Broadband Internet, Competition, and Media Content: The Case of State-Controlled Television in China *

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Abstract As broadband infrastructure provides easy access to information on the Internet, it has large impacts on traditional media and advertising markets. In countries where media are heavily regulated, broadband Internet is often viewed as a threat to state-owned media. This paper provides a first systematic study on the impact of broadband expansion on market outcomes and consumer welfare in Chinas television industry for the decade of 2005-2014. Using new provincial-level data and information on infrastructures as an instrument, we first establish causal effects of broadband Internet on a series of market outcomes. We find that the Internet has lead to significantly lower advertising rates and revenues despite more cable subscribers and viewers for local stations, and that it has made the state-owned TV channels to broadcast more ads but less service contents. We then build and estimate a model of consumer and advertiser demand, with additional high-frequency data on TV program ratings. We use the structural model to shed lights on the micro-mechanism through which the Internet has (re)shaped China's television markets.

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1 Introduction

The Internet has profoundly changed the way that consumers acquire information. Therefore, it has especially large impacts on traditional media and advertising markets. In countries with an authoritarian government, traditional media are often used as a tool to influence what information people receive and ultimately how they think and what they believe. As broadband Internet provides easy access to alternative sources of information, it is often viewed as a threat to government-controlled media in authoritarian states.

This research aims to provide a first systemic examination of the effect of broadband expansion on market outcomes and welfare in China's television industry for the recent decade of 2006-2015. Using new data on China's provincial-level markets and high-frequency TV ratings, we combine a reduced-form regression analysis and structural estimation to (i) establish causal effects of broadband Internet on a series of outcome variables, and (ii) investigate empirically on the micro-mechanism through which the Internet has (re)shaped China's television markets.

1.1 Related Literature

This research is closely related to several literatures in economics. First, there is a large literature that looks at the effect of the Internet on various industries, such airlines (Ater and Orlov, 2015; Orlov, 2011) and retailing (e.g. Forman *et al.*, 2009; Goldmanis *et al.*, 2010). Because the Internet has profoundly changed the way that consumers acquire information, it has naturally more pronounced effects on traditional media and advertising markets. More recently, Chandra and Kaiser (2014) study the effect of the Internet on targeted ads in magazines; Athey *et al.* (2016) building a theory regarding how consumers adhere to different media platforms at the same time (or "multi-homing") and investigate theoretically how the Internet affects prices and advertising; and Chiou *et al.* (2017) use data on Yellow Pages to study not only entry and prices but also how firms reposition their products. The research uses previously unexplored Chinese data and employs a combination of regression analysis and structural estimation to not only establish the casual effects of broadband Internet but also shed lights on the micro-mechanism through which broadband affects media markets.

Television markets, like most media markets, exhibit features of a two-sided market - an important concept introduced to the fields of industrial organization and media economics by foundational works, such as Rochet and Tirole (2003), Armstrong (2006), and Anderson and Coate (2005). Rysman (2004) pioneers the empirical literature by estimating a structural model of two-sided markets of U.S. Yellow Pages. There are many important structural empirical works thereafter, for which there is a long list that we do not name at this moment. More related papers on U.S. cable television markets include Wilbur (2008); Crawford and Yurukoglu (2012) on channel bundling; Crawford *et al.* (2017) on vertical integration; and Crawford *et al.* (2015) on endogenous quality. This research takes many important insights from the above-mentioned theory and empirical papers to build and estimate structurally both consumer and advertiser demand in China's television markets.

Lastly, there is a small but emerging literature especially on media in China. Most studies on Chinas media focus on the political-economy side. An exemplary work is Qin *et al.* (2017), that constructs a novel measure of media bias and finds that newspapers in regions with larger advertising markets and those that were historically more exposed to Western culture are less biased. In contrast, this research uses publicly available data and put them under the lens of economic theory. Our focus is on the business model of Chinas state-owned television industry and how it has been (re)shaped by the Internet.

2 Data and Summary Statistics

2.1 The television industry in China

China's television industry has one of the largest and the most important media networks in the world: more than 200 million Chinese households are connected to cable television, receiving programs broadcast by TV stations and firms that are affiliated with different levels of the government. With billions of advertising dollars poured into China's television markets to reach the audience, on the one hand, the economic reason for its importance is rather obvious. On the other hand, because of the government's role in ownership, production and delivery of television programs, the TV industry also has some profound impacts on the selection and presentation of information - whether entertainment, news, or other - that Chinese households access and consume.

In terms of market structure and organization, the television industry in China has the following distinct features:

State monopoly and censorship. Historically, all entities related to TV cable networks and broadcasting were a part of the government. After China's reform and opening-up in 1980's, they first became agencies that affiliated with various levels of the government. In recent years, both cable companies and TV stations are mostly state-owned businesses similar to other public-utility firms like power grids in China. While nowadays they do not usually receive subsidies from the government, the government also does not explicitly redistribute the profits made in this industry to its citizens. In the meantime, the government and the Communist Party often take active roles in censoring the content of TV programs, usually news - which can be highly sensitive politically - and entertainment - which may contain undesirable elements like explicit violence or sexuality. For reasons along the same line, no private firm is allowed to run its own TV channels or cable service.

Hierarchal structure parallel to levels of the government. Due the history, China's television media industry has a hierarchal structure parallel to bureaucracies in China. On the top, there is the China Central TV station, or CCTV, that has about 15-20 free channels that every cable subscriber can receive and a few more high-definition (HD) pay channels. However, there is now not a central TV cable company. At the regional level, there is first a provincial television station that has 5-10 free channels broadcast to the local audience plus usually one flagship channel broadcast nation-wide. Lower than that, there are prefecture-level stations and county-level ones, each carries 5-10 channels for the local audience. Below the provincial-level, television stations are mostly independent financially from the ones that are one-level above, but they often do have to answer to the relevant parallel or higher government agencies in terms of making annual plans and censorship.

In summary, for any cable subscriber in China, when she turns on the TV, she has access to 15-20 CCTV channels, 5-10 provincial channels, about 30 "satellite" channels (that are each the flagship of a province), 5-10 prefecture/municipal ones, and a few more from the county. While most channels are free, TV cable does come with a monthly fee. More recently, there are HD channels subject to additional charges, but overall, those channels have extremely small market shares collectively (on the magnitude of 0.1 percent). In increasingly more regions, there is no program accessible via the TV antenna, so consumers either subscribe to the cable or do not watch TV at all.

Vertical relationship between cable and TV channels. In the more progressive era of 1990's under China's Premier Zhu Rongji, there were waves of reform in China's television industry that pushed towards the goal of "disintegration of cable networks and TV channels." In recent years, due to huge impacts of the Internet on traditional media, many cable providers and content producers have merged to form local media conglomerates.

Commercialization and advertising. Unlike many public media in more developed economies that serve as complements to private TV programs, China's public television has become increasingly commercialized and heavily reliant on revenues from TV advertising. Its dependency on ad revenues profoundly affects what they broadcast to attract more viewers while staying safe by making sure that no content touches the line of censorship.

2.2 Data description

In this paper, we utilize a unique data-set on China's cable television and ad markets from 2006 to 2015. For provincial level statistics, data are collected from two publicly-available sources: the *China Broadcasting and Television Yearbooks* and *China Television Rating Yearbooks.* For a few earlier years, digitalized copies are unavailable, so we manage to input those data manually. The current data-set contains information on cable subscription and revenues, program viewership, time length of advertisements and other different types of program, and advertising revenues of all China's provinces and four municipalities (Beijing, Shanghai, Chongqin and Tianjin). In particular, we observe market shares of bundles of channels (e.g., central TV, satellites, or local ones) in different demographic groups and distribution of viewers' demographics for each program bundle. Those data help will help us to estimate structural parameters that link consumers' taste for program genres to their personal characteristics.

We complement our main data on provincial markets with high-frequency TV ratings data purchased from a marketing research company, CSM, jointly run by Kantar Media and China Central Television. We observe in the data TV ratings, market shares and program characteristics of every piece of program broadcast between March 16, 2015, to March 30, 2015. We organize those data to obtain ratings and program characteristics of every channel for all half-hour time intervals within the two weeks.

Lastly, provincial-level data on socio-economics indicators (such as GDP, population, and government cultural expenditure), broadband penetration and infrastructures are collected from the *China Statistics Yearbooks* of various years.

Table 4 summarizes the main variables that we use for both reduced-form regression analysis and structural estimation of demands.

3 Regression Analysis

3.1 The causal effects of broadband use

To have a better overall picture of the net effect of broadband Internet use on China's state-owned television markets, we first run regressions of Internet penetration on a series of outcome variables using provincial-level data. Specifically, we have

$$Y_{ct} = \beta_0 + \beta_1 Internet_{ct} + X_{ct}\gamma + F_c + F_t + \varepsilon_{ct}; \tag{1}$$

where Y_{ct} is an outcome variable; $Internet_{ct}$ is the Internet penetration level of province c in year t; X_{ct} is a vector of socio-economic control variables, such as income, population, and culture-related government expenditures; the coefficients F_c and F_t are fixed effects for each province and year.

To identify the main parameter of our interest, β_1, we need to address the potential endogeneity problem of $Internet_{ct}$. Internet penetration can be endogenous for various reasons. First, there may exist omitted variables in the error term that correlate with both Internet penetration and the outcome variable. For instance, the diffusion of other ICT technology concurrent to broadband Internet can also affect outcomes in the television markets. Second, there is a concern of reverse causality in the sense that consumers' Internet use might be affected by their consumption of television products. Due to such endogeneity concerns, OLS is likely to yield biased estimate of β_1.

To address this problem, first, we exploit the panel structure of our data to include province and year fixed effects, which will capture any confounding factors common to all provinces in a year and specific to a province across years. Second, we use an instrument to provide additional exogenous variation for $Internet_{ct}$. Our data-set has a major advantage of having panel data on ICT infrastructures. In particular, we use the length of long-distance optical fiber as an instrument for broadband penetration. Because optical fibers are often shared for usage in telecommunication, residential and non-residential Internet access, it is unlikely that building of the infrastructure is affected by any factor related to the television markets once we include fixed effects and control for local economic indicators and government expenditures. Therefore, it serves as a valid instrument. Due to the well-known non-linearity in diffusion of broadband Internet (Czernich *et al.*, 2011), we take a control function approach to utilize this instrument.[1] Specifically, we first run OLS of the following

[1]To examine the causal effect of broadband Internet on economic growth, Czernich *et al.* (2011) take advantage of the documented non-linearity in broadband diffusion to create their instrument based on one-year data on the infrastructure and time-series variation introduced by a model of technological diffusion or functional forms. Here, we have panel data on the infrastructure that directly explain Internet penetration in a non-linear way.

equation on log of $Internet_{ct}$, the endogenous variable of our concern:

$$\ln(Internet)_{ct} = \alpha_0 + \alpha_1 \ln(Z_{ct}) + X_{ct}\delta + F_c' + F_t' + e_{ct}; \tag{2}$$

where Z_{ct} is the instrument; X_{ct} are exogenous variables included in the original equation, and the coefficients F_c' and F_t' are province and year fixed effects. We then collect the residuals $\hat{e}_{ct}$, generate $\exp(\hat{e}_{ct})$, put them back in equation (1) as an additional regressor and run OLS. The estimated coefficient attached to $\hat{e}_{ct}$ will inform us about the severity of any endogeneity problem. However, we have to in turn assume independence between e_{ct} and ε_{ct}, which is stronger than just exogeneity in the usual 2SLS.

3.2 Reduced-form results

We run regressions of broadband penetration without and with the control-function regressor on 49 outcome variables related to China's television markets for a decade (2006 - 2015), and the results are reported in Tables 2, 3 and 4. For each outcome variable, we report estimates based on simple OLS and the control function approach, all with additional control variables (i.e., log real income, log population, log government expenditure on cultural affairs) as well as year and province fixed effects. Estimates based on the control function approach are referred informally as "IV estimates". For the IV estimates, we adjust the standard errors using bootstrapping due to the inclusion of generated regressor.

All estimates can be interpreted as change or percentage change in the outcome variables when broadband penetration increases by 100 percentage points. Over the sample period 2006 - 2015, on average, provincial-level penetration has increased by 50 percentage points, roughly. So, a simple way to understand these estimates would be to divide the coefficients by 2. For instance, in Table 2, the IV coefficient for (log) ad rate is -1.615, which means that as the broadband penetration has gone up by 50 percentage points, ad price per minute of ads has dropped by about 80.7 percent over the years.

Table 2 includes the estimated coefficients attached to outcome variables related to price and quantity in cable and advertising markets. Based on the IV estimates, with lower ad rates, broadband Internet has lead to large reduction of ad revenues of regional TV stations by 68 percent. Broadband Internet has lead to 15-percent more cable subscribers while its effects on the subscription price and revenues are not significantly different from zero. The results suggest that access to broadband weakens the local television ad markets despite more subscribers, who become the potential viewers. Furthermore, we look the effects on the (average) number of viewers of each bundle of channels and find that Internet use has significantly increased audience for regional channels and decreased that for CCTV, or channels broadcast by the central authority in China, which are more political in nature. Noticeably, *ceteris paribus*, more viewers of regional programs should lead to stronger regional TV ad markets because advertisers value more reachable consumers. So, one can reasonably say that broadband Internet must affect the ad markets through some channel other than the audience size.

Table 3 includes the estimated coefficients attached to outcome variables related to overall length of different types of programs broadcast by regional channels. One of the main findings is that Internet use has caused local channels to broadcast less service-type program and TV series but significantly more ads, both in terms of total length and ratio. Higher ad levels are consistent with lower ad rates and revenues, or weakened ad markets. From the perspective of viewers, these are hardly good news - unless consumers really like ads but hate service-type programs. From the perspective of public finance, this implies that Internet has made state-run television more commercialized and deviating from its role of serving public interests.

We further look at the estimated effects of broadband penetration on the demographic composition of TV viewers, reported in Table 4. Besides the minor ones, several main findings emerge: our results suggest that over the sample period during which broadband penetration has gone up by approximately 50 percentage points, an average TV viewer has become less likely (i) to be in the highest income group (i.e., -5.8 points), (ii) to have higher education (i.e., -3 points for college education, negative but imprecisely estimated effects for high-school), and (iii) to be student (-3.4 points) or self-employed and in private sector (-2.6

points) or senior government official (-0.8 points). In the meantime, the profile of an average viewer has become less-educated (+2.7 points for no schooling, +3.2 points for middle school) and more likely to have a blue-collar (+3.9 points) job or a job in the agricultural sector (+4.3 points). The changing demographic composition not only tells us about who are more likely to switch from television to Internet use, but also may help us to better understand what happened in the TV ad markets.

To summarize, we provide in this section the first systematic analysis of the causal effects of broadband Internet penetration on traditional television markets served by China's regional state monopolist. We use a decade of provincial-level data that are previously unexplored by researchers and establish causality by using unique panel data on broadband infrastructure. Nevertheless, this paper does not stop here. We will move forward to build and estimate a structural model that links consumer demand and advertiser demand in the TV markets.

4 Structural Model and Estimation

In this section, we build a model of consumer choices and advertising demand, which will give us structural equations to estimate. Estimation of the two-sided demand equations allows us (i) to investigate the micro-mechanisms through which Internet use affects television markets in China, and (ii) possibly to conduct further welfare analysis based on counterfactual simulations.

4.1 Consumer Demand

We begin by considering media consumers' choices in China's television markets. In particular, there are two stages of consumer decision-making. In Stage 1, in each year t, consumers make a binary choice of whether to subscribe to the cable service provided by a regional state monopolist. In Stage 2, conditioned on having cable subscription, consumers choose a television channel j to watch at any occasion l of t. In our model, consumers rationally expect the value of watching TV programs when making their cable subscription decision in the earlier stage, so we first describe consumers' viewing utility at the second stage.

At the viewing stage, an individual i's conditional indirect utility from watching a television channel j in province c at a moment of time lt is

$$u_{ijclt} = q_{jlt}\theta_{ict} + x_{jlt}\beta + \eta_d + \eta_h + \eta_{jt} + \Delta\xi^{(p)}_{jlt} + \varepsilon^{(p)}_{ijclt}; \tag{3}$$

where q_{jlt} is a vector of important program characteristics central to this study, such as the proportions of ads and service programs in a 30-minute time interval; the coefficients $\theta_{ict} = \theta_0 + \theta_1 z_{ict} + \sigma\nu_{ict}$ contain baseline taste parameters θ_0, demographic-dependent tastes θ_1 as well as unobserved taste coefficients σ; we assume that $z_{ict} \sim z^{(c)}$, where $z^{(c)}$ is the empirical distribution of demographic characteristics of all viewers unique to our data, and that ν_{ict} is standard normal. Other program characteristics are included in x_{jlt} without random coefficients. The coefficients η_d and η_h capture any factor affecting utility of watching television in a particular day of a week and in a 30-minute time interval in a day while η_{jt} is the unobserved quality component of channel j in year t. Any unobserved, channel-time-specific quality factor that does not vary across individuals is reflected in $\Delta\xi^{(p)}_{jlt}$. Lastly, $\varepsilon^{(p)}_{ijclt}$ is the idiosyncratic taste shock and i.i.d. with a Type-1 extreme value distribution.

We can rewrite it to the following one:

$$u_{ijclt} = \delta^{(p)}_{jlt} + \mu^{(p)}_{ijclt} + \varepsilon^{(p)}_{ijclt}; \tag{4}$$

where $\delta^{(p)}_{jlt} = q_{jlt}\theta_0 + x_{jlt}\beta + \eta_d + \eta_l + \eta_{jt} + \Delta\xi^{(p)}_{jlt}$ is the vertical component of consumers' taste, and $\mu^{(p)}_{ijclt} = (\theta_1 z_{ict} + \sigma\nu_{ict})q_{jlt}$ captures consumers' heterogeneous tastes for television program characteristics.

The utility from choosing the outside option is $u_{i0clt} = \varepsilon^{(p)}_{i0clt}$, where we normalize its mean value to zero. Given the formulation above, we can then express the nation-wide market share of a channel among *all television viewers* at any moment as

$$s_{jt}^{(p)} = \int\int \left(\frac{\exp(\delta_{jlt}^{(p)} + \mu_{ijclt}^{(p)}(\nu, \mathbf{z}))}{1 + \sum_{h \in J} \exp(\delta_{hlt}^{(p)} + \mu_{ihclt}^{(p)}(\nu, \mathbf{z}))} \right) dP_{\nu} dP_{z^{(c)}}; \tag{5}$$

that is, the integration of individual viewing probabilities over distributions of viewers' observed characteristics and unobserved heterogeneity in their tastes for program characteristics.

Now at the cable subscription stage, consumers' utility from subscribing to the cable service depends on - among other things - their expectation of the value of TV channel bundles accessible through the cable network. Since we do not observe in data program ratings nor characteristics of all channels at every moment in a year, we approximate the total value of a bundle of television channels, b, to the viewers as follows:

$$U_{ibct} = m(q_{bct}\theta_{ict} + x_{bct}\beta) + \omega_b^{(b)} Internet_{ct} + \eta_b + \eta_t^{(b)} + \eta_c^{(b)} + \Delta\xi_{bct}^{(b)} + \varepsilon_{ibct}^{(b)}, \tag{6}$$

where q_{bct} and x_{bct} are vectors of characteristics of bundle b in market ct, such as the proportion of each type of programs in all program time, and in particular, θ_{ict} and β are the same parameters as in equation (3), where m is a scaling parameter to be estimated. New to this equation, we allow Internet penetration to affect the mean utility of each bundle in potentially different ways, so the coefficient $\omega_b^{(b)}$ is bundle-specific. The coefficients η_b, $\eta_t^{(b)}$ and $\eta_c^{(b)}$ capture any component of utility that is specific to a bundle, a year and a provincial market, respectively. Any unobserved, bundle-market specific quality factor that does not vary across individuals is reflected in $\Delta\xi_{bct}^{(b)}$. Lastly, $\varepsilon_{ibct}^{(b)}$ is the i.d.d. taste shock with a Type-1 extreme value distribution, and furthermore, we assume that this part of utility is realized only after consumers have access to the cable service.

So, at the time of deciding whether to purchase cable subscription, consumers' expected value of having access to bundles of TV channels should be

$$v_{ict} = \mathbb{E}\left(\max_{b\in B_c} U_{ibct}\right).$$

Given the distributional assumption of $\varepsilon^{(b)}_{ibct}$, this expected value has a unique closed-form representation, also known as the *inclusive value*:

$$v_{ict} = \mathbb{E}\left(\max_{b\in B_c} U_{ibct}\right) = \ln\left(1 + \sum_{b\in B_c} \exp(\delta^{(b)}_{bct} + \mu^{(b)}_{ibct})\right) + C, \tag{7}$$

where we write again $\delta^{(b)}_{bct} = m(q_{bct}\theta_0 + x_{bct}\beta) + \omega^{(b)}_b Internet_{ct} + \eta_t + \xi^{(b)}_{bct}$ and $\mu^{(b)}_{ibct} = (\theta_1 z_{ict} + \sigma\nu_{ict})q_{bct}$; C is some constant value.

Finally, we can describe consumers' indirect utility from subscribing to the cable service as follows:

$$V_{ict} = v_{ict} - \alpha p_{ct} + \omega^{(c)} Internet_{ct} + \eta^{(c)}_t + \eta^{(c)}_c + \Delta\xi^{(c)}_{ct} + \varepsilon^{(c)}_{ict}, \tag{8}$$

where p_{ct} is the annual cable subscription fee, $\eta^{(c)}_t$ and $\eta^{(c)}_c$ capture any quality shifter that is specific to a year and a province. Any unobserved, market-specific quality factor that does not vary across individuals, such as marketing efforts or price discounts, is in $\Delta\xi^{(c)}_{bct}$. The taste shock $\varepsilon^{(c)}_{ibct}$ is i.d.d. with a Type-1 extreme value distribution. Since there is only one option of cable service in any market, the value of not having access to cable television is normalized as usual; i.e., $V_{i0t} = \varepsilon^{(c)}_{i0t}$.

Therefore, the market share of the government-run cable service in a market ct is

$$s^{(c)}_{ct} = \int\int \left(\frac{\exp(\bar{V}_{ct} + v_{ict}(\nu, \mathbf{z}))}{1 + \exp(\bar{V}_{ct} + v_{ict}(\nu, \mathbf{z}))}\right) dP_v dP_z, \tag{9}$$

where we a similar notation with $\bar{V}_{ct} = -\alpha p_{ct} + \omega^{(c)} Internet_{ct} + \eta^{(c)}_t + \eta^{(c)}_c + \Delta\xi^{(c)}_{ct}$. It follows that the number of subscribers in market ct, $N^s_{ct} = H_{ct}s^{(c)}_{ct}$, where H_{ct} is the total number of households in ct.

One of the main purposes of this exercise is to investigate the micro-channels through which broadband Internet affects consumer behavior in China's television markets. In the context of consumers' two-stage decision, we allow Internet penetration (i) to have differential effects on consumers' choices of TV bundles to watch, and (ii) to affect directly their value of cable access. Due to the "two-sidedness" of media markets, the effects of broadband in the consumer market will carry through to the advertising market, which we describe in the following text.

4.2 Advertiser Demand

To study China's television advertising markets with market-level data, we follow Rysman (2006) to estimate the following (inverse) demand function for advertising:

$$\ln P_{ct}^{a} = \lambda_0 + \lambda_1 Internet_{ct} + \lambda_2 \ln a_{ct} + \lambda_3 \ln N_{ct}^{s} + X_{ct}^{(a)}\phi + \eta_c^{(a)} + \eta_t^{(a)} + \epsilon_{ct}, \tag{10}$$

where on the LHS, P_{ct}^{a} is the price per minute of ads charged in province c in year t. On the RHS, a_{ct} is the total length of ad program broadcast at provincial-level channels, measured in minutes; N_{ct}^{s} is the number of viewers in ct; $X_{ct}^{(a)}$ is a vector of socio-economic variables controlling for factors that shift advertisers' willingness to pay for a unit of ads. The coefficients $\eta_t^{(a)}$ and $\eta_c^{(a)}$ capture any demand shifter that is specific to a year or a province. Any unobserved, market-specific demand component is in ϵ_{ct}.

In particular, the coefficient λ_1 has a structural interpretation: it represents the percentage change in the aggregate value per look of TV viewers to advertisers when Internet penetration increases by one hundred percentage points.

To summarize, Internet use can affect the advertiser demand via three channels. Indirectly, Internet can change the number of viewers of television ads and conditioned on the number, also the demographic composition of viewers (included in $X_{ct}^{(a)}$). Moreover, Internet use may affect the (aggregate) value of a viewer to advertisers as it opens the door to powerful online alternatives for both consumers and advertisers

4.3 Estimation and Identification

We will estimate separately taste parameters in utility functions (3), (6) and (8), and the ad demand function (10). Below we provide a verbal description of the estimation methods that will be used.

For estimation of consumer taste parameters, we will use the Method of Simulated Moments (MSM). The first set of moments will be constructed by employing the standard BLP routine. Specifically, first use the BLP contraction mapping to "invert" high-frequency (30-minute) TV ratings data that we observe for two weeks to the channel-time-specific mean taste component, $\delta_{jlt}^{(p)}$, in equation (3). Second, obtain the residual, $\Delta\hat{\xi}_{jlt}^{(p)}$, and the (theoretical) moment conditions are that $\Delta\xi_{jlt}^{(p)}$ should be orthogonal to some (vector of) instruments. The first moments help us to estimate taste parameters that enter $\delta_{jlt}^{(p)}$. The second moments are constructed by matching market share functions of bundles to real data on shares in all viewers' demographic group - a unique feature of our data. Thus, we will have estimates on taste parameters that enter bundle utility (6) and (vectors) of individual-specific tastes (θ_1 and σ). The third set of comments are constructed by using the standard BLP routine to market shares of cable, and the (theoretical) conditions are that $\Delta\hat{\xi}_{jlt}^{(p)}$ should be orthogonal to some instruments. They will help us estimate parameters in the cable utility function (8). In practice, since we cannot evaluate the integrals analytically, we will simulate the related market shares using standard techniques.

The advertiser demand (10) is estimated separately from the reader demand side using a control function approach similar to what we have done in the previous section.

To identify the structural parameters, we need to address the potential endogeneity problem of a few main variables in the analysis. For instance, one might worry about endogeneity of program characteristics: channels with higher-quality programs tend to be more popular and to broadcast more ads at the same time. Ignoring the unobserved quality factor would lead to a wrong conclusion that viewers like ads. To tackle this problem, we first use high-frequency data on TV ratings for each 30-minute time interval in two weeks to estimate the main taste parameters attached to characteristics of programs or bundles. With the data, we can use fixed-effects at a highly disaggregated level. Based on equation (3), after removing fixed effects for each day, half-hour and channel-year, the endogeneity would persist only if q_{jlt} correlates with $\Delta\xi_{jlt}^{(p)}$. For the remaining concern, one candidate instrument is the so-called "BLP-type" instruments, which are essentially mean values of some exogenous program characteristics of the competing channels. Another possible set of instruments are cost shifters that we observe in the data, including detailed information on personnel statistics and staff costs. In addition, in structural equations (3) and (10), Internet penetration is endogenous. Due to its highly non-linear path, we will again take a control function approach similar to what we have described for the reduced-form analysis.

5 Preliminary Results

5.1 Consumer demand estimates

We will present and discuss estimates for consumer taste parameters in this section.

5.2 Advertiser demand estimates

We will present and discuss estimates for parameters in advertising demand function in this section. While the full GMM results are pending, below we report in Table 5 some estimates from our preliminary analysis, in which we have only addressed the endogeneity of Internet penetration (by taking the control function approach) but not the other ones.

Recall that one advantage of the control function approach is that the estimated coefficient for the additional regressor can inform us about the seriousness of endogeneity. In specification (3), the estimated coefficient is positive and highly significant, suggesting that the problem is indeed very severe if not properly address.

Based on our preliminary results, we first observe that the (inverse) demand curve seems to behave well: it slopes down (with constant price elasticity of demand), and *ceteris paribus*, if program viewers double their number, advertisers are willing to pay roughly 10 percent more. Both OLS with different specifications and the control-function results suggest significantly negative effects of broadband Internet. Over the sample periods, broadband penetration has gone up by 50 points on average, and that has caused advertisers' willingness to pay per-minute of ads to drop by 84 percent. In the context of this structural model, it translates to that the value per viewers' look has gone down by 84 percent on average, due to use of broadband Internet. Therefore, we can some clear evidence on the micro-mechanism through which broadband Internet has changed the landscape of China's TV ad markets.

6 Conclusion

(To be written.)

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Tables

Table 1: Summary Statistics of Main Variables

Variable	Mean	S.D.	Obs.	Variable	Mean	S.D.	Obs.
Total program length (10^4 *hours*):				*Viewer demographic composition*:			
News	6.26	3.61	309	*Income group*:			
Service	5.48	2.79	309	0-600	0.508	0.196	340
Entertainment	4.21	2.84	309	600-1200	0.178	0.076	340
TV series	22.03	13.30	309	1200-1700	0.160	0.093	340
Ads	6.20	3.59	309	1700-2600	0.079	0.099	340
Other	5.59	4.06	309	2600-3500	0.046	0.066	340
Total	49.78	27.59	309	3500-5000	0.025	0.045	340
				Above 5000	0.005	0.026	340
Program ratio:							
News	0.130	0.334	309	*Age group*:			
Service	0.124	0.061	309	4-14	0.129	0.045	340
Entertainment	0.083	0.033	309	15-24	0.122	0.039	340
TV series	0.429	0.073	309	25-34	0.149	0.026	340
Ads	0.124	0.025	309	35-44	0.180	0.024	340
Other	0.110	0.046	309	45-54	0.180	0.039	340
				55-64	0.131	0.035	340
Ad rev. (10^8 yuan)	17.48	16.99	234	Above 65	0.108	0.030	340
Ad rate (10^4 yuan/hour)	3.94	7.89	234				
Cable rev. (10^8 yuan)	9.44	7.34	234	*Education*:			
Cable price (yuan)	147.44	38.75	234	No school	0.077	0.033	340
No. subscr. (10^4)	614.44	467.15	296	Elementary	0.262	0.077	340
No. viewers (10^4)	301.97	282.75	232	Junior hight	0.396	0.060	340
				Secondary	0.188	0.068	340
Broadband penetration	0.258	0.188	311	College & beyond	0.076	0.060	340
Optical fiber (10^4 km)	4.97	13.76	311				
				Occupation:			
Viewer demographic composition:				Senior official	0.018	0.013	340
Female	0.502	0.015	340	Private sector	0.103	0.033	340
Male	0.498	0.015	340	Junior official	0.086	0.058	340
				Blue collar	0.104	0.050	340
Urban	0.300	0.127	287	Student	0.137	0.049	340
Rural	0.700	0.117	287	Unemployed	0.267	0.085	340
				Other	0.288	0.135	340

Notes:

Table 2: Broadband Effects on TV Cable and Ad Markets

Dependent variables:	log(*cable market outcomes*) No. subscribers	Price	Revenue	log(*ad market outcomes*) Ad price	Ad revenue	No. viewers local channels	No. viewers CCTV	No. viewers satellites
OLS: *broadband penetration*	0.165	-0.242	-0.137	-1.534***	-1.097***	0.216	0.073	0.407
	(0.131)	(0.298)	(0.249)	(0.495)	(0.270)	(0.290)	(0.208)	(0.389)
IV: *broadband penetration*	0.300**	-0.509	-0.098	-1.615***	-1.359***	0.967***	-0.459*	-0.597
	(0.153)	(0.518)	(0.423)	(0.324)	(0.376)	(0.337)	(0.263)	(0.700)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	296	234	234	234	234	283	283	283

Notes:

Table 3: Broadband Effects on Television Programs

(a) Broadband effects on length of television program

Dependent variables:	log(*program length*)						
	News	Service	Entertainment	TV series	Ads	Other	Total
OLS: *broadband penetration*	-0.408**	-0.600***	0.212	-0.040	0.482***	0.712**	-0.068
	(0.199)	(0.214)	(0.287)	(0.200)	(0.178)	(0.340)	(0.150)
IV: *broadband penetration*	-0.465	-0.871***	0.110	-0.497**	0.481*	0.749	-0.292
	(0.324)	(0.302)	(0.545)	(0.286)	(0.276)	(0.509)	(0.227)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	309	309	309	309	309	309	309

(b) Broadband effects on ratio of television program

Dependent variables:	*Program ratio* (%)					
	News	Service	Entertainment	TV series	Ads	Other
OLS: *broadband penetration*	-0.053***	-0.089***	0.016	-0.003	0.061***	0.067**
	(0.019)	(0.023)	(0.021)	(0.038)	(0.019)	(0.027)
IV: *broadband penetration*	-0.035	-0.082**	0.032	-0.096*	0.086***	0.095**
	(0.036)	(0.040)	(0.035)	(0.053)	(0.025)	(0.043)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	309	309	309	309	309	

Notes:

Table 4: Broadband Effects on Composition of TV Viewers

Dependent variables:	*Individual monthly income group* (%)						
	0 - 600	*600 - 1200*	*1200 - 1700*	*1700 - 2600*	*2600 - 3500*	*3500 - 5000*	*Above 5000*
OLS: *broadband penetration*	0.052	-0.035	0.050	0.055	0.019	-0.030	-0.112***
	(0.054)	(0.048)	(0.056)	(0.034)	(0.024)	(0.021)	(0.013)
IV: *broadband penetration*	0.156**	-0.291***	0.033	0.101	0.074**	0.033	-0.116***
	(0.071)	(0.062)	(0.091)	(0.064)	(0.038)	(0.047)	(0.028)
Dependent variables:	*Gender* (%)		*Education* (%)				
	Female	Male	No School	Elementary	Junior High	Secondary	College & beyond
OLS: *broadband penetration*	-0.003	0.003	0.033*	-0.023	0.057*	0.009	-0.050***
	(0.009)	(0.009)	(0.019)	(0.027)	(0.030)	(0.024)	(0.020)
IV: *broadband penetration*	-0.018*	0.018*	0.055***	0.014	0.064*	-0.0449	-0.059***
	(0.011)	(0.011)	(0.020)	(0.035)	(0.037)	(0.030)	(0.016)
Dependent variables:	*Age group* (%)						
	4 - 14	*15 - 24*	*25 - 34*	*35 - 44*	*45 - 54*	*55 - 64*	*Above 65*
OLS: *broadband penetration*	0.003	-0.022	-0.040***	-0.026*	0.081***	-0.011	0.005
	(0.016)	(0.017)	(0.014)	(0.014)	(0.016)	(0.013)	(0.013)
IV: *broadband penetration*	0.028	-0.025*	-0.029	-0.055***	0.119***	-0.002	-0.017
	(0.024)	(0.022)	(0.021)	(0.019)	(0.028)	(0.019)	(0.016)
Dependent variables:	*Occupation* (%)						
	Senior official	Private sector	Junior official	Blue collar	Student	Unemployed	Other
OLS: *broadband penetration*	-0.002	-0.033	-0.040**	0.084***	-0.058***	0.056*	-0.007
	(0.007)	(0.023)	(0.018)	(0.024)	(0.027)	(0.034)	(0.065)
IV: *broadband penetration*	-0.016*	-0.052*	-0.020	0.078**	-0.068**	-0.009	0.087*
	(0.009)	(0.028)	(0.034)	(0.041)	(0.030)	(0.036)	(0.050)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes:

Table 5: Preliminary Estimation of Ad Demand

Dependent variable: *ln(per-minute ad rate)*			
	OLS		IV
	(1)	(2)	(3)
ln(ad quantity)	-0.815***	-0.804***	-0.785***
	(0.105)	(0.102)	(0.123)
ln(no.viewer)	0.117**	0.083	0.123*
	(0.058)	(0.059)	(0.072)
Broadband penetration	-1.117***	-1.137***	-1.676***
	(0.276)	(0.285)	(0.426)
CF regressor	-	-	0.409**
	-	-	(0.207)
Viewer-demographic controls	No	Yes	Yes
Province dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R-squared	0.98	0.98	0.98
No. observations	229	228	228

Notes: