“Free and Paid”

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Abstract

Since the introduction of the App Store in 2008 the mobile applications (apps) market has been growing rapidly. Currently there are about 1.8 million apps in the App Store and that number increases every day. That is why app developers have to develop strategies that will generate revenue and make their app noticeable in the App Store. One possible solution is to pair a paid app with a free trial version ("free and paid app" strategy). Previous studies on apps have proved that free trials improve visibility and increase demand for the paid app. Demand for an app is reflected in its rank performance in the App Store charts. A high rank in the charts improves visibility of an app. Furthermore, earned media like features by the App Store and consumer reviews significantly affect visibility and demand for apps.

Despite the benefits of a free trial, developers remain skeptical if the free trial app attributes to demand increase for the paid app. That is why this article aims to answer the following question: **"How is the rank performance of the free app interrelated with the rank performance of the paid app over time, and what impact do earned media have on rank performance?"** To answer this research question various relationships between rank performance and earned media have to be identified. Hence persistence modeling is used because it is a time-series method that is able to identify various direct, indirect and feedback relationships between variables. This modeling approach is used on panel data of 15 pairs of free and paid apps.

The results show that free app trials do have long-term impact on the rank performance of paid apps. Earned media also have an effect on rank performance. Features by the App Store are able to significantly improve rank performance in the short term of both free and paid apps, but consumer reviews have only a small effect on rank performance. Based on these findings several managerial and academic implications will be provided.

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Chapter 1. Introduction

1.1 Research Background

Since Apple launched the App Store in 2008, the growth of mobile applications (apps) has been explosive. Easy entry to the App Store allowed third-party developers to launch their apps quickly. With about 1.8 million active apps in the App Store,[1] apps cover a wide range of subjects and target users. The downside of easy entry is growing competition. New apps are continually added to the already large number, which makes it increasingly difficult for apps to stand out, especially when newcomers are similar in functionality to existing apps. Because app concepts are often easy to copy, developers can clone popular paid apps (apps that can be downloaded for a fee) and launch them for free. This naturally results in the loss of potential revenue for the original app. For example, in early 2014 the mobile puzzle game Threes! was launched as a paid app. When it quickly gained popularity, many clones, such as 2048, started to emerge. The clones had the same game concept as Threes!, but were offered for free. Because Threes! was a popular but paid app, many consumers who wanted to try the app without cost chose a similar free version. After careful consideration the developers finally launched a free trial version in June 2015 to appeal to consumers who preferred not to pay for apps (Webster, 2015). The move proved to be successful; in July the developers of the game revealed on Twitter that the introduction of the free version doubled their revenue.[2] This example suggests that consumers would rather download a free app than spend money on a paid app. One possible way of interpreting this is that apps are experience goods because consumers can only form their opinion about it through experience (Nelson, 1970). Paid apps are thus viewed as risky because consumers have to pay for the app before they can judge its quality. A free trial of the paid app reduces perceived risk and increases the appeal of the paid app (Jung, Baek, & Lee, 2012).

Pairing a paid app with a free trial version not only reduces perceived risk but also combines revenue streams. The free apps, for example, may include advertising revenue and in-app purchases, while the paid app might rely on paid downloads and in-app purchases. This strategy is often used by firms that offer digital goods in an online environment; their revenue stream options include charging for content, online advertising, or a combination of

[1] http://www.pocketgamer.biz/metrics/app-store/app-count/, retrieved on August 9, 2015
[2] https://twitter.com/AsherVo/status/623264369242013700

both (Lambrecht, et al., 2014). In their article Prasad, Mahajan, and Bronnenberg (2003) describe the value of business models that combine revenue streams. For example, a combination of paid content with ad-supported free content can be optimal to earn revenue from two sources by attracting different consumer segments. The downside of having a free trial version is potential cannibalization. Halbheer, Stahl, Koenigsberg, and Lehmann (2014) considered this effect of product trials on sales. They concluded that product trials of digital content, despite cannibalization, increase demand for the paid content, but only if the quality of the paid content is expected to be higher than the quality of the free content. All in all, the inclusion of the free trial version not only allows consumers to experience the paid version, but can also provide an additional revenue source. Therefore the business strategy of pairing a paid app with a free trial version (what will be called a “free and paid app” strategy in the rest of the paper), is a relevant and timely subject to examine.

Previous research studies on apps have also included the “free and paid app” strategy in their analysis. Ghose and Han (2014) showed that this strategy works well to increase demand for the app. The App Store lists apps in charts. The rank in a chart reflects the relative popularity of a particular app and is mainly based on past downloads. When the free and paid strategy is used, there are two versions of an app in the store, which are listed in two separate charts. Therefore the visibility of the app increases. Furthermore, Jung et al. (2012) found that apps with the “free and paid app” strategy stay longer in the App Store charts than other apps. Not only is the business strategy important, but visibility in the App Store is important as well. As was already noted, there is a great deal of competition. Having a good rank performance is essential, as it not only indicates past performance but also influences future demand. For example, if an app is ranked in the top 10 it will have a disproportional amount of demand compared to any lower rank (Carare, 2012).

Visibility and demand of an app can also depend on features. The App Store promotes various apps by featuring them in the store on the home page or within the app category and sub-category pages. Features are comparable to in-store displays. In a physical store, in-store communications such as displays are often used to highlight certain brands or products. Displays are effective at increasing product visibility at the point of purchase (Van Nierop, Bronnenberg, Paap, Wedel, & Franses, 2010). App features differ from in-store displays in that the developers do not pay the App Store to promote the app; they are generally not paired with price promotions, but rather include other products, and they change by day.

Nevertheless, features in the App Store have the same goal, which is to expose apps to many consumers in order to increase downloads. Figure 1 in the Appendix shows an example of features as seen in the App Store.

If consumers have no experience with an app, they can make use of reviews to make a decision. In the App Store each app has its own reviews. As with other products where the quality cannot be evaluated based on the description alone, a review by other consumers can be an important source of information. Jung et al. (2012) and Ghose and Han (2014) have shown that reviews influence app demand.

What features and reviews have in common is that they both depend on a third party and must be earned. Therefore they can be grouped together as earned media (Stephen & Galak, 2012).

The existing research on “free and paid app” strategy is quite general. For example, it is still unclear how much impact a free app has on the rank performance of the paid app. Although previous work has covered many potential drivers of app demand, features have not been included in these analyses. Features (and reviews as well) might have a significant effect on app demand. Furthermore, it would be interesting to know how long that impact lasts over time. Business managers and developers could profit from a better understanding of the App Store dynamics in the short and long term. Thus, the goals of this paper are to fill the gap in research regarding the “free and paid app” strategy and to study the impact earned media have on rank performance over time. Based on these goals, the following research question was formulated:

“How is the rank performance of the free app interrelated with the rank performance of the paid app over time, and what impact do earned media have on rank performance?”

To answer the research question in a more substantial way, the following sub-questions were developed:

- What effect does the rank performance of the free app have on the rank performance of the paid app over time?

- What effect do earned media have on the rank performance of both free and paid apps?
- Is there an interrelationship between earned media and what effect do they have on one another?

The last question aims to shed light on the possible interrelationship between reviews and features. Because Apple does not disclose why they decide to feature certain apps, it would be valuable to know whether the decision is based on other variables, such as reviews.

Due to the nature of the research questions, persistence modeling will be used for the methodological approach. Persistence modeling addresses over-time response of performance variables to a change in other variables and includes any complex indirect and feedback effects (Dekimpe & Hanssens, 1995). The approach includes unit root tests, Granger causality tests, a vector autoregressive model and impulse response functions. This methodological approach is explained in detail in chapter four.

1.3 Academic relevance

The present paper aims to fill gaps in two research fields. First, as mentioned above previous work on mobile applications is still general in its nature. This paper is more specific because it addresses the "free and paid app" strategy on its own. Also, features by the App Store are included as a factor that drives app demand, which has not been studied before. Jung et al. (2008) and Ghose and Han (2014) included only app characteristics and reviews in their article, and Carare (2012) studied only the effect past rank performance has on future rank performance. In addition, persistence modeling is a new way to analyze app rank performance.

Second, this subject fits in with previous research regarding the effect of free product trials on purchases. This subject has been studied for several decades, and thus most work addresses physical and re-purchasable products (Scott, 1978; Lammers, 1991; Gedenk & Neslin, 1999; Bawa & Shoemaker, 2004). More recently, Pauwels and Weiss (2008) carried out a study using persistence modeling with regard to subscriptions to a digital content provider. They included own marketing actions which influence consumers' conversion from free content to paid content. In their analysis they did not include earned media. This paper will contribute by adding a new type of digital product and by including earned media as a factor that drives consumer demand.

1.4 Managerial relevance

Managers and developers are concerned that consumers prefer to download apps for free and at the same time they are skeptical about the effectiveness of free trial apps on paid app downloads. They do not want to incur additional costs to maintain a second app when it is not effective. Moreover, mangers are concerned about the visibility of their app and they often search for ways to improve rank performance.

This paper will study the interrelationship between the free and paid app, thus enabling managers to determine whether it is worth maintaining two apps instead of one. This research will also help managers understand various dynamics over time within the App Store, by showing what impact certain factors such as earned media have on rank performance, and for how long. With this knowledge managers may form a strategy in order to improve the rank performance.

Mobile game developers may also profit from this research, because this article uses games as a case study. Games are not only the largest app category, but also the most downloaded and most competitive. There are only a few big players in this category, compared to a large number of relatively unknown apps (long-tail distribution). For an app in this category, achieving a high rank may be very profitable.

1.5 Structure

The subsequent chapters are structured as follows: chapter two presents the theoretical background that supports hypotheses relating to free trials, reviews and features. Chapters three and four describe the data set and the methodological approach respectively. Chapter five discusses the results based on impulse response functions. Finally, chapter six presents the conclusion, as well as limitations and ideas for further research.

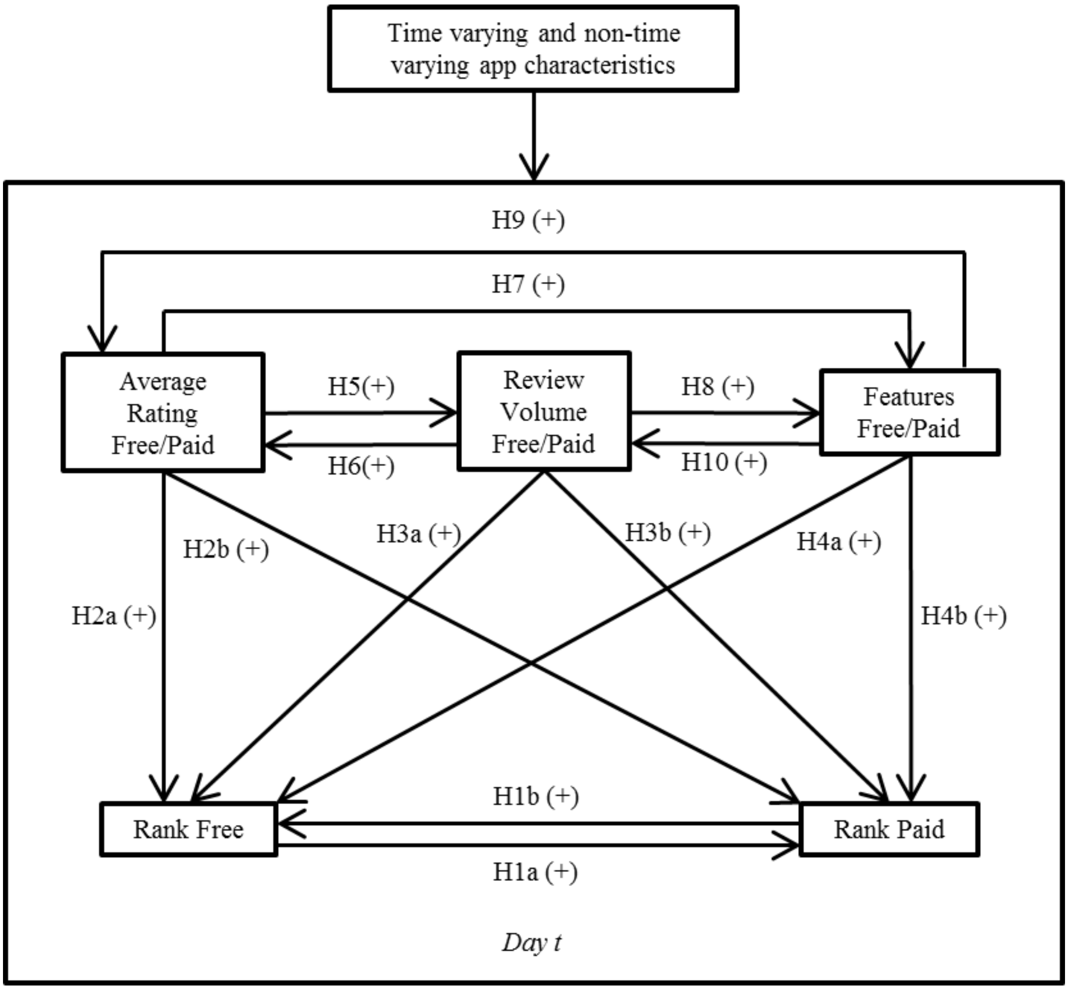
Chapter 2. Theoretical Background

This chapter will cover previous research focusing on the effect of free product trials on incremental sales increases, provide evidence from the app market and dive deeper into the subject to form the hypotheses that will be tested in this paper.

2.1 Conceptual framework

The conceptual framework shown in Figure 1 presents the various relationships between variables.

Figure 1 Conceptual framework



Note. Free/Paid indicates the difference between free and paid app variables. For example, average rating free/paid represents the average rating of free apps and the average rating of paid apps.

The conceptual framework figure represents several relationships. First, there is a positive interrelationship between free and paid app ranks, which is indicated by H1a and H1b.

Consumers who try the free app and download the paid app afterwards improve the rank performance of the paid app. Paid apps may also increase the visibility of the free app. Consumers may download the free app after viewing the paid app in the App Store. Therefore an improvement in the rank performance of the free app should lead to an improvement in the rank performance of the paid app, and vice versa. Figure 1 also includes *Day t* to indicate that the effects are influenced by time. The relationship between the two rank performance variables is expected to be immediate, short- and long-term. Following H1a and H1b, H2 to H10 are subdivided between free and paid apps to account for the difference between free and paid apps.

Second, the direct relationship between review variables and rank performance variables is depicted by H2 and H3. Reviews consist of two variables: average rating and review volume. Previous studies found that a high average rating and review volume have a positive impact on sales. Hence rank performance may be positively influenced by an increase in average rating or an increase in review volume. The effect of reviews on rank performance is expected to be immediate, short- and long-term.

Third, the direct relationship between features and rank performance is indicated by H4. In this paper features by the App Store are compared to in-store displays, which have a positive short-term effect on sales. Like in-store displays, features increase the visibility of apps within the App Store. Because an app can be featured by the App Store in multiple lists at the same time; an increase in the number of features may have a positive immediate and short-term effect on rank performance.

Furthermore, H5 and H6 represent the interrelationship between review variables. As suggested by previous studies reviews may have a dynamic interrelationship that could affect rank performance. For example, an increase in the average rating may have a positive effect on review volume. Similarly, an increase in review volume may have a positive impact on the average rating.

Moreover, H7 to H10 depict an interrelationship between reviews and features. With H7 and H8 it is hypothesized that average rating and review volume have a positive effect on the number of features an app receives. The opposite interrelationship is represented by H9 and

H10; features have a positive effect on the average rating and review volume. These hypotheses aim to increase the understanding of the App Store dynamics.

Finally, time-varying and non-time varying app characteristics are added as mediating variables, because Jung et al. (2012) and Ghose and Han (2014) concluded that app characteristics have an effect on app demand.

2.2 Interrelationship between free and paid app rank performance

The way apps move in the rankings is defined as their rank performance. As rank performance is influenced by downloads, an increase in downloads results in a better rank performance, i.e. a higher rank. Consumers who download the paid app after trying the free app improve the rank performance of both apps. Conceptually, the rank performance of the paid app should be correlated with the rank performance of the free app.

Some evidence from previous research on apps shows how the free app influences the demand for the paid app. Although the “free and paid app” strategy was not the main subject of their research, Jung et al. (2012) included the strategy in their analysis of the survival of mobile apps in the App Store charts. They concluded that this strategy was the most successful for long-term survival in the App Store. They also showed that consumers are usually more cautious with paid apps than with free apps, because consumers are risk-averse and reluctant to incur costs. The “free and paid app” strategy reduces the perceived risk of paying because it is possible to download the free version and, based on that, decide to purchase the paid version. They also concluded that a high-ranked free app may have an impact on the performance of the paid app due to visibility in the charts. Likewise, a high-ranked paid app can increase the demand for the free app. More recently Ghose and Han (2014) performed a general study on app demand. Their research examined which app characteristics have the greatest effect on the demand for an app and included the free and paid strategy as a control variable. They found a positive correlation for cross-chart listing. Thus when free and paid versions of an app appear in both charts the rank movement of both apps is positively correlated. Overall, both articles concluded that free and paid apps have a mutual effect in which the increased visibility of both apps in the charts eventually led to more downloads of both apps. Therefore an improvement in the rank performance of the free app should lead to an improvement in the rank performance of the paid app, and vice versa.

Because downloads of paid apps may be viewed as sales, taken out of the app market context, the subject is essentially the use of free product trials in order to increase sales. Previous research on this subject includes experiments with physical goods and stores as well as digital goods in an online environment.

In general free product sampling is a popular tool among marketers for new product promotion and has been the subject of many studies. Surprisingly, only a few published studies have examined the direct effect of free samples on sales. Scott (1976) carried out a field experiment with free trials and examined their impact on six-month subscriptions to a newspaper. This research found that only 3.9 percent of the consumers that received a free two-week trial subscribed to the newspaper. Compared to the subscription percentage of the control group that did not receive any trials (9 percent), providing a free trial was less successful. Thus the article concluded that offering a free trial was less effective than offering no trial at all. While this research showed that free trials did not have a positive impact on sales, it is important to note that only one product type was used in the experiment and that subscriptions followed long after the initial sampling of the product.

Lammers (1991) also carried out a field experiment in which free samples of chocolates were distributed among chocolate store customers. The experiment showed that providing samples resulted in more immediate purchases in the store. Gedenk and Neslin (1999) also examined the effect of free samples on in-store purchases. They found that free samples generally had a positive effect on mineral water purchases. In addition, the effect was stronger in the long term than the short term, meaning that consumers were likely to purchase the brand in the future, and not immediately. Drawing on previous studies, Bawa and Shoemaker (2004) further elaborated on the effect of free product samples. Their research consisted of two field experiments with fast-moving consumer products and included potential positive and negative consequences of product sampling. They found that free samples had positive short- and long-term effects on incremental sales in both experiments.

While the articles mentioned above focused primarily on physical products that could be bought in stores, Pauwels and Weiss (2008) examined a case in an online market where consumers are not accustomed to paying for products. Specifically, they examined the effect of free trials on subscriptions to an online content provider. In their article, Pauwels and Weiss looked at potential revenue loss when moving suddenly from free content to a combination of free and paid content, and how marketing actions affected potential revenue gains. They used persistence modeling to test their theory. From the analysis it appeared that the move from free to fee caused the growth of free users to slow down in the long term, and marketing actions had less effect in generating new free users. However, marketing actions encouraging free users to subscribe had a positive effect on subscriptions in both the short and long term. The article concluded that the success of converting users from free to paid content was dependent on the momentum of free user subscriptions and that the marketing mix played an important role in conversion to the paid product.

In general, it appears that free product trials can have positive short- and long-term effects on sales. In-store sampling led to immediate purchases and to greater brand awareness. Hence an improvement in rank performance of a free app could have an immediate as well as a long-term impact on the rank performance of the paid app. Based on the research by Gedenk and Neslin (1999), the impact might be stronger in the near future or even in the long term, after consumers have had the time to experience the app. Additionally, in the field research presented in these articles, physical products were sampled for a short period in time. In contrast, digital products like apps have unlimited shelf space, and free trials can be permanently available for consumers. Pauwels and Weiss (2008) demonstrated the importance of acquiring free users with regard to digital content. The rank performance of free apps is a priority for this reason as well.

Evidence form the app store

Some evidence from previous research on apps shows how the free app influences the demand for the paid app. Although the "free and paid app" strategy was not the main subject of their research, Jung et al. (2012) included the strategy in their analysis of the survival of mobile apps in the App Store charts. They concluded that this strategy was the most successful for long-term survival in the App Store. They also showed that consumers are usually more cautious with paid apps than with free apps, because consumers are risk-averse and reluctant to incur costs. The "free and paid app" strategy reduces the perceived risk of paying because it is possible to download the free version and, based on that, decide to purchase the paid version. They also concluded that a high-ranked free app may have an impact on the performance of the paid app due to visibility in the charts. Likewise, a high-ranked paid app can increase the demand for the free app. More recently Ghose and Han

(2014) performed a general study on app demand. Their research examined which app characteristics have the greatest effect on the demand for an app and included the free and paid strategy as a control variable. They found a positive correlation for cross-chart listing. Thus when free and paid versions of an app appear in both charts the rank movement of both apps is positively correlated. Overall, both articles concluded that free and paid apps have a mutual effect in which the increased visibility of both apps in the charts eventually led to more downloads of both apps. Therefore an improvement in the rank performance of the free app should lead to an improvement in the rank performance of the paid app, and vice versa.

Considering the findings in previous research and the evidence form the App Store, the following two hypotheses were formed:

Hypothesis 1a: Rank performance of the free app has a positive immediate, short- and long-term effect on rank performance of the paid app.

Hypothesis 1b: Rank performance of the paid app has a positive immediate, short- and long-term effect on rank performance of the free app.

As previously discussed, Pauwels and Weiss (2008) found that marketing actions played an important role in converting consumers from free to paid. Similarly, earned media could play an important role in free user acquisition and conversion to paid. The following two sections examine the effect of reviews and features on rank performance.

2.3 The impact of reviews on rank performance

Reviews are evaluations by consumers who have tried the product. In the App Store each app has its own reviews, which are accumulated over time and consist of two variables, average rating and review volume. Average rating indicates the average valence of reviews, and can be distributed between one (lowest) and five (highest) stars. Review volume is the number of reviews an app has accumulated over time.

In an online environment, it is often not possible to judge the quality of a product. Consumer opinion in the form of reviews is therefore very important to other consumers because it is impartial and can reveal information about product quality. App downloads can thus be highly dependent on the average rating and review volume in the App Store. The effect of average rating and reviews on sales performance has been examined thoroughly using data on books, movies and games, but the results remain mixed. Liu (2006) examined the effect of the volume and average rating of reviews on movie box office revenue. The author observed that a high volume of reviews generated during the pre-release stage of a movie had a positive effect on the box office revenue during the first weeks of the movie's release, as well as on the subsequent weeks. Chevalier and Mayzlin (2006) examined the relationship between online in-store reviews and sales of books, and found that only an increase in the average rating resulted in sales. The effect was not immediate, but was manifested some time after the reviews were posted. They also found that negative (one-star) reviews influenced sales more than positive (five-star) reviews. Duan, Gu, and Whinston (2008) also studied the effects of reviews on movie box office revenue and found evidence for a direct effect of review volume, but not average rating, on revenue. The effects of an increase in volume were positive on the same day as well as on subsequent days, but the effect decreased each successive day. Zhu and Zhang (2010) examined the game market and concluded that the average rating and review volume had a positive influence on the sales of less popular and online games. Reviews proved a valuable and scarce source of information when the game was unknown. Another finding was that reviews had less impact in the early stages of the product life cycle, when companies use advertising to promote the product. Moe and Trusov (2011) studied product reviews on the website of an online retailer and included dynamic effects. They concluded that average ratings had a direct and immediate positive effect on sales. In the App Store, Jung et al. (2012) noted that apps with lower average ratings did not survive as long in the charts as better-rated apps. Significantly, their analysis included average ratings but not volume. Ghose and Han (2014) found that both volume and average rating had a positive effect on app demand.

Although the articles reviewed have diverse findings, most concluded that either the volume or the average rating of reviews, or both, had a direct impact on sales. The differences in the findings could be due to the product popularity. Zhu and Zhang (2010) illustrated this well in their article. For example, less popular products are not reviewed as often, so the average rating is more important to consumers. Popular products were reviewed more often. A high volume of reviews sends a signal that many other consumers have already tried the app, which could result in herd behavior (Banerjee, 1992). Furthermore, some articles showed evidence for effects over time. High average rating can have a positive short- and/or long-term impact on sales depending on product popularity and when the reviews are viewed (Moe & Trusov, 2011; Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010). An increase in the average rating, for example, could lead to an improvement in rank performance. Depending on the past rank, the effect can be immediate or even long-term. An increase in volume can also have a short- and long-term impact on sales, but the effect seems to diminish over time (Liu, 2006; Duan et al., 2008). Initially, an increase in review volume may result in immediate and short-term rank performance improvement of an app, but the effect would gradually decrease in the long-term.

Based on the findings in the articles, the following two hypotheses were formed and subdivided to determine whether there is a difference between free and paid apps[3]:

Hypothesis 2a: An increase in average rating of free apps has a positive immediate, short- and long-term effect on rank performance of free apps.

Hypothesis 2b: An increase in average rating of paid apps has a positive immediate, short- and long-term effect on rank performance of paid apps.

Hypothesis 3a: An increase in review volume of free apps has a positive immediate, short- and long-term effect on rank performance of free apps.

Hypothesis 3b: An increase in review volume of paid apps has a positive immediate, short- and long-term effect on rank performance of paid apps.

2.4 The impact of features on rank performance

As previously mentioned, the App Store chooses to feature apps in lists, which are either automatically generated or curated by the App Store editors. These lists of featured apps appear for several days to a week on the home page of the App Store and on app category and sub-category pages. Most importantly, an app can be featured in multiple lists on the same

[3] The difference could be due to the moderating effect of price. Consumers would choose free over fee every time (Shampanier, Mazar, & Ariely, 2007). The effect of reviews could have a stronger impact on paid apps because consumers do not want to risk paying for an app they will not like, so they focus more on quality cues. For free apps, consumers might rely less on reviews because they do not incur any costs. If they do not like the app they can delete it without cost.

day. The more lists an app is featured in, the more visibility it has in the store. An increase in the number of features an app receives a day could therefore lead to an improvement in rank performance of that app.

Being featured improves an app's visibility in the App Store and is therefore comparable to in-store displays, which effectively increase the visibility of products or brands at the point of purchase (Van Nierop et al., 2010). Previous research on in-store displays showed that they significantly increased sales (Chevalier, 1975; Wilkinson, Mason, & Paksoy, 1982; Gagnon & Osterhaus, 1985). Abratt and Goodey (1990) demonstrated that in-store stimuli such as signs on the shelf and displays affected unplanned purchases and helped consumers remember present or future needs. Inman, Winer, and Ferraro (2009) also concluded that displays were very effective in increasing unplanned purchases across product categories. Hedonic goods were more likely to be purchased under impulse. Features can therefore have a positive immediate impact on unplanned downloads of hedonic apps such as games. With regard to the difference between physical and online stores, Breugelmans, Campo, and Gijsbrechts (2007) found that the use of in-store stimuli in an online shop was quite similar to the physical shop. Building on that Breugelmans and Campo (2011) looked at the effect virtual in-store displays have on brand sales. They included different display types and their positions in the store. In general in-store displays had a positive effect on brand sales. In the articles only short-term increase in sales was measured. Due to the short time features are shown in the App Store it is likely that they too have only a short-term impact on downloads.

Another line of inquiry has studied the effect of in-store displays on brand consideration set, which is defined as the set of brands a consumer would consider buying (Roberts & Lattin, 1997). Court, Elzinga, Mulder, and Vetvik (2009) view this as the final step before the actual purchase in the consumer decision journey. Allenby and Ginter (1995) found that in-store displays decrease price sensitivity and significantly influence the consideration set. Zhang (2006) added that displays made it easier for consumers to process information and simplified purchase decisions. This conclusion was also supported by Van Nierop et al. (2010). More recently, Baxendale, Macdonald, and Wilson (2015) studied how various touchpoints influence the brand consideration set. They found that displays and their frequency, i.e. how often consumers are exposed to the display, have a significant impact on brand consideration because they make the brand more noticeable in the store. They also concluded that the effect on sales was indirect, mediated through the consideration set. Thus in-store communication did significantly influence decisions, regardless of when and where the purchases were made. As displays can influence the consideration set, it is likely that these can lead to purchases in the near future. Likewise, being featured can increase immediate and short-term downloads of apps. First, consumers can directly download the app after viewing it in the store, resulting in an immediate impact. Second, if consumers do not download it immediately, the app could be put into the consideration set to download in the near future, resulting in a short-term impact. Furthermore, apps are featured in multiple lists at the same time, which could increase the overall visibility in the store. Not only might more consumers view it, but individual consumers may be exposed to the app more often in the store and decide to download the app because of increased familiarity. Therefore the following hypothesis was formulated and subdivided into free and paid apps[4]:

Hypothesis 4a: An increase in the number of features free apps receive has a positive immediate and short-term effect on rank performance of free apps. [5]

Hypothesis 4b: An increase in the number of features paid apps receive has a positive immediate and short-term effect on rank performance of paid apps.

2.5 Interrelationship between review variables

As seen in section 2.3, neither the average rating nor the volume of reviews always had direct impact on sales. However, if one of the variables does not have a direct effect on rank performance, an indirect effect may be present. For example, such an effect occurs when the average rating influences volume but not product sales, while the volume does directly influence sales. Thus the interrelationship between average rating and review volume should be taken into account.

Moe and Trusov (2011) found evidence for a positive effect of average rating on sales. They also found evidence that volume had an indirect impact on sales by influencing average ratings. In their analysis they included variance in the average rating, which had impact on subsequent reviews. When average ratings varied greatly and were quite low, additional

[4] See previous footnote 4. A fee could deter consumers from downloading the featured app.
[5] The features variable is measured as the number of features an app received by the App Store on a particular day.

volume of reviews helped the average rating recover and converge at a higher level. Thus, based on the average rating of previous reviews, additional reviews changed future average ratings. Duan et al. (2008) drew a similar conclusion: positive movie reviews led to an increase in review volume which had indirect effect on revenue.

Based on these findings, the following hypotheses were formed[6]:

Hypothesis 5a: An increase in average rating of free apps has a positive effect on review volume of free apps.

Hypothesis 5b: An increase in average rating of paid apps has a positive effect on review volume of paid apps.

Hypothesis 6a: An increase in review volume of free apps has a positive effect on the average rating of free apps.

Hypothesis 6b: An increase in review volume of paid apps has a positive effect on the average rating of paid apps.

2.6 Interrelationship between features and reviews

The App Store does not disclose why they feature certain apps, but one can presume that reviews may be a factor. Positive reviews or an increase in the number of reviews for an app might incentivize the App Store to feature the app. For example, positively reviewed content is more likely to be shared by others (Berger & Milkman, 2012). Positive reviews by consumers could indicate that the app is useful or of particularly high quality. Upon receiving this signal the App Store might decide to share the app with other consumers by featuring it. Just as a marketing manager may increase marketing expenditures because of favorable reviews (Reinstein & Snyder, 2005), the App Store may increase the number of features. Stephen and Galak (2012) suggest that social earned media such as blog posts can predict traditional earned media in the form of publicity, because early volume of word of mouth can indicate popularity. Thus, an increase in review volume might be another indicator the App

[6] Hypotheses H5-H8 were differentiated between free and paid apps to correspond to H1-H4 in the analysis.

Store bases the features on, reasoning that if many consumers like the app already, others will like it as well. Based on these findings, the following hypotheses were formed:

Hypothesis 7a: An increase in average rating of free apps has a positive effect on the number of features free apps receive.

Hypothesis 7b: An increase in average rating of paid apps has a positive effect on the number of features paid apps receive.

Hypothesis 8a: An increase in review volume of free apps has a positive effect on the number of features free apps receive.

Hypothesis 8b: An increase in review volume of paid apps has a positive effect on the number of features paid apps receive.

The opposite interrelationship may take place as well. Features may have a positive effect on the average rating and review volume of apps. For example, Berger and Schwartz (2011) examined why consumers recommend certain products more often. The authors concluded that consumers share their experience more often about products that are more visible. Because an increase in the number of features increases visibility of an app, it may positively impact review volume of that app. Furthermore, features may have a positive effect on the average rating. According to Bornstein (1989) and Bornstein and D'Agostino (1992), mere exposure to a stimulus and its frequency can create a more favorable feeling. Janiszewski (1993) also found that mere exposure to a brand name or product package can lead to a more positive feeling. This effect persists even if exposure was unintended. Therefore, an increase in the number of features may increase the exposure of an app to consumers, which may positively impact the average rating. Based on these findings, the following hypotheses were formed:

Hypothesis 9a: An increase in the number of features free apps receive has a positive effect on the average rating of free apps.

Hypothesis 9b: An increase in the number of features paid apps receive has a positive effect on the average rating of paid apps.

Hypothesis 10a: An increase in the number of features free apps receive has a positive effect on the review volume of free apps.

Hypothesis 10b: An increase in the number of features paid apps receive has a positive effect on the review volume of paid apps.

Chapter 3. Data

This chapter gives a brief overview of the empirical setting for the data, describes the data collection process and the variables in the data, and provides a short explanation of why these variables may influence app performance.

3.1 The Apple App Store

The empirical setting for the data is the Apple App Store. On July 10, 2008, a year after the release of the first iPhone device, Apple launched the App Store as a platform for iPhone and iPad applications. On the launch date of the App Store there were only 552 apps available, of which 135 were free of charge.[7] As of June 2015 there are about 1.8 million apps available in the United States (US) App Store, of which 22 percent belong to the most popular category: games.[8] In total there are 20 categories in the store. In addition to the charts that include all app categories, each category has its own charts. All chart rankings are re-computed every 24 hours and re-downloads of the same app are not counted.

3.2 Data collection

The data sample was selected based on the app revenue strategy relevant to the research topic: “free and paid app” strategy. Daily panel data was collected for 15 game apps which had a free and a paid version in the App Store during the months March through May 2014. Apps were chosen randomly from App Annie and the App Store websites by searching for the terms free, pro and lite. To capture the improvement in rank performance and how it is affected by the “free and paid app” strategy, data was collected for 60 days beginning immediately after each app’s release date. Also, because the app market is very dynamic two months of data should be enough to capture any short- and long-term effects. For their interaction to be measurable, both apps in each pair had to be launched simultaneously and were therefore chosen based on this criterion. To sum up the criteria: the app had to be an iPhone app; a mobile game; available in the US App Store; active in the store during data collection; ranked at least in the overall game category download chart; and finally, both versions had to be launched simultaneously. In total, data was collected for 30 individual iPhone apps in the US App Store. The data includes the information consumers see when they browse the App Store as well as the app characteristics. For each app the following

[7] http://www.wired.com/2008/07/pinch_media_552_applications__135_free_on_app_store_launch/

[8] http://www.pocketgamer.biz/metrics/app-store/app-count/, retrieved on August 9, 2015

information and app characteristics were measured: advertisements, age rating, developer, rank, featuring on the home page, number of times featured, in-app purchases, languages, price, average rating, review volume, and updates.

All the data was collected from the website AppAnnie.com, a business intelligence company. This company collects and analyzes all data on apps and lists it on their website. App Annie also makes use of the free and paid business model. They provide a limited free version for customers to try their service with access, for example, to historical ranking data. The premium version, available only for paying customers, provides the number of downloads and revenue information. For this paper the free version was used.

In the following section, the data is described and the research evidence is briefly discussed. Table 1 presents the definitions and descriptive statistics of variables for the final sample of 15 pairs of free and paid apps.

3.3 Data description

Table 1 Variable definitions and descriptive statistics

	Definition	Mean	Std. Dev.	Min.	Median	Max.
Advertisements $Free_i$	Advertisement dummy for free app ***i*** (1=has advertisements, 0=none).	0.73	0.44	0	1	1
Age Rating: $4+_i$	Age rating 4+ dummy for app ***i*** (1=4+, 0=other).	0.87	0.34	0	1	1
Age Rating: $9+_i$	Age rating 9+ dummy for app ***i*** (1=9+, 0=other).	0.07	0.25	0	0	1
Age Rating: $12+_i$	Age rating 12+ dummy for app ***i*** (1=12+, 0=other).	0.07	0.25	0	0	1
$Developer_i$	Type of developer dummy for app ***i.*** (1=top developer, 0=other).	0.27	0.44	0	0	1
Rank $Free_{i,t}$	Download rank of the free app ***i*** in the games chart on date ***t.***	0.09	0.23	0	0	1
Rank $Paid_{i,t}$	Download rank of the paid app ***i*** in the games chart on date ***t.***	0.05	0.18	0	0	1
Features $Free_{i,t}$	Number of features free app ***i*** received on date ***t***.	1.35	1.64	0	1	8
Features $Paid_{i,t}$	Number of features paid app ***i*** received on date ***t***.	2.59	2.12	0	2	10

Feature Home Page(HP) Paid$_{i,t}$	Feature on the iTunes home page dummy for paid app ***i*** on date ***t*** (1=has a feature on the home page, 0=none).	0.03	0.18	0	0	1
In-App Purchases Free$_{i}$	In-app purchase option dummy for free app ***i*** (1=has in-app purchase options, 0=none).	0.42	0.49	0	0	1
In-App Purchases(IAP) Paid$_{i}$	In-app purchase option dummy for paid app ***i*** (1=has in-app purchase options, 0=none).	0.53	0.50	0	1	1
Languages$_{i}$	Number of languages app ***i*** was translated in.	4.60	6.20	1	1	20
Price Paid$_{i,t}$	Price in US dollars of the paid app ***i*** on date ***t***.	1.86	1.07	0	2	4.99
Reviews Free$_{i,t}$	Cumulative number of reviews free app ***i*** received on date ***t.***	2471.80	9595.03	0	48	64734
Reviews Paid$_{i,t}$	Cumulative number of reviews paid app ***i*** received on date ***t.***	784.18	3967.64	0	60	28611
Rating Free$_{i,t}$	Average cumulative rating free app ***i*** received on date ***t***.	2.99	1.81	0	3.50	5
Rating Paid$_{i,t}$	Average cumulative rating paid app ***i*** received on date ***t***.	4.12	0.88	0	4.49	5
Update$_{i,t}$	Update dummy of app ***i*** on date ***t*** (1=update, 0=none).	0.03	0.16	0	0	1

The dataset includes two types of variables, those that can be controlled by the developer and those that cannot. In the App Store *Rank, Features, Rating* and *Reviews* are not decided by the developer but depend on the actions of consumers and the App Store. The variables that are controlled by the developer were all added as control variables: *Advertisements*, *Age rating*, *Developer*, *In-app purchases*, *Languages*, *Price*, and *Update.* In subsequent sections the variable terms displayed here are subdivided between Free and Paid, when the data within the variables differs between free and paid apps.

Ranks and earned media

Since the App Store does not disclose the true download data, download ranks (*Rank*) are used as the performance measure. Other studies by, among others, Ghose and Han (2014); Brynjolfsson, Hu, and Smith (2003) and Chevalier and Mayzlin (2006) also use ranks as the sales performance measure when sales data is unavailable. Because the games category is used for this case study, only the game category download ranks were included in the data set. This decision was made because these rankings have no competition from other categories and not all collected apps were ranked in the overall download chart. The website data was collected from includes information regarding ranks from 1 to 1500. Ranks lower than 1500 were not given and were therefore incorporated as a rank of 0. The program used for analysis (Eviews) uses 1 as the lowest number, so an inverse of the original rank values was taken to redistribute them between 0 and 1 using the following formula:

$$y=\frac{1}{x}$$

Where *y* is the inverse rank and x the original rank.

The sample mean for the free app download rank is 0.09, which would originally be 11 in the App Store chart. The sample mean value for the paid app download rank is 0.05, which would originally be 20 in the App Store chart.

Features are curated lists of apps and are either generated automatically or curated by App Store editors. Features appear on the App Store home page, app category pages and sub-category pages. The features variable is the number of times an app was featured on a particular day. The mean number of features for free apps is 1.35 per day and for paid apps the number is higher with 2.59 features per day. This clearly shows that the App Store features paid apps more often than free apps.

In an online environment, just as in a physical store, the place of the feature has an effect on the sales performance of a product. In particular, displays on the home page (first screen) had a twice as large effect on sales than category (aisle) displays, where other brands were present. Displays on the home page of the website had more effect since that is where all consumers start their journey from (Breugelmans et al., 2007). Because the home page of the App Store is the starting point for all consumers, a dummy was added to control for features that appear on the home page (*Feature HP*). An app can only be featured on the home page once per day. From all observations in the sample there was only 3 percent likelihood of a paid app being featured on the home page during the sampling period. No free apps were featured on the home page at all during the study.

The *Reviews* variable was collected as the cumulative number of reviews an app received on a specific day. Additionally, *Rating* was added as an average cumulative value per day. The average rating and the review volume are shown as cumulative in the store and were therefore collected as such. The average number of reviews received by free apps during the sampled period was 2471, compared to 784 for paid apps. Looked at from a different perspective, on average free apps received 107 reviews per day while paid apps received 36 reviews per day. Free apps received more reviews, but they were less favorable on average, with a mean rating of 2.99 stars, compared to free apps with 4.12 stars.

Other Variables

In-app *Advertisements* are added as a dummy because their presence may cause irritation for the app user. Evidence shows that advertisements lower app demand (Ghose & Han, 2014). In the sample, most free apps (73 percent) make use of advertising as a source of revenue, while, as expected, paid apps have no in-app advertising.

Age rating is how developers rate their app based on age restrictions. In the sample three age ratings were present. Thirteen apps had an age rating of 4+, one app of 9+ and one of 12+. Age restrictions can influence app downloads because they apply to different consumer segments. Ghose and Han (2014) found evidence that higher age restriction lowers app demand.

A *Developer* dummy was added to control for apps that are published by a top developer. These developers perform exceptionally well in the App Store as measured by downloads and revenue. An example of a top developer is King, who published the immensely popular Candy Crush Saga game. Ranks of an app published by a top developer may be higher because the app may be perceived as of higher quality due to the bandwagon effect (Carare, 2012). In the sample, four app pairs (27 percent) were published by a top developer.

In-app purchases (IAP) are a revenue source for developers. Within the app small transactions are added to improve the app experience by adding extra features. Ghose and Han (2014) found that IAPs increase app demand, and Jung et al. (2012) found that apps with IAPs have the highest mean ranks. In the sample 42 percent of free apps have IAPs while 53 percent of paid apps have IAPs.

Languages were added to determine how many countries an app is localized for. The popularity of the localized version could lead to increased international popularity of the app.

While there is no empirical evidence from previous research, App Annie conducted a case study looking at the rank response to localization. They found that not only did ranks improve in all targeted localization countries but the app was featured more often as well (App Annie, 2015). In the sample, the mean number of languages per app is 4.6, with one language (English) as the median value.

Price is a variable the developer can affect directly in the store. For consumers price is very important. When products are free, people tend to consume more, a phenomenon known as the zero-price effect. A price of zero invokes the norms of social exchange whereas a positive price, even if it is just 1 cent, invokes market exchange norms (Shampanier et al., 2007). Thus when apps are free consumers may download as many apps as they want. When apps are not free, the demand is expected to be lower because consumers are more cautious when spending their money on apps they have no experience with (Jung et al., 2012). Ghose and Han (2014) found a 3 percent demand increase for App Store apps that had a 10 percent price discount. In the sample the average price of paid apps is $1.86 USD. In addition, some price promotions were observed; certain paid apps were temporarily offered for free. The highest price found was $4.99 USD.

Updates cause a change in apps' characteristics. With each update, an app may change in terms of quality, functionality, description, size and/or other values. The update dummy was added to control for any sudden changes to the characteristics and the performance in the store. According to Ghose and Han (2014) updates may lead to a perception of better quality and can therefore have a positive effect on demand. In the sample, app pairs were always updated at the same time. From all observations in the sample there was only a 3 percent likelihood of an app being updated on a particular day.

Chapter 4. Methodology

The methodological approach in this paper consists of multivariate time series analysis with time series panel data. The approach includes the unit root test, Granger causality test, VAR modeling, and impulse response functions. This chapter explains the methodological steps followed to answer the research question.

4.1 Model requirements

Given the subject and the research questions of this paper, the chosen methodology should be able to show what kind of effect the variables in the model have on each other and how long the effect lasts. To do this, the model must fulfill certain criteria. First, the model needs to be able to control for the presence of non-stationary variables. The movement of a variable should be predictable, because unpredictable movements could lead to spurious regression and consequently to false conclusions (Granger & Newbold, 1974). Second, the model should include and distinguish between the short- and long-term effects of the variables (Dekimpe & Hanssens, 1995). Third, the model should reflect the interaction among performance variables, among earned media variables, and between performance and earned media variables (Dekimpe & Hanssens, 2003). Fourth, the model should show how variables move from their baseline in the event of an unexpected shock (Dekimpe & Hanssens, 1995). Finally, the model should allow for any feedback effects among performance and earned media variables (Dekimpe & Hanssens, 1995).

The modeling approach that fulfills these criteria is called 'persistence modeling' and is illustrated by, among others, Dekimpe and Hanssens (1995, 1999); Pauwels, Hanssens, and Siddarth (2002); Nijs, Dekimpe, Steenkamp, and Hanssens (2001). The modeling approach will be described step by step in the following section.

4.2 Methodological steps

Unit root

The first major step is to test each variable for evolution or stability of its behavior over time. If the variables appear to be stable over time they are moving around a fixed mean. If this is not the case, then the variables show evolution over time. This occurs when the data points permanently move away from the mean and do not revert back. In such cases, other variables can cause a permanent change in the evolving variables. The unit root test determines whether a variable is stationary or evolving. When there is a unit root present in a variable, the variable can show a permanent reaction to a change in another variable (Dekimpe & Hanssens, 1995). Based on the results of the unit root test the variables will enter the model in levels if stationary, or in differences if evolving. Evolving variables are differenced, following the suggestion of Granger and Newbold (1974) to remedy spurious regression by differencing the variables with a unit root. A popular test to distinguish different behavior is the augmented Dickey-Fuller (ADF) test. The null hypothesis in the ADF test is the presence of a unit root. This test is carried out in two forms, one with and one without a deterministic trend (Enders, 2014). Testing for a unit root with a deterministic time trend means establishing whether the variables might permanently move away from the trend line (Dekimpe & Hanssens, 2003). Similar conclusions from both unit root tests will increase confidence in the classification of the variables. If two or more variables have a unit root they are tested for cointegration. If the cointegration tests show long-run equilibria, a vector error correction model must be estimated. When there is no cointegration or only one variable is stationary, a vector autoregression model (VAR) with differencing is estimated (Engle & Granger, 1987).

Granger causality

The second step in the approach is to test variables for endogeneity or to determine whether they are explained by their past values or the values of other endogenous variables. The Granger causality test is used to reveal variables that cause and/or are caused by other variables in the system. These variables enter the model as endogenous. All other variables enter the model as exogenous. The test is also used to test the conceptual links that were proposed in chapter 2 (Granger, 1969). Finally, the Granger causality test might shed light on unexpected relationships that the model should capture, but wouldn't have been without the test.

VARX model

Unit root and Granger causality tests enable the use of the vector-autoregression model with exogenous variables (VARX). A VARX model measures not only the dynamic performance response, but also complex feedback loops and any direct (immediate and lagged) response between performance and marketing variables (Dekimpe & Hanssens, 1995; Nijs et al., 2001). Following the results of the unit root and Granger causality tests, endogenous and exogenous variables are added in either levels or differences to the model. The following step would be to specify the appropriate number of lags or, in other words, the order of the model. The number of lags is based on the Bayesian information criterion, also known as the Schwarz criterion, which is consistent for estimating lag length (Lütkepohl, 2005).

Impulse response

For each endogenous variable, the VARX model estimates a baseline and forecasts its future value based on its interaction with other endogenous variables in the model. Impulse response functions (IRF) are used to analyze the dynamics of a VARX model. On the basis of VARX coefficients, impulse response functions show how a variable reacts over time to an unexpected Cholesky one standard deviation shock in another variable at t=0. When variables are stable, the shock will eventually dissipate. A shock to an evolving variable, however, may lead to a permanent change (Dekimpe & Hanssens, 1995). To test if the impulse response values are significantly different from zero, the estimates will be divided by the standard deviation to acquire the t-statistic and will be rejected for p-values larger than 0.05 (see, e.g., Pauwels et al., 2002). The interpretation of the impulse responses focuses on immediate, short-term and long-term effects. Immediate effects cannot be measured by the VARX model. A contemporaneous correlation matrix of residuals, calculated from the VARX model, will be used to reflect the immediate effects. The matrix, however, is not able to capture the direction of the effects (Dekimpe & Hanssens, 1995). Short-term effects are measured as the cumulative effect after the immediate effect and before the IRF converges to a certain value. The time it takes for the convergence to occur is called the dust-settling period. This is the sum of periods starting with the first significant IRF and ending with the first stable long-term effect (Dekimpe & Hanssens, 1999). Long-term effects are shocks that settle over time and are also referred to as persistence effects. In the event persistent effects are absent, effects that occur after a week (on day 8 and onward) will be considered as long-term. Finally, individual effects can fluctuate widely, and therefore accumulated impulse response functions will be used for interpretation. They show the total response by a variable to a shock (Dekimpe & Hanssens, 1999).

4.3 Model estimation

Unit root

As the first step in the analysis summary ADF unit root tests were conducted for dynamic variables. The variables were tested twice, once with a deterministic trend and once without a deterministic trend. Dummy variables such as *Feature HP Paid*, *Update* and *IAP* were not included in the test. The results are shown in Table 2.

Table 2 Summary of the unit root test results

	Free		**Paid**	
	ADF test statistic	**“ with trend**	**ADF test statistic**	**“ with trend**
Features	77,430 (0,000)	74,214 (0,000)	169,187 (0,000)	153,917 (0,000)
Price	N/A	N/A	38,648 (0,000)	40,209 (0,000)
Rank	86,589 (0,000)	119,969 (0,000)	75,835 (0,000)	86,472 (0,000)
Rating	202,073 (0,000)	199,462 (0,000)	242,816 (0,000)	170,563 (0,000)
Reviews	83,265 (0,000)	54,035 (0,000)	110,206 (0,000)	80,274 (0,000)

Note. *p-values are given in ( )

All variables have a p-value lower than 0.05. They are revealed to be stationary by both tests and will therefore enter the model in levels.

Granger causality

The second step in the analysis is to test pairs of variables for Granger causality. The Granger causality test requires choosing the right number of lags. An incorrect number of lags may lead to a wrong conclusion about the presence of Granger causality (Hanssens, 1980). Since the point is to test whether there is a possible causal relationship at all instead of a causal relationship at a specific lag, up to 30 lags were used in the test (see, e.g., Trusov, Bucklin, & Pauwels, 2009). All variables that pass the Granger causality test were added as endogenous in the model while other variables were added as exogenous (Enders, 2014). Table 1 in the Appendix shows the Granger causality test results including the lowest p-value between two variables.

The results of the test establish that there are indeed causality links and their directions are as proposed in the conceptual framework. Specifically, all of them support the conceptual model except for the causality link between average rating and review volume. For free apps there was no Granger causality found between *Rating Free* and *Reviews Free*. For paid apps only one direction was found: *Reviews Paid* is causal for *Rating Paid*. It seems that as review volume grows the average rating does not vary greatly, and therefore the Granger causality test found no link. Furthermore, the test showed that Granger causality is present between various control variables, and performance and earned media variables. Some control variables are therefore added as endogenous to the model. For example, *Update* seems to Granger-cause all other variables and is Granger-caused by all except *Features*. *IAP* Granger-causes *Features* and is Granger-caused by *Features* and *Rating*. *Price* is Granger-causal for all variables except for *Features Paid* and *IAP Free*, and is Granger-caused by *Rank Free*, *Rank Paid* and *Features Paid*. Another interesting finding is that *Features HP Paid* is Granger-caused by *Rank Paid, Rank Free*, *Rating Paid*, *Features Free, Price* and *Update.*

VARX model

The VARX model is specified based on the results from the unit root and Granger causality tests. Based on the Schwartz Criterion, a VARX of order 1 was selected:

$$\begin{pmatrix} Rank\ Free_t \\ Rank\ Paid_t \\ Price\ Paid_t \\ Update_t \\ Rating\ Free_t \\ Rating\ Paid_t \\ Reviews\ Free_t \\ Reviews\ Paid_t \\ Features\ Free_t \\ Features\ Paid_t \\ Feature\ HP\ Paid_t \\ IAP\ Free_t \end{pmatrix} = C + \sum_{k=1}^{K} B_k \times \begin{pmatrix} Rank\ Free_{t-k} \\ Rank\ Paid_{t-k} \\ Price\ Paid_{t-k} \\ Update_{t-k} \\ Rating\ Free_{t-k} \\ Rating\ Paid_{t-k} \\ Reviews\ Free_{t-k} \\ Reviews\ Paid_{t-k} \\ Features\ Free_{t-k} \\ Features\ Paid_{t-k} \\ Feature\ HP\ Paid_{t-k} \\ IAP\ Free_{t-k} \end{pmatrix}$$

$$+\ \Gamma \times \begin{pmatrix} Ads\ Free \\ Age\ Rating \\ Developer \\ IAP\ Paid \\ Languages \end{pmatrix} + \begin{pmatrix} U_{rank\ free,t} \\ U_{rank\ paid,t} \\ U_{price\ paid,t} \\ U_{update,t} \\ U_{rating\ free,t} \\ U_{rating\ paid,t} \\ U_{reviews\ free,t} \\ U_{reviews\ paid,t} \\ U_{features\ free,t} \\ U_{features\ paid,t} \\ U_{feature\ hp\ paid,t} \\ U_{iap\ free,t} \end{pmatrix}$$

where C is a (12×1) vector of intercepts, K is the ordering of the model, B_k is the (12×12) vector of dynamic coefficients of endogenous variables, $\boldsymbol{\Gamma}$ is the (12×5) vector of coefficients of exogenous variables, and $(U_{rank\ free,t}, \ldots, U_{iap\ free,t}) \sim N(0,\sum_{U})$.

The model explains rank performance well. The adjusted R-squares for *Rank Free* and *Rank Paid* are 0.967 and 0.916 respectively. Other R-square and adjusted R-square values are shown in table 2 in the Appendix.

Chapter 5. Results

The numbers of the sections presenting the estimated results correspond to the sections in chapter 2. Table 3 in the Appendix gives a summary of hypothesis test results.

5.1 Interrelationship between free and paid app rank performance

First, the immediate impact between the two ranks is reflected in the contemporaneous correlation matrix. The contemporaneous correlation matrix can be found in Table 3. *Rank Free* and *Rank Paid* show a moderate positive correlation of 0.329. The ranks do react to each other on the same day but the effect is small.

Table 3 Contemporaneous correlation matrix

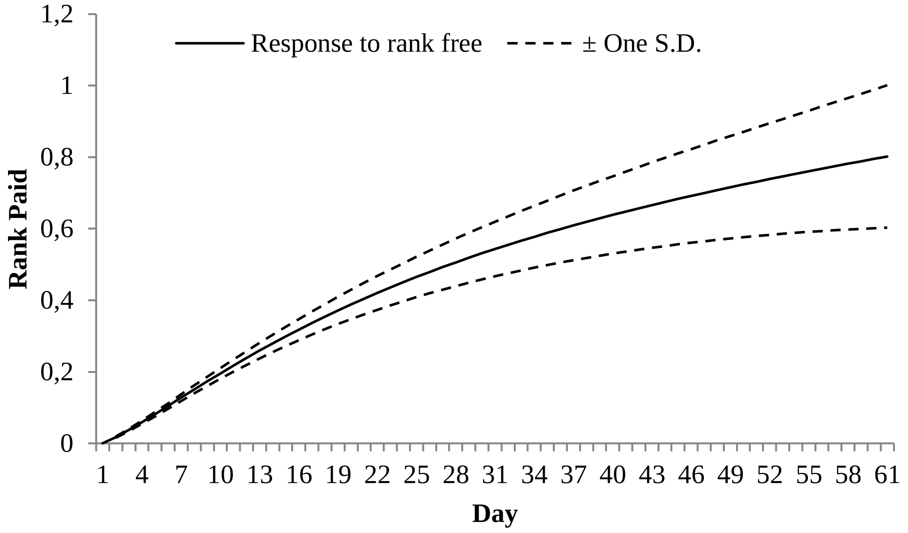
	Feature HP Paid	Features Free	Features Paid	Price Paid	Rank Free	Rank Paid
Feature HP Paid	1					
Features Free	0.003	1				
Features Paid	0.150	0.317	1			
Price Paid	0.016	-0.022	0.068	1		
Rank Free	0.052	0.070	0.108	-0.030	1	
Rank Paid	0.007	0.007	0.072	-0.056	0.329	1
Rating Free	-0.081	0.035	-0.041	0.016	0.039	0.024
Rating Paid	0.041	0.047	0.099	-0.008	0.038	0.019
Reviews Free	-0.031	-0.020	0.069	-0.016	0.132	0.178
Reviews Paid	-0.036	-0.029	0.043	-0.020	0.036	0.139
Update	0.009	-0.052	-0.056	-0.172	0.030	0.013
IAP Free	-0.028	-0.019	0.011	0.001	0.007	-0.005

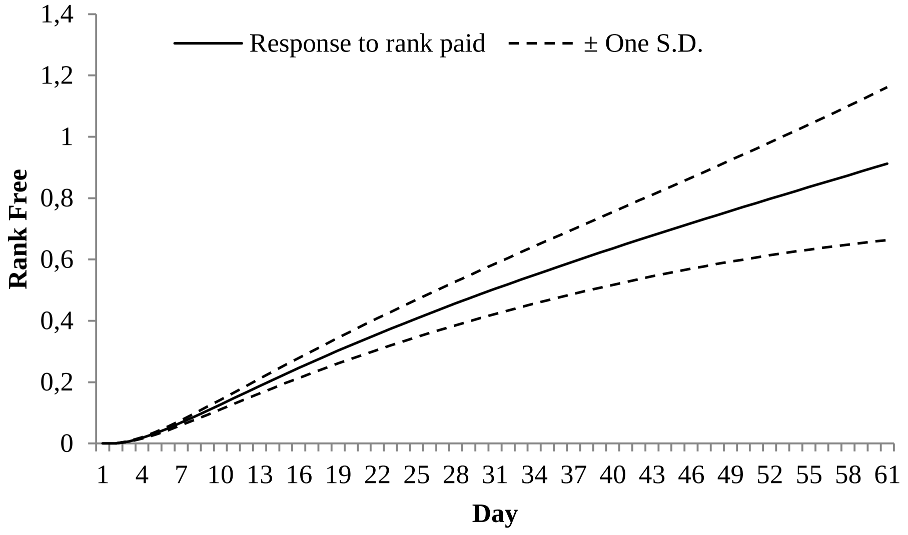
	Rating Free	Rating Paid	Reviews Free	Reviews Paid	Update	IAP Free
Rating Free	1					
Rating Paid	0.197	1				
Reviews Free	0.015	-0.006	1			
Reviews Paid	0.008	-0.008	0.763	1		
Update	-0.009	0.023	-0.027	-0.033	1	
IAP Free	0.011	-0.005	0.000	-0.010	-0.006	1

To see the effect of rank performance of the free app on the rank performance of the paid app and vice versa, impulse response functions were computed based on the estimated VARX parameters. Figure 2 plots two IRFs, including the influence that *Rank Paid* has on *Rank Free* and vice versa.

Estimating the two impulse response functions between paid and free ranks reveals significant responses during all periods. Both rank responses start off slowly but gradually increase and keep moving upward, but neither rank stabilizes within the two months studied. In the short term, the total effect starts slowly but increases over time until ranks are in the proximity of rank one in the long term. Therefore it can be concluded that having two apps in the App Store helps to improve rank performance. Hypotheses H1a and H1b are supported. An improvement in the rank performance of the free app has an effect on the rank performance of the paid app immediately and in the short- and long-term, and vice versa.

Figure 2 Impulse Response Functions: *Rank* response to *Rank*



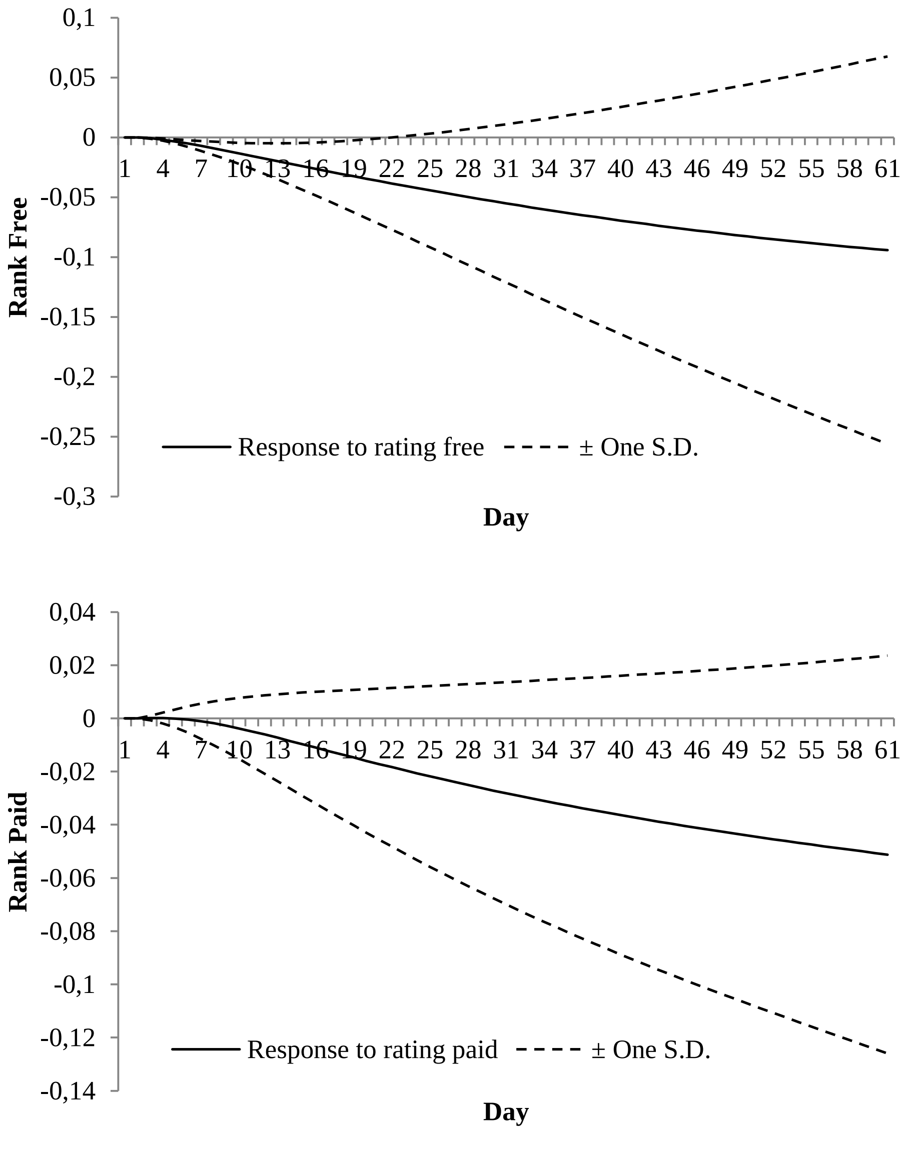


5.2 The impact of reviews on rank performance

The immediate impact between the average rating and rank is practically non-existent. The contemporaneous correlation is 0.039 and 0.019 for free and paid apps respectively.

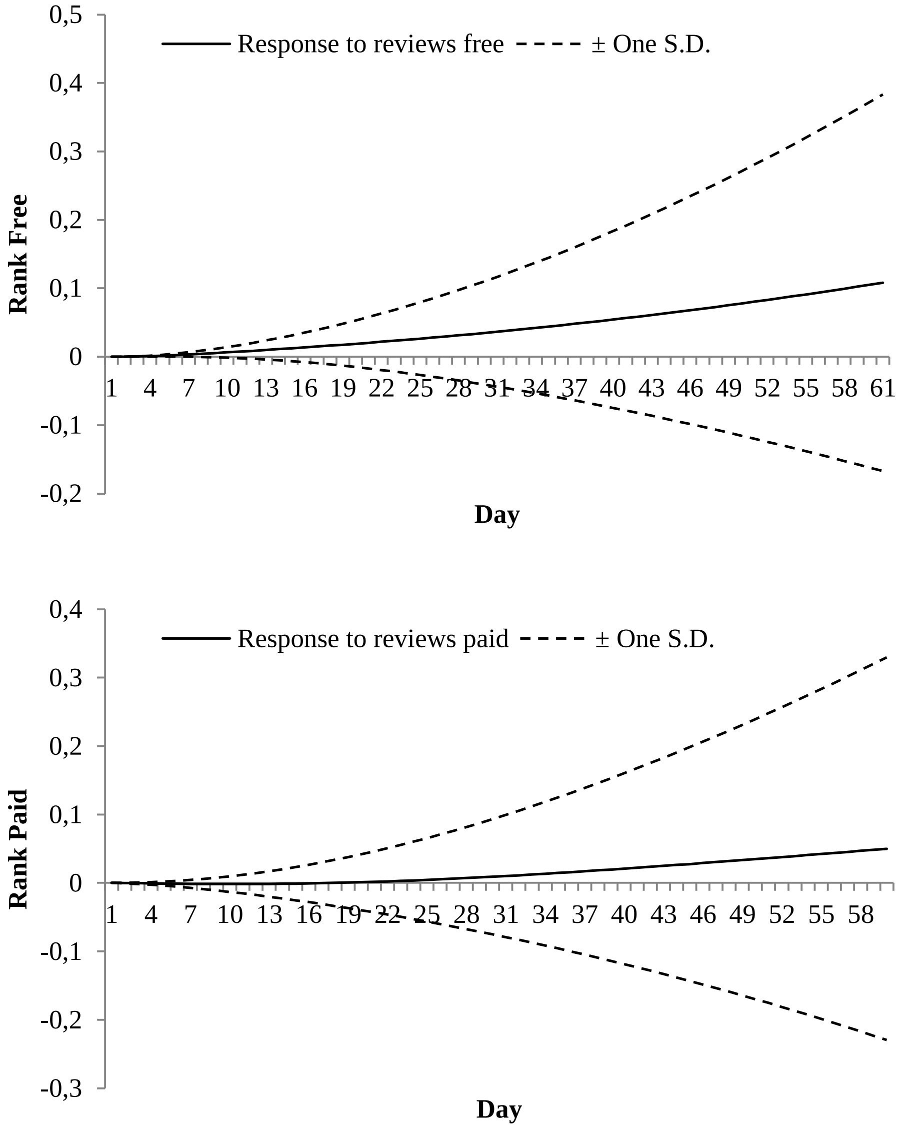
IRFs of rank response to the average rating are show in figure 3. A shock to *Rating Free* has only a short-term impact on *Rank Free*; the effect is significantly negative on day two and three. *Rank Paid* did not significantly react to a shock in *Rating Paid.* Therefore H2a and H2b are rejected.

Figure 3 Impulse Response Functions: *Rank* response to *Rating*



Compared to the average rating there is weak positive relationship between *Reviews Paid/Free* and *Rank Paid/Free*. The contemporaneous correlation is 0.132 and 0.139 for free and paid apps respectively. Although there is some small immediate effect, no other effects were present. *Rank Paid* and *Rank Free* did not show significant short- or long-term response to *Reviews Paid* and *Reviews Free* respectively. H3a and H3b are therefore partially supported. Figure 4 shows the rank response to a change in review volume.

Figure 4 Impulse Response Functions: *Rank* response to *Reviews*

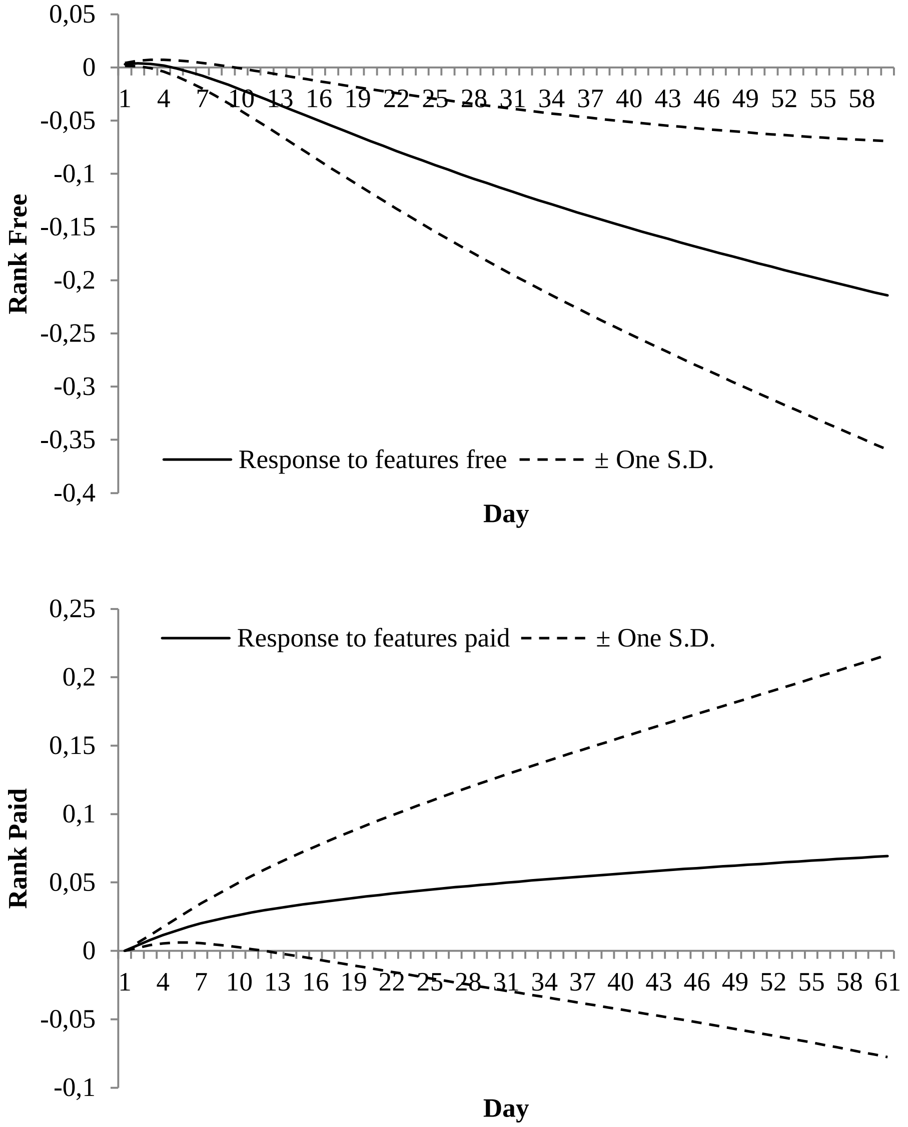


5.3 The impact of features on rank performance

The immediate impact between features and ranks is non-existent, because the contemporaneous correlation values as shown in table 3 are below 0.1 for *Features Free*, *Features Paid* and *Features HP Paid*.

The IRFs between Features and Ranks are shown in figure 5.

Figure 5 Impulse Response Functions: *Rank* response to *Features*



The impact of *Features Free* on *Rank Free* is only significant on the first day. Similarly, *Features Paid* had a significant impact on *Rank Paid* on days one and two. H4a and H4b are both partially supported. Features work well for a temporary short-term increase in rank. Interestingly, a shock to *Features Paid* led to a significant response in *Rank Free*, which lasted from day one to day three. Thus an increase in *Features Paid* led to more visibility and an increase in downloads for both apps. It was surprising that a shock to *Features HP Paid* did not have a significant impact on either rank.

Due to the last finding an alternative model was estimated excluding *Features Paid* and *Features Free* to find if *Feature HP Paid* has significant effect on *Rank Paid* or *Rank Free*. Impulse response functions computed using this model revealed that *Feature HP Paid* has a significant negative long-term effect on both *Rank Paid* and *Rank Free,* but no immediate or short-term effect.

5.4 Interrelationship between review variables

First, there was no Granger causality found between review volume and average rating, except that *Reviews Paid* Granger-causes *Rating Paid*. However, impulse response functions show no significant support for the latter though they agree with other Granger causality test results. There was no dynamic relationship found between average rating and review volume. H5a, H5b, H6a and H6b are therefore rejected. A possible explanation is that the average ratings did not vary enough to influence review volume as proposed in the hypotheses.

5.5 Interrelationship between features and reviews

As mentioned before, it is unknown why the App Store chooses to feature particular apps, therefore it is interesting to see whether and how features can be influenced by other variables. First, *Features Paid* shows moderate contemporaneous correlation with *Features Free* (0.317). *Features Paid* also has weak contemporaneous correlation with *Features HP Paid* (0.150) and *Rank Free* (0.108). Otherwise, *Features Paid* has very little contemporaneous correlation with other variables such as *Rank Paid*, *Reviews Paid* or *Rating Paid.* The same is true of *Features Free,* which does not have a correlation higher than 0.1 with any other variables except *Features Paid.*

Impulse response functions show that features respond to certain variables. Average rating, however, is not among these, because a shock to *Rating Free* or *Rating Paid* has no significant impact on either *Features Free* or *Features Paid*. H7a and H7b are therefore rejected. A shock to *Reviews Paid* on the other hand has positive short-term and almost permanent long-term effect on *Features Paid*. The effect is significant up to day 59, and only on day 60 returns back to the baseline. Hypothesis H8b is therefore supported. On the other hand, *Reviews Free* did not have any significant impact on *Features Free*. H8a is thus rejected.

Although they do not significantly influence the rankings, *Features HP Paid* is positively influenced by *Rating Paid* and *Update* in the short and long term. *Update* even has a permanent impact. The App Store clearly values quality improvement but, on the other hand, *Features Free* and *Features Paid* do not significantly react to *Update*. *Features Free* does positively respond to the presence of *IAP Free* in the short-and long-term. *Features Free* also has a significant positive response to a shock to *Features Paid* for one week, and conversely *Features Paid* has a significant positive response to *Features Free* for 40 days. Additionally, *Features Paid* positively responds to *Features HP Paid* in the short and long term up to about 40 days. In sum, not only do quality measures matter, but the number of paid app features is interrelated with the number of free app features.

Furthermore, because H3b was not supported but H4b was, *Reviews Paid* has an indirect impact on *Rank Paid* through *Features Paid*. *Rank Paid* is also indirectly influenced by *Features HP Paid* and *Features Free* through an increase in *Features Paid*. Likewise, because H4a was supported, *Rank Free* is indirectly affected by *IAP Free* and *Features Paid* through the increase of *Features Free*.

With regards to the review variables, *Features Free* and *Features Paid* do not have an immediate effect on *Reviews Free/Paid* and *Ratings Free/Paid*. Contemporaneous correlation between the variables is lower than 0.1. Impulse response functions show that *Reviews Paid* is negatively influenced by *Feature HP Paid* in short and long term, but it does not respond to a shock to *Features Paid*. *Reviews Free* is not influenced by *Features Free*. Thus, H10a and H10b are rejected. Comparable results were found for the average rating variables. *Rating Paid* shows a negative response to *Features Paid* and *Price*, and *Features Free* did not have an effect on *Rating Free*. Based on these results H9a and H9b are rejected.

5.6 Feedback effect

Persistence modeling not only shows direct and indirect effects, but also has the advantage of including feedback effects that might exist among and between features, reviews and rank performance of apps. Feedback effects occur when past performance influences future performance and actions. Rank performance, for example, indicates a relative number of downloads by other consumers in the past. Because people often choose products that have been bought by others, a high-ranked app will cause more people to download it, thus affecting future rank performance. Carare (2012) studied this phenomenon in the App Store and used rank as an indicator of other consumers’ past choices. He found evidence that information about past popularity of an app has a significant effect on demand. Carare also found that this effect was the most meaningful for ranks between 1-10, became less effective for 11-50, and had an insignificant effect for lower ranks. The conclusion is therefore that observational learning is the main driver in consumer decision making. In addition to affecting future performance, past performance can influence earned media as well. Duan, Gu, & Whinston (2008) included feedback effects in their analysis and found evidence for a positive sales performance feedback on reviews.

The Granger causality test provides evidence for feedback effects between variables. The ranks, for example, both Granger-cause all other variables except for in-app purchases. In particular, a shock to *Rank Free* and *Rank Paid* significantly improves the future values of *Rank Free* and *Rank Paid* in the short and long term. A shock to the ranks also has an impact on the volume of reviews. The effect is short- and long-term and applies to both free and paid apps. An increase in downloads leads to more reviews. A shock to the ranks has a positive effect on *Features* as well. For free apps the effect is both short- and long-term and is significant for 44 days. For paid apps the effect is only long-term; the accumulated response becomes significant on day 24.

5.7 Other Results

Price

Other interesting result is that consumers are price sensitive. An increase in *Price* has a significant negative short-term effect on *Rank Paid*, which returns back to the baseline after 12 days. *Price* also has a negative effect on *Rank Free*, which is significant on day 4 and lasts until day 15. The effect is thus temporary; the rank returns back to the original baseline.

Interrelationship between earned media of free and paid apps

Results show that not only are free and paid apps interrelated through rank performance; they are also interrelated through earned media. For example, *Features Free* has a contemporaneous correlation of 0.317 with *Features Paid*. *Features Paid* also has a positive short-term effect on *Features Free*; and *Feature Free* has a significant short- and long-term effect on *Features Paid*. Thus, they have a synergetic relationship. Moreover, *Features Paid* responds significantly to *Rating Free, Reviews Free* and *IAP Free*. *Features Free* responds significantly to *Rating Paid*. Other findings regarding *Features Free/Paid* were already discussed in the previous sections.

The review variables are also interrelated. *Rating Free* has a small contemporaneous correlation with *Rating Paid* (0.197) and *Reviews Free* has a strong contemporaneous correlation with *Reviews Paid* (0.763). *Rating Free* has a positive short-term effect on *Rating Paid*; and *Rating Paid* has a positive short and long term effect on *Rating Free*. *Reviews Paid* responds positively to *Reviews Free* in short and long term, however, the opposite effect is absent. Furthermore, *Reviews Free* is negatively influenced by *Feature HP Paid* in the short and long term and positively by *Features Paid* in the short term. *Rating Paid* is positively influenced by *Features Free,* and *Rating Free* is negatively influenced by *Features HP Paid* and *Features Paid.*

Chapter 6. Conclusion

6.1 General discussion

The main objective of this research was to study how the "free and paid app" strategy and earned media impact the rank performance of apps. The data used for analysis covered app characteristics, rank performance and earned media dynamics of game apps in the App Store. Persistence modeling was used to answer the main research question and the three sub-questions.

Results show that an improvement in rank performance of the free app is positively related to the improvement in rank performance of the paid app. This finding supports the use of the "free and paid app" strategy. Moreover, rank performance of the paid app has an effect on rank performance of the free app. Cannibalization of the paid app is a likely reason for this effect. In a competitive market such as the app market, however, cannibalization does not have to result in a loss. The free app, for example, is able to increase the app user base and attract consumers who like to experience an app before purchasing the paid version. Offering a free trial version is thus an effective way to increase visibility and downloads of the paid app in the short and long term.

Previous research studies proved that reviews increase product demand; it is therefore surprising that they have almost no effect on the rank performance of apps. The reason for that may be because consumers use reviews when they are not familiar with a product and its quality. When there is a free trial present consumers do not have to rely on reviews since they are able to experience the app for themselves. Results also showed that the average rating and review volume have no dynamic relationship. Contradicting the findings in previous studies, the average rating did not significantly impact review volume and review volume did not significantly impact the average rating. Moreover, features did not have a positive effect on the average rating or review volume of free and paid apps.

On the other hand support was found for the direct effect features have on rank performance. Findings suggest that an increase in the number of features has a positive short-term effect on rank performance of free and paid apps. Features temporarily increase visibility and demand. Features on the home page surprisingly did not impact rank performance directly.

Further analysis showed that features can be influenced by other variables. These findings give a better understanding of the reason why the App Store features apps. First, a difference is found between free and paid apps. The number of features a paid app receives is impacted by review volume of the paid app, features on the home page and by an increase of the number of features a free app receives. Thus, review volume and a feature on the home page indirectly impact rank performance through an increase in the number of features. The number of features a free app receives is positively impacted by the presence of in-app purchases and an increase in the number of features of the paid app. Second, features of the paid app that appeared on the home page are positively affected by updates, and a higher rating of the paid app. Overall, results show that there are various indirect effects present. With regards to featuring, the App Store favors apps that show revenue potential (paid downloads and in-app purchases) and quality improvement (updates and positive reviews). Furthermore, the number of features free and paid apps receive is interrelated, which is another benefit of the “free and paid app” strategy.

Finally, additional analysis shows that there is a feedback effect present. Past rank performance has significant impact on future rank performance and earned media values. Price was also included in the analysis; results indicate that an increase in price has a temporary negative impact on the rank performance of both free and paid apps. Most importantly, earned media of free apps are found to be interrelated with the earned media of paid apps. The free trial app is able to influence the paid app in other aspects except for rank performance.

6.2 Academic implications

In some cases this paper supports previous work on apps and free samples, and adds new insights as well. Based on the results found in this research ample support was found for the positive effect free trials have on paid app rank performance. In line with Pauwels and Weiss (2008), the effect free trials have on rank performance is influenced by marketing actions. Though they used only paid media, the contribution of this paper is that earned media can have a positive effect as well. In addition, with regard to understanding app demand it is important to include indirect effects and account for features, which clearly have a significant impact on app demand.

6.3 Managerial implications

For managers and app developers, the findings in this paper have important implications with regards to the "free and paid app" strategy. First, adding a free trial version is effective to improve visibility and increase downloads for the paid app. The benefits of the free app therefore outweigh additional maintenance costs. The free app helps to improve the rank performance of the paid app, and the paid app helps to improve the rank performance of the free app. Earned media are able to improve rank performance as well. Managers should focus on App Store features in particular. Features, however, cannot be influenced directly; therefore the developers should increase the likelihood of their app being featured by the App Store. The results clearly show that apps with the potential to earn revenue are featured more often. A possible reason is that the App Store retains 30% of all app revenue. Adding in-app purchases to the free app or increasing price of the paid app are a couple of options to improve the revenue potential. The App Store also prefers to feature high quality apps. Updates and high average rating have an effect on the features that appear on the home page, and review volume has an effect on the number of features an app receives. Review volume can be increased by actively asking app users to review the app, and the average rating can be increased by regularly improving the quality of both apps.

The apps are also positively interrelated through earned media. Thus, developers can take advantage of the synergetic relationship between the apps. For example, if a free app receives positive reviews, the paid app will also receive more positive reviews.

Furthermore, developers may fear potential cannibalization of the paid app, but findings suggest that the acquisition of free users has a positive effect on paid app downloads. However, most importantly, when developers choose the free and paid app strategy they must keep in mind that, to avoid cannibalization, they have to differentiate the two apps enough to make it worthwhile for consumers to purchase the paid app.

6.4 Limitations and further research

There are several limitations to this work that could be improved upon in future research. First, the data collection included only historical data and not live data. For this reason, not all dynamics of app characteristics were captured. Characteristics change with each update. Because reviews did not have a significant impact on rank, other variables such as screenshots or app description could show consumers a better depiction of app quality. Second, different business scenarios were not taken into account. As Dekimpe and Hanssens (1999) proposed, multiple business scenarios can exist in one market. It might therefore be beneficial to compare various business scenarios in the app market, either within one category or across various app categories, because apps, like other products, may follow various ranking paths. Finally, the data in this study did not reflect how much content was restricted in the free app. There might be a relationship between content restriction and willingness to buy the paid app. When there is not enough content available for the user to form an opinion, or there is too much content, consumers will not feel the need to convert to the paid version (Kumar, 2014) and cannibalization will be a more likely scenario.

As there is little research available about mobile applications, there is room for further research outside of this paper's context. Given the experience with the game app Threes!, mentioned in the introduction, it would be interesting to study what effect copycat apps have on the demand of the original app. Comparing app launch strategies across platforms could be valuable too. For example, does launching the app at the same time on various platforms have more effect than launching the app sequentially? Threes!, for example, was first launched only on Apple devices (Webster, 2015). It was successful from the start, but while the app was not yet launched on Google Play copycat apps had time to take advantage of the fact that Android users also wanted to try the new game.

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Appendix

Figure 1: Example: Features on the Dutch App Store home page

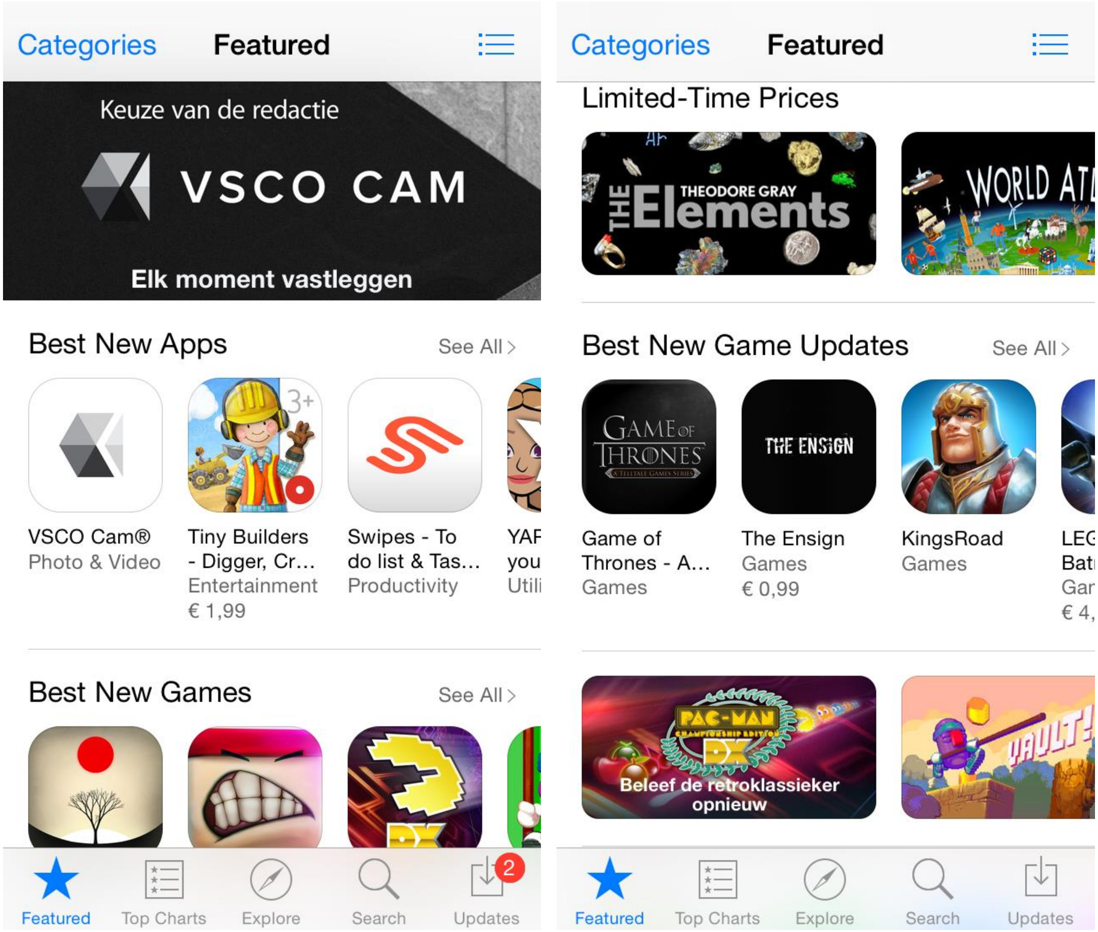

Table 1 Results of the Granger causality tests including minimum p-values between two variables across 30 lags

Dependent Variable is Caused by	**Rank Free**	**Rank Paid**	**Rating Free**	**Rating Paid**	**Reviews Free**	**Reviews Paid**
Rank Free	-	0.00	0.00	0.00	0.00	0.00
Rank Paid	0.00	-	*0.96*	0.00	0.00	0.00
Rating Free	0.00	*0.17*	-	0.00	*0.36*	*0.62*
Rating Paid	0.00	0.00	0.00	-	0.00	0.00
Reviews Free	0.00	0.00	*0.99*	*0.42*	-	0.00
Reviews Paid	0.00	0.00	*0.99*	*0.75*	0.00	-
Features Free	0.00	0.00	0.00	0.00	0.00	0.00
Features Paid	0.02	0.00	0.02	0.05	0.00	0.00
Feature HP Paid	0.01	0.00	*0.63*	0.02	*0.96*	*0.98*
Price Paid	0.00	0.00	0.00	0.00	0.00	0.00
Update	0.00	0.00	0.00	0.00	0.00	0.00
IAP Free	*0.24*	*0.16*	*0.90*	*0.92*	*0.25*	*0.47*

Dependent Variable is Caused by	**Features Free**	**Features Paid**	**Feature HP Paid**	**Price Paid**	**Update**	**IAP Free**
Rank Free	0.00	0.00	0.00	0.01	0.00	*0.76*
Rank Paid	0.00	0.00	0.00	0.00	0.00	*1.00*
Rating Free	0.00	0.00	*0.32*	*0.42*	0.00	0.00
Rating Paid	0.00	0.01	0.00	*0.20*	0.00	*0.59*
Reviews Free	0.00	0.00	*0.99*	*0.18*	0.00	*0.84*
Reviews Paid	0.00	0.00	*0.91*	*0.15*	0.00	*1.00*
Features Free	-	0.00	0.02	*0.49*	*0.23*	0.05
Features Paid	0.02	-	*0.07*	0.02	*0.06*	*0.08*
Feature HP Paid	0.04	0.00	-	0.00	0.00	*0.95*
Price Paid	0.03	*0.10*	0.00	-	0.00	*0.54*
Update	0.01	0.00	0.00	0.02	-	0.00
IAP Free	0.00	0.00	*0.86*	*0.63*	*0.70*	-

Note. Cursive values are **not** significant at the 0.05 significance level.

Table 2 Model Fit based on R-square and adjusted R-square

Dependent variable:	Feature HP Paid	Features Free	Features Paid	Price Paid	Rank Free	Rank Paid
R-squared	0.901	0.750	0.779	0.938	0.968	0.917
Adj. R-squared	0.899	0.745	0.774	0.937	0.967	0.916

Dependent variable:	Rating Free	Rating Paid	Reviews Free	Reviews Paid	Update	IAP Free
R-squared	0.987	0.837	0.993	0.996	0.017	0.996
Adj. R-squared	0.987	0.833	0.993	0.996	-0.003	0.995

Table 3 Summary hypothesis results

Hypothesis		Result
H1a	Rank performance of the free app has a positive immediate, short- and long-term effect on rank performance of the paid app.	Supported
H1b	Rank performance of the paid app has a positive immediate, short- and long-term effect on rank performance of the free app.	Supported
H2a	An increase in average rating of free apps has a positive immediate, short- and long-term effect on rank performance of free apps.	Rejected
H2b	An increase in average rating of paid apps has a positive immediate, short- and long-term effect on rank performance of paid apps.	Rejected
H3a	An increase in review volume of free apps has a positive immediate, short- and long-term effect on rank performance of free apps.	Partially supported
H3b	An increase in review volume of paid apps has a positive immediate, short- and long-term effect on rank performance of paid apps.	Partially supported
H4a	An increase in the number of features free apps receive has a positive immediate and short-term effect on rank performance of free apps.	Partially supported
H4b	An increase in the number of features paid apps receive has a positive immediate and short-term effect on rank performance of paid apps.	Partially supported

H5a	An increase in average rating of free apps has a positive effect on review volume of free apps.	Rejected
H5b	An increase in average rating of paid apps has a positive effect on review volume of paid apps.	Rejected
H6a	An increase in review volume of free apps has a positive effect on the average rating of free apps.	Rejected
H6b	An increase in review volume of paid apps has a positive effect on the average rating of paid apps.	Rejected
H7a	An increase in average rating of free apps has a positive effect on the number of features free apps receive.	Rejected
H7b	An increase in average rating of paid apps has a positive effect on the number of features paid apps receive.	Rejected
H8a	An increase in review volume of free apps has a positive effect on the number of features free apps receive.	Rejected
H8b	An increase in review volume of paid apps has a positive effect on the number of features paid apps receive.	Supported
H9a	An increase in the number of features free apps receive has a positive effect on the average rating of free apps.	Rejected
H9b	An increase in the number of features paid apps receive has a positive effect on the average rating of paid apps.	Rejected
H10a	An increase in the number of features free apps receive has a positive effect on the review volume of free apps.	Rejected
H10b	An increase in the number of features paid apps receive has a positive effect on the review volume of paid apps.	Rejected