Project Proposal for second year summer paper

Complementarity and Substitution of App-Category in App-Store:

Empirical Study of Nigerian App-store

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**Abstract**

Fueled by widespread smartphone adoption and increasing mobile internet access the mobile app market has experienced significant growth during the last 3 years. The mobile app market reached 64 billion download in 2012 up from 8.2 billion downloads in 2010 and its total revenue in 2012 was $18 billion up from $5.2 billion in 2010. In this market three types of agents operate: (1) platform owners (2) app developers and (3) consumers. For the platform owner that seeks the diffusion of its platform, it is important to understand which app-category can drive the diffusion of its platform, and what app-categories are substitutes. In this study we develop a structural model that seeks to find the level of substitution and complementarity between different app-store app-categories. We test our model using 9 month unique panel data of consumer purchases. We use state space model and hierarchical Bayesian to model consumer’s choice. Our counterfactual analysis of the incentive of the firm for different product categories has managerial implication for app-store platform owners.

**Model**

In contrast to prior studies such as Carare (2011) do not account for consumers’ decision within the category, we start our model with product category. In this sense, we assume that each product category has a model of bass diffusion, or formally



where denotes the cumulative number of users of each product category j at day t on the platform,  market size of the category j, and error term of diffusion. Our incorporation of the sum of number of users of different product categories (sigma term), allows us to account for complementarity and substitution of different product categories. Finally  and are external and internal market forces in Bass diffusion model. Needless to say we account for heterogeneity in these parameters, and we later explain this heterogeneity in terms of characteristics of each mobile-app category (i.e. type of service, and demographic of users).

The second portion of our model accounts for evolution of preference for each mobile app. To model this evolution of preference for the app, we use the following Bass structure as well:



where  denote the cumulative number of mobile app a users at day t, and denotes the market size of mobile app-a in category j, which is proportional to the market size of the category.  and are external and internal market forces in Bass diffusion model. Needless to say allow for heterogeneity in these parameters, and further on we explain this heterogeneity in terms of observed characteristics of mobile app (i.e. file size as a signal of quality and sophistication of the mobile app).

Consumer search apps in the product category, and based on their utility they decide whether to purchase and which app to purchase given they have decided to purchase, therefore, we define consumer i’s utility from purchasing mobile app a, according formally as:



where  denotes price of mobile app a at time t,  whether the app is featured, the tenure of the app (number of days from creation), and  unobserved demand shock (market time dummy). Finally, , , , and  are the parameters to estimate. We allowed heterogeneity in this parameters, and we later on explain this based on individual characteristics, such as download counts and tenure, and region (IP) of the downloader.

The logit form of the error term of the utility, allows us to define purchase probability of consumer in the following form:



where  is the number of mobile apps in category j.

This closes our model specification.

**Extension**

We later on can add the supply side to the model to account for app-developer/publisher’s decision to select the product category to develop mobile app.

**Data**

We have the 9 month daily purchase of consumer on the whole platform. For each user we have created time, and number of downloads. This allows us to distinguish between heavy and light users, and the experience of user with the platform owner. For each purchase we know the price, the number of downloads, source of download, whether the mobile app is featured and the device name. This allows us to explain heterogeneity in each user purchase decision. For each app we also know the category, language and file size which allow us to explain heterogeneity.

**Estimation**

We use Metrapolist-Hasting, Hierarchical Bayesian, and Kalman filter forward filtering backward smoothing for our estimation. We use MPEC algorithm modified for Bayesian estimation, and we estimate it using Metrapolist-Hasting algorithm.

**Conclusion**

We model consumer’s decision to purchase from mobile app category. We used the panel data to estimate our model. Our model explains the level of substitution and complementarity of the mobile app categories. We run counterfactual to understand how incentivizing one category can impact the revenue of the platform. We believe our study has various managerial implications.