RETURN ON INVESTMENT ANALYSIS FOR IMPLEMENTING BARRIERS TO REVERSE ENGINEERING

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ABSTRACT
Reverse engineering (extracting information about a product from the product itself) is a competitive strategy for many firms and is often costly to innovators. Recent research has proven metrics for estimating the reverse engineering time and barrier and has shown that products can strategically be made more difficult to reverse engineer, thus protecting the innovator. Reverse engineering, however, is only the first phase of attempting to duplicate a product. Imitating – the process of discovering how to physically reproduce the performance of the reverse engineered product in one or more of its performance areas – is the second and final phase. This paper presents metrics for the time and barrier to imitating and shows how they can be joined with reverse engineering metrics to estimate a total time and total barrier to duplicate a product. As there is a cost associated with the design of barriers to reverse engineering and imitating it is important that a return on investment analysis be performed to ensure a profitable endeavor. Details of such an analysis are presented here.

NOMENCLATURE
B Barrier to extract information during reverse engineering or imitating
C Costs related to a product
F The rate of information extraction during reverse engineering or imitating
K Quantity or units of information
n Bass Diffusion Model sales probability density function
m Estimated market size in number of units
P Fraction of power exerted to extract information
Q Return on investment ratio
r Product revenue
S The ability of a product to store information as it relates to reverse engineering or imitating
X The dollar sales of a product
T Total time to extract information from a product (during reverse engineering or imitating)
α Bass Diffusion Model coefficient of early adoption
β Bass Diffusion Model coefficient of following
Ψ The sales volume of a product
ρ Product retail price
τ Time

Subscripts
0 Indicates the initial value for [ ]
b Indicates [ ] is evaluated at the break even point
c Indicates [ ] pertains to a competitor
d Indicates [ ] pertains to product development
f Indicates [ ] is evaluated at the end of product life
g Indicates [ ] pertains to goods sold
i Indicates [ ] pertains to imitating
l Indicates [ ] is evaluated during the growth phase
m Indicates [ ] pertains to manufacturing

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INTRODUCTION

Recent research has led to findings that allow designers to characterize how long it takes to reverse engineer a product or artifact. Reverse engineering is defined as the process of extracting information about a product from the product itself [1]. Innovators often have their competitive advantage diminished by imitators that have reverse engineered the innovation in order to create an imitation. Imitating is the process of discovering how to physically reproduce the performance of the reverse engineered product in one or more of its performance areas [2]. Imitations will often capture market share from an innovation and reduce the return on investment for the innovator [3, 4]. Patents are one way to secure intellectual property. The downfall of patents, however, is that they disclose the enabling technology of a product and aid imitators in avoiding patent infringement while maintaining comparable performance [5]. Some firms use an imitating strategy to quickly enter a market and/or gain a competitive edge [6]. Gruca and Sudharshan propose a framework for deterring competitors from entering the market [7]. Their framework is based on business strategies that can range from single elements of the marketing mix to overall corporate strategy. Porter provides measures that help a company structure its strategy so it can maintain a competitive advantage [8]. Part of Porter’s model calls for analyzing the possibility of a competitor imitating a product. These are just a couple examples of how an anti barrier business strategy can help to maintain competitive advantage.

As with patents, barriers to reverse engineering have tradeoffs. The mechanisms that make a product more or less difficult to reverse engineer and imitate are referred to as barriers to reverse engineering and imitating, respectively [9]. McEvily [10] describes a situation where a product was not successfully reverse engineered and imitated. He explains that it was a faulty butterfly valve in an airplane engine that caused the airplane to crash. The valve was designed by reverse engineering an identical valve. The firm performing the reverse engineering accurately duplicated the original alloy and dimensions of the valve, but failed to determine the heat treating process required to properly reconstruct the valve. Therefore, the valve was inadequately reconstructed and failed during use. The necessity of a specific manufacturing process is one example of a barrier to reverse engineering and imitating.

Researchers have expressed, from various perspectives, the need to estimate and quantify the time and barrier to imitate a product [11–13]. Product developers can influence the effectiveness of barriers based on calculated and sometimes even uncalculated design decisions. Those design decisions can range from how to obtain parts (i.e., make versus buy) to what the composition of the material microstructure should be. The effectiveness of a barrier is measured relative to the person trying to break the barrier. In conjunction with calculating the barrier, the time it takes to reverse engineer and imitate an artifact can be calculated. Knowing these parameters is necessary to estimating what the return on investment will be for a product. Knowing how design decisions affect a firm’s bottom line is a key factor in making barrier implementation decisions.

This paper (i) recommends a barrier strategy as a method to protecting intellectual property and maintaining competitive advantage, (ii) outlines the metrics necessary to evaluate the barrier and time to reverse engineer and imitate a product, and (iii) proposes a framework for calculating the return on investment when implementing a barrier strategy, thus helping designers to manage the tradeoffs of barrier implementation.

TECHNICAL PRELIMINARIES

Harston and Mattson [1] have developed metrics for evaluating the barrier and time to reverse engineer a product. In the next section, we will explain how those same metrics can be extended to predict the time and barrier to imitating. Before we proceed, however, a discussion of published reverse engineering metrics is necessary.

Using the basic principles of Ohm’s law, Harston and Mattson define the quantitative barrier to reverse engineer a product as

\[ B_R = \frac{P_R}{F_R^2} \]  

(1)

where \( P_R \) is the power (effort) exerted per time to extract information, and \( F_R \) (flow rate) is the rate at which information is extracted from the product. \( F_R \) is generally dependant on three factors: information complexity, skills of the team, and available resources. \( P_R \) is constrained by

\[ 0 < P_R \leq 1 \]  

(2)

where “0” represents no effort put forth to reverse engineer and “1” represents the maximum effort one can put forth to reverse engineer. The \( R \) subscript is present to distinguish these as being for reverse engineering. Noting Eqn. (1), the reverse engineering barrier will increase as the flow rate decreases with power.
being held constant. If flow rate is held constant and power is free to increase, then the barrier increases, signifying that more effort is required to reverse engineer the product. A conservative approach assumes

\[ P_R = 1 \]  

(3)

Just like a capacitor in an electrical circuit, a product has a storage ability. Instead of storing electricity, like a capacitor, the product stores information. The storage capacity, \( S_R \), of a product is defined as

\[ S_R = \frac{K_R F_R}{P_R} \]  

(4)

where \( K_R \) is the amount of information contained in the product that has not yet been extracted. With that, we now have all the parameters necessary to predict the time, \( T_R \), required to reverse engineer a product, which is defined using an exponential decay

\[ T_R = -B_R S_R \ln \left( \frac{K_R}{K_{R0}} \right) \]  

(5)

where \( K_{R0} \) is the total initial amount of information stored by a product. Thus,

\[ 0 < K_R \leq K_{R0} \]  

(6)

At this point it is important to note that information is separated by types and the preceding metrics are applied separately to each type of information. Therefore, if \( K_R, F_R, \) and \( P_R \) are known for a given information type, \( S_R, B_R, \) and \( T_R \) can be calculated for that information type.

Since products generally contain more than one type of information, the total product reverse engineering time \( (T_{R*}) \), information content \( (K_{R*}) \), and storage capacity \( (S_{R*}) \) is simply obtained by summing \( T_R, K_R, \) and \( S_R \) of every information type, respectively. The effective information flow rate is calculated by

\[ F_{R*} = \frac{K_{R*}}{T_{R*}} \]  

(7)

which allows for the calculation of the effective power applied to reverse engineer the entire product

\[ P_{R*} = \frac{K_{R*} F_{R*}}{T_{R*}} \]  

(8)

With \( F_{R*} \) and \( P_{R*} \) defined, the total quantitative barrier is

\[ B_{R*} = \frac{P_{R*}}{F_{R*}^2} \]  

(9)

It is beneficial to consider both \( B_R \) and \( T_{R*} \) as reverse engineering measures, as they are related, yet distinctly different. It is possible for a product to have a small \( B_R \), but a large \( T_{R*} \) due to the amount of information contained by the product. For example, consider a large flat plate with numerous holes of various sizes throughout. The barrier to measure the diameter of any single hole is small. The time it takes to reverse engineer the entire product is relatively large due to the large amount unique measurements that need to be made. Therefore, it is possible to have a small value for \( B_{R*} \) and a large value for \( T_{R*} \).

**NEW THEORETICAL DEVELOPMENTS**

**Barrier and Time Metrics for Imitating**

Just like reverse engineering, the key step in imitating is extracting information. With the information that has been gathered from reverse engineering the imitator now has the task of gathering the information that allows the reverse engineering information to be put to use. For example, an imitator might know, from reverse engineering, what the material microstructure is of a given product. However, in order to imitate that product the imitator needs to know how to produce that microstructure. This means that the imitator needs to find a source that the material can be purchased from or determine how to manufacture it. The information extraction phase of imitating can be much more time consuming than that of reverse engineering. In the reverse engineering phase all information is extracted from the product itself. In the imitating phase, the information can come from two different sources: internal and external. *Internal* information is that which can be obtained from the product itself. *External* information is that which is obtained from sources other than the product. Recall that when calculating the reverse engineering barrier and time, each information type is separately considered and analyzed. By definition, the reverse engineering barrier and time are only a function of internal information. On the other hand, a barrier to imitation is a function of both internal and external sources of information. Therefore, the reverse engineering metrics are easily extended to include both internal and external information.
The butterfly valve mentioned above [10] is a good example of how internal information can differ from external information, as well as how reverse engineering information differs from imitating information. For instance, the heat treating process that was required to duplicate the performance of the butterfly valve is an example of imitating information. A small portion of the information associated with the heat treating process can be extracted from the product itself, but in order to obtain all the information sources other than the product are required. Some of those external sources can be industry experts, experimental design, or trial and error.

Calculating the reverse engineering time and barrier is based upon separating information into types; there is no limitation to how many types of information can exist within a product. It is important to note that how the information is grouped into types is up to the discretion of the designer. Since some imitating information is classified as internal, just like reverse engineering information is, it follows that information needed to imitate a product introduces additional types of information. Therefore, the reverse engineering metrics are easily extended to include the new information types. It now becomes a question of what is the appropriate \( F \) for each information type. Harston and Mattson outline a process for estimating the information flow rate of a competitor. They assume that the fastest a competitor can extract information is no faster than the innovator. Therefore, a conservative estimate for the information flow rate, from the innovator’s perspective, is to use the innovator’s information flow rate. Adapted from Harston and Mattson, the equations for imitating are

\[
B_I = \frac{P_I}{F_I^2} \tag{10}
\]

\[
S_I = \frac{K_I F_I}{P_I} \tag{11}
\]

\[
T_I = -B_I S_I \ln \left( \frac{K_I}{K_{I0}} \right) \tag{12}
\]

The calculation of \( F^*, P^*, \) and \( B^* \) is performed as shown in Eqns. (7, 8, 9).

The fastest total time it takes for someone to reverse engineer, imitate, and release the imitation is the time to market entry and is defined as

\[
T_M^* = T_R^* + T_I^* \tag{13}
\]

and it is assumed that the imitator is not able to release an imitation any sooner than \( T_M \).

**Return on Investment**

The business strategy behind implementing barriers to reverse engineering is two fold. The first is to protect trade secrets. The second objective is to capture and maintain a large majority of the market share for as long as possible. Maintaining a large market share helps increase return on investment (\( Q \)). There are two key components to estimating the \( Q \). The first is an estimation of the total costs associated with the product’s development and production. The second is an estimation of the sales and market performance of the product. This section will explore how, with given models, a firm can estimate the sales and costs of its product. In the past, most designers have been far removed from financial estimations [14]. The development of concurrent engineering has drawn designers closer to the estimation of financials for a project and helped them make better design decisions. The purpose here is not to prescribe estimation models, but to show how given models can be applied to help designers make better barrier implementation decisions based on \( Q \).

**Product Development Costs**

There are a variety of methods for estimating project costs and how those costs will be distributed over time. The method used is usually determined by the firm developing the product. Product complexity can be a major factor in determining product development costs. At the onset of a project it can be difficult to get an estimate of the product development costs. Ulrich and Eppinger [15] give us some direction. They state that the costs associated with the product can be separated into four categories: development, ramp-up, marketing and support, and production. Development costs include all design, testing, and refinement costs up to production. Magrab [16] outlines several models for determining the development costs. Magrab states that the product’s total cost is computed as

\[
C_p = N_p(M + L + R) + T_0 + S + D \tag{14}
\]

where \( N_p \) is the lifetime product volume, \( M \) is the material cost per unit, \( L \) is the manufacturing labor per unit, \( R \) is the production resource usage/unit, \( T_0 \) is the capitalization costs, \( S \) is the indirect costs, and \( D \) is the development costs.

There is no model that is assumed to be a “one-fits-all” solution. As stated above, it is left up to the individual firm to decide which model works best for it. The information content of a product is one way to measure product complexity [17]. Because more complex products are, in most cases, more expensive to develop we use information content as a key measurement for product development costs in the example below.
Market Revenue Prediction  Predicting a product’s sales can often be a very involved process. Some companies commit massive amounts of resources into predicting how a product will perform in the market and some go by gut instinct. There are methods and models that are available to alleviate some of the uncertainty and help a developer estimate the future sales of a product. The purpose of this paper is not to prescribe a specific method to predicting how a product performs in the market, but to show how, with a given model, a developer can predict the return on investment (\( Q \)). This is done under the assumption that a competitor will eventually release an imitation of the product of interest to market (no sooner than the reverse engineering and imitating time). Thus, stealing market share and reducing the innovator’s \( Q \).

One model that has proven to be a good predictor of sales for a given product is the Bass Diffusion Model [18]. This model works well for our application because it tells us how the sales vary over time and not just a lump sum of sales. It has proven to be a good predictor of how quickly sales of new consumer durables grow and how much of the potential market a product can capture. The term “consumer durables” refers to products that are replaced by the consumer at a very low rate. Examples of consumer durables are refrigerators, televisions, washing machines, and lawn mowers. More recently, the Bass model has proven its adaptability by predicting the growth rate of social networking websites [19]. For this paper, we assume that the product in question will have no repeat buyers; lending itself easily to the Bass Model.

The Bass model is expressed as a probability density function that spreads the total expected market sales of a product over time and is defined as

\[
n(\tau) = \frac{(\alpha + \beta)^2}{\alpha} \frac{e^{-(\alpha + \beta)\tau}}{(\beta e^{-(\alpha + \beta)\tau} + 1)^2}
\]

where \( \alpha \) is the coefficient of early adoption and represents the probability of an initial purchase at \( \tau = 0 \), and \( \beta \) is the coefficient of late adoption and represents the influence that previous buyers have on future buyers.

Fig. 1 is a generic representation of the Bass Diffusion curve where is area under the curve represents to cumulative sales probability of a product.

The Bass model places buyers into two categories: early adopters and late adopters. The timing of early adopters’ purchases is not based on how many previous buyers there have been, while the timing of the late adopters’ purchase is based on the quantity of previous buyers. The last component needed in order to predict the quantity of sales at \( \tau \) is the overall market size for the entire life of the product, \( m \). Once again, we assume that the total sales of the product coincides with the number of one time purchases. With the total market size estimated, the sales at time \( \tau \) are

\[
\Psi(\tau) = m \frac{(\alpha + \beta)^2}{\alpha} \frac{e^{-(\alpha + \beta)\tau}}{(\beta e^{-(\alpha + \beta)\tau} + 1)^2}
\]

and the time at which sales peak is found by differentiating \( \Psi \) and solving for \( \tau \) when \( d\Psi/d\tau = 0 \). Therefore,

\[
\tau_u = \frac{1}{\alpha + \beta} \ln \left( \frac{\beta}{\alpha} \right)
\]

The cumulative sales \( \Psi_t \) at \( \tau \) is

\[
\Psi_t(\tau) = m \int_0^\tau n(\tau)d\tau
\]

It should be obvious at this point that in using the Bass Model, obtaining a good prediction of sales is based upon good estimates of \( \alpha \), \( \beta \), and \( m \). Obtaining good estimates of \( \alpha \), \( \beta \), and \( m \) can be done in various ways, but one simple way is to use data from a similar product and market. Research suggests that when time is in years an average value for \( \alpha \) is 0.03, but is often less than 0.01, and \( \beta \) ranges between 0.3 and 0.5 with an average value of 0.38 [20]. The parameters should be scaled according to the time scale. It is important to emphasize that this discussion of the Bass model has been to facilitate the discussion
of how a given sales model can be applied to make design decisions. Once again, we are not suggesting that the Bass model is one that should be used for all applications. Firms should use discretion when deciding what model to use to estimate the sales of its product.

**PRODUCT LIFE-CYCLE**

In the preceding we have discussed how to quantify the barrier and time to reverse engineering and imitating, a method to calculating product development costs, and a method to predicting product sales. This section will illustrate how these ideas are used in conjunction to help designers make barrier implementation decisions.

**Return on Investment Calculation**

Calculating $Q$ starts with estimating the costs and revenues of the product. The costs are broken down into two categories: development and manufacturing. The product development time is calculated using a baseline cost and the reverse engineering metrics with an information flow rate specified for development. This flow rate is simply the estimated rate at which a piece of product information is developed. In most cases, firms will be able to relate product development time to cost, because they will know their costs per time to utilize their resources. Therefore, product development cost has a linear relationship with product information content and is defined as

$$C_d = C \tau_d \quad (19)$$

where $C$ is the cost per unit time and $\tau_d$ is the product development time.

The manufacturing cost correlates directly with sales and is defined as

$$C_g = C_m \Psi(\tau) \quad (20)$$

where $C_g$ is the cost of goods sold, $C_m$ is the unit cost of manufacturing. The total product cost is defined as

$$C = \int_{0}^{\tau_d} C_d d\tau + \int_{\tau_d}^{\tau_f} C_g d\tau \quad (21)$$

where $\tau_f$ is the time at which the product reaches the end of its life.

The revenues for the product are obtained using the Bass Diffusion model, but with one caveat: the sales will be diminished by the entrance of an imitation to the market, thus affecting the distribution and quantity of sales. To accomplish this the total market diffusion, $\Psi(\tau)$, is first calculated assuming that no imitation enters the market. Second, the amount of market that an imitation is able to capture is then calculated. Predicting the rate and magnitude at which an imitation will sell is done using the Bass model as well. An *early adoption* and *late adoption* rate, $\alpha$ and $\beta$, respectively, is defined for the imitation product and the potential market size is reduced to what is currently remaining after sales of the innovative product. Actual sales for the innovator are then defined as

$$X_i(\tau) = X(\tau) - X_e(\tau) \quad (22)$$

where $X_i(\tau)$ is the total sales in dollars for the innovator up to time $\tau$, $X(\tau)$ is the total potential market sales in dollars up to time $\tau$, and $X_e(\tau)$ is the total sales in dollars for the competitor up to time $\tau$.

An alternate approach to calculating $Q$ is to choose a required $Q$ for a project. Then, designers can solve for the information flow rate needed to achieve the required $Q$. Once the information flow rate is calculated, designers can use intuition and/or estimation methods outlined by Harston and Mattson to decide if the flow rate will, in reality, allow the firm to capture the required $Q$.

**Example: KitchenAid Stand Mixer**

In order to illustrate how the models described above are used together, we examine a KitchenAid Stand Mixer. According to Euromonitor International, KitchenAid sold approximately 800 million units of small kitchen appliances from 2005 to 2009. KitchenAid has numerous product offerings, but we focus on its popular stand mixer for this example. Based on the number of different small kitchen appliances offered, we assume for this example that the market size for the stand mixer is 100 million units. To illustrate the return on investment analysis for implementing barriers to reverse engineering we will first invoke the Bass model where no barriers have been strategically implemented, and a competitor is introduced. Under this scenario, KitchenAid’s return on investment is calculated to be 2.45. This means that the project will return 100% of the costs for the product plus 145% above the total cost. Second, we will introduce strategic barriers to reverse engineering and imitation, and re-execute the Bass model. Though the added cost of designing and manufacturing the barriers, material barriers can be used to achieve a 3% gain in $Q$.

The parameters used in this example are listed in Table ##. Here we see the development rate, $F_d$, set to 0.036, which is the
rate at which barriers can be designed into the product in units of information per hour. The parameters $F_R(1)$, $F_I(1)$, $K_R(1)$, and $K_I(1)$ are the geometry flow rate and information content of the stand mixer as they pertain to reverse engineering and imitating. The parameters $F_R(2)$, $F_I(2)$, $K_R(2)$, and $K_I(2)$ are the material microstructure and information content of the stand mixer. Notice that $F_R(1)$ and $F_I(1)$ are noticeably larger than $F_R(2)$ and $F_I(2)$. This is simply due to the fact that geometric information (i.e., dimensions) can be extracted much faster than microstructure information (i.e., size, orientation, and distribution of crystallographic grains). The power exerted by KitchenAid’s product development team to develop the stand mixer is represented by $P_d$. The reverse engineering and imitating power is represented by $P_R$ and $P_I$, respectively. Recall that we set these values to “1” as it is the most conservative approach.

As stated above we invoke the Bass model to illustrate the diffusion of the stand mixer market. The parameters $\alpha$ and $\beta$ are the coefficients of early adoption and late adoption, respectively, for the Bass model. The values for these coefficients were chosen based on research presented by Sultan et. al [21] for both KitchenAid’s stand mixer and the competitor’s product. The retail price is represented by $\rho$. The cost for KitchenAid to manufacture the stand mixer is represented by $C_m$. Note that the product development costs, $C_d$, include all pre-launch costs, including engineering costs, marketing, tooling, and production ramp-up (30 day supply of product) and are evenly distributed over the development time.

For this example, we assume that the stand mixer is a new and innovative product and that the percentage of market share a competitor can capture is inversely proportional to its launch time as shown in Eqn. (23).

$$m_c = m \left(1 - \frac{T^*_M}{\tau_u}\right) \left(1 - \frac{e^{-(\alpha+\beta)T^*_M}}{\alpha e^{-(\alpha+\beta)T^*_M} + 1}\right)$$

where $T^*_M$ is the time to competitor market entry and $\tau_u$ is time to the upper bound of potential sales. The upper bound of potential sales is also thought of as the market saturation.

Figs. 2, 3, 4, and 5 (plotted on the same scale for ease of visualization) aid in visualizing how the costs and revenues are distributed over the life of the product. Fig. 2 illustrates the distribution of development costs. Fig. 3 illustrates the distribution of sales starting immediately after product launch and if an imitation product is never released. Fig. 4 illustrates the sales of an imitation released at $T^*_M = 4.771$ hours. Fig. 5 illustrates the cost of goods sold over the life of the product and accounts for the release of an imitation. These figures can then be superimposed to make a composite graph, as represented in Fig. 6. Note that in Fig. 6 there is very short period where KitchenAid is alone in the market, which is depicted by the “spike” in sales immediately after development. This is also the reason for the apparently vertical line in Fig. 5.

The return on investment is calculated through integration as

$$Q = \frac{\tau_f}{\tau_d} \int_s^{s_c} d\tau - \int_{\tau_d}^{\tau_f} C_m d\tau$$

$Q$ can also be visualized as the ratio of the difference in areas under the curves of Figs. 3 and 4 to the sum of the areas under the curves of Figs. 5 and 2. From the model, $Q$ is calculated to be 1.145. Also, the calculated barrier is $1.3 \times 10^{-3}$. 

\[ \text{FIGURE 2. Estimated per time product development costs.} \]
\[ \text{FIGURE 3. Estimated per time potential sales.} \]

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<th>Value</th>
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</tbody>
</table>

KitchenAid can influence $Q$ and $B$ by incorporating different types of information and/or by varying the quantity. Doing so will likely affect the product development time, cost, and manufacturing cost, however, the added barrier will also likely delay the competitor’s market entry. It is important to understand this tradeoff in order to effectively increase $Q$ by implementing barriers. For the above example, assume KitchenAid strategically manipulates the material microstructure of the stand mixer in order to increase the barrier. Because the analysis of a given material’s microstructure is intricate and time consuming, there will be a significant change in $F$ for the competitor. Due to the increased difficulty of extracting microstructure information and added information the values of the following parameters are changed: $F_R(2) = 0.04$, $F_I(2) = 0.01$, $K_R(2) = 15$, and $K_I(2) = 30$. The additional information included in the product also increases the product development time, cost, and the manufacturing cost. The addition of more information and a slower information flow rate for the competitor results in $T_M = 14,797$ hours. This change leads to $Q = 2.48$, which provides the firm with an extra 3% return over what was previously calculated. This equates to an extra $311$ million in net sales for KitchenAid. Also, the barrier is improved to $78.0 \times 10^{-3}$. It is important to note that the
barrier values are intended as a comparative measure. Typically the barriers of various designs are compared to the barrier of a benchmark design. The product life-cycle plot for the improved barrier is shown in Fig. 7. A substantial change in the revenues of KitchenAid’s stand mixer can be noticed from the plot alone.

**DISCUSSION**

This paper has developed and presented metrics for estimating the time it takes a competitor to launch an imitation product. The launch of the imitation can have a significant impact on the Q of an innovator’s product, because it steals away market share and reduces sales from what they could potentially be. In order to understand how implementing a barrier strategy affects Q we have developed a framework that considers design decisions, competitor behavior, and market performance. This framework allows designers to see how the implementation of certain design features affects the Q of a product. The insight provided by the framework presented enables designers to make more educated design decisions and increase a firm’s Q. In addition to the framework, existing models that can be applied to the framework have been discussed.

The discussion of existing market models has been brief and it is recommended that a firm seeks out models that best fit its situation. Also, we have suggested that F can be obtained by methods presented by Harston and Mattson or setting a required Q and solving for F. Either method is acceptable. The key to successful application of the reverse engineering and imitating
metrics is a good estimate of $F$.

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