The Case of iOS and Android: Applying System Dynamics to Digital Business Platforms

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Abstract. Platforms are multi-sided marketplaces that bring together groups of users that would otherwise not have been able to connect or transact. The app markets for Apple iOS and Google Android are examples of such markets. System dynamics is a powerful method to gain useful insight into environments of dynamic complexity and policy resistance. In this paper, we argue that adapted to the context of digital business platforms, the practice of system dynamics facilitates understanding of the role of incentives in such marketplaces for increasing participation, value generation, and market growth. In particular, we describe our efforts to simulate the market competition between iOS and Android in terms of the interacting markets for devices and their apps.

Keywords: Android · iOS · Platform economy · System dynamics

1 Introduction

Digital business platforms, such as Apple App Store, Uber, and AirBnB, are dramatically reducing search and transaction costs. They are multi-sided marketplaces in which two or more user groups benefit from finding each other more easily [1], thus creating *indirect network effects.*[1] For example, in the case of AirBnB[2] and CouchSurfing,[3] the platforms originally allowed people willing to let others use their apartments, to find others who were looking for affordable, cosy accommodation while travelling. In the case of smartphone app stores, the consumers know that they can easily find apps for their smart devices from the store, while the app developers know that the users will look there for apps.

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[1] Direct network effects are positive feedback loops created *within* the same market, meaning that the benefit of a technology to a user depends positively on the number of users of this technology on the *same* side of the market. Indirect network effects are positive feedback loops created *across* the same market, meaning that the benefit of a technology to a user depends positively on the number of users of this technology on *another* side of the market.

[2] https://www.airbnb.com/.

[3] https://www.couchsurfing.com/.

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From the modelling point of view, the market dynamics of digital business platforms has thus far gained relatively little attention (see Sect. 2). Although there have been efforts to model digital business platforms using system dynamics, no studies have yet attempted to model the user and the developer side of the market together in the iOS and Android ecosystems.

In this paper, we model the competition between Apple and Google in the smartphone market using the stocks and flows elements of the *system dynamics modelling* (SDM) methodology. We focus on the dynamic market competition between iOS and Android smartphone platforms in terms of the interplay between the user and developer sides of the market. At this point, a simulation model has been calibrated with publicly available data. The model is able to adequately replicate the historical dynamic interplay between these two competing two-sided markets, based on statistical parameters of *sensitivity* and *threshold*. Our simulation results show that the whole market can be easily captured by an initially inferior player, provided that such a player reaches sufficiently early the exponential feedback loops depicting the direct or indirect network effects.

In particular, we shed light on the factors affecting the competition between Apple and Google in the smartphone industry. With this initial step, we pave the way towards a better understanding of not only digital business platforms in general, but also the reason that digital business platforms tend to show a winner-take-all structure.

To our knowledge, this is the first paper that applies SDM to study the competition between particular, historically recorded digital business platforms. In other words, the prior art on using SDM to model multi-sided markets has focused on abstracting a generic market model, without any reported serious attempts to calibrate the model using historical data.

The rest of the paper is organised as follows. In Sect. 2, we describe the overall background, focusing on previous attempts to capture the dynamics of multi-sided markets and especially the market encompassing Apple and Google. In Sect. 3, we introduce our models and describe the simulation results, which are then discussed in Sect. 4. Section 5 concludes the paper suggesting future work.

2 Background

Before the Internet, many industries were dominated by large search and transaction costs. However, the advent of the Internet and search engines has brought a significant change resulting in companies being able to reach their customers all over the world. This has created a new problem in the form of fake companies and fraudulent services.

Digital business platforms have emerged to solve this second problem by creating an incentive for the suppliers to act in a trustworthy manner, thereby allowing them to enhance their reputation. eBay was perhaps the first platform that managed to capture the required dynamics.

2.1 Related Work

The term "platform", in the meaning of a digital multi-sided market, was coined by Rochet and Tirole in 2003 [6]. Platforms create value by acting as conduits between two (or more) categories of consumers, who would have been unable to connect or transact otherwise [10]. The more consumers enter the platform, the more value they capture as a result of the *indirect network effects* between the user groups. These network effects reflect the exogenous interdependence of demand between consumer groups and shape platform competition [8]. The network effects in such a platform form a self-reinforcing feedback loop, which creates an advantage for early adopters. In addition, as these network effects grow, they act like a barrier to entry for potential competitors [3], under certain conditions, leading to a winner-take-all outcome [4].

Attempts to model digital business platforms using system dynamics are quite rare. Dutta et al. use system dynamics to model the diffusion of iOS and Android based handsets [2]. Ruutu et al. provide a system dynamics simulation model to analyse platform development and platform based competition [7]. Scholten et al. depict network and complementarity effects of a Platform-as-a-Service (PaaS) ecosystem [9]. Von Kutzschenbach and Brønn use a feedback systems approach to illustrate Uber's 'get big fast' (GBF) strategy [11]. Finally, Zolfagharian et al. provide an evidence-based framework that demonstrates why, when, and how system dynamics is combined with other methods [12].

Closest to our present work, Meyer considers path dependency in the context of two-sided markets with indirect network effects which commit users to an inferior technology platform [5]. Meyer uses *agent-based modelling* (ABM) in order to show that third-degree[4] lock-ins exist, but are rather rare. Our work differs from that of Meyer's in that we mainly focus on the historical market share evolution of smartphone platforms, while he has investigated a number of more generic scenarios. Based on these scenarios, we hypothesise that the behaviour of contingent events determining the outcome of market lock-ins could be explained, and possibly driven by, imperfect information and the bounded rationality of the actors.

3 Models

In this paper, we present a high-level and a low-level simulation model for depicting the network effects of users and developers in the two major smartphone platforms, iOS and Android. Our models are based on expert interviews and earlier models presented in the literature. At the time of writing, the models form two architectural layers: a narrow layer that models expert knowledge in a concise *causal loop diagram* (CLD), and an extended layer for simulation purposes.

[4] A first-degree lock-in refers to the dominance of a single "best" technology. In contrast, both second- and third-degree lock-ins designate the dominance of an inferior one. A second-degree lock-in describes the dominance of a technology, while a better alternative has since become available. A third-degree lock-in occurs when an inferior technology dominates the market, even though a superior one is available.

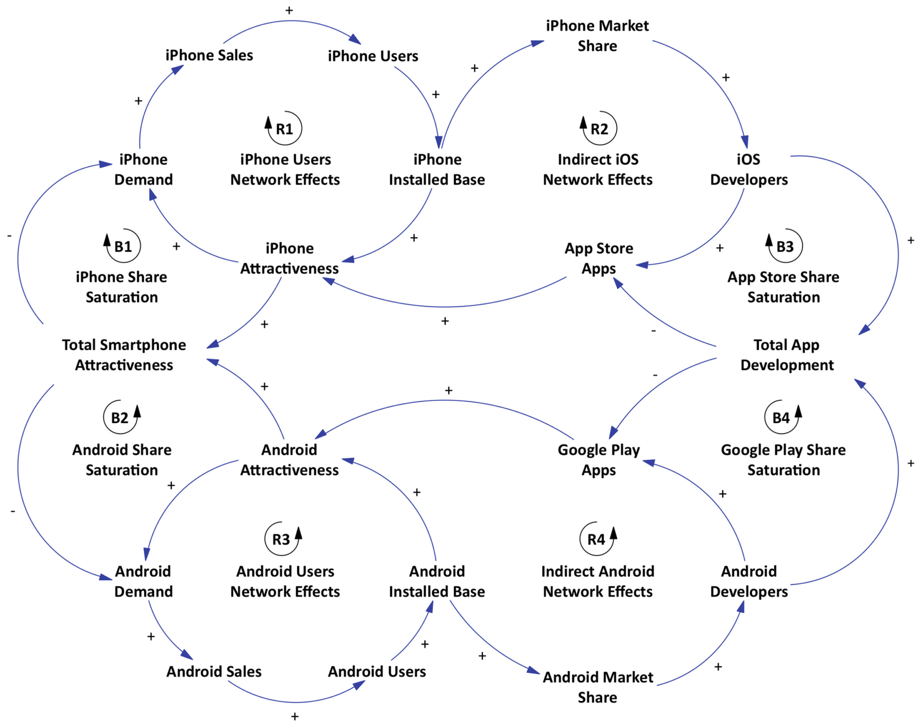

Fig. 1. Smartphone users and developers network effects high-level model

3.1 Expert Models

Figure 1 depicts the high-level model illustrating the overall structure of a multi-sided market. The figure portrays the main network effects of the market: the direct and indirect network effects. The direct network effects are those occurring among the users, who benefit from other users of the respective platform by lowering transaction and learning costs. In contrast, the indirect network effects are those interactions manifested between the users and developers. Furthermore, a negative network effect is postulated among the developers, since the more developers there are on a platform, the fiercer the competition among them. Finally, the phenomena of saturation exemplify the natural limit for smartphone demand and app development. The low-level version can be found in Fig. 3 in the Appendix.

3.2 Simulation Model and Results

Our work focuses on matching historical data with a low-level simulation model. We use publicly available data from Statista[5] for the total smartphone demand, total number of apps, and market shares.

[5] https://www.statista.com/.

At the present stage, we have explicit sensitivity and threshold parameters to describe the strength of the direct and indirect network effects. These parameters allow us to easily change the end-states of the simulation. Our goal is to eventually replace these with input variables describing real world effects and the overall ethos in the markets. The manually calibrated models allow us to investigate differences in the effects of static product-specific quality and utility on the lock-ins occurring in the market.

Interestingly, we observed a large number of parameter values forcing the market into a third-degree lock-in. That is, causing an inferior incumbent product to drive out a far "better" product, despite the "better" product being initially able to gain significant market share from the incumbent.

To calculate the effect of the size of the user and developer networks on smartphone attractiveness, we use the following equation:

$$\exp(\mathit{Sensitivity} * \text{Installed Base} \ / \ \mathit{Threshold})$$

As shown in the equation, attractiveness rises exponentially as the installed base grows relative to the threshold. The sensitivity parameters allow us to vary the strength of the effect of both user and developer network sizes on smartphone attractiveness in sensitivity tests. The threshold parameters are scaling factors representing the users and developers in terms of the size of the installed base and number of apps, respectively. Only above these threshold parameter values do network effects become important. Finally, except for the size of the user and developer networks, the *effect of other factors* parameter aggregates factors, such as the effect of price, features, and availability of the smartphone and the effect of tools and policies for app development.

Figure 2 shows one sample run from our simulation. In this run, iPhone and Android market shares start at the same level, with the remainder of the market being comprised of the shares of other competitors based on historically recorded market data from Statista. Initially, iPhone and Android market shares parallel each other, reaching roughly equal market shares. Thereafter, Android begins to overtake iPhone, whose market share then drops back to 20%. The corresponding sensitivity, threshold, and other factors parameter values for this simple run are shown in Table 1.

4 Discussion

Unlike Meyer's AB model, our SD model integrates phenomena of positive, negative, direct, and indirect network effects with market saturation. At this point, our approach to modelling the difference between iOS and Android is still somewhat ad hoc. Our goal is to eventually replace the current vague sensitivity and threshold parameters with historical market data.

The phenomena related to path dependency, including both positive and negative feedback loops, are of such strength that they will inevitably dominate the simulation results. Meyer describes the market's commitment to an inferior technology platform by investigating first-, second-, and third-degree lock-ins. Although

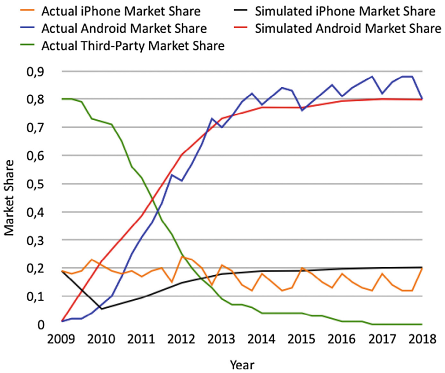

Fig. 2. Comparison of simulation results and real world data

Table 1. Simulation parameter values

Parameter	Variable	iPhone	Android
Sensitivity	Attract. of installed base	1	1
	Attract. of apps	100	100
Threshold	Users network effects	2B	8.5B
	Devs network effects	100k	100k
Other	Attract. of smartphone	1	4.1
	Attract. of app development	1	1

our model is inherently capable of modelling first- and third-degree lock-ins, we are currently unable to investigate second-degree lock-ins. This is due to the ability of our SD model to reflect static quality differences, but inability to yet represent incomplete information, needed by the concept of a second-degree lock-in.

5 Conclusions and Future Work

While platform economy and multi-sided markets are well-established concepts, only a few works have focused on modelling competing platform ecosystems based on historical data. In this paper, we have presented our ongoing work towards understanding the dynamic and multi-dimensional competition between the two major smartphone platforms, iOS and Android. In particular, we have observed that changing generic sensitivity and threshold parameter values, which express the strength of network effects and their relationship to the underlying social penetration factors, can easily lead to major differences in the market share of otherwise similar products. Our model is highly sensitive to changes in these parameter values due to them governing the quantitative exponential effect of the feedback.

In the near future, we will focus on enhancing our model in order to better conform with actual historical data. For this purpose, we plan to add input variables for quantifying the differences between the two companies' strategies, such as the level of product differentiation and resulting price structures. In other words, our goal is to replace the generic feedback loops with more details that describe the manner in which people valuate the differences between products in terms of quality and price.

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Appendix

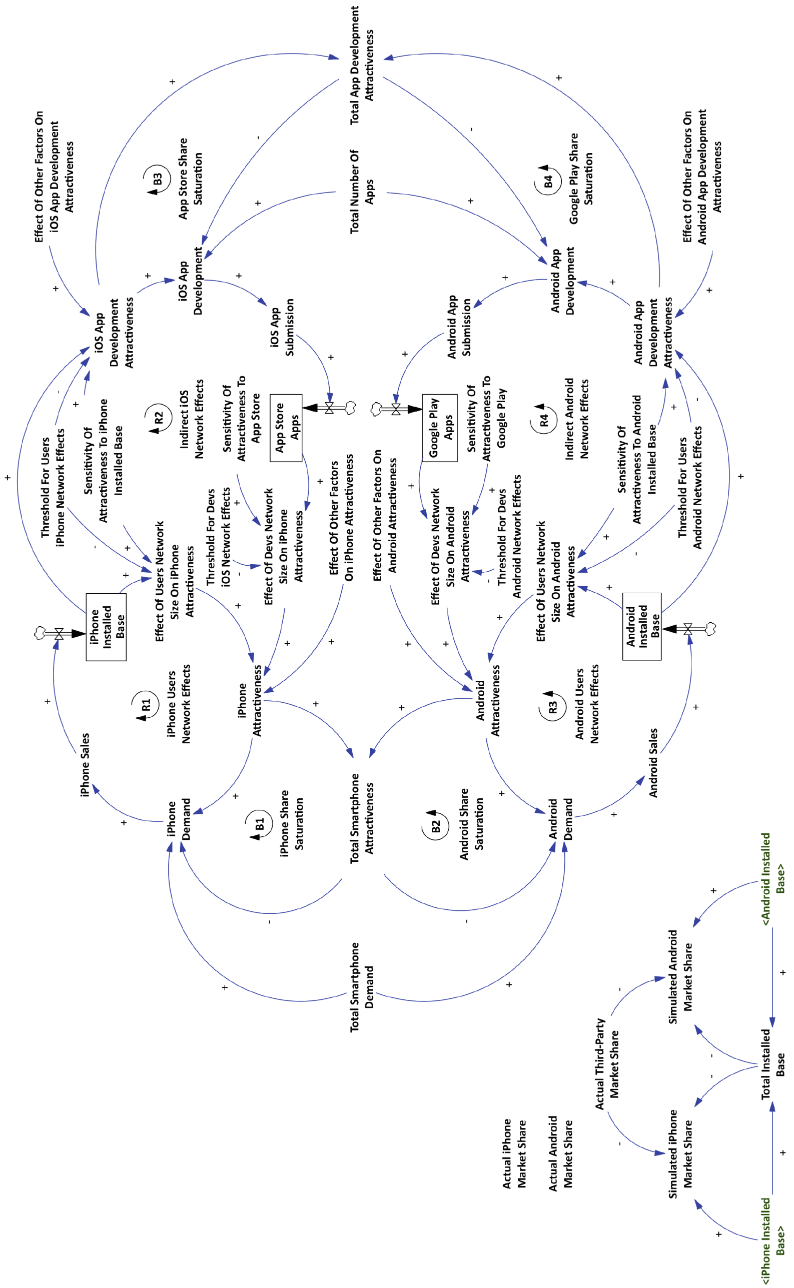

Fig. 3. Smartphone users and developers network effects low-level simulation model

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