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DISCUSSION PAPER

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Keywords: Intangibles, depreciation, SNA, capital stock, Google Trends

JEL classification: C80, E01, E22, O34, O47

John Lourenze Poquiz, King's College London
john_lourenze.poquiz@kcl.ac.uk

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King's College London
Strand
London
WC2R 2LS
United Kingdom
www.escoe.ac.uk

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†King's Business School, King's College London, Bush House, 30 Aldwych, London WC2B 4BG. Email: john-lourenze.poquiz@kcl.ac.uk.

1 Introduction

One of the reasons why statistical agencies present Gross Domestic Product instead of Net Domestic Product as their headline measure of economic growth is the difficulty of measuring depreciation. While net figures arguably better reflect welfare changes as compared to gross figures (O'Mahony & Weale, 2021; Oulton, 2004; Stiglitz et al., 2009; Division, 2023; Weitzman, 1976), statistical agencies often find it difficult to separate the value of depreciation from gross operating surplus (Division, 2023; Stiglitz et al., 2009). This is true for many categories of physical capital assets, but the challenge is more pronounced for intangible assets such as research and development, creative originals, and software, where the physical decline in the condition of the asset cannot be observed.

There is growing evidence that suggests that advanced economies are strongly reliant on intangible investments as a source of growth and productivity. Corrado et al. (2009) demonstrated that integrating intangibles into economic measures enhanced observed output per worker growth in the US. Additionally, Corrado et al. (2014) revealed that intangibles' impact on labor productivity growth surpasses labor quality's contribution. Research also suggests that intangible capital expansion correlates with total factor productivity gains (Corrado et al., 2022; Haskel et al., 2018). Moreover, the data shows that for sectors such as the Information and Communication Industry (ISIC code J), investments in intangibles have outstripped investments in tangible capital for some industries in the past two decades (see figure B.2).

In light of the increasing body of research underscoring the crucial role of intangible investments in contemporary economies, the necessity to comprehensively quantify both intangible investments and the accumulation of intangible assets is becoming apparent. There are various strategies for measuring intangible investments. Van Criekingen et al. (2022) provides a comprehensive review of the modern approaches for the measurement of intangible assets. This review also highlights intricate challenges inherent to aspects of the measurement process, notably pertaining to issues such as depreciation and price deflators. For depreciation, it is the difficulty of observing the asset service life that makes the measurement exercise particularly challenging. Current approaches involve making assumptions on the service life of these assets (Corrado et al., 2009), surveys, or using projected future cash flows from production (Huang & Diewert, 2011; Soloveichik, 2010), which present their own difficulties.

Simulations conducted by Pionnier et al. (2023) show that the choice of depreciation rate for the estimation exercise largely affects the estimates of the capital stocks, and by extension, other aggregates such as productivity statistics. As such, it is imperative that the challenge of measuring depreciation should be addressed in order to accurately account for growth in the modern economy.

In this study, we develop a methodology for measuring the depreciation of intangible assets using data from Internet sources. In particular, we employ information from Google Search Volume (GSV), popularly known as Google Trends (trends.google.com), to generate estimates for the depreciation rates of software and creative originals. One can view depreciation as a form of obsolesce. As software and creative originals become obsolete, their ability to generate future output/revenues diminishes. GSV is potentially a practical way of gauging the popularity of intangible assets. For instance, if a large number of internet users search for the name of a particular movie, then we can assume that the movie is popular. As the number of searches fades over time, it follows that the movie's popularity is fading as well, along with its ability to produce future revenues. Often, the number of searches would peak at the month and year of a movie's release. Searches fade gradually following its release.

We assume that the decay in the search index is directly tied to obsolescence, which we argue is an appropriate measure of depreciation. In our analysis, we employ Poisson Pseudo-Maximum-Likelihood (PPML) and negative binomial regressions to estimate the rate of decline of GSV for a sample of software and movie titles. Our findings reveal a depreciation rate for software originals ranging from 13.4 to 19.4 percent. This is lower than the estimates typically employed by statistical agencies, which is around 20 to 25 percent. In contrast, estimates for movies are comparable to estimates by statistical agencies, notably the US and Germany. Furthermore, our research shows that searches for recently released movies and software exhibit a steeper downward trajectory compared to movies released earlier, highlighting the need to regularly update depreciation rate estimates. We also find that if we apply the depreciation rates we generated from this methodology to estimate capital stock, TFP growth for the Information and Communication industry would be higher for non-crisis years, particularly from 1996 to early 2008, and again from 2011 to the end of 2016.

This study contributes to the literature on addressing the challenges related to the accounting of intangible assets. There have been various proposals on how to capture intangible capital (Van Criekingen et al., 2022; J. Martin, 2019; Soloveichik, 2010; Corrado et al., 2009). Corrado et al. (2009) examines how the inclusion of intangibles would affect Macroeconomic aggregates in the US. This exercise incorporates non-SNA intangibles such as brands and firm-specific resources. Soloveichik (2010) provides a set of methodologies for the estimation of investments in artistic originals in the US. Her paper includes a methodology to estimate the depreciation of creative originals using the decline in their net present value. This approach requires an assumption of the asset's future revenue streams. Nadiri & Prucha (1996) proposes methodologies for measuring depreciation rates for Research and Development. The work outlined by J. Martin (2019) details the initiatives pursued by the UK's Office for National Statistics to address the measurement challenges associated with intricate intangibles like in-house branding investments, employer-sponsored training outlays, and in-house investments targeting organizational capital. These assets are currently not captured by conventional National Accounts estimates.

This study extends the literature in three ways. First, we provide a methodology for the estimation of depreciation using readily available data. Except for Soloveichik (2010) and survey-based approaches, most efforts rely on making assumptions about asset lives. Our methodology instead assumes the Google Trends results correlate with popularity, an indicator of the asset's ability to generate revenue streams for the asset owner, and consumer value for the households. We evaluate this hypothesis by testing the predictive power of GSV results on movie revenues. We also provide a methodology that can regularly be updated to adjust to changing preferences and economic conditions. Many statistical agencies and researchers rely on static depreciation rates that are rarely updated. Our methodology would allow for the estimation of depreciation rates for assets released at different periods. Changes in technology such as the availability of low-cost streaming and piracy have drastically changed how consumers experience and access media. This has led to many changes in the industry, including the shortening of the theatrical window (Ahouraian, 2021). The impact of this change is likely not reflected by depreciation rates that are rarely updated. Our methodology also has the advantage of being flexible for the adoption of different dimensions such as geographic coverage and asset classes.

Second, our methodology captures the depreciation of original software for reproduction. Survey-based approaches, where firms are asked the expected service lives of the software they employ in production likely capture the depreciation of software copies. The literature and current practices provide little information on the depreciation of original software (e.g.. the decline in the value of the Microsoft Office program to Microsoft). In an age where software as a service is becoming more prominent[1], further exploration into the dynamics of original software depreciation is essential for understanding its economic implications and informing more accurate accounting practices.

Third, we also contribute to the literature on the mismeasurement hypothesis on the productivity puzzle. The continued slowdown in productivity in most developed countries following the 2008 financial crisis has been widely documented using both macro and micro-level data (Riley et al., 2015; Barnett et al., 2014; Goodridge et al., 2018). We examine the impact of changing the asset life on estimates of capital stocks and total factor productivity. The mismeasurement of outputs and inputs has frequently been cited as a potential contributor to the *observed* productivity slowdown (Goodridge et al., 2013a; Riley et al., 2018; Fernald & Inklaar, 2022; Roth, 2019). However, some scholars argue that mismeasurement accounts for only a relatively small portion of the slowdown. For instance, Syverson (2017) notes that "the empirical burdens facing the mismeasurement hypothesis are heavy, and more likely than not, much if not most of the productivity slowdown since 2005 is real." Similarly, Byrne et al. (2016) conclude that "information technology and other measurement issues that we can quantify (such as increasing globalization and fracking) are also quantitatively small relative to the slowdown."

We stress the broader applicability of implementing our approach for the compilation of official statistics. While this exercise focuses on software and theatrical movies, the methodology we propose is flexible and scalable, offering opportunities for reuse across other intangible asset classes, including those that are not yet capitalized in the National Accounts such as branding and marketing assets. Our approach largely relies on Google Trends data, which is publicly available and up-to-date, making it both repeatable and adaptable to changing economic conditions.

This paper is structured as follows. In the next section, we discuss how the depreciation of intangibles is characterized in the System of National Accounts and current approaches to estimating their value. We proceed by elaborating our empirical methodology in section 4. We describe our data in section 5 and discuss our results in section 6. We present the impact on capital stock estimates and productivity figures in section 7. We end with some

[1]Noted by the Harvard Business Review as the fastest-growing business model for tech entrepreneurs: https://hbr.org/2023/04/the-rebirth-of-software-as-a-service

applications and concluding remarks and ways forward.

2 Conceptual underpinnings

In summary, we propose using patterns in Google search data to estimate the depreciation of intangible assets. The core idea is that when software, movies, or music albums are released, internet searches for these titles typically spike during their initial period of release. Over time, these searches diminish, and we argue that this decline can serve as a proxy for the corresponding decrease in the economic value of the intangible assets associated with these releases.

In this section, we clarify some of the conceptual issues surrounding our proposed methodology. In particular, we define some of the concepts concerning depreciation and intangible capital. We discuss how these concepts are manifested in the data. The goal is to clarify what we will essentially capture if we apply patterns in search volumes to track the changes in the value of intangibles.

In particular, we discuss the difference between depreciation, obsolescence, and revaluation. We argue that the decline in search volumes reflects primarily depreciation and obsolescence rather than revaluation. We also explain the difference between age-price and age-efficiency profiles and argue why we believe that search volume provides a valid indicator of both metrics.

2.1 Depreciation versus obsolescence

The 2008 SNA refers to depreciation as the consumption of fixed capital (CFC). Conceptually, CFC captures the economic cost of expected physical wear and tear and anticipated obsolescence (Schreyer, 2004; OECD, 2009). Unanticipated reductions in the asset's value—for instance, the damages due to natural calamities—are not recorded as part of CFC. Rather, these changes in the book value are recorded as "other changes in volume assets". Paragraph 6.24 of the SNA writes:

> Consumption of fixed capital is the decline, during the course of the accounting period, in the current value of the stock of fixed assets owned and used by a producer as a result of **physical deterioration, normal obsolescence or normal accidental damage**. The term depreciation is often used in place of

> consumption of fixed capital but it is avoided in the SNA because in commercial accounting the term depreciation is often used in the context of writing off historic costs whereas in the SNA consumption of fixed capital is dependent on the current value of the asset.

The presence of intangible capital adds complication to the concept of depreciation. By definition, intangibles are assets that do not have a physical form. In the 2008 SNA[2], these are called intellectual property products, which include expenditure items such as software and databases, artistic and entertainment originals, mineral exploration, and research development[3].

Given the nature of intangibles, the notion of "wear and tear" as a form of depreciation is less applicable. Instead, depreciation is predominantly linked to obsolescence (OECD, 2010; Del Rio & Sampayo, 2014; Görzig & Gornig, 2015). This could be driven by factors such as shifts in market relevance, changes in competitive landscapes, or technological obsolescence. As paragraph 6.242 of the SNA puts it:

> The value of assets may decline not merely because they deteriorate physically but because of a decrease in the demand for their services as a result of technical progress and the appearance of new substitutes for them.

For intangibles, depreciation is uniquely tied to obsolescence rather than physical wear and tear. Given this, the term "depreciation" for intangibles can be used interchangeably with "normal obsolescence" within this specific context, as it captures the essence of how these assets lose value over time. This distinction aligns with the SNA framework, where the decline in the demand for an asset's services due to external factors is emphasized as the primary driver of depreciation for intangible assets. This is not a new perspective. In practice, statistical agencies often assume fixed service lives for intangible assets, despite the absence of observable physical wear and tear.

We acknowledge that certain intangibles, such as movies and other creative originals, may never become fully obsolete. Cult films, niche titles, or content revived through sequels or anniversaries can maintain a degree of popularity well beyond their initial

[2]The 2025 SNA would also include data as an asset

[3]Corrado et al. (2009) propose a more expansive set of assets, which includes brands and human capital, among others.

lifecycle. While such cases may introduce some noise into our estimates, they remain relatively rare compared to the overall downward trend observed in revenue data and search patterns.

2.2 Depreciation versus revaluation

A significant challenge in this exercise lies in determining whether changes in the value of intangible assets should be attributed to depreciation or revaluation. To make things clearer, consider the standard user cost formula:

$$u_{i,t} = r_t p_{i,t} + \delta_i p_{i,t+1} + (p_{i,t+1} - p_{i,t}) \tag{1}$$

where $u_{i,t}$ is the user cost for asset i at time t, δ_i is the depreciation rate, $p_{i,t}$ is the investment price, and r_t is the rate of return. In this formulation, $p_{i,t}$ represents the price of a new asset and not the market value of an asset that has already been in use.

The absence of "wear-and-tear" depreciation for intangibles makes it difficult to isolate depreciation reflected by the term δ_i and revaluation, represented by $(p_{i,t+1} - p_{i,t})$, when examining an observed decline in value of intangible assets.

We argue that the patterns observed in search volume data primarily capture obsolescence. As highlighted in Section 2.1, which we propose to equate to depreciation for intangible assets. Based on the SNA's definition, depreciation reflects the "normal decline in value due to physical deterioration or obsolescence" (OECD, 2009). For intangibles, where physical deterioration does not apply, obsolescence becomes the dominant driver of depreciation.

The OECD (2009) manual defines revaluation as the "expected price change of the asset, corrected for a measure of overall inflation." Traditionally, this captures holding gains or when an asset appreciate in value without improvements in its productive capacity. Moreover, the SNA makes a clear distinction between depreciation and revaluation. Depreciation captures the intrinsic decline in the value of an asset as it ages, while revaluation reflects changes in asset prices due to market-wide factors, such as inflation or demand shocks.

Unexpected changes in the value of assets, meanwhile, would fall under category of revaluation. For instance, the introduction of movie sequels may result to a temporary spike in interest for the original movie. This spike in interest could result to people buying or renting the original movie from streaming providers, temporarily improving the productivity of the asset, years after the movie was introduced. We can think of these temporary spikes as revaluation.

Patterns in search volume track changes in the asset's ability to generate economic returns by capturing shifts in public interest or relevance over time. They reflect the diminishing usefulness *to the asset owner*. In this case, the main use of the asset is to generate revenue. While revaluation reflects external market forces, such as inflation or platform-specific factors, depreciation and obsolescence are intrinsic to the asset's lifecycle.

We believe that events leading to revaluation will have a minimal impact on our overall estimates. Temporary spikes in search volumes, such as those observed before the release of sequels, tend to be infrequent and relatively small in magnitude. Compilers of official statistics can control for these events by applying time dummies for periods where they observe unusual spikes in the data that may contribute to revaluation.

While it can be argued that there is no decline in the physical capacity of intangibles—a movie, for instance, retains its original form regardless of its age—and that changes in the asset's value could be attributed solely to asset-specific inflation or revaluation (as described by Diewert (2005)), current practices by statistical agencies often assume a fixed asset life for intangibles. These assumptions assign depreciation rates based on service life estimates, despite the lack of observable physical deterioration. Our approach merely provides an empirical methodology for the calculation of asset lives and depreciation rates that statistical agencies are already using.

2.3 Cross-sectional depreciation versus relative price declines

Closely linked to the issue of revaluation is the issue on whether or not obsolescence captured by our proposed approach reflects the differences in the value of an asset at different ages ("cross-sectional depreciation") or whether it captures changes in relative prices. Whether or not depreciation should include the latter has been debated and was discussed in the OECD (2009). In this section, we argue that patterns in search volume provide a valid indicator for the former.

Diewert & Wykoff (2007) describes obsolescence due to the downward shifts in demand causing deterioration of relative prices as "disembodied obsolescence". These are primarily driven by economic factors such as changes in input prices or changes in taste. The appearance of new products that renders the old capital obsolete (e.g. the invention of cars makes horse-drawn carriages obsolete) also contributes to this form of obsolescence. This is in contrast to "embodied obsolescence", which is linked to the introduction of a new/improved model (Diewert & Wykoff, 2007). Recall that in the national accounts, changes in quality are reflected as volume changes. Even though the productive efficiency of the old asset is kept intact, improvements in new assets reduce the volume for the measure of the old assets. To put it simply, it is as if the volume of the asset is declining because of the relative quality change triggered by the introduction of a new model. This reduction in quality also diminishes the asset's ability to generate revenues for its owner. We provide a simplified summary describing the difference between the two concepts, based on Diewert & Wykoff (2007) in table A.1.

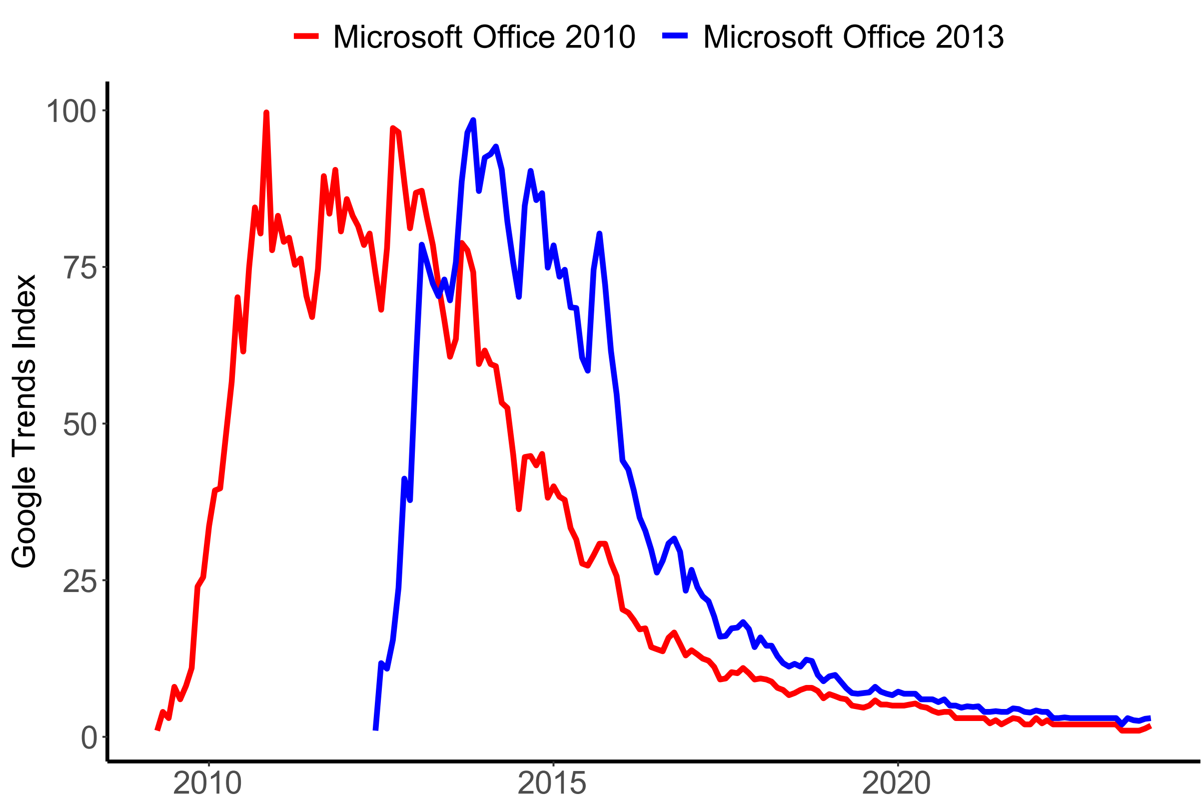
Some scholars advocate for capturing changes in relative prices as part of depreciation, with Hill (2000) arguing that deterioration in real asset prices reflects embodied technical change. Compilers of official statistics, however, traditionally exclude changes in changes in real asset price in their interpretation of depreciation. The OECD (2009) also supports this position, arguing that the supply-side perspective of depreciation should be separated from the demand side.

In the context of our proposed methodology, it begs the question: do patterns in search volume data reflect standard cross-sectional obsolescence, or do they reflect changes in relative prices? We believe that declines in Google search patterns indicate embodied obsolescence rather than changes in relative prices for three reasons.

First, changes in relative prices are driven by market-wide factors such as changes in technology or platform dynamics that alter the overall valuation of assets without affecting their intrinsic ability to generate revenue. These price changes are often external to the asset's lifecycle. For instance, the entry of a new streaming platform could increase licensing revenues for *all movies*, regardless of their actual relevance or demand. Declining patterns of search volumes indicate a decline in the value of specific assets driven by their diminishing relevance, rather than market-wide factors. This decline reflects the intrinsic lifecycle of the asset, capturing the natural process of obsolescence, as indicated by its ability to generate public interest. Unlike relative price changes, which impact entire categories of assets due to external economic shifts, the decline in search volumes is tied specifically to a particular asset's ability to generate revenues. Moreover, our tests reveal a systematic relationship between lifetime box office revenues—-which we use as a proxy for the net present value of movies—-and Google Trends data, even after accounting for a time trend that captures external time-varying market factors such as market-wide price changes (see section 6.4).

Second, the supply-side approach emphasizes measuring the economic capacity of an asset to contribute to production, focusing on the gradual erosion of its productive utility as the asset ages. Declining search volume reflects how older assets lose their economic utility to the asset owner, or its ability to generate revenues. This is consistent with supply-side concepts of depreciation preferred by compilers of official statistics and the OECD (2009) manual.

Figure 1: Difference between Google trends results for Microsoft Office 2010 and 2013



Lastly, our sense is that declines in the patterns in search volume for intangibles such as software and movies are largely driven by the introduction of "new models" or "versions" of the asset rather than any market-wide phenomenon causing changes in relative prices.

One way to think about this is that interest in a certain movie or television series declines because new movies and TV shows become available. The value of a particular software declines because there are better versions of the same software available. This is consistent with "embodied obsolescence" described Diewert & Wykoff (2007). As an illustration, we can observe this in Google Trends results for software. Notice that Google Trends results for Microsoft Office 2010 only started declining after the introduction of Microsoft Office 2013. As explained by Diewert & Wykoff (2007), we can think about the decline in search volume for Microsoft 2010 as "volume change", because of the improvement put forward by the 2013 version.

While we acknowledge the inherent complexity in empirically disentangling depreciation from revaluation, we argue that our approach is more closely aligned with capturing embodied obsolescence and cross-sectional depreciation, as outlined in the principles established in the OECD (2009). Our reasoning provides a robust justification for using Google Trends data as a valid proxy for measuring the depreciation of intangible assets, particularly in the context of their intrinsic lifecycle dynamics.

We recognize that it is possible that some degree of relative price changes are reflected in Google Trends patterns, as external market factors may occasionally influence search behavior. However, we argue that the patterns predominantly capture the concept of depreciation desired by statistical agencies, as they reflect the diminishing economic utility and productive capacity of individual assets over their lifecycles. Furthermore, the challenge of not having a valid indicator for the depreciation of intangible assets presents a far greater concern than the potential conceptual issues arising from minor instances of revaluation. By offering a pragmatic and empirically grounded approach, our methodology contributes meaningfully to addressing this critical gap in national accounting practices.

2.4 Age-price versus age-efficiency

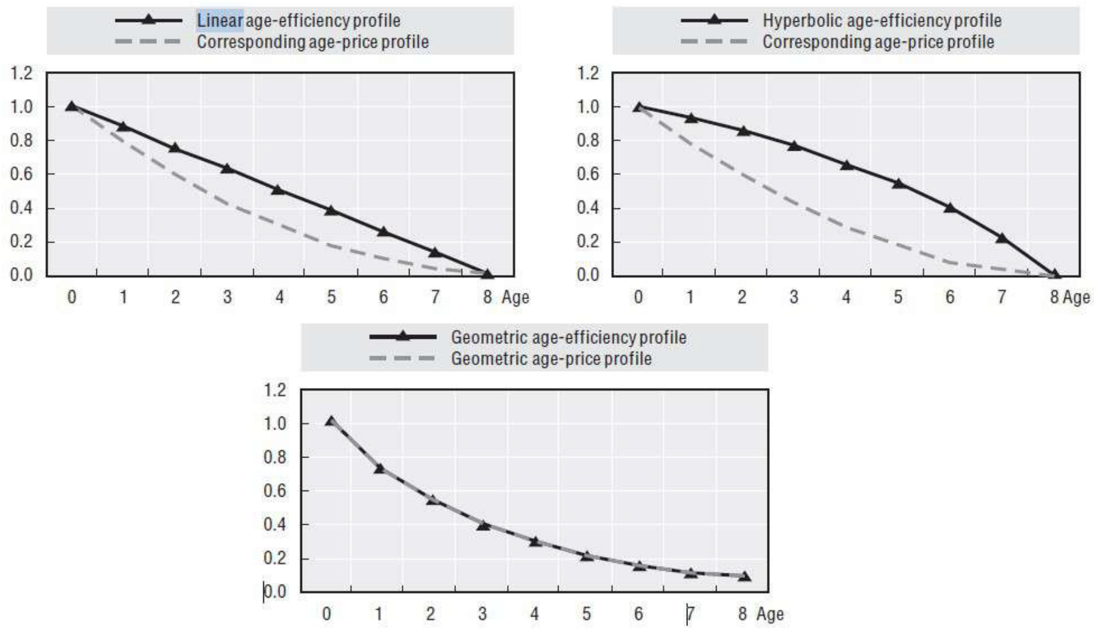
In capital theory, two elements are essential in understanding how the value of capital evolves as they age: age-price profiles and age-efficiency profiles. To put it simply, age-efficiency profiles (or age-efficiency functions) relate to the loss of an asset's "productive efficiency" as it ages. Meanwhile, age-price profiles (age-price function) represent the decline in the value of an asset as it ages (OECD, 2009). While the former presents the decline in the productivity of an asset as it ages, the latter incorporates a discount factor to reflect the diminishing value of future returns.

Depreciation is calculated when age-price functions are superimposed onto gross capital stocks to estimate net capital stock. Meanwhile, age-efficiency profiles are used to calculate productive capital stock, which measures the stock of capital adjusted for its ability to provide productive services.

Our sense is that Google search patterns more closely reflect a ge-efficiency profiles, providing an indicator for the decline in the productive or economic utility of intangible assets over their lifecycles. Google Trends data inherently tracks public interest and engagement, which for assets like movies or software, likely correlates with their ability to generate revenue or provide services. This aligns with the concept of age-efficiency, which measures the reduction in an asset's productive capacity as it progresses through its lifecycle. We prove this empirically in section 6.4.

Compilers of official statistics commonly recognize three forms age-efficiency profiles: 1) linear, 2) hyperbolic, and 3) geometric. A linear profile assumes that an asset's productive capacity declines at a constant level throughout its lifespan. A hyperbolic profile, on the other hand, assumes that an asset maintains high productive efficiency during its initial years, followed by a sharp decline as it approaches the end of its service life. Finally, a geometric profile assumes that an asset's productive capacity decreases at a constant proportionate rate over time, resulting in a steeper decline initially that slows in later years.

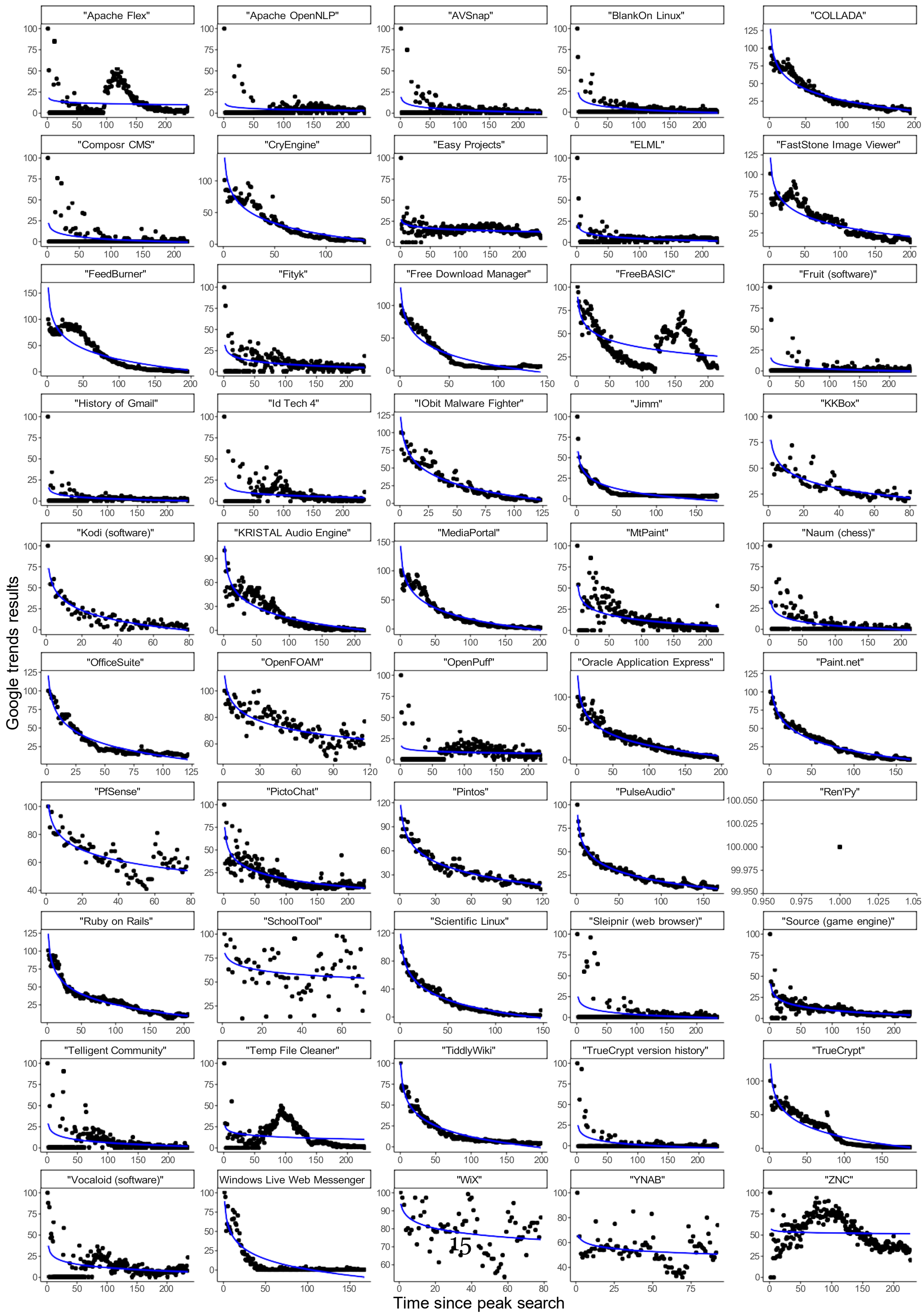
Figure 2: Age-efficiency and corresponding age-price profiles



Note: Image is lifted from OECD (2009) page 36.

We show the pattern for each profile in table 2. It is important to note that for assets with geometric age-efficiency profiles, the age-efficiency and age-price profiles will be identical.

Figure 3: Google trends patterns for software released in 2004



A visual inspection of the raw data (see figure 3) suggests that Google Trends patterns more closely resemble a geometric profile rather than linear or hyperbolic profiles. If this is the case, Google Trends data can also serve as an indicator of age-price patterns. Since, by definition, age-price patterns directly reflect the economic value lost due to depreciation, our proposed method can provide an indicator of depreciation. This alignment supports the feasibility of using Google Trends as a proxy for measuring the decline in the productive and economic value of intangible assets over their lifecycles, consistent with national accounting principles.

The observation that patterns of decline in Google Trends data closely mirror a geometric depreciation profile also informs the specification of our empirical model, as will be discussed in section 4.

It is important to highlight that even if a one-hoss-shay age-efficiency profile is assumed—-where an asset maintains 100 percent productive efficiency until the end of its service life before dropping to zero—-an economy-wide geometric age-efficiency profile can emerge when there is a retirement distribution of such assets. This observation, originally articulated by Hulten (2007, 1991) and discussed in the OECD (2009), underscores how aggregate profiles differ from individual asset profiles due to the distribution of retirements across the economy.

This detail has particular relevance for intangibles, where productive efficiency may remain constant over an asset's lifecycle, but the heterogeneity in asset retirements across industries or firms gives rise to a geometric pattern at the macroeconomic level.

3 Empirical literature and country practices

In this section, we discuss the current approaches to measuring the depreciation of intangibles. In practice, quantifying the rate at which the value of intangibles declines due to obsolescence can be a complex endeavor and was subject to many scholarly investigations. For R&D, approaches range from the use revenues attributable to patents (De Rassenfosse & Jaffe, 2017), the estimation of a profit model (Li & Hall, 2020), the estimation of a production function (Hall, 2007; Huang & Diewert, 2011), amortization (Lev & Sougiannis, 1996; Ballester et al., 2003), and market valuation (Hall, 2007; Warusawitharana, 2015).

The strong interest in measuring the obsolescence of R&D stems from the notion that depreciation rates for this asset also reflect the rate of technological progress. Perhaps a more dramatic way of phrasing it would be, the rate at which ideas die. There is relatively less scholarly attention directed towards other forms of intangible assets, notably software and artistic originals, notwithstanding their substantial economic importance. In the year 2020, software, which covers both purchased and own-account software, constituted half of the intangible assets incorporated into the core National Accounts of the UK. Moreover, artistic originals constituted 10 percent of the total intangible assets within the National Accounts for the same year. Most depreciation rate estimates are implied from the assumed service lives of the assets.

Despite accounting for the majority of SNA intangibles in most countries, there is little scholarly work on the depreciation of software. OECD (2010) recommends making assumptions on the service life of software to estimate their depreciation rates. The manual states that some of the ways to empirically inform the assumptions include: surveying software users, surveying software suppliers, and consulting software consultants. This approach may involve asking users about their expectations of their software's service lives or the service life of their recently retired software. However, this approach would likely be more informative on the service life of software copies to asset users and less informative on the ability to generate revenues for developers of the software.

For artistic originals, OECD (2010) recommends the use of empirical data such as the net present values of royalties to estimate their service lives. The manual also notes that the depreciation function must reflect relatively rapid depreciation in the first few years of an asset's life.

The focus of this paper is to estimate the obsolescence of software and creative originals. Table 1 shows the depreciation rates employed by selected OECD member countries for software and creative originals as published by Pionnier et al. (2023). In this table, software was classified into three categories, packaged software, custom software, and own account software. France, Germany, Italy, and the UK employ the same depreciation rate for all three categories. Meanwhile, the US and Canada apply a higher rate for packaged software.

Interestingly, Canada applies a depreciation rate of 1.00 for theatrical movies and long-lived TV programs. This implies that it does not recognize movies and TV shows as assets but as intermediate consumption. France, Italy, and the UK apply the same depreciation rate for all categories of creative originals.

Table 1: Depreciation rate for Software and Artistic Originals by country

	US	Canada	France	Germany	Italy	UK
Packaged software	0.550	0.550	0.244	0.359	0.325	0.256
Custom software	0.330	0.330	0.244	0.359	0.325	0.256
Own account software	0.330	0.330	0.244	0.359	0.325	0.256
Theatrical movies	0.093	1.000	0.331	0.110	0.172	0.183
Long-lived TV programs	0.168	1.000	0.331	0.181	0.172	0.183
Books	0.121	0.121	0.331	0.137	0.172	0.183
Music	0.267	0.267	0.331	0.273	0.172	0.183
Other entertainment originals	0.109	0.109	0.331	0.125	0.172	0.183

Source: Pionnier et al. (2023)

The available documentation regarding the calculation methodologies for these figures by statistical agencies is limited, However, certain resources are accessible for reference.Calderón et al. (2022) notes that estimates by the BEA for the depreciation of software are based on assumed service lives. According to the authors, the service life for software is determined through estimates of the correlation between computer and software expenditures. Moreover, they also consider anecdotal evidence regarding the typical duration of software use prior to replacement, as well as the service lives of software as defined by tax laws. The study also includes an informal survey of business software usage.

Soloveichik (2010) provides a detailed methodology on how the depreciation of artistic originals can be estimated using net present value (NPV). Her approach requires calculating the NPV of each original as revenues less the non-art cost[4] of the asset, plus the discounted future NPV of the asset:

[4]This includes physical costs like construction of broadcast towers, DVD markings, marketing and advertising expenditures, and other spending not directly associated with the production of movies, TV series, or songs (Soloveichik et al., 2013c,a; Soloveichik, 2014; Soloveichik et al., 2013b).

$$NPV_{t=0} = revenue_0 - nonartcost_0 + \frac{NPV_{t=1}}{1+\rho}$$

$$NPV_{t=1} = revenue_1 - nonartcost_1 + \frac{NPV_{t=2}}{1+\rho}$$

$$NPV_t = revenue_t - nonartcost_t + \frac{NPV_{t+1}}{1+\rho}$$

where ρ is the discount rate. She then represents depreciation as the rate of decline in the asset's NPV. The methodology and data sources for each set of creative originals are detailed in Soloveichik et al. (2013c), Soloveichik et al. (2013a), Soloveichik et al. (2013b), Soloveichik (2014). The approach is highly data-intensive requiring a wealth of information on revenues, retail sales, production costs, and assumptions on the discount rate.

For the UK, depreciation rates are determined by the assumed service life of an asset. The initial asset lives for software were determined through a survey by Awano et al. (2010) and a second survey by Field et al. (2012). The methodology for the estimation of capital stocks for creative originals was developed by Goodridge et al. (2013b). However, this paper did not specify how the service lives were determined. The assumed asset lives and effective depreciation rates currently being used by the ONS are detailed in Rincon-Aznar et al. (2017). These estimates were determined using analysis of depreciation from company accounts, consultation with UK industry experts, and comparisons with other countries' experiences.

As noted in this section, traditional methods for estimating depreciation often rely on survey-based approaches or assumptions about asset service lives. However, these methods may lack precision and can be subjective. Moreover, intangible assets, such as software and creative originals, are inherently dynamic and subject to rapid changes in technology and consumer preferences. Existing methods may struggle to capture these dynamics effectively. In the next section, we discuss a framework on how we can possibly use data on Internet searches as an objective and readily-available source of information on the depreciation of intangibles.

In the next section, we discuss our empirical approach to estimate these parameters.

4 Econometric strategy

Our approach is predicated on the assumption that the GSV results represent a form of obsolescence. We further assume that the high search level (the period when the index takes the value 100) represents the period when the asset is capitalized. For instance, when a movie is released, searches for the movie peak during the month of release. Searches decay over time, following a decrease in the popularity of the movie. We assume that decay in the search index corresponds to the rate of obsolescence for the particular movie. The same assumption is made for software. We estimate the rate of decline in the GSV index using a log-linear model as follows:

$$log(\bar{G}_{k,l,t}) = \delta\tau_t + \Gamma_k + \theta_l + \varepsilon_{k,r,t} \tag{2}$$

where $\bar{G}_{k,l,t}$ are GSV results at time t for keyword (movie/software titles) k released on year r; τ is a linear time trend; Γ_k and θ_l are fixed effects for the keywords and release dates, respectively. Since we are omitting the constant term from the empirical model, the asset-specific fixed effects, Γ_k, would absorb both the initial value of the asset V_{k0} and other time-invariant characteristics of the asset, γ_k. Lastly, the error term $\varepsilon_{k,r,t}$ can be decomposed into the error attributable to $\mu^r{}_{k,t}$ the relationship between searches and revenues, and a pure error term $\tilde{\varepsilon}_{k,r,t}$. As discussed in a previous section, a visual inspection of the data indicates that Google Trends patterns closely follow a geometric profile. Consequently, we adopted a double-log specification to appropriately capture this behavior.

The dataset consists of an unbalanced panel comprising GSV results related to various movie and software titles. We employ truncation to initiate the dataset precisely when the index takes the value of 100. This point in time signifies the period at which we presume the asset begins to be capitalized. For instance, this may represent the month when the movie is shown in theaters or when software is released for distribution. We then estimate the semi-elasticity parameter δ in equation 2.

In many instances, GSV takes the value of zero. This could mean many things, including the possibility that searches for that month did not reach the threshold to be included in the GSV sample. This adds a complication to our specification in 2 since we can only take logs of positive numbers. As such, we add an arbitrary value, Δ, to all in order to apply the log transformation. As an alternative, we also employ other estimators such as the Poisson Pseudo Maximum Likelihood (PPML) by Silva & Tenreyro (2006), which allows for the estimation of semi-elasticities for observations with zero values. This is a common methodology in the empirical trade literature. We also employ Negative binomial regression since PPML can be restrictive in the sense that it assumes that the mean and the variance are equal. The Negative Binomial model is a generalization of the Poisson model that allows for overdispersion (variance greater than the mean). While the PPML is considered a more restrictive model over the Negative Binomial because of this assumption, simulations find the this model performs better in the presence of heteroskedasticity due to zero observation (W. Martin & Pham, 2020) and is widely used in the trade literature.

5 Data and descriptives

Two sets of information are required for the exercise: a list of movies and software, and GSV results. In this section, we discuss the data that we use, particularly how the data was obtained and managed.

5.1 Data sources

To facilitate the extraction of GVS results, it is necessary to compile a comprehensive catalog of titles to be employed as keywords within our search queries. Our objective is to maximize the representativeness of our estimate by covering a wide array of titles. Consequently, we undertook extensive efforts to assemble an exhaustive list of keywords. Our primary source for this exercise was the Internet Movie Database (IMDb) for theatrical movies and Wikipedia for software-related titles.

IMDb (imdb.com), a subsidiary of Amazon, serves as an extensive online repository encompassing movies, television series, video games, and related forms of media. This platform offers a wealth of information on each title, including details such as release year, ratings, run time, box office earnings, directorial credits, cast members, genre classifications, and reviews, among other pertinent attributes. Information from IMDb has been used in various research in economics and marketing, particularly those involving sentiment analysis (Shaukat et al., 2020; Harish et al., 2019; Topal & Ozsoyoglu, 2016) and the prediction of movie ratings (Hsu et al., 2014; Oghina et al., 2012; Gogineni & Pimpalshende, 2020).

Meanwhile, Wikipedia serves as a limited source of data. Although the platform has the potential to offer a substantial amount of information for each software entry, the majority of this data is within the individual articles dedicated to each software. We are not able to systematically extract this information for practical reasons. Furthermore, the consistency of information across these entries is notably variable. Revenue-related data is frequently absent. Consequently, our utilization of this resource is primarily limited to extracting the names of software titles, as well as the categories each titles were tagged with.

For the exercise, we confine our analytical scope to movies that have garnered box office revenues exceeding $1 million. This criterion led to the inclusion of 4,623 movie titles and 1,089 software titles in our dataset. To formulate precise search queries, we combine the movie title with its respective year of release (e.g., ”Avengers: End Game 2019”). This naming convention aligns with the typical referencing of movie titles and helps mitigate any potential confusion between the movie title and unrelated search results. Conversely, for software, we employ the software title verbatim as our search query. To avoid confusion with common terms, we include the word “software” in the search query, and in some cases, the category of the software. For example, we use the queries, “Vala (programming language)” and “Songbird (software)”. Queries such as these account for less than 5 percent of our total software queries.

The main dataset we employ for this exercise is Google Search Volume (Google Trends) results. GSV provides a real-time index for a *random sample* of queries in Google’s search engine. According to Google News Lab, the sample is unbiased (Rogers, 2016), though Google does not disclose the specifics of its sampling design.

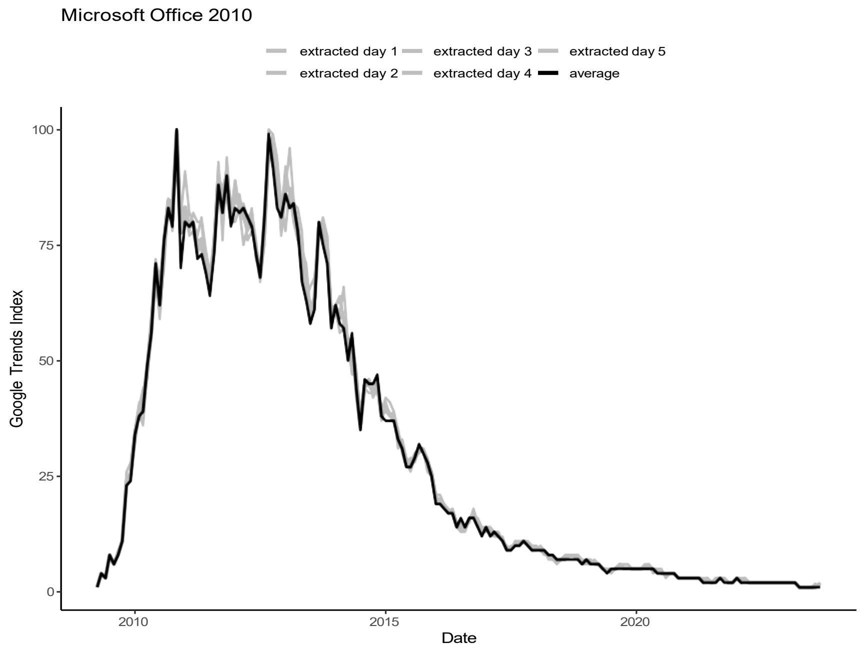
Users of Google Trends can filter the data in two ways: real-time and non-real-time. Within the real-time filtration, a random selection of queries from the preceding seven days is employed. Meanwhile, the non-real-time approach involves the use of a randomized subset of search queries extracted from the Google dataset, which covers data points spanning from 2004 up to roughly 36 hours prior to the search. Moreover, Google Trends allows users to compare five search queries simultaneously.

One of the major limitations of GSV data is that it does not present the number of searchers for each keyword. Instead, GSV reports an index that undergoes a two-tier standardization process. Initially, all search volumes are standardized in relation to the total number of searchers during a reference period. This adjustment compensates for the substantial variations in Google's user base over time, such as the significant increase in users since 2004. The number of searches for a particular query is divided by the number of searches during that specific year (or month) to render the index comparable. Secondly, this index is further normalized to a scale ranging from 0 to 100, where 100 signifies the highest frequency of search queries for a given topic and zero signifies the lowest. Consequently, GSV results are conventionally interpreted as indicative of the relative popularity of specific search queries.

Numerous researchers have employed GSV to illustrate its potential in forecasting macroeconomic indicators, including GDP and unemployment (Woloszko, 2021; Kohns & Bhattacharjee, 2023; Ferrara & Simoni, 2022), as well as in predicting trends in tourism (Havranek & Zeynalov, 2021). Furthermore, GSV has been utilized in diverse domains, such as monitoring COVID prevalence during the pandemic (Hamulka et al., 2020; Effenberger et al., 2020; Cervellin et al., 2017; Zattoni et al., 2021).

For this research, we would employ non-real-time Google Trends results. Given the large number of keywords that we intend to use in the analysis, manually extracting individual Google Trends data for each keyword within a reasonable timeframe is impractical. As such, we employ an R package designed to systematically retrieve Google Trends data for all keywords in our lists. We pool the data for all GSV results for all keywords to construct an unbalanced panel that we used for the analysis.

Figure 4



Note: The figure shows Google trends results for the query "Microsoft Office 2010". The figure overlays the results extracted on five (5) separate days (grey line) and the average of the cross-sectional average of five results.

Since the index reported by GSV is based on a sample, the results extracted today could be different from the index extracted the next day and the days following (Choi & Varian, 2012; Cervellin et al., 2017). The literature recommends extracting GSV results for the same keyword on multiple days and calculating the cross-sectional mean across different samples at *t* (McLaren & Shanbhogue, 2011; Carrière-Swallow & Labbé, 2013; Eichenauer et al., 2022).

At present, there is no standard set by the literature on the number of samples required to construct a reliable index. Some papers recommend a sample of 7 (McLaren & Shanbhogue, 2011), some 50 (McLaren & Shanbhogue, 2011). Extracting a large volume of GSV results is not straightforward. Google blocks the IP address of users after too many queries within a short period. Carrière-Swallow & Labbé (2013) explains that in practice, the number of samples extracted is a result of a balancing act between the reduction of the sampling problem and stressing the Google API. Given that our cross-section is substantially large (4,624 movie titles and 1,089 software titles), we were only able to draw 4 to 7 times for each keyword before stressing the Google IP address.

To illustrate, we show in figure 4 GSV results after 5 draws, as well as the average for each draw. While there are some variations between draws, we can see that the general oscillation tends to move in the same direction. We will use the cross-sectional average across different draws as our dependent variable in estimating equation 2.

5.2 Descriptive statistics

In this section, we present some descriptive statistics on the software and movie titles we employ in our sample. For software, we were able to classify the titles into broad categories. We exploit the category tags at the bottom of each Wikipedia entry as the basis of our classification. We explain in detail how we were to come up with these categories in appendix C. For movies, we present some summary statistics from the data extracted from the IMDb website.

Table 2: Count and share by software type

	Operating System	Media Players	Office Tools	Web Browser	Social Media
n	212	24	19	47	42
Share (%)	21	2.4	1.9	4.7	4.2

Around 21 percent of our sample is a form of operating system. Around 2.4 percent were categorized as media players, 1.9 percent were office tools, 4.7 percent were web browsers, and 4.2 percent were tagged as social media. Note that the shares do not add to 100 percent. This is because of the way we have categorized the software entries. We have only highlighted the categories we find most interesting and intuitive, acknowledging that there are countless other ways to categorize software.

Table 3: Count and share by operating system

	Windows	Android	IOS	MacOS	Linux
n	257	172	164	133	169
Share (%)	25.5	17	16.3	13.2	16.7

More than a quarter of the software in our sample can run on the Windows operating system, while 13.2 percent can run using MacOS. About 17 percent of our sample can run in Android OS, while 16.3 percent can run in iOS.

Table 4: Count and share of free and open-source software

	With Free Version	Open-Source	Strictly Open-Source
n	401	83	13
Share (%)	39.7	8.2	1.3

According to the category tags, around 40 percent of the software in our sample has a free version. Only 8.2 percent of the sample was classified as open-source and only 1.3 percent of the sample was tagged as open-source but were not tagged as having a free version.

Table 5: Descriptive Statistics for Revenues and Run Time

Variables	Mean	SD	Min	Max
Revenues (in million US$)	23.4	59.5	1.0	936.7
Run time (in minutes)	104.8	20.3	8.0	321.0

For movies, the average revenues we calculated for our sample was at $23.4 million. Variation in our sample is notably high. The standard deviation for revenues at $59.5 million, was more than double the mean. The maximum revenue in our sample is $936.7 million, while the minimum is $1 million by construction.

In terms of the run time, the average run time in our sample is 1.8 hours. The standard deviation is only 20 minutes. The shortest movie in our sample is only 8 minutes and the longest movie in the sample is 5.3 hours long.

6 Empirical measures of depreciation

In this section, we present the estimates for the depreciation rates of movies and software. We present the estimates using OLS, PPML, and the negative binomial regression. We also compare our estimates with the depreciation rates being employed by a select set of countries. Lastly, we present the implied service lives arising from the depreciation rates.

Estimating equation 2 requires taking the natural log of GSV results. However, there are instances when GSV results take the value of zero. As such, log transformation is not possible. The typical solution is to add a constant, Δ. In our OLS specification, we choose $\Delta = 1$. We suspect that the OLS results are biased because of the heteroskedasticity from zero observations.

6.1 Software

We present the results for software in table B.3. We interpret these semi-elasticities as monthly depreciation rates or the percentage decline in the value of the asset each month. The coefficient from using OLS is smaller than those from PPML and negative binomial. For software, however, the estimates from the latter two are almost identical.

Table 6

	OLS (1)	PPML (2)	Negative Binomial (3)
δ	-0.006^{***} (0.0003)	-0.008^{***} (0.00001)	-0.009^{***} (0.0001)
Keyword FE	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes

We note that our sample also includes software titles that are either distributed without any explicit monetary cost to their users or can be classified as open-source. Among these software titles, certain ones function as loss leaders and were conceived not solely with the aim of generating revenue for their developers. As such, these titles would not qualify under the capitalization criteria of the National Accounts. We show in table 7 that removing software titles with free versions, as well as those classified as open-source, does not make any changes to the estimates.

Table 7: Results for PPML model removing free and open-source software

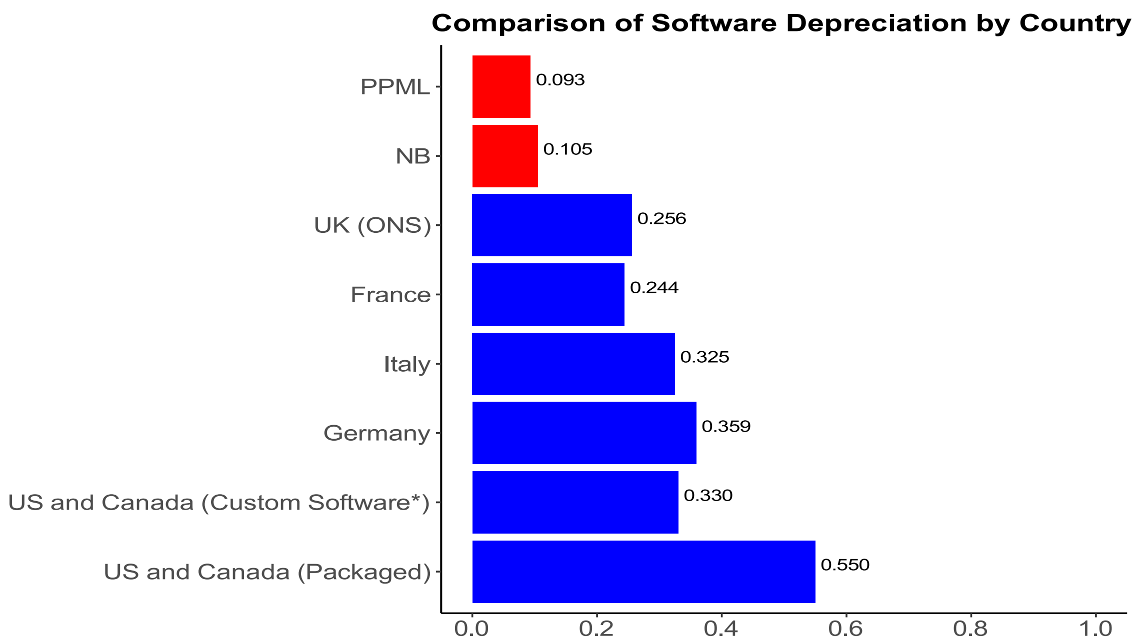
	All Software (1)	Removing those tagged "Free & Open Source" (2)	Removing those tagged Open Source only (3)
δ	-0.008^{***}	-0.008^{***}	-0.008^{***}
	(0.00001)	(0.00002)	(0.00001)
n	161,735	135,186	144,453
Keyword FE	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes

We calculate the annual depreciation[5] and compare them to the estimates employed by a select set of statistical offices, as reported by Pionnier et al. (2023). All our estimates are materially smaller than the depreciation rates employed by other countries (see figure 5). In particular, the estimates are approximately half the depreciation rates employed by statistical offices.

[5]Assuming a geometric pattern, we calculate the annual depreciation rate (δ^a) from the monthly depreciation rate (δ^m) as:

$$\delta^a = ((1 + \delta^m)^{12}) - 1$$

Figure 5: Comparing the annual depreciation rates estimates for software with those from other countries



Note: The figure compares results from PPML and negative binomial (NB) model for software with the annual depreciation rates employed by a select set of countries. The monthly estimates from table B.3 were annualized assuming a geometric pattern. The depreciation rates employed by other countries were sourced from Pionnier et al. (2023) *Custom software also includes own-account software.

We calculate the implied service life as $1/\delta$. The difference between the estimates using GSV and depreciation rates employed by statistical agencies is also reflected in the implied service life. The implied service lives from our estimates for software are more than double those assumed by statistical agencies.

Table 8: Implied Service Life of Software by Country

Country	Implied Service Life
PPML	10.8
NB	9.5
UK (ONS)	3.9
US and Canada (Packaged)	1.8
US and Canada (Custom Software*)	3.0
France	4.1
Germany	2.8
Italy	3.1

*Custom software also includes own-account software.

There are two possibilities that we can draw from these results. First, current levels of capital stock are grossly underestimated. Our estimates suggest that the existing stocks of software assets are possibly double the current estimates. Doubling the estimates for software stocks would have substantial implications for both growth accounting and estimates of net domestic product. Second, it is possible what we are capturing is not the depreciation rates for *all forms* of software assets.

To explain the second possibility, it is important to note that software assets can be classified under two categories: *original software* and *software copies* (OECD, 2010). Original software can be further broken down into *originals for reproduction* and *other originals* (OECD, 2010). The first subcategory refers to software intended to be reproduced for sale or leased. Other software originals refer to custom-made software produced by a firm intended for the production of other goods and services.

Statistical agencies estimate software depreciation either by making an assumption on the asset's service life (as documented by Calderón et al. (2022) and recommended by OECD (2010)) or, as with the UK, by conducting a survey on firms about the assumed service life of their existing software (Awano et al., 2010; Field et al., 2012).

The use of surveys appears to be the more scientific of the two approaches since it requires the use of empirical data. However, the estimated depreciation rate employing this approach (as demonstrated by the UK) is still double the estimates from the approach in our study. Since the respondents of these surveys are firms that use software to produce their own products, we suspect that the service life that they estimate generally captures the asset lives of software copies and other software originals. These surveys were not designed to draw from a representative sample for each category. Considering that originals for reproduction are "generally produced by specialist software companies", it is unlikely that surveys would be representative enough to account for this category.

On the other hand, the rate at which search volumes decay likely represents the obsolescence of originals for reproduction. We can think of it as the value of the codes behind software titles such as Microsoft Office or Zoom. We interpret our estimates as the depreciation rates for the assets by software developers such as Microsoft or Zoom. As such, our estimate reflects a different category compared to those captured by surveys on the asset life of software employed by firms.

Software developers could earn revenues from the master copy of software far longer than the average service life of a software copy for firms that purchase software copies. This could explain why our estimates are substantially slower than those being employed by statistical agencies. Little is known about the depreciation rate of originals for reproduction. Software companies do not usually present revenues from specific products they release. Moreover, since software-as-service is becoming more popular as a business model for developers, one can argue that in the future, companies will be less reliant on capitalizing software copies. Most of the capitalization would occur with software developers and using GSV would likely be a more appropriate strategy in measuring the obsolescence of this software class.

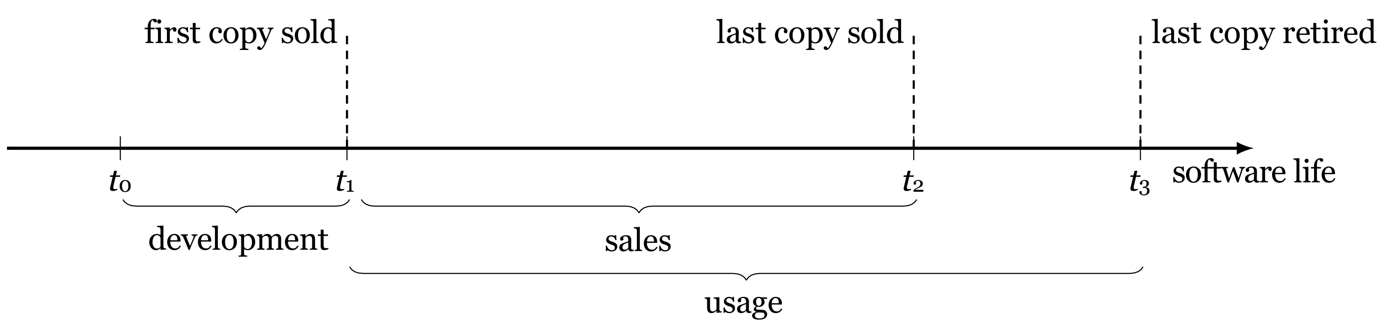
6.2 Original software

While original software is capitalized in the National Accounts estimates by all countries subscribing to the 2008 version of the SNA, the asset category could be different for each country. Following BEA's National Accounts update in 2018, software originals were reclassified to *software R&D* rather than software investments (Chute et al., 2018). Meanwhile, most European countries, including the UK, purposely remove expenditures for software development from R&D investments, following the European System of Accounts (ESA) Guidelines 2010. Investments in original software are classified under own-account software under the software development industry (under SIC sector J).

To effectively capture the depreciation of original software, we must argue that the decline in Google GSV results corresponds directly to the decrease in revenues experienced by software developers. However, we explain later that this assumption is only partially true. In this section, we would argue that search queries are indicative of software usage, thereby warranting careful consideration in our analytical framework.

We show in the figure 6 a simplified illustration of a software's lifespan. Development of software begins at time t_0 and ends at t_1. In this simplified version of a software's life cycle, we assume the sales begin after development at time t_1 and end until the last copy is sold at time t_2. From the perspective of the asset owner of the original software (the software developer), the original is fully depreciated at time t_2 because it no longer profits from the sale of copies of the software. However, usage of the software extends up to the time that the last copy bought is retired, which is at time t_3.

Figure 6



The service life of the software original is reflected by the distance between t_1 and t_2. Meanwhile, Google Trends is likely capturing usage, which is from t_1 to t_3. Given that the last copy is sold at t_2 and retired at t_3, this distance would likely reflect the service life of software copies. As such, if we are confident about estimates of the depreciation of software copies, then we can work out the depreciation of software originals.

We subtract our estimates of the service life for software originals from the service life of software copies in table 8. On average, we find that the difference between our estimate and the estimates by statistical agencies is about 3 years for PPML and only 0.8 years for Negative Binomial. While our approach still implies that the services life of software R&D is overstated, the difference is only by a maximum of 4 years.

Table 9: Implied Service Life of Software Originals by Country

	PPML	NB
UK	6.9	6.0
US	7.8	5.0
Canada	7.8	5.9
France	6.7	5.0
Germany	8.0	4.5
Italy	7.7	4.5
Ave Diff	3.1	0.8
Ave	7.5	5.2
δ	0.134	0.194

As mentioned earlier, European countries account for software originals as part of software assets. The service life they employed are the same as those shown in table 8. Our estimates for the asset life of original software in table 9 is longer than the asset life of software employed by statistical agencies in Europe. The US, which records original software as part of R&D, employs a service life of 4.5 years (Pionnier et al., 2023) for original software, which is closer to the lower bound of our estimates.

How do we know if these estimates are valid? We do not observe the actual service life of original software and in most cases, software companies do not present revenues that can be traced to specific software titles. This makes it easier to verify another form of intangibles, specifically, theatrical movies. We present estimates for movies in the next section.

6.3 Movies

Unlike software, it is relatively easier to determine the revenues attributable to specific movie titles. Box office revenues (which account for the majority of the movie revenues) and DVD sales are tracked and published on various websites such as IMDb.com and TheNumbers.com. Therefore, it is possible to empirically track how much revenues decline over time. Soloveichik et al. (2013c) takes this further by estimating the net present value of movies. She calculates the depreciation rates of movies from the rate of decline in their net present value.

This is the approach taken by the BEA, which, we believe to be the appropriate way to estimate the depreciation of such assets. This is also the approach recommended by OECD (2010). If estimates using our approach match those from the BEA, this could support the validity of our methodology.

We are able to distinguish the residency of the studio producing each movie. This allows us to estimate different depreciation rates for different countries. We show the regression results for the US and Germany in table 10. We chose to present results for these countries because it would be easier to compare our estimates to official data later on.

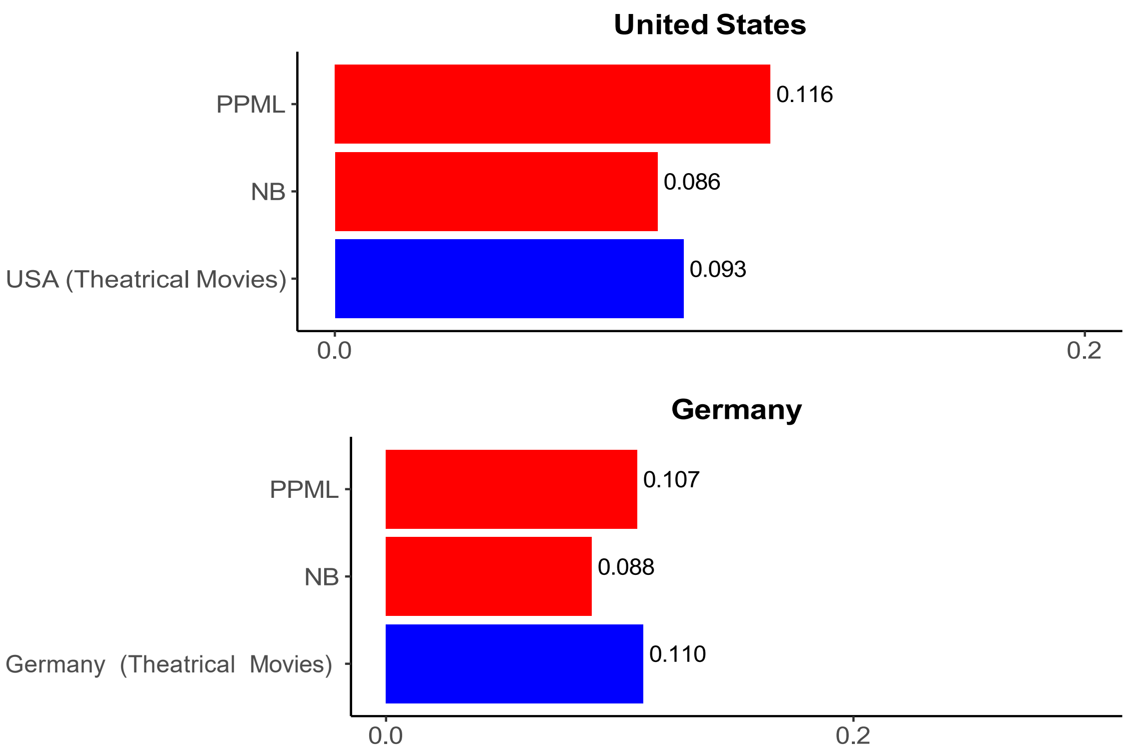
Table 10

	OLS	PPML	Negative Binomial
		All Countries	
	(1)	(2)	(3)
δ^{All}	-0.004^{***}	-0.011^{***}	-0.008^{***}
	(0.0001)	(0.00001)	(0.00002)
		United States	
	(4)	(5)	(6)
δ^{US}	-0.004^{***}	-0.010^{***}	-0.007^{***}
	(0.0001)	(0.00001)	(0.00003)
		Germany	
	(7)	(8)	(9)
δ^{DE}	-0.004^{***}	-0.009^{***}	-0.008^{***}
	(0.0002)	(0.00003))	(0.0001)
Keyword FE	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes

Results from OLS are substantially smaller compared to those from PPML and the Negative Binomial models. We suspect that the large difference stems from the fact that most zero observations occur at the tail end of the GSV results. Typically, four to five years following a movie's release, search activity tends to diminish to a point where it falls below Google's inclusion threshold, resulting in these instances registering as zero entries. To test this hypothesis, we employ a truncation approach, wherein all observations within three years of a movie's release are removed from the dataset. Results in appendix B.2 show that OLS and PPML estimates are similar if the value of delta is small. However, we do not use these results because in many cases, we observe sparse spikes for movies released many years after their debut. This could be driven by many factors including seasonality (for instance, people watching Top Gun every Christmas) or sequels (people watching the Tobey Maguire Spider-Man movies before the release of No Way Home).

From the regression results, we also note estimates for the US and Germany are similar, with Germany's being slightly faster. This could imply that American films depreciate slower than German films.

Figure 7: Comparing the annual depreciation rates estimates for movies with those from other countries



Note: The figure compares results from PPML negative binomial (NB) model with the annual depreciation rates for theatrical movies employed by the United States and Germany. The monthly estimates from table 10 were annualized assuming a geometric pattern. The depreciation rates employed by the US and Germany are sourced from Pionnier et al. (2023).

While we would prefer to compare our estimates to the estimates for the depreciation rates by other statistical offices, we can only find estimates for movies from the US and Germany. Other countries present estimates at the aggregate level, as part of "artistic originals" (see table 1). We compare our estimates to the depreciation rates employed by

Table 11: Implied Service Life by Country

Country	Implied Service Life
United States	
PPML	8.6
NB	11.6
Official Estimate	10.8
Germany	
PPML	9.3
NB	11.4
Official Estimate	9.1

the US and Germany. We show the comparison in figure 7. Estimates for the UK, France, and Italy are shown in appendix table B.1.

For the US, our estimates are not materially different from those employed by BEA. Our estimated asset life for movies (see table 11) of 8.6 to 11.6 years is close to the estimates of BEA, at 11 years. Similarly, estimates for Germany also approximate the official data. Our estimated service life for German films of 9.3 to 11.4 years is only slightly above the official estimates of 9.1 years.

Our methodology presents a notable advantage in its flexibility for frequent updates and the ability to compute depreciation rates for specific time intervals. As demonstrated in table 12, we partitioned the dataset into two segments: one that includes movies released between 2004 and 2010 and another comprising movies released from 2011 to 2016. Although the depreciation rate exhibits only a subtle disparity in the monthly rates, this translates to a substantial difference in the implied asset life.

Our estimates show that the service life of films released from 2011 to 2016 is almost half of that of movies released between 2004 to 2006. Technological advancements, like the rise of affordable streaming services and piracy, have significantly altered how consumers interact with and obtain media. This transformation has brought about various industry shifts, notably the reduction of the theatrical release window (Ahouraian, 2021). Traditional depreciation rates, which are not frequently revised, may not accurately capture the repercussions of this shift.

Table 12: Estimates for movies by release dates

	Monthly	Annual	Service Life
All Release Dates	1.1	12.3	8.2
Released 2004 to 2010	0.9	10.0	10.0
Released 2011 to 2016	1.7	18.6	5.4

6.4 Validity check

There is a consensus that the obsolescence of intangibles is generally linked to the asset's ability to generate revenues (Pakes & Schankerman, 1984; Nakamura, 2010; De Rassenfosse & Jaffe, 2017; Li, 2014; Li & Hall, 2020). There are limited avenues on how to test the relationship between GSV results and revenues that can be directly attributed to the asset. In the case of software, for instance, firms rarely break down revenue streams directly linked to specific software titles. The case is not the same for movies, however. Data is available on box office revenues from IMDb.com. To a limited extent, DVD sales data is also available from the-numbers.com. These were the data sets employed by Soloveichik et al. (2013c) and Goodridge et al. (2013b). By combining these datasets with GSV results, we can test whether there is a statistically significant relationship between Google Trends results and movie revenues.

For the first part of this validation exercise, we construct variable $\bar{V}^{B}_{k,l,d,t}$, which represents lifetime box office revenues for movie k, released on year l, by taking the sum of all future revenues[6] of the movie from time, t up to the end of the theatrical window at time, T:

$$\bar{V}^{B}_{k,l,d,t} = \sum_{t=1}^{T} V^{B}_{k,l,d,t}. \tag{3}$$

Since daily data on streaming revenues and DVD sales are scarce, lifetime revenues, in this case, only cover revenues earned from the theatrical release. However, the majority of movie revenues are generated from the box office[7]. As such, we believe that our analysis is still valid despite this limitation.

[6] Data on box office revenues were sourced from the-numbers.com.

[7] https://www.statista.com/statistics/1194522/box-office-home-and-mobile-video-entertainment-revenue-worldwide/

We estimate the model:

$$log(\bar{\ }^{B}_{k,l,d,t}) = \tilde{\beta} \cdot log(\bar{G}_{k,l,d,t}) + \tilde{\delta}\tau_t + \Gamma_k + \theta_l + \omega_d + \tilde{\mu}_{k,r,d,t} \tag{4}$$

where $\bar{G}_{k,l,t}$ are GSV results, τ_t is a time trend; Γ_k, ω_d are day of the week fixed effects, and θ_l are movie title and release date (year) fixed effects, respectively; and $\tilde{\mu}_{k,r,d,t}$ is a random error term.

We are interested in the parameter $\tilde{\beta}$, which is expected to be positive, implying a direct relationship between GSV results and box office revenues. Box office revenues generally decline following the first day of the release of the movie. As such, regressing box office revenues with any variable that is also trending downward will generate significant results. This part of the exercise aims to uncover whether $\bar{G}_{k,l,t}$ can explain some of the variations in the decline in revenues, *on top of what can be absorbed by the time trend*.

Table 13: Testing the relationship between Box Office revenues and Google Trends Results

	Dependent Variable:			
	Google Trends	Lifetime Box Office Revenues		
	(1)	(2)	(3)	(4)
$\tilde{\delta}$ (time trend)	-0.005^{***}	-0.072^{***}		-0.071^{***}
	(0.0003)	(0.001)		(0.001)
$\tilde{\beta}$ (Log Google Trends)			0.291^{***}	0.046^{***}
			(0.017)	(0.005)
AdjR2	0.347	0.900	0.451	0.900
n	118,050	118,050	118,050	118,050
Keyword FE	Yes	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes

The results are presented in table 13. We observe from the first two columns that box office revenues decline faster than the Google Trends index. This is not surprising since the lifespan of movies often exceeds their screening dates. As such, there would still be some search activities for movie titles even though they are no longer shown in cinemas. In the last column, the coefficient for GSV results is positive and significant, confirming that there is a direct relationship between Google Trends results and box office revenues, other than what can be explained by the normal passage of time.

We can also extend this analysis by exploring the dynamics between GSV and box office revenues. Equation 5 incorporates lagged terms for GSV results, acknowledging the potential scenario wherein individuals frequently conduct internet searches for movies prior to viewing them:

$$log(\bar{B}_{k,l,d,t}) = \sum_{n=0}^{N} \tilde{\beta}_{t+n} \cdot log(\bar{G}_{k,l,d,t-n}) + \tilde{\delta}\tau_t + \Gamma_k + \theta_l + \omega_d + \tilde{\mu}_{k,r,d,t} \tag{5}$$

Results shown in table 14 show that lagged GSV results explain some of the variations in box office revenues, on top of what can be absorbed by the time trend. We also observe that as we increase the number of lags, the coefficient for the time trend gets smaller, implying lags contribute to the reduction of the omitted variable bias. In other words, incorporating lagged GSV results captures additional information that the time trend alone cannot, enhancing the model's explanatory power and reducing potential distortions caused by omitted variables. The relationship is also positive, suggesting that both variables move in the same direction. We believe that our results provide evidence of a direct and systematic relationship between Google Trends and movie revenues, which is a requirement in the framework that we discussed in section 6.4.

Table 14: Testing the relationship between box office revenues and Google Trends Results

	Dependant Variable: Lifetime Box Office Revenues				
	(1)	(2)	(3)	(4)	(5)
$\tilde{\delta}$ (time trend)	-0.071^{***}	-0.071^{***}	-0.070^{***}	-0.070^{***}	-0.070^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tilde{\beta}_{t+n}$ Log Google Trends					
Lag 0	0.040^{***}	0.035^{***}	0.031^{***}	0.027^{***}	0.025^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Lag 1	0.038^{***}	0.034^{***}	0.030^{***}	0.027^{***}	0.023^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Lag 2		0.033^{***}	0.030^{***}	0.027^{***}	0.024^{***}
		(0.004)	(0.004)	(0.004)	(0.003)
Lag 3			0.029^{***}	0.027^{***}	0.025^{***}
			(0.004)	(0.004)	(0.003)
Lag 4				0.025^{***}	0.023^{***}
				(0.004)	(0.004)
Lag 5					0.023^{***}
					(0.004)
AdjR2	0.902	0.903	0.904	0.905	0.905
n	114,142	110,889	107,750	105,069	102,563
Keyword FE	Yes	Yes	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes	Yes

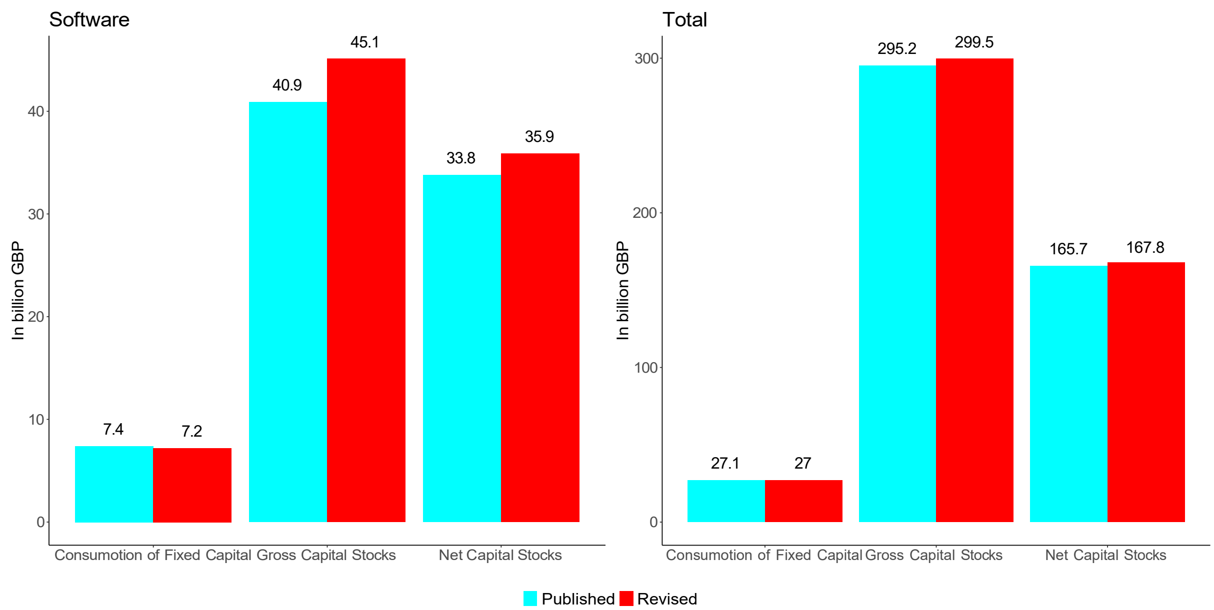
7 Impact on industry aggregates

Due to time and resource constraints, we do not estimate a perpetual inventory model ourselves. Rather, we employ the codes provided by the Office for National Statistics on their websites[8]. The ONS provides the raw data, R codes, and the set of assumptions to replicate their estimates of various aggregates relating to capital at the 2-digit SIC

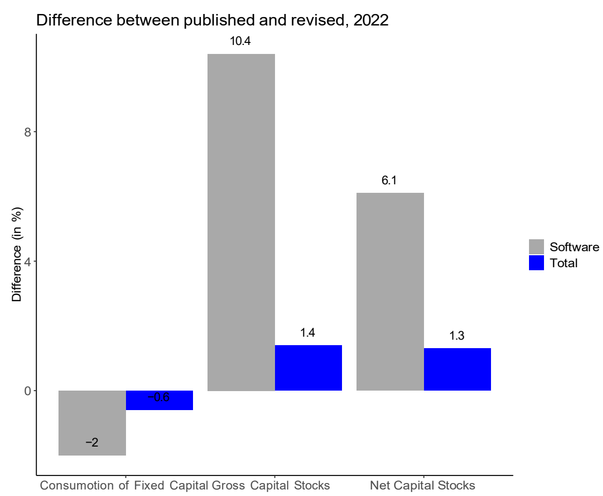
[8]https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/capitalstocksuserguideuk last accessed: 15 February 2022

industry level.

Figure 8: Estimates for Sector J, 2022



(a) Levels



(b) Percent difference

For this exercise, we changed the service life assumption for own-account software under SIC industries 62 (Computer programming, consultancy and related activities) and 63

(Information service activities)[9] from 4 years to 7 years, following our estimates for the original software. Since the ONS was not able to provide a breakdown of the type of software capital, we assumed that all software investment that goes to these industries are original software for reproduction.

Our results show that for 2022 (see figure 8), our estimates on the consumption of fixed capital for software are slightly lower than the published data. Our estimate of gross capital stock of software for sector J is 10.4 percent higher than the published data, while our estimates of net capital stock are 6.1 percent higher.

Not surprisingly, the difference is more modest for the total capital stocks. Our estimate of total gross capital stocks for sector J is only 1.4 percent higher than published, while the estimate for total net capital stocks is only 1.3 percent higher than what was published by the ONS.

Between 2002 and 2006, our estimates of total net capital stocks (chain volume measure) for sector J are consistently higher than those published by the ONS, as illustrated in Figure 9. However, the disparity between our estimates and the published data varies over time, ranging from as low as 0.92 percent to as high as 1.2 percent.

The impact on growth rates also exhibits variability across different periods. Some years demonstrate faster growth in net capital stocks according to our calculations, while in others, our growth rates are slower than the published data. This could have implications for Total Factor Productivity (TFP) growth. Notably, from 2015 to 2018, our estimates indicate consistently slower growth rates in net capital stocks for sector J compared to the published data. This observation suggests that TFP growth during that period may be higher than initially estimates.

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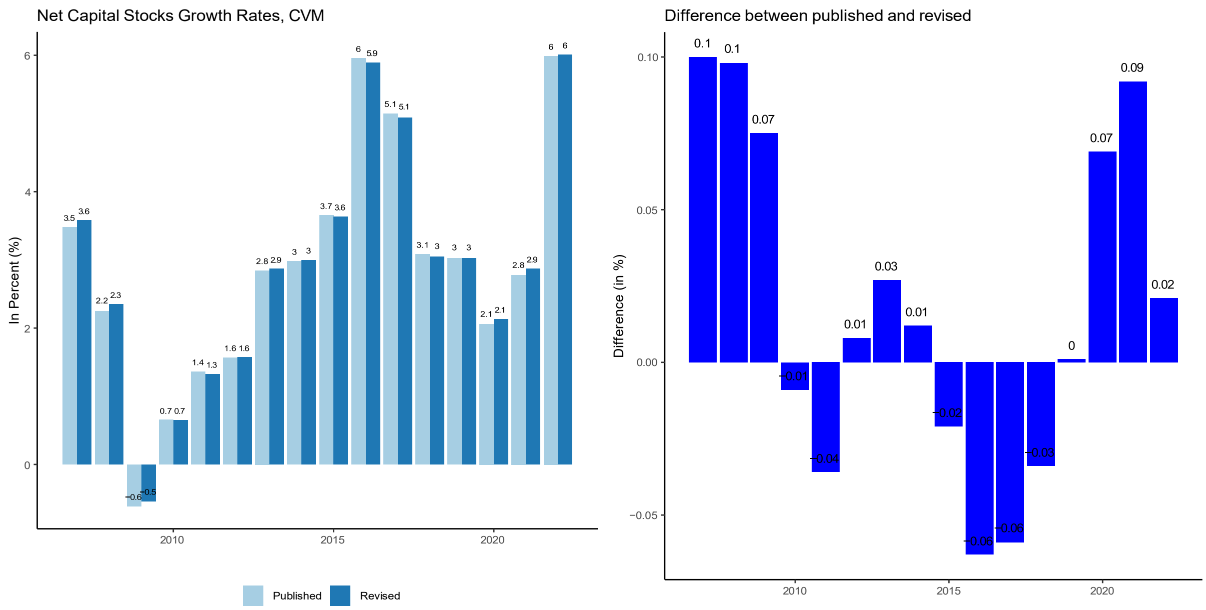
[9]The ONS combines the two industries in their database. We are not able to separate the investments going to the two industries

Figure 9: Estimates for Sector J, 2006 to 2022

(a) Levels



(b) Growth rates

Note: Figure describes the differences in net capital stocks (chain volume measure) for sector J calculated using the asset life from the GSV estimates against the published data on net capital stocks. The upper-left panels show the levels over time. Upper-right panels the differences between the levels (revised vs published) in percent. The lower-left panel shows the growth rates. The lower-right panel shows that difference in the growth rates revised vs published) in percentage points.

7.1 Impact on the productivity growth of the UK's Information and Communication industry

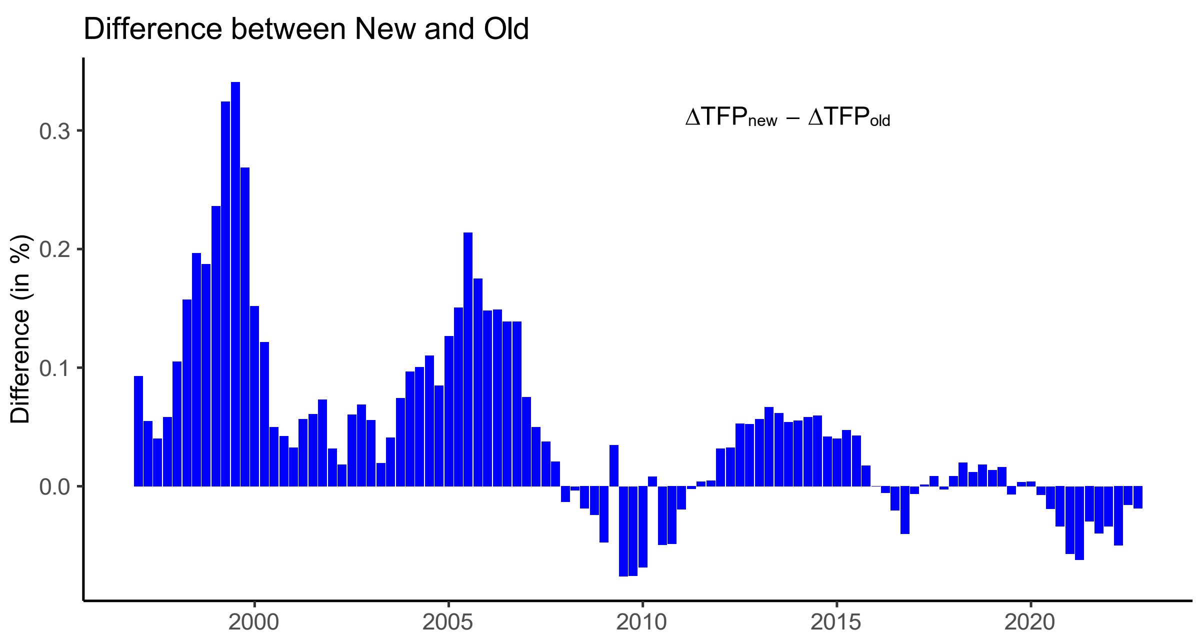
We estimate TFP following Bontadini et al. (2023) and Organisation for Economic Co-operation and Development (2021). We also tried to remain consistent with Office for National Statistics (2007). Details on the methodology are discussed in appendix D.

There are some differences between the capital stocks that are part of the National Accounts of the ONS, and capital stocks employed in their calculation of TFP. The National Accounts assume a hyperbolic rate for all assets with the exception of R&D, which applies a geometric rate[10]. For capital stocks employed in productivity calculation, the

[10] https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/capitalstocksuserguideuk

ONS applies a geometric rate for all assets. Moreover, there are some technical differences, as well namely, 1) TFP statistics only cover the market sector, removing stocks employed by the government, and 2) the use of user cost (see appendix D) to ensure that assets with higher depreciation rates are given higher weights than assets with longer services lives. The combination of these factors would cause differences between the intuition laid out in the previous section and the final results.

Figure 10: TFP difference for sector J, 1995 to 2022



Note: Figure shows the difference between the TFP calculated using the asset life of own-account software from estimates from the GSV methodology and TFP calculated using current assumptions on the own-account software's asset life (New - Old). Results are percentage points differences in TFP growth.

Figure 10 shows the difference between TFP using our estimated asset life ('New') and TFP growth calculated while maintaining the current assumptions of the ONS ('Old').

We find that TFP is largely underestimated from the years from 1995 up until the 2008 financial crisis for sector J. We also observe evidence of TFP growth being underestimated from 2011 to 2016. During the financial crisis and the years following the COVID recession and Brexit, we find that TFP is likely overestimated during those periods, the magnitude of overestimation is not large relative to the rate of underestimation in other periods.

Our calculations suggest that official TFP growth estimates are likely understated during the period leading to the 2008 financial crisis. Current assumptions on asset lives compressed the service life of software stocks when they should have been spread out over a longer period.

This discrepancy is likely attributable to the significant surge in software investments during the late 1990s and early 2000s. We notice that investments in intangibles overtook investments in tangible assets in the early 2000s for sector J (see Figure B.2). Moreover, the share of own-account software investments to total intangibles for the sector also saw a substantial increase from 5.9 percent to 18.2 percent (see Figure B.3). Capital stocks of the rising software were compressed to periods, coupled with a decline in tangible capital investment, which likely resulted in the underestimation that we observed in our results.

Perhaps we can interpret this as recent period software capital being more productive than those from the early 2000s. Clearly, more research is needed in this area. More importantly, given that these differences are systematic for certain periods, it is highly likely that this points to structural issues underlying the estimation of productivity and economic performance, particularly in sectors heavily reliant on intangible assets like software.

While our analysis is focused on TFP growth rates, we also find some systematic differences in the levels of the TFP index. In particular, we find that estimates of the TFP index, which employs the software asset life from our approach are consistently higher from 1995 to 2006. From 2007 onwards, we find that the TFP index from our estimates is consistently lower than TFP estimates using existing assumptions on the asset life (see table D.11).

8 Concluding remarks

While various methodologies have been employed to measure intangible investments, persistent challenges remain in accurately estimating the depreciation of intangibles. We demonstrate that utilizing GSV can assist in this endeavor. Preliminary findings suggest a depreciation rate for software that diverges from estimates employed by statistical agencies, emphasizing the importance of refining measurement approaches to capture the true value dynamics of intangible assets within contemporary economic landscapes.

While our proposed methodology using Google Search Volume (GSV) provides a novel and practical way to estimate the depreciation of intangible assets, it is not without limitations.

First, our method relies on Google Search data, which may not capture the behavior of all consumers. Some users may bypass Google entirely by searching directly on streaming platforms, tailored websites like IMDb. This limitation could underestimate certain forms of engagement, particularly for niche audiences.

Second, differences in consumer behavior across demographic groups and media formats may introduce bias. For instance, older users are less digitally active may not contribute significantly to Google search trends.

Despite this, we argue that Google remains the dominant search engine globally, and its trends data provide a broad and consistent measure of public interest, making it a reasonable proxy for consumer demand at scale. We acknowledge that future extensions of this research could incorporate complementary data sources to enhance coverage, such as the use of sentiment analysis from social media content,

Morever, while differences in the consumer behavior across demographics presents a limitation, the growing shift toward digital consumption and online engagement across most age groups mitigates this concern over time. Nonetheless, acknowledging this gap highlights the need to triangulate Google Trends data with alternative measures when analyzing specific subpopulations.

Despite these limitations, the advantages of our approach are clear: it provides a scalable, dynamic, and cost-effective way to measure depreciation for intangible assets, addressing a critical gap in the literature and statistical practice. The advantage of our approach is its relatively easy implementation, requiring only the assumption that GSV directly correlates to changes in revenue streams associated with these assets–an assumption that we also tested and found support for in the study.

For statistical agencies, this method could be incorporated incrementally, starting with specific asset categories where public interest is a strong indicator of economic obsolescence. For example, branding assets—where consumer engagement drives value—may benefit from this approach. This study lays the foundation for further extensions that address the challenges of measuring other critical components of modern economies.

Additionally, the methodology holds the potential to extend its application to estimate the depreciation rates of other intangibles, such as TV series, songs, books, and music, as well as non-SNA intangibles, such as brands. Furthermore, the approach can incorporate additional dimensions into estimates, such as estimating the depreciation of intangibles for specific localities, and facilitate more frequent updates of asset lives required for capital stock measurement.

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Appendix

A Summary on the difference between concepts of obsolescence

Table A.1: Comparison of Embodied and Disembodied Obsolescence

Aspect	Embodied Obsolescence	Disembodied Obsolescence
Primary Cause	Introduction of new, improved models.	Market or economic factors, such as input price changes or demand shifts.
Mechanism	Older assets lose value due to relative inefficiency compared to newer models.	Assets lose value because they are no longer suited to economic conditions.
Adjustment	Measured using quality-adjusted price indices.	Linked to shifts in demand or relative input costs, not technical changes.
Scope	Tied to technological progress and embodied technical change.	Not tied to new models; occurs even in the absence of technological progress.
Economic Impact	Reduces the relative economic value of older assets.	Reduces the absolute viability of the asset's continued use.
Example	Older cars lose value due to the release of more fuel-efficient models.	A factory closes because energy costs rise, making production unprofitable.

B Additional results

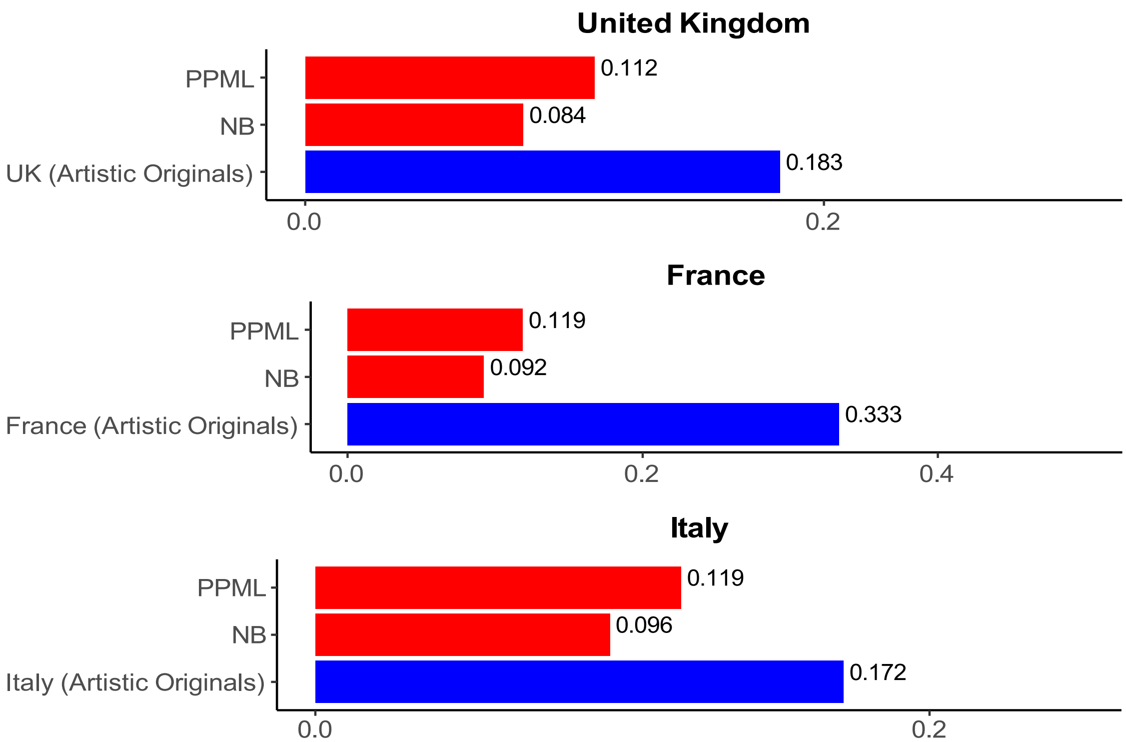
Table B.2

	OLS (1)	PPML (2)	NB (3)
δ	-0.109^{***} (0.002)	-0.092^{***} (0.0001)	-0.065^{***} (0.001)

Table B.3: Results for Negative Binomial model removing free and open-source software

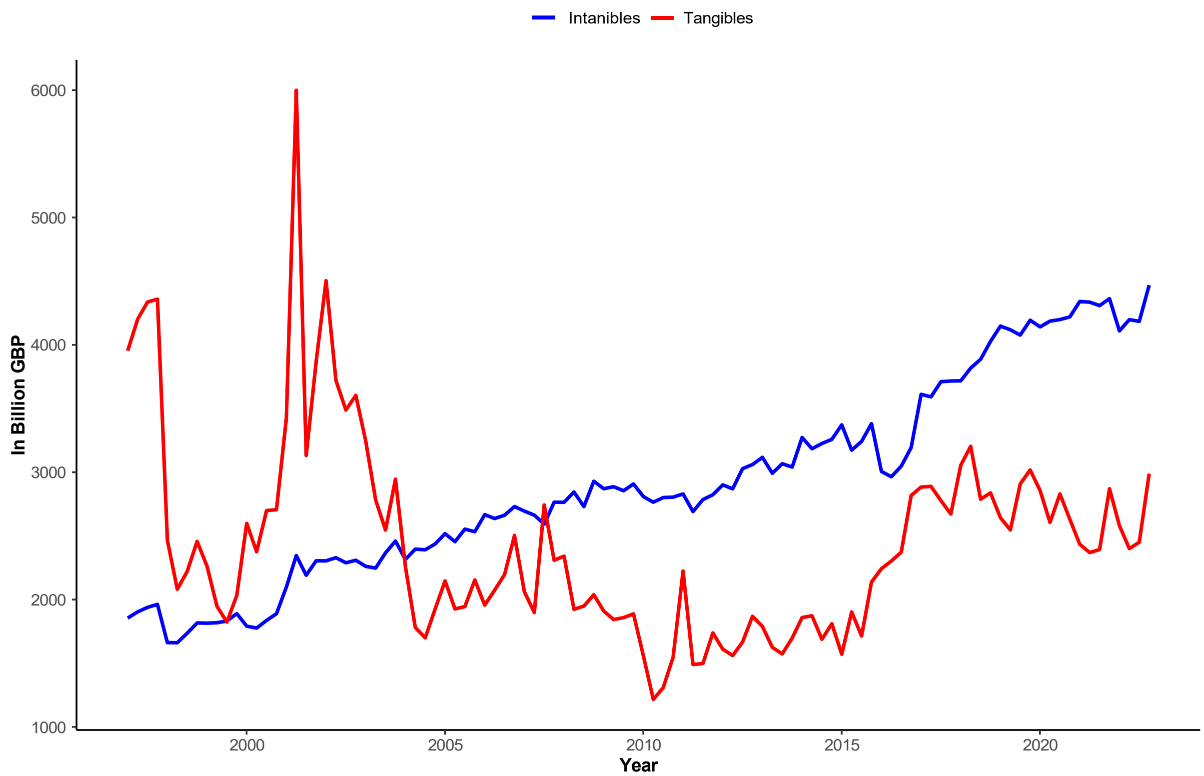
	All (1)	No Free & Open Source (2)	No Open Source Only (3)
δ	-0.009^{***} (0.0001)	-0.009^{***} (0.0001)	-0.009^{***} (0.0001)
n	161,735	135,186	144,453
Keyword FE	Yes	Yes	Yes
Release Date FE	Yes	Yes	Yes

Figure B.1: Comparing the annual depreciation rates estimates for movies with those from other countries



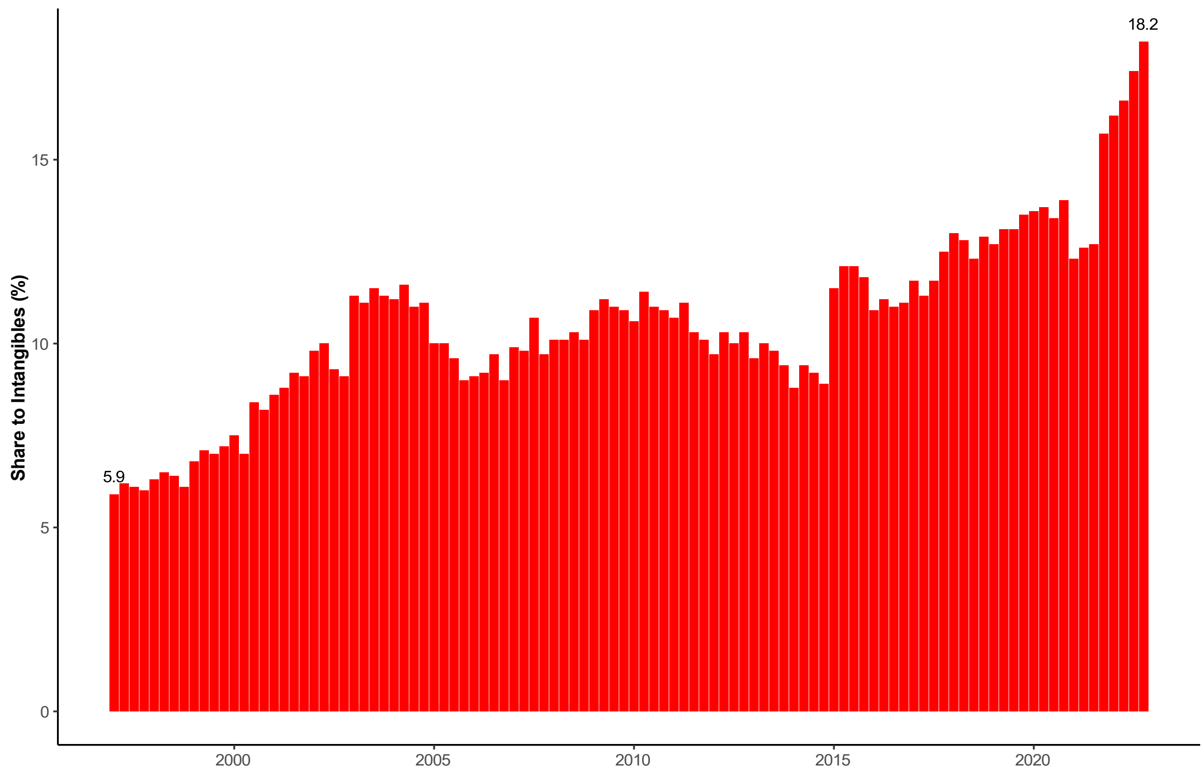
Note: The figure compares results from PPML and negative binomial (NB) model with the annual depreciation rates for theatrical movies employed by a select set of countries. The monthly estimates from table 10 were annualized assuming a geometric pattern. The depreciation rates employed by other countries were sourced from Pionnier et al. (2023).

Figure B.2: Investments for sector J from 1996 to 2022, current price estimates



Note: Figure shows the gross fixed capital formation for sector J at current price. In this figure, intangible investments only include intellectual property products (IPP) capitalized in the National Accounts, namely purchased and own-account software, literary and entertainment originals, mineral exploration, and research and development. The figure covers the period from 1996 to 2022.
Source of basic data: Office for National Statistics, UK

Figure B.3: Share of own-account software to total intangibles for sector J from 1996 to 2022, current price estimates

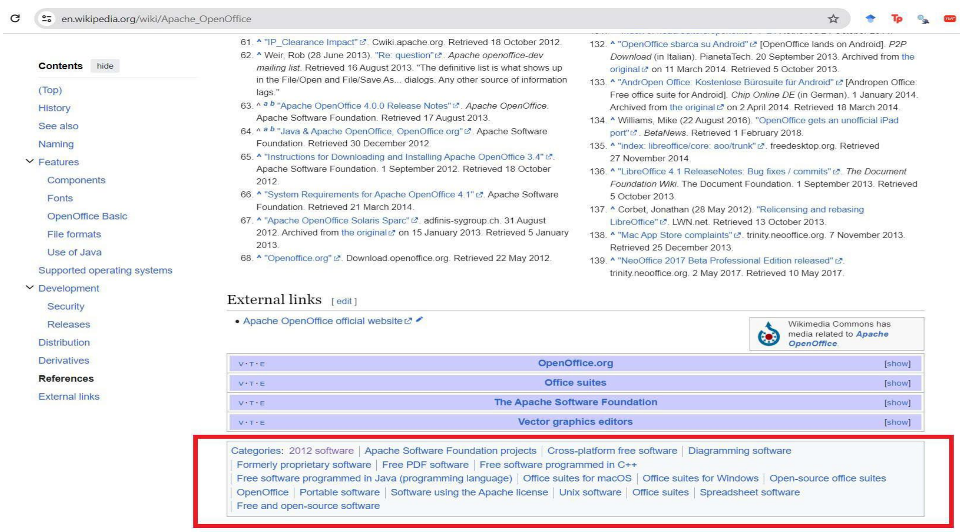


Note: Figure shows the share of own-account software investments to total gross fixed capital formation on itangibles for sector J at current price. In this figure, intangible investments only include intellectual property products (IPP) capitalized in the National Accounts, namely purchased and own-account software, literary and entertainment originals, mineral exploration, and research and development. The figure covers the period from 1996 to 2022.
Source of basic data: Office for National Statistics, UK

C Classifying software into categories

To classify software into categories, we exploit the categories tag at the bottom of the Wikipedia page of each software title. See example below:

Figure C.4: Example: Wikipedia page for Open Office



We scrape all of the tags and attach them to their corresponding software title. Each title would often have more than one tag. We were able to scrape 2,119 tags. Each of these tags corresponds to one or more software titles. For instance, the tag “Office suites” was attached to both Open Office, Microsoft Office Versions, and other office software. We show in figure C.5 as word cloud for the top 1,000 most common tags.

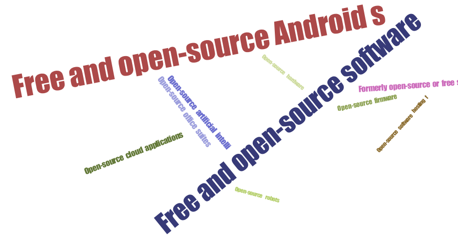
Figure C.5: Word cloud of the category tags from software Wikipedia entries

Our interest is to see whether the estimates would change if we remove "free-to-use" and "open-source" software. As such, we generated broad categories by identifying tags with the words "free" and "open source" and lumping them into a single broad category. We also created a third category that identifies tags containing the word "open source" but does not contain the word "free". We show the word cloud for these tags in figure C.6.

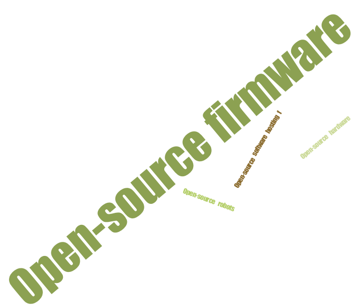
To extend our descriptive analysis, we also generated other broad categories using the same method. We identified the operating system with which these software are compatible and the type of software they can be classified into. We show the word cloud for the tags identified for each category in figures C.7 and C.8, respectively.

Figure C.6: Free and open-source software

(a) Free software



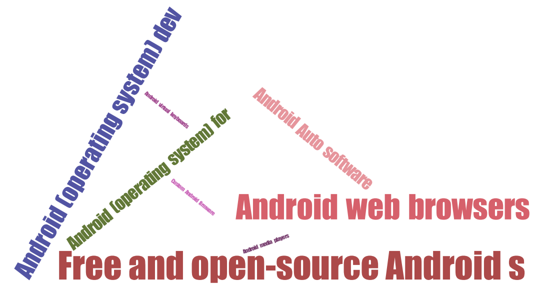
(b) Open-source software



(c) Strictly open-source software

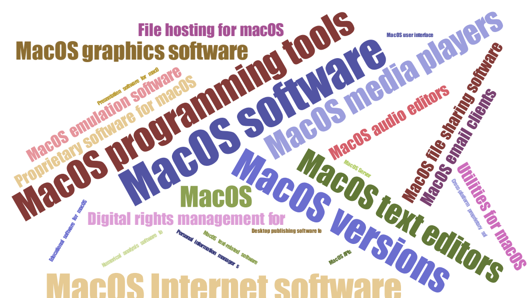
Figure C.7: By operating system

(a) Windows

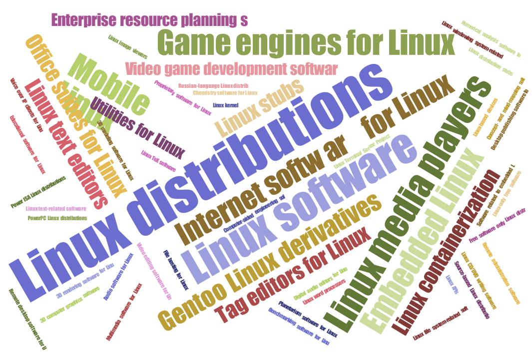


(b) Android

(c) iOS

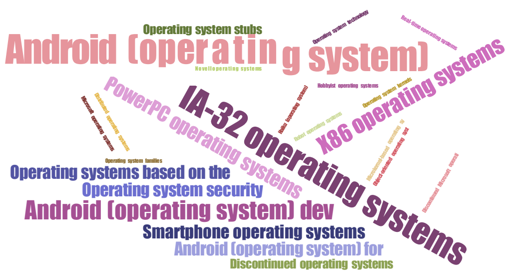


(d) MacOS



(e) Linux

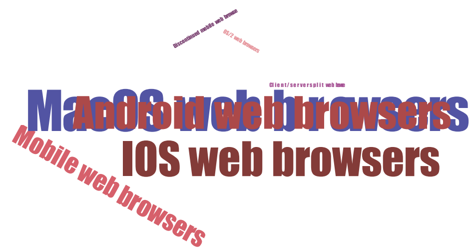
Figure C.8: By type



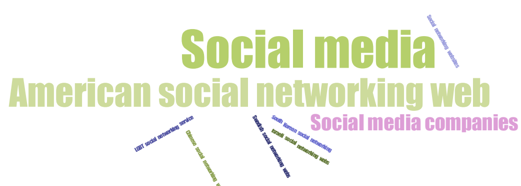
(a) Operating system

(b) Media

(c) Office



(d) Web browser



(e) Social media and social network

D Constructing TFP estimates for sector J

We estimate TFP following Bontadini et al. (2023) and Organisation for Economic Co-operation and Development (2021). We also tried to remain to be consistent with Office for National Statistics (2007). The first step was to calculate user cost:

$$u_{i,t} = r_t p_{i,t} + \delta_i p_{i,t+1} - (p_{i,t+1} - p_{i,t}) \tag{D.1}$$

where $u_{i,t}$ is the user cost for asset i at time t, is the rate of return, δ_i is the depreciation rate, $p_{i,t}$ is the investment price, and r_t is the rate of return. We assumed a geometric pattern for the depreciation rate for all assets. To maintain consistency with the official methodology, we also used the internal rate of return, which we calculate by taking the ratio of Gross Operating Surplus to GDP[11]. We sourced all our data from the ONS website[12]. We proceeded by calculating thing net capital stock K_t:

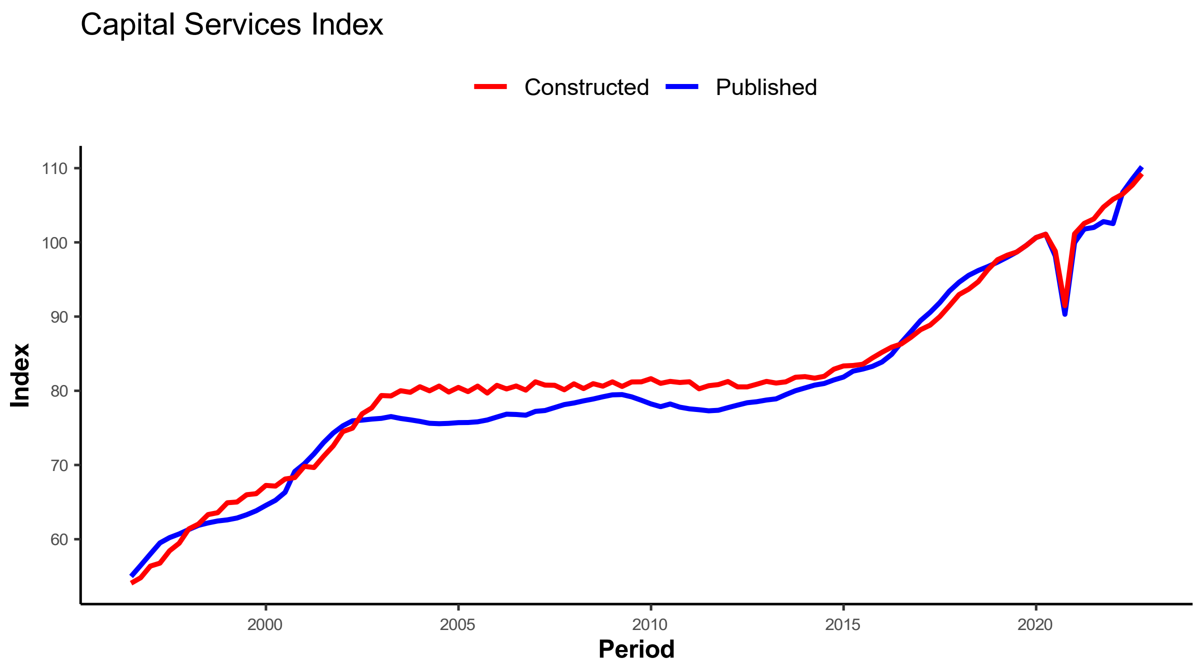
$$K_{i,t} = k_{i,t} \times \frac{k_{i,t} \times u_{i,t}}{\sum_i k_{i,t} \times u_{i,t}} \tag{D.2}$$

Our estimates of the capital services index do not align with the capital services index published by the ONS. One of the reasons is likely due to the tax adjustment that the ONS applies when computing for user cost, as well as the difference in deflating computers. Note that at this point, we have not made any changes yet to the assumptions on the service life for any asset.

[11] This is also the recommendation of Bontadini et al. (2023).

[12] https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/capitalstocksuserguideuk

Figure D.9: Constructed versus published Capital Services Index



Note: The figure shows the capital service index we estimated (red line) and the capital services index employed by the ONS for their TFP calculations (blue line).

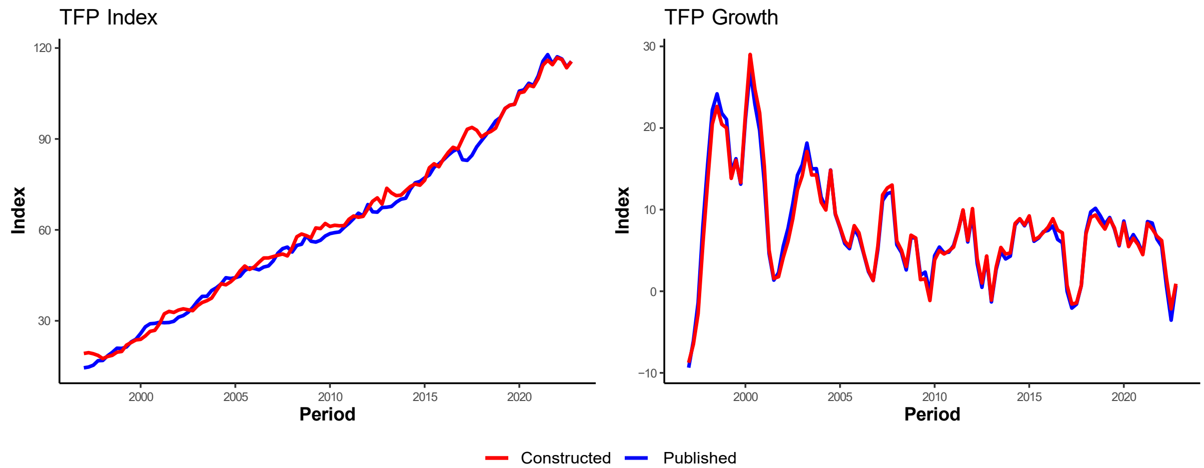
We proceed by calculating TFP using the standard growth accounting formula.

$$\Delta log(TFP_t) = \Delta log(Y_t) - v^l_t \Delta log(L_t) - v^k_t \Delta log(K_t) \tag{D.3}$$

where we express TFP_t as the difference between changes in the output Y_t and changes in Labor inputs L_t, and capital inputs K_t. The terms v^l_t and v^k_t are labor and capital weights.

Despite the difference in our constructed capital services index to those published by the ONS, we see little discrepancies between the published TFP index and those that we constructed using equation D.3 (see figure D.10). We do not find any systematic difference between our constructed index and the TFP index and growth rates published by the ONS.

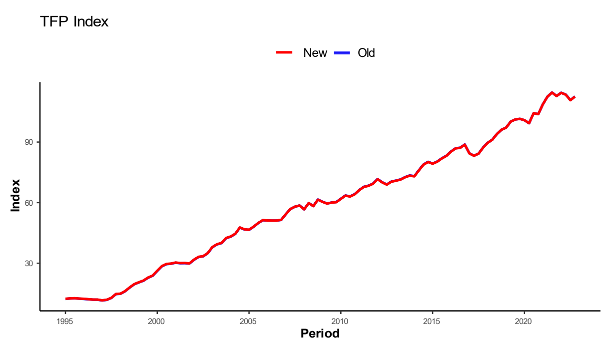
Figure D.10: Constructed versus published TFP



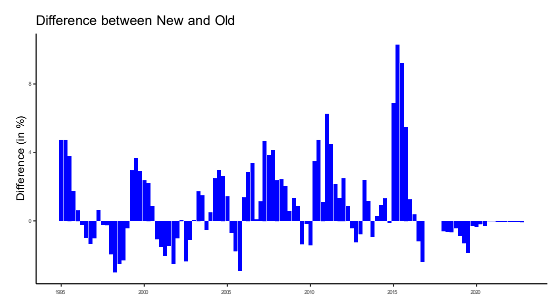
Note: The figure shows TFP we estimated (red line) and the TFP published by the ONS (blue line).

Following the steps earlier, we constructed a third TFP index for sector J where we changed the assumption on the asset life of own-account software for industries 62 and 63, using the asset life we estimated using GSV results. We also made changes to the user cost of own-account software by employing the new set of depreciation rates in our calculations. We compare the indices in figure D.11.

Figure D.11: TFP Index



(a) Levels



(b) Difference

Figure D.12: TFP growth rates