \cdot \mathbf{1}(v \neq v_{ij}) \tag{10}$$

As discussed in the main text, the final productivity measure ω_{ijt} is the ratio between resource usage of the cost-minimizing firm and firm i's actual resource usage on job j on the day t: $\omega_{ijt} = c(v^*_{ijt})/c(v_{ij})$.

C.2 Microfoundation of Compute Productivity as Rescaled TFP

We note that while ω_{ijt} is fundamentally a measure of how effectively firm i solves a cost minimization problem, holding output fixed, it also has an interpretation as a more traditional total factor productivity measure if the production function is Leontief in computing.

Suppose that firm i produces a single product sold at exogenous price p. For ease of exposition, suppose the firm only uses computing for one job j. Let the firm's production function at a given moment in time s be $f_{is}(\ell_{ijst}, z) = \min\{\ell_{ijst}, g_{is}(z)\}$, z are other inputs that are assumed fixed in the short run and $g_{is}(z)$ reflects the amount of computing input that firm i can turn into output at moment s. Assume the price of computing power is linear in the amount of computing power used, and normalize the per-core-hour price to 1. Assume that each moment s is h hours long. Then the firm solves:

$$\max_{\{\ell_{ijst}\}_s, v} \sum_s (p f_{is}(\ell_{ijst}, z) - hc(v)) \quad \text{s.t.} \quad v \text{ satisfies the constraint of (9)} \tag{11}$$

If p is high enough such that the firm does not want to "waste" any fixed input z, then the profit-maximizing firm will choose to set $\ell_{ijst} = g_{is}(z)$ at each moment. In this case, the first part of the maximization problem becomes a constant and the problem can be rewritten as

$$\max_v \sum_s -hc(v) \quad \text{s.t.} \quad v \text{ satisfies the constraint of (9)} \tag{12}$$

which is equivalent to the cost minimization problem in (9). Under these assumptions, firm i's profits on day t are given by

$$\sum_s p f_{is}(\ell_{ijst}, z) - hc(v_{ij}) = \sum_s p f_{is}(\ell_{ijst}, z) - \frac{hc(v^*_{ijt})}{\omega_{ijt}} \tag{13}$$

where the equality is by definition of ω_{ijt}. The typical TFP would enter as a multiplier of the production function f_{is}; that is, the profit function would be $\sum_s pA_{ijt} f_{is}(\ell_{ijst}, z) - hc(v^*_{ijt})$, and A_{ijt} is TFP. From the formulation in (13), it is clear that the profit function using TFP and the production function using our cost productivity measure are the same up to a rescaling. As such, under these conditions, our productivity measure ω_{ijt} is simply a linear transformation of a TFP measure, where the coefficient is the productivity of the most productive (cost-minimizing) firm.

D Estimation Details

D.1 Details of Productivity Calculation

We use the following procedure to implement the measures represented in Section 4. First, for each possible VM configuration (a combination of VM series, data center, operating system, memory, and cores) a firm could choose, we evaluate whether that configuration is downsizable on each day (another VM configuration of the same type, data center, operating system, and memory is available on that day). We also evaluate whether the configuration is *twice downsizable*, which is defined as there existing a machine that the configuration could be downsized to that is itself downsizable. As discussed in the main text, cores scale in powers of two; therefore, if a VM is twice downsizable, this means there exists a VM with the same machine type, data center, operating system, and memory that has a quarter of the number of cores.

Second, for each VM on each day, using the daily inverse utilization CDF, we compute the peak (95th percentile) CPU utilization for all seven-day streaks that include that day. For VMs that last for fewer than seven days, we compute the peak CPU utilization over the life of the VM. We then assign the productivity measure at the VM-day level using the following hierarchical definition:

1. If a VM-day is part of a seven-day streak with a peak CPU utilization lower than 10%, it is idle and assigned a value of 0.
2. Else if a VM-day is part of a seven-day streak with a peak CPU utilization lower than 20% AND the VM configuration is twice downsizable, it is overprovisioned, with the correct configuration being a VM a quarter of the size, and assigned a value of 0.25.
3. Else if a VM-day is part of a seven-day streak with a peak CPU utilization lower than 45% AND the VM configuration is downsizable, it is overprovisioned, with the correct configuration being a VM half the size, and assigned a value of 0.5.
4. Else a VM-day is properly provisioned and assigned a value of 1.

We also define alternative independent variables that decompose productivity from idleness and from overprovisioning separately. The idleness variable equals 1 if and only if the main productivity dependent variable is equal to 0, while the overprovisioning variable equals 1 if and only if the main productivity dependent variable is greater than 0, but less than 1. To remove the negative mechanical correlation between these two variables, we estimate a firm's overprovisioning inefficiency excluding all idle observations;

that is, overprovisioning inefficiency will be the share of VMs that are overprovisioned, conditional on not being idle.

Once we have defined a dependent variable, we then regress this dependent variable on a fixed effect that is either at the firm, firm-month, firm-month-VM profile, unit, unit-month, or unit-month-VM profile level.[49] We weight by core-hours in order to properly account for the resources used by each VM on each day. Our baseline estimates include no controls, meaning that the resulting fixed effects simply represent the weighted average of the dependent variable; these are the productivity estimates used throughout the main text of the paper. We also regress these accounting for day-of-week fixed effects and an indicator for whether there is a holiday in the region on the given date; day-of-week plus holiday plus machine type fixed effects; day-of-week plus holiday plus machine type interacted with data center region fixed effects; and day-of-week plus holiday plus VM profile fixed effects.[50] Results with these alternative levels of controls are located in Appendix H.

In these regressions, a location normalization is to be made — one can add and subtract a constant from two different fixed effects and arrive at the exact estimates for all units. Our normalization is to make the average productivity according to each of these fixed effect regressions equal to the average productivity without controls. Finally, for all the alternative controls, we verify that the controls form a connected set, and that therefore the fixed effects resulting from the estimation procedure are directly interpretable and comparable with one another.

D.2 Details of Dispersion and Persistence Estimation

This section provides the details of the estimations presented in Table 3.

In our dispersion analysis, we use the firm-month level productivity estimates detailed in the prior section. We restrict the sample to firm months with at least 50 VM-day observations to include firms with precisely estimated productivity levels. Column (1) presents statistics calculated from the firm-month level data without controls. For columns (2-4), we compute the same statistics within each group listed in the column name (industry, month, and industry-by-month). After calculating these statistics for each group, we take the weighted average across the groups, using the number of firms in each group as weights. This weighting approach ensures smaller industries with fewer firms do not disproportionately influence the average statistics.

In the decomposition analysis in Panel B, the goal is to estimate the variance explained

[49] A VM profile is a unique combination of VM series, data center, and operating system.

[50] For the firm-month-VM profile and unit-month-VM profile regressions, the final three sets of controls are extraneous because they are nested by VM profile.

by within and between-firm heterogeneity for the first analysis and within-region across-region analysis for the within-firm for the second analysis. To do the within-between firm decomposition, we aim to estimate the following decomposition.

$$\mathrm{Var}(\omega_{im}^{k} - \bar{\omega}_{m}) = \mathrm{Var}(\omega_{im}^{k} - \bar{\omega}_{im}) + \mathrm{Var}(\bar{\omega}_{im} - \bar{\omega}_{m})$$

where i denotes firm, k denotes unit, and m denotes month. We further decompose within-firm dispersion into within-firm between-region and between-firm within-region components using:

$$= \mathrm{Var}(\omega_{im}^{kr} - \bar{\omega}_{im}^{r}) + \mathrm{Var}(\bar{\omega}_{im}^{r} - \bar{\omega}_{im}) + \mathrm{Var}(\bar{\omega}_{im} - \bar{\omega}_{m}^{r}) + \mathrm{Var}(\bar{\omega}_{m}^{r} - \bar{\omega}_{m})$$

where r denotes region. For this analysis, we only use multinational firms, which are firms that have units in multiple geographic regions, classified as US, EU, and domestic.

To achieve these decompositions, we use a regression framework and obtain the adjusted R^2 from those regressions. Specifically, for the within-firm decomposition, we regress unit-level productivity on firm fixed effects and take the R^2 from that regression as the between-firm component. We repeat the same exercise while including the controls reported in Columns (2-4) of Table 3. For these specifications, we first run the fully saturated regression with the control variables and record the resulting R^2 as R_0^2. Then, we include firm fixed effects by interacting them with the control variables and record the resulting R^2 as R_1^2. To find the within-firm variation, we calculate $R_1^2/(1 - R_0^2)$, which quantifies the share of variance explained by firm fixed effects after controlling for the specified set of control variables.

The calculation of within- and between-region decomposition is similar. We restrict the sample to the multi-national firms and estimate the contribution of region-fixed effects with or without control variables in the specification.

For persistence results, we use the month-firm level data and regress the productivity on 1-month, 1-year, and 5-year lagged values separately for productivity, idleness productivity, and overprovisioning productivity. Results in Columns (2-4) run the same regressions by adding the corresponding control variable specific in the column name to the regression. In these regressions, standard errors are clustered at the firm level.

D.3 Details of Learning Estimation

In our learning analysis, we make the following sampling restrictions. First, we remove all firms with an average of less than 50 VM days per month. Second, for the learning analyses that are based on within-cohort variation in productivity over July 2022-June 2023 (including Figure 7 and Table 6), we limit to a balanced panel of firms, i.e., firms that have usage in each month from July 2022 to June 2023.

In all figures in this section, we normalize the productivity estimate for firms in each month by dividing by the productivity estimate of firms in their first month. We then compute the standard errors of the ratio between the productivity estimate of firms in a given month and the productivity estimate of firms in their first month using the delta method. In particular, suppose that $\overline{\omega}_t$ is the expected productivity of firms that are t months old, and σ_t is the standard error. Using the delta method, a first-order approximation of σ_t^{norm}, the standard error of $\overline{\omega}_t/\overline{\omega}_0$, is:

$$\sigma_t^{\text{norm}} \approx \frac{1}{\overline{\omega}_0}\sqrt{\sigma_t^2 - \frac{2\overline{\omega}_t}{\overline{\omega}_0}\text{cov}(\overline{\omega}_0, \overline{\omega}_t) + \frac{\overline{\omega}_t^2}{\overline{\omega}_0^2}\sigma_0^2} \tag{14}$$

To compute an estimated $\widehat{\sigma}_t^{\text{norm}}$, we plug in the estimated average productivities, along with the estimated variances and covariances from the coefficient covariance matrix of regression of productivity on firm experience indicators. In this regression, standard errors are clustered by the firm; this implies a nonzero covariance across months in the first year in Figure 7 and Table 6. In Figure 6, the unit of observation is the firm, and therefore, the standard errors are computed using the empirical standard deviations, and the covariance in the estimates is assumed to be zero. The exception is when $t = 0$, in which case we know that $\text{cov}(\overline{\omega}_0, \overline{\omega}_0) = \sigma_0^2$, and therefore this expression simplifies to $\sigma_0^{\text{norm}} = 0$.

D.4 Details of Learning Decomposition Analysis

In our learning decomposition, we restrict our sample to the period from July 2022 to June 2023 to be able to calculate month-to-month productivity growth. Following Melitz and Polanec (2015), we decompose the log productivity change into five components specified in the main text. In some rare cases, firm or unit productivity in a given month is zero. For those months, we set productivity to 0.01 so that we do not drop those observations when we take the logarithm.

In rare cases where an account or machine does not have any usage in a given month but we observe usage afterward, we do not treat those months as entry and exit, but we impute the productivity of that machine series or unit from the previous month, and we set its core-hours to zero.

In this decomposition, we first implement the decomposition for each firm or unit, depending on the specification, and then take an unweighted average of each component across firms or units within each experience group given in the x-axis of Figure 8(a). The firm experience is measured as of the end of the sample, June 2023.

In calculating Figure 8(b), we first subset the data to firms that are more than three years old and have an account that began using cloud computing in July 2022 and continued usage through June 2023. These new accounts constitute our sample of new units within experienced firms. We then subset the units of these firms that started using cloud computing after July 2019, ensuring that these units have at least three years of experience by July 2022. We calculate the average productivity of these groups for each month from July 2022 to June 2023 and report the productivity levels by normalizing them relative to the productivity level of new units in July 2022.

For Figure 9(b), we employ a similar approach with one key distinction. Unlike for firms and accounts, we lack separate data on when a firm began using a particular machine. Instead, we infer this information from the VM utilization data. As our 2022 data begins in July, we identify new machines as those first used by a firm in August. This method could introduce a minor error if a firm had previously used a machine before July 2022 but skipped usage in July. However, such cases are rare, and if they occur, they make our results more conservative. After identifying the first use date of a machine, we proceed with the analysis as described in the previous paragraph.

D.5 Measuring Relationship Between Utilization and Electricity

We combine the public cluster usage and power data provided by Google Cloud (GC) to estimate the basic relationship between cloud resources and power utilization. A description of the datasets is provided in Appendix B.6. First, we describe the aggregation of the GC cluster data used in the analysis of Section 8.1, and then in Section D.5.2, we describe the simple regression we estimate.

D.5.1 Calculating Utilization by PDU

The GC cluster trace denotes each of the 8 clusters contained in the data by a through h. When compressed, the full size of the cluster trace alone is nearly 2.6 terabytes. Therefore, in order to attenuate the computational burden of aggregating and merging the entire data, we focus on cluster a.

In Appendix B.6, we described the task as the unit of observation in the usage data of the cluster trace. Each task in the cluster trace is identified by an index relative to a *collection ID*. A collection is either a set of resources where jobs executing tasks run or stand-alone jobs submitted directly to the scheduler to run on a machine. Hence, the unique usage observation is identified by the pairing (collection ID, task ID).

Each PDU is uniquely associated with a cluster. Moreover, each PDU supplies power to a specific subset of machines within a cluster. Every task is scheduled on a single machine. As noted in Appendix B.6, CPU utilization (in terms of GCUs) is reported after being normalized. However, the normalizing factor is the same across all observations. Hence, for each 5-minute interval t and PDU p, we compute CPU utilization at the PDU level as

$$U_{pt} = \frac{\frac{1}{c}}{\frac{1}{c}} \cdot \frac{\sum_{m_{jt} \in \mathcal{M}(p,t)} \sum_{i \in m_{jt}} u_{i,m_{jt}}}{\sum_{m_{jt} \in \mathcal{M}(p,t)} \sum_{i \in m_{jt}} r_{i,m_{jt}}}, \tag{15}$$

where c is the resource specific normalizing factor, $\mathcal{M}(p,t)$ denotes the set of active machines belonging to PDU p at time t, i indexes the pair (collection, task) at t, and $u_{i,m_{jt}}$ and $r_{i,m_{jt}}$ are the used and requested CPU resources of i, respectively. Since c enters the reported measures linearly, it gets canceled out in the computation of U_{pt} to yield a genuine CPU utilization measure in percentage terms. While one would expect utilization to be less than or equal to 100%, the Borg cluster manager allows tasks to utilize available CPU capacity so long as the machine executing the task is not overloaded (Tirmazi et al., 2020). For this reason, utilization can exceed 100%.

D.5.2 Estimating Idle Power Consumtpion

In the computer science and electrical engineering literature, researchers have estimated the relationship between CPU utilization and power consumption through a combination of regression analysis and experimental methods. Experimental studies utilize machines with fixed characteristics and controlled computing environments to generate data on CPU utilization and power consumption.

These studies employ various metering techniques to accurately measure these factors (Kansal et al., 2010; Waßmann et al., 2013; Jiang et al., 2013). Power consumption is modeled as a linear function of CPU utilization and then estimated on the experimental data (Husain Bohra and Chaudhary, 2010; Jiang et al., 2013; Osei-Opoku et al., 2020). These are conventional techniques for estimating the relationship between consumption and utilization; however, Veni and Bhanu (2016) note that non-linear models are better suited for robust power consumption prediction across workloads when one wants to capture better the interaction between CPU utilization and features such as disk space unavailable in our sample.

Since we are primarily interested in the relationship between power consumption and

CPU utilization, the regression in Figure 10 is specified as

$$power_{pt} = \alpha_{pt} + \beta \cdot U_{pt} + \varepsilon_{pt},$$

where $power_{pt}$ is the total power utilization of PDU p at time t, α_{pt} represents power consumption when VMs are utilizing no CPU, β is the effect of a percentage increase of CPU utilization on consumption, and ε_{pt} is an error term. The parameters of this regression are estimated via ordinary least squares. As noted above, we estimate $\beta_{pt} = 0.5$, which predicts a 0.5 percentage point (pp) increase in power consumption from a 1pp increase in CPU utilization.

In real-world cluster traces, we rarely observe VMs that consistently use 0% CPU. For example, in our sample from the GC trace, CPU utilization seldom falls outside the range of 30%-50%. Additionally, the completely idle VMs are mostly short-lived, likely created for testing the provisioning or scaling of VMs (Cortez et al., 2017). Therefore, the constant term in the linear model of power consumption is used to extrapolate the level of consumption at 0% CPU. In our regression, we estimate a value of α_{pt} corresponding to 50%. This value is consistent with the experimental literature discussed above.

D.6 Counterfactual Resource Calculations

In this analysis, we calculate the total core-hours that would have been saved if all firms below the benchmark productivity level ω_{it} reached the productivity level $\bar{\omega}_{it}$. For this, we denote the counterfactual productivity:

$$\omega_{it}^{c} = \bar{\omega}_{it} \cdot 1(\omega_{it} < \bar{\omega}_{it}) + \omega_{it} \cdot 1(\omega_{it} \geq \bar{\omega}_{it}) \tag{16}$$

We ask what would be the total core-hours needed if all firms had a productivity of ω_{it}^{c}. This calculation is relatively straightforward because it does not depend on whether firms increase productivity through idleness or overprovisioning; the core-hours that would be saved will be the same regardless of the mechanism of improvements.

We use $s_{im} = \sum_{j \in J_{im}} c(v_{ij}) h_{ijt}$ to denote the total core-hours used by firm i in month m. We categorize these core-hours into three types of machine utilization:

$$s_{im} = s_{im}^{i} + s_{im}^{o} + s_{im}^{p} \tag{17}$$

Here s_{im}^{i}, s_{im}^{o}, and s_{im}^{p} denote idle, over-provisioned, and productive core-hours, respectively. The output from these different types of machines is denoted by $y_{im}^{i} = 0$, $y_{im}^{o} = 0.5 s_{im}^{o}$, and $y_{im}^{p} = s_{im}^{p}$; thus, $y_{im} = y_{im}^{i} + y_{im}^{o} + y_{im}^{p}$ represents the total output.

Let s^c_{it} denote the total core-hours needed for firms to produce the same output with the counterfactual productivity ω^c_{it}. Therefore, we have:

$$\omega_{it} = \frac{y_{im}}{s_{im}}, \qquad \omega^c_{it} = \frac{y_{im}}{s^c_{im}} \tag{18}$$

By taking the ratio, we can find s^c_{it} as:

$$s^c_{it} = s_{it}\frac{\omega^c_{it}}{\omega_{it}} \tag{19}$$

This calculation shows that the mechanism by which firms achieve efficiency gains does not matter since we are counting only core-hours that are used anymore in the counterfactual scenario.
By aggregating firm-level counterfactual core-hours, we can calculate s^c_t as:

$$s^c_t = \sum_i s_{im}\frac{\omega^c_{im}}{\omega_{im}} \tag{20}$$

By further aggregating these over time

$$s^c = \sum_t s^c_t, \qquad s = \sum_t s_t$$

The total resource savings in the economy is the ratio between counterfactual and factual resources:

$$\Delta s = \frac{s - s^c}{s}. \tag{21}$$

D.7 Counterfactual Electricity Calculations

This section calculates how much electricity would have been saved in the counterfactual.

Let s_{ijmt} denote the core-hour for VM j, used by firm i, in month m and let $u_{ijmt} \in [0,1]$ denote the utilization at time (5-min interval) t. Based on the relationship between utilization, We assume that power consumption takes the following form:

$$p_{imtj} = (0.5 + 0.5u_{imtj})k^{max}_m$$

where k^{max}_j represents the power consumption when machine j is utilized at 100%. This power utilization assumes that when the machine is idle, the power consumption is 50%

of maximum power and then increases linearly with utilization. This assumption is based on the relationship between power and utilization that we estimated in Section 8.1.

We further assume that $k_j^{max} = kc_j$, where c_j is the number of cores of machine j, and we normalize $k = 1$. This assumption is reasonable because the computation power required for a machine typically increases linearly with the number of cores. This functional form is particularly convenient because additivity is preserved under integration, meaning that the core-hours of a machine is a sufficient statistic. In particular, the power consumption of VM m during its duration t_m is given by:

$$\int_t p_{imtj}\, dj = \int_t (0.5 + 0.5u_{imtj})c_{im}\, dt = 0.5c_{imt}T_{imt} + 0.5c_{imt}T_{imt} \int_t u_{imt}\, dt \tag{22}$$

$$= 0.5(1 + \bar{u}_{imt})s_{imt} \tag{23}$$

where $\bar{u}_{imt}$ is the average utilization of machine m, T_{imt} is the duration of VM, and $s_{imt} = c_{imt}T_{imt}$ is the total core-hours of machine m. Furthermore, we can aggregate this at the firm level as follows:

$$p_{it} = \sum_{m(it)} 0.5(1 + \bar{u}_{imt})s_{imt} = 0.5 \sum_{m(it)} s_{imt} + 0.5 \sum_{m(it)} \bar{u}_{imt}s_{imt} \tag{24}$$

$$= 0.5s_{it} + 0.5\bar{u}_{it}s_{it} \tag{25}$$

where u_{it} is the firm i's utilization in month t. This form suggests that a firm's total power requirement depends on the number of core-hours they use and the average utilization in a given month. This makes counterfactual power calculations tricky because whether firms improve idleness or overprovisioning will affect both core-hours and the average utilization.

To make progress, we introduce additional notation to separate efficiency gains from changes in idleness and overprovisioning. Let $s_{it}^{i,c}$, $s_{it}^{o,c}$, and $s_{it}^{p,c}$ denote the counterfactual idle, overprovisioned, and productive core-hours respectively, and $\Delta s_{it}^i = s_{it}^i - s_{it}^{i,c}$, similarly for other utilization types. We have that:

$$\frac{s_{it}^p + 0.5s_{it}^o}{s_{it}} = \omega_{it}, \qquad \frac{s_{it}^{p,c} + 0.5s_{it}^{o,c}}{s_{it}^c} = \omega_{it}^c \tag{26}$$

Moreover,

$$s_{it}^p + 0.5s_{it}^o = s_{it}^{p,c} + 0.5s_{it}^{o,c} = y_{it} \tag{27}$$

since we condition on the actual output in counterfactual calculations. This implies that:

$$0.5\Delta s^{p}_{it} = -\Delta s^{o}_{it}$$

so an X core-hours reduction in overprovisioned machines should add $X/2$ core-hours of productive VM. Using Equations (26) and (27), we also obtain:

$$\frac{s^{p}_{it} + 0.5 s^{o}_{it}}{s_{it}} = \omega_{it}, \qquad \frac{s^{p,c}_{it} + 0.5 s^{oc}_{it}}{s_{it} - 0.5\Delta s^{o}_{it} - \Delta s^{i}_{it}} = \omega^{c}_{it}.$$

where the denominator in the second equation specifies the total core-hours used in the counterfactual. This gives:

$$0.5\Delta s^{o}_{it} - \Delta s^{i}_{it} = s_{it}\left(\frac{\omega^{c}_{it} - \omega_{it}}{\omega^{c}_{it}}\right)$$

This provides an equation, but two unknowns Δs^{o}_{it} and Δs^{i}_{it}. So we need another assumption to pin down Δs^{o}_{it} and Δs^{i}_{it} separately. For this, we make the following assumption:

$$\frac{s^{i}_{it} - \Delta s^{i}_{it}}{s^{i}_{it}} = \frac{s^{o}_{it} - \Delta s^{o}_{it}}{s^{o}_{it}} \qquad \Longrightarrow \qquad \frac{\Delta s^{i}_{it}}{s^{i}_{it}} = \frac{\Delta s^{o}_{it}}{s^{o}_{it}}. \tag{28}$$

The underlying idea behind this assumption is that core-hour savings from each mechanism are proportional to the initial waste from each mechanism. Without additional information, this assumption seems reasonable and assumes that firms split efforts equally between different mechanisms.

Now, under the assumption given in Equation 28, one can compute Δs^{i}_{it} and Δs^{o}_{it} as follows:

$$\Delta s^{i}_{it} = s_{it}\left(\frac{\omega^{c}_{it} - \omega_{it}}{\omega^{c}_{it}}\right)\left(\frac{s^{i}_{it}}{s^{i}_{it} + 0.5 s^{o}_{it}}\right), \qquad \Delta s^{o}_{it} = s^{i}_{it}\frac{s^{o}_{it}}{s^{i}_{it}} \tag{29}$$

With this, we know the counterfactual distribution of idle, overprovisioned, and productive machines. We can calculate average counterfactual utilization of firm i at time t, u^{c}_{it} as:

$$\bar{u}^{c}_{it} = \bar{u}_{it}\frac{s_{it}}{s^{c}_{it}}$$

Thus, we can calculate both factual and counterfactual firm-level power requirements:

$$p_{it}^c = s_{it}^c + 0.5\bar{u}_{it}^c s_{it}^c, \qquad p^c = \sum_{it} p_{it}^c,$$

The total power saving in the economy is given by:

$$\Delta p = \frac{p - p^c}{p}.$$

E Robustness Checks

E.1 Robustness to Other Utilization Measures

In cloud computing, network and memory utilization are commonly monitored alongside CPU utilization to measure the performance and efficiency of virtual machines (VMs) and other resources.

Network utilization refers to the amount of data being transferred in and out of a VM or across the cloud infrastructure. High network utilization reflects significant data traffic, while low utilization indicates minimal use of the available bandwidth. Memory utilization measures the amount of allocated memory actively being used by a VM. High memory utilization suggests that a VM is using most of its allocated memory, whereas low utilization indicates that the memory allocation may exceed the needs of the workload.

We focus on CPU utilization because it is the most relevant metric in the industry and the most resource-intensive component of computing infrastructure. CPUs typically consume the majority of power in servers, making their efficient use crucial for minimizing energy consumption and operational costs. Additionally, CPU utilization is a standard measure of performance and efficiency in cloud computing, as it directly reflects how well the processing power is being used. By concentrating on CPU utilization, we align our analysis with industry practices and address the most significant aspect of resource management in cloud environments.

Still, one potential concern with the analysis is that while some firms may show high efficiency based on their CPU utilization, they might be less efficient in their use of memory and network resources, leading to wasted resources in other areas of computing. To address this, we conduct a robustness check to ensure that network or memory utilization does not undermine our CPU utilization results.

We have limited data on memory and network utilization for one-month periods in 2022 and 2023. Using this data, we estimate the correlation between CPU utilization and other utilization measures. The direction of this correlation is unclear beforehand. Some jobs may be memory-intensive, using more memory and less CPU, while others may be compute-intensive, relying more on CPU than memory. This variation could result in a negative correlation between these utilization measures. Conversely, if a job is truly idle, it would likely use neither memory nor CPU, potentially generating a positive correlation between the two measures.

In Figure OA-17, we report the correlation between utilization measures and find that CPU utilization is positively correlated with both network and memory utilization. This suggests that the firms identified as inefficient in terms of CPU utilization also tend to be inefficient in other dimensions of computing resource utilization.

E.2 Robustness to Time Period of Utilization Measurement

As mentioned in Section 4.1, and detailed further in Appendices C.1 and D.1, we define our productivity and inefficiency using the peak VM utilization over a seven-day period. Doing so ensures that our measure is conservative with respect to the potential costs that short-term provisioning changes represent, particularly given the predictable volatility in load associated with days of the week. In addition, it is consistent with the internal measures of cloud providers.

However, one might be concerned about the sensitivity of our results to this choice. To investigate this, we re-estimate our productivity measures using different periods over which we calculate peak productivity: one-day, three-day, and 15-day. We then repeat our analyses using these alternative productivity measures to ensure that our main results are robust to these alternative productivity definitions. Figure OA-12, OA-14 and Table OA-5 report the results from these robustness checks, which are broadly similar to the results from our main specification.

E.3 Robustness to Controlling for Machine Characteristics

As explained in Section 4.1, we first estimate the productivity of individual VMs based on their idleness and overprovisioning and then aggregate these measures at the firm level at different frequencies. In our main specification, we treat all machines the same and simply sum up the VM-level efficiencies to the firm level. One potential concern with this approach is that VMs have different machine characteristics that could affect utilization. We believe focusing on peak utilization mitigates this concern, as peak utilization is less sensitive to machine type. For instance, a memory-intensive or network-intensive workload will naturally have lower average utilization; for example, the CPU will spend idle time waiting for data transfer, and this should not affect peak utilization. However, we still provide several robustness checks to show that our results are not driven by different machine characteristics.

To account for these differences, we aggregate VM-level productivity to firm-level using a weighted regression by controlling for several job characteristics as follows:

$$\omega_{ijt} = \omega_{im} + \beta Z_{jt} + \varepsilon_{ijt}$$

This regression essentially estimates firm-level fixed effects by accounting for systematic productivity differences between machine types in different control bins.

Our first control includes day of the week and holiday fixed effects to account for temporal variations in productivity differences. For example, if less productive firms, for unrelated reasons, run their jobs on weekends and jobs on weekends are systematically less productive, this specification will accommodate that. Our second control adds product-fixed effects by interacting day and holiday fixed effects with product machines. We then gradually add more controls, including machine and region-by-machine fixed effects. These machine characteristics address potential differences due to hardware specifications.

In these fixed effect regressions, we can only compare the fixed effects of firms within a connected set (Abowd et al., 1999; Metcalfe et al., 2023). This means firms must be linked directly or indirectly in the graph of firm-to-machine characteristics. In our setting, due to the high number and variety of machines used by firms, we either have all firms in one connected set, or we have one large connected set that covers more than 99% of the firms and a few small connected sets that cover firms using only a few specialized VMs. This allows us to compare almost all firms, even if we control for detailed machine characteristics.

The results from these robustness checks are reported in Figure OA-11, Figure OA-15 and Table OA-4. The findings are similar to our main specification, with the notable exception that controlling for machine characteristics reduces the magnitude of long-term learning in the cohort-by-cohort analysis. This reduction is likely because some of the learning comes from firms better choosing their VMs, as we documented in Section 7. Therefore, controlling for VM types can account for this mechanism and reduce the magnitude of the learning effect, especially in the long run, as there are large changes in machine types over time.

E.4 Robustness to Load Volatility Measures

One important identification threat in our paper is that inefficiency is rational because firms maintain idle capacity when facing a volatile workload to reduce the probability of hitting capacity. Even though we argued that due to the nature of cloud computing and the available tools, there is no reason for firms to maintain idle machines, we still analyze whether productivity measures are correlated with important load volatility outcomes and the probability of hitting capacity. For these reasons, we calculate the following volatility measures: (1) standard deviation, (2) coefficient of variation, (3) fourth-month, (4) tail event type 1; defined as the probability of load larger than (mean + 2*sd), (5) tail event type 2; defined as the probability of load larger than (mean + 3*sd), (6) tail event type 2; defined as the probability of load larger than (mean + 4*sd). In these calculations, we calculate the load the firm faces at the daily level, which quantifies the aggregate compute demand by integrating the area under the CPU utilization curve.

We then regress firm-month level productivity measures on these measures of time-varying firm-level demand volatility. This regression suggests that volatility measures explain only 1.8 % of firm productivity.

E.5 Robustness: Measurement of Downsizability

An important aspect of measuring compute productivity is the concept of downsizability: identifying alternative VMs that a firm could select if a VM is overprovisioned. When discussing downsizability in VMs, it is important first to establish the criteria for an appropriate substitute with fewer cores. A good substitute VM should maintain equivalent performance across all specifications, except having a reduced number of CPU cores.

Several key factors should be considered when defining a substitute VM. These are primarily memory, machine type, operating system, region, and data center. For example, the memory capacity should remain the same or be higher to ensure that the job can run in the alternative VM. The operating system should also remain the same to maintain software compatibility. Another but less clear dimension is the machine type. Machines are different in many dimensions, including type, manufacturer, and series. In principle, the same job can be run on different hardware versions and even on hardware from different manufacturers. However, firms might prefer to maintain the same machine types for consistency, performance predictability, and ease of management.

Another critical factor when considering VM downsizing is a geographical region or data center. The location of the data center might be important as firms tend to choose data centers close to their customers or employees to reduce latency (Greenstein and Fang, 2020). Moreover, firms might prefer to use a particular data center because their data is stored there. Finally, regulatory compliance and data sovereignty requirements can dictate the need for specific regional or data center locations.

Considering these factors and the nuanced nature of downsizability, we define various levels of downsizability. In each measure, we maintain the constraint that the alternative VM should have the same memory and operating system while allowing for variations in machine type and location.

- "Data Center-Machine Series-OS-Memory" Downsizing: This is the most restrictive measure, requiring VMs to be in the same data center, machine type, and series, with identical OS and memory.
- "Region-Machine Series-OS-Memory" Downsizing: This variation relaxes the data

center requirement to the regional level while maintaining other restrictions.

- "Region-Machine Type-OS-Memory" Downsizing: This measure allows for different machine series within the same region, type, OS, and memory specifications.
- "Region-OS-Memory" Downsizing: This variation permits downsizing across different machine types within the same region, maintaining OS and memory consistency.
- "OS-Memory Downsizing": The least restrictive measure, allowing downsizing across different regions, only requiring the same OS and memory specifications.

In our baseline specification, we choose "Region-Machine Series-OS-Memory Downsizing" to balance the need for consistent performance with the flexibility of using different machine types within the same region. However, we also conduct robustness checks using other downsizability measures to ensure the reliability of our findings.

E.6 Correlation Between Idleness and Over-provisioning Productivity

In this robustness check, we analyze the relationship between idleness and overprovisioning productivity. A positive relationship between these two productivity measures would suggest that inefficiency is not driven by a particular mechanism that generates only one type of inefficiency. For example, one explanation for inefficiency could be that a firm's workload is volatile for a given job, so firms overprovision to ensure they can meet additional demand. However, this explanation is less likely to account for idleness because an efficient firm could easily manage volatility across VMs using available tools.

For this robustness check, we regress overprovisioning productivity on idleness productivity using firm-month-level data, controlling for industry and time fixed effects. This regression yields a coefficient of 0.064 with a standard error (clustered by firm) of 0.004. This suggests that firms with idle machines tend to have overprovisioned machines. The result provides suggestive evidence that underlying firm-level factors drive both compute productivity measures rather than simply mechanical explanations.

E.7 Relationship between Productivity and Firm Exit

There is a large literature showing that less productive firms are more likely to exit. In this section, we test this hypothesis by investigating the relationship between firm productivity and the probability that firms leave the cloud.

For this exercise, we use data from 2022 and 2023. We classify each firm as "high" or "low" productivity based on whether they are above or below median productivity in their industry in 2022. Then, we look at the exit probability for these groups from January 2023 to June 2023. Our data ends in June, so to be conservative, we consider a firm to have exited if we do not see any VM deployment one month before the sample period ends. We find that low-productivity firms are 60.0% (SE: 3.8%) more likely to leave the cloud than high-productivity firms.

E.8 External Validity: Dispersion in Public Traces

Although the data used in our main text comprises a large compute trace from a global cloud provider, one concern might be that our analysis lacks external validity. To the extent that public compute traces are characteristic of computing environments outside of our sample, we show that our results on productivity dispersion summarized in Figure 3 hold out-of-sample.

To do this, we use the public compute traces described in Appendix B. These public traces differ from our data in both structure and duration. Therefore, for each trace used below, we describe the construction of the sample we used to analyze productivity.

For both traces, we either directly applied the assumptions used in cleaning our own data or selected observations that resembled the operative objects of our analysis as closely as possible. These steps ensure that the analysis of productivity in these public traces serves as a valid test of our findings.

E.8.1 Azure Cloud Trace

The 2019 Microsoft Azure (henceforth, Azure) data traces one month of VM utilization readings and characteristics. For utilization, we observe the average and maximum CPU utilization over every five-minute interval within the VM's lifetime. For characteristics, we observe requested cores and memory (in gigabytes), as well as the timestamp of when the VM was created and deleted. We also observe a "machine category" variable that describes whether a VM is "delay insensitive," "interactive," or "unknown."

As expected, we observe core and memory request levels that mainly scale by a factor of two. For cores, we observe request levels of 2, 4, 8, 24, and 30. For memory, we observe request levels of 2, 4, 8, 32, 64, and 70. As in the main text, we define downsizeability in terms of cores for a given set of machine characteristics. In particular, for a VM's given level of memory request and machine category, the VM is downsizeable if another VM with the same memory and category exists with half as many cores. By definition, no VM with two cores is downsizeable.

Also as in the main text, we consider productivity based on the 95th percentile of max

CPU utilization. Unlike our data, the Azure trace only contains obfuscated user identifiers. Hence, we analyze the users' dispersion of productivity.

Before computing productivity, we clean the trace data in accordance with the sampling done on our main data. We drop all users observed to have less than 10 VMs throughout the duration of the trace, resulting in a loss of 2.8% of users. We also remove VMs with a lifetime of less than 20 minutes, resulting in a more significant loss of about 39% of the available VMs in the data. This finalized sample contains information on the resource usage of 3,503 users with 1,632,952 VMs.

Next, we define for VM j of user i on day t a productivity measure $\omega_{ijt} \in [0, 1]$. This definition follows that of ω_{ijt} in Section 4. Using this, we can aggregate the VM-level productivity to a user-day-level productivity. The productivity for user i on day t with jobs J_{it} is given by

$$\omega_{it} = \frac{\sum_{j \in J_{it}} \omega_{ijt} ch_{ijt}}{\sum_{j \in J_{it}} ch_{ijt}}, \tag{30}$$

where ch_{ijt} is the core-hours of job j on day t. Unfortunately, the Azure trace only contains timestamps in seconds, and it is unknown when the trace began. Hence, we have no mapping between timestamps and particular dates. Thus, we determine the days where observations fall to be the modulus of the timestamp divided by the number of seconds in a day.

Appendix Figure OA-18(a) plots the distribution of user-day level productivity throughout the duration of the Azure Trace. There is a significant mass at the one-half productivity level due to the relatively small sample size in the public data. However, the dispersion and the distribution of productivity are broadly similar to our main results reported in Figure 3.

E.8.2 Google Cluster Trace

Similar to the Azure trace, the cluster data provided by GC traces one month of CPU usage and characteristics from May 2019. Whereas the Azure trace concerned genuine VMs, the cluster trace concerns cluster usage by jobs submitted by Google engineers and services (see Appendix Section B.6). We use the detailed information in the trace provided by GC to focus on jobs resembling the structure of VMs as closely as possible.

As described in Appendix Section B.6, the task is the fundamental unit of observation in the usage data in this trace. Tasks are executed as instances of jobs that either run independently and directly on a physical machine or as part of a *alloc set*, which represent sets of fixed resources. In the GC trace, jobs and alloc sets are referred to as *collections*. For each collection, we observe whether auto-scaling is enabled and whether, if enabled, it is constrained. For this data, we take collections without auto-scaling enabled to be our VM-like objects. Henceforth, we will refer to these collections as VMs. We focus on these VMs because the provisioning decisions for CPU and memory are made by the user rather than the cluster manager. In this way, this subset of collections helps us focus on compute resources most similar to our sample and enables us to focus on user-made provisioning decisions.

The GC trace contains observations of nearly 5.2 million collections. Only about 360,000 (6.8%) of these have vertical scaling disabled. Since these VMs run on a cluster, they start using compute resources when scheduled on a machine. Thus, we consider the lifetime of the VM as beginning at its scheduled time. We remove all collections that do not have an explicit scheduling event. This preserves 99.5% of the collections. We also know exactly when the trace started and ended, so we do not deal with the timestamp-to-date conversion difficulties as with the Azure trace.

Some VMs have multiple scheduling events observed. To the best of our knowledge, these cases correspond either to VMs that failed and were restarted, or to VMs that were booted from a machine due to a higher-priority VM needing to be scheduled. For these kinds of VMs, we take the minimum scheduling event observed as the start time of the VM. As in the main text, we remove VMs with a lifetime of less than 20 minutes and all users with less than 10 VMs. This results in a sample of 24,909 VMs. While this is a small subset of all available collections, it was created so that the VM-like objects we analyze resemble the VMs in our data as much as possible.

In our data and the Azure trace, we observe core and memory requests that scale by a factor of two. This is not the case in this trace. Since our VMs are cluster jobs, they are able to request memory in terms of bytes rather than just gigabytes, and therefore, requests can differ at a much more granular level. Given the availability of provisioning resources at such a granular level, users are able to provision VMs efficiently at virtually any level of compute usage. Thus, we consider all VMs to be downsizeable, and hence, the productivity of a given VM will be solely based on its CPU utilization.

Another aspect of this setting is that the cluster manager used by GC's clusters allows VMs to utilize available CPU resources on the physical machine as long as that machine is not at full capacity. From the analysis in Section D.7, we know that the utilization of machines in the GC trace is well below capacity throughout the sampling period. As a result, virtually all VMs will not see their workload throttled from hitting 100% utilization of their requested resources. This fact, along with the assumed downsizeability of all VMs, should attenuate the inefficiencies observed in the more traditional VM settings of our data and the Azure trace. Indeed, in Appendix Figure OA-18(b), we see that productivity is skewed toward the right, but there is still dispersion in the productivity of users.

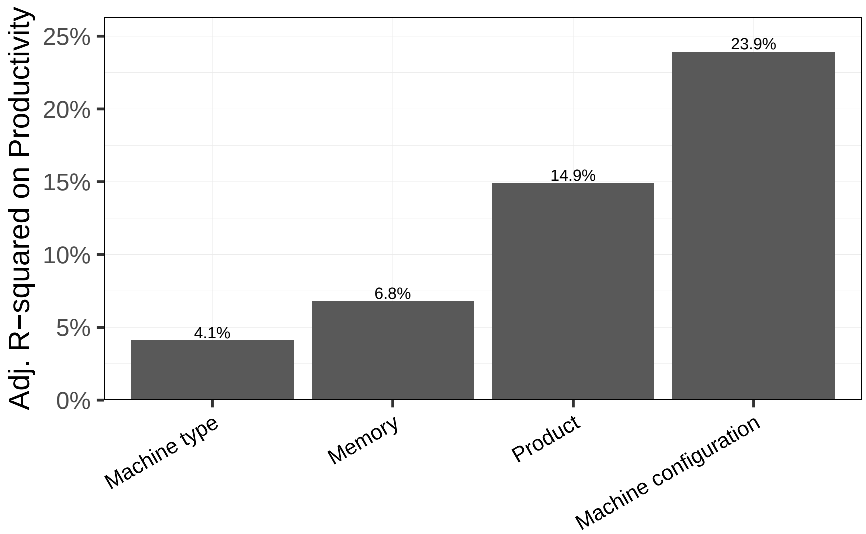
As above, we define the productivity of the VM j of user i on the day t by the measure ω_{ijt}. In this case, ω_{ijt} is zero for VMs with CPU utilization under 10%, one-half for VMs with between 10% and 45% utilization, and one for VMs with greater than 45% utilization. As normal, we consider the 95th percentile of maximum CPU utilization. With this, we aggregate VM level productivity to the user-day level using a similar notation as above:

$$\omega_{it} = \frac{\sum_{j \in J_{it}} \omega_{ijt} ch_{ijt}}{\sum_{j \in J_{it}} ch_{ijt}}. \tag{31}$$

Figure OA-18(b) presents the distribution of productivity calculated in Google Cloud. A few points to note: First, similar to Azure traces, we observe a mass at 0.5, coming from users with only over-provisioned resources. Second, we see that the productivity distribution is more skewed to the right than our main result in Figure 3. This is likely due to the fact that Google Cloud data only includes internal users or jobs of external customers implemented by Google engineers. It is likely that Google engineers are more productive than typical firms. However, despite this, we still see substantial productivity dispersion even in this sample, where productivity ranges from 0 to 1, with a substantial mass between 0.5 and 1.

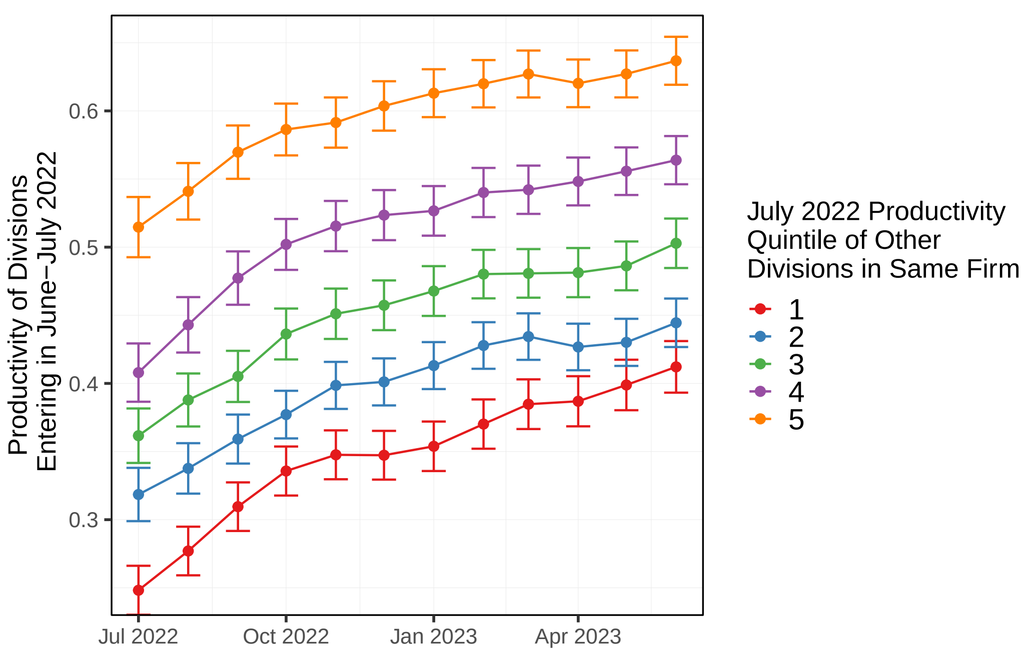
F Additional Figures

Figure OA-1: Explanatory Power of Virtual Machine Characteristics



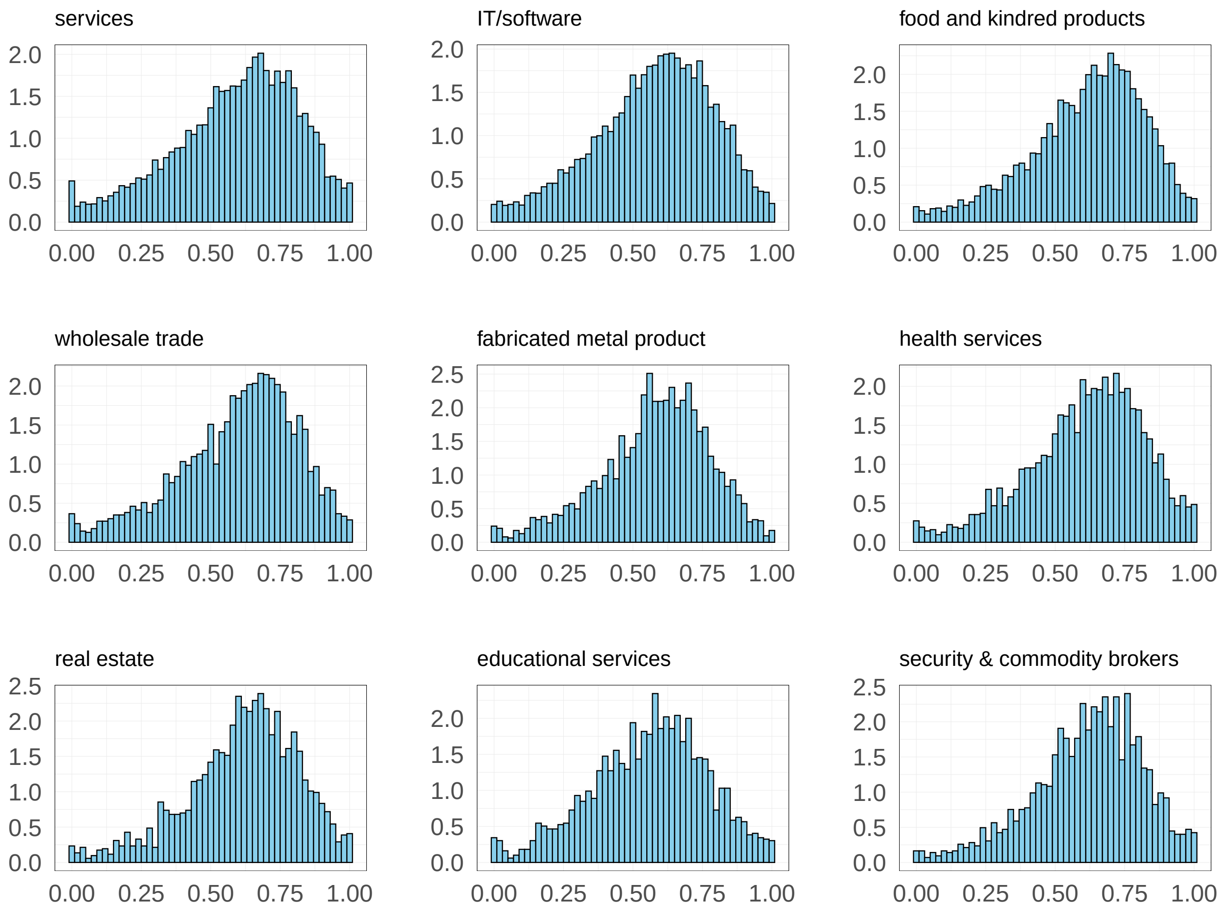
Notes: Adjusted R^2 from the regression of VM-day level productivity on increasingly detailed levels of fixed effects. Fixed effects included in bars to the right always nest the fixed effects used in preceding (left) bars.

Figure OA-2: Productivity Trajectories of Units in Existing Firms



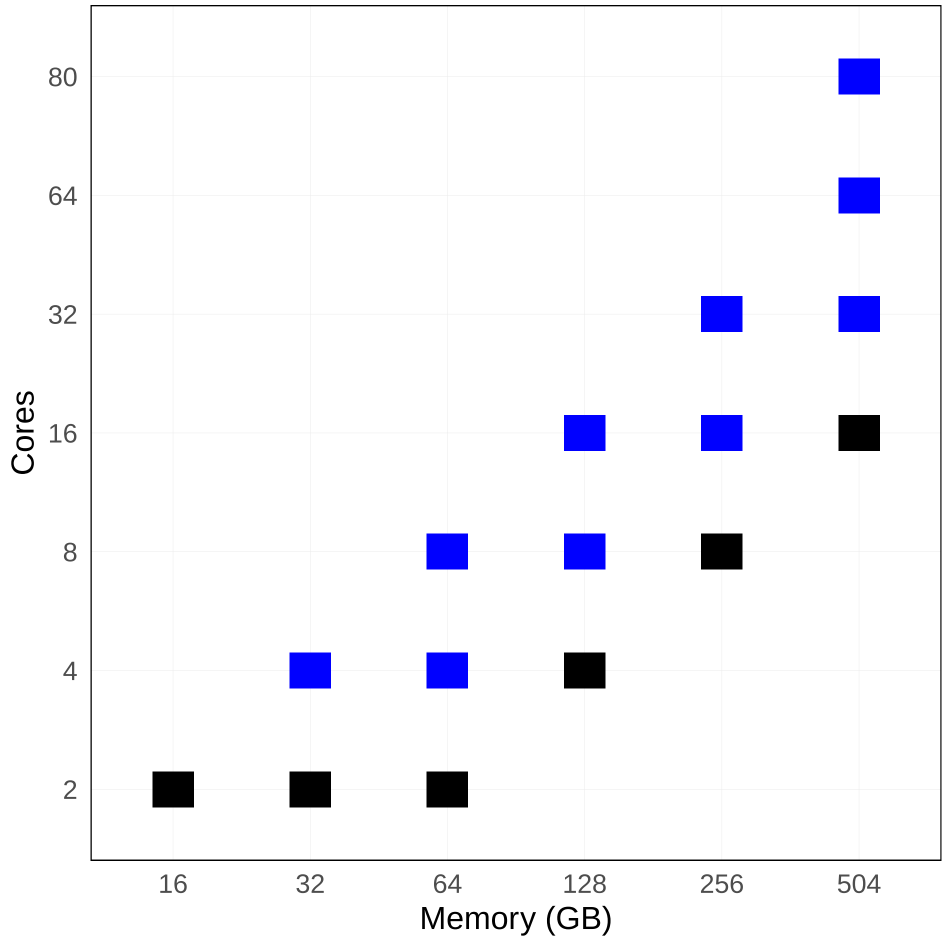
Notes: In panel (b), we group firms into five evenly sized groups based on the productivity of existing units in July 2022 and then plot the average productivity of the new units over time.

Figure OA-3: Productivity Dispersion by Industry



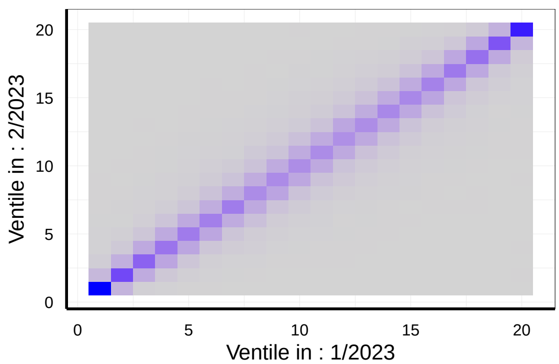
Notes: This figure displays the productivity distribution by industry, calculated in the same way as in Figure 3. Industry classification is based on 1-digit SIC codes, which are converted from the provider's internal industry classification.

Figure OA-4: Downsizability Example: Memory and Core Combinations

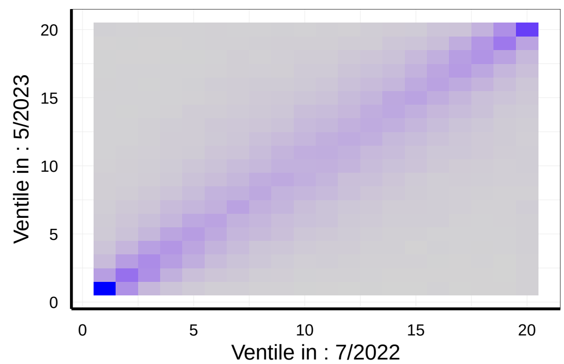


Notes: This figure represents one example VM series from our data, where we list all combinations of available memory (GB) and cores within this series. Each point represents a specific VM configuration. The green-colored points indicate downsizable machines, where an alternative VM exists with the same memory capacity but fewer cores.

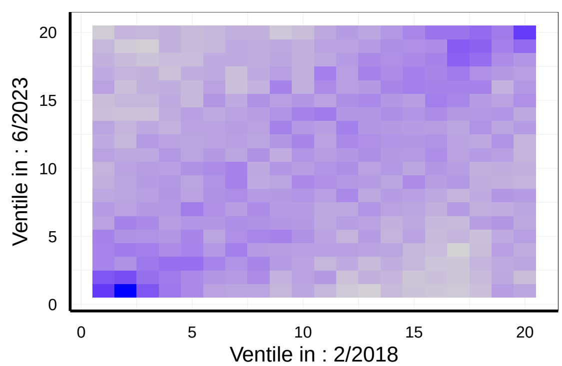
Figure OA-5: Persistence of Productivity in the Short, Medium, and Long Run



(a) 1-Month Persistence



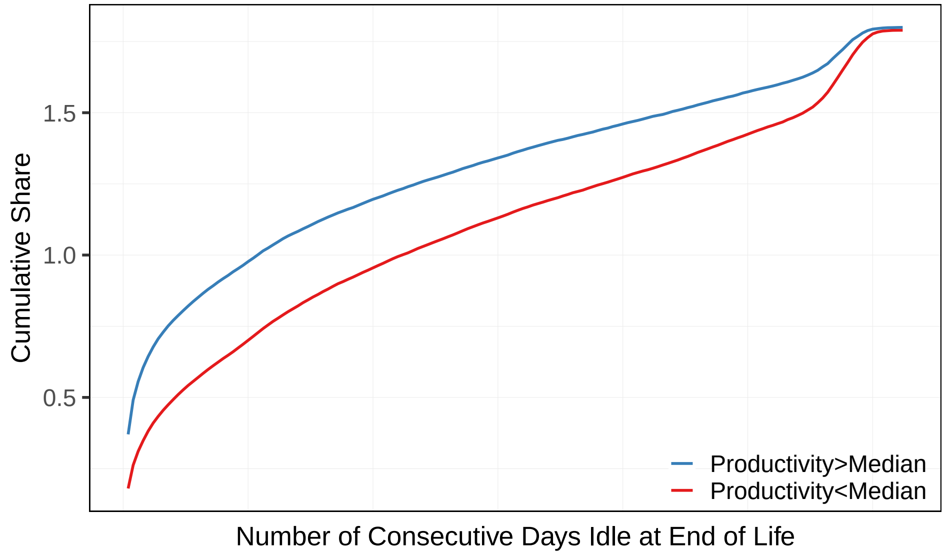
(b) 1-Year Persistence



(c) 5-Year Persistence

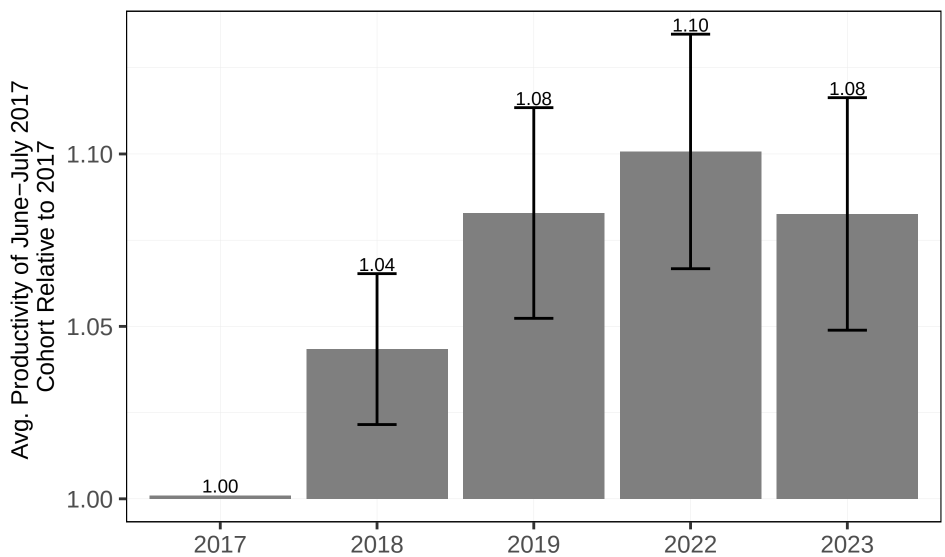
Notes: Presents heatmaps illustrating productivity persistence across three different time horizons: (a) 1-Month, (b) 1-Year, and (c) 5-Year. Each heatmap's axes are divided into 20 equally sized bins, representing the ventilates of the productivity distribution. The x-axis shows the ventile at the start of the period, while the y-axis shows the ventile at the end of the period. Each cell's color intensity corresponds to the frequency of firms moving from one ventile to another over the specified time horizon. Panel (a) depicts 1-month persistence from January 2023 to February 2023, panel (b) shows 1-year persistence from July 2022 to May 2023, and panel (c) illustrates 5-year persistence from February 2018 to June 2023.

Figure OA-6: Number of Days Idle at the end of VM-High and Low Productive Firms



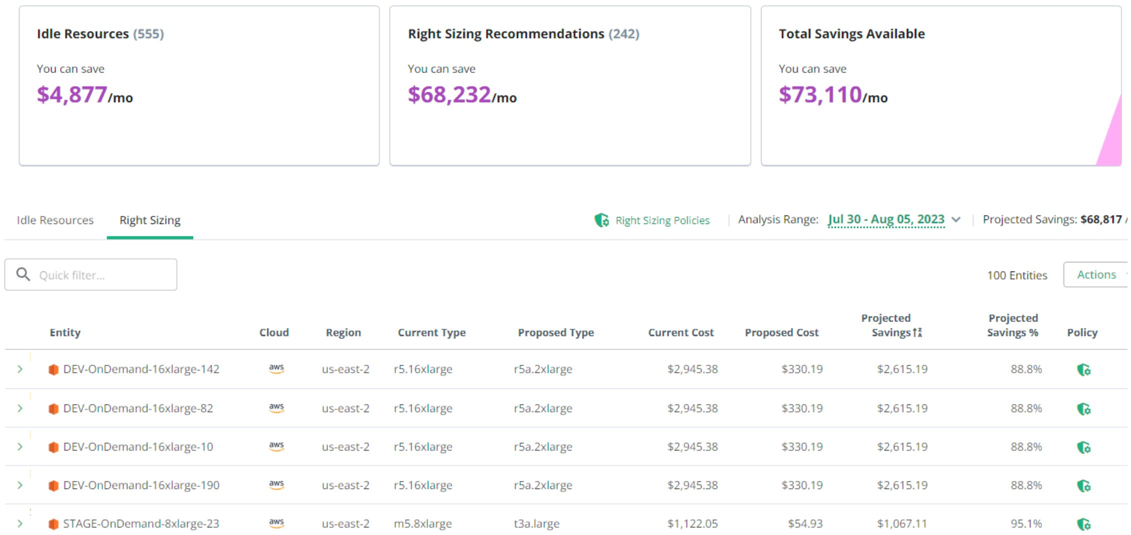
Notes: Firms are categorized as high or low productivity according to 2022 data. Then, for all multi-day VMs that end with at least one consecutive idle day in a row and that end before the end of our sample, we plot the CDF of the number of consecutive days each VM is idle at the end of its life for low and high productivity firms.

Figure OA-7: Productivity of Firms Joining in June-July 2017 Over Six Years

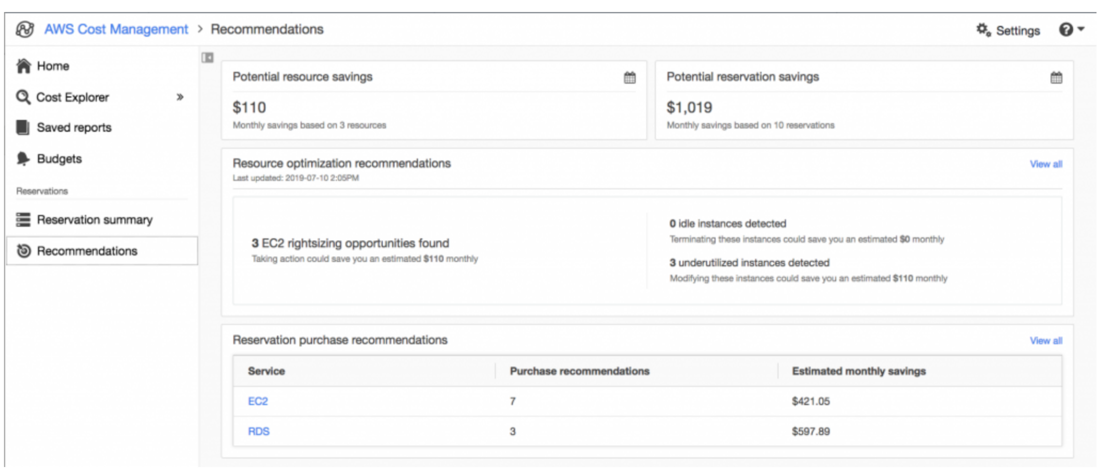


Notes: The average productivity in 2017 is normalized to 1. The crossbars represent the 95% confidence interval. Standard errors are clustered by firm To be included, a firm must have had its first usage in June-July 2017 and had usage in or after May 2023.

Figure OA-8: Idleness and Overprovisioning Detection Tools from Industry



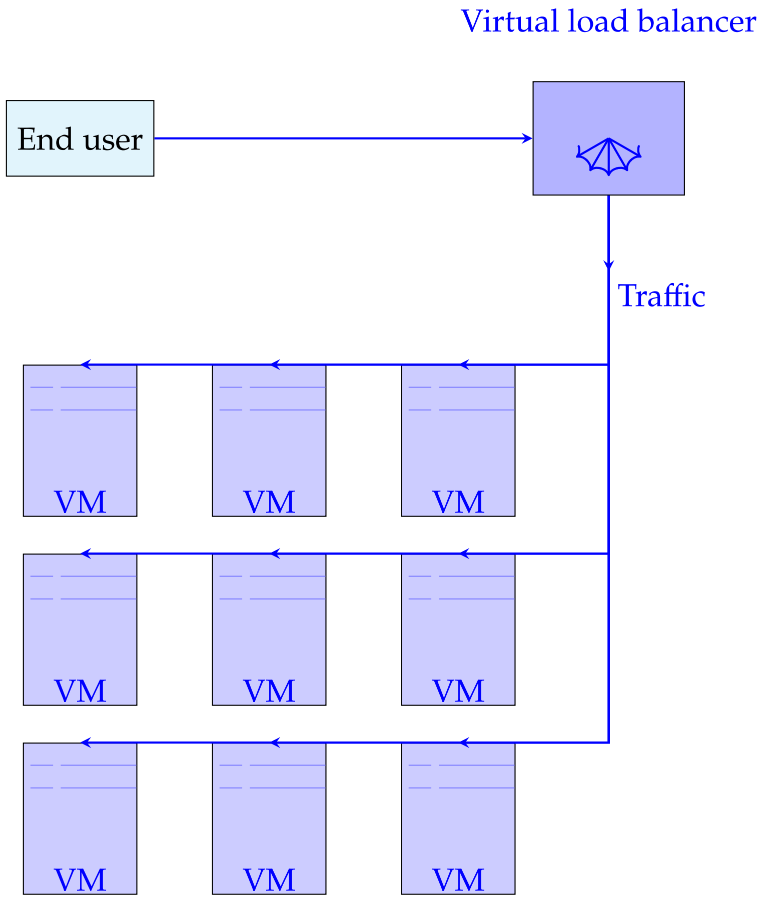
(a) Virtana Cost Management Tool



(b) AWS

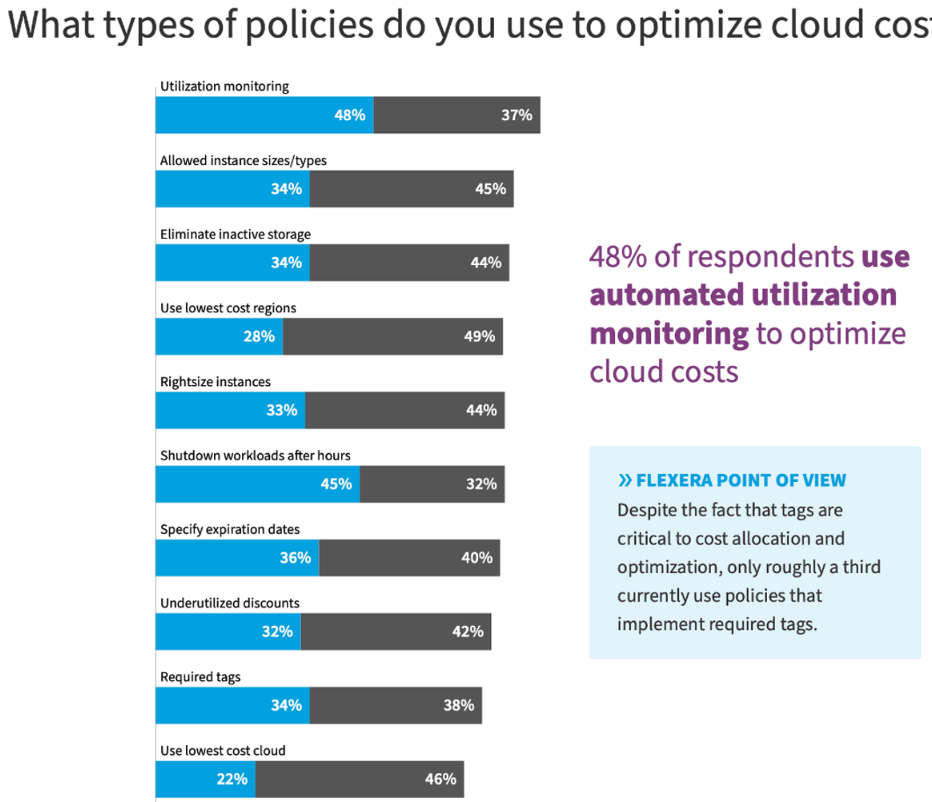
Notes: This figure presents two examples of tools for detecting idleness and overprovisioning in cloud computing. Panel (a) shows a dashboard from cloud optimization startup Virtana, taken from `https://www.virtana.com/products/cloud-cost-management` while Panel (b) displays the cost management interface of AWS obtain from `https://aws.amazon.com/blogs/aws-cloud-financial-management/launch-resource-optimization-recommendations/`.

Figure OA-9: Representation of Load Balancer

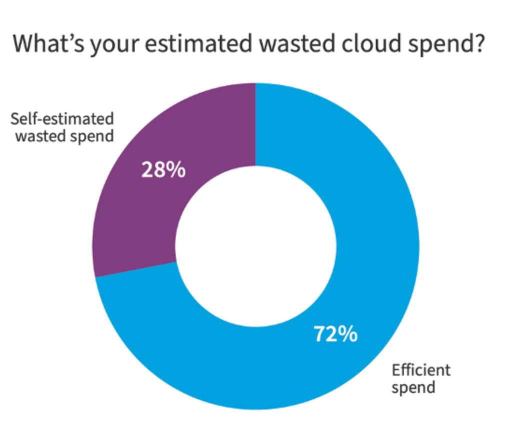


Notes: This figure illustrates a virtual load-balancing architecture in cloud computing. It depicts the flow of traffic from end users through a virtual load balancer, which then distributes the requests across multiple virtual machines (VMs). The load balancer directs traffic (indicated by a blue arrow) to three rows of VMs, each row containing three VMs. This architecture is designed to optimize resource utilization and improve system performance by efficiently distributing incoming requests across available compute resources.

Figure OA-10: Surveys About Cloud Utilization



(a) Survey Response to a Question about Cloud Optimization tools



(b) Survey Response to a Questions about Spending

Notes: This figure is a screenshot from a survey conducted by Flexera titled "State of the Cloud" (Flexera, 2023). It shows the responses to two questions asked in the survey. Panel (a) illustrates the types of policies companies use to optimize cloud costs, while Panel (b) displays the respondents' estimates of their wasted cloud spend.

G Additional Tables

Table OA-1: Comparison of Virtual Machine Types Offered by Major Cloud Providers

VM Type	AWS	Azure	GCP
General Purpose	M5, T3	B-series, Dsv3-series	E2, N1, N2, N2D
Compute Optimized	C5	Fsv2-series	C2
Memory Optimized	R5, X1	Esv3-series, Mv2-series	M1, M2
Storage Optimized	I3, D2	Lsv2-series	-
GPU/Accelerated Computing	P3, G4	NC-series, NV-series	A2
High Performance Compute	-	H-series	-
Shared-core	-	-	f1-micro, g1-small

Notes: This table summarizes the main types of virtual machines offered by Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP). The categories are general and may not be exhaustive. Each provider offers multiple sizes and variants within each type. "-" indicates that the provider doesn't have a direct equivalent or the information wasn't specified in the given context.

Table OA-2: Virtual Machine (VM) Types, Key Considerations, and Ideal Applications

VM Type	**Key Considerations**	**Ideal For**
General Purpose	Cost-effective, balanced CPU, memory, temporary storage	Web servers, application servers, development environments, small to medium databases
Compute Optimized	High core counts, faster CPUs	Scientific computing, HPC, video editing, simulations
Memory Optimized	Large RAM capacities	Databases, caching layers, in-memory analytics
Storage Optimized	Local SSDs, high I/O performance	Large databases, data warehousing, Big Data analytics, real-time applications
GPU	Diverse GPU types and configurations	Machine learning, deep learning, video editing, scientific simulations
High-Performance	Exceptionally high compute power, massive memory, ultra-fast storage	Scientific modeling, simulations, weather forecasting

Notes: Source: https://www.cloudoptimo.com/blog/the-ultimate-guide-to-choosing-the-right-azure-virtual-machine/.

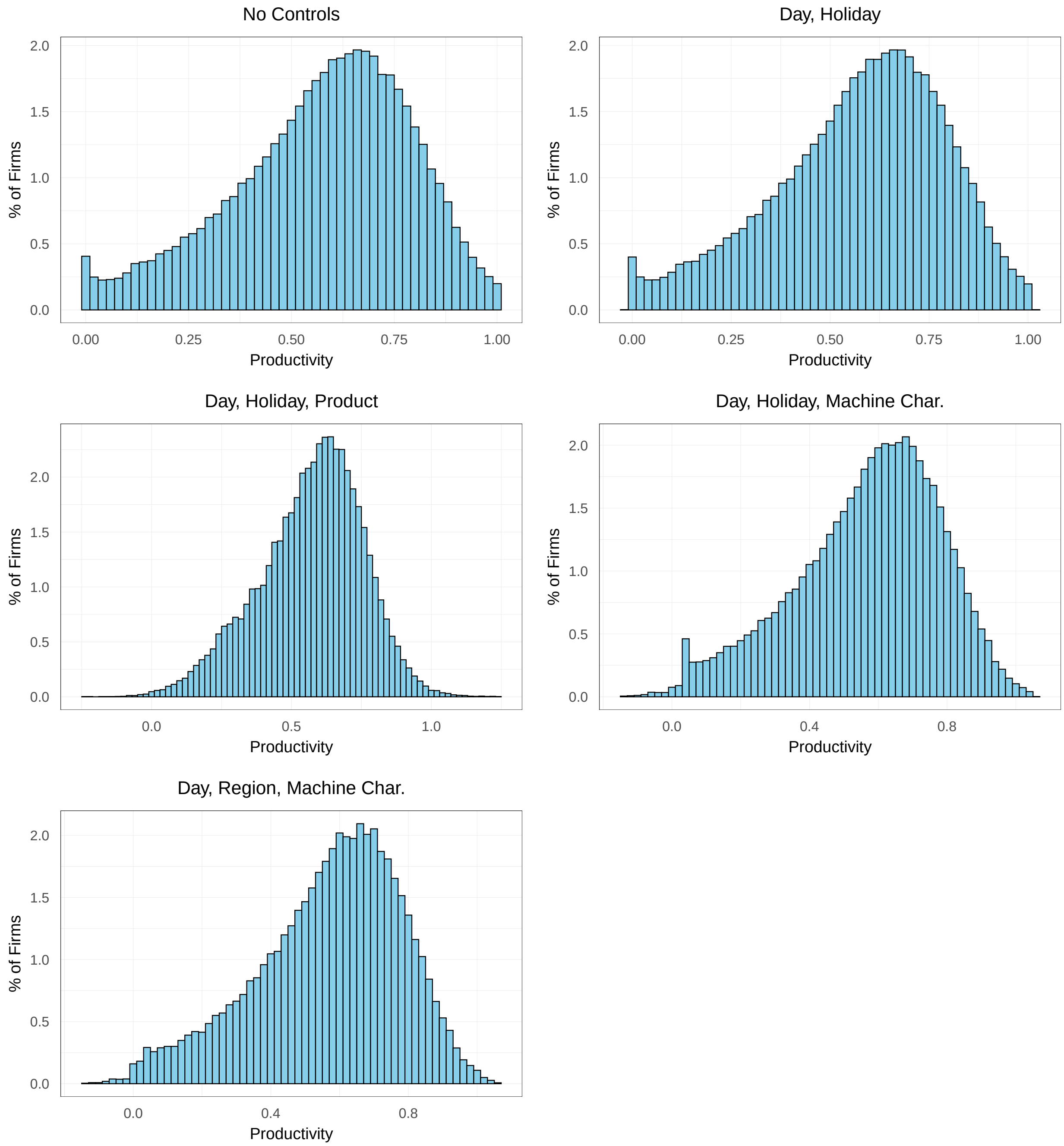
Table OA-3: Cost Optimization Tools by Cloud Provider

Cloud Provider	Cost Optimization Tool	Description
AWS	AWS Cost Explorer	Interface to view costs, usage, and ROI for AWS services, with data for the past 13 months and forecasting capabilities.
	AWS Budgets	Allows setting and enforcing budgets for AWS services, with notifications when budgets are exceeded or reached.
	AWS Trusted Advisor	Provides automated recommendations for cost optimization, including EC2 reserved instance optimization and idle resource identification.
	Amazon CloudWatch	Monitoring service that can set alarms based on metrics, commonly used for cost optimization by identifying underutilized resources.
	AWS Instance Scheduler	Automates starting and stopping of EC2 and RDS instances based on defined schedules to save costs.
	AWS Pricing Calculator	Estimates the cost of use cases on AWS, helping to model solutions and explore pricing points before deployment.
Azure	Azure Cost Management and Billing	Provides cost analysis, budgeting, and recommendations for cost optimization, integrated with Azure portal.
	Azure Advisor	Offers personalized best practices and recommendations to optimize Azure resources, including cost optimization.
	Azure Pricing Calculator	Helps estimate costs for Azure services and solutions, allowing users to model and forecast expenses before deployment.
GCP	Google Cloud Cost Management	Includes tools for cost visibility, budgeting, and recommendations to optimize cloud spending.
	Google Cloud Pricing Calculator	Estimates costs for Google Cloud services, allowing users to model and forecast expenses before deployment.
	Google Cloud Recommender	Provides recommendations for cost optimization, including rightsizing VM instances and identifying idle resources.
	Google Cloud Budgets and Alerts	Allows setting budgets and receiving alerts when costs exceed predefined thresholds, integrated with Google Cloud Console.

Notes: This table summarizes the main cost optimization tools offered by Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP).

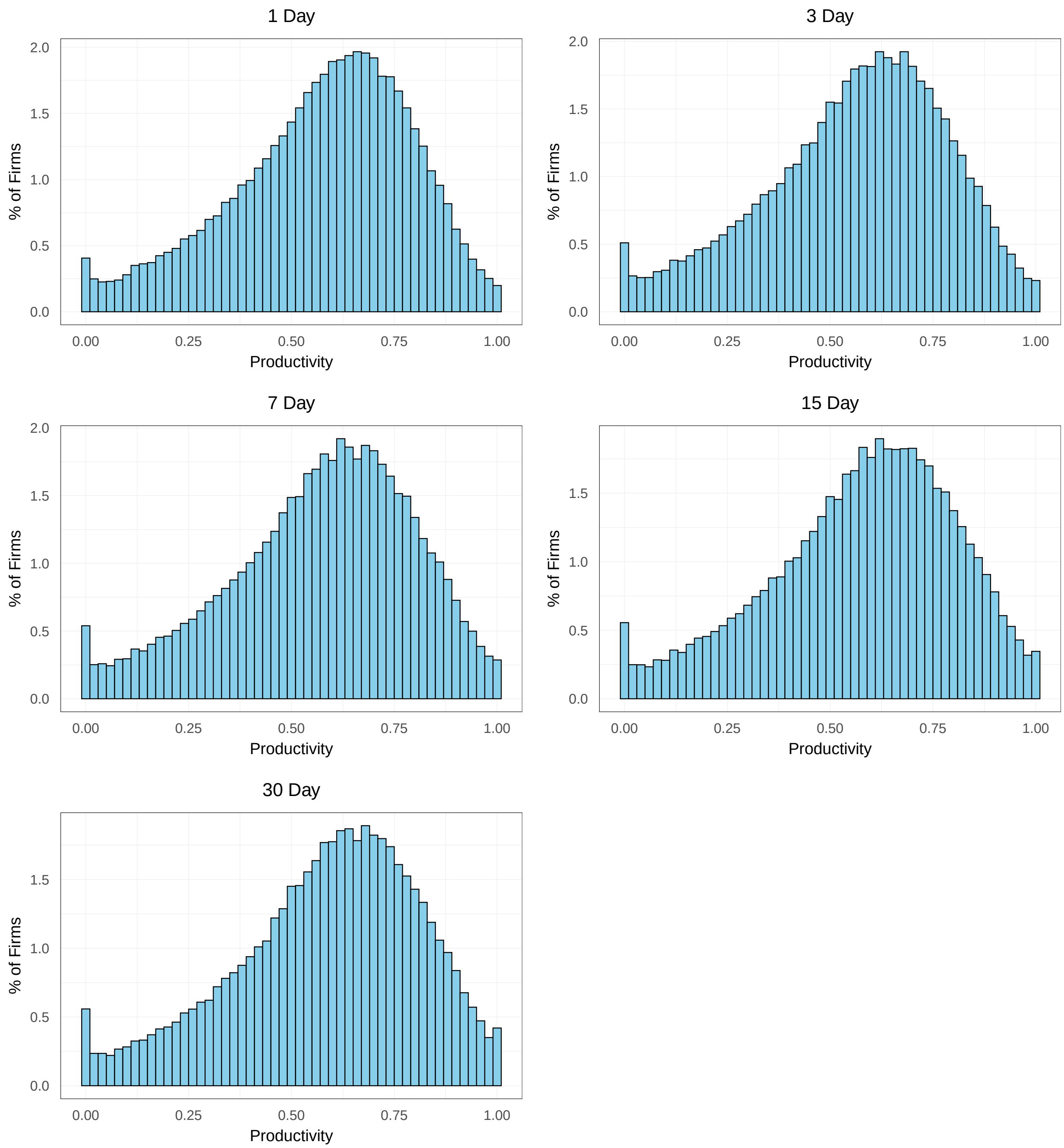
H Robustness Results

Figure OA-11: Robustness: Dispersion Histogram With Different Machine Controls



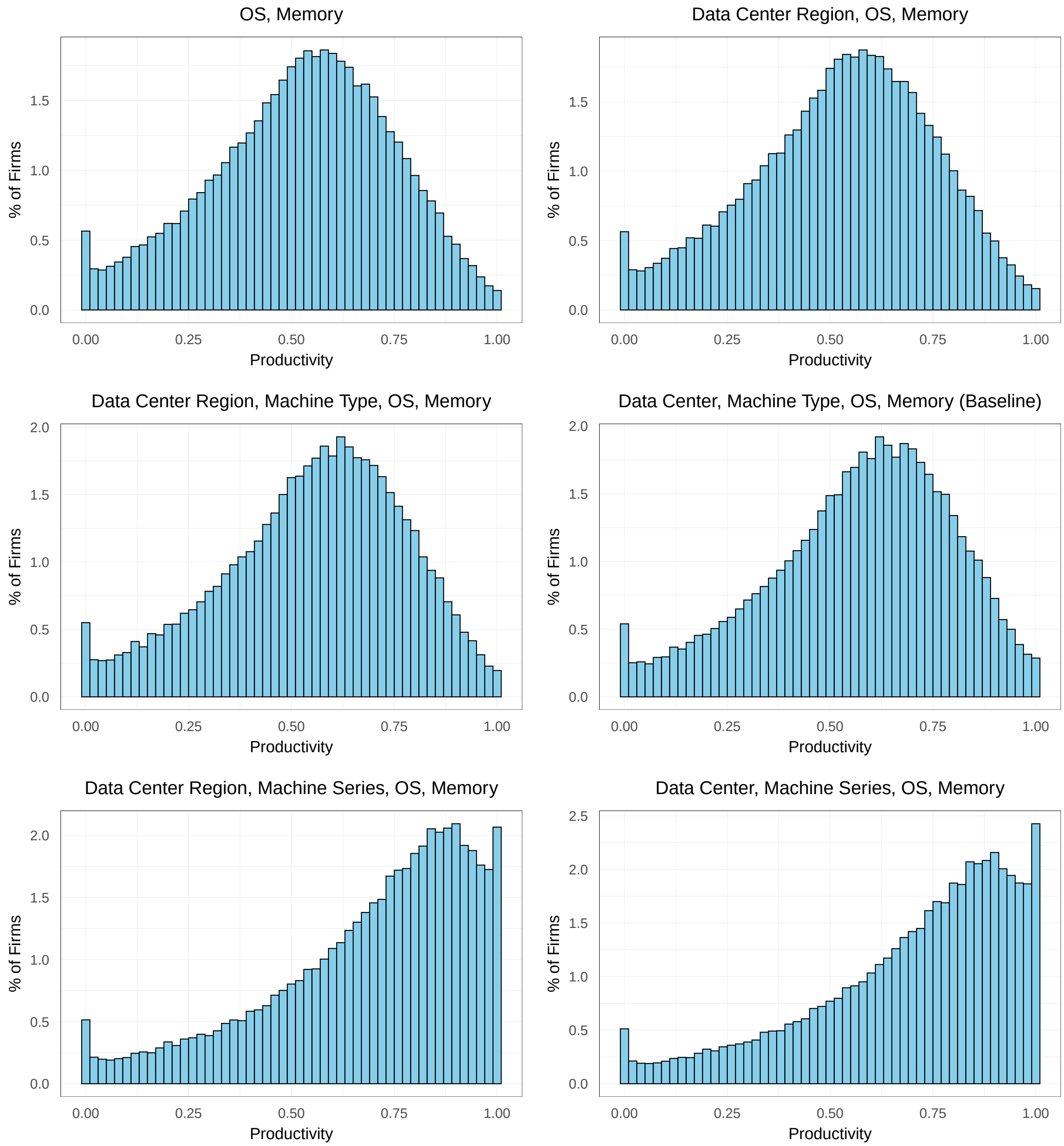
Notes: This figure presents the distribution of firm-level productivity estimates using productivity measures that control for different machine characteristics, as detailed in Section E.3. The histograms show the dispersion in productivity under various control specifications, including the day of the week, holiday, product ID, and machine type.

Figure OA-12: Robustness: Dispersion Histogram With Different Peak Utilization Definition



Notes: This figure presents the distribution of firm-level productivity estimates using productivity measures that control for different days of measurement of peak utilization as detailed in Appendix E.2.

Figure OA-13: Robustness: Dispersion Histogram With Downsizability



Notes: This figure presents the distribution of firm-level productivity estimates using productivity measures that control for different days of measurement of peak utilization as detailed in Appendix E.2.

Table OA-4: Robustness: Dispersion and Persistence of Productivity - Controls

	No Controls (1)	Day Holiday (2)	Day, Holiday, Product (3)	Day, Holiday, Machine Char. (4)	Day, Region, Machine Char. (5)
			Panel A. Dispersion		
Dispersion:					
Mean	0.60	0.60	0.58	0.59	0.59
Median	0.62	0.62	0.60	0.61	0.62
10-90th perc ratio	3.51	3.51	3.08	3.41	3.39
Inter Quartile Range	1.72	1.72	1.65	1.71	1.70
Within-Firm:					
Within-firm	33.08	33.10	30.00	33.12	33.10
Between-firm, within-industry	66.92	66.90	70.00	66.88	66.90
Within-Firm-Between-Region:					
Within-region	5.88	5.89	5.70	5.82	5.89
Between-region, within-industry	94.12	94.11	94.30	94.18	94.11
			Panel B. Persistence (AR(1) Coefficients)		
1-month persistence:					
Productivity	0.93	0.93	0.92	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.93	0.93	0.92	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.91	0.91	0.90	0.91	0.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1-year persistence:					
Productivity	0.64	0.64	0.59	0.64	0.64
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.66	0.66	0.61	0.66	0.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.60	0.60	0.55	0.58	0.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5-year persistence:					
Productivity	0.32	0.32	0.26	0.34	0.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.33	0.33	0.24	0.33	0.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.10	0.10	0.14	0.12	0.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: This table reports the dispersion and persistence of productivity measures across different specifications that differ by the control variables included in Equation 2. Panel A presents the dispersion of compute productivity. Panel B shows the persistence of productivity, idleness, and overprovisioning measures with 1-month, 3-month, and 5-month autoregressive (AR(1)) coefficients, including their standard errors in parentheses. The control variables in each column are (2) day-of-week and holiday fixed effects, (3) day-of-week, holiday, and product ID fixed effects, (4) day-of-week, holiday, and machine type fixed effects, (5) day-of-week, holiday, data center region, and machine type ixed effects.

Table OA-5: Robustness: Dispersion and Persistence of Productivity - Peak Definition

	1 Day (1)	3 Days (2)	7 Days (3)	15 Days (4)	30 Days (5)
	Panel A. Dispersion				
Dispersion:					
Mean	0.60	0.59	0.60	0.60	0.61
Median	0.62	0.61	0.62	0.62	0.63
10-90th perc ratio	3.23	3.47	3.51	3.48	3.42
Inter Quartile Range	1.68	1.72	1.72	1.71	1.69
Within-Firm:					
Within-firm	33.46	33.08	33.08	32.96	32.93
Between-firm, within-industry	66.54	66.92	66.92	67.04	67.07
Within-Firm-Between-Region:					
Within-region	5.98	5.90	5.88	5.84	5.79
Between-region, within-industry	94.02	94.10	94.12	94.16	94.21
	Panel B. Persistence (AR(1) Coefficients)				
1-month persistence:					
Productivity	0.94	0.94	0.93	0.93	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.94	0.94	0.93	0.93	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.91	0.92	0.91	0.91	0.92
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1-year persistence:					
Productivity	0.66	0.65	0.64	0.64	0.64
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.68	0.67	0.66	0.65	0.65
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.61	0.62	0.60	0.59	0.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5-year persistence:					
Productivity	0.32	0.32	0.32	0.31	0.31
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.34	0.34	0.33	0.33	0.32
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.10	0.11	0.10	0.10	0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

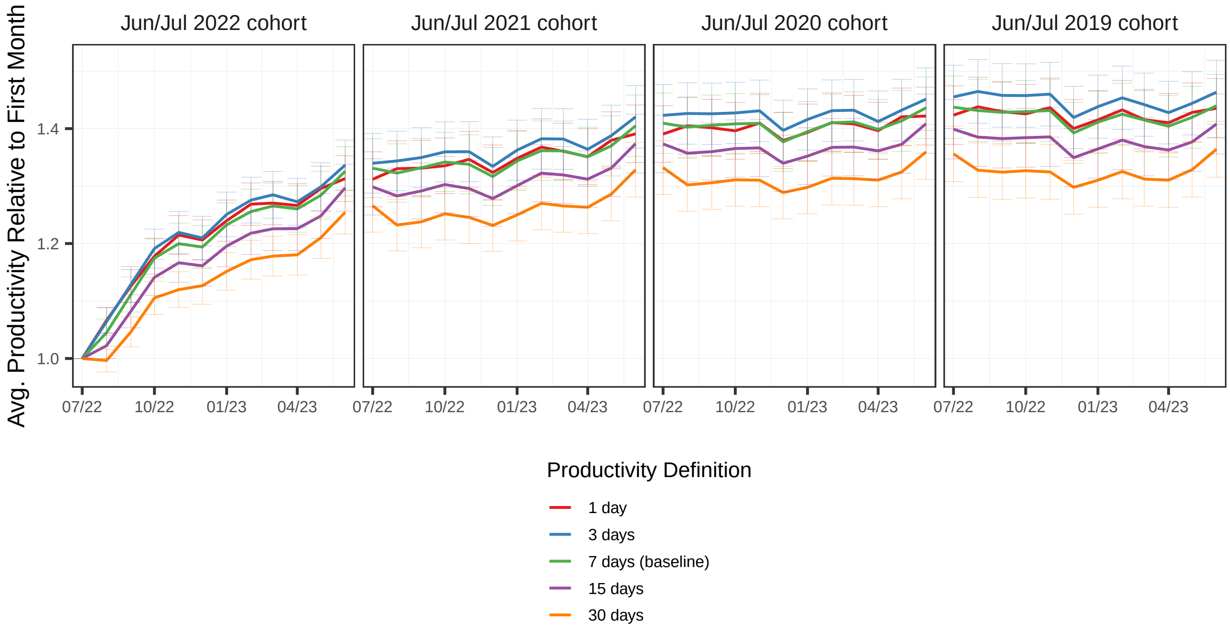
Notes: This table reports the dispersion and persistence of productivity measures. Panel A presents the dispersion of compute productivity across different productivity measures. Panel B shows the persistence of productivity, idleness, and overprovisioning measures with 1-month, 3-month, and 5-month autoregressive (AR(1)) coefficients, including their standard errors in parentheses.

Table OA-6: Robustness: Dispersion and Persistence of Productivity - Downsizability

	OS, mem (1)	Region, OS, mem (2)	Region, type, OS, mem (3)	DC, type, OS, mem (4)	Region, series, OS, mem (5)	DC, series, OS, mem (6)
			Panel A. Dispersion			
Dispersion:						
Mean	0.55	0.56	0.58	0.60	0.71	0.72
Median	0.56	0.57	0.60	0.62	0.77	0.78
10-90th perc ratio	3.76	3.70	3.56	3.51	3.06	3.01
Inter Quartile Range	1.82	1.81	1.75	1.72	1.64	1.63
Within-Firm:						
Within-firm	33.87	33.98	33.31	33.08	32.34	32.23
Between-firm, within-industry	66.13	66.02	66.69	66.92	67.66	67.77
Within-Firm-Between-Region:						
Within-region	5.76	5.76	5.71	5.88	5.42	5.45
Between-region, within-industry	94.24	94.24	94.29	94.12	94.58	94.55
			Panel B. Persistence (AR(1) Coefficients)			
1-month persistence:						
Productivity	0.93	0.93	0.93	0.93	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.93	0.93	0.93	0.93	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.90	0.90	0.91	0.91	0.93	0.93
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
1-year persistence:						
Productivity	0.65	0.65	0.65	0.64	0.64	0.65
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.66	0.66	0.66	0.66	0.66	0.66
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.60	0.61	0.61	0.60	0.58	0.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5-year persistence:						
Productivity	0.32	0.32	0.32	0.32	0.32	0.32
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Idleness	0.33	0.33	0.33	0.33	0.33	0.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overprovisioning	0.11	0.10	0.09	0.10	0.16	0.19
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

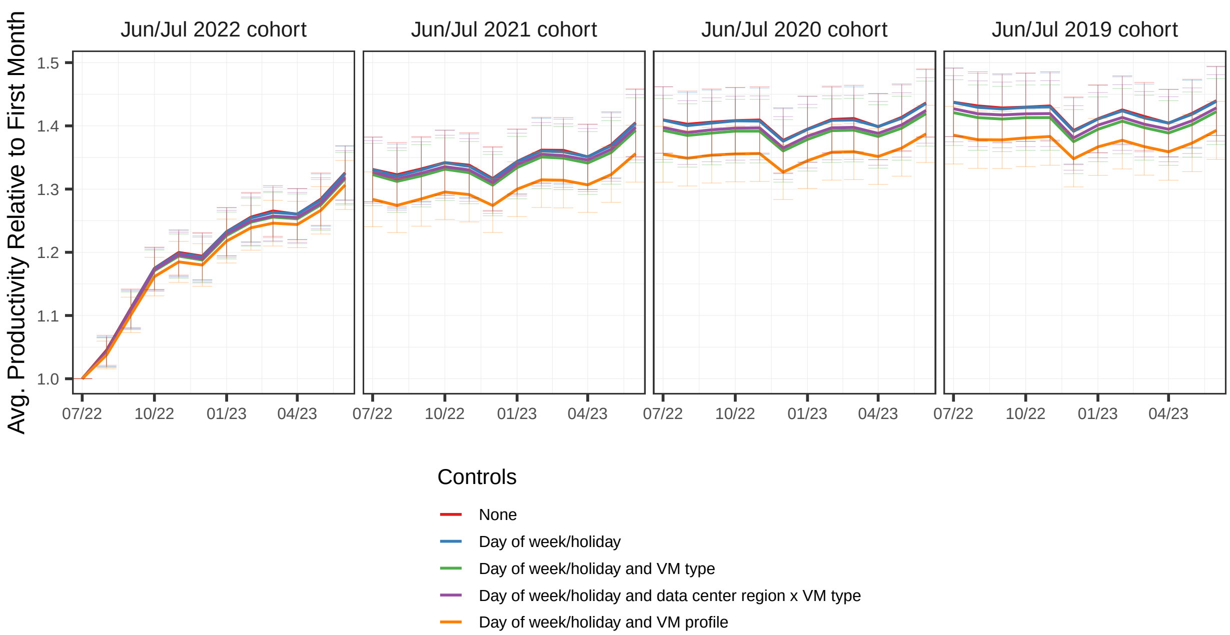
Notes: This table reports the dispersion and persistence of productivity measures under different downsizability definitions given in Appendix E.5. Panel A presents the dispersion of compute productivity across different productivity measures. Panel B shows the persistence of productivity, idleness, and overprovisioning measures with 1-month, 3-month, and 5-month autoregressive (AR(1)) coefficients, including their standard errors in parentheses. The columns represent different downsizability definitions: (1) "OS, mem" for OS and memory; (2) "Region, OS, mem" for data center region, OS, and memory; (3) "Region, type, OS, mem" for data center region, machine type, OS, and memory; (4) "DC, type, OS, mem" for data center, machine type, OS, and memory (baseline); (5) "Region, series, OS, mem" for data center region, machine series, OS, and memory; and (6) "DC, series, OS, mem" for data center, machine series, OS, and memory.

Figure OA-14: Robustness: Productivity by Cohort Over Time - Different Days



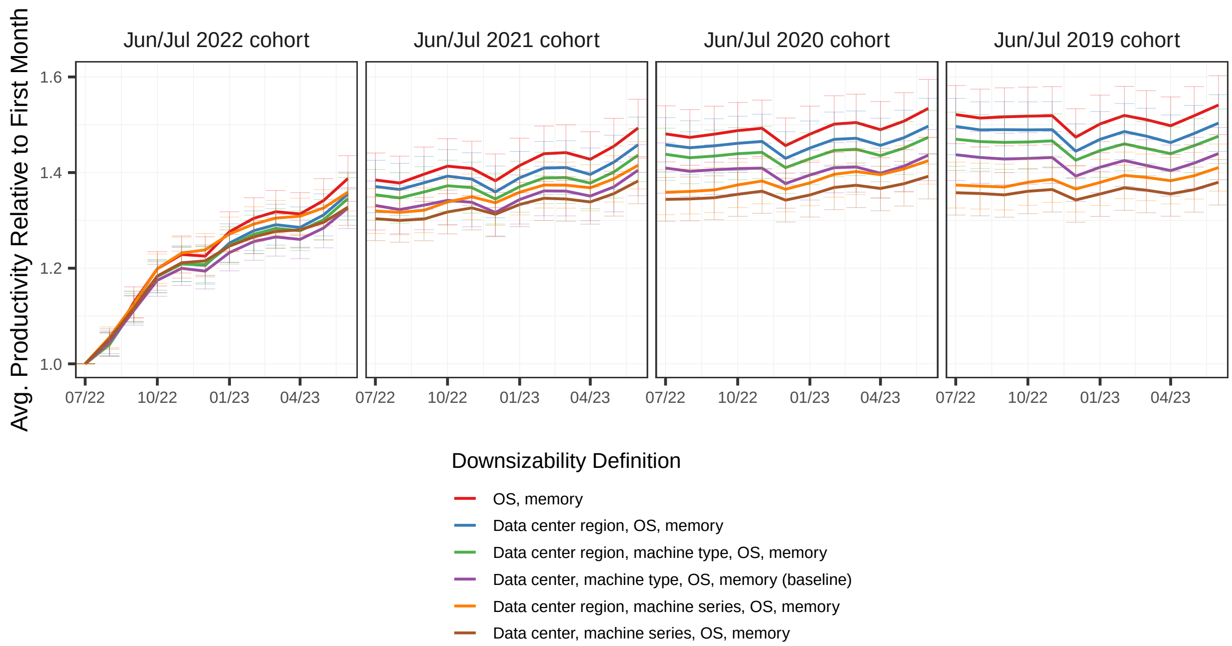
Notes: This figure shows the learning analysis of Figure 7 using a different number of days in the definition of productivity.

Figure OA-15: Robustness: Productivity by Cohort Over Time - Controls



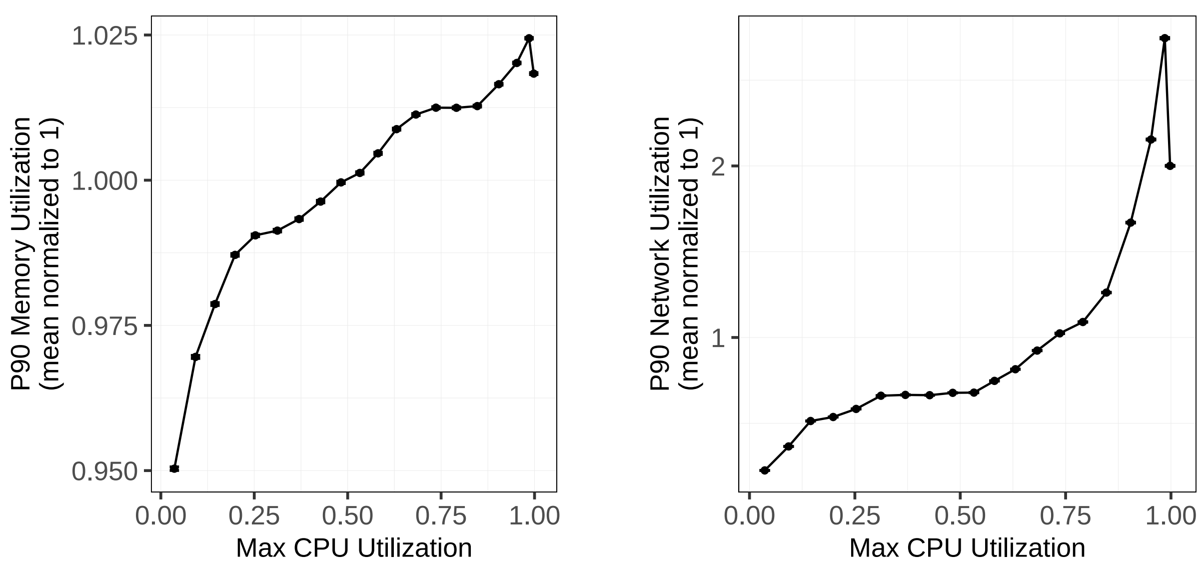
Notes: This figure shows the learning analysis of Figure 7 using different control variables in the productivity estimation.

Figure OA-16: Robustness: Productivity by Cohort Over Time - Downsizability



Notes: This figure shows the learning analysis of Figure 7 using different definitions of what types of machines are substitutable with each other in the determination of whether a machine is downsizable.

Figure OA-17: Robustness: Correlation of CPU Utilization with Other Measures

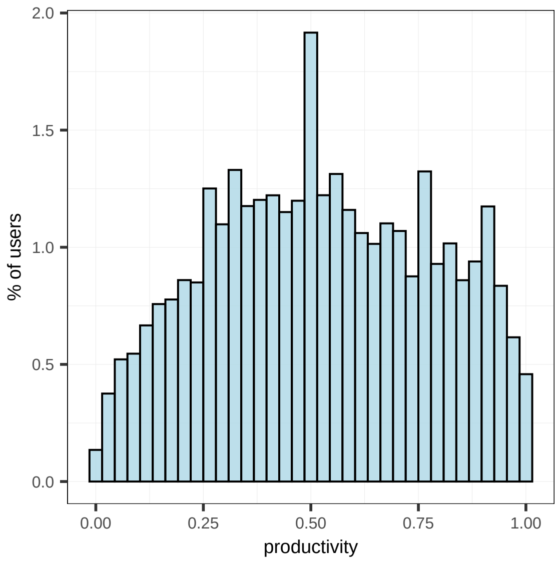


(a) CPU and Memory Utilization

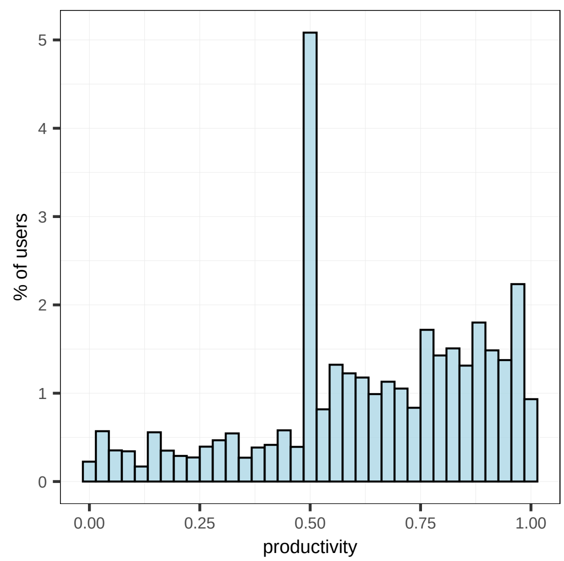
(b) CPU and Network Utilization

Notes: This figure illustrates the correlation between CPU utilization correlations and other resource measures. For each figure, we divide VM-days by the max CPU utilization into twenty equally sized bins, then plot the average max CPU utilization of VMs in that bin against the max memory utilization and 90th percentile network utilization of VMs in that bin. The average max memory and the average 90th percentile network across all bins is normalized to 1.

Figure OA-18: Dispersion of User Compute Productivity



(a) Azure



(b) GCP

Notes: These figures illustrate the distribution of user-day level compute productivity, estimated using the entire sample, weighting each VM by its core hour as shown in Equations (30) and (31) for Azure and GCP respectively. The x-axis represents productivity levels ranging from 0 to 1, while the y-axis shows the percentage of firms. Each observation corresponds to a user, and the histogram bars reflect the unweighted distribution of users across different productivity intervals.