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BOUNFOUR, Ahmed
Université Paris-Saclay

EDAMURA, Kazuma
Kanagawa University

ISHIKAWA, Takayuki
Rissho University

MIYAGAWA, Tsutomu
RIETI

NONNIS, Alberto
Université Paris-Saclay

TONOGI, Konomi
Rissho University

Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
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The Productivity J-curve from an International Perspective: Is the U.S. a unique case? *

Ahmed Bounfour (Université Paris-Saclay)

Kazuma Edamura (Kanagawa University)

Takayuki Ishikawa (Rissho University)

Tsutomu Miyagawa (RIETI)

Alberto Nonnis (Université Paris-Saclay)

Konomi Tonogi (Rissho University)

Abstract

Many economists have argued that progress in digitalization contradicts the productivity slowdown in advanced countries in the 2010s. Among these discussions, Brynjolfsson, Rock and Syverson (2021) showed that although large associated costs for investment booms for new technology decrease productivity growth in the current statistics, this TFP growth is underestimated when these costs are recognized as intangible investment. They call the gap between the standard measure of TFP growth and the revised measure of TFP growth the 'productivity J-curve'.

Following their article, we measure the productivity J-curves in five advanced countries (France, Germany, Japan, the UK and the US). Before we measured the productivity J-curves, we estimate firm value function with multiple assets where estimated coefficients of assets show associated costs with capital formation of these assets. Using the estimated results of all assets, we find the productivity J-curves in the 2010s. Our finding shows that the productivity slowdown in the 2010s in these advanced countries is overstated.

Next, we focus on the productivity J-curves in each asset, following Brynjolfsson, Rock and Syverson (2021). Our measurement of productivity J-curve shows that in Europe and Japan in the late 2010s, we do not find large underestimations of TFP growth caused by intangibles associated with capital formation in R&D, software and organizational capital. However, we still find a large underestimation of TFP growth rate in the US due to the large costs associated with investment booms for software generated by the rapid digitalization that was undertaken. This implies that the productivity gap, when accounting for the adjustment costs of investment between the US and other advanced countries, is larger than that measured using standard statistics. To conduct innovative activities in the area of digitalization, European countries and Japan should focus on the associated costs of innovative capital formation targets such as training skilled workers and changes in their overly conservative management behavior.

Keywords: digitalization, TFP, intangibles, productivity J-curve

JEL classification numbers: E22, E23, G31, L86, O34, O47

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1. Introduction

Digitalization in the 21st century has greatly revolutionized our lives and businesses. We expected this digital transformation to lead to further productivity growth and help us attain a better life. However, productivity growth rates in the advanced countries seemed to stagnate in the 2010s. On the other hand, there were two digital innovations in the same time: one is the rise of platform businesses such as Airbnb and Uber in the early 2010s, the other is the development of generation AI business such as Open AI emerging at the same time. These contradictory facts have led to discussions on the economic effects of digitalization on productivity growth.

The center of these discussions is a measurement issue. Aghion et al. (2019) argued that official statistics do not capture prices provided by new entrants. As new entrants enter the markets at lower prices than those provided by incumbents, true price levels are lower than those published by official statistics and the true real value added is higher. Brynjolfsson also published three papers regarding measurement issues. The first paper (Brynjolfsson et al. (2019)) discussed the measurement of GDP. As the official GDP is a measure from the production side, the value of software provided for free is not counted in the current framework of GDP. Hence, they suggested that GDP in the digital age should be measured from the consumer side. They call this GDP measured from consumer side “GDP-B”. The second paper (Tambe et al. (2020)) measured the digital capital estimated from the number of workers in digital firms. They discovered a positive relationship between digital capital and productivity growth.

The last paper (Brynjolfsson, Rock and Syverson, 2021) focused on the measurement of intangibles and total factor productivity (TFP) growth. Although Corrado, Hulten and Sichel (2009) estimated intangibles in the US by using several types of published data related to the topic, Brynjolfsson, Rock and Syverson (2021) developed an alternative approach to the measurement of intangibles. They started from the standard neoclassical investment theory with adjustment costs such as from Lucas (1967) and Uzawa (1969). In this theory, capital formation is accompanied by additional expenditures used for employee training and organizational change. Brynjolfsson, Rock and Syverson (2021) recognized that these expenditures turn to be a production factor as intangibles, although they are temporary expenditures in the traditional theory of investment. They estimated the parameters of adjustment costs of investment. Using these parameters, they revised the standard measure of TFP growth rate.

Following the standard measure of TFP, the TFP growth rate is low during the period of high levels of investment in digitalization because increasing adjustment costs associated with the investments decreases GDP. As a result, the TFP growth rate decreases during the period of investment boom. However, once the adjustment costs are recognized as intangible investment, the revised GDP does not fall and the revised TFP growth rate becomes stable. Because the standard TFP growth rate recovered after the investment boom, the movements in the gap between the standard TFP growth rate and the revised TFP growth rate resembles the letter J. With this, Brynjolfsson, Rock and Syverson (2021) called these movements the "productivity J-curve".

They argued that this theory can explain the low productivity rate during the investment boom in the platform industry and AI. Miyagawa, Tonogi and Ishikawa (2021) found a couple of productivity J-curves from the late 1990s to the 2010s in the ICT-intensive industries.

In this paper, we extend the approach to measure intangibles and the revised TFP growth rate developed by Brynjolfsson, Rock and Syverson (2021) to large countries in Europe as well as the US and Japan. As Goldin et al. (2022) pointed out, not only Japan and the US, but also many European countries suffered from productivity slowdown in the 2010s from the viewpoint of official statistics. However, the speed in the digitalization and the technological progress in the US may be different from that in the other advanced countries. For example, due to strict regulations, ridesharing services have not yet been permitted in Japan.

The aim of our study is twofold. First, we aim to examine to what extent the productivity slowdown in the advanced countries in the 2010s is exaggerated, by measuring the productivity J-curve. If we find the productivity J-curve in the 2010s, the TFP growth rate in this period is likely to be underestimated. Second, we aim to clarify the differences in digitalization by the accumulation in intangibles for the selected advanced countries.

Our empirical study shows that productivity slowdown in the 2010s in advanced countries is partially overstated, because we find the productivity J-curves in all countries. When we focus on capital formation required for new technology such as R&D, software and organizational capital, productivity growth rate in the US is largely underestimated as Brynjolfsson, Rock and Syverson (2021) pointed out. In particular, rapid accumulation in intangibles accompanied with software investment generates underestimation of TFP growth rate in the US. On the other hand, compared to the US, the scale of underestimations of TFP growth rates in European countries and Japan are relatively small. Our results imply that European and Japanese firms depend on software created by the US firms which spend large costs for the development of software. As for organizational capital, the low associated costs with capital formation in organizational capital in European countries and Japan imply the conservative management behavior in these countries.

Our paper consists of six sections. In the next section, we review the related literature. We focus on the literature which studies the measurement issues on GDP and intangibles, productivity slowdown in advanced countries, and the capital formation with multiple assets. In the third section, we present an equation estimating the parameters of adjustment costs of investment and explain the data for these estimations. Using listed firms' data in five advanced countries (France, Germany, Japan, the UK and the US), we estimate two types of equations where explanatory variables are multiple assets: one consists of four assets (construction and buildings, machinery, R&D and software) and the other consists of five assets (construction and buildings, machinery, R&D, software and organizational capital)

In the fourth section, we show our estimation results. We find many assets are accompanied by associated costs with investment. In particular, the capital formation of R&D assets is accompanied by large costs. This implies that R&D investment requires skilled workers. In the case of US, the estimated coefficients of all assets show that its capital formations generate large expenditures for intangibles which are consistent with the study by Brynjolfsson, Rock and Syverson (2021).

In the fifth section, using the parameters from these estimations, we measure the revised TFP growth rate and show the productivity J-curve. First, we focus on productivity J-curves using intangibles associated with R&D, software and organizational capital which are required for 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 to R&D. As for software, we find that the US expends large associated costs with software investment generated by the rapid digitalization in the 2010s. Our study shows the US productivity growth rate is underestimated up to 1.2% when these costs are count as intangibles. In France and Japan, we find small underestimation of TFP growth rate generated by the organizational capital, which implies that the management in French and Japanese firms is likely to be conservative.

Next, we measure the productivity J-curve using estimated coefficients of all assets, as we find large associated costs of capital formation in all assets in estimation results using all samples. This productivity J-curve implies that the productivity growth in the 2010s in the advanced countries is underestimated.

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

2. Related Literature

Our paper is related to multiple research areas such as the measurement issues on GDP and intangibles, productivity slowdown in advanced countries, and the capital formation with multiple assets. Regarding the measurement issue on GDP, we have already discussed several important articles provided by Brynjolfsson[1]. In addition to these articles, Coyle and Nakamura (2022) argued that GDP should be measured not from the production side but the consumer

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

side. Hasegawa (2023) and Miyagawa (2024) referred the trial measurement of the digital economy by the Cabinet Office, Government of Japan. This trial measurement shows that the digital economy in Japan made up 8.6% of GDP in 2018. Miyagawa (2024) also measured the scale of digitalized inputs that are not recognized as assets, such as the cloud and AI procured services. The World Bank also estimates that the digital economy contributes to more than 15% of global domestic product.[2]

There are many studies on productivity slowdown in the advanced countries. As stated in the previous section, Aghion et al. (2019) and Tambe et al. (2020) argued that true productivity would be higher than official productivity growth if the statistics captured the new economy due to digitalization correctly. On the other hand, Gordon (2016) did not evaluate the effects of new technology through the digitalization of the economy and society. He argued that digital transformation is less effective in improving the standard of living than progress in the social infrastructure was in the 20th century. He refers to new products and services like running water, electricity, automobiles, washing machines, and vacuum cleaners. According to his arguments, the recent US slowdown in productivity is within expectations. Acemoglu et al. (2014) also argued that the US productivity growth was caused mainly by the decline in employment in the manufacturing sector and not by the technological progress that was a result of digitalization. Goldin et al. (2022) surveyed studies on the productivity slowdown in the advanced countries and examined which factors affected it. They divided labor productivity growth into three factors: capital deepening effects, labor composition, and TFP growth. In the US, both capital deepening effects and TFP growth slowed labor productivity growth. In France, the TFP growth rate was a major factor behind a slowdown in productivity. In particular, mismeasurement and allocative inefficiency had a large effect on TFP growth. In Japan, capital deepening has slowed significantly. Moreover, the slowdown in TFP growth caused by spillover effects from intangibles and trade was also found to be a crucial factor slowing productivity growth.

The theoretical background of our paper is based on the neoclassical theory of investment with multiple assets. After the neoclassical theory of investment with a single asset was developed by Lucas (1966), Uzawa (1969) and Hayashi (1982) as mentioned in the previous section, the theory with multiple assets was developed by Wildasin (1984).

Developing the argument by Wildasin (1984), Hall (2001), Miyagawa and Kim (2008) and Miyagawa, Takizawa and Edamura (2015) showed that a firm's value is expressed as the weighted sum of each asset under the assumption of a linear homogeneous production and investment functions. Hall (2001) argued that when we measure Tobin's q, the firm value

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2 https://www.weforum.org/stories/2022/08/digital-trust-how-to-unleash-the-trillion-dollar-opportunity-for-our-global-economy/

exceeding 1 expresses the value of intangibles. Miyagawa et al. (2015) showed that Tobin's q measured by only tangibles is greater than 1 for ICT firms. As they found that when they consider intangibles, the revised Tobin's q becomes close to 1, they argue that intangibles in ICT firms contribute to the increase in the value of these firms.

3. Data for the Estimations

As noted by Brynjolfsson, Rock and Syverson (2021) and Miyagawa, Tonogi and Ishikawa (2021), the introduction of a new General Purpose Technology (GPT) into the economy often triggers an initial phase of investment during which many associated intangible assets may go unaccounted for, causing a mismeasurement of TFP. This measurement issue could arise directly from the exclusion of certain intangible assets from national accounts and from what Brynjolfsson, Rock and Syverson (2021) call *intangible correlates.* These are complementary, correlated intangible investments, such as those used for adapting both workers and organizational structures of enterprises to technological advancements, that often do not appear in national accounts, due to the inherent nature of intangibles. While these intangible correlates are not included in the investment aggregates of national accounts, they are correctly evaluated by financial markets, and thus detectable when estimating market value regressions with multiple asset types.

Following Brynjolfsson, Rock and Syverson (2021), we estimate firm value functions as shown in the following two equations.

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

(2) $V_{it} = const. + b_1 TA_{1it-1} + b_2 TA_{2it-1} + b_3 RD_{it-1} + b_4 SOFT_{it-1} + b_5 SG\&A_{it-1} + \mu_t + \upsilon_i + \epsilon_{it}$

In Equations (1) and (2), V_{it} is the firm value of firm i. $V_{it} = p_{sit} S_{it} + D_{it}$. 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 assets of buildings and construction and machineries. RD_{it}, $SOFT_{it}$ and $SG\&A_{it}$ are R&D assets, software assets and organizational capital, respectively.

We obtain all data except $SOFT_{it}$ and $SG\&A_{it}$ from the Orbis dataset directly. We measure the software asset of firm *i* by multiplying the total assets of firm *i* by the ratio of software to total assets at the industry level. The industry-level data is obtained from EUKLEMS/INTANProd data released in 2023 and the Japanese Industrial Productivity (JIP) 2023 database. However, some software programs such as AI and online meeting tools are often subscribed by users. These subscription costs are not counted as assets but as a part of sales, general and administration costs. The Basic Survey of Japanese Business Structure and

Activities (BSBSA) conducted by Ministry of Economy, Trade and Industry, the Government of Japan shows that the share of these information and communication costs in the total sales and general administration costs is 3% with a deprecation rate of 33% based on the Japanese SNA. Using this data, we capitalize information and communication costs in SG&A. Then, $SOFT_{it}$ is a sum of software stock constructed from the industry-level data and capitalized asset constructed from information and communication costs data[3].

Although we use the sales and general administration costs data in the Orbis dataset to construct $SG\&A_{it}$, we make additional manipulations. Hulten and Hao (2008) and Eisfeldt and Papanikolaou (2013) recognized 30% of SG&A costs as capital formation in organizational capital. However, as we recognize one tenth of organizational capital defined by the previous studies as capital formation in software, we recognize the rest of organizational capital defined in the previous studies as capital formation in the newly defined organizational capital. To measure capital formation in organizational capital, we construct organizational capital stock by the perpetual inventory method. The depreciation rate of organizational capital stock is 40% based on Corrado, Hulten and Sichel (2009).

The Orbis dataset includes financial statements of listed firms in the main advanced countries. We pick up firms in France, Germany, Japan, the UK and the US. Table 1 shows a summary of statistics in these five countries.

(Insert Table 1 around here)

We expect that all coefficients of each asset will 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.[4]

4. Estimation Results

We estimate Equations (1) and (2) for the period from 2006 to 2020. We conducted pooled regressions and fixed effects estimations.[5] Estimation results are divided in two parts: estimation results using all samples and estimation results by country. Table 2 shows the basic estimation results for Equation (1). In Table 2, we find almost all coefficients are positive and

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[3] Although BSBAE 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 advanced countries.

[4] However, as price indices usually move around 1, we focus on whether an estimated coefficients is over 1 for the condition to draw a productivity J-curve.

[5] We also tried GMM estimations. However, as all results did not clear exogenous tests, and so results will not be shared.

significant. This implies that all assets contribute positively to the firms' values.

(Insert Table 2 around here)

In the estimations using all samples, all coefficients in the pooled estimation are positive, significant and greater than 1, while the coefficient of machinery asset is less than 1 in the fixed estimation. In particular, the coefficients on R&D stock are greater than 3 in both estimations.

In the country-level estimations, we find the results differ by country. In the pooled regressions, the estimation results in the US shows that all assets accumulate intangibles as their coefficients are positive, significant and greater than 1. These results are consistent with the estimation results in the US shown in Brynjolfsson, Rock and Syverson (2021). However, in the fixed estimation in the US, only coefficient of machinery is less than 1. In other countries, coefficients on R&D asset are greater than 1 except Germany and the largest in all assets in France and the US. As for the software asset, the coefficients in Germany, the UK and the US are larger than 1[6].

In Table 3, we show estimation results of Equation (2). Number of positive and significant coefficients which are greater than 1 in Table 3 are less than that in Table 2. The positive and significant coefficients in R&D assets which are greater than 1 are found in only France, and the US. As for organizational capital, all coefficients are positive, significant and greater than 1 in the case of pooled estimations.

(Insert Table 3 around here)

5. Measurement of Productivity J-curve

Brynjolfsson, Rock and Syverson (2021) measured productivity J-curve using estimated coefficients in Equations (1) and (2). As explained in Section 1, estimated coefficients include adjustment costs of investment. If an estimated coefficient in an asset *i* divided by price of asset *i* is over 1, we are able to measure intangible investment associated with capital formation in asset *i* and to revise the standard measure of TFP growth rate. The productivity J-curve is expressed as the movements of the gap between the standard measure of TFP growth (g_A) and (g_A^*) as follows,

(3) g_A-$g_A^* = \theta g_A - \theta(g_{I_Z} - g_K)$.

[6] The reason that the associated costs with software investment in Japan is small may be caused by the large share of customized software in Japan which do not require additional training costs for employees.

The locus of left side of Equation (3) shows the productivity J-curve over an investment cycle. θ is the share of intangibles investment in the value added including intangible investment. Equation (3) implies that when the growth in investment in intangibles (g_{I_Z}) which is measured from the associated costs of capital formation is higher than growth in traditional capital (g_K), the left side of Equation (3) is likely to be negative. This negative gap between the standard measure of TFP growth rate and the revised measure of TFP growth rate means that the standard measure of TFP growth rate is underestimated.

Hence, we measure the adjusted TFP curves for each intangible asset type (buildings and construction, machinery, R&D, software, and organizational capital) both individually and aggregately to show the combined effect of all five assets. To do so, if the country-level coefficients from the pooled estimation results in Section 3 are positive, significant, and larger than the respective asset prices, we use those coefficients. However, if there are coefficients that do not satisfy this condition, we use the corresponding coefficients from the estimation results using the full sample instead.

In this section, we measure two types of productivity J-curves. The first type of J-curve focuses on the gap between the standard TFP growth rate and the revised TFP growth rate generated by additional costs associated with capital formation in a specific asset. We choose three assets (R&D software and organizational capital) for the first type of productivity J-curve. The second type of productivity J-curve focuses on the gap between the standard TFP growth and the revised TFP growth generated by additional costs of all assets (buildings and construction, machinery, R&D, software)

In Table 4, we list the coefficients which we use for making the above productivity J-curves. These coefficients are obtained from pooled estimations in Tables 2 except the case of organizational capital. As for the organizational capital, we obtain country-level estimated coefficients in Table 3. Basically, we use coefficients from country-level estimation results to make productivity J-curve. However, if there are coefficients that are not positive, significant, or larger than the respective asset prices, we use the corresponding coefficients from the estimation results using the full sample instead. These coefficients are marked * in Table 4.

(Insert Tables 4 around here)

5.1 TFP Revised for Individual Intangibles

R&D

In Figures 1-4 we show the difference between traditional TFP and the revised TFP based on our estimates[7]. 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 are aligned with those of Brynjolfsson, Rock and Syverson (2021), even though we employ different data and methodologies, particularly on the measurement of software and organizational capital.

In Figure 1, we isolate the effect of R&D, finding that our results for the US are quite similar to those from Brynjolfsson, Rock and Syverson (2021) and with the arguments by Aghion et. al (2019). As shown in Figure 1, the R&D-adjusted TFP measure for the US diverges only slightly from traditional TFP, with differences peaking below 0.4%, despite a slight undervaluation in the sample's later years. This pattern is similar across other countries in our sample, where the difference between the two TFP measures is even less pronounced, confirming, as stated by Brynjolfsson, Rock and Syverson (2021), that "intangible-related challenges for productivity estimation coming from R&D are likely to be minimal at present" (page 23).

(Insert Figure 1 around here)

More in detail, we observe a slight underestimation of TFP in the US, particularly after 2016, and, even to a lesser extent in France (late 2000s and the early 2010s) and Japan (early 2010s). We do not find any underestimation in the UK.

Software

For Software, a direct comparison with Brynjolfsson, Rock and Syverson (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, creating a software investment variable based on both industry and firm level data, as previously discussed. Figure 2 shows an undervaluation of TFP in the US comparable in timing to Brynjolfsson, Rock and Syverson's findings, being more severe after 2015 and less earlier, even though our estimated magnitude of underestimation reaches 1.3%, significantly higher than peak of 0.7% in the post 2006 period. This underevaluation appears unique to the US, likely due to the large costs associated with software investment in the 2010s. These results are consistent with the fact that many important digital innovations such as AI and platform businesses are developed in the US.

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[7] We measure productivity J-curves on a 5-year moving average.

(Insert Figure 2 around here)

In Germany and in the UK, software-related TFP underestimation seems negligible, remaining below 0.5% for most of the period, and even turns positive in recent years in the UK, resembling a minor J-curve with smaller magnitudes and probably influenced by spillover effects from other countries. In Germany, the low underevaluation may reflect the lower intangible capital investment patterns of the country , especially in software (Nonnis, Roth, Bounfour, 2024), though a change of tendency is observable after 2018. Additionally, France and Japan show rather flat patterns, due to coefficients less than 1 obtained in Section 4, which do not allow the identification of unmeasured intangibles associated with software in these countries.

Organizational capital

The results for organizational capital are more mixed, but suggest again the uniqueness of the US, where traditional TFP is underestimated throughout most of the sample period, but without a J-curve type change of tendency. This pattern is instead observable in the UK, where the difference between the two measures becomes positive after 2018, following a peak difference of 1%. In the other countries, the revised TFP measure shows no substantial variations from traditional TFP. However, the scale of mismeasurements by the associated costs in capital formation in organizational capital are relatively small compared to software. In particular, the underestimations of TFP growth rate caused by the associated costs of investment in organizational capital in the continental Europe and Japan are smaller than those in the case of the UK and the US. These results imply that the management styles in the continental European countries such as France and Germany and Japan seem to be more conservative than those in the US.

(Insert Figure 3 around here)

5.2 TFP Revised for All Assets

In Figure 4, we combine the effects of all three intangible asset types to provide insights into the impact of GPTs on TFP. We do so as we assume that the next generation of investment, which includes AI, will include elements of all three intangibles we considered, and that it will be exceptionally disruptive. Figure 4 highlights the uniqueness of the US once more, as the underestimation of TFP is present in almost the entire period, even reaching 1.3%. This effect indicates that the US is still in a phase of strong intangible investments, with positive effects on traditional TFP yet to be realized or are more than offset by further new investments. Germany and France are the only countries that seem to follow a pattern somewhat similar to the US, but with much smaller magnitudes. This implies the presence of some J-curve effects in these countries, though their impact is much smaller. In the UK, an underestimation is observed between 2011 and 2015, which is compensated by a strong overestimation shortly after, resembling an enhanced J-curve. The magnitude of these effects suggests strong spillover effects in the UK. Japan, with smaller magnitudes, also appear to follow a similar pattern to the UK, with minor undestimations in the early 2010s followed by a more sizeable overestimation, suggesting that Japan too is experiencing positive spillover effects.[8]

(Insert Figure 4 around here)

6. Concluding Remarks

Brynjolfsson, Rock and Syverson (2021) showed that the productivity growth is likely to be underestimated, when the investment boom stimulated by new technology such as AI and platform businesses occurs. This results from value added and productivity induced by the new business in the digital age potentially not being captured correctly by current statistics, and to the presence of *intangible correlates*, intangible asset investments associated with new technologies that are difficult to evaluate and account for.

In this paper, we extend their study to European countries and Japan, which also suffered from the productivity slowdown in spite of digitalization. Using data from the Orbis dataset, covering listed firms in advanced countries, and industry-level databases such as the EUKLEMS/INTANProd data and the Japanese Industrial Productivity (JIP) database , we measure the productivity J-curve not only in the US but also in France, Germany, the UK and Japan.

Brynjolfsson, Rock and Syverson (2021) argued that although associated costs of investment associated with the investment boom decrease value added and TFP at the same time, the value added and TFP can be revised when these associated costs of investment as intangible assets which are one of production factors. Then, they call the locus of the gap between the standard TFP growth and revised TFP growth 'productivity J-curve', because its locus resembles letter J. These additional costs are estimated by the regressions of firm value on multiple assets as shown in Equations (1) and (2). Our estimation results show that almost all coefficients are positive and significant, as the theory expects.

As shown in Equation (3), the locus of productivity J-curve depends on coefficients of

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[8] In the case of Japan, the measured productivity J-curve is consistent with the results by Miyagawa, Tonogi and Ishikawa (2021), because both results show underestimations of TFP growth rate in the 2010s.

assets and the scale of capital formation in each asset. If a coefficient in an asset is large which means that additional costs of investment is large, the gap between the standard measure of TFP growth and the revised measure of TFP growth rate becomes large, which implies large underestimation of TFP growth generates.

Hence, we show the difference between traditional TFP and our revised measures of TFP. 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 observed by Brynjolfsson, Rock and Syverson (2021) for the US, we find that while the effects due to R&D are small and negligible, the effects for software and organizational capital are present, but are mostly limited to the US.

In particular, we show that most of the observed effects come from software. This result is consistent with the fact that many important digital innovations such as AI and platform businesses are developed in the US. As we count associated costs of software investment are not reflected as intangibles in the standard productivity statistics, the standard measure of TFP growth is underestimated up to 1.2%. In the service sector, we also find that the mismeasurement of TFP growth in the US are very large in the 2010s.

Regarding organizational capital, the estimated mismeasurements caused by the associated costs in its capital formation are relatively small compared to software. Although we find the underestimation of TFP growth rate caused by the associated costs of investment in organizational capital, the gaps between the standard measures of TFP growth rate and the revised measures of TFP growth rate are very small in the continental European countries and Japan. These results imply that the management styles in the continental European countries and Japan seem to be more conservative than those in the UK and the US.

Our study shows that the effect of unaccounted intangibles on the productivity slowdown in the 2010s in the advanced countries is very different from country to country. We do not find the large underestimation of TFP growth caused by the intangibles associated with the capital formation in intangibles in the late 2010s in the continental European countries and Japan, while there is still large underestimation of TFP growth rate in the US. This implies the productivity gap adjusted by the adjustment costs of investment between the US and other advanced countries are larger than that measure by the standard statistics.

These results do not directly reflect differences in investment levels between the countries in our sample, as some countries, like Germany, have invested much less compared to the US in recent decades, but, others, such as France, have been leaders in intangible capital investment, particularly in software. The level of investment of France in intangibles in similar to that of US (17% of Gross value-added). The reason for the non observance of a J-Curve for high investing countries should be considered further.

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 investments trends across countries. According to the Artificial Intelligence Index report (Perrault et al., 2024), the US leads in private AI investment, investing nearly twice than the UK in terms of GDP percentage in the last ten years and at least four times more than the other countries. This suggests that J-curve effects due to AI will likely be much stronger in the US than in other countries, as a result of both the uniqueness of the US highlighted in this study, and its superior investment levels in AI. To catch up, by conducting real impactful innovative activities in the digitalization, the continental European countries and Japan should focus on the associated costs of innovative capital formations such as training skilled workers and change in conservative management behavior. Market structures for intangibles – especially those related to GPT- should also be reevaluated, in order to take full benefit from the next generation of investment.

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Table 1: Summary of Basic Statistics

France						mil USD
	N	Mean	S.D.	Median	Min	Max
Market Value	2057	5613.63	13143.97	553.18	2.95	91921.74
BLD	2057	474.54	1473.03	51.54	0.00	13587.52
Mac	2057	1019.05	3246.97	64.01	0.00	28823.19
RD	2057	171.75	555.31	1.93	0.00	4538.88
SOFT	2057	795.22	2755.96	46.09	0.25	51916.65
Org. Capital	2057	1000.77	3346.53	108.34	0.06	39714.42

Germany						mil USD
	N	Mean	S.D.	Median	Min	Max
Market Value	2058	4880.47	11224.39	552.00	8.68	91304.40
BLD	2058	570.80	1563.37	73.62	0.00	20428.32
Mac	2058	1185.26	4002.56	96.66	0.00	43796.14
RD	2058	346.15	1269.93	14.68	0.00	16819.26
SOFT	2058	143.99	412.03	18.41	0.16	5850.94
Org. Capital	2058	736.40	1742.02	112.71	0.45	14495.31

Japan						mil USD
	N	Mean	S.D.	Median	Min	Max
Market Value	14650	1986.50	4636.51	492.07	7.65	49470.42
BLD	14650	419.08	981.74	111.92	0.00	27276.77
Mac	14650	600.98	1896.20	76.05	0.00	25197.24
RD	14650	186.59	731.89	20.27	0.00	14682.83
SOFT	14650	167.13	1173.84	31.23	0.07	45568.79
Org. Capital	14650	273.70	675.57	71.73	0.40	10522.13

the UK						mil USD
	N	Mean	S.D.	Median	Min	Max
Market Value	2432	2978.41	7789.84	555.01	2.02	86791.63
BLD	2432	195.69	620.45	25.45	0.00	5464.80
Mac	2432	336.03	841.83	44.26	0.00	10775.82
RD	2432	123.81	937.07	2.22	0.00	15099.88
SOFT	2432	193.44	671.12	16.41	0.05	7424.01
Org. Capital	2432	384.09	1117.45	57.18	0.14	11520.51

the US						mil USD
	N	Mean	S.D.	Median	Min	Max
Market Value	7734	7384.97	13648.11	2020.27	4.56	145527.90
BLD	7734	508.40	1864.81	92.10	0.00	30603.00
Mac	7734	1128.13	2921.14	222.22	0.00	44841.00
RD	7734	289.46	801.75	16.21	0.00	9058.85
SOFT	7734	155.80	458.67	42.96	0.03	27792.65
Org. Capital	7734	596.48	1171.29	196.21	0.23	17687.28

Table 2: Estimation Results of Equation (1) (four assets case)

	(1)	(2)	(3)	(4)	(5)	(6)
Buildings and Construction	**2.092***	**2.153***	**1.208***	**0.973***	**2.075***	**1.900***
	(0.035)	**(0.074)**	**(0.198)**	**(0.327)**	**(0.129)**	**(0.319)**
Machinery	**1.235***	**0.643***	**1.691***	**0.142**	**1.027***	**0.269***
	(0.020)	**(0.035)**	**(0.108)**	**(0.173)**	**(0.045)**	**(0.076)**
R&D	**3.021***	**3.245***	**5.857***	**8.244***	**0.595***	**0.408***
	(0.053)	**(0.090)**	**(0.567)**	**(0.603)**	**(0.139)**	**(0.209)**
Software	**1.074***	**1.205***	**0.967***	**0.452***	**9.683***	**6.451***
	(0.034)	**(0.047)**	**(0.083)**	**(0.054)**	**(0.455)**	**(0.576)**
constant	**103.309**	**1352.054***	**2529.945**	**3309.935***	**167.971**	**1946.124***
	(3184.875)	**(75.388)**	**(5725.322)**	**(244.650)**	**(5405.619)**	**(284.938)**
Industry Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Industry X Year Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**29792**	**29792**	**2057**	**2057**	**2058**	**2058**
Number of Groups		**2345**		**172**		**158**
Adjusted R-squared	**0.557**	**0.176**	**0.621**	**0.303**	**0.768**	**0.256**
Country	**All**	**All**	**France**	**France**	**Germany**	**Germany**
Estimation Method	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**

	(7)	(8)	(9)	(10)	(11)	(12)
Buildings and Construction	**2.547***	**0.878***	**0.485***	**2.949***	**2.083***	**2.352***
	(0.035)	**(0.059)**	**(0.272)**	**(0.404)**	**(0.057)**	**(0.154)**
Machinery	**0.047****	**-0.222***	**3.033***	**1.675***	**1.323***	**0.609***
	(0.019)	**(0.035)**	**(0.179)**	**(0.186)**	**(0.043)**	**(0.086)**
R&D	**2.210***	**1.352***	**1.714***	**0.465****	**6.282***	**6.654***
	(0.038)	**(0.074)**	**(0.147)**	**(0.190)**	**(0.126)**	**(0.234)**
Software	**0.587***	**0.634***	**4.548***	**1.846***	**6.988***	**4.500***
	(0.017)	**(0.037)**	**(0.212)**	**(0.215)**	**(0.225)**	**(0.190)**
constant	**-8.825**	**1391.834***	**787.387**	**1287.587***	**190.358**	**2033.464***
	(2316.491)	**(39.677)**	**(2271.898)**	**(159.621)**	**(5558.687)**	**(220.948)**
Industry Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Industry X Year Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**14650**	**14650**	**2432**	**2432**	**7734**	**7734**
Number of Groups		**1161**		**207**		**566**
Adjusted R-squared	**0.75**	**0.066**	**0.575**	**0.223**	**0.668**	**0.364**
Country	**Japan**	**Japan**	**UK**	**UK**	**US**	**US**
Estimation Method	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**

The lower cell in each estimation result shows standard deviation.
*, **, and *** show significance at 10%, 5%, and 1% levels, respectively.

Table 3: Estimation Results of Equation (2) (five assets case)

	(1)	(2)	(3)	(4)	(5)	(6)
Buildings and Construction	**1.194*****	**1.787*****	**0.551*****	**1.291*****	**0.388*****	**0.888*****
	(0.036)	**(0.078)**	**(0.192)**	**(0.324)**	**(0.115)**	**(0.325)**
Machinery	**0.911*****	**0.583*****	**0.418*****	**0.685*****	**0.897*****	**0.236*****
	(0.019)	**(0.035)**	**(0.132)**	**(0.185)**	**(0.036)**	**(0.073)**
R&D	**2.113*****	**2.899*****	**7.004*****	**7.671*****	**0.386*****	**-0.276**
	(0.052)	**(0.093)**	**(0.539)**	**(0.598)**	**(0.111)**	**(0.213)**
Software	**0.620*****	**1.059*****	**0.671*****	**0.532*****	**2.417*****	**4.229*****
	(0.032)	**(0.048)**	**(0.080)**	**(0.055)**	**(0.426)**	**(0.599)**
Organizational capital	**2.736*****	**1.224*****	**1.725*****	**-0.856*****	**4.077*****	**3.138*****
	(0.043)	**(0.083)**	**(0.114)**	**(0.114)**	**(0.127)**	**(0.307)**
constant	**68.219**	**1229.026*****	**5231.61**	**3378.056*****	**-15.305**	**1207.471*****
	(2988.902)	**(75.559)**	**(5390.595)**	**(240.717)**	**(4287.695)**	**(285.508)**
Industry Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Industry X Year Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**29792**	**29792**	**2057**	**2057**	**2058**	**2058**
Number of Groups		**2345**		**172**		**158**
Adjusted R-squared	**0.609**	**0.182**	**0.664**	**0.326**	**0.854**	**0.301**
Country	**all**	**all**	**France**	**France**	**Germany**	**Germany**
Estimation Method	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**

	(7)	(8)	(9)	(10)	(11)	(12)
Buildings and Construction	**1.701*****	**0.512*****	**-1.193*****	**2.526*****	**0.757*****	**0.547*****
	(0.035)	**(0.062)**	**(0.266)**	**(0.416)**	**(0.068)**	**(0.177)**
Machinery	**-0.019**	**-0.291*****	**2.744*****	**1.747*****	**1.017*****	**0.421*****
	(0.017)	**(0.035)**	**(0.165)**	**(0.186)**	**(0.041)**	**(0.084)**
R&D	**0.322*****	**0.655*****	**-0.367****	**0.441****	**5.161*****	**4.699*****
	(0.049)	**(0.083)**	**(0.173)**	**(0.189)**	**(0.124)**	**(0.249)**
Software	**0.362*****	**0.463*****	**1.371*****	**1.449*****	**4.752*****	**3.769*****
	(0.016)	**(0.038)**	**(0.256)**	**(0.236)**	**(0.223)**	**(0.189)**
Organizational capital	**3.896*****	**2.145*****	**4.579*****	**0.704*****	**4.474*****	**6.246*****
	(0.073)	**(0.121)**	**(0.236)**	**(0.176)**	**(0.141)**	**(0.323)**
constant	**-99.55**	**1268.900*****	**783.817**	**1220.051*****	**175.499**	**975.770*****
	(2116.734)	**(39.829)**	**(2095.874)**	**(159.899)**	**(5216.761)**	**(221.991)**
Industry Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Industry X Year Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	**14650**	**14650**	**2432**	**2432**	**7734**	**7734**
Number of Groups		**1161**		**207**		**566**
Adjusted R-squared	**0.792**	**0.087**	**0.638**	**0.229**	**0.708**	**0.397**
Country	**Japan**	**Japan**	**UK**	**UK**	**US**	**US**
Estimation Method	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**	**Pooled**	**Fixed Effect**

The lower cell in each estimation result shows standard deviation.
*, **, and *** show significance at 10%, 5%, and 1% levels, respectively.

Table 4: Estimated Coefficients used for the measurement of Productivity J-curve

	FR	DE	JP	UK	US
	The first type of J-curve (indivisual assset case)				
R&D	**5.857**	**3.021***	**2.210**	**1.714**	**6.282**
Software	**1.074***	**9.683**	**1.074***	**4.548**	**6.988**
Organisational Capital	**1.725**	**4.077**	**3.896**	**4.579**	**4.474**
	The second type of J-curve (integrated assets case)				
Buildings and construction	**1.208**	**2.075**	**2.547**	**2.092***	**2.083**
Machinery	**1.691**	**1.027**	**1.235***	**3.033**	**1.323**
R&D	**5.587**	**3.021***	**2.210**	**1.714**	**6.282**
Software	**1.074***	**9.683**	**1.074***	**4.548**	**6.988**

Note: All coefficients are obtained from country-level estimations except coefficients marked * which are obtained from estimations using all samples.

Figure 1: International Comparison of Productivity J-curves for R&D

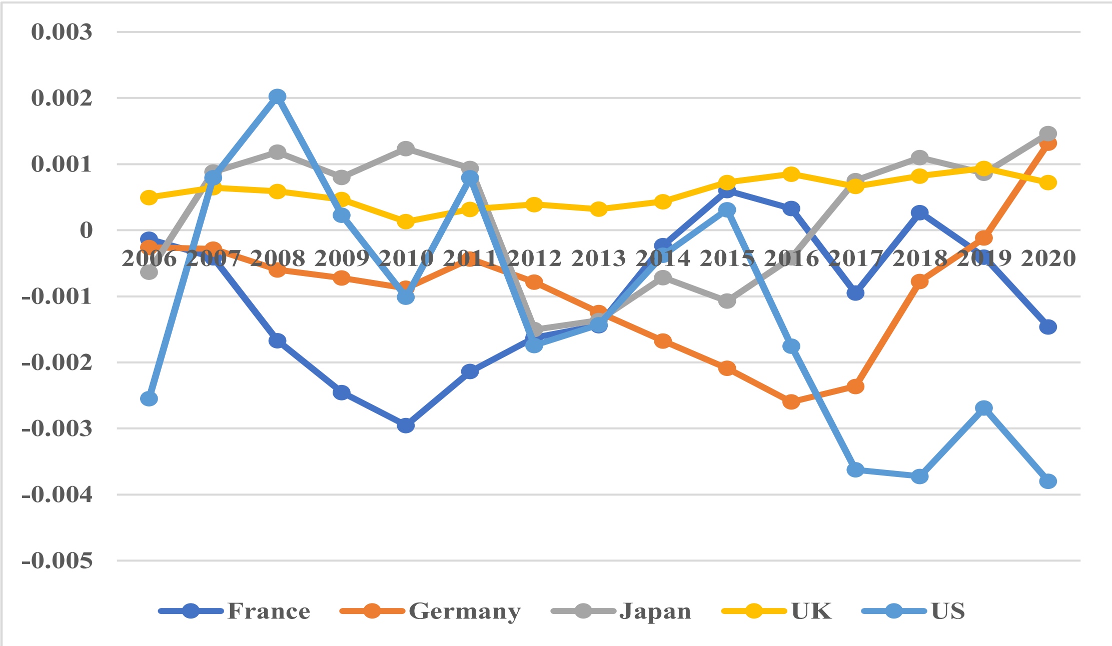

Figure 2: International Comparison of Productivity J-curves for software

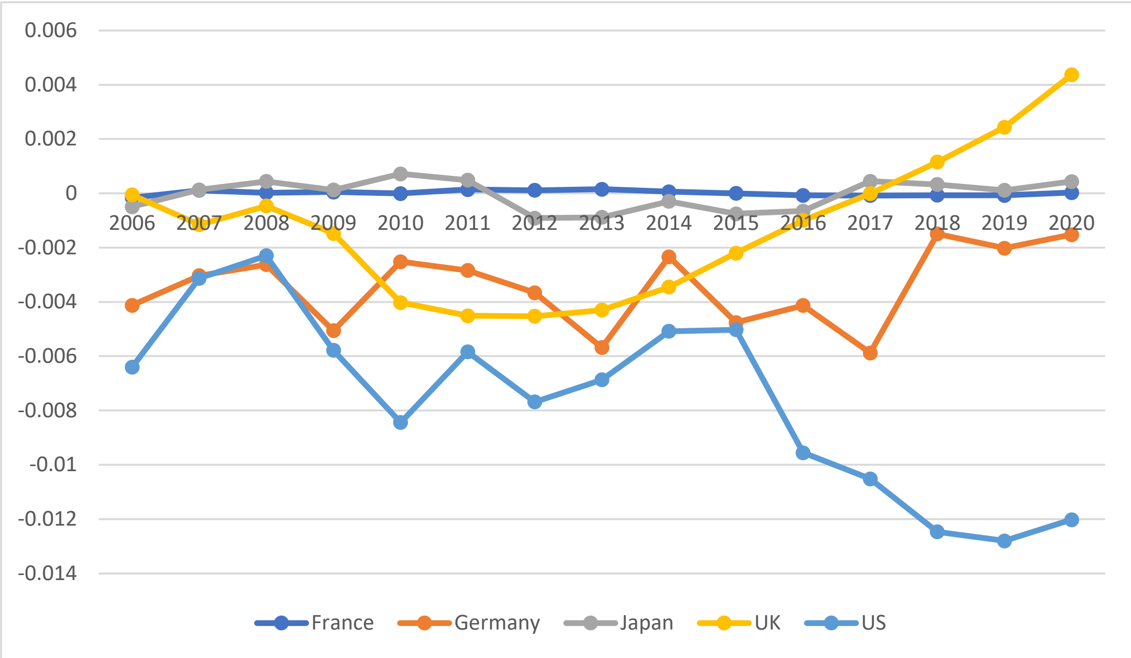

Figure 3: International Comparison of Productivity J-curves for organizational capital

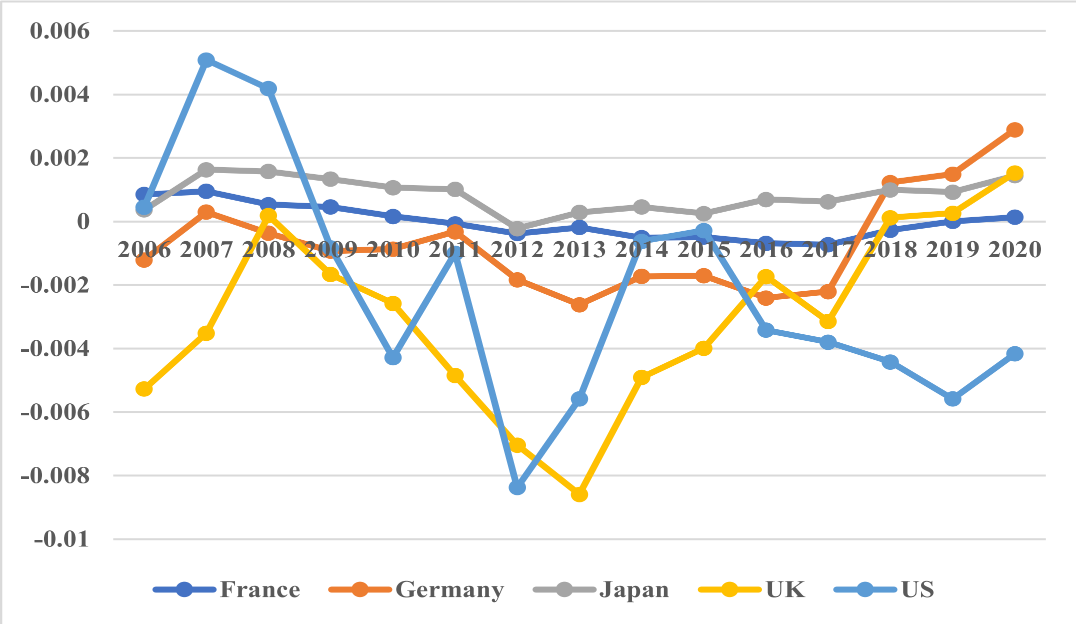

Figure 4: International Comparison of Productivity J-curves aggregated for all assets