Competition in Cloud Computing

Juan Camilo Castillo
Assistant Professor of Economics
University of Pennsylvania

Amit Gandhi
Professor of Economics
University of Pennsylvania

EODS Economics of Digital Services @Penn

CTIC Center for Technology, Innovation and Competition

The Warren Center for Network & Data Sciences

Penn University of Pennsylvania

Economics of Digital Services (EODS) is an initiative of the University of Pennsylvania's Center for Technology, Innovation and Competition (CTIC) and The Warren Center for Network & Data Sciences. Its aim is to generate independent research on the economics of digital services and the role of data and algorithms in the business strategies of digital platforms. The initiative was funded by a major grant from the John S. and James L. Knight Foundation to support scholarly inquiry and novel approaches in the evolving digital age.

To learn more about the initiative, visit www.law.upenn.edu/digitaleconomics/.

Center for Technology, Innovation and Competition (CTIC)

CTIC is an interdisciplinary academic center at the University of Pennsylvania Carey Law School that bridges law and technology for academia and students. Focusing on intellectual property, antitrust, internet law, and privacy law and policy. CTIC delivers foundational research that shapes the way legislators, regulatory authorities, and scholars develop policy and regulatory frameworks. CTIC also produces programming that explores the full range of scholarly perspectives, engages with industry experts, and prepares the next generation of technology scholars, lawyers, and policymakers.

www.pennCTIC.org

The Warren Center for Network & Data Sciences

The University of Pennsylvania's Warren Center fosters research and innovation in interconnected social, economic, and technological systems. Collaborating with Penn affiliates, it focuses on the role of data and algorithms to understand networked systems and how they can improve lives. The center also produces events that connect researchers, students, and entrepreneurs across the spectrum of network science.

www.warrencneter.upenn.edu

Competition in Cloud Computing*

Juan Camilo Castillo† Amit Gandhi‡

September 1, 2021

Abstract

In this paper we investigate whether cloud computing markets are competitive. We assemble a dataset of the historic prices of Infrastructure as a Service products from the three largest cloud computing providers. We find that prices are surprisingly sticky, with most products experiencing zero price changes over a six year period. Newer generations of products are introduced at lower price levels, but prices go down much more slowly than semiconductor prices. These patterns differ from what one would expect in a competitive environment. We set up a model of the cloud computing market that we will estimate in future versions in order to quantify the welfare losses from lack of competition.

Preliminary and incomplete. Please do not cite or distribute without permission of the authors.

1 Introduction

Cloud computing is a paradigm shift in the way companies use information technology (IT) to satisfy their computing and data storage needs. Traditionally, they had

*We are grateful to Aarón Mora and Caleb Shack for excellent research assitance. This research was supported by the University of Pennsylvania Center for Technology, Innovation, and Competition and by The Warren Center for Network and Data Sciences.

†Economics Department, University of Pennsylvania. E-mail: jccast@upenn.edu

‡Economics Department and The Wharton School, University of Pennsylvania. E-mail: akgandhi@sas.upenn.edu

to install their own computing infrastructure and pay upfront for expensive software licenses, which required costly capital expenditures with high lead times. A new possibility emerged around 2005 with cloud computing providers like Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP), which sell data storage, computing power, and software on-demand. Cloud providers transform IT into a variable cost, giving companies a large degree of flexibility and allowing them to scale up quickly and experiment with new technologies at a low cost. Businesses ranging from technology startups to well-established blue chip companies have thus been avid adopters of cloud computing, which is already a $270 billion market—accounting for over 10% of global IT spending—and has been growing over 20% per year (Gartner, 2021).

One open question that has important social consequences is whether cloud computing markets are competitive. The basic infrastructure products offered by cloud providers—computing power and data storage—are essentially commodities, suggesting a highly competitive environment with low switching costs. However, there are reasons to think the market is not that competitive. It is highly concentrated: one dominant player (AWS) has around 48% market share, and a few secondary players have 16%, 8%, and 4% market shares (Azure, Alibaba Cloud, and GCP, respectively; Su, 2021). Concentration might be a result of providers' strategy of offering bundles of services that include infrastructure products as well as more differentiated services like software and customer support that is tailored to specific clients, which often leads to customer lock-in.

The goal of this project is to quantify the degree of competitiveness in the cloud computing market and to measure the welfare losses due to any lack of competitiveness. We collect a dataset of historic prices over the last six years of computing infrastructure products from the three main players (AWS, Azure, and GCP), and complement it with a dataset of usage by Azure customers. We present a descriptive analysis that documents the main patterns in these companies' pricing schemes. In future versions of this project, we will also present a structural analysis of the cloud computing market that will allow us to measure the degree of competition and to quantify welfare.

We first document all dimensions over which prices vary for cloud services. We focus on the prices charged by AWS for virtual machines (VMs), fully-functioning computers that are hosted in the cloud.[1] We find that prices are linear in the size of the machine: doubling the number of cores and the amount of RAM memory leads to a price that is higher by a factor of two. Other than the size of the machine, the drivers of price variation from most important to least important are pre-installed software (such as SQL), the type of VM (the type of processor, the memory per core, whether it has GPUs, etc.), the operating system, and the physical location of the virtual machine.

We then focus on price variation over time. Our first main finding is that price changes are extremely rare. 90% of the products we observe experience no price changes over the whole period of our data. Those products that do have price changes exhibit only a couple of price reductions, none of which is larger than 10%. This is striking given that this is a market that rents out semiconductors, a product whose prices fall drastically over time (Byrne et al., 2018b).

We also analyze the price levels at which new products are introduced. Over time, cloud providers introduce newer VMs with more advanced processors. We find that each newer generation is introduced at a lower prices that the previous generation. However, the fall in the prices of new products is on the order of 10% per year, which is not nearly as large as the yearly fall in semiconductor prices, which is on the order of 40% (Byrne et al., 2018b).[2]

These pricing patterns do not correspond to what one would expect in a perfectly competitive market, in which prices would fall in line with the drop in prices of semiconductors. This suggests a lack of competitiveness in the market despite the fact that the product that is transacted is in many ways like a commodity. There are several reasons why the market might not be competitive. First of all, consumers might be locked in to certain types of VMs and might therefore be unwilling to upgrade to newer generations. They might also be locked in to certain providers due to the services they offer along with simple compute infrastructure.

In order to understand what happens in the market and in order to quantify the

[1] We also show similar results for disks and storage, the other two basic infrastructure products that are offered in the cloud.

[2] This pattern still holds if one accounts for the fact that newer generations are somewhat more powerful than previous generations.

welfare impact of this lack of competitiveness, we introduce a model of the cloud computing market. On the demand side, we have a model with random coefficients along the lines of Berry et al. (1995) in which consumers' demand not only depend on VM characteristics but also on switching costs they incur if they change VM type or if they change providers. On the supply side, we assume that providers choose prices in order to maximize profits. We assume that the set of products they offer is exogenous. This is a reasonable assumption given that all providers offer newer generation VMs soon after new processors start to be sold in the market.

The next steps in these project will be to estimate the main parameters of our model, and then to run counterfactuals to measure the welfare effects of different market structures. One goal is to understand how more competitiveness, in the form of more providers, might increase the welfare in the market. And we would also like to understand how mergers between providers might result in larger welfare losses.

Related work A few economics papers analyze different aspects of cloud computing. Byrne et al. (2018a) collects a dataset similar to our price data for AWS for the period 2009-2016 and documents price drops on the order of 12% per year. Wang et al. (2020) focus on VM clients' preferences over distance to data centers. They estimate demand across providers and across different data centers using data similar to ours (rich for one particular provider—Azure—and less so for other providers). Kilcioglu et al. (2017) highlight that, although one might think that cloud computing is a natural industry for peak-load pricing, cloud providers do not price dynamically. They then suggest a solution to this puzzle by showing that users' demand patterns are mostly uncorrelated, which means that aggregate demand only has small fluctuations.[3] Although these works relate to ours since they focus on demand and pricing in cloud computing, they do not touch on the central issue of our work—competition between providers.

A few other papers about cloud computing analyze issues that are somewhat less closely related to what we do. Kannan et al. (2021) characterize which countries have been more avid adopters of cloud computing. Other works highlight the

[3] Kilcioglu et al. (2017) also find much larger variation in cloud use intensity, which suggests these patterns might change in the future as users learn to optimize their usage.

impact of the cloud industry on other parts of the economy such as young manufacturing firms (Jin and McElheran, 2017) and the economy as a whole (Byrne and Corrado, 2017). These works also relate to a broader literature on the effects of IT on productivity (Bresnahan and Yin, 2017; Brynjolfsson et al., 2019; Bloom et al., 2021).

Our work also relates to the literature about prices in the closely-related semiconductor industry, which might drive prices in the cloud market. Some papers document a drop in prices of the order of 40% per year (Byrne et al., 2018b; Gorodnichenko et al., 2021). This trend is part of the more general pattern predicted by Moore's law (Flamm, 2018). Nosko (2010) sets up a structural model to analyze competition, pricing, and product choice in the semiconductor industry.

Finally, an interdisciplinary literature with contributions from legal, communications, and policy backgrounds analyzes how the cloud industry should be regulated across several dimensions (see Yoo and Blanchette, eds, 2015, for a broad overview). Some aspects such works focus on include security (Blumenthal, 2011), copyright (Determann and Nimmer, 2015), privacy (Renda, 2012), and health records (Seddon and Currie, 2013).

2 Setting and data

Setting We analyze the Infrastructure as a Service (IaaS) segment of the cloud computing market, where customers can rent hardware. We focus on three types of products, which account for the needs of most cloud customers: virtual machines, disks, and storage. Our description of these products will follow the conventions followed by AWS. Other providers offer essentially the same menu of products, but they use somewhat different terminology.

A *virtual machine* (VM), or *instance*, as AWS calls it, is a bundle that includes a processor and a certain amount of RAM memory and that customers rent for some hourly rate. Providers only charge for the time that the VM is on, although customers can reserve instances for a longer period (a month or a year, for instance) in order to obtain a lower price. In order to have a fully functioning computer, customers must also rent a *disk*—a hard disk drive or a solid state drive—for a certain rate per GB-month and attach it to a VM so that it serves as the main place to store the files the VM needs to operate, including the operating system. Consumers can also use *storage*, a service to which they simply upload files and download them whenever they want in the future. This service can be thought of as a more powerful (but less user-friendly) Dropbox that allows for greater customization. Providers charge a certain rate per GB-month.

We now describe all the dimensions along which VMs vary. The first dimension is the geographic location of the data center where the VM is physically located. AWS has 25 *regions* around the world, which are broad geographic areas such as US West-Oregon, US East-North Virginia, or Asia Pacific-Tokyo. Some VMs are also located in *local zones*. These are smaller geographic areas that tend to be located close to large urban centers, which is useful in order to reduce latency. Some examples of local zones are Boston, Houston, and Philadelphia. Recently, customers have also been able to choose VMs that are located in *wavelength zones*, which are even closer to urban regions to provide the lowest latency, and which are currently available only in the US, England, South Korea, and Japan.

VMs also vary by the *VM type*, which describe the processor, number of cores, and RAM memory type and size. AWS give VM types names such as m3.small, c5.xlarge, or r5.x4large. The initial letter refers to the broad category—general purpose (m), compute optimized (c), memory optimized (r), storage optimized (i), and accelerated computing (p)—which describes the purpose the hardware is optimized for. Memory optimized VMs, for instance, have a large memory-to-core ratio, and accelerated computing VMs have specific features such as GPUs that can be used for machine learning. The number after the category refers to the generation. m5 VMs, for example, have more advanced components than m2 VMs. Finally, the text after the dot refers to the size of the VM, which typically increase in powers of two. For example, an m5.medium VM has twice as many cores and twice as much memory as an m5.small VM, and a c4.8xlarge has twice as many cores and twice as much memory as a c4.4xlarge VM.

Customers also choose the VM's operative system—Linux, Windows, SUSE, or Red Hat Linux—and the VM can include preinstalled software such as Microsoft SQL Server for an extra fee.

Disks and storage are much simpler products that vary along fewer dimensions. They both vary depending on the location of the data center where the product is physically located. Disks also come in different types depending on the technology of the disk, such hard disk drives and solid state drivers with different throughputs. Storage products vary by classes, which determine the degree of availability of the data. Apart from high availability products in which the data is always readily available, customers can also pay a lower price for a lower availability level, in which case they can only access data with a lag after requesting it. This product is useful for backups and for data that companies believe they are unlikely to access in the future, such as record keeping.

Data Our main dataset is composed of prices from AWS products. We first collect a dataset at a daily frequency. We set up a script that collects the prices that are quoted in the AWS website every day. We collect VM prices for all regions, operative systems, preinstalled software and all VM types. For disks, we collect prices for all volume types in all regions, and, for storage, we collect prices for all storage classes on all regions. A typical daily snapshot for VM products contains over 70,000 price records and over 30 variables describing the features of each VM. We started running this procedure in May 2021 and will keep on collecting data for at least one year.

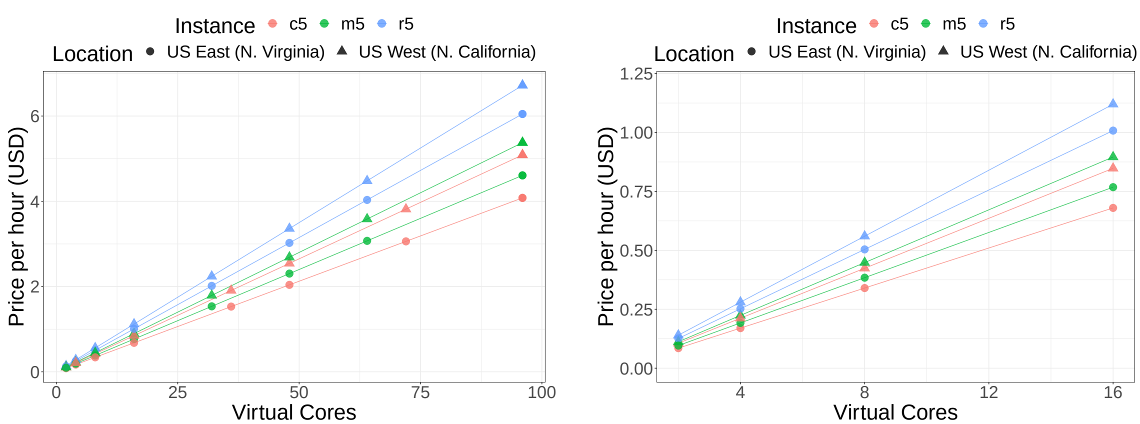
We also obtained historic price data from AWS at a monthly frequency. AWS offers an API that provides roughly monthly snapshots of all prices and characteristics at the SKU level for all AWS products, including both on-demand and reserved prices. Our data includes prices for VMs, disks, and storage between December 2015 until the present. The earliest snapshot contains price records for about 8,800 SKUs. The size of snapshots increased as AWS started offering more products. The latest snapshot includes 511,000 SKUs.

Apart from the AWS data we focus on this draft, we will obtain two historic datasets from Azure that will allow us to greatly extend the scope of our analysis. First, we will obtain a dataset including all price changes that took place between 2016 and the present. Second, we will obtain transaction-level data that will allow us to measure customers' consumption patterns. Finally, we also started scraping daily data from GCP in July 2021.

3 Descriptive analysis

In this section we present a descriptive analysis of pricing by AWS. We first analyze how prices look at any given point in time, and then we analyze how prices evolve over time.

Cross-sectional variation We focus on a snapshot with the prices on July 29th, 2021, although other snapshots show very similar patterns. We start by exploring the prices of on-demand virtual machines (VMs). Our first finding is that, for a fixed location, instance group, operating system, and software, prices are linear in the number of cores. Figure 1 shows that, for an arbitrary sample of some of the most important products and regions, prices grow linearly in the number of cores. Similar figures for other VM types show the same pattern. We thus focus for the rest of our analysis on the price per core.



(a) Prices by core configuration

(b) Prices for low core configuration

Figure 1: Behavior of prices as the number of cores increases

Note: These figures show prices by number of cores for AWS instances of type m5 (General Compute), c5 (Compute Optimize), and r5 (Memory Optimize) located in the US East (N. Vriginia) and US West (N. California) regions. The right hand side panel zooms in on configurations with a small number of cores.

We now analyze the remaining determinants of prices. Consider VM i—defined at the SKU level—in location $l(i)$ that belongs to instance group $g(i)$, uses OS $o(i)$, is of tenancy $\tau(i)$ (whether the VM is in a fixed pysical server or AWS has the flexibility to choose it), and uses software $s(i)$. These five dimensions account for essentially all the remaining variation in prices. A regression of log price per core on the interaction of fixed effects for these five dimensions has an R^2 of 0.953, and of 0.970 if we focus on the most important products. We then decompose price variation across these four dimensions by running a regression of the form

$$\log(p_i) = \alpha_{l(i)} + \beta_{g(i)} + \gamma_{o(i)} + \delta_{s(i)} + \eta_{\tau(i)} + \epsilon_i, \tag{1}$$

where p_i is the price per core and the first five terms represent fixed effects at the location, instance group, OS, software and tenancy level.

Table 1 shows the fraction of variation that each of the four dimensions account for. As we can see, software accounts for the largest fraction of the variation. We show below that the reason is that VMs with some versions of SQL have prices that are an order of magnitude larger than other VMs. The instance group also accounts for a large fraction of variation, since products vary from compute-optimize VMs that are simply a CPU with a small amount of memory to high-memory products and sophisticated products with GPUs that have higher prices per core. Finally, we see that tenancy, the OS and location determine prices to some extent, but they only result in price variations on the order of 19%, 11% and 7%, respectively.

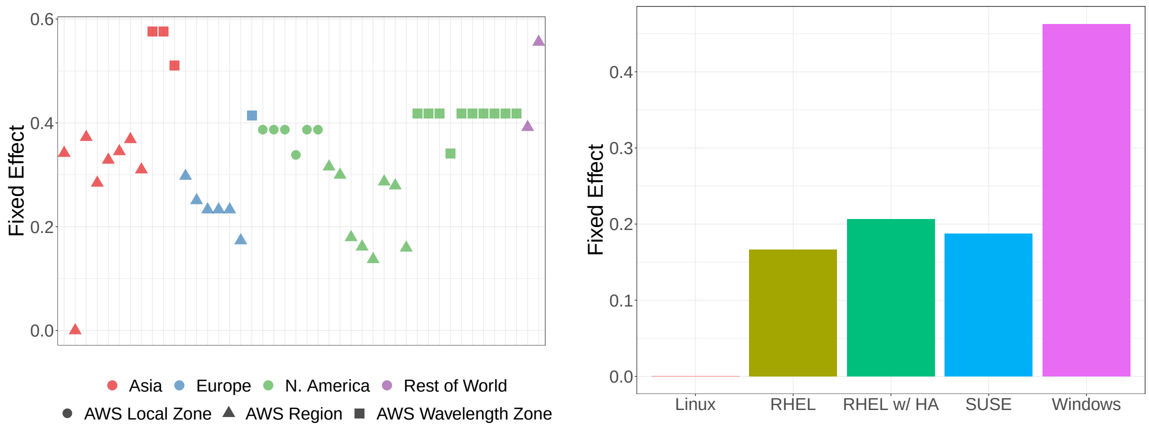
Table 1: Variation Decomposition by Fixed Effect

Variable	Standard Deviation
Software	0.642
Instance Group	0.295
Tenancy	0.187
Operating System	0.110
Location	0.069

Notes: Standard deviation of the fixed effects estimated based on equation (1).

We then run hedonic regressions to quantify how specific characteristics affect prices by focusing on the main products. Our main specification takes the form

$$\log(p_i) = \alpha \log(r_i) + \beta_{l(i)} + \gamma_{o(i)} + \epsilon_i, \tag{2}$$



(a) Location

(b) Operative System

Figure 2: Estimate Fixed Effects by VM dimension

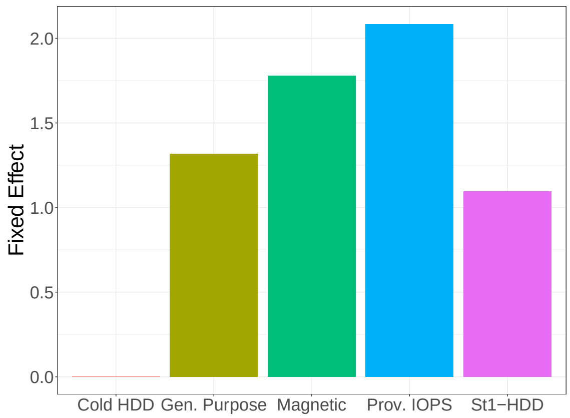
Note: These figures show estimated fixed effects according to equation (1). All estimated coefficients have a p-value lower than 10^{-4}. The reference category for location is the Asia Pacific (Mumbai) region. The "Rest of the world" category in subfigure (a) is composed of the Cape Town and Sao Paulo AWS regions.

where r_i represents the RAM memory per core. We obtain an estimate $\hat{\alpha} = 0.249$ (s.e.=0.003), which implies that increasing the RAM memory by 10% leads to a price increase of 2.5%. Figure 2 plots the values of the fixed effects coefficients. We can see how certain versions of SQL lead to prices that are an order of magnitude higher than VMs without specialized software. VMs with Windows, SUSE, and Red Hat Linux (RHEL) are more expensive by 15%-45% than VMs that use free Linux distributions. Finally, we observe that locations defined at the local-zone level are more expensive than those that are defined at the region level (typically by 38%), and wavelength-zone locations are more expensive by 44%.

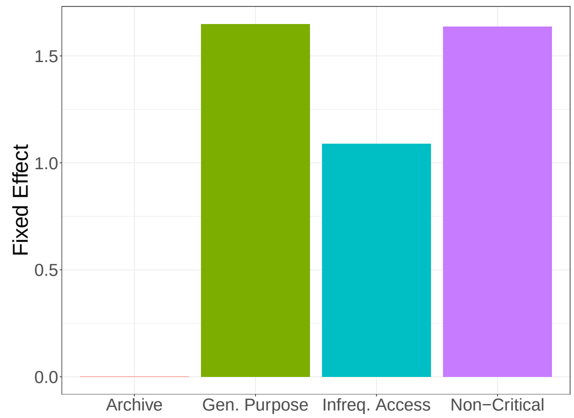
Figure 3 shows similar patterns for storage and disk products. The main dimensions that drive price variation, other than location, are storage class for storage and the volume type for disks.

Price patterns over time We now look into the ways prices change over time. We start by creating a price index to measure aggregate price changes across all products by running regressions of the following form:

$$\log(p_{it}) = \alpha_i + \beta_t + \epsilon_{it}, \tag{3}$$



(a) Disks Volume Type



(b) Storage Class

Figure 3: Estimated Fixed Effects for AWS storage and disks

Note: These figures show estimated fixed effects for AWS disks and storage. All estimated coefficients have a p-value lower than 10^{-4}. Subfigure (a) shows the volume type fixed effects. General Purpose and Provisioned IOPS are Solid State Drives; Cold HDD, Magnetic and Throughtput Optimized HDD (st1-HDD) are Hard Disk Drives. The storage class Archive in subfigure (b) correspond to AWS Glacier, a low-availability product.

where p_{it} is the price per core at time t for product i (again, defined at the SKU level), α_i is a fixed effect at the SKU level, and β_t is a time period fixed effect. We then use our estimate for β_t as a measure of overall price levels.

Figure (4) plots the price indices we construct for virtual machines, storage, and disk, using the first period as the base level. We see that prices mostly remain constant, except for a few periods during which prices go down. For comparison, the dashed line shows how prices would have behaved if they followed the price trend for semiconductors measured by Byrne et al. (2018b) for 2008-2013—i.e., a price drop of 43% per year. The aggregate price decrease is nowhere near what one would expect if prices followed the same trend as CPU prices—which roughly follow Moore's law.

In order to get a better understanding of the price changes shown by this figure, we now focus on the behavior of the prices of a few key products. Figure 5 plots the log prices of general-purpose, compute optimized, and memory optimized VMs located in North Virginia.[4] Prices almost never change. The most important pattern is that new generations are introduced at a lower price than the previous generation. This pattern is consistent with the pricing scheme followed by Intel since 2010, as

[4]Figures for other locations are almost identical.

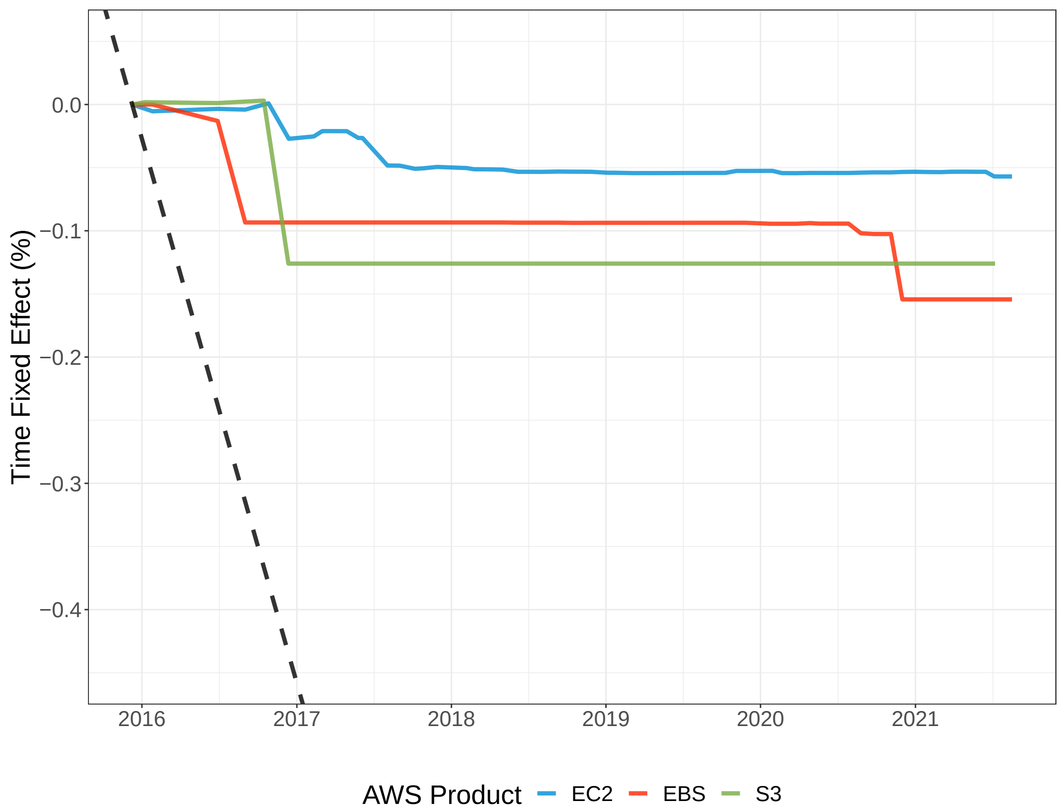


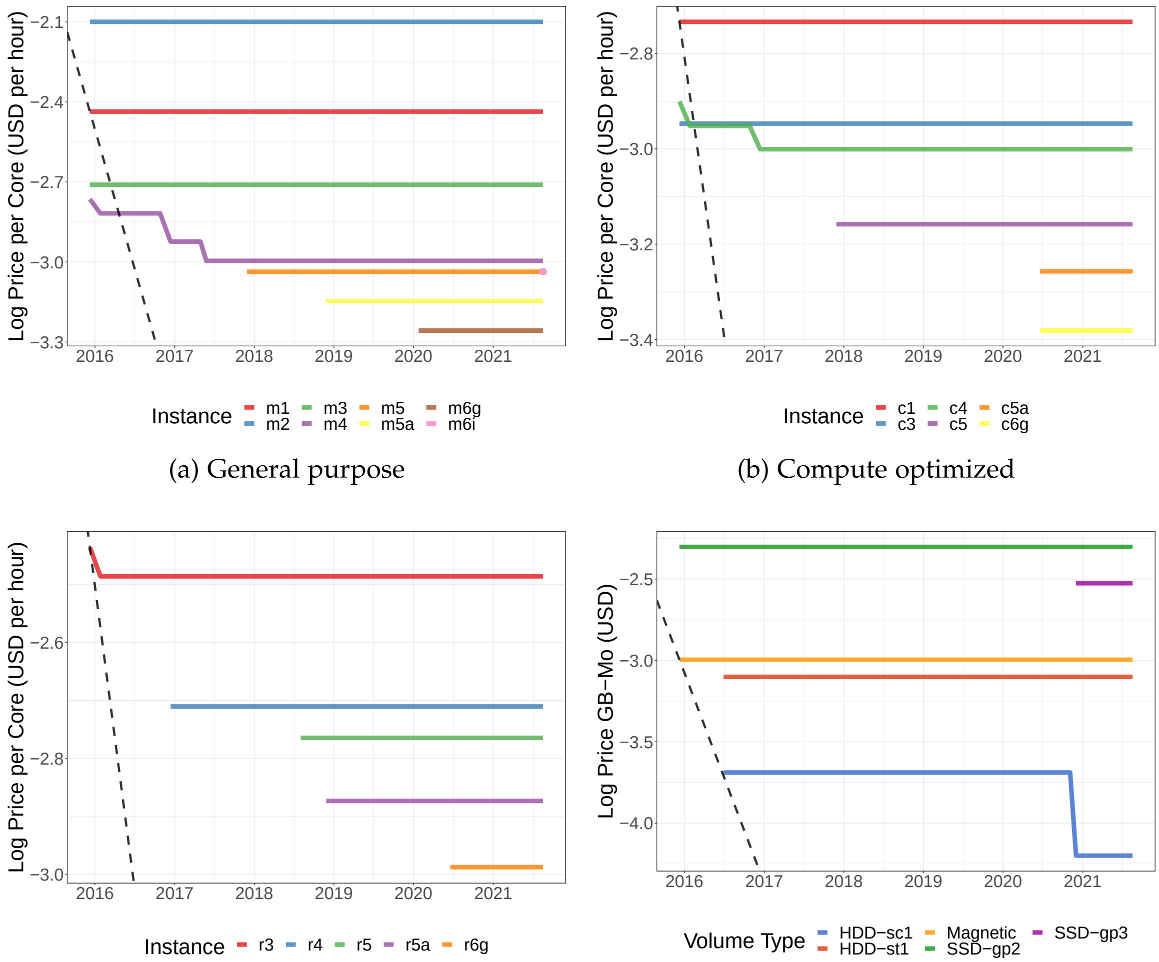
Figure 4: Price Indices for AWS

Note: The figure shows the time fixed effects for AWS products estimated from model (3). Price reductions are with respect to the set of prices for December 2015. The dashed black line represents an annual trend decreasing at 43%.

documented by Byrne et al. (2018b). But the price decreases are in fact of a much smaller magnitude, as is evident when one compares it with the dashed time trend, which is consistent with the price drops found by Byrne et al..

One concern with figure 5 is that newer VM generations might have more powerful processors. They might thus be even cheaper in terms of price per unit of computing power. Figure 6 is an almost identical figure in which we show prices per EC2 Compute Unit (ECU), a system of units created by AWS that measure how much computing power instance types have in order to allow customers to better compare products. We observe very similar patterns, although we are not able to show more recent instance types for which AWS does not report an ECU value.

Discussion The price patterns we observe in the data are substantially different from what one would expect in a perfectly competitive market. Figure 4 should



(a) General purpose

(b) Compute optimized

(c) Memory optimized

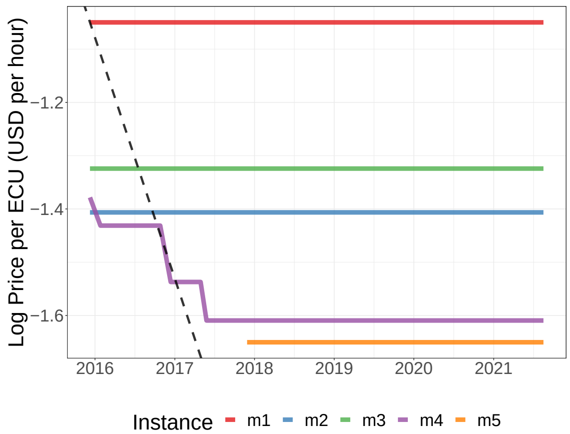
(d) Disks

Figure 5: Log Price behavior over time for a few select products

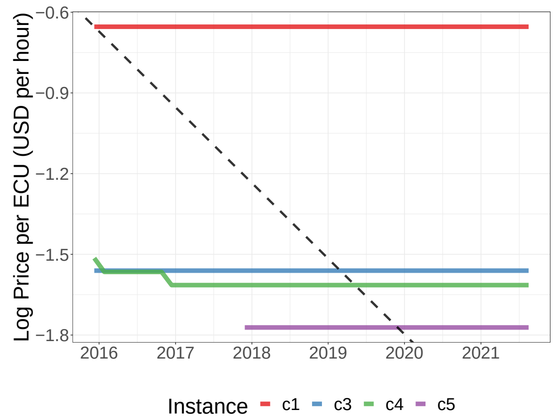
Note: These figures show the price evolution for AWS VM's key products in the region US East (N. Virginia). Subfigure (a) shows the main generations for the family of General purpose VMs; subfigure (b) shows the main instances of the family of Compute Optimize VMs and subfgure (6c) shows the main products for the Memory Optimize family of VMs. Subfigure (6d) shows the evolution of main AWS's EBS disk products to serve VMs. Prices fos VMs are on-demand prices for xlarge sizes running Linux with not other software preinstalled and a shared tenancy. The dotted black line in all subplots represents an annual trend decreasing at 43%.

show a gradual decline in prices as competitors are able to buy cheaper processors that allow them to offer lower prices. We, instead, observe prices that are mostly constant, except for a few episodes with small price decreases on the order of 10%.

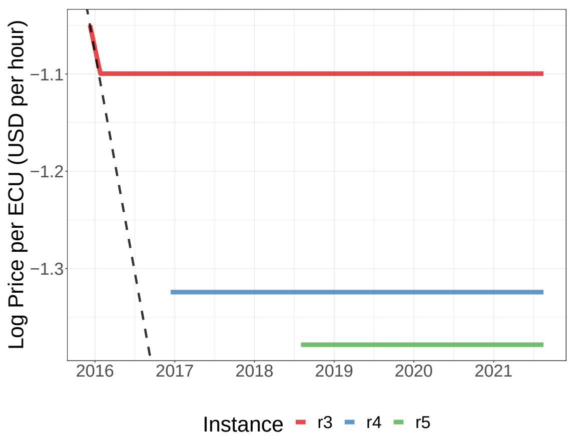
One might be tempted to think that the price patterns in figure 5 are driven by the sticky prices within processor type that are documented by Byrne et al.. However, processors are not a marginal cost for cloud providers. They are, instead, a capital cost that in fact becomes a sunk cost at the time newer processors that are



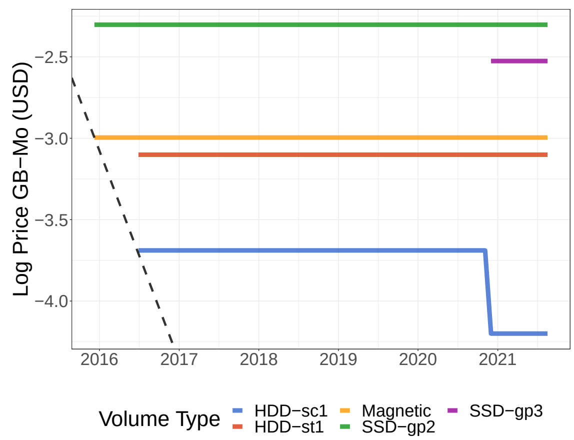
(a) General purpose



(b) Compute optimized



(c) Memory optimized



(d) Disks

Figure 6: Price per ECU behavior over time for a few select products

Note: These figures show the price per ECU evolution for AWS VM's key products in the region US East (N. Virginia). Subfigure (a) shows the main generations for the family of General purpose VMs; subfigure (b) shows the main instances of the family of Compute Optimize VMs and subfigure (6c) shows the main products for the Memory Optimize family of VMs. Subfigure (6d) shows the evolution of main AWS's EBS disk products to serve VMs. Prices fos VMs are on-demand prices for xlarge sizes running Linux with not other software preinstalled and a shared tenancy. The dotted black line in all subplots represents an annual trend decreasing at 43%.

both cheaper and more powerful are introduced. Thus, the fact that processor prices do not change should not have an impact on the prices of old instance generations.

The question that remains is then: what kind of environment might induce prices like those we observe in the data? One possibility is a setting in which customers are locked in to a certain type of instance. That might occur if companies design their systems in a way that only works with a very specific type of instance. Another possibility is that customers are inattentive and therefore do not respond as they should when new instance generations are introduced.

4 Model

We now present a model of the cloud market in order to formalize the ideas discussed in previous sections.

Demand Consider customer i, who wants to satisfy one unit of computing needs at time t in location l. If he chooses product j from provider k, he obtains utility

$$u_{ltikj} = \alpha p_{ltkj} + \beta_i x_{ltkj} - \gamma 1(y_{l,t-1,i} \neq kj) - \lambda 1(y_{l,t-1,i} \notin J_k) + \xi_{ltkj} + \epsilon_{ltikj}, \tag{4}$$

where p_{ltj} is the price of product j at time t in location l and x_{ltj} is a vector of product characteristics (including the type of processor, the amount and type of memory, and any additional features such as GPUs or higher disk throughput). The variable y_{lti} represents the product chosen by consumer i during the previous period, and J_k represents the set of all VMs offered by provider k. The term $\gamma 1(y_{l,t-1,i} \neq kj)$ thus represents a cost of switching VM types and $\delta 1(y_{l,t-1,i} \notin J_k)$ represents a cost of switching providers. Finally, ξ_{ltj} represents a product-market unobservable term.

In reality, corporate customers do not demand single units of computation. A large company that relies on cloud computing, such as Airbnb, demands a large number of computation units. In practice, we treat such companies as a large number of customers that use computing services on behalf of the company, each one of which has different tastes.

With this specification for utility, and if we assume the error term ϵ_{ltij} is distributed iid extreme value type I, the market share for product jk in market lt is given by

$$\sigma_{ltkj} = \frac{\exp(\delta_{ltkj})}{\sum_{k'j'} \exp(\delta_{ltk'j'})}, \tag{5}$$

where $\delta_{ltkj} = \alpha p_{ltkj} + \beta_i x_{ltkj} - \gamma 1(y_{l,t-1,i} \neq kj) - \lambda 1(y_{l,t-1,i} \notin J_k) + \xi_{ltkj}$. If we define Q_{lt} to be the total market size in location l at time t, then the demand for product jk in market lt is given by $q_{ltkj} = \sigma_{ltkj} Q_{lt}$.

Supply We assume providers have no choice over the set of products they offer. This is a reasonable assumption if (a) the only reasonable set of products to offer are the five main categories (general purpose, compute optimized, memory optimized, storage optimized, and accelerated computing) at a large range of sizes—the set of products offered by all major providers—and (b) all providers introduce new instance generations as soon as processor manufacturers develop new products.

Consider provider k, whose main choice variable are the prices it sets for every product. The profits it obtains in period t are given by

$$\pi_{ltk}(p_{lt}) = \sum_{j \in J_{kt}} \left[(p_{ltkj} - c_{lkj}) q_{ltkj}(p_{lt}) - C_{lkj}(q_{ltkj}(p_{lt}) - n_{l,t-1,k,j})_+ \right], \tag{6}$$

where J_{kt} refers to the set of instance types that k is able to offer at time t, c_{lkj} is the marginal cost of one unit of demand (which includes all costs that are required to run a data center running, such as energy and maintenance costs), C_{lkj} is the cost of installing additional capacity of type j, and $n_{l,t-1,k,j}$ is the type j capacity that was installed in the previous period. Thus, $C_{lkj}(q_{ltkj}(p_{lt}) - n_{l,t-1,k,j})_+$ represents the cost of the capital investments that are necessary to meet demand. A price that is missing any indices (such as p_{lt}) refers to the vector of all prices running over the missing indices.

The state space for providers' actions is then a vector s_t that involves the levels of capacity investment n_{ltkj} and the sets of available products J_{kt}. Given a certain state, a provider would like to maximize expected future profits

$$\mathbb{E}\left[\sum_{\tau=t}^{\infty} \pi_{ltk} \middle| s_t \right], \tag{7}$$

where the expectation is over transition probabilities and others' actions. We assume providers have rational expectations over the introduction of new products and competitors' actions. The optimization problem can be written recursively as

$$V(s_t) = \max_{p_{ltk}} \pi_{ltk}(p_{ltk}, p_{l,t,-k}; s_t) + \mathbb{E}[V(s_{t+1})|s_t]. \tag{8}$$

An equilibrium in this market is a Markov perfect equilibrium.

Future steps The next step will be to use our data to estimate the main model parameters. The main variation we will use in order to estimate demand is the introduction of new products. We will use various sources of data in order to back out the marginal and capital costs of cloud providers.

After having estimated the model, we can then measure welfare across different counterfactuals. The first counterfactual is an approximation of a perfectly competitive market where we introduce a large number of competitors. By comparing this counterfactual to the status quo we can quantity the welfare losses due to a lack of competition in this market. We can also simulate intermediate counterfactuals in which a limited number of competitors enter in order to asses how large are the barriers to entry. Finally, we can also run counterfactuals in which the current cloud providers merge in order to assess how large are the potential welfare losses if regulators allowed the market to turn into a monopoly.

5 Conclusions

With the goal of measuring the degree of competitiveness in the cloud industry, we collected a dataset with historic prices of AWS, the largest cloud provider. A descriptive analysis reveals many patterns that one would not observe in a perfectly competitive market, suggesting a low degree of competition in this market. We will complement our data with prices from the other two major cloud providers, as well as a dataset with transactions for Microsoft Azure. We will use that data to estimate a structural model of the cloud computing market, which will allow us to quantify the welfare effects of a lack of competition.

References

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Bloom, Nicholas, Tarek Alexander Hassan, Aakash Kalyani, Josh Lerner, and Ahmed Tahoun, "The Diffusion of Disruptive Technologies," *Working paper*, 2021.

Blumenthal, Marjory S, "Is security lost in the clouds?," *Communications and Strategies*, 2011, (81), 69–86.

Bresnahan, Timothy and Pai-Ling Yin, "Adoption of new information and communications technologies in the workplace today," *Innovation policy and the economy*, 2017, *17* (1), 95–124.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson, *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics*, University of Chicago Press, 2019.

Byrne, D and C Corrado, "ICT Prices and ICT Services: What do they tell us about Productivity and Technology? Washington. Board of Governors of the Federal Reserve System," *Working Paper*, 2017.

Byrne, David, Carol Corrado, and Daniel E Sichel, "The rise of cloud computing: minding your P's, Q's and K's," *Working paper*, 2018.

Byrne, David M, Stephen D Oliner, and Daniel E Sichel, "How fast are semiconductor prices falling?," *Review of Income and Wealth*, 2018, *64* (3), 679–702.

Determann, Lothar and David Nimmer, "Software Copyright's Oracle from the Cloud," *Berkeley Tech. LJ*, 2015, *30*, 161.

Flamm, Kenneth, "Measuring Moore's law: evidence from price, cost, and quality indexes," *Working paper*, 2018.

Gartner, "Gartner Forecasts Worldwide Public Cloud End-User Spending to Grow 23% in 2021," [Press release] 2021. Click here to open URL.

Gorodnichenko, Yuriy, Oleksandr Talavera, and Nam Vu, "Quality and price setting of high-tech goods," *Economic Modelling*, 2021, *98*, 69–85.

Jin, Wang and Kristina McElheran, "Economies before scale: survival and performance of young plants in the age of cloud computing," *Working paper*, 2017.

Kannan, Aadharsh, Jacob LaRiviere, and R Preston McAfee, "Characterizing the Usage Intensity of Public Cloud," *ACM Transactions on Economics and Computation (TEAC)*, 2021, *9* (3), 1–18.

Kilcioglu, Cinar, Justin M Rao, Aadharsh Kannan, and R Preston McAfee, "Usage patterns and the economics of the public cloud," in "Proceedings of the 26th International Conference on World Wide Web" 2017, pp. 83–91.

Nosko, Chris, "Competition and quality choice in the cpu market," *Working paper*, 2010.

Renda, Andrea, "Competition, neutrality and diversity in the cloud," *Communications & Strategies*, 2012, (85), 23–44.

Seddon, Jonathan J.M. and Wendy L. Currie, "Cloud computing and trans-border health data: Unpacking U.S. and EU healthcare regulation and compliance," *Health Policy and Technology*, 2013, *2* (4), 229–241.

Su, Jeb, "Amazon Owns Nearly Half Of The Public-Cloud Infrastructure Market Worth Over $32 Billion: Report," *Forbes*, 2021. Click here to open URL.

Wang, Shuang, Jacob LaRiviere, and Aadharsh Kannan, "Spatial competition and missing data: An application to cloud computing," *Working paper*, 2020.

Yoo, Christopher S. and Jean-Francois Blanchette, eds, *Regulating the cloud: Policy for computing infrastructure*, MIT Press, 2015.