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Effects of Innovation and ICT on Structural Change and Productivity Growth: Insights from the latest KLEMS Dataset

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Abstract

This paper examines the effects of structural change, digital transformation, and innovation on productivity growth in industrialized economies. To capture the different patterns of structural change, the study introduces two measures: productive structural change (PSC) and unproductive structural change (USC). The paper finds distinctive evidence and rich policy insights into the effects of structural change, digital transformation, and innovation on productivity growth. In particular, while the effect on productivity growth is positive and robust for PSC, it is negative and substantial for USC. Furthermore, innovation has a strong positive effect on PSC, but its negative effect on USC is insignificant. Finally, both digital transformation and innovation have a strong positive link with productivity growth, but these links become insignificant when endogeneity concerns are addressed, which implies that allocating more budgets for digital and R&D investments is less effective if ignoring efforts to create a more enabling environment for efficiency improvements that drives productivity growth.

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1. Introduction

Structural change, defined as the reallocation of productive resources among sectors in the economy, is a prominent feature of economic growth. The important role of structural change in driving economic growth and productivity improvements has been empirically supported by influential studies such as Lewis (1954), Clark (1957), Kaldor (1966), Kuznets (1966, 1979), Denison (1967), Cheery and Syrquin (1975), Syrquin (1988), Lin and Monga (2010), and Lin (2009, 2012a, 2012b). The expected nature of structural change dynamics is the continual shift of factor inputs from lower- to higher-productivity sectors, which consequently raises productivity at the aggregate level. For example, Lewis (1954) uses a classical framework of a dual economy to demonstrate that the shift of surplus labor from subsistence agriculture toward the modern sector increases worker productivity, a country's overall productivity, and output per capita.[2] Echevarria (1997), employing general equilibrium methods and simulation techniques, confirms a positive link between sectoral composition change and growth.

Empirical evidence on the effect of structural change on growth has been found in a number of previous studies. Using growth decomposition methods, Denison (1967) shows that reallocation of productive inputs from agriculture to other sectors was a significant factor explaining why the United States outperformed the UK but was behind Germany in GDP growth between 1950 and 1962. Employing regression techniques to analyze OECD countries, Peneder (2002) and Dietrich (2012) provide further evidence that structural change plays an important role in driving economic growth. Caselli and Coleman (2001), examining the growth dynamics

[2] Lewis (1954) also points out that this pattern of growth will reach a turning point as the surplus of labor is exhausted. Then, the modern sector would need to raise wages to attract labor from agriculture for further expansion; hence it may be more challenging for the economy to sustain previous high rates of growth.

of the U.S. states, present evidence that structural transformation is a main factor driving the U.S. regional convergence. With regard to Asia, van Ark and Timmer (2003) show that resource reallocation from agriculture toward other sectors is a powerful source of growth for lower income countries, while for more advanced economies, the shift of labor toward services sectors such as finance makes a notable contribution to overall productivity growth. Fan et al. (2003) find the essential role of sectoral composition change in China's economic growth.

Structural change, however, is not always found to be growth-enhancing. For example, McMillan, Rodrik, and Verduzco-Gallo (2014) show that, unlike in Asia, the contribution of structural change to productivity growth was negative for Latin America during the period 1990-2005 and for Africa during 1990-2000.

There are also studies contending that structural change may not be conducive to productivity growth. Baumol (1967) shows that labor may shift from a sector with higher and rapidly growing productivity to a sector with lower and stagnant productivity, causing a decline in the overall economy's productivity growth rate, ceteris paribus. The case of rapid expansion of lower-productivity service employment in the US can serve as a piece of evidence (Baumol, 1985). Furthermore, Ngai and Pissarides (2007) introduce a model that suggests that the effect of structural change may not appear in aggregate growth, while using a theoretical approach with restrictive assumptions, Meckl (2002) asserts that sectoral composition change may be a byproduct of economic growth and may have no feedback effect on the growth process. At the sector level, Fagerberg (2000), examining manufacturing industries from a sample of 39 countries over the period 1973-1990, finds that structural change does not contribute to productivity growth. Likewise, Timmer and Szimai (2000) arrive at a similar conclusion for Asian manufacturing. [3]

The discussions above call for new studies that provide not only more conclusive evidence on the effect of structural change on economic growth but also a deeper understanding of the nature of structural change and the mechanism through which structural change influences growth. This paper aims to make contributions in this direction by introducing a new approach to measuring structural change, in which the dynamics of structural change can be divided into two patterns, "productive structural change" (PSC) and "unproductive structural change" (USC). Note that in a given economy, PSC and USC can take place in parallel, and they may have opposite effects on overall productivity growth.

To conduct this study, the paper uses panel data on industrialized economies over the period from 1995 to 2019 provided by the 2021 version of the EU-funded KLEMS database. Details of this database are provided in Section 2.

Among its main findings, the paper provides robust evidence that PSC has a significant positive effect on productivity growth, while USC has a negative effect. In addition, digital transformation (DX) and innovation have strong positive links with productivity growth, but these links are not robustly causal due to the presence of endogeneity. Furthermore, innovation has a significant positive effect on PSC, while its effect on USC is negative or insignificant, which means that innovation has a significant indirect positive effect on productivity growth by fostering PSC.

[3] Silva and Teixeira (2008), Krüger (2008), and Herrendorf et al. (2014) provide excellent reviews of major studies on the link between structural change and growth.

The paper proceeds as follows. Section 2 provides an overview of the KLEMS database and introduces the two measures of structural change, PSC and USC. Section 3 introduces the empirical models for investigating the effects of PSC, USC, DX, and innovation on productivity growth. Section 4 presents the empirical results. Section 5 concludes with a brief policy discussion.

2. The KLEMS database and structural change measures

2.1. The KLEMS database

The EU KLEMS database, which is the product of a research project financed by the European Commission, contains industry-level measures of output, inputs, and productivity for 27 European Union member countries, the UK, the US, and Japan. The latest version of this database, which was released in October 2021[4], provides detailed data for each country across 40 industries and 23 industry aggregates over the period from 1995 to 2019. The methodology for constructing this database is presented in Bontadini et al. (2021).[5]

The key variables of the KLEMS database used for this study include the following: labor productivity (measured as value added divided by total number of hours worked) and its growth; total factor productivity (TFP) growth; employment (measured in hours worked); the contribution of innovative property to labor productivity growth, which is used as a proxy for innovation effort; and the contribution of software and databases to labor productivity growth, which is used as a proxy for efforts to embrace digital

[4] The database can be downloaded at https://euklems-intanprod-llee.luiss.it/

[5] One can also learn more about the theoretical concepts and frameworks for constructing the KLEMS database from previous studies such as Timmer et al. (2007) and Timmer and O'Mahony (2011).

transformation. As the data for these variables are available at the industry level, our study can construct more detailed measures of structural change and conduct more rigorous investigations of its effects on productivity growth. For economy-level data, we use the data for total industry.

3. Measures of structural change

Previous studies have made substantial efforts to assess the effect of structural change on economic growth. For most studies, the main measure of structural change is based on the extent of labor reallocation across sectors over a period of interest. Two widely used approaches to capturing the magnitude of structural change include the shift-share analysis (SSA) method and the Norm of Absolute Values (NAV) index. These two approaches, however, are limited in capturing the direction of changing dynamics while focusing mainly on their magnitude.

The new measures of structural change introduced by this study, which are built on these two existing approaches, aim to overcome this limitation. The paragraphs below provide a quick review of the SSA and NAV approaches before introducing the two new measures of structural change, PSC and USC.

3.1 The shift-share analysis (SSA) approach

This analysis is often used for capturing the contribution of structural change to labor productivity growth in a given economy.[6]

[6] For example, see Syrquin (1984), Peneder (2002), Van Ark and Timmer (2003), Felipe et al. (2009), McMillan and Rodrik (2011), McMillan, Rodrik, and Verduzco-Gallo (2014). This analysis can also be conducted for a multi-industry sector such as manufacturing. For example, see Fagerberg (2000), Timmer and Szirmai (2000).

A simplified framework of the SSA approach takes the following form[7]:

$$\frac{\Delta P}{P_0} = \sum_{i=1}^{n} \frac{\bar{S_i}\Delta P_i}{P_0} + \sum_{i=1}^{n} \frac{\bar{P_i}\Delta S_i}{P_0} \qquad (1)$$

where Δ in front of a variable indicates its change over period of examination [0, T]; subscripts i and 0 indicate sector i and the initial year, respectively; the bar on the top of a variable denotes its average value over the period [0, T]; P denotes the level of labor productivity computed as the value-added[8] divided by the number of hours worked; and S represents the employment share (measured in hours worked) by sector in the economy.

As such, Framework (1) decomposes labor productivity growth $(\frac{\Delta P}{P_0})$ over period [0, T] into two main sources:

+ $\sum_{i=1}^{n} \frac{\bar{S_i}\Delta P_i}{P_0}$, the first part of Eq. (1), which captures the aggregate contribution of productivity improvements within each sector. This source is also referred to as the "within-sector" effect.

+ $\sum_{i=1}^{n} \frac{\bar{P_i}\Delta S_i}{P_0}$, the second part of Eq. (1), which captures the aggregate contribution of labor relocation across sectors. This source is also referred to as the "shift-share" effect.

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[7] This approach has been employed by several previous studies. For example, Timmer and Vries (2009) use this framework to analyze the contribution of structural change to productivity growth in Asian and Latin American economies.

[8] The value-added is measured in constant price. The shift-share analysis implicitly assumes that value-added generated by each sector has the same price deflator as the entire economy's GDP.

Although the shift-share method provides an intuitive way to quantify the contribution of labor reallocation to productivity growth, its results may be problematic due to its assumption that productivity growth within each sector is independent of structural change (Timmer and Vries, 2009).[9] Likely due to this unjustified assumption, a number of studies using the shift-share method do not find significant evidence confirming the positive contribution of structural change to growth. For example, Timmer and Vries (2009) find that growth accelerations in 19 countries in Asia and Latin America over the period from 1950 to 2005 are explained by within-sector productivity growth, not by reallocation of employment to more productive sectors, while Fagerberg (2000), examining a sample of 39 countries between 1973 and 1990, finds that the contribution of labor reallocation to productivity growth was negative for most countries.

3.2. Norm of Absolute Values (NAV) Index

For a given economy, the Norm of Absolute Values (NAV) index is calculated for period [0, T] as follows:

$$NAV = 0.5 * \sum_{k=1}^{n} |S_{iT} - S_{i0}| \qquad (2)$$

where n is the number of sectors in the economy and S_{i0} and S_{iT} represent the employment share of sector i at times 0 and T, respectively. The 0.5 factor is used to correct the double count of employment share changes. This measure is also called the Michaely Index or Stoikov Index; more details can be found in Dietrich (2012).

[9] For example, for a given economy, labor productivity growth in the agriculture, which is considered as its "within-sector" effect, is largely driven by the reallocation of labor from this sector to other sectors.

This method provides a simple measure of the overall magnitude of structural change. However, this does not make a distinction as to whether the structural change experienced by a sector is productivity-enhancing or decreasing. This limitation, therefore, makes the measure less meaningful in providing insights into the growth effects of structural change.

3.3 New measures of structural change: PSC and USC

The productive structural change (PSC) and unproductive structural change (USC) measures introduced below are built on the SSA and NAV approaches. To make these new measures more meaningful in capturing the dynamics of structural change in a given economy, PSC and USC are constructed to overcome the limitations inherent in the SSA and NAV approaches.

To factor in the possible dependence between the "within-sector" and "between-sector" effects in the SSA approach, we combine them into a combined term, defined as

$$C_i = \frac{\bar{S}_i \Delta P_i}{P_0} + \frac{\bar{P}_i \Delta S_i}{P_0} \tag{3}$$

where C_i is the total contribution of sector i to the economy's overall labor productivity growth.

Note that the two components of C_i ($\frac{\bar{S}_i \Delta P_i}{P_0}$ and $\frac{\bar{P}_i \Delta S_i}{P_0}$) are likely interdependent. Let us take the agriculture sector as an illustrative example. It is rather obvious that labor productivity growth in the agriculture sector in many countries is driven not only by technological progress within its own sphere but also by its reallocation of labor to other sectors, such as manufacturing and services.

Therefore, for a given sector i, the combined effect, C_i better captures its contribution to the economy's overall labor productivity growth.

Combining Eq. (1) and Eq. (3) yields

$$\frac{\Delta P}{P_0} = \sum_{i=1}^{n} \left[\frac{\bar{S}_i \Delta P_i}{P_0} + \frac{\bar{P}_i \Delta S_i}{P_0}\right] = \sum_{i=1}^{n} C_i \tag{4}$$

That is, the overall labor productivity growth in an economy can be decomposed into the structural change-related contributions of its constituent sectors. Note that C_i can be positive or negative.

C_i is positive in the following scenarios:

(i) The sector's productivity is growing, and its employment share is expanding. In this scenario, the sector is booming, which may be driven by rapid technological progress and substantial structural reforms that foster synergy and expansion.

(ii) The sector's productivity is growing, and its employment share is shrinking, while the effect of the former outweighs that of the latter. This scenario can be observed for sectors experiencing significant restructuring;

(iii) The sector's productivity is declining with its employment share expanding, while the effect of the latter is greater than that of the former. This scenario can be observed for the sectors that enjoy a rapid increase in market demand for their products and services, while its technological/efficiency improvement is behind the pace of its employment expansion.

In addition, C_i is negative in the following settings:

(i) The sector's productivity is declining, and its employment share is contracting.
(ii) The sector's productivity is growing, and its employment share is contracting, while the effect of the former is dwarfed by that of the latter.
(iii) The sector's productivity is declining, and its employment share is expanding, while the effect of the former is greater than that of the latter.

The discussion above paves the way for our introduction of PSC and USC. These new measures can be considered an extension of the SSA and NAV approaches while overcoming their limitations.

The PSC and USC indices are defined as follows:

$$PSC = \sum_{i \in X} |S_{iT} - S_{i0}| \qquad X = \{i\}\ such\ that\ C_i > 0 \tag{5}$$

$$USC = \sum_{i \in Y} |S_{iT} - S_{i0}| \qquad Y = \{i\}\ such\ that\ C_i < 0 \tag{6}$$

where n, S_{i0}, S_{iT}, and the subscripts are the same as in the NAV index defined above; and X is the set of sectors i such that $C_i > 0$ and Y is the set of sectors i such that $C_i < 0$.

By definition, we have

$$NAV = (PSC + USC)/2 \tag{7}$$

That is, the total structural change as defined in Eq. (2) can be split into two parts: productive structural change (PSC) and unproductive structural change (USC). As we will show in Section 4, PSC has a positive effect on productivity growth, while USC has a negative effect. This implies that it would likely be inconclusive if a study relies on NAV as a proxy to examine the effect of structural change on productivity growth. Because the effects of PSC and USC cancel each other out, the overall effect of NAV could be positive, negative, or insignificant, depending on the relative strengths of the effects of PSC and USC on productivity growth.

3.4. Patterns of PSC and USC in major economies

Table 1 provides summary statistics of PSC and USC for the six G7 economies for which data are available (the US, Japan, Germany, the UK, France, and Italy) and the two aggregates of EU economies (EU11 and EU28).

To extend insights into the patterns of PSC and USC, Table 1 also provides summary statistics for the sum of PSC and USC (SSC=PSC+USC) and their net change (NSC=PSC-USC). Note that for a given economy, SSC captures the magnitude of total structural change during the period of interest, while NSC reveals the effectiveness of the dynamics of structural change. A positive NSC implies that PSC (productive structural change) outweighs USC (unproductive structural change), while a negative PSC-USC indicates a reverse pattern.

Figure 1 provides illustrative insights into the annual patterns of PSC and USC during the period 1995-2019. The magnitudes of PSC and USC and their relative positions, as shown in the figure, reveal the effectiveness of structural change in each country in a given year and for the entire period 1995-2019.

From Table 1 and Figure 1, one can draw the following observations of the dynamics of structural change in the G7 economies and EU11 and EU28 during 1995-2019.

First, the UK economy has the largest magnitude of structural change in terms of the mean value of SSC (2.02), followed by the US (1.76). The UK is also the economy with the strongest productive structural change, as indicated by the mean value of PSC (1.25), followed by the US (1.14).

Second, the US is the leading economy in terms of structural change effectiveness as captured by the mean value of NSC (0.52), followed by the UK (0.48).

Third, Japan is the only economy for which the mean value of NSC is negative (-0.01), which means that, on average, productive structural change was dwarfed by unproductive structural change. In addition, Figure 1 shows that the negative NSC caused by PSC being below USC is most notable in 1998 and 2009, which tends to suggest that Japan’s structural change was more vulnerable to regional and global crises: the Asian financial crisis in 1997 and the global financial crisis in 2008.

Fourth, regarding the structural change effectiveness captured by NSC, Italy (NSC=0.03) significantly lagged behind France (0.44) and Germany (0.28). Furthermore, as shown in Figure 1, PSC was below USC for Italy in 13 years, while this negative pattern took place in only three years for Germany (2001, 2006, and 2009) and France (2007, 2008, and 2009).

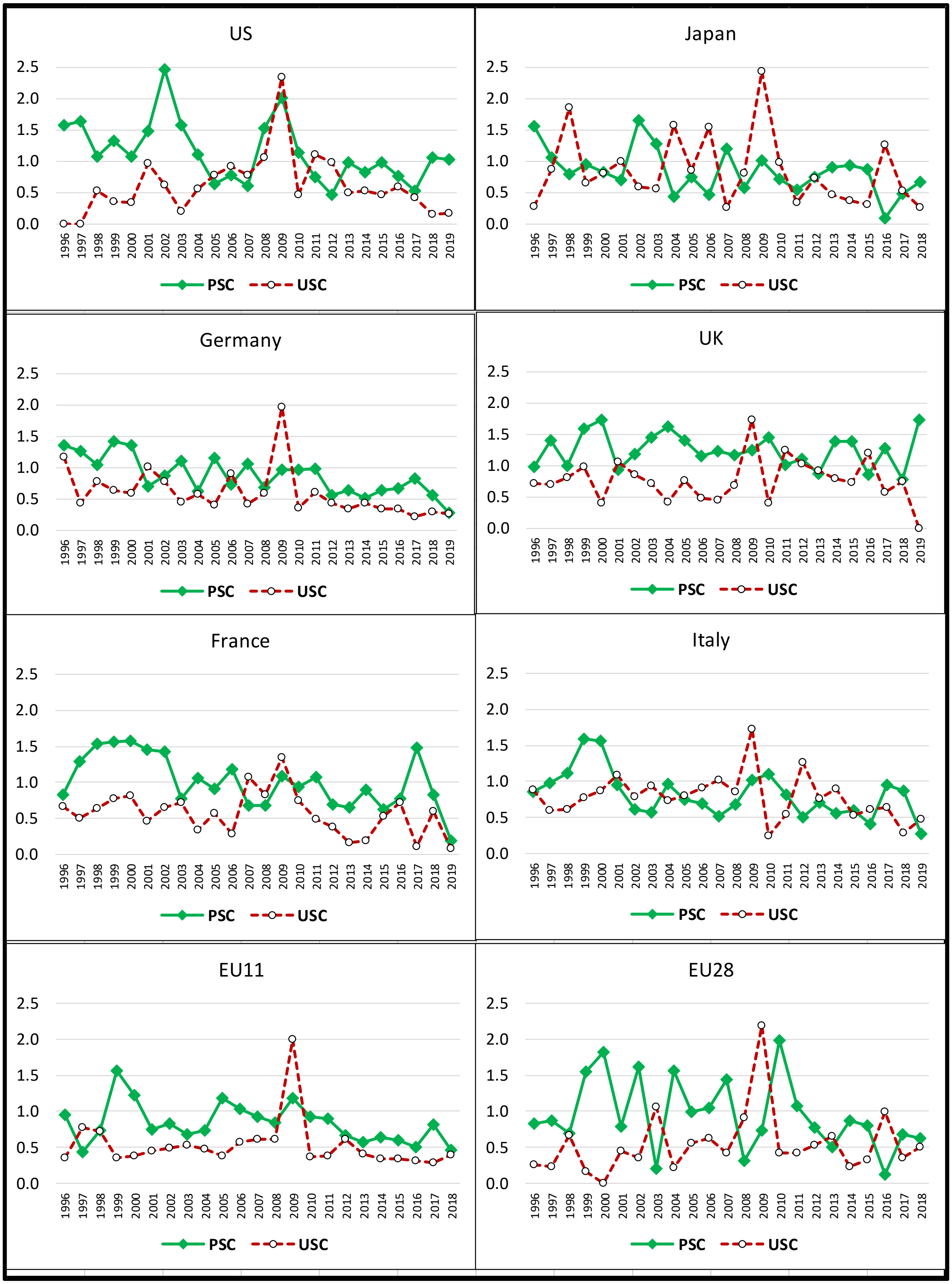
Fifth, EU11 and EU28 in their aggregate data showed rather healthy patterns of structural change, with PSC consistently outweighing USC in most years (Figure 1). It is also interesting to compare the US and EU11, which are comparable to the US in economic and employment sizes[10], on the dynamics of structural change over 1995-2019. As shown in Table 1, the US notably outperformed EU11 on PSC (1.14 vs. 0.80), SCC (1.76 vs. 1.30) and NSC (0.52 vs. 0.29). As the US economy is believed to be more integrated than the EU11, this observation tends to suggest that economic integration plays an important role in making structural change more productive (as captured by PSC), more robust (as captured by SSC), and more effective (as captured by NSC).

Table 1. Summary statistics of PSC and USC for major economies, 1995-2019

	PSC	USC	SSC= PSC+USC	NSC= PSC-USC	PSC	USC	SSC= PSC+USC	NSC= PSC-USC
	US				**Japan**			
Mean	**1.14**	***0.62***	**1.76**	**0.52**	**0.84**	***0.84***	**1.68**	**-0.01**
SD	0.48	*0.49*	0.72	0.65	0.36	*0.56*	0.57	0.75
Min	0.47	*0.00*	0.94	-0.51	0.09	*0.26*	0.89	-1.41
Max	2.46	*2.35*	4.36	1.84	1.65	*2.43*	3.45	1.28
	Germany				**UK**			
Mean	**0.88**	***0.60***	**1.48**	**0.28**	**1.25**	***0.77***	**2.02**	**0.48**
SD	0.30	*0.38*	0.55	0.42	0.27	*0.35*	0.32	0.54
Min	0.27	*0.22*	0.53	-1.00	0.78	*0.00*	1.53	-0.48
Max	1.42	*1.97*	2.93	0.84	1.74	*1.73*	2.99	1.73
	France				**Italy**			
Mean	**1.01**	***0.57***	**1.58**	**0.44**	**0.82**	***0.79***	**1.60**	**0.03**
SD	0.37	*0.30*	0.51	0.44	0.32	*0.31*	0.45	0.45
Min	0.19	*0.08*	0.27	-0.40	0.27	*0.25*	0.74	-0.76
Max	1.58	*1.35*	2.43	1.38	1.59	*1.73*	2.75	0.85
	EU11				**EU28**			
Mean	**0.80**	***0.51***	**1.30**	**0.29**	**0.95**	***0.54***	**1.50**	**0.41**
SD	0.32	*0.35*	0.54	0.40	0.50	*0.44*	0.47	0.82
Min	0.00	*0.00*	0.00	-0.81	0.12	*0.00*	1.03	-1.45
Max	1.56	*1.99*	3.17	1.21	1.98	*2.18*	2.91	1.83

[10] In 2018, GDP (measured in billions of US$) is 19,200 for the US and 12,165 for EU11, while the employment (measured in millions of hours worked) is 272,000 for the former and 237,000 for the later.

Figure 1. Patterns of PSC vs. USC in major economies



4. Effects of structural change, digital transformation, and innovation on productivity growth

This section examines the effect of structural change, digital transformation, and innovation on productivity growth. For structural change, we include both PSC and USC in the examination to gain a more comprehensive understanding of their effects on productivity growth.

As the effect of structural change on productivity growth is our main focus, we also investigate how digital transformation and innovation affect PSCs and USCs. This investigation may reveal some indirect effects of digital transformation and innovation on productivity growth via their role in influencing PSCs and USCs.

4.1. Regression models

Hall and Jones (1999), Acemoglu et al. (2001, 2008), and Eicher and Schreiber (2010) provide a useful approach to dynamic panel data analysis with a parsimonious model to detect the causal link between a variable of interest and the dependent variable.

Following this approach, the investigation of the effect of structural change, digital transformation, and innovation on productivity growth is based on a simple dynamic model below:

$$g_{i,t} = \beta_0 + \beta_1 g_{i,t-1} + \beta_2 PSC_{i,t} + \beta_3 USC_{i,t} + \beta_4 DX_{i,t} + \beta_5 INNO_{i,t} + \beta_6 W_{i,t-1} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (8)$$

where $g_{i,t}$ is the growth rate of labor productivity ($g_{i,t} = LPG_{i,t}$) or total factor productivity ($g_{i,t} = TFPG_{i,t}$) for country i in year t; the lagged variable $g_{i,t-1}$ is included to capture the effects of unobservable factors underlying the persistent pattern of the growth variable $g_{i,t}$; and $PSC_{i,t}$ and $USC_{i,t}$ are PSC and USC, respectively. As PSC is associated with productivity-enhancing structural change, we expect that its coefficient β_2 is positive, while the coefficient β_3 of USC is expected to be negative.

DX, which measures the contribution of software and database capital to total industry labor productivity growth, represents the digital transformation efforts of the economy. Similarly, INNOV, which estimates the contribution of innovative property to total industry labor productivity growth, captures its innovation efforts. Both DX and INNO are directly drawn from the KLEMS database. As digital transformation and innovation have a positive effect on growth, the coefficients β_4 of DX and β_5 of INNOV are expected to be positive.

$W_{i,t-1}$ is a vector of controlled variables, which include the lagged values of productivity level, $lnLP_{i,t-1}$, and the size of employment (log of total hours work) $LnH_{i,t-1}$. Variable $lnLP_{i,t-1}$ is included to examine the convergence effect, for which productivity growth tends to be lower for an economy with a higher level of labor productivity (Barro, 1991; Barro and Sa-la-i-Martin, 1995). At the same time, variable $LnH_{i,t-1}$ is included to detect whether the employment scale has an effect on productivity growth.

Finally, μ_i and ω_t capture country-specific and time-fixed effects, respectively, while $\varepsilon_{i,t}$ represents random errors.

Note that country-specific and time-fixed effects as well as the lagged dependent variable capture a substantial amount of the effects caused by unobserved factors that can influence a country's growth, which range from geographic conditions to the dynamism of the business environment, from human capital endowment to technological progress (López, 2007 and Antoci, Russu, and Ticci, 2009).

We also examine the effect of DX and INNOV on PSC and USC using the following model:

$$XSC_{i,t} = \theta_0 + \theta_1 XSC_{i,t-1} + \theta_2 DX_{i,t} + \theta_3 INNOV_{i,t} + \theta_4 X_{i,t-1} + \mu_i + \omega_t + \varepsilon_{i,t} \quad (9)$$

where XSC is one of two measures of structural change, PSC and USC. We expect that the coefficients of θ_2 and θ_3 would take a positive sign for PSC, while they may have a negative sign for USC.

The summary statistics of the key variables specified above are provided in Table 2. They show that the values taken by these variables follow reasonable patterns and have no outliers.

Table 2: Summary statistics of key variables, 1995-2019

Variable	Description	Unit	N	Mean	SD	Min	Max
LPG	LP growth	%	306	1.3	1.6	-4.9	7.6
TFPG	TFP growth	%	306	0.4	1.6	-10.5	5.2
HG	Hours worked growth	%	306	0.6	1.7	-7.7	4.8
PSC	Productive Structural Change	% points	306	1.2	0.6	0.2	3.5
USC	Unproductive Structural Change	% points	306	0.8	0.6	0.0	3.5
DX	Contribution of software and database to LP growth	% points	306	0.08	0.07	-0.10	0.41
INNOV	Contribution of innovative property to LP growth	% points	306	0.07	0.12	-0.52	0.88
LP	Labour productivity (per hour)	PPP$	306	58.1	11.7	26.1	76.8
H	Total hours worked	Million hours	306	40.8	62.4	1.6	276.2
lnLP	Ln(LP)	---	306	4.0	0.2	3.3	4.3
lnH	Ln(H)	---	306	16.8	1.2	14.3	19.4

Sources: All data, with the exception of labor productivity (LP), are from the KLEMS database. Data for LP is computed from GDP drawn from the World Bank's WDI database and total hours worked from KLEMS. Note: LP is measured in PPP$ (2017 price).

4.2. Estimation methods

The least squares dummy variable (LSDV) estimation is a good start for analysis. The advantage of this method is its control for unobservable factors associated with the time invariance of countries. As shown by Nickell (1981), this estimation reduces substantial biases caused by country-specific and time-fixed effects and serves as a useful benchmark to examine the magnitude of coefficients provided by other estimation methods. The approach, however, is subject to potential bias caused by the endogeneity associated with possible reverse effects of the left-hand side variable (productivity growth) on the explanatory variables of interest, including PSC, USC, DX, and INNOV.

To address the endogeneity problem, the generalized method of moments (GMM) estimation strategy provides an effective tool as it allows endogenous variables to be instrumented with their own lags (Roodman, 2006). Two commonly used GMM estimators are first-difference GMM (DIF-GMM) and system GMM (SYS-GMM).[11] For this analysis exercise, the SYS-GMM estimator is chosen due to its superior performance (Blundell and Bond, 1998).[12] The greater asymptotic efficiency of the SYS-GMM estimator is also evident in other studies, such as Bond et al. (2001) and Soto (2009). In particular, Soto (2009) demonstrates that SYS-GMM is more valid than DIF-GMM when the number N of entities (countries in this study) is small.

[11] The DIF-GMM estimator developed by Holtz-Eakin et al.(1988) and Arellano and Bond (1991) uses first-differences to remove entity-fixed effects, and instruments these first-differences with the earlier values of explanatory variables. The GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998) augments the DIF-GMM to obtain a system of two equations: one in differences and one in levels. In the levels equation the variables are instrumented with the lagged values of their own first differences.

[12] The GMM estimator, however, requires a mild assumption about the orthogonality between the lagged first difference in the dependent variable (Δy_{t-1}) and the composite error terms in the levels equation. This assumption allows Δy_{t-1} to be used as valid instruments for the levels equation.

5. Empirical results and discussions

The results from regressions based on Eq. (8) are reported in Table 3 for labor productivity growth (LPG) and in Table 4 for total factor productivity growth (TFPG). At the same time, the results from regressions for PSC and USC based on Model (9) are reported in Table 5.

For each of the GMM regressions, it is necessary to conduct the two tests to validate the soundness of its estimation, which are the test of serial correlation and the test of overidentifying restrictions of instrumental variables. P values from testing the null hypotheses of these two tests as reported at the bottom of each table confirm the validity of all the GMM estimation results.

For analysis, we report the estimation results from both LSDV and GMM estimators for each model specification. Because the SYS-GMM estimator is believed to be more effective in addressing the endogeneity problem (Roodman, 2009; Wintoki et al., 2018), we rely more on the results from GMM than from LSDV estimations to draw conclusions from the findings.

5.1. Results from regressions for labor productivity growth

The following observations stand out from the estimation results for labor productivity, which are reported in Table 3.

First, the coefficient on the lagged dependent variable g[t-1] is positive but not significant in most regressions. This result suggests that LP growth in industrialized economies does not follow a strong persistent pattern. As LP growth is a sum of the contributions of capital deepening and TFP growth, we will discuss this issue in the next subsection, which presents the results from regressions for TFP growth.

Second, the coefficients on PSC and USC are robustly significant at the 1% significance level in all regressions, while they take opposite signs. On the one hand, the positive sign and large magnitude of the coefficient on PSC indicate its strong positive effect on LP growth. On the other hand, the negative sign and large magnitude of the coefficient on USC suggests its substantial negative effect on LP growth. Furthermore, these results are even more pronounced in the GMM estimations, which demonstrates the significance of these findings.

This finding demonstrates that structural change has a significant effect on labor productivity growth, but its effect could be positive or negative depending on its pattern. This implies the importance of policy initiatives in fostering productive and lessening unproductive structural change in promoting productivity growth.

Third, the coefficient on LP[t-1] is negative and significant in all regressions, which provides evidence of the convergence effect. This suggests that it is harder for an economy to promote productivity growth at a higher level of labor productivity.

Fourth, the coefficients on DX and INNOV are positive in both regressions (2a) and (2b). However, while they are very significant at the 1% significance level in regression (2a), their significance in regression (2b) is not as convincing, as only their combined effect is significant at the 10% significance level. These results suggest that while DX and INNOV have a strong association with LP growth, their causal effects on LP growth are not robustly significant. This finding can be explained by the presence of endogeneity in the link between DX (INNOV) and LP growth. In particular, the strong positive link between DX and LP growth is likely caused more by the reverse effect of LPG on DX. That is, an economy with strong productivity growth tends to invest more in digital transformation. Similarly, the strong positive link between INNOV and LP growth is probably driven by the reverse effect from LPG. That is, an economy with strong productivity growth tends to invest more in innovation efforts.

Fifth and finally, the coefficient on LnH[n-1] is positive and significant in all regressions, except for regression (2b). Although this evidence is not robust across regressions, it tends to suggest that employment size has some significant positive effect on LP growth. That is, a country with a larger labor force likely enjoys more conditions that drive LP growth (Desmet and Parente, 2010).

Table 3: Results of labor productivity growth (LPG) regressions

Explanatory Variable	g [t]=Labor Productivity Growth (LPG)			
	LSDV		SYS-GMM	
	(1a)	(2a)	(1b)	(2b)
g [t-1]	0.087*	0.044	0.049	0.050
	(0.049)	(0.046)	(0.070)	(0.068)
PSC [t]	1.120***	1.011***	1.442***	1.261***
	(0.167)	(0.155)	(0.279)	(0.282)
USC [t]	-1.268***	-1.095***	-1.915***	-1.943***
	(0.176)	(0.164)	(0.320)	(0.311)
DX [t]		4.228***		3.113
		(0.998)		(2.729)
INNOV [t]		2.538***		1.541
		(0.540)		(1.267)
LnLP [t-1]	-1.565***	-1.142**	-2.618**	-1.975**
	(0.517)	(0.480)	(1.153)	(0.849)
LnH [t-1]	6.263***	5.135***	0.914**	0.264
	(1.971)	(1.860)	(0.402)	(0.381)
N	294	294	294	294
R2	0.664	0.719	---	---
AR(2) test	---	---	0.206	0.190
Hansen test of overid.	---	---	0.285	0.638
[# Instruments]	---	---	[17]	[23]

Notes: Robust standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1.*

5.2. Effects of PSC, USC, DX, and INNOV on TFP growth

The following findings are drawn from the estimation results for TFP growth, which are reported in Table 4.

First, the coefficient on lagged dependent variable TFPG[n-1] is positive and significant at the 1% significance level in all regressions, except for regression (2b). This result suggests that TFP growth follows a more persistent pattern in comparison to LP growth, as examined in the previous subsection. As LP growth is a sum of the contributions of capital deepening and TFP growth, the more persistent pattern of TFP growth compared to LP growth indicates the lack of persistence in the pattern of capital deepening in contributing to labor productivity growth. That is, it is challenging for industrialized economies to sustain capital deepening as a key driver of LP growth. Therefore, promoting innovation and pushing for structural reforms are critical for industrialized economies to foster LP growth.

Second, similar to what was observed in the previous subsection for LP growth, the coefficients on both PSC and USC in all regressions are significant, and their signs are opposite. These results show that structural change has strong effects on TFP growth, which could be positive or negative depending on its pattern. While the effect on TFP growth of PSC is positive and strong, that of USC is negative and substantial. In addition, it should be noted that the magnitude of the coefficient on USC is notably larger than that on PCS, which implies that efforts to promote structural change for productivity growth should focus not only on fostering PSC but also on lessening USC.

Third, the coefficient on DX is positive but not significant in both regressions (2a) and (2b), while the coefficient on INNOV is positive but significant only in regression (2a). That is, although capital investments in digital transformation and R&D have some positive effect on TFP growth, which capture efficiency improvements in the economy, their causal effects are insignificant when controlling for endogeneity. These results again tend to suggest the significance of the reverse effect of TFP growth on DX and INNOV. That is, creating an environment that fosters efficiency improvements in the economy, which is captured by TFP growth, tends to have a strong positive effect on digital transformation and innovation. This finding has some important policy implications. This implies that fostering the vibrancy and efficiency of the economy in fundamental areas such as structural reforms, global integration, and entrepreneurship may be more urgent and effective in promoting digital transformation and innovation than just allocating more budgets for these efforts, with the aim of boosting TFP growth.

Table 4: Results for TFPG regressions

Variable	g [t]=Total Productivity Growth (TFPG)			
	LSDV		SYS-GMM	
	(1a)	(2a)	(1b)	(2b)
g [t-1]	0.243***	0.224***	0.189***	0.041
	(0.052)	(0.051)	(0.056)	(0.105)
PSC [t]	0.675***	0.567***	0.889***	1.476**
	(0.164)	(0.161)	(0.276)	(0.626)
USC [t]	-1.218***	-1.091***	-2.297***	-2.810***
	(0.177)	(0.174)	(0.374)	(0.970)
DX [t]		1.072		4.101
		(1.032)		(3.917)
INNOV [t]		2.250***		2.360
		(0.563)		(2.302)
LnLP [t-1]	-0.157	0.072	-0.908	0.117
	(0.508)	(0.497)	(1.053)	(3.650)
LnH [t-1]	0.513	-0.748	0.468	-0.902
	(1.950)	(1.935)	(0.453)	(1.881)
N	291	291	291	291
R2	0.699	0.720	---	---
AR(2) test	---	---	0.108	0.407
Hansen test of Overid.	---	---	0.282	0.375
[# Instruments]	---	---	[17]	[16]

Notes: Robust standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1.*

5.3. Effects of DX and INNOV on PSC and USC

This subsection examines how DX and INNOV affect PSC and USC, which are the two measures that capture the dynamics of structural change in an economy.

The results from the regressions based on Model (9) for XSC=PSC and XSC=USC are reported in Table 5. The following findings are drawn from the table.

First, the coefficient on PSC[n-1] is positive and significant in both regressions (1a) and (1b), while the coefficient on USC [n-1] is positive in both regressions (2a) and (ab) and significant at the 1% significance level in regression (2b). These findings indicate that both PSC and USC follow a significant persistent pattern. It should be noted, however, that the persistence is more robust and stronger (in terms of significance and the magnitude of the coefficient) for PSC than for USC.

Second, the coefficient on INNOV is positive and significant at the 1% significance level in both regressions (1a) and (1b), which means that INNOV has a strong positive effect on PSC. This result, therefore, implies that investing in innovation indirectly boosts LP growth and TFP growth by fostering PSC. On the other hand, the coefficient on USC is negative and significant at the 5% significance level in regression (2a) but is negligible and insignificant in regression (2b). This result implies that INNOV has some negative effect on USC, but this link is not significantly causal. That is, an economy with strong innovation tends to see less unproductive structural change. This association link, however, is likely driven by the reverse effect of USC on INNOV: a high level of unproductive structural change weakens efforts for innovation, while a low level of unproductive structural change boosts them.

Third, LnH[n-1] is positive in both regressions (2a) and (2b), while it is only significant in regression (2a). This result suggests that employment size has a strong association with USC, but it is not a causal effect. The association link between LnH and USC is likely influenced by unobserved factors related to employment size. For example, an economy with a larger employment size tends to have more opportunities for workers to find jobs in sectors that are less productive, which results in unproductive structural change.

Table 5: Results of regressions for PSC and USC

Variable	XSC=PSC		XSC=USC	
	LSDV	SYS-GMM	LSDV	SYS-GMM
	(1a)	(1b)	(2a)	(2b)
XSC [t-1]	0.131**	0.402***	0.043	0.259***
	(0.064)	(0.105)	(0.060)	(0.062)
DX [t]	-0.000	0.004	-0.006	0.007
	(0.004)	(0.005)	(0.004)	(0.009)
INNOV [t]	0.007***	0.013***	-0.005**	0.000
	(0.002)	(0.004)	(0.002)	(0.004)
LnLP [t-1]	0.003	0.006	-0.001	0.003
	(0.002)	(0.004)	(0.002)	(0.006)
LnH [t-1]	0.005	-0.003	0.028***	0.000
	(0.007)	(0.003)	(0.007)	(0.003)
N	295	295	295	295
R2	0.632	---	0.648	---
AR(2) test	---	0.704		0.633
Hansen test of Overid.	---	0.463		0.409
[# Instruments]		[17]		[17]

Notes: Robust standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1.*

6. Conclusion

Previous studies on structural change have laid a solid foundation for the hypothesis that reallocation of productive inputs, particularly labor, among sectors plays an important role in driving economic growth. However, this hypothesis is still challenged by a number of studies that find no conclusive evidence of a positive contribution of structural change to growth. Moreover, the existing methods used to capture the effectiveness of structural change and quantify its contribution to growth have significant limitations that may compromise the accuracy of their empirical results.

This paper employs a novel approach to investigate the effect of structural change among other sources on productivity growth. To capture the different patterns of structural change, the study introduces two new measures. One is “productive structural change”, labeled PSC, which captures the shift of labor among sectors that enhances the economy’s overall labor productivity growth. The other is “unproductive structural change”, labeled USC, which gauges the magnitude of labor reallocation that weakens the economy’s overall labor productivity growth.

As digital transformation and innovation have become important drivers of productivity growth, the study includes them in its regression analysis. The proxy for digital transformation is the contribution to LP growth of software and database capital, which is labeled DX. The proxy for innovation is the contribution to LP growth of innovative property (INNOV), which accumulated over time by R&D investment flows.

The study produces important results with rich policy insights. Among them, the following contributions and findings are most notable.

First, the study constructs meaningful measures to monitor the dynamics of structural change in an economy over a period of interest. PSC measures the productive dynamics of structural change in an economy, while USC gauges its unproductive dynamics. In addition, the sum of PSC and USC (SSC=PSC+USC) captures the magnitude of structural change, while their net effect (NSC=PSC-USC) reveals the effectiveness of structural change dynamics.

Second, the patterns of structural change captured by the introduced measures provide valuable insights. In particular, PSC generally outweighs USC in magnitude for most economies, but this pattern varies largely by country and year. Among the major industrialized economies, the US and the UK are the leading players, while Japan and Italy are the laggards in the efforts to embrace structural change for productivity growth during 1995-2019. In addition, the stronger performance of the US on all measures of structural change (PSC, SSC, and NSC) compared to EU11, which is comparable to the US in employment size and GDP, implies that economic integration plays an important role in making structural change more productive, more robust, and more effective.

Second, the effects on labor productivity growth and total factor productivity growth of both PSCs and USCs are robustly significant and sizable in magnitude. However, while the effect of PSC is positive, that of USC is negative. In addition, the marginal effect of USC is more sizable than that of PSC. These results suggest the importance of strategy and efforts in embracing structural change for productivity growth. That is, embracing structural change should focus not only on fostering PSC but also on reducing USC.

Third, DX and INNOV have a positive effect on productivity growth, but the robust significance of their strong links with productivity growth are likely driven more from the reverse effects of the latter. That is, promoting digital transformation and innovation for productivity growth should not simply focus on allocating more budgets for these efforts but, more effectively, should strategically create a more enabling environment for productivity growth, which could come from more robust structural reforms, deeper global integration, and more vibrant entrepreneurship.

Fourth, innovation has a strong positive effect on PSC. This means that innovation can indirectly boost productivity growth by fostering PSC.

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