Zwick Center for Food and Resource Policy
Working Paper Series
No. 37

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July 2015

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Selected paper presented at
The Agricultural and Applied Economics Association Meetings
July 26 – 28, 2015, San Francisco, California

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Abstract

As in previous studies on traditional media, previous work has assumed that online and offline advertising are substitutes. However, empirical evidence for this premise is lacking. This paper investigates the substitution between online advertising and offline advertising as well as the impact of the introduction of new media technology on the cost of advertising. Using a rich dataset of monthly observations for 52 carbonated soft drink brands between 2005 and 2011, we estimate a translog cost function that considers the mix of on/off line advertising and online advertising adoption at the brand level. As in previous work, we find that TV and print media are close substitutes. Surprisingly, however, we find that online advertising is a complement to rather than a substitute for both TV and print media advertising. This might be explained by online advertising's targeting younger market segments and acting as a reinforcement of TV and print media advertising exposure. Further results show that the adoption of online advertising has lowered the cost of advertising for achieving a sales target but that its role as a complement rather than a substitute is weakening.

Keywords: Online advertising; media substitution; translog cost function; CSDs

JEL classification: L13; M37; D12

1. Introduction

Ever since online advertising started in 1994, when the website magazine HotWired sold a banner ad to AT&T and displayed the ad on its webpage (Kaye and Medoff, 2001), online advertising revenue has increased both in absolute terms and as a fraction of all advertising revenues. The fast rise of internet advertising has transformed the advertising industry landscape, with both internet penetration and internet advertising revenues continuing to climb, reaching a historical high of $12.4 billion in the third quarter of 2014 in the U.S. (Interactive Advertising Bureau, 2014), while traditional media (offline) advertising, newspapers in particular, lost audience to online advertising.

The most notable difference between online advertising and offline advertising (ONLA and OFFLA, respectively) is that online advertising has a more precise targeting ability than traditional media (Evans, 2009; Bergemann and Bonatti, 2011; Athey, Calvano and Gans, 2013), and that online advertising has a much lower cost per viewer (Gentzkow, 2014). In spite of the lack of empirical studies focused on the potential substitution between ONLA and OFFLA, the conventional wisdom is that they are substitutes. Previous work either offers a descriptive perspective (Goldfarb, 2014; Goldfarb and Tucker, 2011a; Goldfarb and Tucker, 2011b; Gentzkow, 2014)[1] or has only focused on traditional offline media platforms (Seldon, Jewell, and O'Brien, 2000; Frank, 2008; Giannakas, Karagiannis, and Tzouvelekas, 2012). To our knowledge, no empirical studies have explicitly investigated cross-substitution possibilities between ONLA and OFFLA. The absence of studies on substitution possibilities between them becomes particularly apparent nowadays as firms aggressively increase their ONLA.

Determining the direction and quantifying the substitution or complementarity between ONLA and OFFLA in the food industries is of interest for at least two reasons. First, the effectiveness of any ban on TV advertising, as proposed by some to promote

[1] The study by Goldfarb and Tucker (2011a) uses a lab experiment to elicit the effects of a ban on TV advertising by comparing those who have been exposed to those who have not been exposed to internet advertising. The paper by Gentzkow (2014) presents a simple theory and then descriptive evidence to support the theoretical claims at the national level aggregated over products and services.

healthier food and beverage choices, critically depends on how easily such a ban might be offset by increasing advertising in other media (Frank, 2008; Seldon, Jewell, and O'Brien, 2000). Second, from an industry perspective, the cost of advertising to achieve target sales might be optimized by the right mix of ONLA and OFFLA platforms, so understanding their inter-relationship is critical for managerial decisions.

The goal of this paper is to empirically examine the degree of substitution between ONLA and OFFLA, using the carbonated soft drink (CSD) industry as a case study. Specifically, the questions raised by conventional wisdom are: Are ONLA and traditional OFFLA substitutes or complements? How price elastic is the demand for these media in the carbonated soft drink industry? What is the extent of cost reduction brought about by ONLA adoption? To answer these questions, we estimate an advertising translog cost function with 2005-2011 data for 52 CSD brands purchased at U.S. supermarkets.

As in previous work, we find that TV and print media advertising are close substitutes and that ONLA is a complement to OFFLA, although its complementary role weakens over time. Further results confirm that ONLA has lowered the cost of advertising for achieving a sales target and that there are economies of size in advertising in the CSD industry.

2. Empirical model

Following Seldon, Jewell and O'Brien (2000), we assume separability between production and advertising, and use a translog cost function to estimate media substitution. The cost function is represented by a translog second-order approximation of the following form:[2]

$$lnC_{kt} = \alpha_0 + \phi_q lnQ_{kt} + (1/2)\phi_{qq}(lnQ_{kt})^2 + \sum_i \alpha_i lnP_{it} + (1/2)\sum_i \sum_j \beta_{ij} lnP_{it} lnP_{jt} + \sum_i \gamma_{qi} lnQ_{kt} lnP_{it} + b_t lnT + (1/2)b_{tt}(lnT)^2 + \sum_i b_{ti} lnP_{it} lnT + b_{qt} lnQ_{kt} lnT + u_{kt}, \quad (1)$$

where k is the brand index; t is the time index; i, j *is* the media type; C_{kt} is the total advertising cost for brand k at time t; Q_{kt} is the total quantity sales units of brand k

[2] In fact, a cost function cannot be a translog function. A translog cost function can be used as an approximating function, but then the coefficients no longer need to satisfy the homogeneity constraints. In this study, however, the likelihood ratio test for homogeneity restrictions suggests homogeneity restrictions cannot be rejected. Therefore, we still add homogeneity restrictions in the estimation.

at time t; P_{it} is the price of advertising medium i; T is the state of ONLA technology; and u_{kt} is an error term.

Applying Shepard's Lemma yields the cost share function for the platform i:

$$s_{kit} = \alpha_i + \sum_j \beta_{ij}(lnP_{jt}) + \gamma_{qi}(lnQ_{kt}) + b_{ti}lnT + u_{kit} \,. \tag{2}$$

Any well-specified cost function must be homogeneous of degree 1 in input prices. In the translog cost function, this requires that

$$\sum \alpha_i = 1,\ \sum \beta_{ij} = 0, \sum \gamma_{qi} = 0, \tag{3}$$

and $\beta_{ij} = \beta_{ji}$ can be imposed for symmetry.

A proxy to the rate of technological change can then be obtained from (1),

$$TC = \frac{\partial lnC}{\partial T} = \frac{\partial lnC}{\partial lnT}\frac{\partial lnT}{\partial T} = \frac{\partial lnC}{\partial lnT}\frac{1}{T} = (b_t + b_{tt}lnT + \sum b_{ti}lnP_i + b_{qt}lnQ)/T \tag{4}$$

Equation (4) shows that the technological change can be divided into three elements: pure technical change $(b_t + b_{tt}lnT)$; non-neutral technical change $(\sum b_{ti}lnP_i)$; and scale-augmenting technical change $(b_{qt}lnQ)$.

Estimated returns to scale measured by

$$\eta_S = \partial(\mathrm{LnQ})/\,\partial(\mathrm{LnC}) = 1/\phi_q \tag{5}$$

The translog form is flexible in the sense that specific features of the cost function (like returns to scale or homotheticity) can be tested by examining the estimated model parameters. Specifically, if the technology is homothetic, the dual cost function is multiplicatively separable in output quantity and input prices. In the translog case, this requires that $\gamma_{qi} = 0$ (for all i), so that the quadratic interaction terms between output levels and input prices should disappear.

Instead of using a time trend to capture the state of advertising technology, we first estimate a probit model of online advertising adoption and then include the predicted probability as T in equations (1), (2), and (4). First, firms decide whether to adopt online advertising or not. If a brand uses online advertising, then this variable equals 1; otherwise, it equals 0. We model the decision as a discrete choice model:

$$Y_{it} = \begin{cases} 1 & if\ X_{it}\beta + \varepsilon_{it} > 0 \\ 0 & otherwise; \end{cases} \quad (6)$$

where Y_{it} denotes whether a firm chooses online advertising for brand i or not, X_{it} is a vector of all explanatory variables, specified as market share for brand i, internet penetration rate among consumers, and a time trend. We use the probit model to estimate the online advertising adoption choice and then use the predicted probability of online advertising adoption in the translog function to measure the impact of online advertising adoption on advertising cost.

3. Data and Estimation

The data to operationalize the empirical model consist of a database matching three main sources: (1) advertising expenditures; (2) sales output; and (3) advertising prices. Advertising expenditures at the brand level came from Kantar Media's Strategy database, consisting of monthly observations for 125 Designated Market Areas on 25 media platforms (online and offline), which we aggregate into four types: TV, online, magazine, and radio[3]. However, since our target here is to measure the substitutability of ONLA and OFFLA and radio consists of only a small portion of advertising expenditure by CSD companies, we omit radio advertising expenditure and focus on the three types: TV, online and magazine advertising.

Output is measured as physical units sales during the time period. Brand sales came from Academic Dataset by Information Resources Inc. (IRI), obtained from the Booth School of Business at the University of Chicago. This dataset contains 11 years (2001-2011) of weekly sales data at the store-UPC level in 47 US markets (Bronenberg, Kruger, and Mela, 2008).

The third and most challenging data task was to obtain appropriate prices for ONLA and OFFLA faced by the CSD industry. We employ two alternative measures to interpolate the price of different media types. One, proposed by Gentzkow (2014), uses the average price per hour of attention to internet[4] and offline (TV, radio, and magazines) media. To

[3] Kantar Media's Stradegy database was obtained through a customized agreement by the Zwick Center for Food and Resource Policy.

[4] Gentzkow (2014) measures total minutes of internet use 2008-12 from comScore and extends the series back to 1992

interpolate the monthly online price data from the yearly price per hour of attention online developed by Matthew, we use the monthly producer price index, published by the U.S. Bureau of Labor Statistics for internet publishing and web search portals.[5] We use Denton's interpolation[6] method (Di Fonzo, T., & Marini, M., 2012) to interpolate the monthly online price. As for TV price, we use the TV advertising price per hour of attention developed by Gentzkow and the monthly periodical publishers' producer price index from BLS as the monthly price basis to interpolate the monthly TV price. Similarly, we use magazine per hour of attention developed by Gentzkow together with monthly television broadcasting producer price index from BLS as the monthly price basis to interpolate the monthly price index of magazine advertising.

Consistent figures for online advertising since 2001 are available from the Kantar media database, which contains online advertising information since that year. However, because the BLS internet publishing and web search portal data is available only from July 2004, our data starts from 2005 M1 and ends on 2011 M4.

Considering that online advertising is a public good in the sense that it is read worldwide, we use national-level online advertising data for each brand. To make online, TV, and magazine advertising comparable, we also use national-level TV and magazine advertising data; thus, this study was conducted on the national level for different brands.

We merged the CSD sales data with advertising data and delete observations whose total advertising expenditures (the sum of TV, online and magazine advertising expenditures) equals 0, yielding 1,190 observations after deleting outliners and

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by multiplying the estimated number of Americans using the internet (from Pew Research Center for the People and Press data) times total minutes per internet user extrapolated linearly from the 2008-12 data. The internet advertising revenue data are total digital advertising collected from various sources and reported by eMarketer,. The unit of internet use is minutes per person per day. The unit of online advertising revenue is 2012 $millions.

[5] The producer price index for internet publishing and web search portals is a monthly indicator, which we aggregate into quarterly data by averaging the monthly indexes. It should be noted that there is some inconsistency for the PPI index for internet publishing and web search portals, industry 519130 in the 2007 NAICS classification. In prior versions of NAICS, the activities of this industry were split between NAICS 516110, internet publishing and broadcasting, and NAICS 518112, web search portals. The PPI index for NAICS 518112 has been discontinued. So the PPI index for this industry is actually for NAICS 5118112 from 2004 to 2009, and for NAICS519130 from 2010 to 2011.

[6] Denton computes the proportional Denton method of interpolation of an annual flow time series using an associated "indicator series", imposing the constraint that the interpolated series obeys the annual totals. The method is recommended in the IMF publications as "relatively simple, robust, and well-suited for large-scale applications."

observations without lag variables.[7] The dataset used for estimation consists of 1,010 observations for 52 brands.

Table 1 presents summary statistics of the main variables in this study. Overall, TV advertising expenditures take up approximately 70% of total advertising expenditures, online advertising accounts for about 24%, and magazine advertising accounts for about 16%. However, TV advertising's share decreased from 82% in 2005 to 61% in 2011, while online advertising's share increased from 3% in 2005 to 22% in 2011, and magazine advertising's share remained relatively stable at 15%. As for advertising prices, magazines' is the highest with an average price of 2.47, while TV's is the lowest with an average price of 0.28; the internet's is 0.65. Advertising prices for the three different types remained relatively stable over the sample period.

An important issue that should be taken into consideration is the continuing effects of past advertising on present sales. If this effect persists, then one should pay attention to the error term of our model. Following Berndt and Savin (1975), we correct for this type of autocorrelation. The autocorrelation correction equations are substituted directly into the cost equation and the share equation, and the system are estimated using nonlinear iterated seemingly unrelated regressions. The model parameters for equations (2) and (3) and the autocorrelation parameters can be estimated simultaneously.[8]

After dropping one share equation, we estimated the remaining share equations together with the translog cost function by ITSUR and IT3SLS.[9] We chose the iterated

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[7] However, since our model accounts for the autocorrelation of error terms, and we need to use the lag of variables, we had to delete observations with no lag information, reducing the number of usable observations to 1,122. Moreover, considering that some brands spend little on advertising, we dropped observations in the lower tenth percentile of advertising of expenditures to avoid the impact of extreme values. The bottom tenth percentile of the advertising expenditure is $6,100.

[8] For the system of share equations, $S_t = \Pi X_t + U_t$, we need to ensure that $L\Pi X_t = 1, where\ l = (1,1,1)$, so we need to ensure that $\sum u_{f,i,t} = 0\ that\ is\ u_{f,tv,t} + u_{f,online,t} + u_{f,magazine,t} = 0$. We specify the three-element vector U_t as

$$\begin{bmatrix} u_{tv,t} \\ u_{online,t} \\ u_{magazine,t} \end{bmatrix} = \begin{bmatrix} \rho_{tv,tv} - \rho_{tv,magazine} & \rho_{tv,online} - \rho_{tv,magazine} \\ \rho_{online,tv} - \rho_{online,online} & \rho_{online,online} - \rho_{online,online} \\ \rho_{magazine,tv} - \rho_{magazine,magazine} & \rho_{magazine,online} - \rho_{magazine,magazine} \end{bmatrix} \begin{bmatrix} u_{tv,t-1} \\ u_{magazine,t-1} \end{bmatrix} + \begin{bmatrix} v_{tv,t} \\ v_{online,t} \\ v_{magazine,t} \end{bmatrix}$$

[9] The general triangular system can be estimated consistently by using the seemingly unrelated regressions (SUR) method. However, efficiency will only be gained if the covariance matrix, Σ, is known, which is almost never the case

SUR (ITSUR) as the procedure for our triangular system estimation.[10] The systems of equations are estimated using Zellner's iterated procedure for seemingly unrelated regressions. Estimation is performed using the MODEL procedure of the SAS computer package.

4. Empirical results

Table 3 presents the estimation results for the linear homogeneity in the cost function with input prices. Alternative versions of the model were also estimated to test for constant returns to scale and homotheticity. The homothetic model is estimated with the restriction that $d_1 = d_2 = 0$. The constant returns to scale model is estimated with restrictions $d_1 = d_2 = 0$, $C_{11} = 0$, and $C_1 = 1$. An appropriate test of the hypothesis of equality of the full model and the restricted model is the likelihood ratio statistic:

$$LR = -2Log\Lambda = N[log|\Omega_r| - log|\Omega_u|],$$

where $|\Omega_r|$ and $|\Omega_u|$ are absolute values of the determinants of the estimated error covariance matrices for the restricted and unrestricted models, respectively, and N is the number of observations.

The log-likelihood statistic of the homotheticity restriction is 12.12, suggesting that the homothetic model is rejected in favor of the homogeneous model. The LR statistic for constant returns to scale restriction is 20.43, indicating that the constant returns to scale assumption should be rejected in favor of the homogeneous model. Therefore, we can confidently reject the homothetic model and constant returns to scale hypothesis, and focus on the homogeneous model. Given the panel nature of the data, the homogeneous model fits well with an adjusted R^2 of 0.36 for the translog cost function, and the R^2 is 0.43

in practice. Lahiri and Schimidt (1978) suggest the iterated SUR (ITSUR) to achieve the algebraically same results as the full information maximum likelihood (FIML) estimator. However, the convariance matrix from the ITSUR may not be consistent. It is well known that when the covariance matrix, Σ, is unknown, FIML and 3SLS are equally efficient.

[10] We estimate the equation system using iterated 3SLS (IT3SLS) as well. The coefficients remain almost the same as with ITSUR.

and 0.37 for the TV advertising and online advertising cost shares, respectively. Parameter estimates with no restriction other than symmetry and homogeneity of cost in input prices are presented in Table 2.

Table 3 shows Morishima elasticies of substitution between the three media types. Note that TV and online advertising are complements, with their substitutability coefficient ranging between -0.92 and -9.83. The case is the same with online and magazine advertising: online and magazine advertising are complements, with the substitutability coefficient ranging from -0.367 to -10.42. Moreover, the complementarity between online advertising and traditional media types decreased gradually. However, TV advertising and magazine advertising are always substitutes, with an average substitutability coefficient of 0.49 or 1.08.

The estimated demand elasticities are reported in Table 4. The cross-price elasticities of demand also present evidence that magazine and TV advertising are substitutes, with elasticities ranging from 0.20 to 1.13. TV and online advertising are, however, complements, as are online advertising and magazine advertising.

Table 5 presents the estimated results of the ONLA probit model. The results suggest that brands with larger market share are more likely to adopt online advertising, with higher internet penetration rate leading to higher online advertising adoption and, over time, the increasing probability of adopting online adverting. The estimated results are in line with expectations.

Considering that the emergence of online and social media advertising might change advertising effectiveness, we compute the rate of technological change caused by online advertising adoption following equation (4).

The estimated rate of technological change in Table 6 suggests that online advertising adoption by the CSD industry decreases the cost of advertising. According to the estimated results, the rate of decrease in the cost of production has been 1.60% on average each year, and the rate of decrease is accelerating each year. Thus, the calculations confirm that the adoption of online advertising technology decreased the advertising costs of CSD industry..

The estimated average degree of economies of size reported in Table 6 is 1.65, indicating that advertising in the CSD industry exhibits economies of size. That is, advertising costs decrease with output sales.

5. Conclusions

This paper investigates the substitutability of ONLA and OFFLA. Based on monthly data spanning 2005 to 2011 for the carbonated soft drinks (CSD) industry, we estimate a translog cost function of advertising.

First, the online advertising adoption model suggests that CSD brands with higher market share are more likely to adopt online advertising. In addition, a higher internet penetration rate and the passage of time increase the probability of a brand's adopting online advertising. Empirical results point out that online advertising and traditional offline media are complements rather than substitutes based on estimated cross-price elasticities as well as Morishima elasticies. Moreover, the estimated rates of technological change indicate that the adoption of online advertising decreases the cost of achieving a sales target but cost-reducing and complementary roles are weakening. Furthermore, this is a preliminary empirical study of the substitutability between ONLA and OFFLA. Future studies can be extended to other industries to see if our findings also hold in other industries.

Figure 1: Trend in advertising expenditure shares by media type: 2005-2011

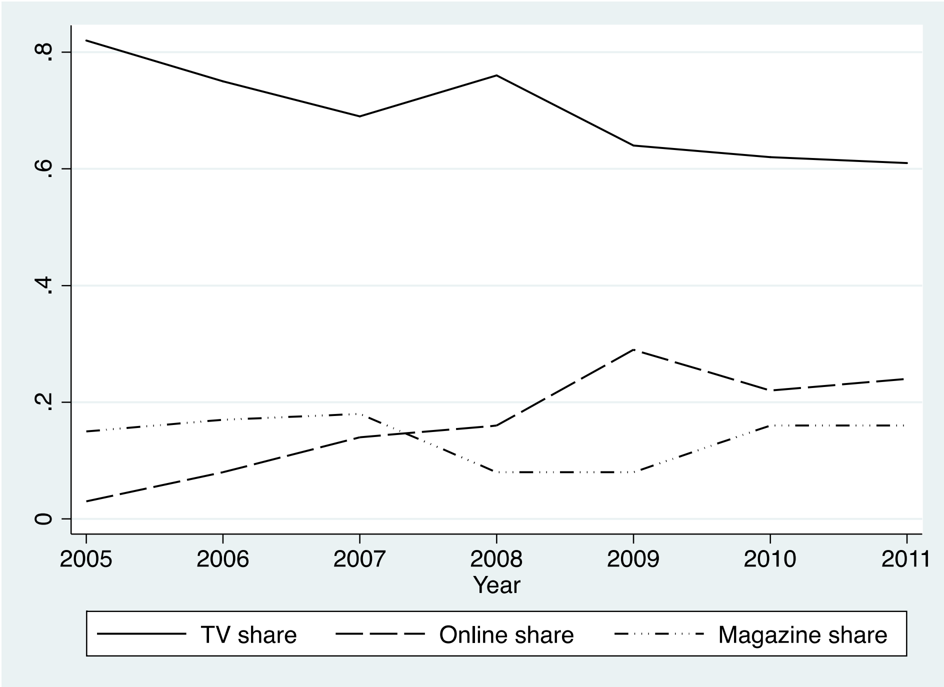

Figure 2: Trend in advertising price by media type: 2005-2011

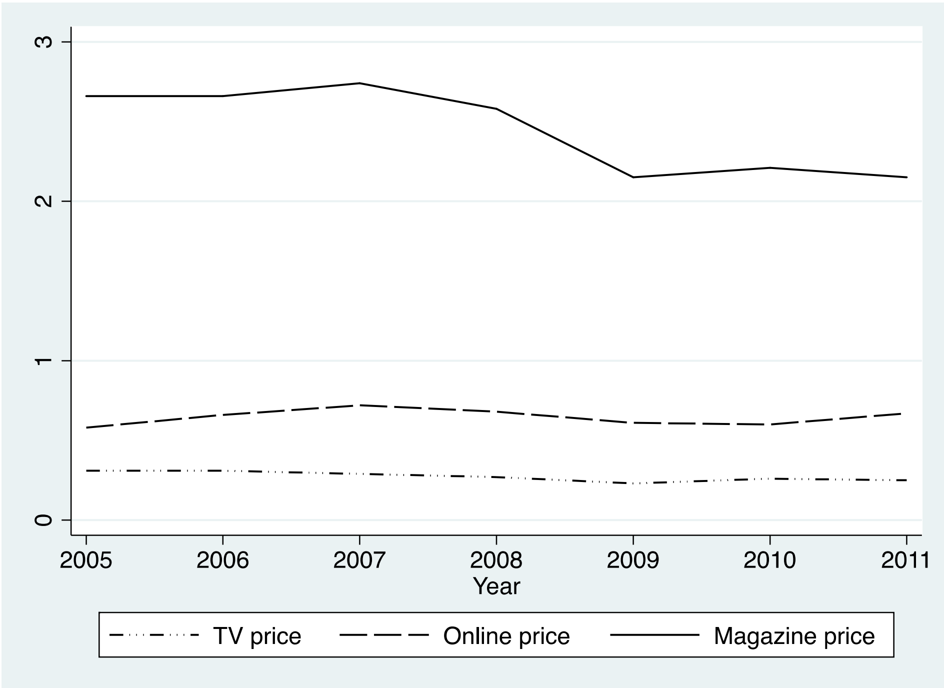

Figure 3: Trend in rate of technological change: 2005-2011

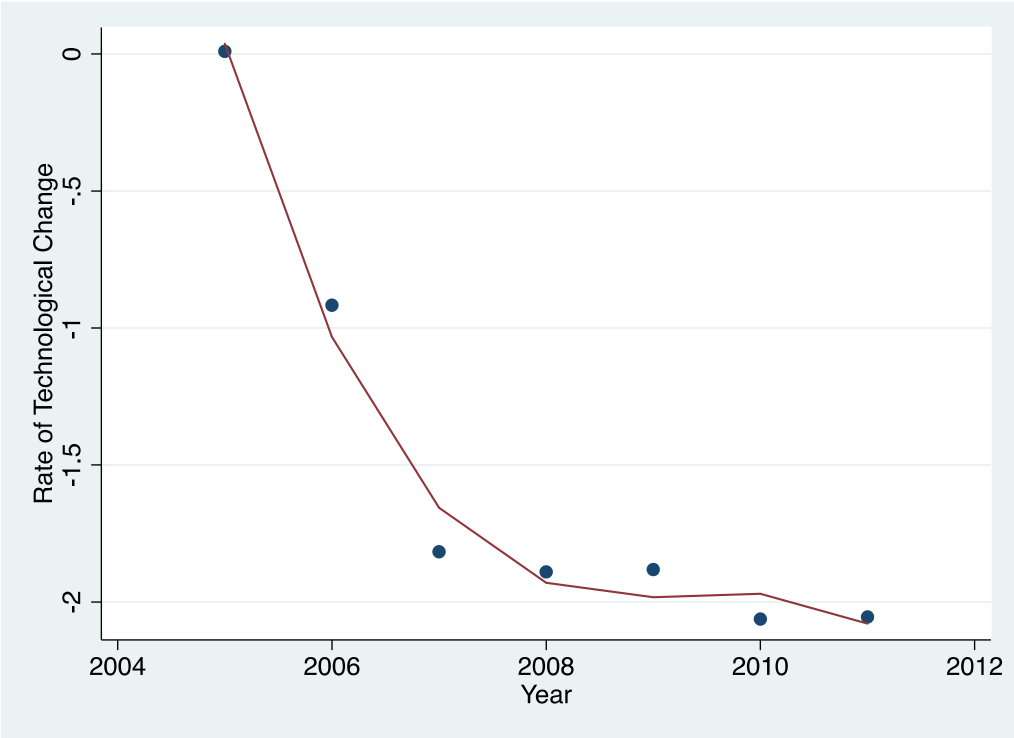

Table 1: Summary statistics

Year	Notation	2005	2006	2007	2008	2009	2010	2011
Total units	Q	980347.1	1021325	889231.4	954639	1046511	960843.2	711254.4
Expenditures								
Total advertising expenditures	C	2762.75	2452.46	1777.8	1939.13	1530.69	1955.13	1416.48
TV advertising expenditures	C_{TV}	2487.2	2193.02	1471.49	1760.99	1265.24	1653.91	1281.72
Online advertising expenditures	C_{Online}	61.48	55.15	126.91	49.12	130.82	137.4	68.53
Magazine advertising expenditures	$C_{Magazine}$	214.07	204.29	179.4	129.01	134.63	163.82	66.23
Expenditure shares								
TV advertising share	S_{TV}	0.82	0.75	0.69	0.76	0.64	0.62	0.61
Online advertising share	S_{Online}	0.03	0.08	0.14	0.16	0.29	0.22	0.24
Magazine advertising share	$S_{Magazine}$	0.15	0.17	0.18	0.08	0.08	0.16	0.16
Price								
TV advertising price	P_{TV}	0.31	0.31	0.29	0.27	0.23	0.26	0.25
Online advertising price	P_{Online}	0.58	0.66	0.72	0.68	0.61	0.6	0.67
Magazine advertising price	$P_{Magazine}$	2.66	2.66	2.74	2.58	2.15	2.21	2.15
N		153	164	167	123	115	127	161

Table 2: Estimated Coefficients of Translog Cost Function for Advertising CSDs

Variable	Parameter	Estimate	Approx Std Err	t Value
Constant	α_0	-15.9313	7.7855	-2.05
LnQ_f	ϕ_q	0.237549	0.2136	1.11
$(LnQ_f)^2$	ϕ_{qq}	0.043563	0.0153	2.84
LnP_{TV}	α_1	0.849231	0.4422	1.92
LnP_{Online}	α_2	-0.19295	0.2923	-0.66
$LnP_{Magazine}$	α_3	0.343718	0.3894	0.88
$(LnP_{TV})^2$	β_{11}	0.190918	0.2106	0.91
$LnP_{TV}LnP_{Online}$	β_{12}	-0.23626	0.138	-1.71
$(LnP_{Online})^2$	β_{22}	0.362626	0.1378	2.63
$(LnP_{Magazine})^2$	β_{33}	0.081018	0.1834	0.44
$LnP_{TV}LnP_{Magazine}$	β_{13}	0.045344	0.1666	0.27
$LnP_{Online}LnP_{Magazine}$	β_{23}	-0.12636	0.1139	-1.11
LnQ_fLnP_{TV}	γ_{q1}	0.058936	0.0134	4.38
LnQ_fLnP_{Online}	γ_{q2}	-0.0223	0.0102	-2.18
$LnQ_fLnP_{Magazine}$	γ_{q3}	-0.03663	0.00904	-4.05
LnT	b_t	9.743697	4.0052	2.43
$(LnT)^2$	b_{tt}	-2.64195	1.0382	-2.54
$LnP_{TV}LnT$	b_{t1}	-0.17587	0.0667	-2.64
$LnP_{Online}LnT$	b_{t2}	-0.36918	0.2199	-1.68
$LnP_{Magazine}LnT$	b_{t3}	0.060776	0.0497	1.22
$LnQLnT$	b_{qt}	-0.02214	0.0333	-0.66

Table 3: Estimated Morishima Elasticities of Substitution between Pairs of Inputs

	TV	Online	Magazine
2005:			
TV	-	-9.836	0.497
Online	-6.105	-	-3.234
Magazine	1.08	-10.418	-
2011:			
TV	-	-0.923	0.561
Online	-0.314	-	-0.0479
Magazine	0.972	-1.334	-
At sample means:			
TV	-	-1.628	0.496
Online	-0.765	-	-0.367
Magazine	1.046	-2.178	-

Table 4: Estimated Price Elasticities of Input Demands

	TV	Online	Magazine
2005:			
TV	-0.0207	-0.254	0.2
Online	-6.052	3.041	-3.53
Magazine	1.133	-0.836	-0.554
2011:			
TV	-0.179	-0.153	0.233
Online	-0.393	-0.181	-0.376
Magazine	0.893	-0.565	-0.565
At sample means:			
TV	-0.114	-0.18	0.207
Online	-0.793	0.0285	-0.656
Magazine	1.018	-0.73	-0.55

Table 5: Online Advertising Adoption Probit Model Estimates

	Online Advertising Adoption
Market share	8.82***
	(0.87)
Internet Penetration Rate	4.78***
	(1.74)
Time Trend	0.13***
	(0.02)
Constant	-4.02***
	(1.23)
N	1010

Table 6: Rate of Technological Change and Economies of Size in CSD Advertising

Year	Rate of Technological Change	Economies of size
2005	0.009555389	1.6141253
2006	-0.916881212	1.6080923
2007	-1.816732516	1.6736785
2008	-1.890295303	1.7085842
2009	-1.881733989	1.6435057
2010	-2.062293809	1.6238553
2011	-2.054648085	1.7173954
Sample mean	-1.600675716	1.6544631

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