Capturing the Productivity Impact of the 'Free' Apps and Other Online Media

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Abstract

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A recent Wall Street Journal article (Aeppel 2015) argued that measured productivity growth is badly underestimated because measured GDP does not include 'free' apps and other online media services. This paper introduces an experimental GDP methodology which includes advertising-supported entertainment like Facebook in final output as part of personal consumption expenditures. This paper then uses that experimental methodology to recalculate measured GDP back to 1998. Contrary to the Wall Street Journal article, including 'free' apps in measured GDP has almost no impact on recent growth rates. Between 1998 and 2012, real GDP growth rises by only 0.009% per year.

This paper also recalculates total factor productivity (TFP) growth when 'free' apps are included as both final output and business inputs. For example, Google Maps would be counted as final output when it is used by a consumer to plan vacation driving routes. On the other hand, the same website would be counted as a business input when it is used by a pizza restaurant to plan delivery routes. Measured TFP changes for both media companies and the rest of the business sector. Internet publishing companies are producers of 'free' apps, so including 'free' apps in the input-output accounts raises their TFP growth by 1% per year. The rest of the business sector uses 'free' apps, so including 'free' apps **lowers** their TFP growth. The net impact is an increase in business sector TFP growth of only 0.004% per year.

Our method for accounting for 'free media' is minimalist in the sense that it is a measure of the resource input into the entertainment (or other content) of the medium, rather than a measure of the consumer surplus arising from the content. Brynjolfsson and Oh (2012) attempt to capture some of consumer surplus by measuring the time expended on the Internet. Varian (2009) argues that much of the value of the Internet is in time saving, an additional metric for capturing consumer surplus. BEA uses a similar minimalistic approach when measuring GDP.

In particular, this minimalist accounting has no method to account for instances where the app precedes the advertising revenue that it eventually generates. This is the disruptive business model described as URL: Ubiquity now, Revenues Later. Over the past two decades, many Silicon Valley firms have followed the URL business model. Some firms have been creating software, which is already captured in the national accounts as investment. Other firms have been creating intangible investments in marketing, customer contact, business know how or other organizational capital. These intangible investments can pay off either in (1) eventual use of advertising or (2) moving customers to a premium service that does charge a fee. Despite their long-run value, expenditures on organizational capital are not currently captured in the national accounts as output. If we treat these expenditures on organization capital as intangible capital investment, then the productivity boom from 1995 to 2000 becomes even stronger and the weak productivity growth of the 2000's is nearly unchanged.

Introduction

"Free" consumer entertainment and information from the Internet, largely supported by advertising revenues, has had a major impact on consumer behavior. This paper recalculates productivity growth when 'free' apps are included as both final output and business inputs. We estimate the contribution of 'free' apps from the supply side by measuring the advertising expenditures that support them. That is, we do not directly capture the value of Google Maps, but only measure the cost of providing it. This is a lower bound on the contribution of these 'free' apps to output and productivity – but it is consistent with the standard methodologies for estimating an industry's contribution to output and productivity. Therefore, our supply side numbers will be comparable to other productivity research.

We impute a barter transaction between media users and media companies: media users watch ads in return for free content. Our experimental methodology has at its heart two balancing components. On the expenditure side, we impute media purchases equal to the cost of providing media services. These costs are paid by advertisers, so free 'apps' are actually advertising-supported entertainment. The media services of advertising-supported media could have been supplied through non advertising-supported media, and, indeed, they can be thought of as having been bid away from alternatives. For example, driving directions can be downloaded from an advertising-supported website like Google or a subscriber-supported website like PCmiler.

This paper studies all advertising-supported digital content which provides valuable services to media users. Some apps receive all of their revenue from advertisers, and users pay nothing out of pocket. Other apps receive some revenue from advertisers and some from users. None of the economics in this paper depends on whether users pay a positive amount out of pocket. It only matters that users pay less than the production cost of the websites or apps. On the other hand, spam e-mails, viruses and other unwanted media are excluded from our research. We also exclude 'free' media like PBS which are supported by governments and non-profits because those media outlets are already counted in GDP as part of government or non-profit output.

The identity of the user determines both the terminology used and also the impact on measured GDP. When consumers use 'free' apps, we call the apps "consumer entertainment" and add the value of that entertainment to personal consumption expenditures (PCE) and GDP. Balancing that additional PCE, we impute labor income to households that are, in effect, paid to view advertising, with those payments being equal to the cost of providing entertainment programs. This additional labor income precisely cancels out the additional PCE, so there is no change in household savings. When businesses use ‘free’ apps, we call the apps “business information” and add the value of that information to intermediate inputs. Balancing that additional intermediate input, we impute business income for ad viewership. This additional business income precisely cancels out the additional expenditures on intermediate inputs, so measured value-added and GDP do not change.

Measured productivity changes for both online media companies and the rest of the economy. Online media companies are producers of ‘free’ apps. Our experimental methodology raises their gross output by the value of ‘free’ apps produced, raises their labor input by the value of consumer ad viewership used and raises their intermediate input by the value of business ad viewership used. In contrast, the rest of the business sector uses ‘free’ apps. Our experimental methodology raises their gross output by the value of business ad viewership produced and raises their intermediate input by the value of ‘free’ apps used.

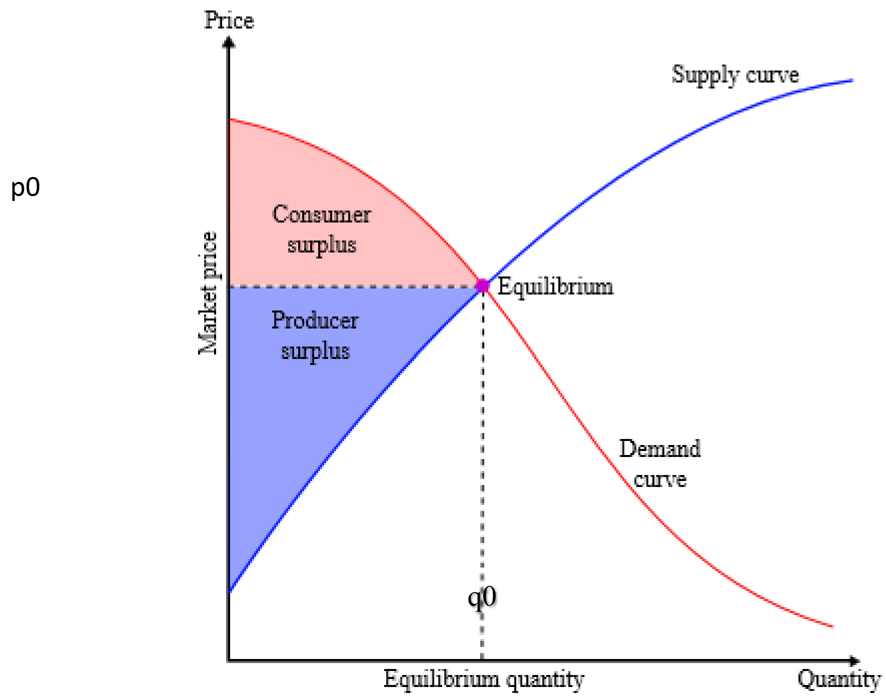
This paper focuses on online media because that industry has been experiencing the most growth over the past few decades and has attracted the most media attention (Aeppel 2015) and (Ito 2013). In earlier papers, we studied the impact of advertising-supported newspapers, magazines, radio and television on measured GDP (Nakamura and Soloveichik 2015), (Soloveichik 2014) and (Nakamura 2005). We hope to study the productivity impact of those media categories in future papers.

Our paper will be divided into five parts. Section 1 provides a theoretical discussion of advertising-supported media and gives background on the previous literature. Section 2 collects data on online media expenditures and online media use in the United States. We then use that data to recalculate nominal output and nominal inputs by industry from 1997 to 2013. Section 3 introduces our price indexes for online media in the United States. Section 4 calculates real output, real inputs and productivity by industry using the earlier data on nominal output and prices. In this section, our productivity numbers are calculated using the standard formulas – and so they may not reflect special features of the online media industry. Finally, Section 5 discusses how network effects and organization capital are absolutely essential for understanding the online media industry. We then show that the standard productivity formulas produce a lower bound on the true productivity impact of online media. We then recalculate prices and productivity when network effects are accounted for.   This section is speculative.

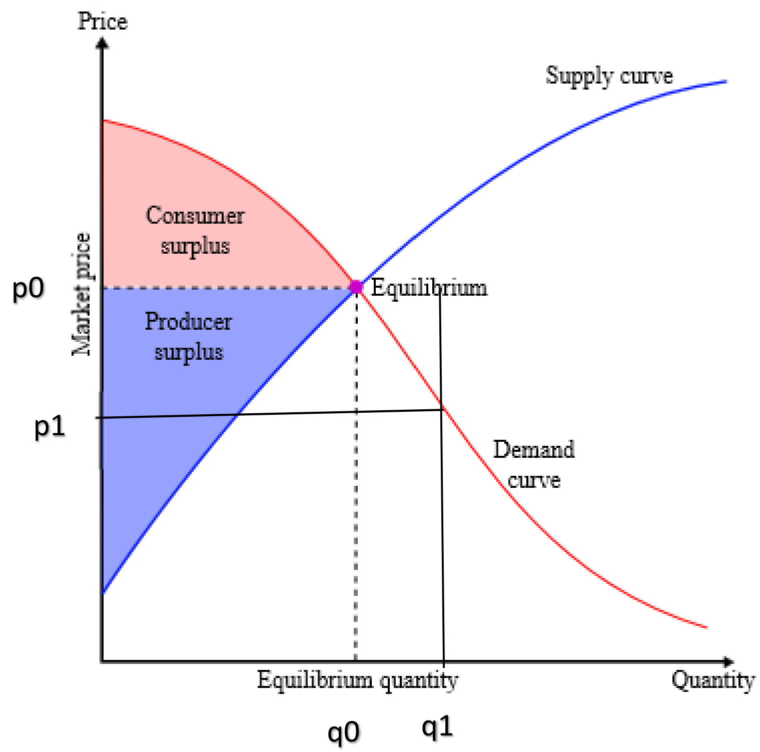
Section 1. Conceptual Discussion of Advertising-Supported Media

Measuring GDP and Consumer Surplus

We'd like to start out with a general discussion of how BEA measures the economy. Below is a simple supply and demand graph from Econ 101:



The graph above has three areas potentially interesting to economists. The rectangle with dotted lines shows spending. In other words, how much are consumers **actually** spending on the good studied. The red triangle above shows consumer surplus. In other words, how much would consumers be **willing** to spend on the good over and above the market price. Finally, the blue triangle below shows producer surplus. In other words, how much profit do producers make from the good in question. Here total output is p0q0, the area of the rectangle shown with the dashed lines.



When productivity increases and the supply curve shifts down and to the right, price falls from p0 to p1 and quantity increases from q0 to q1, the red triangle expands and the blue triangle shifts downward and to the right. The consumer now pays p1q1. Consumer surplus is now much larger. An upper bound to the increase in consumer surplus is captured in a quantity index that values the added production (q1-q0) at the old, higher price p0, so that the real output increases to the rectangle bounded by the dashed horizontal line and the solid vertical line. Thus the real increase in output, measured at prices in the base year (p0), captures the increase in consumer surplus.

Advertising-supported media has zero out-of-pocket costs for consumers. Therefore, the dotted rectangle has no volume and BEA's current methodology assigns no value it. Its impact on the consumer is thus inherently difficult to capture in measures of economic output. Brynjolfsson and Oh (2014), attempt to capture some of consumer surplus by measuring the time expended on the Internet. Varian (2009) argues that much of the value of the Internet is in time saving, an additional metric for capturing consumer surplus. He performs a back-of-the-envelope calculation of the savings of time from search, based on the search time savings estimate in Chen et al (2013), which is 15 minutes per search. Noting that on average Americans search once a day and calculating the average value of time as $22, for employed workers, and multiplying by the number of employed workers, he concludes that Google save Americans $65 billion a year.

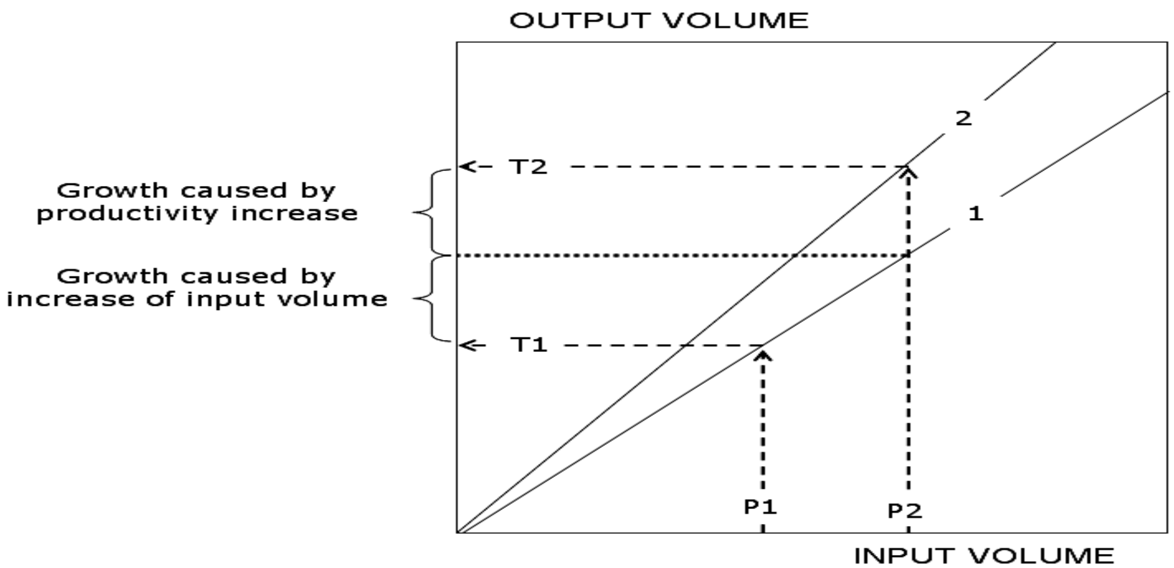
However, those measures of consumer surplus are based on the implied opportunity cost of leisure time, with leisure time being based on surveys. This implied value of leisure time is estimated based on regression analysis, and has not been used in other contexts within GDP measures. In particular, we do not have any clear idea of how closely tied this measure of consumer surplus might be to economic activity. To make the argument differently, the weather may have a large impact on how much consumers enjoy certain recreational activities, but because this weather impact is not closely tied to economic activities, we do not include it in GDP; by comparison the improvement in consumer surplus captured in the demand-supply diagram is very closely tied to economic activity and direct economic measures.

This paper uses an experimental methodology to value for advertising-supported media. Our estimated value is based on the **actual** costs of producing 'free' media. Like the published PCE numbers, these cost numbers are a lower bound on the total value of media. By design, our estimated value is calculated using very similar methodology to BEA's published GDP statistics. Accordingly, we can compare our estimated value for 'free' media to overall GDP without conceptual problems. Furthermore, we can also use standard productivity formulas to calculate the productivity impact of 'free' online media by industry.

Table 1 shows how our experimental methodology raises both measured personal expenditures and measured personal income. It should be noted that when we measure value from the cost side we may not track consumer surplus or consumer welfare as closely as we would in the presence of prices. A similar problem arises in the measure of the real output of government services such as public education or national defense. Nevertheless, our minimalistic accounting is much less dependent on modeling assumptions than competing estimation techniques.

Measuring Total Factor Productivity (TFP) and TFP Growth

Productivity researchers generally work with a stylized model of the firm: it uses inputs and produces output for sale in the market. In that stylized model, the precise production process doesn't matter much. The only thing that matters is how much inputs the firm requires and how much output it produces. The basic problem for TFP measurement is shown in the figure below.



If all inputs were held completely fixed. TFP growth would be easy to measure. The formula to calculate TFP growth would simply be:

$$\text{TFP growth from Years 0 to t} = (\text{Output}_t)/(\text{Output}_0)$$

However, the situation is much more complicated when inputs change over time. In that case, researchers need to break down the problem into two stages. First, they predict the output that would be produced in year t **if** technology and other outside factors were held fixed from year 0 to t. After they've made this prediction, they can then calculate:

$$\text{TFP growth from Years 0 to t} = (\text{Output}_t)/(\text{Predicted Output}_t)$$

Unfortunately, predicting output is a hard problem. Most researchers studying TFP use a standard productivity formula that implicitly predicts output from input changes. That standard productivity formula is based on a simplified model that assumes constant returns to scale, smooth production functions, and competitive industries with profit-maximizing firms. In addition, current output and prices are assumed to be unrelated with past output or prices.

Obviously, this simplified model is not a perfect match for Silicon Valley firms. For example, the URL business model assumes that lower prices now help companies become more efficient and eventually profitable. This completely contradicts the assumption that current output is unrelated with past prices. However, many other industries also violate some of the assumptions listed above. A researcher who tried to account for all the complexities of each industry would quickly find the calculations impossible. Most researchers use the standard productivity formula as a starting point when comparing TFP across industries, over time or across countries. We will follow the literature and use the standard TFP formula to estimate the impact of 'free' apps on aggregate productivity.

Current Treatment of Advertising-Supported Media[1] in SNA 2008 and the U.S. National Income Accounts

In the SNA 2008 and the U.S. Bureau of Economic Analysis (BEA) National Income Accounts, advertising-supported media is treated simply as an intermediate input to the production of advertising slots. If we think of soap as being the advertised good, then a YouTube video produced to entertain households is as an expense of the media company, which then sells the advertising slot to the soap manufacturer. In turn, the cost of the advertising slot is an expense of the soap manufacturer just like physical inputs such as lye or fat. In this treatment, there is no measured consumption benefit to the consumer of the entertainment provided, except to the extent that the consumer pays for the hardware and services associated with receiving the entertainment, such as the computer or internet service.

The difficulty with that treatment is advertising-supported media provides a much greater value to consumers than the cost of a computer. Because advertising-supported media provides so much value to consumers, it seems wrong not to count it in the final output. This difficulty is

[1] Our discussion assumes that media companies earn money by selling advertising services to outside companies, but the economics are the same if media companies collect and sell private information for non-advertising purposes. We just use the word "advertising" because it would be too cumbersome to say "advertising or information collection."

highlighted when the Internet bids entertainment providers, such as NFL teams away from the paid entertainment sector into advertising-supported media. Under the current treatment, these sports teams cease to be providing consumer recreation services and become advertising instead.

It is useful to clarify the conundrum with the following highly stylized model. We consider a soap manufacturer, an entertainer, and households.[2] The soap manufacturer must advertise to sell the soap. Initially, the soap manufacturer spends $1,000 to make the soap, spends $1,000 on advertising with no entertainment value, and sells 1,000 bars of soap for $2 each. The entertainer sells tickets to her act for $1 each. One thousand households each spend $2 for soap and $1 for entertainment. Now, suppose the soap manufacturer hires the entertainer for $1,000. The entertainer acts for free but includes a soap announcement. The 1,000 households receive the soap and the entertainment but pay only $2 each (and listen to a soap announcement). For simplicity, we assume that the demand for entertainment is unaffected by this switch. In other words, households act as if they were paying $1 for the entertainment, but instead, they are viewing the advertising and they appear to perceive that viewing the advertising costs them $1 each. Roughly speaking, the households consume the same amount but pay less out of pocket.

In the current national income accounts treatment, output drops. The entertainment is no longer measured as part of personal consumption, only the soap is. In the initial case, $3,000 in economic resources was used to produce $3,000 in consumption output. With advertising-supported entertainment, $2,000 is used to produce $2,000 in consumption output. Effectively, $1,000 has disappeared from real output. However, this appears to be a misrepresentation in that the households are still consuming the same real amount of entertainment, but it has disappeared from measured output.

One possible treatment would be to view the entertainment with advertising as having the same real value but falling in price to zero. That is, nominal output is $2,000, but real output is $3,000. While we do not actually observe the market value to the consumer of the entertainment in most cases, we can impute the market value from the payment to the entertainer. But zero prices are uncomfortable within the national accounts. For example, it is difficult to explain why

[2] For simplicity, we assume that the soap company produces content in-house and then broadcasts the entertainment itself. In a more realistic model, the soap company might purchase advertising slots from a broadcasting company. In turn, that broadcasting company might content from a production studio. The imputed barter transaction of advertising viewership in return for content is the same and measured GDP is the same.

consumers sometimes pay to avoid advertising if the price for advertising-supported media is zero. Furthermore, if the situation should reverse and a price be paid, the rate of inflation for that item cannot be calculated.

A more satisfactory treatment, proposed by Cremeans (1980), and pursued in this paper, would be to consider transaction as a barter trade of entertainment received by the consumer in exchange for which the consumer agrees to view the advertisement. We would record a dollar as paid by the consumer to the soap manufacturer for the entertainment, and the soap manufacturer would pay it back to the consumer for viewing the advertisement. In this treatment, advertising-supported media increases the real income and consumption of the consumer. This reflects the true value of entertainment to modern society and in a way which finds parallels with the treatment of similar products with no out-of-pocket price, such as residential services of owner occupied dwellings and financial services of checking accounts.

An alternative satisfactory treatment was recently proposed by Charles Hulten. He argued that 'free' media can be viewed as a gift from media companies to consumers. In that case, we record the entertainment received by the consumer but do not record any service received by the media company. Conceptually, this is parallel to the treatment of non-profit organizations serving households.[3] This treatment has the same impact on measured GDP and gross industry output as Cremean's 1980 treatment. But the standard productivity formulas do not work when businesses receive gifts from other businesses.

Previous Research on Noncash Payments in GDP

Our experimental methodology does not require any major conceptual changes to SNA. In this paper, we treat advertising-supported media as a payment in-kind for services produced by households. SNA 2008 already counts other noncash payments as labor income (Section 7.51). SNA also imputes cash values for barter transactions (Section 3.75), owner-occupied housing (Section 6.34), and financial services indirectly measured (Section 6.163). Just as with

[3] The gift classification makes the most sense for media that is expensive to provide yet earns very little advertising revenue. Many Silicon Valley firms spend enormous amounts of money to create useful services which do not yet earn money. Those useful services could be viewed as either gifts or investments in future demand.

those transactions, we impute a value for advertising-supported media based on estimated costs. However, since the household is not "employed" by the media producer, we treat the household production of the service of providing access to advertising as a form of production by an unincorporated household enterprise.

Our paper is not the first to discuss treating advertising supported media as payment in-kind. Imputation for advertising-supported media was first raised in *The National Income – 1954 Edition* and was extensively discussed in the 1970's (Ruggles and Ruggles 1970, Okun 1971, Jaszi 1971, Juster 1973, Eisner 1978, and Kendrick 1979). The paper "Consumer Services Provided by Business Through Advertising-Supported Media in the United States" (Cremeans 1980) estimated that advertising-supported media was worth \$28 billion in 1976.[4] Vanoli discusses this issue in *A History of National Accounting* (2005). More recently, *Businessweek* published an article in 2013 (Ito) and the Wall Street Journal published an article in 2015 (Aeppel) criticizing the BEA's GDP numbers for excluding free online media (Ito 2013).[5] In addition, we have previously written papers studying advertising-supported media and advocating that it be treated as a payment in kind (Nakamura 2005) (Soloveichik 2014) and (Nakamura and Soloveichik 2015).

This paper extends the earlier research by considering how to account for the URL model within our methodology and by developing input-output accounts for advertising-supported media. We then use those input-output accounts to calculate productivity by industry. Like other productivity statistics, this decomposition does not directly change aggregate GDP measurements. Instead, the decomposition allows researchers and policy makers to better understand the sources of GDP growth. In particular, our productivity statistics show faster TFP growth in the online media industry and slower TFP growth elsewhere.

[4] For the same year, we estimate that advertising-supported entertainment added \$9.2 billion to GDP. The main reason for the difference is how we handle non-media costs such as advertising agency markups. We consider those non-media costs to be intermediate expenses and, therefore, do not count them as media services provided to consumers. We also exclude media costs for business publications.

[5] Some websites are purely amateur productions, with no subscription revenue or advertising revenue. Our paper will not capture them, but they account for only a small fraction of time spent online.

Theoretical Effects on Measured Consumer Welfare and Measured Productivity

Our experimental methodology produces more intuitive welfare comparisons. In the United States, many sporting events are now moving from broadcast television to cable television. Cable television networks generally show the same amount of advertising as broadcast networks, so consumers are unambiguously worse off from the switch. They are now required to pay subscription fees to get content they had previously viewed for free. Yet, SNA's current methodology treats the new cable subscribers as a real GDP increase.[6] Under the alternative method, real GDP falls if some viewers choose to miss the sporting event rather than pay cable subscription fees. This drop in viewership is considered a decrease in final expenditures. Nominal GDP does rise with the switch from broadcast television to cable television. However, that nominal GDP growth is more than canceled by higher prices for entertainment caused by the switch.[7]

Similarly, our experimental methodology produces more intuitive productivity comparisons. In the early 2000's, many drivers purchased GPS software like Garmin or TomTom which provided driving directions. In recent years, advertising-supported services like Waze or Google Maps have taken over the industry. Even counting the implicit cost of viewing ads, the new advertising-supported services are cheaper to use. Accordingly, restaurants which require driving directions are unambiguously better off from the switch. SNA's current methodology treats these lower costs as a TFP increase in the restaurant industry. Under the experimental method, TFP in the restaurant industry is unchanged. Instead, the TFP growth is allocated to the Silicon Valley firms which are offering high quality driving directions cheaper.

By construction, the nominal income "earned" by consumers watching advertising is equal to the nominal value of entertainment "purchased". As a result, our experimental methodology has no effect on consumer savings. Similarly, the nominal income "earned" by business users watching advertising is equal to the nominal value of information "purchased"

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[6] This is assuming that the larger viewership for cable sports is counted as a quantity increase. In practice, the U.S. Bureau of Labor Statistics' (BLS) current price index for cable television does not adjust for programming quality improvements. BEA uses the BLS's price index to deflate consumer expenditures on cable, so measured output is basically the number of subscribers.

[7] This discussion focuses on the short-term effects of a switch. In the long-term, the higher earnings caused by the switch of sporting events from broadcast television to cable television may well result in more sporting events becoming available in more markets as well as in higher salaries to players, inducing higher-value workers to enter the competition and improving the quality of entertainment.

and our experimental methodology has no effect on corporate profits or industry value-added. If the media provider is located in the same country as the viewer, imports and exports will be unaffected. If the media company is located in a different country, imports and exports will increase by the same amount with no effect on the net nominal balance of trade.

Other Research on Advertising, Brand Equity and Entertainment Originals

Our research on advertising-supported media is distinct from the rich literature on advertising. Previous researchers have studied why advertising exists and calculated how much firms should optimally spend on advertising (e.g. Dorfman and Steiner 1954; Nerlove and Arrow 1962). Other papers have argued that advertising increases sales over the long run, and therefore, they should be considered an investment in brand equity (Nakamura 2005; Corrado, Hulten, and Sichel 2009). All of this research is focused on the companies which purchase advertising viewership and then use it to sell products and build brand equity.[8] In contrast, our research is focused on the online media companies which produce content, barter the content for advertising viewership and then sell the advertising viewership to the rest of the economy. None of the results in this paper depend on how companies use their purchased viewership. The only thing that matters is that companies want advertising viewership and are willing to pay for it.

Advertising-supported media is also distinct from entertainment originals. Entertainment originals are long-lived intangible assets owned by media companies and artists. It is true that entertainment originals are sometimes used to produce advertising-supported media such as broadcast television. However, the categories are not at all identical. Advertising-supported media includes short-lived media such as newspapers, sports broadcasting, and other entertainment that is not part of capital stock. Conversely, entertainment originals are used to produce consumer products such as DVDs or books that are sold to consumers and counted in personal consumption expenditures. This paper uses some of the data originally collected for a project on entertainment originals (Soloveichik 2013a, b, c, d, and e), but none of the results in this paper depend on the treatment of entertainment originals in GDP.

[8] In addition, the marketing expenditures studied in those papers include more than ads shown on 'free' media. For example, companies can increase sales with telemarketing calls, in-person sales visits, junk mail and other products that aren't generally bundled with entertainment or useful information.

Section 2. Nominal Production and Expenditures on Online Media

This paper is focused on 'free' apps and other online media, but the general methodology developed here applies equally well to broadcast television and other advertising-supported media. In previous papers, we have re-calculated GDP when those media categories are counted in consumer entertainment together with online media. In future papers, we hope to recalculate TFP when those media categories are counted in business information together with online media. For now, we'd like to show readers our preliminary estimates of consumer entertainment and business information over time.

Figure 1 shows our best guess of nominal consumer entertainment expenditure supported by advertising from 1929 onwards. The most important result is that the explosion in online entertainment has been almost exactly canceled out by a drop in print media. In fact, the nominal value of advertising-supported entertainment has hovered around 0.5% of GDP throughout the entire time period studied. Accordingly, our experimental methodology has almost no effect on nominal GDP growth. Like the standard GDP methodology, our experimental methodology does not estimate consumer welfare or consumer surplus. Therefore, we can't say anything definitive about aggregate consumer surplus from advertising-supported entertainment over time. Nevertheless, it seems likely that the consumer surplus increase from online media is at least partially canceled out by a consumer surplus decrease from print media.

Figure 2 shows our best guess of business information from 1929 onwards. Unlike Figure 1, the explosion in online business information has not been canceled out by a decrease in print media. As a result, advertising-supported media is becoming more important when calculating industry productivity. Despite the recent increase, advertising-supported media still represents a very small share of total business information. Most businesses get their information from consultants, professional conferences, textbooks, and other sources.[9]

Online Media Production by Industry

Every industry produces some online media. Nearly every modern company and government agency has a website containing helpful information. However, most companies do not sell ads on their corporate websites – and so we do not consider their websites to be advertising-supported media. This paper will focus on the publishing and broadcasting industries, which produce the vast majority of online media. Most online media is produced by internet-only publishers like Google or Yahoo (NAICS 519). Other online media is produced by print publishers like the New York Times (NAICS 511) or broadcast networks (NAICS 515).

The Internet Advertising Bureau (IAB) provides annual data on total online advertising. IAB is a non-profit organization devoted to researching the online economy and helping companies navigate it. As part of their research, they publish an annual report estimating online advertising in the United States. IAB's reports start in 1996, when they report $0.3 billion in advertising and continue until 2014, when they report $49.5 billion in advertising. BEA's published input-output tables are based on the 2007 Economic Census. In order to make our numbers comparable, we benchmarked all of IAB's numbers to same 2007 Economic Census data used by BEA. In practice, IAB's published data match closely with the Economic Census and so the benchmarking has little practical impact.

We use the Economic Census to split online media by industry. According to the Economic Census, internet publishers (NAICS 519) earned $44.9 billion from online advertising in 2012 (preliminary) and $19.1 billion in 2007. The 2002 and 1997 Economic Censuses use different NAICS codes for internet publishers, so those published numbers are not fully comparable. In order to ensure that the time series is consistent, we will use IAB's numbers as a proxy before 2007. The Economic Census also reports that broadcasters (NAICS 515) earned

[9] Some of these sources are indirectly supported by interested parties. For example, many medical conferences feature speakers partially paid by drug companies. If data on this type of activity was available, we could easily extend our model to include it. Unfortunately, this type of sales activity is less measurable than advertising.

$1.3 billion from online advertising in 2012 (preliminary) and $0.5 billion from online advertising in 2007. We use the IAB data to interpolate revenue between 2007 and 2012 and extrapolate revenue before 2007 and after 2012.

Unfortunately, the Economic Census does not report online advertising data for newspapers and magazines. The only data tracked is total advertising revenue.[10] Newspaper publishers (NAICS 51111) earned $18.1 billion from advertising in 2012 (preliminary), $34.7 billion in 2007 and $31.4 billion in 2002. Periodical publishers (NAICS 51112) earned $13.6 billion from advertising in 2012 (preliminary), $22.1 billion in 2007 and $18.7 billion in 2002. According to the Newspaper Association of America, digital advertising accounted for 15% of total advertising in 2012, 7% in 2007 and 2% in 2002.[11] We were not able to find similar data on magazines, but the Service Annual Survey does track total online revenue.[12] We assume that online revenue accounts for the same proportion of subscription revenue and advertising revenue. Based on that assumption, we estimate that digital advertising accounted for 18% of magazine revenue in 2012, 9% in 2007 and 4% in 2002.[13] We calculate that print publishers earned $5.2 billion of online advertising in 2012, $4.4 billion in 2007 and $1.4 billion in 2002. Just like before, we use IAB revenue to proxy for the remaining years of our sample.

Figure 3 shows our best estimate of online advertising from 1997 to 2013. The most striking finding is how rapidly the Internet has grown. In 1997, total online advertising was less than $2 billion. By 2013, online advertising was almost $60 billion. Annual growth rates have averaged 24% from 1997 to 2013. The other important result is that internet publishers account for a growing fraction of the online media industry. In 2002, print publishers and broadcasters produced approximately 20% of total online content. By 2012, their market share had fallen to only 13%. As a result, the output of internet publishers has grown even faster than the online media industry.

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[10] The 2002 Economic Census does track online advertising revenue separately. But the numbers are very small and hard to extrapolate forward.

[11] The Newspaper Association of America only reports digital advertising back to 2003. Between 2003 and 2004, the digital share grew from 2.63% to 3.19%. Assuming that the digital share grew at the same rate between 2002 and 2003, we calculate that digital advertising may have accounted for 2% of newspaper advertising in 2002.

[12]For newspapers, the Service Annual Survey reports total online revenue smaller than the Newspaper Association of America reports for online advertising alone. We are not sure for the reason behind this difference.

[13] The SAS does not report online revenue before 2005. Just like for newspapers, we extrapolate backwards.

Not all of the advertising revenue in Figure 3 is available for media production. Websites spend some money on sales activities like billing customers, helping advertisers design ads and other non-media costs. None of those activities benefit media users at all – so they're not included in the imputed value of media services bartered for advertising viewership. In other words, companies who buy advertising viewership pay a higher price than media users who barter advertising viewership in return for media content. Conceptually, this is similar to the markups charged by wholesalers and retailers. We do not currently have data on the markups charged by media companies over time. For now, we assume that average markups have been fixed at 33% from 1995 to 2013. We welcome suggestions to refine this part of our model.

Media Usage by Consumers vs. Businesses

As we discussed earlier, our primary data on advertising expenditures is taken from the Internet Advertising Bureau (IAB). IAB splits advertising by format and product category – but it has no data on whether consumers or businesses are viewing the ads. 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 MRI machines – so websites with pop-up ads boasting low prices for MRI machines are probably targeting hospital executives. But most websites target a general audience and have advertising unrelated to the precise media services provided.[14] We talked to Hal Varian, who is the chief economist at Google, and he said that Google does not have much information on whether consumers or businesses are viewing their ads. To the best of our knowledge, no company or researcher has published any estimates of the consumer share of 'free' websites or online advertising.

In the final version of this paper, we plan to take our data on consumer Internet usage is from Forrester Research. Since 2007, they have asked consumers to report both 'hours using the Internet for personal purposes' and 'hours using the Internet for work purposes'. Forrester Research is a mail survey, so it should include individuals without home Internet access. We will assume that each worker who uses on-the-job Internet uses one unit of 'free' media per hour

[14]Even when a business is using a website for work, the advertisements may still push consumer products. Conversely, consumer entertainment products might push business inputs. In both cases, the advertisers are hoping that the website users carry the message between work and home.

and each individual who uses personal Internet uses one unit of 'free' media per hour. Therefore, we plan to calculate on-the-job share with the formula:

On-The-Job Time Share = (Total Hours of Work Internet) /

[(Total Hours of Personal Internet)+(Total Hours of Work Internet)]

Unfortunately, we were not able to buy the Forrester data by the time this draft was written. For now, we use the summary statistics reported in Table 1 of 'The Attention Economy: Measuring the Value of Free Goods on the Internet' (Brynjolfsson and Oh 2012). Those summary statistics are based on a selected sample of the Forrester data and may not be representative.

In BEA's GDP statistics, owner-occupied housing is treated as if it were part of the business sector. Consistent with that treatment, we treat online websites which help people buy, finance or maintain their homes as intermediate inputs rather than final consumption. However, the Forrester survey respondents almost certainly define home purchases as a personal activity rather than a work activity. We will assume that all housing-related Internet is currently included with personal Internet usage in the Forrester data. We also assume that the housing share of GDP is a proxy for the housing share of personal media usage. Based on those assumptions, we can calculated the business share for 'free' media:

Business Time Share = On-The-Job Time Share + (1-On-The-Job Time Share)*(Housing Share)

We have not been able to find any data before 2007 tracking both leisure Internet and work Internet. In the absence of better data, we will use data on Internet access from the Current Population Survey (CPS). Since 1997, the CPS has asked respondents about Internet usage periodically. In most years, the CPS focused on personal Internet usage – but the 1997, 2003 and 2011 surveys included questions about work Internet as well. We will assume that each worker with on-the-job Internet uses one unit of 'free' media on the job and each individual with home Internet access uses one unit of 'free' media off-the-job.[15] Therefore, we calculate on-the-job share with the formula:

On-The-Job Access Share = (Number of Workers with On-The-Job Internet) /

[15] A few individuals use the Internet at other locations like school or libraries. For simplicity, we ignore these users.

[(Number of Workers with On-The-Job Internet)+(Individuals with Home Internet)]

We then benchmarked the CPS on-the-job share to the more accurate Forrester on-the-job time share estimated earlier.

Figure 4 shows our best estimate of the business share from 1995 to 2013. In 2012, we estimated that business and homeowners received \$11.2 billion of advertising-supported online media. This is not a tiny number, but it represents only 0.1% of total intermediate inputs. Because online media represents such a small share of total inputs, standard productivity formulas predict a relatively small impact on measured TFP.

Online Media Usage by Industry

We plan to use the same Forrester Research data described earlier to split Internet usage by industry. Forrester Research tracks only 30 industries and the industries tracked do not correspond perfectly to the 63 private sector industries tracked in the joint BLS-BEA production accounts. We will use our best judgment to map the Forrester codes into NAICS codes. Forrester's industry-level data only goes back to 2013.

We have not yet been able to purchase the Forrester Research data. In the meantime, we use CPS survey data tracking on-the-job Internet by industry. That data is available in 1997, 2001, 2003, 2011 and 2013. In theory, we could use that data to calculate industry-specific growth rates for Internet usage. Unfortunately, the CPS has slightly different questions and different industry codes in each survey year. For example, the 2011 survey asks about 'Internet access' at work and the 2013 survey asks about 'Internet usage' at work. As a result, usage rates are not consistent over time. For now, we will use the 2013 CPS survey data as a proxy for relative Internet usage by industry.

Figure 5 shows Internet usage rates across industries in 2013. Internet usage differs dramatically across industries. High skill industries like finance are much more likely to use online media than low skill industries like agriculture or construction. Within industries, high skill workers are more likely to use online media than low skill workers. These differences in Internet usage may lead to differences in wages, job characteristics and other outcomes.

Section 3: Price Indexes for Media and Advertising Viewership

This paper argues that 'free' media is actually a barter transaction between media users and media companies: users provide eyeballs in return for 'free' media. In the input-output tables, this barter transaction requires a new line tracking output produced by media companies and a new line tracking inputs purchased by media companies.[16] This section will estimate two new price indexes, one for each side of the barter transaction. Later in this paper, we will recalculate real output, real inputs and productivity by industry using those new price indexes. Our experimental methodology keeps all of the inputs and outputs currently tracked in BEA's input-output tables and keeps BEA's current price indexes for those inputs and outputs.

Prices for 'Free' Media Content

Media is a very difficult service to deflate properly. One issue is that media users constantly demand original content – so we cannot track the cost of producing the exact same website over time. In addition, media is a non-rival good with poorly defined units of output. For example, 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, media quality depends on the quality of the consumer durable goods used in the home production and the creation of the entertainment services has risen dramatically. For example, the quality of Google searches is enhanced by improvements in the cloud hardware and software employed by Google in conducting the searches as well as by the growing availability of websites to be searched. Similarly, high-definition televisions (HDTVs) and monitors enhance the quality of videos and television programs being watched and, indeed, the videos have higher production values to take advantage of the improved receiver quality.

It might seem simple for us to measure Internet publishing prices. After all, BLS has published a producer price index (PPI) for Internet publishers since 2009. Unfortunately, we can't use that PPI to track prices in the United States. BLS's published methodology reports that

[16] Advertising viewership produced by consumers is considered a labor input and advertising viewership produced by businesses is considered an intermediate input. However, the two inputs have the exact same price index.

average price per click or page view is a major component to their PPI. According to Google's 10-K's, advertising prices are much lower in the developing world – and so the average price per click falls when Google expands its business abroad. In other words, the falling prices observed by BLS are mostly driven by export sales and not domestic Internet users. In contrast, our paper is focused on domestic Internet usage and advertising viewership.

We start by constructing a price index for online media. The three main inputs to online media are software, computers to run the software, and everything else. For example, search engines start out with complex algorithms to optimize the search process. They then run those algorithms on server farms every time someone enters a query. In addition to those direct costs, online media companies also have overhead costs such as salespeople, utilities, and rent. We were unable to find price indexes specific to the software used by online media companies, the computers used to process requests, or their overhead costs. Instead, we use the BEA's price indexes for prepackaged business software (Table 5.6.4, line 3) and the BEA's price index for computers purchased by private businesses (Table 5.3.4, line 11) and personal consumption services (Table 1.1.4, line 6).

Figure 6 shows prices for online media from 1998 to 2013. We find that online media prices have fallen approximately 5% per year. Most of this decline is due to plummeting computer prices; the small price declines for software mostly cancel out the small price increases for overhead. Over this same time period, nominal online media advertising has been skyrocketing. The net impact is a real growth rate of 28% per year from 1998 to 2013.

At first glance, our price index appears to assume zero productivity growth in the online media industry. In fact, we assume that modern computer programmers are much more productive at writing software than they were in 1995. This rising productivity has allowed prepackaged software prices to fall 4% annually even as programmer wages rose. We assume that programmers producing own-account software for online media companies have enjoyed similar productivity gains as programmers producing prepackaged software, and therefore output prices for own-account software track output prices for prepackaged software.

The price index in Figure 6 does not account for network effects or other Internet-specific factors. We believe that those factors raise quality over time and therefore lower quality-adjusted prices. As a result, our inflation rate of -5% per year should be seen as an upper bound on the true inflation rate. Later in this paper, we estimate how much these factors contributed to quality growth over time.

Prices for Online Ad Viewership

As with all labor inputs, neither the price nor quantity of advertising viewership has any direct effect on measured GDP. However, input prices and quantities do affect measured productivity. In the next section of the paper, we will calculate TFP by industry from 1998 to 2012. Those calculations depend enormously on the price for online ad viewership. In addition, many researchers are interested in the price and quantity of labor for other reasons. For example, policy-makers often use real wages as a proxy for consumer welfare.

We have not been able to find any reliable data on Internet advertising prices for US viewers. Google tracks cost-per-click and reports that number in their 10-K. Unfortunately, that cost-per-click number combines web users around the world. There are many other firms that report some price data for the online advertising market. However, those firms are generally short-lived and only report data for a few years. Furthermore, online advertising is a very heterogeneous market with different prices for each keyword, demographic group and location. As a result, the average price growth reported depends enormously on the precise sample tracked. We were not able to identify which price indexes were representative of the entire market or to figure out how to combine the multiple price indexes available. We welcome suggestions on reliable data to use or methodologies for existing combining price indexes.

We have also been unable to find reliable data on Internet advertising viewership over time. Television programs typically separate advertising from programming – so we can easily observe how much advertising viewers are exposed to. In contrast, online advertising is generally displayed at the same time as media content. Furthermore, the line between advertising and media content is often very thin. For example, search engines sometimes sell placement on the results page (Nicholson et al 2006). Are those results advertising or content?

In the absence of better data, we will calculate advertising viewership prices indirectly. First, we use a variety of data sources to calculate the total time spent online from 1995 to 2013. We then combine that time use data with the nominal advertising data shown in Figure 1 and calculate advertising expenditures per hour online. This proxy requires two major assumptions.

First, we assume that the share of time spent on advertising-supported websites has been constant over time. In other words, subscription websites like Netflix and non-profit websites like Wikipedia, in aggregate, have grown at exactly the same rate as advertising-supported websites. Second, we assume that advertising-supported websites show the same number of ads over time.[17] Note that this assumption appears to conflict with the URL business model, where start-ups focus on building their network first and only later monetize their content by selling ads. However, it is possible that new start-ups are always entering the market and therefore the average amount of advertising on the entire Internet is constant. We welcome suggestions to measure advertising exposure more accurately.

Our primary data on time use is provided by eMarketer, a media research company. They have published annual estimate of digital time use since 2008. EMarketer reports time use for mobile Internet, computer Internet and other Internet separately. We added all three to get total time spent online.[18] Marketer's data appear to include both on-the-job Internet and off-the-job Internet. Before 2008, we use estimates of Internet usage published periodically in the Historical Statistics of the United States. The Historical Statistics of the United States explicitly focuses on leisure Internet and does not include on-the-job Internet at all. We adjust their numbers by the on-the-job shares shown in Figure 2 to get total Internet usage.

Figure 7 shows prices for advertising viewership from 1998 to 2013. We find that advertising viewership prices grew 6% annually from 1995 to 2013. In other words, the nominal cost of content per advertising view has grown steadily over time. This increased nominal cost occurred even as entertainment production costs have fallen steadily. In combination, we calculate that Internet users enjoyed a 10% annual increase in real media content per hour of advertising viewership.

However, advertising viewership prices do not grow smoothly. Advertising prices increased rapidly during the late 1990's and then crashed in the early 2000's. This price decrease is caused by the end of the dot-com bubble in the early 2000's. This bubble and collapse has been studied in detail by many economists and the popular press. On the other hand, the stagnant advertising prices since 2009 are less well known. Unlike the early 2000's,

[17] This does not mean that advertising technology has been fixed over time. Rather, pop-up ad technology is canceled out by ad blocking technology. The net effect of the arms race is assumed to be zero.

[18] Many individuals consumer multiple categories of leisure at once. For example, they might watch TV and read Facebook at the same time. EMarketer counts both activities separately in their statistics. As a result, total time spent with any media is less than the sum of the individual components.

these stagnant prices are caused by a dramatic **increase** in online media usage associated with smartphones and other mobile devices. Between 2009 and 2013, eMarketer reports that online time more than doubled. This quantity increase almost precisely matches the increase in nominal advertising expenditures. As a result, advertising viewership prices have been almost constant since 2009. We do not know if those trends will continue going forward.[19]

Section 4. Real Output, Real Input and Productivity by Industry

Aggregate Changes to Real GDP

Figure 8 recalculates our GDP quantity indexes when 'free' online entertainment is included in final output. Between 1998 and 2012, real GDP growth increases by 0.009% per year when 'free' apps are included in final output. The increased growth is very steady from one year to the next, with only a small deceleration during the dot.com crash and no deceleration during the Great Recession. If policy-makers were only interested in real GDP, Figure 8 would be enough to fully measure the impact of 'free' apps on the economy.

However, most policy-makers and researchers are interested in decomposing real GDP growth into the component parts of TFP growth for individual industries and quantity growth of labor.[20] In this paper, we consider advertising-viewership to be a type of labor. Holding real media output fixed, our experimental methodology treats more Internet surfing as an increase in labor inputs and therefore a reduction in TFP for the media industry. For other industries, more Internet surfing is considered an increase in gross output and therefore an increase in TFP.

Recalculating TFP Using Our Experimental Treatment of 'Free' Online Media

This section calculates industry-level statistics for each of the 63 business sector industry categories tracked by BEA and BLS in their joint production accounts. Because there are so

[19] By 2014, eMarketer reports that the average American spent nearly 6 hours online. This already more than television viewership time and seems likely to hit a ceiling soon.
[20] Capital deepening can also contribute to real GDP growth, but our experimental methodology does not change any capital stock numbers. For simplicity, we will focus on labor and TFP in our discussion.

many industries, it is not feasible to show each one separately. Instead, we split the 63 industries between media companies and all other industries in the business sector.[21] We then show how our experimental methodology impacts each category.[22]

Figure 9 shows how our experimental methodology changes measured TFP. We find that measured TFP for media companies rises, raising business sector TFP growth by 0.008% per year. Internet publishing companies (NAICS 518 and 519) contribute the lion's share of the TFP increase, but newspaper publishers also produce significant quantities of online media and contribute to the business sector TFP increase. Measured TFP for the rest of the business sector falls, lowering TFP growth by 0.004% per year.[23] The net effect is a combined TFP increase of only 0.005% per year. This change is not nearly enough to reverse the recent productivity slowdown.

At first glance, the numbers in Figure 9 appear implausibly small. Figure 8 showed that real GDP growth increases by 0.009% per year when online entertainment is included in final output. Yet business sector TFP growth increases by only half that amount. The difference is especially striking after 2009. Between 2009 and 2012, our experimental methodology produces virtually no effect on business sector TFP growth. Over the same time period, we calculate real GDP growth increased by 0.02% per year. The difference is due to advertising viewership quantities. Between 2009 and 2012, eMarketer reports that time spent online increased 93%. This increased time cancels out the increase in real media output. Conceptually, the real quantity of media received per hour online is roughly comparable to real wages. When labor hours increase, real GDP increases faster than real wages. Similarly, real media output can increase faster than TFP.

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[21] In order to make our TFP numbers more comparable to the existing literature, we treat consumers watching advertising-supported entertainment as an entirely new industry. That new industry is not included in the 63 industry categories tracked in our spreadsheet. We also exclude the government sector. Because of this focus, our TFP numbers only track private sector business and are not representative of the entire economy.

[22] Our exact TFP calculations are based on internal numbers collected by BEA for research purposes. These numbers do not always match perfectly with the joint BLS-BEA production accounts. However, the differences are typically very small and do not impact the revisions to TFP shown in this paper.

[23] At first glance it seems surprising that new technology like Waze is associated with lower TFP. However, Figure 9 is not showing actual TFP – but rather the revision to measured TFP caused by our experimental methodology. For example a restaurant might use Waze to get delivery directions. BEA's current TFP statistics treat an improvement in the Waze directions as an increase in TFP for the restaurant industry. Our experimental methodology shifts the better directions from the restaurant industry to Silicon Valley, lowering measured TFP for restaurants and raising measured TFP for Silicon Valley.

The revisions to measured TFP shown in Figure 9 are much smaller than predicted by the popular literature (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. Even in 2013, online media accounts for a very small share of the overall economy. Accordingly, higher TFP growth for Internet publishers has little effect on aggregate TFP growth. In contrast, the popular literature assigns weights in proportion to time use. By 2013, Americans spent more than 20% of their time online. If we used that weight to value 'free' apps, aggregate TFP growth would increase dramatically.

Recalculating TFP with Quality Growth

The TFP numbers in Figure 9 are based on the price index for online media developed in Figure 6. As we've discussed earlier, the price index in Figure 6 does not include any quality adjustment for network effects, user generated content or factors unique to Silicon Valley. In this section, we explore using bytes of data to proxy for these quality issues. Between 1998 and 2012, Cisco reports that IP traffic grew 79% per year. This growth rate continued throughout the dot.com bubble and bust, the Great Recession and the recent recovery. Based on that quantity growth, we calculated that quality-adjusted prices might have fallen as fast as 31% per year. As a robustness test, we will recalculate business sector TFP using that price index.

Figure 10 shows how the quality adjusted prices change measured TFP growth. Between 1998 and 2012, measured TFP growth now increases by 0.02% per year. This is five times the effect calculated in Figure 9, suggesting that quality growth may be very important when measuring advertising-supported media. However, even a TFP increase of 0.02% per year is not enough to reverse the recent productivity slowdown (Syverson 2016).

Recalculating TFP when the Government Supplies 'Free' Media

The TFP numbers in Figures 9 and 10 only study the impact of advertising-supported media produced by the private business sector. In addition, the government also produces media. For example, the Federal government spends $1 billion per year on GPS. This government-supported media is already counted in GDP as part of government output – but it is not currently treated as an intermediate input when calculating TFP by industry. As a robustness test, we explore how treating government-supported media as an input might change measured TFP.

In this robustness test, we track three categories of government media: a) statistical reports like BLS's unemployment series or Census's population data; b) weather reporting; and c) Global Positioning Satellites (GPS). We use a variety of datasets to track nominal government expenditures for each media category.[24] We then use the online price deflator estimated earlier to calculate real expenditures. Combining all those data sources, we estimate that the federal government spent $8.9 billion on government-supported media in 2012.

Earlier in this paper, we chose to value advertising-supported media at its imputed production cost. In order to be consistent, we will value government-supported media based on its production cost.[25] This choice is consistent with previous economic research estimating the impact of government capital stock on measured TFP (Gramlich 1994). On the other hand, some case studies have estimated social values for government media much larger than government expenditures (Department of Commerce Report 2014 and Pham 2011). We also used the same TFP formulas to calculate the TFP impact of government-supported media.

Figure 11 shows our best guess of the TFP impact of government-supported media. We find that private sector TFP growth falls by 0.003% per year. This decline is almost as large as the TFP increase found earlier in Figure 9. In other words, the net TFP impact of all 'free' media is almost zero. However, the result for government-supported media result is very sensitive to the price index used. The proper price index for government output is a complex subject that deserves more research.

[24] A large fraction of government media expenditures are devoted to producing long-lived capital assets. For example, satellites account for a large majority of GPS costs. Furthermore, many data products are used for years. We calculate capital services based on a 10-year-lifespan for government media capital and a zero rate of return. Our annual values are based only on government expenditures and do not include survey respondent costs.

[25] The standard productivity formula assumes profit-maximizing firms. This assumption clearly doesn't apply to government agencies – but they may maximize total consumer surplus or other economic outcome variables. The assumption of rational government is more plausible for noncontroversial products like weather predictions.

Other Effects of Silicon Valley on Measured Productivity

In theory, the joint BLS-BEA production accounts already capture everything except advertising-supported media. For example, Netflix subscriptions are already in personal consumption expenditures (PCE) when purchased by consumers and already in intermediate inputs when purchased by businesses. As a result, measured TFP should include the dramatic price decreases and quality improvement characteristic of IT products and services. In practice, quality improvement is sometimes hard to measure and may be underestimated for some IT products and services.

Consumers spend substantial sums on their connections to the Internet and these sums have been rising relative to total expenditure. These include access to wired Internet service providers and to cellular networks. According to BEA's published statistics, nominal personal consumption expenditures on cellular phone services and Internet access amounted to 0.1 per cent of GDP in 1994, 0.7 percent in 2004 and 1.2 percent in 2014. BEA's published statistics on business intermediate usage do not report detailed breakdowns of telecommunication services by commodity. However, the aggregate intermediate usage of telecommunication shows a similar pattern to PCE.

Usage of these networks has risen extremely swiftly, at rates that are at similar orders of magnitude to Moore's Law. For example, cellular data traffic, according to CTIA's annual survey rose from .39 petabytes to 4.06 petabytes between 2010 and 2014. According to Cisco, Internet data traffic in the US rose from 3.0 exabytes a month in 2008 to 13.1 in 2012. These rapid rates of growth in quantity, however, are not mimicked by similar rates of growth in BEA's published statistics. According to BEA's Table 2.4.5U, real personal consumption expenditures on cellular phone services rose from $97 billion in 2010 to $119 billion in 2014 (2009 $'s). Similarly, real personal consumption expenditures on Internet access rose from $50 billion in 2008 to $82 billion in 2012 (2009 $'s). Thus it would appear that the measures being used by BEA for these series may be seriously mismeasuring the rate of quality improvement in these consumer services.

In the period from 2004 to 2009, Greenstein and McDevitt (2011a,b) take two different routes to measure the price of broadband services. Both studies find very modest declines in quality-adjusted prices, on the order of 2 % annually. These studies imply that the implied willingness-to-pay for broadband speeds and rapid increases in data downloads is not very high. However, these studies do not take into consideration the heterogeneity of broadband customers, which appears to be very high. This heterogeneity can be seen in the work of Nevo et al (2015), which uses hour-by-hour Internet data usage to estimate some 50 types of users, taking advantage of usage based plan differences across different plans. These usage based plans have different download speeds, covered by a fixed fee with a monthly download allowance and a linear price for downloads beyond the allowance. They calculate that consumer surplus for existing broadband customers is $85 a month, while they pay $70 a month. They further estimate that the adoption of Google Fiber (which has 14 times the download speed of the 2011 broadband average in the study) at $70 a month (the current price offered in Kansas City) would increase consumer surplus to over $200 a month, while tripling downloads.

Exactly how far quality-adjusted prices should fall is a difficult question to answer. An important issue is that the willingness-to-pay at a point in time is affected by the rapid change in the uses and usefulness of applications. For example, the use of smartphones for turn-by-turn navigation has become a widely adopted use that was not available to cell phone users at all. Broadband speeds make possible the rapid dissemination of videos, which has in turn led to very widespread video creation.

Detailed technical data on the cost side of cellular and data networking, estimated by Byrne and Corrado (2015), suggest a rapid rate of technological progress and real growth. For cellular networking equipment, they estimate that between 1993 and 2009, prices declined at a 16.8 percent annual rate. In comparison, BEA's published price index for cellular services declines by only 4 percent annually. For data networking equipment, their price index falls at a 15.9 percent annual rate from 1992 to 2000 and 11.6 percent from 2000 to 2009. In comparison, BEA's published price index for Internet service falls at a 2.5 percent annual rate in each period. If we were to accept the Byrne and Corrado estimates as measures of the quality of cellular service and Internet access, this faster quality growth would raise TFP growth in the broadcasting and telecommunications industry.

The telecommunications sector is much larger than the Internet published industry alone, so it has a significant potential to impact business sector TFP growth. It is possible that the revision to measured TFP from new telecommunication prices could dwarf the revisions to TFP shown in Figures 9-11. However, new price indexes for telecommunications or other IT services are not directly related to the conceptual question of how to track advertising-supported media in GDP. After all, research on hedonic computer prices started long before the Internet (Triplett 1989). This paper will focus on the advertising-supported media produced by Silicon Valley and will not attempt to track any other digital product or service.

Section 5. Network Effects and Organizational Capital

If we consider Internet sites such as Google, Facebook, Yelp!, or Waze, they may provide services to advertisers and to consumers but a key feature of these firms is that they have positive user network externalities, that is, when more consumers use these sites each individual consumers benefit more from their own use. The more people who use Google, the better each individual's search becomes; the more people who report their opinions on Yelp!, the more each can learn about, say, restaurant quality.

This poses an immediate challenge for price measurement, to the extent that the utility of the service may not be constant from period to period. Rather, quality increases over time: Demand shifts outward over time, referring back to the figures in section 1, generating increases in consumer surplus that will not be well captured in standard price measures (see Nakamura, 2013 for a discussion). Unfortunately, we are not aware of any method that would permit us to capture this type of utility gain.

Another concern that arises is that our model of advertising-supported free media assumes that the advertising that subsidizes the free media is currently being displayed on the media and that the revenues from the advertising can be evaluated in the way that we do in section 2. But in the world of the Internet, some of that advertising revenue is displaced into the future. While firms are rapidly growing, building out their brands and market reach, they are expending more resources than they will need to once they have reached optimal size. One obvious example is Facebook, which has been growing rapidly and in the process of growing rapidly has had a lot of expenditures in building intangible assets. It has invested in much more than its physical plant and equipment and as a consequence, since expenditures in intangible assets are generally expensed rather than capitalized, it has had relatively low profitability (and, despite that, a very high equity market value). Facebook has been an Internet firm that provides utility to consumers but has not permitted much advertising in its period of rapid growth. This does not entirely fit our basic model, to the extent that consumers are not having to watch an amount of advertising commensurate with the expenditures being made by the Internet firm on their behalf.

URL: Ubiquity Now, Revenues Later

Our methodology for capturing the value of media to consumers is minimalist in the sense that it captures the cost of producing the on-line media from the advertising revenue stream that supports it. However, as just noted, many Internet startups do not immediately seek to fully monetize their websites. In these cases, their growth is often fueled by angel and venture capital, and ultimately IPOs. For example, Facebook reportedly raised $350 million between 2004 and 2007 before finally becoming cash-flow positive in late 2009, by which time it had some 300 million users visiting the site at least once a month. Similarly, Google Translate, Google Maps, and Waze have been to a large extent supported by advertising on Google Search rather than through a direct use of advertising.

One reason for not immediately adopting advertising is the concern that customers view the advertising as costly – as in our proposed model. If there are network externalities, as there are in social networks like Facebook and Waze, the utility provided by the network to each user rises as the network expands. If advertising is viewed as a cost, it will often be better to impose this cost after the network has expanded to close to its optimal size to facilitate the growth of the network.

The expenses of a firm that has pursued the URL model represent the expenditures the firm has made that might be considered to have been supported by the expectation of future advertising revenues. The equity value of the firm might represent the expected value of those future advertising revenues, that is, the discounted present value of the flow of producer surplus that future advertising is expected to generate. As such, the equity value should have some relationship to the past value received by consumers during the period of growth of the firm's network. Under free entry, the ex ante expenses and the ex ante equity value should be equal, across the set of firms competing to enter the market. In turn, overall ex ante and ex post equity value also should be equal. This would include the expenses of the firms that fail in their efforts to establish a network.

However, it is possible that some entrant may be able to exploit a uniquely valuable entry point that results in quick establishment of a monopoly, as Facebook did in its base in Harvard College, with its unique prestige. Such an early monopoly may break the equality between ex ante expenses and ex ante equity value. And the equity value will include the expected producer surplus of investments yet to be made, as the market value of a strong user base may well enable investments that have positive NPV.

Another difficulty, for the US national income and product accounts, is that the advertising base for an Internet firm may be the entire world, while we seek to measure the consumer gains to US domestic households.

With these caveats, two measures of the economic value to consuming households of these free media websites might be (1) the expenditures for setting them up, one measure of which is the money raised from investors plus the expected future value of equity shares that reward the site's employees and (2) the equity value of the firm.

Leading examples of US social networks include Google, Facebook, Yahoo!, LinkedIn and Twitter. Together these five firms had an equity value of over $650 billion in the middle of 2015, almost all of it generated in the past decade; only Google ($50 billion in mid-2005) had a significant market value ten years ago. Thus these firms alone added $600 billion in expected future value over the past decade, $60 billion a year.

On top of that, worldwide the private valuation of the 131 start up private companies that had an individual valuation of $1 billion or more, based on their financing round valuations, was some $485 billion, according to KPMG CB Insights (2015). Of course, many of these firms are not US based, and many are not media firms that expect to be supported by advertising; the US based firms amount to roughly $300 billion. Assuming this investment was created over the past decade, this would add another $30 billion a year to this investment.

Data from CB Insights on venture capital funding of US startups from 2011 to the third quarter of 2015 totaled $218.5 billion (covering some 21 thousand deals), or $46 billion a year for 4.75 years. This data does not include the additional funding raised through IPOs, but again, this will include many firms that do not expect to pursue an advertising model.

In order to be able to obtain a longer time series, we go to Standard and Poors Global Market Intelligence data service. We further limit the data to private equity funding of Internet firms, where we included all records for private placements in the US in six industries: Application Software, Data Processing and Outsourced Services, Internet Retail, Internet Software and Services, Online Gaming Operations, and Online Ticketing Agencies, going back to 1990. Notably, we see that in the Internet bubble era of 1999-2001, there was a sudden burst of private placement investments, amounting in total in the three years to $84.5 billion. By comparison, in the period 2013-2015, we have recorded a total of $75.4 billion. Thus the current episode does not imply an acceleration with respect to the earlier one in 1999-2001. On the other hand, it is possible that the current episode may prove to have more solid foundations.

Table 2 shows our annual numbers for private equity funding of Internet firms. The case can be made based on these equity values that URL investments subsidize as much expenditures on behalf of consumers as are currently directly funded by Internet advertising, if we sum up the roughly $1 trillion in equity value created. On the other hand, the streams of private placement investment flows underlying the expenditures made by these Internet firms appear to be considerably less than this, more like $20 to $40 billion at most. Moreover, while there has been acceleration in this spending over the past few years, investments made were larger during the Internet bubble of 2000.

Figure 12 shows how aggregate measured TFP would change 'free' online media is valued based on **both** advertising revenue and equity investment. The general pattern is the same as Figure 9, but increase in measured TFP more than doubles, from 0.004% per year to 0.011% per year. Most of this increase occurs during the dot.com bubble, when equity investment in Internet companies was very high. These revisions to measured TFP follow the same pattern as previously measured TFP. As a result, accounting for Internet network effects actually makes the slowdown in TFP growth during the 2000's worse.[26]

Beyond "Free" Media:

An important type of intangible capital not captured in the US national income accounts is organizational capital. Organizational capital includes private investments in organizational adaptations to innovation, including reorganization and training, and in marketing. Marketing, of course, includes the advertising that supports intangible assets.

Just as Facebook when it was building was expending more resources needed, there are a wide variety of Internet firms that pursue the growth before monetization strategy. One obvious example is Amazon, which has invested in much more than its physical plant and equipment and as a consequence, since expenditures in intangible assets are generally expensed rather than capitalized, it has had very low profitability (and, despite that, a very high equity market value). If intangible assets were capitalized, then Amazon would show greater profits and more investment in its income statement. The same holds true for the national accounts. Although some intangible assets are now capitalized, others like marketing are not.

Section 6. Concluding Remarks

The Internet poses a number of difficult questions for the national income accounts and the measurement of productivity. In this paper we have sought to address two rather narrow questions: how best to account for media on the Internet subsidized by advertising, and how to account for Internet websites that expend money on behalf of consumers (URL), but have no or minimal contemporaneous advertising revenue. The national income accounts provide a consistent framework for analyzing economic production. In practice, we can measure the inputs that go into free media and URL. But we have more difficulty measuring the real output of the Internet in a way that parallels other products that have prices.

[26] Our TFP numbers end in 2012, so we do not yet include the recent acceleration in equity investment.

Brynjolfsson and Oh (2014), as we discuss in section 1, attempt to capture some of consumer surplus by measuring the time expended on the Internet. Varian (2009) argues that much of the value of the Internet is in time saving, an additional metric for capturing consumer surplus. He performs a back-of-the-envelope calculation of the savings of time from search, based on the search time savings estimate in Chen et al (2013), which is 15 minutes per search. Noting that on average Americans search once a day and calculating the average value of time as $22, for employed workers, and multiplying by the number of employed workers, he concludes that Google saves Americans $65 billion a year. This does not include the value of other Google products, which could raise the figure to $160 billion. Other difficulties presented in measuring the contribution of the Internet to consumer welfare are learning and organizational capital.

The fertility of the entrepreneurial imagination constantly challenges national income accounting, which must attempt to not only capture lightning in a bottle but to do so in a replicable and predictable way. In this paper, we have attempted both to take a small step towards capturing the output of new models of economic activity, and to indicate some of the further steps that remain to be taken.

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Figure 1: Advertising-Supported Consumer Entertainment

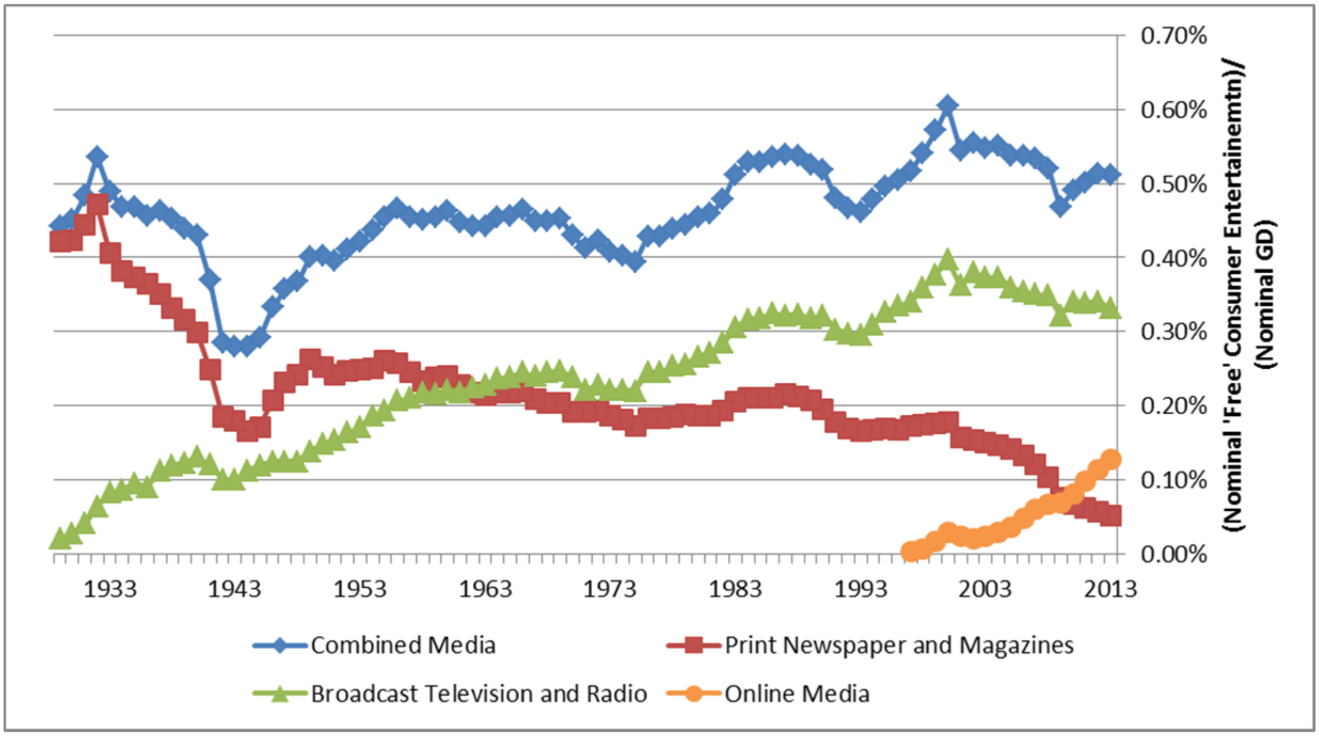

Figure 2: Advertising-Supported Business Information

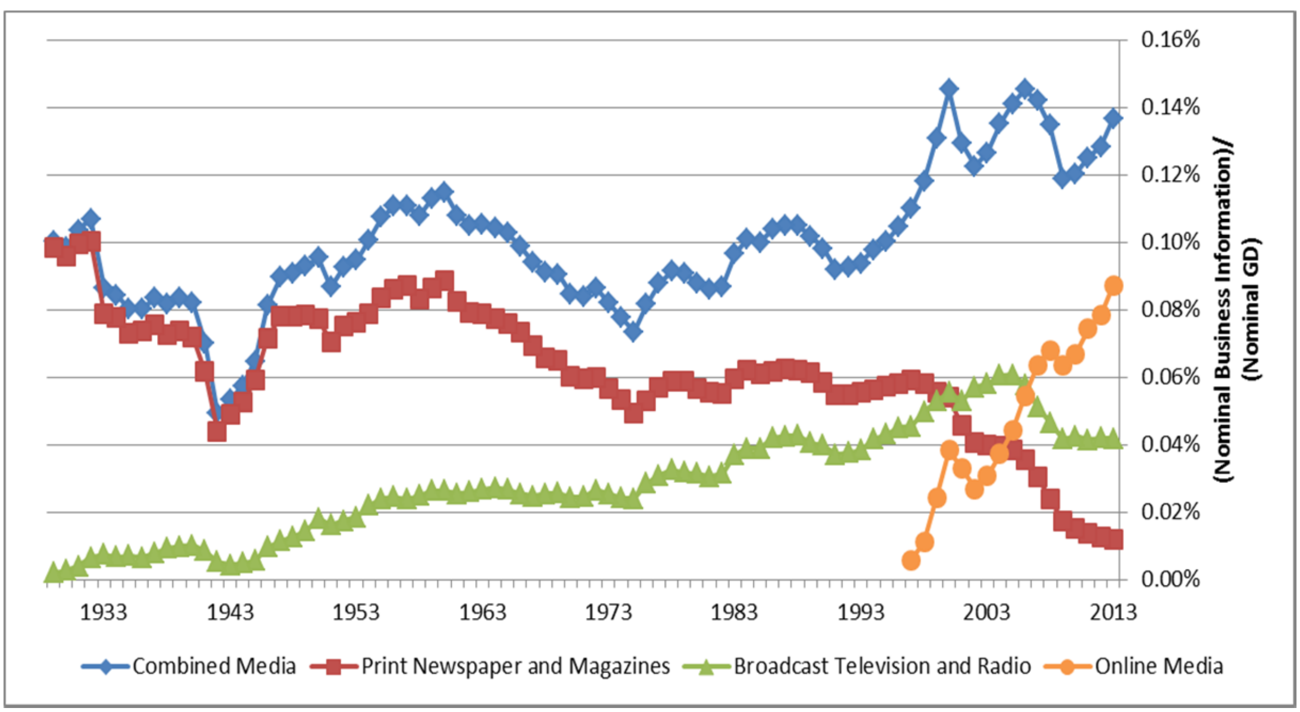

Figure 3: Nominal Advertising Expenditures by Industry

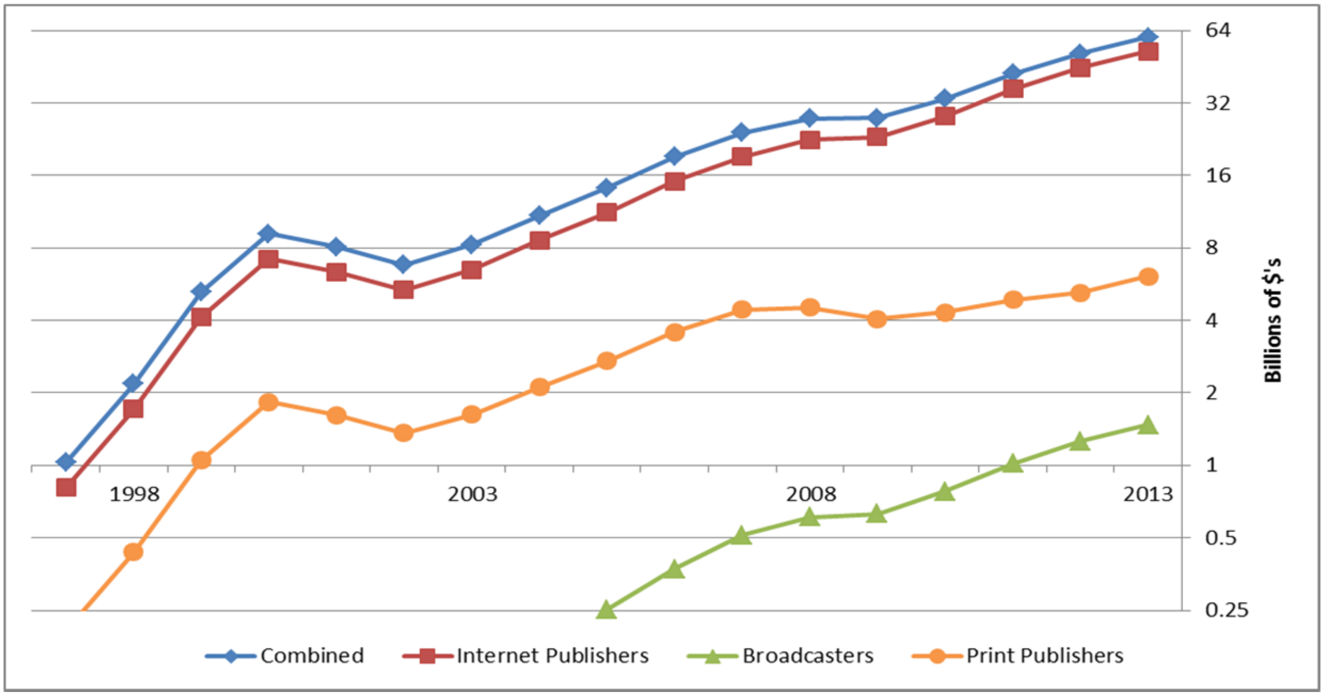

Figure 4: Intermediate Usage of 'Free' Apps over Time

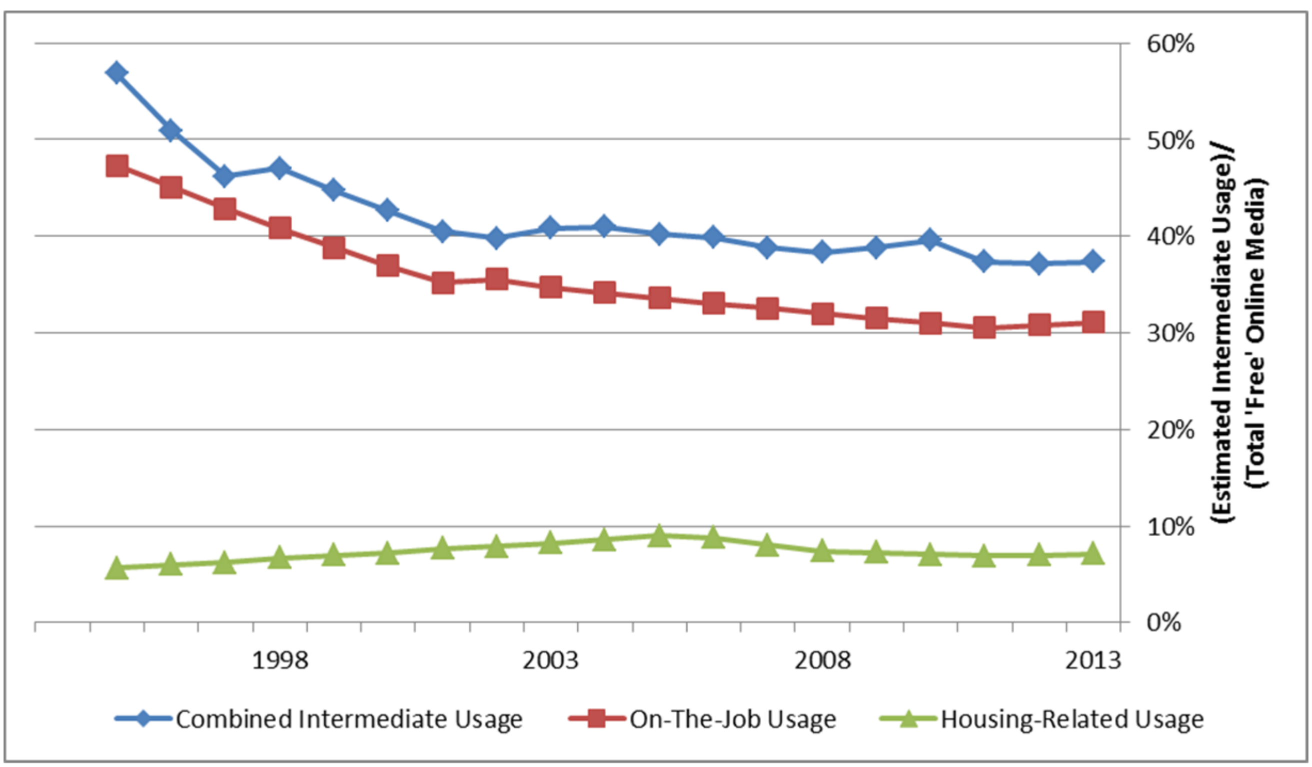

Figure 5: Intermediate Usage of 'Free' Apps by Industry

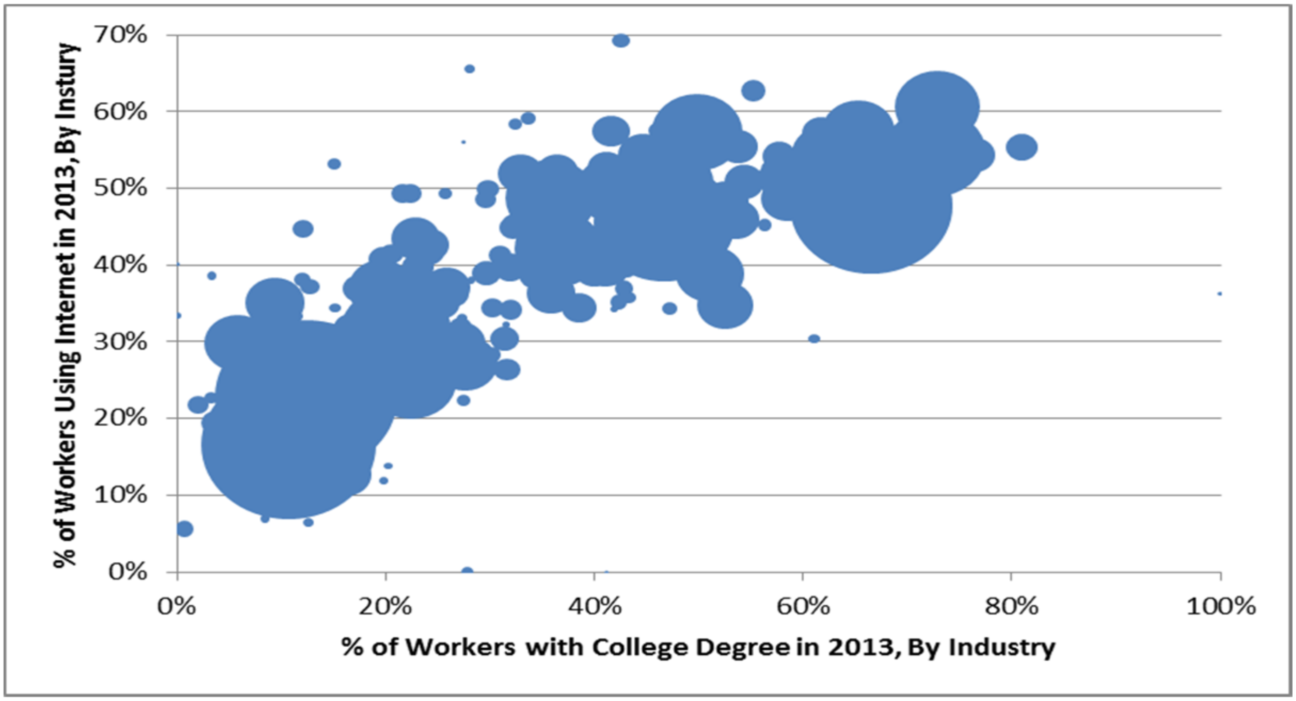

Figure 6: Prices for Online Media Content over Time

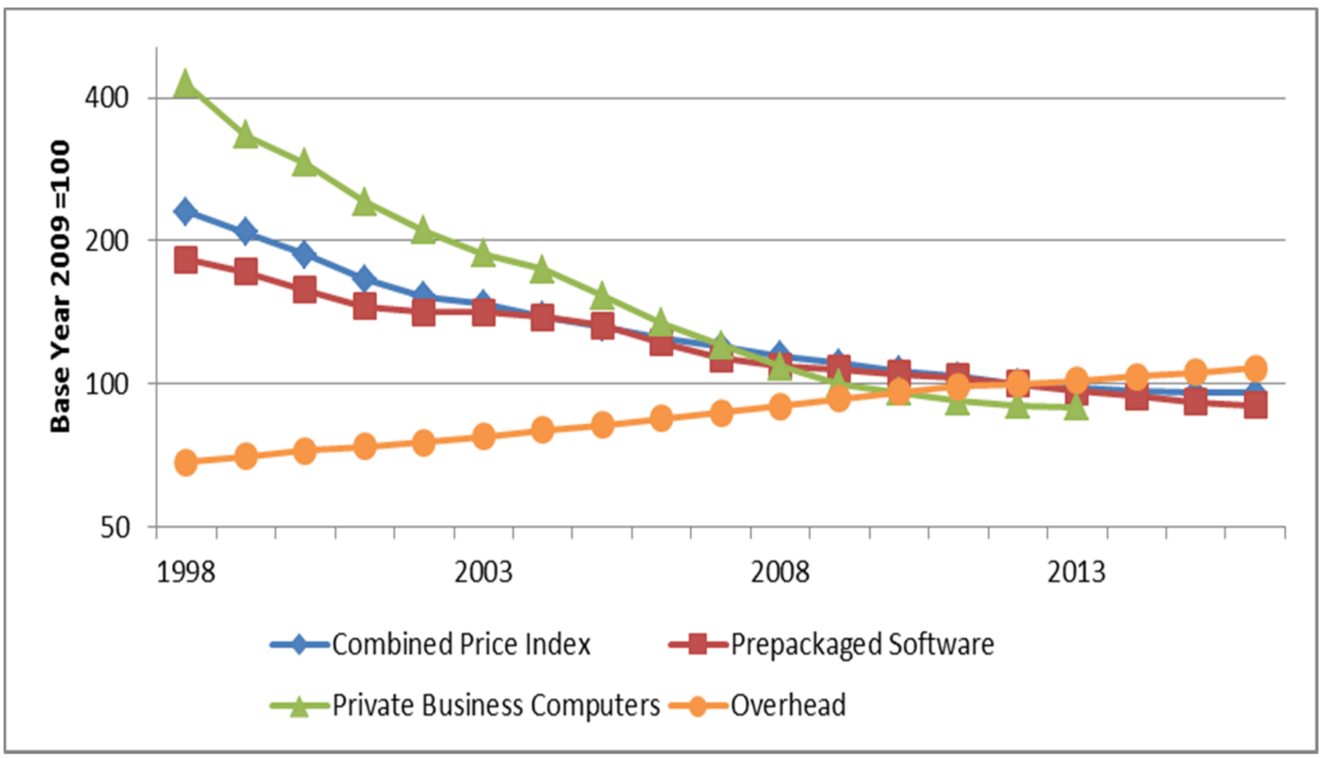

Figure 7: Prices for Online Ad Viewership over Time

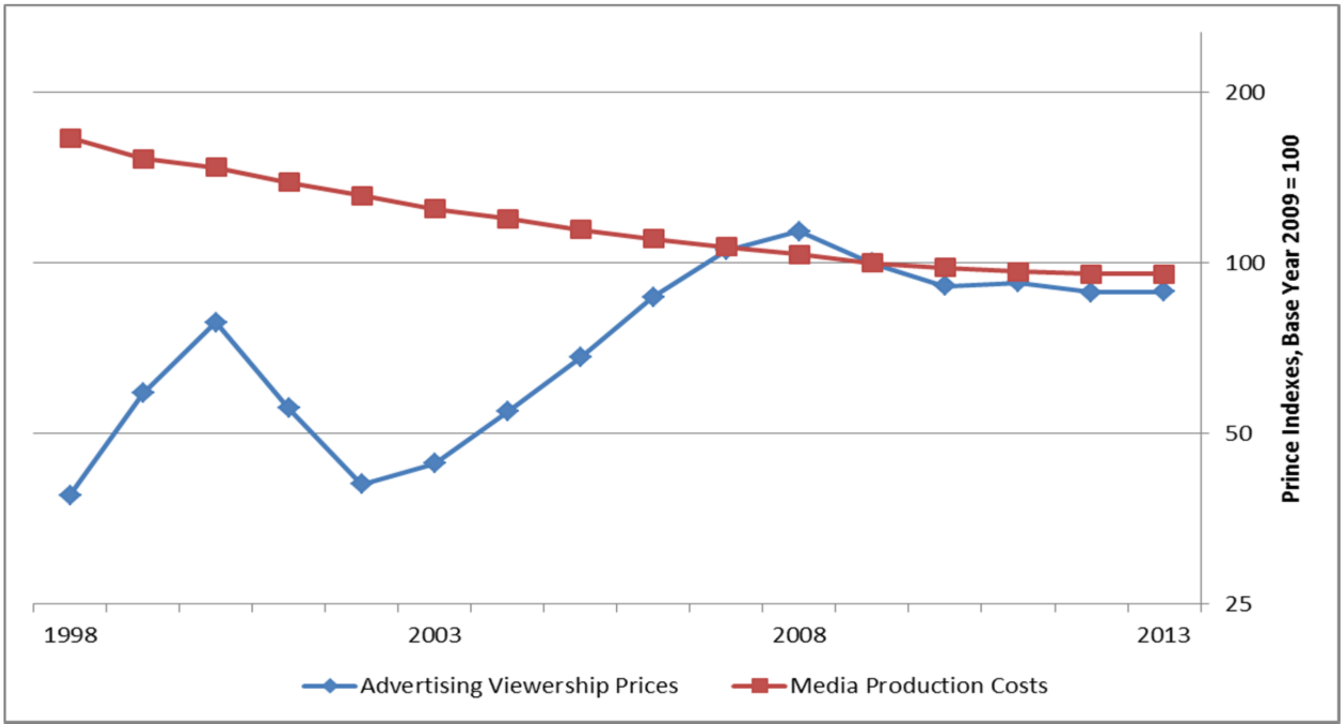

Figure 8: Change to Real GDP from Online Media

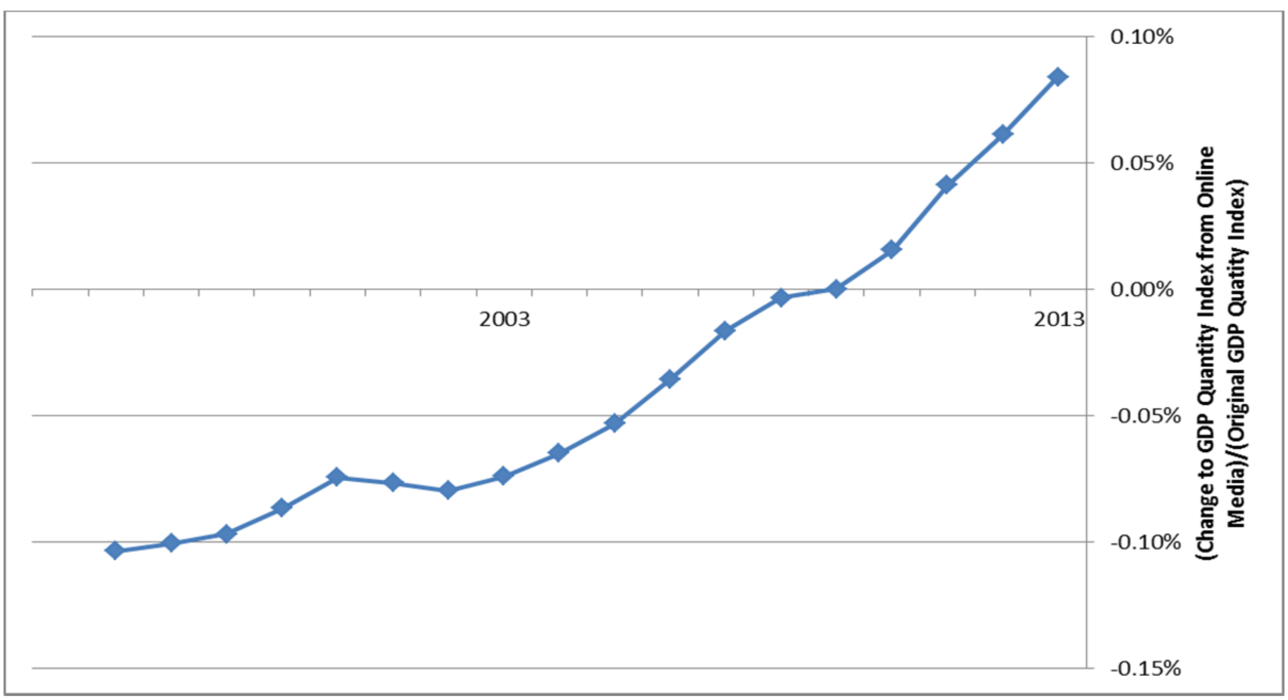

Figure 9: Change in Business Sector TFP from Online Media

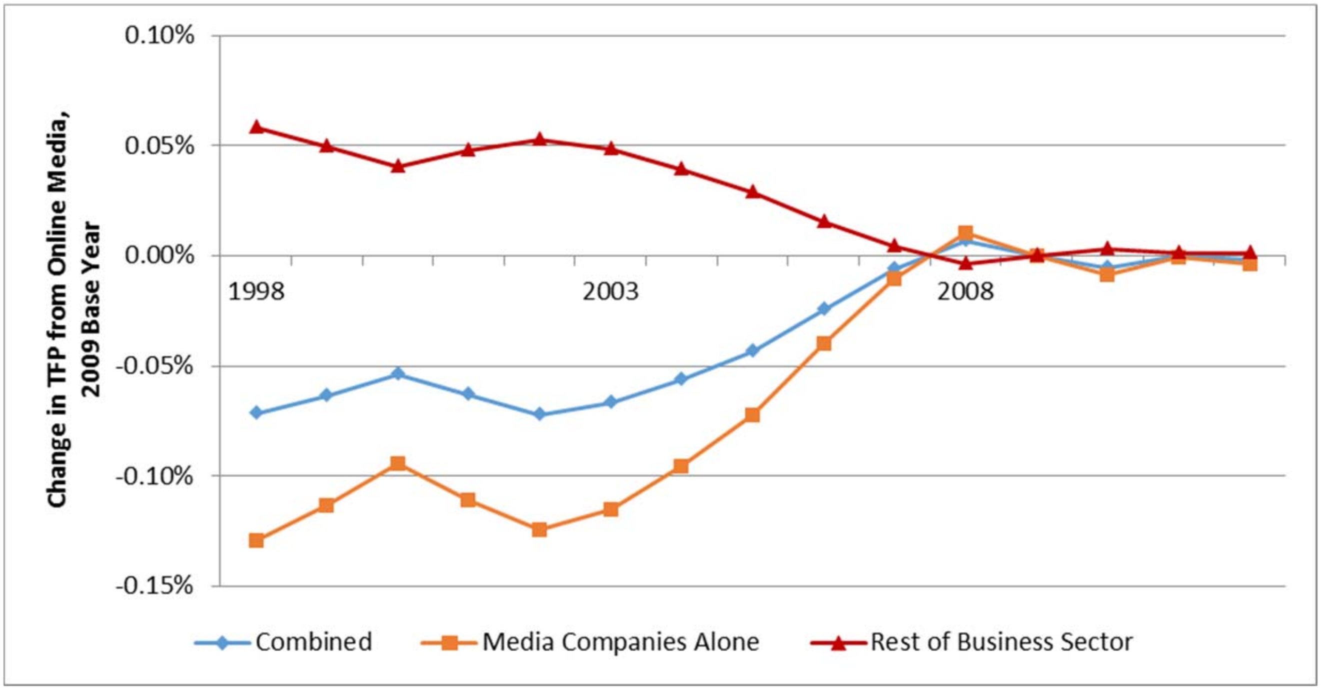

Figure 10: Change in Business Sector TFP from Quality-Adjusted Online Media, an Upper Bound Based on Bytes of Data

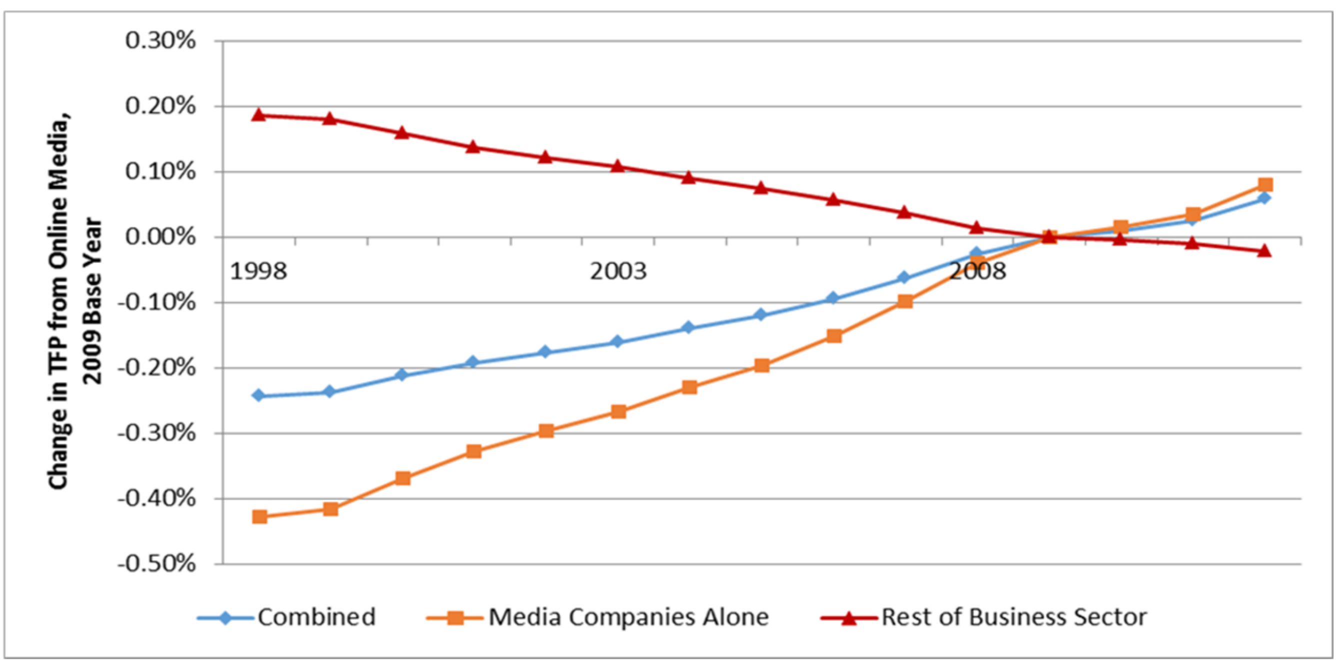

Figure 11: Change in Business Sector TFP from Government-Supported Media, Preliminary

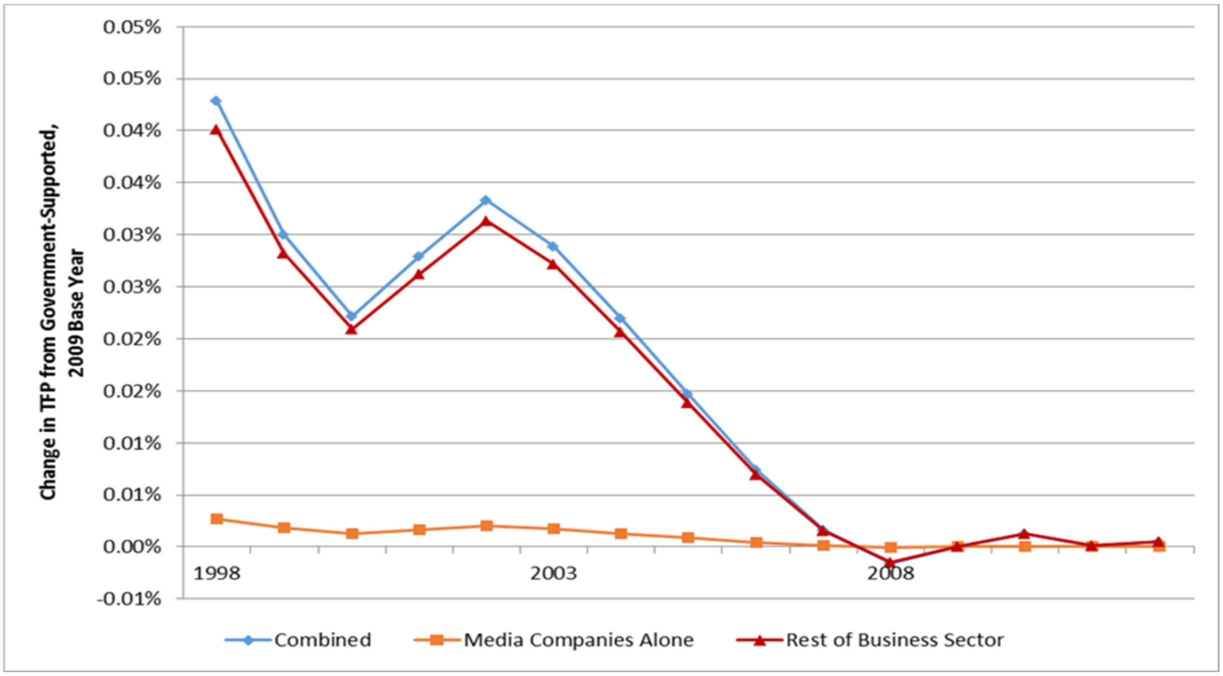

Figure 12: Change in Business Sector TFP from Online Media with Equity Investment

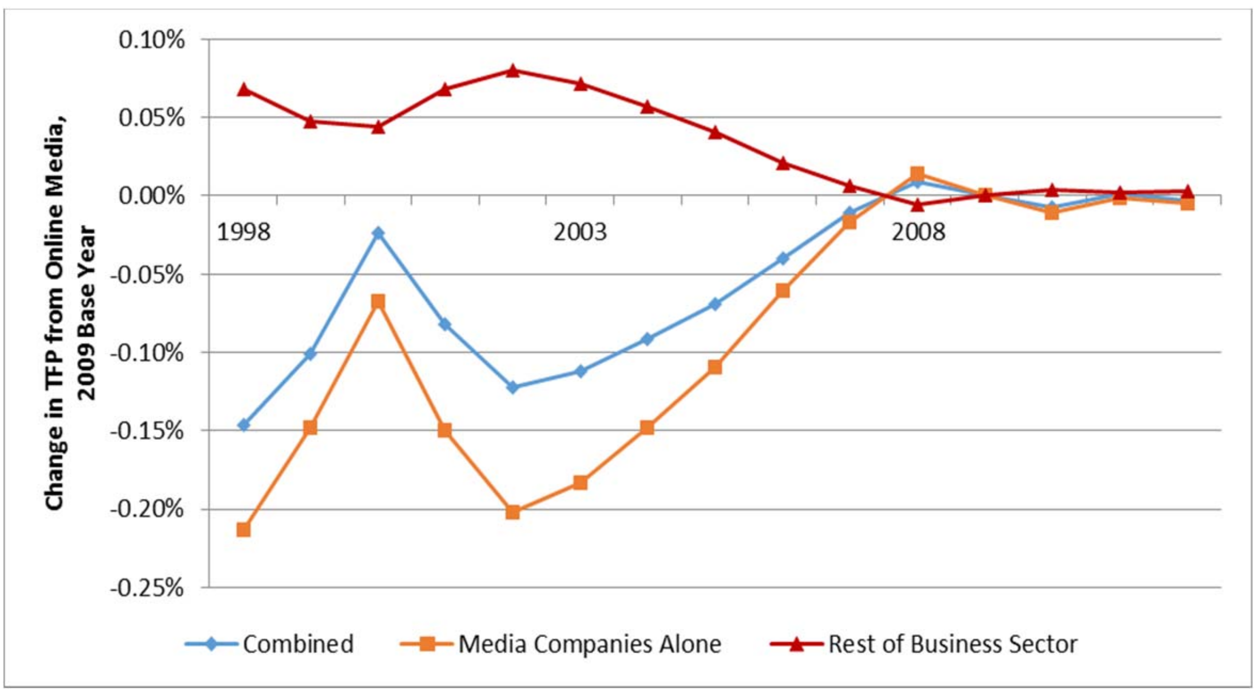

Table 1: Changes to BEA's Personal Income and Outlay Account in 2012

Line			Line		
1	Personal current taxes (4-15)	0	10	Compensation of employees, received	0
2	Personal outlays	82.8	11	Wage and salary disbursements	0
3	Personal consumption expenditures (1-15)	82.8	12	Domestic (1-3)	0
4	Personal interest payments (3-20)	0	13	Rest of the world (5-3)	0
5	Personal current transfer payments	0	14	Supplements to wages and salaries (1-5)	0
6	To government (4-25)	0	15	Employer contributions for employee pension and insurance funds	0
7	To the rest of the world (net) (5-17)	0	16	Employer contributions for government social insurance	0
8	Personal saving (6-9)	0	17	Proprietors' income with inventory valuation and capital consumption adjustments (2-9)	82.8
			18	Rental income of persons with capital consumption adjustment (2-10)	0
			19	Personal income receipts on assets	0
			20	Personal interest income (2-2 plus 3-4 plus 4-7 plus 5-5 less 2-21 less 4-21 less 5-13)	0
			21	Personal dividend income (2-16 less 4-22)	0
			22	Personal current transfer receipts	0
			23	Government social benefits (4-4)	0
			24	From business (net) (2-6)	0
			25	Less: Contributions for government social insurance (4-19)	0
9	PERSONAL TAXES, OUTLAYS, AND SAVING	82.8	26	PERSONAL INCOME	82.8

Table 2: New Funding of Internet Firms in Private Placements, U.S.

Date	Total Internet Private Placements, in millions
1998	$5483.8
1999	$21370.2
2000	$44629.3
2001	$18536.3
2002	$5902.8
2003	$5198.6
2004	$6923.75
2005	$6404.1
2006	$7470.4
2007	$10112.2
2008	$11161.4
2009	$6713.7
2010	$9284.9
2011	$18617.3
2012	$11954.2
2013	$14889.5
2014	$26082.0
2015	$34447.5

Source: S&P Global Market Intelligence