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Research Article

Keywords:

Posted Date: November 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11658852/v1

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Additional Declarations: No competing interests reported.

Determinants of total factor productivity: An interactive fixed-effects analysis with time-varying coefficients

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November 7, 2026

Abstract

This paper examines the drivers of total factor productivity (TFP) growth and convergence in 17 OECD countries over 1900–2016. We propose a time-varying-coefficient panel model with interactive fixed effects that lets the elasticities of TFP determinants evolve smoothly while controlling for unobserved common shocks with heterogeneous country loadings, and we estimate it using a semiparametric, kernel-based local least-squares method. The results reveal substantial temporal heterogeneity in the effects of domestic R&D, foreign R&D spillovers, education, institutional quality, geopolitical risk, and climate change. In the postwar period, foreign R&D spillovers, education, and the rule of law emerge as the dominant drivers of productivity growth and convergence. Foreign R&D spillovers boost productivity across the board, but their contribution declines steadily as OECD economies approach the technological frontier, while education and the rule of law strengthen markedly. These findings suggest that, near the frontier, productivity gains depend increasingly on absorptive capacity and institutional quality rather than imported technology.

Keywords: Convergence; Cross-sectional dependence; Institutions; R&D spillovers; Time-varying coefficients; Total factor productivity

JEL Classification: C14, C23, O43, O47

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1 Introduction

Total factor productivity (TFP) growth is widely recognised as the principal source of sustained improvements in living standards. The literature on total factor productivity (TFP) asks two closely related key questions: what drives productivity growth? and why do some economies converge towards the technological frontier while others remain behind? In the neoclassical growth model, sustained growth in output per worker ultimately depends on exogenous technological progress (Solow, 1956). Endogenous growth theory instead explains technological progress through purposeful investment in innovation, knowledge accumulation, and human capital (Romer, 1990). Both traditions imply that long-run productivity depends on a country's capacity to generate new knowledge and on its ability to adopt and adapt technologies developed elsewhere.

Coe and Helpman (1995) and Coe et al. (1997) showed that domestic R&D capital and foreign R&D spillovers embodied in trade are important determinants of productivity in advanced economies. Their findings establish a useful distinction between an innovation margin, through which countries generate new knowledge domestically, and a technology-adoption margin, through which they benefit from knowledge created abroad. Subsequent work extends this framework by considering trade openness, foreign direct investment, and the conditions under which foreign knowledge can be absorbed. In particular, Engelbrecht (1997) shows that human capital strengthens the productivity effects of international R&D spillovers, while Fracasso and Marzetti (2015) provides further evidence that greater international integration facilitates knowledge diffusion.

Human capital (education) raises productivity directly by improving the skills and problem-solving capacity of the labour force and indirectly by increasing an economy's absorptive capacity (Caselli et al. (1996) and Madsen (2014). The empirical evidence shows that the productivity returns to education and foreign R&D spillovers depend on a country's distance to the world technology frontier. These views point to time-varying elasticities; we will return to this later in this section.

Following Acemoglu et al. (2001) and Acemoglu et al. (2005), institutions are viewed as fundamental drivers of income because they shape incentives for innovation, the se-

curity of property rights, the allocation of resources, and the adoption of new technologies. Weak governance and corruption can reduce productivity by distorting investment decisions and directing resources towards unproductive activities (Grigorian and Martinez, 2000; Enste and Heldman, 2017). Conversely, stronger legal and regulatory institutions can encourage innovation and improve economic efficiency (Ngo and Nguyen, 2020; Góes and Bekkers, 2022). Institutional quality affects productivity directly and is likely to complement R&D and education by raising the returns to innovation and facilitating the diffusion of foreign technology.

More recent studies broaden the set of productivity determinants to include geopolitical and environmental conditions. Geopolitical conflict and uncertainty may impede productivity growth by discouraging investment, disrupting trade, and weakening international technology transfer (Weede, 2016). Climate change may affect productivity through changes in agricultural conditions, labour efficiency, infrastructure, energy use, and the allocation of productive resources Dell et al. (2012) and Kalkuhl and Wenz (2020). These factors are conceptually distinct from innovation, education, and institutions, but their effects are unlikely to be independent. Geopolitical disruptions may restrict access to foreign knowledge, while institutional quality may influence an economy's capacity to adapt to climate-related shocks.

A prominent closely related line of research studies convergence. The conventional convergence framework asks whether initially poorer economies grow faster than richer economies, either unconditionally or after conditioning on structural characteristics. Much of this literature focuses on income per capita (Acemoglu and Molina, 2021; Kremer et al., 2022). Productivity convergence is nevertheless the more direct counterpart to theories of technology diffusion, because convergence in TFP reflects the extent to which lagging economies absorb frontier knowledge and close technological gaps. Existing evidence identifies foreign R&D spillovers and education as important mechanisms of productivity convergence (Madsen, 2007, 2014). Comparatively less is known about whether institutional quality, geopolitical risk, and climate change systematically influence the pace of TFP convergence.

Although there is substantial evidence on the determinants of productivity, three

limitations remain. First, most studies focused on a restricted set of explanatory variables. From the foregoing discussion, a comprehensive set of determinants of TFP includes domestic R&D, foreign R&D spillovers, education, institutions, geopolitical conditions, and climate change. However, empirical studies have included a subset of these variables in the models. Such inadequate models cause unobserved heterogeneity and omitted-variable bias in the elasticities.

Second, the TFP literature is silent on what determines TFP convergence. Empirical studies by Madsen (2007) and Madsen (2024) shed light on the role of R&D and education in TFP convergence. The roles of institutions, geopolitical risk, and climate change in explaining cross-country convergence have not been examined. This paper considers a unified model of productivity growth and convergence with seven determinants.

Third, we allow time-varying elasticities, whereas most empirical studies impose constant elasticities. Our approach is motivated by the view that productivity dynamics reflect the interaction of two fundamental margins: domestic innovation and international technology adoption. The innovation margin is driven by domestic R&D, human capital, and institutional quality, which shape incentives and absorptive capacity. The adoption margin captures convergence towards the global technology frontier through knowledge diffusion (Nelson, 1966; Eaton and Kortum, 1999). These mechanisms imply that both effects of key determinants are inherently time-varying. Additionally, the constant coefficient assumption doesn't hold particularly in a historical panel data extending from 1900 to 2016. Over this period, OECD economies experienced major technological transformations, two World Wars, changing trade regimes, institutional reforms, and repeated episodes of global integration and disruption. These developments are likely to have changed both the available channels of technology diffusion and the capacity of individual countries to exploit them. Constant-coefficient estimates may therefore conceal economically important shifts in the sources of productivity growth.

This study contributes to the TFP literature by examining collective importance of domestic R&D, foreign R&D spillovers, education, institutional quality, geopolitical risk, and climate change in the century-long panel of OECD economies. The empirical framework that evolved from economic theory combines time-varying coefficients with inter-

active fixed effects (Section 3). The former permit the effects of observed productivity determinants to evolve smoothly over time, while the latter capture unobserved common shocks with heterogeneous country-specific responses. The analysis also finds the determinants of TFP σ- and β-convergence.

The remainder of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 introduces the economic framework and econometric methodology. Section 4 presents the empirical findings, while Section 5 investigates TFP convergence. Section 6 assesses the robustness of the findings to additional control variables and alternative model specifications. Section 7 concludes. Appendix A details the bootstrap procedure for constructing confidence bands, and Appendix B provides supplementary tables and figures.

2 Data and variable construction

2.1 Data

Our empirical analysis uses an annual panel of 17 OECD countries covering the period 1900–2016.[3] The sample includes Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.[4]

Our analysis considers seven determinants of TFP representing four complementary channels of long-run productivity growth: innovation, international knowledge diffusion, human capital and institutions, and the external environment.

Productivity. The dependent variable is the land-adjusted total factor productivity (TFP) index constructed by Madsen (2007). The index is derived from a Cobb–Douglas production framework with time-varying factor shares and provides a consistent measure of productive efficiency for OECD economies over the period 1900–2016. Higher values of TFP indicate more efficient use of labour, capital, and land in production.

[3] We thank Jakob Madsen for providing historical data on land-adjusted TFP, domestic R&D stocks, international R&D spillovers, and educational attainment for 21 OECD countries.

[4] Austria, Greece, Ireland and New Zealand are excluded because comparable geopolitical risk data are unavailable over the study period.

Innovation and international knowledge diffusion. Innovation is measured by the domestic stock of research and development (RDD), constructed using the perpetual inventory method with a 15% depreciation rate. The variable represents the accumulated stock of domestically generated knowledge and reflects a country's capacity to develop new technologies, products, and production processes.

International knowledge diffusion is captured by foreign R&D spillovers (RDF), which measure the stock of knowledge embodied in imports from trading partners. Foreign R&D spillovers are constructed as the import-weighted sum of the domestic R&D stocks of 21 OECD economies:

$$\mathrm{RDF}_{it} = \sum_{\substack{j=1 \\ j \neq i}}^{21} \left(\frac{M^s_{ijt}}{Y^{s,n}_{jt}} \right) \mathrm{RDD}_{jt}, \tag{1}$$

where M^s_{ijt} denotes smoothed imports of high-technology goods from country j to country i, $Y^{s,n}_{jt}$ is country j's smoothed nominal income, and RDD_{jt} is country j's stock of domestic knowledge. The import share serves as a measure of exposure to foreign technology, implying that countries with greater openness to international trade receive larger knowledge spillovers from abroad; see Madsen (2014). The RDD and RDF represent, respectively, the innovation and technology-adoption margins of long-run productivity growth.

Human capital and institutions. Human capital is measured by educational attainment (EDU), defined as the average years of schooling of the population aged 15–64. Following Madsen (2014), EDU is constructed by aggregating years of primary, secondary, and tertiary education. Education contributes to productivity by strengthening both innovation and technology adoption. It enhances the skills required for domestic research while increasing the absorptive capacity needed to adopt and implement frontier technologies.

Institutional quality is measured using two complementary indicators: the rule of law (ROL) index and the corruption (CORR) index. The rule of law index measures the extent to which governments, firms, and individuals operate within transparent, predictable, and effectively enforced legal systems, with higher values indicating stronger legal institutions. The corruption index, compiled by Transparency International, mea-

sures perceived public-sector corruption, with higher values indicating greater corruption. Together, these variables characterise the institutional environment in which innovation and technology diffusion occur. Strong legal institutions encourage investment, protect property rights, and facilitate knowledge diffusion, whereas corruption weakens incentives for innovation and leads to inefficient resource allocation.

External environment. To account for broader structural forces that may influence long-run productivity, we include measures of geopolitical risk (GPR) and climate change (CLIMATE). Geopolitical risk is measured using the index developed by Caldara and Iacoviello (2022), which captures the threat and realisation of adverse geopolitical events, including wars, terrorism, and international political tensions. Higher values of GPR indicate greater geopolitical uncertainty, which may discourage investment, disrupt international trade, and slow the international diffusion of technology.

CLIMATE is measured by annual temperature anomalies relative to the 1910–2000 average. Since consistent country-level temperature series are unavailable for the entire sample period, each country is assigned the temperature anomaly of its respective continent (Asia, Europe, North America, or Oceania).[5] The data are obtained from the National Centres for Environmental Information.[6] Temperature anomalies provide a long-run measure of climate change that may affect productivity through agricultural production, labour productivity, infrastructure resilience, and the reallocation of economic resources.

Notation. Unless otherwise stated, all variables are expressed in natural logarithms. Accordingly, the transformed variables are denoted by $\ln$ TFP, $\ln$ RDD, $\ln$ RDF, $\ln$ ROL, $\ln$ CORR, and $\ln$ GPR, while EDU and CLIMATE enter the empirical models in levels. Throughout the paper, we refer to the period 1900–1949 as the pre-war period and 1950–2016 as the post-war period.

[5] Country-specific station-level temperature data are available from 1900 in NOAA, but the starting dates differ across stations, so country-specific temperature anomalies could not be constructed.

[6] National Centres for Environmental Information database https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series

2.2 Summary statistics

Table B.1 reports summary statistics for the pre-war (1900–1949) and post-war (1950–2016) periods. Several long-run patterns emerge.

First, average productivity increased substantially over the sample period. Mean $\ln$ TFP rose from -3.69 before the Second World War to -2.70 afterwards, indicating a marked improvement in productive efficiency across OECD economies. This increase was accompanied by substantial increases in both domestic and foreign knowledge stocks, consistent with the expansion of innovation and international technology diffusion during the twentieth century. Mean $\ln$ RDD increased from 9.66 to 10.37, while mean $\ln$ RDF rose even more rapidly, from 3.19 to 5.19.

Second, the average EDU increased from 6.58 to 9.83 years, consistent with the widespread expansion of secondary and tertiary education across OECD countries in the post-war peiod.

Third, the institutional and external environment changed considerably over the sample period. $\ln$ ROL improved on average, whereas $\ln$ CORR and GPR exhibit greater cross country variations. Meanwhile, the average temperature anomaly CLIMATE increased from -0.14°C in the pre-war period to 0.35°C later, providing clear evidence of long-run behaviour of CLIMATE. Together, these observed patterns suggest that productivity growth occurred alongside substantial changes in technological capability, human capital, institutional quality, and the external environment.

Furthermore, Figure B.2 plots the distance to the technological frontier, DTF_{it}, for each of the 17 countries, measured relative to the UK.[7] The figure points to widespread convergence over the sample period: DTF_{it} declines for every country, and the cross-country average falls steadily; see Figure B.3.

[7] We first took the US as the frontier, defining $\mathrm{DTF}_{it} = \ln \mathrm{TFP}_{\mathrm{US},t} - \ln \mathrm{TFP}_{it}$. Under this definition, DTF is negative for several countries; that is, their measured TFP exceeds that of the US. We therefore take the UK as the benchmark frontier, $\mathrm{DTF}_{it} = \ln \mathrm{TFP}_{\mathrm{UK},t} - \ln \mathrm{TFP}_{it}$, under which DTF is positive for all countries.

3 Theoretical Framework and Empirical strategy

3.1 Time-Varying Elasticities of TFP

3.1.1 Baseline decomposition: innovation versus diffusion

We decompose TFP growth in country i at time t into a domestic innovation component and a technology diffusion (catch-up) component, following the two faces of R&D framework of Griffith et al. (2004) and the appropriate growth policy view of Aghion and Howitt (2006):

$$\ln \text{TFP}_{it} = \phi(t)\ \ln \text{RDD}_{it} + \psi(t)\ \ln \text{RDF}_{it}\, g(\text{DTF}_{it}) + \varepsilon_{it}, \tag{2}$$

where TFP_{it} is the level of TFP, $\ln \text{RDD}_{it}$ is domestic R&D stock, RDF_{it} is the stock of foreign/frontier R&D accessible through trade, FDI, and patent citation channels, and $\text{DTF}_{it} = \ln \text{TFP}_{ft} - \ln \text{TFP}_{it}$ is the log distance to the world technology frontier DTF_{ft}. The function $g(\cdot)$ governs how the elasticity of TFP growth with respect to lnRDF varies with DFT.

3.1.2 Why the RDF elasticity declines as the DTF $\to 0$?

Two complementary mechanisms from the Schumpeterian growth literature motivate $g'(DTF_{it}) > 0$, i.e. a declining lnRDF elasticity as $\text{DTF}_{it} \to 0$.

(a) Diminishing imitable knowledge. The stock of unexploited frontier technology available for absorption is proportional to the remaining DTF itself. If diffusion effort converts foreign R&D into domestic TFP growth at a rate that scales with the remaining knowledge stock, then $g(\text{DTF}_{it})$ is increasing and concave in DTF_{it}, so the composite elasticity $\partial \ln TFP_{it} / \partial \ln \text{RDF}_{it}$ mechanically falls as countries converge.

(b) Imitation-to-innovation regime switching. Acemoglu et al. (2006) show that economies far from the frontier maximise growth through selection mechanisms and institutions suited to large-scale *imitation*, while economies near the frontier require selection for *innovation*, skill-intensive lnRDD, risk-tolerant finance, and competitive product markets. As $DTF_{it} \to 0$, the growth-maximizing weight shifts from lnRDF toward lnRDD, independently of mechanism (a).

3.1.3 Absorptive capacity: education, rule of law, and corruption as elasticity moderators

In the spirit of Nelson (1966), Cohen and Levinthal (1990), and Benhabib and Spiegel (2005), education and institutional quality are modelled as arguments of the diffusion function itself:

$$g(\text{DTF}_{it}) = \text{DTF}_{it} h(\text{EDU}_{it}, \ln \text{RoL}_{it}, \ln \text{CORR}_{it}). \tag{3}$$

Human capital raises the *speed* of technology adoption (Nelson, 1966), while rule of law and corruption shape the contracting environment for technology transfer (FDI, licensing) and the allocative efficiency with which absorbed technology is deployed across firms, consistent with the misallocation channel documented by Hsieh and Klenow (2009). Because $h(\cdot)$ evolves slowly and endogenously with each country's institutional trajectory, the composite elasticity on $\ln \text{RDF}_{it}$ is not a structural constant even conditional on DTF_{it}, which is the substantive justification for leaving its time path unrestricted rather than imposing a parametric interaction.

Geopolitical risk as a diffusion-channel friction. Geopolitical risk is modelled as a multiplicative friction on the trade/FDI channel through which $\ln \text{RDF}$ operates, following the measurement framework of Caldara and Iacoviello (2022). Elevated geopolitical risk raises the effective cost of cross-border technology transfer (export controls, FDI screening, supply-chain rerouting), providing an observable candidate driver of drift in $ln\text{RDF}$ that is conceptually distinct from, and can be used to help separately identify, the pure distance-to-frontier convergence mechanism.

Climate change as a level/growth drag. Climate change is modelled as a direct drag on TFP growth operating through labor productivity, capital depreciation, and reallocation costs, largely orthogonal to the diffusion mechanism above, following Dell et al. (2012) and Kalkuhl and Wenz (2020). It therefore enters (2) as a separate additive term rather than as a further moderator of $g(\cdot)$.

3.2 Empirical Strategy

We show the evolution of the time-varying elasticities in the panel specification for $\ln TFP_{it}$ from the economic model (2). Aggregating the mechanisms discussed in the

previous section yields the reduced-form estimating equation:

$$\begin{aligned}\ln \mathrm{TFP}_{it} = {} & \gamma_{\mathrm{RDF},t} \ln \mathrm{RDF}_{it} + \gamma_{\mathrm{RDD},t} \ln \mathrm{RDD}_{it} + \gamma_{\mathrm{EDU},t} \mathrm{EDU}_{it} + \gamma_{\mathrm{CORR},t} \ln \mathrm{CORR}_{it} \\ & + \gamma_{\mathrm{RoL},t} \ln \mathrm{RoL}_{it} + \gamma_{\mathrm{GPR},t} \ln \mathrm{GPR}_{it} + \gamma_{\mathrm{CLIMATE},t} \mathrm{CLIMATE}_{it} + \lambda_i' F_t + \varepsilon_{it}.\end{aligned} \tag{4}$$

Two different identification problems motivate distinct features of the econometric specification.

Time-varying coefficients. As the sample-average DTF_t shrinks over a long panel, and as institutional quality and geopolitical risk trend, the composite elasticity implied by $g(\cdot)$ and $h(\cdot)$ in (3) drifts smoothly over time. Further, the effects of innovation, international knowledge diffusion, education, and institutions are unlikely to remain constant over a sample spanning more than a century.

Interactive fixed effects. Independently of coefficient drift, unobserved common shocks such as global technology cycles, financial crises, commodity price shocks, tend to be correlated with RDF_{it}, GPR_{it}, and Clim_{it} across countries simultaneously. In the presence of such cross-section dependence, the conventional two-way fixed-effects panel model estimates $\gamma_{\mathrm{RDF},t}$ and others are biased. The interactive fixed effects $\lambda_i' F_t$ in (4) absorb this cross-sectional dependence, following Bai (2009) and the approach to common correlated effects of Pesaran (2006), where F_t is the unknown factors r and λ_i are the factor loadings, which are the responses of the country i to global shocks captured by F_t.

The latent factors capture unobserved global shocks that are common to all countries, whereas the factor loadings determine how strongly each country responds to those shocks. Consequently, the IFE specification allows countries to exhibit heterogeneous responses to common technological, economic, and geopolitical events, providing a more flexible representation of cross-sectional dependence than the additive fixed-effects model.

We call (4) the time-varying coefficient interactive fixed effects (TVCIFE) model. Since the functional forms of $g(\cdot)$ and $h(\cdot)$ in models (2) and (3), respectively, are unknown, the semiparametric time-varying coefficient model (4) is estimated by the kernel-weighted local linear estimation proposed by Casas et al. (2021). This method, for example, allows the data to trace the shape of the decline in $\beta_{\mathrm{RDF},t}$ rather than imposing linearity or

a specific parametric interaction with DTF_{it}.

We consider slightly different versions of time-varying coefficient models, and select the most suitable model using the RMSE model selection criterion.

Furthermore, as a robust check, we consider the following panel models with constant coefficients: two-way fixed effects model and an interactive fixed effects panel model, defined respectively, as,

$$\begin{aligned}\ln \text{TFP}_{it} = \psi_i + \nu_t + \gamma_1 \ln \text{RDD}_{it} + \gamma_2 \ln \text{RDF}_{it} + \gamma_3 \ln \text{RoL}_{it} + \gamma_4 \text{EDU}_{it} \\ + \gamma_5 \ln \text{GPR}_{it} + \gamma_6 \ln \text{CORR}_{it} + \gamma_7 \text{CLIMATE}_{it} + u_{it},\end{aligned} \tag{5}$$

where ψ_i denotes country fixed effects, ν_t denotes common time effects, and u_{it} is an idiosyncratic error; and

$$\begin{aligned}\ln \text{TFP}_{it} = \gamma_1 \ln \text{RDD}_{it} + \gamma_2 \ln \text{RDF}_{it} + \gamma_3 \ln \text{RoL}_{it} + \gamma_4 \text{EDU}_{it} \\ + \gamma_5 \ln \text{GPR}_{it} + \gamma_6 \ln \text{CORR}_{it} + \gamma_7 \text{CLIMATE}_{it} + \lambda_i' F_t + u_{it},\end{aligned} \tag{6}$$

3.3 Estimation and inference

We re-wite (4) in a compact matrix form, defined as

$$Y_i = X_i' \gamma_\tau + \lambda_i F + U_i, \tag{7}$$

where $X_i' \gamma_\tau = (x_{i1}' \gamma(\tau_1), \ldots, x_{iT}' \gamma(\tau_T))'$, and $\tau = t/T$, and varies from $1/T, ..., 1$.

Define the kernel weighting matrix:

$$K_\delta = \text{diag}\left\{ K_h\left(\frac{\tau_1 - \delta}{h}\right), \ldots, K_h\left(\frac{\tau_T - \delta}{h}\right)\right\},$$

where $K(\cdot)$ is the Epanechnikov kernel.

The estimation proceeds in three steps:

Step 1. For each $\delta \in [0,1]$, obtain initial estimates:

$$(\hat{\gamma}^0(\delta), \hat{F}^0) = \text{argmin}_{\gamma, F \in D_0} \sum_{i=1}^{N} (Y_i - X_i \gamma)' K_\delta M_F K_\delta (Y_i - X_i \gamma), \tag{8}$$

where $D_0 = \{F : (1/T) F'F = I_J\}$ with $J = \min(N^{1/2}, T^{1/2})$, and $M_F = I_T - FF'/T$.

Step 2. Compute the residual covariance matrix:

$$\hat{\Sigma}(\delta) = \frac{1}{N}\sum_{i=1}^{N} K_\delta(Y_i - X_i\hat{\gamma}^0(\delta))(Y_i - X_i\hat{\gamma}^0(\delta))'K_\delta. \tag{9}$$

Estimate the number of factors $\hat{r}$ using the eigenvalue ratio criterion of Ahn and Horenstein (2013).

Step 3. Given $\hat{r}$, update the estimates:

$$(\hat{\gamma}(\delta), \hat{F}) = \text{argmin}_{\gamma, F\in D_1} \sum_{i=1}^{N} (Y_i - X_i\gamma)'K_\delta M_F K_\delta (Y_i - X_i\gamma), \tag{10}$$

where $D_1 = \{F : (1/T)F'F = I_{\hat{r}}\}$.

This procedure yields the time-varying coefficients $\hat{\gamma}(\delta)$.

The TVCIFE model is estimated using the local least-squares procedure of Casas et al. (2021). At each rescaled time point, kernel-weighted observations are used to estimate the γ_t coefficient functions, while the latent factors and factor loadings are updated iteratively following the interactive fixed-effects algorithm of Bai (2009). The Epanechnikov kernel is used in the estimation.

Recent work on nonparametric panel models with time-varying coefficients provides the foundation for our empirical specification. Contributions such as Connor et al. (2012), Li et al. (2011), Li et al. (2020), Sun et al. (2009), and Casas et al. (2021) develop flexible approaches to modelling structural change in panel settings. Importantly, these frameworks remain valid under nonstationarity and cointegration—features that are central to long-run macroeconomic data—see Eberhardt and Bond (2009) and Li et al. (2020).

Under standard regularity conditions, Casas et al. (2021) establish the consistency and asymptotic normality of the estimator in the presence of nonstationarity and cointegration. Construction of 90% confidence band is based on the residual bootstrap procedure of Casas et al. (2021), which preserves both the estimated factor structure and the temporal dependence of the data. A brief details of how the bootstrap implementation are provided in Appendix A.

4 Empirical Results

4.1 Model diagnostics

Table B.2 reports the results of the cross-sectional dependence (CSD) tests of Pesaran (2015). The null hypothesis of weak cross-sectional dependence against the strong dependence alternative is rejected for TFP and the seven explanatory variables, indicating that OECD economies are subject to pervasive common shocks. The estimated factor-strength measure α of Bailey et al. (2016) is close to one for almost all variables, indicating strong cross-sectional dependence throughout the sample. Furthermore, substantial cross-sectional dependence remains in the residuals of conventional fixed-effects models, indicating that additive fixed effects alone do not adequately capture unobserved global shocks.

The results of the panel unit-root test of Pesaran (2007) in Table B.3 fail to reject the null hypothesis of nonstationarity for all variables, and the residuals of FE panel and IFE panel models with constant parameters.

Further, the constancy test of Casas et al. (2021) strongly rejects the constant-parameter specification in favour of the TVCIFE model; the t-statistic is -14.5 with 5% normal critical value of 1.96. In addition, while the conventional fixed-effects and interactive fixed-effects models fail to establish linear cointegration, the TVCIFE specifications show nonlinear cointegration. Finally, among the competing models, the TVCIFE model with two latent factors and a common trend achieves the lowest RMSE (Table B.4) and is therefore selected for empirical analysis.

4.2 Time-varying elasticities and global factors

Figure B.1 presents the estimated coefficient functions from the TVCIFE model, and we observe the following features of time-varying elasticities/coefficients.

First, the elasticity of $\ln$ RDD is positive before the First World War, becomes negative throughout much of the twentieth century, and returns to positive values after 2000. The prolonged negative phase is difficult to reconcile with standard endogenous growth models, which generally predict a non-negative contribution of domestic knowledge

capital. One possible explanation is that wars, resource reallocation, limited international openness, and weak absorptive capacity reduced the productivity gains from domestic innovation during much of the twentieth century. The recovery after 2000 coincides with greater international integration and stronger knowledge diffusion, allowing domestic innovation to contribute positively to productivity once again.

The elasticity of ln RDF has been consistently positive throughout the sample period. However, it declines steadily from approximately 0.10 at the beginning of the twentieth century to around 0.03 by 2016. This pattern suggests that international technology diffusion remained an important engine of productivity growth, but its marginal contribution of ln RDF diminished as OECD economies gradually converged towards the world technology frontier.

Second, EDU contributes positively to TFP throughout most of the sample and becomes particularly important after the Second World War, reflecting the rapid expansion of secondary and tertiary education across OECD economies. The elasticity of ln ROL is close to zero before the early 1980s but increases steadily thereafter, indicating that improvements in legal institutions and governance became increasingly important for sustaining productivity growth. These findings are broadly consistent with the institutional development literature of Acemoglu et al. (2001) and Acemoglu et al. (2005). In contrast, the estimated effect of corruption (ln CORR) gradually declines towards zero over time, suggesting that improvements in governance and regulatory quality reduced the influence of corruption on long-run productivity.

Third, the elasticity of ln GPR has been positive during the two World Wars, followed by a relatively stable level since the mid-1980s. Although surprising, this result may reflect wartime mobilisation, accelerated technological innovation, and large-scale industrial restructuring, which temporarily raised productivity despite heightened geopolitical uncertainty. By contrast, the effect of CLIMATE becomes negative after 1980, consistent with the growing evidence that rising temperatures reduce productivity. The effect remains negative throughout the later part of the sample.

Fourth, the estimated latent factors provide additional insight into the sources of productivity dynamics. The first common factor exhibits a persistent downward trend

with temporary spikes during the two World Wars. This pattern is consistent with a convergence process in which DTF_{it} of OECD economies gradually converges to the world technology frontier, while wartime disruptions temporarily widen productivity gaps. Fig A2 and Fig A3, respectively show downward trends of DTF_{it} and the plot of their cross-sectional averages and the factor.

The second common factor displays an upward trend over the sample period, interrupted only by temporary declines during periods of the two World Wars. This factor appears to capture global technological progress, adopted by the OECD countries.

5 TFP convergence

This section identifies the drivers of σ- and β-convergence of TFP in the OECD countries. σ-convergence measures productivity dispersion; β-convergence examines whether countries with lower initial productivity grow faster afterwards.

5.1 σ-convergence

To examine the σ-convergence, we consider three TVCIFE specifications:

1) Unconditional model specification: Model (4) with all determinants omitted.

2) Conditional model 1: Model (4) with $\ln$ RDF, $\ln$ ROL, and EDU and the other four determinants omitted.

3) Conditional model 2: The full model (4) with all seven determinants.

Comparing these model specifications lets us identify the determinants that reduce the cross-country productivity dispersion.

Following the convergence literature (Madsen 2007), we measure σ-convergence by the cross-sectional standard deviation of the country-specific residuals from the above three TVCIFE models at each point in time. Figure B.4 reports the resulting convergence paths.

TFP convergence is clearly evident throughout most of the sample period, although the process is far from monotonic. Cross-country productivity dispersion declines markedly

after the Second World War, during the post-war reconstruction period, and again during the decades associated with increasing international economic integration. Temporary reversals are associated with the two World Wars and the Global Financial Crisis.

Second, convergence slows noticeably after approximately 2010. The stabilisation of cross-country productivity dispersion suggests that many OECD economies have approached the technological frontier, making further convergence progressively more difficult.

A comparison of the three specifications indicates that $\ln$ RDF, EDU, and $\ln$ ROL account for most of the observed convergence. Conditioning on these three variables substantially reduces productivity dispersion relative to that of the unconditional specification. A noteworthy observation is that additional variables, $\ln$ RDD, and $\ln$ CORR, and $\ln$ GPR, and CLIMATE, collectively produce only negligible additional reductions. These findings suggest that $\ln$ RDF, EDU, and $\ln$ ROL are the drivers of long-run σ-convergence of the OECD economies' productivity.

5.2 β-convergence

The unconditional convergence model is specified as

$$\Delta \ln \text{TFP}_{it} = \alpha + \beta_{uc} \ln \text{TFP}_{it-1} + \lambda_i' f_t + u_{it}, \tag{11}$$

where $\Delta \ln \text{TFP}_{it} = \ln \text{TFP}_{it} - \ln \text{TFP}_{it-1}$. A negative coefficient β_{uc} indicates unconditional convergence.

The conditional convergence model extends (11) by including the observed determinants of productivity,

$$\Delta \ln \text{TFP}_{it} = \beta_c \ln \text{TFP}_{it-1} + X_{it}'\gamma + \lambda_i' f_t + u_{it}, \tag{12}$$

where X_{it} contains the seven explanatory variables introduced in model 4. The coefficient β_c measures conditional β-convergence after accounting for impacts of $\ln$ RDF, $\ln$ ROL, and EDU, $\ln$ RDD, and $\ln$ CORR, $\ln$ GPR, and CLIMATE, and unobserved two global factors.

Because the lagged dependent variable is endogenous, it is instrumented using a linear combination of its four lagged values.

Table B.5 reports the estimation results. Strong evidence of both unconditional and conditional β-convergence is obtained in both the pre-war and post-war periods. In every specification, the estimated convergence coefficient is negative, implying that countries with lower initial productivity experience faster subsequent productivity growth.

Conditional convergence is consistently stronger than unconditional convergence, indicating that differences in structural characteristics explain an important component of cross-country productivity differences. The mechanisms underlying convergence differ across the two periods. During the pre-war period, convergence is primarily associated with domestic innovation, geopolitical conditions, and climate. In contrast, post-war convergence is driven predominantly by $\ln$ RDF spillovers, $\ln$ ROL, and EDU. This shift closely mirrors the time-varying coefficient estimates reported in the previous section and reflects the increasing importance of technology diffusion, absorptive capacity, and institutional quality in advanced economies.

5.3 Drivers of TFP convergence

Taken together, the σ- and β-convergence results point to a consistent conclusion. International knowledge diffusion, human capital accumulation, and institutional quality explain most of the observed convergence in productivity across OECD countries.

The declining elasticity of foreign R&D spillovers documented in Section **??** is consistent with countries progressively narrowing their technological gaps with the frontier. At the same time, the increasing contributions of education and the Rule of Law indicate that, as countries approach the frontier, further productivity gains depend less on importing foreign technologies and more on strengthening domestic absorptive capacity and institutional quality.

These results support a two-margin interpretation of long-run productivity convergence. International knowledge diffusion plays the dominant role during the catch-up stage by narrowing technological gaps, whereas education and institutional quality become increasingly important as countries approach the global technology frontier and rely more heavily on domestic absorptive capacity.

6 Robustness

6.1 Sensitivity to control variables

We estimate two TVCIFE specifications for TFP: a restricted model containing only the three core variables, ln RDD, ln RDF and EDU, and the proposed unrestricted model, which adds ROL, CORR, GPR and CLIMATE. Figure B.5 superimposes the estimates from the two specifications. The elasticity of TFP with respect to RDD is positive throughout 1900–2016 in the restricted model but predominantly negative in the unrestricted model, and is therefore sensitive to the four additional controls. By contrast, the estimated coefficients on ln RDF and EDU have broadly similar signs and time paths in the two specifications.

6.2 Robustness of the models

To assess how strongly these results depend on the treatment of unobserved heterogeneity, we re-estimate the restricted and unrestricted models with constant coefficients over the pre-war (1900–1949) and post-war (1950–2016) periods. We consider two benchmarks: (i) the two-way fixed-effects (TWFE) model widely used in this literature[8] and (ii) an interactive fixed-effects (IFE) model with two factors. Table B.6 reports the estimates.

Restricted models. In the TWFE model, the coefficient on ln RDD is negative in both periods and the coefficient on ln RDF is positive in both periods, while the coefficient on EDU changes from negative before the war to positive after it. In the IFE model, the coefficients on ln RDD and ln RDF are positive in both periods, and the coefficient on EDU is negative in both.

Unrestricted models. In the TWFE model, the coefficient on ln RDD remains negative in both periods. The coefficient on ln RDF is positive before the war but negative and insignificant after it, and the coefficient on EDU again changes from negative to positive. In the IFE model, the coefficient on ln RDD is positive before the war and negative after

[8] See, for example, Madsen (2007), Isaksson et al. (2007), Madsen (2014), Fracasso and Marzetti (2015), Madsen and Murtin (2017), Acemoglu and Molina (2021) and Kremer et al. (2022).

it. The coefficient on $\ln$ RDF is positive and significant in both periods, though smaller after the war, and the coefficient on EDU changes from negative to positive.

Comparison across specifications. Adding the controls has different consequences in the two frameworks. In the TWFE model, the sign patterns of $\ln$ RDD and EDU are unchanged, and the main change is that the post-war coefficient on $\ln$ RDF becomes negative and insignificant. In the IFE model, the pre-war signs are unchanged, but the post-war coefficients on both $\ln$ RDD and EDU reverse, while the coefficient on $\ln$ RDF remains positive.

The relative stability of the TWFE estimates should not be taken as evidence that confounding is absent. The TWFE model allows common shocks to enter only through year effects with identical impacts across countries, and those year effects also absorb the component of the added controls that is common to all countries. If common shocks affect countries heterogeneously, the remaining cross-sectional dependence stays in the error term and can bias the coefficients in both TWFE specifications when it is correlated with the regressors. The IFE model accommodates such dependence through country-specific factor loadings. The differences between the two sets of estimates are therefore consistent with cross-sectional dependence that the TWFE model does not capture, although changes in the IFE estimates may also reflect the reduced identifying variation that remains once both the factors and the additional controls are included.

Finally, the constant-coefficient estimates are period averages and cannot show the gradual changes within each period that the TVCIFE model is designed to capture.

Endogeneity. RDD and RDF enter the model as stocks, and EDU serves as a proxy for the stock of human capital. Because the current-year flow is typically small relative to an accumulated stock, this specification limits the scope for contemporaneous simultaneity between the regressors and TFP. It does not rule out feedback, however: past productivity gains may raise subsequent investment in R&D and education and thus later values of the stocks, which would violate strict exogeneity. The latent factors address endogeneity arising from unobserved common shocks with heterogeneous country impacts, but not from country-specific, time-varying shocks. We therefore interpret the estimates as conditional associations rather than causal effects.

7 Conclusion

This paper connects the economic framework and the econometric model of TFP more closely than the existing literature. On the theoretical side, we broaden the set of TFP determinants and argue that their elasticities should vary over time. On the econometric side, we propose an interactive fixed-effects panel model with time-varying coefficients, estimated by a semiparametric kernel method. Using annual data for 17 OECD countries over 1900–2016, we examine the drivers of TFP growth and convergence. The framework brings domestic innovation, international knowledge diffusion, education, institutional quality, geopolitical risk, and climate change into a single empirical model.

Three main conclusions emerge. First, the determinants of productivity are inherently time-varying. Constant-coefficient specifications mask large shifts in the contributions of innovation, technology diffusion, education, institutions, and external conditions across successive phases of development. Second, the diffusion of international knowledge through foreign R&D spillovers, education, and the rule of law (institutional quality) are the dominant drivers of long-term productivity growth. Foreign R&D spillovers raise productivity throughout the sample, but their marginal contribution declines as OECD economies approach the technological frontier. In contrast, the contributions of education and the rule of law rise steadily, which underscores the growing importance of absorptive capacity and institutional quality. Third, both σ- and β-convergence analyses provide strong evidence of long-run productivity convergence. The diffusion of international knowledge, human capital and institutional quality account for most of the convergence observed across OECD economies, especially in the post-war period.

These findings carry clear policy implications. Economies below the technological frontier can realise substantial productivity gains by facilitating international technology diffusion and strengthening their capacity to absorb foreign knowledge. As they near the frontier, however, sustained growth depends increasingly on domestic capabilities, above all education, effective legal institutions, and innovation systems. Policies that pair openness to global knowledge with sustained investment in human capital and institutional quality are therefore likely to yield the largest long-run gains.

Although our analysis focuses on OECD economies, the framework applies more

broadly. A natural extension is to emerging and developing economies, where the balance between technology diffusion and domestic capability may differ markedly. Future work could also examine how digital transformation, artificial intelligence, industrial policy, and financial development shape the evolution of productivity growth and convergence.

Acknowledgments

We thank Jacob Madsen and Russell Smyth for their detailed and constructive comments, which significantly improved both the methodological framework and the empirical analysis of the paper. An earlier version of this paper was presented at the 2025 IAAE Annual Conference (Torino, 25–27 June 2025) and the 2025 International Panel Data Conference (Montpellier, 30 June–1 July 2025). We are grateful to participants at both conferences for their helpful comments and suggestions. We also thank Song Li for excellent research assistance.

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Appendix

A A bootstrap method for confidence intervals

To construct confidence intervals for the time-varying coefficient functions $\hat{\gamma}(\delta)$, we use the bootstrap procedure introduced by Casas et al. (2021):

1) Estimate $\hat{\gamma}(\delta)$ and $\hat{F}$.

2) Compute factor loadings:

$$\hat{\lambda}_i = T^{-1}\hat{F}'(K_\delta Y_i - K_\delta X_i \hat{\gamma}(\delta)),$$

and residuals:

$$\hat{U}_i = K_\delta Y_i - K_\delta X_i \hat{\gamma}(\delta) - \hat{F}\hat{\lambda}_i.$$

3) Generate bootstrap samples:

$$K_\delta Y_i^* = K_\delta X_i \hat{\gamma}(\delta) + \hat{F}\hat{\lambda}_i + \hat{U}_i \xi_i,$$

where ξ_i are i.i.d. random variables.

4) Re-estimate $\tilde{\gamma}(\delta)$:

$$\tilde{\gamma}(\delta) = \left(\sum_{i=1}^{N} X_i' K_\delta M_{\hat{F}} K_\delta X_i\right)^{-1} \sum_{i=1}^{N} X_i' K_\delta M_{\hat{F}} K_\delta Y_i^*.$$

5) Repeat M times and construct 90% confidence bands.

B Tables and Graphs

Table B.1: Descriptive statistics

	Pre-war sample				Post-war sample			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
ln TFP	-3.694	0.363	-4.633	-2.843	-2.698	0.335	-3.862	-2.151
ln RDD	9.664	1.623	6.185	13.058	10.367	1.722	6.338	14.670
ln RDF	3.187	2.640	-3.473	8.878	5.194	2.120	-0.190	10.742
EDU	6.582	1.994	1.483	11.389	9.830	2.100	3.486	15.010
CLIMATE	-0.140	0.371	-1.200	0.720	0.349	0.591	-1.020	1.970
ln ROL	-0.185	0.305	-1.625	-0.002	-0.057	0.140	-0.821	-0.001
ln CORR	-2.856	1.226	-6.215	-0.701	-3.505	1.265	-6.215	-0.707
ln GPR	-1.867	1.772	-6.397	2.558	-2.106	1.342	-5.298	1.668

Table B.2: Cross-sectional dependence test for variables and model residuals

Variable	Test Stat	p-value	Avg. Corr.	α	95% CI
ln TFP	28.076	0.000	0.362	0.98	(0.875, 1.082)
ln RDD	17.693	0.000	0.449	0.94	(0.870, 1.020)
ln RDF	15.216	0.000	0.628	1.00	(0.816, 1.187)
EDU	24.442	0.000	0.528	0.98	(0.800, 1.158)
CLIMATE	88.721	0.000	0.703	1.00	(0.947, 1.056)
ln RoL	27.497	0.000	0.506	0.74	(0.549, 0.928)
ln CORR	24.983	0.000	0.639	0.48	(0.323, 0.637)
ln GP	87.445	0.000	0.693	1.00	(0.865, 1.138)
FE residuals:					
with WWII break	19.484	0.000	0.497	1.00	(0.865, 1.134)
without WWII break	13.210	0.000	0.412	0.92	(0.893, 1.072)
Δ ln TFP:					
Pre-war period	-0.39	0.694	0.249	0.70	(5.990, 8.110)
Post-war period	-1.92	0.058	0.276	0.82	(7.111, 9.001)
Convergence model residuals:					
Pre-war period	1.29	0.198	0.234	0.67	(0.568, 0.791)
Post-war period	-1.12	0.262	0.182	0.71	(0.618, 0.822)

Notes: The cross-section dependence test developed by Pesaran (2021) is used for testing the presence of CSD in variables and model residuals, and the method proposed by Bailey et al. (2016) for estimating alpha, which measures the strength of the CSD. If alpha =1, then strong factors are needed to account for the CSD. These methods were applied, and the results are reported for: (i) all the variables included in our study; (ii) FE panel model residuals (with and without the World War II structural break); (iii) TFP growth in the pre- and post-war periods; and (iv) convergence panel model residuals.

Table B.3: Pesaran (2007) panel unit root tests in the presence of cross-sectional dependence

	Without time trend		With time trend	
Variables	t-bar	p-value	t-bar	p-value
ln TFP	-1.804	0.610	-2.252	0.721
ln RDD	-1.226	0.991	-1.411	0.998
ln RDF	-1.185	0.990	-1.231	0.995
EDU	-0.335	1.000	-1.866	0.993
Climate	-1.988	0.250	-2.320	0.189
ln ROL	-1.775	0.838	-1.682	0.991
ln CORR	-2.014	0.153	-2.159	0.841
ln GPR	-1.814	0.371	-2.560	0.160
FE panel residuals:				
without WWII break	-2.014	0.120	-2.390	0.250
with WWII break	-1.732	0.544	-2.311	0.331
	Critical values (no trend)		Critical values (trend)	
	cv10	cv5	cv10	cv5
	-2.11	-2.20	-2.63	-2.70

Notes: Pesaran (2007) panel unit root test results are reported for all variables in the presence of cross-sectional dependence. The null hypothesis is unit root nonstationarity. FE residuals are tested both with and without a World War II structural break. Critical values at the 10% and 5% levels are reported for reference.

Table B.4: Tests for linear and nonlinear cointegration

Model	t-bar	p-value	RMSE
IFE (without WWII break)	-2.019	0.140	0.095
IFE (with WWII break)	-1.199	0.090	0.084
TVC models:			
TVC FE	-1.990	0.015	0.412
TVC FE (common trend)	-2.410	0.019	0.314
TVCIFE	-2.520	0.007	0.080
TVCIFE (common trend)	-2.800	0.000	0.073

Notes: The null hypothesis of no cointegration is tested against a linear panel cointegration alternative using the IFE model without structural breaks. Nonlinear cointegration is examined using models that allow for a World War II break, time-varying coefficients (TVC), and latent factors. The preferred specification is selected based on the RMSE criterion.

Table B.5: Estimates of the β-convergence model

	Pre-war period		Post-war period	
	Estimate	S.E.	Estimate	S.E.
Panel A: Unconditional model				
Lagged ln TFP	-0.008*	0.001	-0.023	0.005
Constant	-0.015*	0.004	-0.092*	0.001
Panel B: Conditional model				
Lagged ln TFP	-0.012*	0.001	-0.030*	0.002
ln RDD	-0.043*	0.012	-0.040	0.034
ln RDF	-0.024	0.021	-0.023*	0.011
EDU	0.041	0.050	-0.034*	0.013
CLIMATE	-0.040*	0.014	-0.016	0.012
ln ROL	0.023	0.032	-0.034*	0.014
ln CORR	-0.041*	0.003	-0.030	0.041
ln GPR	0.034*	0.012	0.011	0.023
Constant	-0.025	0.090	-0.059	0.041

Notes: The dependent variable is TFP growth, which is defined as the change in ln TFP. Estimates and standard errors in the conditional model are scaled by a factor of 10, except for the coefficient on lagged ln TFP. $*$ indicates significance at least at the 5% level.

Table B.6: Estimates of restricted and unrestricted TFP models: Two-way fixed effect and IFE models with constant parameters

Panel A: Two-way fixed effects model

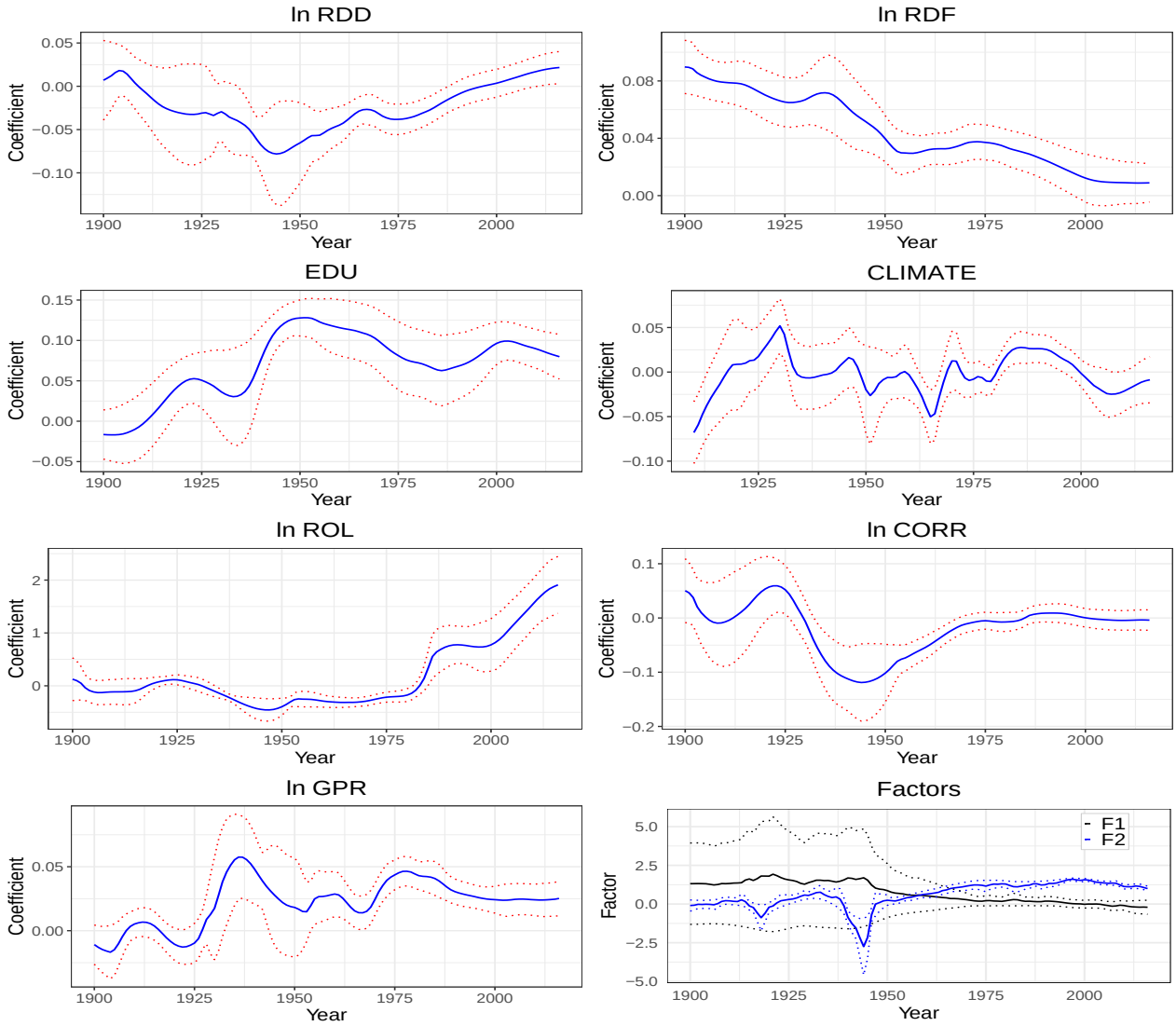
	Restricted model				Full model			
	Pre-war		Post-war		Pre-war		Post-war	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
ln RDD	-0.018	0.020	-0.052*	0.007	-0.017	0.019	-0.041*	0.007
ln RDF	0.023*	0.009	0.014*	0.006	0.031*	0.009	-0.007	0.008
EDU	-0.021	0.012	0.025*	0.005	-0.032*	0.012	0.023*	0.005
CLIMATE					0.084*	0.023	-0.009	0.011
ln RoL					0.023	0.033	0.183*	0.053
ln CORR					0.088*	0.023	0.019	0.012
ln GPR					-0.005	0.009	0.037*	0.007

Panel B: Interactive fixed effects model (two factors)

	Restricted model				Full model			
	Pre-war		Post-war		Pre-war		Post-war	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
ln RDD	0.127*	0.011	0.014*	0.001	0.096*	0.006	-0.020*	0.001
ln RDF	0.114*	0.005	0.041*	0.004	0.118*	0.004	0.002*	0.001
EDU	-0.135*	0.007	-0.063*	0.001	-0.094*	0.007	0.142*	0.005
CLIMATE					0.123*	0.007	-0.057*	0.002
ln RoL					-0.046*	0.010	0.261*	0.018
ln CORR					0.036*	0.010	-0.013*	0.002
ln GPR					-0.023*	0.005	0.014*	0.001a

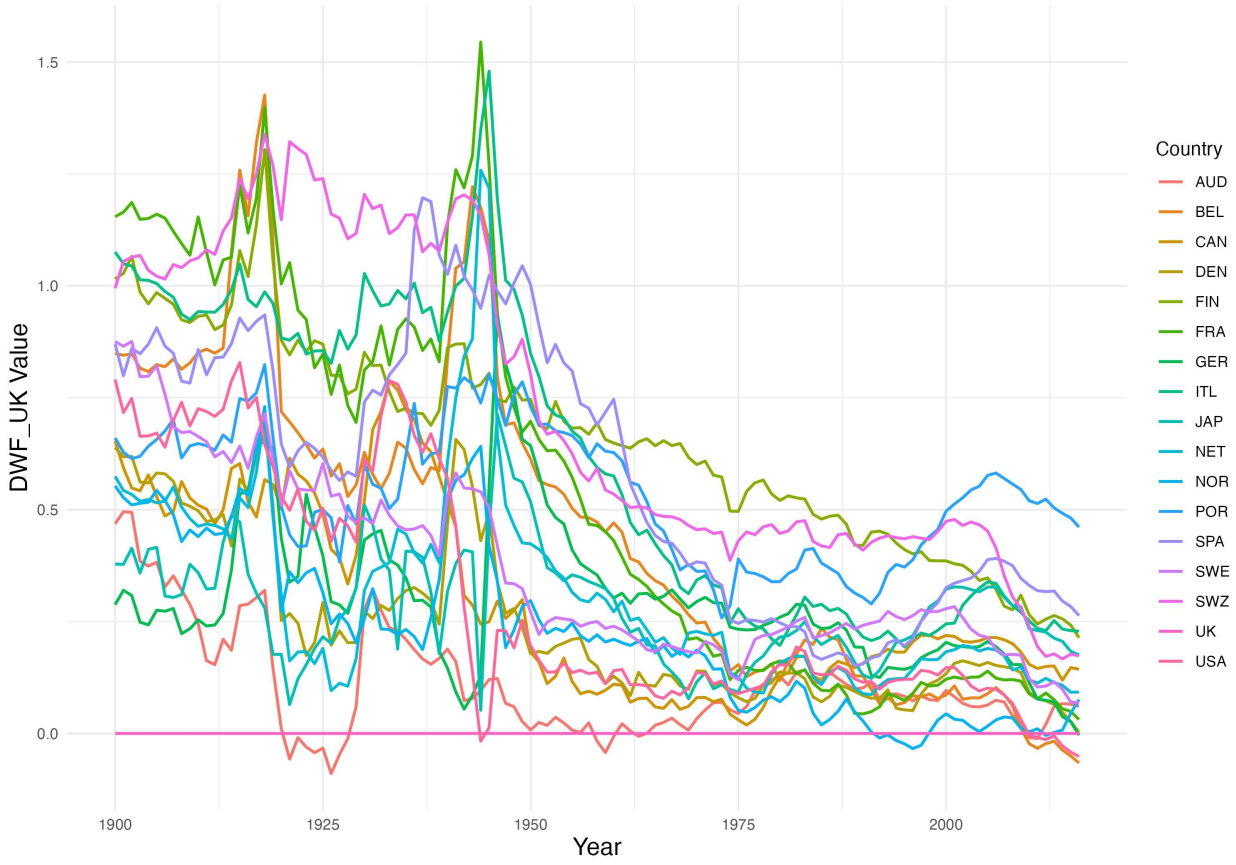
Notes: The restricted model includes ln RDD, ln RDF, and EDU only, while the full model includes all seven covariates. Standard errors marked with "a" are scaled by a factor of 10. $*$ indicates significance at least at the 5% level.

Figure B.1: Visualization of estimates of TVCIFE coefficient functions and factors



Notes: The plots represent TVC functions of time, estimated by a kernel method, and the estimates of two factors.

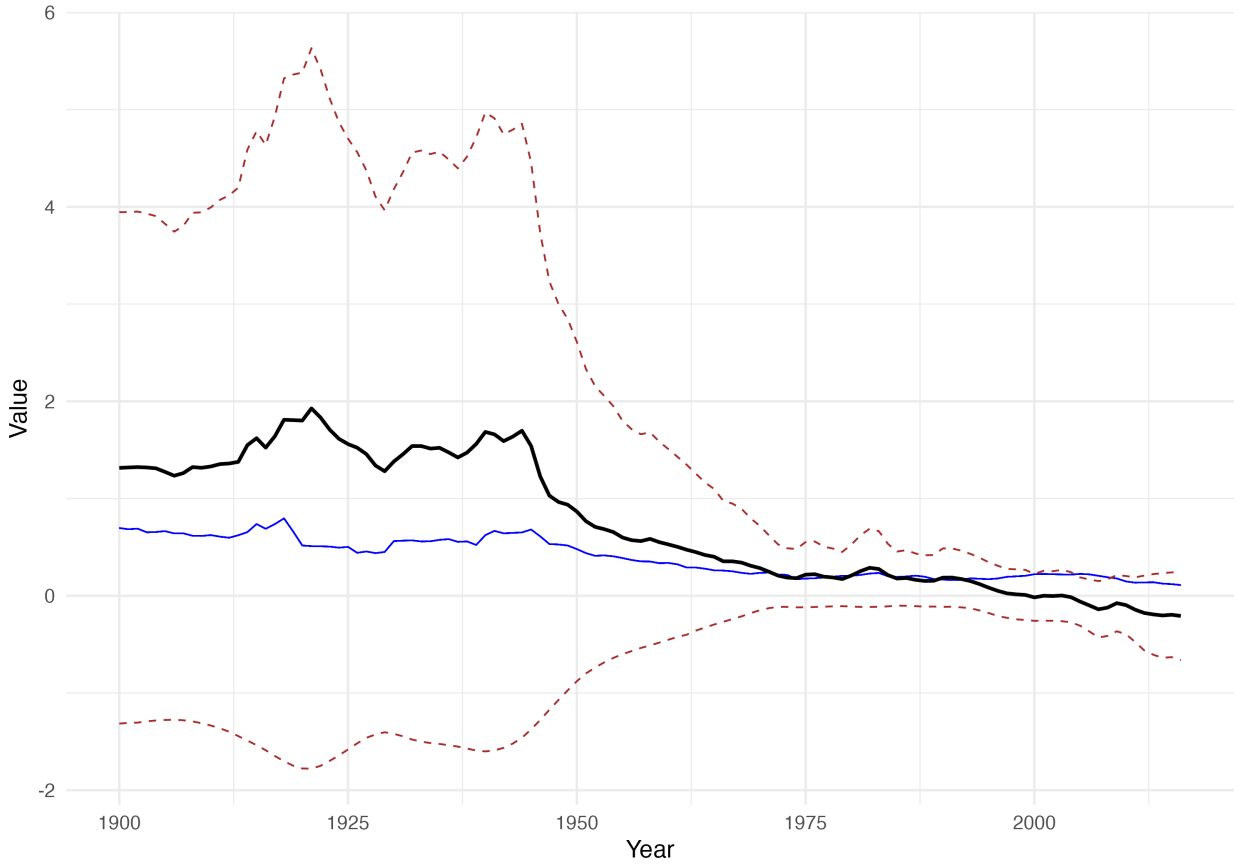
Figure B.2: Country-specific distances to the frontier DTF_{UK}



Notes: The United Kingdom (UK) is the world frontier in this sample.

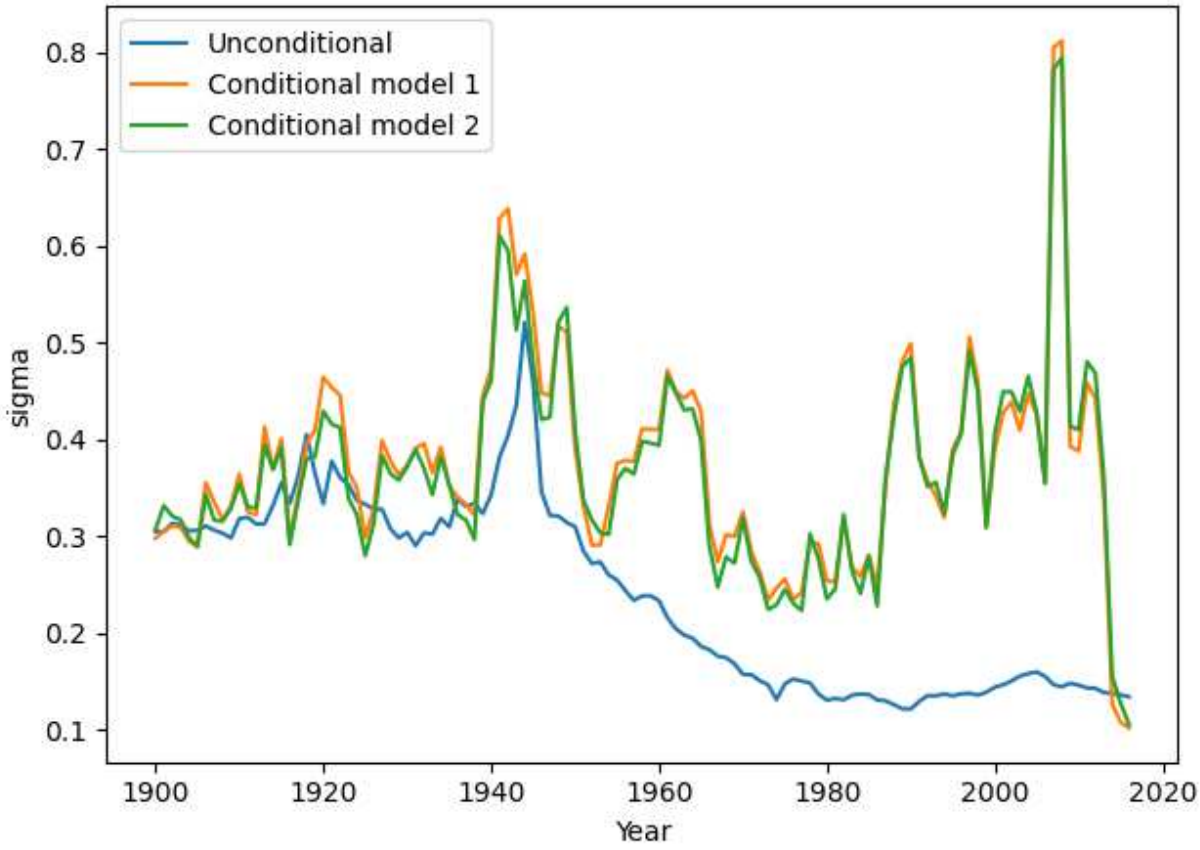
.

Figure B.3: Estimate of factor 1 with 90% confidence intervals and cross-sectional average of country-specific distances to the frontier



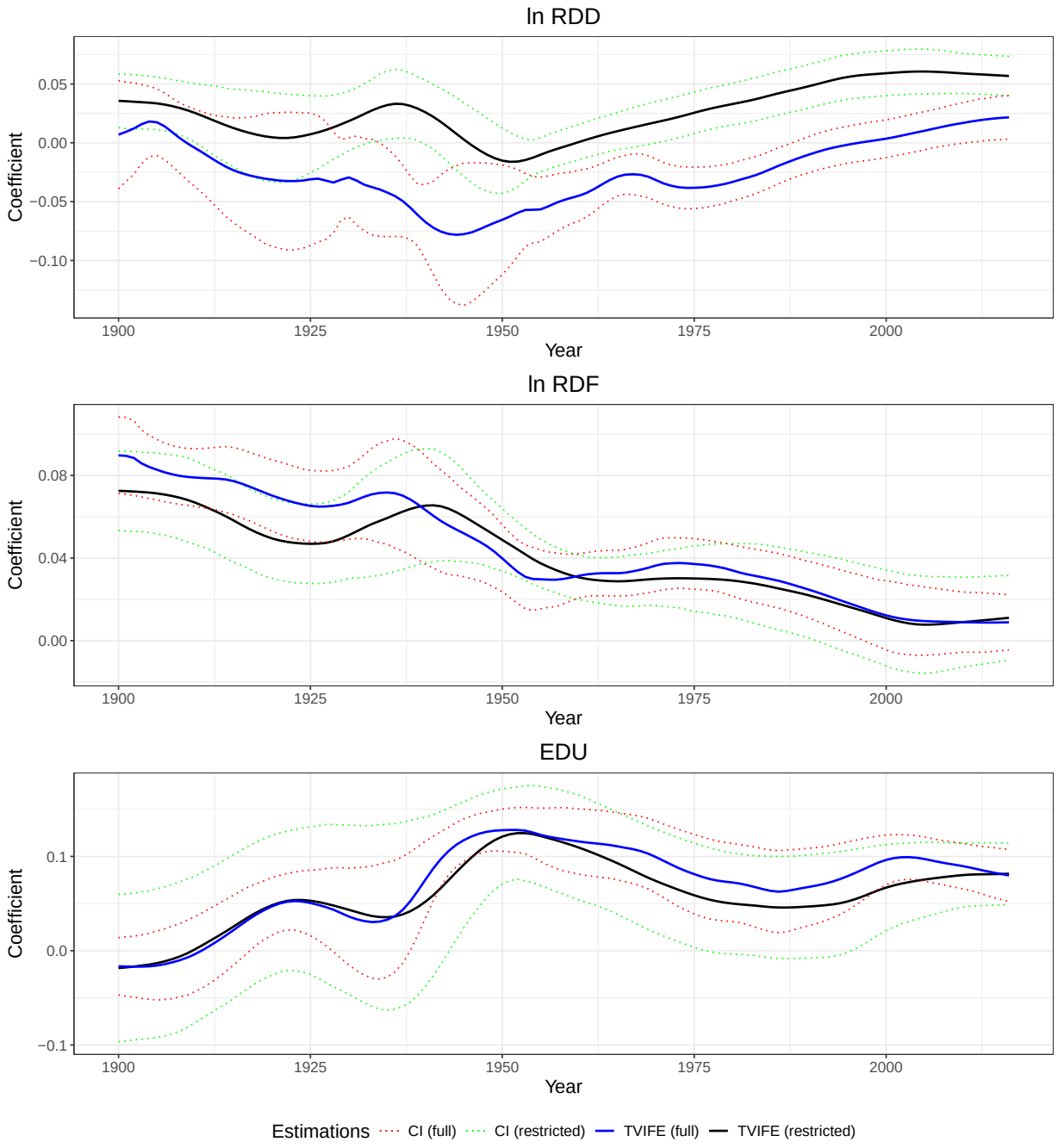
Notes: The black line shows the estimated first common factor. The blue line shows the cross-sectional average of distance to the frontier (DTF_UK) of 16 OECD countries (Figure B.2).

Figure B.4: Sigma convergence plots



Notes: (i) Unconditional convergence TVCIFE model of TFP growth includes only a constant and two factors; (ii) the conditional convergence TVCIFE model 1 includes ln RFD, EDU, and ln RoL, as control variables; and (iii) the conditional convergence TVCIFE model 2 includes all seven variables as control variables.

Figure B.5: TVCIFE coefficient functions of restricted and unrestricted ln TFP Models



Notes: The black lines show the TVCIFE estimates of the three key variables ln RDD, ln RFD, and EDU, obtained from the restricted specification, which includes only these three variables. The blue lines, together with the red confidence bands, show the corresponding estimates from the unrestricted specification, which includes all seven control variables.