Working Paper Document

**Social Learning and diffusion over Pervasive Products:**

**An Empirical Study of an African App-store**

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Date: 08/27/2014

**Abstract**

Fueled by the widespread smartphone adoption and an increase in the mobile internet access, the mobile app market has experienced a significant growth during the last 3 years. The mobile app market reached 64 billion downloads 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) two-sided platform owners (2) app developers/publishers and (3) consumers. As mobile phones are pervasive, the consumers’ preferences for an app in an app category can influence the peer consumers’ preferences in many ways, ranging from the psychological benefits of social identifications, social learning, and social inclusion to the utilitarian benefits of network externalities and direct network effects. Two types of forces may drive consumers’ decision to adopt an app: innovation forces, or imitation forces. World Wide Web (WWW) has enabled nations to apply each type of these forces globally, but for products that diffuse over another pervasive product, local forces may be more relevant. To optimize its marketing mix and to target heterogeneous consumers differently, an app store owner not only needs to know which type of force affects each consumer’s choices, but also needs to know heterogeneity in both consumers and app categories. Knowing the effect of each force for individual consumers, an app platform can use either viral marketing or app trial strategies. In addition, to design an optimal platform and incentive mechanisms, a platform owner needs to know the effect of the breath of app assortment in the category and the complementarity or substitution of different app categories.

Thus, given exceptional characteristics of pervasive products (e.g. mobile apps), we use hierarchical Bayesian non-linear state space and structural models[[1]](#footnote-1) to study the effects of both innovation and imitation forces, preference interdependences, mobile app category assortment breadth, and consumers and app categories heterogeneity on consumers’ individual adoption choices. In addition our model allows us to study the substitution or complementarity of different mobile app categories. We apply our model to a unique dataset of eighteen weeks of consumer’s download choices on a newly launched app store in Africa[[2]](#footnote-2). We find that local, rather than global, diffusion forces explain individual’s consumer choices on the app store. Our findings show an interesting pattern of app category heterogeneity and complementarity, yet it does not find any significant effect for app category assortment breadth. The imitation rather than the innovation force drive diffusion of mobile app categories, and consumer preference for some mobile app categories has bimodal distribution. These results have various implications for mobile app platform management and mechanisms design. Our results should be of interest to academics and business community.

Keywords: mobile app store platform, interdependence of consumer preferences, social learning, simultaneous local and global diffusion model, app category complementarity and substitution, hierarchical mixture Bayesian, state space, structural model, Markov Chain Monte Carlo, big data

**Introduction**

Smartphones are so pervasive in the telecommunication market that no matter which mobile operator anyone selects in U.S (e.g. T-Mobile, Verizon, AT&T, or Sprint), she has an option to adopt a long term contract that includes a smartphone handset. All three dominant mobile operating system (OS) companies, Google, Apple, or Microsoft, have opened their platform to third party developers to develop mobile apps, the mobile apps which help the diffusion of the OS platform. Fueled by this decision of the OS platforms, and the flood of mobile app developers to this eco-system, new intermediaries called app-stores stepped in. App stores are two sided platforms, as they match consumers and app developers, without taking the ownership of the apps.

App stores garner their revenue share either from advertisings or from paid app sales, so for them efficiency of app market translates into more revenue. Some app-store platforms show to the potential consumers the current install base of mobile apps, while others do not. For example while Google play shows the range of number of installs of an app to consumers, Apple, Microsoft, and Amazon do not do so. Showing global number of installs may only be relevant if it affects individual consumer choices at each local market. However, observing peer consumers’ choice does not have to be online. Mobile phones are pervasive, as consumers carry their smartphones in most of their social life events[[3]](#footnote-3). This pervasiveness may help the diffusion of the mobile apps in a local market. More precisely, social learning process through observing others’ choices of mobile app may play a role in the mobile apps’ diffusion in local markets. This social learning process may even be central for mobile apps to create interdependence of consumers’ preferences, as mobile phones are classified as disruptive innovations[[4]](#footnote-4). The interdependence of consumers’ preferences has long been studied in marketing in the context of the geographical or social neighborhood by Yang and Allenby (2003), Stephen and Toubia (2010), Lehmmes and Croux (2006), Nair et al. (2010), etc.

For a mobile app platform it may be important to know whether global WWW or local pervasiveness of mobile phones explains individual consumers’ choices better, because each mechanism suggest different set of marketing mix strategies. Furthermore, a platform owner may precisely be interested to know for each type of mechanism whether imitation or innovation force drives consumers’ adoption choices, because while the imitation forces suggest viral marketing strategies, the innovation forces suggest app trail strategies.

An app store platform may also be interested to know the complementarity between different mobile app categories. This knowledge may suggest a mobile app platform owner to redesign its online platform to cross sell more apps. In addition, an app platform can recommend new mobile app categories or propose trial to consumers to increase the cross selling chance. Another alternative strategy could be to use an app category as a loss leader to encourage use of apps in the other app categories. For example, the app store owner may find the app category of Book and References to be complement to the app category of Puzzle and Trivia, so she may decide to give an incentive on one to drive the diffusion on the other.

To design an optimal app store platform and optimal mechanisms, an app store platform owner may be interested to know whether an optimal assortment size exists. Scheibehenne, et al. (2010) asserts that currently there are mixed evidences about the influences of assortment breadth, or variety in product line on consumers’ choices. Many studies hinge upon search theories to argue that large assortment breath can lead to no purchase choice, including Kuksov (2010), Villas-Boas (2009), Diehl and Pynor (2010), Chernev and Hamilton (2009), Timmermans (1993), Kahn and Lehmann (1991), Sela, Berger, and Liu ([2009](http://www.jstor.org/stable/10.1086/651235#rf110)), Gourville and Soman (2005) . However, there are studies that support the idea that greater choice is always desirable, as each consumer can find a great product fit, and that  variety a brand offers serves as a quality cue (Villas-Boas 2010, Anderson [2006](http://www.jstor.org/stable/10.1086/651235#rf2), Arnold et al. 1983, Bown et al. 2003, Craig et al. 1984,  Koelemeijer and Oppewal [1999](http://www.jstor.org/stable/10.1086/651235#rf72); Oppewal and Koelemeijer [2005](http://www.jstor.org/stable/10.1086/651235#rf90), Boatwright and Nunes [2001](http://www.jstor.org/stable/10.1086/651235#rf10); Borle et al. [2005](http://www.jstor.org/stable/10.1086/651235#rf11); Drèze, Hoch, and Purk [1994](http://www.jstor.org/stable/10.1086/651235#rf29); Sloot, Fok, and Verhoef [2006](http://www.jstor.org/stable/10.1086/651235#rf116), Berger et al. 2007). On mobile apps it is not clear whether consumers also enjoy navigating in the app store or they intentionally search for specific mobile app they have heard about. Therefore, to design an optimized app store platform, and mechanisms, the owner may be interested to know the effect of assortment breath.

Individual choice data and models allow not only capturing these intricacies, but also simulating policies. Policy simulation allows the app store platform to jointly optimize its marketing mix policies. For example a given firm may find a corner or an interior solution for optimal level of imitation and innovation forces at local and global level to optimize each mobile app categories’ diffusion. This optimization has merits, especially for app store platform owner, as she can target consumers differently by their smartphones. Targeting optimization requires accounting for heterogeneity not only in app categories, but also in consumers’ responses. Therefore the model should be flexible enough to allow for any type of heavy tail distribution in consumers’ or categories’ heterogeneity.

Thus given exceptional features of the diffusion and management of an app-store platform, we consider the following substantive questions: (1) whether global or local diffusion of mobile app categories drive the individual choices of consumers? (2) Whether imitation or innovation forces drive the diffusion of an app category? (3) How can an app-store platform optimize its targeted marketing mix policies (e.g. encourage trial, or encourage sharing) to increase the choice probability of individual consumers of an app in a given app category? (4) Which mobile app categories are substitute, and which are complements? (5) What is the optimal assortment breath of each mobile app category?

To address these questions about mobile app categories’ simultaneous diffusion and their complementarities or substitutions, we cast Bass Diffusion Model (BDM) into simultaneous state-space models. Further, to address consumers’ interdependent preferences, we extract imitation and innovation forces from our simultaneous state space model, and we adopt individual choice model that uses flexible mixture of normal hierarchical Bayesian approach to model individual’s heterogeneity. To avoid multicollinearity in mobile app category characteristics, we adopt a factor model, rather than discarding the data. We capture diffusion of mobile app categories in a latent measures that evolves with parameters of innovation (p), and imitation (q), observed cumulative adoption(y), and app category market potential (M). This modeling approach allows us to capture not only direct network effect of an app and an app category in imitating parameter, but also complementarity and substitution of different apps and app categories over the app store in innovation parameter. We find that diffusion over a pervasive product (mobile phones) hypothesis fits our data better than global diffusion cross country interaction over World Wide Web. However, there is an interesting pattern of complementarity between diffusion of mobile app categories globally. Word of mouth rather than innovation forces drive the diffusion of mobile app categories and preferences of consumers on some mobile app categories have bimodal distribution. We also find that distribution of market sizes is bimodal, and that there is a significant heterogeneity in the choice response of consumers to mobile app category characteristics. Last but not least, we do not find a significant impact for assortment breath of the mobile app categories influence on the individual choice of mobile app categories.

Our study of interdependence of consumer choices is mostly related to studies by Yang and Allenby (2003), Stephen and Toubia (2010), Lehmmes and Croux (2006), Nair et al. (2010), who model the peer effect either due to geographical (distance) or social network neighborhood. In addition our study is related to study by Sriram et al. (2007) and Liu et al. (2010) on the complementarity and substitution of digital goods, and study by Putsis et al. (1997) and Dekimpe et al. (1997) on global simultaneous diffusion. Although these studies have contributed greatly to our understanding of the phenomenon, none has considered the impact of visibility of goods (e.g. mobile app) diffused over pervasive products (e.g. mobile phones) on the individual consumer decision. Given ubiquity of smart phones, it may be important to consider the influence of visibility of goods diffused over pervasive products, to understand whether global village buzz translates to global diffusion force or local diffusion force to affect individual choices. In addition, to understand complementarity or substitution of mobile app categories, it may be important to consider the joint diffusion of mobile app categories simultaneously. Needless to say, we may also expect a significant heterogeneity both in the individual consumers and in the mobile app categories parameters.

To address some of these limitations and research questions, we extended the use of the state space and the individual logit choice models to model the interdependence of consumers’ choices. To do so, we incorporated Bass Diffusion Model (BDM) to model simultaneous diffusion of the mobile app categories and their substitution and complementarity. The resulting combination of the state space and the choice models is information about dynamic, nonlinear, and heterogeneous phenomena of diffusion and choice over pervasive goods. In contrast to many studies, to allow the model to be flexible, and in order to separate state dependence from heterogeneity, we use normal mixture model for both mobile app category and individual choice parameters, as a substitute for normal model of heterogeneity. Moreover, we extract the aggregate innovation and imitation forces from a latent BDM diffusion model. For estimation, we re-cast BDM differential equations into non-linear discrete-time, state-space forms; and then estimate them using hybrid MCMC approach to jointly estimate diffusion and choice models by Extended Kalman Filter and normal mixture logit model.

This paper, thus, contributes to the emerging literature on pervasive products and mobile app store platforms in various ways. First, it introduces a choice model to investigate several factors that could affect choices of mobile app categories on the app store platforms. Although other studies in marketing have considered the dynamic choice models of digital goods, none has molded the effect of innovation and imitation forces on individual consumer choices, to account for interdependence of consumer choice preferences. Second, the paper examines the complementarity and substitution of different mobile app categories. This information can help the app store platform to optimize its promotion strategies on mobile app categories. Third, rather than selecting the mobile app characteristics, we use a factor model to summarize the variations, and then we use the factors in the choice model. Fourth, to ease the estimation rather than discarding the big data on the whole app store, we first use the whole data to recover imitation and innovation forces, and then wen select a stratified sample to get intuition about underlying mechanism of individual choice behavior. Fifth, despite mixed evidence and normative suggestions about the effect of assortment breadth, to the best of our knowledge we are the first to empirically test the predictions over app store platforms. Sixth, to estimate the resulting model, the paper employs hierarchical Bayesian mixture normal on the top of both choice and Extended Kalman Filter estimation. These approaches should be of interest to academia and a number of commercial entities interested in the performance of products diffused over pervasive products, and their relevant store platforms.

**Literature Review**

This study draws upon several streams within the literature that have investigated: *i*) Interdependence of consumer preference; *ii*) Product Category Complementarity; *iii)* Mobile app store dynamics; *iv)* Global simultaneous diffusion; and *v*) Assortment breadth and product line variety. Given the breadth of these areas across multiple disciplines, what follows is only a brief review of these relevant streams. Table 2 presents a summary of the position of this study.

**Interdependence of consumer preference**

Quantitative models of consumer purchase behavior often do not recognize that consumer choices may be driven by the underlying innovation and imitation forces within the population. Economic models of choice typically assume that an individual’s latent utility is a function of brand and attribute preferences, not the preferences of others, yet for pervasive experience goods, a new model which accounts for these underlying forces and preferences may explain the choice of consumers better. In other word, preferences and choice behaviors are influenced not only by the consumers’ own tastes and awareness, but also by the taste and awareness of others. People who live in the same geographical area often become aware of an innovation sooner and their preference are more coherent, so their choices of pervasive goods may be interdependent. Interdependence may be driven by social concerns, by endorsements from respected individuals that increase a brand’s credibility, or by learning the preferences of others through the diffusion of information. Many studies tried to address this issue. Yang and Allenby (2003) uses cross sectional data to model consumer preference dependency. Stephen and Toubia (2010) studies value implications of social network between sellers in a large online social commerce marketplace. Lehmmes and Croux (2006) apply bagging and boosting classification techniques to a customer database of an anonymous U.S. wireless telecommunication company to find that both methods significantly improve the churn prediction accuracy.

Bell and Song (2007) examine customer trials at Netgrocer.com to find that exposure spatially to proximate others (through direct social interaction or observation) can influence decisions of those who have yet to try. This study finds that trials arise from utility-maximizing behavior and that neighborhood effect is significantly positive and economically meaningful. Hartmann et al. provides a selective review of how insights from other disciplines can improve and inform the modeling choices of social interactions. Aral and Walker (2011) present a method that uses in vivo randomized experimentation to identify influence and susceptibility in networks and to avoid the biases inherent in the traditional estimates of the social contagion process to identify social influence in the networks.

Nair et al. (2010) quantify the impact of social interaction and peer effects in the context of physicians’ prescription choices. This study uses detailed individual-level prescription data, along with self-reported social network information to find that the physicians’ prescription behavior is significantly influenced by the behavior of research-active specialists, or “opinion leaders,” in the physician’s reference group. Bradlow et al. (2005) reviews literature on generalizing the notion of a map to include demographic and psychometric representations to argue for spatial models that capture a variety of effects that impact firms’ or consumers’ decision behaviors. Hartmann (2010) develops a model for demand estimation in the context of social interactions. This study models the decision of a group of customers as an equilibrium outcome of an empirical discrete game, in which group members must be satisfied with chosen outcome. Yang et al. (2005) estimate the preference independency in television program viewership between spouses using simultaneous equation model to show that the models that ignore interdependency of preference yield biased estimates of consumers’ sensitivity to observed attribute preferences.

Narayan et al. (2011) studies how multi-attribute product choices are affected by the peer influences. This study proposes a two-stage conjoint-based approach to examine three behavior mechanisms of peer influence, and it finds that when faced with information on the peer choices, consumers update their attribute preferences in Bayesian manner. Kurt et al. (2011) investigate the interactive influence of the presence of an accompanying friend and consumer’s agency communion orientation on the consumers’ spending behavior. This study finds that shopping with friends can be expensive to agency-oriented consumer (e.g. males) but not for communion-oriented consumer (e.g. females). Chung and Rao (2012) present a general consumer preference model for experience products that allows for situations in which it is not easy to consider some qualitative attributes of a product or when there are too many attributes relative to the available amount of preference data. This study captures the effects of unobserved product attributes with the residuals of reference consumer for the same products. Choi et al. (2010) develop a Bayesian spatio-temporal model to study two imitation effects in the evolution of the demand at an Internet retailer. This study allows imitation behavior to be reflected both in geographic proximity and in demographic proximity, and it finds that the proximity effect is especially strong in the early phases of demand evolution; whereas the similarity effect becomes more important with time.

**App Category Complementarity**

Investigating the complementarity between different product categories has long been the interest of marketing scholars. Sriram et al. (2007) presents a framework of durable good purchasing behavior in related technology product categories; using a household level information on category-level first-time adoption decisions in three categories—personal computer, digital cameras, and printers--- this study finds a strong complementary relationship between the three categories. Liu et al. (2010) study complementarities and the demand for home broadband internet services, with an eye on the demand side explanation rather than the supply side for large share of phone companies in the DSL broadband market. This study finds the evidence of strong complementarities between the consumption of broadband and its related categories. Yang and Ching (2013) develop a structural consumer life-cycle model to investigate consumer’s adoption and usage decision of ATM cards. This study uses the data on ATM cards adoption in Itly, and it finds that one could significantly overestimate adoption costs for the elderly when ignoring their shorter life span.

Ma et al. (2012) models household’s contemporaneous brand choice outcome in the complement product categories; explicitly this study captures the cross-category dependencies in the brand choice outcome of household, and by using the scanner panel data on cake mix and frosting categories, it finds that complementarity accounts for the vast majority of the estimated cross category effects in demand. Karaca-Mandic (2011) estimates complementarities between DVD player adoption and the DVD content. This study uses the household level quasi-panel data on adoption decision of households, the data on availability of movies for rental on DVD at local regions and on the number of movies released on DVD nationally, and it finds a significant complementarity between DVD player and DVD content.

Lee et al. (2013) propose a direct utility model with a latent decision sequence to measure asymmetric complementarity effects and to capture differential response to cross-category purchases and inventories. This study uses the scanner panel data on milk and on cereal purchases to investigate cross-price elasticities and spillover effects of merchandising variables. Niraj et al. (2008) model more than one purchase decision of the household simultaneously. Using two-stage bivariate model of incidence and quantity outcome in multiple categories, this study finds that cross-category promotional spillovers are asymmetric between the two product categories of bacon and eggs. Using store-level sales data, Wedel and Zhang (2004) develop a sales model that can be used to assess the cross-category price effects that are specific to individual items (stock keeping units).

Song and Chintagunta (2006) study the cross-category effects of marketing activities using the aggregate store-level scanner data on four product categories--- liquid laundry detergents, powdered laundry detergents, and liquid fabric softeners, and sheet fabric softeners—, and it finds evidence for a complementary relationship between liquid softeners and both forms of detergents. It also finds that the magnitude of cross-category elasticities are brand specific, i.e., different brands in a category have a different price impact on the demand for a brand in another category.

Oestreichter-Singer and Sundrararajan (2008) tests the conjectures that the explicit visibility of “product networks” can alter the demand spillover across the constituent items. Using the data about copurchase networks and demand levels associated with more than 250,000 interconnected books offered on Amazon.com, this study finds that on average the explicit visibility of a copurchase relationship can lead to up to an average threefold amplification of the influence that complementary products have on each other’s demand level. Bezawada et al. (2009) investigate the effects of aisle and display placement on the sales affinities between categories. This study develops a spatial model of brand sales that allows for asymmetric store-specific affinity effects between two or more product categories.

**Mobile app store dynamics**

There is an emerging stream of literature that interests the dynamics of mobile app stores. Ghose and Han (2014) build a structural econometrics model to quantify the vibrant platform competition between mobile (smartphone and tablet) apps on the Apple iOS and Google Android platforms. Estimating consumer preferences toward different mobile app characteristics, this study finds a positive effect of in-app purchase options wherein user can complete transactions within the app, and it finds a negative effect of in-app advertisement options. Carare (2012) uses daily data on the ranking by sales of the top 100 apps sold through Apple’s App Store, and it finds that lagged bestseller rank information has causal effect on mobile apps’ demand. Garg and Telang (2013) present an innovative method to use public data to infer the rank-demand relationship for the paid apps on Apple’s iTune App store, and it finds that the top-ranked paid apps for iPhone generates 150 times more downloads compared to the paid apps ranked at 200. Liu et al. (2012) examines the effect of the freemium strategy on Google play, and by analyzing a large panel dataset, it finds that the freemium strategy is positively associated with the increased sales volume and the increased revenue of the paid apps.

Ghose et al. (2011) explores how the internet browsing behavior varies between the mobile phones and the personal computers. This study argues that smaller screen sizes on mobile phones increase the user information browsing cost, and that wider range of offline locations for mobile internet usage increases the importance of local activities. This study finds significant effects for ranking and geographic match relevance on mobile internet. Ghose and Han (2011b) develop and estimate a dynamic structural model of user behavior and learning with regard to content generation and usage activities in mobile multimedia environments, the environments in which users learn about two different categories of web contents: social network and community and mobile portal. This study allows for both direct experience and indirect experience from neighbors, and it finds that learning based on direct experience is more accurate (has less variability) than learning based on indirect experience. Ghose and Han (2011a) quantify how user mobile internet usage relates to unique characteristics of the mobile internet. By examining how the mobile-phone-based content generation behavior of users relates to content usage behavior, this study analyzes whether there is a positive or negative interdependence between these two activities. Kim et al. (2008) develop a structural model to examine user demand for voice service and short message service (SMS), and it measures the own- and cross-price elasticity of these services to find a significant cross price elasticity for complementarity and substitution of these two services.

**Global Simultaneous Diffusion models**

There are two main relevant stream of literature in product diffusion related to this study: micro diffusion models, and global simultaneous diffusion models. Chaterjee and Eliashberg (1990) develop a model of innovation diffusion using a micro-modeling approach that explicitly considers the determinants of adoption at the individual level in a decision analytic framework. Incorporating heterogeneity in preference characteristics and responsiveness to information, this study models consumers’ Bayesian learning from information items that enter with Poisson rate. More recently, Young (2009) examines three broad classes of diffusion models—contagion, social influence, and social learning—to show how to incorporate heterogeneity into each at a high level of generality without losing analytical tractability. Lelarge (2012) studies a model of diffusion where the individuals’ behavior is the result of strategic choice. This study uses simple coordination game with binary choice, and it describes the condition of a new action to become widespread in a random network.

Iyengar and Van den Bulte (2011) study how opinion leadership and social contagion within social networks affect the adoption of new products, and it finds evidence of contagion operating over network ties, even after controlling for marketing efforts and arbitrary system wide changes. Moon and Russel (2008) develop a product recommendation mechanism based on the principal that customer preference similarity stem from prior purchase behavior, a principle that is a key to predict customer product purchases. Song and Chitagunta (2003) develop an empirical model for the adoption process of a new durable product that accounts for consumer heterogeneity as well as consumers’ forward-looking behavior, and it decomposes the effect of the entry of Sony into primary demand expansion and switching from other brands. This study finds that there exist several segments in the market with different preferences for the brand and different price sensitivities, and that there are differences in adoption timing and brand choice across segments.

Dover et al. (2012) shows how networks modify the diffusion curve by affecting its symmetry, and it demonstrates that network’s degree distribution has a significant impact on the contagion properties of the subsequent adoption process. This study proposes an agent based method for uncovering the degree distribution of the adopters’ network that underlies the dissemination process. Trusov et al. (2013) proposes an approach to identify systematic conditions that are stable across diffusions, and conditions that can be transferred to new product introduction within a given network. Using the Facebook applications data, this study shows that incorporating systematic conditions improve prelaunch forecast. For more complete review of models please review Peres et al. (2010).

Parallel with micro diffusion literature, there is a stream of literature that focus on the global simultaneous diffusion. Putsis et al. (1997) investigates the importance of pattern of interactions (mixing) across countries for VCR, microwave, computer disks, and personal computers in European community (EC). It develops simultaneous model of mixing patterns across multiple countries, the mixing patterns that can occur across a continuum with segregation (no mixing) at one end and random mixing (Berounlli mixing) at the other. This study finds that mixing behavior across segments is an important consideration in new product diffusion. Using the diffusion data between 1979 and 1992 of cellular telephone adoption over 70 countries, Dekimpe et al. (1998) use “coupled-hazard approach” and it estimates the Bass model using NLLS applied separately to data. However, this study suggests that network externalities (e.g. computer adoption decision affected by the number of sites on the World Wide Web) are likely to create between-country interdependencies. Putsis and Srinivasan (2000) suggest that there are clearly not only supply-side relationships (e.g. production economies), but also omitted variables (e.g. income) that are correlated across countries that make it exceedingly unlikely that diffusion in multiple countries be independent.

Talukdar et al. (2002) studies diffusion of 6 products in 31 developed and developing countries from Europe, Asia, and North and South America to investigate the impact of several macro-environmental variables on penetration potential and speed. This study finds that the average penetration potential for developing countries is about one-third of that for developed countries, and that it takes developing countries on average 17.9% longer to achieve peak sales. This study also finds that pooling data across countries can lead to a substantial improvement in prediction accuracy. Van den Bulte and Joshi (2007) propose a mixture model of diffusion of innovations in markets with two segments: influential who are more in touch with new developments and who affect another segment of initiators whose own adoption do not affect the influential. This study finds that two-segment model fits better than standard mixed-influence, the Gamma/Shifted Gomperz, and the Weibull-Gamma models, especially in cases where two-segment structure is likely go exist.

**Assortment Breadth**

. Scheibehenne, et al. (2010) asserts that currently there are mixed evidences about the influences of assortment breadth, or variety in product line on consumer choices. Many studies hinge upon search theories to argue that large assortment breath can lead to no purchase choice. Kuksov and Villas Boas (2010) argue that if too many alternatives are offered, then the consumer may have to engage in many searches or evaluations to find a satisfactory fit. This may be too costly, so the consumer may avoid making a choice altogether. If too few alternatives are offered, then the consumer may not search or choose, fearing that an acceptable choice is unlikely. Diehl and Pynor (2010) argue that even when consumers make a purchase, the same item may generate lower satisfaction when chosen from a larger rather than a smaller assortment.

Chernev and Hamilton (2009) present evidence that the relationship between assortment size and option attractiveness is concave, such that the marginal impact of assortment size on choice decreases as the attractiveness of the options increases. Sela et al. ([2009](http://www.jstor.org/stable/10.1086/651235#rf110)) uses five studies to demonstrate that because choosing from larger assortments is often more difficult, it leads people to select options that are easier to justify. However, there are studies that support the idea that greater choice is always desirable, as each consumer can find a great product fit, and that variety a brand offers serves as a quality cue.

Using six studies, Berger et al. 2007 demonstrate that compared to brands which offer fewer products, brands which offer increased compatible variety are perceived as having higher quality, and that this effect is mediated by product variety’s impact on perceived expertise. Anderson 2006, hinges upon the idea of long tail, “products that are in low demand or have low sales volume can collectively make up a market share that rivals or exceeds the relatively few current bestsellers and blockbusters, if the store or distribution channel is large enough”, and it argues in favor of long tail aggregators which are “companies or services that collects a huge variety of goods and makes them available and easy to find, typically in a single place. Saloot et al. (2006) finds that on an aggregate level, a major assortment reduction can lead to substantive short-term category sales losses but only a weak negative long-term category sales effect.  Oppewal and Koelemeijer (2005) posits that although effect of assortment size is observed for a few specific products, there is no evidence of a generic ‘favorite available’ effect as reported in earlier studies, nor is there indication that smaller assortments suffice if they contain a consumer's favorite alternative.

This study is different from above mentioned studies in that it uses a unique long time series of a panel of consumers over a course of 6 months over mobile apps within mobile app categories, which allows us to identify not only the diffusion of mobile app categories, but also the effects of imitation and innovation forces on individual consumer’s decision. To the best of our knowledge we are the first to juxtapose global imitation and innovation forces to local imitation and innovation forces to find the one that gives us a better fit. Our use of Hierarchical Bayesian and SUR model to model the simultaneous diffusion of mobile app categories allows us not only to infer complementarity of different mobile app categories but also to deal with the inherent scarcity of data in the context of our study. Our structural model allows marketing scholars to optimize marketing mix policies targeted for each consumer. In addition, we do not discard the big data we have, yet we use it efficiently by filtering and factor model to infer components that we use in our choice model.

**Model**

FWe observe choice data for a set of individuals. In contrast to the prior studies such as Carare (2011), which do not account for consumers’ decision within the app category, we start our model with a choice of app category. More specifically, we assume consumers go through two stages of decision making: First consumer selects an app category that she is interested in among the available app categories, where  denotes the outside good option, and then given the app category in the second stage consumer selects among available apps within the app category, where  denotes outside good option or any app other than the apps under the study. In this specification we assume that if a consumer selects an app category, she will definitely download one of the apps within that category. This modeling decision may be justified by referring to sunk opportunity cost of consumer for decision making, and the miniscule cost of download. More formally we can define the probability of purchase of an app in a given category as:



Consumer information processing theory and household production model assume that consumer considers perceived risk of a purchase decision, and she is more prone to select a product that she has more familiarity with. These studies including Ratchford (1982) and Kok and Xu (2011) suggest that consumer decision can be modeled using nested logit structure. Our different formulation of app choice probability by conditioning on category, allows us to have a more structural model, which in turn facilitates studying search behavior of consumers over different app categories on the app store. Our two stage modeling approach is close to the specification of Kok and Xu (2011) on consumer’s decision among product types in the first stage and among the brands for a given product type in the second stage. Figure below shows consumer’s decision to download an app. Another interpretation of our model is that first consumer faces a universal set, and in this universal set she uses an screening rule to filter only relevant choice sets. We assume the screening rule in our context is selecting the app category. Other screening rules could be to select one of the attributes, as Gilbrid and Allenby (2004) suggest.

Now that we discussed the logic, we can simplify our problem. Conditioning on the choice data, the probability of mobile app choice and the probability of mobile app category choice are independent. Therefore, we can break the problem of choice of an app to two portions: the probability of selecting an app category, and the probability of selecting an app. The first portion is app store platform’s problem, and the second is app developer’s problem. Given that in this study we focus on the app store platform owners’ problem, we focus our study on the first portion, which is selecting a mobile app category. Figure 4 presents box and arrow representation of our model.

We specify the utility of consumers’ choice of app categories on the app store in the following form:

 (1)

Table 1 presents the definition of the variables and the parameters. We accounted for state dependence in our model by incorporating the history of consumers’ downloads of apps in categories j from inception until time t in the individual state variables (). If a consumer downloads an app from the app category j in previous time slot, t-1, then  , otherwise if the consumer selects outside option, then  remains unchanged: i.e. . This specification induces a first-order Markov process on the choices. We explain how we derive factors  from mobile app category characteristics later in this section. Our characterization of the imitation and innovation forces of category j at time t filtered from aggregate diffusionresembles the approach used in choice models to incorporate featured and displayed products in grocery stores at aggregate levels. Our approach serves as an alternative to micro-modeling approach used by Yang and Allenby (2003) to incorporate interdependence of awareness and preferences of consumers, yet it may be more relevant to the context of pervasive goods, as these goods are more conspicuous.

Assuming that random utility term, is type I extreme value distribution, consumer’s i's probability of selecting app category j at time t is given by a multinomial logit model as follows:

 (2)

Here, we assume that the mean utility of outside good is zero, i.e. .

We use the whole dataset to filter innovation and imitation forces in our data. To do so, we use observed cumulative number of downloads, and we cast the Bass model into a state space form as follows:





The first equation denotes the observation equation and the second one the state equation of our state space model. Table 1 presents the definition of the variables and the parameters. Bass diffusion model (1969) suggests a specific hazard rate functional form for the diffusion of a product. In our model  and  are parameters of innovation and imitation forces respectively and  denotes the market size of each app category. In addition,  and denote cumulative observed and latent number of the app categories’ adopters. In the form of seemingly unrelated regressions (SUR), our simultaneous modeling approach of state equations allows us to identify complementarity or substitution of mobile app categories. An alternative approach could be to solve Riccati differential equation as proposed by Bruce et al. (2010). However, such an approach may not fit to our purpose, because in the context of diffusion, as the mean of the state variable is always increasing, we may expect considerable correlation between latent cumulative numbers of adopters. However, such a correlation may not suggest complementarity or substation, so we are interested in the non-word of mouth and non-innovative forces that drive the diffusion of the cumulative mobile apps jointly.

We account for heterogeneity in individual and category parameters, through a random effect model. In order to avoid misspecification of the distribution of consumer heterogeneity in preferences, and allow for multimodal densities of preferences across groups (or “segments”) of consumers, we adopt the method proposed by Dube et al. (2010) to use a flexible semi-parametric heterogeneity specification that consists of a mixture of multivariate normal distributions, to allow for thick tail, skewness, and multimodality. We denote vector of non-state consumer-level parameters by  and vector of non-state category level parameters by . We accommodate consumer and category heterogeneity by assuming that  and are drawn from two separate distribution common across consumers and common across categories. We employ mixture of normal as the first stage prior, to specify an informative prior, and to avoid the over-fitting problem. The first stage consists of a mixture of  multivariate normal distributions respectively, and the second stage consists of priors on the parameters of the mixture of normal:

 (5)

 (6)

represents the hyper-parameters of the priors on the mixing probabilities and the parameters governing each mixture component. To obtain a truly non-parametric estimate using the mixture of normal model it is required that the number of mixture components  increase with the sample size. We adopt the approach proposed by Dube et al. (2010) to fit models with successively large numbers of components and to gauge the adequacy of the number of components by examining the fitted density associated with each number of components. In summery we have molded the interrelated diffusion of mobile app categories using both hierarchical Bayesian and simultaneous equation approach.

To estimate innovation and imitation forces at each point in time, we filter latent cumulative number of app category adopters, and we split the rate of diffusion to innovation and imitation forces as follows:



As app category characteristics result in multicollinearity in our estimation, we use factor model to decompose the variation in app category characteristics into their principle components. Formally, we use the following model as our factor model:



Table 1 presents the definition of variable and parameters. Our use of factor model is also useful to account for inherent sparsity in our data. This closes our model specification.

**Data**

Our data were collected by an African telecom operator on individual choices of downloading mobile apps from the app store platform of its global partner. The app-stores are a type of two sided platform, as they match consumers’ and developers/publishers without taking the ownership of mobile apps. The app-store we studied is launched within around 330 days prior to our study in 2013 and 2014, so we use the aggregate download data for a period of 190 days, and the data on download choices of consumers over this newly launched app store for a period of around 140 days. To deal with sparsity in our data, we aggregate our choice and aggregate diffusion data at weekly level. In addition, we dealt with the inherited sparsity in the data using Bayesian shrinkage method for both mobile app categories’ and individuals’ parameters. We selected 10 different dominant app categories, which have enough data for our estimation, and within each app category we stratified a sample of individual consumers who have at least one downloaded app during the time frame of our study. We investigate geographic source of interdependence of consumer preferences (i.e. within the city) versus global sources of interdependence of consumer preferences (i.e. across the globe).

We create geographic neighborhood (i.e. city) by physical proximity, through mapping IP address of each consumer to the corresponding city. For this purpose we wrote a crawler and scraper in Perl to scrape the location of each corresponding IP in an IP-location mapping website. The data consists of around 20,000 consumers, with around 3,000 consumers in a local city under study, in Africa. This local city has around 4,000 app downloads for the duration of our study. Twenty thousand or three thousand consumers’ daily choice for a course of six month classifies our data as a big data. Structural modeling approaches may not perform well over our big data in a limited estimation time frame. As a result, we draw a random stratified sample of 147 consumers’ individual to study consumers’ choices. Table 4 illustrates the list of the categories that we select and their corresponding total downloads within the local city under this study.

Our data also included longitude and latitude of each IP address, yet as mobile phones are nomadic and ubiquitous, we find the choice of city a more reasonable one. Social nature of mobile phones and mobile apps that diffuse over these pervasive products is another reason which may reinforce that our assumption is innocuous. Particularly, mobile phones have become inseparable part of societies, to the point that not only customers use them when they are alone in the bus, when they are to sleep, or even when they are in the class, but also they use them in their parties, in their offices, in their leisure times, and generally in any social events. Mobile phones use in social events makes mobile apps visible, so it creates social learning opportunities. In the figure I, we plot the diffusion curves of cumulative adoptions of a sample of six mobile app categories.

For each mobile app category, we have average file size, total number of apps featured, average and variance of app prices, and number of paid and free options. Table 3 presents the basic statistics of these variables. To explain heterogeneity in individual responses, we use data on tenure of each customer. We define tenure as the number of days since each customer has subscribed to the app-store. As different types of consumers (i.e. innovator and adopters) with different psychological traits adopt technology at different points in time (Kirton 1976), we use tenure of consumers as a proxy for the psychological traits that can explain heterogeneity in consumers’ choice responses. To explain heterogeneity in app store categories, we use popularity of mobile app categories on the Apple app store. As the Apple app store was the innovator of app-store platforms and its consumers are more affluent ones[[5]](#footnote-5), we may expect that popularity of mobile app categories on the Apple app store explain diffusion of mobile app categories on other app stores as well. Therefore, we use mobile app categories’ popularity on the Apple app store to explain heterogeneity in the mobile app category parameters. These popularity statistics is presented in figure 2.

Finally, it may be relevant to note that mobile apps are more a durable good than a grocery store type of good. Therefore, the consumers’ choice of downloading a mobile app may be sparse in nature filled with outside option choices. Therefore, the time varying characteristics of mobile app categories and the strength of imitation and innovation forces may be an alternative explanation to the consumers’ learning theory. In this alternative explanation, we assume that the consumer is ignorant and passive, rather than learner and active, yet she become interested in downloading a mobile app either when imitation or innovation forces strengthen, or when the mobile app categories’ characteristics becomes more favorable.

**Identification and Estimation**

In order to identify our choice model we use a logit specification, which has a fix scale. To set the location of the utility, we normalize the utility of outside option to zero, as explained before. We identify individual level parameters using a large panel of individuals in our sample. As the likelihood for non-selected choices are unbounded, we adopt the method used by Rossi et al. (2005) to use weighted approach with pooled parameters likelihood to build our proposal density. In addition, Bayesian shrinkage allows us to borrow data across individuals’ choices to overcome this shortcoming. We identify the latent cumulative number of adopters of mobile app categories with observed cumulative number of adopters in the complete dataset. We also use Bayesian shrinkage to overcome inherent sparsity in the data and to identify mobile app categories across our study. In addition, variation in the diffusion level across 27 weeks and simultaneous modeling of app category diffusions allow us to identify joint diffusion of parameters.

In order to estimate our model we use a hybrid sampler, and we break our joint sampler into a series of conditional distributions to make our estimation computationally tractable. Appendix A presents the Direct Acyclic Graph (DAG) of conditional distributions. Our hybrid sampler nests Extended Kalmn Filter (EKF) forward filtering backward sampling recursion into a Gibbs sampler (GS) that incorporates block Metrapolis Hasting (MH) sampler around the mode. Our algorithm is adaptive to find the appropriate tuning parameter for block M-H automatically. We use stochastic time varying estimation method with stationary random walk noises that are orthogonal, per assumption. Putsis and Srinivasan (1999) and Xie et al. (1997) posit that this type of estimation method unlike log likelihood and nonlinear least square methods bring robustness by filtering process and measurement noises. Our estimation consists of three blocks, as presented in Appendix B.

The first block filters the innovation and imitation forces of diffusion, and it consists of three stages. In the first stage, we use EKF recursive algorithm to draw unobserved state of diffusion of mobile app categories. This procedure linearizes the Bass diffusion model (BDM), and it runs through two steps: time updating and measurement updating. In time updating step, the procedure forms the prior on mean and variance of state parameters given fixed parameters. In the measurement updating step, we form posterior on mean and variance of unobserved parameters, by using Kalman gain, which is simply the fraction of variance of observation equation to state equation. Given the latent parameter mean and variance, we draw new latent cumulative diffusion level. In the second stage, given the observation and the state equations, we draw non-state parameters by using standard unconstrained Gibbs sampler algorithm. In the third stage, we use standard unconstrained Gibbs sampler to draw first and second stage hyper parameters of a mixture of normal distribution of category specific fixed parameters. The “label-switching” problem for identification in mixture of normal is not relevant in our application, as we are interested only in the joint posterior distribution of quantity which is label-invariant. Given the results of this block we find the estimated level of innovation and imitation forces of diffusion of each of the mobile app categories.

The second block of estimation consists of a normal factor model that gives us principle component of the categories characteristics. Given the factor loading parameters of each principle component, the result of this block gives us the estimated level of each of the principle components for each of the categories at each point in time. The results of the two blocks together create the input data for the third block which estimates the choice model. The third blocks’ MCMC sampler consists of two stages. The first stage uses Metropolis Hasting algorithm over the pooled MNL proposal density tuned for each consumer by MNL likelihood. We adopted the method proposed by Rossi et al. (2005), chapter 5, to optimize the proposal density to this end. This procedure avoids the problem of undefined likelihood for tuning purposes as suggested by Rossi et al. (2005). In the second stage, we use standard unconstrained Gibbs sampler to draw first and second stage hyper parameters of a mixture of normal distribution of category specific fixed parameters. Again, the “label-switching” problem for identification in mixture of normal is not relevant in our application, as we are interested only in the joint posterior distribution of quantity which is label-invariant. Given the results of this block we find the estimated level of innovation and imitation forces of diffusion of each of the mobile app categories.

**Results**

Table 7 presents the log likelihood, AIC and BIC of the proposed models. The local diffusion model explains the choice of customers better than the global diffusion model. This may suggest that innovation and imitation forces at local level can predict consumers’ choices better than the imitation and innovation forces at global level. In other word, unlike previous studies (e.g. Putsis et al. (1998)), we find that global coordination across countries is not so much relevant on the mobile app stores, stores for mobile apps that are diffused on the pervasive smartphones. Figure 5 and 6 present the one-step ahead forecast versus the observed cumulative number of adopters at both the local and the global level. Table 8 presents the Mean Absolute Deviation (MAD) and the Mean Square Error (MSE) of these one-step ahead forecasts. We benchmarked these two performance criteria against MSE and MAD criteria proposed in Xie et al. (2007), and they follow the same scale. Again, it may worth noting that the advantage of our estimation method is that it allows filtering the process and the measurement noises.

To avoid multicollinearity in mobile app characteristics we use a factor model. Figure 3 and table 5 present the result of the principle component analysis procedure. We limit our analysis to the first 3 factors/principle components that explain most of the variation. The parameter estimates of these three components guided us to name them the assortment breadth, the innovative apps, and the paid categories respectively. To ease our interpretation, we negate the first factor before including it into our choice model.

Table 9 explains local diffusion parameter estimates. At local level we find positive significant imitation forces for all the mobile app categories except Logic/Puzzle/Trivia, Humor/Jokes, and Games. Looking at the innovation forces, we find insignificant innovation forces across app categories, except for Health/Diet/Fitness, Internet/WAP, Logic/Puzzle/Trivia and Reference/Dictionaries app categories. The results may suggest that at local level imitation forces is the main driver of mobile app diffusion. The insignificant imitation forces for three leisure categories may be explained by hedonic nature of these leisure categories, a hedonic nature that drives impulse downloads rather than planned contemplated downloads based on imitation or innovation forces (Tifferet and Herstein 2012). On the other hand negative significant innovation factor may explain resistance to innovation (Cho and Chang 2008). More particularly, one may have technophobia, or she may not be interested in using references and dictionaries. Therefore, although there could be positive chatter about the products within the population, this customer may resist adopting the relevant mobile apps.

Table 10 explains global diffusion parameter estimates. At global level, we find positive significant imitation forces for almost all the mobile app categories. Looking at the innovation forces, we find significant innovation forces only for categories such as games, health/diet/fitness, reference/dictionaries and university. The significant innovation forces within these mobile app categories may suggest that consumers are self-motivated to adopt these types of mobile apps, or that they actively search for them. Again this result also suggests that at global level word of mouth is a dominant force to drive mobile app category adoption. The imitation factor for mobile apps at global level is at the range of imitation factor for VCR, CD-player, Video games, digital watch and radio, while innovation factor for mobile apps at global level is at the range of CD-Player, PC, Cellular phone and VCR (Kohli and Lehmann 1999).

Table 11 and 12 present covariance parameter estimates for state equations of local and global diffusion models. At the local level, we do not observe any significant pattern of substitutions or complementarities between mobile app categories, yet at the global level we observe interesting patterns of complementarities. The reason that we could not find any of such patterns at the local level may be attributed to the inherited sparsity in our data. At global level we find the Internet/WAP mobile app category more complement to the Device Tools app category, than the Games, Health/Diet/Fitness, Reference/Dictionaries and Social Networks mobile app categories, in order. This pattern of complementarity may suggest that those who care about their smartphone devices may also care about their internet first, their leisure next, their health and finally to the references and the socialization. Needless to say, as we identify these patterns at the global level, this may suggest the complementarity at clique or supopulation level rather than the individual levels. Our data does not show any significant pattern of complementarity for eBooks, but we find significant greater complementarity for the Games, with the Health/Diet and the reference and dictionary app categories, than for the Games, with the Humor/Jokes and the Logic/Puzzle/Trivia mobile app categories. This pattern may suggest that the individuals or the subpopulations of consumers who play Games are also concerned about their health and their knowledge. There are anecdotal evidences about the impact of Games on health as well[[6]](#footnote-6). We find the Health/Diet/Fitness app categories to be complement highly to the reference and dictionaries and the university and internet/WAP app categories, but less and significant complement to the Social Networks and the Logic/Puzzle/Trivia app categories. This finding may suggest that those who are more knowledgeable and updated are probably more conscious about their health. To support this finding, we nudge to studies that find health conscious consumers are more educated (Robinson and Smith 2003). We find Humor/Jokes app categories to be complement to Social Networks app categories. This finding can be traced back to the studies that find group members who occupy the key humor roles are over-chosen on in the social interactions (Duncan 1984). We find the Logic/Puzzle/Trivia mobile app category complement to the University and Reference/Dictionary mobile app categories. This finding also may suggest the existence of a segment of consumers that seek the intellectual challenge. All in all, an app store platform owner may be interested to know these complementarity patterns to reform its website so that complement products be put together to increase the chance of upselling.

We explain the heterogeneity in local and global diffusion parameters with data on the popularity of mobile apps on Apple app store. Table 13 and 14 present the result of this estimation of hierarchy. The only significant parameter is local market size. Local market sizes of mobile app categories have negative relation with the mobile app category popularities on the App store. This result may suggest that the preferences of the users of the mobile app categories on Apple app store are different from the preferences of the users of the mobile app-store platform under our study. This may suggest the different attitude of target customers of these two mobile app-store platforms toward mobile apps. Figure 7 and 8 present heterogeneity in diffusion parameters at the local and the global level. At the local level we observe the bimodal distribution of market size parameters. Allowing a flexible procedure to capture this bimodality is important, as otherwise the parameters’ estimates are biased. In addition, for app-store platform owner, it may be interesting to know this bimodality, as it suggests different mechanism design for different mobile app categories. On the global level we observe a thick tail of Market size distribution. Again allowing for the flexible distribution to estimate the correct thick tail distribution is important, because otherwise the fixed parameters are biased.

Figure 9 and 10 present the extent of imitation and innovation forces at both local and global markets. We scaled the innovation force levels for ease of exposition. At local level we observe different level of forces at each point in time. The curve for mobile games has a different form compared with the social network and eBooks mobile app categories. In Mobile games we observe that innovation forces increase, yet imitation forces decrease during time. This form of effect can be attributed to consumers’ awareness of the app-store. In other word, although chatter about the game category increases suddenly, yet it acts more as a fad[[7]](#footnote-7). However, as time passes, those who are really interested in game app category discover their favorite apps. At global level we find decrease in the imitation forces during time for the social network and games app categories. This decrease can be attributed to the saturation of the market size of these mobile app categories.

Table 15 and table 16 summarize the individual choice parameter estimates for both local and global imitation and innovation forces. Almost all mobile app categories have negative preferences compared with no download option. This may be explained by the choice of the consumers, as if mobile apps were more important than normal life activities, or if they have created huge value for consumers, consumers would have gone to the app store every day to download new mobile apps. However, on average level we observe a higher preference for the social networks, the humor/jokes, the eBooks and the Device tools mobile app categories. These preferences may be explained by the use of mobile phones for the socializing and the fun activities[[8]](#footnote-8). The negative significant state dependence is expected as on average the life time of a smartphone is around two years[[9]](#footnote-9), and during this life span one may not need to download mobile apps multiple times. Although none of the innovation and imitation forces are significant on average, we observe a right skewed distribution of innovation forces. This may suggest that on individual level a targeting strategy should focus more on trial based strategies than viral marketing strategies, on average, yet individual level parameters allow the app-store platform owner to target different consumers differently. Although none of the assortment breadth, innovative apps and paid categories parameters are significant we observe a right skewed innovative app and left skewed innovative app square effects on the average level. This form of response function looks like a concave parabola, which suggests that on average there should be an optimum number of innovative apps in each mobile app category. Again we should note that these estimates are at average level across individuals within our sample, yet our model gives us the individual level parameters which allow the firm to optimize its marketing mix policies for each consumer.

We explain the heterogeneity in both the locally and the globally driven choice models with the tenure of consumers in table 17 and 18. The findings indicate that consumers with higher tenure have significantly higher preferences for the Health/Diet/Fitness and the Social Networks mobile app categories. These consumers are significantly more sensitive to the assortment breadth square. However, they are significantly less sensitive to the innovation forces. These findings may be rooted to the study by Roger (1983) that notes that innovators have higher income, and that they can afford greater economic sacrifice to adopt the innovation. These psychological risk seeking traits and demographic characteristics of innovators together with the positive link of the social capital and the affluence suggest that consumers with high tenure, or the early adopters of the mobile app-stores are more likely to prefer the social networks and the Health/Diet/Fitness mobile app categories. These consumers prefer the higher assortment, but rather than being influenced by the innovation forces, they are probably more conscious about the adoption of peripheral features. This behavior may be attributed to the learning costs. Another possible explanation for this finding could be analogous with the buying of full feature expensive car, or so called buying unnecessary add-ons[[10]](#footnote-10).

Finally Figure 11 and 12 present the heterogeneity in the individual choice parameters for both the locally and the globally driven choice models. We can observe the bimodal distributions of preferences for the device tools, the games, the health/diet/fitness, the humor/jokes and the internet/WAP mobile app categories. This information may be useful for the app store platform mechanism designer to design different incentive compatible mechanisms for the high and low valuation consumers. The thick tales of consumer heterogeneity distributions also suggest that to avoid biased parameters’ estimates, the analysts should allow for flexible mixture of normal distributions of parameters.

**Managerial implications**

First, many industry publications suggest the tradeoff between localization and globalization[[11]](#footnote-11). Finding better fit for local level imitation and innovation forces suggests mobile app store platform’s owners to adopt the localized marketing policies rather than the global ones. In other words, our finding suggests managers either to use local cultural factors on their app store platform, or use local physical elements in their marketing mix to promote the mobile app category usage. Second, although currently many app stores customize the experience of individual consumers by suggesting preferred mobile apps extracted by collaborative filtering, our findings suggest even more targeted strategies. In particular, our model gives the app store platforms a ground to target customized promotion messages to its consumers based on their sensitivity to the imitation and the innovation forces. In particular, our model allows the app store owner to know what fraction of its promotion budget for each individual should be spend on viral marketing strategies to push imitation force, and what fraction should be spend on the trial based strategies. Third our findings suggest that at the population level the app stores should focus more on viral marketing forces to encourage word of mouth rather than to use the trial based strategies. Fourth, the interesting patterns of complementarities between the different mobile app categories give the app-store platform owners the ground to optimize the design of their app-stores. Particularly, knowing that two products are complements, an app store platform owner can only promote one app category to increase the diffusion of the other app categories, or it can even present bundles of complement or non-complement products based on its objective function. In addition, putting the complement mobile app categories closer on the app store front may increase the upselling of the mobile app store platform, by decreasing the search cost of consumers. The observed heterogeneity in the mobile app categories market sizes and the individuals’ preferences for mobile app categories may also guide the app store platform owners to design incentive compatible mechanisms to maximize their profits contingent upon circumstances. Finally, our findings do not suggest any optimal breadth of assortment within the app stores. Therefore, they do not suggest limiting the assortment breadth to increase individual choice probabilities, by reducing the consumers’ search costs.

**Conclusion**

We model the consumer’s decision to download from the mobile app store, focusing on the complementarity and the substitution of the mobile app categories and the social dependency of consumers’ preferences. Our modeling approach combines the advantages of big data with the advantages of the structural modeling approach. Particularly, we use our whole dataset to filter the imitation and the innovation forces of diffusion within the population. Then we stratified a random sample of the dataset to analyze the effects of filtered innovation and imitation forces on the consumers’ individuals’ decisions. We adopted a flexible modeling approach to allow the individual choice parameters and the category diffusion parameters to have various shapes. To do so, we adopted the normal mixture distribution for the first and second level priors. We estimated our model using Extended Kalman Filter (EKF) nested into a hybrid MCMC sampler to estimate the simultaneous diffusion differential equations. We used a unique panel data to estimate our model.

We find that for the mobile apps that diffuse over the pervasive products (i.e. mobile phones) local diffusion forces explain consumers’ choices better than global diffusion forces. This finding suggested that perhaps the mobile app store platform owners can perform better if they focus their promotional policies more on localization than on sending universal message across the globe. Second, we find an interesting pattern of global complementarity of mobile app categories. This finding suggests the mobile app platform owners to redesign their online app-store, or to design their mobile app bundles to increase the chance of the mobile apps upselling. We further find that to drive the mobile apps diffusion, an optimal policy may involve more the viral marketing strategies to increase the imitation forces rather than trial based strategies that increase the innovation forces. The benefits of our individual choice modeling approach that accounts for individual heterogeneity in response are twofold. First, it allows the app store platform to design targeted marketing mix bundles, based on the individual parameters of innovation and imitation forces. Second, it guides the app store platform to design the incentive compatible mechanisms to maximize its objective function. Last but not least, we do not find any significant impact of breadth of the mobile app categories assortments. This may suggest the app stores that they can remain open to developers and publishers, without worrying about the search cost of consumers.

One extension of this research could involve adding the supply side to this model. In particular, we may be able to model the strategic interaction between mobile app publishers and developers and the heterogeneity in their entrances. Another extension of this research may involve modeling the simultaneous diffusion of the mobile app categories across all 28 cities in our data. This approach may allow us to find the global mixing adoption behavior. The third extension of this work can be to model consumers’ learning in the category. We may posit that consumers have misperception about the merit of mobile apps in each mobile app category, and they solve this misperception with the information items that enter with Poisson rate. Another extension could be to consider that consumers are forward looking, and they form a step-ahead expectation about the diffusion of the mobile app categories. Also, we can probably use the handset type of individuals to approximate the opportunity cost of their search, and then model the forward looking behavior of consumers to download the mobile apps. We can also analyze “what if” scenarios to find the optimal trial and viral marketing policies and the mobile app bundle designs. In addition, we can simulate how applying the different level of local and global forces can result in an increase in the individual’s choice probabilities.

**Appendix A: Direct Acyclic Graph of Conditional Distributions**





























Mobile app category











**Appendix B: Conditional Distributions for Estimation**

We present list of conditional distributions for our estimation in the following:

First block of estimation:





 (B1)

Here have conjugate prior of Inverse-Wishart (IW) and Multivariate Normal (MVN) distribution, and V has Inverse Gamma (IG) distribution.

Third block of estimation:



 (B2)

The priors for normal mixture distribution of the individual and the category specific parameters used are:



We assessed the prior hyperparameters to provide proper but diffuse distributions:



The Dirichlet prior on  is conjugate to the multinomial distribution, and can be interpreted as the size of a prior sample of data for which the classification”observations” is known. The number of observation of each “type” or mixture component is given by the appropriate element of . This prior assumes that each type is equally likely and that there is only a very small amount of information in the prior equal to a sample size of .5. As the number of normal components increases, we do not change how informative the prior is, through scale of elements of the a vector by .

For drawing from multinomial distribution we have the following conditional probabilities:

 (15)

Where  is discrete random latent variables with outcome probabilities . This conditioning allows us to draw from mixture of normal distribution. Similarly we have conditions to draw from mixture of normal distribution for mobile app categories.

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**Table 1**

**Add-on Basic Statistics**

|  |  |
| --- | --- |
| Variable | Description |
| App Category Weekly Download() | Cumulative number of consumers who download an app in app category j up until a given week t |
| App Category Weekly Download Latent () | Latent cumulative number of consumers who download an app in app category j up until a given week t |
| Internal Market Force () | BDM parameter of ratio of innovators who adopt an app in app category j at a given week |
| External Market Force () | BDM parameter of ratio of imitators who adopt an app in app category j at a given week |
| Market size () | BDM parameter of market size of a given app category |
| Category hierarchy parameters () | Parameter of hierarchical mixture of normal components of app category diffusion parameters |
| Full covariance matrix of state equation() | Full covariance matrix of state equation of BDM model to find complementarity or substitution of app categories |
| Variance of observation equation () | Variance of observation equation of BDM model |
| Category data () | Category j characteristic data at week t, including Average file size, total number of adds featured in the category, average price, variance of price, paid app options, free app options, fraction of free to paid apps within the category, average tenure of each app category, total app options within the category |
| Category Factors() | Reduced factors explaining the variation in category data |
| Factor loading of Category | Factor loading of data item j of category data vector |
| Innovation Force () | Filtered estimated amount of innovation force for app category j at week t |
| Imitation Force () | Filtered estimated amount of imitation force for app category j at week t |
| Consumer utility from app category () | Consumer i’s utility from selecting an app in app category j at week t |
| App category preference () | App category j’s preference of consumer i |
| Individual category state () | State of individual i’s purchase in a given category j at week t |
|  | Utility parameters of consumer i |
|  | Probability of selecting an app in category j at time t |
|  | Parameter of hierarchical mixture of normal components of individual choice parameters |
|  | Error terms of observation/state equation and factor model |

**Table 2**

**Literature Position of this Study**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Stream of Study | Interdependence of consumer preference | Product complementarity and app store | App Store | Global Simultaneous Diffusion | Assortment breadth |
| Current study | \* | \* | \* | \* | \* |
| Yang and Allenby (2003), Stephen and Toubia (2010), Lehmmes and Croux (2006), Bell and Song (2007), Aral and Walker (2011), Nair et al. (2010), Bradlow et al. (2005), Hartmann (2010), Yang et al. (2005), Narayan et al. (2011) , Kurt et al. (2011), Chung and Rao (2012), Choi et al. (2010) | \* | - | - | - | - |
| Striram et al. (2007), Yang and Ching (2013), Ma et al. (2012), Karaca-Mandic (2011), Lee et al. (2013), Niraj et al. (2008), Wedel and Zhang (2004), Song and Chintagunta (2006) , Oestreichter-Singer and Sundrararajan (2008), Bezawada et al. (2009) | - | \* | - | - | - |
| Ghose and Han (2014) , Carare (2012), Garg and Telang (2013) , Liu et al. (2012) , Ghose et al. (2011) , Ghose and Han (2011b) , Ghose and Han (2011a) , Kim et al. (2008) , | - | - | \* | - | - |
| Putsis et al. (1997), Dekimpe et al. (2000), Neelamegham and Chintagunta (1999), Talukdar et al. (2002), van den Bulte and Joshi (2007), Gatignon et al. (1989), Takada and Jain (1991) | - | - | - | \* | - |
| Kuksov (2010), Villas-Boas (2009), Diehl and Pynor (2010), Chernev and Hamilton (2009), Scheibehenne and Greifeneder (2010), Gourville and Soman (2005), Guo et al. (2012), Kuksov (2004), Kamenica (2008), Boatwright and Nunes (2001), Sela et al. (2009), Sloot et al. (2006), Oppewal and Koelemeijer (2005), Iyengar and Kamenica (2006) | - | - | - | - | \* |

**Table 3**

**Categories Basic Statistics**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Category Data Summary | Mean | Variance | Min | Max |
| Number of available apps in the Category | 35 | 1250 | 12 | 141 |
| Average Tenure of App’s in the category (Days) | 316 | 6,386 | 169 | 498 |
| Number of available free apps in the category | 32 | 908 | 7 | 120 |
| Average day’s that an app is featured in the category | 0.12 | 0.05 | 0.00 | 0.71 |
| Average file size of app’s in the category (MB) | 2.00 | 4.00 | 0.50 | 8.00 |
| Variance of prices of app’s in the category | 0.51 | 1.09 | 0.00 | 3.75 |

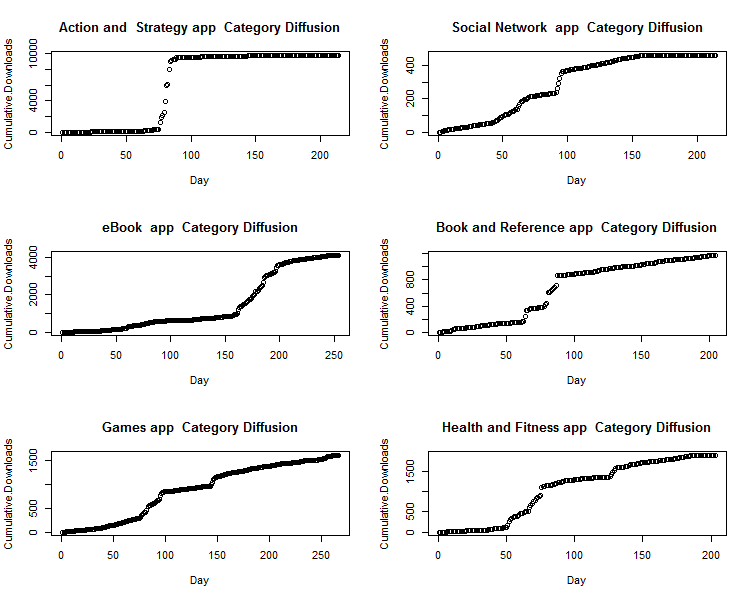
**Table 4**

**Categories Basic Statistics**

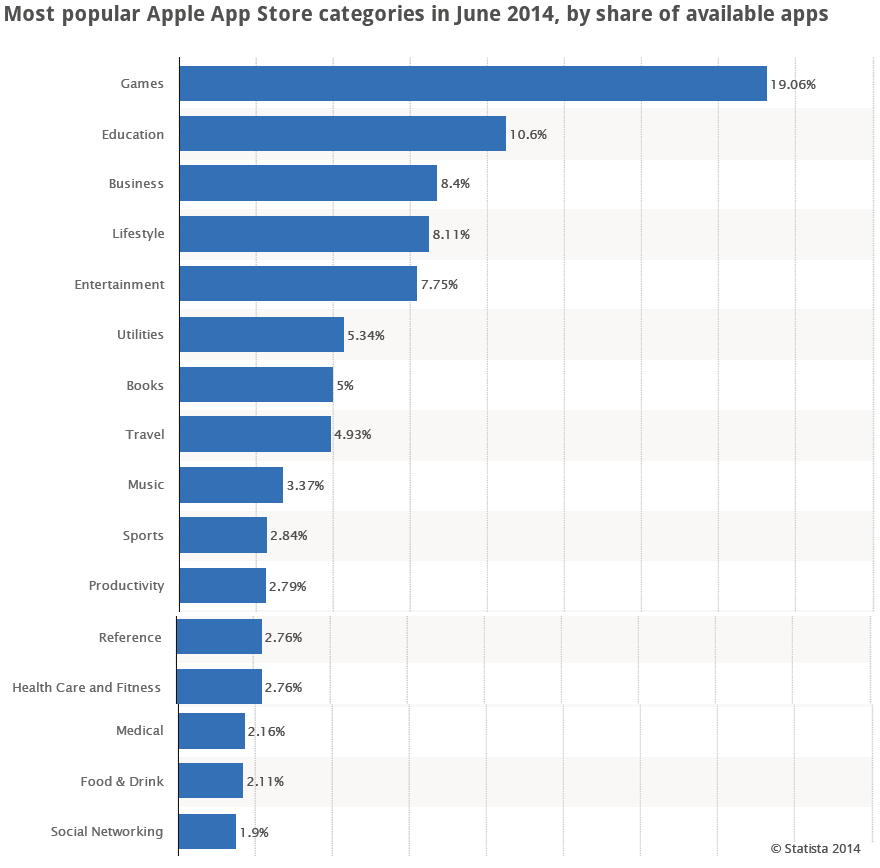
|  |  |  |
| --- | --- | --- |
| index | Category | Total Downloads |
| 1 | Dating | 27 |
| 2 | eBook | 414 |
| 3 | Education & Learning | 24 |
| 4 | Health/Diet/Fitness | 42 |
| 5 | Internet & WAP | 52 |
| 6 | Movie/Trailer | 597 |
| 7 | POI/Guides | 22 |
| 8 | Reference/Dictionaries | 55 |
| 9 | TV/Shows | 135 |
| 10 | Video & TV | 105 |

**Figure 1**

**International Diffusion Curves of Categories**

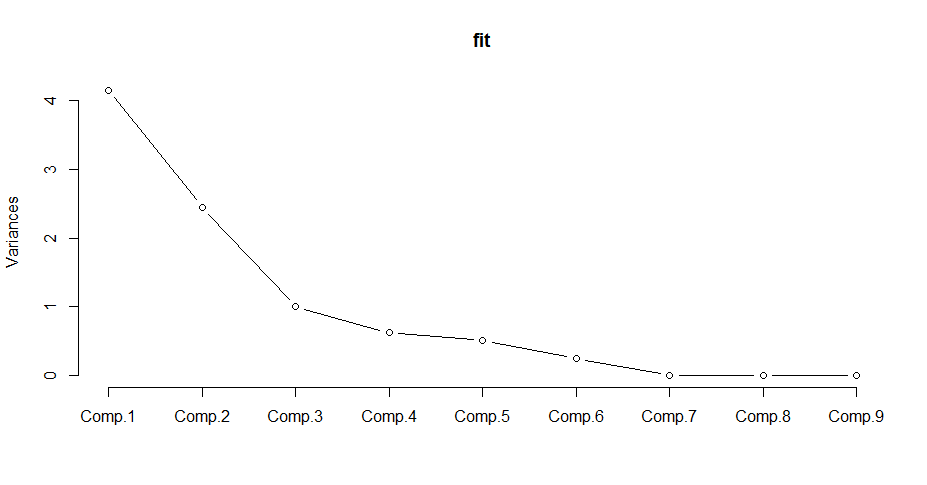


**Figure 2**

**Popularity of App Categories on Apple App Store**

**Figure 3**

**Factor Model Fit Curve**

****

**Table 5**

**Factor Loading Matrix**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Loadings/Components** | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** | **C8** | **C9** |
| Average File Size | -0.38 |  |  | -0.13 | 0.81 | -0.43 |  |  |  |
| Featured Apps in Category | -0.37 | -0.26 | -0.18 | 0.23 | 0.28 | 0.80 |  |  |  |
| Average of Price |  | -0.61 |  | 0.22 |  | -0.21 | 0.21 | -0.69 |  |
| Variance of Price |  | -0.60 |  | 0.33 |  | -0.21 | -0.14 | 0.67 |  |
| Paid app options | -0.48 |  |  |  | -0.27 | -0.19 | -0.79 | -0.20 |  |
| Free app options | -0.48 |  |  |  | -0.31 |  | 0.45 | 0.12 | -0.67 |
| Fraction of Free to Paid Apps |  | 0.30 | -0.77 | 0.51 |  | -0.21 |  |  |  |
| Average Tenure | 0.11 | -0.33 | -0.61 | -0.71 |  |  |  |  |  |
| Total Options | -0.48 |  |  |  | -0.31 |  | 0.33 |  | 0.74 |

**Table 6**

**Factor Names**

|  |  |
| --- | --- |
| **Factor** | **Name** |
| C1 | Assortment Breadth |
| C2 | Innovative Apps |
| C3 | Paid Category |

**Figure 4**

**Box and Arrow Representation of the Model**

App Store Platform

(Assortment Size, Popularity,

Price Variance, Heterogeneity)

App Category 1

Paid

Free

App Category J

Paid

Free



Pervasive Product

Mobile apps

….

App1

Featured

Price

File Size

AppA

Featured

Price

File Size



Simultaneous Diffusion

Consumers

(Segments, Tenure, Heterogeneity)

….

Location 1

Direct NE

Innovation

Market Sz

Location L

Direct NE

Innovation

Market Sz



Complementarity

**Table 7**

**MODEL COMPARISON**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Description** | **LL** | **AIC** | **BIC** |
| 1 | Local Diffusion | -5721.04 | 5781.04 | 11515.495 |
| 2 | Global Diffusion | -5.683e13 | 5.68E+13 | 1.14E+14 |
| 3 | Choice Explained by Local Diffusion | -355.41 | 5647.41 | 9.77E+03 |
| 4 | Choice Explained by Global Diffusion | -512.44 | 5804.44 | 1.01E+04 |

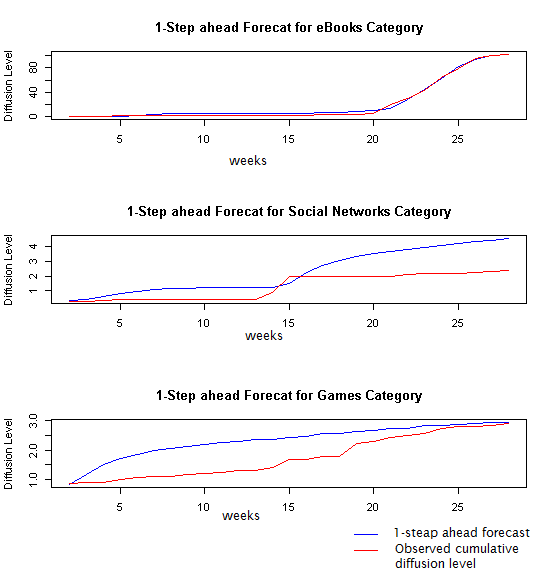
**Table 8**

**Performance of the Proposed Model for Four Sample Add-ons and Platform**

|  |  |  |
| --- | --- | --- |
| **Description** | **MAD** | **MSE** |
| Local Category Diffusion | 9.24 | 18.69 |
| International Category Diffusion | 38.52 | 280.01 |

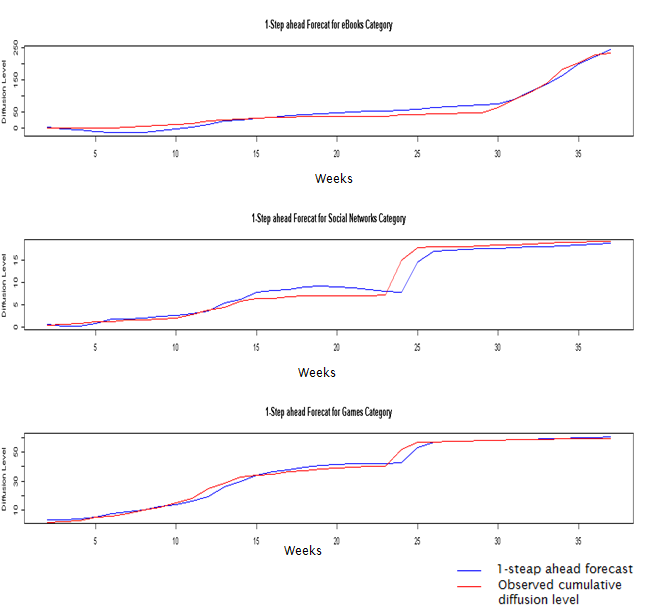
**Figure 5**

**1-Step-ahead Forecast for Local Diffusion of Categories**

****

**Figure 6**

**1-Step-ahead Forecast for Global Diffusion of Categories**

****

**Table 9**

**PARAMETER ESTIMATES: Local Diffusion**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Market Size: |  |  |  |  |
| Device Tools | 99.19 | 2.14 | 95.77 | 102.82 |
| eBooks | 102.31 | 0.24 | 101.93 | 102.71 |
| Games | 3.96 | 2.83 | 2.72 | 9.27 |
| Health/Diet/Fitness | 117.03 | 2.57 | 112.86 | 121.30 |
| Humor/Jokes | 82.53 | 1.91 | 79.51 | 85.87 |
| Internet/WAP | 99.17 | 2.14 | 95.73 | 102.77 |
| Logic/Puzzle/Trivia | 4.96 | 2.61 | 2.72 | 6.85 |
| Reference/Dictionaries | 117.00 | 2.57 | 112.87 | 121.14 |
| Social Networks | 34.57 | 15.73 | 2.74 | 53.53 |
| University | 62.87 | 1.97 | 59.97 | 66.24 |
| External Market Force: |  |  |  |  |
| Device Tools | -0.0008 | 0.0008 | -0.0020 | 0.0006 |
| eBooks | 0.0006 | 0.0004 | -0.0001 | 0.0011 |
| Games | -0.0085 | 0.2878 | -0.3484 | 0.2575 |
| Health/Diet/Fitness | -0.0022 | 0.0006 | -0.0031 | -0.0011 |
| Humor/Jokes | -0.0032 | 0.0045 | -0.0105 | 0.0025 |
| Internet/WAP | -0.0020 | 0.0005 | -0.0027 | -00011 |
| Logic/Puzzle/Trivia | -0.3961 | 0.4517 | -1.1706 | -0.0059 |
| Reference/Dictionaries | -0.0016 | 0.0004 | -0.0021 | -0.0010 |
| Social Networks | 0.0042 | 0.0126 | -0.0028 | 0.0266 |
| University | -0.0028 | 0.0021 | -0.0059 | 0.0010 |
| Internal Market Force: |  |  |  |  |
| Device Tools | 0.102 | 0.0008 | 0.0099 | 0.1911 |
| eBooks | 0.745 | 0.0004 | 0.7356 | 0.7554 |
| Games | 0.847 | 0.2878 | -0.0512 | 2.0762 |
| Health/Diet/Fitness | 0.109 | 0.0006 | 0.0693 | 0.1405 |
| Humor/Jokes | 0.099 | 0.0045 | -0.0459 | 0.3653 |
| Internet/WAP | 0.109 | 0.0005 | 0.0861 | 0.1265 |
| Logic/Puzzle/Trivia | 0.924 | 0.4517 | -0.0055 | 3.0764 |
| Reference/Dictionaries | 0.113 | 0.0004 | 0.0955 | 0.1276 |
| Social Networks | 0.363 | 0.0126 | 0.0289 | 0.5928 |
| University | 0.068 | 0.0021 | 0.0035 | 0.1170 |
| Variance of Observation Equations: |  |  |  |  |
| Device Tools | 2.045 | 0.8826 | 0.8420 | 3.6270 |
| eBooks | 2.7511 | 0.0753 | 0.1635 | 04113 |
| Games | 3.0195 | 5.8025 | 0.4727 | 10.7122 |
| Health/Diet/Fitness | 2.2033 | 0.8128 | 1.0804 | 3.6999 |
| Humor/Jokes | 3.1551 | 1.8861 | 0.06489 | 6.5830 |
| Internet/WAP | 1.4211 | 0.4553 | 0.7809 | 2.2444 |
| Logic/Puzzle/Trivia | 2.9640 | 3.1260 | 0.5883 | 7.1989 |
| Reference/Dictionaries | 1.2121 | 0.3670 | 0.7022 | 1.8857 |
| Social Networks | 1.7677 | 1.8793 | 0.3136 | 5.5010 |
| University | 2.0125 | 0.6813 | 1.0282 | 3.2575 |

**Table 10**

**PARAMETER ESTIMATES: Global Diffusion**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Market Size: |  |  |  |  |
| Device Tools | 29.96 | 17.68 | 25.32 | 32.98 |
| eBooks | 330.91 | 42.35 | 297.24 | 416.54 |
| Games | 61.75 | 8.67 | 58.09 | 67.38 |
| Health/Diet/Fitness | 84.16 | 4.25 | 80.90 | 91.54 |
| Humor/Jokes | 75.06 | 48.79 | 68.45 | 80.24 |
| Internet/WAP | 81.47 | 4.22 | 75.66 | 87.03 |
| Logic/Puzzle/Trivia | 72.68 | 3.33 | 69.04 | 76.69 |
| Reference/Dictionaries | 76.85 | 24.48 | 69.15 | 87.45 |
| Social Networks | 19.81 | 14.97 | 16.83 | 22.45 |
| University | 103.23 | 3.35 | 97.13 | 107.05 |
| External Market Force: |  |  |  |  |
| Device Tools | 0.004 | 0.024 | -0.016 | 0.022 |
| eBooks | -0.008 | 0.006 | -0.013 | 0.002 |
| Games | 0.013 | 0.016 | 0.000 | 0.021 |
| Health/Diet/Fitness | 0.016 | 0.005 | 0.006 | 0.019 |
| Humor/Jokes | 0.030 | 0.039 | -0.003 | 0.046 |
| Internet/WAP | 0.006 | 0.006 | -0.002 | 0.015 |
| Logic/Puzzle/Trivia | 0.018 | 0.011 | -0.004 | 0.031 |
| Reference/Dictionaries | 0.014 | 0.007 | 0.001 | 0.021 |
| Social Networks | 0.010 | 0.011 | -0.008 | 0.024 |
| University | 0.020 | 0.008 | 0.012 | 0.036 |
| Internal Market Force: |  |  |  |  |
| Device Tools | 0.16 | 0.044 | 0.103 | 0.236 |
| eBooks | 0.30 | 0.048 | 0.200 | 0.358 |
| Games | 0.17 | 0.032 | 0.117 | 0.224 |
| Health/Diet/Fitness | 0.22 | 0.030 | 0.164 | 0.269 |
| Humor/Jokes | 0.18 | 0.065 | 0.109 | 0.301 |
| Internet/WAP | 0.21 | 0.026 | 0.165 | 0.246 |
| Logic/Puzzle/Trivia | 0.42 | 0.087 | 0.284 | 0.574 |
| Reference/Dictionaries | 0.17 | 0.040 | 0.115 | 0.243 |
| Social Networks | 0.20 | 0.058 | 0.115 | 0.299 |
| University | 0.48 | 0.060 | 0.385 | 0.583 |
| Variance of Observation Equations: |  |  |  |  |
| Device Tools | 3.08 | 17.30 | 0.152 | 7.21 |
| eBooks | 173.69 | 184.09 | 0.002 | 456.55 |
| Games | 11.47 | 29.45 | 0.063 | 54.28 |
| Health/Diet/Fitness | 34.40 | 73.08 | 0.022 | 206.66 |
| Humor/Jokes | 69.09 | 112.93 | 0.011 | 324.53 |
| Internet/WAP | 32.02 | 71.53 | 0.027 | 199.87 |
| Logic/Puzzle/Trivia | 67.18 | 108.71 | 0.017 | 312.67 |
| Reference/Dictionaries | 48.32 | 92.62 | 0.014 | 271.74 |
| Social Networks | 1.99 | 6.90 | 0.225 | 5.25 |
| University | 81.24 | 117.91 | 0.013 | 328.56 |

**Table 11**

**COVARIANCE PARAMETER ESTIMATES: Local Diffusion**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Device Tools |  |  |  |  |
| Device Tools | 7.33E-03 | 0.0233 | 0.0028 | 0.0161 |
| eBooks | 2.61E-04 | 0.0016 | -0.0019 | 0.0027 |
| Games | 3.65E-04 | 0.0063 | -0.0032 | 0.0045 |
| Health/Diet/Fitness | 6.89E-05 | 0.0013 | -0.0018 | 0.0020 |
| Humor/Jokes | 1.55E-05 | 0.0023 | -0.0022 | 0.0022 |
| Internet/WAP | 1.63E-04 | 0.0014 | -0.0018 | 0.0022 |
| Logic/Puzzle/Trivia | 7.37E-05 | 0.0053 | -0.0044 | 0.0043 |
| Reference/Dictionaries | 2.23E-04 | 0.0014 | -0.0017 | 0.0024 |
| Social Networks | 2.70E-04 | 0.0023 | -0.0025 | 0.0033 |
| University | 1.00E-04 | 0.0017 | -0.0020 | 0.0022 |
| eBooks |  |  |  |  |
| eBooks | 5.89E-03 | 0.0022 | 0.0033 | 0.0101 |
| Games | 6.66E-04 | 0.0029 | -0.0024 | 0.0049 |
| Health/Diet/Fitness | 2.63E-04 | 0.0012 | -0.0016 | 0.0023 |
| Humor/Jokes | 1.50E-04 | 0.0013 | -0.0018 | 0.0023 |
| Internet/WAP | 4.70E-04 | 0.0013 | -0.0013 | 0.0026 |
| Logic/Puzzle/Trivia | -1.53E-04 | 0.0030 | -0.0045 | 0.0040 |
| Reference/Dictionaries | 5.46E-04 | 0.0013 | -0.0013 | 0.0028 |
| Social Networks | 9.42E-04 | 0.0019 | -0.0015 | 0.0043 |
| University | 2.07E-04 | 0.0013 | -0.0018 | 0.0023 |
| Games |  |  |  |  |
| Games | 1.72E-02 | 0.0592 | 0.0032 | 0.0557 |
| Health/Diet/Fitness | 2.50E-04 | 0.0024 | -0.0026 | 0.0035 |
| Humor/Jokes | 1.59E-04 | 0.0027 | -0.0031 | 0.0036 |
| Internet/WAP | 4.56E-04 | 0.0025 | -0.0023 | 0.0039 |
| Logic/Puzzle/Trivia | 4.08E-04 | 0.0093 | -0.0073 | 0.0085 |
| Reference/Dictionaries | 5.28E-04 | 0.0028 | -0.0022 | 0.0043 |
| Social Networks | 9.05E-04 | 0.0036 | -0.0030 | 0.0065 |
| University | 2.91E-04 | 0.0027 | -0.0028 | 0.0039 |
| Health/Diet/Fitness |  |  |  |  |
| Health/Diet/Fitness | 4.38E-03 | 0.0014 | 0.0026 | 0.0070 |
| Humor/Jokes | 6.33E-05 | 0.0011 | -0.0016 | 0.0017 |
| Internet/WAP | 1.58E-04 | 0.0011 | -0.0015 | 0.0019 |
| Logic/Puzzle/Trivia | 1.49E-05 | 0.0025 | -0.0031 | 0.0032 |
| Reference/Dictionaries | 1.36E-04 | 0.0011 | -0.0015 | 0.0019 |
| Social Networks | 2.85E-04 | 0.0015 | -0.0018 | 0.0028 |
| University | 9.44E-05 | 0.0010 | -0.0015 | 0.0018 |
| Humor/Jokes |  |  |  |  |
| Humor/Jokes | 4.85E-03 | 0.0026 | 0.0027 | 0.0084 |
| Internet/WAP | 1.20E-04 | 0.0011 | -0.0016 | 0.0020 |
| Logic/Puzzle/Trivia | -1.36E-06 | 0.0028 | -0.0037 | 0.0035 |
| Reference/Dictionaries | 8.77E-05 | 0.0012 | -0.0018 | 0.0020 |
| Social Networks | 2.71E-04 | 0.0017 | -0.0021 | 0.0030 |
| University | 5.51E-05 | 0.0012 | -0.0018 | 0.0019 |
| Internet/WAP |  |  |  |  |
| Internet/WAP | 4.58E-03 | 0.0016 | 0.0027 | 0.0075 |
| Logic/Puzzle/Trivia | 8.33E-05 | 0.0030 | -0.0034 | 0.0035 |
| Reference/Dictionaries | 3.32E-04 | 0.0012 | -0.0014 | 0.0023 |
| Social Networks | 5.73E-04 | 0.0016 | -0.0016 | 0.0035 |
| University | 1.71E-04 | 0.0011 | -0.0015 | 0.0020 |
| Logic/Puzzle/Trivia |  |  |  |  |
| Logic/Puzzle/Trivia | 1.79E-02 | 0.0627 | 0.0035 | 0.0552 |
| Reference/Dictionaries | 5.22E-05 | 0.0029 | -0.0035 | 0.0037 |
| Social Networks | 6.97E-06 | 0.0047 | -0.0058 | 0.0056 |
| University | 1.09E-04 | 0.0030 | -0.0033 | 0.0036 |
| Reference/Dictionaries |  |  |  |  |
| Reference/Dictionaries | 4.73E-03 | 0.0017 | 0.0028 | 0.0079 |
| Social Networks | 6.41E-04 | 0.0016 | -0.0015 | 0.0034 |
| University | 1.69E-04 | 0.0012 | -0.0016 | 0.0021 |
| Social Networks |  |  |  |  |
| Social Networks | 7.47E-03 | 0.0049 | 0.0030 | 0.0164 |
| University | 2.91E-04 | 0.0016 | -0.0020 | 0.0030 |
| University |  |  |  |  |
| University | 4.62E-03 | 0.0017 | 0.0027 | 0.0077 |

**Table 12**

**COVARIANCE PARAMETER ESTIMATES: Global Diffusion**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Device Tools |  |  |  |  |
| Device Tools | 2.57 | 47.64 | 0.82 | 2.77 |
| eBooks | 0.75 | 7.95 | -3.01 | 4.11 |
| Games | 2.79 | 22.79 | 1.39 | 4.05 |
| Health/Diet/Fitness | 2.48 | 1.40 | 1.18 | 4.32 |
| Humor/Jokes | 1.10 | 0.95 | -0.11 | 2.49 |
| Internet/WAP | 3.16 | 7.34 | 1.78 | 5.28 |
| Logic/Puzzle/Trivia | 1.37 | 1.05 | -0.08 | 3.15 |
| Reference/Dictionaries | 2.23 | 3.42 | 1.03 | 3.92 |
| Social Networks | 1.50 | 0.64 | 0.80 | 2.50 |
| University | 1.71 | 2.43 | -0.11 | 4.00 |
| eBooks |  |  |  |  |
| eBooks | 45.61 | 21.50 | 16.49 | 80.75 |
| Games | 1.46 | 5.48 | -4.73 | 7.81 |
| Health/Diet/Fitness | 1.93 | 5.48 | -7.32 | 10.64 |
| Humor/Jokes | -1.14 | 7.47 | -12.17 | 9.64 |
| Internet/WAP | 1.83 | 4.66 | -5.46 | 9.60 |
| Logic/Puzzle/Trivia | 5.14 | 8.27 | -9.47 | 18.24 |
| Reference/Dictionaries | 0.12 | 5.25 | -8.54 | 8.11 |
| Social Networks | 0.46 | 2.34 | -3.35 | 4.17 |
| University | 1.92 | 10.62 | -15.76 | 17.82 |
| Games |  |  |  |  |
| Games | 4.65 | 13.84 | 2.66 | 7.20 |
| Health/Diet/Fitness | 4.86 | 1.81 | 2.62 | 7.94 |
| Humor/Jokes | 2.32 | 1.60 | 0.35 | 4.75 |
| Internet/WAP | 5.27 | 5.06 | 2.99 | 8.52 |
| Logic/Puzzle/Trivia | 3.31 | 1.75 | 0.99 | 6.42 |
| Reference/Dictionaries | 4.25 | 2.17 | 2.19 | 7.13 |
| Social Networks | 2.47 | 0.88 | 1.41 | 4.01 |
| University | 4.22 | 2.63 | 1.18 | 8.37 |
| Health/Diet/Fitness |  |  |  |  |
| Health/Diet/Fitness | 7.24 | 2.56 | 3.85 | 11.78 |
| Humor/Jokes | 2.62 | 2.15 | -0.33 | 5.78 |
| Internet/WAP | 5.75 | 2.18 | 2.61 | 9.74 |
| Logic/Puzzle/Trivia | 4.87 | 2.54 | 1.36 | 9.43 |
| Reference/Dictionaries | 6.11 | 2.24 | 3.03 | 10.18 |
| Social Networks | 2.63 | 1.01 | 1.32 | 4.49 |
| University | 7.40 | 3.42 | 2.82 | 13.39 |
| Humor/Jokes |  |  |  |  |
| Humor/Jokes | 5.44 | 49.75 | 1.62 | 9.82 |
| Internet/WAP | 2.77 | 2.05 | -0.32 | 5.87 |
| Logic/Puzzle/Trivia | 1.36 | 2.50 | -2.08 | 5.62 |
| Reference/Dictionaries | 2.37 | 2.12 | -0.84 | 5.45 |
| Social Networks | 1.25 | 0.92 | 0.03 | 2.66 |
| University | 3.23 | 3.24 | -0.95 | 8.28 |
| Internet/WAP |  |  |  |  |
| Internet/WAP | 7.73 | 3.72 | 3.96 | 12.69 |
| Logic/Puzzle/Trivia | 2.95 | 2.16 | -0.19 | 6.60 |
| Reference/Dictionaries | 5.47 | 2.22 | 2.74 | 9.11 |
| Social Networks | 3.28 | 1.09 | 1.82 | 5.26 |
| University | 4.22 | 3.21 | -0.07 | 9.61 |
| Logic/Puzzle/Trivia |  |  |  |  |
| Logic/Puzzle/Trivia | 7.86 | 4.48 | 3.07 | 16.45 |
| Reference/Dictionaries | 3.59 | 2.30 | 0.56 | 7.61 |
| Social Networks | 1.36 | 0.96 | -0.02 | 2.98 |
| University | 6.92 | 4.05 | 1.45 | 14.04 |
| Reference/Dictionaries |  |  |  |  |
| Reference/Dictionaries | 6.38 | 2.90 | 3.31 | 11.30 |
| Social Networks | 2.45 | 0.94 | 1.23 | 4.09 |
| University | 5.99 | 3.43 | 1.35 | 11.62 |
| Social Networks |  |  |  |  |
| Social Networks | 1.59 | 0.67 | 0.79 | 2.71 |
| University | 1.94 | 1.40 | 0.09 | 4.41 |
| University |  |  |  |  |
| University | 13.93 | 7.35 | 7.02 | 28.39 |

**Table 13**

**PARAMETER ESTIMATES: Heterogeneity in Local Diffusion Parameters**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| External Market Force |  |  |  |  |
| Popularity | -0.012 | 0.047 | -0.088 | 0.063 |
| Internal Market Force |  |  |  |  |
| Popularity | 0.041 | 0.066 | -0.058 | 0.158 |
| Market Size |  |  |  |  |
| Popularity | -6.90 | 0.280 | -7.281 | -6.446 |

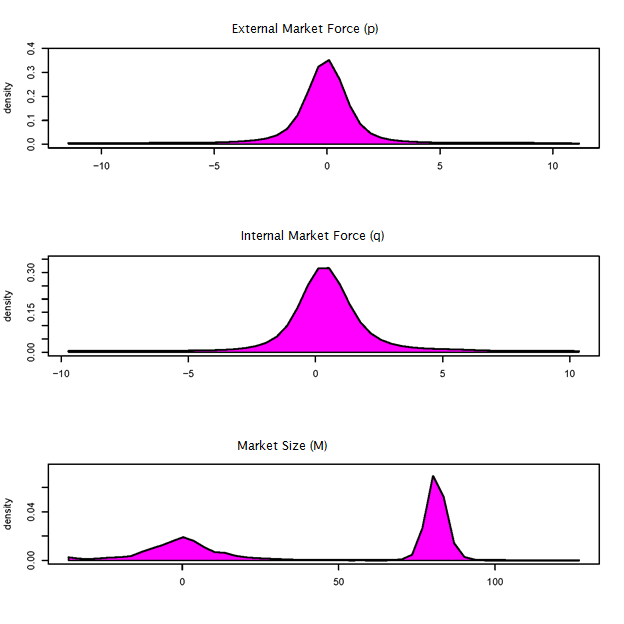
**Table 14**

**PARAMETER ESTIMATES: Heterogeneity in Global Diffusion Parameters**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| External Market Force |  |  |  |  |
| Popularity | 0.0004 | 0.0380 | -0.061 | 0.063 |
| Internal Market Force |  |  |  |  |
| Popularity | 0.0078 | 0.0400 | -0.056 | 0.073 |
| Market Size |  |  |  |  |
| Popularity | -1.1858 | 3.704 | -7.212 | 5.0440 |

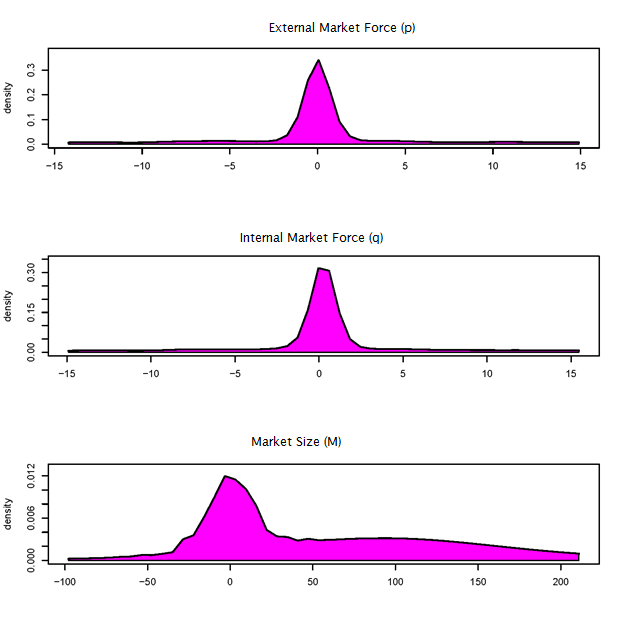
**Figure 7**

**PARAMETER DISTRIBUTION: Heterogeneity in Local Diffusion Parameters**

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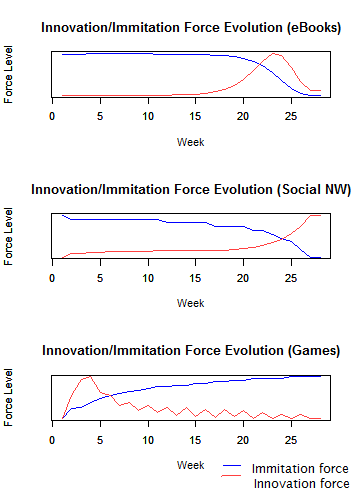
**Figure 8**

**PARAMETER DISTRIBUTION: Heterogeneity in Global Diffusion Parameters**

****

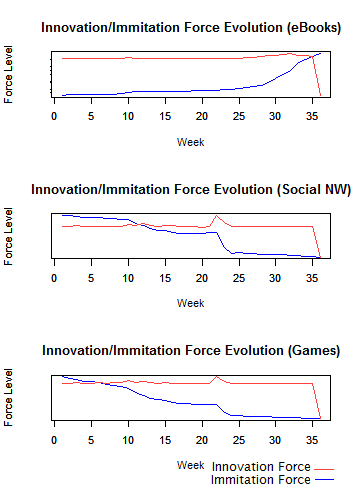
**Figure 9**

**Evolution of Forces: Imitation/Innovation Force in Local Market (scaled variation)**

****

**Figure 10**

**Evolution of Forces: Imitation/Innovation Force in Global Market (scaled variation)**

****

**Table 15**

**PARAMETER ESTIMATES: Individual Choice effect (Local imitators/innovators Model)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Category Preference: |  |  |  |  |
| Device Tools | -10.36 | 5.27 | -16.19 | -2.83 |
| eBooks | -12.46 | 3.01 | -17.55 | -8.19 |
| Games | -14.63 | 5.61 | -21.80 | -5.92 |
| Health/Diet/Fitness | -10.70 | 6.29 | -19.49 | -0.15 |
| Humor/Jokes | -10.15 | 4.69 | -16.85 | -2.38 |
| Internet/WAP | -12.95 | 5.62 | -21.98 | -4.10 |
| Logic/Puzzle/Trivia | -17.20 | 6.73 | -27.38 | -7.50 |
| Reference/Dictionaries | -9.34 | 4.83 | -17.75 | -2.66 |
| Social Networks | -9.39 | 3.32 | -14.66 | -2.21 |
| University | -11.75 | 6.50 | -22.64 | -2.46 |
| States Forces: |  |  |  |  |
| Individual Category State | -77.70 | 8.33 | -89.61 | -65.35 |
| Innovation Force | 4.05 | 6.42 | -5.11 | 14.95 |
| Imitation Force | -1.52 | 1.78 | -4.16 | 2.15 |
| Design components: |  |  |  |  |
| Assortment Breadth | -1.12 | 4.53 | -7.06 | 8.19 |
| Assortment Breadth Square | 0.49 | 5.16 | -6.97 | 8.66 |
| Innovative Apps | 3.37 | 4.47 | -1.92 | 12.09 |
| Innovative Apps Square | -3.36 | 5.29 | -10.96 | 3.86 |
| Paid Category | 0.14 | 3.14 | -5.04 | 5.61 |

**Table 16**

**PARAMETER ESTIMATES: Individual Choice effect (Global imitators/innovators Model)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Category Preference: |  |  |  |  |
| Device Tools | -10.17 | 4.96 | -19.01 | -2.75 |
| eBooks | -47.82 | 26.25 | -97.84 | -4.12 |
| Games | -14.33 | 9.67 | -31.01 | -2.88 |
| Health/Diet/Fitness | -11.16 | 3.42 | -14.68 | -3.52 |
| Humor/Jokes | -12.88 | 6.21 | -19.50 | -1.00 |
| Internet/WAP | -14.70 | 5.28 | -20.66 | -2.78 |
| Logic/Puzzle/Trivia | -20.12 | 5.94 | -28.80 | -12.53 |
| Reference/Dictionaries | -11.50 | 6.34 | -18.52 | 2.19 |
| Social Networks | -9.16 | 3.23 | -14.42 | -3.06 |
| University | -12.71 | 6.87 | -20.67 | -0.14 |
| States Forces: |  |  |  |  |
| Individual Category State | -20.73 | 5.67 | -31.04 | -14.52 |
| Innovation Force | -9.13 | 9.65 | -28.88 | 4.07 |
| Imitation Force | -0.20 | 0.94 | -2.18 | 0.95 |
| Design components: |  |  |  |  |
| Assortment Breadth | 1.02 | 1.67 | -1.22 | 3.32 |
| Assortment Breadth Square | -0.23 | 5.88 | -11.51 | 5.55 |
| Innovative Apps | -5.73 | 4.44 | -14.74 | -1.83 |
| Innovative Apps Square | 1.82 | 4.73 | -3.13 | 11.76 |
| Paid Category | 3.89 | 5.28 | -4.80 | 11.66 |

**Table 17**

**PARAMETER ESTIMATES: Heterogeneity in Individual Choice ( Local imitators/innovators Model)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Tenure Explaining the following parameters Heterogeneity | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Category Preference: |  |  |  |  |
| Device Tools | 0.0063 | 0.0134 | -0.0116 | 0.0363 |
| eBooks | 0.0142 | 0.0245 | -0.0255 | 0.0610 |
| Games | 0.0033 | 0.0137 | -0.0175 | 0.0282 |
| Health/Diet/Fitness | 0.0374 | 0.0180 | 0.0056 | 0.0673 |
| Humor/Jokes | -0.0001 | 0.0183 | -0.0283 | 0.0355 |
| Internet/WAP | 0.0229 | 0.0175 | -0.0019 | 0.0564 |
| Logic/Puzzle/Trivia | -0.1238 | 0.0586 | -0.1816 | -0.0035 |
| Reference/Dictionaries | 0.0282 | 0.0193 | -0.0011 | 0.0612 |
| Social Networks | 0.0339 | 0.0110 | 0.0160 | 0.0522 |
| University | -0.0080 | 0.0178 | -0.0385 | 0.0188 |
| States Forces: |  |  |  |  |
| Individual Category State | -0.0591 | 0.0916 | -0.1644 | 0.0778 |
| Innovation Force | -0.0580 | 0.0222 | -0.0915 | -0.0123 |
| Imitation Force | 0.0005 | 0.0063 | -0.0096 | 0.0101 |
| Design components: |  |  |  |  |
| Assortment Breadth | -0.0366 | 0.0330 | -0.0962 | 0.0184 |
| Assortment Breadth Square | 0.1099 | 0.0623 | 0.0066 | 0.1915 |
| Innovative Apps | -0.0664 | 0.0371 | -0.1062 | 0.0051 |
| Innovative Apps Square | 0.0649 | 0.0380 | -0.0012 | 0.1077 |
| Paid Category | -0.0285 | 0.0365 | -0.0762 | 0.0296 |

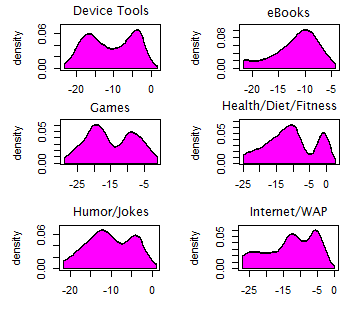
**Table 18**

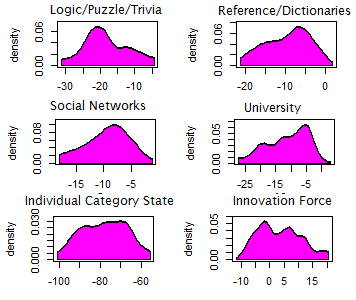
**PARAMETER ESTIMATES: Heterogeneity in Individual Choice ( Global imitators/innovators Model)**

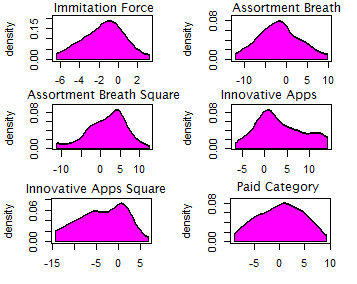
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Tenure Explaining the following parameters Heterogeneity | **Estimate** | **Std. Dev.** | **2.5th** | **97.5th** |
| Category Preference: |  |  |  |  |
| Device Tools | -0.031 | 0.018 | -0.06 | 0.00 |
| eBooks | -0.152 | 0.022 | -0.19 | -0.12 |
| Games | 0.006 | 0.019 | -0.02 | 0.04 |
| Health/Diet/Fitness | -0.012 | 0.018 | -0.04 | 0.02 |
| Humor/Jokes | 0.030 | 0.015 | 0.00 | 0.05 |
| Internet/WAP | -0.041 | 0.024 | -0.08 | 0.00 |
| Logic/Puzzle/Trivia | -0.034 | 0.022 | -0.07 | 0.00 |
| Reference/Dictionaries | 0.041 | 0.028 | 0.00 | 0.08 |
| Social Networks | 0.007 | 0.011 | -0.01 | 0.03 |
| University | -0.025 | 0.018 | -0.06 | 0.01 |
| States Forces: |  |  |  |  |
| Individual Category State | -0.014 | 0.024 | -0.05 | 0.02 |
| Innovation Force | -0.033 | 0.013 | -0.05 | -0.01 |
| Imitation Force | 0.014 | 0.004 | 0.01 | 0.02 |
| Design components: |  |  |  |  |
| Assortment Breadth | 0.008 | 0.020 | -0.02 | 0.04 |
| Assortment Breadth Square | 0.014 | 0.017 | -0.01 | 0.04 |
| Innovative Apps | 0.000 | 0.017 | -0.03 | 0.03 |
| Innovative Apps Square | 0.018 | 0.018 | -0.01 | 0.05 |
| Paid Category | -0.052 | 0.050 | -0.13 | 0.02 |

**Figure 11**

**PARAMETER DISTRIBUTION: Heterogeneity in Individual Choice ( Local imitators/innovators Model)**

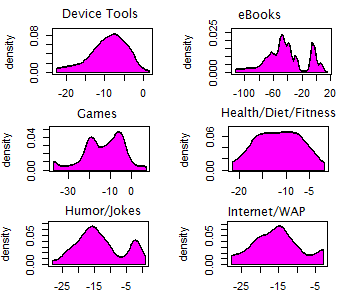
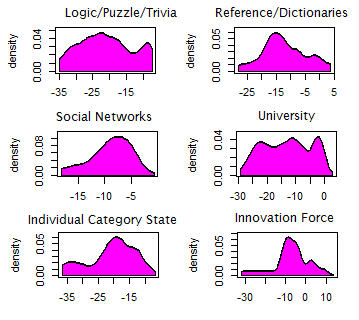
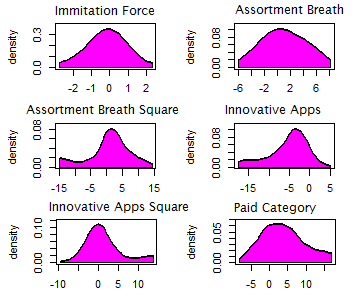
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**Figure 12**

**PARAMETER DISTRIBUTION: Heterogeneity in Individual Choice ( Global imitators/innovators Model)**

1. I would like to thank Dr. Soysal and Dr. Ratchford for sending me to Duke workshop on structural modeling, and teach me related techniques. Also I would like to thank Dr. Bruce for teaching me how to conduct a quality empirical research in marketing, and how to code Kalman Filter. [↑](#footnote-ref-1)
2. I would like to thank Dr. Ying Xie and Dr. Elisabeth Honka for their revision of the proposal I send out to the company. I also would like to thank Dr. Rao for making me to write a lot during his spring seminar, which allowed me to organize my mind, and to position my research paper. [↑](#footnote-ref-2)
3. This process has been so extensive that some scholars study how cell phone affects social interaction of individuals http://www.michigandaily.com/news/%E2%80%98u%E2%80%99-researchers-identify-link-between-cell-phones-and-socialization-habits [↑](#footnote-ref-3)
4. http://www.businessweek.com/articles/2014-02-20/uber-leads-taxi-industry-disruption-amid-fight-for-riders-drivers [↑](#footnote-ref-4)
5. http://en.wikipedia.org/wiki/App\_Store\_(iOS) [↑](#footnote-ref-5)
6. http://theweek.com/article/index/241121/7-health-benefits-of-playing-video-games [↑](#footnote-ref-6)
7. http://www.forbes.com/sites/briansolomon/2014/08/12/king-digital-pummeled-as-candy-crush-fad-fizzles-out/ [↑](#footnote-ref-7)
8. http://www.pewinternet.org/fact-sheets/mobile-technology-fact-sheet/ [↑](#footnote-ref-8)
9. http://smallbusiness.chron.com/life-expectancy-smartphone-62979.html [↑](#footnote-ref-9)
10. http://editorial.autos.msn.com/listarticle.aspx?cp-documentid=1171403 [↑](#footnote-ref-10)
11. http://www.sajan.com/blog/global-marketing-isnt-dead-marketing-localization-matters-now-ever/ [↑](#footnote-ref-11)