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TRADING EXPERIMENTS USING FINANCIAL AGENTS IN A SIMULATED CLOUD COMPUTING COMMODITY MARKET

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Abstract: In September 2012, Amazon, the leading Infrastructure as a Service (IaaS) provider, launched a secondary marketplace venue for users to buy and sell cloud resources between themselves—the Amazon EC2 Reserved Instance Marketplace (ARIM). ARIM is designed to encourage users to purchase more long-term reserved instances, thus generating more stable demand for the provider and additional revenue through commission on sales. In this paper, we model ARIM using a multi-agent simulation model populated with zero-intelligence plus (ZIP) financial trading agents. We demonstrate that ARIM offers a new opportunity for market makers (MMs) to profit from buying and selling resources, but suggest that this opportunity may be fleeting. We also demonstrate that altering the market mechanism from a retail market (where only sellers post offers; similar to ARIM) to a continuous double auction (where both buyers and sellers post offers) can result in higher sale prices and therefore higher commissions. Since IaaS is a multi-billion dollar industry and currently the fastest growing segment of the cloud computing market, we therefore suggest that Amazon may profit from altering the mechanism of ARIM to enable buyers to post bids.

1 INTRODUCTION

In recent years, cloud computing has enjoyed a meteoric rise that continues to trend. The worldwide public cloud services market for 2013 has been estimated at $131 billion, with Infrastructure as a Service (IaaS; estimated at $9 billion) expected to continue as the fastest growing segment of the market (Gartner, 2013). The largest (and oldest) IaaS provider is Amazon Web Services (AWS). AWS deliver scalable, pay-as-you-go compute capacity through their Elastic Cloud Compute (EC2) service. EC2 has three virtual machine (VM) instance tariffs: (1) *On-Demand*, pay per hour with no long-term commitment; (2) *Reserved*, pay a one-time payment for each instance reserved and then receive a significant discount on the hourly charge for that instance; and (3) *Spot*, bid on unused capacity and run those instances for as long as the bid exceeds the current spot price, which fluctuates with supply and demand. The reserved instance (RI) model offers users the cheapest predictable access to compute resources, and benefits the provider by offering more predictable revenue and resource demand. However, since RIs are sold with terms of either 12-months or 36-months, to efficiently utilise this option users must be able to accurately forecast their personal demand over the (relatively long) lifetime of the instance. As a result, many users opt for the less risky on-demand model, which makes resource and revenue planning more difficult for the provider.

To overcome this, in September 2012, AWS launched a *secondary* marketplace venue for cloud users to re-sell unwanted time (in whole months) remaining on RIs; thereby making RI purchases more flexible and hence less risky for users. For instance, a user predicting high sustained demand over the next two months may purchase a 12-month reserved instance from the provider, and then re-sell the remaining 10 months on ARIM once the RI is no longer needed. Alternatively, if a RI with 2-months remaining is available on ARIM, then the user can purchase the exact time required. Therefore, as long as ARIM is a *liquid* market—such that it is easy for a seller to find a buyer and vice versa—then much of the risk involved in purchasing RIs is removed. As a result, more users gain access to the cheaper RI tariff, while the provider benefits from more predictable demand (i.e., the ratio of RI to on-demand sales increases). Further, the provider also generates additional revenue by charging sellers a commission (currently 12%) on all ARIM transactions.

ARIM is likely to have significantly impacted the dynamics of the market for cloud computing resources. To investigate this potential impact, we present a multi-agent simulation model of ARIM using CReST, the Cloud Research Simulation Toolkit (Cartlidge & Cliff, 2013). Agents have intrinsic demand for cloud resources, which is satisfied either by purchasing directly from the provider (on-demand or reserved) or via the secondary market (reserved). To model financial trading behaviour, agents use the zero-intelligence plus (ZIP) pricing algorithm (Cliff & Bruten, 1997) to trade on the secondary market.

We demonstrate that ARIM offers an opportunity for *market makers* (MMs)—speculators with no intrinsic desire for a commodity—to buy and sell resources for profit. However, we estimate that this opportunity will be fleeting—as the market becomes more liquid, the average price of a resource will fall too low for a MM to profit. We also demonstrate that if the market mechanism of ARIM is changed from a *retail market*, where sellers post offers to sell and buyers stay silent, to a *continuous double auction*, where buyers can also post offers to buy, then the market dynamics are significantly altered. In particular, we demonstrate that a continuous double auction is likely to generate more commission for the provider. Given that ARIM is operated by the largest provider in a multi-billion dollar industry, this result could have significant commercial impact.

This paper is organised as follows. In Section 2 we review the literature on financial markets and trading agents, before describing our experimental method in Section 3. In Section 4 we present results from a series of experiments investigating the impact of market mechanism and MMs on market dynamics. Conclusions are drawn in Section 5.

2 BACKGROUND

2.1 Cloud Computing

Cloud computing is the latest step-change in the delivery of computing services, offering on-demand network access to a shared pool of configurable computing resources. By accessing shared resources, cloud users reduce costs associated with managing hardware and software, while benefitting from the economies of scale enjoyed by ultra-large scale cloud providers (Hayes, 2008; Mell & Grance, 2011).

The term "cloud computing" encapsulates both the applications delivered *"as a Service"* and the underlying hardware and software infrastructure located in ultra-large scale data centres that make the concept viable (Armbrust, Fox, Griffith, Joseph, Katz, Konwinski, Lee, Patterson, Rabkin, Stoica, & Zaharia, 2009). This infrastructure is commonly known as *a cloud* and can be *public* (available to all, at a cost), *private* (owned by an organisation and accessible only to members), or a *hybrid* of the two; while a cloud service application delivered to end users is often referred to as *Software as a Service* (SaaS), *Platform as a Service* (PaaS), or *Infrastructure as a Service* (IaaS), depending on which level of the software stack is provided. SaaS describes high-level end user applications that are accessed remotely over the internet and includes ubiquitous software applications such as GoogleMail, Facebook, and Twitter. IaaS describes lower-level applications that offer users access to the underlying cloud hardware via a virtualisation layer. Typically, for IaaS, users purchase Virtual Machine (VM) instances that are installed with a user selected operating system (OS) and offer access to virtual CPU, RAM, and hard disk storage. These VMs can then be configured by the user to provide the specific functionality required. From the user's perspective, accessing a VM instance in the cloud is equivalent to remote accessing their own physical hardware. Finally, at the intermediate level, PaaS offers a suite of software libraries and interfaces—a *platform*—upon which users can build and integrate their own software applications. However, for clarity, in this paper, when we consider cloud resources, we refer to IaaS VM instances and not the higher-level software applications (Facebook, Twitter, etc.) that are built on top.

The *on-demand* delivery model for cloud computing resources offers a variety of benefits for business consumers: the ability to start and stop VM instances when required affords flexibility and scale-out opportunities; no up-front capital expenditure on (often under-utilised) compute infrastructure needed to cover peak business demand increases efficiency; and outsourcing maintenance and support reduces costs (Armbrust et al., 2009). However, the on-demand model is not necessarily ideal for cloud providers, as they attempt to adhere to strict Service Level Agreements in the face of fluctuating demand. If providers could accurately forecast future resource demand, then they would have the opportunity to reduce costs by optimising electricity purchases, engineering staff, and hardware utilisation, etc. (Rogers & Cliff, 2013). Unlike on-demand VM instances that can be started and stopped by users with no warning, long-term RIs offer providers an opportunity for capacity planning. For this reason, AWS have introduced ARIM—a secondary marketplace for users to buy and sell RIs between themselves. This introduction increases the flexibility of RIs and is designed to increase their relative popularity.

2.2 Continuous Double Auction

An auction is a mechanism whereby sellers and buyers come together and agree on a transaction price. Many different auction mechanisms exist, each governed by a different set of rules. In this paper, we focus on the *Continuous Double Auction* (CDA), the most widely used auction mechanism and the one used to control all the world's major financial exchanges. The CDA enables buyers and sellers to freely and independently exchange quotes at any time. Transactions occur when a seller accepts a buyer's "bid", or when a buyer accepts a seller's "ask". Although it is possible for any seller to accept any buyer's bid, and vice versa, it is in both of their interests to get the best deal possible at any point in time. Thus, transactions execute with a counter party that offers the most competitive quote.

Many CDAs utilise an "orderbook" to match counterparties for execution. The orderbook is an ordered list of all bids (in price descending order) and an ordered list of asks (in ascending order). The best bid and ask at any given time are the current highest bid and the lowest ask. If a new bid (ask) enters the orderbook at a price higher (lower) than the best ask (bid), it will immediately execute against it at the price of the ask (bid). If the bid (ask) has a value lower (higher) than the best ask (bid), then it will enter the orderbook and remain in the list of bids (asks). If the orderbook is visible, then traders are able to see the price and volume available at any given time.

The auction design of ARIM allows sellers to post asks at any time. These asks are ordered by price (ascending) and visible to all market participants. Thus, ARIM can be considered as equivalent to the ask-side of a standard orderbook. However, ARIM contains no equivalent of an orderbook's bid-side. That is, there is no stored list of bids. At any time, a buyer can choose to accept (execute against) an ask that is displayed, but a buyer cannot post a bid offer that is lower than the best ask price. Therefore, buyers cannot advertise their willingness to trade. We describe this kind of auction as a "retail" market.

Vernon Smith (1962) explored the dynamics of CDA markets in a series of Nobel Prize winning experiments using small groups of human participants. Smith showed that markets quickly tended towards the theoretical equilibrium price (the price at which the quantity demanded equals the quantity supplied). However, when Smith explored a variation on the CDA where only sellers could post asks (a retail market), he showed that the experimental market tended to a price *lower* than the theoretical equilibrium. Smith suggested that this may have been a result of irrational human behaviour. However, in a series of experiments designed to replicate Smith's work, but using artificial trading agents (the ZIP trading algorithm; see below) rather than humans, Dave Cliff was able to repeat Smith's result. Once again, retail markets tended to a price lower than the market equilibrium (Cliff & Bruten, 1997, pp. 49-55). However, since there were no humans in the market (only software trading agents), this time the result could not be attributed to human behaviour.

In this paper, we model ARIM using a population of ZIP trading agents and investigate the effect of altering the market structure of ARIM from a retail market (where the orderbook contains only asks) to a CDA (where the orderbook contains both bids and asks). Given the results independently achieved by Smith using a population of humans, and Cliff using a population of trading agents, we may expect the price of cloud resources to be *lower* in a retail market than a CDA market. We test this in Section 4. However, first, we introduce the ZIP algorithm.

2.3 Zero-Intelligence Plus (ZIP)

ZIP agents are profit-driven traders that adapt using a simple learning mechanism: adjust profit margins based on the price of other bids and offers in the market, and decide whether to make a transaction or not. When a decision to raise or lower a ZIP trader's profit margin is taken, ZIP modifies the value using market data and an adaptation rule based on the Widrow and Hoff (1960) "delta" rule (for full details of the ZIP algorithm, refer to Cliff & Bruten, 1997, pp. 41-45).

The ZIP strategy has become a popular benchmark for CDA experiments. In their IBM study, Das, Hanson, Kephart, and Tesauro (2001) concluded that ZIP was a dominant strategy, beating humans in experimental trials and matching the performance of their own modified GD (Gjerstad & Dickhaut, 1998) algorithmic trader. ZIP has since been used in many experimental economics papers (for a detailed literature review, see De Luca, Szostek, Cartlidge, & Cliff, 2011), and has been modified in many studies to accommodate different market designs (for a review, see Stotter, Cartlidge, & Cliff, 2013).

However, in the majority of studies, ZIP traders are designated as either "buyers" or "sellers" and are presented with a series of assignments to trade; for example *"buy one unit of stock at price no more than \$200"*. This process inherits directly from Smith's original behavioural economics experiments (Smith,

1962) and is equivalent to ZIP acting as a "Sales Trader"—that is, executing orders on behalf of somebody else. One notable exception to this is a Master's thesis study that enabled ZIP traders to act as electronic arbitrageurs (i.e., to buy and sell on their own behalf for profit) to investigate the role of arbitrage in equilibrating trade prices across segmented markets (van Montfort, Bruten, & Rothkrantz, 1997).

In this study, we also allow ZIP traders to buy and sell on their own behalf. Each trader contains a ZIP pricer for pricing bids and a separate ZIP pricer for pricing asks. Within the population, traders have intrinsic demand for cloud resources (i.e., they are cloud users). Each month, traders can either buy resources (RIs, or on-demand instances) directly from the provider, or trade RIs on ARIM. While most traders are only concerned with buying and selling resources to fulfil their intrinsic demand, we open the possibility for traders to buy and sell RIs even when they don't have demand. Such traders can be considered as "market makers" (MMs)—that is, they aim to *buy low* and *sell high* to gain a profit and have no intrinsic demand for the underlying commodity. We use this model to investigate the impact that MMs have on the dynamics of ARIM, and under what conditions market making offers a profitable opportunity.

3 EXPERIMENTAL METHOD

The Cloud Research Simulation Toolkit (CReST) was developed at the University of Bristol to address the need for a robust simulation modeling tool for research and teaching of data center management and cloud provision. CReST is a stand-alone application, written in Java, and is freely available open source under a GNU General Public License v3.0 (CReST, 2013). For details on the architecture of CReST, refer to Cartlidge and Cliff (2013). All code used to run experiments reported in this paper is available to download in CReST version 0.5.0 (CReST, 2013).

For the experimental model, we have a population of trading agents (size P), a cloud provider, a marketplace for trading RIs, and two types of cloud resource: RIs (with m-month term) and on-demand. The marketplace has two design settings: *CDA*, which contains a full orderbook; and *retail*, in which the orderbook contains only sellers' asks. Each month, a proportion of traders, D, is given a unit of demand for a cloud resource. To satisfy their demand, traders can either purchase resources in the marketplace, or purchase directly from the provider. A trader that purchases an on-demand instance from the provider is forced to use that instance immediately (to satisfy their demand). However, a trader that purchases a RI can either: use the first month to satisfy demand and then resell the remaining $m-1$ months in the marketplace; use the first month to satisfy demand and then continue to use the RI in subsequent months to satisfy further demand; or sell the entire m-months term of the RI in the marketplace without ever using it. We consider traders that only ever buy RIs to resell in the marketplace (i.e., traders that never have intrinsic demand) as market makers. To trade in the marketplace, each trader has an internal ZIP engine for pricing bids and a separate internal ZIP engine for pricing asks (using the same parameters as Cliff & Bruten, 1997, p. 45). We run the model for a fixed number of months and collect statistics each month on the traders' profits and loss, the provider's balance sheet and inventory of sales, and the sequence of trades that execute in the marketplace.

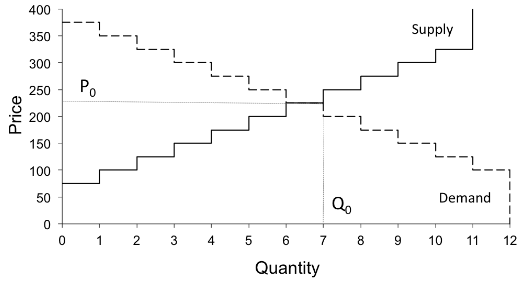

Figure 1: Supply and Demand

In the following section, we present results from a series of experiments. In particular, we investigate: (1) the effect of the marketplace design, i.e., CDA or retail; and (2) the impact of market makers. Each experimental condition is repeated 30 times, with mean values recorded for each run. Following the Central Limit Theorem, with 30 observations the mean approximately follows a Normal distribution. Therefore, 95% confidence intervals can be calculated and plotted. Where confidence intervals do not overlap, then results are significant at the 0.05 level.

4 RESULTS

4.1 Retail versus CDA

To observe the effect of changing the market design from CDA to retail, here we perform a strict replication of Cliff's retail market ZIP trader experiments (Cliff & Bruten, 1997, pp. 49-55), which were themselves a replication of Smith's retail market human trader experiments (Smith, 1962). We model a set

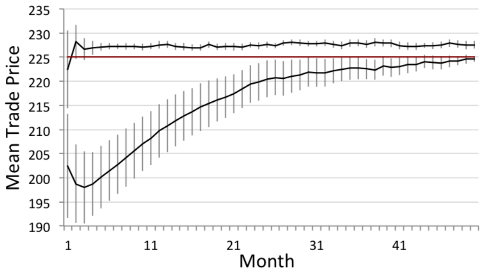

Figure 2: Mean monthly trade prices (30 runs; $\pm 95\%$ confidence interval). The red line plots $P_0 = 225$. In the CDA market (top line), prices quickly stabilise within 1% of P_0. In the retail market (bottom line), prices are initially 10% *below* P_0 before asymptotic convergence to P_0.

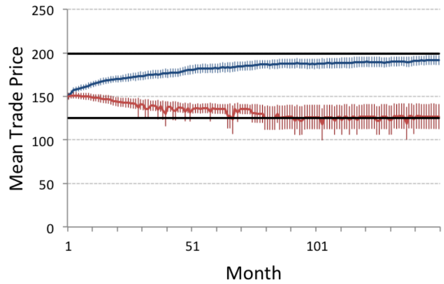

Figure 3: Mean monthly trade prices (30 runs; $\pm 95\%$ confidence interval) in a market where only MMs sell on ARIM. The CDA market (blue) converges to $D_{buy} = 199$, while the retail market (red) converges to $M_{sell} = 125$.

of 12 buyers and 11 sellers, each with a unique limit price (the maximum bid price, or minimum ask price) to trade. Here, we do not allow traders to trade on their own behalf, i.e., there are no MMs. Each month, buyers are issued with one unit of demand and sellers are issued with one RI to sell, with each trader always having the same limit price. Figure 1 presents the supply and demand curves for the market (identical to Smith, 1962, p. 21). These curves plot the quantity demanded and quantity supplied at every price point (the limit prices of traders). The theoretical market equilibrium is the point where the two curves intersect, that is: $(Q_0, P_0) = (7, 225)$. Therefore, if the market equilibrates, we expect 7 RIs to trade each month at a value of \$225.

Figure 2 plots mean monthly trade price for both markets. In the CDA market (top-line), we see that prices approach equilibrium ($P_0 = 225$; red line) within the first few months and then stabilise approximately 1% *above* equilibrium (this elevation may be caused by a bias in the conversion of real-valued profit margins to integer-valued order prices, but this requires further investigation). In contrast, for the retail market (bottom-line), we see prices are initially 10% below equilibrium, before steadily converging on P_0 around month 50. Interestingly, this behaviour has qualitative similarity with the early human trader experiments, where Smith concluded: "*that markets in which only sellers competitively publicize their offers tend to operate to the benefit of buyers at the expense of sellers*" (Smith, 1962, p.22). Results are also qualitatively similar to those of Cliff's 10 period retail market experiments, where mean price was consistently below \$200, but steadily rising each month (Cliff & Bruten, 1997, p. 52). Had Cliff run his experiment for longer, it is likely that he would have achieved the same result.

It is clear from these results that the retail market design is less efficient than the CDA design—although the retail market eventually converges to equilibrium, during the time that the market is trading away from equilibrium, there are inefficiencies in the market that can be exploited. For this reason, in the following experiments, we investigate the impact of MMs that attempt to profit from inefficiencies in the market.

4.2 Market Makers

Here, we create a simplified model of ARIM. We assume that on-demand instances cost $P_{OD} = \$200$ per month and RI instances have a term of 2 months and cost $P_{RI} = \$250$ per unit (and therefore cost $P_{RI}/month = \$125$ when fully utilised). Each month, traders have unit demand with probability 0.5. Therefore, on average, half the population of traders are issued with one unit of demand; we call these traders "demand traders". Demand traders are prepared to buy a one-month RI on ARIM for a maximum limit price of $D_{buy} = \$199$ (i.e., one dollar less than P_{OD}). If a demand trader does not purchase on ARIM, the unit demand for the month can be satisfied by purchasing either an on-demand resource (with probability $p(od)$, or a 2-month RI (with probability $1 - p(od)$). If the demand trader purchases a 2-month RI, then the following month the RI can be used to satisfy next months demand (occurring with probability 0.5). If the demand trader has no demand the following month, the trader can sell the remaining month on ARIM. On such occasions, the demand trader sets a sell limit price of $D_{sell} = \$50$, i.e., the marginal difference between P_{OD} and P_{RI}. The model also contains MM traders that each purchase RIs at the start of each month and then immediately attempt to resell them on ARIM over the following two months. MMs set a sell limit price of $M_{sell} = \$125$, i.e., equal to $P_{RI}/month$.

Figure 3 shows mean monthly trade price for a market in which only MMs sell on ARIM—i.e., $p(od) = 1.0$, so no demand traders select to purchase RIs from the provider. The population contains 50 agents and therefore mean demand each month is 25. There is one MM in the population. The MM initially purchases $i_{t=0} = 10$ RIs each month (and therefore, from the second month onwards can sell 20 resources on ARIM). Each month, the MM updates i following a simple rule—if all units were sold this month, then next month $i_{t+1} = i_t + 0.2$, else $i_{t+1} = i_t - 0.2$. In this way, the MM attempts to balance supply of RIs on ARIM to fulfil population demand. Since the demand each month fluctuates (with constant mean=25), the MM sometimes has over-supply and sometimes has under-supply. Therefore, the equilibrium price in the market fluctuates rapidly between $P_0 = D_{buy} = 199$ (when MM supply is less than demand) and $P_0 = M_{sell} = 125$ (when MM supply is greater than demand). When demand exactly equals supply, $P_0 = 162$. Figure 3 shows the mean monthly trade price in a retail market (red) and a CDA market (blue). In retail markets, mean trade price converges to $P_0 = M_{sell} = 125$. At this price, the MM no longer makes a profit on each unit traded. However, in the CDA market, mean trade price converges to $P_0 = D_{buy} = 199$. At this price, the MM makes a profit of \$74 per unit sold. This is a striking result. We can explain this by considering the sensitivity of retail markets to oversupply. As shown in Figure 2, and concluded by Smith (1962), retail markets "operate to the benefit of buyers". As such, each month the MM oversupplies the market, the market has a stronger downwards movement than the corresponding upwards movement when the MM undersupplies the market. Therefore, despite the MM continually trying to balance supply and demand, prices continue to fall until there is no marginal profit on each unit of trade. In contrast, the CDA market does not react more strongly to oversupply than undersupply. Therefore, using the same update rule on supply, the MM does not force down prices and by marginally undersupplying the market is able to continue to profit from each trade. This demonstrates that a change in market mechanism can lead to a radical divergence in mean market price.

In the previous experiment, ARIM sellers were all MMs. In reality, however, we expect demand traders to make use of ARIM. To model this behaviour, we repeat the previous experiment but this time allow demand traders to purchase RIs. At the start of the run, $p(od) = 1.0$, but is then reduced each month by 0.025 (purposely chosen to be an order of magnitude smaller than the responsiveness, $\delta i = 0.2$, of the MM). Initially, therefore, no demand traders are re-selling on ARIM. However, more demand traders are attracted to ARIM each month. By month 100, a quarter of demand traders are re-selling on ARIM, and by month 200 half of all demand traders are re-selling on ARIM. There is only one MM, set to initially purchase $i_{t=0} = 5$ RIs per month (each month $i_{t+1} = i_t + 0.2$ if all RIs sold, else $i_{t+1} = i_t - 0.2$). Thus, the market initially has excess demand.

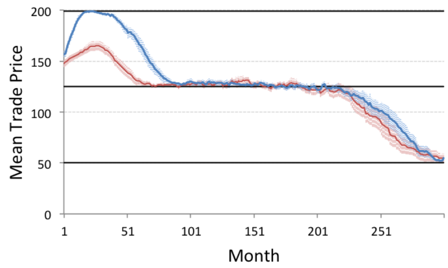

Figure 4: Mean monthly trade prices (30 runs; ±95% confidence interval) in a retail (red) and CDA (blue) ecology.

Figure 4 plots mean trade prices in a retail ecology (red) and a CDA ecology (blue). We see that there are three distinct phases. Initially, the excess demand for RIs on ARIM leads to a price increase. This encourages the MM to supply more RIs on ARIM, which drives the price lower, eventually converging on $M_{sell} = 125$. At this point, the MM no longer makes a profit on each unit traded. During the second phase, the market price remains stable at $M_{sell} = 125$. During this period, the MM gradually reduces supply and at the same time there is an increase in demand traders re-selling RIs on ARIM. For demand traders, selling under utilised RI capacity for \$125/month is attractive, since this is greater than $D_{sell} = \$50$, the marginal monthly unit cost of an RI to a demand trader. Eventually, there are so many demand traders re-selling on ARIM that the market enters the third stage around month 200. At this point supply on ARIM exceeds demand and the price falls once again, eventually converging on $D_{sell} = \$50$. During this phase the price is too low for the MM to profit and the MM leaves the market entirely. Note, however, that although the phases are qualitatively similar in both ecologies, during phase 1 and phase 3, the CDA market (blue) trades at consistently higher prices than the retail market (red). This demonstrates that when the market is not at equilibrium saturation (i.e., when there is not a prolonged over-supply) then the CDA market will trade at higher prices than the retail market. We present this as evidence that it may be beneficial (in terms of commission revenue) for Amazon to alter the design of ARIM from a retail to a CDA.

5 CONCLUSIONS

We have presented a simple multi-agent based simulation model of the Amazon EC2 Reserved Instance Marketplace (ARIM); a secondary market venue for trading cloud computing resources. Within the simulation model, a population of zero-intelligence plus (ZIP) financial trading agents buy and sell resources in the market. Some traders act as market makers (MMs), such that they buy resources for the sole purpose of re-selling for profit. Other traders are "demand traders" that have intrinsic demand for cloud resources and utilise the secondary market only to buy resources at a cheaper price than offered by the provider, or to offload underutilised resources that have previously been bought. ARIM is a "retail" marketplace, where only sellers can advertise prices; unlike a continuous double auction (CDA), where both buyers and sellers can advertise their desire to trade at any time. We have demonstrated that retail markets can produce *lower* trade prices than a CDA and conclude that Amazon may increase commission on sales if they alter the mechanism of ARIM from a retail market to a CDA. Given that the market for cloud resources is a multi-billion dollar industry, even small increases in commission could equate to significant profit. On the evidence presented here, we suggest that this is what Amazon should do. Finally, we have demonstrated that ARIM has opened an opportunity for MMs to profitably enter the market. However, as ARIM becomes more popular, this opportunity will disappear.

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