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ARTICLE INFO	Kuei-Yuan Cheng, Yao-Hsien Lee and Mei-Yu Lee (2016). Price competition between shrink-wrap software and cloud service firms under a stochastic model. <i>Problems and Perspectives in Management</i> , 14(2-2), 272-276. doi: 10.21511/ppm.14(2-2).2016.02
DOI	http://dx.doi.org/10.21511/ppm.14(2-2).2016.02
RELEASED ON	Monday, 13 June 2016
JOURNAL	"Problems and Perspectives in Management"
FOUNDER	LLC "Consulting Publishing Company "Business Perspectives"



NUMBER OF REFERENCES

0



NUMBER OF FIGURES

0



NUMBER OF TABLES

0

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Price competition between shrink-wrap software and cloud service firms under a stochastic model

Abstract

The authors establish a stochastic model of the price competition between shrink-wrap software and cloud service firms. They show that cloud service firms earn higher profits, but face higher risks compared to shrink-wrap software firms. In order to attract customers and earn higher profits, the authors obtain the result that shrink-wrap software firms need to focus on pricing strategies, by contrast, cloud service firms need to focus on quantity strategies.

Keywords: stochastic process, price competition, cloud service, shrink-wrap software, computer simulation.

JEL Classification: D81, C73, C63, L11, L86.

Introduction

This study uses computer simulation to generate a price competition model for shrink-wrap software and cloud service firms. Cloud service firms produce services on the Internet, where market demand is more elastic than shrink-wrap software demand. After Hotelling (1929) first established a horizontal differentiation model wherein consumers have different tastes assumed by a uniform distribution, the distribution assumption has been used to represent the spread of tastes and is extended to represent the quantity demanded of firms (Tirole, 1992). In the literature on software competition, one of the methodologies comes from the assumption of externality (Shy, 2001), while the other comes from software delivery and maintenance services (McAfee et al., 1989; Fan et al., 2009; Lee et al., 2012). The probability or distribution assumptions are always viewed as assisting the theoretical analysis (Jellal et al., 2005; Sandmo, 1971; Klemperer and Meyer, 1986; Narayanan et al., 2005).

However, the above papers use the distributions or stochastic processes without considering higher moments to grab entirely random properties, which come not only from subscribers, but also from an unpredictable economic environment. Moreover, to address an unpredictable economic environment for software price competition, they did not consider that uncertain demand or supply should be assumed by random variables with different distributions and the parameters should also be assumed by random variables.

We show that, although the M/M/1 queue is an important instrument for highlighting the network properties of cloud services, as seen in the discussion by Fan et al. (2009), it may come at the interaction

between random parameters and the randomization of the M/M/1 queue. We argue that a static model derived from the M/M/1 queue undermines the stochastic incentives in a price competition between shrink-wrap software and cloud service firms. In our simulation, the assumptions of random parameters intend to determine the pattern of the stochastic optimum. It is important to note that we do not doubt that cloud service firms, such as Amazon.com Inc., are more likely to understand the market scale for cloud services or shrink-wrap software through big data analysis. In this case, the random parameters are inconsistent with constant parameters leading to static conclusions in the literature. Subsequently, the addition of random parameters to optimal formulas discloses information that static models are unable to provide.

The mechanism we highlight is related to the literature on game theory (Lee, 2014; Lee and Lee, 2014, 2015; Lin and Lee, 2015) in which two players tend to maximize their payoffs from two randomly strategic payoffs rather than from two constant payoffs. However, our analysis suggests that the randomization of strategic payoffs should extend to the discussion of a stochastic price competition, wherein firms might be faced with uncertainty of demand or cost. The scope of our random price competition goes well beyond the settings of the previous literature. Therefore, our paper can address the case where firms have information about demand and cost, but may be hit by occasional events that fluctuate their prices, outputs, and profits.

This study proceeds as follows. In Section 1, we set up the model and describe the simulation procedures. In Section 2, we explore the simulation results divided into three parts: outputs and prices, costs of cloud service firms, and the profits of the two firms. Final section provides conclusions.

1. Model and simulation procedures

1.1. Model setting. The model follows Fan et al. (2009) and considers two firms. One firm is a shrink-wrap software firm (firm 1) and the other is a cloud service firm (firm 2). Consumers are

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uniformly distributed between 0 and “a,” where “a” is a parameter guaranteeing the taste range of consumers who have the following utility:

$$U = \begin{cases} V - P_1 - \theta c_1, & \text{if consumer uses SWS} \\ V - P_2 - \theta c_2, & \text{if consumer uses CS} \end{cases}$$

where c_i , $i = 1, 2$ is the disutility cost of consumers who buy shrink-wrap software and cloud services. Thus, the indifferent consumer is located at $\theta^* = (P_2 - P_1) / (c_1 - c_2)$. As the market is uncovered, the indifferent consumer on the right side is $\theta^{**} = (V - P_2) / c_2$.

The profit function for shrink-wrap software firms is $\pi_1 = P_1 D_1$ and for cloud service firms is $\pi_2 = P_2 D_2 - \gamma_0 - \gamma_1 \mu$, s.t. $1 / (\mu - \lambda) \leq d$, where D_1 is the demand function of firm 1, D_2 is the demand function of firm 2, and d is the guaranteed average delay time.

Thus, the optimal profits are

$$\pi_1(\lambda, c_2, k, \gamma_1, d, \gamma_0) = P_1(\lambda, c_2, k, \gamma_1, d, \gamma_0) D_1(\lambda, c_2, k, \gamma_1, d, \gamma_0),$$

$$\pi_2(\lambda, c_2, k, \gamma_1, d, \gamma_0) = P_2(\lambda, c_2, k, \gamma_1, d, \gamma_0) D_2(\lambda, c_2, k, \gamma_1, d, \gamma_0) - \gamma_0 - \gamma_1 \mu$$

1.2. Simulation setting and procedure. We use a desktop computer with Windows 7 operating system to run the C++ program, the probability distribution simulator. First, we obtain a random number, labeled RND, from the cumulative density function of a specific probability distribution, $F_x(x) = P(X \leq x)$. The cumulative density function method and random number method can obtain the inverse function of the cumulative density function with which to determine the values of the random variable: $x = F_x^{-1}(\text{RND})$. The random variable can be viewed as a data set, $\{X_1, X_2, \dots, X_n\}$. By increasing the data size, the discrete data set becomes a continuous set through the law of large numbers. Meanwhile, a frequency table can be constructed using the data set. The probability function and the distribution graph and corresponding coefficients may also be obtained from the frequency table. Thus, the sample frequency table closely resembles the specific probability distribution, as do

The constraint of firm 2 represents that $1 / (\mu - \lambda)$ is the average delay time in which λ is the mean of Poisson process and $\lambda = kD_2$, or the average usage of all subscribers, and μ is the processing rate represented as IT capacity and formed as $\mu = kD_2 + 1 / d$. The average delay time is less than the average guaranteed delay time of the cloud service d . Thus, the firm 2 has total cost of $\gamma_0 - \gamma_1 \mu$, where γ_0 is the fixed cost and γ_1 is the marginal cost for capacity. The relation between optimal prices is $P_2 = 2P_1$. Without loss of generalization, set $c_1 = 3c_2$. Due to the conditions $D_2 = \lambda/k$ and $D_2 = \theta^{**} - D_1$, the numerous simulation indicates that $D_2 \in [0, 10]$. Consider, therefore, $\theta^{**} = 10$, then, obtain $V = 2P_1 + 10 c_2$, which is substituted into the optimal price formula to obtain the optimal prices as

$$P_1 = \frac{20c_2 + 3\gamma_1 k}{7}, P_2 = \frac{40c_2 + 6\gamma_1 k}{7}$$

the coefficients of the data set. The sample frequency table is close to the special probability distribution, and the coefficient of the data set is close to the coefficient of the special probability distribution, based on 216 values. The coefficient result error is approximately 1/1000 to 1/10000. Therefore, the model can be simulated through the following steps:

Step 1. The distributions of the model parameters are set in Table 1¹.

In Step 1, the parameters of optimal prices, outputs, and profits are set as follows: (1) the exponential distribution with $\lambda = 4$ and $c = 2$, thereby replacing the Poisson process; (2) the guaranteed delay time, d , is an exponential distribution with $\lambda = 3$ and $c = 5$; (3) the disutility cost of consumers who buy cloud service, c_2 , the marginal cost γ_1 , and the fixed cost γ_0 , are uniform distributions with different parameters; and (4) the average usage rate k is a semi-circle distribution (Fan et al., 2009).

Table 1. Distributions of parameters

Variable	X1	X2	X3	X4	X5	X6
Parameter	λ	c_2	k	γ_1	d	γ_0
Distribution	Exponential (4,2)	U (0,5)	Semi-circle (0.3,0.1)	U (0,0.1)	Exponential (3,5)	U (1,3)

After setting the distributions in Step 1, the computer, then, calculates the optimal outputs, parameter combinations, prices, costs, and profit formula using a step-by-step process.

Step 2. Calculate D_2 , $1/d$, $\gamma_1 k$, $20c_2/7$, and $1/c_2$.

Step 3. Calculate $3\gamma_1 k/7$, γ_1/d , $1/2d$, $\gamma_1 k D_2$, and $k D_2$.

Step 4. Calculate P_1 , μ , and $\gamma_0 + \gamma_1/d$.

Step 5. Calculate $P_1 D_2$ and D_1 .

Step 6. Calculate the profits of firm 1 and firm 2.

2. Results

After the probability distribution transformation steps, the randomization of exogenous variables interacts in the model. Our results highlight the

¹ The distributions that this study uses in Table 1 can be referenced at <http://goo.gl/e6urC0>.

distribution of the optimal outputs, prices, profits, and costs of firm 2 in Tables 1, 2, and 3. The simulation outcomes indicate that the distribution effects of the parameter differences are significant when transforming the probability distributions for forming optimal prices, outputs, and profits.

Result 1. Firm 1 has a more stable and smaller consumer base compared to firm 2; this is shown through expected values and standard deviations.

Result 1 is supported by Table 2, which indicates the probability distributions and coefficients of the optimal price and outputs. The output of firm 1 is spread over a smaller range from 1.4286 to 1.4302, compared to the range of firm 2, which is spread over the range 5.0101 to 9.9907. Shrink-wrap software consumers are individuals who prefer not to shift to another software. Therefore, firm 1 loses

a number of consumers when their dislikes slightly increase. Conversely, consumers have a high tolerance for cloud services shown by a wild range where they are located from 5.0101. An unpredicted environment leads to a sum of outputs that are not equal to 10, but that may be limited from 6.44 to 11.42. The optimal output variance of shrink-wrap software is nearly 1.4290, and the optimal output of cloud services fluctuates significantly.

The relationship between optimal prices is $P_2 = 2P_1$. Therefore, we show the density function of P_1 in the right-hand side of Table 2. Surprisingly, the optimal price of firm 1 is a uniform distribution with a mean of 21.4348 and variance of 17.0097 and ranges from 14.3123 to 28.5615. Therefore, the price of firm 1 is drawn randomly with probability 0.0703 and is not always fixed at a specific price.

Table 2. Demands of firm 1 and firm 2 and the optimal price of firm 1

D2		D1		P1	
(A)		(B)		(C)	
Mathematical mean:	7.39119	Mathematical mean:	1.42903	Mathematical mean:	21.43477
Variance:	1.48489	Variance:	0.00000	Variance:	17.00974
S.D.:	1.21856	S.D.:	0.00029	S.D.:	4.12429
Skewed coef.:	0.25148	Skewed coef.:	0.55809	Skewed coef.:	0.00014
Kurtosis coef.:	2.09984	Kurtosis coef.:	2.81707	Kurtosis coef.:	1.79978
MAD:	1.02778	MAD:	0.00024	MAD:	3.57185
Range:	4.99919	Range:	0.00170	Range:	14.30214
Median:	7.27822	Median:	1.42900	Median:	21.43420

In this model, only the serving cloud service generates an IT cost for firm 2. Thus, the next result focuses on the optimal processing rate and the cost structure of firm 2's IT capacity.

Result 2. Optimal processing rate of usage has a similar shifted-exponential distribution.

Result 2 is supported by Table 3, which indicates the probability distributions and coefficients of the optimal processing rates and cost structure of IT capacity.

Table 3-A represents the plot and coefficients of IT capacity – the optimal processing rate. The distribution of the optimal processing rate is similar to a shifted-exponential distribution, although the processing rate indicates a relatively positively

skewed and more centralized distribution. This result is attributable to their different skewness and kurtosis coefficients, but shows the same expected values, variances, and standard deviations when the shifted-exponential distribution's parameters are $\lambda = 4.8326$ and $c = 2.1977$, respectively. By contract, if the figure was a shifted-exponential distribution, then, the highest probability is λ and the distribution starts at c ; hence, the expected value is 2.3550 and the variance is 0.0603. These values are different from the coefficients in Table 3-A. Therefore, the distribution of IT capacity is similar to (but not the same as) a shifted-exponential distribution. This distribution result implies that the cloud service firm faces unstable subscribers, so that the firms need to pay more attention on consumers' emotion feedbacks.

Table 3. Cost structure of firm 2

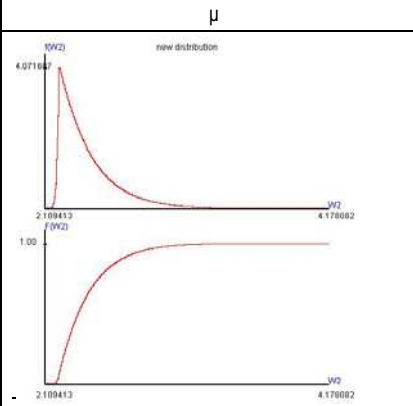
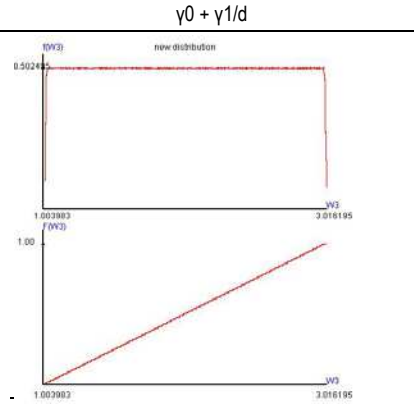
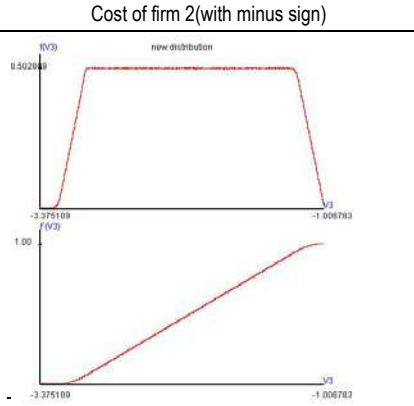
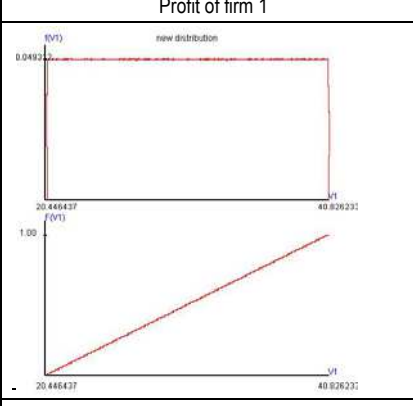
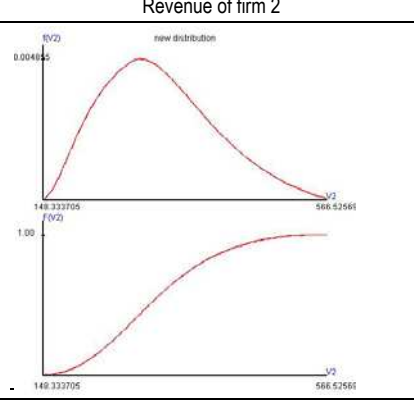
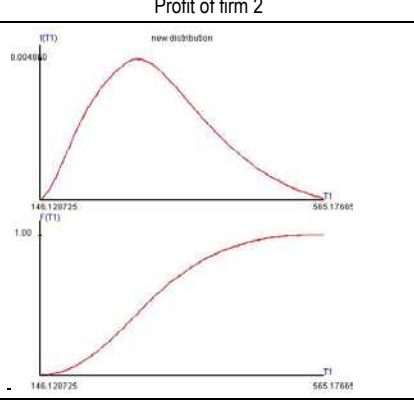
μ	$\gamma_0 + \gamma_1/d$	Cost of firm 2(with minus sign)
 <p>(A)</p>	 <p>(B)</p>	 <p>(C)</p>
Mathematical mean: 2.40460 Variance: 0.04282 S.D.: 0.20692 Skewed coef.: 1.71662 Kurtosis coef.: 6.88631 Range: 2.07636 Median: 2.34295	Mathematical mean: 2.00946 Variance: 0.33339 S.D.: 0.57740 Skewed coef.: 0.00009 Kurtosis coef.: 1.80004 Range: 2.01969 Median: 2.00948	Mathematical mean: -2.12139 Variance: 0.33822 S.D.: 0.58157 Skewed coef.: -0.00009 Kurtosis coef.: 1.83394 Range: 2.37713 Median: -2.12152

Table 3-B represents part of the cost functions, excluding demand D_2 . Here, $\gamma_0 + \gamma_1 / d$ denoted as the constant cost of IT capacity, which is distributed around 2.009, occurs with probability 0.502 and has a variance of 0.333. The constant cost of IT capacity shows a uniform distribution with a lower bound of 1.004 and a higher bound of 3.016. Table 3-C represents the entire cost of IT capacity, which is distributed around -2.121 , with variance 0.338 and is shaped as a trapezoid.

Given the cost of demand, the density function in Table 3-C obtains a higher average absolute value and range than the density function in Table 3-B. The errors here are less than 0.001 in terms of their highest probabilities, variances, standard deviation, skewness, and kurtosis coefficients. This result implies that the cost of demand significantly affects the averages, ranges, and medians. If the moments are higher, then, the coefficients in Tables 3-B and 3-C show relative error equal to 0.001.

Table 4. Profits of firm 1 and firm 2

Profit of firm 1	Revenue of firm 2	Profit of firm 2
 <p>(A)</p>	 <p>(B)</p>	 <p>(C)</p>
Mathematical mean: 30.63126 Variance: 34.71012 S.D.: 5.89153 Skewed coef.: 0.00008 Kurtosis coef.: 1.80000 Range: 20.45556 Median: 30.63113	Mathematical mean: 316.85703 Variance: 6545.10582 S.D.: 80.90183 Skewed coef.: 0.43772 Kurtosis coef.: 2.66216 Range: 428.14894 Median: 308.57480	Mathematical mean: 314.73413 Variance: 6543.96971 S.D.: 80.89481 Skewed coef.: 0.43739 Kurtosis coef.: 2.66175 Range: 429.02526 Median: 306.45812

The final result shifts the focus to the optimal profits of firm 1 and 2 in the stochastic environment.

Result 3. The optimal profit of firm 2 is higher than that of firm 1.

Result 3 is supported by Table 4, which shows the probability distributions and coefficients of the revenue distribution of firm 2 and the profit distributions of firms 1 and 2. Firm 1's profit has a

uniform distribution ranging between 20.4464 and 40.8262. Given that this profit consists of price and demand quantities, it is dominated by the distribution of price P_1 and not its demand D_1 . This result implies that the price decision is the main source of profits for the shrink-wrap software firm. If the shrink-wrap software firm seeks higher profits, setting a higher price for its products is the preferred option by which to create new customers.

The revenue and profit distributions of firm 2 have the same distribution shape, as seen through the standard deviation, skewness, and kurtosis coefficients ($|80.90183 - 80.89481| < 0.001$, $|0.43772 - 0.43739| < 0.0001$, $|2.66216 - 2.66175| < 0.0005$). The profit distribution here is, primarily, dominated by revenue, but not cost. Thus, cloud service firms must be increasing their marketing efforts to attract more customers, who have weaker loyalty than those who demand cloud services in Table 2-A. Given the model setting, cloud service firms only focus on operating a smooth network gateway at all times to maintain the cost of IT capacity.

When compared to two firms, the cloud service firm also faces relatively higher risk than the shrink-wrap software firm depending on the range of customers for cloud services. But the cloud service firm can earn higher risky profits, these profits are more than 10 times that for shrink-wrap software firms. This implies that the cloud service firm should build a strategy of tolerable queue time to provide satisfactory cloud services for consumers.

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Conclusion

Allowing for the randomization of the M/M/1, queue and parameter create a real stochastic model of price competition. We have simulated and demonstrated that optimal prices have a uniform distribution. With regard to the optimal outputs, the output for shrink-wrap software is small and stable. By contrast, a concave shape of the output distribution for cloud services widespread a half range of the distributed assumption of consumers. Although our model limits the shrink-wrap software firm with no cost, the simulated profits evidence that the cloud service firm might earn higher profits and face higher risks than the shrink-wrap software firm. Our results also demonstrate that few customers buy shrink-wrap software, whereas most of them buy cloud service and have higher elasticity of cloud service.

Furthermore, we have demonstrated that the optimal price and profits of shrink-wrap firms have a uniform distribution, and that the optimal output, revenue, and profits of cloud service firms have almost the same distribution. This finding explicitly highlights the concept that with regard to shrink-wrap software, the price distribution dominates profit distribution. For cloud services, the output distribution dominates revenue distribution, enabling the profit distribution to be similar to that of revenue. These results imply that cloud service firms should implement marketing strategies to keep consumers using cloud services, so that they can earn more profits.