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Does an aging capital stock adversely affect productivity?*

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Abstract

The capital stock in Germany and other advanced economies has been aging persistently since 1970s, raising concerns about its implications for productivity, economic growth, and resilience. This study investigates the relationship between capital stock modernity and productivity dynamics using a panel dataset covering 24 European countries between 1997 and 2020. We employ a panel local projections model with split-panel jackknife corrections to address the Nickell-type bias inherent in dynamic panel models with fixed effects. Our analysis controls for human capital, research and development, trade openness, institutional quality, and financial development. The results show that improvements in capital stock modernity exert a positive and statistically significant effect on both total factor productivity (TFP) and labor productivity, although the timing of these effects varies across measures. Specifically, labor productivity growth responds immediately to capital modernization, whereas potential TFP growth increases only from the second year following the shock.

Keywords: total factor productivity; labor productivity; capital stock; modernity grade.

JEL codes: C23, E22, O47.

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1. Introduction

The capital stock in Germany and other advanced economies is increasingly aging. This trend poses significant challenges not just to productivity but also to economic growth and resilience. Given that new capital increments are based on more recent investment activities, up-to-date technology is incorporated. In contrast, older capital becomes obsolete, the further it is away from the technological frontier, and its efficiency diminishes. At the same time, the risk of (sudden and) complete failure increases dramatically; for example, when a run-down bridge suddenly collapses or capital goods used in production processes break down, potentially causing environmental damages or even public safety hazards. Moreover, older capital goods — such as cars and houses — typically conform to less stringent energy consumption and CO₂ emission standards than current regulations require, rendering them both less efficient and more environmentally damaging. Overall, a substantial share of infrastructure assets is old and approaching the end of its operational lifetime.¹ Countries have been resting on their capital asset laurels and are generally neglecting the investments necessary to just maintain their respective capital stock, never mind investing in its modernization.

Capital stock and productivity — measured as total factor productivity — are fundamental drivers of long-run growth and national prosperity. Thus, against the backdrop of an aging capital stock, it is unsurprising that potential GDP estimates have been repeatedly revised downward. Current estimates of potential GDP for Germany, for example, indicate that long-run growth will approach zero in the near future (Projektgruppe Gemeinschaftsdiagnose, 2026, p. 59). While the labor component is often pointed to as the main culprit, already contributing negatively to overall potential GDP growth, the (yet positive) contributions of capital and TFP are declining as well. While worrisome, this also presents countries with a choice. The capital stock and TFP both can be more readily affected than the labor component: Investment in physical capital increases and modernizes the capital stock, while investments in research and development, human capital, as well as more efficient markets, institutions, and governments

¹See, among others, IEA (2023) for the age of the electricity grids or the European Unions' Europe's Rail for railway networks, tunnels and bridges (<https://rail-research.europa.eu/latest-news/extending-the-life-and-capacity-of-europes-ageing-tunnels-and-bridges/>). According to the authors' estimates, the median age of German housing stock increased from 28 years in 1972 to 54 years in 2022.

can increase productivity.

The capital stock and TFP are not distinct components; rather these overlap to a certain extent. The capital embodiment hypothesis postulates that technological progress and productivity growth are embodied in the improvement of physical capital. Thus, new investments are closer to the current technological frontier and are more productive than older capital. Consequently, even just replacing parts without adding to the physical capital stock will result in additional productive capacity. Conversely, the book value of physical capital stock, i.e., the gross capital stock, may be unchanged. However, if capital ages and deteriorates, the effective net capital stock shrinks and, thus, the production capacity of an economy declines.

In this study, we examine how the age of the capital stock evolved in different European countries. We capture the evolution of the modernity of the capital stock in a single metric and then empirically investigate the relationship between the modernity of the capital stock and respective productivity dynamics. To this end, we employ a longitudinal data set covering 24 countries (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Slovenia, and Slovakia) between 1997 and 2020 as compiled from the databases of Destatis, Eurostat, and the OECD. We estimate panel local projections models with two-way fixed effects. To isolate the causal effect of changes in the modernity of the capital stock, we control for a wide set of productivity determinants. We find that changes in modernity rate of capital stock exert statistically significant positive effects on the growth rate of total factor productivity and labor productivity, thus, confirming the embodiment hypothesis. The timing of the impact is different, with labor productivity reacting immediately and potential TFP experiencing the impact two years after the shock to modernity growth. The results remain robust to excluding individual countries from the data set.

The paper proceeds as follows. Section 2 presents the state of empirical literature on the age of capital stock alongside its implications for productivity and the main determinants of aggregate productivity. Section 3 describes the data and econometric methodology. Section 4 presents the estimation results. Section 5 concludes.

2. Literature review

2.1. Embodiment hypothesis

Our analysis draws on two main bodies of literature. The first involves the empirical testing of the embodiment hypothesis. The embodiment hypothesis (also known as the vintage capital growth model) posits that technological progress is primarily “embodied” in new and, thus more productive, capital goods (machinery, equipment, and infrastructure) (Solow, 1962); i.e., technological progress is “capital-augmenting.” As a result, productivity gains occur only when new investment takes place — not through the mere passage of time. Older vintages of capital become obsolete; thus, economic growth and productivity improvement are driven by replacing them with newer, more efficient equipment on the current technological frontier.

However, while theoretically appealing, empirical testing of the embodiment hypothesis has so far produced mixed results. Existing papers testing embodiment using aggregate time-series data do not find support for the hypothesis (Wickens, 1970; You, 1976). McHugh and Lane (1983) argue that the effects of embodiment may be washed out in the aggregate capital stock while stressing the importance of examining cross-sectional data to detect effects. Based on a standard Cobb-Douglas production function they derive a relation between labor productivity and the average age of capital, which, given the theory outlined above, should be negative. Estimating their specification using capital stocks by U.S. Census regions for the period 1960 to 1972, however, they find positive coefficients of the age of capital, thus failing to find support for embodiment.

A crucial aspect in the literature has been the correct specification of the capital stock used. In a follow-up analysis, McHugh and Lane (1987), arguing that the age of the capital stock has been mismeasured, propose that the age of utilized capital should be used rather than just the age of the capital, because in a cyclical downturn the oldest — and by assumption — least productive capital would be idled first. Adjusting for cyclical deviations between measured and potential output utilizing 2-digit U.S. manufacturing industries they indeed find a negative impact of the age of capital on productivity and, therefore, support for the embodiment hypothesis.

Another important issue for empirical analyses is raised by Hulten (1975), pointing out potential reverse causality in estimating the effects of embodiment, because productivity growth

in turn affects the rate of investment and thus changes in the capital stock.

Since then, several papers (for example, [Cole et al. 1986](#); [Gordon 1990](#)) found quality changes in different durable-equipment goods to be an important component of their prices, suggesting that embodied technological change indeed plays a role.

Based on these findings, while analyzing U.S. manufacturing industries in a framework that allows for both disembodied and embodied technological change, [Hulten \(1992\)](#) finds that embodied technological change accounts for as much as 20% of TFP growth in the 1949–1983 period. While he finds empirical evidence for the newest capital vintage to be more efficient than the average capital used in production, he notes that the effects of increased capital formation through higher investment are quite small, as a one percentage points increase in durable equipment investment raises real output growth by only 0.127 percentage points.

Empirical evidence supporting the embodiment hypothesis is also found by [Wolff \(1991\)](#), who investigates the role capital formation plays in the convergence of productivity across G7 countries between 1870 and 1979. He finds support for interaction effects between technological progress and capital formation, all with a significant vintage effect, i.e., that new capital is more productive than older capital, implying a role for embodied technological progress. [Wolff \(1996\)](#) confirms the importance of the vintage effect for the decline in productivity growth in several OECD countries between 1950 and 1989. By contrast, [Whelan \(2007\)](#), empirically examining the embodiment hypothesis using industry-level data for the U.S., finds evidence for a positive effect of the age of the capital stock on TFP growth, thus rejecting embodiment. He points out, however, that his result may be due to the fact that if improvements in capital quality are mismeasured (i.e., embodiment), then so are the depreciation rates of the capital stock, ultimately concluding that the latter effect is more important. [Whelan \(2007\)](#) also stresses the importance of using industry-level data to analyze the effects of embodiment, as the simultaneity in aggregate data prohibits causal interpretations.

A more recent paper by [Belitz and Gornig \(2023\)](#) finds that a higher degree of digitalization leads to a more modern capital stock.

Overall, the embodiment hypothesis has been studied both theoretically and empirically for

a long time.² While broadly in support of the embodiment hypothesis, several constraining factors have been identified and the exact results differ. Importantly, most of the empirical work has focused on the U.S. and is of “vintage age” itself. However, high-quality and consistent granular data are now available for many countries, allowing for an up-to-date assessment of the questions at hand. In addition, econometric methods and sophistication has also improved dramatically.

2.2. Determinants of productivity

The second strand of literature we relate to examines the determinants of (aggregate) labor productivity and TFP in general. Given that the growth of productivity plays a central role in explaining long-run growth and the prosperity of countries, it has been at the center of macroeconomic research from the very beginning. An excellent and comprehensive overview (Kim and Loayza, 2019) examines the determinants of productivity and identifies five major categories.

The first is innovation, defined as the possibilities to generate (fundamentally) new technologies or adopt existing ones to improve production capabilities, technology, and effectiveness. This aspect is usually measured by public and private expenditures on research and development, the number of new patents applications, or the number of scientific and technological journal publications.

The second category includes education and human capital, capturing how new technologies and knowledge diffuse across the economy and are employed by workers. This aspect is critical to bridge the gap between the creation of new technology and its efficient use and implementation in the production process. At the same time, the education of the workforce lays the foundation for more efficient research and development in the future. Typical indicators for this category are the average number of schooling years of the workforce, completion rates of secondary and tertiary education, as well as government expenditure on education.

The third determinant concerns the efficiency of input, output, labor, and financial markets

²Several literature reviews have looked at the role of the embodiment hypothesis for the analysis of productivity growth in both theoretical models of vintage capital as well as empirical analyses trying to quantify the effects of embodiment. See, for example, Intriligator (1992) and Boucekkin et al. (2011) for the references cited therein for additional work not cited above.

in enabling the flexible and effective allocation of resources across firms and sectors. Not only well-functioning markets allow young, productive firms to expand and unproductive firms to exit, but also, more generally, they ensure that resources are deployed to their highest-value uses. A number of indices have been developed to capture this multidimensional aspect, including the World Bank’s Doing Business Index and the IMF’s Financial Development Index.

The fourth determinant is infrastructure, particularly public infrastructure, which facilitates market access and connectivity among economic agents. This encompasses both the quality and quantity of the public capital stock — including roads, bridges, and railway networks — that underpins not just physical economic activity, but also digital infrastructure, whose importance has grown considerably with time.

The fifth, and last, category, institutions, covers the quality of governments, its regulatory framework, bureaucracy, and the rule of law. The World Bank publishes indices trying to capture this category with its many different dimensions in its Worldwide Governance Indicators.

A similar literature review on the determinants of productivity was also done by the OECD and the Asian Productivity Organization ([OECD/Asian Productivity Organization, 2022](#)). In addition to the determinants identified by [Kim and Loayza \(2019\)](#), they also stress the importance of digitalization and investment in intangible assets as a major driver of productivity, highlighting the complementarity of both aspects with especially human capital. Moreover, they also explicitly list globalization as a determinant, because it facilitates technology spillovers across countries and improves access to international markets. A typical measure capturing this aspect is a country’s openness to trade.

We include these categories of determinants as control variables in our empirical analysis in section [3.1](#) to trace out the effects of the modernity of the capital stock.

3. Empirical approach

3.1. Econometric methodology

Macroeconomic panel data often pose challenges for dynamic causal inference due to fixed effects, heterogeneous treatment responses, and cross-sectional dependence. Standard vector autoregressions (VARs) require correct specification of the lag order and impose common dynamics across units. As an alternative, [Jordà \(2005\)](#) introduced local projections, a flexible,

robust method for estimating impulse response functions (IRFs). Here, we consider local projections model in panel data context.

Let $i = 1, \dots, N$ index cross-sectional units (e.g., countries) and $t = 1, \dots, T$ index time periods. Define $y_{i,t}$ as the outcome variable of interest and $\mathbf{X}_{i,t}$ as a vector of control variables. The panel local projection for horizon $h = 0, 1, \dots, H$ is given by:

$$y_{i,t+h} = \alpha_i^{(h)} + \beta^{(h)} s_{i,t} + \gamma^{(h)'} \mathbf{z}_{i,t} + \varepsilon_{i,t+h}^{(h)} \quad (1)$$

where $\alpha_i^{(h)}$ are country-specific fixed effects that absorb time-invariant unobserved heterogeneity; $\beta^{(h)}$ is the cumulative impulse response at horizon h ; $\mathbf{z}_{i,t}$ is a vector of control variables (typically lags of $y_{i,t}$, $s_{i,t}$, and $\mathbf{X}_{i,t}$) to account for persistence and feedback effects; $\varepsilon_{i,t+h}^{(h)}$ is the error term, which may be autocorrelated across h for a given i and t .

For each horizon h , equation (1) is estimated separately using ordinary least squares with appropriate standard errors (e.g., Driscoll-Kraay, cluster-robust at the unit level, or two-way clustering).

To control for the dynamic structure of the data, $\mathbf{z}_{i,t}$ typically includes p lags of the outcome and the shock:

$$\mathbf{z}_{i,t} = (y_{i,t-1}, \dots, y_{i,t-p}, s_{i,t-1}, \dots, s_{i,t-p}, \mathbf{X}_{i,t-1}, \dots, \mathbf{X}_{i,t-p})'. \quad (2)$$

The shock series, $s_{i,t}$, is derived from a structural vector autoregression model estimated on the set of variables contained in $\mathbf{X}_{i,t}$. To identify the structural shock, the change in the modernity rate is ordered first in the Cholesky decomposition, thereby assuming it contemporaneously affects all other variables in the system but is not itself contemporaneously affected by them. The resulting structural innovation corresponding to the modernity rate is then extracted and used as the exogenous shock s_{it} in the local projections.

To address persistence in the data without resorting to differencing, we adopt the lag-augmented local projection approach. Including additional lags of the control variables purges the persistent, low-frequency components from the shock, isolating the “innovative” variation that identifies the impulse response. This innovation-like variation is well-behaved for standard inference, even when the original data are highly persistent or contain unit roots.

Theoretically, [Montiel Olea and Plagborg-Møller \(2021\)](#) prove that lag-augmented local projections with normal critical values are asymptotically valid uniformly over both stationary and non-stationary data. Consequently, standard normal inference is reliable without requiring knowledge of the degree of persistence.

In order to quantify the dynamic impact of the variables in question, one can use empirical impulse response functions. The sequence of coefficients $\{\beta^{(h)}\}_{h=0}^H$ directly forms the impulse response function. Specifically:

- $\beta^{(0)}$ gives the immediate (impact) effect of a one-unit shock to $s_{i,t}$ on $y_{i,t}$.
- $\beta^{(1)}$ gives the cumulative effect after one period, and so on.

Confidence intervals (e.g., 95%) are obtained from the standard errors of $\hat{\beta}^{(h)}$, typically assuming asymptotic normality. Alternatively, one may use bootstrap methods (e.g., clustered wild bootstrap) to account for cross-sectional dependence and small-sample bias.

A well-documented econometric issue in panel local projections is the presence of a Nickell-type bias in the standard fixed effects (FE) estimator ([Mei et al., 2026](#)). This bias persists even in the absence of a lagged dependent variable in the specification. In the context of our model, the bias arises because the local projection residual constitutes a forecast error that is inherently correlated with the fixed-effects transformation of the shock variable — in our case, the modernity grade.

The practical implications of this bias for our analysis are threefold. First, the FE estimator exhibits attenuation bias, tending to shrink coefficient estimates toward zero, thereby understating the true magnitude of the relationship between the modernity grade and productivity growth. Second, and more critically for our research design, the bias is not constant across horizons; it increases monotonically with the forecast horizon h . This feature is particularly consequential for our investigation of the medium-term effects of the modernity grade. Third, the bias contaminates inference: standard errors and confidence intervals computed from the FE estimator are unreliable, producing under-covered confidence intervals and potentially leading to erroneous conclusions regarding statistical significance.

To address these concerns, we adopt the split-panel jackknife (SPJ) estimator developed by [Mei et al. \(2026\)](#). The SPJ estimator offers a computationally straightforward correction that

eliminates the first-order bias without requiring the researcher to specify the complete dynamic data-generating process.

The implementation proceeds in three steps. First, we estimate the panel local projection using the FE estimator on the full sample, yielding the coefficient vector $\widehat{\beta}_{\text{FE}}^{(h)}$ for each horizon h . Second, we partition the panel dataset into two equal halves along the time dimension and re-estimate the model using FE on each subsample separately, obtaining $\widehat{\beta}_a^{(h)}$ and $\widehat{\beta}_b^{(h)}$. Third, we compute the SPJ estimator as:

$$\widehat{\beta}_{\text{SPJ}}^{(h)} = 2\widehat{\beta}_{\text{FE}}^{(h)} - \frac{1}{2} \left(\widehat{\beta}_a^{(h)} + \widehat{\beta}_b^{(h)} \right) \quad (3)$$

The intuition underlying this correction is as follows. The bias of the FE estimator is of order $O(T^{-1})$, where T denotes the number of time periods. By splitting the sample, the bias in each subsample is approximately twice as large as that in the full sample (since $T/2$ periods yield a bias of order $O((T/2)^{-1}) = O(2T^{-1})$). The linear combination in equation (3) cancels the leading $O(T^{-1})$ bias term, yielding an estimator that is asymptotically unbiased and exhibits substantially reduced finite-sample bias (Mei et al., 2026).

We construct confidence intervals for the SPJ estimator using the delta method. The SPJ estimator is a linear combination of the full-sample and split-sample fixed effects estimates:

$$\widehat{\beta}_{\text{SPJ}}^{(h)} = 2\widehat{\beta}_{\text{FE}}^{(h)} - \frac{1}{2} \left(\widehat{\beta}_a^{(h)} + \widehat{\beta}_b^{(h)} \right) \quad (4)$$

Assuming independence between the subsample estimates, the delta method yields the following variance approximation:

$$\widehat{V} \left(\widehat{\beta}_{\text{SPJ}}^{(h)} \right) = 4 \widehat{V} \left(\widehat{\beta}_{\text{FE}}^{(h)} \right) + \frac{1}{4} \widehat{V} \left(\widehat{\beta}_a^{(h)} \right) + \frac{1}{4} \widehat{V} \left(\widehat{\beta}_b^{(h)} \right) \quad (5)$$

The $100(1 - \alpha)\%$ confidence interval is then:

$$\widehat{\beta}_{\text{SPJ}}^{(h)} \pm z_{\alpha/2} \times \sqrt{\widehat{V} \left(\widehat{\beta}_{\text{SPJ}}^{(h)} \right)} \quad (6)$$

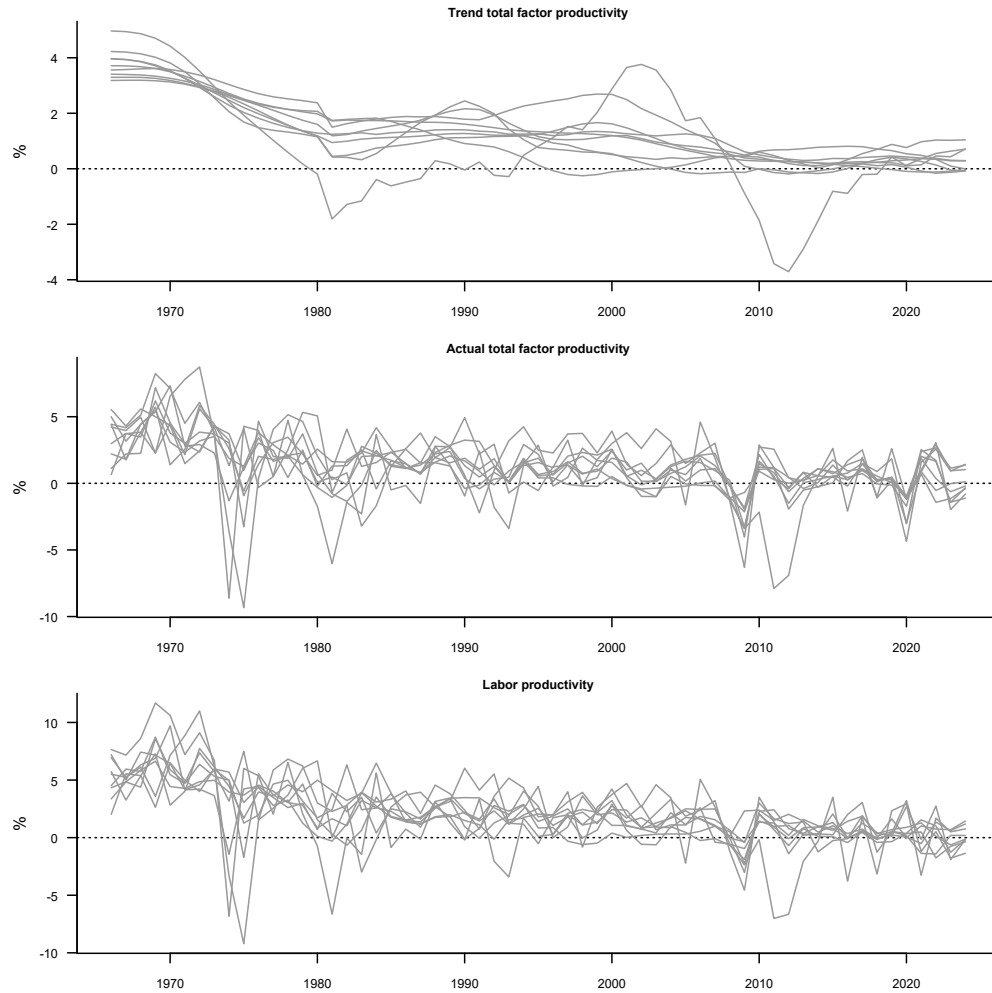
where $z_{\alpha/2}$ is the standard normal critical value. This approach is computationally efficient and yields conservative intervals when the independence assumption is violated, as the ignored

covariance terms are negative (Mei et al., 2026).

3.2. Data

Dependent variables. In this analysis, we rely on three productivity metrics: trend total factor productivity, actual total factor productivity, and labor productivity. Figure 1 reports the annual growth rates for each of these series.

Figure 1: Long-term dynamics of alternative productivity measures



Source: EU Commission and own construction.

Note: Each gray line corresponds to a country.

All three indicators are downward sloped. Notably, trend total factor productivity demonstrates considerably smoother dynamics than the other two series, whereas actual total factor productivity and labor productivity display very similar fluctuations. However, the volatility of labor productivity is higher, especially at the beginning of the sample.

Degree of capital stock modernity. To compute the degree of modernity of the capital stock, we rely on the data on the gross and net capital stock. These data are drawn from three sources.

First, Eurostat provides detailed information on both gross and net capital stock, disaggregated by asset type (including buildings, machinery and equipment, computer software and hardware, among others) and by NACE economic activity (such as mining and quarrying, manufacturing, construction, and wholesale and retail trade). The dataset covers 31 countries — comprising the 27 EU member states, along with Iceland, Montenegro, Norway, and the United Kingdom — over the period from 1975 to 2024.

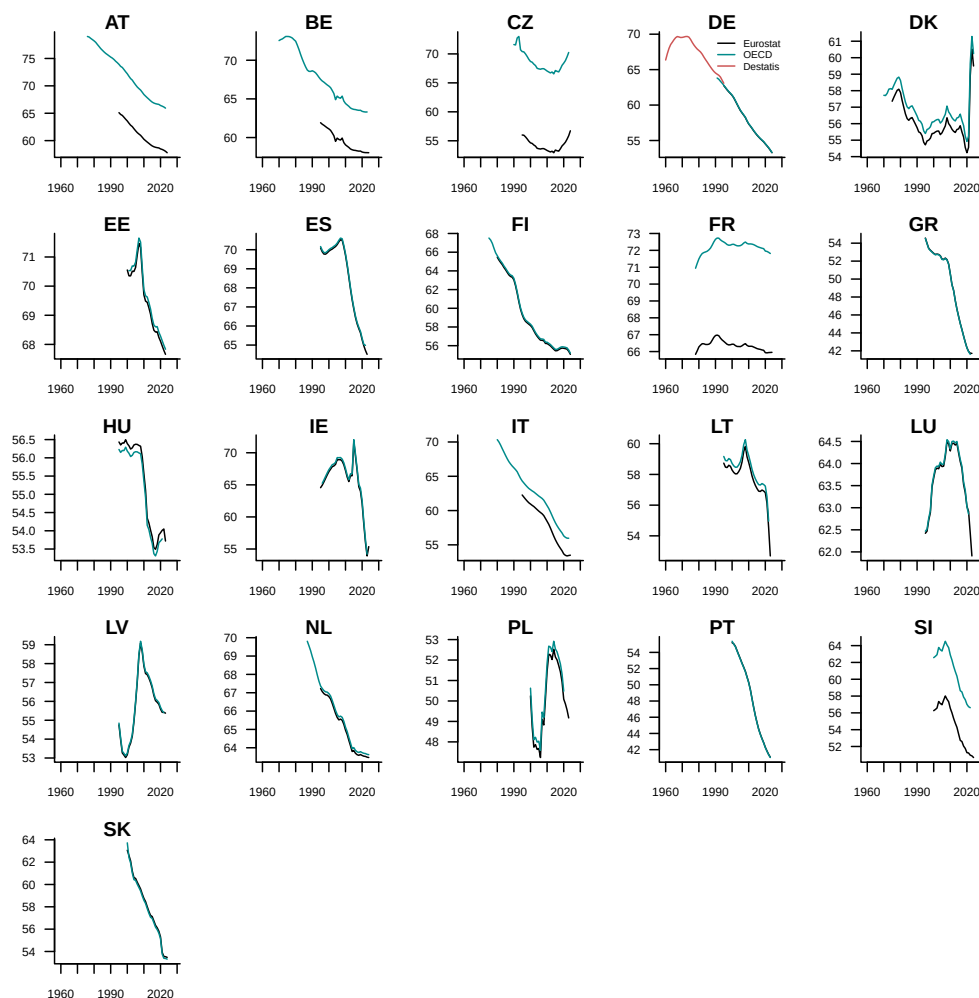
Second, the OECD provides data on both gross and net capital stock for 25 countries: Austria, Belgium, Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Slovenia, the Slovak Republic, South Korea, Spain, and the United Kingdom. For Australia, Iceland, Japan, and the United States, however, only net capital stock figures are available.

Third, the German Statistical Office (Destatis) offers detailed capital stock data for Germany. In this study, we utilize a dataset that includes gross and net capital stock figures from 1960 to 1995, disaggregated by asset type (total, buildings, and equipment) and by economic activity.

The degree of capital modernity is calculated as the ratio of net capital stock to total capital stock. Figure 2 displays the resulting estimates derived from Eurostat, OECD, and Destatis data. This measure is computed using chained linked volume estimates of capital stock, rather than those based on current replacement costs.

For most countries, the time series derived from alternative sources are quite similar. However, for Austria, Belgium, the Czech Republic, Denmark, France, Italy, and Slovenia, the Eurostat- and OECD-based indicators exhibit a parallel shift, with OECD values consistently exceeding Eurostat levels by 2 to 18 percentage points. In these instances, we rescale the OECD series to align with the Eurostat benchmarks. In addition, for Austria, Belgium, Finland, Germany, Italy, and the Netherlands, both the OECD and Destatis series start earlier than those of Eurostat. The final combined estimates are obtained by taking the median across all alternative

Figure 2: Alternative estimates of total capital stock modernity



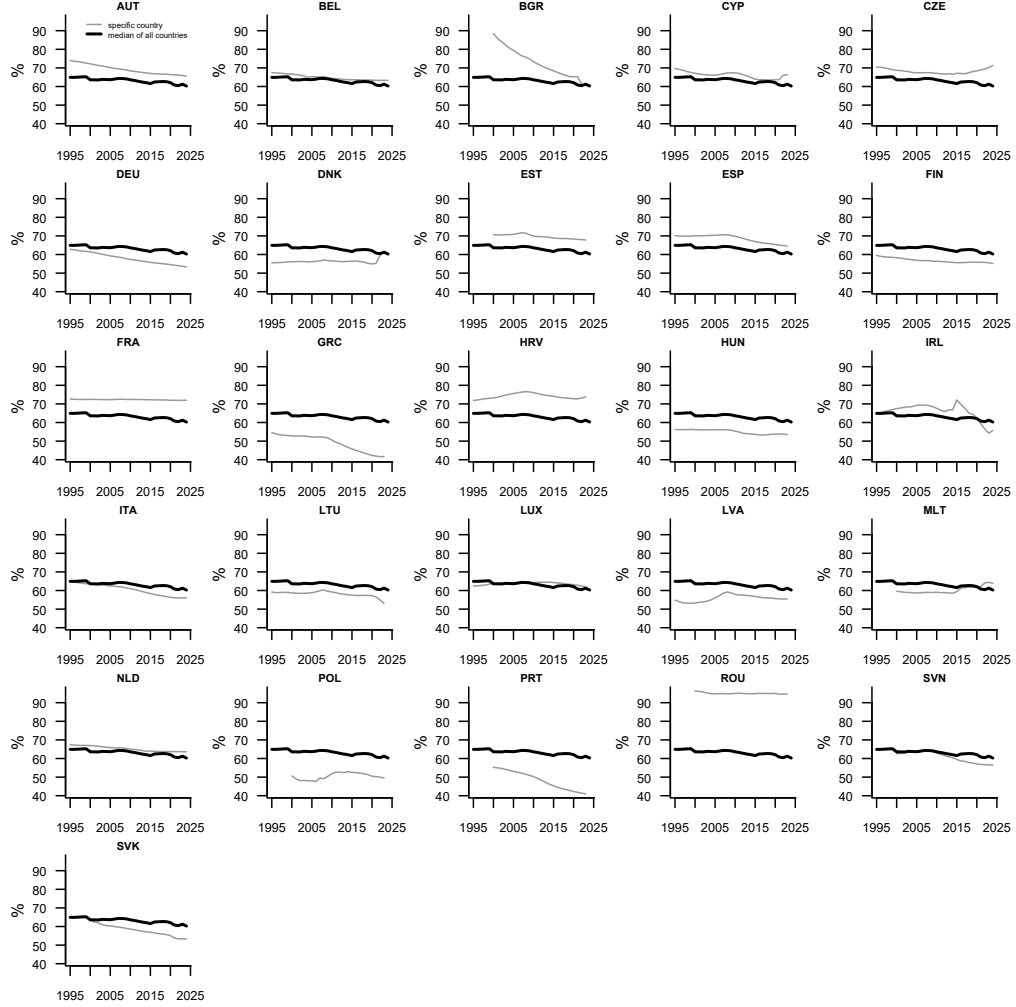
Source: Destatis, Eurostat, OECD, and own construction.

Note: Data from Eurostat are shown in black, those from the OECD in green, and those from Destatis in red.

modernity measures.

Figure 3 shows the evolution of the modernity of different types of capital stock between 1995 and 2024.

Figure 3: Total capital stock modernity by countries



Source: Destatis, Eurostat, OECD, and own construction.

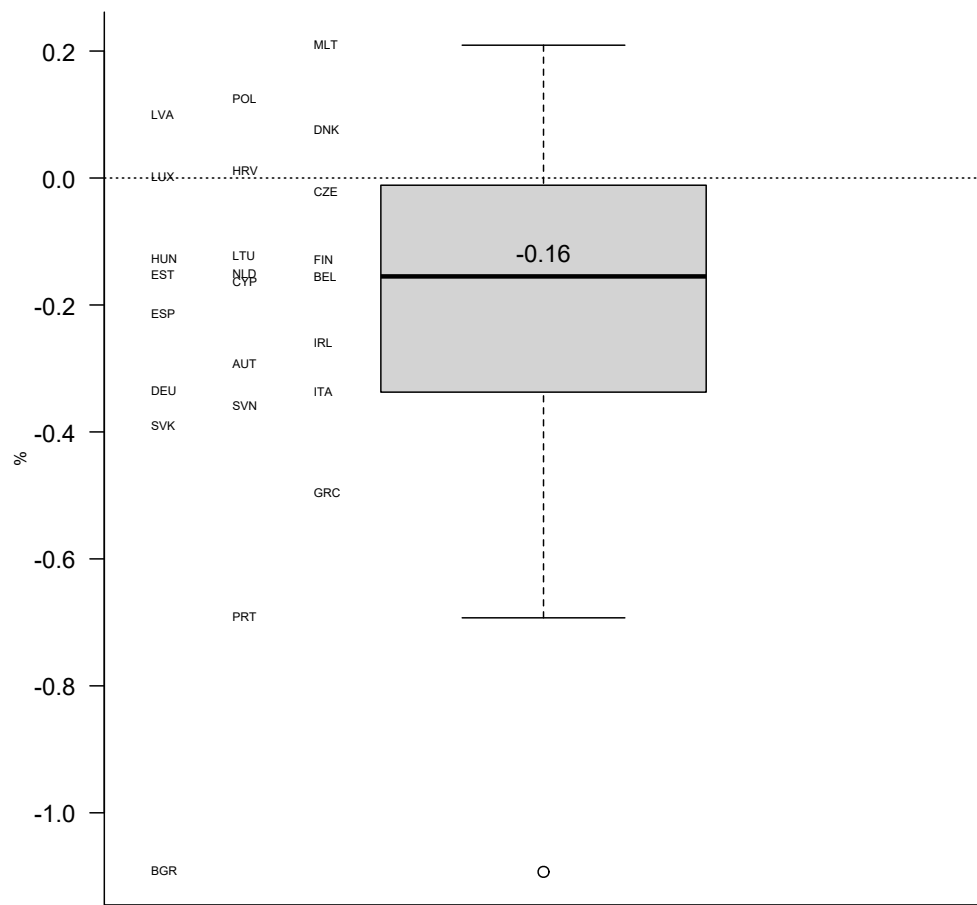
Note: Gray lines denote individual countries, while black thick line shows the median of all countries.

While the majority of countries exhibit downward-sloping trends — suggesting a persistent decline in capital-stock modernity over time — France and Romania present notable exceptions. In France, the trajectory remains largely flat, whereas Romania maintains a consistently high level, hovering near 100%. Therefore, in what follows, we exclude these countries from our analysis. Most countries follow a path close to the median, with three significant outliers: Bulgaria, which starts with an exceptionally high modernity level before converging rapidly

toward the median, as well as Poland and Portugal, which register modernity levels substantially below the median throughout the period.

To highlight the downward trend of the degree of modernity more clearly, we estimate a linear regression (with intercept and linear time trend) for each of the 24 countries and plot the resulting trend coefficients as a boxplot in Figure 4. France and Romania are excluded from analysis.

Figure 4: Boxplot of estimated country-specific linear trend coefficients of capital modernity degree



Source: Destatis, Eurostat, OECD, and own construction.

Note: Thick black line in the box indicates median value, with the corresponding figure reported above the median line. Estimated country-specific trend coefficients are denoted by ISO 3166-1 alpha-3 codes.

The median trend amounts to -0.16 percentage points, corresponding to a cumulative de-

cline of 1.6 percentage points per decade. Country-level estimates fall into four distinct groups: (i) five countries with positive trends — Croatia, Denmark, Latvia, Malta, and Poland (0.01–0.21 percentage points annually); (ii) Luxembourg, with a zero coefficient; (iii) 17 countries with negative trends, ranging from -0.02 to -0.69 percentage points; and (iv) Bulgaria, which is a pronounced outlier at -1.09 percentage points.

Controls for productivity growth. To control for additional productivity determinants, we draw on indicators commonly used in the literature. Table 1 reports the definitions, sources, and descriptive statistics for all dependent and explanatory variables employed in our analysis.

Table 1: Descriptive statistics

Definition	Unit	Source	Minimum	Mean	Median	Maximum	Standard deviation	Number of observations
Trend total factor productivity	billion euro	EU Commission	0.1	0.8	0.7	2.0	0.4	1376
Actual total factor productivity	billion euro	EU Commission	0.1	0.8	0.7	2.0	0.4	1379
Productivity: GDP per working hour	euro per hour	EU Commission	4.0	33.6	28.7	111.0	20.4	1405
Degree of modernity of total capital stock (combined estimate)	%	Destatis, Eurostat, OECD	41.0	64.0	64.1	96.3	9.1	890
General government expenditure on education (current, capital, and transfers) is expressed as a percentage of GDP. It includes expenditure funded by transfers from international sources to government. General government usually refers to local, regional and central governments.	% of GDP	UNESCO	1.1	4.8	4.8	8.6	1.2	962
Gross domestic expenditures on research and development, expressed as a percent of GDP. These include both capital and current expenditures in the four main sectors: Business enterprise, Government, Higher education, and Private non-profit. R&D covers basic research, applied research, and experimental development.	% of GDP	World Development Indicators	0.2	1.5	1.3	3.9	0.9	757
Patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention—a product or process that provides a new way of doing something or offers a new technical solution to a problem. A patent provides protection for the invention to the owner of the patent for a limited period, generally 20 years.	per 1000 people	WIPO Patent Report: Statistics on World-wide Patent Activity, World Intellectual Property Organization (WIPO)	3	18777.0	1829	621453	76421.6	1007
Degree of trade openness	%	World Bank	9.2	96.9	84.3	412.2	57.5	1326

Table 1: continued...

Definition	Unit	Source	Minimum	Mean	Median	Maximum	Standard deviation	Number of observations
Government Effectiveness (GE) captures perceptions of the quality of public services, the civil service, policy formulation and implementation, as well as the credibility of a government's decisions. Governance score is a linear transformation of the governance estimate using hypothetical worst-case and base-case countries. It is an absolute score ranging from 0-100. Larger values correspond to better governance.	score (0-100)	World Bank	34.3	72.3	71.6	96.5	13.0	728
Regulatory Quality (RQ) captures perceptions of the government's ability to design and implement policies and regulations that promote private sector development. Governance score is a linear transformation of the governance estimate using hypothetical worst-case and base-case countries. It is an absolute score ranging from 0-100. Larger values correspond to better governance.	score (0-100)	World Bank	46.7	72.5	72.5	90.5	8.4	728
Rule of Law (RL) captures perceptions of the extent to which agents respect and follow the rules of society, including contract enforcement, property rights, the police, courts, as well as the likelihood of crime and violence. The governance score is a linear transformation of the governance estimate using hypothetical worst-case and base-case countries. It is an absolute score ranging from 0-100. Larger values correspond to better governance.	score (0-100)	World Bank	45.3	75.2	75.4	93.3	10.5	728
Index of financial development based on 9 subindices that summarize how developed financial institutions and financial markets are in terms of their depth, access and efficiency	Index	IMF Financial Development Index (FDI)	0	0.4	0.5	0.9	0.2	1148

Sample sizes for the productivity indicators are the largest, varying between 1376 and 1405 observations. By contrast, the capital modernity measures are based on considerably shorter samples (748–890 observations), significantly constraining the effective sample for econometric analysis.

4. Results and discussion

4.1. Basic results

We estimated local projection models for degree of modernity of the total capital stock and six control variables: government expenditure on education (as % of GDP), research and development expenditure (as % of GDP), trade openness (as % of GDP), government effectiveness, regulation quality, and financial development indices (see section 2). For each of these variables we use three lags to account for persistence in the dependent and shock variables.

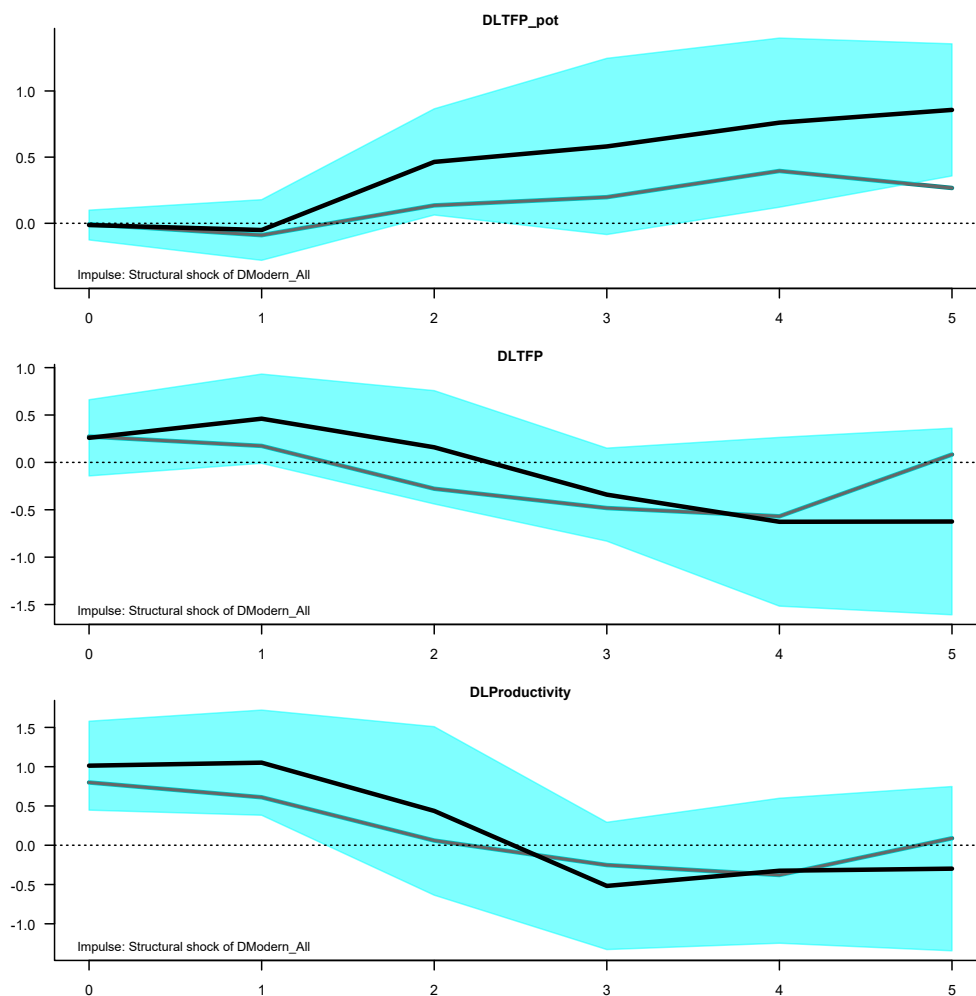
Figure 5 shows the responses of the growth rate of trend and actual total factor productivity and labor productivity to a shock in modernity of the total capital stock estimated using panel local projection models. It shows coefficients obtained using both standard and split-panel jackknife estimators.

Both total factor productivity and labor productivity respond positively to an increase in the modernity of the aggregate capital stock, yet the temporal dynamics of these responses differ markedly. Actual TFP and labor productivity rise immediately following the shock and continue to increase through the first post-shock year, although the response of actual TFP lacks statistical significance. In contrast, trend TFP exhibits a positive and statistically significant effect only in the second year after the shock, with a secondary significant response emerging after the fourth year. This discrepancy in reaction speed is attributable to the varying degrees of smoothness among the three indicators: whereas trend TFP is dominated by low-frequency components, actual TFP and labor productivity contain substantial high-frequency variation. The economic implications are substantial. According to our estimates, each 1-point loss in capital modernity costs half a point of TFP and 1 full point of labor productivity growth. Over the average year in our sample, modernity drops by half a point — so we estimate a permanent annual loss of 0.25 points in trend TFP and 0.5 points in labor productivity.

4.2. Robustness checks

Our econometric approach requires a certain number of lags of the dependent variable to be included in the estimation. A drawback of this approach is, however, that the number of observations are insufficient to estimate the model for single countries. To nevertheless assess whether the results are driven by a specific country in our data set, we re-estimate the impulse

Figure 5: Impulse responses for the panel local projection model: TFP and labor productivity regressed on overall degree of modernity

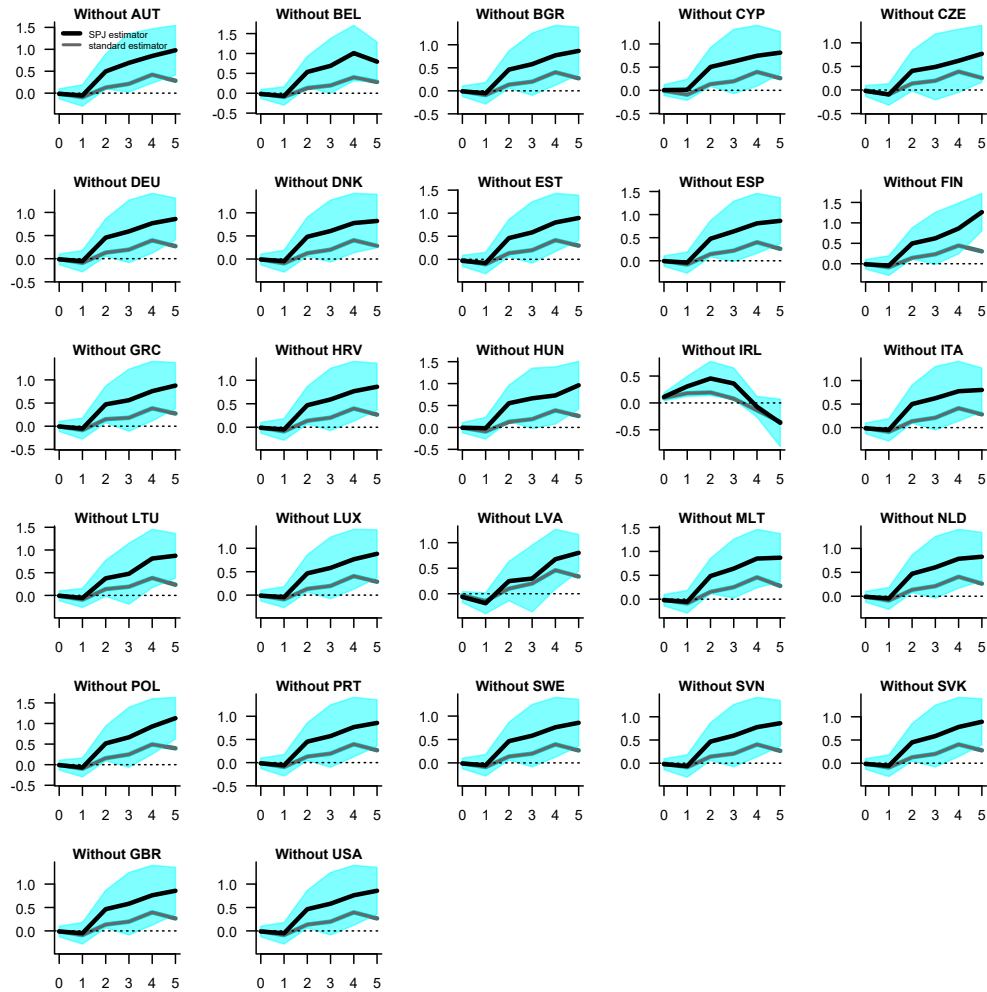


Source: own construction.

Note: Light green shading corresponds to the 95% confidence intervals obtained using delta method. The thick black line represents the split-panel jackknife estimator, whereas the gray line depicts the standard estimator.

responses of trend TFP to shocks in overall capital stock modernity by panel local projections. The 24 panels in Figure 6 each display the estimates from a model that excludes a different country. The models are specified in exactly the same way as the basis model.

Figure 6: Impulse responses from panel local projections excluding one country at a time: trend TFP response to overall capital stock modernity



Source: own construction.

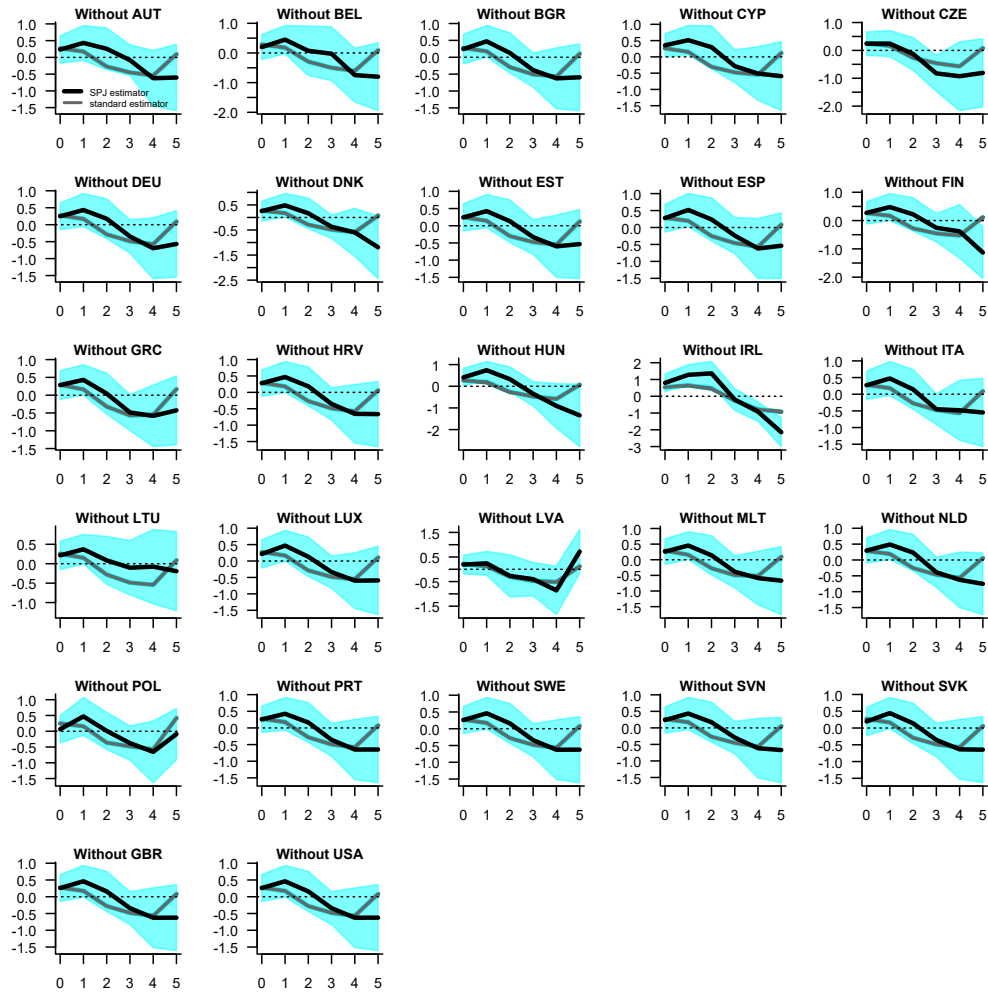
Note: Light green shading corresponds to the 95% confidence intervals obtained using delta method. The thick black line represents the split-panel jackknife estimator, whereas the gray line depicts the standard estimator.

Most impulse responses, except those for Ireland, display similar dynamics. A positive shock to the modernity triggers an initial negative, albeit statistically insignificant, response, that subsequently reverses to a positive response from year four onward. These dynamics are consistent with the J-curve effect commonly observed in investment economics. The introduc-

tion of new machinery or technologies entails substantial adjustment costs: existing processes must be phased out, new equipment requires adaptation and fine-tuning, while workers need training to operate the novel systems. In the immediate aftermath, these frictions generate disruptions and temporary productivity losses. However, once the initial hurdles are overcome, productivity rises markedly.

Figure 7 displays the impulse responses of actual TFP to shocks in overall capital stock modernity. As before, each panel depicts estimates leaving out one country.

Figure 7: Impulse responses from panel local projections excluding one country at a time: TFP response to overall capital stock modernity



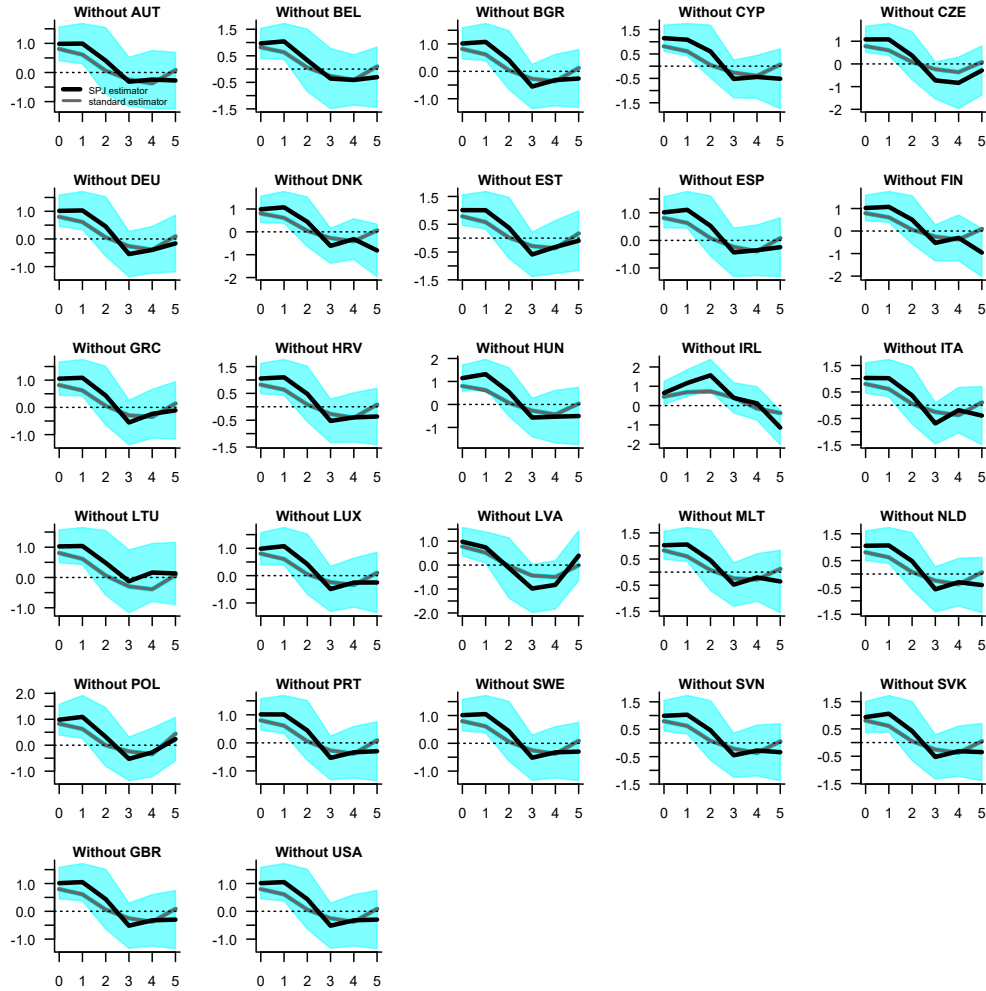
Source: own construction.

Note: Light green shading corresponds to the 95% confidence intervals obtained using delta method. The thick black line represents the split-panel jackknife estimator, whereas the gray line depicts the standard estimator.

Overall, the results are quite similar across sub-models, in this specification even for the model without Ireland. Notably, the response of TFP to a capital modernity shock is positive on impact and during the first two years before becoming negative thereafter.

Finally, Figure 8 displays the impulse responses of labor productivity to shocks in capital stock modernity, estimated via panel local projections. As before, the 24 graphs each report estimates from a model that excludes a different country from the sample and the models are otherwise specified in exactly the same way as the basis model.

Figure 8: Impulse responses from panel local projections excluding one country at a time: labor productivity response to overall capital stock modernity



Source: own construction.

Note: Light green shading corresponds to the 95% confidence intervals obtained using delta method. The thick black line represents the split-panel jackknife estimator, whereas the gray line depicts the standard estimator.

In all submodels, we observe a strong positive reaction to the shock to capital modernity that lasts for about four years. As before, the overall results do not appear to be driven by one specific country, as the heterogeneity across submodels is remarkably small.

5. Conclusion

In this study, we examine the relationship between capital stock modernity and productivity dynamics across 24 European economies over the 1997–2020 period. Using panel local projections with split-panel jackknife corrections to address the Nickell-type bias inherent in dynamic fixed-effects models, we document several key findings.

Improvements in the modernity of the total capital stock exert a positive and statistically significant effect on both total factor productivity and labor productivity. However, the timing of these effects differs markedly: labor productivity responds immediately upon the shock and continues to rise through the second year, while TFP exhibits a delayed positive response, materializing only in the second and third years. This temporal discrepancy likely reflects the different degree of smoothness of the dependent variable: the trend TFP is by construction much smoother than the actual labor productivity.

Cross-country heterogeneity is evident. While most countries exhibit declining modernity trends across all asset categories, Bulgaria stands out with annual aging rates exceeding 1% for total capital and structures, whereas Malta shows rapid modernization at the pace over 0.2 percentage points per year. These divergent trajectories suggest that national investment policies, institutional frameworks, and technological catch-up dynamics play a critical role in shaping the age composition of capital stocks.

Our findings point to several policy-relevant conclusions. First, the ongoing aging of the capital stock poses a direct threat to productivity and, hence, to economic growth. Second, given the persistently low investment rates observed during the 2020s, this aging process is set to continue unless countervailing measures are taken. Third, reversing this trend would necessitate large-scale investment to upgrade the capital stock. Finally, this modernization task will be particularly arduous over the coming decades, as it coincides with demographic aging, which simultaneously reduces the supply of skilled labor and weakens the economy’s ability to mobilize savings for investment.

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