Analysing a Segmentation Pricing for ERP Systems under Diffusion Patterns

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RÉSUMÉ / ABSTRACT

In a highly uncertain and dynamic industrial business network, Enterprise Resource Planning (ERP) systems vendors face great challenges to enhance their market position and maximize their profit. Being able to simultaneously determine the right price for an ERP system and to anticipate the diffusion of the system in an industrial sector is a complex task. In this paper, we evaluate the options of developing a price discrimination policy for ERP systems in a business sector governed by a diffusion pattern influenced by the network position of each customer. Based on a real scenario in the automotive industry, the proposed strategy is operationalized through discounts and optimized through a simulation-based model coupled with design of experiment and response surface techniques. Our experimental findings suggest that a segmentation pricing strategy are likely to increase total revenues in network with low initial adoption rates and that price discounts should be adapted according to adoption rates in order to maximize total revenues.

Mots clés / Key words:

- ERP
- Pricing
- Diffusion
- Network
- Centrality
- Exposure
- Simulation
- Optimization.
1. INTRODUCTION

Enterprise Resource Planning (ERP) systems are configurable commercial software systems designed to facilitate business process integration by replacing disparate legacy systems across business organizations with synchronized suites of enterprise-wide applications (Markus and Tanis, 2000). ERP systems have now been adopted by most Fortune 500 firms for which SAP and Oracle, the dominant ERP providers, share respectively 42% and 25% of the market of ERP licenses as of 2006 (Jacobson et al, 2007). Consequently, it is not surprising to note that most ERP providers try to adapt their business and sales strategies to enhance their market position in the middle market to continue their growth.

In recent years, the power balance between software vendors and customers has profoundly changed due to a confluence of economic, market, and technological factors (Hamerman, 2010). These changing dynamics are having a significant impact on how software is priced (Wang, 2009b). Software prices are under pressure from constrained IT budgets and customer perceptions that software is overpriced. Software vendor revenues are also shifting from licenses fees to maintenance fees (Wang, 2009a). From a strategy perspective, ERP providers need more than ever to react properly to market fluctuation as the perceived value of their ERP solution continuously changes.

While the reason to adopt an ERP is mostly associated with the relative advantage it provides (Ranganathan and Brown, 2006), an ERP system perceived value is influenced by the extent this technology diffuses in industries. First, ERP systems are a complex configurable technology which requires important investments to adapt to a specific firm. Therefore, it is not possible for a customer to try and experience the technology before its adoption. Also, not all ERP systems are equal: industrial practices supported by a specific ERP system are the results of the adaptation to different industrial norms. Therefore, the larger the installed base in an industry, the more value the ERP system has for new adopters as it requires less customization to support the industry’s best practices. In other words, the ERP systems’ perceived value often depends on the number of adopters within an industry segment. This economic phenomenon, called network externality, emerges when the value of goods is directly linked to the installed base of the product. The greater the critical mass of users of a certain network, the more value its product will have for the customers. Earlier work has demonstrated evidence of this network effect in the ERP software industry (Pellerin et al, 2007).

While ERP systems have been studied extensively over the last decade from a diffusion or adoption point of view, only few researchers have studied the marketing issues encountered in this market. As such, researches related to ERP system pricing have been rather sparse. Determining the right price and anticipating the adoption rate of an ERP product is however a very complex task.

Based on recent contributions where we proposed a quantitative model for predicting ERP diffusion (St-Georges et al. 2008), we intend in this paper to investigate the benefit of adopting a segmentation pricing strategy in a business network governed by diffusion patterns. The remainder of the paper is organized as follows. Section 2 presents a literature review on quantitative diffusion models and on software pricing strategies. The proposed segmentation pricing strategy is then exposed in Section 3. Section 4 presents the simulation-based...
optimization approach used to test the proposed strategy and a discussion of the experimental results obtained is reported in Section 5. The paper concludes in Section 6 by underlining our contribution and future research activities in this area.

2. LITERATURE REVIEW

Pricing takes a central role in the strategy of most companies as it is an effective tool to maximize revenues (Karpowicz and Szajowski, 2007; Lehmann and Buxmann, 2009). However, the pricing strategy is not an easy one to determine in the software industry as it is subject to economic rules fundamentally different than other industries (Lehmann and Buxmann, 2009). Traditional pricing concepts such as margins and mark-ups cannot be easily applied. Software products require huge investments for development but once developed, the supplementary costs are generally not prevalent (Arthur, 1996). Compared to other types of software, ERP systems have a very long sales cycle which generally leads to a substantial cost of selling the software. Still, this sales cost is somewhat negligible compared to the development cost of the application. As such, software products, especially ERP system, cannot be priced the same way as a regular consumption goods because of their low marginal cost.

While many pricing models and strategies have been proposed for the software industry, there is no universal pricing model for software providers (Bontis and Chung, 2000) and pricing models may consist of several elements (Lehmann and Buxmann, 2009). One pricing model largely used in the software industry is the price discrimination strategy. The basic idea of price discrimination is to offer the same product to every customer at a different price. According to Pigou and Aslanbeigui (2002) there are three basic forms of price discrimination, called degrees. The first degree of price discrimination is based on the fact that every customer will be offered a price corresponding to his willingness to pay. This form of discrimination is less important in the software industry since the detailed knowledge of every customer’s willingness to pay is difficult to obtain or evaluate (Lehmann and Buxmann, 2009). The second degree is characterized by the principle of self-determination. Every customer has to decide between all the alternatives that are proposed. The second degree can be adapted in three different approaches in the software industry, which are windowing, versioning and bundling (Linde, 2009). The third degree of price discrimination is based on market segmentation where each customer can receive a different price offer depending on its allocated group. In market segmentation strategies, targeted groups and related prices are usually defined based on different parameters and market attributes such as total sales value or quantity. While useful in the retail business, this segmentation mechanism may be difficult to apply in the software market.

As discussed earlier, diffusion of ERP system is not influenced solely by software pricing. The ERP software industry benefits of network effects, which has an impact on the perceived value by adopters. Consequently, the current ERP adopters influenced the decision of future adopters, and not just simply the price of the application. Many authors suggest that the adoption process of ERP systems is in part influenced by sources external to the organization. Tarafdar and Roy (2003) found that firms consider external sources of information when adopting an ERP. Benders et al. (2006) suggest that firms adopting an ERP are likely to imitate the decision of their peers to reduce the uncertainty related to the technological decision. Ugrin (2009) finds that the mimicry is likely to be more important when firms have not yet adopted an ERP, when benefits to adopt
difficult to quantify and when the ERP is expected to have an organizational impact across the supply chain.

Building on the facts that ERP are prone to network externalities and that ERP adopters are likely to be influenced by external sources when making their decision, several authors are building on models of diffusion of innovation in networks to better understand the propagation of this technology within an industry. Using social network theory, this literature posits that individuals adopt innovations based on their direct relations with others in their social system (Valente, 1995). Pellerin et al. (2007) find significant correlation between the IT decisions of firms sharing board members. Millaire et al. (2009) suggest that the strength of the external partners influence may vary along the diffusion process. Using a longitudinal network of firms related by various types of external links, they find that the overall external influence of neighbour firms appears to be more important in early stages of the diffusion process. These results also suggest that firm with high value of centrality and betweenness, two common measures used to evaluate the network position of firm, play a major role in the diffusion process of ERP systems. An entity with high degree centrality, which is simply calculated by the number of direct relationships that an entity has with its business partners, is generally an active player in the network by acting as a connector or hub in the network. Similarly, betweenness values can be used to measure a firm's position within a network in terms of its ability to make connections to other pairs or groups in a network.

Based on these recent results, we proposed a price discrimination mechanism which includes price discounts according to a firm’s network position. The proposed ERP diffusion model and pricing strategy are presented in the following section.

3. THE PROPOSED DIFFUSION AND PRICING APPROACH

In order to predict the diffusion of an ERP system with respect to the network structure, we proposed a decisional model which takes into account the network structure of a market (St-Georges et al., 2008). This approach allowed us to describe ERP systems diffusion in industrial networks, and keep track of periodical development of the diffusion phenomenon for each enterprise within the network.

Three hypotheses have been set. First, the model assumes that the decision to adopt is influenced by the previous decisions of other firms in an industry; when adopting, firms considered the behaviour of the nodes they are connected to. The second hypothesis relates to an irreversible process; the large investment required to implement this technology create a strongly inertia and very few adopter are likely to switch to another technology once they have adopted. This means that an enterprise that adopted a technology will remain an adopter until the end of the simulation and will continue to influence his neighbourhood as well. Finally, the model uses a binary decisional process where only one ERP system can be selected by a company. The hypothesis well reflects the case of a majority of enterprises that decides to adopt a unique and complete ERP suite in order to simplify the communication between the systems as well as their maintenance.
In order to analyze the diffusion phenomenon, we first developed a decision model of one ERP system available to the network based on the hypothesis stated previously. The probability of adoption is expressed as follows:

\[
P(\lambda_i = 1|\lambda_{i(t-1)} = 1) = P(V_i > C_i | \lambda_{i(t-1)} = 0)
\]

subject to:

\[
\sum_{t} \lambda_i \leq 1
\]

\[
V_i = a + \omega_i \times Y_i \times b
\]

where:

- \(t\): time period
- \(i\): firm number
- \(\lambda_i\): firm status at time \(t\) (0 = non adoption state, 1 adoption state)
- \(V_i\): ERP systems’ value for firm \(i\) at time \(t\)
- \(a\): value of an ERP system for all the firms (the perceived benefits)
- \(b\): network exposure constant \((\omega_i Y_i)\)
- \(\omega_i\): proximity vector of node \(i\)
- \(Y_i\): binary adoption vector at time \(t\)
- \(C_i\): price of the system at time \(t\)

The firm status is a function of the system’s value given by the firm with respect to the system’s cost. The system’s value varies with respect to the enterprise’s environment as it is a function of the exposition of the system in the network. The more an enterprise is surrounded by adopters, the more its value increases.

Note that the total cost of the ERP system depends partially on the software price. In this paper, we consider that the total cost of adopting an ERP system is equal to a constant (i.e., implementation cost) plus the software price (license fees). We propose to operationalize the pricing segmentation strategy via price discounts calculated based on a firm’s value of centrality (number of in and out degree) and betweenness (vertex within a graph) (Wasserman, 1994). This model is built upon the assumption that the more a firm has the potential of influencing others due to its strategic network position in terms of centrality or betweenness, the more discount it should get in order to create the conditions for an early adoption. More precisely, Equation (2) computes the ERP segmentation discounted price by subtracting the two discount values to the ERP base price. Both discount values are scaled through two decision variables \((\alpha\) and \(\gamma))\), which need to be determined in order to maximize total revenue.
\[ P = P_b \left( \frac{CENT_i}{CENT_{\text{max}}} \alpha + \frac{BET_i}{BET_{\text{max}}} \gamma \right) \times P_b \] (2)

subject as:

\[
\begin{align*}
\alpha & \leq [0, LIM_1] \\
\gamma & \leq [0, LIM_2] \\
0 & \leq LIM \leq 1
\end{align*}
\]

where:

- \( P \): ERP discounted price
- \( P_b \): ERP base price
- \( CENT_i \): centrality of firm \( i \)
- \( CENT_{\text{max}} \): maximum value of centrality for all firms within the network
- \( \alpha \): centrality discount
- \( BET_i \): betweenness of firm \( i \)
- \( BET_{\text{max}} \): maximum value of betweenness for all firms within the network
- \( \gamma \): betweenness discount
- \( LIM_1 \) and \( LIM_2 \): maximum discount limits

To make the strategy practical, one should consider the fact that parameters are function of the market situation at the beginning of the horizon. Thus, the problem is not only evaluating a segmentation strategy in an industrial network governed by an ERP diffusion model, but should be observed as an optimization problem over a finite horizon.

The objective of the following sections is to present a simulation-based optimization approach aiming to find the best values of the segmentation pricing strategy parameters \( \alpha \) and \( \gamma \) which maximize the total revenue in an ERP industrial network. The case considered is based on real adoption data in the North American automotive industry.

4. EXPERIMENTAL RESULTS

4.1. Approach

In order to bring an approach which could be applied to represent and predict the diffusion phenomena in a given network, the descriptive capacities of discrete/continuous event simulation models were combined with analytical models, design of experiment and a response surface methodology. A block diagram of the proposed approach is depicted in Figure 1 and can be summarized as follow:
Step 1: The first step consists in developing the quantitative models to express the ERP diffusion phenomena and the segmentation pricing strategy. Those models were presented in Section 3 and will govern the following steps.

Step 2: We then developed a simulation model to describe the dynamics of the ERP network diffusion. The simulation model is governed by the diffusion model (Equation 1) and uses the segmentation pricing strategy parameterized by the 2 parameters $\alpha$ and $\gamma$ defined previously (Equation 2). Those factors are considered as input of the simulation model. The calculated total revenue and the number of adopters at each period are defined as its output. Our model was developed using Visual SLAM simulation language (Pritsker and O’Reilly, 1999). Note that the simulation was validated with real historical data in order to confirm its validity.

Step 3: We determine, using an experimental design approach (Montgomery, 2001), the input factors or interactions, which have significant effects on the output.

Step 4: Finally, the significant factors or interactions are considered as input of a response surface methodology, to fit the relationship between the total revenue and the input factors. From this estimated relation, the optimal values of the input factors, called $\alpha^*$ and $\gamma^*$ are determined.
The objectives of this approach are: (i) to determine whether the input parameters $\alpha$ and $\gamma$ affect the response (i.e., total revenue), (ii) to estimate the relationship between the total revenue and significant factors, and finally, (iii) to compute the optimal values of the estimated factors. Note that the total revenue is a function of the number of ERP adopters in a given period and includes the maintenance revenue for subsequent periods.

Within this approach, the simulation model, presented in Figure 2, allows to reproduce the continuous evolution of an enterprise status with respect to the adoption of an ERP system for a fixed number of periods. The status change of a firm (i.e., adoption vs. non-adoption) is governed by the diffusion model (Equation 1). This change is a function of the ERP’s value given by the enterprise with respect to the ERP’s cost which is partially influenced by the licence price. As discussed previously, the price of the ERP licence at time $t$ is based on a standard price and two discounts which values depend on the centrality and the betweenness of a given firm in the network, as governed by Equation 2.

![Figure 2 – Simulation model](image-url)
4.2. Experimentations and Discussion

Our experiments were conducted using an industrial network composed of the top fifty-four (54) firms in the North American automotive industry. Real and public data were used in this study with regards to the dynamic evolution of the networks (i.e., connections between firms). Our main objective consisted in running the proposed optimization approach to measure the gain on the revenue function of the market status (i.e. initial adopter rate) if a segmentation pricing model is adopted.

The experimental design is concerned with (i) selecting a set of input variables (i.e., factors $\alpha$ and $\gamma$) for the simulation model; (ii) setting the levels of selected factors of the model and making decisions on the conditions, such as the length of runs and number of replications, under which the model will be run. Two independent variables and one dependent variable (the total revenue) are considered. The levels of independent variables or design factors must be carefully selected to ensure a good representation of the experimental domain. For optimization purpose, the first-order response surface model is rejected. Hence, we selected a $3^2$ response surface design since we have 2 independent variables, each at three levels.

Four replications were conducted for each combination of the factors, and therefore, 36 ($3^2 \times 4$) simulation runs were made. To reduce the number of replications, we used a variance reduction technique called common random numbers (Law and Kelton, 2000). The statistical analysis of the simulation output consists of the multi-factor analysis of the variance (ANOVA). This was done using a statistical software application (i.e. STATGRAPHICS) to provide the effects of the two independent variables on the dependent variable.

Table 1 illustrates the ANOVA for the basic case of Table 2 corresponding to an initial adopter rate equal to 0.05. The base ERP price before possible discount is equal to 0.37. From Table 1, we can see that the main factors $\alpha$ and $\gamma$ as well as their quadratic effects are significant at the 0.05 level (i.e., $P$-value < 0.05). One more result that stands out in the ANOVA table is the blocks effect, which appears to be non-significant (i.e., $P$-value > 0.05). This effect is due to the aforementioned variance reduction technique. The technique guarantees the generation of the same sequence of random numbers within the different runs of one block (one replication). However, a different sequence of random numbers is generated from one block to another (one replication to another). Consequently, it was expected that the block effect would be non-significant. It is interesting to note that the interaction effect between $\alpha$ and $\gamma$ is not significant.
Table 1- Analysis of Variance for Revenue

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum of Squares</th>
<th>Df</th>
<th>Mean Square</th>
<th>F-Ratio</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A:Alpha</td>
<td>0.132893</td>
<td>1</td>
<td>0.132893</td>
<td>6.13</td>
<td>0.0199</td>
</tr>
<tr>
<td>B:Gama</td>
<td>7.19321</td>
<td>1</td>
<td>7.19321</td>
<td>331.67</td>
<td>0.0000</td>
</tr>
<tr>
<td>AA</td>
<td>0.191579</td>
<td>1</td>
<td>0.191579</td>
<td>8.83</td>
<td>0.0062</td>
</tr>
<tr>
<td>AB</td>
<td>0.00538666</td>
<td>1</td>
<td>0.00538666</td>
<td>0.25</td>
<td>0.6223</td>
</tr>
<tr>
<td>BB</td>
<td>3.44815</td>
<td>1</td>
<td>3.44815</td>
<td>158.99</td>
<td>0.0000</td>
</tr>
<tr>
<td>blocks</td>
<td>0.0101217</td>
<td>3</td>
<td>0.00337388</td>
<td>0.16</td>
<td>0.9252</td>
</tr>
<tr>
<td>Total error</td>
<td>0.585566</td>
<td>27</td>
<td>0.0216876</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total (corr.)</td>
<td>11.5669</td>
<td>35</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

R-squared = 94.9376 percent  R-squared (adjusted for d.f.) = 94.0938 percent

The residual analysis was used to verify the adequacy of the model. A residual versus predicted value plot and normal probability plot were used to test the homogeneity of the variances and the residual normality, respectively. Moreover, the R-squared value equal to 0.949 indicates that more than 94% of the total variability is explained by the model (Montgomery, 2001), which is very satisfactory.

The Response Surface Methodology is a collection of mathematical and statistical techniques that are useful for modeling and analyzing problems in which a response of interest is influenced by several variables, and the objective is to optimize this response. We assume here that there exists a function $\Phi$ of $\alpha$ and $\gamma$ that provides the value of the revenue corresponding to any given combination of input factors, i.e., Revenue $= \Phi (a,y)$. The model obtained includes two main factors $(a$ and $y$), two quadratic effects $(a^2$ and $y^2)$, and the interaction effect $a \times y$.

The function $\Phi$ is called the response surface, and is assumed to be a continuous function of $\alpha$ and $\gamma$. The second order model is thus given by:

$$\Phi = \beta_0 + \beta_{11}a + \beta_{12}\gamma + \beta_{21}a^2 + \beta_{22}\gamma^2 + \beta_3a\gamma + \varepsilon$$  \hspace{1cm} (3)

where $\alpha$ and $\gamma$ are the input variables; $\beta_0$, $\beta_{11}$, $\beta_{12}$, $\beta_{21}$, $\beta_{22}$ and $\beta_3$ are unknown parameters, and $\varepsilon$ is a random error. From STATGRAPHICS, the estimation of unknown parameters is performed, and the following six coefficients achieved.

The values of these coefficients are:
$\beta_0 = 12.4813$, $\beta_{11} = 1.68957$, $\beta_{12} = 7.51541$, $\beta_{21} = -6.87775$, $\beta_{22} = -10.5043$, and $\beta_3 = -0.489292$.

The corresponding response surface is presented in Figure 3. The optimum is obtained for $a^* = 0.110076$ and $y^* = 0.355239$, and the revenue $\Phi^*$ is 13.9089.
To ensure the robustness of the proposed approach, additional experimentations were conducted. Thus sensitivity analysis is carried out to illustrate the effect of the initial adopters on the optimal revenue and the segmentation pricing parameters. Table 2 details the initial adopter variations (i.e., from 0.05 to 0.15), and presents the optimal parameters and revenues for the sensitivity analysis cases. The results obtained confirm our expectations in the sense that the segmentation pricing parameters depend on the initial market state and should not be fixed for the whole horizon.

Figure 4 illustrates the variation of $a$ and $y$ as a function of the initial adopter rate. It clearly appears that the optimal total revenue obtained is significantly higher (relative gain up to 12%) than those obtained under fixed pricing strategy or even under a segmentation pricing strategy with fixed parameters. Figure 5 illustrates these results.

It is interesting to observe that segmentation pricing performs better at the beginning of the ERP introduction cycle (i.e., initial adopter ratio < 8 %). Moreover, the results show that even if a segmentation pricing strategy is adopted one should be able to guarantee that it will perform better than a fixed pricing strategy. In fact, with fixed parameters, the segmentation pricing
strategy can react against our expectations and provide lower revenue compared with that under a fixed pricing strategy (see Table 2 and Figure 5 for cases 9 to 11).

### Table 2 - Optimal Revenue and related parameters

<table>
<thead>
<tr>
<th>Case</th>
<th>Initial Adopter Rate</th>
<th>Optimal Revenue with Segmentation pricing</th>
<th>Revenue with fixed price</th>
<th>Revenue with $\alpha=0.15$</th>
<th>$\gamma=0.25$</th>
<th>$\alpha$</th>
<th>$\gamma$</th>
<th>Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>13.9089</td>
<td>12.4813</td>
<td>13.7839</td>
<td></td>
<td>0.11</td>
<td>0.355</td>
<td>11.44%</td>
</tr>
<tr>
<td>2</td>
<td>0.06</td>
<td>14.098</td>
<td>12.9549</td>
<td>13.8766</td>
<td></td>
<td>0.1101</td>
<td>0.334</td>
<td>8.82%</td>
</tr>
<tr>
<td>3</td>
<td>0.07</td>
<td>14.3256</td>
<td>13.3782</td>
<td>14.0559</td>
<td></td>
<td>0.0997</td>
<td>0.312</td>
<td>7.08%</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
<td>14.4855</td>
<td>13.7371</td>
<td>14.2654</td>
<td></td>
<td>0.09801</td>
<td>0.295</td>
<td>5.45%</td>
</tr>
<tr>
<td>5</td>
<td>0.09</td>
<td>14.6895</td>
<td>14.1376</td>
<td>14.4694</td>
<td></td>
<td>0.08856</td>
<td>0.266</td>
<td>3.9%</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
<td>14.9122</td>
<td>14.6530</td>
<td>14.6983</td>
<td></td>
<td>0.082</td>
<td>0.23</td>
<td>1.77%</td>
</tr>
<tr>
<td>7</td>
<td>0.11</td>
<td>15.1535</td>
<td>14.858</td>
<td>14.9631</td>
<td></td>
<td>0.08233</td>
<td>0.206</td>
<td>1.99%</td>
</tr>
<tr>
<td>8</td>
<td>0.12</td>
<td>15.3635</td>
<td>15.1591</td>
<td>15.2292</td>
<td></td>
<td>0.081998</td>
<td>0.176</td>
<td>1.35%</td>
</tr>
<tr>
<td>9</td>
<td>0.13</td>
<td>15.6021</td>
<td>15.5216</td>
<td>15.3864</td>
<td></td>
<td>0.01765</td>
<td>0.124</td>
<td>0.52%</td>
</tr>
<tr>
<td>10</td>
<td>0.14</td>
<td>15.8299</td>
<td>15.7815</td>
<td>15.5637</td>
<td></td>
<td>0.000001</td>
<td>0.099</td>
<td>0.31%</td>
</tr>
<tr>
<td>11</td>
<td>0.15</td>
<td>16.0496</td>
<td>16.0496</td>
<td>15.8153</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

![Figure 5: Optimal revenue as a function of initial adopter ratio](image)

### 5. CONCLUSION

This paper investigates the use of segmentation pricing by software manufacturers in a context of network externalities, such as the one that can be observed in the ERP software industry. Our experimental findings suggest that a segmentation pricing strategy is likely to increase total revenues in networks with low initial adoption rates and that price discounts should be adapted according to adoption rates in order to maximize total revenues. We find that optimal total
revenue obtained is significantly higher than those obtained under fixed pricing strategy or even under a segmentation pricing strategy with fixed parameters. Also, it appears that segmentation pricing performs better at the beginning of the ERP introduction cycle.

The key contribution of this paper relies on the fact that the simulation model is run on real longitudinal adoption data in a specific section. Future work will focus on replicating these results in sector with different supply chain structures such as the pharmaceutical and chemical sector. Among the limitation of this paper, it should be noted that the proposed pricing model makes no assumptions about the behaviour of other market players. Future researches will be devoted to relax some assumptions and to explore other segmentation pricing strategies.
REFERENCES


