The Progression of "Free" Digital Content to AI: Impacts on U.S. Economic Growth and Productivity

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Abstract We use a barter transaction methodology to measure the impact of advertising-supported media and marketing-supported information, including artificial intelligence (AI), on GDP. We find that including "free" content in consumer entertainment has a substantive impact on recent GDP growth with trend breaks around 1995 and 2022. Including free content increases average GDP quantity growth between 1929 to 1995 by 0.04 percentage point per year, increases average growth between 1995 to 2022 by 0.09 percentage point per year and increases average growth between 2022 and 2025 by 0.22 percentage point per year. Similar trend breaks are observed for total factor productivity growth. It is likely that the trend break around 1995 was due to the development of the internet and the trend break around 2022 was due to the development of AI.

Keywords Technology, productivity, internet, information, economic measurement, GDP, artificial intelligence

JEL codes C82, L81, M37, and O3

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1. Introduction

The seismic rise in artificial intelligence (AI) rekindles an existing problem in economic measurement. When for-profit firms provide a good or service that does not reflect its cost of production, it is not consistently recorded either in the gross domestic product (GDP) accounts as an output or as an input in the productivity accounts. In this paper, we make an imputation to the GDP and productivity accounts to include the cost of digital content that is currently commercially subsidized. To avoid double counting, we exclude the portion of digital content that is paid for directly or bundled with other paid products or otherwise already included in the national economic accounts.[1] We conceptualize commercially subsidized content as barter. The barter transaction model that we employ tracks the costs to producers and users of content.

In the extreme, users pay zero out of pocket for some content and thus this content appears to be "free" from the perspective of the user and the national accountant. The remainder of the paper defines free content as content that is supported by advertising or marketing expenditures rather than payments by users.[2] Our scope includes, for example, the free versions of AI chat tools. Our assumption is that the free version is marketing for the paid version and therefore impute an estimate of the cost of providing free content. Any AI content that is directly paid for by consumers or businesses, or bundled into paid software or services, like after transitioning to a paid version, is excluded from our imputation.

The application to AI is a simple extension of our previous paper that covered publicly available online content, such as internet search, and other marketing and advertising supported content, but predated the expansion of AI. Due to additional source data that was not available when the previous paper was written and refinements to the empirical techniques used, the exact numbers presented in this paper do not exactly match the numbers in the previous paper. However, the pre-2017 qualitative results in this paper are almost identical to the qualitative results in the previous paper. The key innovations in this paper are an extension of the time series studied from 2017 to 2025 and a focus on AI.

Using currently available data and our barter model, we produce preliminary estimates of the effects of free content on output, inputs, and productivity at the aggregate and industry. We find 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). Over 2015–2025, free content raises nominal GDP growth by 0.03 percentage point per year, real GDP growth by 0.15 percentage point per year, and total factor productivity (TFP) growth by 0.15 percentage point per year.

[1] The existing national accounts include nonprofit and government output measured at cost. Therefore, the costs of some AI tools provided by either nonprofits or governments are already included in the existing national accounts. But, to follow the general treatment of nonprofits and governments, we subtract a measure of sales.

[2] If free information is bundled with sold products, then the value of this information is already captured in the purchase price. For example, traffic information bundled with a sold GPS device. The more general framework that we apply in our empirical exercise admits partially subsidized content like newspapers. We apply our barter model to only the portion that is subsidized by advertising or marketing, the remainder is already counted as an output and input in the standard productivity accounting methods.

These adjustments noticeably ameliorate the recent growth slowdown but do not reverse it. We also find that marketing-supported information contributes more to GDP and productivity than advertising-supported media, implying that analysis that focuses only on advertising-supported media underestimates the true value of free content. These preliminary estimates rely on strong assumptions about prices emphasizing the importance of continuing the progress in economic measurement.

The final contribution of this paper is a valuation of user-generated digital content (UGC). Unlike advertising and marketing supported content, user-generated content is an amateur activity which is unambiguously outside the scope of traditional GDP and productivity measurement. Nevertheless, UGC is a foundation of digital content and it is important to have consistent measures. We estimate that users generated $407 billion of content in 2025, lower than the $1,489 billion of advertising and marketing supported content for the same year, but substantial enough to warrant tracking and discussion, again with the intention of improving the measures.

Finally, this is not a paper about the welfare effects of free content or the strategic rationale for why content is provided for free instead of through direct payment, or why amateurs choose to produce user-generated content without any expectation of payment or material reward. These are all important questions, but our narrow focuses are to first value free content consistently with other components of the national accounts and then to calculate what GDP and productivity would be if free content was included in measured output.

The remainder of this paper proceeds as follows. Section 2 develops a simple two-sector model to present the standard approach to measuring advertising-supported content and demonstrates why this content appears to be free. We then present our barter transaction model that allows us to estimate the productivity impact of advertising supported content (marketing supported content is a simpler version of this model). Section 3 maps this model to the actual GDP and productivity accounts in the United States. Section 4 describes the price deflators. Section 5 presents revisions to overall GDP prices, overall GDP quantities, and total TFP. Our estimates of the value of digital user generated content are given in section 6 and section 7 concludes.

2. Measurement With and Without Free Content

We begin with nominal output in a simple two-sector model. This section is taken almost entirely from our previous work. The two sectors are a Manufacturing (M) sector and an Information (I) sector. The manufacturing sector produces a standard good like soap and the information sector produces AI services and advertising slots (for soap ads).[3] To clarify the issues, we assume only limited industry interactions. Advertising slots produced by the AI service industry are purchased by the manufacturing sector, and the information sector doesn't purchase manufactured goods. This two-sector model is

[3] Notice that this simple model excludes the production costs of the advertisements themselves. Later in the paper, we adjust the advertising and marketing expenditures for those production costs.

easily extended to the full industry accounting with 63 separate industry sectors which we use to do our empirical estimates.

2.1. Standard GDP and Productivity Model

The economic accounting model pertinent for productivity measurement includes prices (P) and quantities (Q). Each industry uses capital (K) and labor (L). The information sector (I) uses only capital and labor services to produce gross output (Y), which is represented as price multiplied by quantity ($P_{Y,I}Q_{Y,I}$). The manufacturer uses advertising slots as an intermediate input (X) to sell its goods and this value is reflected in the value of gross output. Like the official input-output tables, the underlying assumption is that the value of output equals the value of all inputs. This model can be written as:

$$P_{Y,I}Q_{Y,I} = P_{K,I}Q_{K,I} + P_{L,I}Q_{L,I}$$
$$P_{Y,M}Q_{Y,M} = P_{K,M}Q_{K,M} + P_{L,M}Q_{L,M} + P_{XI,M}Q_{XI,M}$$

The economics underlying this accounting framework is that the manufacturer pays the information industry only the value of advertising slots ($P_{XI,M}Q_{XI,M}$) as a useful input in its production process. As an accounting relationship, this is modeled by equating the payments made by the manufacturer to the information sector as the value of advertising output, that is: $P_{XI,M}Q_{XI,M} = P_{Y,I}Q_{Y,I}$. To emphasize, this basic formulation is consistent with official input-output tables that underly the measurement of GDP and productivity; that is, the information sector produces advertising slots. In the official Make table component of the Input-Output Accounts, the information sector produces advertising services, and the value of this output is the revenue earned from selling advertising slots.

With this treatment, it is easy to see that nominal GDP derived as total gross output less total intermediate input equals the value of manufacturing output $P_{Y,M}Q_{Y,M}$ which equals the sum of payments to factor services across the two industries: $\sum_{j\in\{I,M\}} P_{K,j}Q_{K,j} + P_{L,j}Q_{L,j}$.

Furthermore, the TFP growth rate of the individual industries and the aggregate economy can be measured with standard productivity formulations. Specifically,

$$\Delta \ln T_j = \Delta \ln Q_{Y,j} - \sum_{i\in\{X,K,L\}} \overline{w}_{i,j}\Delta \ln Q_{Xi,j}$$
$$\Delta \ln T_{Agg} = \sum_{j\in\{I,M\}} \overline{v}_j \Delta \ln T_j$$

That is, TFP growth ($\Delta \ln T_j$) is the growth rate of real output ($\Delta \ln Q_{Y,j}$) less total (weighted by cost share $\overline{w}_{i,j}$) real inputs ($\Delta \ln Q_{Xi,j}$). And aggregate TFP growth is the Domar-weighted ($\overline{v}_j$) sum of the industry TFP growth rates.

The key (related) points in this framework are 1) the value of advertising slots are tracked ($P_{Y,I}Q_{Y,I}$) as output of the information sector, 2) the value of free AI services to household users does not appear as a component of final output, and 3) the value of free AI services to the manufacturing sector does not appear as a component of intermediate input for that sector. In other words, free AI services are not tracked at all in the account shown above, since there is no recorded transaction. The only recorded transaction is the value of the advertising slot.

2.2. Barter Model to Account for the Value of Free Content

The jumping off point of this paper is that AI services are more than just an advertising vehicle. The key point is that regardless of whether users are spending time viewing advertising or giving up personal data, they must be receiving something from the search industry in exchange. This content is free in that it has a zero out-of-pocket cost—but the content is not costless to the user. Importantly, there are two types of users: firms and households. When firms use AI services, the services become an input into their production process, for example, when a salesperson uses a chatbot to translate a question into the customer's native language. Including this input changes the firm's measured inputs but does not impact the firm's value added and does not directly impact overall GDP. When households use AI services, the services become part of personal consumption expenditures and overall GDP increases by the value of the newly recognized consumer AI services.

We label the value of free AI services as $P_{Y,S}Q_{Y,S}$. In our example, this is written as $P_{Y,S}Q_{Y,S} = P_{XS,M}Q_{XS,M} + P_{S,U}Q_{S,U}$ so that the value of content equals the sum of values allocated to the manufacturing sector and the individual user (U) sector. We incorporate this into the economic accounting of production by assuming a barter transaction between the producers of the content and users of the content. With this barter transaction, the accounting relationships become:

$$P_{XS,M}Q_{XS,M} + P_{S,U}Q_{S,U} + P_{Y,I}Q_{Y,I} = P_{K,I}Q_{K,I} + P_{L,I}Q_{L,I} + P_{U,M}Q_{U,M} + P_{U,U}Q_{U,U}$$
$$P_{V,M}Q_{V,M} + P_{Y,M}Q_{Y,M} = P_{K,M}Q_{K,M} + P_{L,M}Q_{L,M} + P_{XI,M}Q_{XI,M} + P_{XS,M}Q_{XS,M}$$
$$P_{S,U}Q_{S,U} = P_{U,U}Q_{U,U}$$

It is more intuitive to explain this new system of equations by starting with the last equation. That equation is simply an accounting identity for household users: the value of content received equals the value of user services supplied by viewing advertising and giving up personal data. The second equation shows the manufacturing industry. The manufacturing industry uses the free content ($P_{XS,M}Q_{XS,M}$) in production, again think chatbots, and produces viewers for the information industry $P_{U,M}Q_{U,M}$.

The first equation shows the new outputs and inputs for the information sector. In our barter model, the information industry produces web search content ($P_{XS,M}Q_{XS,M} + P_{S,U}Q_{S,U}$) which captures the value of AI services themselves which were sold to the manufacturing industry as an intermediate input ($P_{XS,M}Q_{XS,M}$) and the household user sector as entertainment ($P_{S,U}Q_{S,U}$) in addition to advertising slots (the original $P_{Y,I}Q_{Y,I}$). To produce the advertising slots, the information industry relies on user services, which are represented by the value $P_{U,U}Q_{U,U}$, as an intermediate input in addition to the capital and labor already tracked. These three inputs are then used to produce the advertising services already tracked as output.

Like the standard GDP model given above, GDP is defined as gross output less intermediate input. This yields the new GDP identity:

$$P_{Y,M}Q_{Y,M} + P_{S,U}Q_{S,U} = P_{U,U}Q_{U,U} + \sum_{j\in\{I,M\}} P_{K,j}Q_{K,j} + P_{L,j}Q_{L,j}$$

The value of adjusted GDP equals the original value plus the added value of content produced by the information sector. On the income side, total income is augmented by the implicit payment for user services produced by households. A distinguishing feature of our approach is that we value the new content, ($P_{XS,M}Q_{XS,M} + P_{S,V}Q_{S,U}$), based on its production cost, as is standard in GDP and productivity accounting. This stands in stark contrast to approaches like Brynjolfsson et al 2018 and Hulten and Nakamura 2017 that sought to value consumer surplus. Our approach allows us to stay within the standard GDP and productivity measurement frameworks, so that we can evaluate the productivity impact using standard methods.

Before moving on to the empirical application, there are two final points that require discussion. The first is the actual value of the new content in nominal terms ($P_{XS,M}Q_{XS,M} + P_{S,V}Q_{S,U}$). In the context of the model specified above, this approach reduces to measuring the value of new content using the equation that the value of the services equals their cost of provision: $P_{XS,M}Q_{XS,M} + P_{S,U}Q_{S,U} = P_{Y,I}Q_{Y,I}$. Imposing this implies that $P_{S,U}Q_{S,U} = P_{Y,I}Q_{Y,I} - P_{XS,M}Q_{XS,M}$, that is the addition to GDP equals the production costs in producing the original content less the value that is used by the manufacturing industry. This split between individual and business use is an important part of our empirical implementation below, but we maintain the same basic assumption that the total value of free content equals the production cost in creating the content.

A second point in the new accounting is that for the two original sectors nominal value added is unchanged before and after the barter transaction. That is, the value of new output, whether it is the new user services produced by the manufacturing sector or the new content produced by the information sector, corresponds to the value of new input as a barter transaction. The increase in nominal output is due to recognizing the input of households into producing advertising services in exchange for content. Importantly, however, real output and measured productivity are not necessarily the same for industries under the modified model. The reason for this is the price of the new content ($P_{S,U}$) is not equivalent to the price of the user services bartered for content ($P_{U,U}$). The simple intuition for why content prices may not track user service prices is that they are distinct services with different production technologies. AI services, and also more conventional services like web search or podcasts, rely heavily on capital inputs like computers that experienced consistently falling prices for decades. In contrast, user services such as advertising viewership rely heavily on labor inputs that have experienced consistently rising prices for decades. The result of these different prices is that while nominal value added at the industry level is unchanged from the standard model, real value added grows because content output has grown much faster than real viewership input under our barter model. This growth rate difference captures the GDP and productivity impacts of free content.

The increase in nominal output is due to recognizing the input of households into producing advertising services in exchange for content. Our modified methodology does not require any major conceptual changes to the official guidelines for national accounting, *System of National Accounts 2025* (*SNA 2025*). The *SNA 2025* already counts noncash payments to workers as labor income *(SNA 2025*, Section 8.52), imputes cash values for barter transactions (*SNA 2025*, Section 4.49), imputes rental payments for owner-occupied housing (*SNA 2025*, Section 7.127), and imputes financial services for bank accounts (*SNA 2025*, Section 7.180). Just as with those transactions, we impute a value for free content and treat that value as a payment in-kind for user services. Since the household is not "employed" by the content producer, we treat the household production of user services as a form of production by an unincorporated household enterprise (*SNA 2025*, Sections 22.55). To minimize the deviation from the U.S. Bureau of Economic Analysis (BEA) official accounts, we do not consider the production process for user services within households. As a result, we only analyze the impact on measured TFP (which requires real outputs and inputs) within the private business sector. However, we do measure the impact on economy-wide GDP from the expenditure side by aggregating expenditure on free content with total GDP.[4]

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. Vanoli discusses this issue in A History of National Accounting (2005). Furthermore, this paper is an updated version of a previous paper which discussed both advertising-supported media and marketing-supported information (Nakamura et al. 2018).

The remainder of the paper discusses how we measure $P_{Y,S}Q_{Y,S}, P_{XS,M}Q_{XS,M}, P_{U,U}Q_{U,U}$ within the U.S. productivity accounts. We then apply these measures using our barter transaction model and compare these to the measures from the standard model.

[4] The intuition for why we cannot assess the impact on economy-wide TFP can be understood quickly by recalling the formula for aggregate TFP: $\Delta \ln T_{Agg} = \sum_{j \in \{I,M\}} \bar{v}_j \Delta \ln T_j$. Aggregate TFP growth is the weighted sum across all sectors of the economy including the user sector. We have not modeled the inputs to the household user sector, so we cannot calculate its productivity or aggregate productivity. Furthermore, we exclude the impact on the government sector because the large majority of government output is measured using input costs.

3. Accounting for Free Content within the U.S. Productivity Accounts

The actual system of U.S. accounts is significantly more complicated than the stylized model presented earlier. The starting point for our model application is the BEA-U.S. Bureau of Labor Statistics (BLS) Integrated Industry-Level Production Account that includes output and input information for 63 industries that make up GDP from the industry side. The stylized example focused on AI services, but our empirical analysis measures prices and quantities of content and user services for four separate types of free content: (1) printed newspapers, magazines, directories, mail, signs, and other physical goods; (2) television, radio, online videos, podcasts, and other non-AI audiovisual content; (3) web search, websites, video games, and other non-AI digital content; and (4) AI services and content created by AI. These subcategories were chosen because each has a different production process, and each is likely affected differently by technological innovations.

3.1 Advertising Revenue Associated with Free Content

The barter model presented in section 2.2 shows how the information sector resells the user services which it obtains in exchange for its free content. This resale of user services makes measuring the value of advertising-supported content relatively easy. Advertising revenue for each category of free content is directly available in the Economic Census and other government surveys.[5] Because these advertising revenues reflect both full and partial subsidies of the free content, the advertising revenues reflect the total value of free content. For example, web search is 100 percent paid for by advertising revenues, while many newspapers are only partially subsidized. Out-of-pocket spending on newspapers is already tracked in the standard accounts, so the advertising revenue accurately captures the free portion that is not already tracked.

Recall that total value corresponds to total production costs, so that this is a cost-based measure of the value of free content, just as in the experimental barter model above. Next, we allocate this revenue between other industries that use the content as business information (like the manufacturing industry in the model above) and individuals who use the content as consumer entertainment. We then apply best-available price indexes to split these values into price and quantity. The quantity indexes are relevant for assessing impacts on real growth and productivity, while the prices are relevant for estimating the impact on inflation. Note that each type of free content has its own output price and user service price.

This section measures the total value of advertising slots produced by information sector companies. We start out by identifying five advertising-related product lines in the Economic Census: (1) advertising space in printed publications; (2) television air time for advertising; (3) radio air time for advertising; (4) internet advertising; (5) and other advertising space, time, and similar services. For these five sold product lines, valuation is relatively easy because we do have arms-length transactions. Many information sector companies devote a portion of their advertising slots to in-house advertising of

[5] Our analysis of advertising-supported media focuses on industries in the Information sector. The small amount of advertising revenue earned by other industries is tracked with marketing-supported information.

subscriptions and other premium content. Between 2015 and 2025, smartphone game revenue grew from $4 billion to $69 billion, and in-house advertising is assumed to have tracked that growth. For years without Economic Census data, advertising revenue and in-house advertising are interpolated and extrapolated using both official government surveys and industry sources.

Advertising revenue as a share of nominal GDP is shown in Figure 1. Since 1995, digital media, both human-created and AI-created, has grown from almost nothing to more than 1 percent of nominal GDP. Over the same time period, print advertising shrank from 0.6 percent of nominal GDP to almost nothing. The growth of digital media is almost certainly responsible for most of the print decline. Classified advertising has moved from newspaper sections to websites and printed Yellow Pages are being replaced by web search. Between 1995 and 2025, audiovisual advertising, that is, radio and television advertising, rose from 0.5 percent to 0.7 percent of nominal GDP. The increase in free audiovisual content took place even as consumer spending on subscription television, audiovisual streaming, and audiovisual rental rose from 0.4 percent to 0.5 percent of nominal GDP.

3.2 Marketing Expenditures Associated with Free Content

The experimental barter model with marketing-supported free content is simpler than the model presented above for advertising-supported content. The reason is that marketing is a two-way transaction between the industry producing the marketing and the users. For example, any company that creates a website is exchanging free content on its website for users viewing marketing materials or giving personal data. In the earlier example, the manufacturing industry supplies free marketing-supported content directly to users without an information sector that serves as an intermediary.

While the model of marketing-supported content is somewhat simpler, measuring the value of marketing slots is significantly more complicated because there is not necessarily an arm's-length transaction tracked in the Economic Census. So, we infer output costs from input costs as we do for many investments in intangible assets. It is important to emphasize that all sectors of the economy can potentially produce marketing-supported information (e.g. corporate websites) while only the Information sectors produce advertising-supported content. All sectors of the economy can *use* both marketing-supported and advertising-supported content.

We start out by identifying nine marketing-related services 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) direct mail and distribution of advertising materials other than by mail in NAICS 5418; (5) signs and advertising specialties in NAICS 5418; (6) remaining marketing-supported information in NAICS 5418; (7) website development and hosting in NAICS 518 and 5415; (8) commercial photography in NAICS 5419; and (9) event sponsorship in NAICS 71. For these nine marketing-related services, valuation is relatively easy because we do have arm's-length transactions. In total, the Economic Census reports the $238 billion of revenue associated with these nine product line industry combinations in 2022.[6]

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[6] Previous paper drafts adjusted the Economic Census data for self-employment, underreporting, and misreporting. To simplify the calculations, this paper did not make those adjustments. Accordingly, neither the

Next, we use the Occupational Employment and Wage Survey (OEWS) data to impute the value of other marketing services. Most other marketing services are own-account production that is used in-house by companies without an explicit market transaction—but some of the other marketing services are secondary products that are sold by companies outside of the industries studied. The OEWS does not track individuals who are employed producing either own-account marketing or secondary product marketing directly, but it does report employment and earnings for selected industry and occupation combinations. We use earnings for marketing specialists in non-marketing industries as a proxy for in-house marketing services. For example, a writer employed at an automobile manufacturer probably produces in-house marketing services. Next, we multiply earnings for those specialists by an adjustment ratio taken from the Economic Census data to estimate total costs.[7] Our cost 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. This is the conceptually equivalent measure to the total costs used in the production of advertising-supported content and sold marketing services.

In total, we calculate that U.S. businesses created $723 billion of marketing output in 2022. This number includes $238 billion of marketing services purchased from the industry product line combinations studied, $360 billion of operating expenses devoted to other marketing production, and $124 billion of forgone profits that companies might have earned if they had sold their marketing output rather than using it in-house. Our previous paper draft calculated marketing output in 2012 and compared it with estimates for that same year by the research firm Outsell. That comparison found that our methodology produced a slightly higher level than the one estimated by the research firm, but qualitatively similar results. Our empirical results are qualitatively unchanged if we use Outsell's estimate as our benchmark for marketing expenditures.

Estimates of marketing expenditures for the Economic Census years of 2002, 2007, 2012, and 2017 are calculated using the same methodology described earlier for the 2022 benchmark year. A similar methodology was also used for the 2001 to 2023 period – the only difference is that the Service Annual Survey and the Annual Integrated Economic Survey are used as interpolators and extrapolators for the Economic Census revenue. After 2023, fewer official government surveys were available and therefore the methodology was adapted. Nominal revenue for the broad industry NAICS 5418, as reported in the Quarterly Survey of Services, is used as an extrapolator for marketing output from 2023 onwards. The exact level of free marketing content calculated for 2023 and 2024 is somewhat sensitive to the extrapolators, but the qualitative trends are not.

Historical estimates of marketing expenditures are extrapolated using a variety of sources. Most product lines are extrapolated using data from Sveikauskas et al. 2024. That paper used a variety of sources to track both purchased marketing services and own-account marketing back to the early 1900s.[8] That paper

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advertising revenue nor the marketing expenditures estimated in this paper draft are completely consistent with BEA's published national accounts.

[7] Website hosting has few labor costs and no specialist occupation associated with it. Accordingly, this paper uses the stock of IT equipment by industry as a proxy for in-house website hosting.

[8] The published paper focused on the post-1987 period, but data were collected going much further back.

found that own-account marketing generally tracked purchased marketing. Accordingly, this paper uses estimates of purchased marketing services by type from that paper as extrapolators for all types of marketing. Website development and hosting is extrapolated back to 1998 using aggregated earnings for network specialists and then extrapolated back to 1995 using internet advertising. Results are qualitatively similar when purchased marketing from the industry product line combinations studied, own-account marketing, and marketing as a secondary product are extrapolated separately. However, those calculations require more calculations and trends are more sensitive to the assumed ratio of total costs to earnings.

Figure 2 shows output of marketing relative to GDP over time. We find that marketing-supported information output has been larger than advertising-supported media output for the entire time period studied. In 1929, businesses created $3.0 billion in marketing-supported information, more than double the $1.1 billion of advertising-supported media in that same year. In 2025, businesses created $951 billion of marketing-supported information, almost double the $538 billion of advertising-supported media in that same year. 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.

3.3 Splitting Free Content by Type

Figures 1 and 2 both split free content between four output types: print, non-AI audiovisual, non-AI digital, and AI. The pre-2023 growth in both advertising-supported media and marketing-supported information is almost entirely driven by non-AI digital. After 2023, AI-created marketing content has also started to grow rapidly. Websites account for the largest portion of this non-AI digital marketing, but companies are also spending heavily on social media, smartphone apps, and other mobile marketing. Despite the recent explosion in digital marketing, neither the nominal growth rate for advertising-supported media nor the nominal growth rate for marketing-supported information are exceptional in the past decade. Advertising-supported media was 0.8 percent of nominal GDP in 1975 and marketing-supported information was 1.6 percent of nominal GDP in that same year. Since then, the nominal GDP share for advertising-supported media has increased at 0.02 percent per year and the nominal GDP share for marketing-supported information has increased at 0.02 percent per year. We have not yet fully identified a reason for the trend break in 1975. One related observation is that the intellectual property investment proportion rose from 1.6 percent in 1975 to 5.2 percent of GDP in 2025. 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.

3.4 Subtracting Noncontent Costs

Not all of the advertising revenue shown in Figure 1 nor the marketing expenditures shown in Figure 2 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 approximately half of print revenue and one quarter of audiovisual and digital revenue (Soloveichik 2013 a, b, c, d, and e). 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 of the same output type. Due to the shift away from print, noncontent costs have grown much slower than advertising or marketing costs.

3.5 Splitting Business Information and Consumer Entertainment

It is intuitive that free content like chatbots, web search, GPS navigation, and corporate webpages are potentially useful as a business input, and the model above makes clear that these uses should be split from consumer uses. Consumer uses are basically final demand, while business uses are intermediate inputs. Furthermore, business inputs impact the measured productivity of using industries. In this section we describe how we make this split for all industries in the U.S. productivity accounts.

Advertising-supported media is split between consumers and businesses using a variety of sources. For print media, we use genre data reported in the Economic Census and other sources to split consumer media from business media. Next, we assume that advertising-supported audiovisual content and video games are almost entirely targeted towards consumers for leisure use. For digital media, we use survey data from Forrester Research. Between 2007 and 2016, Forrester Research asked survey respondents to report both “work internet” time and “personal internet” time.[9] Before 2007, we use data from the Current Population Survey to track home internet access as a proxy for personal usage. We then adjust those consumer shares of total internet time to account for audiovisual internet time, which is assumed to be almost entirely consumer, and user-generated content time, which is assumed to be amateur and therefore out of scope for GDP. Finally, we extrapolate the consumer share of internet time forward using survey data from Ofcom and expert judgment. For now, AI-created media is allocated using the same methodology as non-AI audiovisual media and non-AI digital media. In short, we allocate the value across all industries in the BEA-BLS Integrated Industry-Level Production Account using estimates of internet time spent by industry.

Marketing-supported information is more difficult to allocate between consumers and businesses. To start out, we assign marketing bundled together with media using the same allocations 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. We use research purchased from the firm Outsell to split print and audiovisual marketing which is not bundled with media.[10] Finally, we allocate digital marketing like corporate webpages, social media accounts, or downloadable apps using the split developed earlier for online media.

Figures 3 and 4 show free consumer entertainment over time. Both of these series display the same qualitative trends as the overall free content shown in figures 1 and 2. However, the level of digital entertainment is less than half the level of digital content. Both the absolute revision to nominal GDP

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[9] We also use Forrester survey data to split free business content between the 63 using industries.

[10] Their annual data are somewhat noisy, so we averaged across the reports purchased. Outsell also tracks digital marketing, but we do not use their B2B versus B2C splits because business often use consumer content like Waze.

levels and the absolute revision to GDP growth are very sensitive to the source data and the assumptions used to estimate the consumer share of digital content. Nevertheless, the qualitative impact of including free digital content is similar for all plausible consumer share estimates.

4. Prices for Free Content and User Services

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

Similarly, price deflators for user services should track production costs for the same amount of viewership or personal data over time. But advertisers and marketers constantly demand new viewers and new data over time. Thus, we cannot track the cost of showing the same commercial to the same viewer over time. In addition, both viewership and personal data are nonrival goods with difficult-to-define units of output. Is a switch from a few long commercials to many short product placements an increase or decrease in total user services? Finally, user service quality depends on their future purchases—but even the users may not know which products or services they will buy soon.

Complementary goods add more complexity. Both free content quality and user service quality depend on the durable goods used in the production. For example, the quality of free digital content is enhanced by an advanced smartphone with faster processing and better screens. Conversely, advanced smartphones may be more efficient at collecting personal data than early smartphones. In addition, the quality of "free" digital content and digital user services are enhanced by network effects,[11] cultural expectations, or other factors. Similarly, the switch from black and white media to color media may have produced both a better audience experience and also better response to advertisements.

4.1. Prices for Content Creation

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. For non-AI digital content, our price index for software is an equally weighted average of BEA's price index for own-account software (National Income and Product Accounts (NIPA) table 5.6.4, line 3) and a price index for cloud computing services that is based on Byrne, Corrado, and Sichel 2018.[12] For AI-created content, our price index for software is taken

[11] Network effects probably raise quality growth of digital content over time, and therefore lower its quality-adjusted price growth. The impact of network effects on other content categories is more ambiguous.

[12] After 2016, an index posted on Datahub suggests that cloud computing prices were quite stable. Information on cloud computer service prices before 2009 was not located. For now, this paper uses BEA's price index for computers and peripheral equipment (NIPA table 5.5.4, line 4) as an extrapolator.

from industry research that shows that the datasets used for training AI have doubled in size every eight months (Gil and Perrault 2025). AI content prices are calculated as an equally weighted average of the AI software index and the price index for cloud computing services described earlier. Note that these price indexes are output prices and therefore include some productivity growth over time. We assume that the internet publishing companies that produce advertising-supported online media and the marketing divisions that produce marketing-supported online information enjoyed similar productivity growth as software publishers and cloud computing services.

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. In addition to the writing costs, print media also requires communication in order to deliver printed material to users. We use a price index for marketing mail from previous research on marketing as an intangible asset (Sveikauskas et al. 2024). We assign book originals an 85 percent weight and marketing mail delivery a 15 percent weight and calculate the price as a geometric average.

The two inputs to non-AI audiovisual content are: programming, which we breakdown further into sports and nonsports programs, 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), local landline telephone services (NIPA table 2.4.4U, line 283), cellphone services (NIPA table 2.4.4U, line 285) as proxies for the inputs listed earlier. We then assign sports programs a 13.3 percent weight, nonsports programs a 53.3 percent weight, and the two telecommunication services the remaining weight with the share for local landline telephone services based on the cable television share of audiovisual content. Prices are then calculated as a geometric average of these component price indexes. AI-created audiovisual content is assumed to decline in price at the same rate as AI-created digital content.

Figure 5 shows the price indexes relative to the GDP price index. We find that non-AI digital prices fell approximately 8 percent per year from 1995 to 2017 and then stabilized. This decline was due to both falling hardware prices and the spread of efficient server farms which dramatically decreased cloud computing prices relative to hardware costs. Even more dramatically, AI-created content prices fell 41 percent per year from 2022 to 2025. This decline is due to a rapid ramp-up of AI model investment and is likely to stabilize soon. In contrast to the falling digital content prices, print content prices have been rising steadily since the early 1980s. Finally, human-created audiovisual content has fallen slightly relative to GDP prices. Intuitively, human-created audiovisual content uses more computers than print content and fewer computers than digital content.

4.2 Prices for Viewership Services

We calculate viewership prices as nominal content value divided by viewership quantities. Each content type is calculated separately. Between 2022 and 2025, the number of AI users more than quadrupled. Viewership prices for AI are simply free AI content divided by the number of users. The other three viewership prices are more complex. Viewership prices for non-AI digital content are calculated as a chain weighted average of search viewership prices[13] and nonsearch viewership prices. [14] Similarly, the viewership price for print content is calculated as a chain weighted average of print newspaper viewership prices, print periodical viewership prices, and print mail viewership prices. And the viewership price for audiovisual content is calculated as a chain weighted average of radio listenership prices, television viewership prices, and movie theater promotional viewership prices.

Figure 6 shows the implicit price indexes for user services from 1929 to 2025 relative to the GDP deflator. Viewership prices for AI content were highest when AI was introduced in early 2020s and then fell in 2023. There is also a similar high early price for non-AI digital content during the dot-com bubble and perhaps a similar high early price for television in the late 1940s. The Silicon Valley business model of "ubiquity first, revenue later" provides one lens to interpret this early spike. Companies spent heavily building brands and creating content to attract early users because the companies believed that later users would gravitate toward products and services with a preexisting network of users. Since 2012, the viewership price for both non-AI audiovisual and non-AI digital has increased noticeably, reflecting growth in spending on content that is much faster than the growth in the time spent viewing content.

5. The Impact of Free Content on GDP, Inflation, and Productivity

We quantify the impact of free content on GDP, inflation, and productivity by constructing new price and quantity index numbers including the new content. Relating this to the model in section 2.2, this means including the price and quantity of entertainment consumed by individuals ($P_{S,V}Q_{S,V}$) in the GDP and inflation aggregates, and weighting up the new TFP growth rates for each sector.

5.1 Aggregate GDP Prices

Figures 7 and 8 show that both non-AI digital and AI content lower overall GDP price growth in recent years. Even if one were to argue that free content is somehow bundled with paid content and therefore already included in nominal GDP, the price declines shown in figures 7 and 8 would still apply. Accordingly, tracking free digital content impacts the national accounts even if the barter model would be rejected.

5.2 Aggregate GDP Quantities

Figures 9 and 10 show that all types of free content raise overall GDP quantity growth. Between 1929 and 2025, average growth increases by 0.05 percentage point per year when free content is included in consumer entertainment. Furthermore, the growth increase associated with free content has been

[13] Information on the number of mobile searches was not located, so the viewership price index focuses on content per desktop search. The desktop search series displays unusual behavior after 2023, so recent viewership prices are only based on the viewership price for nonsearch digital content.

[14] Time spent online captures both growth in the number of users and also growth in time per user. Total online time is adjusted to remove time spent using AI services, time enjoying subscription audiovisual content like Netflix, and time spent with user-generated content like X. Time spent with free online audiovisual content like Youtube is tracked as part of audiovisual time.

growing over time. Including free content increases average growth between 1929 to 1995 by 0.04 percentage point per year, increases average growth between 1995 to 2022 by 0.09 percentage point per year and increases average growth between 2022 and 2025 by 0.22 percentage point per year. These increases in real GDP growth are much larger than the increases in nominal GDP growth shown in figures 3 and 4. Intuitively, the plummeting price for digital content reinforces the explosive nominal growth of digital content.

5.3 Aggregate TFP

Figure 11 shows that TFP growth after 1995 rises when free content is included in the productivity accounts for the private business sector.[15] In 2025, the level of TFP would have been higher by 0.6 percentage points, and in 1995, it would have been lower by about 2.1 percentage points. Thus, over the period 1995–2025, TFP would have grown by about 0.09 percentage point per year faster than the currently published growth rate; it would have grown 0.18 percentage points per year faster during the post-Covid recovery period of 2022–2025, 0.07 percentage point per year faster in the recovery period of 2010–2016, and 0.04 percentage points per year faster during the jobless recovery period of 2001–2007. These TFP revisions are qualitatively similar to the GDP quantity revisions shown in figures 9 and 10.

The impact on measured TFP from including free digital content shown in figure 11 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 2025, free digital content accounts for only 3 percent of the overall economy. Accordingly, higher TFP growth for digital content creation has only a modest impact on aggregate TFP growth. In contrast, the popular literature assigns weights in proportion to time use. By 2025, Americans spent nearly one-third of their time online. If we used that weight to value online content (whether digital or audiovisual), 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.

Figure 11 also shows that TFP growth before 1995 falls slightly when free content is included in the productivity accounts for the private business sector. It may be true that figures 9 and 10 show that GDP quantities rise when free content is included in consumer entertainment. But this growth can be more than explained by an increase in viewership quantities. In particular, television viewership grew from almost nothing in 1948 to the most important leisure activity in 1995. The trend break around 1995 is even more striking when historical viewership quantities are adjusted for quality factors like color television ownership. The revisions to both recent TFP growth and historical TFP growth noticeably ameliorate the recent productivity growth slowdown but do not reverse it.

[15] Business usage of free content has an offsetting impact on measured TFP for the content-producing industry and content-using industry. As a result, the aggregate results are driven by free consumer content.

5.4 Industry-Level Total Factor Productivity

Figure 12 shows the impact on TFP for the industries associated with advertising-supported media. The publishing sector, which produces both print media and video games, shows a slight increase in productivity growth before 1975. And the broadcasting and telecommunication sector, which produces audiovisual media, shows a slight decline in productivity growth before 1975 and a slight increase in productivity growth after 1995. Because these two productivity revisions are so small, the sign is sensitive to changing the treatment of viewers switching from black and white to color or other assumptions. In contrast, the data processing and hosting sector, which produces digital media, shows a large increase in productivity growth after 1995. To be clear, the aggregate productivity revision shown in figure 11 is larger than can be explained by the industry productivity revisions shown in figure 12. Many industries outside the media sector produce marketing-supported content.

6. Beyond the GDP and Productivity: Amateur User-Generated Digital Content

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 websites would likely not exist without user-generated content. Some apparently user-generated content is generated by on-the-job marketing specialists – and therefore is included in the marketing output studied earlier. But user-generated content that is genuinely generated by amateurs is out of scope of our previous analysis. Thus, to provide comprehensive coverage of the production value of free digital content, we extend the scope of our analysis to cover amateur user-generated content. To provide a concrete example: X, which was once Twitter, is currently a free social media platform whose main source of revenue is advertising. In the production accounts, this advertising revenue is the nominal value of X's output. While it may be tempting to think that the value of amateur content is reflected in X's advertising revenue, the value of the user-generated content is not part of X's costs and therefore not included in X's revenue.

Amateur user-generated content is different from the advertising- and marketing-supported content studied earlier in this paper. User-generated content is produced without the expectation of revenue or other material rewards, and so its creation is considered household production and is out of scope for official GDP. Conceptually, user-generated content creation is a type of volunteer service which is intended to benefit a community, the environment, or another social purpose. Like other volunteer service, amateur content is considered part of the household sector and therefore not counted in official GDP.

Our starting point 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. Our primary dataset is the Technology User Profile (TUP) data produced by Metafacts. 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. 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 is 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 14 percent a year. At the aggregate, estimated content generation time increased from 13 billion hours in 2006 to 76 billion hours in 2016,[16] or the ratio of hours spent generating content to economywide hours worked increased from 3 percent in 2006 to 22 percent in 2016. Precise information on the time spent creating content after 2016 was not located. However, sources suggest that the total time spent on social media sites plateaued from 2017 onwards.

An optimistic approach might assume that amateur content generators are just as productive per hour as professional programmers; this would value user-generated content at $2.5 trillion in 2016. 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. 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 $120 billion [($1.5 trillion-$1.5 trillion*0.2)/10] to $200 billion [($2.5 trillion-$2.5 trillion*0.2)/10] annually from 2006 to 2016. This growth is large enough to completely offset GDP stagnation.

A conservative approach might assume that amateur content creators are just as unproductive as 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 professional wages. Earlier in this paper, we estimated that television viewers "earned" approximately $1.48 of content for every hour they spent watching commercials in 2016.[17] If we use the same $1.48 hourly output to value user-generated content, we calculate that Americans contributed $113 billion of labor inputs, about a third of the estimated value for free digital content in that year.

Our preferred approach relies on a paper that studied the wage impact of introducing Facebook to college campuses (Armona 2025). That paper found that students who were given access to Facebook in

[16] It is difficult to measure total hours spent on user-generated content. Due to limited data and as a first pass, we use a simple methodology. We allocate time spent online (as measured by the TUP) to online content generation and other time using the proportion of activities which generate "content." It is possible that a few people are creating content offline which is not tracked in the TUP. We do not study that content creation in this paper.
[17] This $1.48 includes both advertising revenue earned by the television station and also marketing costs associated with television programs (like sponsorship of sports events shown on television) and marketing costs associated with television commercials.

2004 had 1 percent higher earnings a decade later.[18] This paper multiplies that 1 percent earnings increase with BEA's estimates of both labor compensation and net operating surplus to calculate that social media might have increased personal income by $137 billion in 2014. This works out to an hourly rate of $2.10 for user-generated content. This is much lower than the hourly rate for employment in the market sector but higher than the hourly rate for television viewership. This intermediate hourly rate likely reflects the intermediate level of mental effort involved in creating content compared to working in the market sector and television viewership. Before and after 2014, this paper uses hourly earnings of television viewership as an extrapolator.

Figures 13 and 14 show user-generated content relative to overall household production. In nominal terms, the value of user-generated content stabilized at approximately 1 percent of nominal GDP from 2016 onwards. However, this stability does not mean that user-generated content is a stagnant sector. Many of the AI tools associated with the transition from Web 2.0 to Web 3.0 are designed to allow ordinary people to create high quality content on their own. Figure 14 shows that quantities of non-AI user-generated content have been growing steadily since 2005 and quantities of AI user-generated content have been growing very rapidly since 2020.

7. Conclusion

The free digital economy poses many challenging questions for understanding and measuring the sources of economic growth. We have addressed one important difficulty: how to account for content when there is no explicit payment from the users of the content to the suppliers of the content. We have demonstrated that many of the measurement issues can be addressed by a relatively simple tweak to the current measurement methodologies: accounting for free content as a barter transaction. Important context for our work is that digital content is not the first content category to be subsidized by advertising and marketing.

We use the barter transaction methodology to measure the impact of advertising-supported media and marketing-supported information, including AI, on GDP. We find that including free content in consumer entertainment has a substantive impact on recent GDP quantity growth with trend breaks around 1995 and 2022. Including free content increases average GDP quantity growth between 1929 to 1995 by 0.04 percentage point per year, increases average growth between 1995 to 2022 by 0.09 percentage point per year, and increases average growth between 2022 and 2025 by 0.22 percentage point per year. The trend break around 1995 is likely due to the development of the internet and the trend break around 2022 is likely due to the development of AI.

We also use the same barter transaction methodology to measure the impact of free content on industry level productivity. Just like with GDP quantities, we find trend breaks around 1995 and 2022. But the 1995 trend break is even stronger because tracking free content before 1995 actually lowers historical productivity growth.

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[18] These higher earnings are from 0.6 percent higher wages and 0.4 percent higher employment. Armona argues that the higher employment is due to easier job search rather than less household production. Accordingly, this paper uses the full earnings increase in its analysis.

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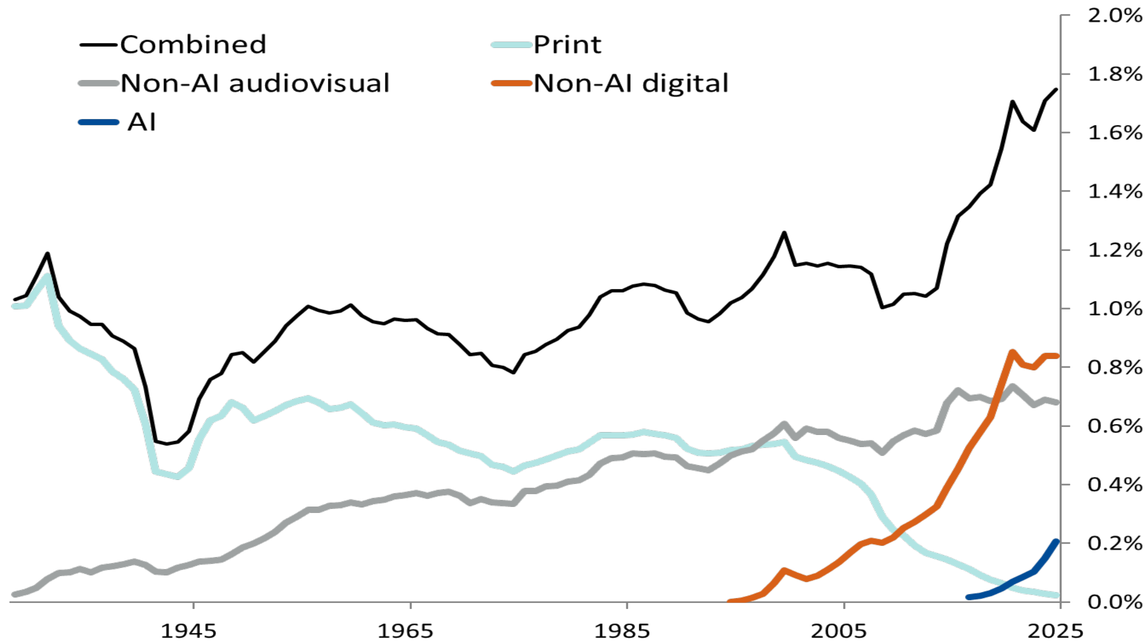
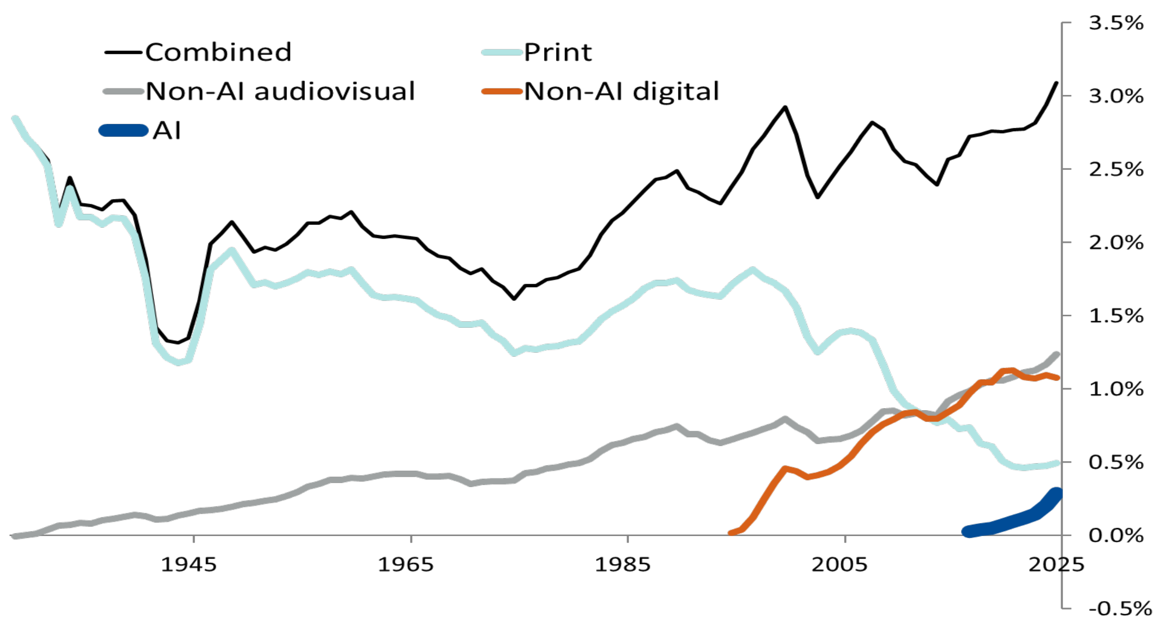
Figure 1: Nominal Revenue from Advertising-Supported Media



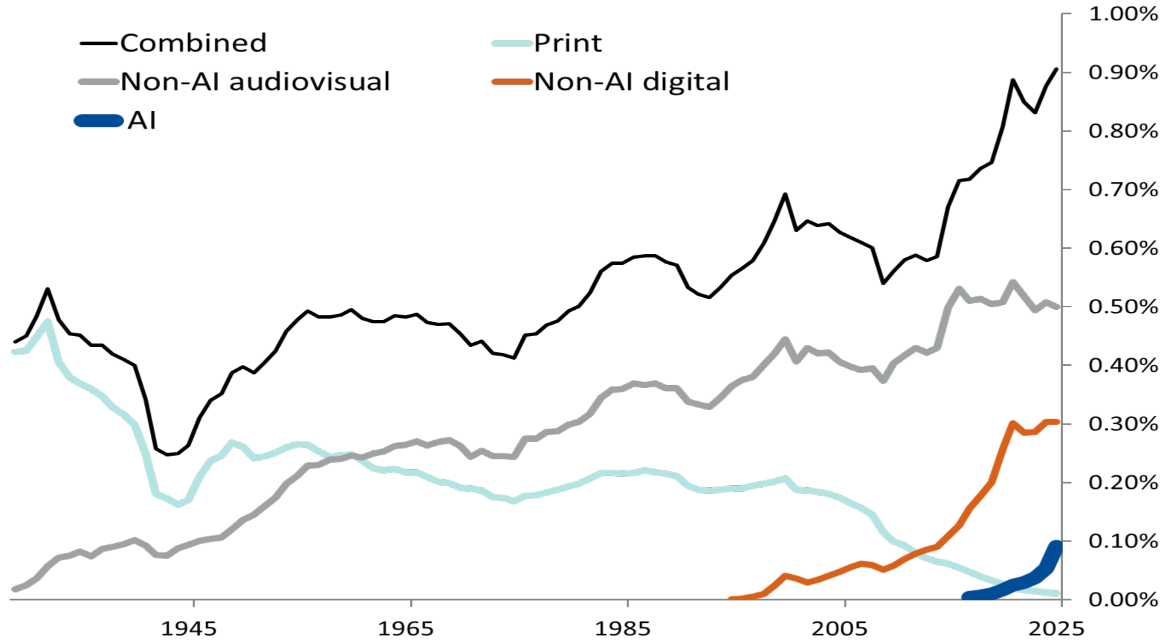
Note: Authors' calculations. Share of nominal GDP.

Figure 2: Nominal Expenditures on Marketing-Supported Information



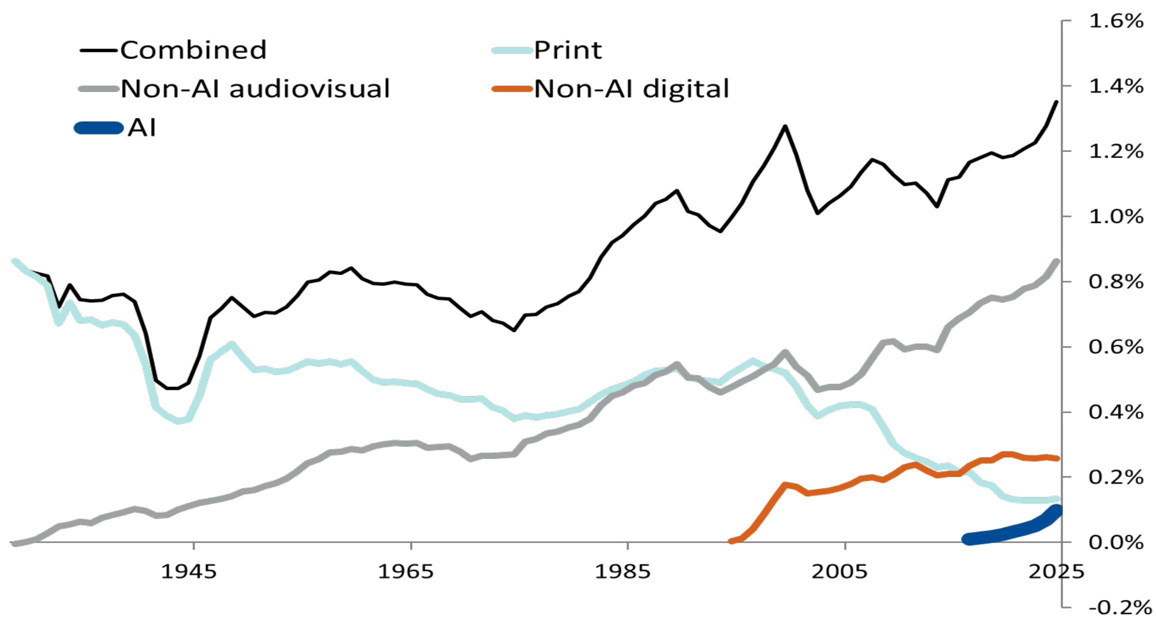
Note: Authors' calculations. Share of nominal GDP.

Figure 3: Advertising-Supported Consumer Entertainment



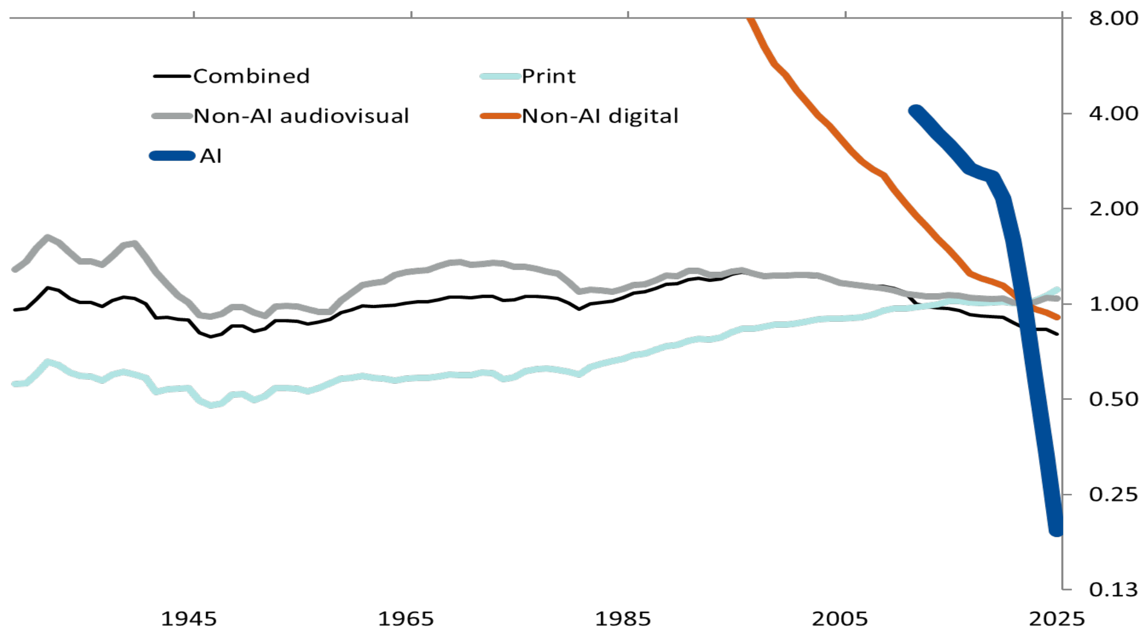
Note: Authors' calculations. Share of nominal GDP.

Figure 4: Nominal Marketing-Supported Consumer Entertainment



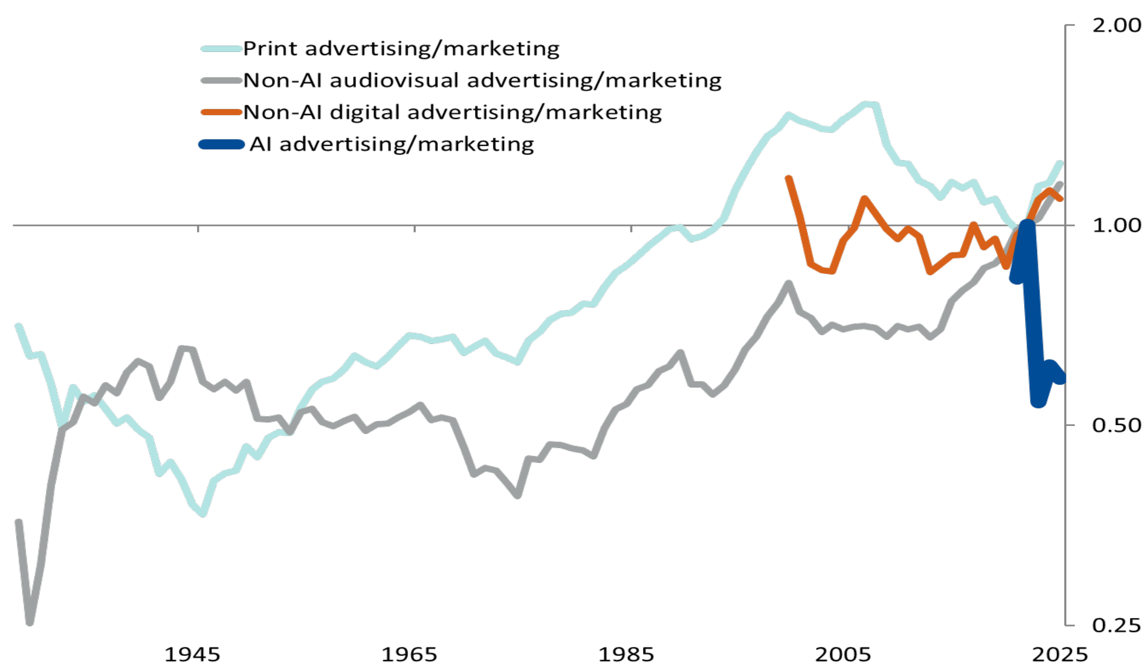
Note: Authors' calculations. Share of nominal GDP.

Figure 5: Content Creation Costs Relative to Overall GDP Prices



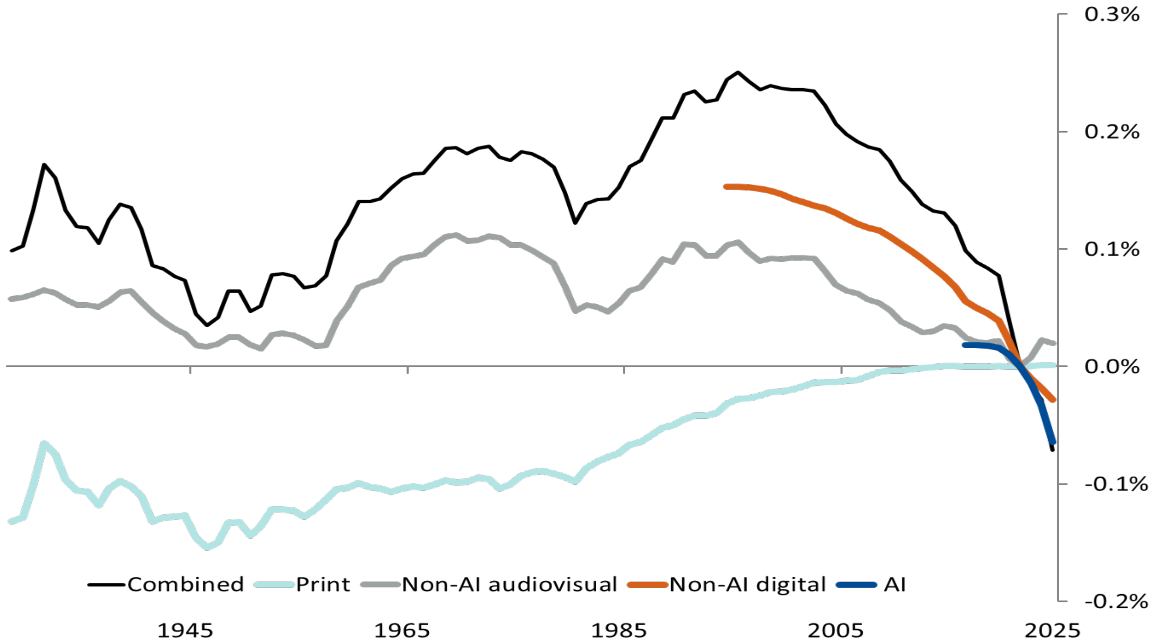
Note: Authors' calculations. Content price index relative to the GDP deflator, normalized to zero in the base year 2022. Log scale.

Figure 6: Viewership Compensation Relative to Overall GDP Prices



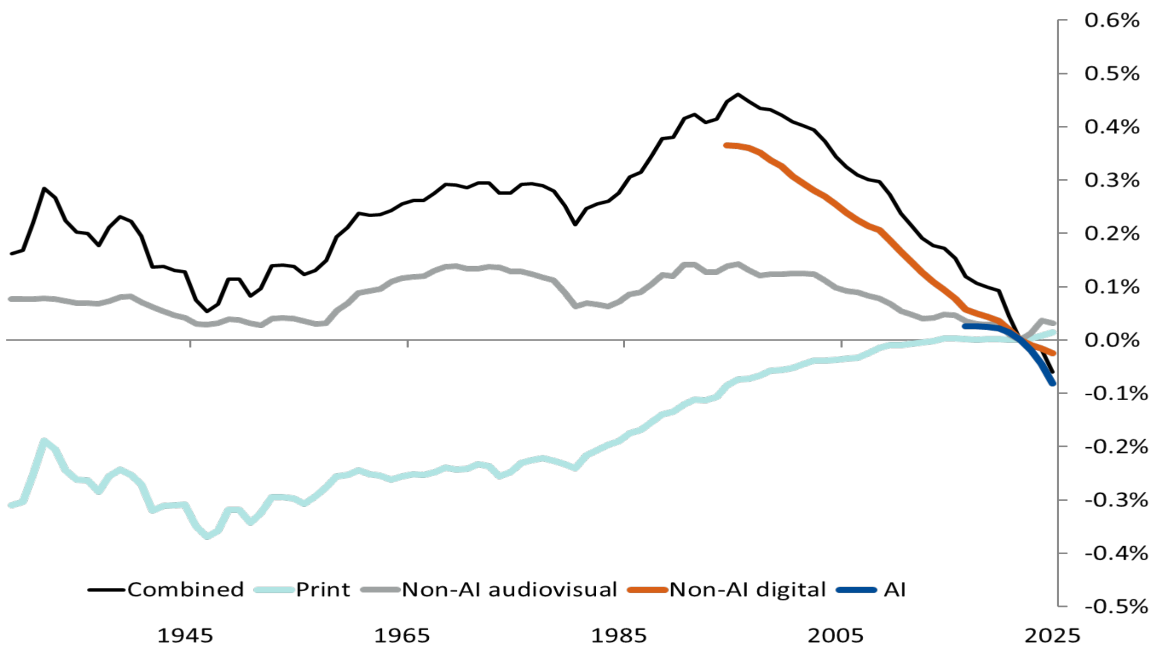
Note: Authors' calculations. Viewership price index relative to the GDP deflator, normalized to zero in the base year 2022. Log scale

Figure 7: Revision to Overall GDP Prices from Advertising-Supported Consumer Entertainment



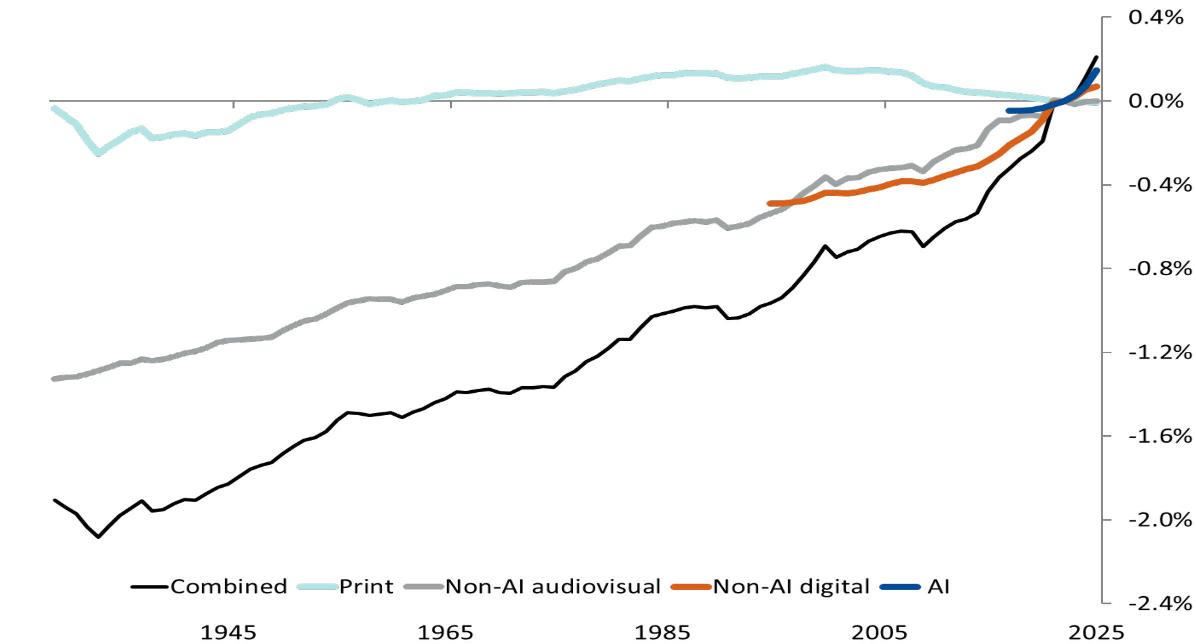
Note: Authors' calculations. Cumulative impact on the overall GDP prices normalized to zero in the base year 2022.

Figure 8: Revision to Overall GDP Prices from Marketing-Supported Consumer Entertainment



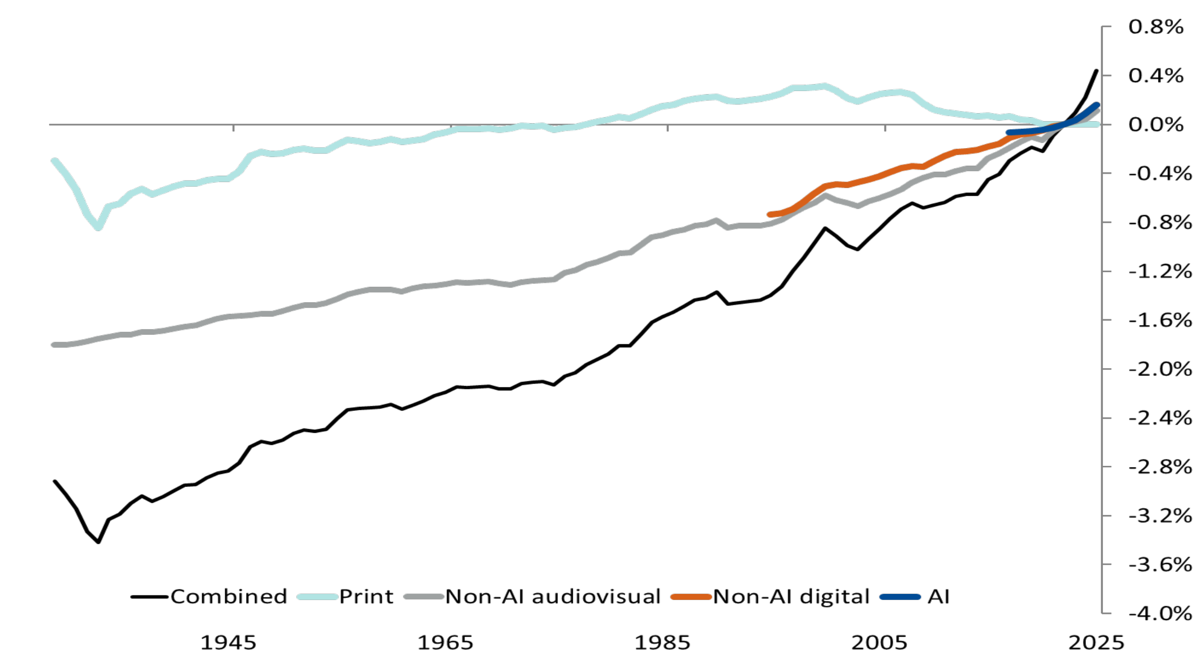
Note: Authors' calculations. Cumulative impact on the overall GDP prices normalized to zero in the base year 2022.

Figure 9: Revision to Overall GDP Quantities from Advertising-Supported Consumer Entertainment



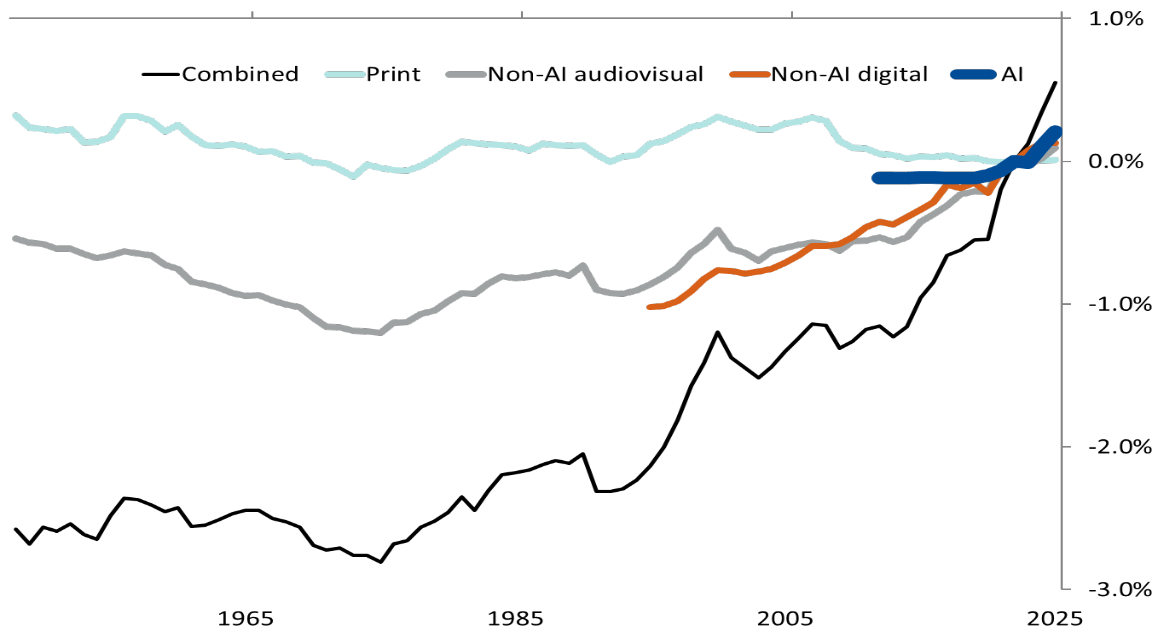
Note: Authors' calculations. Cumulative impact on the real GDP level, normalized to zero in the base year 2022.

Figure 10: Revision to Overall GDP Quantities from Marketing-Supported Consumer Entertainment



Note: Authors' calculations. Cumulative impact on the real GDP level, normalized to zero in the base year 2022.

Figure 11: Aggregate Productivity Impact of Free Content



Note: Authors' calculations. TFP index relative to the original TFP index, normalized to zero in the base year 2022.

Figure 12: Productivity Impact of Free Content for Select Industries

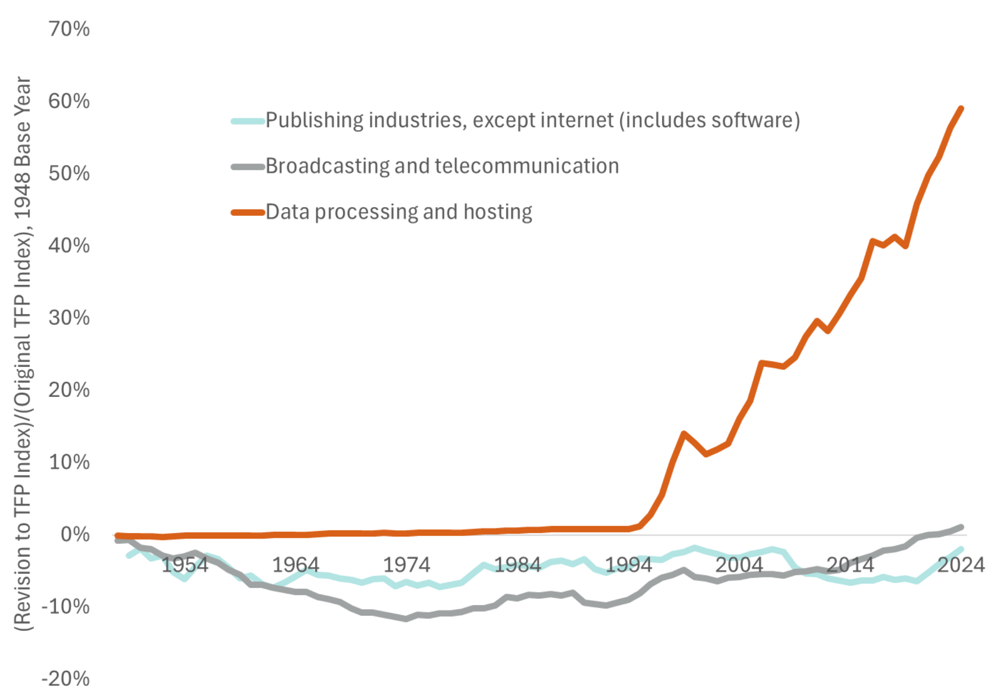
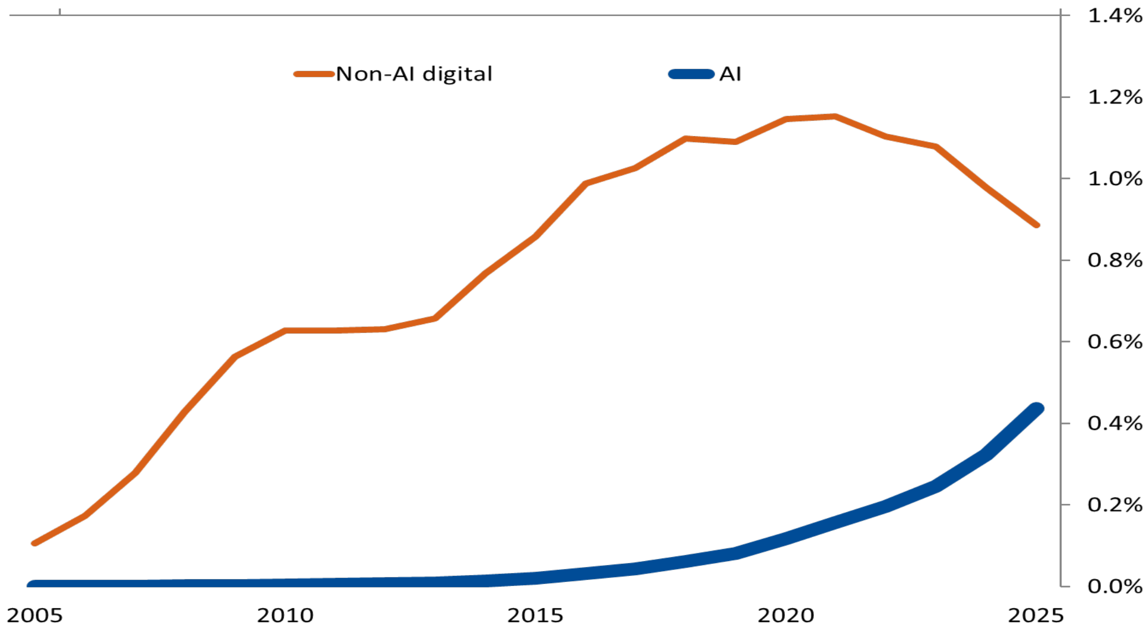
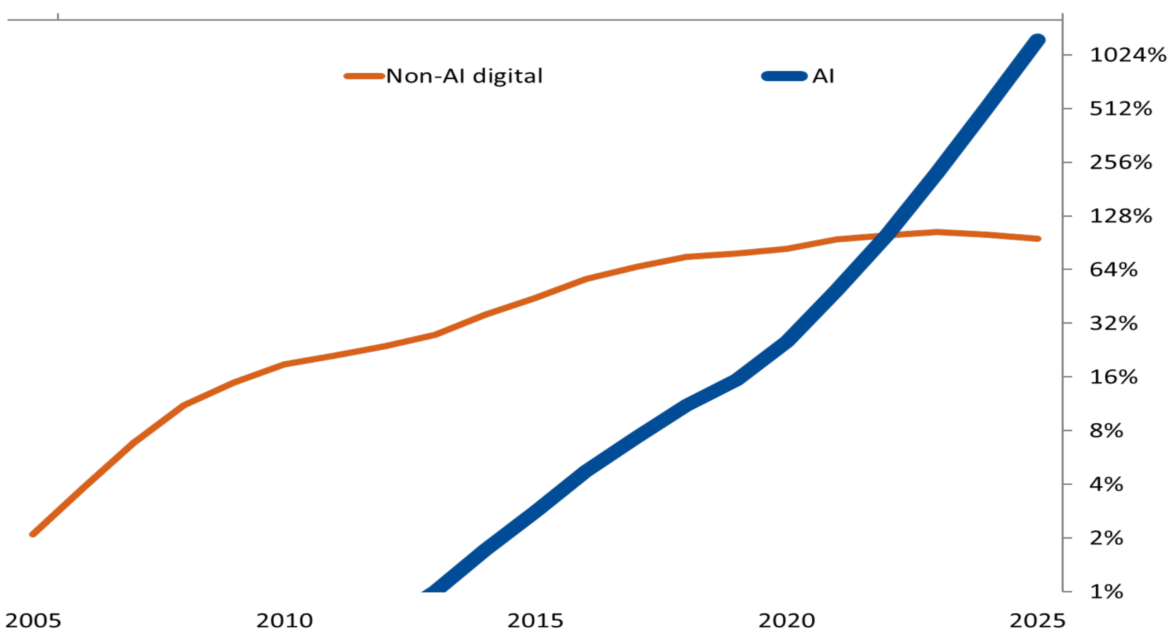


Figure 13: Nominal User-Generated Content



Note: Authors' calculations. Share of nominal GDP.

Figure 14: Quantity Indexes of User-Generated Content



Note: Authors' calculations. Quantity index relative to the GDP quantities, normalized to 100% in the base year 2022. Log scale.