Product platform replacements: impact of performance objectives, innovation speed, and competition

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Abstract - **Product platforms are assets that are shared by multiple products. They are frequently used to offer a wide product variety, while keeping down the time-to-market as well as the operational costs. As new products are developed over time, the question arises when to replace the platform. Re-using the same platform for multiple consecutive product introductions reduces platform development times and costs; yet as the platform becomes obsolete it requires more effort to adapt the platform to the newest product. We develop a simulation model to gain insight in the optimal platform replacement frequency, taking these dynamics into account. We study how the platform replacement decision is impacted by the firm's performance objectives, the speed of new product innovations, and the competitive landscape.**

Keywords - **product platforms, platform replacement, simulation, performance objectives, innovation**

1 Introduction

The increased product variety due to diverse customer needs and fierce competition puts pressure on operations: costs related to inventory, production, research and development, as well as the time-to-market tend to go up (Sawhney, 1998). To manage this variety in a cost- and time-efficient manner, several companies in diverse industries have introduced product platforms (Simpson et al., 2014; Muffatto and Roveda, 2002). Meyer and Lehnerd (1997) define product platforms as 'a set of subsystems and interfaces that form a common structure from which a set of products can be derived'. The use of platforms is well-known in automotive, where the chassis of the car is used as a common platform for multiple products (Alizon et al., 2009); but also other companies like HP, Xerox, Canon, Sony, Boeing, and

Swatch make use of platforms (de Weck et al., 2003). Platforms enable mass customization by combining the benefits of mass production, such as reduced development time and cost, with the ability to offer a wide range of customized products (Muffatto, 1999; Fogliatto et al., 2012). However, they also come at additional costs, such as the cost and time of customizing the platforms to end products (Van den Broeke et al., 2015), the cost of potential over-design of the platforms (Krishnan and Gupta, 2001), and the risk of platform obsolescence (Kang et al., 2012; Tyagi et al., 2015).

The literature on product platforms is rich, as illustrated by the reviews of Jiao et al. (2007), Simpson et al. (2014), and Zhang (2015). Extensive studies are devoted to finding the optimal platform design and configuration (e.g., Agard and Bassetto, 2013; Farrell and Simpson, 2010). In this article, we focus on a research aspect in the platform literature that surprisingly has not received much research attention: *platform replacement*. Although several authors, such as Meyer and Lehnerd (1997), Krishnan and Gupta (2001), and Halman et al. (2003), highlight that platform replacement is a concern, up till now the topic is relatively under-explored (as also discussed by Sköld and Karlsson (2012) and Zhang (2015)). On the other hand, it is an important decision for companies, as illustrated for instance by Volvo, who is now replacing its current platform to deal with electrical cars (Lambert, 2017), or by Apple, who needs to constantly change their platform to offer products with the latest technologies (McGrath, 1996). Barco is another example that introduced product platforms in the development of its high-tech medical displays, for which the timing of its platform replacements is a growing concern (Boute et al., 2017). Also Wortmann and Alblas (2009) express the need to not only manage the life-cycles of products, but also those of platforms.

The goal of our study is to support managers in their platform replacement planning. We have found at several companies that platform replacement is often not only driven by technology changes or incentives to reduce cost (as discussed in Kang et al., 2012), but also by the company's performance objectives (i.e., maximize profit, maximize market share, or minimize risk), the speed of new product innovations, and the competitor's behaviour in platform replacement (factors respectively called for by Keeney and Raiffa (1993), Kang et al. (2012), and Magnusson and Pasche (2014)). Our objective is to analyse the impact of these drivers on the firm's platform replacement planning.

To study the impact of these drivers, we make use of an extensive simulation experiment. While its logic spurs from existing literature and reality, it is a stylized, generalizable model. Although it is subject to certain assumptions, the model allows to study various driver settings, which would be very cumbersome or even impossible based on pure empirical data collection. This leads to interesting insights which support the management of platform replacement.

2 Related work on platform replacement planning

Product platforms may be altered, modified, or even abandoned over time, driven by the continuous change in technologies and their fast obsolescence (Mäkinen et al., 2014). As such, platforms also have a life cycle, which is different from the products derived from it, and is dependent on the industry (Wortmann and Alblas, 2009). When new products are introduced, it is to be decided whether they will be developed from an existing platform or whether an entirely new platform will be developed (Halman et al., 2003). Meyer and Lehnerd (1997) refer to the former as 'platform adaptation', indicating that particular subsystems of the platform are enhanced or changed, or new subsystems are added without completely overhauling the existing system, whereas the latter is referred to as 'platform replacement', indicating that the product architecture is redesigned to incorporate major new platform subsystems and interfaces. Replacing platforms too frequently involves unnecessarily high development costs (Halman et al., 2003), whereas the platform may become obsolete to cope with new product innovations if companies fail to embark in a new platform in a timely manner.

Pasche and Magnusson (2011) study the renewal and improvement of platforms to cope with changing market demand, through component and architectural innovation. Kang et al. (2012) develop a stochastic product introduction model to determine the optimal platform lifetime. Their model trades off cost efficiency of platform development with lost sales due to obsolete technologies. They assume that products are successively introduced and newer products always offer a better performance than older ones. In the model that we present in this article, we will use a similar logic. We present a simulation model that takes into account the trade-off of the platform development time and cost, which is incurred upon each platform replacement, with the adaptation time to adjust an existing platform to the new product needs (which goes up as the platform ages). Our simulation model examines the impact on the optimal platform replacement frequency of different performance objectives, such as profit and market share maximization or minimization of financial risk (whereas Kang et al. (2012) only focus on profit maximization), competition (proposed as a relevant future research direction by Kang et al. (2012)), and innovation speed (described as a key factor in product development decisions by Fredericks (2005)).

The underlying motivation behind these research questions is as follows. Product development decisions, such as platform replacement, almost always entail multiple objectives, between which there are trade-offs or preferences (Keeney and Raiffa, 1993). We examine three different performance objectives: market share, profit and risk (defined as the variance of profit (Van Mieghem, 2011)), as these KPIs are traditionally used in R&D project success

Platform replacement frequency	$q_{\max}$	Product introductions						
		j=1	j=2	j=3	j=4	j=5	j=6	j=...
4 (High)	0	x	x	x	x	x	x	x
3	1	x	o	x	o	x	o	x
2	2	x	o	o	x	o	o	x
1	3	x	o	o	o	x	o	o
0 (Low)	4	x	o	o	o	o	x	o

Table 1: Number of products covered by one platform for a given replacement frequency. 'x' indicates that the platform is replaced, and 'o' indicates that the existing platform is adapted.

and new product development (McNally et al., 2013). Magnusson and Pasche (2014) found that contingencies, such as demand characteristics and speed of innovation, play a crucial role on platform design, and Mäkinen et al. (2014) call for more research on platforms in light of different contingency factors. Therefore, we consider innovation speed, reflecting speed of change (Fredericks, 2005), as an important driver in our model. In addition, we also consider competition as a driver of platform replacement decisions. Until now, the impact of competition on platform replacement planning remains unclear (Kang et al., 2012). As competition impacts the order of market entry, the company's performance, and the so-called first-mover advantage (Kerin et al., 1992; Lieberman and Montgomery, 2013), we believe it is essential to include the impact of the competitor's platform replacement strategy.

3 Problem description and simulation model

We simulate a duopoly setting with two competing firms, where each company launches n new products over time. New product introductions $j \in \{1, 2, \ldots, n\}$ result from the availability of a new technology and/or demand for a new product. Similar to Huisman (2013), we characterize the speed of new product introductions (i.e., the speed at which new technologies become available) by a Poisson process with rate parameter λ; we denote this parameter the speed of innovation.

Each product is derived from a platform. We assume a company only has one platform in use at a time. Both firms decide whether product j is derived from a new platform $i = j$ (i.e., the existing platform is replaced by a newer one) or whether the product is derived from an existing platform $i = j - q$ (i.e., the old platform is adapted to the product's needs), with $0 < q \leq q_{\max}$, and $q_{\max} + 1$ the number of consecutive products covered by a single platform. The value of $q_{\max}$ is related to the platform replacement frequency: $q_{\max} = 0$ indicates that a new platform is developed for each new product (i.e., the platform is never

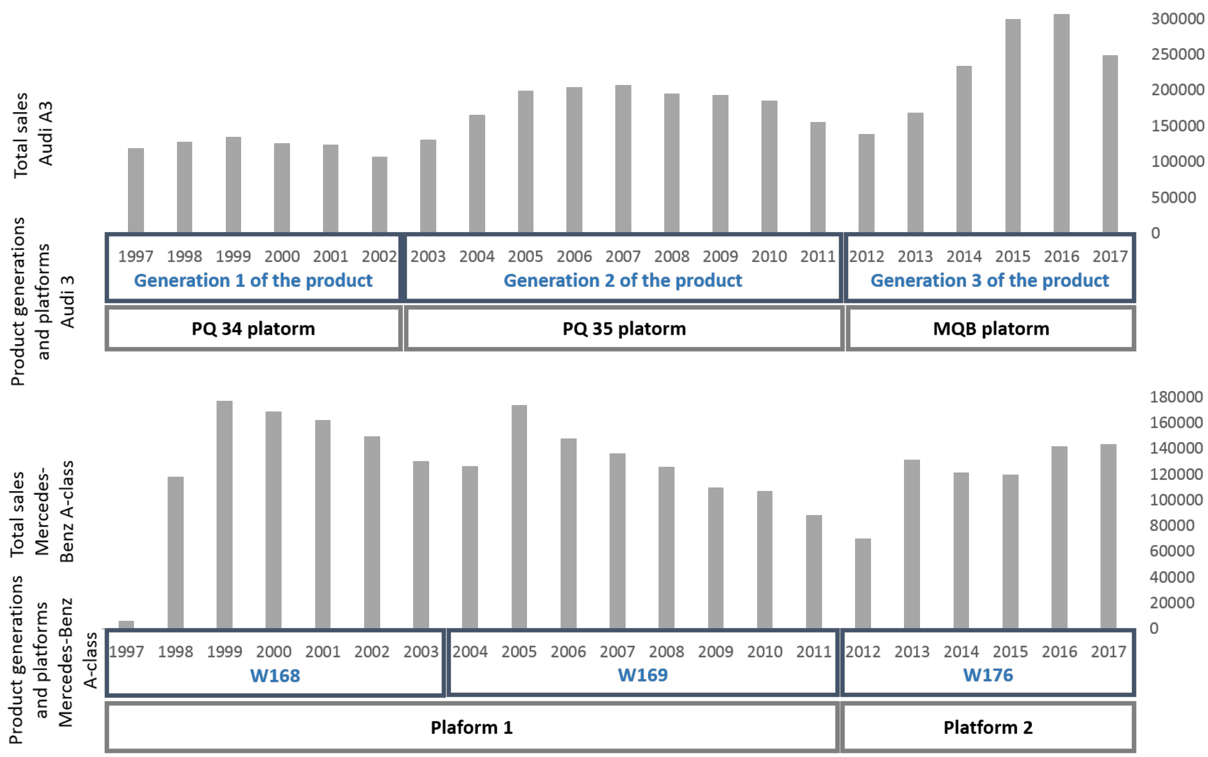

Figure 1: Total sales figures, and product generation and platform replacement planning, from 1997 till 2017, for the Audi A3 and Mercedes-Benz A-class cars (this figure is constructed based on information from Carsalesbase-website (2018)).

re-used for a subsequent product); when $q_{\max} = 1$, a new platform is used for two consecutive products, etc. The higher $q_{\max}$, the slower the platform replacement frequency. Without loss of generality, we assume five products to be the maximum number of products to be derived from a platform before it becomes technically infeasible to derive a new product from that platform (i.e., $q_{\max}$ is at most 4). The platform replacement frequency then equals $4 - q_{\max}$ (see Table 1).

In Figure 1 we illustrate the practical relevance of our model for the Audi A3 and Mercedes-Benz A-class, considered to be competing products. We look at the sales and platform replacement in the years 1997 till 2017, during which both companies introduced three new product generations. For Audi A3, the first and second product generations were respectively derived from platform PQ34 and PQ35., while in 2012 a new MQB platform was introduced, from which the third generation of Audi A3's was derived. For the Mercedes-Benz A-class, the first two product generations (W168 and W169) were derived from the same platform, while in 2012 they developed a new platform from which the third product generation (W176) was derived. Note that the time before replacing a platform is much higher at these automotive companies (i.e., more than 6 years), compared to the high-technology global technology company Barco, where the average time between platform replacement is around each 3 years. At Barco, over the last years, a platform typically lasted around 2 to 3 product generations (Boute et al., 2017).

In what follows, we first discuss the trade-off between the time to develop/adapt a platform. Next, we characterize the demand distribution used in our simulation model, and explain how competition is modelled. We also define three performance objectives, and discuss the design of the simulation experiment.

3.1 Trade-off between platform development and adaptation time

The company's platform replacement frequency is mainly driven by the trade-off between the time to develop a new platform and the time to adapt an existing platform to the newest product. We refer to Van den Broeke and Boute (2014) for an illustration of platform development and adaptation time for the development of high-tech screens. In our model, we assume that both platform development time and adaptation time are stochastic, and denote $\tilde{t}_i^d$ the random variable of the time required to develop platform i (matching product i), and $\tilde{t}_{j,q}^a$ the random variable of the time required to adapt product j from platform $i = j - q$ (with $\tilde{t}_{j,0}^a = 0$).

In line with Krishnan and Gupta (2001), we assume that developing a platform from scratch takes more time than adapting an existing platform to the product's needs, unless the platform is getting close to obsolescence, at which point the adaptation time can exceed the platform development time (Mäkinen et al., 2014). We model the time to adapt product j from its previous platform $i = j - 1$ as a percentage $0 \leq \alpha_a \leq 1$ of the time to develop a new platform $i = j$. As the gap between i and j increases, the adaptation time increases accordingly. More specifically, the time required to adapt product j from platform $i = j - q$ is given by:

$$\tilde{t}_{j,q}^a = \sum_{i=j-q+1}^{j} \alpha_a \tilde{t}_i^d. \tag{1}$$

For instance, if $\alpha_a = 0.50$, then the adaptation time to derive product j from platform $i = j - 1$ is half as long as the time to develop a new platform $i = j$, or $t_{j,1}^a = 0.50 t_j^d$.

Figure 2 illustrates two different platform replacement strategies. In strategy 1, platform 1 is used for three consecutive product generations; in strategy 2 a new platform is developed for each new product. Whereas strategy 1 benefits from more platform commonality and less platform development time and cost, strategy 2 avoids platform obsolescence,

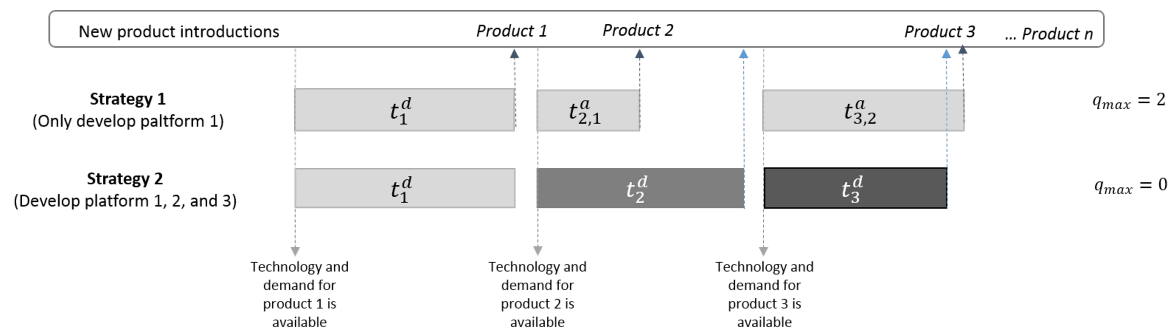

Figure 2: Illustration of the simulation model: two different platform replacement strategies for three consecutive product introductions.

and minimizes platform adaptation time. Clearly, the platform replacement planning impacts the timing of entering the market with the different products. Take for instance the introduction of product 2: when it takes longer to develop a new platform 2 instead of adjusting platform 1 to meet the requirements of product 2 (i.e., if $t_{2,1}^a < t_2^d$), product 2 will be launched sooner in strategy 1 compared to strategy 2. However, as platform 1 gets older and more obsolete, it may as well be that developing a new platform is less time consuming than adjusting an old one, so that for instance strategy 1 could have a longer introduction time for product 3 than strategy 2 when $t_{3,2}^a > t_3^d$.

3.2 Demand distribution

We characterize the demand of each product j over time t after its product launch by a Chi-squared distribution, resembling its product life cycle. The assumption for a Chi-squared distribution is supported by the sales statistics in Figure 1, and this distribution has the advantage that it can easily be adapted using different parameter settings. A product is introduced to the market by one of the companies at time T_j. The market follower launches the same product at time T_j^f. The firms' time to market depends on its platform replacement planning. The product demand that can be captured within a period t after its introduction is given by the cumulative density function of demand after its launch, represented by $F(t)$ (e.g., see the example in Figure 3).

The duration of market demand for a product depends on the timing of the subsequent product introduction and the cannibalization effect with this product. When product $j+1$ is launched, a portion α_c of the demand for product j may be cannibalized or lost, with $0 \leq \alpha_c \leq 1$ (Mason and Milne, 1994). A higher value of α_c means more cannibalization; a value of $\alpha_c = 1$ represents the extreme case where demand drops to zero after the launch

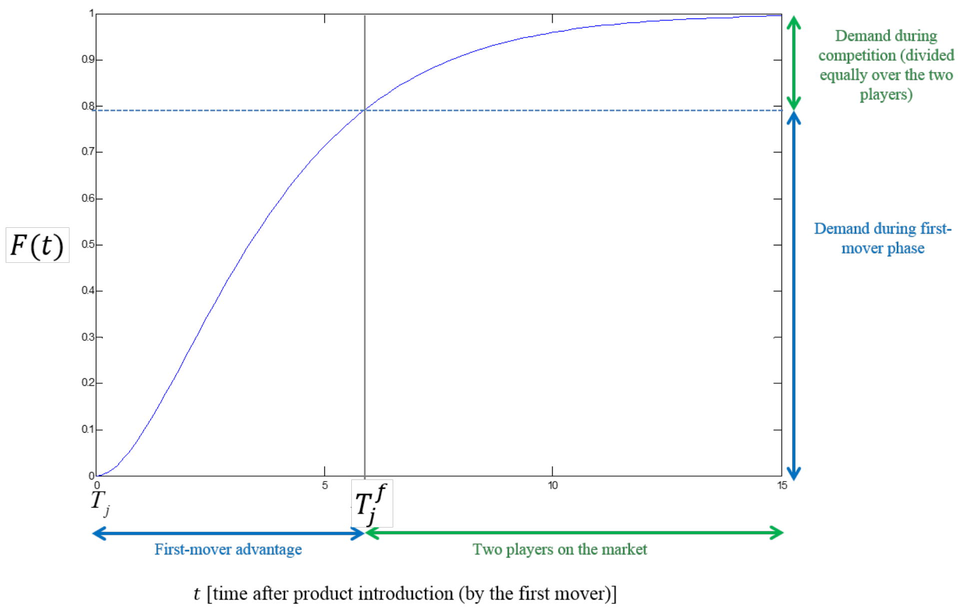

Figure 3: Cumulative distribution function of demand if the focal company is the first to introduce product j and there is no cannibalization from consecutive products.

of a product successor. We assume that product j only cannibalizes the demand of product $j-1$.

3.3 Competition

Both the focal firm and its competitor decide on their platform replacement planning. A firm can replace platforms slower, faster, or at the same speed as its competitor. At each new product introduction, the focal firm competes with its competitor to capture market share, while being confronted with the market entry timing of their platform replacement decision.

The company with the shortest time-to-market for product j (denoted by T_j) is first to launch product j in the market (the first mover). The time-to-market for the second company to market for product j (the market follower) is denoted by T_j^f, with $T_j \leq T_j^f$. We assume that, as soon as the market follower introduces its product to the market, the market demand is shared over the two companies.

3.4 Performance objectives

We study platform replacement planning under three distinct performance objectives. The first objective is maximizing the market share. The market share obtained by the focal firm

Parameter	Values	Interpretation when parameter value increases
α_a	$\{0, 0.50, 1\}$	Longer platform adaptation time
α_d	$\{0, 0.2, 0.4, 0.8\}$	Higher platform development cost
α_c	$\{0, 0.50, 1\}$	Higher cannibalization
λ	$\{0.5, 1, 4, 20\}$	Higher speed of innovation

Table 2: Parameter settings used in the computational experiment

for product j is denoted by V_j. Without loss of generality, we assume the price at which products are sold to be fixed over time and equal to 1. This means that revenue is purely driven by market share. As $F(\infty) = 1$, the maximum attainable revenue for product j is $V_j^{\max} = 1$. The total expected market share over all n products is denoted by $V = \sum_{j=1}^{n} V_j$, and the average market share per product is then reported by V/n.

The second performance metric that we consider is profit. Each time a new platform is developed, a development cost is incurred, which we express by α_d, with $0 \leq \alpha_d \leq 1$. For instance, the development costs of the platforms at Barco, the global technology company producing medical screens, represent the lionshare of their product cost, representing around 35% of the revenues ($\alpha_d = 0.35$). The total profit over all n products can then be expressed as $\Pi = V - \frac{n}{q_{max}+1}\alpha_d$, with $\frac{n}{q_{max}+1}$ the number of platforms developed (see Table 1), and the average profit per product is reported by Π/n.

Finally, we consider the risk, measured by the variance of the profits (Van Mieghem, 2011), as the third performance metric. Shareholders may indeed want to minimize the uncertainty in profits. Especially in competitive and innovative markets, the uncertainty in profits can be significant.

3.5 Design of the simulation experiment

We set up a computational experiment to analyse the optimal platform replacement planning strategy under different environments. The parameter values of our experimental design are summarized in Table 2 and cover a wide range of industry settings. Note that the interpretation of these parameters was explained in the previous section. In addition, we assume the development time $\tilde{t}_i^d$ to be uniformly distributed between 50 and 150 time units. In total, 144 model settings are observed over $n = 60$ product introductions. The simulation model was coded in Visual Studio C^{++}. We used common random numbers and 450.000 simulation iterations in order to guarantee the accuracy of our results.

4 Results and insights

In this section, we first discuss the general impact of the platform replacement planning on the firm's performance. Next, we discuss the impact of platform adaptation time, platform development cost, cannibalization, and innovation speed. Last, we consider the impact of competition. As previously explained, we evaluate the firm performance on three dimensions: market share, profit, and risk.

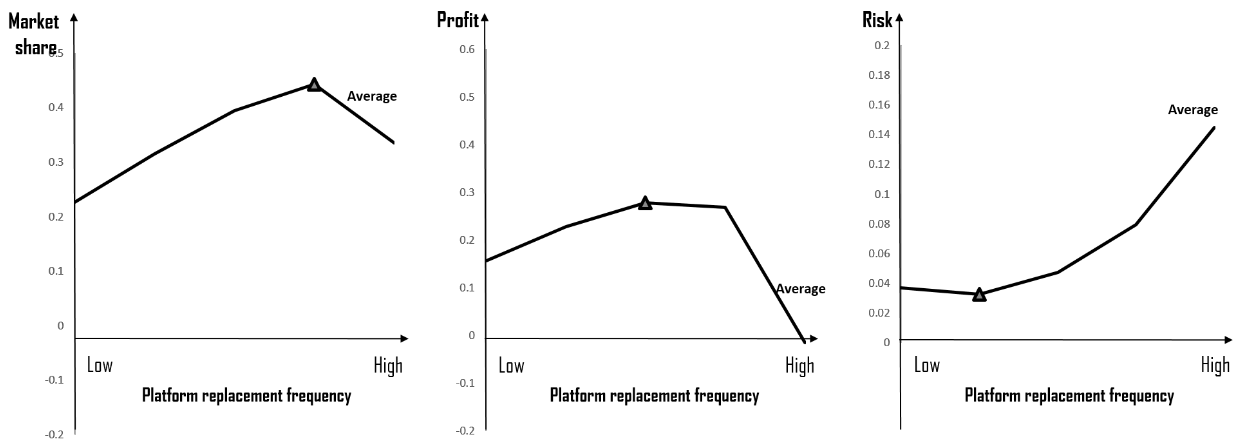

Figure 4: The market share, profit and risk under different platform replacement frequencies (the optimal replacement frequency is indicated with a triangle) averaged over all computational results.

Figure 4 reports on these performance measures, averaged over all 144 settings in our simulation experiment (the triangle indicates the optimal platform replacement frequency). We observe that the platform replacement frequency is a concave function of market share and profit (maximization), whereas it is a convex function of risk (minimization). In other words, extreme platform replacement strategies (i.e., always/never replace) are often suboptimal, and it is worthwhile to seek for the right balance. This makes practical sense, as it is too costly/time-consuming to develop a new platform for each new product, and it becomes too costly/time-consuming to adapt an obsolete platform to match the needs of new product innovations. When risk minimization is key, it also makes sense to avoid extreme strategies as they make it more likely to launch a new product either very early or very late. We also observe that the optimal platform replacement frequency is higher under market share maximization when compared to profit maximization. This can be explained by the fact that a myopic focus on market share ignores the costs of developing a new platform, and hence platforms will be replaced faster. When profit maximization is compared with risk minimization, however, we see that platforms are less often replaced when minimizing risk. This also makes practical sense as platform replacement induces more risk than adapting an existing platform. The observation that different performance objectives lead to different optimal platform replacement frequencies has not been shown before academically, but is important for companies. As different departments in a firm often have different performance objectives (e.g., operations, sales, and finance might respectively strive to minimize costs, maximize market share, or minimize risk), cross-functional collaboration is key when making platform replacement decisions. Moreover, it means that companies with a similar product portfolio might still adapt a different platform replacement strategy depending on their performance objective.

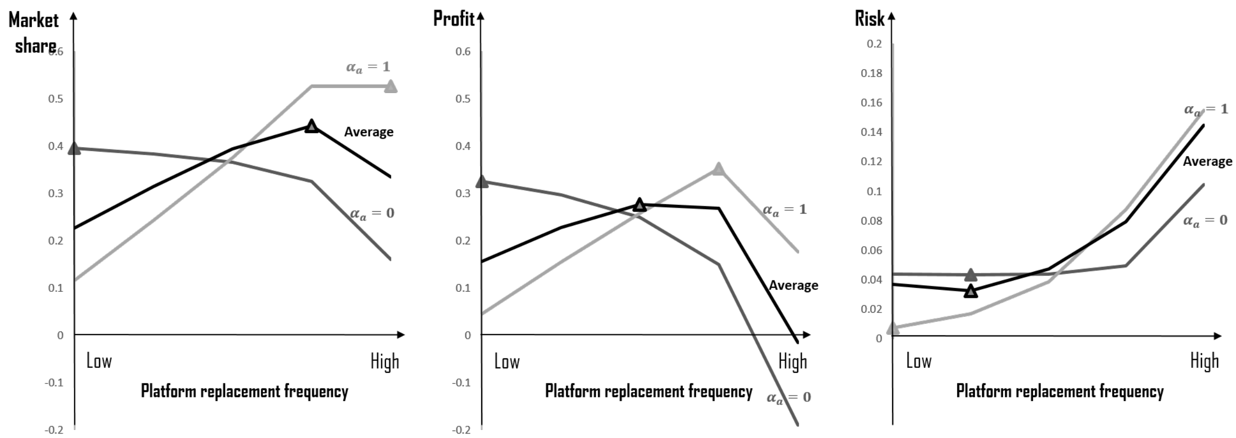

Figure 5: The impact of platform adaptation time (short and long platform adaptation time are respectively indicated by $\alpha_a = 0$ and $\alpha_a = 1$) on the optimal platform replacement frequency under market share, profit and risk. The optimal replacement frequency is indicated with a triangle.

Figure 5 illustrates the impact of platform adaptation time on the optimal platform replacement frequency (a higher value of α_a represents a longer adaptation time). If market share and profit are key, we observe that it is optimal to replace platforms faster if adaptation times increase. If adaptation times increase, the disadvantage of replacing a platform becomes less outspoken, and hence a new platform can be launched without endangering first-mover advantages and hence market share and profits. If, on the other hand, the objective is to minimize risks, the opposite is true: if platform adaptation time increases, the optimal platform replacement frequency decreases.

The impact of platform development cost is as expected, we find that the platform replacement frequency generally increases under the objective of maximizing profit when platform development costs decrease (see Figure 6). As development costs increase, firms want to leverage the large investment in development over more product generations. Whereas previous research has mostly focused on the impact of platform development costs, our results

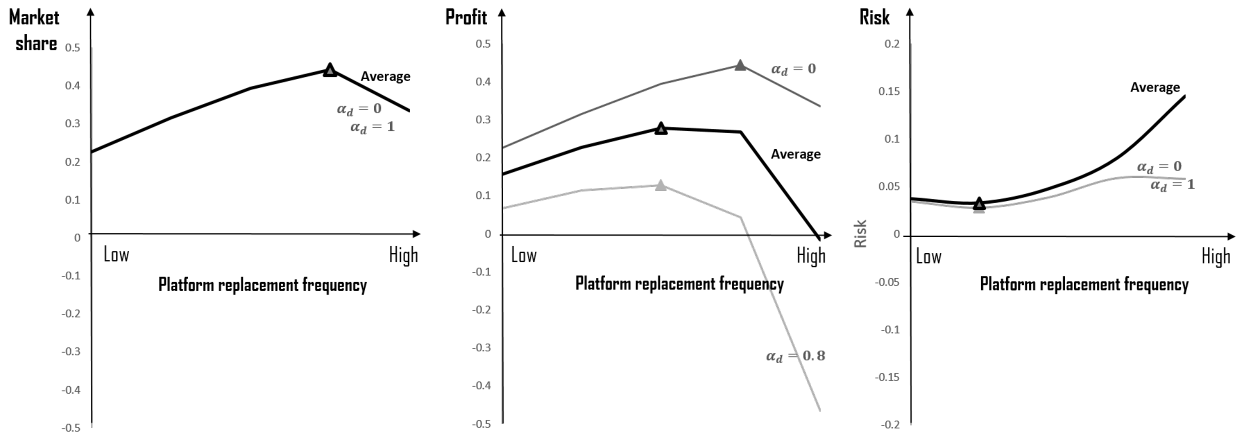

Figure 6: The impact of platform development cost (low and high platform development cost are respectively indicated by $\alpha_a = 0$ and $\alpha_a = 0.8$) on the optimal platform replacement frequency under market share, profit and risk. The optimal replacement frequency is indicated with a triangle.

show the importance of taking platform adaptation time into account when making platform replacement decisions.

Next, we discuss the impact of innovation speed and cannibalization on the optimal platform replacement frequency (results are shown in Figure 7 where a smaller value of λ indicates a slower innovation speed; note that the results for the impact of cannibalization are almost identical). We observe that the innovation speed does not necessarily have a big impact on the optimal replacement planning, and in case it does, a higher innovation speed would lead to a faster platform replacement when the objective is to maximize profit. We do observe, however, that the differences in replacement frequencies become less outspoken as innovations are introduced more rapidly. This can be explained as follows. If innovations speed is low, there is less cannibalization, and the full potential of the demand can be realized. If innovation speed is high, on the other hand, cannibalization kicks in, and profit/market share is lost. This also explains why the impact of cannibalization itself is almost identical to that of innovation speed: higher levels of cannibalization result in less profits/market share (for the same innovation speed). If risk minimization is key, a higher innovation speed (or level of cannibalization) results in a lower platform replacement frequency. Although platform replacement decisions at companies are often taken based on the innovation speed, it turns out that a change of this innovation speed does not necessarily have a huge impact on the optimal platform replacement decisions.

Last, firms are not operating in a competitive vacuum. The competitor also makes platform replacement decisions that (in turn) impact the optimal platform replacement frequency of the focal firm (see our earlier example of Audi A3 and Mercedes-Benz A-class). Figure 8

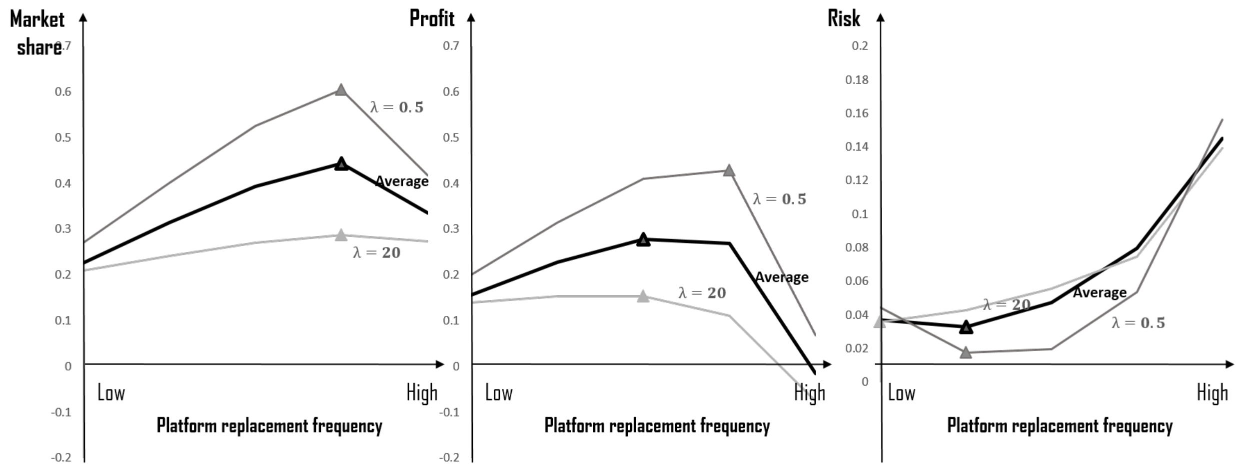

Figure 7: The impact of speed of innovation (low and high innovation speed are resp. indicated by $\lambda = 0.5$ and $\lambda = 20$) on platform replacement frequency (the optimal speed is indicated with a triangle) under different firm objectives.

summarizes the optimal strategies of the focal player depending on: (1) the platform replacement strategy of the competitor and (2) the performance objective that is considered. We conclude that it is mostly optimal for the focal firm to mimic the strategy of the competitor (i.e., if the competitor replaces platforms faster, the focal firm will also replace platforms faster, and vice versa). Trying to mimic the competitor's platform replacement frequency could lead to a rat-race in platform development. This explains why a company like Audi invests over 60 billion dollar in its MQB platform to keep up with competitors. However, under market share and profit maximization, we find that the focal firm is better off deviating from the competitor's strategy by respectively having a slightly higher or lower replacement frequency when the competitor has an extremely low or high replacement frequency. Under risk we find that there is an overall tendency towards replacing slower or equally fast as the competitor. Overall, replacing platforms faster than the competitor is thus not always optimal.

From the simulation results, we also observe that the profit loss of not making the optimal platform replacement decision increases as platform adaptation time, innovation speed and cannibalization increase.

5 Conclusion

In this article, we address the question when a platform should be replaced to cope with future product generations. Replacing a platform requires substantial development time and costs, but failing to do so may result in platform obsolescence, leading to longer platform

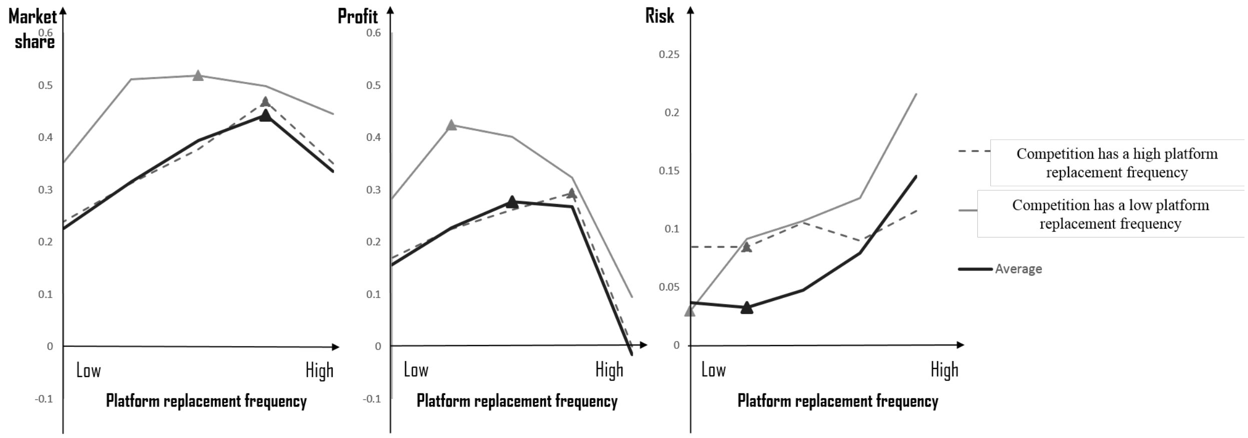

Figure 8: Impact of competitor's platform planning on platform replacement decisions (the optimal platform replacement frequency is indicated with a triangle) under different performance objectives.

adaptation times to customize the platform into the latest product. The platform replacement planning thus does not only impacts development costs, the resulting time to market also impacts the market demand that can be captured. The latter is in turn dependent of the competitor's platform replacement decision, impacting his time to market. We develop a simulation model that takes these dynamics into account. We find that higher innovation speed does not necessarily lead to faster platform replacement, and that replacing platforms faster than its competitor is not always preferred. We also find that the optimal platform replacement timing is strongly dependent on the performance objectives: shareholders may want to minimize financial risk, sales are driven by market share maximization, whereas the firm should strive to maximize profit. Given the impact of platform replacement on several departments, different departments may have differing opinions, leading to philosophical discussions and few decisions. Using our model those philosophical discussions can be framed in terms of dollars, and can be objectively assessed.

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