"Free" Internet Content: Web 1.0, Web 2.0 and the Sources of Economic Growth

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Abstract

The Internet has evolved from Web 1.0, with static Web pages and limited interactivity, to Web 2.0, with dynamic content that relies on user engagement. This change increased production costs significantly, but the price charged for Internet content has generally remained the same: zero. Because no transaction records the "purchase" of this content, its value is not reflected in measured growth and productivity. To capture the contribution of the "free" Internet, we model the provision of "free" content as a barter transaction between the content users and the content creators, and we value this transaction at production cost. When we incorporate this implicit transaction into U.S. gross domestic product (GDP), productivity, and household accounts, we find that including "free" content raises estimates of growth, but not nearly enough to reverse the recent slowdown.

Keywords: Internet, productivity, advertising, marketing, measurement, GDP

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1. Introduction

"Free" digital content is pervasive. Yet, unlike the majority of output produced by the private business sector, many facets of the digital economy are provided without an explicit market transaction between the final user of the content and the producer of the content. For those used to thinking about measured output from the expenditure side, this raises immediate concerns that the value of "free" digital content is not only unmeasured within the current GDP and productivity statistics, but is also fundamentally unmeasurable within the current framework. Furthermore, because "free" digital content is so pervasive and has induced such large changes in consumer behavior and business practice, this concern has evolved into arguments that the lack of measurement leads to a significant downward bias in official estimates of growth and productivity.

At the outset, it is important to distinguish between "free" content produced by the market sector and content produced by the nonmarket sector. We analyze two types of "free" content that are produced by the market sector: advertising-supported media and marketing-supported information. Advertising-supported media includes digital content like Google search, but it also includes more traditional media content like print newspapers and broadcast television. Marketing-supported information includes digital content like downloadable apps for smartphones, but it also includes more traditional information content like print newsletters and audiovisual marketing. "Free" content produced by the nonmarket sector includes user-generated content like restaurant reviews posted on Yelp. Because there is no expectation of payment, user-generated content is outside the scope of the official GDP accounts, but is instead included in household production. The value of this nonmarket content is important for capturing the overall value of the "free" digital economy, and we present it separately from our GDP and productivity estimates.

The first contribution of this paper is to demonstrate how "free" content can be measured via the lens of a production account. We model the provision of "free" content as a barter transaction. For "free" content produced by the market sector, consumers and businesses receive content in exchange for exposure to advertising or marketing. Our approach reduces to treating the professional provision of ``free" digital content as payment-in-kind for viewership services produced by households and businesses. This approach requires no major conceptual changes to the international guidelines for national accounts (*System of National Accounts 2008* or *SNA 2008*); thus, it could be implemented easily. Put differently, the national accounts currently ignore the role of households in advertising and marketing. In the methodology that we apply in this paper, households are active producers of viewership services and are therefore unincorporated household businesses (*SNA 2008,* Sections 4.155-157).

We construct a production account to separate the costs of producing "free" digital content and equate these costs to the content value. For advertising- and marketing-supported content, the additions to the output side of the production account corresponds to additions to GDP, while the corresponding additions to the input side corresponds to additions to gross domestic income (GDI). The ratio of quantity of output to quantity of input is defined as total factor productivity (TFP), and this provides the link between GDP and productivity accounts. A main motivation for framing our analysis within the production account is to highlight important consistency issues between "free" content and the other components of GDP. To be clear at the outset, this approach does not provide a willingness to pay or welfare valuation for "free" content. But this approach does provide a value for "free" content that is consistent with national accounting estimates of production.

The second contribution of this paper is to assess the empirical impact of "free" content on output, value added, and productivity at the aggregate and industry level. To preview the results, Figures

1 and 2 show the impact on real GDP by content type, by funding source, and by year. An important result from our analysis is that most of the impact on GDP and productivity is due to marketing-supported information. Analysis that focuses on advertising-supported media only underestimates the true value of "free" content. Our results also show that the impact of "free" digital content on real GDP starts around 1995, a year that has been previously identified as an inflection point in the production of information technology equipment (Jorgenson 2001). The growth increase from digital content is partly offset by a decrease in "free" print content, but it is reinforced by an increase in "free" audiovisual content. From 1995 to 2016, together, the "free" content categories raise nominal GDP growth by 0.031 percentage point annually, real GDP growth by 0.085 percentage point annually, and TFP growth by 0.076 percentage point annually. These impacts slightly ameliorate the recent slowdown in economic growth—but not nearly enough to reverse the slowdown. These estimates, as discussed above, exclude user-generated content.

Table 5 shows the impact of our treatment on measured inflation. GDP price inflation between 1995 and 2016 slows by about 0.057 percentage point. A slightly larger effect is on personal consumption expenditures (PCE) and core PCE inflation: PCE inflation and core PCE inflation fall by 0.082 percentage point and 0.091 percentage point, respectively. This lower inflation rate is primarily driven by price decreases for online content, which falls at an 11 percent annual rate even as online nominal content is expanding rapidly.

A third contribution of this paper, while admittedly more speculative in its empirics, is to study user-generated content. Digital user-generated content includes comments posted on Facebook and other Web sites, reviews posted on Yelp, fanfiction, Wikipedia articles, (some) Tweets, (some) YouTube videos, and more. Because this content is produced by amateurs as a hobby, it is considered household production and therefore is excluded from the GDP accounts.[2] Abstracting from technical issues around the national accounts, it is of value to estimate household production to present a broader measure of output (Abraham and Mackie 2005). We extend the household production accounts by constructing estimates that capture and separate the value of user-generated content from other "free" digital content. Our estimates indicate that user-generated content is an important and rapidly growing component of "free" online content.

The remainder of the paper proceeds as follows. Section 2 describes the current treatment of advertising-supported content and of marketing-supported content in the official U.S. GDP accounts. In this section, we introduce the barter model that captures the transactions present in the "free" digital economy. A more comprehensive description of accounting methodology is available in online appendix A. Section 3 describes the empirical estimation and data. More details on the data work are available in online appendix B. In this section, we compare our results with the existing industry literature on "free" content and advertising and marketing. Section 4 covers the deflators we use to transform the nominal values to quantity indexes. Section 5 presents our calculations of real GDP growth when "free" content is included in final output. In this section, we also describe the input prices for advertising and marketing viewership, and present estimates of total factor productivity when "free" content is included in the production accounts. Section 6 estimates the production value of user-generated content. Section 7 concludes.

[2] According to Moulton (2015), household own-account non-housing services (such as cleaning, child care, and home meal preparation) are excluded from the SNA because most services are self-contained activities that typically have no suitable market prices for valuation, and generally do not influence economic policy.

2. ``Free” Content Within the Production Account

2.1 Background Discussion

In the *SNA 2008* and the U.S. Bureau of Economic Analysis (BEA) national income and product accounts, advertising-supported media is treated as an intermediate input to the advertising viewership. If we think of soap as the advertised good, then a YouTube video produced to entertain households is an expense of the media company, which then sells the advertising viewership to the soap manufacturer. In turn, the cost of the advertising viewership is an intermediate expense of the soap manufacturer similar to the cost of physical inputs such as lye or fat. Conceptually, marketing-supported information is nearly identical to advertising-supported media. The main difference is marketing viewership is not resold, so it is not even tracked as an intermediate expense. Instead, the soap manufacturer’s production accounts combine marketing inputs, such as actors or writers, who are used to produce in-house YouTube videos with physical inputs, such as lye or fat, that are used in actual soap production. For both advertising-supported media and marketing-supported information, there is no part of personal consumption expenditures that directly represents YouTube entertainment. The difficulty of the current treatment is highlighted when the advertising or marketing sector bids entertainment providers, such as baseball teams, away from the paid entertainment sector into the “free” entertainment sector.

Another way to think about this is to consider how the value of a smartphone increases when new advertising-supported Web sites are posted or marketing-supported apps are released. Should this improvement in viewing opportunities be reflected in the quality-adjusted price for smartphones? Even if there is no change in the direct product or process of smartphone equipment production, this quality-adjustment would result in a real output increase for smartphone-producing industries.

Our methodology avoids the problem of trying to capture the value of "free" content in quality-adjusted prices by treating the production and use of "free" content as a new economic transaction.

It is useful to clarify the conundrum with the following highly stylized example. We consider a soap manufacturer, an entertainer, and households. The soap manufacturer must spend money on selling costs before households buy the soap. Initially, the soap manufacturer spends $550 to make the soap, spends $250 on selling costs with no value to households, and sells 800 bars of soap for $1 each. The entertainer sells 100 tickets to her online show for $2 each. One hundred households each spend $8 for soap and $2 for entertainment. Now, suppose the soap manufacturer pays the entertainer $200 to include a video for soap in her show and cuts other selling costs by $200. The entertainer now allows the same 100 households to watch her act without charging for tickets.[3] The 100 households receive soap and entertainment but pay only the $8 per household for soap (and watch a soap video). The households consume the same amount but pay less out of pocket.

In the current treatment, measured output drops when entertainment is supported by either advertising or by marketing. The entertainment is no longer measured as part of personal consumption, only the soap is. In the initial case, $1,000 in economic resources was used to produce $1,000 in consumption output. With advertising- or marketing-supported content, $1,000 is used to produce $800 of consumption output and $200 of intermediate input. Effectively, $200 has disappeared from consumption output. However, this appears to be a misrepresentation because the households are still consuming the same entertainment.

One possible treatment would be to view the entertainment as having the same real value but falling in price to zero; that is, nominal output is $800, but real output is $1,000. However, zero prices

[3] If the entertainer is an independent contractor, her show would be classified as advertising-supported media. If she is an employee, her show would be classified as marketing-supported information.

have conceptual issues; for example, it is difficult to explain why consumers sometimes pay to avoid advertising if the price for advertising-supported media is zero. Furthermore, if the situation were reversed and a price was paid, inflation for that item would be indeterminate.

The treatment we pursue in this paper is to construct a barter transaction: consumers receive entertainment in exchange for the consumer's agreement to view the advertising or marketing. We record a dollar paid by the consumer for the entertainment and then paid back to the consumer by the entertainer for viewing the advertising or marketing. In this treatment, both advertising-supported media and marketing-supported information are reflected in the real income and consumption of the consumer.[4] To measure the value of ”free” content, we first measure total spending by advertisers and marketers and then subtract noncontent costs such as administrative costs for billing advertising clients or printing costs for the classified sections placed within newspapers.[5] This approach follows the data available.

2.2 Other Non-Cash Transactions in GDP

Our experimental methodology does not require any major conceptual changes to the SNA. The *SNA 2008* already counts noncash payments to workers as labor income (*SNA 2008,* Section 7.51), imputes cash values for barter transactions (*SNA 2008,* Section 3.75), imputes rental payments for owner-occupied housing (*SNA 2008,* Section 6.34), and imputes financial services for bank accounts (*SNA 2008,* Section 6.163). Just as with those transactions, we impute a value for ”free” content and treat that value as a payment in-kind for viewership services. Since the household is not ”employed” by the content producer, we treat the household production of viewership as a

[4] A similar alternative was suggested informally by Charles Hulten. He proposed that ”free” content can be viewed as a gift from companies to consumers. This parallels the treatment of nonprofit institutions serving households. This treatment has the same impact on measured GDP as a barter transaction but a different impact on TFP.
[5] We entirely disregard marketing that is not bundled with wanted content, such as telemarketing or junk mail. This is equivalent to assuming that these categories have noncontent costs equal to 100 percent of expenditures.

form of production by an unincorporated household enterprise (*SNA 2008,* Sections 4.155–157). To minimize the deviation from BEA's official accounts, we do not consider the viewership production process within households.[6] As a result, when we analyze the impact of our methodology on measured TFP (which requires real outputs and inputs), we only analyze the private business sector and not the aggregate economy. However, we are able to analyze the full GDP on the expenditure side.

Our paper is not the first to discuss treating advertising-supported media as personal consumption. Imputation for advertising-supported media was first raised in *The National Income – 1954 Edition* and was extensively discussed in the 1970s (e.g. Ruggles and Ruggles 1970; Okun 1971; Jaszi 1971; Juster 1973; Eisner 1978; Kendrick 1979). Cremeans (1980) estimated that advertising-supported media was worth $28 billion in 1976.[7] Vanoli discusses this issue in *A History of National Accounting* (2005). More recently, *Bloomberg Businessweek* published an article in 2013 (Ito) and *The Wall Street Journal* published an article in 2015 (Aeppel) suggesting that BEA's GDP numbers should include "free" digital content. However, our paper expands on previous research by presenting new productivity accounts by industry and by media category, and uses the latest data sources to capture previously unidentified "free" content. This paper presents new productivity accounts by industry and by media category. This decomposition allows researchers and policymakers to better understand the sources of GDP growth and the impact of different categories on perceived biases in the official measures.

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[6] We assume that advertising and marketing viewership is produced only using capital and labor, without any intermediate expenses. Therefore, gross output is equal to value added.

[7] We estimate that advertising-supported entertainment added only $8 billion to GDP in that year. The main reason for the difference is our exclusion of nonmedia costs and business usage of "free" media from final output.

A major extension that we make in this paper is to include marketing-supported information in "free" content together with advertising-supported media. To the best of our knowledge, our paper is the first to propose treating marketing-supported information as a barter transaction and the first to recalculate GDP when marketing-supported information is included in final output. Furthermore, by including marketing-supported information, we capture the exchange of value that occurs under the ubiquity first, revenues later economic model. That economic model embeds a barter transaction of content in exchange for building a network of users. The ubiquity first, revenue later model is prevalent in Silicon Valley and accounted for a substantial share of "free" digital content during the dot.com bubble of the late 90's.

To emphasize the importance of marketing, Table 2 shows that nonadvertising marketing expenditures totaled $441 billion in 2015, almost double advertising expenditures in 2015. Of this, we estimate that nonadvertising marketing contributes $177 billion to personal consumption expenditures and advertising contributes $117 billion to personal consumption expenditures. Accordingly, adding marketing considerably increases the potential GDP impact of "free" content.

3. Estimating Content Values

3.1 Total Output of Advertising-Supported Media

Our primary data is taken from the Economic Census, which tracks revenue from the sale of advertising slots. We supplement the Economic Census data with industry research on in-house advertising viewership.[8] In practice, we calculate that the opportunity costs of in-house advertising are very small, totaling less than 0.08 percent of nominal GDP in 2015. For simplicity, we combine

[8] Freemium games like Candy Crush are the best known category of in-house advertising viewership. These games are free to download and play, and they sell little advertising. Instead, they continually push users to buy content.

in-house advertising with sold advertising in our figures and discussion. Appendix B contains detailed information on the data used and the benchmarking procedures.

When measuring advertising-supported media, we categorize media into three separate subcategories: (1) printed newspapers, magazines, and directories, (2) television, radio, and other audiovisual content,[9] and (3) digital content like blogs or search engines.[10] These sub-categories were chosen because each has a different production process, and each may be affected differently by technological innovations like computers. In addition, previous researchers and policymakers have focused on digital content, so it is useful to provide numbers for digital content alone. Note that we are excluding out-of-pocket spending on media such as Internet access charges or cable subscription fees from our analysis.[11]

Advertising revenue by media category over time as a share of nominal GDP is shown in Figure 3. Since 1995, online media has grown from almost nothing to 0.49 percent of nominal GDP. Over the same time period, print advertising shrank from 0.63 percent to 0.16 percent of nominal GDP. The growth of the Internet is almost certainly responsible for most of the print decline. Classified advertising has moved from newspaper sections to Web sites and printed Yellow Pages are being replaced by Web search. Between 1995 and 2016, audiovisual advertising, that is, radio and television advertising, rose from 0.50 percent to 0.65 percent of nominal GDP. The increase in

[9] This category includes television shows watched online, videos hosted on YouTube, radio podcasts hosted on iTunes, etc. We exclude online audiovisual content from the digital category, so there is no double-counting.
[10] Some companies also earn money from collecting personal data and reselling it to third parties. These payments for lost privacy are particularly common for downloadable apps. We treat data collection just like advertising.
[11] Advertising-supported media is often offered at a subsidized price rather than a zero price. For example, newspapers and magazines typically charge a low but nonzero subscription price. We include the implicit advertising subsidy in our estimates of "free" media and exclude out-of-pocket spending from our analysis.

”free” audiovisual content took place even as spending on subscription television rose from 0.32 percent to 0.47 percent of nominal GDP.

3.2 Total Output of Marketing-Supported Information

Marketing expenditures that flow through media companies are not the only marketing expenditures that support “free” content. For our work, one main difference is the greater difficulty of measuring expenditures outside of the advertising-supported media industry. With advertising, there is a clear transaction that provides an arms-length measure of the nominal output. Yet, table 3 shows nonadvertising marketing expenditures have grown faster than advertising. So, when we focus on advertising, we miss out on the full growth of content supported by marketing.

We estimate total output in two basic steps. First, we use the Economic Census to estimate business expenditures on purchased marketing services from 2002 until 2012. Next, we use data from the Occupational Employment Survey (OES) to impute the value of in-house marketing services. Total marketing output is the sum of the two series.[12] Our expenditure estimates are an attempt to measure total costs and therefore include labor costs for marketing specialists, labor costs for support staff, intermediate inputs like electricity, and capital services used in production.

We start out by identifying seven product lines of interest in the Economic Census: (1) media representation services in NAICS 5418; (2) public relations services in NAICS 5418; (3) advertising planning, creation and placement services in NAICS 5418; (4) remaining marketing-supported information in NAICS 5418; (5) Web site development and hosting in NAICS 518 and 5415; (6) commercial photography in NAICS 5419; and (7) event sponsorship in NAICS 711. In

[12] The conceptual framework makes no distinction between marketing-supported information purchased from outside companies and marketing-supported information produced in-house. Accordingly, we combine both production methods in all of our figures and discussion.

total, these seven product lines accounted for $140 billion worth of sales in 2012. Only a small portion of the $140 billion in product-line sales is for completed marketing campaigns that are ready for public consumption immediately. Instead, companies combine purchased marketing inputs with in-house marketing production before rolling out a completed marketing campaign.

Next, we use the Occupational Employment Survey (OES) data to impute the value of in-house marketing services. That survey reports employment and earnings for selected industry and occupation combinations. The OES does not track individuals who are employed producing in-house marketing directly, but we have identified a list of marketing specialist occupations. For example, a writer employed at an automobile manufacturer probably writes for marketing. Next, we multiply earnings for those specialists by an adjustment ratio taken from the Economic Census data to estimate total expenditures. Appendix B contains more information on our estimates.

In total, we calculate that U.S. businesses created $387 billion of marketing output in 2012. This number includes $140 billion of purchased marketing, $177 billion of operating expenses devoted to in-house marketing production, and $70 billion of forgone profits that companies might have earned *if* they had sold their marketing output rather than using it in-house.[13] In comparison, the research firm Outsell reports that U.S. businesses spent $218 billion on marketing in 2012. So, our estimate of $317 billion in out-of-pocket spending and $70 billion in forgone profits is only slightly higher than the industry literature.

[13] Our ratio of operating expenses to revenue is taken from the Service Annual Survey. At first glance, the low ratio might suggest that marketers are reselling creative services produced by others, and therefore, our statistics double-count some marketing. We thank Jonathan Haskel for this point. We checked and found advertising agencies (NAICS 54181) earn similar profit rates as publishers (NAICS 511) and broadcasters (NAICS 515). So, it appears that creative industries genuinely do earn a very high return on their capital.

Figure 4 shows output of marketing relative to GDP over time. We find that marketing-supported information output is currently larger than advertising-supported media output and has grown faster over time. In 1929, businesses created $520 million in marketing-supported information, approximately 0.5 percent of aggregate nominal GDP. In 2016, businesses created $465 billion of marketing-supported information, approximately 2.5 percent of aggregate GDP. In contrast, advertising revenues have hovered around 1 percent of nominal GDP from 1929 to 2016. Yet, advertising-supported media receives the vast majority of policymaker and researcher attention. This paper aims to rectify the imbalance by tracking both components of "free" content.

Figure 4 also shows our best estimate of marketing output by category.[14] We find that marketing-supported information grew dramatically over the past decade, and this growth is entirely driven by digital marketing. Web sites account for the largest portion of this digital marketing, but companies are also spending heavily on social media, smartphone apps, and other mobile marketing. Despite the recent explosion in online marketing, the nominal growth rate for total marketing-supported information in the past decade is not exceptional. Instead, marketing-supported information has steadily increased its nominal GDP share by 0.04 percent per year after 1975, but it was relatively steady before 1975. We have not yet fully identified a reason for the trend break in 1975. One observation is that the increase in intellectual property investment occurred after 1975, when the proportion rises from 1.6 percent to 4.0 percent of GDP. To the extent that an important value of marketing lies in introducing innovative products to potential customers, rising innovation may be associated with rising marketing expenses.

[14] Neither the product line information provided by the Economic Census nor the occupation codes provided by the OES specify precisely what type of marketing-supported information is being produced. For example, a "writer" might write a column for a print newsletter, contribute to a corporate blog, or write dialogue for a filmed ad. Many writers do all three simultaneously. Our current splits are based on reports from the firm Outsell and other sources.

3.3 Production Costs for "Free" Content

Not all of the advertising revenue shown in Figure 3 nor the marketing expenditures shown in Figure 4 are used to produce content that is of value to consumers and businesses. Media companies need a sales staff to reach out to advertisers, plan the exact placement of advertising slots, and bill the advertisers afterward. Moreover, physical costs of classified sectors account for a substantial share of print advertising expenditures. In earlier research, we estimated that noncontent costs account for 50 percent of print newspaper revenue; 72 percent of print magazine revenue (Nakamura 2015); 55 percent for print directory revenue; and 25 percent of audiovisual, and digital revenue (Soloveichik and Wasshausen 2013; Soloveichik 2013 a, b, c, d and e).[15]

Just like advertising-supported media, a large share of marketing output does not directly benefit users. We were not able to find any data tracking printing and distribution costs for marketing. For now, we assume that marketing-supported information has similar printing and distribution costs as advertising-supported media.[16]

3.4 Splitting Consumer Content from Business Content

To assess the industry origins of the digital economy and its impact across industries that use "free" content as an input into production, we extend our basic barter transaction model to distinguish between the use of "free" content by households and by private businesses. The identity of the user determines both the terminology used and the impact on measured GDP. When households use "free" content, we call it "consumer entertainment" and add the value to personal consumption

[15] We assume that the noncontent cost share for each category is fixed from 1929 to 2016. As a robustness check, we collected summary data from the Internal Revenue Service on total expenditures relative to total revenue by industry and by year. We found that adjusting for this variation increases the value of online media during the dot. com bubble and reduces volatility over the business cycle slightly, but it has little long-term impact.

[16] Note that printing and distribution costs can be thought of as a lower bound on the true noncontent costs. Take the case of a car company that biases road tests and then uses the biased road test results in marketing. Our analysis only subtracted printing and distribution costs, so the cost of biasing road tests is in content.

expenditures and GDP. Balancing that addition to personal consumption expenditures, we imputed income to viewers that are, in effect, paid to view advertising or marketing. When private businesses use “free” content, we call it “business knowledge” and add the value of that content to intermediate inputs. Balancing that additional intermediate input, we impute income to businesses for their viewership output. The imputed payments for viewership are always precisely equal to the imputed value of “free” content, so there is no change to either household saving or nominal business value added.

This paper uses a variety of data sources to split advertising-supported media usage between consumers and businesses. For digital media, we use survey data from Forrester Research. Since 2007, Forrester Research has asked survey respondents to report both ”work Internet” time and “personal Internet” time. Before 2007, we use data from the Current Population Survey to track home Internet access as a proxy for personal usage. For print media, we use genre data reported in the Economic Census and other sources to split consumer media from business media. For example, we assume that scientific journals are used for work rather than leisure. Finally, we assume that radio, television, and freemium games are almost entirely targeted towards consumers for leisure use. More information on the procedures used is given in appendix B of this paper.

Marketing-supported information is a more diverse category. To start out, we assign marketing bundled together with media using the same allocations discussed earlier for advertising-supported media. In particular, we allocate television and radio commercials, public relations spokespeople interviewed on television and radio, and sponsored sports aired on television and radio almost entirely to the consumer sector. We allocate print commercials and public relations spokespeople interviewed in print journals using the same business and consumer split developed earlier for newspaper, magazine, and directory media. Finally, we allocate digital marketing like corporate

Web pages, social media accounts, or downloadable apps using the split developed earlier for online media.

Next, we use research purchased from the firm Outsell to split other marketing (that is, not bundled with media). For each year, they publish two reports: one tracking business-to-consumer marketing (B2C) and one tracking business-to-business marketing (B2B). Their annual data are somewhat noisy, so we averaged across the reports purchased. For print and audiovisual media, the consumer share has remained relatively constant over time. We calculate that consumers receive 51 percent of separated print marketing and 90 percent of separate audiovisual marketing. Outsell also tracks digital marketing, but we do not use their B2B versus B2C splits, because businesses often use online content directed towards consumers, and so the Forrester survey data described earlier is a better proxy for business usage. Altogether, we calculate that the consumer share of marketing fell gradually from 75 percent in the 1970s to 58 percent in 2016. This fall is due to the rise in online marketing, which has a lower consumer share than other marketing categories.

3.5 Tracking Consumer Content Over Time.

Figure 5 shows that advertising-supported online entertainment has grown rapidly in the past decade and now accounts for 0.17 percent of nominal GDP. However, this nominal growth is largely canceled out by a decrease in advertising-supported print entertainment. Total advertising-supported entertainment only rose from 0.56 percent of GDP in 1995 to 0.70 percent of GDP in 2016. As a result, including "free" media in final output only increases nominal GDP growth slightly. In sharp contrast, we will document in the next section that marketing-supported information has grown more rapidly than overall GDP. This growth of content—led by growth in online and audiovisual marketing—contributes to our finding that "free" content has a substantive effect on real output and private business productivity.

Figure 6 shows the increase in nominal GDP from including marketing-supported consumer entertainment. Consistent with Brynjolfsson's research, online consumer information has grown enormously in the past decade and now accounts for 0.65 percent of nominal GDP (Brynjolfsson and Oh 2012; Brynjolfsson, Eggers, and Gannamaneni 2017). However, some of this increase is offset by decreases in other types of marketing-supported consumer entertainment. Altogether, "free" content increases nominal GDP growth by 0.025 percentage point per year between 2005 and 2016. This is not a trivial change, but it is not nearly enough to reverse the recent slowdown.

Table 3 shows data for nominal "free" content, by medium, back to 1930. This long, historical sweep enables us to see that the contribution of content in 1930 was 0.6 percent of nominal GDP, almost entirely from print. By 1965, audiovisual media has become larger than print, at a point when TV dominates leisure time. Yet, combined "free" content is still only 0.8 percent of nominal GDP in 1965. The total GDP share for "free" content did not start rising consistently until 1975, long after TV had become nearly universal. It is interesting as well that, while print content declines in nominal terms beginning in 2006, audiovisual content continues to grow quite strongly and adds nearly as much nominal content between then and the present as online does. The extreme importance of online for real growth is due to the rapid decline of input costs for online content.

Before we move on, it is useful to summarize the nominal estimates. Table 2 shows that for 2015, total business output of advertising and marketing amounted to \$661 billion. Of this sum, costs that do not add to household or business entertainment or information were about \$198 billion. This leaves about \$463 billion in entertainment and information content. Consumers earn and use \$294 billion, while businesses earn and use (as intermediate input) \$167 billion. Thus, our methodology would add \$294 billion to the measured 2015 U.S. GDP of \$18,121 for a total expanded GDP total of \$18,415 billion.

3.6 Comparing Our Results to Previous Literature.

In 2011, we estimate that “free” online content added $128 billion to the U.S. GDP, $16 billion of advertising-supported media, $78 billion of marketing-supported information, and $34 billion of user-generated content that we will discuss later. This is not a trivial amount, but it is far lower than alternative estimates. For 2011, Brynjolfsson and Oh (2012) estimated a value of $376 billion based on time-use data. The Boston Consulting Group (Dean et al. 2012) estimated a value of $500 billion in 2011, based on consumer surveys and an economic model. More recently, Brynjolfsson, Eggers, and Gannamaneni (2017) use willingness-to-accept estimates to show that the median consumer in 2016 valued online search at $14,760 per year and valued the rest of the Internet at $10,937 per year. Across the entire U.S. population, that adds up to $8.3 trillion in total consumer surplus. Consistent with that high valuation for search engines, the paper ”A Day Without a Search Engine” (Chen, Jeon, and Kim 2014) finds that research offline takes triple the time (22 minutes versus 7 minutes), so online search saves an enormous amount of time in aggregate.

The much higher numbers in the earlier studies are primarily a consequence of their focus on measuring the consumer utility gained from leisure time spent online. This paper is trying to estimate only the cost of producing online information, which our results indicate is much lower than consumer surplus. Similarly, Brynjolfsson et al (2018) use willingness-to-accept estimates to value access to prescription drugs at $50,000 per year per person, approximately forty-fold BEA’s estimates of prescription drug spending in 2016, and to value access to medical care at $600,000 per person per year, approximately seventy-fold BEA’s estimates of health care spending in 2016.[17] If the same ratio of consumer-surplus-to-production costs applies to online media, then

[17]BEA’s estimates for prescription drugs are from NIPA table 2.4.4U, line 121, and the estimates for total health care spending are from NIPA table 2.4.4, lines 40, 60, and 93.

the $8.3 trillion value for the Internet implies spending of $118 billion–$208 billion per year. This range matches well with our estimated $181 billion in "free" consumer content available online in 2016. Another measure of consumer surplus was conducted by Noll et al. (1973). They examine how much viewers were willing to pay for access to the three major TV networks in areas of the U.S. outside the broadcast range of these networks in 1969 (these are payments for no-frills community cable TV). This permits them to estimate that the willingness of U.S. TV viewers to pay was close to $20 billion in nominal terms, nearly ten times the value we estimate for "free" television content in 1969. A large difference between consumer spending and willingness to pay is common in many other sectors of the economy.

4. Price Indexes for Content

4.1 General Discussion on Price Measurement Issues

Both media and information are difficult services to deflate. Conceptually, the deflators should track production costs for the same item over time and productivity growth. But content users constantly demand original content. Thus, we cannot track the cost of producing the exact same Web site or video over time, for example. In addition, both media and information are nonrival goods with difficult-to-define units of output. A blogger might switch from writing a few long posts to writing many short tweets. Is this change an increase or decrease in total output? Finally, information quality generally depends on its accuracy, yet accuracy is extremely hard to measure.

Complementary goods add more complexity. The user experience depends on the quality of the durable goods used in the production of the entertainment services, and durable-goods quality has risen dramatically. This rise in quality applies to both the production of entertainment services in the home and of information services outside the home. For example, the quality of "free" audiovisual content is enhanced by high-definition televisions, and indeed, the videos have higher production values to take advantage of the improved receiver quality. Similarly, the quality of "free" digital content is enhanced by improvements in smartphones and data transmission services.

The price indexes that we employ do not account for network effects, positive externalities from content consumption, or other factors. We think that these factors probably raise online content quality over time and therefore lower quality-adjusted prices. As a result, the inflation rates shown for online content should be seen as being on the upper end of the true inflation rate. However, the size and direction of bias of other content categories is harder to measure. In this paper, we use a combination of input prices and output prices to construct price indexes for "free" content. More information on the exact methodologies are given in Appendix B.

4.2 Prices for Digital Content

We start by constructing a price index for digital content. The main inputs to "free" digital content are software and computer processing. For example, search engines start out with complex algorithms to optimize the search process. They then run the algorithms on server farms every time someone enters a query. Our price index for software is taken from BEA's price index for own-account software (NIPA table 5.6.4, line 3). Our price index for computing services is based on (Byrne, Corrado, and Sichel 2017). We assign each input a 50 percent weight and calculate the price as a geometric average.

Table 4 shows the combined price indexes, and figure 7 shows the price indexes relative to the GDP price index. We find that digital prices have fallen approximately 15 percent per year. This decline is due to plummeting cloud computing prices which reflect declining hardware prices and more efficient server farms. In contrast, own-account software prices increased over the period, reflecting the underlying wages of the programmers that create the unique projects. We assume the same productivity gains for Internet publishing companies that produce advertising-supported online media and the marketing divisions that produce marketing-supported online information.

4.3 Prices for Print Content

Book publishers produce a similar product to print media, and therefore, wholesale book prices are a good proxy for the costs of writing, editing, printing, and delivering newspapers. We used BEA's price index for entertainment, literary, and artistic originals for books (NIPA table 5.6.4, line 25) as a proxy for all the costs. Note that this is an output price and therefore includes some productivity growth over time. In addition to the writing costs, print media also requires communication in order to interview sources and to submit articles remotely. We use BEA's price index for telecommunications (NIPA table 2.4.4, line 97) as a proxy for those costs. We assign book originals an 85 percent weight and telecommunications a 15 percent weight and calculate the price as a geometric average.

Table 4 and figure 7 show the combined price index for print content. Unlike online media, print content prices have been rising steadily since the early 1980s. It is true that cell phones and search engines make reporting much easier and more efficient. However, the basic job of writing and then editing a story has not changed much, so there is little increase in labor productivity. Furthermore, wages for white collar professionals like authors or journalists have risen substantially over time. The net impact is steady price growth for print content production. Before 1980, the prices for print content changed at about the same rate as the GDP deflator.

4.4 Prices for Audiovisual Content

The three main inputs to audiovisual content are: sports programs to show, nonsports programs to show, and transmission services to send the content to viewers. We use BEA's price indexes for sporting event tickets (NIPA table 2.4.4U, line 212), long-lived television programs (NIPA table 5.6.4, line 24) and telecommunications (NIPA table 2.4.4, line 97) as proxies for the inputs listed earlier. We then assign sports programs a 13.3 percent weight, nonsports programs a 53.3 percent weight, telecommunications a 33 percent weight and calculate the price as a geometric average.

Table 4 and figure 7 show the combined price index for audiovisual content. Since the early 1990s, prices fell relative to GDP but not nearly as much as the price declines in digital content. Intuitively, wages for sports stars, actors and other audiovisual professionals have risen much faster than wages for programmers. Furthermore, audiovisual content uses more computers than print content and fewer computers than digital content.

5. The Economic Impact of "Free" Content

5.1 The Impact of "Free" Content on GDP, PCE, and Core PCE Prices

Overall, the introduction of advertising- and marketing-supported consumer content to U.S. national income and product accounts has a small but still noticeable impact on the measured inflation rate over the past 20 years. As table 5 shows, from 1929 to 1995, the average annualized inflation rate as measured in the GDP, personal consumption expenditures (PCE), and core PCE price indexes is almost unaffected by consumer content. The impact rises after 1995. From 1995 to 2005, the inflation rate falls from 2.01 percent to 1.96 percent for the GDP price index, from 1.91 percent to 1.84 percent for the PCE price index, and from 1.70 percent to 1.63 percent for the core PCE price index. From 2005 to 2016, the inflation rate falls from 1.64 percent to 1.58 percent for the GDP price index, from 1.57 percent to 1.48 percent for the PCE price index, and from 1.52 percent to 1.42 percent for the core PCE price index.

5.2 The Impact of "Free" Content on Measured Real GDP

We introduced our results by showing the impact of advertising-supported media in figure 1 and marketing-supported information in figure 2. In order to save space, we will refer to the same figures in this discussion. Both figures measure real GDP growth from the expenditure side, which we estimate by deflating the nominal estimates with the price deflators described above and constructing a new chained Fisher estimate of real GDP. We find that our experimental methodology raises GDP growth from 1995 to 2005 by 0.086 percentage point per year, and it raises GDP growth from 2005 to 2016 by 0.084 percentage point per year. These increases in real GDP growth are much larger than the increases in nominal GDP growth shown in figures 4 and 6. Intuitively, the plummeting price for online information reinforces the explosive nominal growth of online information.

5.3 Measuring Viewership Quantities over Time

The analysis up to this point fully measures the impact of "free" content on real GDP (output), but it does not address the impact of "free" content on measured productivity across industries and in the aggregate. Policymakers and researchers are interested in measuring the extent to which private business sector output can be explained by growth in total factor productivity (TFP) relative to input accumulation and the industry origins of the aggregate sources of economic growth. This decomposition is particularly important for analyzing advertising-supported media because the content is produced in a narrow set of industries but is used broadly throughout the economy. The missing pieces in constructing productivity measures that account for both the production and the use of "free" media and information are viewership quantities and prices. To clarify this, for industries that use "free" content (like a business traveler getting directions from Waze), "free" content is an input to production, while viewership of advertising and marketing is a new industry output. For industries that produce the content, viewership is an input, and content is an output.

In nominal terms for each industry, viewership and content are equal and thus business sector value added in nominal terms is unchanged; this is the underlying assumption of the barter transaction model. Because the household viewership sector is outside the private business sector, the household viewership inputs into private business gross output are excluded, by definition, from private business sector value added. Moreover, fundamental inputs, such as quality- adjusted labor and capital services, into private business sector production, are also unchanged. However, the real value added, and thus TFP, is changed, because the real inflation rates and the real quantities of viewership and content are not the same. In particular, online content in real terms grows substantially faster than the growth of online hours (viewership inputs in the private business sector) because online marketing accelerated. However, it is worth noting that adding our barter transaction for "free" content does not necessarily lead to upward revisions to TFP growth. In practice, the revision depends on the productivity effect of producing the new content versus the effect of using the new content.

We calculate viewership quantities and implicit prices based on time use. By construction, our indexes only track viewership of the advertising and marketing that is viewed during content usage time and that is separated from the media content. For example, a print newspaper might print news articles on one page and paid advertisements on the next page. The cost of the paid advertisements includes not only the cost charged by newspapers to advertisers for the page space, but also the implicit cost incurred by marketers designing the ad and placing it in a relevant location. We then construct price indexes as the ratio of total nominal advertising and marketing content divided by the viewership quantity. Between 2006 and 2016, total time spent online increased by approximately 50 percent. This time increase was largely due to time spent on subscription websites, like Netflix, and time spent on user-generated content. Therefore, we adjust our estimates of time online to remove this portion of time online to arrive at an estimate of time spent on advertising and marketing supported content. In particular, we exclude portions of the following activities: (1) social media, because most comments and Tweets are generated by amateur users; (2) Wikipedia, because most articles are written by amateurs; and (3) e-commerce, because most product reviews are written by amateurs.

Figure 8 shows the implicit price indexes for viewership from 1929 to 2016 relative to the GDP deflator. Viewership prices for digital content spiked during the dot-com bubble. The Silicon Valley business model of "ubiquity first, revenue later" provides one lens to interpret this early spike. Companies spent heavily building Web sites and creating digital content to attract early Internet users because the companies believed that later Internet users would gravitate toward products and services with a preexisting network of users. Viewership prices fell rapidly between 1998 and 2002, reflecting the influx of people viewing content online. Since 2002, the price for viewership of online content has increased slightly relative to GDP, reflecting simultaneous growth in spending on digital content and time spent viewing digital content.

5.4 The Impact of "Free" Digital Content on Measured TFP

This section incorporates our estimates of "free" content production and use into industry-level statistics. All of our data on labor and on nonlabor inputs for the 63 business sector industries that we track is based on (Jorgenson, Ho, and Samuels 2014). We show the results for the private economy as a whole by aggregating the industries. To be clear, business usage of "free" content has an offsetting impact on measured TFP for the content- producing industry and the content-using industry. As a result, the aggregate results shown are driven by "free" consumer content. Results for the individual industries are available upon request.

Figure 9 shows that TFP growth rises when "free" digital content is included in the productivity accounts for the private business sector. In 2014, the level of TFP would have been higher by 0.5 percentage point, and in 1995, it would have been lower by about 0.5 percentage point. Thus, over the period 1995-2014, TFP would have grown by about 0.05 percentage point per year faster than the currently published growth rate; it would have grown 0.10 percentage point per year faster during the recovery period of 2010-2014, 0.07 percentage point per year faster during the jobless recovery period of 2001-2007, and 0.01 percentage point per year between 1995 and 2001.

The impact on measured TFP from including "free" digital content shown in figure 9 are much smaller than the revisions suggested in the popular press (Ito 2013; Aeppel 2015). The main cause of this difference is how we weight "free" apps in our TFP numbers. The standard productivity formula assigns weights in proportion to gross output in order to reflect the production-based valuation consistent with GDP. Even in 2014, "free" digital content accounts for less than 1 percent of the overall economy. Accordingly, higher TFP growth for digital content creation has little effect on aggregate TFP growth. In contrast, the popular literature assigns weights in proportion to time use. By 2014, Americans spent more than one-sixth of their waking time online. If we used that weight to value digital content creation, private sector TFP growth would increase dramatically, but this estimate would be inconsistent with standard GDP and TFP constructs where weights are based on the economic theory of production.

As a reminder of the issues that we discussed earlier, the price indexes that we use do not include any quality adjustment for network effects, and therefore may underestimate real growth of "free" digital content. As a robustness test, we explore the use bytes of data, which were tracked by the Minnesota Internet Traffic Studies as a potential proxy for quantities of "free" digital content. Based on the quantity index that we construct, we calculated that quality-adjusted prices could have fallen as fast as 26 percent per year. Using this price index, we calculate that "free" digital content would have increased aggregate TFP growth by 0.13 percentage point per year between 1995 and 2014 (about triple the effect reported above). This upward revision to TFP growth is not trivial, and it suggests that quality growth may be very important when measuring "free" online media. However, even a TFP increase of 0.13 percentage point per year is not nearly enough to reverse the recent productivity slowdown (Syverson 2017).

5.5 The Effect of Other "Free" Content on TFP

Even though the Internet receives the most popular attention, it is not the only category of "free" content. Figures 4 and 6 show that "free" digital content represents less than half of total consumer entertainment. Like digital content, our experimental methodology includes "free" print and audiovisual content in final output and GDP. Thus, it is just as important to account for how these non-digital content categories affect TFP growth using our experimental methodology.[20]

Figure 9 shows the combined effect of all the "free" categories on measured private sector TFP. From 1947 to 2014, adding "free" content to the productivity accounts would raise measured productivity growth by about 0.04 percentage point per year. To put this in context, Jorgenson, Ho, and Samuels (2016) estimate that aggregate TFP grew by 0.64 percentage point per year over that same period, a substantive difference.[21] Between 1995 and 2000 (the dot-com boom), our imputations add about 0.12 percentage point per year in comparison with 0.79 percentage point per year for the aggregate economy, but we note that we have not carefully considered the cyclical properties of our estimation methods. After 2000, our experimental accounting for advertising-

[20] Some small portion of print and audiovisual content contains user-generated content, such as letters to the editor and audience participation on local radio shows, but we have not account for this in our estimates here.
[21] The aggregate TFP estimate from Jorgenson, Ho, and Samuels (2016) covers economy-wide TFP, but our TFP estimates cover only the private sector.

and marketing-supported content adds about 0.06 percentage point per year to measured private sector TFP growth. Since 1948, including the “free” audiovisual content would add 0.01 percentage point per year to private sector TFP growth, and adding “free” print media would add another 0.01 percentage point per year to private sector TFP growth.

6. Production of User-Generated Content

6.1 Conceptual Framework

User-generated content is different from the content generated by advertising and marketing professionals studied earlier in this paper. Professionally generated content is produced by private sector businesses with the expectation that this content will yield sufficient viewership to cover production costs. Even though this content is provided without explicit costs, there is a clear implicit transaction of viewership services for “free” content. Since user-generated content is produced without the expectation of revenue or other material rewards, both this content and the viewership associated with it are out of scope for official GDP. Conceptually, content creation is a type of volunteer activity which is intended to benefit a community, the environment or another social purpose. Like other volunteer activities, this output is not part of the market sector and therefore not counted in official GDP.

Nevertheless, the transition from Web 1.0 to Web 2.0 would not have been possible without user-generated content, and many of the most popular Web sites would likely not exist without user-generated content. Thus, to provide comprehensive coverage of the production value of “free” digital content, we extend the scope of our analysis to cover user-generated content. Twitter is currently a “free” social media platform whose main source of revenue is advertising. In BEA’s input-output accounts, this advertising revenue is the nominal value of Twitter’s output. While it may tempting to think that the value of amateur Tweets is reflected in Twitter's advertising revenue, the value of the user-generated content is not part of Twitter's production costs and therefore not included in Twitter's revenue.[22] Despite the exclusion of user-generated content from official GDP, values of user-generated content are important for assessing the overall economic impact of the digital economy,

6.2 Time Spent on Digital Content Generation

Our primary dataset is the Technology User Profile (TUP) data produced by Metafacts.[23] The TUP data are a representative sample of adults that own connected devices and that include weights that are constructed to yield totals for adults in the United States. The TUP data provide information on time spent on each device and the activities done using that device.

Our first step in measuring the production of user-generated content is to estimate the number of people engaged in content production. User-generated content spans many different types of activities, from simple activities such as "liking" someone's post to more sophisticated activities such as sharing original videos online. We calculate production on an extensive margin by tabulating the number of people involved in any activity tied to user-generated content. An implicit underlying assumption that we make is that the TUP covers all relevant activities in a given year, so any omitted activities can be set to zero.[24]

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[22] Conceptually, we assume a competitive environment with multiple possible "free" platforms, minimal network effects and minimal switching costs. In that environment, users gravitate towards the "free" platform which provides the best content hosting features in return for their viewership and advertising revenue is only sufficient to cover its own platform management costs. The provision of some user content is enforced by technology. For example, Twitter users automatically provide location data when they use the service. This location data are considered part of the barter transaction with Twitter and therefore are included in advertising viewership.

Our first step in measuring the production of user-generated content is to estimate the number of people engaged in content production. User-generated content spans many different types of activities, from simple activities such as "liking" someone's post to more sophisticated activities such as sharing original videos online. We calculate production on an extensive margin by tabulating the number of people involved in any activity tied to user-generated content. An implicit underlying assumption that we make is that the TUP covers all relevant activities in a given year, so any omitted activities can be set to zero. Appendix B contains more information on TUP data and our empirical analysis.

Among the online population, content creators grew from 28 percent of those online in 2006 to about 80 percent in 2016. This, to a first order, shows the tremendous growth in the production of user-generated content. This growth in reinforced by a 30 percent increase in the number of people online in the United States from 153 million in 2006 to 208 million in 2016. In total, we calculate that the number of people who were online and producing content grew from 43 million in 2006 to 166 million in 2016, a growth rate of 136 percent.

It is difficult to measure the total hours spent on user-generated content. Due to limited data and as a first pass at assessing the potential magnitude of user-generated content, we use a simple methodology. We allocate time spent online (as measured by the TUP) to online time generating content and other time using the proportion of activities that generate "free" content. For example, if a survey respondent engaged in 30 activities online and 10 of them were those that are associated with the production of online content, then we would allocate a third of that person's online time to the production of user-generated content.

At the aggregate, estimated content generation time increased from 13 billion hours in 2006 to 76 billion hours in 2016, or the ratio of hours spent generating content to economywide hours worked increased from 3 percent in 2006 to 22 percent in 2016. It is possible that a few of the digital content creators had previously been creating offline content; for example, some print newspaper readers might have written letters to the editor. However, new technologies like cloud computing, smartphones, and social media software have made content creation and distribution much easier than it was before. As a result, many people who were previously passive consumers of professionally-generated content have started actively creating amateur content.

6.3 Valuing User-Generated Content.

Some optimistic researchers might assume that amateurs are just as productive as professionals; therefore, they value user-generated content at $2.5 trillion in 2016.[25] Other researchers (Goolsbee and Klenow 2006; Varian 2009) use the average wage for the valuation of Internet time and therefore value user-generated content at $1.5 trillion in 2016. Earlier, we showed that the time devoted to user-generated content quintupled from 2006 to 2016. Hence, one might calculate that nominal output of user-generated content grew by at least $120 billion [($1.5 trillion-$1.5 trillion*0.2)/10] annually from 2006 to 2016. This growth is large enough to completely reverse the previously reported stagnation in GDP.

We believe that even a $1.5 trillion value is implausibly high and should be seen as an upper limit. It may be true that the existing household production accounts use either professional wages or opportunity costs to value household production. Based on these proxies, some researchers calculate a large value for the categories of household production that they studied (Abraham and Mackie 2005). However, traditional household production such as cooking, cleaning, and childcare

[25] Programmers earned $40 per hour in the OES data, so that's $2.5 trillion [(62 billion hours)*($40 per hour)].

are necessary for survival, so families must outsource those activities to the market sector if they do not produce them within the household. As a result, it makes greater sense to use market wages to value those activities. In contrast, user-generated content is not necessary for survival and is rarely outsourced.

Our preferred alternative is to value aggregate user-generated content at a conservative $43 billion in 2016. This calculation is based on the assumption that amateur content generators have an opportunity cost similar to television viewers. Both writing Facebook comments and watching television commercials are primarily leisure activities that create incidental output, so their hourly output value may be much lower than market wages. Earlier in this paper, we estimated that television viewers "earn" approximately $0.69 cents of content for every hour they spent watching commercials.[26] If we use the same $0.69 hourly output to value user-generated content, we calculate that Americans contributed $43 billion of labor inputs, about a third of the estimated value for "free" digital consumer entertainment shown in table 3. This is likely to be a lower bound because content creators are active rather than passive and because the value of TV viewership is measured by the content creation cost rather than by the value to the viewer.

Capital services play an important part in home production as well. To measure the capital services used in the production of user-generated content, we start with the capital service flow from three types of assets: Computers, Communications equipment, and Software from (Jorgenson, Ho, and Samuels 2017). In 2015, this was about $142 billion. We then split this into the portion used to generate UGC and other using the ratio of hours online spent generating UGC versus to total time

[26] Section 5.3 also estimates hourly values for Internet advertising and marketing viewership. It might seem preferable to use that value – except that this hourly value is empirically dependent on the estimated value for digital user-generated content. As a result, there are major circularity issues we prefer to avoid.
We experimented with calculating hourly labor inputs and hourly capital inputs separately, but we dropped this calculation for simplicity. The $0.69 hourly output for television commercial viewership combines both inputs.

online. Based on data in the TUP, the share of time online generating content increased from about 2.5% of device time in 2006 to 7.9% of device time in 2010 and to 9.4% of device time in 2016. Using these shares, we estimate additional value added in user-generated content of $2.0 billion in 2006, $6.8 billion in 2010, and $13.0 billion in 2015 from the capital services employed in the production of user generated content.

7. Conclusion

The "free" digital economy poses a number of challenging questions for measuring the sources of economic growth. In this paper we have addressed one important difficulty: how to account for advertising- and marketing-supported content when there is no directly measured transaction between the producers of the content and the users of the content. An important context for our work is that digital content is not the first content category to be subsidized by advertising and marketing. We have demonstrated that many of the measurement issues can be addressed by a relatively simple tweak to the current measurement methodologies by accounting for "free" content through a barter transaction.

We use the barter transaction methodology to recalculate GDP, GDP growth, aggregate productivity of the business sector, and industry-level productivity growth. We find that including advertising-supported media and marketing-supported information in final output has a substantive impact on measured real GDP growth and TFP growth, and the impact of including marketing-supported information is larger than the impact of including advertising-supported media. Between 1929 and 2016, adding "free" content to final demand increases real GDP growth by about 0.026 percentage point per year and aggregate TFP for the private sector by 0.030 percentage point per year. Most of this increase in growth occurred after 1995. From 1995 to 2016, our experimental methodology raises real GDP growth by 0.084 percentage point per year and TFP growth by 0.076 percentage point per year.

Much previous research studying the Internet has focused on advertising-supported digital content like Google search. These “free” services are more straightforward to study because advertising revenue is tracked in the Economic Census and in other government surveys. Yet advertising-supported digital content accounts for less than a quarter of total expenditures on “free” digital content. Our research demonstrates that measuring the full value of the Internet requires that one goes beyond Internet publishing companies that produce advertising-supported media to the universe of companies with webpages and Twitter accounts. Finally, the value of user-generated content, while outside of scope for the official GDP and productivity accounts, plays an important (and growing) part in the provision of “free” digital content.

Bibliography

Aguiar, Mark, and Mark Bils, Kerwin Kofi Charles, and Erik Hurst. 2017. "Leisure Luxuries and the Labor Supply of Young Men."

Abraham, Katherine, and Christopher Mackie, editors. 2005. *Beyond the Market: Designing Nonmarket Accounts for the United States.* Washinton, DC: The National Academies Press.

Aeppel, Tim. 2015. "Silicon Valley Doesn't Believe U.S. Productivity Is Down." *Wall Street Journal*, July 16

Brynjolfsson, Erik, Felix Eggers, and Avinash Gannamaneni. 2017. "Using Massive Online Experiments to Measure Changes in Well-being." Slides presented at the Society of Economic Measurement. These slides discuss the paper, and include additional material.

Byrne, David, and Carol Corrado. 2016. "ICT Prices and ICT Services: What Do They Tell Us About Productivity and Technology?" http://scholar.harvard.edu/files/jorgenson/files/1.1.pdf?m=1463778496.

Chen, Yan, Grace YouJoo Jeon, and Yong-Mi Kim. 2014. "A Day without a Search Engine: An Experimental Study of Online and Offline Search." *Experimental Economics* 17 (December): 512-536.

Cremeans, John. 1980. "Consumer Services Provided by Business Through Advertising-Supported Media in the United States." *Review of Income and Wealth* 26 (2), 151–174.

Eisner, Robert. 1978. "Total Incomes in the United States, 1959 and 1969." *Review of Income and Wealth.* 24 (1), 41-70.

Goolsbee, Austin, and Peter Klenow. 2006. "Valuing Consumer Products by the Time Spent Using Them: An Application to the Internet." *American Economic Review Papers and Proceedings* 96 (2, 108-113.

Greenstein, Shane, and Ryan McDevitt. 2011. "The Broadband Bonus: Estimating Broadband Internet's Economic Value." *Telecommunications Policy 35*, 617-632.

Ito, Aki. 2013. "The Free Web Has Economists Puzzled." *Business Wee*k (November 21).

Jaszi, George. 1971. "An Economic Accountant's Ledger." *Survey of Current Business* 51 (July) Part II, 183–227.

Jaszi, George, and Charles Schwartz. 1954. "National Income–1954 Edition." *Survey of Current Business* Supplement. Discussion of "free" content on page 38. https://fraser.stlouisfed.org/files/docs/publications/nipab/nipa_1929_1954.pdf.

Jorgenson, Dale W. 2001. "Information Technology and the U.S. Economy." *American Economic Review* 91 (1), 1-32

Jorgenson, Dale W, Mun S.Ho, and Jon D. Samuels. 2014. "Long-Term Estimates of U.S. Productivity and Growth." Unpublished Manuscript. http://www.worldklems.net/conferences/worldklems2014/worldklems2014_Ho.pdf.

Jorgenson, Dale., Mun S. Ho, and Jon Samuels. 2017. Education, Participation, and the Revival of U.S. Economic Growth." NBER Working Paper 22453. http://www.nber.org/papers/w22453

Juster, Thomas. 1973. "A Framework for Measurement of Economic and Social Performance." *The Measurement of Economic and Social Performance,* edited by Milton Moss. Washington, DC: National Bureau of Economic Research.

Kendrick, John. 1979. "Expanding Imputed Values in the National Income and Product Accounts." *Review of Income and Wealth* 25, No. , 349–363.

Nakamura, Leonard. 2015. "Advertising, Intangibles, and Unpriced Entertainment." In *Intangibles, Market Failure and Innovation Performance*, edited by Ahmed Bounfour and Tsutomo Miyagawa. Springer, 11–26.

Nakamura, Leonard, Jon Samuels, and Rachel Soloveichik. 2016.“Valuing Free Media in GDP: An Experimental Approach.” BEA Working paper 2016–3.

Noll, Roger G., Merton J. Peck, and John G. McGowan. 1973. *Economic Aspects of Television Regulation.* Washington DC: Brookings Institution.

Okun, Arthur. 1971. “Social Welfare Has No Price Tag.” *Survey of Current Business,* 51 (Part II), 129–33

Ruggles, Nancy, and Richard Ruggles. 1970. *The Design of Economic Accounts.* New York, NY: Columbia University Press.

Soloveichik, Rachel. (2013a, b, c, d, and e), “Music Originals as Capital Assets,” “Long-Lived Television Programs as Capital Assets,” “Theatrical Movies as Capital Assets,” “Miscellaneous Artwork as Capital Assets,” “Books as Capital Assets.” www.bea.gov/research/bio/soloveichik_rachel_h.htm.

Soloveichik, Rachel, and David Wasshausen. 2013. “Copyright-Protected Assets in the National Accounts.”

Syverson, Chad. 2017 “Challenges to Mismeasurement Explanations for the U.S. Productivity Slowdown.” *Journal of Economic Perspectives 31*, Spring, 165-186

Triplett, Jack. 1989. “Prices and Technological Change in a Capital Good: A Survey of Research on Computers.” In *Technology and Capital Formation, e*dited by Dale W. Jorgenson and Ralph Landau, 127-213. Cambridge, MA: MIT Press.

United Nations Statistics Division. 2008. *Updated System of National Accounts 2008*. Accessed May 20, 2013. http://unstats.un.org/unsd/nationalaccount/sna2008.asp

Varian, Hal. 2009. “Economic Value of Google.” http://cdn.oreillystatic.com/en/assets/1/event/57/The%20Economic%20Impact%20of%20Google%20Presentation.pdf.

Figure 1: Impact of Advertising-Supported Media on Real GDP, Percent

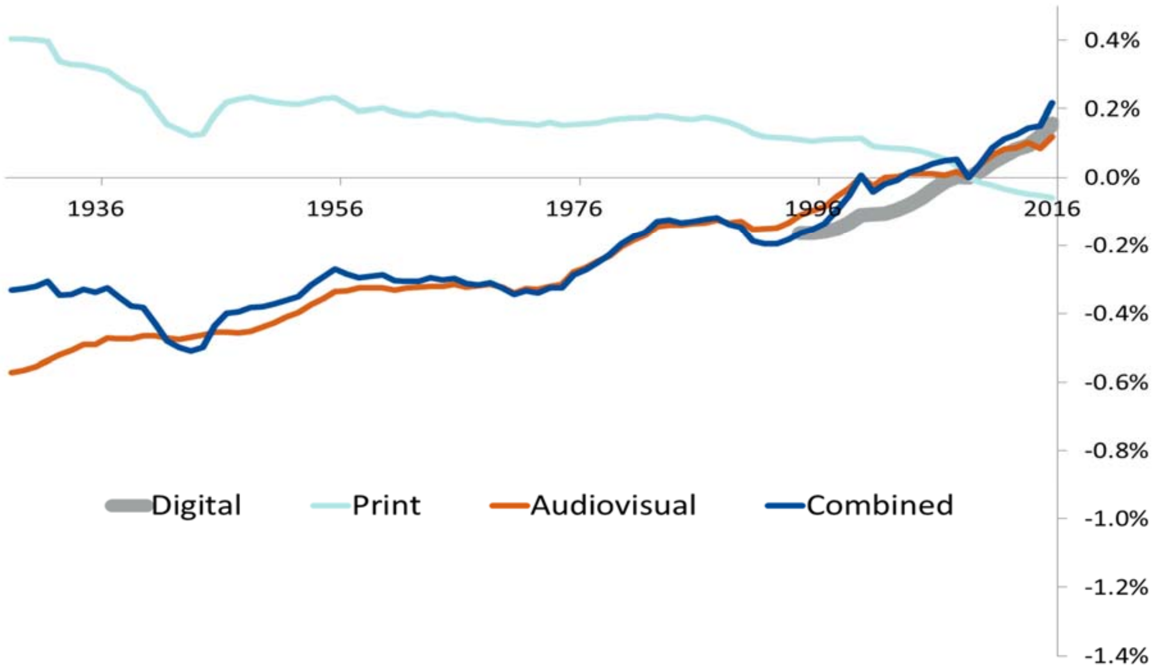

Figure 2: Impact of Marketing-Supported Information on Real GDP, Percent

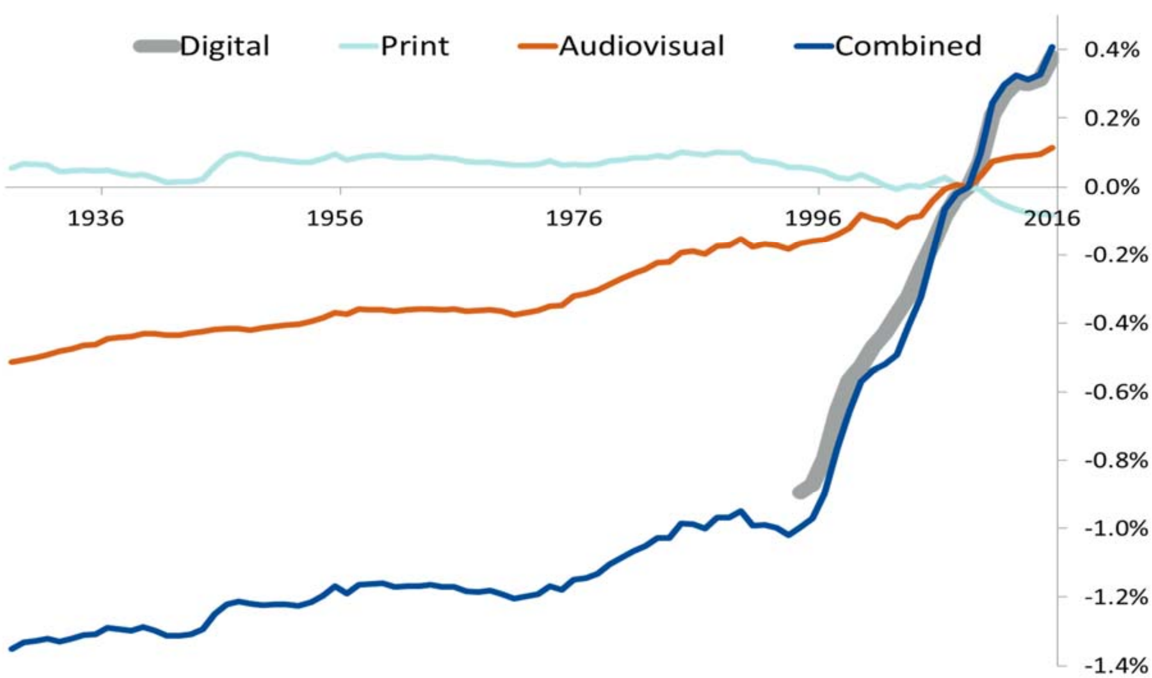

Figure 3: Advertising Revenue as a Share of GDP, Percent

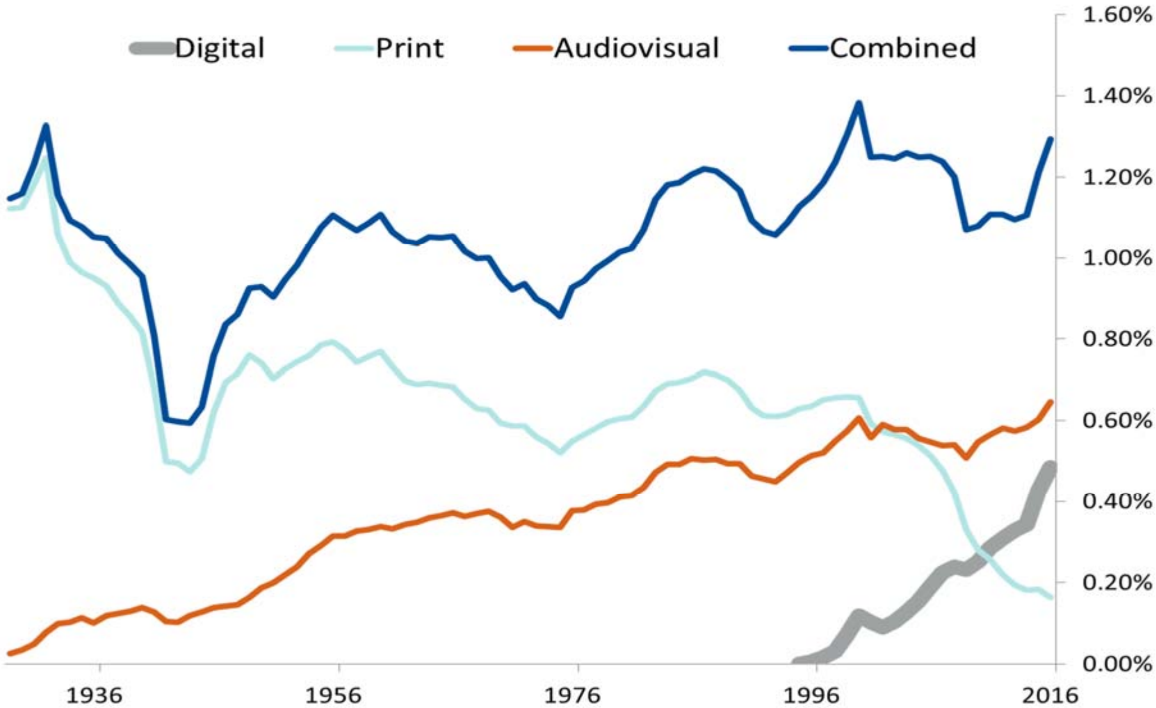

Figure 4: Marketing Output as a Share of GDP, Percent

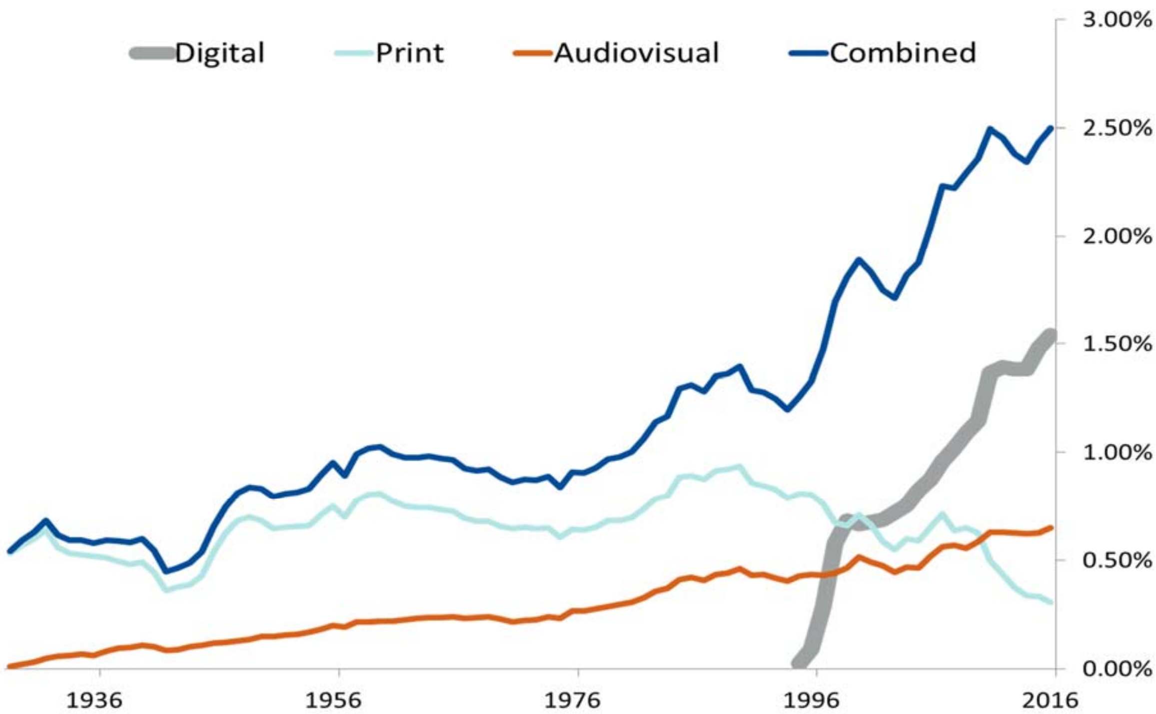

Figure 5: Consumer Media Content as a Share of GDP, Percent

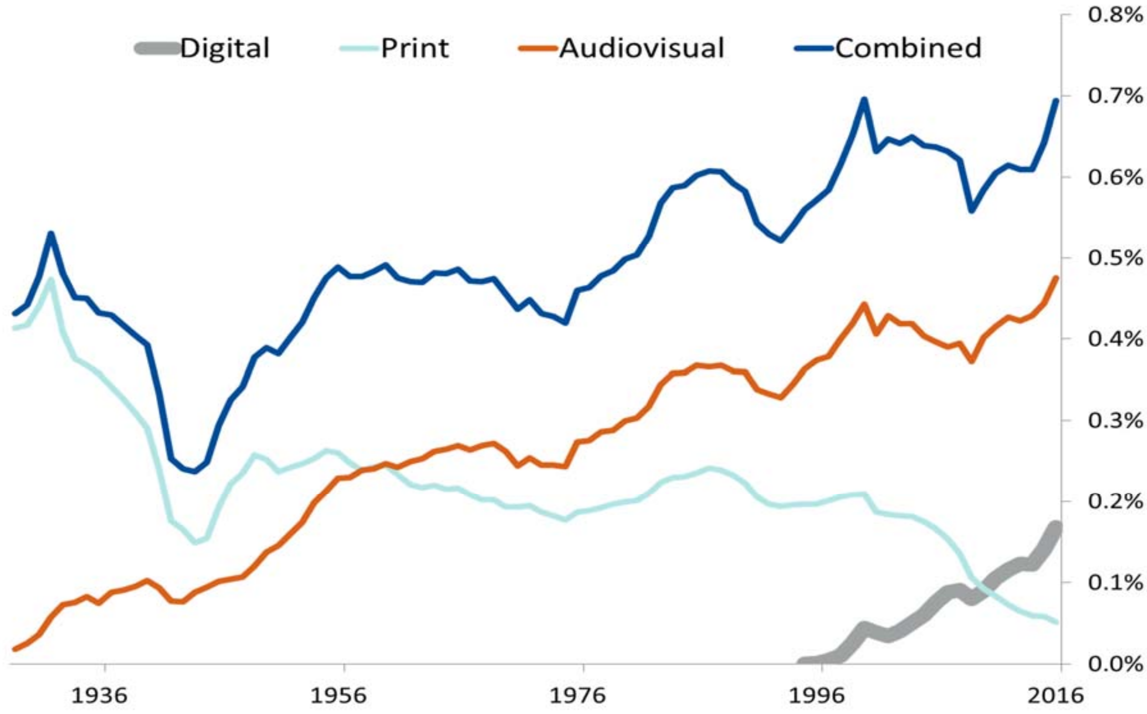

Figure 6: Consumer Information Content as a Share of GDP, Percent

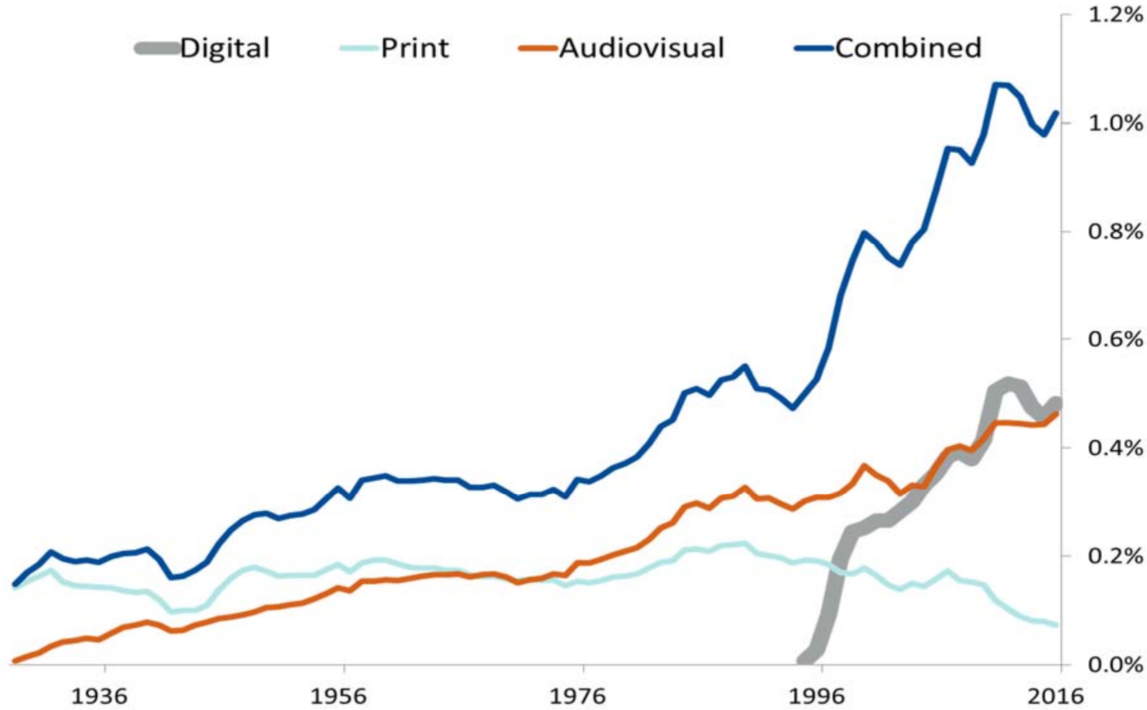

Figure 7: Content Prices Relative to the GDP Deflator

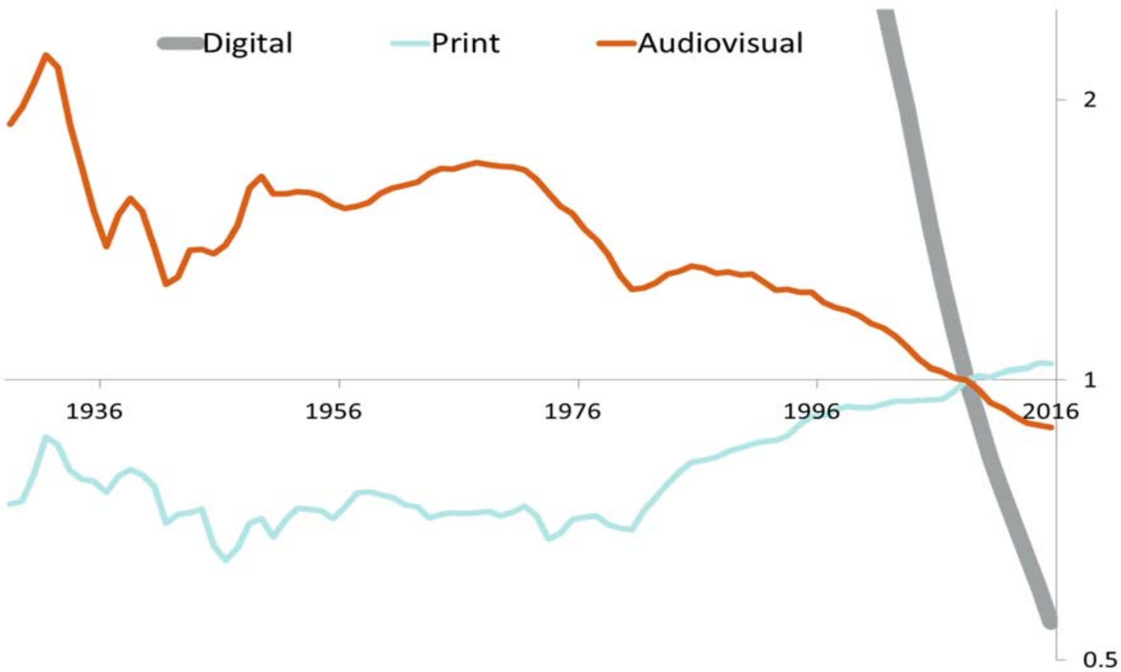

Figure 8: Viewership Prices Relative to the GDP Deflator

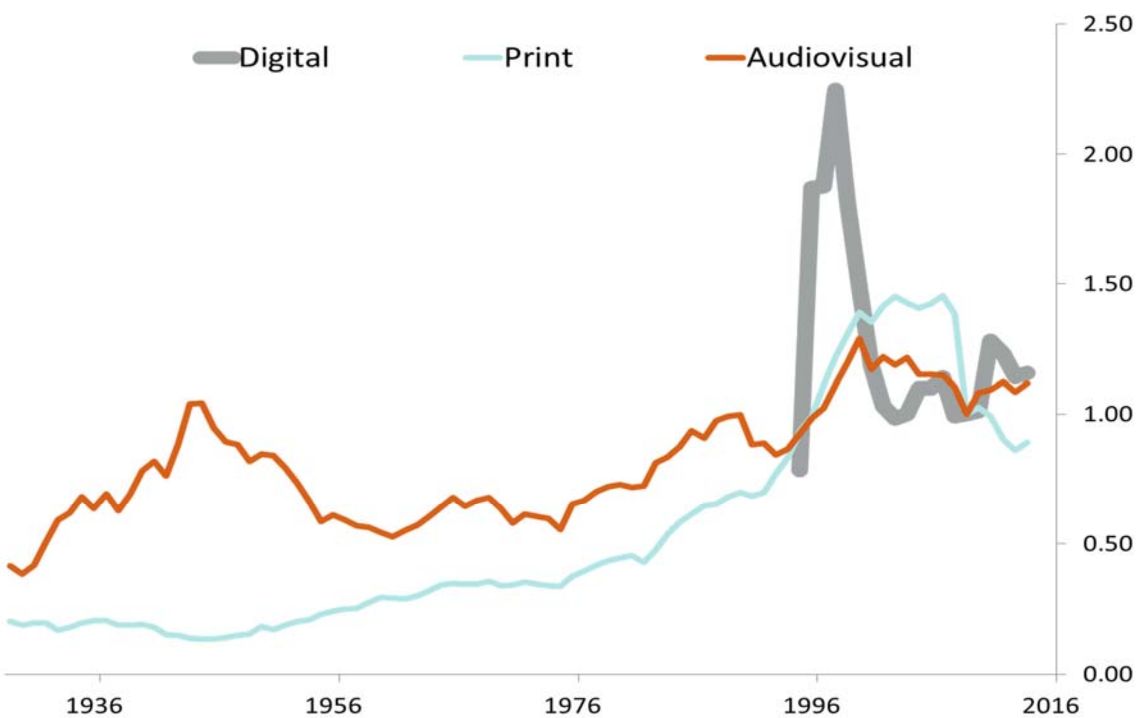

Figure 9: Impact of "Free" Content on TFP, Percent

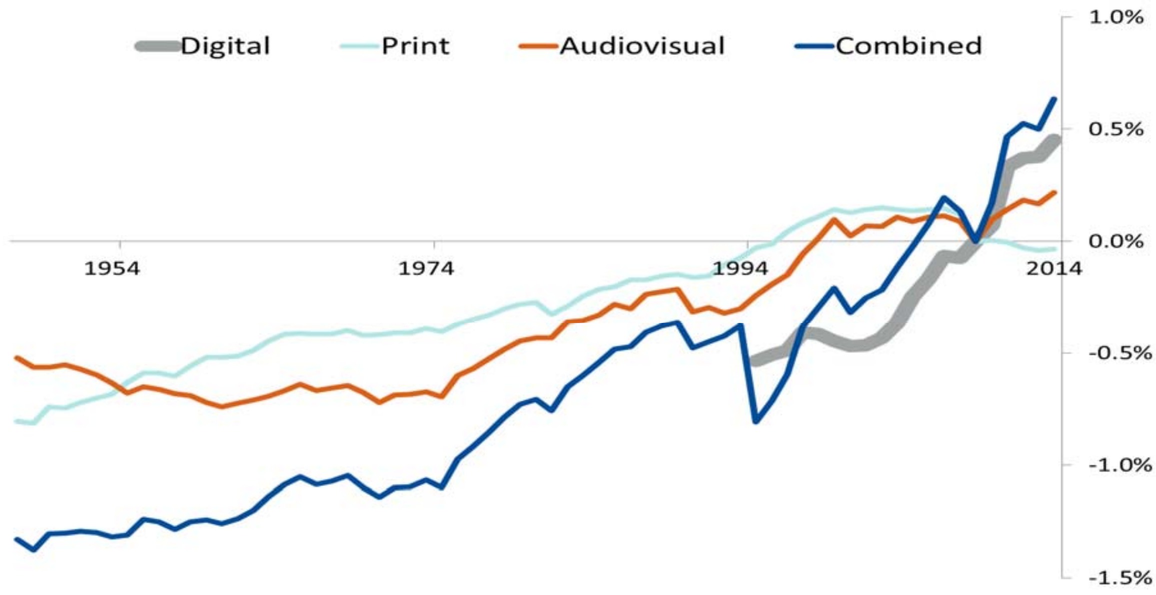

TABLE 1: Quantity Indexes, 2009=100

	BEA GDP (As of 3.23.18)	Advertising-Supported Media				Marketing-Supported Information				UGC
		Comb.	Print	AV	Digital	Comb.	Print	AV	Digital	
2016	115.9	162.8	53.9	151.8	442.7	174.4	53.3	151.8	265.3	227.7
2015	114.2	145.1	59.2	139.1	337.3	158.4	56.3	142.8	226.9	206.4
2010	102.5	109.7	88.5	112.1	127.7	113.7	97.6	111.1	123.5	117.9
2005	98.7	103.2	171.2	101.1	44.5	68.4	98.5	78.0	51.1	33.6
2000	87.1	88.2	183.0	87.5	13.6	43.7	108.2	69.3	16.4	10.7
1995	70.5	55.2	146.1	54.6	0.0	18.3	99.2	43.4	0.1	0.1
1990	62.0	50.0	153.9	45.5	-	17.6	107.4	39.7	-	-
1985	52.6	43.3	144.1	37.6	-	13.9	91.7	29.6	-	-
1980	44.6	32.8	122.2	26.5	-	9.3	69.1	18.2	-	-
1975	37.3	20.8	92.1	15.0	-	5.9	52.0	10.1	-	-
1970	32.7	18.2	84.5	12.7	-	5.0	47.3	7.9	-	-
1965	27.5	16.1	79.0	10.7	-	4.5	43.8	6.9	-	-
1960	21.5	13.0	66.7	8.3	-	3.6	36.2	5.4	-	-
1955	19.0	11.3	65.7	6.3	-	2.9	30.2	4.0	-	-
1950	15.1	7.4	51.6	3.1	-	2.1	24.2	2.4	-	-
1945	15.4	5.0	31.5	2.6	-	1.5	15.2	2.2	-	-
1940	8.8	4.2	31.0	1.5	-	0.9	9.8	1.1	-	-
1935	6.5	3.5	29.3	0.8	-	0.6	7.8	0.5	-	-
1930	6.7	3.6	35.8	0.0	-	0.5	9.1	0.1	-	-

Table 2. Summary Nominal Experimental Estimates, 2015

	Advertising	Marketing	Total Professionally- Generated Content	User-Generated Content
Total Output	219.7	441.2	660.9	43.7
Costs	67.1	131.3	198.4	-
Total Content	152.7	309.8	462.5	43.7
Consumers	116.5	177.4	293.9	43.7
Business	36.2	132.4	168.6	-

TABLE 3: Nominal "Free" Consumer Content, Billions of US $

	BEA GDP (As of 3.23.18)	Advertising-Supported Media			Marketing-Supported Infor.			UGC
		Print	AV	Digital	Print	AV	Digital	
2016	18,624.5	9.6	88.4	31.1	13.6	86.1	90.0	50.5
2015	18,120.7	10.6	80.4	25.5	14.3	80.4	82.7	43.7
2010	14,964.4	13.8	60.2	13.5	22.0	62.5	62.0	27.0
2005	13,093.7	22.9	52.8	7.9	19.0	43.0	43.3	6.2
2000	10,284.8	21.5	45.6	4.5	18.2	37.8	25.9	4.3
1995	7,664.1	15.1	27.8	0.0	14.7	23.1	0.5	0.1
1990	5,979.6	13.3	21.5	0.0	13.4	19.5	0.0	0.0
1985	4,346.7	10.0	15.6	0.0	9.2	12.6	0.0	0.0
1980	2,862.5	5.7	8.6	0.0	4.7	6.0	0.0	0.0
1975	1,688.9	3.0	4.1	0.0	2.5	2.8	0.0	0.0
1970	1,075.9	2.1	2.8	0.0	1.7	1.7	0.0	0.0
1965	743.7	1.6	2.0	0.0	1.3	1.2	0.0	0.0
1960	543.3	1.3	1.3	0.0	1.0	0.8	0.0	0.0
1955	426.2	1.1	0.9	0.0	0.7	0.6	0.0	0.0
1950	300.2	0.8	0.4	0.0	0.5	0.3	0.0	0.0
1945	228.2	0.4	0.2	0.0	0.3	0.2	0.0	0.0
1940	102.9	0.3	0.1	0.0	0.1	0.1	0.0	0.0
1935	74.3	0.3	0.1	0.0	0.1	0.0	0.0	0.0
1930	92.2	0.4	0.0	0.0	0.1	0.0	0.0	0.0

TABLE 4: Deflators for “Free” Content, 2009 Base Year

	BEA GDP (As of 3.23.18)	GDP + “Free”	Professional Content Creation				Viewership		
			Comb.	Print	AV	Digital	Print	AV	Digital
2016	111.42	110.93	95.25	114.63	99.11	61.06	-	-	-
2015	110.01	109.59	96.66	114.59	98.28	65.68	-	-	-
2010	101.23	101.16	98.95	102.34	98.78	91.94	103.61	109.30	102.30
2005	91.99	92.22	99.84	87.34	96.76	154.94	129.64	106.23	101.23
2000	81.89	82.36	100.93	76.49	95.89	289.32	114.51	106.12	122.57
1995	75.39	75.95	101.03	67.46	93.51	707.96	70.88	70.32	59.68
1990	66.84	67.34	88.62	56.46	86.51	-	46.94	67.12	-
1985	57.34	57.75	73.73	45.56	74.9	-	33.73	50.42	-
1980	44.48	44.77	52.35	30.69	57.44	-	20.01	32.59	-
1975	31.43	31.66	39.46	21.44	48.25	-	10.67	17.62	-
1970	22.84	23.02	30.63	16.25	38.7	-	7.79	14.62	-
1965	18.74	18.89	25.36	13.4	31.56	-	6.48	12.12	-
1960	17.52	17.65	24.36	13.15	27.77	-	5.18	9.58	-
1955	15.57	15.68	21.36	11.25	24.53	-	3.61	9.19	-
1950	13.75	13.85	19.38	9.74	22.76	-	2.53	11.72	-
1945	10.31	10.38	13.93	7.46	14.2	-	1.41	10.83	-
1940	8.12	8.19	12.43	6.42	12.33	-	1.57	6.40	-
1935	7.91	7.98	12.67	6.19	13.4	-	1.56	5.42	-
1930	9.52	9.59	15.79	7.06	18.72	-	1.80	3.67	-

Table 5. Summary Deflator Experimental Estimates, 1929-2015

	1929 to 1975	1995 to 2005	2005 to 2016
GDP plus Free Content	3.12%	1.96%	1.58%
BEA GDP	3.12%	2.01%	1.64%
Difference in GDP Prices	0.00%	0.05%	0.06%
PCE plus Free Content	3.14%	1.91%	1.57%
BEA PCE	3.14%	1.84%	1.48%
Difference in PCE Prices	0.00%	0.07%	0.08%
Core PCE plus Free Content	3.15%	1.63%	1.42%
BEA Core PCE	3.15%	1.70%	1.52%
Difference in Core PCE Prices	0.00%	0.07%	0.10%

Online Appendix A: Primer on Accounting for "Free" Content

The basic premise of the economic accounting framework experimented with above is that values for "free" content can be imputed in the input-output tables based on the marketing expenditures that fund "free" content. Conceptually, the idea of imputing components of current production that are not paid out-of-pocket is not new to GDP accountants. The largest imputed estimate in the national income and product accounts is owner-occupied housing services. Other examples include food furnished to employees and financial intermediation services indirectly measured (FISIM).

The purpose of this section is to provide details and discussion of the experimental accounting framework for "free" content and how it relates to the current treatment in BEA's accounts. We demonstrate our experimental approach to measuring advertising-supported media and marketing-supported information by presenting a series of input-output tables that include the pertinent transactions. An advantage of viewing this through the input-output accounts is that these accounts form the foundation both for measuring GDP by industry and for measuring productivity at the industry level.

We begin with a stylized example with four sectors: a sector (C) that produces content (e.g., viral videos or television programs), a sector that produces advertising/marketing (AM), an everything-else sector (EE),[27] and a household viewership sector (HV). GDP is measured two equivalent ways: 1) the sales to final demand (FD) and 2) the sum of value added generated by industry. Value added is comprised of payments to factor services and taxes, but in this example, can be thought of as payments to labor services.

We start with the case of direct sales of content to final demand, compare this to the case of "free" content under our current methodology, and then proceed to "free" content under our experimental methodology. In all our initial examples with "free" content, the full value of the content is supported by advertising/marketing, so the viewer pays zero for the content. Partially supported content can be treated within the same framework, but the free information highlights the conceptual issues involved.

A.1 Direct Sales of Content

Table A1 depicts the input-output table for this stylized economy with direct sales of the information to final demand. Nominal GDP is $1,000, comprised of $800 of industry EE sales to final demand and $200 sales of content directly to final demand. Total final sales equal $1,000, the value added generated by the four sectors. In this economy, advertising is required to sell industry EE's output (industry EE purchases $250 worth of advertising services; think of this as direct mailings) and industry EE supplies $200 worth of product used in producing the advertising. In this example, the $200 of output of the content company C is sold directly to final demand. We imagine this information comprises $100 of print content, like recipes, and $100 of digital content, like video games. The household viewership sector (HV) has no role in this economy.

[27] Companies sometimes produce market-supported information entirely in-house. As a result, the current input-output tables will not show any flow of either marketing or information. But this stylized example shows separate industries in order to make the accounting easier to follow.

Table A1.

	EE	M	C	HV	FD	Commodity Output
EE		200			800	1000
M	250					250
C					200	200
HV						0
VA	750	50	200			
Gross Output	1000	250	200			

A.2 Current Treatment of "Free" Content

To produce an input-output table with "free" content, we impose the following assumptions. First, actual consumption of the output of industry EE is unchanged from the case of direct sales. Second, real consumption and the price of digital content is unchanged from the case of direct sales. Third, by substituting the direct mailing with content-based marketing, industry EE is able to save on dollar-for-dollar labor.[28] In this example, we imagine print content is used to distribute marketing, but the two are basically equivalent in this stylized model.

Table A2 lays out an example of an economy with "free" content and demonstrates some of the measurement drawbacks of the current approach to accounting for content's role in the economy.[29] Because the consumer values this print content at $100, the M industry must pay the content company at least $100 for the content company to be willing to make the content free to consumers. We assume that the M industry pays exactly $100. In this economy, industry EE switches between direct marketing and marketing bundled with the print content. For this privilege, industry EE pays M $350, reflecting the value of the content and other marketing-related services. The viewership sector has no explicit role in this representation, even though the M sector is implicitly serving as an intermediary in delivering viewership to sector EE.

[28] This precise assumption is made for modeling convenience. It ensures that GDP prices remain fixed. This may seem like a strong assumption, and it is, but it is relatively innocuous since the pertinent comparison is between the current treatment of "free" content and our proposed treatment with the barter transaction. When comparing those two approaches, we need not make this assumption. We impose this here to make a broad comparison between how the input-output accounts would look with direct sales of content to make the point that the value of the content to the consumer must be bid away. We do not make use of any evidence to tell us how industries adjust when with the introduction of "free" content. We could have alternatively chosen to allow the value of the output of industry EE to increase, for example.

[29] We do not consider the underlying reason for the advertising/marketing-supported approach to selling content or the role of content in selling industry output, but our approach allows for it to be used as a productive input.

Table A2.

	EE	M	C	HV	FD	Commodity Output
EE		200			800	1000
M	350					350
C		100			100	200
HV						
VA	650	50	200			
Gross Output	1000	350	200			

It is worthwhile to compare the aggregate economy measured in table A1 to table A2, even though this comparison embeds the assumptions imposed above. Imposing fixed prices allows for an easy comparison of aggregate nominal and real GDP. By assumption, the "free" content does not increase the final sales of industry EE, thus consumption of industry EE's output is unchanged from the example of direct sales. Similarly, the consumption of digital content and its price is the same. It is obvious from table A2 that real measured GDP is lower than the economy measured in table A1 because the same quantity of industry EE output is consumed, while only the digital content is? measured in final consumption. Under this set of assumptions, the consumer is indifferent between the economy in tables A1 and A2 (the same level of real consumption) and real production measured from final demand is the same, but measured GDP is lower. This is the crux of the measurement issue.

A.3 Content Consumption as a Barter Transaction

Our experimental treatment recognizes the barter transaction that is implicit in the above example of advertising-supported media or marketing-supported information. The role of our imputed barter transaction is highlighted in table A3. One way to think about the exchange is that the consumer was spending \$100 for the print content (the direct sales case), but the current accounting does not capture this. Thus, we impute \$100 to consumption of the content, which in this case is provided by the M industry to final consumers. How does the consumer fund this consumption? This \$100 of consumption is funded by an implicit payment from the M industry, which in exchange for this payment gets exposure to the household viewership sector (people watching advertising/marketing). Thus, the M sector generates "free" content (to be viewed by the household viewership sector) in addition to primary marketing services (which are purchased by the EE sector). Finally, the household viewership sector produces viewership output. Note that the digital content still is sold directly to consumers in this example.

Table A3.

	EE	M	C	HV	FD	Commodity Output
EE		200			800	1000
M	350				100	450
C		100			100	200
HV		100				100
VA	650	50	200	100		
Gross Primary Output	1000	350	200			
Imputed Output of “Free” Content		100				
Viewership Output				100		

A complementary interpretation of the barter transaction in table A3 is that the M industry needs to deliver viewership to the EE industry. To deliver this viewership, the M industry must compensate the HV sector. In this framework, the M industry compensates the viewership sector exactly the amount that the viewer is willing to pay for the content.

At this point, we highlight that in our application we do not observe the amount that the consumer is willing to pay for the information if it was sold directly. To estimate these values, we use observed advertising revenue and imputed marketing output. That is, we use observations on the output of the advertising/marketing industry (the $350 in table A3) to estimate the value of content to consumers and use this estimate as the value of the barter transaction. It is instructive to compare the measurement framework with the imputed barter transaction to the current treatment. First, value added across the private industries is the same in the two treatments. The implication of this is that the additional imputed consumption is balanced by the additional value added produced by the viewership sector.

It is immediately apparent that conditional on the assumptions listed above, our experimental approach produces the same nominal and real GDP as would have occurred under the direct-sales model. This is the fundamental justification for our experimental approach. Conceptually, we believe that “free” content is a very close substitute for directly purchased content, so the two content types should be handled similarly in the national income and product accounts. Under the current GDP formula, “free” content is entirely excluded from final expenditures and contributes to GDP only indirectly. In contrast, our experimental approach includes both directly purchased content and “free” content in final expenditures. Furthermore, we argue that this is a useful feature since a significant portion of content consumed is through “free” content.

A.4 Viewership Sector as Part of the Broader Household Sector

In these stylized examples and in the analysis in the main text, we have introduced a viewership sector that is beyond the scope of BEA’s current set of economic accounts. To minimize the deviation of our analysis from BEA’s official accounts, we do not consider the production process for this viewership. Presumably, viewership requires capital inputs, such as a television, a mobile phone, or a kitchen table to read the magazine. On the other hand, we do impose the assumption that intermediate inputs are minimal, so gross output is equal to value added. Measuring the outputs and inputs of this process is entangled with measuring overall household production and productivity in the household sector. We intentionally avoid this due to the plethora of issues involved in measuring household production. Our estimates of TFP at the industry level, however, are separable from measuring the inputs to household viewership, thus our focus is on the role of "free" content in industry TFP measurement.

A.5 Content Use By Business

Our examples in tables A1–A3 assumed that information content was valuable only to consumers. Tables A4–A6 revisit the same conceptual issues when the content is valuable to business. In table A4, the content produced by industry I is purchased directly by industry EE. To clarify, we imagine a situation where the content itself is directly relevant to the production process of industry EE, for example, an accounting manual for a financial industry or cooking apps for a restaurant. This is distinct from the case above in which the industry only valued the content as a conduit to reach marketing viewers. Just like the earlier consumer entertainment example, businesses provide viewership in return for information content.

Table A4.

	EE	M	C	HV	FD	Commodity Output
EE		200			1000	1200
M	250					250
C	200					200
HV						0
VA	750	50	200			
Gross Output	1200	250	200			

In this example, economy with direct sales of information to business, nominal GDP is $1,000. Like the case above, industry EE requires $250 worth of marketing to sell its output, and the content producer makes $200 worth of content. Unlike the case above, this content is purchased as an intermediate input into the production of EE.

Table A5 provides a demonstration of what happens to the I-O account with "free" content. Again, we imagine that $100 of content is provided by the C industry, and as above, whether it is the digital or print content, the input-output accounting is the same. In this case, the industry EE values the information at $100, so the M industry must pay the content producer, C, $100 to bid this away. Given the value of the "free" content embedded in the marketing services produced by the M industry, industry EE pays the marketing industry $350 for the marketing services including the "free" content. Under this model, industry EE is indifferent between the direct-sales model and the "free" content because it receives the same quantity of intermediate inputs for the same prices as under the direct sales. Because content is used as an intermediate input, aggregate GDP is unchanged with the "free" content model when compared with the case in which the content is purchased directly as an intermediate input.

Table A5.

	EE	M	C	HV	FD	Commodity Output
EE		200			1000	1200
M	350					350
C	100	100				200
HV						
VA	750	50	200			
Gross Output	1200	350	200			

Like the case with "free" content consumed by households, the advertising/marketing-supported content model leaves out the implicit transaction between the viewer and producer of the marketing. Table A6 highlights these barter transactions. In this case, industry EE produces viewership in addition to its primary output. Like in the case of consumers, the M industry implicitly compensates the viewers $100, which funds the business consumption of "free" content in sector EE. The M industry has $100 of imputed output of "free" content, so that a total of $450 of input from the M industry is purchased by industry EE. The intuition for this is that industry M paid $100 to obtain the rights to use the content, so this must be worth at least $100 to the M industry. This value accounts for an implicit payment that must be made to the viewers of the marketing. The account in table A6 makes this payment explicit and produces an internally consistent accounting for "free" content that reflects both the recorded and implicit payments for the content as an output and an input.[30]

Table A6.

	EE	M	C	HV	FD	Commodity Output
EE		200			1000	1,200
M	450					450
C	100	100				200
HV		100				100
VA	750	50	200			
Gross Primary Output	1200	350	200			
Imputed Output of "Free" Content		100				
Viewership Output	100					

[30] The household viewership sector is uninvolved in this example. The payment for viewership goes to the business sector, which produces viewership as a secondary product. Thus, there is no entry in value added for HV.

A.6 Industry Productivity Measurement, with our Experimental Approach

Given our reconstructed input-output table, measures of industry growth and productivity that reflect our experimental approach are relatively straightforward. Productivity measures require prices and quantities for the outputs and inputs of each sector. Productivity growth is defined as the growth rate of the ratio of the output quantity index to the input quantity index.

On the output side of each industry's production account there are the six new outputs discussed in the main text: (1) "free" print content, (2) "free" audiovisual content, (3) "free" digital content, (4) print viewership, (5) audiovisual viewership, and (6) online viewership. We construct new measures of the price and quantity of industry output as the Tornqvist index of the original industry output with these six new outputs. Data for the prices and quantities for each of these is described in the body of the paper and in Appendix B.

At first glance, it seems surprising to create so many new outputs for each industry. In fact, having a single industry produce multiple outputs is common in productivity measures. The official BEA-BLS integrated industry-level accounts employ this approach, and industries are classified by their primary production. When a single industry produces multiple outputs in the official BEA accounts, industry output growth is a chained index over multiple outputs. On the input side of the production account, each industry has these same six potentially new inputs.

We reiterate that by construction the nominal value of new outputs equals the nominal value of new inputs by industry. However, the price of each of these is different on the output side and the input side of the account, thus the barter transaction has implications for measured industry TFP. The government and viewership sectors complicate aggregation across industries. Thus, we focus on the measured productivity impact on the private economy.

Free information in the 2007 I-O accounts

Table A7 demonstrates how the barter transactions impact the 2007 BEA input-output table (modified to include a viewership sector) for 15 broad sectors that encompass U.S. GDP. We reiterate that the starting point for these values is data on marketing expenditures. In the main text and in Appendix B, we describe how we estimate the value of each form of information embedded in marketing viewership.

Table A7a shows the production and use of marketing-supported information content, that is, our estimate of the value of information content embedded in marketing expenditures. In 2007, print, audiovisual, and online content combined for $300 billion in content. We estimate that $228 billion accrued to the household viewership sector. The remainder of the value was used by U.S. businesses and government. To be clear, by construction, the sum of the value added generated by the viewership sector plus the intermediate use of the content equals the estimated value of "free" content. Table A7b highlights that the value of "free" content equals the value of viewership output across the economy, that is, the total value of output from viewership across all sectors equals the value of "free" content. The table makes it clear that within industries, the value of content being used equals the secondary production value of viewership.

Table A7a

Commodities/Industries	11	21	22	23	31G	42	44RT	48TW	51	FIRE	PROF	6	7	81	G	HV
11: Agriculture, forestry, fishing, and hunting	71.1	0.1	0.0	1.7	202.9	1.5	1.6	0.1	0.0	0.0	1.1	0.5	5.7	0.1	1.8	
21: Mining	2.1	54.7	74.7	12.3	422.2	0.1	0.2	4.6	0.3	4.8	1.3	0.6	1.3	0.5	18.6	
22: Utilities	5.2	4.9	5.2	3.3	80.2	6.9	16.1	6.4	3.8	80.7	11.5	19.8	15.3	4.3	26.5	
23: Construction	2.3	7.2	7.4	0.2	13.9	1.5	2.9	4.3	2.2	111.5	2.1	2.2	2.5	3.0	57.0	
31G: Manufacturing	70.6	37.2	31.5	364.0	1897	40.7	44.7	162.0	82.3	82.5	131.1	149.5	119	47.6	337.1	
42: Wholesale trade	21.6	5.7	5.2	51.0	257.3	28.0	17.0	22.0	12.9	11.6	17.8	31.7	16.7	7.0	37.0	
44RT: Retail trade	0.2	0.2	0.5	76.8	11.4	0.6	5.0	4.2	0.3	7.4	2.0	1.0	6.2	4.1	0.5	
48TW: Transportation and warehousing	10.3	9.0	23.1	21.4	123.2	46.4	54.7	93.8	16.6	28.1	35.2	16.2	11.0	4.2	48.8	
51: Information	0.4	0.9	2.1	3.8	22.8	12.2	13.3	5.4	164.4	65.0	56.2	22.6	9.2	8.1	72.3	
FIRE: Finance, insurance, real estate, rental, and leasing	15.5	13.8	19.4	29.2	92.6	92.6	140.9	76.8	61.3	928.5	222.6	231.9	83.5	80.2	115.6	
PROF: Professional and business services	4.2	22.7	28.5	44.0	339.6	146.0	124.0	51.0	124.2	420.3	419.0	166.2	106	31.9	254.2	
6: Educ. services, health care, and social assist.	0.2	0.0	0.1	0.0	0.1	0.5	2.2	0.1	0.2	0.1	0.5	20.4	1.3	1.5	13.8	
7: Arts, entertain., rec., accomm., and food service	0.4	0.6	3.6	2.1	15.5	5.1	3.7	3.2	26.4	45.7	45.6	19.3	22.0	2.9	26.5	
81: Other services, except government	0.8	0.5	1.0	4.4	16.1	15.0	10.5	4.8	7.7	30.3	27.2	22.5	10.3	6.1	23.4	
G: Government	0.1	0.0	0.8	0.0	5.2	11.5	6.4	18.7	3.7	9.2	8.7	5.7	6.1	1.8	8.1	
Original Intermediate	205	157	203	614.4	3500	409	443	457	506	1826	982.0	710	416	203	1041	
“Free” Print Content	0.1	0.2	0.3	1.4	2.0	1.4	0.9	0.7	1.4	3.8	4.2	2.2	0.9	0.8	2.3	
“Free” Audio-Visual Content	0.0	0.1	0.1	0.3	0.5	0.3	0.2	0.2	0.3	0.9	1.0	0.5	0.2	0.2	0.6	
“Free” Digital Content	0.3	0.5	0.7	3.7	5.3	3.6	2.3	1.8	3.6	10.0	11.2	5.7	2.4	2.0	7.8	
Print Viewership	0.2	0.1	0.6	0.3	3.4	2.9	2.0	0.3	31.0	5.5	19.8	2.3	1.3	0.2	0.0	
Audio-Visual Viewership	0.3	0.1	0.8	0.5	5.0	4.3	3.0	0.5	62.0	8.1	29.2	3.4	2.0	0.3	0.0	
Online Viewership	0.3	0.6	1.9	1.0	10.8	12.6	3.3	1.9	29.5	6.6	53.1	5.4	0.5	0.7	0.0	
Total Intermediate	206.4	158.5	207.6	620.2	3529	436.9	456.0	462.1	625.6	1877.2	1117.8	728.9	423.2	206.3	1046.9	.
V001: Compensation of employees	41.5	62.7	63.1	439.8	944.4	429.2	506.1	255.8	260.4	730.0	1183.3	895.8	324.7	231.1	1541.0	.
V002: Taxes on production and imports, less subsidies	-2.5	33.6	54.6	7.9	60.2	175.3	184.3	24.6	43.1	247.9	49.8	32.0	70.5	17.3	-18.7	.
V003: Gross operating surplus	103.0	217.7	117.4	267.3	849.7	256.3	187.2	129.1	398.8	1899.2	424.1	136.8	137.0	82.1	382.9	.
Total Value Added	142.0	314.0	235.1	715.0	1854.3	860.8	877.6	409.6	702.4	2877.1	1657.2	1064.6	532.1	330.5	1905.2	228.6

Table A7b

Commodities/Industries	11	21	22	23	31G	42	44RT	48TW	51	FIRE	PROF	6	7	81	G	HV
Original Industry Output	346.9	471.4	438.2	1329.4	5354.4	1269.5	1320.7	866.9	1208.6	4702.8	2639.2	1774.7	948.0	533.8	2946.7	.
Media Related Output																
“Free” Print Content	0.2	0.1	0.6	0.3	3.4	2.9	2.0	0.3	31.0	5.5	19.8	2.3	1.3	0.2	0.0	
“Free” Audio-Visual Content	0.3	0.1	0.8	0.5	5.0	4.3	3.0	0.5	62.0	8.1	29.2	3.4	2.0	0.3	0.0	
“Free” Digital Content	0.3	0.6	1.9	1.0	10.8	12.6	3.3	1.9	29.5	6.6	53.1	5.4	0.5	0.7	0.0	
Print Viewership	0.1	0.2	0.3	1.4	2.0	1.4	0.9	0.7	1.4	3.8	4.2	2.2	0.9	0.8	2.3	47.4
Audio-Visual Viewership	0.0	0.1	0.1	0.3	0.5	0.3	0.2	0.2	0.3	0.9	1.0	0.5	0.2	0.2	0.6	113.9
Online Viewership	0.3	0.5	0.7	3.7	5.3	3.6	2.3	1.8	3.6	10.0	11.2	5.7	2.4	2.0	7.8	67.2
Total Industry Output	348.4	473.0	443.4	1335.8	5386.0	1299.3	1335.1	872.3	1414.9	4759.4	2791.9	1796.3	956.5	537.4	2953.4	228.6

Online Appendix B: Detailed Discussion of Datasets Used

The line between advertising-supported media and marketing-supported information is often very thin. Media companies frequently collaborate with marketers to produce content. Furthermore, the jointly produced content is sometimes published without fully informing users of its funding. In this paper, we will use the Economic Census's industry classifications to distinguish between the categories in our discussion. "Free" content produced by the information sector (NAICS 51) is considered advertising-supported media and "free" content produced by the rest of the private business sector is considered marketing-supported information. Both advertising-supported media and marketing-supported information have the same impact on final output, so measured GDP does not depend on how we classify an item.

It is common for sellers to bundle information with a purchased good or service without charging separately for the information. For example, electronics generally come with a detailed manual that helps new owners set up and use the product. The value of this manual is already counted in the price of the electronics, so it would be double-counted if we included it in "free" content. The crucial distinction between "free" content and bundled manuals is that advertising-supported media and marketing-supported information are both available to purchasers and non-purchasers alike, but bundled manuals are only available to purchasers. For example, General Mills provides recipes to the general public at BettyCrocker.com, and these recipes work for any brand of flour. In contrast, many software and electronics companies restrict their product upgrades and telephone support to individuals with proof of purchase.

B.1 Nominal Expenditures on Advertising-Supported Media, 1929–2015

Our primary dataset is the 2012 Economic Census. All of the numbers reported in this paper are benchmarked to that census. The 2012 Economic Census reports advertising revenue for newspaper publishers (NAICS 51111), magazine publishers (NAICS 51112), directory publishers (NAICS 51114), radio broadcasters (NAICS 51511), television broadcasters (NAICS 51512), cable networks (NAICS 5152) and Internet publishers (NAICS 516 in 2002 and 51913 in 2007 and 2012). We also use the 2002 and 2007 Economic Censuses to get advertising revenue by industry for those years.

For print media, our historical data are mostly taken from the Coen Structured Advertising Expenditure Dataset (Galbi 2008). This dataset tracks newspaper and directory advertising consistently back to 1919, so we use the dataset without adjustment. The dataset is available for public use online and was also published periodically in the Statistical Abstract of the United States.[31] Unfortunately, the dataset does not track magazine advertising consistently, so we used the Service Annual Survey (SAS) as a proxy for 2005–2013 [2012?] and the Economic Census as a proxy for 1947–2005 [2004?]. We use the dataset before 1947 and as an interpolator between Economic Census years.

For radio, we use a variety of sources. The SAS reports radio advertising revenue back to 1998, and the Communications Survey reports radio advertising revenue from 1989 to 1998. Between 1935 and 1988, we use the broadcast radio revenue reported periodically in the *Statistical Abstract of the United*

[31] https://www.purplemotes.net/2008/09/14/us-advertising-expenditure-data/

States.[32] Finally, we use the Coen Structured Advertising Expenditure Dataset to track revenue from 1929 until 1934.

For television, the SAS provides our time series from 2011 onwards. Before 2011, we use data collected earlier for a previous paper on long-lived television programs (Soloveichik 2013b). Unlike the print media and radio, advertising-supported television is included in two NAICS codes: 5151 for broadcast television and 5152 for cable television. We add the two categories of television advertising to get total advertising.

For Internet publishing, we use the Internet Advertising Bureau (IAB) as a proxy. Since 1996, this organization has estimated Internet advertising revenue and published the results online.[33] Internet advertising was very small in 1996, so little data exist before then. We assume that Internet advertising was negligible before then and that it grew 240 percent from 1995 to 1996.

The datasets listed above all track production, not consumption. We were not able to find any data on exports or imports of advertising-supported media. We believe that virtually all print newspapers, magazines, radio and television are consumed domestically, so these media categories do not affect the balance of payments.[34] The situation for online media is much more complicated. Unlike the other media categories, individuals in one country can easily view foreign Web sites. In theory, our experimental methodology requires that Internet use by foreigners should be treated as an export of advertising-supported media content and as an import of advertising viewership. By construction, the nominal export value of media content equals the nominal import value of advertising viewership, so advertising revenue earned from foreign Internet users does not increase nominal GDP. Conversely, nominal GDP rises if U.S. residents view foreign Web sites even if the associated advertising revenue is not tracked in the U.S. Economic Census. We were not able to find any data on net exports of online media. For simplicity, our current calculations assume that imports are precisely equal to exports, therefore, net exports are zero.

B.2 Advertising-Supported Media By Category, 1929-2015

Before the Internet, the mapping between media categories and industries was straightforward: publishers (NAICS 511) produced print media, and networks (NAICS 5151 and 5152) produced audio-visual media. The Internet makes the situation more complicated. The majority of online media is produced by Internet-only publishers like Google or Yahoo (NAICS 519). However, print media publishers also produce online content like digital news stories or blogs. Conversely, Internet publishers like Youtube or Castbox host audio-visual content.[35] Unfortunately, the 2012 Economic Census does not report online advertising revenue for print publishers or video revenue for Internet publishers. The only data tracked are total advertising revenue for each industry, so we are [were?] forced to use a variety of private datasets to split media by industry.

To start out, we estimate the digital content produced by publishers. Between 2001 and 2004, the SAS tracked online advertising revenue for publishers. Accordingly, it is straightforward to calculate digital advertising in these years. After 2005, we are forced to use a variety of proxies. For newspapers, the Newspaper Association of America (NAA) published estimates of print advertising and digital

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[32] This volume was also called the Historical Statistics. Much of our data is taken from the volume *Historical Statistics of the United States: Colonial Times to 1970.*

[33] https://www.iab.com/insights/iab-internet-advertising-revenue-report-conducted-by-pricewaterhousecoopers-pwc-2.

[34] In many cases, the domestic media company buys content from foreign media companies or sells its content abroad. These transactions are already tracked as imports and exports in the U.S. balance of payments account. One might think that the United States exports far more online media than it imports. After all, the United States is a world leader in online media technology. However, most large Internet companies have foreign branches that handle their foreign customers. Only small Web sites are likely to have foreign viewers.

[35] Many of the YouTube networks earn minimal advertising revenue. Nevertheless, we include them in advertising-supported media if the producers aspire to earn advertising revenue eventually. [how do you know their aspirations?]

advertising from 2003 to 2012. From 2012 onwards, the Pew Research Center has published a fact sheet reporting digital advertising for a selection of publicly traded newspapers. Based on these two sources, we are able to estimate the digital share of newspaper advertising relatively precisely. We were not able to find similar data on magazines or directories, but the SAS does track the share of overall revenue earned online from 2005 to 2012. We use this overall digital share as a proxy for the digital share of advertising. After 2012, we use digital newspaper advertising as a proxy for digital magazine and director advertising revenue. Based on all of these sources, we calculate that the online advertising share grew from 2 percent in 2001 to more than 10 percent in 2015. As a result, print advertising revenue has been falling even faster than overall advertising revenue for the publishing industry.

Next, we estimate the audio-visual content produced by Internet publishers. Our main dataset is from the Internet Advertising Bureau. Since 2008, they have tracked the share of online advertising attributed to digital video.[36] We supplement this with estimates of digital radio advertising provided by XAPPMedia for 2014 and 2015. Before 2014, we use XAPPMedia's estimate of digital radio listening time as a proxy for digital advertising revenue.[37] Based on all of these sources, we calculate that the audio-visual advertising share grew from 4 percent in 2008 to nearly 14 percent in 2015. As a result, the explosive growth in Internet publishing revenue slightly overstates the true growth in digital content.[38] In other words, some Internet advertising is really just people canceling their cable subscription and watching the same shows online. This digital delivery of audio-visual content may offer valuable convenience to viewers, but it probably doesn't create nearly as much consumer surplus as new products like Internet search.

B.3 Nominal Opportunity Costs of In-House Advertising, 1929–2015

Our data are taken from a variety of industry sources. For newspapers and magazines, we rely on the Pew article "Digital Advertising and News" (Matsa, Olmstead, Mitchell, and Rosenstiel 2012), which estimated that 9 percent to 10 percent of print advertising is promoting the newspaper or magazine. For cable television, we used data from Kantar Media that directly tracks own-account television advertising time from 1995 to 2010. Those data are described in much more detail in a previous paper "Long-Lived Television Originals as Capital Assets" (Soloveichik 2013b). For theatric movie trailers, we rely on the NPR article "Theaters and Studios Squabble Over Shortening Movie Trailers" (Holmes 2013). That article does not give a precise value for movie trailers, but it estimates they average 20 minutes per movie. If a typical movie is 2 hours, then movie trailers account for approximately 14 percent of active theater time. For freemium games, we rely on two news articles: "Here's How Much You Spend on Iphone Apps Each Year" (Reisinger 2016) and "iOS App Store Brings in 75% More Revenue than Play Store Despite Difference in Downloads" (Miller 2016) to estimate total expenditures by U.S. consumers on freemium games in 2015. We were not able to find any articles that track U.S. expenditures over time, but the article "App Revenue Statistics" (Dogtiev 2017) gives global expenditures on in-app purchases from 2011 onwards. We use those global revenues as a proxy for U.S. freemium game revenue.

We only count a portion of in-house ads in our category of opportunity cost advertising. Broadcast radio and online search engines both earn the vast majority of their revenue from paid advertising. If we counted their in-house ads as opportunity cost advertising, then we would need to subtract those imputed advertising costs from their revenue when calculating content share. The end result would be a reclassification between types of "free" media with no aggregate change. In order to

[36] Their digital video statistics do not include mobile video. We assume that mobile advertising has the same video share as desktop advertising.
[37] http://xappmedia.com/wp-content/uploads/2015/01/Internet-Radio-Trends-Report-2015_january.pdf
[38] Conversely, radio networks and television networks earn approximately 1 percent of their advertising revenue from online content. This revenue source is too small to affect results much.

avoid this problem, we will only count in-house ads that promote subscription content. In many cases, the same newspaper or cable show earns revenue from both subscribers and advertisers. When that is the case, we split in-house ads in proportion to the revenue share. Broadcast television shows are frequently rerun on cable, so we consider in-house broadcast ads to be partly marketing for cable subscriptions in the future. Taken as a whole, the television industry earns half of its revenue from subscriptions, so we allocate approximately half of the opportunity cost of in-house ads to "free" content.

The opportunity costs calculated above represent an upper bound. For movie theaters, television networks, and print media, we assume a perfectly competitive market. Because of that assumption, we can use the average price for sold advertising viewership or movie theaters tickets to estimate the potential revenue from selling that advertising viewership in the market sector. If perfect competition does not hold, then the estimated opportunity cost for in-house advertising may be significantly lower. For freemium games, we assume that the production cost for premium items like extra lives is nearly zero. As a result, the entire revenue earned from in-app purchases can be allocated to the game development costs. However, even the upper bound of opportunity cost advertising is much lower than the advertising expenditures tracked in figure 3. Accordingly, adjusting our opportunity cost estimates has little aggregate effect.

B.4 Consumer vs. Business Usage of Advertising-Supported Media

Unfortunately, it is difficult to find data splitting the usage of advertising-supported media between consumers and businesses. In a few cases, the products advertised provide some clue about the likely industry of the user. For example, hospitals are the main purchasers of X-ray machines, so Web sites boasting low prices for X-ray machines are probably targeting hospital executives. But most Web sites target a general audience and have advertising unrelated to the precise "free" content provided. In correspondence, Hal Varian, chief economist at Google, said that Google does not have much information on whether consumers or businesses are searching online. To the best of our knowledge, no researcher has published any estimates of the consumer share for "free" Web sites, print newspapers, or other media.

This paper uses a variety of data sources to split "free" media usage between consumers and businesses. For online media, we use survey data from Forrester Research. Since 2007, Forrester Research has asked survey respondents to report both "work Internet" time and "personal Internet" time.[39] We use this data to estimate the consumer entertainment share of online media. Before 2007, we use data from the Current Population Survey to track home Internet access as a proxy for personal usage. For print media, we use genre data reported in the Economic Census and other sources to split consumers and businesses. For example, we assume that scientific journals are used for work rather than leisure. Finally, we assume that radio, television, and freemium games are almost entirely targeted towards consumers for leisure use.

B.5 Nominal Expenditures on Marketing-Supported Information, 2002–2015

Because marketing-supported information is produced and used in-house, it is much harder to track than advertising-supported media. In this paper, we use a two-step process to estimate expenditures on marketing-supported information. We start out by identifying sevenproduct lines that are associated with marketing-supported information and the primary industries that produce those product lines for sale. We will list those product lines later. We start with the reported product line revenue in the Economic

[39] Personal Internet time includes time spent on user-generated content. Thus, in splitting the value of content between business and personal, we remove the value of time that we estimate is spent on users generating content. See section 9 for a discussion of how we estimate time on user-generated content.

Census and then adjust for nonemployers, underreporting, and misreporting.[40] Our adjusted Economic Census product line sales yield the aggregate value of marketing produced and sold primary industries in the U.S. economy. The Economic Census data are only available for 2002, 2007 and 2012. Between census years, we use the Service Annual Survey (SAS) to interpolate revenue. Next, we use occupation data to estimate expenditures on marketing that is produced outside the primary industry. In our discussion, we will call marketing produced outside the primary industry "in-house" marketing. In practice, it is possible that some industries may sell marketing as a secondary product. These potential sales do not affect our aggregate estimates of overall marketing expenditures, but they might bias estimates of marketing output and productivity growth for individual industries.

We use the following procedure to estimate total marketing expenditures. First, we identify the occupations that are primarily responsible for its production. We then focus on industries that produce sold marketing and calculate the ratio of gross output to earnings for specialist workers for each marketing category. Finally, we use that ratio to estimate the value of in-house marketing produced by specialty workers employed in the broader economy.[41] For example, suppose that a public relations firm (NAICS 54182) sells $1 billion worth of public relations services, employs 1,000 people in public relations (occupation codes 11–2031 and 27–3031), and pays each person an average salary of $100,000.[42] In the rest of the industries studied, we observe 10,000 individuals employed in public relations with an average salary of $80,000 each. Based on those hypothetical numbers, we calculate that in-house expenditures on public relations are approximately $8 billion [$1 billion/ (1,000*$100,000)]*[(10,000*$80,000)].[43] Note that we exclude public relations specialists employed by the government or charitable institutions because the current GDP methodology already counts expenditures on public relations in measured output.[44] Below is a list of the seven categories:

(1) Media representation services in NAICS 5418 (product line 37720). For this product, we use advertising sales agents (occupation code 41–3011) as a proxy.

(2) Public relations services in NAICS 5418 (product line 37700). For this product, we use public relation specialists (occupation code 27–3031) and public relations managers (occupation code 11–2031) as proxies.

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[40] According to BEA's calculations, NAICS 51 has very few nonemployers, underreporting, or misreporting. As a result, we do not bother adjusting the numbers for advertising-supported media.

[41] This formula misses the in-house marketing produced by industries that sell marketing as their primary product. In addition, we were forced to exclude some industries for some marketing categories because we felt that the occupation proxies might not be reliable for those industries. Furthermore, the OES [spell out] does not cover the farm sector. For all of the missing industries, we assume the ratio of in-house marketing to total wages matches the broader economy. Aggregate results are robust to changing assumption for these specific industries.

[42] In practice, there are many self-employed individuals working in marketing. These individuals are not tracked in the OES, so we cannot observe precise occupations for the self-employed. However, BEA does have data on the self-employment rate by industry. We use that data to impute aggregate earnings for self-employed public relations specialists and add those imputed earnings to the wages discussed above. In-house production of marketing is assumed to be carried out by employees, so we do not adjust for self-employment there.

[43] Although this is a hypothetic example, the ten-fold markup from specialty worker earnings to gross output is not unusual. Public relations specialists generally require an IT staff to help them research and write press releases, a travel department to schedule interviews, and so forth. None of these support staff are identifiable in the OES, so we impute these support labor costs together with nonlabor costs from intermediate inputs and capital.

[44] Nonprofit hospitals generally receive the majority of their revenue from product sales and behave similarly to for-profit institutions in the same industries. We treat these sectors as if they were entirely in the private sector.

(3) Commercial planning, creation and placement services in NAICS 5418 (product lines 37710, 37670 and 37680). For these products, we use art directors (occupation code 27–1011), graphic designers (occupation code 27–1024), editors (occupation code 27–3041), writers/authors (occupation codes 27–3043), multimedia artists (occupation code 27–1014) and producers/directors (occupation code 27–2012) as proxies.

(4) Remaining marketing in NAICS 5418. This category includes a variety of small product lines that appear to marketing-supported information together with our best split for the ambiguous product lines. For proxies, we use all the occupation codes previously mentioned and the additional occupations of marketing managers (occupation code 11–2011), proofreaders (occupation code 43–9081) and all other media workers (occupation codes 27–3099).

(5) Web site development and hosting in NAICS 5415 (product line 37411 and 36120). For this product, we use system administrators (occupation code 15-–1142) as a proxy.

(6) Commercial photography in NAICS 5419 (product line 37870). For this product, we use photographers as a proxy (occupation code 27–4021).

(7) Corporate sponsorship of events. For this product, we took our data directly from the IEG's [spell out] annual reports. Those reports are available at http://www.sponsorship.com/report.aspx. Unlike the earlier six categories, we do not distinguish between purchased marketing services and in-house production.

For all seven marketing categories, we use the formula described earlier to calculate in-house production.[45] Adding up these seven categories, we estimate that U.S. businesses purchased $119 billion of marketing services and spent another $257 billion on in-house production. The precise level of in-house marketing calculated is somewhat sensitive to the exact product categories tracked and to the occupations used as proxies for each category. Just like advertising-supported media, we assume that net exports are negligible. We also assume that marketing-supported information is consumed in the same year it is produced. However, the general growth rate for marketing-supported information is robust to alternative product categories, occupation codes, assumptions about trade, and assumptions about marketing capital.

B.6 Nominal Expenditures on Marketing-Supported Information Before 2002

Unfortunately, we cannot use the formulas and data described above to track marketing-supported information before 2002, because between 2001 and 2002, the OES changed from codes based on the Standard Industrial Classification (SIC) to codes based on the North American Industry Classification System (NAICS). As a result, it is very difficult to identify which industries are producing marketing as their primary product, so we cannot calculate either purchased marketing or in-house marketing reliably. Furthermore, the OES changed its occupation codes dramatically between 1998 and 1999. Instead, we use a variety of datasets to proxy for marketing expenditures in each of the seven categories described earlier.

[45] Note that our formula might not match internal company calculations. A particular issue is that advertising agencies (NAICS 5418) appear to earn extremely high rates of return on their capital. We assume that companies producing in-house marketing would earn those same rates, so the opportunity cost of in-house marketing is equal to the purchase cost. However, companies calculating marketing expenditures may assume a more normal rate of return on the associated capital.

Media representation services. For this category, we use the total income reported by media buying agencies (NAICS 54184 and SIC 7313) in the Economic Census and similar surveys. This data are available periodically until 1948. Before 1948 and between years with data, we use total expenditures on advertising-supported media as an interpolator.

Public Relations services. For this category, we use the total income reported by public relations agencies (NAICS 54182, SIC 8743 in 1987 and 1992 and SIC 7392 for 1963–1982). Before 1963, the Economic Census did not track public relations agencies, so we cannot use that survey. However, the decennial population census does provide some data on self-reported occupation. IPUMS [spell out] published a crosswalk that allows us to calculate that employment in public relations grew 64 percent between 1950 and 1960.[46] IPUMS also publishes the exact occupation string reported to the census until 1940. Based on that occupation string, we calculate that employment in public relations grew 77 percent between 1930 and 1940. Between 1940 and 1950, we assume that public relations grew at the same rate as other marketing categories. We also use other marketing categories as an interpolator between years with data.

Commercial planning, creation and placement services. For this category, we use the net billing reported by advertising agencies (NAICS 54181 and SIC 7311) in the Economic Census and similar surveys. These data are available periodically back to 1935. The Service Annual Survey (SAS) also tracks advertising billing back to 1972. We use the SAS data as an interpolator when the data available. Before 1935 and between Economic Census years, we use total expenditures on advertising-supported media as an interpolator. Finally, we adjust the advertising agency revenue to remove expenditures on audio-visual programs produced in-house. Those expenditures will be studied separately. As a robustness test, we also explored using self-reported employment in the decennial census to track in-house production of media planning, creation, and placement. We found that this method produced similar long-term trends, but the imputed ratio of in-house production to purchased production was noisy from one census to the next.

Remaining marketing. The category is relatively small and diverse. For simplicity, we did not try to collect data back to 1929. Instead, we use the preceding four categories of marketing-supported information as proxies.

Website development and hosting. We use OES tracking employment of system administrators as a proxy. This gives us spending back to 1998. Before 1998, this category was small and so new that the 1997 Economic Census did not even have product codes for it. We were not able to find any official data tracking website development costs during the 1990s. For now, we use online advertising expenditures as a proxy.

Commercial stock photography. This product was studied earlier in the paper "Miscellaneous Artwork as Capital Assets" (Soloveichik 2013d). We took the existing estimate of revenue from commercial stock photography and used that as a proxy back until 1929.

Corporate sponsorship of events. The IEG reports provide sponsorship expenditures back to 2001. Between 1988 and 2000, we use the Olympic Committee's reported revenue from corporate sponsorship as a proxy for overall sponsorship expenditures. These two proxies suggest that sponsorship has grown rapidly, from 2.75 percent of expenditures on advertising-supported media in 1988 to 6.89 percent of expenditures on advertising-supported media in 2000. Before 1988, we were unable to find any data on corporate sponsorship. We use the growth rate after 1988 and the growth rate of advertising-supported media as a proxy.

[46] https://usa.ipums.org/usa/resources/chapter4/occ_50-60.pdf

B.7 Marketing-Supported Information by Category, 1929-2015.

In this paper, we track three categories of marketing-supported information: (1) print marketing, (2) audio-visual marketing, and (3) digital marketing. Unfortunately, it is often very hard to allocate product lines among print, audio-visual, and digital. For example, a writer might write a column for a print newsletter, contribute to a corporate blog, or write dialogue for a filmed ad. Many writers do all three simultaneously. In this paper, we combine a variety of datasets without best judgment to split spending. Our methodology for allocating the various product lines is given below:

Media representation in NAICS 5418 (product line 37720). Between 1997 and 2012, the Economic Census reports product lines for each media category (37721–37725). Between 1963 and 1997, the Economic Census reports revenue separately for publishers' representatives (print marketing) and radio/television representatives (audio-visual marketing). Before 1963 and between census years, we use advertising-supported media as a proxy for media representation services.

Public relations services in NAICS 5418 (product line 37700). Neither the Economic Census nor the industry literature gives much guidance for this product line. We will use our best judgment instead. Public relations agencies typically work to push favorable news stories and rebut unfavorable news stories about their clients; therefore, it seems likely that public relations specialists allocate their time in proportion to news consumption. According to a 2011 Pew survey, print newspapers provided 19 percent of news information, the Internet provided 25 percent and the remainder was supplied by radio or television.[47] The Pew surveys provide data from 2001 until 2010. Before 2001 and after 2010, we use media consumption time as an extrapolator. That media consumption time will be described in more detail in our section calculating viewership prices.

Purchased commercial planning, creation and placement services in NAICS 5418 (product lines 37710, 37670 and 37680). Our primary dataset is the industry group Ad Age. They first report on digital marketing in 2007, when it accounted for 8.74 percent of total marketing services sold. By 2015, digital marketing had grown to 41 percent of total marketing services sold. We were not able to find any data splitting print marketing from audio-visual marketing. For simplicity, we will generally split these two categories in proportion to media representation services. The only exception is that advertising agencies before 1960 sometimes created shows like "The Kraft Television Hour" rather than simply buying commercial time on existing media programs. We allocate those shows entirely to the audio-visual sector. We also use digital media representation services as a proxy for digital marketing before 2007.

In-house commercial planning, creation and placement services; remaining marketing services; website development; website hosting; and commercial photography. For these categories, we use reports from the research firm Outsell. That firm has tracked marketing by category since 2006. Before 2006, we use earnings for systems administrators and computer workers (occupation codes 15-–1131, 15–1132, 15-–1133, 15–1134 and 15–1142) as a proxy for digital marketing. We were not able to find such direct proxies for print marketing. For now, we use the print media as a proxy for print marketing.

Corporate sponsorship of events. The IEG reports split spending between sports sponsorship and other events like live music concerts. We allocate 75 percent of sports sponsorship to television viewers

[47] Individuals were allowed to volunteer two main news sources, so the reported totals sum up to well over 100 percent. The survey did not ask about magazines news. We assume magazine news equaled half of newspaper news. We smoothed across 3 years and divide by the total to get shares. http://www.people-press.org/2011/01/04/internet-gains-on-television-as-publics-main-news-source/.

(audio-visual sector) and 25 percent to the fans in the stadium (in-person sector). We are not studying in-person marketing in this paper, so we will drop this category from our analysis.

B.8 Consumer vs. Business Usage of Marketing-Supported Information

To start out, we assign marketing bundled together with media using the same allocations discussed earlier for advertising-supported media. In particular, we allocate television and radio commercials, public relations spokespeople interviewed on television and radio, and sponsored sports aired on television and radio almost entirely to the consumer sector. We allocate print commercials and public relations spokespeople interviewed in print journals using the same business and consumer split developed earlier for newspaper, magazine, and directory media. Finally, we allocate digital marketing like corporate Web pages, social media accounts, or downloadable apps using the split developed earlier for online media.

Next, we use research purchased from the firm Outsell to split other marketing (that is, not bundled with media). For each year, they publish two reports: one tracking business-to-consumer marketing (B2C) and one tracking business-to-business marketing (B2B). Their annual data are somewhat noisy, so we averaged across the reports purchased.[48] For print and audiovisual media, the consumer share has remained relatively constant over time. We calculate that consumers receive 51 percent of separated print marketing and 90 percent of separate audiovisual marketing. Outsell also tracks digital marketing, but we do not use their B2B versus B2C splits, because businesses often use online content directed towards consumers, and so the Forrester survey data described earlier is a better proxy for business usage. Altogether, we calculate that the consumer share of marketing fell gradually from 75 percent in the 1970s to 58 percent in 2016. This fall is due to the rise in online marketing, which has a lower consumer share than other marketing categories.

B.7 Price Index for "Free" Content: 1929–2015

Below is a brief description of each category:

Digital Content: We start by constructing a price index for digital content. The main inputs to "free" digital content are software and computer processing. For example, search engines start out with complex algorithms to optimize the search process. They then run the algorithms on server farms every time someone enters a query. Our price index for software is taken from BEA's price index for own-account software (NIPA table 5.6.4, line 3). Our price index for computing services is based on the paper "The Rise of Cloud Computing: Minding Your P's and Q's" (Byrne, Corrado, and Sichel 2017).[49] We assign each input a 50 percent weight and calculate the price as a geometric average.

Print Content: Book publishers produce a similar product to print media, and therefore, wholesale book prices are a good proxy for the costs of writing, editing, printing, and delivering newspapers. We used BEA's price index for entertainment, literary, and artistic originals for books (NIPA table 5.6.4, line 25) as a proxy for all the costs. Note that this is an output price and therefore includes some productivity growth over time. In addition to the writing costs, print media also requires communication in order to interview sources and to submit articles remotely. We use BEA's price index for telecommunications (NIPA table

[48] Like most surveys, Outsell treats owner-occupied housing as part of the consumer sector. In contrast, BEA treats it as part of the business sector when measuring GDP. We use our best judgment to adjust for this difference.
[49] The data in this paper do not start until 2009, and the annual changes are quite noisy. We used the three subindexes reported in the paper to measure cloud computing prices in 2009 and 2016. Between these years and before 2009, we use BEA's price index for business computers (NIPA table 5.5.4, line 4) as an interpolator.

2.4.4, line 97) as a proxy for those costs. We assign book originals an 85 percent weight and telecommunications a 15 percent weight and calculate the price as a geometric average.

Audiovisual Content: The three main inputs to audiovisual content are: sports programs to show, nonsports programs to show, and transmission services to send the content to viewers. We use BEA's price indexes for sporting event tickets (NIPA table 2.4.4U, line 212), long-lived television programs (NIPA table 5.6.4, line 24) and telecommunications (NIPA table 2.4.4, line 97) as proxies for the inputs listed earlier. We then assign sports programs a 13.3 percent weight, nonsports programs a 53.3 percent weight, telecommunications a 33 percent weight and calculate the price as a geometric average.[50]

This approach is an oversimplification of the broadcasting and cable industries. Broadcasting stations have implicit ownership of their airwaves, and their transmission costs depend on the shadow price of spectrum as well as the capital costs of transmission equipment. Furthermore, both cable distributors and phone companies are regulated monopolies with prices partially determined by government policy. Our previous paper developed a much more complex price index (Nakamura, Samuels, and Soloveichik 2016). We also considered using an indirect price index using quantity data from IMDB and the quality data from the paper "The Random Long Tail and the Golden Age of Television" (Waldfogel 2016). Both of these complex price indexes match the simple input-based price index reasonably well.

B.8 Price Indexes for Advertising/Marketing Viewership

We will calculate viewership quantities and implicit prices based on time use.[51] To be clear, our viewership quantities do not include time spent watching either purchased content or amateur content. For example, television commercial viewership is included, but not DVD viewership. By construction, our indexes only track viewership of the advertising and marketing that is viewed during media usage time and that is separated from the media content.[52] For example, a print newspaper might print news articles on one page and paid advertisements on the next page. The cost of the paid advertisements includes not only the cost charged by newspapers to advertisers for the page space, but also the implicit cost incurred by marketers designing the ad and placing it in a relevant location. We then construct price indexes as the ratio of total nominal advertising and marketing content divided by the viewership quantity. Between 2006 and 2016, total time spent online increased by approximately 50 percent. This time increase was largely due to time spent on subscription websites, like Netflix, and time spent on user-generated content. Therefore, we adjust our estimates of time online to remove this portion of time online to arrive at an estimate of time spent on advertising and marketing supported content. In particular, we exclude portions of the following activities: (1) social media, because most comments and Tweets are generated by amateur users; (2) Wikipedia, because most articles are written by amateurs; and (3) e-commerce, because most product reviews are written by amateurs.

We measure viewership prices indirectly. First, we create quantity indexes tracking viewership of advertising/marketing. By construction, our indexes **only** track viewership of the advertising/marketing which is viewed during media usage time and which is separated from the media content. For example, a print newspaper might print news articles on one page and paid advertisements in

[50] Relative weights for sports and nonsports are based on data purchased from Kantar Media (Soloveichik 2013b).

[51] Like the split between business and personal, we adjust the time spent viewing by removing the time spent viewing user-generated content from personal viewing time. Although businesses may view this content, our treatment assumes that this is essentially data exhaust that is produced by households, not a barter transaction. In essence, we assume that the user-generated content is exchanged for "likes" or reputation from other household users.

[52] Some marketing categories are embedded in media programs without any clear separation. In that case, the cost of embedded marketing is often bias or omitted facts rather than wasted time.

the next page. The cost of those paid advertisements includes not only the cost charged by newspapers to advertisers for the page space, but also the implicit cost incurred by marketers designing the ad and placing it in a relevant location. We then construct price indexes with the formula:

(Viewership Price) = [(Advertising \$) + (Separated Marketing \$) /(Viewership Quantity)

We construct six viewership quantity indexes for the following categories.

(1) **Print newspaper readership.** For this category, we are able to measure both the time spent reading newspapers and the share of newspaper content devoted to advertising. We then multiply to get our quantity index.

(2) **Print magazine readership.** For this category we are only able to measure the time spent reading magazines. We assume that the share of magazine content devoted to advertising is fixed, so we can use readership time as a quantity index.

(3) **Non-Internet radio listenership.** For this category, we are able to measure both the time spent listening to the radio offline and the share of broadcast time devoted to advertising. We multiply to get our quantity index.

(4) **Non-Internet television viewership**. For this category, we are able to measure both viewership time offline and the share of television network time devoted to advertising. We multiply to get our quantity index.

(5) **Desktop Internet search**. This category covers traditional searches on Google and other search engines. We are able to measure the total number of searches in the United States. We use that as our quantity index.[53]

(6) **All other Internet**. For this category, we use total time spent on advertising- and marketing-supported Internet as our quantity index. Just like magazines, we assume that advertising exposure per hour of advertising- and marketing-supported online time is fixed.

We were not able to track viewership quantities for many categories of marketing, so we impute prices for those categories. In particular, for example, we use viewership prices of desktop search as a proxy for viewership prices of mobile search, viewership prices of audiovisual media as a proxy for viewership prices of audiovisual marketing, and viewership prices for print media as a proxy for viewership prices of print marketing.

B.9 Quantity Indexes of Media Viewership Time, 2007–2014

Our primary data on time use is provided by Forrester, a survey company. They have been surveying Americans about their media time use since 1999. Our paper uses data from their questions on weekly time use for “reading newspapers (not online),” “reading magazines (not online),” “listening to the radio (not online),, “using the Internet for personal purposes,” and “using the Internet for work purposes.” Like most surveys, Forrester relies on self-reported data and does not attempt to check their answers against objective source data like Internet cookies. We do not know either the size or the direction of the possible misreporting. For now, we use Forrester’s data on newspaper readership, magazine readership, radio listenership and total Internet usage without adjustment.

[53] The Bureau of Labor Statistics publishes a price index for search engines (PCE519130519130101). Unlike our indirect price index, it shows a rapid decline in search costs from 2009 to 2016. We believe that this decline is the spread of Internet to the developing world between 2009 and 2016. Advertising prices are much lower in developing countries, so average revenue per click could have fallen even if viewership prices in the United States remained steady.

Forrester's survey does not ask respondents for the exact amount of media usage. Instead, they are asked to check boxes giving the time use category. The lowest category is "none" and the highest category is "30 or more hours." In some of their published reports, Forrester creates a continuous variable by replacing each box with the midpoint of the range. In particular, the mapping is "none" = 0, "less than 1 hour" = 0.5, "1-4 hours" = 2.5, "5-9 hours" = 7, "10-14 hours" = 12, "15-19 hours" = 17, "20-24 hours"= 22, "25-29 hours" = 27 and "30 or more hours" =32. This average usage is held fixed over time. In this paper, we have used a statistical methodology described in Von Hippel et al (forthcoming) to estimate the mean for the top-coded bin, using a Pareto distribution for the top-coded bin (30 + hours per week) and the next-to-top-coded bin (25-29). For the non-top-coded bins, we used midpoints, as Forrester does. In future work, we plan to use a parametric methodology for estimating the mean using the generalized beta distribution to model the entire distribution of binned data. This has the advantage of not throwing away any information, but it leans more heavily on distributional assumptions. Having two methods should enable us to have some notion of how sensitive our estimates are to the statistical methodology employed. Our imputed numbers should not be attributed to Forrester.

The methodology described earlier yields total online time. This paper is focused on advertising- and market-supported content, so we subtract other online time. To start out, we subtracted time spent watching Netflix and other subscription content. Just like Netflix's mailed DVD's, this content is supported by subscription revenue and therefore not included in our analysis of advertising- and marketing-supported content. Our current data tracking Netflix time is taken from Netflix's 10-K and the industry literature. Next, we subtracted time spent enjoying digital user-generated content. We have not yet located any data tracking viewership of user-generated content directly. For now, we will assume it is proportional to nominal value. For example, table 3 shows that user-generated content accounted for approximately one quarter of "free" consumer digital content. We assume that it also accounts for approximately one quarter of online time. Thanks to these two subtractions, adjusted online time remains approximately constant despite the increase in total online time from 2006 to 2016. This steadiness results in faster growth for digital viewership and TFP.

B.10 Other Data on Media Time and Media Consumption: 1929–2014

Newspapers and magazines are the hardest media category to track. From 2007 to 2014, we use Forrester's survey on time usage. From 1991 until 2007, we use readership data from Pew surveys conducted periodically and reported in "In Changing News Landscape, Even Television is Vulnerable" (Kohut et al. 2012). Before the Pew survey data, we use the article "Radio declares: Compare Me" (Sponsor 1961)[54] to get a snapshot of readership in 1961 and the article "More Power" (Sponsor 1949) to get a snapshot of readership in 1949.[55] Between the years with data, we use newspaper and magazine circulation to interpolate annual readership. We also use newspaper and magazine circulation to extrapolate readership before 1949.

For television, we use Nielsen data to track viewership back to its beginning. We did not buy Nielsen's full data for this purpose, but rely on the summaries prepared by the non-profit trade association TVB. All of our Nielsen data were taken from the Web site tvb.org and are available free.[56]

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[54] This article gives an estimate for radio listenership. However, their estimate is much lower than Arbitron's numbers. We believe that this difference is caused by survey respondents underreporting background radio.
[55] The two cities tracked in 1949 were both more highly educated than the broader public and might be unrepresentative (Des Moines, Iowa, and Springfield, Massachusetts).
[56] Forrester also tracks television viewing time, and we could use their data from 2007 onwards. However, their numbers are a little noisier and so our annual TFP numbers are more volatile. The American Time Use Survey tracks television viewing time, but they combine it with DVD watching and online video viewership.

For radio, we use Forrester's survey question on "radio listening (not online)" from 2007 to 2014.[57] From 1980 until 2007, we use Arbitron data. Like the Nielsen data, we did not buy Arbitron's full dataset. Instead, we rely on a summary prepared by the Corporation for Public Broadcasting which reports total radio listenership for each year from 1980 to 2010.[58] We also found Arbitron data for 1972 cited on page 523 of the book "American Broadcasting" (Lichty and Topping 1975). Before 1972, we could not find any systematic ratings for radio. However, we found an article "More Power" (Sponsor 1949) that reports radio listenership in 1949, 1946 and 1943. Before 1943, we could not find any useable data on listenership time. As a rough proxy, we use a geometric average of the number of households who owned radios and the number of cars with radios (Sterling and Kittross 1978).

Our data on desktop searches is taken from Comscore. It tracks a representative sample of computer uses and uses that sample to estimate usage across the entire population.[59] We were not able to buy Comscore's data. Instead, we rely on publicly available news reports to construct a quantity index back until 2003. Before then, we use overall Internet viewership prices as a proxy for search engine prices.

For Internet time, we use a variety of sources. The UK regulator Ofcom surveyed Internet users in 2005 and 2007 about personal Internet and work Internet.[60] Ofcom's 2007 time use numbers are similar to Forrester's 2007 numbers, so it seems reasonable to use Ofcom's 2005 time use numbers as a proxy. Before 2005, we use data from the *Statistical Abstract of the United States* to track Internet usage.[61] We then subtract an estimate of time spent on subscription Web sites like Netflix and time spent enjoying user-generated content to get viewership hours for advertising and marketing.

B.11 Advertising/Marketing Share for Media, 1929 to 2015

In 1979, the *Statistical Abstract* reports that advertising accounted for 64 percent of total newspaper content. Accordingly, we assume that newspaper readers spent 64 percent of their time reading advertising. We are able to track advertising share back to 1929 with data from the *Statistical Abstracts*.[62] Unfortunately, the *Statistical Abstract* stopped tracking advertising linage after 1980. We use the Bureau of Labor Statistics producer price index for newspaper advertising (WPU361102) to construct

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[57] Forrester reports a very small decline in offline listening between 2007 and 2014. Over the same time period, Arbitron's data show a much larger decline. This decline may be associated with measurement changes rather than competition from online radio (http://rainnews.com/radio-aqh-decline-ppm).

[58] In particular, we use the series '6a – Mid, 12+ Persons Using Radio AQH Rating.' That series reports the share of people who are listening to the radio at any given time.

[59] https://www.statista.com/statistics/265796/us-search-engines-ranked-by-number-of-core-searches/
http://ir.comscore.com/releasedetail.cfm?ReleaseID=362732
http://ir.comscore.com/releasedetail.cfm?releaseid=290856
http://blog.ineedhits.com/search-news/google-yahoo-dominate-search-in-december-2006-15052309.html
https://books.google.com/books?id=QVcsBgAAQBAJ&pg=PA76&lpg=PA76&dq=growth+rate+for+search+2005+comscore&source=bl&ots=E-A-60e91z&sig=l0NXWr7pzJvpiOvEfVhbFaQ_DXM&hl=en&sa=X&ved=0ahUKEwju5bz39evVAhVLzoMKHSl_AmwQ6AEISzAH#v=onepage&q&f=false
https://www.informationweek.com/google-widens-search-lead-as-growth-slows/d/d-id/1040924

[60] https://www.ofcom.org.uk/__data/assets/pdf_file/0020/102755/adults-media-use-attitudes-2017.pdf

[61] Taken from table 1094 of the 2010 *Statistical Abstract*, table 1089 of the 2009 *Abstract*, Ttble 1110 of the 2007 *Abstract,* table 1119 of the 2004 *Abstract*, table 1125 of the 2003 *Abstract*, and table 1102 of the 2002 *Abstract.* These tables explicitly focus on leisure Internet usage and exclude on-the-job Internet. We adjust for the on-the-job share to get total Internet usage.

[62] Table 1080 of the 1980 *Abstract*, table 897 of the 1975 *Abstract*, and series T–220, T–221 and T–485 of the *Historical Statistics of the United States: Colonial Times to 1970.*

a quantity index of print advertising content.[63] We use data from the Economic Census and FAO tracking newsprint usage to construct a quantity index of total newspaper content.[64] Based on the two quantity indexes, we are able to infer the newspaper advertising share.

Between 1948 and 1980, advertising hovered around 60 percent of total newspaper content. After 1980, advertising gradually shrank. By 2015, we estimate that advertising accounted for only 37 percent of total content. We assume that advertising readership time has followed the same trends. In other words, print newspaper readers currently spend a lower percentage of their reading time on advertisements than they once did. Accordingly, the decline in print advertising readership is even faster than the decline in print newspaper readership that was documented by Pew earlier.

For audio-visual media, we use the time share devoted to commercial content. Between 1950 and 2010, we use data from IMDB.com to split viewership between programs and advertising. IMDB does not directly report the amount of advertising viewership, but it does report the run-time for individual episodes. Between 1950 and 2010, the time devoted to commercials grew from 15 percent of broadcast time to 28 percent of broadcast time. After 2010, we use the online article "How Many Minutes of Commercials Are Shown in an Average TV Hour? The Number Has Been Steadily Climbing" published by TV Week in 2014 as a proxy. We could not find similar data for radio, but the book *Radio After the Golden Age: The Evolution of American Broadcasting Since 1960* (Cox 2013) suggests that radio commercial time grew at approximately the same rate as television advertising time.

For online media, we could not track advertising shares very precisely. We did locate data tracking Netflix viewership over time.[65] Between 2009 and 2015, Netflix viewership grew from almost nothing to 7 percent of online time. Netflix is a subscription supported Web site that shows very few ads, so time spent watching Netflix is unlikely to be spent watching ads. But we could not locate any other data on advertising viewership. In the absence of any other data, we will assume that the advertising share for non-Netflix time is constant.[66] In theory, it might make sense to subtract time devoted to online search because that search is already tracked in a separate price index. In practice, search is generally a quick process that occupies a small fraction of online time. For simplicity, we will not subtract that time.

B.12 Calculating Content Production by Industry

Advertising-supported media is produced by the information sector (NAICS 51). For simplicity, our current calculations of total factor productivity (TFP) assume that all print media are produced by the publishing sector (NAICS 511), all audio-visual media are produced by the broadcasting and telecommunications sector (NAICS 515) and all online media are produced by the Internet publishing sector (NAIC 518).

It is often quite difficult to determine which industries are bartering marketing-supported information for marketing viewership. Unlike advertising-supported media, virtually all industries produce some marketing-supported information. In addition, most industries outsource a portion of their

[63] That series [This PPI?] starts in 1981. We use the broader PPI PCU511110511110 to extend the price index back to 1979. Newspaper advertising prices are generally quoted on a per edition basis, so the gradual decline in subscribers is not directly reflected in the PPI. We use circulation data from the Newspaper Association of America to adjust for this quality decline. We also adjust the newspaper PPI for digital advertising prices to derive print prices.

[64] The FAO's data is available annually online. The economic census directly reports newsprint consumption for newspaper publishers in 1977, 1982, 1987, 1992 and 1997. After 1997, we use the economic census to measure newsprint consumption by other industries. The residual is assumed to be for newspapers.

[65] http://time.com/4186137/netflix-hours-per-day and http://tdgresearch.com/tdg-netflix-streaming-volume-up-350-in-10-quarters. Netflix does not give total U.S. hours for 2012 and 2013, so we interpolate for those years. https://techcrunch.com/2010/07/12/netflix-hulu

marketing to specialty industries like computer consultants. We have not been able to find any data tracking expenditures on marketing-supported information by industry or by category. In this paper, we use OES data tracking employment for computer related occupations as a proxy for total expenditures on online marketing and OES data tracking advertising and creative occupations as a proxy for total expenditures on print and audio-visual marketing. In order to reduce the random variation, we combine all of the OES sample waves into one and use that as a snapshot of marketing-supported information output in 2009. Finally, we extrapolate expenditures on marketing-supported information from 1948 until 2014 based on preexisting estimates of gross output by industry. As a robustness check, we also calculated TFP using alternative allocations. We find nearly identical results for aggregate TFP.

B.13 Splitting "Consumer Entertainment" and "Business Knowledge"

Forrester's reported split between "work Internet" and "personal Internet" is not equivalent to our split between "business knowledge" and "consumer entertainment." Our paper is focused on measuring productivity by industry in the private business sector, so we consider "business knowledge" to be Internet used on-the-job for job-related purposes. "Consumer entertainment" covers both leisure activities, such as YouTube, and household production, such as scheduling medical procedures or paying bills. In contrast, Forrester's respondents appear to have a broader definition of "work Internet." Approximately two-thirds of full-time students report using the Internet for work, and many of the students report very high usage. These students are almost certainly reporting their homework and other study time as "work Internet." In addition, retirees and other individuals not employed also frequently report using the Internet for work. These individuals are probably reporting household production activities as work. We calculated the true "business knowledge" share by replacing reported "work Internet" with zero for all individuals not employed.

Forrester does not ask respondents to split print media readership, television viewing or radio listening between work and personal. In the absence of reliable time use data, we will use a variety of proxies to split "business knowledge" and "consumer entertainment." For print media, we use genre data reported in the Economic Census and other sources. For example, we assume that scientific journals are used for work rather than for leisure. Very few of the shows on broadcast radio or television are targeted towards business knowledge. For now, we assume that on-the-job users account for only 1 percent of audio-visual advertising.

Finally, we adjust for a conceptual difference between the NIPA's and everyday conversation. In BEA's GDP statistics, owner-occupied housing is treated as if it were part of the business sector. Consistent with that treatment, "free" media products that help people buy, finance or maintain their homes should be treated as intermediate inputs rather than final consumption. However, the Forrester survey respondents and the Economic Census almost certainly define home purchases as a personal activity rather than a work activity. We use data from the Historical Statistics of the United States tracking advertising genre and our best judgement to adjust for this difference in definition.

B.14 "Free" Content Usage by Industry

The TFP calculations

Our primary data are the same Forrester survey described earlier. In 2013 and 2014, Forrester asked respondents "In which industry/field do you work?" They provided only 30 codes for this question and a few of codes do not represent industries. We used our best judgment to match the Forrester codes with the 63 private sector industries tracked in the the integrated BLS/BLS industry-level production account. Reassuringly, reported time usage in the Forrester survey is highly correlated with reported

Internet access in the Current Population Survey (CPS).[67] We were not able to find any data tracking usage of print content or audio-visual content by industry. For now, we use Internet usage by industry as a proxy for these categories. We were also unable to find any data on media usage by industry before 2013. For now, we use total industry output and total work Internet usage as extrapolators. For example, agriculture is assumed to use a very small share of print media output in 2013, but it accounted for a much larger share of business knowledge in 1948. Our aggregate TFP numbers are robust to changing the industry allocation procedure, but TFP numbers for individual industries are more sensitive.

B.15 Amateur User-Generated Content

Our primary dataset is the Technology User Profile (TUP) data produced by Metafacts.[68] The TUP data are a representative sample of adults that own connected devices and that include weights that are constructed to yield totals for adults in the United States. The TUP data provide information on time spent on each device and the activities done using that device.

Our first step in measuring the production of user-generated content is to estimate the number of people engaged in content production. User-generated content spans many different types of activities, from simple activities such as "liking" someone's post to more sophisticated activities such as sharing original videos online. We calculate production on an extensive margin by tabulating the number of people involved in any activity tied to user-generated content. An implicit underlying assumption that we make is that the TUP covers all relevant activities in a given year, so any omitted activities can be set to zero.[69]

In total, we calculate that the number of people who were online and producing content grew from 43 million in 2006 to 166 million in 2016, a growth rate of 136 percent. It is possible that a few of the digital content creators had previously been creating offline content; for example, some print newspaper readers might have written letters to the editor. However, new technologies like cloud computing, smartphones, and social media software have made content creation and distribution much easier than it was before. As

[67]The relationship between Internet access and usage is not one-to-one. In the CPS data, Internet access ranged from 15 percent for industries like agriculture to 70 percent for industries like publishing. The Forrester data show a much more compressed range of "work Internet" time. We believe that this compression is caused by employees without work-provided Internet using their personal smartphones for work.

[68] The survey is based on two phases: the first phase builds a sample frame [framework?] and develops estimates of technology usage (PC, Cell, Tablet, Gaming Device) by demographic groups, in particular, by gender and age groups, and then Metafacts implements the sample within each demographic group based on a total target sample. Beginning in 2006, the initial screening was conducted by telephone on a nationally representative set of adults, and the subsequent survey was conducted online. As in example, in 2016, the total target sample was 7,500 completed surveys, and the age group of 35-44 years had a target of 1,207 completed surveys. Metafacts adjusts the weights to be representative of the target population by compensating for varying response rates and reweighting to be consistent with the entire population of U.S. adults.

The TUP data also handles multiple devices in an inconsistent manner over time and across survey questions. Our take on this at this point is that the TUP reflects almost all the devices and activities at a given point in time. Thus we are hopeful that this coverage issue does not create significant bias in our estimate.

[69] In 2016, the content- generating activities are: Share videos you have made online, Post a comment on other's blog, Like/Recommend/Share/+1 a product on a webpage, Post a comment or review about a product, service, restaurant, etc., Send personal status updates/microblog/Twitter, Share photos online, Add/upload/share photo of yours for your social network, Comment on someone else's status, post, photo, or video. Content categories for the other years are available upon request.

a result, many people who were previously passive consumers of professionally-generated content have started actively creating amateur content.

It is difficult to measure the total hours spent on user-generated content. Due to limited data and as a first pass at assessing the potential magnitude of the production cost of user-generated content, we use a simple methodology: we allocate time spent online (as measured by the TUP) to online time generating content and other time using the proportion of activities that generate "free" content. For example, if a survey respondent engaged in 30 activities online and 10 of them were those that are associated with the production of online content, then we would allocate a third of that person's online time to the production of user-generated content.

At the aggregate, estimated content generation time increased from 13 billion hours in 2006 to 76 billion hours in 2016, or the ratio of hours spent generating content to economywide hours worked increased from 3 percent in 2006 to 22 percent in 2016. Across the subpopulation of content creators, user-generated content averaged 4.4 hours per week in 2006, 7.8 hours per week in 2010, and 6.9 hours per week in 2016. This intensive increase might appear small, but it occurred at the same time content creation numbers were skyrocketing. Across the entire population, user-generated content averaged 0.9 hours per week in 2006, 3.1 hours per week in 2010 and 4.8 hours per week in 2016.

Bibliography for Online Appendix B

Byrne, David, Carol Sichel, and Dan Sichel. 2017. "The Rise of Cloud Computing: Minding Your P's and Q's." https://bea.gov/about/pdf/acm/2017/the-rise-of-cloud-computing-minding-your-ps-and-qs.pdf.

Cox, Jim. 2013. *Radio After the Golden Age: The Evolution of American Broadcasting Since 1960.* Jefferson, NC: McFarland Publishers.

Chen, Yan, Grace YouJoo Jeon, and Yong-Mi Kim. 2014. "A Day without a Search Engine: An Experimental Study of Online and Offline Search." *Experimental Economics* 17 (December): 512-536.

Danaher, Peter J. 1995. "What Happens to Television Ratings During Commercial Breaks?" *Journal of Advertising Research* 35 (1), 37-47.

Dogtiev, Artyom. 2017. "App Revenues 2017." http://www.businessofapps.com/data/app-revenues/.

Galbi, Douglas. 2008. "Coen Structured Advertising Expenditure Dataset." Available online at https://www.purplemotes.net/2008/09/14/us-advertising-expenditure-data.

Holmes, Linda. 2013. "Theaters and Studios Squabble Over Shortening Movie Trailers." *NPR Morning Edition* (May 30). http://www.npr.org/sections/monkeysee/2013/05/30/187096839/as-trailers-eat-up-movie-time-theaters-and-studios-squabble-over-shortening-them.

Kohut, Andrew, Carroll Doherty, Michael Dimock, and Scott Keeter. 2012. "In Changing News Landscape, Even Television is Vulnerable." http://www.people-press.org/files/legacy-pdf/2012%20News%20Consumption%20Report.pdf.

Lichty, Lawrence, and Malachi Topping., 1975. *American Broadcasting.* Hastings House Publishers.

Matsa, Katerina Eva, Kenneth Olmstead, Amy Mitchell, and Tom Rosenstiel. 2012. "Digital Advertising and News." *Pew Research Center.*

Miller, Chance. 2016. "iOS App Store brings in 75% more revenue than Play Store despite difference in downloads." *9to5Mac.* https://9to5mac.com/2016/01/20/app-store-ios-downloads-vs-android-revenue

Nielsen. 2015. "Video Consumer Mapping Study: Additional Data Mining.," http://www.researchexcellence.com/files/pdf/2015-02/id126_video_consumer_mapping_study_data_mining.pdf.

Reisinger, Don. 2016. "Here's How Much You Spend on iPhone Apps Each Year." *Fortune Magazine.* http://fortune.com/2016/03/29/spend-on-iphone-apps/.

Sponsor Magazine. 1949. "More Power!" (October 24), 28-29 and 35-36; https://www.americanradiohistory.com/Archive-Sponsor-Magazine/1949/Sponsor-1949-10-2.pdf

Sponsor Magazine. 1961. "Radio Declares: Compare Me." (November 13), 35-37.

Sterling, Christopher, and John Kittross. 1978. *Stay Tuned: A Concise History of American Broadcasting.* London: Wadsworth Publishing Company.

TVWeek. 2014. "How Many Minutes of Commercials Are Shown in an Average TV Hour? The Number Has Been Steadily Climbing." http://www.tvweek.com/tvbizwire/2014/05/how-many-minutes-of-commercial.

Von Hippel, Paul T., Samuel V. Scarpino, and Igor Holas. 2015. "Robust Estimation of Inequality from Binned Incomes." *Sociological Methodology*.

Waldfogel, Joel. 2016. "The Random Long Tail and the Golden Age of Television." Working Paper