The Ups and Downs of Open Innovation efficiency: the Case of Procter & Gamble

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Abstract:

Open innovation (OI) has become increasingly popular as an enterprise strategy in both industry and academia, and has been adopted, at least in part, by many companies. Despite this popularity, there is a dearth of evaluation of OI efficiency and a lack of suitable quantitative indices. In this study, we used both Data Envelopment analysis (DEA) and Malmquist techniques to compare the pre- and post-transition levels of performance achievement of Procter&Gamble (P&G), a widely recognised and public early adopter of OI, with a group of its main competitors. Most detailed analysis of the time-course revealed that the innovation efficiency of P&G improved rapidly and substantially after its embracing of OI, an effect we term the 'open rise'. However, there is also a transient decline in R&D efficiency at the beginning of OI adoption ('open dip') and an unexpected and marked decline ('open drop') after the peak positive effect.

Keywords:

Open innovation; performance evaluation; Data Envelopment analysis; Proctor & Gamble

1. Introduction

Since the publication of Chesbrough's book in 2003, the concept of open innovation (OI) has continued to receive wide attention from practitioners and researchers (West et al, 2014). The initial studies of OI tended to focus on successful and early OI adopters and to be descriptive conceptually (Hewitt-Dundas and Roper, 2018; Calof et al., 2017), which are essential for establishing our understanding on OI. Although the conclusions from most qualitative studies demonstrate the belief that OI works on the improvement of organisation's innovation capability, it still needs quantitative approach to test the conclusion through measuring the efficiency performance of open versus closed innovation (Huizingh, 2011). Because you cannot manage it if you cannot measure it (Lamberti et al, 2017), it is also important to develop an appropriate metrics system for evaluating the efficiency performance of OI. Therefore, this study aims to fill the research gap by developing a metrics system to measure the efficiency performance of OI. By investigating the performance of the OI adopter's innovation efficiency, we try to answer the research question that how a company's innovation efficiency is affected during the process that OI is adopted in its organisation.

If suitable performance metrics of indices were available and OI were working, there should be a positive differential between OI and pre-OI conditions. In order to assess change over time, we need indices which can reflect the overall efficiency of innovation process. The most suitable candidates are DEA and Malmquist techniques, which have previously been applied to assess the efficiency of economic processes with identifiable multiple inputs and outputs (Li et al., 2017; Cook et al., 2014). By adapting these techniques and applying them longitudinally to time series data, we have created 'indices of OI efficiency' which can show change in OI efficiency over time.

To explore and validate the efficacy of this approach to metrics, we undertook a comparative case study of Procter & Gamble (P&G), an early and public adopter of OI strategy, with a clear comment point circa 1999 (Dodgson et al, 2006). For the comparison and validation, and to better understand the relative efficacy of open versus closed innovation, we identified four leading competitors, based on the categorization of BIS's ranking of top R&D firm.

The rest of this paper is organised as follows. The theoritical background and literature review are introduced in section 2. Section 3 provides an introduction on the research methods that are employed in this research. Section 4 explains the model, research procedure, variable measurement and data. Section 5 summarises the empirical results of both DEA and Malmquist Index Analysis. Finally, section 6 and section 7 discusses the results and makes the conclusion.

2. Theoritical Background and Literature Review

2.1 Open Innovation VS Closed Innovation

OI (Open Innovation) was defined as the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively (Chesbrough, 2003). Once OI is adopted, the organization's boundaries become permeable and that allows combining the company resources with the external co-operators. For closed innovation, companies innovate by using only internal resources. Ideas are evaluated during the innovation process, and only the best and most promising ones are selected for their development and commercialization. The ones that show less potential are abandoned.

The difference between open and closed innovation is that in the case of closed innovation the ideas, inventions, investigations and developments required to place a product in the market, are generated within the company (Chesbrough, 2003). However, when applying the OI system, the company can use external resources such as technology and at the same time make available their own innovations to other organizations. Under the OI paradigm there is an important flow of external knowledge into the organization which turns into projects in co-operation with external partners and causes the purchase and incorporation of external technologies (see Elmquist et al., 2009; Inauen and Schenker-Wicki, 2011). At the same time, the innovations generated within the company can be sold as technology and/or industrial property to other organizations since either they are not applicable within their business model or because the company has no capacity or experience to develop the invention. The final result is that some products reach the market by using exclusively internal resources from the initial idea up to the commercialization of the final product. Other products are the result of incorporating external knowledge at different stages of their development (see Almirall and Casadesus-Masanell, 2010; Chesbrough et al., 2006).

Since the publication of Chesbrough's book in 2003, the studies on OI have received increasing attentions from researchers (West et al, 2014). The initial studies of OI made significant contributions in developing the OI concept (see Chesbrough, 2006; Perkmann and Walsh, 2007), which has primarily been studied in high-tech industries within the context of large firms (Hossain et al., 2016). However, with the development of research on OI, there are more studies tried to explore OI in the context of small and medium-sized enterprises (see Spender et al., 2017; Usman and Vanhaverbeke, 2017), which helped to extend the research focus from inbound open innovation processes to outbound open innovation processes (Enkel et al., 2009). A large number of early research on OI are developed based on qualitative methods in general (Elmquist et al., 2009), But with the continuous development of the concepts related to OI, there are more empirical studies tried to contribute the knowledge of OI based on secondary and panel data (Hossain et al., 2016). Laursen and Salter (2006) conducted one of the early empirical studies on OI and conceived new concepts to describe the nature of a firm's strategies for accessing external knowledge sources. Combining 47 interviews with secondary data from approximately 800 trade journals, West and Gallagher (2006) concluded that open-source software can in many ways enhance competitive advantages by using the open innovation concept. One of the serious concerns has been voiced in previous research about OI is the lack of empirical evidence about the benefits of OI (Wang et al., 2012). To our knowledge, there is no existing research about measuring the change of innovation performance for companies that adopt OI strategy. Therefore, this study is design to contribute the knowledge of OI by filling this research gap.

2.2 Evaluation of OI Performance

Several approaches to the assessment of OI have been put forward in the literature. Cheng and Huizingh (2014) applied multiple performance measures (new product/service innovativeness, new product/service success, customer performance, and financial performance) to assess OI performance. Ahn et al (2016) measured firm's OI performance using various indicators, including strategic, financial and technological performance, such as achievement of business strategic purpose, an increase in total revenue, an increase in technological level and an increase in the degree of in-house development. Bae and Chang (2012) verified the relationship between open innovation and performance in the Korean manufacturing industry using a new approach rather than employing simple indicators such as patents and financial data. Ili et al (2010) summarised the previous research and designed management tools to observe the status of OI in the automotive industry. Remneland-Wikhamn and Wikhamn (2011) designed a three-dimensional assessment tool which they utilised to measure the ‘OI climate’ in an organization. Another attempt at introducing an OI assessment tool was made by Al-Ashaab et al (2011), who developed an operational measurement tool based on the balanced scorecard to measure the outcomes of industry-university.

Most of these previous studies focus on evaluating the circumstances favouring the adoption of OI. Only indices which represent outputs of OI adoption have been proposed or developed to measure the performance of OI strategy. For example, previous quantitative studies for OI normally employed financial indices to reflect the firm's performance, such as turnover relating to new products (e.g., Atuahene-Gima and Wei, 2011; Faems et al, 2010; Laursen and Salter, 2006). Although a firm's financial indices are useful, this may not disclose the efficiency of OI strategy since it typically doesn't consider the inputs including R&D activities and OI cost in the organizations. In fact, the contradictory results received from previous research on OI performance indicate the difficulties in identifying appropriate metrics for OI and the lack of systematic measurement on OI efficiency (Ahn et al., 2016; West et al., 2014). Therefore, an appropriate metrics system that could monitor the performance of OI is still needed (Huizingh, 2011).

2.3 OI Firms

The foregoing studies of OI have referred to many case studies of how firms implement OI strategy to enhance their innovation and commercial capacity (e.g. Chesbrough, 2003, 2006; Sakkab, 2003; Dyer, 2004). P&G is one of the most famous companies which adopted OI strategy at an early date and apparently achieved great success through OI adoption. P&G was first studied as an example of adoption of OI in non-high-tech industry by Chesbrough (2003). After that, P&G has emerged and been studied as an OI company in a number of papers (for example: Chesbrough, 2006; Chesbrough et al., 2006; Gassmann, 2006; Huizingh, 2011; Lichtenthaler, 2011).

In June 1999, P&G launched a specific new strategy to increase growth through innovation called Organisation 2005 (Dodgson et al, 2006). With adoption of Organisation 2005, the firm planned to stimulate innovation by making P&G's internally focused and fragmented communications more outwardly focused and cohesive (Schilling, 2005). Through these efforts, P&G changed its R&D strategy to a 'Connect and Develop' strategy and enjoyed major success in terms of business growth through new, externally sourced products and technology (Gassmann, 2006). The firm announced that they were able to increase their product success rate by 50% and the efficiency of their R&D by 60% by introducing OI strategy (Gassmann et al, 2010). With more than 35% of the company's innovations and billions of dollars in revenue produced by radical strategy of OI (Huston and Sakkab, 2006), to measure whether the adoption of OI strategy has triggered such a big impact on P&G's innovation capability, the performance of the innovation efficiency in P&G is studied in this research.

3. Method

3.1 Data Envelopment Analysis

Data envelopment analysis (DEA) is a nonparametric method in operations research and economics for the estimation of production frontiers. It is used to empirically measure productive efficiency of decision making units (DMUs). Although DEA has a strong link to production theory in economics, the tool is also used for benchmarking in operations management, where a set of measures is selected to benchmark the performance of manufacturing and service operations. In benchmarking, the efficient DMUs, as defined by DEA, may not necessarily form a "production frontier", but rather lead to a "best-practice frontier" (Cook, Tone and Zhu, 2014). DEA is referred to as "balanced benchmarking" by Sherman and Zhu (2013).

Non-parametric approaches have the benefit of not assuming a particular functional form/shape for the frontier, however they do not provide a general relationship (equation) relating output and input. There are also parametric approaches which are used for the estimation of production frontiers (see Lovell & Schmidt 1988 for an early survey). These require that the shape of the frontier be guessed beforehand by specifying a particular function relating output to input. The relative strengths from each of these approaches can be combined in a hybrid method (Tofallis, 2001) where the frontier units are identified by DEA, then fitted to a smooth surface. This allows a best-practice relationship between multiple outputs and multiple inputs to be estimated.

Some of the advantages of DEA are (Berg, 2010):

- no need to explicitly specify a mathematical form for the production function;
- proven to be useful in uncovering relationships that remain hidden for other methodologies;
- capable of handling multiple inputs and outputs;
- capable of being used with any input-output measurement;
- the sources of inefficiency can be analysed and quantified for every evaluated unit.

Some of the disadvantages of DEA are:

- results are sensitive to the selection of inputs and outputs;
- you cannot test for the best specification;
- the number of efficient firms on the frontier tends to increase with the number of inputs and output variables.

DEA has been widely applied to assess production efficiency using multiple inputs and outputs (see, e.g., Lin et al., 2018; Kozmetsky and Yue, 1998; Yeh, 1996). Ground breaking work by Rousseau and Rousseau (1997, 1998) proved the potential of DEA-analysis to assess R&D activities. Subsequent studies have provided supporting evidence for its use in evaluating innovation efficiency, especially for the high-tech industries (see, e.g., Guan and Chen, 2010; Chen et al., 2006; Zabala-Iturriagagoitia et al., 2007; Zhong et al., 2011).

Two standard variations of the DEA model are used in the present study: the CCR model (Charnes et al., 1978) and the BCC model (Banker et al., 1984). The CCR model runs under the assumption that production exhibits constant returns to scale. The BCC model, on the other hand, assumes that there are variable returns to scale (Wang and Huang, 2007). Therefore, in the CCR model there is a linear relation between inputs and outputs; while in the BCC model, outputs can increase by a variable percentage, depending on its position on the efficiency frontier (Hollanders and Celikel-Esser, 2007). This means that in practice the CCR model produces a single index, whereas the BCC produces two indices which reflect both pure technical efficiency and scale efficiency.

The following section describes the two models in more detail. Assume that there are n DMUs (decision making units) ($\mathrm{DMU}_j, j = 1,2, \dots, n$). Each DMU_j contains m inputs x_{ij} ($i = 1,2, \dots m$) and s outputs y_{rj} ($r = 1,2, \dots s$). So the m*n input matrix, X, and s*n output matrix, Y, represent the data of all n DMUs. The efficiency rate of a unit DMU_j can be generally expressed as:

$$\frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}},$$

where u_r ($r = 1,2, \dots s$) and v_i ($i = 1,2, \dots m$) are separately output weights and input weights. The value of the DEA model in measuring the efficiency of productive unit $\mathrm{DMU_j}$ lies in maximising its efficiency rate, subject to the condition that the efficiency rate of any other units must not be greater than one. The model must also include all characteristics relevant, that is the weights of all inputs and outputs must not be smaller than zero. We let $\mathrm{DMU_o}$ be the one which need to be evaluated. Its input-output vector is (x_o, y_o). Such a model is defined as a linear divisive programming model:

$$\max_{u,v} \ (uy_o/vx_o)$$

$\text{subjecttou} Y/vX \leq 1$

$$u, v \geq 0$$

This can be converted into a linear programming model which is called CCR model or BCC model by adding a constraint. For each type of model, the relevant constraints are:

We let DMU_o be the one which need to be evaluated. Its input-output vector is (x_o, y_o). θ is the efficiency score and λ is a n*1 vector of constants.

The CCR model is:

$\min \theta$

$s.t. \theta x_o \geq X\lambda$

$$Y\lambda \geq y_o$$

$$\lambda \geq 0$$

The BCC model adds a convexity constraint. It is shown as follow:

$\min \theta$

$s.t. \theta x_o \geq X\lambda$

$$Y\lambda \geq y_o$$

$\Sigma\lambda = 1$

$$\lambda \geq 0$$

Both the CCR and BCC variants of the DEA model are employed in this research. This permits the calculation of three critical indices: the technical efficiency (TE) score, pure technical efficiency (PTE) score and scale efficiency (SE) score. The TE score is calculated as the ratio of the actual productivity to the maximum attainable productivity (Sharma and Thomas, 2008). It is calculated in the CCR DEA model under the assumption of constant returns to scale: in this case, the maximum attainable productivity is presented as the distance from the constant returns to scale frontier. The PTE score is calculated in the BCC DEA model as the ratio of the actual productivity to the maximum attainable productivity: in this case, the maximum attainable productivity represents the distance from the variable returns to scale frontier, which means, in contrast to the TE score, the PTE score excludes scale effects (Gulati, 2011). The SE score can be derived from the BCC model if the technology exhibits variable returns to scale. If there is a difference between the TE score and PTE score for a particular sector DMU, then this unit is characterized by scale inefficiency (Wang and Huang, 2007). The SE score is then defined as the ratio of constant returns to scale Technical Efficiency to the Variable Returns to Scale Technical Efficiency (Sharma and Thomas, 2008). Once the BCC is established, the analysis can be used to determine whether a particular DMU is experiencing increasing, constant, or decreasing returns to scale (Chen et al., 2006). Thus the DEA analysis process as adapted here generates three key indices: the SE scores, PTE scores and TE scores. These scores can then be used to evaluate the R&D investment efficiency by industry, sector, or company over time.

3.2 Malmquist Index Analysis

The Malmquist index we use was derived by Fare et al. (1994), based on Shephard's work (1970), defined as:

$$\mathrm{M}_{t,\ t+1}=\left[\frac{\mathrm{D}^{t}(x^{t+1},y^{t+1})}{D^{t}(x^{t},y^{t})}\times\frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^{t},y^{t})}\right]^{\frac{1}{2}}$$

Here $D^{t}(x^{t},y^{t})$ is the distance function given by Shephard (1970), given by the following equation:

$$D^t(x^t, y^t) = \inf_{\theta}\{\theta : (\theta X^t,\ Y^t) \in P(X)\}\ ;$$

P(X) is the set of production possibilities of a firm at a certain technology point.

Actually, the distance function $D^t(x^t, y^t)$ represents the distance from the production configuration (x^t, y^t) to the system frontier at time t, and can be determined by the following model:

$$D^t(x^t, y^t) = \min\ \theta$$

$$\text{(CCR)s.t.}\begin{cases} \sum_{j=1}^{n} X_j \lambda_j \le \theta X_k \\ \sum_{j=1}^{n} Y_j\ \lambda_j \ge Y_k \\ \lambda_j \ge 0,\ j = 1,\dots,n \end{cases}$$

In this representation the distance function is the efficiency function value. Malmquist could be divided (Fare et al., 1994) into:

$$\mathrm{M}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \left[\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})}\right]^{\frac{1}{2}}$$
$$\times \frac{D^{t+1}(x^{t+1}, y^{t+1}) / D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t) / D^t(x^t, y^t)} = Te \times T \times S$$

Where Te is the technical efficiency improvement; T is technology improvement; S is scale efficiency.

4. Model and Data

4.1 Model

Although the OI model provides broader strategy selection throughout its innovation process, both OI and Closed Innovation paradigms follow the same principle: minimise the firm's R&D investment inputs, and maximize the firm's benefit at the same time. In the OI model, R&D inputs could either occur inside or outside of the firm, and the firm could select other ways (out-licensing et al.) to increase the corporate profit in addition to marketing and selling products. The goal of adopting of this strategy is still to improve the R&D investment efficiency i.e. – minimise the R&D inputs and maximise the outputs at the same time. So, by observing the variation of the R&D investment efficiency, the performance of the OI model could be compared with the performance of closed innovation model (see Figure 1).

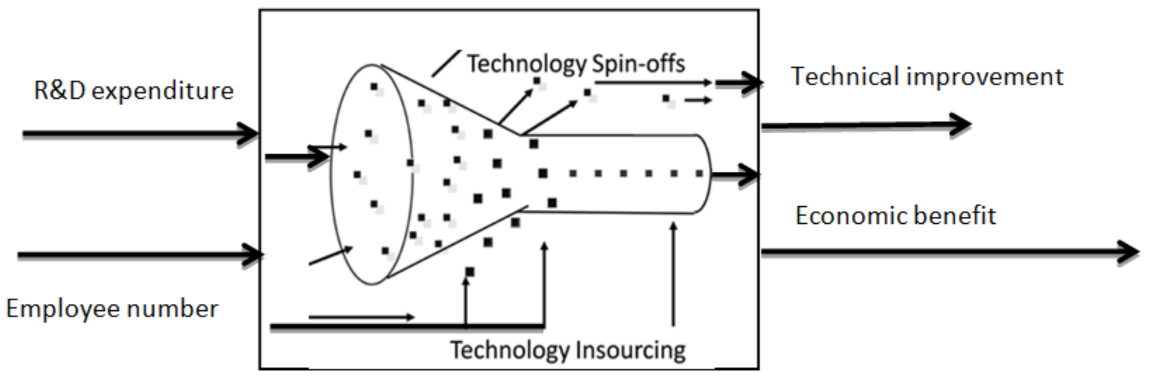


Figure 1: OI Performance Model

4.2 Inputs and Outputs

The two main inputs selected in this study are R&D expenditure and employee number. The R&D expenditure refers to the total R&D expense, covering all projects involving both internal and external ones supported by the firm. The R&D expenditure input index has been widely used, and found to be suitable in previous studies (Chun et al., 2015; Han et al., 2017; Zhong et al., 2011). The R&D personnel input figure includes all staff are engaged in either fundamental research, application research or experimental development (Zhong et al., 2011). The number of research staff on R&D activities can be taken as the R&D personnel input index. In the absence of this data, the employee number is adopted to represent the human resource inputs in this study.

The main outputs of R&D activities are technical improvement and economic benefit. The initial, direct outcome of R&D investment is the technical improvement, estimated in this case as the issued patent number. The other key outcome is the economic benefit, estimated in this case by the net sales and operating incomes as the final outputs in this study.

Because of the time needed to complete a R&D, introduce products to market (e.g. packaging, pricing and marketing) and gain a market share, there is a sector-dependent time lag for the economic consequences and impacts of R&D to show up following the initial R&D 'priming' investment (Kafouros and Wang, 2012). In this study, we adopted 1-year lag for the issued patent number and 2-year lag for the net sales and operating incomes.

4.3 Case Data Sources

To reference P&G's performance to other firms from the same sector, four R&D-intensive companies from the same sector are selected to do the comparison study. The reference companies were picked from the BIS (Department for Business, Innovation and Skills in the UK)'s R&D ranking of the top 1000 world companies by their R&D spending. BIS's ranking includes all the R&D intensity companies around the world and ranks them based on their R&D expenditure. Following the ranking, four companies – Unilever, Henkel, Reckitt Benckiser and Clorox, which are the top R&D intensity companies, are selected (see table 1). All the five sample companies are from 'Nondurable household products' sector based on the categorization by BIS's R&D ranking of the top 1000 world companies. Although the other four companies are all innovation-intensive, P&G is the only company that is reported as a famous practitioner of OI strategy in this industry (see Gassmann et al., 2010; Huston and Sakkab, 2006).

Table 1: the sample firms in this research			
Firm Name	Founded	Revenue (2018)	Number of employees (2018)
Procter & Gamble	1837; 181 years ago	US$66.83 billion	95,000
Unilever	1929; 89 years ago	€50.982 billion	155,000
Henkel	1876; 143 years ago	€19,899 million	53,000
Reckitt Benckiser	1999 (merger of Reckitt & Colman and Benckiser)	£12.597 billion	40,000
Clorox	1913; 106 years ago	US$6.1 billion	8,700

The data's time series is from 1990 to 2018. And much of the data required was available from official government sources and established business databases. The R&D expenditure, the employee number, net sales and operating incomes were collected from Datastream (Thomson Reuters) and the issued patent number was collected from the database offered by United States patent and Trademark Office (USPTO). All monetary values are adjusted for inflation using the US domestic manufacturing Producer Price Index (with index year 1989).

5. Results

5.1 DEA Result

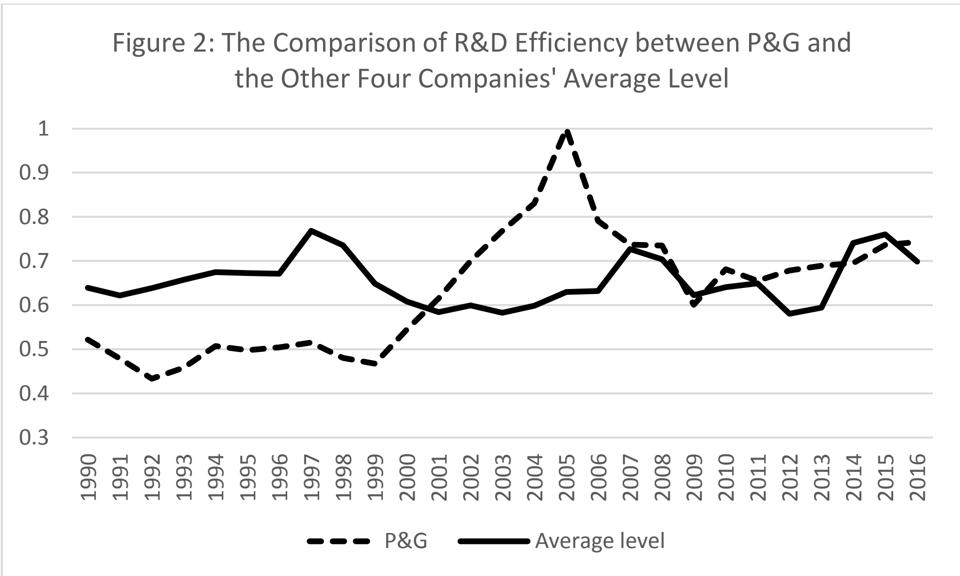
5.1.1 Technical Efficiency

In the DEA analyses, the TE scores reflect the overall R&D investment efficiency: the bigger the score, the higher the R&D efficiency. A firm has the highest possible R&D efficiency if its score is 1 in a given year. The detailed results are shown below. Based on the average score for the period 1990 to 1999 (pre-open period), Reckitt Benckiser was the most efficient company on R&D among these five companies. Clorox and Unilever were ranked second and third, and P&G was the least efficient R&D Company, with Unilever only slightly better than Unilever. For the period 2000 to 2016 (post-open period), P&G's average R&D efficiency across the whole period rose significantly, second, only to Reckitt Benckiser. Clorox ranked third, though its average score was higher than for pre-open period. Unilever and Henkel, which both showed the lower R&D efficiency, ranked fourth and last (see Table 2).

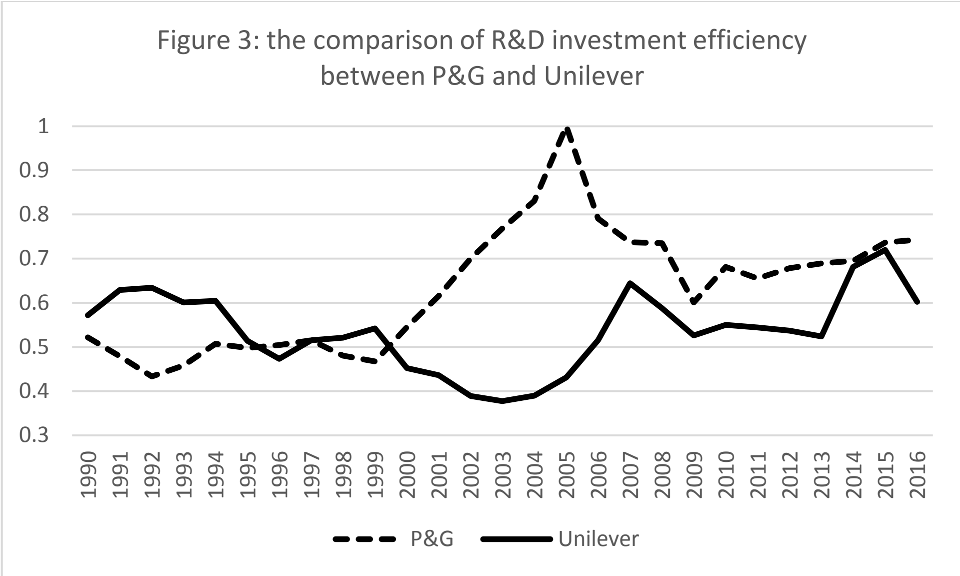
Table 2 DEA technical efficiency index

Year of R&D activity input	Firm				
	P&G	Unilever	Henkel	Reckitt Benckiser	Clorox
1990	0.522	0.572	0.448	1	0.537
1991	0.479	0.629	0.411	1	0.446
1992	0.433	0.634	0.403	1	0.516
1993	0.458	0.601	0.413	0.974	0.64
1994	0.507	0.604	0.507	0.888	0.7
1995	0.498	0.514	0.635	0.722	0.819
1996	0.504	0.473	0.639	0.73	0.841
1997	0.515	0.515	0.564	0.995	1
1998	0.48	0.521	0.576	0.948	0.898
1999	0.467	0.542	0.538	0.781	0.733
Average 1990-1999	0.486	0.561	0.513	0.904	0.713
2000	0.545	0.452	0.364	0.826	0.791
2001	0.615	0.436	0.337	0.776	0.787
2002	0.7	0.389	0.463	0.731	0.815
2003	0.768	0.377	0.511	0.744	0.699
2004	0.831	0.39	0.512	0.843	0.648
2005	1	0.431	0.453	0.911	0.724
2006	0.791	0.515	0.451	0.866	0.696
2007	0.737	0.644	0.458	1	0.806
2008	0.735	0.588	0.431	1	0.797
2009	0.601	0.526	0.442	0.918	0.604
2010	0.681	0.55	0.48	0.93	0.601
2011	0.655	0.544	0.493	0.921	0.64
2012	0.678	0.537	0.49	0.686	0.61
2013	0.689	0.524	0.56	0.628	0.666
2014	0.695	0.681	0.597	0.948	0.736
2015	0.736	0.72	0.526	1	0.795
2016	0.743	0.602	0.494	0.955	0.743
Average 2000-2016	0.718	0.524	0.474	0.864	0.715

P&G's average R&D efficiency in the pre-open period was 0.486, the lowest in relation to the reference companies. The average R&D efficiency score of the five companies in the pre-open period is 0.673 which is higher than P&G's performance. The situation changed dramatically after 1999 when P&G launched its OI initiatives. Over the post-open period P&G's average score of R&D efficiency is 0.718 which is the second most efficient of all the firms. In Figure 2, we develop a comparison of R&D efficiency between P&G and the other four companies' average level. With the average score0.644, the average level of R&D efficiency performance for the other four companies was flat during the whole test period (see Figure 2). This may indicate that the general performance of the companies' R&D efficiency is not affected by the macroeconomic environment such as the economic recession in 2007.



Because Unilever is widely recognised as P&G's big competitor (Iguchi and Hayashi, 2009),a comparison of R&D efficiency of P&G and Unilever is developed in this research (see Figure 3). We can see that P&G's R&D efficiency kept increasing monotonically from 2000 to its post-open peak in 2005. Strikingly, at the peak P&G's R&D efficiency score (value) was more than double that of Unilever's (value) (see Figure 3). Intriguingly, the DEA model also disclosed an equally sharp decline in P&G's Technical Efficiency score over the five years from 2005 to 2009.



5.1.2 Pure Technical Efficiency (PTE)

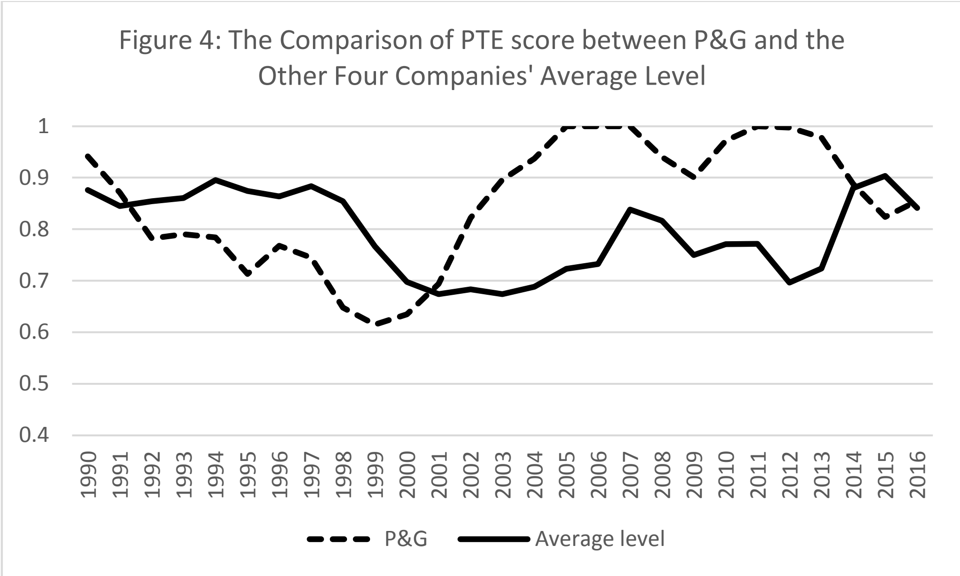
The PTE scores reflect the pure R&D investment efficiency excluding scale effects. Reckitt Benckiser owned the highest average PTE score during the pre-open period. Clorox and Unilever followed it, ranking second and third, with P&G fourth. Over the post-open period, P&G became the most efficient company on PTE with an average score 0.902,with Reckitt Benckiser and Unilever second and third and Henkel last (Table 3).

Table 3 DEA pure technical efficiency index

Year of R&D activity input	Firm				
	P&G	Unilever	Henkel	Reckitt Benckiser	Clorox
1990	0.941	0.914	0.591	1	1
1991	0.871	0.994	0.534	1	0.851
1992	0.782	0.981	0.524	1	0.912
1993	0.79	0.935	0.533	0.974	1
1994	0.784	0.984	0.666	0.96	0.971
1995	0.713	0.774	0.865	0.857	1
1996	0.768	0.706	0.872	0.876	1
1997	0.745	0.761	0.774	0.998	1
1998	0.648	0.765	0.806	0.948	0.899
1999	0.615	0.776	0.773	0.785	0.733
Average 1990-1999	0.766	0.859	0.694	0.940	0.937
2000	0.635	0.653	0.492	0.832	0.813

2001	0.694	0.613	0.486	0.778	0.819
2002	0.822	0.534	0.632	0.745	0.823
2003	0.896	0.512	0.703	0.768	0.713
2004	0.937	0.531	0.703	0.857	0.663
2005	1	0.591	0.635	0.941	0.724
2006	1	0.705	0.634	0.879	0.712
2007	1	0.902	0.642	1	0.807
2008	0.94	0.822	0.625	1	0.818
2009	0.901	0.776	0.642	0.947	0.635
2010	0.972	0.801	0.7	0.944	0.638
2011	1	0.792	0.711	0.922	0.66
2012	0.997	0.751	0.709	0.692	0.633
2013	0.978	0.75	0.837	0.642	0.666
2014	0.888	0.949	0.885	0.949	0.736
2015	0.824	1	0.818	1	0.796
2016	0.855	0.865	0.756	1	0.743
Average 2000-2016	0.902	0.738	0.683	0.876	0.729

Figure 4 shows a comparison of PTE performance between P&G and the other four companies' average Level. As for the TE analysis, here we use the average PTE score of the other four companies as the index to represent the general performance of the other companies on PTE score. P&G has showed a higher PTE score than the average level of the other companies since 2001. In the post-open period, P&G showed the highest score and a more stable PTE performance. This seems to suggest that the adoption of OI strategy has improved innovation productivity in P&G. Moreover, comparing with its TE score, which exhibited ‘inverted curvilinear performance’, P&G’s PTE exhibited a more stable performance after reaching the peak in 2005.



5.1.3 Scale Efficiency (SE)

Scale efficiency (SE) scores reflect various classes and levels of returns to scale on R&D investment. There are three possible classes of returns to scale: decreasing (DRS), increasing (IRS) and constant (CRS). CRS is indicated by an SE score of 1; DRS, signified by a decrease in the relative output for a given incremental input, and an associated decline in the consequent profit; IRS, signified by an increase in the relative output for a given incremental input.

In the pre-open period, Reckitt Benckiser and Clorox were first and second on average SE score. Both of them were experiencing increasing return to scale (IRS), indicates that a given level of R&D inputs was producing a relative increase in R&D output in these two companies. Henkel, Unilever and P&G were ranked third, fourth and fifth respectively. All these three companies were suffering from decreasing returns to scale (DRS), indicating that for a given level of increase in the R&D input, less relative R&D output was produced. In the post-open period, Reckitt Benckiser and Clorox were still ranked at first and second for the average SE score, while P&G has moved from fifth to third, and Henkel had the lowest average score.

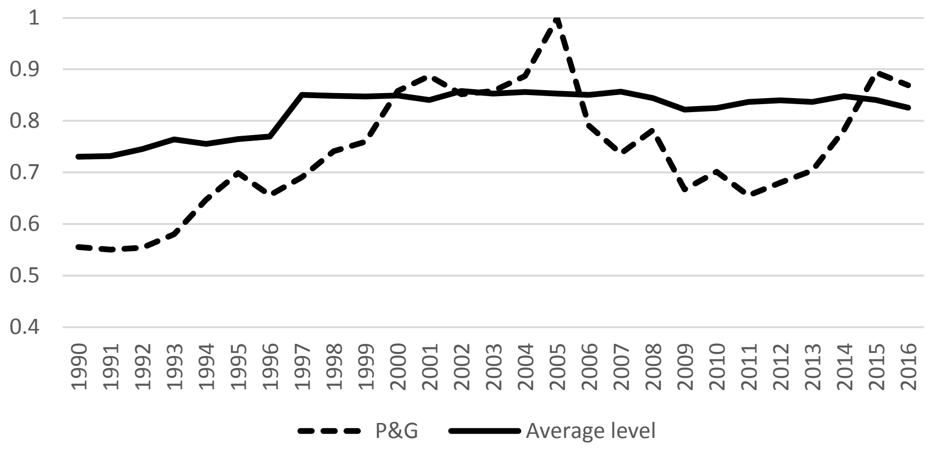
During this time post-open period, all five companies suffered from DRS at some point (see Table 4).

Table 4 DEA scale efficiency index

Year of R&D activity input	Firm									
	P&G		Unilever		Henkel		Reckitt Benckiser		Clorox	
1990	0.555	drs	0.626	drs	0.759	drs	1	-	0.537	irs
1991	0.55	drs	0.633	drs	0.769	drs	1	-	0.524	irs
1992	0.554	drs	0.647	drs	0.768	drs	1	-	0.566	irs
1993	0.58	drs	0.643	drs	0.774	drs	1	-	0.64	irs
1994	0.647	drs	0.613	drs	0.761	drs	0.925	irs	0.722	irs
1995	0.699	drs	0.664	drs	0.734	drs	0.842	irs	0.819	irs
1996	0.656	drs	0.67	drs	0.733	drs	0.834	irs	0.841	irs
1997	0.691	drs	0.676	drs	0.729	drs	0.997	drs	1	-
1998	0.741	drs	0.681	drs	0.715	drs	1	-	0.998	irs
1999	0.76	drs	0.698	drs	0.696	drs	0.995	drs	1	-
Average 1990-1999	0.643		0.655		0.744		0.959		0.765	
2000	0.858	drs	0.693	drs	0.74	drs	0.993	drs	0.972	irs
2001	0.887	drs	0.711	drs	0.694	drs	0.997	drs	0.961	irs
2002	0.852	drs	0.728	drs	0.733	drs	0.981	irs	0.991	irs
2003	0.858	drs	0.735	drs	0.726	drs	0.969	irs	0.981	irs
2004	0.887	drs	0.735	drs	0.729	drs	0.984	irs	0.976	irs
2005	1	-	0.73	drs	0.714	drs	0.968	irs	1	-
2006	0.791	drs	0.73	drs	0.711	drs	0.985	irs	0.976	irs
2007	0.737	drs	0.714	drs	0.714	drs	1	-	0.999	-
2008	0.782	drs	0.715	drs	0.69	drs	1	-	0.973	drs
2009	0.667	drs	0.677	drs	0.689	drs	0.969	drs	0.953	irs
2010	0.701	drs	0.687	drs	0.686	drs	0.986	drs	0.942	irs
2011	0.655	drs	0.686	drs	0.693	drs	0.999	irs	0.969	irs
2012	0.68	drs	0.715	drs	0.691	drs	0.991	drs	0.963	irs
2013	0.704	drs	0.698	drs	0.669	drs	0.979	drs	1	-
2014	0.783	drs	0.717	drs	0.675	drs	0.999	irs	1	-
2015	0.894	drs	0.72	drs	0.644	drs	1	-	0.999	irs
2016	0.869	drs	0.695	drs	0.653	drs	0.955	drs	0.999	irs
Average 2000-2016	0.800		0.711		0.697		0.986		0.980	

P&G's SE score showed a similar pattern to its TE score. P&G's SE score increased after 1996 and reached a peak in 2005, followed by a subsequent decline (Figure 10). Adopted the average SE score as an index to show the general performance of the other companies on SE score, from the comparison we could see that P&G had lower Scale Efficiency (SE) than the average level of the other companies before 2000. But from 2002-2006 the company made an inverted curvilinear performance and surpassed the average performance on this index, only to return to lower performance again after 2006 (Figure 5).

Figure 5: The Comparison of SE score between Procter & Gamble and the Other Four Companies' Average Level



5.2 Malmquist Results

Table 5 shows the results of the Malmquist test. In the Malmquist test, a score larger than 1 means that the efficiency of the DMU has improved in the test year compared with the previous year. Conversely, if the score is smaller than 1, it indicates that the DMU is less efficient than in the last year. A score at or very near to 1 means there are no change during the two years. Therefore, based on the result, we can say that the R&D efficiency of P&G had constantly improved since its adoption of OI strategy in year 1999. It strongly supports the conclusion of previous qualitative studies, and demonstrates the significant benefit of OI strategy for P&G. Even compared with the other four firms, the development trend of R&D

efficiency for P&G is still obvious, especially compared with its big competitor Unilever which had experienced several years' decline of R&D efficiency after year 1999. Intriguingly, P&G's R&D efficiency score has declined since 2006.

Table 5 Malmquist index

Firm	Year of R&D activity input								
	1990	1991	1992	1993	1994	1995	1996	1997	1998
P&G	1	0.948	0.994	1.248	1.059	1.175	0.97	1.355	0.834
Unilever	1	1.041	1.043	1.065	1.005	0.897	1.023	1.353	0.949
Henkel	1	0.935	1.039	1.131	1.04	1.071	1.066	1.326	0.899
Reckitt Benckiser	1	1.04	0.974	0.96	0.956	0.815	0.968	1.278	0.966
Clorox	1	0.932	1.159	1.234	1.075	1.167	1.038	1.271	0.865
	1999	2000	2001	2002	2003	2004	2005	2006	2007
P&G	0.567	1.108	1.112	1.163	1.084	1.07	1.138	0.851	1.035
Unilever	0.822	1.064	0.93	0.954	0.993	1.122	1.051	0.966	1.144
Henkel	0.828	1.069	0.977	1.071	0.918	1.039	1.043	0.968	1.098
Reckitt Benckiser	0.851	1.096	1.001	0.957	1.01	1.167	1.105	0.985	1.199
Clorox	0.651	1.153	1.019	1.062	0.917	0.981	1.072	0.954	1.087
	2008	2009	2010	2011	2012	2013	2014	2015	2016
P&G	0.987	0.806	1.088	0.988	1.02	1.008	1.068	1.06	0.935
Unilever	0.949	0.891	0.984	0.922	0.865	0.825	1.445	1.141	1.001
Henkel	0.979	0.889	0.991	1.016	0.917	0.933	1.214	1.002	0.967
Reckitt Benckiser	0.984	0.893	1.027	0.919	0.789	0.88	1.474	1.102	0.975
Clorox	0.973	0.811	1.02	1.08	0.953	1.032	1.094	0.999	0.935

6. Discussion

Our first finding is that P&G's average scores for all three indices increased in the post-open period when compared with pre-open period, while the average scores for all 3 indices across the other four companies were effectively flat for the whole period. All three primary 'indices" of innovation follow a similar 'curvilinear' developmental sequence, with a characteristic initial dip, followed by a significant rise and then a drop of similar magnitude and ratio, except that the PTE scores did not show any drop.

Given the flat, stable, performance of the reference group, and the magnitude and duration of the change, we consider the simplest interpretation of the 'Open Rise' at P&G to be that it does indeed reflect a positive effect of the switch to an OI strategy. The transient 'Open Dip' could reasonably be interpreted as a temporary loss of efficiency during transition to the new strategy. The 'Open Drop' observed was unexpected, as was its magnitude, and invites a number of possible interpretations ranging from absorption of the relevant market opportunities to inconsistent execution of partnering activities: in any event, not what adopters of OI are seeking. Further research on indices may identify other cases of the observed 'Open Drop', which so far as we are aware has not been reported previously (see Figure 6).

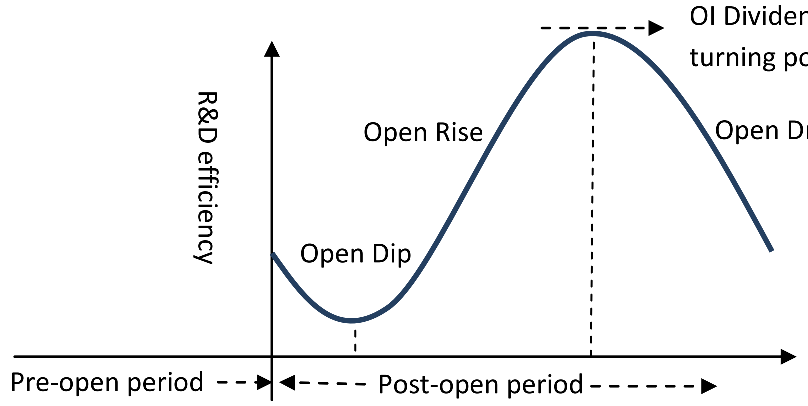


Figure 6: Three-Stage OI Adoption Model

As both the DEA and MI analyses revealed, the overall indices of R&D performance exhibited an 'inverted curvilinear' profile. The graphical profile observed for P&G in this study supports the previous conclusion of Laursen and Salter (2006), based on a Tobit regression analysis of the UK manufacturing sector. From which they concluded that 'searching widely and deeply is curvilinear relative to performance', based on the 'inverted curvilinear' relationship they observed between OI and firm performance. Our interpretation is that at one extreme the risk may be to set the research net too wide and catch an unmanageable number of opportunities and at the other to set it too narrow and catch too little. Another implication would be that secondary management indicators of performance trends that correlate with the overall econometric performance indices applied here would be useful additions to the management toolset for informed innovation.

With respect to the individual indices, since PTE reflects pure R&D efficiency exclusive of Scale Efficiency, we can also conclude that the pure R&D efficiency of P&G increased after the OI adoption point, again supporting the notion that the adoption of OI strategy appears to have helped the company improve its pure R&D efficiency. In contrast to the TE result, PTE did not show a continuing and obvious decline in the post-open period, leading us to conclude that other factors, such as scale effects, must be responsible for the overall decline of R&D efficiency at P&G over that period.

Interestingly, the majority of the companies studied– including P&G – tended to suffer from greater decreasing return to scale (DRS) effects in the post-open period than in the pre-open period. Our interpretation of this observation is that in a closed innovation scenario, given the limitation of the scope of management to a company boundary and the production principles in use inside that boundary, increasing R&D inputs might be expected to follow the law of diminishing marginal returns and lead to decreasing R&D outputs.

In an OI scenario, firms can access and absorb sources of R&D beyond their internal R&D activities and can thus expand their R&D horizons and maintain scale efficiency, which was account for the 'Open Rise' seen in the SE score after adoption of OI. Since the PTE score did not show 'Open Drop' effect, it maybe that the inverted curvilinear profile of P&G's overall R&D efficiency may be driven or determined by its Scale Efficiency (SE) performance. One explanation might be that external R&D projects normally operate outside the firm by another organization or individuals, and an increase in external R&D projects could entail a risk that the company who launched the projects loses management control, and lead to a reduction of scale inefficiency.

7. Concluding Remarks

Our quantitative methods appear to meet the needs identified in the preceding literature (Huizingh, 2011) for more quantitative approaches to the measurement of OI, which in this paper we have attempted to address by applying DEA and Malmquist linear programming techniques. Using these techniques, it would appear we have shown a convincing quantitative index which track increases in OI efficiency in the case of P&G relative to its competitors.

Although the most obvious interpretation of the results is that adopting OI can lead to a dramatic improvement in R&D performance, other explanations are of course possible. For example, a bull market could have an uplift effect; a change of management might have impact, and so forth. However, the temporal apposition of the effect, the existence of parsimonious causal mechanisms, and the lack of similar effects in competitors not making the strategic shift to OI – in effect a control – suggest that there may indeed be an effect worthy of further investigation with a wider range of cases, and perhaps at sector or industry level. The period of adoption also coincided with an extended period of stock market decline: the 'dot bomb' era, also seeming to rule out any general market.

Companies who are adopting and will adopt OI strategy should recognise that implementation has to be managed and monitored to realize OI efficiency gains. Our research appears to suggest that one of key indices to manage is the scale efficiency of R&D within the industrial OI ecosystem, where Scale Efficiency may affect OI efficiency in two distinct phases, at the initial and later stages of execution.

Although more efficient R&D is what the companies seek in moving to OI, moving to OI is not a guarantee for more efficient R&D: if companies are less than totally prepared for the new management challenges likely to emerge from the strategic transition from closed to open, they might for example anticipate problems in R&D source allocation and external project control, which in turn could impact the scale inefficiency in the companies' R&D, and this kind of scale inefficiency might be expected at the beginning of OI adoption.

This study has several potential contributions both in practice and research. Since few studies have been concerned with measuring the performance of OI, this study is one of the first to provide quantitative indices to evaluate the performance of OI. In this comparative study, the relative performance of OI versus closed innovation appears to be a clear win for open, at least in one adoptive organization. This finding and these tools should help companies to find the right balance and monitor the development of OI in their organizations. With the means of measuring the performance of OI, scholars could go beyond the descriptive study and pursue further applicable research about the efficacy of OI in a wider range of companies, sectors, and industries. For practitioners who plan to do OI, the management control might be developed to face the emergence of R&D efficiency deadline at the beginning and later stages of OI adoption. For practitioners who are already opened, they should understand staying in OI does not mean continuous higher R&D efficiency: management of OI efficiency should be paid more attention after the adoption of OI strategy. To keep their successful story, they might keep innovative not only for OI but also for OI efficiency.

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