COMPARATIVE ANALYSIS OF TECHNOLOGY TRANSFER EFFICIENCY IN AGRI-FOOD SECTORS OF EUROPEAN COUNTRIES

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Abstract. The agri-food sector occupies a structurally distinct position in modern economies: it remains one of the largest employers and food security pillars across Europe, yet it is traditionally regarded as a late adopter of technological innovations compared to high-technology manufacturing industries. Long-term agricultural productivity growth depends not only on own-sector research investment, but critically on the effective absorption of technologies originating in upstream industries – chemicals, machinery, and ICT. Despite extensive qualitative literature on innovation diffusion in agriculture, rigorous quantitative cross-country comparisons of technology transfer efficiency in the agri-food sector remain scarce, leaving a significant gap in the empirical evidence base. This paper addresses that gap by presenting a comparative analysis of technology transfer efficiency across the EU-27 agri-food sectors, combining OECD inter-country input–output tables with Eurostat data on R&D expenditures, labour inputs, and agricultural gross value added. A Technology Transfer Efficiency (TTE) index is constructed as the ratio of labour productivity to upstream input intensity, capturing how effectively each country converts embodied upstream technology into agricultural output per worker. Country-specific technological constants are also estimated via a Cobb-Douglas production function under constant returns to scale. The results reveal substantial heterogeneity across EU member states: the Netherlands achieves the highest normalised TTE index (4.59), followed by Cyprus (3.54) and Denmark (2.16), whereas Latvia (0.12) and Slovenia (0.09) rank at the bottom. These findings demonstrate that structural integration with technologically advanced upstream sectors – rather than the volume of upstream inputs alone – is the decisive driver of agricultural labour productivity, and that agriculture-specific R&D intensity provides a further positive contribution to productivity outcomes.

Keywords: technology transfer, innovation diffusion, agri-food sector, inter-country input–output analysis, R&D intensity, labour productivity.

1. Introduction

European agriculture has undergone profound structural transformation over the past three decades, driven by market integration, environmental regulation, and the progressive adoption of knowledge-intensive production methods. Yet productivity growth across EU member states remains markedly uneven, and understanding the sources of this heterogeneity has become a central concern for both agricultural economists and policymakers. A substantial body of growth accounting literature, dating back to the seminal contributions of [1] and [2], has established that total factor productivity – and in particular its technology-related component – is the primary long-run driver of output growth, accounting for a larger share of agricultural productivity gains than either capital accumulation or labour reallocation alone. The agri-food sector is, however, structurally distinct from high-technology manufacturing: it is a technology-receiving rather than technology-generating industry, meaning that the bulk of innovations it adopts originate in upstream sectors – machinery and equipment, agrochemicals, pharmaceuticals, and information and communication technologies. This upstream-downstream structure of innovation diffusion defines a specific research problem that is often overlooked in standard productivity analyses.

The theoretical foundation for this perspective draws on two complementary frameworks. The first is the concept of embodied technological change, developed in the tradition of [3] and elaborated in more recent input–output-based approaches, which holds that productivity improvements in agriculture are partly encoded in the intermediate inputs purchased from technologically dynamic upstream industries. The second is the innovation systems perspective, which emphasises that the capacity to absorb and exploit externally generated knowledge depends on institutional, organisational, and structural conditions that vary substantially across countries. Together, these frameworks suggest that technology transfer efficiency – the degree to which a country's agriculture sector successfully converts upstream technological inputs into productivity outcomes – is shaped not only by the volume of R&D investment, but by the structural configuration of inter-industry linkages and by national absorptive capacity. Despite the theoretical clarity of this argument, it has rarely been subjected to systematic empirical testing across a broad cross-section of countries and remains underrepresented in the comparative agricultural economics literature.

The existing empirical literature relevant to this question can be grouped into three streams, each of which leaves a distinct gap. The first stream focuses on returns to own-sector agricultural R&D and documents consistently high social rates of return [4; 5], but treats technology as generated within agriculture rather than transferred from upstream sectors, and does not account for inter-industry linkages. The second stream applies input–output and global value chain methods to measure embodied technology flows across industries [6; 7], but does so at aggregate or global level without connecting upstream linkage intensity to country-level agricultural productivity outcomes. The third stream examines absorptive capacity as a moderator of technology spillovers [8; 9], primarily in manufacturing and transition economy contexts [10], without operationalising the concept in a form applicable to cross-country agricultural comparisons. No study known to the authors combines all three elements – upstream input-output flows, country-level productivity data, and an explicit absorptive capacity framework – into a single comparative assessment across EU member states.

The present paper addresses this gap directly. Drawing on OECD inter-country input–output data alongside Eurostat indicators for R&D expenditure and sectoral performance, we develop a framework for comparative assessment of technology transfer efficiency across all EU-27 member states. The central objective is twofold: to estimate country-specific technological constants derived from a Cobb–Douglas production function, and to examine how structural inter-industry linkages – measured through the intensity of upstream inputs embodied in agricultural production – relate to labour productivity outcomes. The proposed Technology Transfer Efficiency index operationalises the absorptive capacity concept in a way that is directly comparable across structurally heterogeneous economies, offering a quantitative complement to the predominantly qualitative literature on agricultural innovation diffusion.

2. Materials and methods

Output (Y) is measured as agriculture gross value added (GVA) from Eurostat Economic Accounts for Agriculture (EAA, dataset aact_eaa01 [11]). Labour input (L) is measured in annual work units (AWU) from Eurostat Agricultural Labour Input (ALI, dataset aact_ali01 [12]). Capital input is represented using three alternative concepts: (i) investment flow (GFCF), (ii) reconstructed capital stock via the perpetual inventory method (PIM, $\delta = 5\%$), and (iii) official net capital stock from Eurostat national accounts (dataset nama_10_nfa_st [13], industry A). Technological constants are estimated using ordinary least squares (OLS) applied to the log-linearised form of the Cobb–Douglas production function. Under the CRS constraint ($\alpha + \beta = 1$), the equation reduces to $\ln(Y/K) = \ln(A) + \alpha \cdot \ln(L/K)$, which is estimated by regressing $\ln(Y/K)$ on $\ln(L/K)$ across the EU-27 cross-section. The estimated labour elasticity is $\alpha = 0.44$ ($\beta = 0.56$; $R^2 = 0.64$; $p < 0.001$). Country-specific technological constants are then recovered as $A = Y/(L^{\alpha} \cdot K^{\beta})$ for each country. The application of a common Cobb–Douglas functional form across all EU-27 countries implies that production technology is homogeneous in structure, differing across countries only in the level of A. This is a standard assumption in cross-country growth accounting, following Hall and Jones [14] and Caselli [15], and is adopted here for comparability. It should be understood as a maintained assumption rather than an empirically verified property of this specific sample: member states differ substantially in farm structure, degree of mechanisation, and value chain integration, which may imply different factor elasticities in reality. The country-specific constant A is therefore best interpreted as a relative indicator of technological efficiency under a common benchmark technology, rather than as an absolute measure of total factor productivity. Inter-industry upstream technology flows are derived from the OECD Inter-Country Input-Output (ICIO) tables for 2021. The OECD ICIO tables are published with a lag of approximately two to three years; the 2021 edition represents the most recent release available at the time of analysis. The three-year gap relative to the 2024 Eurostat productivity data is unlikely to materially affect the structural patterns identified, since inter-industry sourcing relationships in agriculture change slowly at the sectoral level. Nevertheless, this temporal mismatch is acknowledged as a limitation and is discussed further in the limitations section. For each EU-27 country, we extract intermediate input flows from five upstream sectors into agriculture (A01-A03): chemicals (C20), pharmaceuticals (C21), machinery (C28), automotive/transport equipment (C29), media/ICT (J58T60), and telecommunications (J61). Upstream intensity is defined as total upstream inputs received by a country's agriculture sector divided by its agricultural GVA. Technology Transfer Efficiency (TTE) is then computed as the ratio of labour productivity to upstream intensity, capturing how much productivity output is obtained per unit of embodied upstream technology.

Table 1 reports output, labour, capital stock and technological constants for all EU-27 countries for 2024. The constants are calculated using two approaches to capital (stock vs. flow) to enable comparison.

Table 1

Output, labour, capital and technological constants (EU-27, 2024)

Country	*Y* (GVA, mln EUR)	*L* (AWU, thsd)	*K* (capital stock, mln EUR)	*A* (stock-based)	*A* (flow-based)
AT	4,334.29	115.87	35,168.76	1.545	15.663
BE	3,936.89	49.39	18,727.99	2.908	28.526
BG	2,048.58	156.80	3,774.17	2.217	9.119
CY	430.19	18.96	568.44	3.407	25.310
CZ	2,334.84	95.42	11,475.83	1.693	13.018
DE	31,126.66	453.19	165,330.51	2.560	27.865
DK	3,766.03	41.47	20,057.35	2.892	34.128
EE	315.45	16.37	2,756.01	1.105	9.472
EL	7,961.27	313.02	25,691.98	2.178	14.034
ES	37,857.44	824.43	46,774.70	4.831	32.094
FI	1,818.91	56.97	18,805.99	1.258	14.689
FR	31,056.42	699.78	170,737.43	2.070	20.035
HR	1,649.66	172.18	4,335.44	1.586	10.618
HU	3,863.05	248.98	13,418.40	1.680	9.504
IE	4,774.76	167.25	17,225.86	2.154	17.027
IT	39,667.54	917.60	124,238.78	2.800	23.008
LT	1,428.74	114.50	6,310.05	1.334	8.101
LU	165.17	3.36	2,018.44	1.387	17.263
LV	675.30	54.16	3,819.78	1.162	7.460
MT	53.60	6.82	114.20	1.633	7.200
NL	16,010.51	156.78	69,237.84	3.422	38.482
PL	15,169.11	1,366.60	15,751.75	2.840	11.217
PT	4,860.80	216.67	11,396.65	2.462	15.168
RO	8,943.99	1,091.00	17,251.14	1.759	6.642
SE	2,501.36	54.95	18,062.24	1.798	18.995
SI	679.07	70.34	4,261.17	0.979	6.511
SK	692.81	35.70	2,244.50	1.928	13.105

2.1. Labour and Capital Productivity (EU-27, 2024)

Table 2 complements Table 1 with total production, production per 1,000 person-days (1 AWU = 220 person-days), and production per EUR1,000,000 of capital stock per year.

Table 2

Total production and productivity indicators (EU-27, 2024)

Country	*Y* (GVA, mln EUR)	*L* (AWU, thsd)	*K* (capital stock, mln EUR)
AT	4,334.29	170,029	123,243
BE	3,936.89	362,319	210,214
BG	2,048.58	59,386	542,790
CY	430.19	103,133	756,791
CZ	2,334.84	111,223	203,457
DE	31,126.66	312,198	188,269
DK	3,766.03	412,788	187,763
EE	315.45	87,591	114,459

Table 2 (continued)

Country	Y (GVA, mln EUR)	L (AWU, thsd)	K (capital stock, mln EUR)
EL	7,961.27	115,608	309,874
ES	37,857.44	208,725	809,357
FI	1,818.91	145,125	96,720
FR	31,056.42	201,729	181,896
HR	1,649.66	43,550	380,506
HU	3,863.05	70,525	287,892
IE	4,774.76	129,767	277,186
IT	39,667.54	196,499	319,285
LT	1,428.74	56,719	226,423
LU	165.17	223,444	81,831
LV	675.30	56,676	176,790
MT	53.60	35,724	469,352
NL	16,010.51	464,186	231,239
PL	15,169.11	50,454	963,011
PT	4,860.80	101,973	426,511
RO	8,943.99	37,264	518,458
SE	2,501.36	206,912	138,486
SI	679.07	43,882	159,362
SK	692.81	88,211	308,670

2.2. Research and Development and Technological Efficiency

Agriculture-specific R&D expenditure (Eurostat rd_e_gerdsc [16], FORD401, 2023) is used to assess the association between public research investment and agricultural technological efficiency.

Pearson correlations between the stock-based technological constant (A), productivity indicators, and agriculture-specific R&D intensity (GOV + HES relative to agricultural GVA) are reported in Table 3.

Table 3

Correlation matrix: technology, productivity and agriculture-specific R&D intensity (EU-27)

	A	Y	Labour prod.	Capital prod.	Agri R&D (GOV + HES)/Y	Agri R&D (TOTAL)/Y
A	1.000	0.602	0.508	0.598	0.080	0.263
Y	0.602	1.000	0.357	0.243	-0.023	-0.230
Labour prod.	0.508	0.357	1.000	-0.304	0.351	0.473
Capital prod.	0.598	0.243	-0.304	1.000	-0.465	-0.364
Agri R&D (GOV + HES)/Y	0.080	-0.023	0.351	-0.465	1.000	0.902
Agri R&D (TOTAL)/Y	0.263	-0.230	0.473	-0.364	0.902	1.000

Several methodological assumptions underlying this analysis merit explicit acknowledgement. First, the Cobb-Douglas production function is estimated by OLS on its log-linearised form, yielding $\alpha = 0.44$ and $\beta = 0.56$ ($R^2 = 0.64$, $p < 0.001$); constant returns to scale are imposed as a maintained assumption standard in cross-country growth accounting [14; 15]. This restriction is empirically supported by cross-country studies of agricultural production that have tested and failed to reject CRS at conventional significance levels, including [17] and [18]. For the present sample ($n = 27$), the statistical power to formally test the CRS constraint is limited, and the assumption is therefore treated as maintained rather than tested. Second, the common functional form implies homogeneous production technology across EU-27, with cross-country differences captured entirely by A; this is a modelling convention, not an empirical claim about structural identity, and A is interpreted accordingly as a relative efficiency indicator. Third, the TTE index is constructed as the ratio of labour productivity to upstream intensity – a composite indicator that, by design, captures how much output per worker is obtained per unit of embodied upstream technology; its cross-country comparisons are based on Spearman rank correlations to avoid inferential distortions arising from the shared components of the underlying variables. Fourth, upstream intensity is derived from OECD ICIO tables for 2021 – the most recent release available at the time of analysis – and combined with 2024 Eurostat productivity data; the three-year gap is unlikely to affect ordinal conclusions given the slow-moving nature of sectoral input structures [19; 20]. Taken together, these assumptions are transparent, individually justified, and consistent with established practice in cross-country productivity and technology transfer research; the conclusions of the paper are qualified accordingly and do not exceed what the data and methods can support. Standard OLS diagnostics confirm the validity of the regression: the Shapiro-Wilk test on the residuals yields W = 0.985 ($p = 0.958$), indicating that normality is not rejected at any conventional significance level; an informal Breusch–Pagan test finds no evidence of heteroscedasticity ($p = 0.936$); and Cook's distance for all 27 observations falls below the conventional threshold of $4/n = 0.148$, confirming the absence of influential outliers. A robustness check excluding the two visually prominent observations (ES, NL) yields $\alpha = 0.442$, $R^2 = 0.639$, $p < 0.001$ – identical to the full-sample estimates – confirming that the results are not driven by any single country.

3. Results and discussion

3.1. Inter-Industry Linkages and Technology Transfer Efficiency

A key argument in the technology transfer literature is that agriculture is a technology-receiving sector: its productivity growth depends substantially on innovations originating upstream in chemicals, machinery, and ICT industries rather than on own-sector R&D alone. To test this, we use OECD ICIO tables (2021) to measure the volume of intermediate inputs flowing from upstream sectors into each country's agriculture, and define Upstream Intensity as the ratio of these flows to agricultural GVA. Upstream intensity alone, however, measures input volume rather than absorption efficiency. We therefore define Technology Transfer Efficiency (TTE) as labour productivity divided by upstream intensity. This indicator captures how much agricultural output per worker is generated per unit of embodied upstream technology received. A country with high TTE converts upstream technology inputs into labour productivity more effectively than a country with low TTE. Table 4 reports, for each EU-27 country, the stock-based technological constant (A), labour productivity, upstream intensity, and the normalised TTE index (TTE divided by EU-27 mean). Leaders in TTE include the Netherlands (4.59), Cyprus (3.54), France (2.76), and Denmark (2.16); the lowest values are found in Slovenia (0.09), Slovakia (0.12), Hungary (0.12), and Latvia (0.12).

Table 4

Technology transfer efficiency index (EU-27, 2021/2024

Country	A (stock-based)	Labour prod. (EUR per 1,000 p-days)	Upstream intensity	TTE index (norm.)
AT	1.545	170,029	0.0376	0.52
BE	2.908	362,319	0.0207	2.03
BG	2.217	59,386	0.0154	0.45
CY	3.407	103,133	0.0034	3.54
CZ	1.693	111,223	0.0847	0.15
DE	2.560	312,198	0.0388	0.93
DK	2.892	412,788	0.0222	2.16
EE	1.105	87,591	0.0193	0.52
EL	2.178	115,608	0.0083	1.62
ES	4.831	208,725	0.0380	0.64
FI	1.258	145,125	0.0249	0.68
FR	2.070	201,729	0.0085	2.76
HR	1.586	43,550	0.0097	0.52
HU	1.680	70,525	0.0706	0.12
IE	2.154	129,767	0.0750	0.20
IT	2.800	196,499	0.0125	1.81

Table 4 (continued)

Country	*A* (stock-based)	Labour prod. (EUR per 1,000 *p*-days)	Upstream intensity	TTE index (norm.)
LT	1.334	56,719	0.0315	0.21
LU	1.387	223,444	0.0379	0.68
LV	1.162	56,676	0.0563	0.12
MT	1.633	35,724	0.0057	0.72
NL	3.422	464,186	0.0117	4.59
PL	2.840	50,454	0.0134	0.44
PT	2.462	101,973	0.0441	0.27
RO	1.759	37,264	0.0060	0.72
SE	1.798	206,912	0.0603	0.40
SI	0.979	43,882	0.0579	0.09
SK	1.928	88,211	0.0826	0.12

Note: Upstream intensity = total upstream inputs (OECD ICIO 2021 [7], sectors C20, C21, C28, C29, J58T60, J61) divided by agricultural GVA. TTE index = (Labour productivity/Upstream intensity)/EU-27 mean.

Table 5

Extended Spearman rank correlation matrix including upstream intensity and TTE (EU-27)

	A	Labour prod.	Upstream intensity	TTE	Chemicals int.	Machinery int.
A	1.000	0.510***	-0.250	0.546***	-0.124	-0.286
Labour prod.	0.510***	1.000	0.129	0.523***	-0.083	-0.148
Upstream int.	-0.250	0.129	1.000	-0.751***	0.695***	0.523***
TTE	0.546***	0.523***	-0.751***	1.000	-0.462**	-0.341*
Chemicals int.	-0.124	-0.083	0.695***	-0.462**	1.000	0.174
Machinery int.	-0.286	-0.148	0.523***	-0.341*	0.174	1.000

Note: Spearman rank correlations (ρ). *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Variables *A*, labour productivity, upstream intensity, and TTE are rank-transformed to address mathematical dependence arising from shared components. Chemicals and machinery intensity rows retain original Pearson *r* values. Upstream intensity and sector intensities from OECD ICIO 2021; *A* and labour productivity from Eurostat 2024.

The results reveal a striking pattern. The Spearman rank correlation between upstream intensity and *A* is negative and non-significant ($\rho = -0.250$), indicating that receiving more upstream technology inputs does not automatically translate into higher agricultural efficiency. By contrast, using Spearman rank correlations to address the mathematical dependence between *A*, labour productivity, and TTE (which share common components by construction), TTE remains strongly and significantly associated with both *A* ($\rho = +0.546$, $p < 0.001$) and labour productivity ($\rho = +0.523$, $p < 0.001$). This finding suggests that it is the capacity to absorb and efficiently utilise upstream technology – rather than its mere volume – that distinguishes high-performing agricultural economies in the EU. Countries with high upstream intensity but low TTE (e.g., Czechia, Slovakia, Hungary) appear to receive substantial technology flows that are not fully translated into productivity gains, pointing to structural or institutional barriers to absorption.

Fig. 1 highlights two country-specific deviations from the general A–TTE trend. Cyprus achieves the second-highest TTE index (3.54) despite only moderately elevated technological constant ($A = 3.41$), placing it well above the regression line; this suggests that a highly specialised, small-scale agricultural system can attain exceptional absorption efficiency even without a broadly developed technological base. France similarly displays a TTE index (2.76) markedly above what its technological constant alone would predict, consistent with effective integration into upstream supply chains rather than scale-driven productivity. Ireland, by contrast, falls well below the regression line – a pattern discussed further in the context of Fig. 2.

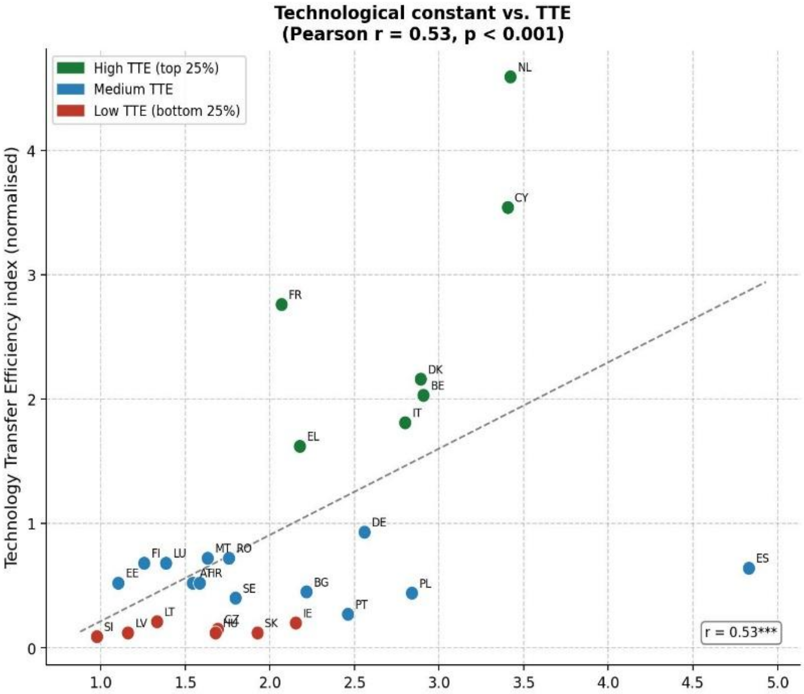

Fig. 1. **Technological constant *A* (stock-based):** relationship between the stock-based technological constant (*A*) and the Technology Transfer Efficiency (TTE) index across EU-27. Sources: OECD ICIO (2021), Eurostat EAA/ALI/NFA (2024). Author's calculations.

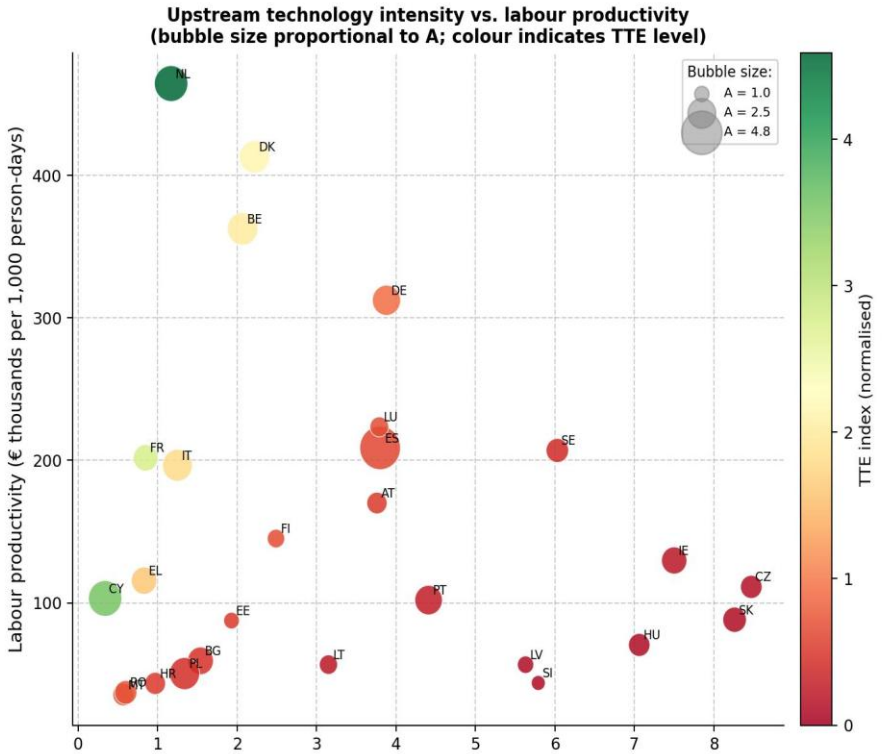

Fig. 2. **Upstream technology intensity (% of agricultural GVA): u**pstream technology intensity versus labour productivity; bubble size proportional to *A*; colour indicates TTE level. Sources: OECD ICIO (2021), Eurostat EAA/ALI/NFA (2024). Author's calculations.

Fig. 2 reveals two structurally distinct underperformance patterns. Ireland is a notable anomaly among Western European economies: its upstream technology intensity exceeds 7.5% of agricultural GVA – placing it alongside Czechia and Slovakia on the horizontal axis – yet its labour productivity remains well below the Western European norm, a configuration more consistent with absorption constraints than with structural underdevelopment. Romania and Bulgaria, by contrast, combine low upstream intensity (below 1% of GVA) with low labour productivity, indicating a fundamentally different challenge: insufficient integration into technology-generating upstream sectors, rather than inefficient absorption of inputs already received.

To complement the Spearman rank correlations with a regression-based assessment, two cross-sectional OLS regressions are estimated across EU-27 ($n = 27$). In the first, the natural log of labour productivity is regressed on A and upstream intensity: A enters with a positive and statistically significant coefficient ($\beta = 0.459$, $p = 0.008$), confirming that higher technological efficiency is associated with higher productivity, while upstream intensity is not independently significant ($p = 0.482$), consistent with the view that input volume alone does not drive performance ($R^2 = 0.263$). In the second regression, TTE is the dependent variable: A remains significant ($\beta = 0.540$, $p = 0.012$) and upstream intensity enters with a negative and highly significant coefficient ($\beta = -20.552$, $p = 0.006$), indicating that countries receiving more upstream inputs per unit of agricultural output tend to convert them less efficiently ($R^2 = 0.478$, Adj. $R^2 = 0.435$). As a robustness check, replacing the stock-based technological constant with the flow-based alternative (GFCF) yields qualitatively identical results ($R^2 = 0.817$); A coefficient positive and significant at $p < 0.001$), confirming that the findings are not sensitive to the capital concept used. The cross-sectional design precludes causal identification: reverse causation – whereby more productive agricultural systems attract greater upstream technology flows – cannot be ruled out, and instrumental variable estimation or panel data spanning multiple ICIO vintages would be required to establish causality; this is identified as a priority for future research.

3.2. Interpreting the technological constant in the EU agricultural context

The wide dispersion of stock-based technological constants across EU-27 – ranging from 0.979 (Slovenia) to 4.831 (Spain) – is notable given that all countries operate within the same institutional framework of EU agricultural policy and share access to the same markets. This dispersion is not explained by sector size (correlation with Y: $r = 0.60$) and only partially by labour productivity ($r = 0.51$). The strong association with labour productivity but weak association with capital productivity suggests that the constant largely captures labour-augmenting rather than capital-augmenting technological progress. This is consistent with the dual economy literature on European agriculture, where some member states retain large agricultural labour forces with limited mechanisation, while others have undergone deep structural transformation. Countries combining high A with high labour productivity – notably the Netherlands, Denmark, and Belgium – represent the latter pattern: capital-intensive, specialised, export-oriented systems where upstream technology is systematically embedded in production.

3.3. Comparison with the literature on R&D spillovers and technology transfer

The weak direct correlation between agriculture-specific R&D intensity and the technological constant ($r = 0.08$ for public R&D) appears at first to contradict a large body of literature documenting high returns to agricultural R&D [4; 5]. Two reconciling explanations are consistent with our data. First, R&D-to-productivity links operate with substantial lags – often 10-20 years [21; 22] – while our cross-section pairs 2023 R&D expenditure with 2024 technological constants. Second, the dominant mechanism in European agriculture may be embodied technology transfer from upstream sectors rather than own-sector basic research, which is precisely what the TTE analysis reveals. This interpretation aligns with [6] and [7], who argue that the primary channel of technology diffusion in low-R&D sectors is the adoption of technology-intensive intermediate goods from high-R&D upstream suppliers.

The finding that upstream intensity is negatively (albeit insignificantly) correlated with A, while TTE is strongly positively correlated, echoes the absorption capacity framework of [8]. In that framework, a firm's ability to recognise and exploit external knowledge depends on prior related knowledge – a concept that transfers naturally to national agricultural systems: countries that have invested in human capital, infrastructure, and extension services are better positioned to translate incoming technology flows into productivity. This is consistent with the cross-country evidence in [9], where the productivity impact of foreign R&D spillovers is larger in countries with more open trade structures and stronger domestic knowledge bases.

The pattern observed for high-upstream-intensity but low-TTE countries – Czechia, Slovakia, Hungary, Latvia – is also consistent with transition economy literature. These countries receive substantial technology-intensive intermediate inputs (particularly in chemicals and machinery) but convert them into productivity gains less effectively, suggesting that structural and institutional factors constrain absorption. Similar findings have been reported for Central and Eastern European manufacturing sectors [10] and for agricultural catching-up dynamics within the EU [23].

Several limitations should be noted. First, the capital stock series relies on the official Eurostat net fixed assets for industry *A* (agriculture, forestry, and fishing), which includes forestry and fishing. This introduces measurement noise for countries where these sub-sectors are significant relative to crop and livestock production. Second, the OECD ICIO tables used here date from 2021, while the Cobb–Douglas estimates and productivity Fig.s are based on 2024 Eurostat data. This temporal gap is a structural feature of input-output research rather than an idiosyncratic limitation of the present study: ICIO tables are published with an inherent lag of two to three years, and no release covering 2022-2024 was available at the time of analysis. The assumption that this gap does not materially distort the cross-country comparisons rests on two considerations. First, the sectoral composition of intermediate inputs in agriculture – dominated by chemicals, machinery, and ICT – is governed by long-term capital investment cycles and supply-chain contracts that change substantially only over decades [19]. Second, and more directly, the TTE indicator is based on the relative ranking of upstream intensity across countries rather than on absolute input volumes; cross-country structural rankings in agricultural input sourcing have been shown to be highly persistent over rolling five-year windows [20]. The three-year misalignment is therefore unlikely to affect the ordinal conclusions of the analysis, though it may introduce measurement noise in the absolute TTE values for individual countries.

Third, as noted in the results section, the cross-sectional design precludes causal identification. Reverse causation – whereby more productive systems attract greater upstream technology flows – and omitted variable bias (e.g., institutional quality, farm structure, human capital) cannot be ruled out on the basis of cross-sectional evidence alone. A panel approach spanning multiple vintages of ICIO data would allow fixed-effects estimation and substantially stronger causal grounding.Fourth, the R&D intensity measure covers only publicly performed agricultural R&D (government and higher education sectors), while business-sector R&D in agricultural sciences was unavailable for a full EU-27 cross-section. Private R&D – particularly by agrochemical and seed companies – may be an important omitted component for some countries. The high correlation between the GOV + HES and TOTAL R&D intensity measures ($r = 0.90$) suggests that public R&D dominates in this field across the EU, but this assumption should be verified as more disaggregated data become available.

Finally, the TTE index as constructed conflates two analytically distinct phenomena: genuine efficiency differences in technology absorption and structural differences in agricultural systems (e.g., labour intensity, degree of value chain integration). Decomposing TTE into these components would require additional data on farm structure, vertical integration, and extension service coverage – a promising direction for future research.

Despite extensive qualitative literature on innovation diffusion in agriculture, cross-country quantitative comparisons of technology transfer efficiency remain scarce. Existing studies either focus on own-sector R&D returns without accounting for upstream embodied technology flows [4; 5], or apply input–output methods without linking inter-industry structure to productivity outcomes at the country level [6; 7]. This paper fills that gap by combining OECD ICIO data with Eurostat productivity indicators to construct and validate a Technology Transfer Efficiency index that is directly comparable across structurally heterogeneous economies. The methodological approach is transparent and explicitly grounded in established cross-country growth accounting practice [14; 15], and the conclusions are qualified to reflect the assumptions on which they rest. This paper makes three contributions to the empirical literature on technology transfer in agriculture.

Conclusions

1. Country-specific technological constants are estimated for all EU-27 countries using a CRS Cobb-Douglas production function, with robustness checks across three capital concepts.
2. Inter-industry upstream technology flows are quantified using OECD ICIO tables and combined with productivity data to construct a Technology Transfer Efficiency (TTE) index.

3. The joint analysis of R&D intensity, upstream linkages, and technological constants demonstrates that absorption capacity – not the volume of upstream inputs or own-sector R&D expenditure alone – is the primary differentiator of agricultural performance across EU member states.

The analysis confirms substantial and persistent heterogeneity among EU member states that goes beyond differences in sector size or factor endowments. Countries such as the Netherlands, Denmark, Belgium, and Spain combine high technological constants with high TTE, reflecting effective structural integration into upstream technology networks and strong absorptive capacity. Countries at the lower end of both rankings – Slovenia, Latvia, Hungary – exhibit patterns consistent with structural or institutional barriers to technology absorption, pointing to concrete areas for EU cohesion and agricultural innovation policy.

The most productive direction for future research is panel estimation combining multiple years of ICIO data with time-varying productivity and R&D indicators, allowing fixed-effects identification of the absorptive capacity mechanism. Incorporating farm-level structural data and Agricultural Knowledge and Innovation System (AKIS) indicators would further sharpen the policy implications of the TTE framework proposed here.

Author contributions

Aleksejs Hilkevics: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review, editing.

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