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The Productivity J-Curve from an International Perspective: Is the United States Unique?

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Abstract

Despite major advances in technology, productivity growth has slowed across advanced economies. Brynjolfsson, Rock and Syverson (2021) argued that, due to the large intangible investments associated with digitalization, total factor productivity (TFP) growth may be underestimated and be higher after the investment boom. The resulting gap between standard and revised measures produces a J-shaped pattern, the "productivity J-curve".

Building on this work, we examine productivity estimates for five advanced economies: France, Germany, Japan, the United Kingdom and the United States. Using the estimated coefficients on intangibles (research and development, software, and organizational capital) in the value functions of listed firms over 2006-2020, we find that TFP underestimation caused by large intangible investments was largely unique to the United States, and was much smaller in Europe and Japan. This result is consistent with the recent productivity rebound in the U.S. and reinforces the call for investment in innovation in Europe and Japan.

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1. Introduction

Digitalization in the 21st century has revolutionized our lives and businesses. While one would expect this profound digital transformation to lead to faster productivity growth and higher living standards, productivity growth rates in the advanced countries have generally stagnated since the 2010s (Fernald, Inklaar and Ruzic (2025), Goldin, Koutroumpis, Lafond and Winkler (2024) and Van Ark, de Vries and Erumban (2024)). Over this time, two major digital innovations have emerged: first, the rise of platform organizations such as Airbnb and Uber in the early 2010s, and second, the development of generative artificial intelligence (AI) businesses such as OpenAI. These seemingly conflicting developments — of faster digitalization and slower productivity growth — have led to academic and policy debates on the economic effects of digitalization on productivity growth.

The issues can be framed within the broader challenge of measuring the impact of the digital economy, or any other technological revolution, on growth. As argued by Aghion *et al.* (2019), official statistics do not correctly capture prices. Because new entrants tend to offer lower prices than incumbents, true price levels are lower than those published by official statistics, and the true real value added is higher.

One specific challenge concerns the accurate measurement of intangible capital in the national accounts framework. Following the standard measure, total factor productivity (TFP) growth is low during periods of high investment in digitalization, because increasing adjustment costs associated with new investments depress gross domestic product (GDP). As a result, TFP growth decreases during the investment boom.

Brynjolfsson, Rock and Syverson (2021) developed an alternative, finance-based approach to measuring intangibles. They build on the standard neoclassical investment theory with adjustment costs — as developed by Lucas (1967) and Uzawa (1969) — which holds that capital formation requires additional expenditures (such as employee training and organizational change) which should be treated as capital investment, even though traditional investment treats them as temporary outlays. They then estimated the parameters of adjustment costs of investment and used them to revise the standard measure of TFP growth.

Once the adjustment costs are recognized as intangible investments, the revised GDP does not fall and the revised TFP growth rate becomes stable. Because the standard TFP growth rate recovers after the investment boom, the movements in the gap between the standard TFP growth rate and the revised TFP growth rate resemble the letter J. Hence BRS (2021) called these movements the “productivity J-curve”.[1] They argued that this model can explain the low productivity rate during the investment boom in the platform

1 According to BRS (2021), Larry Summers pointed out that the shape of productivity resembles the J-curve in the balance of trade literature.

industry and AI. Miyagawa, Tonogi and Ishikawa (2021) found that, in Japan, the difference between standard and revised TFP in information and communications technology-intensive industries followed a J-curve shape at least twice between the late 1990s and the 2010s.

In this paper, we extend the approach to measure intangibles and the revised TFP growth rate developed by BRS (2021) to several large countries in Europe as well as the U.S. and Japan. As Goldin *et al.* (2024) pointed out, not only Japan and the U.S., but also many European countries suffered from a productivity slowdown in the official statistics in the 2010s. However, the speed of digitalization and technological progress in the U.S. may have been faster than in the other advanced countries. For example, due to strict regulations, ride-sharing services have not yet been permitted in Japan, and the EU has regulated the monopolistic behavior by gatekeepers such as Amazon and Google.

The aim of our article is twofold. First, we examine to what extent the productivity slowdown in the advanced countries in the 2010s is overstated, by computing TFP measures adjusted for intangible capital, and examining whether the resulting gap follows a productivity J-curve pattern. This allows us to evaluate whether TFP growth during the 2010s is likely to have been underestimated. Second, we aim to clarify the scale and speed of digitalization by measuring underestimation of TFP growth induced by software investment.

Our empirical findings show that the productivity slowdown observed in the 2010s may have been overstated, as TFP was underestimated to some extent in all advanced countries. When focusing on capital formation such as R&D, software and organizational capital required to introduce new technologies, we find that productivity growth in the U.S. is largely underestimated, consistently with what was found by BRS (2021). In particular, rapid accumulation of intangible assets associated with software investment generated underestimation of U.S. TFP growth. Compared to the U.S., the scale of the underestimation of TFP growth rates in European countries and Japan is relatively small. Our results imply that European and Japanese firms depend on software created by U.S. firms which make large outlays to develop software. The low associated costs with capital formation in organizational capital in European countries and Japan imply that firms have been reluctant to make large investments in organizational change — which would have generated large adjustment costs, as was the case in the United States.

This article consists of six sections. In the next section, we review the literature on measurement issues related to GDP and intangibles, the productivity slowdown in advanced countries, and capital formation with multiple assets. In the third section, we present our data and model to estimate the parameters of adjustment costs of investment. Using listed firms' data in five advanced countries (France, Germany, Japan, the UK and the U.S.), we estimate two types of equations where explanatory variables consist of multiple assets: one consists of four assets (construction and buildings, machinery, R&D and software) and the other of five assets by adding organizational capital.

The fourth section shows our estimation results. We find that many assets are accompanied by associated costs with investment. In particular, investment in R&D assets is accompanied by high costs, for example because of the need for highly paid, high-skilled R&D workers. In the case of the U.S., the estimated coefficients for all assets suggest that capital formations generate large expenditures for intangibles which are consistent with BRS (2021).

The fifth section computes the revised TFP growth rates, using the parameters from these estimations, and examines whether the resulting gap relative to the standard TFP measures produces under- and over-estimations compatible with the J-curve theory. First, we revise TFP to account for intangibles associated with R&D, software and organizational capital, which are the key components of recent technological progress. As for R&D, we find that the J-curve effects generated by this type of asset are rather small, indicating minimal measurement issues associated with R&D. For software, we find that the U.S. incurred substantial associated costs as rapid digitalization accelerated software investment during the 2010s. Our results suggest that the U.S. productivity growth rate is underestimated by up to 1.4 percentage points when correcting for software, and 1.6 when correcting for software, R&D, and organizational capital. In France and Japan, we find small underestimation of TFP growth rate generated by the organizational capital, implying that those firms appear to have avoided such costs by limiting organizational investment. When we correct TFP for all intangible types in our data collectively, using the combined estimated coefficients, we again find a large underestimation of TFP growth in the United States.

In the last section, we summarize implications obtained from our estimation results and policy implications from our study.

2. Related Literature

Our paper relates to multiple research areas, such as measurement issues on GDP and intangibles, the productivity slowdown in advanced countries, and capital formation with multiple assets. Regarding the measurement of GDP, Erik Brynjolfsson and co-authors published at least three relevant articles. For example, Brynjolfsson *et al.* (2019) discuss the measurement of GDP noting that, as official GDP is a measure from the production side, the value of software provided for free is not counted in the current GDP framework. Hence, they suggest that GDP in the digital age should be measured from the consumer side, which they call "GDP-B". Tambe *et al.* (2020) measure digital capital based on the number of workers in digital firms, and find a positive relationship between digital capital and productivity growth. Brynjolfsson, Rock and Syverson (2021, henceforth BRS), which focuses on the measurement of intangibles and TFP growth, was discussed in the introduction as the central reference for our study.[2]

2 Basu *et al.* (2003) suggested that adjustment costs in the neoclassical theory should be recognized as intangibles.

Coyle and Nakamura (2022) also argue that GDP should be measured, not from the production side, but the consumer side. Hasegawa (2023) and Miyagawa (2024) refer to the experimental measures of the digital economy by the Cabinet Office of the Government of Japan which show that the digital economy accounted for 8.6 per cent of GDP in Japan in 2018. Miyagawa (2024) also measured the scale of digitalized inputs that are not recognized as assets in the current System of National Accounts (SNA), such as the cloud and AI procured services. Finally, the World Bank estimates that the digital economy contributes more than 15 per cent to global domestic product (Hayat, 2022).

There are many studies on the productivity slowdown in advanced countries. As stated in the introduction, Aghion *et al.* (2019) argue that true productivity would be higher than official productivity growth, if the statistics correctly captured the new economy due to digitalization. In contrast, Gordon (2016) argues that the recent U.S. productivity slowdown is to be expected because recent digital transformation has been less effective in improving living standards compared to the main innovations of the 20th century, such as running water, electricity, automobiles and washing machines. Acemoglu *et al.* (2014) argues that slower U.S. productivity growth was caused mainly by the decline in manufacturing employment, rather than technological progress as a result of digitalization. Goldin *et al.* (2024) examine which factors affected the productivity slowdown in the advanced countries by decomposing labour productivity growth into the contributions from capital deepening, labour composition, and TFP growth. In the U.S., both capital deepening effects and TFP growth slowed labour productivity growth, while slower TFP growth was the major factor behind the slowdown in France. Mismeasurement and allocative inefficiency had particularly large effects on French TFP growth. In Japan, capital deepening has slowed significantly while spillover effects from intangibles and trade are also found to be a crucial factor for weaker productivity growth.

The theoretical background of our paper is based on the neoclassical theory of investment with multiple assets. Following the theory of investment with a single asset (Lucas, 1967; Uzawa, 1969; Hayashi, 1982), the theory with multiple assets was developed by Wildasin (1984). Hall (2001), Miyagawa and Kim (2008) and Miyagawa, Takizawa and Edamura (2015) show that a firm's value can be expressed as the weighted sum of each asset under the assumption of linear homogeneous production and investment functions. Hall (2001) argues that when Tobin's q for a firm exceeds 1 it indicates the value of intangibles. This indicates that the stock market evaluates unmeasured intangibles in a firm's balance sheet. Following this argument, Miyagawa *et al.* (2015) show that Tobin's q, when only measured on the basis of tangible capital, is greater than 1 for the Japanese ICT firms. However, when considering unmeasured intangibles on these firms' balance sheets, the revised Tobin's q becomes closer to 1. This suggests that unmeasured intangibles in ICT firms contribute to increased firm valuations.

3. Data

As noted by BRS (2021) and further developed by Miyagawa, Tonogi and Ishikawa (2021) and Bijnens, Konings and Putseys (2025), the introduction of a new General-Purpose Technology (GPT) often triggers an initial phase of investment in many associated intangible assets which may go unaccounted for, resulting in TFP mismeasurement. This measurement problem could arise from excluding certain intangible assets from national accounts, which BRS (2021) call "intangible correlates". These complementary, correlated intangible investments — such as those used to adapt workers and business organizational structures to technological advancements — often do not appear in national accounts because they lack physical form, have ad hoc characteristics, are difficult to quantify, and are often treated as expenses rather than capitalized as investment (Bavdaž *et al.*, 2023; Bounfour and Nonnis, 2025; Nonnis, Bounfour and Kim, 2023). As pointed out by Brynjolfsson, Hitt and Yang (2002) and BRS (2021), the stock market valuation of firms differs from book values at least partly due to the valuation of these intangible correlates, which are not visible in the books, but are reflected in the firm's overall market capitalization.

Assuming financial markets correctly evaluate these intangible assets, their implicit worth can be retrieved by estimating "market value regressions", where the market value of the firm is regressed on its tangible and intangible assets:

$$V_{it} = const. + a_1 TA_{1it-1} + a_2 TA_{2it-1} + a_3 RD_{it-1} + a_4 SOFT_{it-1} + \mu_t + v_i + \epsilon_{it} \quad (1)$$

$$V_{it} = const. + b_1 TA_{1it-1} + b_2 TA_{2it-1} + b_3 RD_{it-1} + b_4 SOFT_{it-1} + b_5 ORG_{it-1} + \mu_t + v_i + \epsilon_{it} \quad (2)$$

In equations (1) and (2), V_{it} is the firm value of firm i at time t, with $V_{it} = p_{sit} S_{it} + D_{it}$, where p_{sit} is the share price, S_{it} is number of shares outstanding and D_{it} is debt for firm i. TA_{1it} and TA_{2it} are the tangible assets of buildings and construction, and machinery. RD_{it}, $SOFT_{it}$, and ORG_{it}, are the research and development capital stock, software assets, and organizational capital, respectively.

We obtain all data, except for $SOFT_{it}$ and ORG_{it}, directly from the Orbis dataset. The software variable $SOFT_{it}$ for each firm i is calculated by multiplying the total assets of firm i by the ratio of software to total assets at the industry level, obtained from the EUKLEMS/INTANProd data released in 2023 (Bontadini *et al.*, 2023; 2024) and the Japanese Industrial Productivity (JIP) 2023 database.

Some software programs such as AI and online meeting tools are often on a subscription basis, whose costs are not counted as assets but as part of sales, general and administration costs (SG&A). The Basic Survey of Japanese Business Structure and Activities (BSBSA) conducted by Ministry of Economy, Trade and Industry shows that the share of these ICT costs in the total

SG&A costs is 3 per cent. Using this data, and a depreciation rate of 33 per cent based on the Japanese SNA, we capitalize information and communication costs in SG&A. Then, $SOFT_{it}$ is a sum of software stock constructed from the industry-level data (EUKLEMS/INTANProd Data), and capitalized assets are constructed from information and communication costs data (BSBSA survey data).[3]

Although we use the SG&A data from the Orbis dataset, we make additional manipulations to construct ORG.[4] Hulten and Hao (2008) and Eisfeldt and Papanikolaou (2013) recognized 30 per cent of SG&A costs as capital formation in organizational capital. Therefore, while we recognize one-tenth of the organizational capital defined in previous studies as software investment, we classify the remainder as investment in our newly defined organizational capital. We construct organizational capital stock by the perpetual inventory method, with a depreciation rate of 40 per cent based on Corrado, Hulten and Sichel (2009).

Table A1 in the annex shows summary statistics for firms in France, Germany, Japan, the UK and the United States. We expect all coefficients on each asset to be positive. When the coefficient of an asset is greater than its asset price, this shows that capital formation in this asset is accompanied by adjustment costs that are accumulated as intangibles.[5]

4. Estimating Firm Value Functions

We estimated equations (1) and (2) for the period from 2006 to 2020 using both pooled OLS and system GMM estimators (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998), which allowed us to control for the potential endogeneity of the explanatory variables. In the GMM specification, we treat firms' investment decisions as fully endogenous and use lagged variables starting from at least the second lag as instruments. This assumes that capital assets may be correlated with current and past shocks, but uncorrelated with future shocks (Ackerberg, Caves and Frazer, 2015).[6] The lag structure in each estimation is selected in order to satisfy the Hansen test for overidentifying restrictions and the Arellano-Bond AR(2) test for second order serial correlation in the residuals.[7]

3 Although BSBSA covers only Japanese firms, we use the ratio of information and communication costs in the total SG&A costs in all samples, because these subscription costs are not counted as assets in firms in the advanced countries.

4 SG&A is widely used as a proxy for organizational capital measurement in finance literature (see Lev and Radhakrishnan, 2003).

5 However, as price indices usually move around 1, we focus on whether an estimated coefficient is greater than 1 for the condition to draw a productivity J-curve.

6 Our endogeneity assumption is relatively strong, as it allows regressors to be correlated with current shocks. A less restrictive assumption would treat regressors as predetermined, i.e. uncorrelated with current shocks, and use lagged variables starting from the first lag as instruments, but resulted in unsatisfactory diagnostics (Hansen and AR(2) tests).

7 We select estimations in which the Hansen test p-value is significant (above 0.10) but not too large, to avoid the risk of instrument proliferation, ideally targeting values around 0.2.

The estimation results for Equations (1) and (2) are reported in Tables 1 and 2, respectively. In each table, the model is estimated for the full sample (columns 1-2) and separately for each country (columns 3-12). Odd-numbered columns are pooled OLS estimates, while even-numbered columns are system GMM estimates.

Tables 1-1 and 1-2 show that almost all coefficients are positive and significant. This implies that all assets contribute positively to firm valuations. In the estimations using data from all countries, all OLS coefficients are positive, significant and greater than 1, even though the coefficient of machinery assets is less than 1 in the GMM estimation. The coefficients for intangibles (R&D and software) are greater than 1 in both estimations.

The country-level estimation results differ across countries. The results for the U.S. (columns 11 and 12) indicate that all assets contribute to the accumulation of intangibles, as their coefficients are positive, significant and greater than 1. These results are consistent with those for the U.S. shown in BRS (2021). In the other countries, the majority of R&D and software coefficients are greater than 1, indicating positive hidden adjustment costs or correlated unmeasured intangibles. Following BRS (2021), we interpret these coefficients as reflecting financial markets' valuation of intangible assets relative to their theoretical investment costs. Occasionally, country-specific coefficients fall below one (e.g., R&D in Columns 5 and 10, or software in columns 3, 4 and 7).[8] In principle, this would imply that financial markets value the asset less than its theoretical investment cost, suggesting rapid obsolescence or inefficiency. However, given the inherent disruptive nature of these assets and the prevalence of coefficients greater than one in our estimations, we interpret these lower values as anomalies, due to statistical limitations of the econometric model or financial market inefficiencies. Therefore, rather than assuming a theoretically implausible negative intangible investment, we substitute these specific estimates with their corresponding full sample baseline to maintain economic consistency.[9]

The same rationale is applied to the estimation of Equation (2) in Table 2. While the number of positive and significant coefficients greater than 1 is lower than in Table 1, the U.S. estimates remain robust, with all intangible coefficients positive, significant and greater than 1. All coefficients of software capital in Table 2 are smaller than those in Table 1. Especially, software coefficients in Japan are less than 1. As for organizational capital, we find positive and significant coefficients greater than 1, except in column 10.

8 The low costs associated with software investment in Japan may be due to the large share of customized software in Japan, which does not require additional training costs for employees.

9 As a robustness check, an alternative approach would be to constrain these coefficients to 1, assuming therefore zero unmeasured intangible investment rather than negative. This test does not alter our final conclusions in the next section.

Table 1-1: Estimation Results of Equation (1), from All Samples to Germany

Four asset cases

	(1) All pooled	(2) All GMM	(3) France pooled	(4) France GMM	(5) Germany pooled	(6) Germany GMM
Buildings and construction	2.09***	2.67***	1.21***	1.91*	2.08***	2.92
	(0.04)	(0.54)	(0.20)	(0.99)	(0.13)	(1.85)
Machinery	1.24***	0.60***	1.69***	2.10**	1.03***	0.71***
	(0.02)	(0.28)	(0.11)	(1.02)	(0.05)	(0.21)
Research and development	3.02***	3.56***	5.86***	8.53***	0.60***	2.84**
	(0.05)	(0.76)	(0.57)	(3.38)	(0.14)	(1.34)
Software	1.07***	1.28***	0.97***	0.60**	9.68***	5.99***
	(0.03)	(0.47)	(0.08)	(0.26)	(0.46)	(3.02)
Constant	103.31	-95.26	2,529.95	-255.40	167.97	-120,036.00
	(3,184.88)	(307.29)	(5,725.32)	(4,218.69)	(5,405.62)	(285,800.00)
Observations	29,792	29,792	2,057	2,057	2,058	2,058
Number of groups		2,345		172		158
Adjusted R-squared	0.56	0.41	0.62	0.27	0.77	0.86
Hansen test (p value)		0.12		0.23		0.50
AR (2) test (p value)		0.41		0.27		0.86

Note: Standard errors shown below estimated coefficients

Source: Authors' calculations. • Created with Datawrapper

5. Revised TFP and Productivity J-Curves

Following BRS (2021), we revised TFP measures to account for intangible correlates using the estimated coefficients in Equations (1) and (2). As explained in Section 1, estimated coefficients include adjustment costs of investment. If an estimated coefficient of an asset i divided by price of asset i is higher than 1, we are able to identify intangible correlates associated with capital formation in asset i and revise the standard measure of TFP growth rate accordingly. The gap between the standard measure of TFP growth, g_A, and the adjusted measure, g_A^*, can be expressed as follows:

$$g_A - g_A^* = \theta g_A - \theta(g_{IZ} - g_K) \quad (3)$$

Table 1-2: Estimation Results of Equation (1), from Japan to U.S.

Four asset cases

	(7) Japan pooled	(8) Japan GMM	(9) UK pooled	(10) UK GMM	(11) U.S. pooled	(12) U.S. GMM
Buildings and construction	2.55***	2.55**	0.49*	4.33*	2.08***	2.25***
	(0.04)	(0.99)	(0.27)	(2.27)	(0.06)	(0.73)
Machinery	0.05**	0.180	3.03***	1.240	1.32***	1.14***
	(0.02)	(0.65)	(0.18)	(1.77)	(0.04)	(0.46)
Research and development	2.21***	2.32***	1.71***	0.610	6.28***	6.19***
	(0.04)	(0.68)	(0.15)	(1.03)	(0.13)	(0.71)
Software	0.59***	1.23**	4.55***	4.03**	6.99***	7.87***
	(0.02)	(0.50)	(0.21)	(1.43)	(0.23)	(2.99)
Constant	-8.83	393.50***	787.39	745.20	190.36	68.81
	(2,316.49)	(182.18)	(2,271.90)	(543.94)	(5,558.69)	(208.52)
Observations	14,650	14,650	2,432	2,432	7,734	7,734
Number of groups		1,161		207		566
Adjusted R-squared	0.75	0.09	0.58	0.46	0.67	0.32
Hansen test (p value)		0.17		0.15		0.20
AR (2) test (p value)		0.09		0.46		0.32

Note: ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively. Standard errors are reported in parentheses. The table reports estimation results from equation (1), where the dependent variable is firm market value and the explanatory variables are capital stock assets. All regressions are estimated using pooled OLS (odd-numbered columns) and system GMM (even-numbered columns). Regressions include industry, year and industry-year interaction dummy variables. In the AR tests, the null hypothesis is the absence of serial correlation in the error term. In the Hansen test, the null hypothesis is the exogeneity of instruments. Instruments are chosen to maximize the efficiency of the Hansen test. For each country, observations with values of the firm value exceeding ±3 standard deviations from the mean have been removed as outliers.

Source: Authors' calculations. • Created with Datawrapper

The gap evidenced in Equation (3) often results in a J-shaped curve (productivity J-curve), which is typical of the investment cycle of disruptive technologies. In the equation, θ is the share of intangible investment in value added, when including intangible investment. When intangible investment, (g_{IZ}), measured by including the associated costs of capital formation, exceeds tangible capital growth, (g_K), the gap between the standard and revised TFP growth becomes negative, meaning that the standard TFP growth rate is underestimated, due to the incorrect measurement of intangible capital.

We construct four revised TFP measures both by accounting for each intangible capital type individually, and all three (R&D, software, and organizational capital) together. To do so, we use the GMM

Table 2-1: Estimation Results of Equation (2), from All Samples to Germany

Five assets cases

	(1) All pooled	(2) All GMM	(3) France pooled	(4) France GMM	(5) Germany pooled	(6) Germany GMM
Buildings and construction	1.19***	0.95	0.55***	-0.33	0.39***	-0.86
	(0.04)	(1.03)	(0.19)	(1.41)	(0.12)	(1.86)
Machinery	0.91***	0.35	0.42***	1.11	0.90***	0.65**
	(0.02)	(0.30)	(0.13)	(0.87)	(0.04)	(0.30)
Research and development	2.11***	2.20**	7.00***	5.86**	0.39***	0.01
	(0.05)	(1.11)	(0.54)	(2.44)	(0.11)	(1.29)
Software	0.74***	0.73*	0.67***	0.53***	2.42***	2.81
	(0.03)	(0.38)	(0.08)	(0.19)	(0.43)	(2.40)
Organizational capital	2.74***	3.80*	1.73***	1.96*	4.08***	4.79***
	(0.04)	(2.09)	(0.11)	(1.03)	(0.13)	(1.81)
Constant	68.22	99.80	5,231.61	364.20	-15.31	-41,727.70
	(2,988.90)	(311.88)	(5,390.60)	(319.47)	(4,287.70)	(80,244.23)
Observations	29,792	29,792	2,057	2,057	2,058	2,058
Number of groups		2,345		172		158
Adjusted R-squared	0.61	0.41	0.66	0.21	0.85	1.00
Hansen test (p value)		0.19		0.15		0.13
AR (2) test (p value)		0.41		0.21		1.00

Note: Standard errors shown below estimated coefficients

Source: Authors' calculations. • Created with Datawrapper

coefficients from Tables 1 and 2 if the country-level coefficients are positive, significant, and larger than the respective asset prices. If a coefficient does not meet these conditions, we replace it with the corresponding full-sample coefficient from columns 1 and 2 in Tables 1 and 2, which pools all countries together. The estimated coefficients used to measure revised TFP growth rate are listed in Table 3, where

10 In Table 3, we use estimated coefficients from GMM estimations in Table 1 for R&D and software and estimated coefficients from GMM estimations in Table 2 for organizational capital. We do so to avoid using coefficients that are not positive, significant, or larger than the respective asset prices. However, using different and more consistent rules did not alter much our results and we do not report them in the main paper. We also measure productivity J-curves using the pooled estimation results. In this case, we also have the same results as the case using the GMM estimation results. When we estimate Equation (1) and (2) including outliers, some estimations do not satisfy the Hansen test. However, productivity J-curves using parameters from pooled

Table 2-2: Estimation Results of Equation (2), from Japan to U.S.

Five assets cases

	(7) Japan pooled	(8) Japan GMM	(9) UK pooled	(10) UK GMM	(11) U.S. pooled	(12) U.S. GMM
Buildings and construction	1.70***	2.39***	-1.19***	5.17**	0.76***	-0.41
	(0.04)	(0.90)	(0.27)	(2.39)	(0.07)	(1.04)
Machinery	-0.02	-0.46	2.74***	0.63	1.02***	0.60**
	(0.02)	(0.40)	(0.17)	(1.44)	(0.04)	(0.30)
Research and development	0.32***	1.26**	-0.37**	0.41	5.16***	5.47***
	(0.05)	(0.61)	(0.17)	(1.48)	(0.12)	(1.04)
Software	0.36***	0.67***	1.37***	4.36***	4.75***	3.79**
	(0.02)	(0.26)	(0.26)	(1.62)	(0.22)	(1.61)
Organizational capital	3.90***	3.08***	4.58***	-0.01	4.47***	5.74***
	(0.07)	(1.13)	(0.24)	(0.24)	(0.14)	(2.17)
Constant	-99.55	237.60	783.82	1077.80**	175.50	314.40
	(2,116.73)	(149.43)	(2,095.87)	(677.86)	(5,216.76)	(247.60)
Observations	14,650	14,650	2,432	2,432	7,734	7,734
Number of groups		1,161		207		566
Adjusted R-squared	0.79	0.15	0.64	0.42	0.71	0.23
Hansen test (p value)		0.17		0.11		0.26
AR (2) test (p value)		0.15		0.42		0.23

Note: ***, **, and * indicate significance at 1, 5, and 10 per cent levels, respectively. Standard errors are reported in parentheses. The table reports estimation results from equation (1), where the dependent variable is firm market value and the explanatory variables are capital stock assets. All regressions are estimated using pooled OLS (odd-numbered columns) and system GMM (even-numbered columns). Regressions include industry, year and industry-year interaction dummy variables. In the AR tests, the null hypothesis is the absence of serial correlation in the error term. In the Hansen test, the null hypothesis is the exogeneity of instruments. Instruments are chosen to maximize the efficiency of the Hansen test. For each country, observations with values of the firm value exceeding ±3 standard deviations from the mean have been removed as outliers.

Source: Authors' calculations. • Created with Datawrapper

full-sample coefficients are marked with an asterisk.[10]

Figures 1-4 show the difference between standard TFP and the revised TFP based on our estimates. When the curve is below zero, the difference is negative, and TFP was underestimated in that period. Conversely, when the curve is above zero, TFP was overestimated. We begin by presenting the revised TFP curves for each individual intangible asset. To a certain extent, our results align with those of BRS (2021), even though we employ different data and methodologies, particularly to measure software and organizational capital.

estimations are similar to Figure 1 to 4.

Table 3: Estimated Coefficients Used for the Measurement of Productivity J-Curves

	France	Germany	Japan	United Kingdom	United States
The first type of J-curve (Figures 1 to 3)					
Research and development	8.53	2.84	2.32	3.56*	6.19
Software	1.28*	5.99	1.23	4.03	7.87
Organizational capital	1.96	4.79	3.08	3.80*	5.74
The second type of J-curve (combined intangibles case, Figure 4)					
Research and development	8.53	2.84	2.32	3.56*	6.19
Software	1.28*	5.99	1.23	4.03	7.87

Note: The table summarizes the coefficients used to compute the TFP measure revised accounting for all three intangible capital types at the same time, shown in Figure 4. Coefficients for R&D and software are obtained from the GMM estimates in Table 1, while those for organizational capital are obtained from the GMM estimates in Table 2. If any coefficient is not positive, significant, or larger than the respective asset price in those tables, it is replaced with the corresponding full sample estimate. Replaced coefficients are marked with an asterisk (*).

Source: Authors' calculations. • Created with Datawrapper

5.1 Research and Development

Figure 1 focuses on the effect of R&D. Our results for the U.S. are similar to BRS (2021) and in line with the arguments forwarded by Aghion *et al.* (2019). The R&D-adjusted TFP measure for the U.S. diverges only slightly from standard TFP, with differences of at most 0.4 percentage points, despite a slight underestimation towards the end of the sample. This pattern is similar for the other countries studied here, where the difference between the two TFP measures is even smaller — confirming that "intangible-related challenges for productivity estimation coming from R&D are likely to be minimal at present" (BRS, 2021).

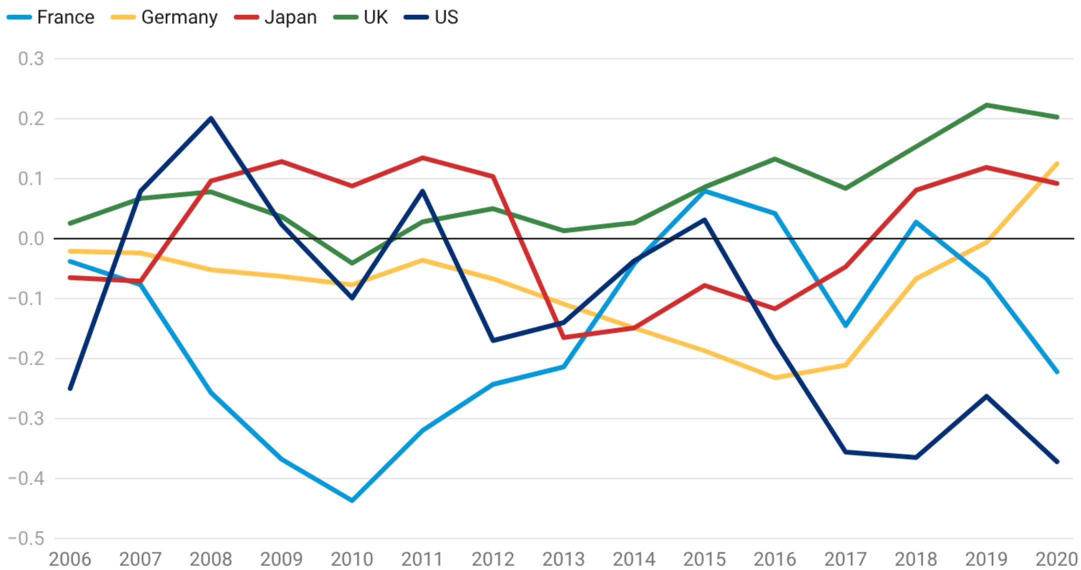
Specifically, we observe a slight underestimation of TFP growth in the U.S., particularly after 2010, and to an even lesser extent in France during the late 2000s and the early 2010s, and in Japan and Germany during the early 2010s. We do not find any underestimation in the United Kingdom.

5.2 Software

For software, a comparison with BRS (2021) is more challenging due to methodological differences. While they suggest a set of plausible values for the software-related coefficient, we estimate adjustment costs econometrically by creating a software investment variable based on both industry and firm level data. Figure 2 shows an under-estimation of TFP growth in the U.S. comparable in timing to BRS's

Figure 1: International Comparison of Productivity J-Curves for Research and Development

Difference between standard and revised TFP growth rates in percentage points



Note: The figure shows the 5-year moving average of the difference between standard and revised TFP growth. Revised TFP accounts for R&D-related intangible investment only. Values below zero indicate underestimation of TFP in standard measures.

Source: Authors' calculations. • Created with Datawrapper

finding, though less severe before 2015 and more since. However, our estimated magnitude of underestimation reaches 1.4 percentage points, which is significantly larger than the peak of 0.7 percentage points in the post-2006 period. This underestimation appears unique to the U.S., likely due to the large costs associated with software investment in the 2010s, which is consistent with the fact that many important digital innovations such as AI and platform businesses are developed in the United States.

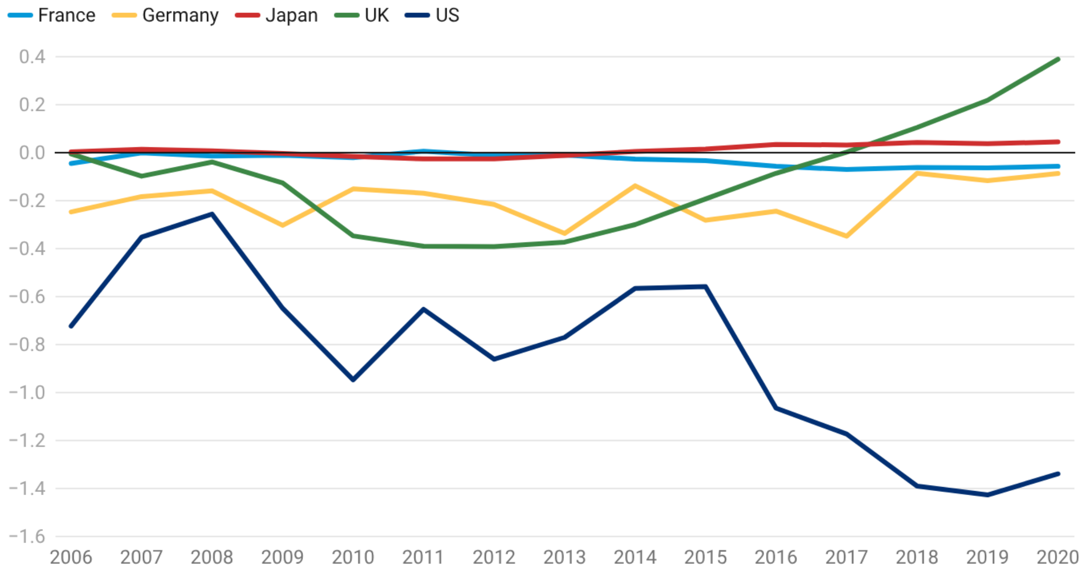
In Germany and in the UK, software-related TFP underestimation seems negligible, remaining below 0.4 percentage point for most of the period. It even turns positive in recent years in the UK, resembling a minor J-curve with smaller magnitudes, probably influenced by spillover effects from other countries. In Germany, the low undervaluation may reflect the lower intangible capital investment patterns of the country, especially in software (Nonnis, Roth and Bounfour, 2024), though a change is observable after 2018. Additionally, France and Japan show rather flat patterns, due to coefficients of less than 1 as obtained in Section 4, which do not allow the identification of unmeasured intangibles associated with software in these countries.

5.3 Organizational Capital

The results for organizational capital are more mixed, but suggest again the uniqueness of the U.S., where standard TFP growth is underestimated throughout most of the sample period, but without a J-curve type of pattern. However, the J-curve is

Figure 2: International Comparison of Productivity J-Curves for Software

Difference between standard and revised TFP growth rates in percentage points



Note: The figure shows the 5-year moving average of the difference between standard and revised TFP growth. Revised TFP accounts for software-related intangible investment only. Values below zero indicate underestimation of TFP in standard measures.

Source: Authors' calculations. • Created with Datawrapper

observable in the UK, where the difference between the two measures becomes positive after 2018, following a peak difference of 0.8 percentage points. In other countries, the revised TFP measure shows no substantial variations from standard TFP. However, the scale of mismeasurement by the associated costs in capital formation in organizational capital is relatively small compared to software. In particular, the underestimations of TFP growth rate caused by the associated costs of investment in organizational capital in continental Europe and Japan are smaller than those in the case of the UK and the United States.

These results imply that the firms in continental European countries such as France and Germany and Japan seem to be more reluctant to invest in organizational capital with large associated costs than those in the United States.[11]

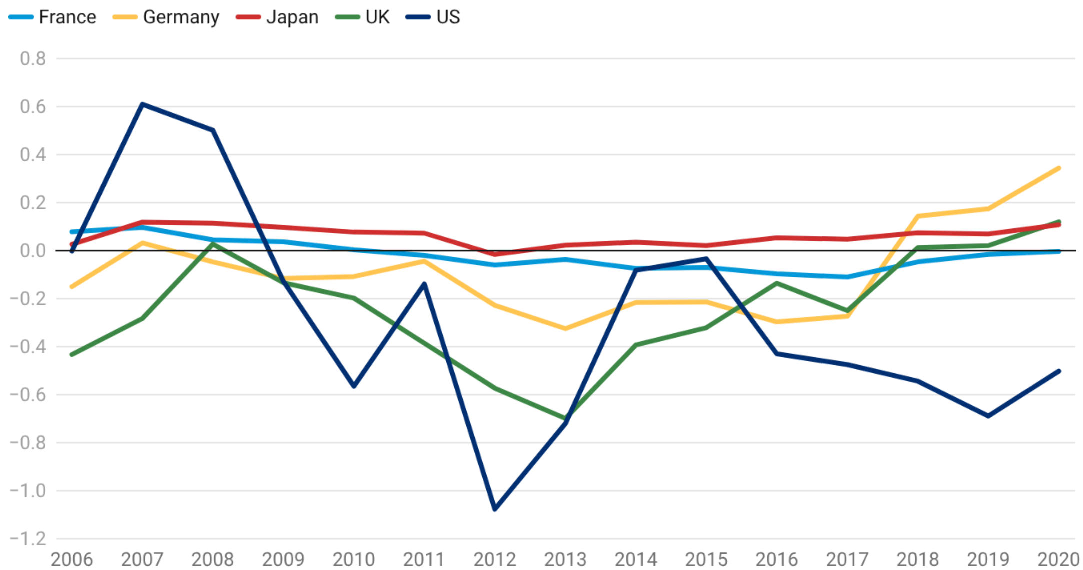
5.4 Combined Effects of All Intangibles

To produce a revised TFP measure that accounts for the additional intangible investment costs associated with R&D, software and organizational capital together, we use a combination of GMM coefficients from Tables 1 and 2, as summarized in Table 3. These coefficients are obtained from the GMM estimations in Table 1, except for organizational capital, where we

11 Although we conduct an alternative estimation using the measure of organizational capital developed by Eisfeldt and Papanikolaou (2013), our main conclusions do not change.

Figure 3: International Comparison of Productivity J-Curves for Organizational Capital

Difference between standard and revised TFP growth rates in percentage points



Note: The figure shows the 5-year moving average of the difference between standard and revised TFP growth. Revised TFP accounts for organizational capital-related intangible investment only. Values below zero indicate underestimation of TFP in standard measures.

Source: Authors' calculations. • Created with Datawrapper

use country-level GMM estimates from Table 2. As before, if any coefficient is not positive, significant, or larger than the respective asset price, we replace it with the corresponding full sample estimate instead. These replaced coefficients are marked with an asterisk (*) in Table 3.

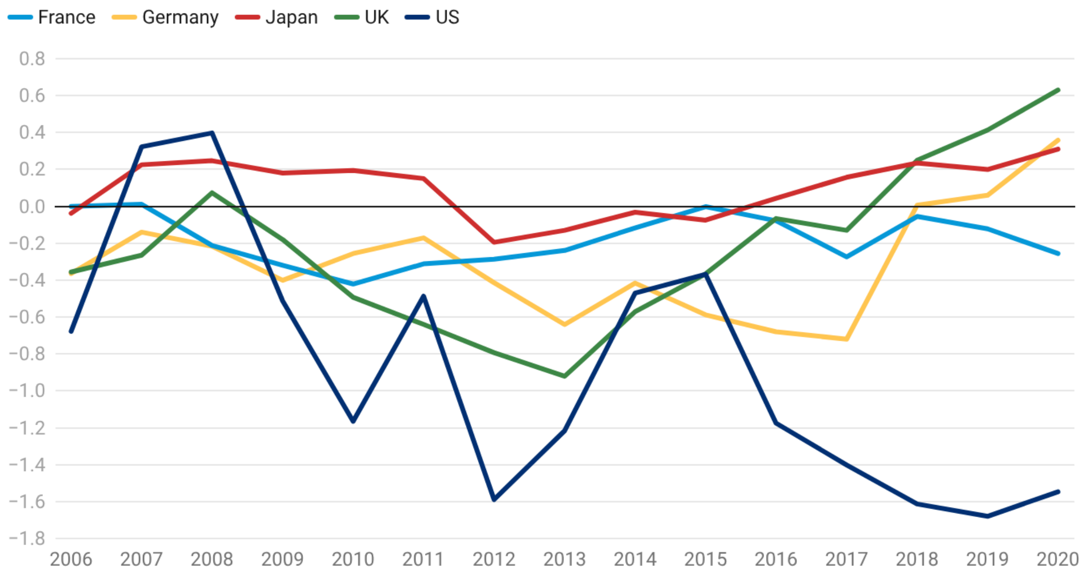
Figure 4 presents the combined effects of intangible correlates associated with three intangibles. Comparing these effects offers better insights into the impact of GPTs like AI on TFP, as it more accurately reflects the next generation of investments, because AI investment incorporates elements of all three intangibles we considered (Fonteneau *et al.*, 2025).[12]

Figure 4 again highlights the uniqueness of the U.S., as the under-estimation of TFP is present for almost the entire period, even reaching 1.6 percentage points in 2019. This suggests that the U.S. remains in a phase of rapid intangible investment growth, with positive effects on standard measures of TFP to be more than offset by further new investments. Germany, France and the UK seem to follow similarly, but with much smaller magnitudes. This implies the presence of some J-curve effects in these countries, though their impact is much smaller. Consistent with Miyagawa, Tonogi and Ishikawa (2021), the Japanese curve seems to be flat except for the minor underestimations in the early 2010s.

12 Although they argue the share of skills related to AI is the largest in the measurement of AI, we are not able to capture this component from the firm-level data.

Figure 4: International Comparison of Productivity J-Curves for All Intangibles

Difference between standard and revised TFP growth rates in percentage points



Note: The figure shows the 5-year moving average of the difference between standard and revised TFP growth. Revised TFP accounts for R&D, software and organizational capital-related intangible investments. Values below zero indicate underestimation of TFP in standard measures.

Source: Authors' calculations. • Created with Datawrapper

6. Conclusions

Productivity growth has stagnated in advanced economies in recent decades, particularly the 2010s. Mismeasurement of intangible capital has been identified as a potential explanation for this productivity slowdown. Productivity may have been underestimated because the additional value added and higher productivity induced by new technologies, such as AI and platform-based businesses, are not fully captured by current statistics. This is partly due to what BRS (2021) call *intangible correlates*, which are intangible assets associated with new technologies that are difficult to evaluate and account for.

Following BRS (2021), who constructed TFP measures corrected for the adjustment costs of intangibles, and observed that the gap between standard and revised TFP formed a J-shaped pattern (the productivity J-curve), this paper extends their analysis to European countries and Japan, which also experienced a productivity slowdown despite digitalization. Using firm-level data from Orbis, covering listed firms, and industry-level data from sources such as EUKLEMS/INTANProd and the Japanese Industrial Productivity (JIP) database, we construct revised TFP measures and assess whether the gap between standard and revised measures followed a productivity J-curve pattern not only in the U.S., but also in France, Germany, the UK and Japan.

Our revised measures are adjusted by three types of intangible capital (R&D, software and organizational capital), considered both individually and aggregately.

In line with what was observed by BRS (2021) for the U.S., we find that while the effects are small and negligible for R&D, they are clear for software and organizational capital, but mostly limited to the United States.

In particular, we show that most of the observed effects come from software in the United States. This result is consistent with the fact that many important digital innovations, such as AI and platform businesses, are developed in the United States. As the costs associated with software investment are not reflected as intangibles in the standard productivity statistics, the standard measure of TFP growth is underestimated by up to 1.4 percentage points, and 1.6 percentage points when considering all three intangibles. This result is in line with the recent productivity trends observed in the United States. The Bureau of Labor Statistics Report (BLS, 2026) issued in March 2026 shows an annualized growth rate of 2.1 per cent in the business cycle starting in the fourth quarter of 2019, higher than that observed in the previous business cycle (1.5 per cent). We argue that this acceleration of productivity growth in the U.S. has been driven by digitalization in the service sector, which is compatible with the underestimations observed in our measures.

We find the underestimation of TFP growth rate caused by the associated costs of investment in organizational capital to be small in the continental European countries and Japan. These results imply the management practices in continental Europe and Japan seem to have caused firms to be more reluctant to invest in organizational capital than in the United States.

Our study shows that the effect of unaccounted intangibles on the productivity slowdown in advanced countries during the 2010s differs by country. We do not find a large underestimation of TFP growth associated with capital formation in intangibles in the continental European countries and Japan, while there is still large underestimation of TFP growth rate in the U.S. in the late 2010s. This implies the productivity gap after taking account of the adjustment costs of investment between the U.S. and other advanced countries is even larger than measured by the standard TFP statistics.

These results do not directly reflect differences in investment levels among the countries in our sample. Countries that appear to invest heavily in national accounts data are not necessarily those that have high intangible correlates. On the contrary, countries that invest less in official statistics may have more intangible correlates if the lower investment is the result of the measurement errors or cross-country methodological disharmonizations highlighted in the cited papers: national accounts do not record those intangibles, but the BRS method captures them through market value regressions. In other words, financial markets value "invisible" assets even when national accounts fail to record them. This implies that unmeasured intangible correlates of different magnitudes in each country are captured by the adjustment costs in our econometric estimations. This discrepancy between investment data and intangible intensity reflects measurement difficulties that are evident when examining official national statistics and EUKLEMS/INTANProd data.

For example, according to these data, Germany has invested considerably less (10.7 per cent of value added) compared to other European countries and the U.S. in recent decades, while France has invested much more (16 per cent of value added), reaching levels comparable to the U.S. (16.3 per cent). These stylized facts reflect potential measurement issues pointed out in Nonnis, Roth and Bounfour (2024, 2025), which the BRS methodology overcomes.

The absence of a clear J-curve pattern in some high investing countries should be considered further. Nevertheless, it reinforces the call for a more focused investment, particularly in new technologies, as emphasized by the recent European Commission report by Mario Draghi (2024a, 2024b), which highlights that Europe is lagging behind the U.S. and China in this respect. Our results suggest that the productivity gap arising from those differences in investment behavior may be even larger, as official productivity growth figures for the U.S. may have been underestimated due to intangible capital mismeasurements, an effect we do not observe as strongly in European countries and Japan.

While it is difficult to predict exact patterns for the next generation of investments, including AI, some lessons can be learned by looking at recent AI investment trends across countries. According to the Artificial Intelligence Index report (Maslej *et al.*, 2024), the U.S. leads in private AI investment, investing nearly twice as much as in the UK relative to its GDP over the last ten years and at least four times more than in the other countries. This suggests that J-curve effects due to AI will likely be much stronger in the U.S. than in other countries, as a result of both the uniqueness of the U.S. highlighted in this study, and its superior investment levels in AI. The intensive investment in AI in the U.S. promises a higher TFP growth rate than other advanced countries as Filippucci, Gal and Schief (2024) estimated. To catch up, continental European countries and Japan should invest more aggressively in digital innovation and in the associated costs of innovative capital formation, such as training skilled workers (Bounfour, Nonnis, Yang, 2025), while also reforming conservative management practices.

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