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Online Bidding Behaviour and Loss Aversion in Cloud Computing Markets: An Experiment

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Abstract

*The last few years have witnessed a rapid growth in commoditization and consumption of IT services particularly due to the growing acceptance of cloud computing services. This in turn has led to newer forms of pricing the cloud services such as dynamic pricing. Infact, spot pricing, a dynamic pricing scheme has become mainstream. Cloud consumers using these schemes need to place their bids in order to procure computing instances. Most of extant research on cloud dynamic pricing focuses on resource allocation problems and bidding strategies. We identify the need to look at behavioural biases of bidders to bring in a holistic perspective to cloud dynamic pricing discussions. In this paper, we conduct an experiment to elicit the impact of a behavioural bias namely, loss aversion, on a cloud consumer's bidding behaviour. We discuss the **social implications** of our result to cloud consumers and the **economic implications** for cloud providers.*

Keywords: Cloud Computing, Dynamic pricing, Loss Aversion, Bidder Behaviour

1.0 Introduction

Cloud Computing is a new paradigm that comprises shifting Information Technology (IT) resources and software from locally independent computers to a more collaborative level (Hayes, 2008). This growing supply and adoption of cloud, which is perceived as the fifth utility has triggered the commoditization of IT. These services have transformed the way IT delivery happens in an organization. Consumers are aggressively pursuing this shift and Forrester predicts that the cloud computing market will cross \$241 billion by the year 2020. Over the years, we find cloud adoption to be on the rise and research indicates that the emerging network of cloud players is expanding (Weinman, 2011). This is primarily because of the flexibility that cloud offers to organizations to meet variable demand without any fixed investment in capacity. This flexibility combined with the cost advantage has led to the growth of

cloud computing and today it not just attracts IT/IS users but also service providers, who see a huge business opportunity in selling cloud services. As large and mid-size cloud vendors try to capture greater market share, demand for robust and efficient pricing models is sure to increase.

As the competitive pressures mount, it is imperative for service providers to look at the cloud market from a user perspective, particularly in the case of dynamic pricing market since the dynamic price is also a function of the user's bid price. There is an implicit assumption that users who are bidders in these markets are rational (Mihalescu & Teo, 2010; Shneidman & Parkes, 2003). However in reality bidders can behave irrationally due to the influence of various behavioural biases that they may possess. For example, data from Amazon indicates that, at times, bids for computing instance exceed the standard pay-as-you-go (PAYG) price. Such irrationality could stem from the biases that a bidder may possess.

The behavioural biases inherent to users could have important implications for IS decisions pertaining to cloud adoption and usage as well as in rendering cloud services. Our research specifically focuses on analyzing pricing and bidding decisions in the context of cloud computing in the presence of *loss-averse* users. In Section 2, we provide the research gaps and motivation. In Section 3, we summarize the background and related work. We discuss the dynamic pricing literature pertinent to cloud computing and the behavioural economics literature on key biases that could impact bidder behaviour with special emphasis on loss aversion. In Section 4, we discuss the context for loss aversion in a dynamically priced cloud services market. In section 5, we present the details and results of our experiment. Next we present the implications namely the social implications for cloud users and the economic implications for cloud providers.

2.0 Research Gaps and Motivation

A lot of research is currently taking place in the technical aspects of cloud and there is an urgent need for understanding the business-related issues surrounding cloud computing (Marston, et al., 2011). A search with 22 different keywords on 9 journal databases returned 2891 unique papers. Of these papers, only 32 comprised of pricing (Sowmya, et al., 2013) and none of these considered behavioural biases.

On the other hand, research on behavioural biases in the context of pricing decision for the cloud cannot be waived of as irrelevant. A snapshot (see Figure 1) from

Amazon's spot price video serves as an evidence of irrational bidding. We can observe from the chart that approximately 15% of the bidders quote a price much higher than the on-demand price and almost 0% quote a price less than 30%.

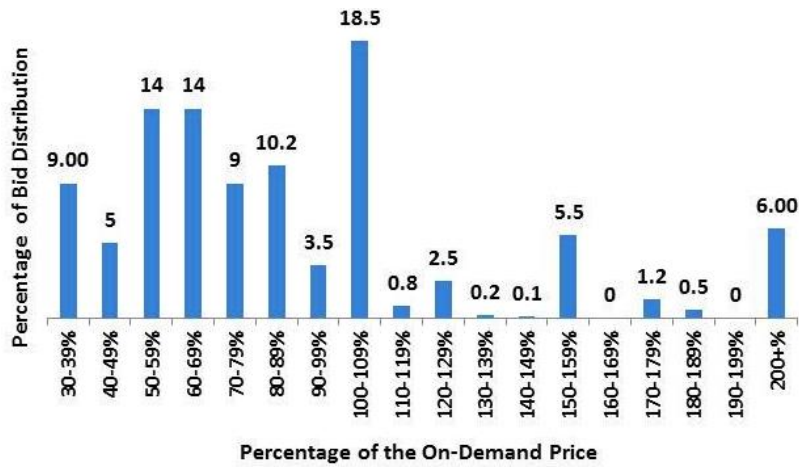


Figure 1: Snapshot from Amazon EC2: Bid distribution as a percentage of OnDemand price.

For any viable business, economic models help in formulating the pricing and tariff structures to optimize return on investment, create critical mass of customers and manage resource deployment more efficiently. Current business models within cloud computing business case have been mainly studied and simulated for defining resource allocation algorithms rather than advocating and creating full-fledged economic models. There are many unresolved issues such as, how to determine and create tariff structures with a view to evolving a sustainable business over a long and lasting period term? The assumptions in the current models need to be examined to improve sustainability. The current models that assume rational users need to be questioned and new pricing models need to be developed which account for the irrationality of users. As a first step in this direction, we examine the effect of a behavioural bias namely loss aversion on the bid prices in an online cloud computing market.

3.0 Background & Related Work

3.1 Pricing in Cloud Computing Markets

Much before the advent of Cloud Computing, researchers have proposed online markets for computational resources. One of the earliest works is the Popcorn Market project by Regev and Nisan (2000). Since then researchers have formulated many

economic models for sharing computing resources. In the case of Cloud service providers, every provider has its own pricing scheme, for example, Salesforce uses “pay per use” scheme (Weinhardt, et al., 2009), Amazon uses “pay-per-use fixed pricing” (Amazon Simple Storage Service) and few others use “pay for the resources” that are assessed based on speed of bandwidth or amount of storage. According to Weinhardt et al. (2009), the most prevalent method of pricing in cloud is pay as you go (also known as the on-demand model or PAYG), which is based on units with constant price. Another common pricing model is subscription (also known as reserved instance model), wherein users sign a contract (subscribe) based on constant price of service unit for a longer period, say six months to a year. Obviously, customers and providers would like to use static and simple pricing models in order to ease payment prediction. Nevertheless, research indicates that dynamic pricing can be more efficient (Anandasivam & Prem, 2009; Mihailescu & Teo, 2010).

3.1.1 Dynamic Pricing in Cloud Computing

Dynamic pricing involves dynamically adjusting the prices of a product or service to customers, based on the value the customers attribute to that product or service (Reinartz, 2001). There are several works that have studied dynamic pricing in the context of cloud computing. Research shows that, users should bid optimally in a dynamic pricing scheme to achieve different objectives with desired levels of confidence in a cloud computing setup (Andrzejak, 2010). Few researchers have gone a step further and examined dynamic price traces and built models around that. Javadi et al (2011) have provided a statistical model of dynamic prices in a public cloud environment. Dynamic pricing, in principle, encourages users to shift their flexible workloads from provider's peak hours to off-peak hours and thus obtain monetary incentives. An analysis of one year dynamic price data by Wee (2011) shows that it is reasonable for users to shift their workloads from PAYG to dynamic price since it was on an average 52.3% cheaper; however, shifting the workload to cheaper spot periods provides only 3.7 % additional cost savings. Research in dynamic pricing has led to the adoption of dynamic pricing schemes by cloud providers. Spot pricing is one such dynamic pricing scheme introduced for computing resources in 2009 by Amazon Web Services.

3.1.2 Spot Pricing

Spot pricing enables users to bid for unused capacity, i.e. the capacity that remains with the cloud provider after fulfilling the on-demand and reserved instance demands. Instances are charged the Spot Price, which is set by the service provider and fluctuates periodically depending on the supply of and demand for Spot Instance capacity. Consider a bidder, who has a certain valuation for executing a task on a particular type of spot instance. In a spot pricing scheme, if the bid price exceeds the current spot price, the instance is allocated until either the user chooses to terminate or the vendor initiates the termination automatically if the spot price exceeds the bid price.

The spot market is like a uniform price auction of multiple homogeneous goods where each client bids for a single good which is the spot instance (Sowmya & Sundarraj, 2013). The provider chooses the top N bidders. The value of N varies based on the supply (unused capacity at hand) and cannot exceed the available capacity. The provider sets the uniform price to the lowest clearing bid. All winning bidders pay this price for the cloud services. Though the above works have studied static and dynamic pricing schemes in the context of cloud computing, none of them have considered behavioural biases. In the following section, we survey the literature in the domain of behavioural biases to contextualize our proposed research.

3.2 Loss Aversion and other Biases

Research on bidder behaviour started since the existence of auctions. One of the interesting aspects is to look at the various biases that can impact bidder behaviour. This section lists some of the common biases and particularly research done in the context of online auctions.

3.2.1 Biases in Bidder Behaviour

Deck et al have shown through experimental evidence that, an individual's willingness to take financial risks significantly affects behaviour; the effect is particularly greater when the task is framed as a financial decision (Deck, et al., 2010). For example, when a bidder is posed the question "If you do not want to lose XYZ you will have to raise your bids to \$500", the bidder is likely to increase the bid value (Ku, 2000). This bias in behaviour is commonly referred to as *framing effect*. According to Bramsen and Martin (2009), bidders may feel a *quasi-endowment effect* towards the object for which they are bidding. Bidders can get a feeling of ownership

of the auctioned item during an auction and behave as if they are real owners. Behavioural economists Ariely and Simonson (2003) claim that, a low starting price can draw more bidders and these bidders bid relatively low because of *anchoring effect* of the starting bid (reference price). In a recent study, Kuruzovich (2012) indicates that mental accounting can increase bidder valuation over time. Dholakia and Soltysinski (2001), provide evidence of *herd behaviour bias*: in online auctions, bidders would herd behind other bidders even when choices did not reveal private information. In this paper, we investigate the effect of *loss aversion* on bidder behaviour. Section 2.3 provides details on loss aversion.

3.2.2 Loss Aversion

The irrational behaviour of bidders could stem from *loss aversion* - the behavioural tendency of individuals to perceive losses as more substantial when compared with gains of the same objective magnitude. When making decisions, people directly compare potential losses and gains and often give more weight to the losses (Benartzi, 1995; Kliger & Levit, 2009; McGraw, et al., 2010). This larger weight given to negative outcomes is attributed to loss aversion, i.e., “losses loom larger than gains” (Lieberman, et al., 2005; Kahneman, et al., 1991). Kahneman & Tversky (1979) suggested that loss aversion be defined by $-U(-x) > U(x)$ for all $x > 0$. We can capture loss aversion using the following utility function:

$$U(x) = \begin{cases} u(x) & \text{if } x \geq 0 \\ \lambda u(x) & \text{if } x < 0 \end{cases}$$

where $\lambda > 1$ is the loss aversion coefficient, commonly known as the loss aversion index. Loss aversion has been used to explain many effects observed in the context of decision-making. In the context of online bidding, Dittrich et al (2008) claim that an actual loss will change bidding dispositions more than an equally large gain due to loss-averse behaviour.

Measuring loss aversion could have important implications for system designers. Researchers have established and observed qualitative support for loss aversion. Few studies have also performed quantitative estimations of loss aversions. Since loss aversion is a function of the utility for gains and utility for losses, to measure loss aversion both must be measured simultaneously. Research has indicated that until

recently, no clear method existed to measure loss aversion unless additional assumptions were imposed (Abdellaoui, et al., 2008).

4.0 Loss aversion in the context of bidding for Cloud services

Spot Instances enable users to bid for unused capacity. Instances are charged the Spot Price, which is set by the service provider and fluctuates periodically depending on the supply of and demand for Spot Instance capacity. Consider a bidder, say X, whose valuation for executing a task on a particular spot instance is \$1. In a spot pricing scheme, if the bid price exceeds the current spot price, the instance is allocated until either the user chooses to terminate upon task completion or the vendor initiates termination upon the spot price increasing above the bid price. In this case, from the spot price history data we list the following scenario:

Choice A: 99% chance of getting terminated before task completion if bid price = \$1

Choice B: 50% chance of getting terminated before task completion if bid price = \$2

Clearly X has to decide between the choices A and B. In both the cases, the spot may be allocated to the user if the bid price is higher than the current spot price and bidder X continues to hold the computing instance until the dynamically generated spot price goes above bidder X's original bid price. If the new spot price is above bidder X's bid price, it can result in X's current computing instance allocation to be abruptly withdrawn. Research has indicated that most bidders might choose option B in order to avoid losing their current spot allocation. This behaviour can be attributed to loss aversion (Kahneman, et al., 1990). In this paper, we intend to test the loss behaviour of bidders and its impact on bid decision. We test our hypothesis using a lab experiment discussed in Section 5.

4.1 Hypothesis

To validate the scenario discussed above, we raise the following hypothesis. Let A-PAYG indicate a bid price above the on-demand/ pay as you go price and B-PAYG indicate a bid price below the on-demand/ pay as you go price.

***H1:** The Loss aversion index for bidders who bid A-PAYG price is higher than the Loss aversion index of bidders who bid B-PAYG price.*

Here For the purpose of testing the hypothesis, we collect user's bids through a bidding experiment and measure the loss aversion of the participants.

5.0 Experiment

To elicit the impact of loss aversion on a cloud consumer's bidding behaviour we conduct a lab experiment to measure the WTA-WTP gap. The details and results of the experiment are discussed in the following sub-sections.

5.1 Design

In this experiment, we elicited the valuations of the participants using a market environment, wherein the subjects had to bid for computing instances that were limited in supply. We did not do perform practice rounds to avoid possible effects of learning. However, we ran two pilot rounds to ensure the flow and the sequence of the experiment are smooth. Based on the feedback received from the participants of the pilot experiment we revised the experiment, particularly the instructions and the post-experiment questionnaire.

5.2 Participants

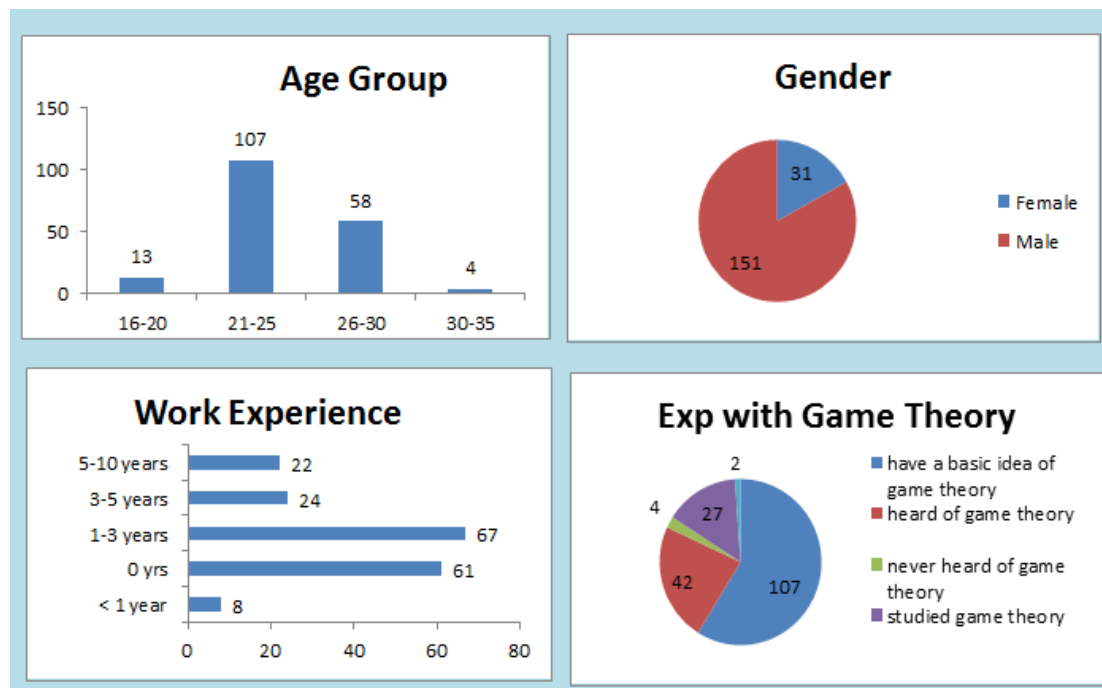


Figure 2: Participant Demographics

One hundred and eighty two students with Graduate and Undergraduate background participated in the experiment. Participation was voluntary and individual. Participants did not receive any payment for participation. We gave oral instructions to all participants. In addition, we also provided the instructions in print form and on

the bidding screen. The profile of participants is shown in Figure 2 and gives the grouping based on age, gender, work experience and participant's experience with game theory. We can observe from Figure 2 that most participants were between the age groups 21-30 and had no or very less work experience.

5.3 Procedure

The experimental conditions involved each of the participants placing bids for cloud spot instance once. A short briefing on how the Cloud spot market works was given. In addition, we gave instructions on paper along with spot price history data. Then, we asked to participants to place their bids on a virtual spot market designed for this experiment. We computed the results of the bidding and published it to the participants at the end of the bidding round. The next step involved calculating the loss aversion index.

5.3.1 Eliciting Loss Aversion using WTA-WTP method

The willingness-to-accept (WTA) and willingness to pay (WTP) method of eliciting loss aversion was established since 1980's. One of the earliest works involving an experiment to test the WTA-WTP gap was by Knetsch and Sinden (1984). Coursey et al (1987) through their experiments established the large disparity between WTA and WTP. Kahneman et al (1990) report several experiments where the measures of WTA exceeds measures of WTP. The gap between WTA and WTP has been interpreted as evidence for loss aversion in riskless choice (Tversky & Kahneman, 1991). Since then several researchers have used WTA-WTP gap to measure loss aversion. Gächter et al (2010) measure individual-level loss aversion in riskless choices in an endowment effect experiment by eliciting both WTA and WTP from about 360 subjects. List of other works could be found in the reviews of Horowitz and McConnell (2002) and Sayman and Öncüler (2005).

We adopt the WTA-WTP gap procedure to calculate the loss aversion index. The bids placed by the participants indicated their WTP. To elicit the WTA, the participants were given a post-experiment questionnaire. Here, they were asked to assume themselves as a cloud vendor and give a price at which they will be willing to accept to provide a cloud service. The participants were given instructions to assume the cloud service to be similar to the one they had bid for in the previous round. Using these two values, i.e., the WTA and WTP, we calculate the loss aversion index for

each participant which is a ratio of the corresponding WTA and WTP for that participant.

5.4 Results

Group	N	Mean	Std. Deviation	Std. Error Mean
A-PAYG	49	2.1833	1.45134	.20733
B-PAYG	133	1.7268	1.08833	.09437

Table 1: Summary Statistics

Table 1 gives the summary statistics. We observed that about one-third of the subjects belong to the A-PAYG group. We use the Levene Test for testing equality of variance (see Table 2). It tests the null hypothesis that the population variances are equal. Since the resulting p-value of Levene's test is greater than the critical value of 0.05. A value greater than .05 means that the variability in the two conditions is about the same and is not significantly different. Next, we perform the t-test for equality of means. The results are summarized in Table 3. The results indicate that the loss aversion index for above PAYG bidders vs below PAYG bidders is statistically different. The average Loss aversion index is higher for above-PAYG bidders (2.18) than the below-PAYG bidders (1.72).

	Levene's Test for Equality of Variances	
	F	Sig.
LAI	3.029	.084

Table 2: Test for Equality of Variance

t	df	Sig.	Mean Difference	Std. Error Difference
2.284	180	.024	.45642	.19986

Table 3: T-test for equality of means

6.0 Implications

6.1 Social implications for Cloud Consumers

As can be observed from the results of the experiment, loss-averse users tend to bid higher. This could have a ripple effect on other bidders in the system. Although, one could view the cloud spot market as an economic setup it is also a social aggregate. The actions of a bidder(s) in the system could have an impact on the other bidders in the system since all these individual bidders comprise a social aggregate. The spot price is a function of supply and demand (see section 3.1.2). Loss averse users, who perceive “not winning a computing instance” as a loss, would start bidding higher and this in turn could lead to an increase in the overall spot price. Presence of such loss averse users could be disadvantageous to the other users in the system as they also face the increased spot price. This type of behaviour in a system comprising a social aggregate could be due to the collective action problem. Thomas Schelling talks about the Collective action problem, in his famous book “Micromotives and Macrobehaviour”, where he explores the relation between the behavioural characteristics of the individuals who comprise some social aggregate (Schelling, 1978). Hence, the behavioural irregularities exhibited by certain users in a system could have an impact on the other users in those systems.

Agents interested in addressing the above social situation could look at alternatives to overcome loss aversion. Kahneman and Lovallo (1993) propose the power of aggregation method to overcome loss aversion. An application of this method can be found in Milkman et al (2012) where they propose policy bundling to overcome loss aversion as a method to improve legislative outcomes.

6.2 Economic implications for Cloud Providers

Psychological factors and behavioural regularities may have important implications on operational problems such as pricing (Su, 2009) . In an environment that comprises of bidders with various behavioural biases, the service provider can benefit by using a price update algorithm that computes the spot prices in a way that exploits the behavioural biases of the bidders. For example, by learning the ratio of users with a certain type of bias such as loss aversion, in the system, the service provider can alter the spot price to accommodate the irrational behaviour of this proportion of bidders and thereby increase provider’s revenues.

7.0 Conclusion

Although large WTA-WTP ratios are well documented and also evidenced in our experiment, the findings do not seem to have had much effect on either economic models or discussions of pricing design for online computing resources. Current dynamic pricing schemes for the cloud are based on demand and supply only. As part of future work, we intend to develop dynamic pricing schemes which are based on factors that capture the behavioural biases of the users. Bidders could also possess other behavioural biases. In this paper, we consider loss aversion, however other biases such as anchoring (Strack & Mussweiler, 1997), mental accounting (Thaler, 1985), herding (Tversky & Kahneman, 1974) need to be studied in the context of our current problem statement. Furthermore, the bid pricing and the dynamic pricing algorithms can be optimized by learning algorithms developed to detect and adapt based on the consumer's biases.

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