Quantifying the Impacts of Digital Rights Management and E-Book Pricing on the E-Book Reader Market*

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Abstract

The introduction of e-book readers such as Amazon's Kindle has been an important driving force behind the success of the e-book market. This paper quantifies the impacts of digital rights management (DRM) and discounted e-book pricing, two of the most controversial issues in this market, on the demand for e-book readers. Using conjoint survey data, we estimate a random coefficient model using a hierarchical Bayesian method. Our counterfactual experiments suggest two things. First, if Kindle or Nook were to drop DRM unilaterally then their market share would increase moderately with only a slight effect on other readers; Consumer welfare would increase by seven percent if all readers dropped DRM. Second, an increase in e-book prices would increase iPad's market share moderately at the expense of Kindle and Nook; Consumer welfare would decrease by six to ten percent if Kindle's and Nook's e-book prices went up by 50 percent.

JEL Code: L13, O33

Keywords: electronic book; demand elasticity; discrete choice; Bayesian estimation

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*We would like to thank the seminar participants at the AMES 2013. We acknowledge the research grants from the Center for the Analysis of Property Rights and Innovation and the Networks, Electronic Commerce and Telecommunications Institute. The usual disclaimer applies.

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1 Introduction

The Internet has drastically changed the business model of the creative industries such as book publishing. The distribution of content (e.g., music, movies, and books) has become increasingly inexpensive in digital formats. Immediate access to such a wide array of content has notably led to consumer piracy. At the same time, however, technological advances have also enabled content creators to adopt technological protection measures that prevent unauthorized copying.

How do these challenges and opportunities affect the dynamics in these markets, and what are the policy implications of the salient features in these markets? We note that one of the key developments is the complementarity between content and hardware. While content providers are facing challenges in keeping their revenues from falling, complementary hardware products such as iPod (for music) and Kindle (for e-books) have been growing rapidly.

Even though the history of the enabling technology for e-books dates back to the 1970s, it was not until the introduction of dedicated e-book readers such as Amazon's Kindle (first released in late 2007) when the market for e-books started to grow. For instance, according to Bowker Market Research, the number of consumers who use computers to read e-books constituted only six percent of the total e-book market in 2012 (a fall from ten percent in 2011).[1]

Since the launch of Kindle, several e-book readers have been introduced to the market. The 2013 Bowker report places the U.S. market share of Apple's iPad at 14 percent, Amazon's Kindle at 55 percent, and Barnes & Noble's Nook at 12 percent. With the development of the competing readers, the e-book market has also grown substantially in recent years. According to the Association of American Publishers' annual statistics, e-book sales grew 46 percent in 2012 and constituted over 20 percent of the $6.6 billion U.S. book market.[2]

Two issues in the e-book market can affect the competition among e-book readers. The first issue concerns copy protection system, known as the Digital Rights Management (DRM). DRM imposes restrictions on what users can read with their e-book readers. For instance, DRM may prevent users from reading e-books purchased at another platform and/or those e-books that are

[1]The fraction of e-book readers who use iPhones or smartphones to read e-books was three percent for each. See http://www.publishersweekly.com/pw/by-topic/digital/devices/article/54705-kindle-share-of-e-book-reading-at-55.html.

[2]Forrestor Research projects the U.S. e-book market to reach $13.6 billion by 2017. See http://www.businessweek.com/articles/2013-02-12/building-a-better-e-book-than-amazon-and-apple.

no longer supported by the seller. While DRM may prevent unauthorized copying, it also limits the consumption of certain available e-books because the DRM encrypts the content specific to the hardware.

The second issue is the pricing model for e-books. Prior to the introduction of Apple's iPad in 2010, publishers sold e-books through a 'wholesale' model, in which online retailers set the book prices. Vertically integrated platforms, particularly Amazon, used the wholesale model to subsidize the sale of their e-book readers. Aiming to challenge the dominance of Kindle in the e-book reader market, Apple made a deal with major publishers to shift to an 'agency' model, in which publishers set the e-book price, and retailers receive a commission. Book prices went up by as much as 50 percent. The U.S. Department of Justice accused Apple and the major publishers of price-fixing in this case.[3]

This paper aims to provide an empirical groundwork for exploring the impacts of these two issues in the market for e-book readers. This goal necessitates a plausible demand model that is consistent with the assumption of complementarity between e-books and e-book readers. Further, the estimation of our model would require repeated observations on consumer's choice of an e-book reader in an environment where both content and hardware prices would have to vary. This type of data, however, is typically either unavailable or hard to obtain. Our approach is thus to design and collect survey data in which respondents are asked to choose among a set of e-book devices and an outside option under different hypothetical scenarios. Because the policy variables such as the adoption of DRM and e-book pricing can be exogenously and randomly varied, this approach allows for a relatively clean identification of the counterfactual effects in our demand model.

Specifically, we build a structural demand model of e-book readers, which is a multinomial logit model with some novel features. We incorporate the availability of e-book varieties into a constant elasticity of substitution (CES) utility function to account for the complementarity between e-book consumption and the choice of e-book readers. We also control for other relevant determinants of the demand for e-book readers. For instance, we estimate the effects of DRM on the range of available e-book varieties, and the effects of e-book discounts on the price integrals

[3] The publishers settled ahead of the trial. Apple went on trial and was found guilty of conspiring with book publishers to raise e-book prices in violation of antitrust law.

in the CES demand model. We allow for a full set of individual-specific coefficients and specify a hierarchical Bayesian model, which can absorb a significant part of the unobserved heterogeneity. Accounting for individual heterogeneity can be advantageous relative to estimating an average effect especially for more accurate evaluation of policy experiments.

We use two carefully designed survey data sets drawn from a large U.S. state university ($N = 1355$) and a commercial Internet survey firm ($N = 1652$), respectively. Using these samples, our estimation results seem to characterize the demand for e-book readers reasonably well. That is, the demand for Kindle is relatively price elastic with own-price elasticities ranging from -1.19 to -0.87. The demand for Nook is also price elastic with own-price elasticities ranging from -1.57 to -1.23. However, the demand for iPad is quite inelastic with own-price elasticities ranging from -0.28 to -0.22. We also show how observable characteristics and consumption experience elicit heterogeneous responses from the respondents. For instance, those who indicate that they currently read e-books are much less likely to prefer hard copy option over e-book readers, and they are also more sensitive to the presence of DRM in e-book readers. Those who have pirated e-books before are more likely to choose the outside option over any e-book readers or hard copy option.

As our model yields a sensible characterization of the demand for e-book readers, we use our model's estimates to conduct counterfactual experiments to assess the quantitative relevance of the two controversial issues in the e-book market. Two results emerge from our counterfactual exercises. First, if an e-book reader were to drop its DRM unilaterally, then in the case of iPad Apple's market share would increase by about zero to one percent, whereas in the cases of Kindle and Nook their market share would increase by about four percent. If all three devices were to abandon DRM, then the overall market share for e-book readers would increase only by one to two percent. Second, if Amazon's and Barnes & Noble's e-book prices increased by 20 percent (assuming an initial 50 percent price discount) during the agency model period, our model predicts that iPad's market share would increase by one to two percent, and Kindle's and Nook's market shares decrease by the same amount. These figures increase further if e-book prices reached the proposed ceiling.

The outline for the paper is as follows. Section 2 discusses relevant literatures and industry background. Section 3 describes the demand model and estimation procedure. Section 4 explains our survey design and data sets. Section 5 contains estimation results. Section 6 presents counterfactual experiments. Section 7 offers concluding remarks.

2 Literature and Market

2.1 Related Literature

As one of the most-studied online retail category, the book industry has been examined by a number of researchers. For instance, Smith and Brynjolfsson (2001) analyze panel data from a price comparison website and show that customers have a strong preference for Amazon. Similarly, Chevalier and Goolsbee (2003) estimate the own- and cross-price elasticities of online book sales at Amazon and Barnes & Noble and find that demand at Barnes & Noble is more price-elastic than that at Amazon.[4] To our knowledge, however, there has been little empirical research on complementary hardware devices in this market, to which we aim to contribute.

The book industry is also facing the same kind of digital disruption that has left the music industry vulnerable to unauthorized copying.[5] Facing the challenges of consumer piracy, content industries have been eager to adopt copy-protection technologies. For instance, proprietary DRM used to be a key feature of digital music sold on Apple's iTunes Store until Apple started dropping DRM in 2009. Theoretical works on DRM (e.g., Sundararajan (2004); Park and Scotchmer (2005); and Bergemann, Eisenbach, Feigenbaum, and Shenker (2011)) have suggested that there are indeed tradeoffs between protecting copyrights and increasing the value of consumption.

There has been a growing interest in studying the spillover effects between complementary goods. For instance, Hendricks and Sorensen (2009) show that the release of a new album substantially increases sales of old albums, and Mortimer, Nosko, and Sorensen (2012) show that music piracy may have a positive effect on live concert demand. Our paper is closest to the study by Chao, Ho, Leung, and Ng (2013), which shows that jailbreaking (which allows the download of additional applications that are otherwise unavailable) could increase smartphone

[4]Using different methodology and data, De los Santos, Hortaçsu, and Wildenbeest (2012) find higher price elasticities for Amazon as well as lower price elasticities for Barnes & Noble than those reported by Chevalier and Goolsbee (2003).

[5]Most studies on the music industry report that piracy hurts record sales (e.g., Blackburn (2004); Liebowitz (2006); Rob and Waldfogel (2006); Smith and Telang (2012); and Zentner (2006)). One notable exception is the work of Oberholzer-Gee and Strumpf (2007), who argue that piracy can boost record sales.

demand. Our focus is different in that we study how DRM affects the hardware demand through changes in available content.

Bayesian random coefficient models are particularly useful in the presence of large consumer heterogeneity that is hard to capture in a parsimonious way (see, e.g., Geweke and Keane (1999, 2001)). For instance, estimates of price elasticities could be biased if the aggregate effect is not the same as the average effect, in which case Bayesian approach via Markov Chain Monte Carlo (MCMC) Techniques allows for more accurate inferences. Recent examples of Bayesian models include Burda, Harding, and Hausman (2008) on supermarket choices; Dubé, Hitsch, and Rossi (2009, 2010) on consumer packaged goods; Leung (2013) on legal and illegal copies of software; and Panagiotelis, Smith, and Danaher (2013) on website visits and sales for online retailers.

2.2 Industry Background

The history of the enabling technology for e-books dates back to the 1970s. The book industry, however, has not undergone the massive transformation that it has only recently experienced (OECD (2012)). Although the digital version of publications can potentially and fundamentally change the way people purchase books, the dramatic growth in the e-book market was made possible by the development of dedicated e-book readers. The year 2007 is a milestone in the market for e-books. During this period Amazon launched its first version of Kindle reader together with the Kindle e-book store. Since the launch of Kindle, the e-book market has exploded with the release of new and competing e-book readers.[6]

Controversial issues have arisen in the e-book market in recent years, which could have considerable impact on its future. The first issue is the copy protection system, or DRM. Even today, many e-book buyers have the misconception that they own similar property rights to the owners of physical books. In reality, e-books are sold with a DRM system that gives consumers conditional access to the content. That is, sellers may cease to support assess to the e-book, and the DRM system also prevents users from reading other e-books that are not encrypted

[6] In a press release (May 19, 2011), Amazon announced that its sales of e-books had overtaken those of all print books (hardcover and paperback combined). See `http://phx.corporate-ir.net/phoenix.zhtml?c=176060&p=irol-newsArticle&ID=1565581&highlight`.

with the same DRM technology. DRM has been frequently criticized by consumer groups, while publishers often claim that DRM is necessary to limit copyright infringements.

A number of vertically integrated manufacturers (such as Amazon, Apple, and Barnes & Noble) have emerged in the e-book market, and most of them use different DRM technologies to encrypt digital content that are sold through their platforms. The choice of reading device therefore affects the range of e-books available to the consumers. This may appear somewhat similar to the interoperability issue in systems markets, but the main issue here is the DRM because without DRM interoperability between different formats can be easily achieved.[7] Critics often argue that using an open standard DRM, or dropping DRM altogether, would increase the range of available content.[8] However, to our knowledge, there has been no formal study investigating these claims.

Second, the pricing model of e-books has undergone significant changes in recent years. The publishing industry has two main value chain models. The first is the traditional wholesale model. In the wholesale model, publishers sell their books to retailers typically at 45 to 55 percent off of the recommended retail price. The most popular e-book platforms are, however, vertically integrated. Sales to these online retailers are made at rates ranging from 55 to 65 percent off retail (OECD (2012)). The wholesale model also gives retailers freedom to set their discounting policy. For example, Amazon presumably wanted to increase the market share of Kindle and decided to heavily discount e-books by setting a price of $9.99 for bestsellers, which made publishers fear that consumers might get used to see such low prices.

Apple launched the iPad three years after Kindle. At that time, Kindle had already dominated the e-book reader market. To overcome Amazon's advantage in selling e-books at subsidized prices, Steve Jobs offered major publishers the ability to set the retail price for their books (known as the agency model). The six major book publishers (Penguin, Harper-Collins, Simon & Schuster, Macmillan, Hachette, and Random House) then switched to the agency model.[9] The collective power of the major publishers eventually forced Amazon to accept the agency

[7] For instance, to read an Amazon e-book on Nook, one must first remove DRM from the e-book, and must also root the e-book reader as well, which allows the user to install third party apps. This process, however, voids the product warranty.

[8] Examples of on-going standard setting efforts for DRM technologies include the Coral Consortium, Sun's DReaM project, and the Digital Media Project.

[9] Random House initially held out, but it adopted the agency model on March 1, 2011, making its e-books available on iBookstore.

model as well, and the price for bestselling e-books increased to $14.99. According to the U.S. Department of Justice, e-book prices had increased on average by more than 20 percent shortly after Amazon and Barnes & Noble switched to the agency model (Palazzolo (2013)).[10]

3 Model and Estimation

3.1 Demand Model

Our demand model is based on the literature that estimates demand for durable goods and their use simultaneously. For instance, Dubin and McFadden (1984) lay out several econometric models consistent with utility maximization that could be used to describe appliance choice and electricity consumption. A key assumption here is that the discrete choice and continuous choice are made simultaneously, and that the continuous choice at the time of the discrete choice is certain.[11] In particular, following Nair, Chintagunta, and Dubé (2004) consumers' taste for variety is represented by a CES utility. This would be necessary because books are not homogeneous products like electricity and cellphone usage.

Specifically, we derive the consumer's optimal e-book consumption using a CES sub-utility over a continuum of variety indexed by ω. Consider a choice set J with different modes of reading (i.e., different e-book readers and hard copies), from which each consumer $i \in \{1, \ldots I\}$ chooses one (and only one). The consumer may also choose not to buy any of the products, in which case the mean utility of the outside good is zero. Let x_j be a vector of non-price attributes of choice $j \in J$ (with the first entry equal to 1), and let $\hat{u}_{ij}$ denote the attribute-based utility. We assume $\hat{u}_{ij} = \gamma_i x_j$ so that the constant term represents the utility (brand loyalty) that is not explained by the other attributes.

Notice that the attributes of choice j do not matter unless this choice is actually selected. Let f_j denote the fixed price for choice j, and let $p(\omega)$ denote the price of variety ω. Consumer

[10]Whether Apple tried to raise the e-book prices through the most-favored nation clause is one of the central issues in the antitrust trial. See, e.g. Johnson (2013).

[11]Applications include the works of Cardon and Hendel (2001), Reiss and White (2005), and Lambrecht, Seim, and Skiera (2007). A number of authors extended this framework to the presence of uncertainty on future consumption (e.g., Miravete (2003); Narayanan, Chintagunta, and Miravete (2007); Iyengar, Jedidi, and Kohli (2008); and Grubb and Osborne (2012)). As our model does not feature a multi-part tariff structure, we assume for simplicity that consumers can perfectly predict their future usage.

i has a budget of w_i to consume books, and he obtains utility from consuming $n_{ij}(\omega)$ units of each variety ω. Consumption decisions are analyzed as if they are contemporaneous with the j alternative mode choice. Formally, the consumer maximizes the following form of utility function subject to a budget constraint:

$$\max_{n_{ij}(\omega), j \in J} u_{ij} = \hat{u}_{ij} + \left(\int_{\Omega_j} n_{ij}(\omega)^{\frac{\sigma_i - 1}{\sigma_i}} d\omega \right)^{\frac{\sigma_i}{\sigma_i - 1}} + \epsilon_{ij} \tag{1}$$

$$\text{s.t., } f_j + \int_{\Omega_j} p(\omega) n_{ij}(\omega) = w_i \text{ for } \forall j \in J, \tag{2}$$

where $\sigma_i > 1$ is the elasticity of substitution, ϵ_{ij} is a standard i.i.d. demand shock, and Ω_j is the range of e-book varieties associated with choice j.

We note here that σ_i and Ω_j cannot be identified in our model. We instead identify certain measures of the price integrals, and argue that these measures are sufficient to capture the effects of changes in DRM protection and e-book pricing. We illustrate this condition as follows. Let $P_{ij} = \int_{\Omega_j} p(\tilde{\omega})^{1-\sigma_i} d\tilde{\omega}$ denote the price integrals for choice j of consumer i. From the first-order conditions, we derive the consumption of variety ω in a symmetric equilibrium: $n_{ij}(\omega) = \frac{p(\omega)^{-\sigma_i}}{P_j}(w_i - f_j)$. Substituting $n_{ij}(\omega)$ into u_{ij}, we can express the indirect utility as

$$v_{ij} = \hat{u}_{ij} + P_{ij}^{\frac{1}{\sigma_i - 1}}(w_i - f_j) + \epsilon_{ij}. \tag{3}$$

A couple of features of $P_{ij}^{1/(\sigma_i - 1)}$ are amenable to our policy experiments. First, P_{ij} depends on the range Ω_j of varieties available to choice j, where a larger Ω_j indicates a higher $P_{ij}^{1/(\sigma_i - 1)}$. As explained previously, DRM can restrict the range of e-books available to the user. In terms of the model, a larger range of e-books available means a higher P_{ij}, so if there is no DRM, then we can plausibly expect that P_{ij} would be higher. We capture this effect flexibly by using an individual scale parameter δ_i in our estimation. That is, the extent to which DRM might affect the available content can vary across users due to, e.g., individual needs or genre preferences. This means that we in fact allow for a positive (as well as negative) value from DRM.

Second, e-book content can be sold at a discount off of a full retail price, which is $p(\omega)$. In particular, integrated platforms used to discount heavily e-books below hard copy prices. If all books associated with choice j are sold at a discount $D_j \in (0,1)$, then $P_{ij}^{1/(\sigma_i - 1)}$ would be higher by a proportion D_j^{-1} because the content price would then be $D_j p(\omega)$. Incorporating these two features into v_{ij} yields

$$v_{ij} = \hat{u}_{ij} + (DRM_j \delta_i + (1 - DRM_j)) D_j^{-1} \beta_{ij} (w_i - f_j) + \epsilon_{ij}, \tag{4}$$

where DRM_j is an indicator for DRM protection, D_j is a discount off the content price, and $\beta_{ij} = P_{ij}^{1/(\sigma_i - 1)}$ is price integral associated with consumer i for choice j.

We note that β_{ij} represents exogenous prices, individual-specific preferences, and the range of available content. As mentioned previously, we cannot separately identify these parameters given the data limitation; however, our policy experiments concern changing only product attributes such as DRM_j and D_j. Further, content prices are given in our survey or in the benchmark, and we assume that the elasticity of substitution σ_i does not change over time. Thus, we believe that the above specification can correctly infer the effects of policy changes at the aggregate level.

Assuming that the random utility term, ϵ_{ij}, is type I extreme value distributed, the likelihood that consumer i will choose j takes the following multinomial logit form:

$$D_{ij}(\mathbf{P}|\Theta_i) = \frac{\exp\left(\hat{u}_{ij} + (DRM_j \delta_i + (1 - DRM_j)) D_j^{-1} \beta_{ij} (w_i - f_j)\right)}{1 + \sum_{k=1}^{J} \exp\left(\hat{u}_{ik} + (DRM_k \delta_i + (1 - DRM_k)) D_k^{-1} \beta_{ik} (w_i - f_k)\right)}, \tag{5}$$

where $\mathbf{P} \equiv [x_1, \ldots, x_J; f_1, \ldots, f_J; D_1, \ldots, D_J; DRM_1, \ldots, DRM_J]'$ is a vector of price and non-price attributes, and $\Theta_i \equiv [\gamma_i, \delta_i, \beta_{i1}, \ldots, \beta_{iJ}, w_i]$ is a vector of individual-level parameters.

As Berry, Levinsohn, and Pakes (1995), Nevo (2000), and Petrin (2002) show, random coefficient models permit more realistic estimates of consumer demands than homogenous coefficient models do. In a fast-growing market such as the e-book market, we can naturally consider that consumers have heterogeneous preferences, hence different coefficient values, depending on observed characteristics. To validate this approach, we will later show how individual parameters are affected by such factors. For instance, those who currently read e-books may have different elasticities, hence values of the price integral (β_{ij}), from those who do not read e-books; those with piracy experience may have different values for DRM protection and thus may react differently to policy changes compared with those with no such experience.

3.2 Bayesian Estimation

We follow Rossi, Allenby, and McCulloch (2005) to estimate a hierarchical Bayesian model with a mixture of K components of normal priors to estimate the proposed random coefficient model. This approach is more flexible than the classical approach because it does not restrict the coefficients to a single normal distribution, but it can approximate arbitrary distributions. This also allows for correlated coefficients.

In the survey (to follow), we asked respondents to provide demographic and other relevant characteristics. Thus, we include a vector Z_i of observable characteristics to capture observed consumer heterogeneity. Let $t = 1, \ldots, T$ indicate a choice occasion. Then, the conditional likelihood of observing the choices consumer i makes across the T choice occasions is given by $\sum_{t=1}^{T} D_{ij}^{t}(\mathbf{P}|\Theta_i)$.

Letting $ind_i \in \{1, \ldots, K\}$ denote the latent variable that indicates the K mixture component from which each consumer's preference parameter vector is drawn, the demand model can be expressed as follows:

$$\begin{aligned} \Theta_i &= Z_i \triangle + u_i \\ u_i &\sim N(\mu_{ind_i}, \Sigma_{ind_i}) \\ ind_i &\sim MN_K(\gamma), \end{aligned}$$

where γ is a vector of hyperparameters for the priors on the mixing probabilities for each component, and $\triangle$ is a matrix of hyperparameters that determine the systematic effects of demographics on individual-level parameters. We define $\zeta = vec(\triangle)$ for ease of illustration. Therefore, parameters Θ_i are drawn from a multivariate distribution of K mixture-of-normals, where μ_k and Σ_k denote the mean and variance-covariance matrix of each component, respectively.

The complete specification with priors over the hyperparameters, including the demographic coefficients ($\bar{\zeta}$ and a_{ζ}^{-1}), the mixing probabilities (α), the means of the unobserved heterogeneity ($\bar{\mu}$ and a_{μ}^{-1}), and the covariance matrices for the unobserved heterogeneity (v and V), is given in the following conjugate forms:

$$\begin{aligned}
\zeta &\sim N(\bar{\zeta}, a_{\zeta}^{-1}) \\
\gamma &\sim Dirichlet(\alpha) \\
\mu_k|\Sigma_k &\sim N(\bar{\mu}, \Sigma_k \times a_{\mu}^{-1}) \\
\Sigma_k &\sim IW(v, V).
\end{aligned}$$

where the joint priors on μ_k and Σ_k are independent, conditional on γ.

The unconditional likelihood function is complicated because it involves multidimensional integrals. We thus use Markov Chain Monte Carlo (MCMC) methods, which avoid the need for numerical integration. The MCMC algorithm provides random draws from the joint posterior distribution, and inference is based on the distribution of the randomly drawn samples. We use a hybrid of a Metropolis algorithm which employs customized candidate density to draw individual-level parameters, and an unconstrained Gibbs sampler for a mixture of normals conditional on the draws of individual-level parameters.[12] (Interested readers can find further details of the implementation in Chapter 5 of Rossi, Allenby, and McCulloch (2005).)

To showcase the reliability of the estimator, we will report the following Monte Carlo experiment as well: Let $M(\psi)$ denote the structural model parameterized by ψ. First, we use the MCMC algorithm to estimate the model's parameters $\hat{\psi}^{obs}$ using the observed data D^{obs}

[12]Specifically, the MCMC algorithm alternately draws between the individual-level parameters in (6) and the hyperparameters in (7):

$$\begin{aligned}
\Theta_i \quad &| \quad ind_i, Z_i\triangle, \mu_{ind_i}, \Sigma_{ind_i} &(6)\\
ind, \gamma, \{\mu_k\}, \{\Sigma_k\} \quad , \triangle| &\quad \{\Theta\}, &(7)
\end{aligned}$$

where the conditional posterior in (6) is proportional to the product of the likelihood in (5) and the prior of the hyperparameters. We use a Random-Walk Metropolis step to draw Θ_i. The draws of the hyperparameters in (7) are broken down into a succession of conditional draws:

$$\begin{aligned}
&ind|\gamma, Z, \triangle, \{\mu_k, \Sigma_k\}, \{\Theta\} &(8)\\
&\gamma|ind &(9)\\
&\{\mu_k, \Sigma_k\}|ind, \{\Theta\} &(10)\\
&\triangle|ind, Z, \{\mu_k, \Sigma_k\}, \{\Theta\}, &(11)
\end{aligned}$$

where the draw of indicators in (8) is a multinomial draw based on the likelihood ratios with γ_k as the prior. The draw of γ conditional on ind in (9) is a Dirichlet draw. The draw of each (μ_k, Σ_k) in (10) is obtained using a standard algorithm to draw from a multivariate regression model. The draw of $\triangle$ in (11) requires that we pool data from all K components into one regression model.

which we describe below. Second, we simulate a synthetic sample D^{syn} from $M(\hat{\psi}^{obs})$ using the estimates. Third, we re-estimate the model $M(\psi)$ using the synthetic sample D^{syn} to obtain pseudo estimates $\hat{\psi}^{syn}$. We then compare $\hat{\psi}^{obs}$ to $\hat{\psi}^{syn}$ as well as the price elasticities obtained from using these two estimation results. In so doing we follow the same estimation protocol applied to the original data such as the choice of the initial values.[13]

4 Data Set

As discussed previously, due to data limitation we use "stated preference" data rather than "revealed preference" data from actual sales. Conjoint survey, a method for eliciting stated preference within an experimental setting, has become the method of choice for quantitative preference measurement in such areas as psychology and marketing.[14] The main part of our survey is thus a choice-based conjoint survey, in which respondents are asked to make hypothetical discrete choices (see, e.g., Louviere and Woodworth (1983)). In the second part of the survey, we ask respondents to report their demographic and other relevant experience.

Questions regarding how closely tasks in a hypothetical setting can match those in a real environment are valid. However, both marketing and economic applications have found considerable support that conjoint surveys can generate reliable demand estimates (e.g., Brownstone and Train (1999); Hensher, Louviere, and Swait (1999); and Carlsson and Martinsson (2001)). We believe that a conjoint survey with proper design principles allows a clean identification of the model and, given the data limitation, is perhaps the only way to gauge quantitative relevance of the issues we are interested in. Further, large quantities of relevant data can be collected at a moderate cost using conjoint survey.

We fielded our survey twice because each data source has advantages and disadvantages, so we can replicate our results using the two samples. The first survey was carried out with a large number of undergraduate economics students at the University of Colorado during a week in Spring 2013. The aim was to effectively force a well-defined group of students to fill out

[13] We simulate the posterior 20,000 times, discard the first 10,000 draws as burn-in iterations, and retain the last 10,000 draws for both real and pseudo samples.

[14] Conjoint survey is also routinely employed by many companies to make such decisions as new product development, pricing, segmentation, positioning, and advertising (see, e.g., Cattin and Wittink (1982); Krieger, Green, and Wind (2004)). Hensher (1994) reviews the use of conjoint analysis in transportation research.

the survey to minimize potential drop-out bias. To this end, we collaborated with intro- and intermediate-level course instructors as well as some higher-level course instructors to administer the survey in class. A sample of 1355 students was established.

Student samples have some drawbacks, however. That is, the sample is not representative of the total population, and some students do not complete the survey. To supplement the student sample and to ensure the robustness of our results, we also launched the same survey with an online survey firm that maintains a panel of random U.S. population.[15] The resultant sample of 1652 respondents has a wide representation in terms of age and geographic location. On the other hand, the survey respondents may be self-selected and limited to Internet users. Hence, the two sets of data can be viewed as complementary.

To design our main survey, we initially conducted a pilot study with 63 undergraduate students at the University of Colorado. We chose Kindle, Nook, and iPad to define the market and also include in our main survey because they were the most popular choices, and this is also consistent with the figures compiled by industry reports such as Bowker Market Research. We also asked the focus group to list important attributes when choosing among e-book readers. Based on the responses, we included screen size and touch screen function in our survey along with the use of DRM, hardware price, and content price discounts.

To determine the viable range of hardware prices, we also asked the group to state the maximum price that they would be willing to pay for a plain e-ink reader and a tablet computer. We then determined \$10 to \$250 as a feasible range for Kindle and Nook and \$100 to \$850 as a feasible range for iPad. The main survey contained a sequence of 16 individualized choice tasks. Each choice set contained the three e-book readers and an option to read hard copies; and the respondent had to choose one of the five options in each task (where the fifth option is to choose none of the above). Figure 1 presents a sample of a conjoint task in our survey.

The 16 tasks were based on an orthogonal array of four inside choices and four attribute levels. We constructed alternatives by using cyclically generated profiles for each set (see Bunch, Louviere, and Anderson (1994)).[16] This mode of construction satisfies the three properties of

[15] We used SurveyMonkey Audience service. Respondents can only receive compensation if they answer all the questions. In addition to a \$100 sweepstakes, the company makes a contribution of \$0.50 to a charity of each member's choice. For details on their recruitment and sampling procedure, see `http://help.surveymonkey.com/articles/en_US/kb/How-do-Academics-use-SurveyMonkey-Audience`.

[16] To be precise, the attribute level of a new alternative adds one to the level of the previous alternative, and

efficient choice design (Sawtooth Software, 2008).[17] In specifying attribute levels, we divided the ranges of each attribute into low, medium low, medium high, and high categories. We then randomly selected a value from the corresponding ranges for each attribute level appearing in each option. We constructed four such versions of the questionnaire that were randomly fielded.

Table 1 reports the summary statistics for the student sample. The average age is around 20, and male students comprise a slight majority of the sample. Household income is coded as 0 for \$0 to 20K, 1 for \$20K to 40K, 2 for \$40K to 60K, and so on. "Reading Habit" is an indicator that equals one if the respondent chose "yes" to the question, "Do you read e-books?" "Piracy Experience" is another indicator that equals one if the respondent chose "yes" to the question, "Have you ever downloaded or pirated e-books?" Finally, respondents were asked to report their annual budget for books. The mean is around \$300.

Table 2 reports the summary statistics for the online sample. Age, gender, income, and education are based on the registration information provided by the survey firm. The category of these variables are as follows: for age, the coding is 0 for 18 to 29, 1 for 30 to 44, 2 for 45 to 60, and 3 for over 60; for income, it is 0 for \$0 to 25K, 1 for \$25 to 50K, 2 for \$50 to 100K, 3 for \$100 to 150K, and 4 for \$150K or above; for education, it is 0 for "less than high school degree," 1 for "high school degree," 2 for "some college," 3 for "associate or bachelor degree," and 4 for "graduate degree." The mean budget for books is around \$145.

Notable differences can be observed between the two samples. While only 35 percent of the students considers themselves as e-book readers, 53 percent of the general population indicates that they read e-books. The fraction of respondents who have piracy experience is 30 percent in the student sample but only six percent in the random sample of the U.S. population. As the online sample consists of older people, the former finding indicates that, in contrast to the popular belief, students or younger people in our sample do not prefer e-books compared with older people. The latter finding shows that the level of e-book piracy in the general population is rather small, although one must consider the possibility of self-reporting bias.

Table 1 and Table 2 also show in the middle columns the breakdown of user demographics

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if the previous alternative is at the highest level, then the assignment re-cycles to the lowest level.

[17] Specifically, they are i) minimal overlap: each covariate level is shown as few times as possible in a single task; ii) level balance: each covariate level is shown an approximately equal number of times; and iii) orthogonality: covariate levels are chosen independently of other attribute levels, such that each level's effect on utility can be measured independently of all other effects.

by the current usage or ownership, where respondents could choose if necessary more than one devices. In both samples, iPad users tend to have a higher income than the other groups; about 70 to 80 percent of iPad users report that they read e-books whereas over 90 percent of Kindle and Nook users do so. The bottom row shows the market shares in our samples. Although Kindle has a similar market share as iPad in the online sample, its share is only about half of iPad's in the student sample. In both samples, Nook has about a quarter of Kindle's share. The notable high share of iPad in both samples indicates that the demand for iPad must be growing rapidly.

5 Estimation Results

Figure 2 and Figure 3 illustrates the kernel density estimates from the $K = 1$ (solid line) and the $K = 3$ (dotted line) normal mixture models. The estimates from the three-component model are clearly different from those from the one-component model, where the differences between the two are due to the flexible non-normal prior (when $K > 1$) which allows for more accurate individual-level inferences. Our model selection is based on the log marginal likelihood, which is higher with the $K = 3$ mixture normal ($LL = -26,596$ and $-34,935$ for the student and the online sample, respectively) than those from the single normal prior ($LL = -27,117$ and $-37,087$, correspondingly). Henceforth, we discuss our main results using the estimates from the three-component model.[18]

The top panel of each figure shows the densities for the brand dummy coefficient in γ_i. Both samples do not show marked differences among the four inside choice options. That is, Kindle and iPad seem to have on average a higher constant coefficient (brand dummy) than Nook (and for online sample hard copy) does, but the magnitude is not so large given other parameter values. The middle panel contains the densities for touch screen, screen size, budget, and the scale parameter. The ranges of screen size and δ_i appear relatively small compared with those of touch screen and budget for books. The bottom panel depicts the densities for the price integral for each choice option, and they are all skewed to the right, which indicates that fewer people

[18]We experimented with different values of K and based on log likelihood concluded that $K = 3$ model can best fit the data in both samples. Notice that the differences in estimates that follows between the two samples are not thus driven by the model selection.

tend to consume a large varieties of e-books.

Table 3 reports the means and standard deviations of posterior densities for the model's parameters in our MCMC procedure. This table also compares for each sample results using the real sample and the pseudo sample we explained in the previous section for model validation. Most of the densities appear fairly close to each other, except perhaps for some dummy (brand) variables, which could be due to some survey respondents choosing consistently only one device. For instance, the densities for the price integrals seem robust to synthetic data, which would be more important for policy counterfactuals. Further, we show below that both the real and the pseudo samples lead to very similar quantitative inferences at the aggregate level such as price elasticities.

Table 4 and Table 5 show the own- and cross-price elasticities using the real samples, where we find that the own-price elasticities of the three e-book devices vary greatly. They are -0.87 to -1.19 for Kindle, -1.23 to -1.57 for Nook, and -0.22 to -0.28 for iPad, depending on the samples used. These estimates seem consistent with the observed price differences between these three devices. That is, iPad is the most expensive among them, and Nook is priced slightly below Kindle. The cross-price elasticities also suggest that Kindle and Nook are closer substitutes than with iPad. This finding is also consistent with the fact that the iPad is a tablet that offers a range of other features (such as web browsing, e-mail, music, and games). Table 6 and Table 7 present the replication results using the pseudo samples, which suggest that these inferences are reliable.

Table 8 and Table 9 show the estimated values of the hyperparameter matrix (Δ), which links the observed characteristics to individual-level parameters. These two tables show that some of the consumer heterogeneity can be explained by the observable characteristics in Z_i. For instance, male respondents across the two samples on average seem to have a higher brand preference for iPad over Kindle, Nook, and hard copies. They also consume more varieties of e-books (higher β_{ij}) offered by Amazon and Barnes & Noble relative to those offered by Apple. Another finding is that in the online sample, older people on average prefer significantly less, not more, hard copy option over any of the three reading devices, whereas those with higher income or education tend to prefer the hard copy option over any of the e-book readers.

Some of these findings are intuitive and add to the plausibility of the model. For instance, those who currently read e-books have distaste for hard copy option as shown by a negative coefficient for hard copy option. They also have a higher sensitivity to DRM protection compared with those who do not read e-books as shown by the higher values of $\log(1-\delta_i)$. This result indicates that the policy impact of dropping DRM would be greater for current e-book users. Meanwhile, piracy experience is significantly negatively associated with the brand dummies for all e-book readers and hard copy option. However, the effects of piracy experience on e-book consumption varieties are mixed. That is, piracy experience is positively associated with the consumption varieties in the student sample, but it is negatively associated with Apple's e-book consumption in the online sample.

6 Counterfactual Experiments

Given the specifications of our demand model in Section 3, we now predict how changes in DRM protection and e-book discounts affect the demand for e-book readers and how consumer welfare changes. Notice that the indirect utility derived in (4) remains unchanged when we perform counterfactual experiments that affect the parameters of the model including the presence of DRM protection (DRM_j) and the rate of e-book discount off retail (D_j). To be precise, the indirect utility is still given by (4) where all individual-level parameters in $\Theta_i \equiv [\gamma_i, \delta_i, \beta_{i1}, \ldots, \beta_{iJ}, w_i]$ are assumed to be invariant to a change in our policy variables.

Table 10 shows the benchmark figures used to represent the current states of the world. That is, all three e-book readers presently employ DRM, and the e-book discount rates are 50 percent for Amazon and Barnes & Noble and 35 percent for Apple's iBookstore. Note that the sources that suggest these numbers were introduced in the earlier part of this paper. Given the \$9.99 pricing that prevailed in the market (before Apple's entry), 50 percent discount implies a full retail price of \$20. Apple then had proposed price caps of \$12.99 (or \$14.99), which corresponds to a 35 (or 25) percent discount off retail. On the other hand, Amazon has sold one in three (or four) hard copy books at a 25 to 35 percent discount in the recent past (Streitfeld (2013)). This scenario indicates that on average hard copies were sold at a discount of approximately 10 percent.

First, Table 11 and Table 12 present our estimates of the counterfactual effect of abolishing

DRM on the demand for e-book readers. The first row of each table represents the predicted market shares using the benchmark figures. The next three rows show how the market shares and consumer welfare would change if the three e-book readers were to drop DRM one at a time. Here, the effect of DRM is not significant for the iPad, but it is large and appears economically meaningful for Kindle and Nook. That is, if Kindle or Nook had no DRM protection in their devices, then the market share of these two devices would increase by approximately four percentage point. These gains in market share come as much from hard copy readers as from the competitors' market shares.

The change in aggregate consumer utility associated with DRM policy change is also considerable. If Kindle were to drop its DRM, then our model predicts that the consumer welfare would increase by more than four percentage point, whereas the effect is slightly lower for Nook in the student sample. In the student sample, dropping DRM for the iPad increases consumer welfare by about five percentage point even though it only increases iPad's market share by one percent. This may occur because iPad users also prefer the absence of DRM. The last row shows the changes in market shares when all three e-book readers were to drop DRM. Although overall market expansion effect is small (less than two percent), consumer welfare increases more than seven percentage point.

Tables 13 to 16 assess the robustness of our counterfactual experiments by investigating heterogeneous consumer responses along some behavioral dimensions. That is, DRM may matter greatly for current e-book readers because they are likely to encounter situations in which DRM restricts their reading experience. Similarly, DRM may matter little for non-pirating individuals because they have little incentive to circumvent DRM protection. The four tables are consistent with these conjectures. Conditional on reading experience, the market shares of Kindle and Nook increase by more than five percentage point, whereas they increase less than three percentage point conditional on not being an e-book reader. The results conditional on the piracy experience are very similar.

Our second counterfactual experiment is to show the effect of reducing price discounts for e-books. As we discussed above, the recent e-book price-fixing probe revealed that Amazon's e-book prices went up by at least 20 percent after publishers pressured Amazon and other online retailers to adopt the agency model. Given the $9.99 e-book pricing in the benchmark, a 20 percent increase means an e-book price of \$11.99, which corresponds to a 40 percent discount off the retail price (\$20). However, Apple's agency model stipulated e-book prices up to \$12.99 or \$14.99. As the recent district court ruling shows, e-book prices for best-sellers went up more than 40 percent. Hence, we also consider policy changes that result in a 35 percent and a 25 percent e-book discounts off retail, corresponding to the \$12.99 or \$14.99 cap.

Table 17 and Table 18 show the predicted market shares and percentage changes in aggregate consumer welfare. The first row in each table represents our benchmark prediction as spelled out in Table 10. That is, the first row includes Apple's entry, but it assumes that Apple's agency model had no impact on the e-book prices sold by Amazon and Barnes & Noble at a 50 percent discount. The recent e-book price-fixing case was associated with the fact that the e-book discount rates were no larger than 40 percent. Our prediction in this scenario is represented in the second row. That is, iPad's market share would increase by one to two percent, whereas those of Kindle and Nook would decrease by similar amount each.

The effects of cutting back e-book price discounts would be larger if Amazon's and Barnes & Noble's e-book prices went up by 50 percent, which corresponds to the 25 percent discount rate. Here, iPad's market share would increase by two to four percent with a corresponding decrease in both Kindle's and Nook's market shares. Meanwhile, the impact of the e-book price increase on consumer welfare, as measured by the percentage change in aggregate utility, is unambiguously negative. The impact ranges between three and five percent welfare loss when the e-book discount is 40 percent off retail, and between six and ten percent welfare loss when the e-book discount is cut back to 25 percent. This implies that the e-book price-fixing had a negative effect on consumer welfare in the market for e-book readers.

Tables 19 to 22 repeat the heterogeneous responses from consumers depending on their previous experience. Similar to the above, consumer reaction to the changes in e-book price discount may differ between those who currently read e-books and those who do not. In line with our expectation, we find that iPad's market share gain is one percentage point higher among those who currently read e-books than those who do not. However, the difference between those who have piracy experience and those who do not does not exist in this policy experiment. This result may be explained by the fact that those who have pirated e-books generally consume more varieties of e-books, but pirating also eliminates the need to purchase.

7 Conclusion

Both e-book and DRM are technological revolution in the history of the publishing industry. As such, they have raised important policy issues on copyrights and pricing. We believe this paper is a reasonable first step towards quantitative assessment of DRM protection and spillover from content pricing on demand for e-book readers. To this end, we estimated a structural demand model for e-book readers while taking into account the complementarity between e-books and e-book readers. And then we flexibly estimated the model using a hierarchical Bayesian method.

Our findings are consistent with some of the literature: Kindle and Nook are price elastic and closer substitutes, and iPad is considerably price inelastic. We also show quantitatively how the demand for these e-book readers (and the hard copy choice) are systematically linked together. That is, our counterfactual experiments show that DRM-free regime would increase the market shares of e-book readers and consumer welfare. E-book price-fixing would increase the iPad's market share at the expense of other e-book readers and decrease consumer welfare.

We close by pointing out a couple of limitations of our approach: First, this study is a short-run analysis of changes in DRM policy because the supply side of e-books was not modeled. Future research may address the challenging question of if and how DRM encourages content creation. Second, it would be worthwhile to examine the effects of DRM and e-book pricing in a two-sided market framework (e.g., Lee (2013)). For instance, if DRM does increase content supply, then allowing for network effects would be important to predict the long-run outcome.

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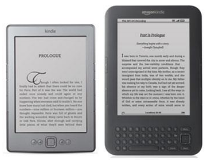
Figure 1: A Sample Conjoint Task

	 Kindle E-Readers	 Nook E-Reader	 iPad	 Hard Copies
DRM	No	Yes	No	N.A.
Touch Screen	No	Yes	Yes	N.A.
Price	$40	$110	$600	$0
Screen Size	6 inch (size of an actual Kindle E-Reader)	7 inch (size of an actual Kindle Fire Tablet)	7.9 inch (size of an actual iPad mini)	N.A.
Price Discount for Books	60% off	40% off	20% off	No Discount

You would choose: Kindle _____ Nook ____ iPad _____ Hard Copies ____ None ____

Figure 2: Kernal Densities of Estimates of Coefficients (Student Sample)

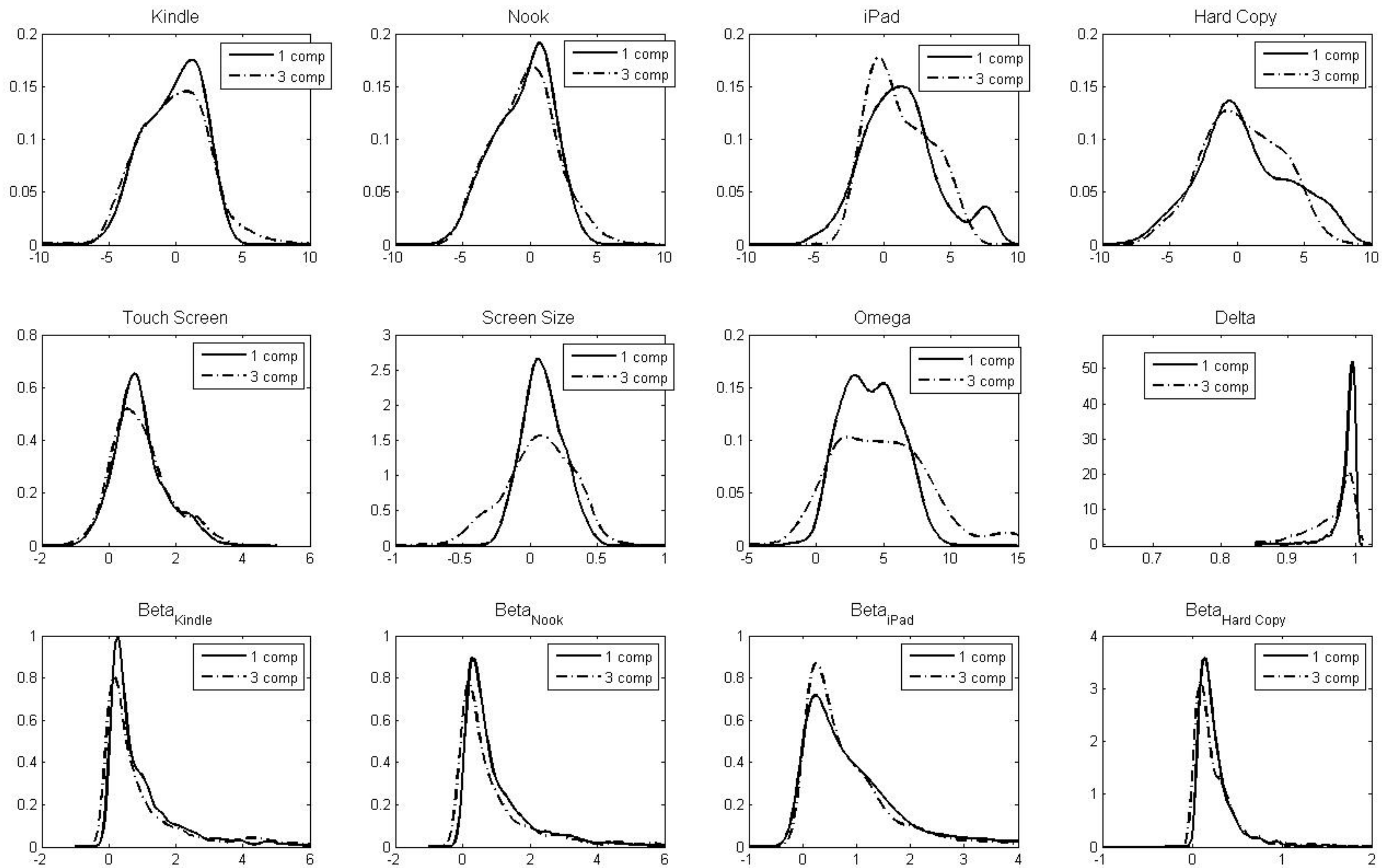


Figure 3: Kernal Densities of Estimates of Coefficients (Online Sample)

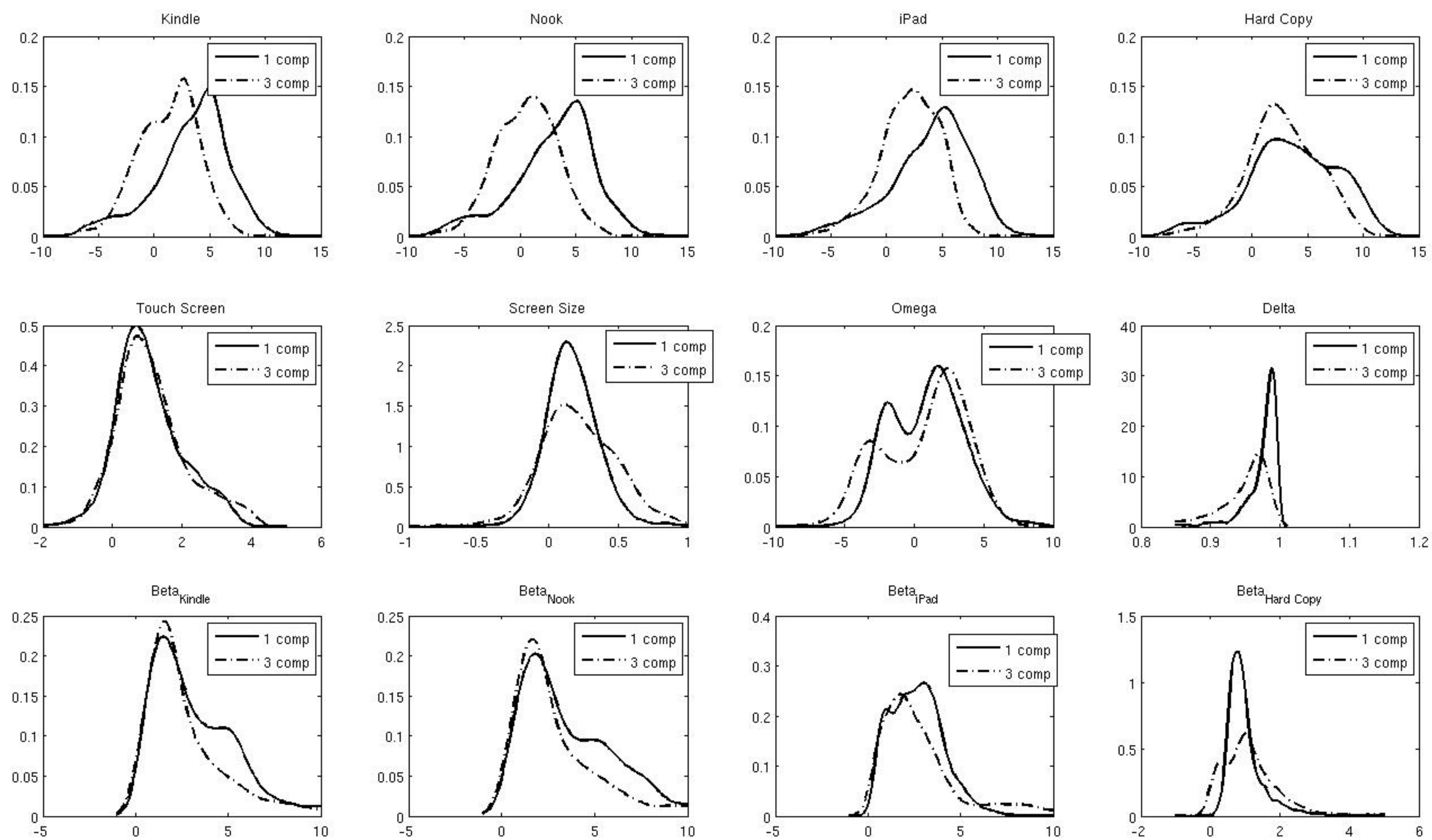


Table 1: Summary Statistics (Student Sample: $N = 1355$)

Variable	Kindle	Nook	iPad	Other	None	Mean (Std. dev.)
Age	19.8	20.0	19.9	20.5	19.8	19.8 (1.7)
Male	0.55	0.50	0.63	0.65	0.64	0.64 (0.48)
Income (in $20K)	4.75	4.23	5.62	3.53	4.69	4.88 (3.40)
Reading Habit	0.95	1.00	0.68	0.83	0.05	0.35 (0.48)
Piracy Experience	0.48	0.42	0.43	0.51	0.20	0.30 (0.46)
Budget for Books ($)	330	$324	384	296	276	304 (411)
% of Sample	12.7%	3.3%	27.3%	4.4%	47.6%	100%

Table 2: Summary Statistics (Online Sample: $N = 1652$)

Variable	Kindle	Nook	iPad	Other	None	Mean (Std. dev.)
Age Group (0-3)	1.68	1.79	1.65	1.55	1.69	1.68 (1.07)
Male	0.44	0.35	0.47	0.57	0.53	0.49 (0.50)
Income Level (0-4)	1.96	2.04	2.23	1.73	1.49	1.79 (1.32)
Education Level (0-4)	2.86	2.87	2.93	2.88	2.63	2.76 (1.00)
Reading Habit	0.94	0.90	0.82	0.91	0.10	0.53 (0.50)
Piracy Experience	0.09	0.06	0.07	0.12	0.03	0.06 (0.24)
Budget for Books (in $20)	8.42	7.76	8.43	7.72	6.60	7.31 (9.21)
% of Sample	26.2%	7.7%	23.9%	7.4%	40.6%	100%

Table 3: Parameter Estimates from Real and Pseudo Sample

	Student Sample		Online Sample	
	Real Sample	Pseudo Sample	Real Sample	Pseudo Sample
Kindle Dummy	-0.14	0.18	1.26	0.23
	(2.62)	(1.96)	(2.65)	(1.88)
Nook Dummy	-0.38	0.10	0.55	-0.41
	(2.38)	(1.85)	(2.72)	(1.93)
iPad Dummy	1.23	1.84	2.05	0.92
	(2.28)	(2.32)	(2.62)	(1.76)
Hard Copy Dummy	0.40	0.63	2.74	1.87
	(2.86)	(2.91)	(3.21)	(2.79)
Touch Screen	0.95	1.01	1.12	1.34
	(0.86)	(1.02)	(1.04)	(1.03)
Screen Size	0.06	0.04	0.23	0.22
	(0.26)	(0.31)	(0.29)	(0.32)
ω	4.92	5.01	0.71	0.98
	(3.68)	(3.75)	(2.98)	(2.90)
δ	0.91	0.92	0.85	0.87
	(0.28)	(0.28)	(0.39)	(0.41)
β_{kindle}	1.89	1.61	1.30	1.53
	(5.25)	(3.13)	(1.67)	(1.02)
β_{nook}	2.72	1.75	1.33	1.44
	(3.08)	(3.91)	(1.37)	(1.04)
β_{ipad}	1.03	1.09	1.04	1.23
	(1.61)	(1.17)	(1.11)	(1.05)
$\beta_{hardcopy}$	0.30	1.29	-0.08	-0.25
	(0.59)	(3.13)	(1.03)	(1.08)

Standard deviations in parenthesis.

Table 4: Own Price Elasticities (Student Sample)

with respect to	Kindle	Nook	iPad
Kindle's price	-1.19	0.77	0.20
	[-1.27, -1.11]	[0.71, 0.84]	[0.18, 0.23]
Nook's price	0.66	-1.57	0.20
	[0.62, 0.71]	[-1.67, -1.49]	[0.18, 0.22]
iPad's price	0.12	0.13	-0.28
	[0.11, 0.14]	[0.12, 0.16]	[-0.31, -0.26]

The 5th and 95th percentiles of the estimates are reported in brackets.

Table 5: Own Price Elasticities (Online Sample)

with respect to	Kindle	Nook	iPad
Kindle's price	-0.87	0.76	0.13
	[-0.92, -0.82]	[0.71, 0.82]	[0.12, 0.15]
Nook's price	0.58	-1.23	0.11
	[0.54, 0.61]	[-1.30, -1.17]	[0.10, 0.13]
iPad's price	0.09	0.10	-0.22
	[0.08, 0.10]	[0.09, 0.11]	[-0.24, -0.21]

The 5th and 95th percentiles of the estimates are reported in brackets.

Table 6: Own Price Elasticities (Pseudo Student Sample)

with respect to	Kindle	Nook	iPad
Kindle's price	-1.18	0.86	0.16
	[-1.30, -1.08]	[0.76, 0.95]	[0.13, 0.20]
Nook's price	0.66	-1.34	0.14
	[0.59, 0.74]	[-1.45, -1.22]	[0.12, 0.17]
iPad's price	0.12	0.15	-0.30
	[0.11, 0.14]	[0.13, 0.17]	[-0.34, -0.28]

The 5th and 95th percentiles of the estimates are reported in brackets.

Table 7: Own Price Elasticities (Pseudo Online Sample)

with respect to	Kindle	Nook	iPad
Kindle's price	-1.06	0.91	0.13
	[-1.13, -0.99]	[0.82, 0.99]	[0.11, 0.15]
Nook's price	0.71	-1.25	0.11
	[0.67, 0.76]	[-1.36, -1.14]	[0.09, 0.14]
iPad's price	0.07	0.08	-0.18
	[0.06, 0.09]	[0.06, 0.09]	[-0.21, -0.16]

The 5th and 95th percentiles of the estimates are reported in brackets.

Table 8: Coefficients Explained by Demographics (Student Sample)

	Kindle	Nook	iPad	Hard Copy	Touch Screen	Screen Size	Budget (w_i)	DRM ($\log(1-\delta_i)$)	β_{kindle}	β_{nook}	β_{ipad}	$\beta_{\text{hard copy}}$
Age	0.10	0.10	0.10	0.12	0.04	0.00	-0.01	0.15	-0.02	-0.01	-0.01	0.00
	(0.04)	(0.05)	(0.03)	(0.06)	(0.03)	(0.01)	(0.03)	(0.06)	(0.02)	(0.02)	(0.01)	(0.02)
Male	-0.06	-0.18	0.13	-0.34	-0.29	0.03	-0.28	-0.20	0.12	0.19	0.09	-0.11
	(0.13)	(0.18)	(0.15)	(0.25)	(0.08)	(0.02)	(0.10)	(0.17)	(0.05)	(0.05)	(0.04)	(0.05)
Reading	0.08	-0.00	0.03	-1.10	0.08	0.03	0.15	0.33	-0.00	-0.14	-0.01	-0.00
Habit	(0.33)	(0.29)	(0.34)	(0.22)	(0.10)	(0.03)	(0.09)	(0.14)	(0.07)	(0.07)	(0.04)	(0.05)
Piracy	-0.49	-0.60	-0.31	-0.51	-0.14	0.02	-0.08	-0.01	0.11	0.18	0.05	0.04
Experience	(0.43)	(0.41)	(0.40)	(0.24)	(0.11)	(0.03)	(0.08)	(0.16)	(0.05)	(0.05)	(0.04)	(0.06)
Budget	-0.29	-0.52	-0.16	-0.51	-0.11	0.03	0.31	-0.25	-0.17	-0.20	-0.09	0.03
(in $1000)	(0.32)	(0.36)	(0.40)	(0.31)	(0.14)	(0.03)	(0.09)	(0.21)	(0.07)	(0.07)	(0.05)	(0.07)
Income	-0.02	-0.03	0.00	0.05	0.02	0.01	0.02	0.04	-0.02	-0.01	-0.01	-0.01
(0-10)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)

Standard deviation of the estimates are reported in brackets.

Table 9: Coefficients Explained by Demographics (Online Sample)

	Kindle	Nook	iPad	Hard Copy	Touch Screen	Screen Size	Budget (w_i)	DRM ($\log(1-\delta_i)$)	β_{kindle}	β_{nook}	β_{ipad}	$\beta_{\text{hard copy}}$
Reading	2.13	1.69	2.24	-0.95	-0.13	-0.06	0.55	0.40	-0.24	-0.28	-0.16	0.06
Habit	(0.29)	(0.31)	(0.35)	(0.41)	(0.10)	(0.03)	(0.11)	(0.11)	(0.06)	(0.06)	(0.04)	(0.06)
Piracy	-1.03	-0.81	-0.82	-2.00	-0.51	-0.01	-0.09	0.25	0.00	-0.11	-0.17	0.20
Experience	(0.49)	(0.40)	(0.37)	(0.49)	(0.23)	(0.04)	(0.18)	(0.24)	(0.11)	(0.12)	(0.08)	(0.11)
Budget	0.01	-0.01	0.03	0.01	-0.01	-0.00	0.01	-0.01	-0.01	-0.00	-0.01	0.01
(in $20)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.39	0.30	0.59	0.21	-0.47	0.07	-0.33	0.41	0.06	0.10	-0.03	0.00
	(0.37)	(0.36)	(0.36)	(0.35)	(0.08)	(0.03)	(0.09)	(0.11)	(0.06)	(0.05)	(0.04)	(0.06)
Age	-0.21	-0.29	-0.37	-0.89	-0.00	0.04	0.02	-0.01	-0.04	-0.10	-0.05	-0.04
	(0.07)	(0.07)	(0.07)	(0.12)	(0.04)	(0.01)	(0.05)	(0.07)	(0.03)	(0.03)	(0.02)	(0.02)
Income	-0.15	-0.02	-0.01	0.33	0.08	0.01	0.06	-0.04	-0.01	-0.01	-0.00	-0.06
	(0.13)	(0.09)	(0.12)	(0.14)	(0.04)	(0.01)	(0.04)	(0.05)	(0.03)	(0.02)	(0.02)	(0.02)
Education	-0.10	-0.12	0.04	0.29	0.03	-0.00	0.08	0.10	0.06	0.05	0.05	0.04
	(0.09)	(0.10)	(0.09)	(0.22)	(0.05)	(0.01)	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)

Standard deviation of the estimates are reported in brackets.

Table 10: Benchmark E-book Market

	Kindle	Nook	iPad	Hard Copy
Device Price	$140	$120	$400	$0
E-book Discount	50%	50%	35%	10%
DRM	Yes	Yes	Yes	-
Touch Screen	Yes	Yes	Yes	-
Screen Size (inch)	6	6	9.7	-

Table 11: Market Shares of Different E-book Readers (Student Sample) (%)*

	Kindle	Nook	iPad	Hard Copy	Welfare Increase
Current	24.39	18.60	27.16	23.97	
	[23.43, 25.35]	[17.95, 19.27]	[26.28. 28.12]	[23.39, 24.51]	
No Kindle DRM	28.50	17.82	26.08	22.41	4.11%
	[27.66, 29.33]	[17.10, 18.59]	[25.32, 26.91]	[21.91, 22.91]	[3.26%, 5.13%]
No Nook DRM	23.51	22.32	26.21	22.66	2.71%
	[22.43, 24.54]	[21.46, 23.20]	[25.33, 27.14]	[22.17, 23.14]	[2.11%, 3.41%]
No iPad DRM	24.15	18.61	28.13	23.60	5.14%
	[23.18, 25.21]	[17.97, 19.27]	[27.18, 29.04]	[23.03, 24.12]	[3.41%, 7.15%]
No DRM	26.12	19.54	26.49	22.51	7.22%
	[25.24, 27.03]	[18.74, 20.39]	[25.53, 27.32]	[21.98, 23.02]	[5.08%, 9.74%]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 12: Market Shares of Different E-book Readers (Online Sample) (%)*

	Kindle	Nook	iPad	Hard Copy	Welfare Increase
Current	26.48	18.58	23.69	26.66	
	[25.82, 27.16]	[18.03, 19.15]	[23.03, 24.35]	[26.24, 27.08]	
No Kindle DRM	29.94	17.90	22.70	25.38	4.51%
	[29.30, 30.60]	[17.33, 18.47]	[22.14, 23.32]	[24.95, 25.83]	[3.56%, 5.47%]
No Nook DRM	25.43	22.21	22.82	25.46	4.51%
	[24.76, 26.07]	[21.63, 22.81]	[22.21, 23.43]	[25.04, 25.88]	[3.77%, 5.41%]
No iPad DRM	26.80	18.84	23.46	26.45	2.23%
	[26.13, 27.44]	[18.29, 19.44]	[22.90, 24.01]	[26.01, 26.90]	[1.60%, 3.03%]
No DRM	27.67	20.36	22.11	25.53	7.38%
	[26.95, 28.38]	[19.72, 21.01]	[21.61, 22.65]	[25.09, 25.97]	[6.02%, 8.88%]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 13: Market Shares by Reading Habit (Student Sample) (%)*

	With Reading Habit			No Reading Habit		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	30.05	19.44	30.55	21.37	18.15	25.35
	[28.48, 31.54]	[18.12, 20.85]	[28.95. 32.06]	[20.15, 22.53]	[17.32, 19.11]	[24.35. 26.42]
No Kindle DRM	35.60	18.23	29.03	24.72	17.61	24.50
	[34.00, 37.08]	[16.89, 19.64]	[27.52, 30.47]	[23.73, 25.78]	[16.62, 18.60]	[23.55, 25.45]
No Nook DRM	28.76	24.69	29.21	20.71	21.06	24.61
	[27.22, 30.26]	[23.08, 26.32]	[27.63, 30.68]	[19.39, 22.06]	[20.08, 22.08]	[23.54, 25.65]
No iPad DRM	29.61	19.40	32.26	21.24	18.18	25.92
	[28.16, 31.01]	[18.08, 20.77]	[30.74, 33.76]	[19.97, 22.52]	[17.34, 19.14]	[24.76, 27.02]
No DRM	32.04	20.82	30.07	22.96	18.86	24.58
	[30.50, 33.48]	[19.21, 22.45]	[28.37, 31.55]	[21.97, 24.08]	[17.96, 19.86]	[23.56, 25.53]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 14: Market Shares by Reading Habit (Online Sample) (%)*

	With Reading Habit			No Reading Habit		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	32.95	20.84	26.82	19.07	15.98	20.09
	[32.01, 33.98]	[20.01, 21.69]	[25.91. 27.77]	[18.30, 19.85]	[15.24, 16.76]	[19.38. 20.87]
No Kindle DRM	37.89	19.97	25.30	20.83	15.53	19.72
	[36.93, 38.84]	[19.19, 20.79]	[24.54, 26.12]	[20.05, 21.65]	[14.75, 16.31]	[18.98, 20.48]
No Nook DRM	31.49	26.02	25.37	18.48	17.84	19.89
	[30.52, 32.48]	[25.18, 26.87]	[24.56, 26.21]	[17.69, 19.21]	[17.05, 18.71]	[19.20, 20.65]
No iPad DRM	33.23	20.92	27.12	19.43	16.46	19.26
	[32.32, 34.21]	[20.11, 21.75]	[26.30, 27.91]	[18.65, 20.22]	[15.72, 17.24]	[18.56, 19.99]
No DRM	34.56	23.16	24.99	19.77	17.14	18.81
	[33.56, 35.58]	[22.26, 24.08]	[24.24, 25.76]	[18.95, 20.54]	[16.37, 18.01]	[18.15, 19.47]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 15: Market Shares by Piracy Experience (Student Sample) (%)*

	With Piracy Experience			Without Piracy Experience		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	25.12	17.75	30.01	24.08	18.95	25.98
	[23.55, 26.76]	[16.38, 19.11]	[28.47. 31.78]	[22.90, 25.16]	[18.22, 19.77]	[25.00. 27.05]
No Kindle DRM	30.45	16.46	28.54	27.70	18.39	25.06
	[28.69, 31.98]	[15.11, 17.83]	[27.08, 30.03]	[26.69, 28.75]	[17.53, 19.33]	[24.15, 26.01]
No Nook DRM	23.46	23.13	28.72	23.53	21.99	25.17
	[21.99, 25.00]	[21.56, 24.73]	[27.26, 30.29]	[22.28, 24.76]	[21.04, 22.97]	[24.13, 26.26]
No iPad DRM	24.78	17.70	31.44	23.89	18.98	26.75
	[23.26, 26.40]	[16.37, 19.04]	[29.69, 33.11]	[22.62, 25.05]	[18.26, 19.76]	[25.64, 27.83]
No DRM	26.69	19.71	29.33	25.88	19.47	25.31
	[25.02, 28.21]	[18.17, 21.32]	[27.72, 30.95]	[24.87, 26.96]	[18.61, 20.37]	[24.31, 26.25]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 16: Market Shares by Piracy Experience (Online Sample) (%)*

	With Piracy Experience			Without Piracy Experience		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	24.03	16.86	23.57	26.64	18.69	23.70
	[21.51, 26.78]	[14.95, 18.99]	[21.31. 25.86]	[25.95, 27.38]	[18.11, 19.29]	[23.02. 24.40]
No Kindle DRM	30.38	16.33	22.37	29.91	18.00	22.72
	[27.78, 32.95]	[14.47, 18.40]	[20.45, 24.36]	[29.24, 30.59]	[17.40, 18.59]	[22.14, 23.37]
No Nook DRM	23.08	22.21	22.59	25.58	22.21	22.83
	[20.74, 25.58]	[20.08, 24.36]	[20.53, 24.79]	[24.90, 26.23]	[21.60, 22.86]	[22.20, 23.44]
No iPad DRM	24.12	17.12	24.15	26.97	18.96	23.41
	[21.51, 26.84]	[15.15, 19.33]	[21.91, 26.55]	[26.29, 27.68]	[18.39, 19.56]	[22.82, 23.99]
No DRM	26.96	20.49	21.34	27.71	20.35	22.16
	[24.38, 29.54]	[18.49, 22.60]	[19.37, 23.53]	[27.00, 28.43]	[19.69, 21.03]	[21.64, 22.75]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 17: Market Shares of Different E-book Readers (Student Sample) (%)*

	Kindle	Nook	iPad	Hard Copy	Welfare Change
Current	24.87	18.69	26.83	23.92	
	[24.04, 25.70]	[17.97, 19.39]	[26.08. 27.67]	[23.30, 24.50]	
Kindle, Nook Discount	23.03	16.52	28.75	25.31	-5.60%
= 40%	[22.29, 23.74]	[15.89, 17.16]	[27.97, 29.62]	[24.70, 25.88]	[-6.07%, -5.07%]
Kindle, Nook Discount	22.16	15.64	29.57	25.91	-7.45%
= 35%	[21.40, 22.89]	[15.04, 16.28]	[28.78, 30.45]	[25.32, 26.48]	[-8.08%, -6.73%]
Kindle, Nook Discount	20.64	14.25	30.94	26.91	-9.97%
= 25%	[19.87, 21.35]	[13.64, 14.89]	[30.13, 31.89]	[26.32, 27.50]	[-10.85%, -8.97%]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 18: Market Shares of Different E-book Readers (Online Sample) (%)*

	Kindle	Nook	iPad	Hard Copy	Welfare Change
Current	26.48	18.58	23.69	26.66	
	[25.82, 27.16]	[18.03, 19.15]	[23.03, 24.35]	[26.24, 27.08]	
Kindle, Nook Discount	25.64	17.49	24.67	27.46	-3.15%
= 40%	[24.95, 26.32]	[16.96, 18.06]	[23.99, 25.34]	[27.01, 27.91]	[-3.46%, -2.88%]
Kindle, Nook Discount	25.21	17.03	25.11	27.83	-4.28%
= 35%	[24.48, 25.89]	[16.51, 17.61]	[24.43, 25.79]	[27.36, 28.29]	[-4.70%, -3.90%]
Kindle, Nook Discount	24.39	16.26	25.91	28.50	-5.93%
= 25%	[23.60, 25.14]	[15.73, 16.82]	[25.22, 26.60]	[27.95, 28.98]	[-6.51%, -5.41%]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 19: Market Shares by Reading Habit (Student Sample) (%)*

	With Reading Habit			No Reading Habit		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	30.05	19.44	30.55	21.37	18.15	25.35
	[28.48, 31.54]	[18.12, 20.85]	[28.95. 32.06]	[20.15, 22.53]	[17.32, 19.11]	[24.35. 26.42]
Kindle, Nook Discount	27.67	17.58	32.89	19.48	15.82	27.42
= 40%	[26.19, 29.11]	[16.43, 18.86]	[31.26, 34.42]	[18.17, 20.68]	[14.99, 16.72]	[26.34, 28.50]
Kindle, Nook Discount	26.64	16.83	33.88	18.64	14.90	28.27
= 35%	[25.16, 28.04]	[15.73, 18.09]	[32.23, 35.45]	[17.28, 19.85]	[14.06, 15.79]	[27.16, 29.34]
Kindle, Nook Discount	24.89	15.63	35.52	17.25	13.49	29.60
= 25%	[23.46, 26.28]	[14.59, 16.80]	[33.88, 37.15]	[15.80, 18.46]	[12.60, 14.40]	[28.45, 30.69]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 20: Market Shares by Reading Habit (Online Sample) (%)*

	With Reading Habit			No Reading Habit		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	32.95	20.84	26.82	19.07	15.98	20.09
	[32.01, 33.98]	[20.01, 21.69]	[25.91. 27.77]	[18.30, 19.85]	[15.24, 16.76]	[19.38. 20.87]
Kindle, Nook Discount	31.99	19.63	28.10	18.36	15.04	20.73
= 40%	[31.00, 32.07]	[18.84, 20.52]	[27.15, 29.08]	[17.58, 19.11]	[14.31, 15.79]	[20.02, 21.50]
Kindle, Nook Discount	31.48	19.12	28.69	18.02	14.63	21.02
= 35%	[30.50, 32.55]	[18.35, 20.04]	[27.73, 29.71]	[17.24, 18.78]	[13.89, 15.39]	[20.30, 21.80]
Kindle, Nook Discount	30.49	18.26	29.74	17.40	13.96	21.53
= 25%	[29.43, 31.60]	[17.51, 19.20]	[28.77, 30.82]	[16.57, 18.26]	[13.21, 14.71]	[20.79, 22.33]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 21: Market Shares by Piracy Experience (Student Sample) (%)*

	With Piracy Experience			Without Piracy Experience		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	25.12	17.75	30.01	24.08	18.95	25.98
	[23.55, 26.76]	[16.38, 19.11]	[28.47. 31.78]	[22.90, 25.16]	[18.22, 19.77]	[25.00. 27.05]
Kindle, Nook Discount	23.12	15.61	32.38	22.00	16.77	28.06
= 40%	[21.61, 24.66]	[14.36, 16.82]	[30.77, 34.31]	[20.74, 23.11]	[16.07, 17.52]	[27.03, 29.15]
Kindle, Nook Discount	22.23	14.77	33.35	21.09	15.91	28.92
= 35%	[20.75, 23.77]	[13.56, 15.97]	[31.70, 35.30]	[19.81, 22.20]	[15.21, 16.62]	[27.88, 30.03]
Kindle, Nook Discount	20.76	13.45	34.89	19.55	14.56	30.32
= 25%	[19.29, 22.25]	[12.24, 14.69]	[33.13, 36.92]	[18.27, 20.66]	[13.87, 15.29]	[29.24, 31.44]

* The 5th and 95th percentiles of the estimates are reported in brackets.

Table 22: Market Shares by Piracy Experience (Online Sample) (%)*

	With Piracy Experience			Without Piracy Experience		
	Kindle	Nook	iPad	Kindle	Nook	iPad
Current	24.03	16.86	23.57	26.64	18.69	23.70
	[21.51, 26.78]	[14.95, 18.99]	[21.31. 25.86]	[25.95, 27.38]	[18.11, 19.29]	[23.02. 24.40]
Kindle, Nook Discount	22.99	16.26	24.53	25.81	17.57	24.68
= 40%	[20.38, 25.84]	[14.42, 18.42]	[22.15, 26.99]	[25.10, 26.51]	[17.01, 18.17]	[23.97, 25.38]
Kindle, Nook Discount	22.54	16.02	24.96	25.38	17.09	25.12
= 35%	[19.87, 25.42]	[14.16, 18.16]	[22.51, 27.41]	[24.64, 26.08]	[16.54, 17.69]	[24.42, 25.84]
Kindle, Nook Discount	21.77	15.63	25.72	24.56	16.30	25.92
= 25%	[19.02, 24.89]	[13.74, 18.00]	[23.20, 28.28]	[23.75, 25.29]	[15.74, 16.89]	[25.19, 26.67]

* The 5th and 95th percentiles of the estimates are reported in brackets.