Catching (Exclusive) Eyeballs: Multi-Homing and Platform Competition in the Magazine Industry

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Abstract Media platforms compete for both consumers and advertisers, especially when consumers divide their attention among multiple platforms. While traditional economics models assume consumers patronize a single platform ("single-homing"), I model consumer demand for multiple products ("multi-homing"), advertiser demand, and platform pricing decisions in the context of magazine markets. Using a novel data set on U.S. magazine sales at the metro level and characteristics from 2003 to 2012, and survey data that reveal consumers' order of magazine choice, I estimate the model and quantify the cross-group externalities in the magazine markets. On the reader side, I find that consumers' ad nuisance cost is approximately 5 cents per ad page - in contrast to the ad-neutrality or ad-loving findings in the print media literature. On the advertiser side, my model relates to an emerging theoretical two-sided market literature that emphasizes the importance of multi-homing. I provide the first direct evidence that media ad prices reflect advertisers' differential valuation of exclusive and shared consumers. I find that advertisers value exclusive consumers at 11 cents per eyeball, more than twice of the value of an overlapping consumer. I illustrate the importance of consumer multi-homing in a counterfactual analysis, in which demand for magazines is assumed to be as strong as in 2003. My results suggest that the rise of the Internet has caused magazines to lose proportionally more exclusive consumers than shared consumers, contributing greatly to the weakening of magazine advertising markets.

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1 Introduction

In the rapidly changing media landscape, a prominent question is how competition affects media advertising volume and revenues. This is especially important as traditional media rely more heavily on advertising revenues to finance their platforms and to provide valuable content to readers. In order to understand this, one needs to recognize the two-sided nature of media markets. In two-sided markets, two distinct groups of users interact via platforms. As applied to media markets, on one side are media consumers, and on the other side are advertisers who want to reach consumers. In between, media platforms, such as magazines, TV stations and online platforms, compete to attract consumer attention, and then sell that attention to advertisers. Standard economic analyses of media markets have been based on the assumption that consumers limit their attention to one single platform, which is called "single-homing" (SH) in the literature. This single-homing assumption implies that platforms are essentially monopolies over the fresh impressions of their consumers (e.g., Anderson and Coate 2005). While insightful, this approach has been challenged by empirical puzzles that the theory cannot explain or that contradict predictions of the theory. Moreover, it simply does not account for the fact that consumers often patronize multiple platforms for content needs (or "multi-home", MH) in reality. In response, new theoretical works that relax the single-homing assumption emerge (Ambrus, Calvano, and Reisinger 2015; Anderson, Foros, and Kind 2015; and Athey, Calvano, and Gans 2014). In this paper, I incorporate consumer multi-homing and insights from the theoretical frontier into an empirical model of two-sided magazine markets. I estimate the model with novel data on metro-level magazine sales, advertising quantities and prices, and consumers' stated order of preference to quantify the cross-group externalities in magazine markets. I demonstrate the importance of consumer multi-homing in estimating the reader demand and in shaping ad prices of platforms. In a counterfactual exercise, I illustrate how multi-homing consumers affect subscription and advertising market outcomes in a decade of Internet expansion.

Consumer multi-homing behavior has important implications for empirical economic analyses of media. First, traditional discrete choice models used in demand estimation often assume that consumers buy only one product. The single-purchasing assumption - which translates exactly to the single-homing assumption in the two-sided market context - can be problematic if the data are in fact generated from consumer multiple purchasing activities. Following Hendel (1999) and Fan (2013), I set up and estimate a multiple discrete choice model of magazine readers. I use a new data set that I collect from multiple sources, including detailed magazine sales at the Metropolitan Statistical Area (MSA) level in six major genres for ten years, magazine characteristics, and survey data that reveal consumers' order of preference for magazines that they have purchased. I construct moments from the novel survey data to identify the parameter that captures consumers' decrease in incremental utility from multiple purchases, which is generally unidentified with market-level data only. In contrast to findings in the established literature on print media, I find that consumers dislike magazine advertisements. In particular, one more page of ad is equivalent to an increase in subscription price by 5 cents, on average. In addition, I find heterogeneity in consumers' ad nuisance cost and in the decision whether or not to purchase magazines at all. I then compare the results to those from standard logit and mixed logit models with single-purchasing consumers. The single-homing models significantly underestimate consumers' distastes for advertisements and overestimates their tastes for other product attributes.

Second, when consumers multi-home in media markets, they spread their attention among multiple platforms. If advertisers' return to consumer attention decreases after the first impression, advertisers' willingness to pay for exclusive consumers and for shared consumers on a platform should differ. Consequentially, platform prices of advertising should reflect this advertisers' differential valuation of consumers, *ceteris paribus*. In fact, these key insights from the somewhat nascent theoretical literature have been long observed by practitioners in advertising and media industries. Regarding this point, Martin (1921, cf. Gentzkow, Shapiro, and Sinkinson 2014) writes that "*The same advertisement seen in two or three newspapers is certainly more effective than if seen in one, but some advertisers are convinced that it is not worth three times as much to have an advertisement seen in three papers, reaching largely the same readers, as to have it seen in one.*" Reflecting that observation, it is not uncommon that media compare their exclusive readerships to their closest substitutes in effort to sell advertising space. For instance, a magazine states upfront to potential advertisers that "*[Their] advertising rates are extremely cost efficient. [Their] targeted and exclusive readership means there is very little wastage.*" (Highlife Magazine 2015).[1] Motivated by these observations, on the advertiser side, I estimate an inverse demand function for advertising, including both the subscription level and the number of exclusive/single-homing consumers as explanatory variables. In particular, I use the reader-side model and the estimates to predict missing data on the number of exclusive consumers on each platform, and use the predicted values to help explain advertiser demand. I find shared consumers worth 4.9 cents per eyeball while exclusive consumers worth 12 cents or twice as much. This is one of the first evidence to support the major hypothesis in the theoretical two-sided market literature. Subsequently, I conduct a counterfactual analysis supposing demand for magazines at the end of my sample period were as strong as in 2003. The results suggest that the Internet has affected the magazine markets not only by lowering revenues from circulation but also by reducing the number of subscribers, and thus making the reader composition less favorable to platforms.

[1] See `http://highlifemagazine.com.au/advertise-with-us/`.

This paper contributes to three strands of literature. First, it is part of the literature on two-sided markets. On the theory side, Armstrong (2006) and Rochet and Tirole (2006) are the foundational pieces in the economic analysis of two-sided markets. Anderson and Coate (2005) introduces the standard model of media economics. Subsequent empirical papers that quantify indirect network effects or cross-group externalities in two-sided markets follow these earlier theory papers to assume single-homing consumers. As mentioned before, the theoretical works that relax the single-homing assumption constitute a somewhat nascent literature. I incorporate the key features of those theory models into empirical modeling. Along with Gentzkow, Shapiro, and Sinkinson (2014), this paper provides the first direct evidence to support hypotheses in the theory literature. While Gentzkow, Shapiro, and Sinkinson (2014) calibrate their model using historical data on advertising revenues of U.S. newspapers, I have data on magazine advertising quantities and prices to investigate factors that affect advertiser demand.

Second, this paper also contributes the empirical literature on media and other ad-funded markets. Like Rysman (2004), Sweeting (2010), Jeziorski (2014) and others, I estimate a micro-founded model of platform competition. Currently, the literature provides conflicting evidence regarding consumer ad preference. For instance, in television markets, Wilbur (2008) finds that the level of advertising has a negative effect on consumer utility and therefore media consumption. However, in print media like newspapers and magazines, the findings are very different. For instance, the number of ads in newspapers tend to have no impact on consumers, which then becomes a "fact" that is generally accepted and assumed in subsequent works (e.g., Gentzkow 2007; Argentesi and Filistrucchi 2007; Gentzkow, Shapiro, and Sinkinson 2014) and is confirmed by Fan (2013). When consumers do not care about advertiser participation, the full two-sided structure of market is lost. Instead, my model preserves the full two-sided market structure with each side caring about participation of the other. In the magazine industry, Kaiser and Wright (2006) find that readers of German magazines value advertisements. Kaiser and Song (2009) further suggests that magazine readers prefer more ads to content pages. [2] Using a previously unexploited data set on metro-area sales of U.S. magazines for 10 years, I find that consumers are mainly averse to magazine advertisements. On average, the ad nuisance cost is approximately 5 cents per page. I discuss the endogeneity issue related to ad pages, and compare my results to related papers with different estimation strategies.

Finally, this paper builds on other empirical models of consumer multi-purchasing behavior. Typically, demand estimation with market-level data in tradition of Berry, Levinsohn and Pakes (henceforth BLP, 1995) assumes that consumers choose only one product from a set of differentiated products. Due to the two-sided nature of media markets, the single-

[2] See Chandra and Kaiser (2015) for an extensive review on the economics of newspapers and magazines.

purchasing assumption has important implications for advertiser behavior and platform competition, as discussed earlier. Following Hendel (1999) and Fan (2013), I estimate a discrete choice model that allows consumers to choose multiple products. I also set up and estimate a model of advertiser demand consistent with multi-homing on the reader side. I augment identification of the model by using novel survey data that reveal consumers' order of preference. More broadly, my work relates to a large literature on empirical models with bundles of products. In one line of research, such as Gentzkow (2007) and Gentzkow, Shapiro, and Sinkinson (2014), the set of possible choices is defined over all bundles of products, and each bundle has an i.i.d. taste shock. A second line of research models consumption of each product as driven by a separate binary choice equation. For example, Augereau, Greenstein, and Rysman (2008) and Hiedemann, Sovinsky, and Stern (2013) use multivariate probit models. In those models, consumption of a product is independent of other products, so each product has a monopoly demand function, which is less useful for analyzing oligopoly markets. In this paper, I show an important equivalence between the type of model I use and the second type of model under some conditions.

This paper is organized as follows. The next section summarizes key features of the magazine industry. Section 3 presents a structural model of reader demand, advertiser demand and magazine decisions. Section 4 discusses the data used in this project with descriptive evidence. Section 5 explains the estimation procedure and discusses identification issues. Section 6 represents results from the estimation and from a counterfactual exercise. Section 7 concludes.

2 Industry Background

The magazine industry is characterized by a large amount of small brands and a number of giant brands. In 2012, there were 7,390 print magazine brands in the United States, and despite the impact of the Internet, this number has hardly changed since 2004 (National Directory of Magazines 2015).[3] Annually, there are approximately 300 million copies of magazine sold for single issues of magazine. Too 200 magazines account for 85% of all sales while top 50 magazines account for about 54%. By industry standards, magazines brands are usually categorized into genres (or categories), which are the bases for market reporting and analysis. In this paper, I define market segments as genres of magazines, following definitions provided by MPA and the Alliance of Audited Media (AAM).

Magazines subscription constitutes more than 93% of all sales.[4] This implies that, on average, U.S. households subscribe to between 2 and 3 magazines annually, which is consistent

[3] Data Source: The Association of Magazine Media (MPA), Kantar Media, GfK MRI and my data set.

[4] I refer to magazine consumers as readers or subscribers throughout this paper,

with Hong (2007)'s study based on the Consumer Expenditure Survey that U.S. households spend \$6-\$7 quarterly on magazines. It further indicates that, among magazine subscribers, multiple purchasing, or multi-homing *across genres* is common. Indeed, according to *Survey of the American Consumer* conducted by the media firm GfK MRI, more than 65% of a total of 23,000 surveyed households indicate a second magazine choice. These facts call for a need to incorporate multi-homing behavior into models of consumer choice in magazine markets.

Due to the rise of the Internet, consumers spend less on magazines. Hong (2007) documents that quarterly spending on magazines has dropped 29% on average from 1996 to 2002. Among Internet users, the drop is almost 50%. However, various anecdotes and researches suggest that impact of the Internet on magazines is moderate in comparison to the effects on traditional newspapers. [5] This may explain partially why the magazine industry surpassed newspapers to become the second largest advertising market in 2000's (Kantar Media 2012; the Appendices). In 2012, 80 percent of the magazine industry revenue, or \$20 billion, came from selling advertiser space. In particular, large magazines set very high prices for advertising. For the top 20 U.S. magazines, advertisers pay $\$280,000$ per page on average. For instance, the mean ad price per subscriber in my sample of major magazines is \$0.15, or \$150 for CPM (i.e., cost per thousand consumers). At the meantime, the CPM for Super Bowl ads is around \$30.

3 The Model

In a two-sided magazine market, magazine platforms sell content to readers and sell advertising space to advertisers. In this section, I describe a model of the demand for magazines, the demand for advertising, and pricing decisions of magazines. The model is estimated with new data on MSA-level magazine circulation, survey data on consumers' order of preference, and data on advertising prices and quantities. It incorporates features of the data and the magazine industry that are most relevant and important to this study - including consumer heterogeneity, multi-homing, and ad pricing based on the composition of consumers. The demand functions in Sections 3.1 and 3.2 are used directly in the estimation, and they also imply testable patterns in the data. Magazine pricing equations in Section 4.3 complete the characterization of market equilibrium. Combining with demand-side estimates, I use the pricing equations to infer marginal costs of magazines.

[5] For example, see Chandra and Kaiser (2015).

3.1 Demand for Magazines

I model consumer demand for magazines as a problem of multiple discrete choices among differentiated products. The regional demand for magazines is derived from the aggregation of multiple discrete choices of consumers. The model is needed to explain consumer multi-homing in the data and to predict the level of exclusive readerships on each platform. Based on Hendel (1999) and Fan (2013), my model allows consumers to purchase multiple magazines with diminishing utility. Using unique data on consumer rankings of products that they purchase, I add richness to identification of this type of model. I take the standard characteristic approach to model utility from a single product. I then describe how consumers may multi-purchase and the aggregation of individual choice probabilities.

Each consumer i in metro area c decides whether or not to subscribe to a set of national magazines, indexed $j \in \{1, ..., J\}$, in year t.[6] Consumers can choose the "outside" option, $j = 0$, which is to not purchase any magazine in the given set. Their utilities depend on product characteristics and also have individual-specific components. A consumer i's conditional indirect utility from purchasing a single magazine j is

$$u_{ijct} = \gamma_{ict} a_{jt} + \alpha_{ict} p^s_{jt} + x_{jt}\beta + \xi_{jt} + \Delta\xi_{jct} + \varepsilon_{ijct} \text{ for } j = 1, ..., J; \tag{1}$$

where a_{jt} is the amount of advertising carried in magazine platform j in year t, and p_{jt} is the annual subscription price. x_{jt} is a vector of magazine characteristics, including the amount of content pages, frequency of publication, and a (time-invariant) brand dummy. ξ_{jt} captures any change in the unobserved quality of magazine j in year t, while $\Delta\xi_{jct}$ captures region-time specific tastes for j and has a mean of zero.

Like in BLP (1995), there are two types of heterogeneity in consumer preferences. First, ε_{ijct} is the household-specific taste shock, and is assumed to be i.i.d. with Type I extreme value distribution. Second, households have heterogeneous tastes for magazine prices and ad levels. I define the random coefficients as

$$\begin{bmatrix} \gamma_{ict} \\ \alpha_{ict} \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\alpha} \end{bmatrix} + \begin{bmatrix} \gamma_1 \\ \alpha_1 \end{bmatrix}' z_{ict} + \Sigma\nu_{ict}, \tag{2}$$

where z_{ict} includes household demographics with $z_{ict} \sim P_{z_c}(z)$, and $\nu_{ict} \sim P_\nu(\nu)$; $P_{z_c}(z)$ is the joint distribution of demographics, $P_\nu(\nu)$ is assumed to be standard normal. γ_1 and α_1 are vectors of parameters. The sum $\bar{\gamma} + \gamma_1' \bar{z}_{ict}$ - which represents consumer mean attitude towards advertising in media - is of particular interest since the current empirical literature on newspapers and magazines provides conflicting results on its sign.

[6] I assume that all purchases are subscriptions. As discussed in Section 2, subscriptions account for 93% of all magazine circulation.

Utility from the outside option, $j = 0$, is given by

$$u_{i0ct} = \delta_{i0ct} + \varphi T - \omega z_{ict} + \varepsilon_{i0ct}, \tag{3}$$

where δ_{i0ct} is normalized to zero, T includes a set of year dummies, and ε_{i0ct} is i.i.d. with Type I extreme value distribution. I allow demographics to affect the decision whether or not to buy any magazine, in addition to interacting them with product characteristics in equation (1). I interpret the year dummies T as the effects of the Internet on traditional print media because entry/exit is not a major concern among media giants during the period that I study. *A priori*, the magnitude of T should increase over time as media consumers find it increasingly more attractive to use the Internet for information and entertainment. A similar interpretation is used in Fan (2013).

Equivalently, I write equations (1) and (3) as:

$$u_{ijct} = \delta_{jct} + \vartheta_{ijct} + \varepsilon_{ijct}, \text{ for } j = 1, ..., J; \text{ and } u_{i0ct} = \varepsilon_{i0ct}, \tag{4}$$

$$\text{where } \delta_{jct} = \bar{\gamma} a_{jt} + \bar{\alpha} p_{jt} + x_{jt}\beta - \varphi T + \xi_{jt} + \Delta\xi_{jct},$$
$$\vartheta_{ijct} = \omega z_{ict} + \gamma_1' z_{ict} a_{jt} + \alpha_1' z_{ict} p_{jt} + \gamma_2 \nu_{ict} a_{jt} + \alpha_2 \nu_{ict} p_{jt}.$$

In this notation, δ_{jct} represents the mean utility for magazine j in market ct, and $\vartheta_{ijct} + \varepsilon_{ijct}$ captures household i' idiosyncratic tastes deviating from the regional mean. Both ε_{ijct} and ν_{ict} are known to consumers but unobservable to firms and econometricians.

I now turn to describe consumer multi-purchasing decisions. The following is a heuristic description of the decision-making process of consumers. Specifically, each household chooses to subscribe to multiple magazines simultaneously, and for each magazine, they buy at most one unit of subscription. Their (first) best choice is the magazine that yields the highest utility. From the second purchase, the incremental utility from buying any product decreases by κ. Their second best choice is then the product that gives the highest utility among the unchosen products. From the n^{th} choice, the incremental utility decreases by κn. They keep purchasing until the no-purchase option prevails. I assume that consumers purchase at most four magazines.[7] The diminishing utility parameter κ captures the intuition that the utility from reading two magazines of the same genre is less than the sum of two stand-alone utilities due to - for instance - overlapping content of the magazines or time limitation of readers.

[7]This assumption is partially due to data limitations and the fact 98% of magazine subscribers buy no more than 4 magazines. Results regarding invertibility of the demand would not change qualitatively if I do not impose such a restriction. However, as I show in Appendix A.1, when $\kappa = 0$, such a restriction is in fact needed for my model to be different from a binary choice model.

Because choice events are mutually exclusive, in general, consumer i's choice probability of *ever* buying magazine j (with ct suppressed) is

$$\Pr\left(u_{ij} \geq \max_{h \in \mathcal{J}} u_{ih}\right) + \sum_{n=1}^{3} \sum_{j^{(1)} \ldots j^{(n)} \neq j} \Pr\left(u_{ij^{(1)}}, ..., u_{ij^{(n)}} > u_{ij} \geq \max_{h \neq j^{(1)} \ldots j^{(n)}} u_{ih}, u_{ij} - \kappa n \geq u_{i0}\right); \tag{5}$$

where the first term is the probability j is i's first best choice, and the subsequent terms are the probabilities of j being the $(n+1)^{th}$ best choice. For illustration, consider the case $n = 1$ (i.e., consumers can buy at most 2 products) in Fan (2013). There, consumer i's choice probability of buying magazine j is

$$\Pr\left(u_{ij} \geq \max_{h \in \mathcal{J}} u_{ih}\right) + \sum_{j^{(1)} \neq j} \Pr\left(u_{ij^{(1)}} > u_{ij} \geq \max_{h \neq j^{(1)}} u_{ih}, u_{ij} - \kappa \geq u_{i0}\right). \tag{6}$$

Let Φ_{ij}^{1} denote the probability j is i's first best choice, $\Phi_{ij}^{1,1}$ denote the probability j is i's best choice with utility decreased by κ once, and $\Phi_{ij-j^{(1)}}^{1,1}$ denote the probability j is i's best choice given $j^{(1)}$ already chosen. Notice that $\Phi_{ij-j^{(1)}}^{1,1}$ is also the probability of j being *at least* the second choice given $j^{(1)}$ may be the first. Therefore, $\Phi_{ij-j^{(1)}}^{1,1} - \Phi_{ij}^{1,1}$ is the probability of j being *exactly* the second choice given $j^{(1)}$ is the first. Since I only use the fact that these events are mutually exclusive, for a general discrete choice model, the probability consumer i purchases magazine j with the restriction $n = 1$ can be written as

$$\Phi_{ij}^{1} + \underbrace{\sum_{j^{(1)} \neq j} \left(\Phi_{ij-j^{(1)}}^{1,1} - \Phi_{ij}^{1,1}\right)}_{\Phi_{ij}^{2}}. \tag{7}$$

Similarly, I derive the expression for the case $n = 3$ in the Appendix A.2. Notice that the parameter $\kappa > 0$ and the restriction on n are needed for this model to work in an oligopoly setting. In fact, when $\kappa = 0$ and $n + 1 = J$ (i.e., consumers is free to choose any number of products without utility decrease from multiple purchases), the consumer choice problem I describe above collapses to a binary choice problem. In other words, it reduces to the situation that consumers say yes or no to each available option. Such a binary choice model implies that each product is a monopoly and all cross-price elasticities are zero. Therefore, it is not useful when I am interested in studying strategic firm behavior. I present formally the result in the Appendix A.1.

Under the assumption that ε_{ijct} is i.i.d. with Type I extreme value distribution, I can write Φ^1_{ij}, $\Phi^{1,1}_{ij-j^{(1)}}$ and $\Phi^{1,1}_{ij}$ in familiar mixed logit terms:

$$\Phi^1_{ij} = \frac{e^{\delta_j+\vartheta_{ij}}}{1+\sum_j e^{\delta_h+\vartheta_{ih}}}, \quad \Phi^{1,1}_{ij-j^{(1)}} = \frac{e^{\delta_j+\vartheta_{ij}}}{e^{\kappa}+\sum_{h\neq j^{(1)}} e^{\delta_h+\vartheta_{ih}}}, \quad \Phi^{1,1}_{ij} = \frac{e^{\delta_j+\vartheta_{ij}}}{e^{\kappa}+\sum_j e^{\delta_h+\vartheta_{ih}}};$$

which I shall use in the estimation.

Given the individual choice probability, the market demand for product j is the aggregation of each individual's choice probability of buying j. Specifically, the market penetration function of j is

$$s_j(\delta,\kappa) = \int\int \left(\Phi^1_{ij}(\delta, z, \nu) + \sum_{n=1}^{3} \Phi^{n+1}_{ij}(\delta,\kappa,z,\nu) \right) dP_v dP_z. \tag{8}$$

As discussed in detail in Section 4, I observe in the data not only sales and market penetration of each magazine at the aggregate level but also the proportion of subscribers who purchase j as their first to fourth choices. So I can match each of $\Phi^m_j = \int\int \Phi^m_{ij} dP_v dP_z$ to corresponding moments in the data.

Via expressions (7) and (8), this model implies that magazines with larger sales, $\mathcal{M}s_j$, should have larger numbers of subscribers who rank them as the best.[8] Intuitively, magazines that sell a lot of subscriptions have higher mean consumer valuations, which lead to many of the subscribers regarding them as the best. This is the first important link that I examine with the data. Fail to see such a relationship in the data would lead to immediate rejection of the model. In Section 5, I present data patterns in support of this relationship.

Furthermore, it is useful to write down the expression for the proportion of exclusive readerships in platform j - consumers who subscribe to magazine j only:

$$\tilde{\tau}_j(\delta,\kappa) = \int\int \left(\Phi^1_{ij}(\delta,z,\nu) \cdot \Phi^{1,1}_{i0-j} \right) dP_v dP_z \tag{9}$$

where

$$\Phi^{1,1}_{i0-j} = \frac{e^{\kappa}}{e^{\kappa}+\sum_{h\neq j} e^{\delta_h+\vartheta_{ih}}}. \tag{10}$$

In words, magazine j's exclusive eyeballs are consumers who choose j as the first choice only and no other magazines. The proportion/number of exclusive eyeballs on platform j is thus a (non-linear) function of the percentage/number of buyers who regard the product as the best. This relationship provides the second important link that I shall revisit when I formulate the demand for advertising in later sections. In addition, for each magazine

[8] To see that, first notice Φ^1_{ij} is increasing in δ_j, the mean utility for j. By invertibility of the market penetration function shown in Appendix A.2, a large penetration s_j, implies a large δ_j. It follows immediately that a large penetration implies large Φ^1_{ij}, hence large Φ^1_j.

j, equation (9) is used to predict missing data on exclusive readerships, which are the key variable to explain ad pricing of magazines.

3.2 Demand for Advertising

I model advertisers through their aggregate demand for advertising on magazine platform j. The model is stylized to best suit the data on aggregate magazine advertising prices and quantities. But nonetheless, it captures consistently important features of the magazine industry. In particular, it echoes the formulation in the theoretical literature on two-sided market competition with multi-homing. Estimating the advertiser demand, I provide the first direct evidence that media advertising prices reflect advertisers' differential valuation of exclusive and non-exclusive eyeballs. The latter hypothesis is constructed in the theoretical literature to confront real-world puzzles that platforms with large audiences often charge higher per-audience ad prices.

Consider a continuum of advertisers indexed by a. Each advertiser can place one ad on platform j in order to reach the subscribers. The first impression to a subscriber is worth λ_1 to advertisers, and all subsequent impressions are worth λ_2, with $\lambda_1 > \lambda_2$. For any given set of demand shifters, advertisers are ranked in terms of their willingness to pay in descending order: the reservation price of advertiser a is $p_j(a)$. The advertiser with the lowest reservation price is willing to pay λ_1 per exclusive subscriber. Therefore, an advertiser is only willing to pay λ_2 for each pair of non-exclusive eyeballs. I assume the following linear inverse demand function for advertising in platform j:[9]

$$p^a_{jt} = \lambda_0 + \lambda_1 \tau^e_{jt} + \lambda_2 \tau^o_{jt} + \lambda_3 a_{jt} + \eta_j + \phi T + \epsilon_{jt}, \tag{11}$$

where p^a_{jt} is magazine j's per-page advertising price. τ^e_{jt} and τ^o_{jt} represents the level of exclusive readers and non-exclusive readers, respectively. By definition, $\tau^e_{jt} = \mathcal{M}\tilde{\tau}_{jt}$ and $\tau^o_{jt} = N^s_{jt} - \tau^e_{jt}$, with N^s_{jt} being the subscription level of magazine j. a_{jt} is the ad level, and T is the set of time dummies. ϵ_{jt} is an i.i.d. and mean zero demand shock.

Substituting $\tau^o_{jt} = N^s_{jt} - \tau^e_{jt}$ into equation (9) yields the following estimatable equation:

$$p^a_{jt} = \lambda_0 + \tilde{\lambda_1} \tau^e_{jt} + \lambda_2 N^s_{jt} + \lambda_3 a_{jt} + \eta_j + \mathcal{T} + \epsilon_{jt}, \tag{12}$$

where $\tilde{\lambda_1} = \lambda_1 - \lambda_2$ while all other coefficients have the same interpretations as in (9). If consumers' first impressions are more valuable than subsequent ones, then I expect $\tilde{\lambda_1} > 0$. Failure to include data on τ^e_{jt} when $\tilde{\lambda_1}$ is significantly greater than zero would create an

[9] I assume that advertisers have always reached non-exclusive subscribers elsewhere besides J platforms. This implies whether advertisers multi-home or not, they never capture the first impressions of non-exclusive consumers.

upward bias in the estimate of λ_2 and would result in incorrectly estimating a platform's pricing capability.

This specification captures important insights in the theoretical two-sided market literature: when consumers multi-home in media markets and returns to consumer impression drops after the first impression, platform advertising prices should reflect advertisers' differential valuation of consumers. In particular, ad prices should reflect the demand-side phenomenon that advertisers value exclusive eyeballs of single-homing consumers more than non-exclusive ones. It becomes useful in explaining the so-called "ITV premium puzzle" - media platforms with larger penetration have greater per-audience ad prices - that contribute to motivate the somewhat nascent literature on multi-homing in two-sided markets. I defer the discussion to Section 3.3, when I lay out the platforms' maximization problem.

3.3 Magazine Platforms

Magazine platforms are assumed to set their product characteristics before prices. So, I view product characteristics as exogenous to both the subscription price and the number of ads. Magazines choose subscription prices and ad levels simultaneously. Observing subscription prices and anticipating the amount of advertising on each platform, consumers make their subscription decisions as the result of utility maximization. Given both the subscription level and the composition of reader base, each magazine chooses the amount of advertising to include, which yields correspondingly the per-page advertising price. At the same time, advertisers get admitted based on their willingness to pay.

In reality, consumers often do not observe the annual total number of ads when they decide to purchase a magazine subscription. However, they should rationally anticipate the amount of ads in each magazine, and in equilibrium, their expectation should be consistent with the realized ad level. Therefore, when setting the number of ads to carry, platforms need to internalize the effects of more ads on the subscription market, which in turn affects the profitability of the advertising market.

Let $N^s_{jt} \equiv \sum_c \mathcal{M}_{ct} s_{jct}$. Magazine j's profit maximization problem is therefore

$$\max_{p^s_{jt}, a_{jt}} \pi_{jt} = \underbrace{N^s_{jt}(\mathbf{p}^s, \mathbf{a})(p^s_{jt} - c^s_{jt})}_{\text{circulation profit}} + \underbrace{a_{jt}(p^a_{jt}(a_{jt}, \tau^e_{jt}(\mathbf{p}^s, \mathbf{a}), N^s_{jt}(\mathbf{p}^s, \mathbf{a})) - c^a_{jt})}_{\text{advertising profit}}; \tag{13}$$

where c^s and c^a are j's marginal costs associated with circulation and providing advertising space, respectively. c^s reflects the marginal cost of physical production of each copy, while c^a captures marginal costs of advertising, such as costs of production and sales efforts. In words, magazine j's total profit comes from both selling and delivering copies to subscribers and selling advertising pages to advertisers.

The Nash equilibrium in magazine markets is closed by each magazine's first-order conditions from the optimization problem:

$$N_{jt}^s + \frac{\partial N_{jt}^s}{\partial p_{jt}^s}(p_{jt}^s - c_{jt}^s) + (\frac{\partial p_{jt}^a}{\partial \tau_{jt}^e}\frac{\partial \tau_{jt}^e}{\partial p_{jt}^s} + \frac{\partial p_{jt}^a}{\partial N_{jt}^s}\frac{\partial N_{jt}^s}{\partial p_{jt}^s})a_{jt} = 0, \tag{14}$$

and

$$\frac{\partial N_{jt}^s}{\partial a_{jt}}(p_{jt}^s - c_{jt}^s) + a_{jt}(\frac{\partial p_{jt}^a}{\partial \tau_{jt}^e}\frac{\partial \tau_{jt}^e}{\partial a_{jt}} + \frac{\partial p_{jt}^a}{\partial N_{jt}^s}\frac{\partial N_{jt}^s}{\partial a_{jt}}) + p_{jt}^a + a_{jt}\frac{\partial p_{jt}^a}{\partial a_{jt}} - c_{jt}^a = 0, \tag{15}$$

where $\frac{\partial N_{jt}^s}{\partial p_{jt}^s} = \sum_c \mathcal{M}_{ct}\frac{\partial s_{jct}}{\partial p_{jt}^s}$.

The FOCs from equations (12) and (13) implicitly define the equilibrium subscription prices and ad levels of platforms. Notice that in (14), the third term captures the effects of a subscription price change on platform j's profitability in the advertising market, due to the two-sidedness of magazine markets. In equilibrium, subscription prices have indirect effects on ad prices through their impacts on both the subscription level and the composition of subscribers. Without the third term, (14) is the FOC in standard Bertrand games. Similarly, in Equation (15), the first term is the effect of a change in the ad level on the subscription market. The second term captures the feedback effects of a change in the ad level on the advertising market through numbers of subscribers and exclusive subscribers. Without these terms, Equation (15) is the standard monopolist FOC. Equation (15) implies that there is no direct price competition in the advertising market, although platforms compete indirectly for advertisers via N_{jt}^s and τ_{jt}^e.[10]

The FOCs - in conjunction with the demand-side equations and observations - are useful to help us understand the empirical puzzle that larger platforms charge greater ad prices per-audience. In particular, the demand functions imply that platforms with larger penetration also have more exclusive eyeballs. Since platform ad prices reflect not only the subscription level but also the composition, one would see larger platforms charge higher ad prices even after accounting for their audience base.

Following BLP (1995) and subsequent papers, I derive the following equations to infer marginal costs of each magazine. Let $\mathcal{O}$ be the ownership matrix with elements $\mathcal{O}(h, j) = 1$ if magazine h and j have the same publisher, and zero otherwise. Let ∇_p^s be a matrix containing all of the first partial derivatives of penetration with respect subscription prices, with elements $\nabla_p^s(h, j) = \frac{\partial N_j^s}{\partial p_h^s}$. Similarly, denote Let ∇_p^r with elements $\nabla_p^r(h, j) = \frac{\partial \tau_j^e}{\partial p_h^s}$. Define ∇_a^s and ∇_a^r similarly for ad pages. So the mark-ups can be computed using the following

[10]Although the advertiser demand function is in the same spirit of recent theoretical advancements; i.e., Anderson et al. (2015). It nonetheless implies monopoly advertising markets while Anderson et al. derives the pricing equation based on a Bertrand-type model. A model that allows both direct price competition for advertisers and consumer multi-homing and that is estimable with aggregate data is yet to be developed.

FOCs written in matrix forms:

$$\mathbf{p^s} - \mathbf{c}^s = -(\lambda_2 \mathbf{a} + (\mathcal{O} * \nabla_p^s)^{-1}(\mathbf{N^s} + \tilde{\lambda}_1(\mathcal{O} * \nabla_p^\tau))); \tag{16}$$

and

$$\mathbf{p^a} - \mathbf{c^a} = (\mathcal{O} * \nabla_a^s) \cdot (-(\mathcal{O} * \nabla_p^s)^{-1}(\mathbf{N^s} + \tilde{\lambda}_1(\mathcal{O} * \nabla_p^\tau))) + (\mathcal{O} * \nabla_a^\tau) \cdot \mathbf{a} - \lambda_3 \mathbf{a}. \tag{17}$$

where I plug the FOC (14) into (15).

4 Data

4.1 Data Description

I estimate the model using new data on magazine circulation at the MSA level, magazine characteristics, consumer rankings of magazines, and household demographics from four main sources. On the reader demand side, I observe circulation of magazines in nearly all MSAs in the U.S. between 2003-2012. For a subset of magazines, I also observe aggregate percentages of subscribers rank a magazine as their first to fifth choice. I match these penetration and circulation data with product-level magazine prices, ad pages, and other attributes to create a panel of 34 magazines for 10 years. The magazines are the major products in six different genres defined by the Association of Magazine Media (MPA) and the Alliance of Audited Media (AAM). Because circulation is at the regional level while product attributes of a magazine do not vary across regions, I include data on household demographics to explain geographical variation in circulation of a same magazine. To estimate the advertiser side of my model, I use product-level data on advertising pages, prices and other characteristics for the panel of 340 magazine/years. For robustness checks, I use a panel of 640 magazine/years, including magazines with missing sales information. I include more details on magazine titles and data sources in the Appendices.

I collect detailed magazine circulation data from the 2003-2012 *Magazine Market Coverage* reports administered by the AAM, the organization that audits U.S. print media circulation and other related information.[11] For each magazine, I observe magazine circulation and penetration in each MSA for 10 years. By definition, market penetration is calculated by dividing total circulation in a region by the number of households. The reports also provide each region's number of households, which is the measurement of market size used in print

[11]The AAM is formerly known as the Audit Bureau of Circulation, or ABC. The name was changed in 2012. Fan (2013) and Gentzkow et al. (2014) use the analogous AAM reports on newspaper circulation; the coverage reports on magazines are relative new.

media industries and in the literature.

Magazine subscription prices, ownership and frequencies of publication come from individual audit reports on magazines from the AAM. In particular, the annual subscription price of a magazine is the reported average of subscription prices paid by all subscribers, accounting for discounts and promotions. It is therefore not the listed price. Frequencies of publication include the number of special issues and supplements in addition to regular issues. Content page numbers come from MA-focus Media, a media research firm that systematically collects page information on major U.S. magazines. Advertising pages and rates come from the Publishing Information Bureau (PIB) affiliated with the Kantar Media. For each magazine/year, I observe the total number of advertising pages and revenues. I calculate the average per-page advertising price by dividing total ad revenues with ad page numbers.

Table 3 reports the summary statistics for magazine sales and attributes. The magazines of this study are large platforms in terms of reader base: an average magazine has about 1.3 million subscribers, reaching more than 1% of all U.S. households. The mean market penetration of all magazines in all regions is 1.53%. For the metro-level penetration data to be useful, market penetration for the same magazine/year should vary across regions. Table 11 in the Appendices provides a snapshot of penetration of all magazines. From that, one can see substantial geographical variation in a magazine's penetration levels for all magazines in 2012. Indeed, similar patterns are observed in all years.

For comparison, I include means of magazine attributes for the panel of 64 magazines. The sample of 34 magazines for my main analysis tends to have slightly more circulation on average, more ad pages, higher ad prices and less content pages. This reflects partially that they are the major players in the most popular genres.

In Table 3, I also include the summary statistics of two more variables constructed from the main variables. They are not used in the estimation, but are important for us to understand large magazine platforms. First, the mean per-page ad price is 15 cents per subscriber or $150 per thousand household. The latter measurement is often called "cost per mille" (CPM) or cost per thousand consumer in the advertising industry. Magazines that I study here have very large CPMs, ranging from $10 to $1240. In other media like online search engines, newspapers, radio and TV, CPMs usually lie between $5 to $30, although CPMs in print media may be not directly comparable to TV and websites.[12] For example, the CPM for Super Bowl ads is between $25 and $30. It follows that advertisers must have derived large benefits per eyeball in these magazine platforms. Second, the average ad-to-non-ad-

[12]The advertising industry uses the term "CPM" indiscriminately in all media. However, as pointed out by Tirole and Rochet (2005), the CPM is charged based on *membership* in print media, while in TV, radio and websites, it is often based on usage.

Table 1: Summary Statistics of Main Variables

	Main sample for analysis (34 magazines)				(64 magazines)
	Mean	SD	Min	Max	Mean
Market penetration (%)	1.53	1.21	0	27.5	-
Total circulation (1000)	1384.86	898.84	362.70	4209.68	1324.12
Subscription price ($)	17.64	6.99	8.42	50.60	20.60
Ad pages (100 pages)	13.19	6.43	2.31	34.86	11.56
Ad price ($1000/page)	166.24	120.10	46.71	1400.57	147.73
Content pages (100 pages)	13.17	3.49	7.21	25.22	14.27
Frequency (issues/year)	12.30	2.74	8	27	15.97
Additional summary stats:					
Per-subscriber ad price ($)	0.15	0.12	0.01	1.24	0.14
Ad/total page ratio (%)	48.25	9.21	14.95	70.11	47.17

Notes: For market penetration, the unit of observation is a magazine/MSA/year. The number of observation is 110,419. For other product-level variables, the unit of observation is a magazine/year. The number of observation is 340 for 34 magazines in 10 years.

page ratio is approximately 1 : 1. This is consistent with the industry average (Magazine Publishing Association 2013). It is high in comparison to ads in other media. For instance, Wilbur (2008) reports a ratio between 1 : 5 to 1 : 4 in various television programs. In other words, consumers encounter more ads relative to the content in magazines than in other media.

I supplement the main data on magazine circulation and attributes with two additional sets of data. I use data on consumer rankings of U.S. magazines from the 2013 *Survey of the American Consumer*, administered by the media research firm GfK MRI. Along with demographics and other questions, the survey particularly asks consumers to rate magazines that they purchase as their best choice and so on. I observe percentages of each rating group for magazines in 2013. I interpret the data as proportions of consumers who regard a magazine as their first to fourth choices, corresponding to the functions in Section 4.1. These data allow me to construct more moments to identify demand parameters, especially the utility decrease parameter κ, which is usually unidentified with only market-level sales data. Finally, household demographics come from the American Community Survey microdata available on IPUMS.

4.2 Descriptive Evidence

The model that I describe in Section 4 implies certain testable patterns in the data. First, the reader demand function (8) implies that magazines should have more consumers regarding them as the first best if they sell more subscriptions. This is the case because there is a one-to-one mapping between market penetration and consumers' mean product utilities. Since higher mean product utilities also lead to more first-best consumers, large platforms should have more first-best consumers. To investigate this relationship in the data, I run a regression of the number of first-best consumers of a magazine on its total subscription. I have only 34 product-level observations since I only have the survey data for the year of 2012-2013. I report the coefficient in Table 4. Despite the small sample size, the correlation is clearly present. In addition, the overall fit (i.e., $R^2 = 0.95$) seems surprisingly good given the sample size. In this regard, the pattern shown in the data is consistent with my model.

One important goal of this paper is to estimate advertiser demand when consumers multi-home. Specifically, a magazine's advertising price should reflect not only the number of its subscribers but also the number of consumers who can be reached only through its platform,*ceteris paribus*. Since the number of exclusive consumers on each platform is not observed in the data, running an OLS regression of ad prices on subscription levels without information on the reader composition would overestimate the weight of a consumer. However, equation (9) states that the number of exclusive consumers is a (non-linear) function of the number of first-best consumers. It suggests that the number of first-best consumers is correlated with the number of exclusive consumers. Table 5 presents the results when I use the number of first-choice consumers as an explanatory variable. In specification (1), I run an OLS of ad price on total subscription. The estimates says that, *ceteris paribus*, a magazine's ad price (per page) increases by \$72.32 for every 1,000 additional subscribers. In my model, it is equivalent to say that advertisers value consumers at \$.72 per eyeball. In specification (2), I include the number of first-best consumers as a proxy for unobserved exclusive eyeballs. The estimated coefficient on the number of subscribers decreases to 43.44. This is evidence that overlooking consumer composition when consumers multi-home generates bias on the advertiser demand estimates. Therefore, it is important to account for the value of exclusive consumers in the study of advertiser demand and platform pricing in two-sided markets.

Table 2: Larger Platforms with More First-Choice Consumers

Dependent variable: Number of 1^{st}-choice subscribers	
Total subscription	0.24*** (0.02)
R^2	0.95
No. magazines	34

Notes: Control variables include publisher dummies. The degree of freedom is 22.

Table 3: Using the Number of First-Choice Subscribers to Explain the Ad Price

Dependent variable: per-page ad price		
	(1)	(2)
Total subscription	72.32*** (6.70)	43.44*** (13.25)
No. 1st-choice subscribers	-	153.03*** (62.57)
R^2	0.89	0.92
No. of magazines	34	34

Notes: Subscription levels are measured in 1,000 subscribers. Control variables include the number of ad pages and a full set of publisher dummies. The degree of freedom is 20.

5 Estimation and Identification

I estimate the reader demand equation (8) using the Method of Simulated Moments in the spirit of Berry, Levinsohn, and Pakes (2004). The parameters to be estimated are the household tastes for price, ad level, and magazine characteristics. In addition to the product-level moments originally used in BLP, I augment identification of the taste parameters with additional moments constructed from survey data on consumer rankings of magazines as described in Section 5.1. The advertiser demand equation (12) is estimated separately using GMM. Below, I first present the moments and the estimation procedure in Section 6.1. In Section 6.2., I discuss identification of the parameters and presents instruments.

5.1 Moments

To estimate the reader demand, I use three sets of moments. First, I use the standard BLP moments that the unobserved product quality ξ_{jt} should be orthogonal to some instruments. Let ξ be a vector of unobserved product quality and $\mathbf{Z_1}$ be a set of instruments. The moment conditions are

$$G^1(\theta_1) \equiv E[\xi' \mathbf{Z_1}] = 0. \tag{18}$$

Since ξ_{jt} is unobserved, I recover ξ_{jt} from the data. Specifically, let $\mathbf{s}(\delta(\theta))$ be a vector of predicted market penetration and $\mathcal{S}$ be a vector of corresponding data. θ_1 consists of parameters entering into the (regional) mean utility part. I solve for $\delta(\theta)$, which is the implicit solution to the system $\mathbf{s}(\delta) = \mathcal{S}$. In the case of a multiple discrete choice model, Fan (2013) establishes the invertibility of demand functions and proves the contraction mapping used in BLP is valid for computing δ. I discuss ingredients of the proof in the Appendices.

In step 1, I use simulation to approximate regional market penetration $\mathbf{s}$. For each MSA/year, I randomly draw individuals from the census data, each characterized by their demographic characteristics and a population weight, ω. Conditional on the draws, I simulate unobserved taste parameter from the standard normal distribution, using antithetic acceleration to reduce variance introduced by simulation error, as suggested by Stern (1997). For a guess of θ_2, which are parameters entering into the individual specific tastes, the simulated market penetration is

$$s_{jct} = \sum_{r}^{R} \left(\Phi^1(\delta(\theta_1), \nu_i^r(\theta_2)) + \sum_{n=1}^{4} \Phi^{n+1}(\delta(\theta_1), \nu_i^r(\theta_2)) \right) \omega_r; \tag{19}$$

where r denotes simulated draws.

In step 2, I use the BLP contraction mapping to obtain a vector of product-region-year specific mean utility parameters δ_{jct}. In particular, the BLP contraction mapping converts a non-linear search problem (i.e., searching for δ such that $\mathbf{s}(\delta(\theta_\mathbf{1})) = \mathcal{S}$) to a linear one. So even δ has a large number of elements, the solution emerges quickly. To recover ξ_{jt} given δ,, I define $\tilde{\xi}_{jt} = \bar{\gamma} a_{jt} + \bar{\alpha} p_{jt} + x_{jt}\beta + \xi_{jt}$ as the mean utility for product j, including both mean tastes for observed characteristics and unobserved quality. It follows that $\delta_{jct} = \tilde{\xi}_{jt} - t + \eta_{jct}$. In step 3, as suggested by Nevo (2001), $\tilde{\xi}_{jt}$ is estimated by running a GLS regression of δ_{jct} on a full set of product dummies. Finally, $\xi_{jt} = \tilde{\xi}_{jt} - \bar{\gamma} a_{jt} - \bar{\alpha} p_{jt} - x_{jt}\beta$.

Notice that the first set of moments consists of product-level moments. Using the condition $\mathbf{s}(\delta(\theta)) = \mathcal{S}$ again, for given $\delta(\theta_1)$, I construct additional moments as follows:

$$G^2(\theta_2) \equiv \sum_t \sum_j \sum_c (\mathcal{S}_{jct} - s_{jct}(\theta_2))\mathbf{Z_2^r} = 0; \tag{20}$$

where the vector of instruments $\mathbf{Z_2^r}$ consists of average simulated demographics interacting with exogenous product-level instruments. I use these moments to search for θ_2 with given δ.

The third set of moments matches the percentages of first to fourth choice consumers predicted by the model to the observed percentages in the magazine survey data. Let $\mathbf{\Phi}_j$ be a vector with elements $\mathbf{\Phi}_j^1$ to $\mathbf{\Phi}_j^4$ as in (6). I stack $\mathbf{\Phi}_j$ for all j to construct the vector $\mathbf{\Phi}$. Let Φ^{data} be a vector of corresponding data. The third set of moments is then given by:

$$G^3(\theta) \equiv (\Phi^{data} - \mathbf{\Phi})' \, \mathbf{Z_1} = 0. \tag{21}$$

As I discuss in the next section, the third set of moments help identify the utility decrease parameter κ.

I stack the moments and search for θ that minimizes the weighted distance; formally,

$$\theta^* = \arg\min_\theta G(\theta)' \mathcal{W} G(\theta), \tag{22}$$

where

$$G(\theta) = \begin{pmatrix} G^1(\theta_1) \\ G^2(\theta_2) \\ G^3(\theta) \end{pmatrix}, \tag{23}$$

and $\mathcal{W}$ is a positive definite weighting matrix. I follow the standard method by first assuming homoscedasticity and using $(Z'Z)^{-1}$ to obtain a consistent estimate of θ. I then use this estimate to get $EG(\hat{\theta})G(\hat{\theta})'$, which is subsequently used to get the final estimate of θ.

The advertiser demand (12) is estimated separately from the reader demand side using GMM. I use estimates from the reader demand to predict the number of exclusive eyeballs on each platform, which enters equation (12) as an explanatory variable. The moment condition is that the unobserved ad demand shifter ϵ_{jt} is orthogonal to some instruments $\mathbf{Z_3}$.

5.2 Identification

There are two issues of identification in this study. The first issue is about identification of non-linear models. In general, besides any endogeneity issue, covariation of market penetration and relevant right-hand-side product attributes identifies parameters in θ_1 that enter into the mean utility part in (8). Geographical variation in penetration of a same magazine identifies parameters in θ_2 that enter into the individual specific tastes. The utility decrease parameter κ is identified with the survey data. In the literature, parameters with a similar connotation are identified either with individual-level data (e.g., Gentzkow 2007) or under the assumption that some markets are monopolies (e.g., Fan 2013). The survey data provide another unique opportunity to identify κ. In particular, the percentages of first choice consumers Φ_j^1 are independent of κ while others are functions of κ. Suppose I can estimate θ solely from Φ_j^1, which are similar to "market share" function generated from the standard mixed logit model. I can then calculate percentages of second- to fourth-choice consumers based on the estimates while assuming $\kappa = 0$. The difference between the calculated percentages and the data is necessarily explained by κ.

The second issue of identification concerns potential endogeneity of some of the variables. In the estimation of reader demand, the subscription price p_{jt}^s and the number of advertising page a_{jt} may be endogenous since they can correlated with the unobserved quality component ξ_{jt}. Due to the three-way panel structure of the data, I can include brand dummies and time dummies in the estimation. Those dummies remove any unobserved product-specific and time-specific factors. To further address the endogeneity problem, I use three sets of instruments commonly used in the empirical IO literature. The first set of IVs consists of "BLP-type instruments". They include the number of products and average characteristics of other products of the same genre. In principle, they should satisfy instrument relevance because of the oligopoly market structure. They are exogenous because it is assumed that product characteristics are per-determined. The second set of so-called "Hausman-type instruments" includes average subscription price, ad pages, and content pages of products of different genres by the same publisher. They are correlated with own price and ad pages due to cost-side factors common to a publisher. They are exogenous because each genre is a separate market segment. Kaiser and Song (2009) use similar instruments in the context of German magazines. I also include a full set of publisher dummies to account for any unobserved time-invariant cost factors. After controlling for product fixed effects, publisher dummies should be uncorrelated with unobserved consumer tastes.

In MSM or GMM, there is no "first stage" as in two stage least stage (2SLS). To test instrument relevance, I run regressions similar to the first stage regression in 2SLS by regressing the endogenous variables on both the included and excluded instruments. I present the

Table 4: Instrument Relevance for Endogenous Price and Ad pages

	Endogenous variables	
	Subscription price	Ad pages
Included instruments		
Content pages	1.36***	1.29***
	(0.09)	(0.10)
Frequency of publication	-0.60***	0.20
	(0.20)	(0.23)
Excluded instruments		
IV BLP 1	-0.28*	-0.10
	(0.15)	(0.17)
IV BLP 2	-0.62***	0.09
	(0.13)	(0.15)
IV BLP 3	-0.58***	0.25
	(0.21)	(0.25)
IV Hausman 1	0.14	-0.82*
	(0.39)	(0.46)
IV Hausman 2	7.92***	0.42**
	(1.24)	(0.18)
IV Hausman 3	-0.05	-0.76
	(0.15)	(1.34)
Publisher dummy 1	-17.93***	-10.27**
	(3.43)	(4.91)
Publisher dummy 2	-13.42***	-0.88
	(4.02)	(1.41)
Publisher dummy 3	-17.13***	-1.30
	(4.15)	(1.03)
Publisher dummy 4	-15.81***	1.49
	4.81	(1.20)
Publisher dummy 5	-5.43*	-16.15***
	(2.91)	(4.04)
Publisher dummy 6	2.81	-8.66*
	(2.78)	(4.44)
Publisher dummy 7	-1.88	-9.76**
	(2.67)	(4.53)
Publisher dummy 8	-6.45**	-4.76
	(2.87)	(4.62)
Publisher dummy 9	16.31***	-5.81
	(3.83)	(4.93)
Publisher dummy 10	-14.70***	-6.10
	(4.37)	(5.14)
R^2	0.79	0.66
F-test	59.08	29.96

Notes: This table summarizes estimates from "first stage" regressions on the endogenous variables. The degree of freedom is 290. *, **, *** denotes 1%-, 5%-, and 10%- significance level, respectively.

Table 5: IV Robustness

Predicted subscription price				
	$\hat{p}^s$	$\hat{p}^s_1$	$\hat{p}^s_2$	$\hat{p}^s_3$
$\hat{p}^s$	1			
$\hat{p}^s_1$	0.94	1		
$\hat{p}^s_2$	0.98	0.92	1	
$\hat{p}^s_3$	0.91	0.85	0.94	1

Predicted ad pages				
	$\hat{a}$	$\hat{a}_1$	$\hat{a}_2$	$\hat{a}_3$
$\hat{a}$	1			
$\hat{a}_1$	0.99	1		
$\hat{a}_2$	0.99	0.99	1	
$\hat{a}_3$	0.95	0.95	0.96	1

Notes: $\hat{p}^s$ is the predicted value of subscription price using all 3 sets of IVs, and $\hat{p}^s_1$ is the predicted value of subscription price using all but the first set of IVs, etc.

"first stage" results in Table 4. In the subscription price equation, coefficients on excluded instruments are mostly significant, and their signs seem largely intuitive. In the ad page equation, many cost-related instruments, such as average subscription price and ad pages of other genres by the same publisher (i.e., IV Hausman 1 and IV Hausman 2) and publisher dummies, are highly correlated with ad pages. Based on the F-statistics, the IVs are also jointly significant in both regressions. I run additional robustness checks on the instruments. In particular, for each endogenous variable, I run three separate "first stage" regressions, removing one set of instruments at a time.[13] Then, I check correlations among the predicted values of an endogenous variable: for the final estimates to be robust to the choice of instruments, the predicted values using only parts but not all of the instruments should be highly correlated. Table 5 summarizes their correlations. For example, the correlation between the predicted value of subscription price without the first set of IVs, $\hat{p}^s_1$, and the predicted value without the second set of IVs, $\hat{p}^s_2$, is 0.92. The correlation between the predicted value of ad pages without the first set of IVs, $\hat{a}_1$, and the predicted value without the second set of IVs, $\hat{a}_2$, is 0.99. Because the predicted values are highly correlated, the results are not sensitive to the inclusion of any particular set of instruments.

[13] For estimates from the "first stage" regressions using subsets of IVs, see Table 14 in the Appendices.

For the advertiser demand, I use similar instruments to address the endogeneity of ad pages, the subscription level and the number of exclusive eyeballs. However, one may argue the endogeneity problem in this case is somewhat questionable since advertisers often observe a similar amount of information when they purchase ad spots on magazines. Therefore, there should not be any omitted variable left in ϵ_{jt}, which is then a pure demand shock to advertisers.

6 Results

6.1 Reader Demand Estimates

In this section, I present results of reader demand estimation. Table 6 summarizes the estimates and standard errors for the main variables. I find that consumers dislike advertising pages in magazines. For an average consumer, one more advertising page in a year is equivalent to an increase to the annual subscription price by $0.05. The magnitude of such equivalence varies across consumers since the random utility associated with the subscription price and ad pages are significant. For example, the males dislike magazine advertising more than the females do. Consumers with less school years and lower income dislike ads more. However, consumers differ only slightly in their attitudes towards magazine advertising. This result is in contract to the findings in other empirical studies on print media. For example, various works find that readers are ad-neutral in newspaper markets.[14] Using data on German magazines, recent works find ad-loving consumers. In particular, Kaiser and Song (2009) find that, in six genres of German magazines, consumers prefer magazines that have higher proportions of ads. Their results can be puzzling since magazine should not include content pages if readers prefer ads to non-ad pages. My finding is largely consistent with findings in other media, such as TV and radio.

Quantifying and understanding cross-group externalities and indirect network effects is important in two-sided markets. To investigate issues behind the identification of consumer ad preference parameter, I estimate a series of logit equations with different specifications. The results are reported in Table 7. Specification (1) is logit model without year fixed effects and product fixed effects, (2) is logit with year and product fixed effects, (3) and (4) are the IV versions of those with instruments as described in Section 5. In my case, the negative correlation between the number of advertising pages and magazine penetration is present in the original data. This is reflected in specification (1), in which the coefficient on ad pages is negative when no effect has been taken to address the endogeneity problem of

[14] See Gentzkow (2007) and Fan (2013) for examples with structural models. A detailed survey on related studies is provided by Chandra and Kaiser (2015).

Table 6: Estimates for Main Reader Demand Parameters

Variable	Parameter	Estimate	Standard Error
Subscription price	$\bar{\alpha}$	-0.267	0.015
Interacting with			
log(HH income)	α_1	0.022	0.001
Ad pages	$\bar{\gamma}$	-1.039	0.203
Interacting with			
log(HH income)	γ_{11}	1.1E-4	1.8E-5
HH sex ratio	γ_{12}	-3.6E-4	1.1E-4
education	γ_{13}	1.2E-5	5.60E-06
Content pages	β_1	0.031	0.018
Frequency	β_2	0.022	0.003
Diminishing utility	κ	-1.920	0.387
Year dummies	φ_{2004}	-0.009	0.006
	φ_{2005}	-0.017	0.006
	φ_{2006}	-0.004	0.006
	φ_{2007}	-0.006	0.007
	φ_{2008}	-0.039	0.008
	φ_{2009}	-0.028	0.008
	φ_{2010}	-0.074	0.008
	φ_{2011}	-0.048	0.008
	φ_{2012}	-0.036	0.008

ad volume. However, one can see both subscription price and ad pages suffer from severe endogeneity issues. This is seen by comparing specification (1) and (3), and (2) and (4). When I use instruments, the coefficient on price and advertising all become more negative, which confirms our suspicion that magazines have higher unobserved quality charge higher prices and have more advertising pages. Nevertheless, I cannot rule out the possibility that difference between my findings and other empirical works is due to cross-country and/or cross media differences in consumers' attitude towards advertising. For example, Kaiser and Song (2009) have product fixed effects and instruments similar to ones used in this study. Yet, they find the opposite results with German magazine data.

Table 7: Inclusion of Brand Dummies and Instruments

Dependent variable: $ln(s_{jct}) - ln(s_{0ct})$				
	Logit		IV logit	
	(1)	(2)	(3)	(4)
Price	-0.046***	-0.001	-0.088***	-0.102***
	(0.000)	(0.001)	(0.001)	(0.006)
Ad pages	-0.344***	-0.024***	-0.897***	-0.566***
	(0.007)	(0.001)	(0.000)	(0.063)
Content pages	0.843***	0.022	1.881***	1.088***
	(0.014)	(0.015)	(0.020)	(0.105
Frequency	0.067***	0.022***	0.124***	0.015**
	(0.001)	(0.002)	(0.001)	(0.006)
Product dummies	No	Yes	No	Yes
Year dummies	No	Yes	Yes	Yes
Ad nuisance cost	-0.7 cents	-	-1.0 cents	-0.6 cents
Similar dummies and/or IVs used in:	-	Kaiser and Wright (2006, IJIO)	Fan (2013, AER)	Kaiser and Song (2009, IJIO)
No. of observations	110419	110419	110419	110419

Notes: Kaiser and Wright (2006), and Kaiser and Song (2009) report positive coefficients for ad level. Kaiser and Song (2009) uses ad/content ratio as the measurement of ad level. Fan (2013) reports a close-to-zero, non-significant coefficient for ad level in footnote 8; thus, in her main specification, it is assumed that readers are ad-neutral.

By comparing specification (4) in Table 8 to my main estimates, I observe that the IV logit model suffers from model specification problems. In particular, the logit model overestimates the coefficients on content pages - a product attributes that consumers like, and underestimates consumers' ad-aversion. In the logit model, one more content page in a year translates to a decrease of subscription price by 1 cent. However, in the main model, the equivalent decrease is approximately 0.1 cent, with other product attributes and quality remained constant. The coefficient on advertising also nearly doubles from 0.57 to

Table 8: Genre-specific parameters

Variable	Genres		
	Women's health	*Shelter*	*Women's general*
Ad pages	(Baseline)	-4.8E-5 (2.7E-5)	7.8E-5 (2.8E-5)
log(income)	-0.176 (0.036)	0.061 (0.039)	-0.499 (0.035)
Age	0.001 (0.001)	0.020 (0.002)	0.012 (0.002)
HH sex ratio	-0.812 (0.206)	-0.915 (0.208)	-0.930 (0.212)
Education	0.244 (0.013)	0.186 (0.013)	0.251 (0.013)
Home ownership	-0.474 (0.126)	0.427 (0.067)	-1.242 (0.055)
Migration	-0.645 (0.126)	-0.513 -0.125	-0.365 (0.103)
	Men's	*Women's fashion*	*Personal finance*
Ad pages	1.4E-4 (3.3E-5)	-4.4E-5 (2.5E-5)	4.2E-5 (2.6E-5)
log(income)	-0.394 (0.041)	0.210 (0.034)	-0.217 (0.047)
Age	-0.003 (0.002)	0.005 (0.001)	0.009 (0.002)
HH sex ratio	2.654 (0.223)	-0.914 -0.210	0.608 (0.247)
Education	0.247 (0.015)	0.115 (0.012)	0.204 (0.016)
House ownership	0.592 (0.079)	1.298 (0.040)	0.254 (0.078)
Migration	-0.785 (0.147)	-0.846 (0.075)	-0.584 (0.145)

1.03. In summary, incorporating consumer multi-homing behavior into the demand model is crucial since doing that would correct for the model specification error when single-homing is assumed.

Table 6 also reports the estimated coefficients on time dummies. As discussed in Section 3, time dummies capture decreases in demand for magazines due to the rise of the Internet. All coefficients are negative and highly significant. For example, the decrease in demand in the year 2010 is equivalent to an increase of subscription price by \$3.5, or about %20 for an average magazine. The drop in demand due to the Internet is indeed very important.

Table 8 indicates that consumer heterogeneity plays an important role in tastes for magazines, especially in determining whether or not to purchase magazines at all. In addition, the role of consumer heterogeneity is qualitatively and sometimes qualitatively different across genres. In the full model, I allow genre dummies to interact with a few parameters. Most interestingly, I find that consumers' ad preferences vary only slightly across genres. For example, the results suggest that consumers are less averse to advertising in men's magazines and women's magazines with a general focus. However, magnitudes of such differences are almost negligible. On the other hand, consumer heterogeneity affects consumer decision to purchase different genres of magazines. In general, consumers with fewer years of education tend to buy magazines less often. consumers who have recently moved from another states and hence are less "settled", tend to purchase magazine subscriptions less often. Consumers who live in households with more male members are more likely to buy men's magazines and personal finance magazines while those live with more female members tend to buy more interior design (or "shelter") magazines besides all kinds of women's magazine.

6.2 Advertiser Demand Estimates

In this section, I present results of advertiser demand estimation. From the reader demand model, I predict the numbers of exclusive eyeballs on each platform, which information is missing in the data. I find, on average, 20% of a magazine's subscribers are exclusive to the platforms. I use the predicted values as an explanatory variable in the inverse advertiser demand function. I report the estimates and standard errors of advertiser demand parameters in column (1) of Table 10. I find that an increase in subscription level by 1,000 subscribers would lead to an increase in advertising price by \$49, holding other factors constant. Moreover, an increase in the number of exclusive subscribers by 1,000 would raise the advertising price by \$71. In context of the advertiser model in Section 3, the results imply that advertisers value exclusive readers at \$0.12 per eyeball while they value non-exclusive readers at \$0.05 per eyeball. In other words, they value exclusive readers twice as much as they value non-exclusive ones. This is direct evidence that platform advertising price reflects advertiser differential valuation of single-homing and multi-homing consumers, which is hypothesizes in the recent theoretical literature on two-sided markets.

Table 9: Estimates for Advertiser Demand

Variable	Parameter	Estimate			
		Main	(1)	(2)	(3)
Ad pages	λ_3	-17.93	-105.52	-105.53	-111.9
		(8.90)	(11.92)	(8.34)	(12.23)
No. subscribers	λ_2	49.42	52.36	46.42	1.60
		(19.89)	(8.47)	(5.55)	(20.99)
No. exclusive eyeballs	$\tilde{\lambda}_1$	71.11	-	-	414.22
		(15.92)			(156.87)
Product dummies	η_j	Yes	Yes	Yes	Yes
Year dummies	ϕ	Yes	Yes	Yes	Yes
No. observations		340	340	640	340

As discussed in Section 5, advertising pages, subscription levels and number of exclusive eyeballs are endogenous. To investigate the effects of endogeneity on the estimates, I run three additional regressions which results are also reported in Table 10. In specification (1), I run an OLS of the advertising price on ad pages and the subscription level while controlling for product fixed effects and year fixed effects. I repeat the same regression with the larger panel of 64 magazines in (2). Comparing these, I find coefficients are almost the same with both samples. I contend that my main results on the advertiser side should be externally valid. In specification (3), I include the predicted numbers of exclusive eyeballs in a similar OLS regression. The result suggests that an increase in the number of exclusive consumers would lead to \$0.41 increase in the advertising price. The estimated coefficient on subscription level is small and insignificant. In other words, once I include the number of exclusive eyeballs which is omitted in specification (1) and (2), the result suggests that advertisers value exclusive eyeballs at \$0.41 per eyeball while they do not value non-exclusive eyeballs at all. In context of our model, it implies that consumers' attention beyond first impressions is worthless to advertisers. However, once the endogeneity issue is addressed, the estimates change and lead to more reasonable interpretations.

6.3 Counterfactual Exercise: The Impact of the Internet

In this counterfactual exercise, I simulate the market outcomes in 2012 if the reader demand for magazines were as strong as in 2003.[15] I interpret the counterfactual results as the effects of the Internet on magazine subscription markets and advertising markets. From Table 5, I estimate a set of time dummies in consumers' indirect utility function. As discussed in Section 3, those dummies would capture any time-specific change in the value of the outside option. Given that there is no entry/exit of major magazines in genres of this study, I attribute those time effects to increasing attractiveness of the Internet. Holding all other exogenous variables constant, I let t_{2012} to be zero, and simulate market outcomes based on demand and cost-side estimates from the estimation. Table 9 summarizes the results.

Table 10: Counterfactual Results

Market Outcome (Mean)	2003 Data	2012 Data	2012 Counterfactual
p^s (\$)	22.04	15.14	18.63
N^s	1311.87	1441.22	1576.34
τ^e	324.03	312.22	383.05
a	14.27	11.24	14.64
p^a	131.75	166.47	174.58
Additional outcome variables (in million \$):			
Ad revenue	190	190	262
Circ. revenue	36.4	23.8	30.1

Several interesting observations emerge from Table 9. In comparison to what really happened in 2012, if the reader demand for magazines were as strong as a decade ago, the average subscription price of the 34 major magazines would have been \$3, or about 20% higher. Even prices are higher, now because of stronger demand, more magazine subscriptions are sold: the average subscription increases by 135,000 or 9%. The average number of single-homing consumers also increases by 70,000 or 22%. Together, they imply (net) market expansion for the six genres. In other words, not only some of the existing consumers buy more magazines, but new consumers also enter the market. With higher subscription levels and more exclusive consumers, strong reader demand translates to boosting effects in magazine advertising markets. Comparing to real data in 2012, platforms charge higher prices and admit more advertisers on average in the hypothetic case. As a result, the average ad revenue increases by \$72 million. Overall, I find that the Internet has very large effects on magazines. The

[15]This counterfactual exercise is based on a simplified version of the model where the effect of ad volume on consumer utility is set to zero.

direct impact of the Internet on the subscription market is considerably large while the indirect impact through reduced consumers and less favorable reader composition on advertising markets is even bigger - especially when magazines rely heavily on advertising revenues.

One caveat is that the above analysis is based on *all other factors being constant*. From 2003 to 2012, there are other changing factors besides the time-specific effects. For example, as I evaluate the counterfactual case, all other factors, such as consumer demographics, exogenous product attributes and unobserved quality, are assumed to take their 2012 value. This explains why outcomes in 2003 data are very different from the counterfactual outcomes in 2012 even strength of the reader demand is exactly the same.

7 Conclusion

Media platforms compete for both consumers and advertisers, especially when consumers divide their attention among multiple platforms. While traditional economics models assume consumers patronize a single platform, in my job market paper, I model consumer demand for multiple magazines ("multi-homing), and magazines subscription price and ad price decisions. Using a novel data set on regional magazine sales, characteristics and consumer rankings of magazines, I estimate the model and quantify the indirect network effects in magazine markets. I provide the first direct evidence that media ad prices reflect advertisers differential valuation of exclusive and non-exclusive eyeballs on platforms.

On the consumer side, I estimate a multiple discrete choice model of demand using new panel data on US magazine regional sales and characteristics from 2003 to 2012 and survey data on consumer rankings of magazines. Consumers have preferences over prices, ad volume, and other characteristics, and they have diminishing marginal utility from multiple purchases. Demand side results suggest that consumers ad nuisance cost is approximately 5 cents per ad page, in contrast to the ad-neutrality or ad-loving findings in the print media literature.

On the platform side, my model relates to the emerging theoretical two-sided market literature that emphasizes the importance of multi-homing. In the model, magazines compete to catch more eyeballs and the accompanying advertising revenues. When consumers are reached on multiple platforms, exclusive eyeballs are more valuable to advertisers and platforms. I estimate that, on average, exclusive eyeballs value 7 cents more or twice as values of shared eyeballs, thus confirming predictions in the theoretical literature.

I use the estimation results to investigate how the market would have differed if demand for magazines remained as strong as in 2003. I interpret the results as possible effects of the Internet on magazine markets over the decade. Subscription prices would increase by 20% on average, exclusive readerships 22% higher, and therefore, ad prices would also increase.

A model without consumer multi-homing tends to overestimate the value of a subscriber, but underestimates the power market of platforms.

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A.1 The Case $\kappa = 0$ Leads to a Binary Choice Model

In Section 4, I introduce a model of multiple discrete choices based on Hendel (1999) and Fan (2013). In this section, I show an interesting result that the multiple discrete choice model is equivalent to a binary choice model when $\kappa = 0$ and no restriction is imposed on the number of products that one can choose.

At the risk of abusing the notation, I denote $\mathbb{P}_{ij}^{m}$ as the probability that product j is *exactly* consumer i's m^{th} choice, and denote $\mathbb{P}_{ij}^{\geq m}$ as the probability that product j is *at least* consumer i's m^{th} choice. Notice that I do not assume any specific functional form, so $\mathbb{P}_{ij}^{m}$ and $\mathbb{P}_{ij}^{\geq m}$ are general probabilities. Observing that the events of j being one's first to m^{th} choice are mutually exclusive, I write $\mathbb{P}_{ij}^{\geq m}$ as

$$\mathbb{P}_{ij}^{\geq m} = \sum_{l=1}^{m} \mathbb{P}_{ij}^{l}. \tag{24}$$

Given that i has n choices from n products plus the no-purchase option, the probability i *ever* purchases j, $\mathbb{P}_{ij}$, is then

$$\begin{aligned}
\mathbb{P}_{ij} \quad = \sum_{l=1}^{n} \mathbb{P}_{ij}^{l} \quad &= \sum_{l=1}^{n-1} \mathbb{P}_{ij}^{l} + \mathbb{P}_{ij}^{n} \\
&= \sum_{l=1}^{n-1} \mathbb{P}_{ij}^{l} + \underbrace{\left(\mathbb{P}_{ij}^{\geq n} - \sum_{l=1}^{n-1} \mathbb{P}_{ij}^{l} \right)}_{\text{by (24)}} \\
&= \mathbb{P}_{ij}^{\geq n}.
\end{aligned}$$

In the context, $\mathbb{P}_{ij}^{\geq n}$ is the probability that i chooses j over the outside option. For example, with an i.d.d. Type I extreme value error and no random coefficients, $\mathbb{P}_{ij}^{\geq n}$ takes the binary logit form. This result is easy to understand intuitively. When a consumer faces n products and is free to choice up to n of them without diminishing utility after each choice, the consumer's choice problem reduces to saying yes-or-no for each product. It further implies that each product is a monopoly to consumers, and specifically, all cross-price elasticities are automatically zero. If one is interested in studying substitution patterns and strategic firm behavior, this type of model may not be useful. In other contexts, binary choice models have been applied extensively. For example, Augereau, Greenstein, and Rysman (2008) uses a multivariate probit model to study R&D decisions; Hiedemann, Sovinsky and Stern (2013) uses a dynamic multivariate probit to study family long-term care decisions.

A.2 Market Penetration Function

In this section, I present details on the expression for the choice probability of household i ever choosing j. With the expression, it is easy to verify results on invertibility of the market penetration function, as shown in Fan (2013).

I first extend the notation used in Section 4. Let $\Phi_{ij}^{m,k}$ denote the probability j is i's m^{th} best choice with utility decreased by k times; $\Phi_{ij-j^{(n)}}^{m,k}$ denotes the probability j is i's m^{th} best choice when $j^{(n)}$ is not in the choice set and utility is decreased by k times. Here, $n = m - 1$. When $k = m - 1$, the superscript k is suppressed. For example, $\Phi_{ij}^{1} = \Phi_{ij}^{1,0}$. Given that, I can write each of Φ_{ij}^{n} recursively as below:

$$\Phi_{ij}^{2} = \sum_{j^{(1)} \neq j} \left(\Phi_{ij-j^{(1)}}^{1,1} - \Phi_{ij}^{1,1} \right); \tag{25}$$

where, as in the main text,

$$\Phi_{ij-j^{(1)}}^{1,1} = \frac{e^{\delta_j + \vartheta_{ij}}}{e^{\kappa} + \sum\limits_{j \neq j^{(1)}} e^{\delta_h + \vartheta_{ih}}}, \quad \Phi_{ij}^{1,1} = \frac{e^{\delta_j + \vartheta_{ij}}}{e^{\kappa} + \sum\limits_{j} e^{\delta_h + \vartheta_{ih}}}.$$

Similarly, I have

$$\Phi_{ij}^{3} = \sum_{j^{(1)}, j^{(2)} \neq j} \left(\Phi_{ij-(j^{(1)}, j^{(2)})}^{1,2} - \Phi_{ij-j^{(1)}}^{2,2} - \Phi_{ij-j^{(2)}}^{2,2} - \Phi_{ij}^{1,2} \right); \tag{26}$$

$$\begin{aligned} \Phi_{ij}^{4} \;\; = \sum_{j^{(1)}, j^{(2)}, j^{(3)} \neq j} \;\; & (\Phi_{ij-(j^{(1)}, j^{(2)}, j^{(3)})}^{1,3} - \Phi_{ij-(j^{(1)} j^{(2)})}^{3,3} - \Phi_{ij-(j^{(1)} j^{(3)})}^{3,3} - \Phi_{ij-(j^{(2)} j^{(3)})}^{3,3} \\ & - \Phi_{ij-j^{(1)}}^{2,3} - \Phi_{ij-j^{(2)}}^{2,3} - \Phi_{ij-j^{(3)}}^{2,3} - \Phi_{ij}^{1,3}). \end{aligned}$$

Given parameters (κ, σ), the market penetration function is

$$s_j(\delta, z, \nu; \kappa, \sigma) = \int \int \left(\Phi_{ij}^{1}(\delta, z, \nu; \sigma) + \sum_{n=1}^{4} \Phi_{ij}^{n+1}(\delta, z, \nu; ; \kappa, \sigma) \right) dP_v dP_z. \tag{27}$$

Following BLP (1995), Fan (2013) shows that there exists a unique solution to $s_j(\delta, z, \nu; \kappa, \sigma) = \mathcal{S}_j$, where $\mathcal{S}_j$ is data; and that $F_j = \delta_j + \ln\mathcal{S}_j - \ln s_j$ is a contraction mapping that can be used to invert s_j. In other words, this exists a one-to-one mapping between market penetration and mean product utilities. Essentially, it boils down to show: (C.1) $\partial s_j / \partial \delta_j < s_j$, (C.2) $\partial s_j / \partial \delta_j > 0$, (C.3) $\partial s_j / \partial \delta_h < 0$ for $h \neq j$, and (C.4) $\sum\limits_{h=1 \ldots J} \partial s_j / \partial \delta_n > 0$. Together they imply the Jacobian of s has a dominate diagonal, therefore is a unique solution to $s_j(\delta, z, \nu; \kappa, \sigma) = \mathcal{S}_j$, and conditions in BLP (1995) met for F_j being a contraction mapping.

Intuitively, conditions (C.1) and (C.2) means that j's penetration increases with its own quality, but the marginal effect cannot be "too large" (i.e., no marginal change in quality can double its sales). Condition (C.3) states products are substitutes. Condition (C.4) means j own quality effect dominates all cross-product quality effects. All of these carry economically sound intuitions, and can be easily verified with logistic functions.

A.3 Data

A.3.1 Sample of Magazines

My data set on U.S. magazines comes from a number of sources, described in the next subsection. I merge various data to create a panel of magazines. I delete magazines with important variables missing. I also delete any genre of magazine in which at least one important magazine is missing or deleted from the data. The result is a sample of 34 major magazines in six genres for the main analysis. For various robustness analyzes, I include 30 more magazines that have complete information on advertising price and quantity.

Table 11: The List of Magazines for Main Analysis

Women's fashion	Women's health
Allure	*Fitness*
Cosmopolitan	*Health*
Elle	*Prevention*
Glamour	*Self*
Harper's Bazaar	
In Style	Shelter
Lucky	*Architectural Digest*
Marie Claire	*Country Living*
More	*This Old House*
Seventeen	*Town & Country*
Vogue	
W	Man's
	Details
Women's general	*Esquire*
Family Circle	*Maxim*
Good Housekeeping	*Playboy*
Martha Stewart Living	
Real Simple	Business
Redbook	*Money*
Woman's Day	*Fast Company*
	Forbes
	Entrepreneur

A.3.2 Data Sources

Below, Table 12 summarizes data sources and definition.

Table 12: Data Description and Sources

	Var	Data description	Data source
Magazine demand	N^s_{jct}	MSA-level circulation	AAM
Ad demand	a_{jt}	Annual number of advertising pages	PIB-Kantar
Price of magazine	p^s_{jt}	Annual subscription price (2012 $)	AAM
Price of ad per page	p^a_{jt}	Average advertising rate (2012 $/page)	PIB-Kantar
Magazine characteristics	x_{1jt}	Annual number of non-ad content pages	MA-Focus
	x_{2jt}	Frequency of publication (issues/year)	AAM
Consumer rankings	Φ^n_{jt}	% consumer ranking groups	GfK MRI
Ownership		Publisher	AAM
MSA demographics	$\mathcal{M}_{jct}$	Number of households	AAM
	z_{1ict}	Log HH income	Census
	z_{2ict}	Age	Census
	z_{3ict}	Household sex ratio	
	z_{4ict}	Education (years)	Census
	z_{5ict}	Homeownership (=1 if owned, =0 otherwise)	Census
	z_{6ict}	Migration (=1 if recently moved)	Census

Notes: AAM: Alliance of Audited Media, formerly Audit Bureau of Circulation (ABC); PIB-Kantar: Publishing Information Bureau; MA-Focus: MA-focus media, formerly Hall's report; Gfk MRI: ; Census: American Community Survey.

A.3.3 Cross-Sectional Variation of Magazine Penetration

Table 13 presents the summary statistics of market penetration of each magazine in 2012. It shows that market penetration of the same magazine varies substantially across metro areas in 2012. Similar patterns (not reported) are present in data of other years.

Table 13: Summary Statistics of Magazine Penetration in 2012

	Mean	SD	Min	Max
Magazine 1	0.77	0.21	0.38	1.68
Magazine 2	0.53	0.23	0.21	2.52
Magazine 3	2.45	0.08	0.83	8.82
Magazine 4	1.56	0.50	0.26	3.24
Magazine 5	0.81	0.38	0.31	6.51
Magazine 6	0.52	0.13	0.16	1.21
Magazine 7	0.47	0.15	0.21	1.15
Magazine 8	3.68	0.90	1.34	6.54
Magazine 9	0.59	0.13	0.32	1.58
Magazine 10	1.20	0.28	0.73	2.92
Magazine 11	0.74	0.16	0.38	1.72
Magazine 12	1.83	0.38	1.13	4.07
Magazine 13	3.93	0.94	1.26	6.74
Magazine 14	0.45	0.19	0.23	1.77
Magazine 15	1.17	0.25	0.52	2.26
Magazine 16	1.22	0.52	0.36	4.70
Magazine 17	0.80	0.22	0.42	1.81
Magazine 18	0.69	0.16	0.39	1.38
Magazine 19	1.67	0.43	0.56	4.13
Magazine 20	2.11	0.44	0.54	4.43
Magazine 21	1.50	0.45	0.55	3.26
Magazine 22	1.02	0.28	0.34	2.13
Magazine 23	2.51	0.44	1.18	4.09
Magazine 24	1.56	0.56	0.39	4.07
Magazine 25	1.93	0.48	0.85	3.41
Magazine 26	1.16	0.36	0.50	5.58
Magazine 27	1.58	0.42	0.81	3.11
Magazine 28	0.83	0.31	0.25	1.96
Magazine 29	0.31	0.15	0.11	1.45
Magazine 30	0.85	0.39	0.35	4.11
Magazine 31	0.30	0.11	0.16	0.87
Magazine 32	3.66	0.97	0.78	8.75
Magazine 33	0.31	0.09	0.15	0.77
Magazine 34	3.04	0.68	1.04	5.25

A.4 Additional Tables and Figures

Figure 1: Advertising Spending in Media

% of ad dollar spent in media	2008	2009	2010	2011	2012
Magazine	18.1	17.1	16.8	16.1	16.2
Internet	6.7	7.9	7.6	9.1	8.7
TV	47.2	49.3	51.1	51.2	53.1
Radio	6.8	6	6.1	6	6.2
Newspaper	16.1	14.8	13.6	12.9	12

(Source: Kantar Media)

Figure 2: Ratio of Ad Pages vs. Content Pages in the U.S. Magazine Markets (MPA)

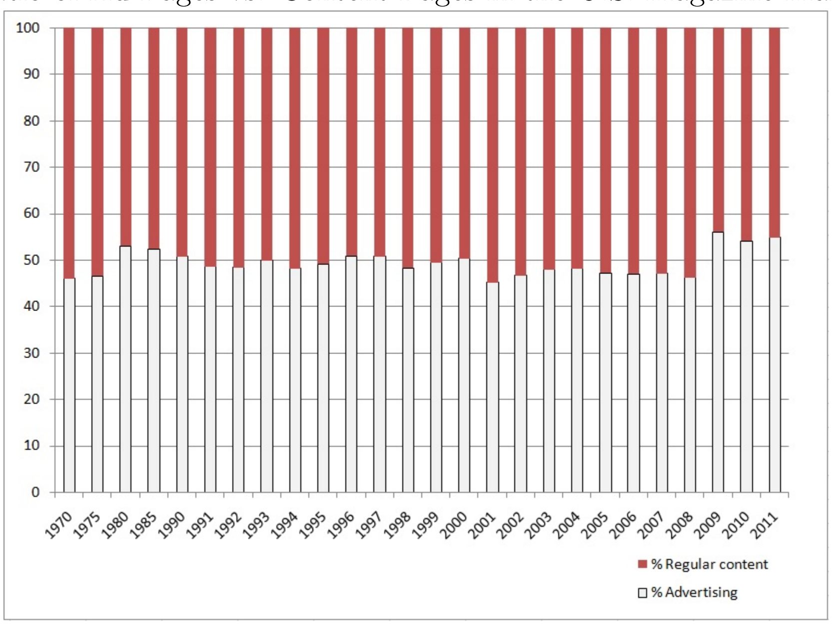

Table 14: Robustness Checks on the instruments

Endogenous variable:	Subscription price			Ad page		
	(1)	(2)	(3)	(4)	(5)	(6)
Included IVs						
Constant	-62.36***	20.42***	1.94	19.44	8.52***	-16.12***
	(17.43)	(3.14)	(2.32)	16.70	(3.37)	(2.28)
Content pages	0.81***	1.38***	1.47***	1.32***	1.31***	1.12***
	(0.08)	(0.09)	(0.10)	(0.08)	(0.10)	(0.10)
Frequency of publication	0.06	-0.52***	0.37***	0.15	0.17	0.51***
	(0.22)	(0.21)	(0.12)	(0.22)	0.22	(0.12)
Excluded IVs						
IV BLP 1	-	-0.60***	-0.55***	-	-0.04	-0.14
		(0.14)	(0.14)		(0.15)	(0.13)
IV BLP 2	-	-0.23*	-0.37***	-	0.11	0.31***
		(0.13)	(0.11)		(0.14)	(0.11)
IV BLP 3	-	-0.42**	0.04	-	0.18	0.25*
		(0.19)	(0.15)		(0.21)	(0.15)
IV Hausman 1	0.33*	-	-0.26**	0.41**	-	0.15
	(0.17)		(0.13)	(0.17)		(0.13)
IV Hausman 2	-0.67	-	0.05	-0.43	-	0.10
	(0.51)		(0.18)	(0.49)		(0.17)
IV Hausman 3	3.77***	-	0.13*	1.25	-	0.04
	(0.97)		(0.08)	(0.92)		(0.08)
Publisher dummies	Yes	Yes	No	Yes	Yes	No
(Adjusted) R-squared	0.67	0.73	0.64	0.65	0.64	0.59
F-stat	45.67	59.96	74.65	41.48	40.07	62.41

Notes: This table summarizes estimates from “first stage” regressions on the endogenous variables using some but not all of the instruments. The degree of freedom is 290. *, **, *** denotes 1%-, 5%-, and 10%- significance level, respectively.