

Volume 43, Issue 3

Dissecting decline in the economy-wide advertising intensity 1997-2017

Darren Filson
Claremont McKenna College

Abstract

The macro-level advertising-to-sales ratio of U.S.-based advertising firms is stable at approximately 3% prior to 2001 and then drops substantially (primarily during 2001-2005) to approximately 2% by 2013-2017. A decomposition shows that changes in advertising intensities in four vertical chains – food, drugs, computers, and tobacco – are critical contributors to the drop. I explore tentative explanations. It is unlikely that the diffusion of the Internet is wholly responsible; food, drugs, and tobacco are among the industries least impacted by ecommerce. Category-specific factors likely matter: commoditization, the rise of warehouse club/supercenters, the changing nature of new products, and public policies and self-regulation.

I thank the Lowe Institute of Political Economy at Claremont McKenna College for support. For research assistance, I thank Evelyn Chen, Chloe Cho, Kevin Choi, Zubin Jotwani, Sarah Malott, Samuel Peterson and Danny Wang. I thank workshop participants at Claremont McKenna College, Rick Gretz, Joseph Harrington and two anonymous referees for comments and suggestions.

Citation: Darren Filson, (2023) "Dissecting decline in the economy-wide advertising intensity 1997-2017", *Economics Bulletin*, Volume 43, Issue 3, pages 1444-1452

Contact: Darren Filson - dfilson@cmc.edu.

Submitted: May 30, 2023. Published: September 30, 2023.

1. INTRODUCTION

This paper documents a substantial decline in the U.S. economy-wide advertising intensity (EWAI) – the macro-level advertising-to-sales ratio of advertising firms – over the period 1997-2017 (see Figure 1). From 1997-2001, the EWAI was approximately stable at 3% (evidence discussed below establishes that it was stable at this level for many years prior to this period as well). From 2001-2005, the EWAI declined substantially to almost 2%, and then it continued to trend down more slowly; it flattened out at approximately 2% during 2013-2017.

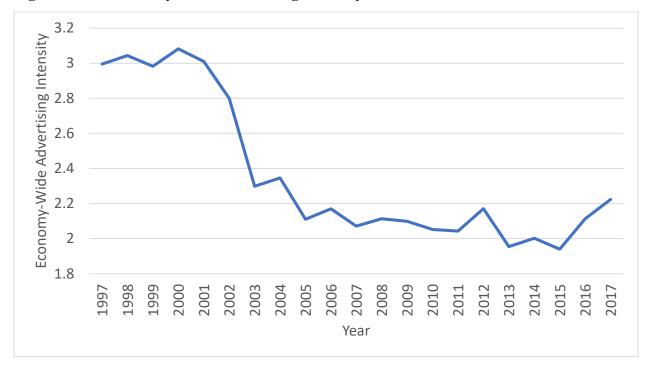


Figure 1. The Economy-Wide Advertising Intensity 1997-2017

Figure 1 suggests that at least one important non-transitory shift in the business environment impacted AIs in the early 2000s and that the impact was particularly strong during 2001-2005. As a step towards investigating potential shifts, I decompose the aggregate change in the EWAI into contributions by industry. The results are intriguing. The period 1997-2017 coincides with the diffusion of the Internet and an increase in targeted advertising online, and one might be tempted to attribute the drop in the EWAI to those forces. However, the decomposition shows that changes in AIs in four vertical chains – food, drugs, computers and tobacco – are critical contributors to the drop, and evidence shows that food, drugs and tobacco are among the industries least impacted by ecommerce. If diffusion of online advertising contributes to the reduction in the EWAI, then it likely does so in part because firms in the food, drugs, and tobacco vertical chains experienced a non-transitory reduction in offline advertising elasticities of demand (particularly over the period 2001-2005) without benefiting from sufficiently high online advertising elasticities of demand. An initial investigation suggests several category-specific factors likely matter too: commoditization, the rise of warehouse club/supercenters, the changing nature of the new products being introduced, and changes in public policies along with self-regulation. Results suggest that future research investigating these factors is warranted.

2. RELATED PRIOR LITERATURE

The literature on advertising is vast; I focus on prior studies that are most related to examining the EWAI. Borden's (1942) seminal work examines macro advertising expenditures both as a percentage of national income and as a percentage of "total sales volume of businesses using an appreciable quantity of advertising." (Borden 1942, p. xxvi). However, subsequent macro-level work focuses on value added (primarily using GDP rather than national income) rather than sales. Two stylized facts summarize the relationship between total advertising expenditure and GDP in the U.S.. First, over long horizons (decades, for example), advertising expenditures are a roughly constant percentage of GDP (approximately 2%; McCombs 1972, Pepall, Richards and Norman 2014, Molinari and Turino 2018). Second, advertising expenditures are procyclical: the advertising-to-GDP ratio tends to rise in business-cycle expansions and fall in contractions (Dekimpe and Deleersnyder 2018).

Figure 1 reveals a macro-level transition that is not revealed by examining advertising-to-GDP. Using the advertising expenditures data from Figure 1, the advertising-to-GDP ratio does not drop substantially during 1997-2017: in 1997-2001 the ratio is 2.3%, and in 2013-2017 the ratio is 2.2% (U.S. GDP data is provided by the Federal Reserve Bank of St. Louis: fred.stlouis.org). In addition, the reduction in EWAI does not coincide with business-cycle turning points. According to the National Bureau of Economic Research Business Cycle Dating Committee (www.nber.org/cycles.html), after a trough in March 1991, the economy expands until reaching a peak in March 2001, contracts until reaching a trough in November 2001, expands until December 2007, contracts until June 2009, and then expands until at least the end of 2017 (information as of June 2019). In contrast, the EWAI remains steady until 2001, falls substantially by 2005, and then continues to trend downward until 2015. The decline in the EWAI is not due to a decline in advertising expenditures; it is due to a change in intensity: total advertising expenditures follow an upward trend from \$184B in 1997 to \$394B in 2009 (which includes an increase from \$256B to \$319B over 2001-2005), drop to \$325B in 2010, rise to reach a peak of \$409B in 2014, and then flatten out to end at \$394B in 2017.

3. DATA AND MEASURES

The data is provided by Schonfeld & Associates, Inc.; it consists of annual estimates of advertising expenditures and revenues by four-digit SIC code for firms traded on U.S. stock exchanges during 1997-2017. Non-advertising industries and firms are excluded. While not all firms that are publicly traded on U.S. stock exchanges are headquartered in the U.S., the overwhelming majority are. Thus, this data is useful for examining trends in the U.S. EWAI.

Where possible, Schonfeld & Associates employ the advertising expenditures firms report. Thus, the data used to construct the EWAI (and the industry-level AIs I examine) originates from firm-level advertising expenditures (and revenues) that reporting firms provide. Under Generally Accepted Accounting Principles (GAAP), advertising expenditures include both offline and online spending (print, TV, radio, digital, and websites). Schonfeld & Associates impute missing values for advertisers who do not report advertising expenditures separately from Selling, General, and Administrative expenses. They allocate fiscal-year expenditures and revenues to calendar years, and they assign firms to industries using primary SIC codes. Firmlevel expenditures aggregate spending in all markets in which the firm operates (revenue is also total revenue in all markets), so the EWAI measures the macro AI of U.S. firms rather than the

AI associated solely with spending and revenues within the U.S. (indeed, the rise of online advertising makes such a restriction impossible: websites are generally available globally).

I define the Economy-Wide Advertising Intensity (EWAI) as the aggregate advertising-to-sales ratio of all firms that have non-trivial levels of advertising expenditures during a period. Schonfeld & Associates' data is ideal for this calculation because they impute missing values and allocate fiscal-year expenditures and revenues to calendar years. However, Compustat data on fiscal-year advertising expenditures (XAD) and total revenues (REVT) of all firms that report both items (in U.S. currency) yields similar conclusions and also establishes that the EWAI was high and stable for many years prior to 1997 (so the puzzle to explain is the drop, not the high initial level): using Compustat data, the mean EWAI during 1980-1999 is 3.0% (SD .25), and the mean during 2000-2017 is 2.3% (SD .11).

To investigate the industries contributing to the drop in the EWAI, I decompose the drop into the contributions of the 210 three-digit industry groups in the Schonfeld & Associates data. I compare the period 1997-2001 to the period 2013-2017 to focus on low-frequency changes. In each five-year period, in each group, I sum all advertising expenditures and all revenues: the advertising intensity (AI) is one sum divided by the other. I decompose the change in the EWAI as follows:

$$EWAI_{t} - EWAI_{t-1} = \frac{\sum_{i} a_{it}}{R_{t}} - \frac{\sum_{i} a_{it-1}}{R_{t-1}} = \sum_{i} \left[\frac{a_{it}}{r_{it}} \frac{r_{it}}{R_{t}} - \frac{a_{it-1}}{r_{it-1}} \frac{r_{it-1}}{R_{t-1}} \right] = \sum_{i} \left[\alpha_{it} \theta_{it} - \alpha_{it-1} \theta_{it-1} \right]$$

$$= \sum_{i} (\alpha_{it} - EWAI_{t-1}) d\theta_{it} + \sum_{i} d\alpha_{it} \theta_{it-1}$$
(1)

where i indexes the group, t indicates the period, a_{it} is group i's advertising expenditures in period t, R_t is aggregate revenue of all advertisers in period t, r_{it} is group i's revenue, α_{it} is group i's AI $(d\alpha_{it} = \alpha_{it} - \alpha_{it-1})$, and θ_{it} is group i's revenue share $(d\theta_{it} = \theta_{it} - \theta_{it-1})$; $\sum_i d\theta_{it} = 0$. Thus, the change in the EWAI consists of a "revenue-share component" $(\sum_i (\alpha_{it} - EWAI_{t-1})d\theta_{it})$ and an "AI component" $(\sum_i d\alpha_{it}\theta_{it-1})$.

The main benefit of the decomposition in (1) is that it isolates the AI component: the revenue-share component is driven more by low-AI groups' revenue shares rising and high-AI groups' shares falling than by changes in advertising efforts, but the AI component is due to changes in advertising efforts within groups holding all groups' revenue shares constant at their initial levels. The subsequent analysis focuses on the AI component. The percentage of the AI component attributable to group i is

$$\frac{d\alpha_{it}\theta_{it-1}}{\sum_{j}d\alpha_{jt}\theta_{jt-1}} \times 100$$
(2)

¹ After this point, the EWAI computed using Compustat data rises somewhat but remains below 3%: the mean during 2018-2022 is 2.6%.

4. RESULTS

The EWAI falls from 3.0% in 1997-2001 to 2.0% in 2013-2017, and 59.5% of the drop is attributable to the AI component. Examining the AI components reveals that the four groups with the highest values of (2) account for 49.3% of the AI component: manufacturing of drugs, food and kindred products, computers and office equipment, and cigarettes. Further, several other high-impact groups are related to the top four (for example, the fifth highest is beverage manufacturing and the sixth is drug wholesaling). Given this, I aggregate the effects of groups related to the top four, including others in the vertical chain (particularly wholesaling and retailing). Considering vertical chains also mitigates against results being driven by shifts in the burden of advertising within the chain.

Table 1. Decomposing the AI Component: The Four Categories

SIC	Industry Group(s)	Percentage of	
Code		the AI	
		Component	
	Food Vertical Chain (Total)	38.9	
200	Manufacturing: Food & Kindred Products	15.0	
208	Beverages	8.6	
206	Sugar and Confectionary Products	3.4	
	The 7 Others in Major Group 20	5.6	
514	Wholesale: Groceries and Related Products	1.1	
581	Retail: Eating and Drinking Places	2.7	
541	Grocery Stores	2.5	
540	Food Stores	.06	
	Drugs Vertical Chain (Total)	22.8	
283	Manufacturing: Drugs	15.9	
512	Wholesale: Drugs, Drug Proprietaries, and Druggists' Sundries	5.4	
591	Retail: Drug Stores and Proprietary Stores	1.5	
	Computers Vertical Chain (Total)	14.5	
357	Manufacturing: Computers and Office Equipment	9.7	
367	Electronic Components and Accessories	2.8	
504	Wholesale: Professional and Commercial Equipment and Supplies	.05	
573	Retail: Radio, Television, Consumer Electronics and Music Stores	1.9	
	Tobacco (Total)	8.8	
211	Manufacturing: Cigarettes	8.7	
210	Tobacco Products	.1	
	Overall Total	85.0	

Table 1 shows that groups in the four categories account for 85.0% of the AI component. Further, Table 2 shows that some excluded high-impact groups are related to the four categories (chemicals & allied products, variety stores), and almost all groups not in one of the four

categories have small effects. The four categories' contribution to the AI component accounts for 50.6% of the drop in the EWAI (85.0% of 59.5% is 50.6%).

Table 2. The Remaining Groups

SIC	Industry Group(s)	Percentage of	
Code		the AI	
		Component	
	Groups with Impacts >2% (Total)	18.5	
280	Manufacturing: Chemicals & Allied Products	4.1	
386	Photographic Equipment & Supplies	3.5	
342	Cutlery, Handtools, and General Hardware	3.5	
596	Retail: Nonstore Retailers	3.8	
533	Variety Stores	3.7	
	Groups with Impacts <-2% (Total)	-18.0	
284	Manufacturing: Soap, Detergents, and Cleaning Preparations;	-7.1	
	Perfumes, Cosmetics		
366	Communications Equipment	-2.8	
233	Women's, Misses', and Juniors' Outerwear	-2.3	
781	Services: Motion Picture Production and Allied Services	-5.8	
	124 Groups with Positive Impacts <2%	31.3	
	54 Groups with Negative Impacts >-2%	-16.8	
	Overall Total	15.0	

Dorfman and Steiner (1954) show that the profit-maximizing advertising-to-sales ratio is equal to the ratio of the advertising elasticity of demand ε_A to the absolute value of the own-price elasticity of demand $|\varepsilon_P|$. When interpreted using this model, the changes in the EWAI and group-level AIs can be linked to firm-level (and brand-level) elasticities. Meta-analyses conclude that ε_A has been falling over time at the brand level (Sethuraman, Tellis and Briesch 2011 and Henningsen, Heuke and Clement 2011) and that $|\varepsilon_P|$ has been rising (Bijmolt, van Heerde and Pieters 2005). Such changes lead to lower firm-level AIs that contribute to lower aggregate AIs. Sethuraman, Tellis and Briesch (2011) attribute the drop in ε_A to several factors, including "increased competition, ad clutter, the advent of the Internet as an alternate information source, and the consumer's ability to opt out of television commercials…" (Sethuraman, Tellis and Briesch 2011, p. 460). The decomposition conducted here suggests that compelling explanations must account for the prominence of the four categories.

5. POTENTIAL EXPLANATIONS

The period 1997-2017 coincides with the diffusion of the Internet, an increase in targeted advertising, and other macro-level trends, but it seems unlikely that such factors explain the timing of the large drop (2001-2005) and the prominence of the four categories. Hortacsu and

Syverson (2015) provide the e-commerce share of retail sales for several product categories in 2013. While computers are near the top of the list (at 32.9%), drugs, health and beauty (4.7%) and food and beverages (0.9%) are at the bottom. If changes in AIs were driven by growth in online sales, then books, toys, furniture, sporting goods, and apparel would be among the goods with substantial contributions to the AI component. If the diffusion of online advertising is an important contributor to the drop in the EWAI, then perhaps it is so because offline advertising elasticities of demand have dropped (as traditional media have become less effective) and food, drugs, and tobacco are associated with particularly low online advertising elasticities of demand. Even if so, the concentration of the impact during 2001-2005 would be difficult to explain: online advertising has continued to diffuse over the entire period 1997-2017 (one can observe steady increases in the revenue of key beneficiaries such as Google/Alphabet and Facebook/Meta over this period).

A definitive assessment of within-group factors that contribute to the prominence of the four categories is beyond the scope of this paper, but at least four factors other than the diffusion of the Internet should be considered. First, the four categories experience commoditization associated with maturing products during 1997-2017, both gradual (computers) and relatively sudden (such as when important drug patents expire). Mature products typically have lower ε_A / $|\varepsilon_P|$ (Sethuraman and Tellis 1991). Table 3 provides evidence consistent with commoditization: gross profitability (gross profit divided by the book value of assets) falls substantially in each category, in absolute terms and relative to a set of comparable groups. Related supportive evidence is provided by Dube, Hitsch and Rossi (2018); they document an increase in the private-label share of retail sales over 2004-2012 (private labels are particularly common for food retailers).

Table 3. Gross Profitability (Percentage)

Category	1997-2001	2005-2009	2013-2017	Difference (1997-2001 to 2005-2009)	Difference (1997-2001 to 2013-2017)
Food	46.0	39.2	29.8	-6.9	-16.2
Drugs	46.0	39.8	30.2	-6.2	-15.8
Computers	35.7	33.6	29.9	-2.1	-5.8
Tobacco	36.6	29.0	24.3	-7.6	-12.3
Comparables	40.5	39.3	36.1	-1.2	-4.4

Note. Data Source: Compustat. Gross profitability is gross profits (GP) divided by total assets (AT). The Comparables consist of all groups not in one of the four categories in which gross profitability in 1997-2001 is at least 30%.

Second, several studies document increases in price competition in bricks-and-mortar retailing during 1997-2017 (which increases $|\varepsilon_P|$). The changes impact food retailing in particular, and food retailers often include drugs and tobacco products, so these categories are also impacted. Notably, Walmart increases its presence. Hausman and Leibtag (2007) find that Walmart's grocery prices are 15-25% lower than those of traditional supermarkets during 1998-

2003, and Walmart's presence in the grocery market continues to grow after 2003. Bronnenberg and Ellickson (2015) document that hypermarkets, mass merchandisers, discounters and warehouse clubs all increase their share of grocery sales during 2000-2014 while the shares attributable to independent stores, specialized food, drink or tobacco retailers, and traditional supermarkets fall. Hortacsu and Syverson (2015) describe how the rise of giant physical stores exceeds the impact of e-commerce: From 1992-2013, sales in the warehouse clubs and supercenters subindustry grow from \$40B to \$420B. In both growth rates and dollar terms, this expansion exceeds growth in electronic shopping and mail order houses (which account for 85% of online retailing). By 2012, the four largest warehouse club/supercenters account for almost 8% of total retail sales, which is 50% more than all e-commerce retail sales.

Third, while new products can offset commoditization, they can also contribute to lower AIs. For example, top-selling drugs in the late-1990s/early-2000s target broad groups of consumers and lend themselves to persuasive advertising efforts aimed at both consumers and physicians: treatments for high cholesterol, heartburn, depression and pain are prominent. As these drugs become commoditized, drugs to treat cancer and blood clots become prominent. Persuasion is less necessary when treating imminent life-threatening conditions, so the changing product mix likely contributes to lower AIs in the drug category. Fischer and Albers (2010) find that sales elasticities associated with pharmaceutical detailing, direct-to-consumer advertising, and journal advertising are all significantly lower for life-threatening diseases, and in a meta-analysis, Sridhar, Mantrala and Albers (2014) conclude that estimates of pharmaceutical detailing elasticities associated with early-stage products are lower in more recent studies. This is consistent with detailing being less effective in recent years (Liu and Gupta (2014) document a decline in detailing expenditures) and a 25% reduction in the US pharmaceutical sales force 2005-2012 (Sridhar, Mantrala and Albers 2014).

Fourth, policy changes and self-regulatory efforts occur, and while it appears unlikely that these efforts account for the substantial drop in the EWAI during 2001-2005, they likely contribute to the non-transitory nature of the drop. The Tobacco Master Settlement Agreement of 1998 and the Tobacco Control Act of 2009 impose bans on some types of tobacco advertising and limitations on others.³ In the drugs category, the effects of policy changes are not all unidirectional. Regulatory changes in 1997 permit an increase in direct-to-consumer advertising (DTCA), and from 1997-2005, DTCA spending quadruples (Liu and Gupta 2014). However, most advertising efforts continue to be directed at physicians (the prescribers), and subsequent events reduce DTCA spending. The Pharmaceutical Research and Manufacturers of America (PhRMA) adopts voluntary guidelines for DTCA in 2005 and revises the guideline in 2008, and this self-regulation contributes to a decline in DTCA. Detailing also declines by 21% during 2004-2010.

6. CONCLUSION

Further work investigating changes in the EWAI is warranted: a dramatic drop occurred in the period 2001-2005, and the stability prior to 2001 and after 2005 suggests that one or more

² Verispan lists top sellers in 2003: https://www.drugs.com/top200_2003.html. Genetic Engineering & Biotechnology News lists top sellers in 2018: https://www.genengnews.com/a-lists/top-15-best-selling-drugs-of-2018/. Schwartz and Woloshin (2019) provide facts on changes in the product mix and marketing since 1997.

³ For details see https://oag.ca.gov/tobacco/msa and https://www.fda.gov/tobacco-products/rules-regulations-and-guidance/family-smoking-prevention-and-tobacco-control-act-overview.

important non-transitory changes in the business environment occurred. The decomposition into contributing industries reveals that explanations must account for the importance of food, drugs, computers, and tobacco, and this makes it unlikely that diffusion of the Internet is wholly responsible for the drop. The initial investigation of the four vertical chains suggests possible areas for further study: commoditization, the rise of warehouse club/supercenters, the changing nature of new products, and public policies combined with self-regulation.

References

Bijmolt, T.H.A., H.J. van Heerde and R.G.M. Pieters (2005) "New Empirical Generalizations on the Determinants of Price Elasticity" *Journal of Marketing Research* **42** (2), 141-56.

Borden, N.H. (1942) The Economic Effects of Advertising, Irwin: Chicago.

Bronnenberg, B.J. and P.B. Ellickson (2015) "Adolescence and the Path to Maturity in Global Retail" *Journal of Economic Perspectives* **29** (4), 113-34.

Dekimpe, M.G. and B. Deleersnyder (2018) "Business Cycle Research in Marketing: A Review and Research Agenda" *Journal of the Academy of Marketing Science* **46** (1), 31-58.

Dorfman, R. and P.O. Steiner (1954) "Optimal Advertising and Optimal Quality" *American Economic Review* **44** (5), 826-36.

Dube, J.P., G.J. Hitsch and P.E. Rossi (2018) "Income and Wealth Effects on Private-Label Demand: Evidence from the Great Recession" *Marketing Science* **37** (1), 22-53.

Fischer, M. and S. Albers (2010) "Patient- or Physician-Oriented Marketing: What Drives Primary Demand for Prescription Drugs?" *Journal of Marketing Research* 47 (1), 103-21.

Hausman, J. and E. Leibtag (2007) "Consumer Benefits from Increased Competition in Shopping Outlets: Measuring the Effect of Wal-Mart" *Journal of Applied Econometrics* **22** (7), 1157-77.

Henningsen, S., R. Heuke and M. Clement (2011) "Determinants of Advertising Effectiveness: The Development of an International Advertising Elasticity Database and a Meta-Analysis" *Business Research* **4** (2), 193-239.

Hortacsu, A. and C. Syverson (2015) "The Ongoing Evolution of US Retail: A Format Tug-of-War" *Journal of Economic Perspectives* **29** (4), 89-112.

Liu, Q. and S. Gupta (2014) "Direct-to-Consumer Advertising of Pharmaceuticals: An Integrative Review" in *Innovation and Marketing in the Pharmaceutical Industry: Emerging Practices, Research, and Policies* by M. Ding, J. Eliashberg and S. Stremersch, Eds., Springer: New York, 629-49.

McCombs, M.E. (1972) "Mass Media in the Marketplace" *Journalism Monographs* **24** (August), 1-104.

Molinari, B. and F. Turino (2018) "Advertising and Aggregate Consumption: a Bayesian DSGE Assessment" *Economic Journal* **128** (613), 2106-30.

Pepall, L., D. Richards and G. Norman (2014) *Industrial Organization: Contemporary Theory and Empirical Applications* 5e, Wiley: Hoboken, NJ.

Schwartz, L.M. and S. Woloshin (2019) "Medical Marketing in the United States, 1997-2016" *JAMA* **321** (1), 80-96.

Sethuraman, R. and G.J. Tellis (1991) "An Analysis of the Tradeoff Between Advertising and Price Discounting" *Journal of Marketing Research* **28** (2), 160-74.

Sethuraman, R., G.J. Tellis and R.A. Briesch (2011) "How Well Does Advertising Work? Generalizations from Meta-Analysis of Brand Advertising Elasticities" *Journal of Marketing Research* **48** (3), 457-71.

Sridhar, S., M.L. Mantrala and S. Albers (2014) "Pharmaceutical Detailing Elasticities: A Meta-Analysis" in *Innovation and Marketing in the Pharmaceutical Industry: Emerging Practices, Research, and Policies* by M. Ding, J. Eliashberg and S. Stremersch, Eds., Springer: New York, 531-56.