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Rethinking Agricultural Support: The Role of Public Policies in Productivity Growth

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Abstract

This paper examines whether the composition of agricultural support matters for productivity growth in Latin America and the Caribbean. We use an annual panel of 17 countries over 1995 to 2023. The analysis links agricultural total factor productivity to policy support measures constructed under the OECD Producer Support Estimate framework and extended to the region through the IDB Agrimonitor initiative. The paper distinguishes between market price support, direct transfers to producers, and general services support, and estimates dynamic panel models using System GMM. To address the potential endogeneity of support, the analysis combines internal instruments with an external instrument based on rural voter turnout. The results show that aggregate support is not positively associated with agricultural productivity. However, this relationship masks substantial heterogeneity across instruments. Market price support is negatively related to TFP under USDA and Färe–Primont indices, and significantly so under the Färe–Primont index, while direct transfers display a positive, though less robust, association. Contemporaneous general services support is not significantly associated with current productivity, consistent with the delayed nature of public goods investments. When public research and development is modeled as a long-lived stock of agricultural knowledge, its association with TFP becomes positive under both productivity indices and statistically significant under the USDA index. These findings suggest that the productivity effects of agricultural policy depend less on the total level of support than on its composition and timing. For LAC, where producer support remains heavily tilted toward price-based interventions, the findings underscore the importance of reducing reliance on distortionary market price support, improving the design of budgetary transfers, and strengthening sustained investment in agricultural public goods, particularly R&D.

Keywords: Agricultural Productivity, Agricultural Policies, Agriculture Support, Latin America and the Caribbean

JEL Codes: Q10, Q18, O54

1. Introduction

Agricultural productivity growth has been an important driver of economic development in Latin America and the Caribbean (LAC). Between 1995 and 2010, the region recorded some of the highest growth rates in agricultural total factor productivity (TFP) in the world, driven primarily by technical change (Ludeña, 2010). However, this dynamism has weakened markedly over the past decade. Evidence based on USDA and Färe–Primont indices shows that TFP growth decelerated after 2010 and was close to stagnant between 2015 and 2020. This slowdown raises an important policy question. Public support remains a central instrument of agricultural policy in the region, but this support can pursue multiple objectives, such as income stabilization, food affordability, risk management, or productivity growth, and different instruments may affect productivity through very different channels. Therefore, the key question is not only how much support agriculture receives, but whether the composition of that support is conducive to productivity growth.

Agricultural support is a large and persistent intervention in LAC rural economies. Total support to the sector averages below 20% of agricultural GDP in the region, compared with about 25% in Canada, 37% in the European Union and 54% in the United States. However, the composition of this support is heavily tilted toward market distorting instruments. Across LAC, market price support (MPS) accounts for about 73% of producer support, with direct transfers accounting for the remaining 27%. Argentina displays negative MPS, implying net transfers from producers to consumers (Conroy et al., 2024). The allocation of general services is equally heterogeneous. Brazil and Ecuador dedicate more than 80% of their general services support (GSSE) to research and development (R&D), while other countries assign only marginal shares. This heterogeneity in both the magnitude and composition of support provides the cross-country and intertemporal variation used in the empirical analysis.

The literature has evaluated agricultural policies through their effects on farm efficiency and technical change, typically finding that broad price-based support and input subsidies are weakly associated or negatively correlated with long-run productivity, while investments in infrastructure, education, and R&D are productivity enhancing (Bravo-Ortega and Lederman, 2004; López and Galinato, 2007; Ludeña, 2010; Anríquez et al., 2016; Minviel & Latruffe, 2017; Piñeiro et al., 2020). In addition, the dynamics of agricultural knowledge show that public R&D raises TFP through a slowly accumulating stock and with substantial lags, so that contemporaneous spending measures understate the long-run productivity contribution of public investments (Alston et al., 2009; Fuglie, 2018; van Dijk et al., 2025). Another strand in the literature drawn from the political economy of agricultural policy explains why support is neither exogenous nor socially optimal. Governments balance welfare objectives against the political returns from supporting organized groups, and under fiscal and electoral pressures often favor visible short-run transfers over less visible long-run

investments (Krueger, 1974; Olson, 1982; Swinnen, 2018). Existing cross-country work for LAC has rarely addressed the endogeneity of policy choice in dynamic productivity models.

This paper examines the relationship between agricultural support policies and TFP in 17 LAC countries over 1995–2023, using the Producer Support Estimate (PSE) methodology developed by the Organization for Economic Co-operation and Development (OECD) and extended to the region by the Inter-American Development Bank through the Agrimonitor initiative. Within this framework, support is decomposed into three components with sharply different economic properties. First, market price support (MPS), which arises from gaps between domestic and international prices; second, direct transfers to producers (DT), which are budgetary payments tied to output, area, animals, income, or input use; and third, general services support (GSSE), which finances public goods such as R&D, sanitary systems, infrastructure, and marketing. The central research question is whether these instruments are differentially associated with agricultural TFP, and whether the composition of support matters more than its aggregate level for productivity outcomes. The empirical analysis uses an annual country level panel for the period 1995–2023. Productivity is measured using two complementary TFP indices, constructed under different assumptions about aggregation, prices, and weights, which are the USDA index and the Färe–Primont index; the latter being computed with data envelopment analysis (DEA). The use of multiple indices triangulates results and reduces reliance on any single methodological approach. Agricultural support variables are drawn from Agrimonitor and expressed as shares of agricultural GDP. Macroeconomic, institutional, and climate controls, including trade openness, control of corruption, inflation, annual precipitation, and extreme heat days, are included to absorb country specific conditions.

The econometric strategy addresses two features of the data that would bias static or pooled estimators. First, agricultural productivity is persistent, so a lagged dependent variable is required to avoid overstating the contemporaneous effects of policy. Second, support is endogenous, i.e. unobserved factors can jointly determine productivity and policy, and productivity shocks can themselves trigger policy responses. The paper estimates a dynamic panel model using the System GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998), which is an efficient approach when there is a lagged dependent variable among the regressors, there are endogeneity issues and a limited number of observations. To address a dimension of endogeneity, rural voter turnout, constructed as the interaction of rural population share and parliamentary voter turnout, is used as an external instrument for agricultural support. The exclusion restriction is motivated by the political economy literature (Krueger, 1974; Swinnen, 2018; Anderson, 2009), which states that higher rural political participation raises the marginal electoral return to rural targeted policies and therefore the equilibrium level of support, while, conditional on controls, it is unlikely to shift the short-run agricultural production frontier.

The main findings establish that the composition of support is substantially more informative than its aggregate level for explaining TFP in LAC. Total support (TSE) and producer support (PSE) are not positively associated with productivity: under the Färe–Primont index, a one percentage point increase in either variable as a share of agricultural GDP is associated with a reduction of roughly 0.14–0.16 points in TFP, significant at the 10% level for PSE, while the USDA estimates are close to zero. Decomposing producer support reveals that this aggregate pattern is driven by market price support (MPS), which is negatively associated with productivity under both indices and significantly so, at the 5% level, under the Färe–Primont index (−0.207), while direct transfers display a positive and marginally significant association under the USDA index (0.312). Budget support, defined as the sum of direct transfers and GSSE, is positively correlated with productivity but not statistically significant. Contemporaneous GSSE itself is not significantly related to current TFP, consistent with the view that public goods deliver delayed returns. A complementary specification that replaces contemporaneous GSSE with a gamma-weighted stock of agricultural public knowledge built from fourteen lags of public R&D expenditure yields a positive coefficient under both indices, significant at the 1% level under the USDA index but not under the Färe–Primont index, supporting the hypothesis that R&D raises productivity over longer horizons. This long-run relationship is further corroborated by an error correction model estimated for both the LAC and OECD samples, which confirms a positive and significant long-run elasticity of TFP with respect to the agricultural public stock of knowledge in LAC; in the OECD sample the elasticity is also positive, significant at the 10% level with a 10-year lag structure and marginally insignificant with the 14-year structure used for LAC, reinforcing the robustness of the central conclusion. The negative association between MPS and TFP is preserved when a dummy for the pandemic years is added and when MPS and direct transfers are estimated jointly, and formal tests do not reject the equality of the estimated coefficients across the two productivity indices (Section 5.5).

This paper makes three contributions. First, it provides the first systematic cross-country evidence for LAC on the differential TFP effects of MPS, DT, and GSSE within a unified PSE framework. Existing regional evidence has either focused on aggregate support or on narrower subsamples, and has not consistently separated price-based from budgetary instruments. Second, it incorporates the lag structure of public R&D explicitly by constructing a stock of agricultural public knowledge (Alston et al., 2009; Fuglie, 2018; Lachaud and Bravo-Ureta, 2021; van Dijk et al., 2025). This allows the empirical model to distinguish the short-run effects of contemporaneous public spending from the long-run effects of accumulated knowledge, and it reconciles the null short-run GSSE estimate with the consensus that public goods are productivity enhancing. Third, the paper incorporates a political economy perspective of agricultural policy empirically by using rural voter turnout as an external instrument within the System GMM framework. To our knowledge, this is the first cross-country application of this instrument to agricultural productivity in LAC, and it

addresses a dimension of endogeneity (policy selection driven by rural electoral incentives) that internal instruments alone cannot fully resolve.

The findings carry direct policy implications for a region in which market price support still dominates producer assistance. They suggest that gradually reducing distortionary MPS in favor of targeted direct support can improve productivity outcomes in the short run, while sustained public R&D and public goods investments are required to lift the long-run production frontier. They also highlight the need to complement PSE accounting with rigorous, counterfactual-based impact assessments of specific interventions, a point developed further in the policy discussion.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework. Section 3 presents the construction and sources of the variables, and their empirical performance during the sample. Section 4 presents the model specifications. Section 5 presents the main findings, including a complementary analysis to address the long dependence effect of R&D. Section 6 concludes with policy implications.

2. Theoretical framework

Policy instruments differ not only in how they are financed but also in how they affect producer incentives, resource allocation, and the accumulation of agricultural knowledge. Three mechanisms are relevant: (i) allocative efficiency under price wedges; (ii) market failures, liquidity, and technology adoption under budgetary transfers; and (iii) knowledge accumulation and delayed productivity effects of public goods.

Let aggregate agricultural output in country *i* at time *t*, denoted by Y_{it}, be produced using a vector of aggregate inputs $X_{it} = (K_{it}, L_{it}, T_{it}, M_{it})$, where K_{it} is capital, L_{it} is labor, T_{it} is land, and M_{it} denotes intermediate materials. Following the standard growth-accounting representation (Solow, 1957; Jorgenson & Griliches, 1967), we write sectoral technology as a constant returns to scale production function:

$$Y_{it} = A_{it}\, F(X_{it}) \qquad (1)$$

TFP, A_{it}, is the portion of output growth that cannot be attributed mechanically to input accumulation. Given that A_{it} is not directly observed, it is approximated through alternative TFP indices constructed under different assumptions about aggregation, prices, and weights. Within this framework, movements in measured TFP can arise from (a) technical change, an outward shift of the production frontier; (b) changes in technical efficiency, movements toward or away from the frontier; and (c) changes in allocative efficiency, shifts in how inputs and outputs are distributed across farms, activities, and regions with different marginal products (Kumbhakar & Lovell, 2000; O'Donnell, 2012). Agricultural support

policies can influence each of these components, which implies that the composition of support must be analyzed component by component rather than through a single aggregate.

First, some agricultural support instruments operate by creating wedges between domestic producer incentives and social opportunity costs. To illustrate, consider a farm with production $y = a * f(x)$, where *a* denotes farm level productivity and *x* is a vector of variable inputs with prices *w*. Output is sold at price *p*. In the absence of policy interventions, profit maximization yields input demand and output supply as functions of *(p, w)* and *a*. Support that affects output prices or input costs can be represented as wedges that modify these incentives.

Let $\tilde{p} = p(1 + \tau_y)$ denote the effective output price under an output wedge τ_y and $\tilde{w}_j = w_j(1 - \tau_j)$ denote the effective price of input *j* under an input wedge τ_j. This formulation is standard in the misallocation literature (Restuccia & Rogerson, 2008; Hsieh & Klenow, 2009) and has been applied specifically to agriculture by Adamopoulos and Restuccia (2014), who show that cross-country dispersion in producer specific wedges accounts for a large fraction of observed farm-size and productivity differences.

In a frictionless representative firm model, uniform wedges alter production levels without changing farm level productivity *a*. Once heterogeneity in productivity, adjustment costs, and incomplete credit, insurance, and land markets are introduced, features that are empirically pervasive in LAC agriculture (de Janvry & Sadoulet, 2020; Adamopoulos & Restuccia, 2020), price wedges lower aggregate TFP through three channels. They reduce allocative efficiency. They sustain production in lower productivity farms, commodities, and regions that would otherwise contract, and slow the reallocation of land, labor, and capital toward higher productivity uses, by raising returns in supported activities (Restuccia & Rogerson, 2017; Chen et al., 2023). A larger share of inputs is employed where marginal products are lower, which shows up as lower measured TFP. In addition, persistent wedges weaken incentives for efficiency enhancing innovation and management. When producer returns are insulated from market signals, the private payoff to adopting cost saving technologies falls, particularly when support is conditional on maintaining existing production patterns (Rizov et al., 2013; Minviel & Latruffe, 2017). Finally, by altering relative returns across commodities and regions, support based on price can push production onto marginal land, lowering average productivity and generating environmental externalities that erode productivity over time (Piñeiro et al., 2020).

Second, other instruments are direct transfers to producers. Direct transfers to producers are budgetary payments that, unlike price wedges, can be designed to relax specific market failures rather than to prop up domestic prices. Two channels dominate. The first operates through liquidity and credit constraints. When credit markets are incomplete, profit maximizing input use falls short of the unconstrained optimum x^*. Farms underinvest in

fertilizers, improved seeds, machinery, animal health, and complementary practices. Transfers that relax the binding constraint move producers closer to x^* and accelerate adoption of productivity enhancing technologies (Banerjee & Duflo, 2010; Karlan et al., 2014; Feder et al., 1985). The second operates through risk. Agricultural returns are subject to substantial climate and price volatility, and insurance markets are thin. When downside risk is binding, farms may forgo investments with high expected returns but high upfront costs (Rosenzweig & Binswanger, 1993; Karlan et al., 2014). Transfers that reduce effective risk exposure can unlock such investments. Unlike R&D, these effects operate through farm level decisions and can materialize relatively quickly. However, the sign of the productivity effect is design dependent. Transfers tightly coupled to specific outputs or inputs can reintroduce the allocative distortions associated with price wedges (OECD, 2001; Rizov et al., 2013), while less distortionary transfers tied to area, animals, or income are more likely to deliver productivity gains.

Third, another distinct channel operates through public goods that shift the agricultural production frontier. Investments in R&D, extension, sanitary and phytosanitary services, infrastructure, and data systems can raise productivity by generating new technologies, lowering transaction costs, improving input quality, and facilitating technology diffusion. A central feature of these investments is that their productivity effects operate with long and distributed lags. Research takes time to generate usable innovations, extension takes time to diffuse them, and adoption by heterogeneous producers is gradual. Following Griliches (1979, 1995) and the knowledge capital tradition (Hall et al., 2010), we write a tractable representation of TFP that depends on both contemporaneous public services and an accumulated stock of knowledge:

$$A_{it} = \exp(\mu_i + \lambda_t)\, S_{it}^{\varphi} \exp(\theta G_{it}) \qquad (2)$$

In equation (2), μ_i captures time invariant country characteristics, λ_t denotes common time shocks, G_{it} is a measure of contemporaneous public services, and S_{it} is the stock of agricultural knowledge generated by past R&D expenditures. The knowledge stock evolves according to a perpetual inventory rule, in which past R&D expenditures depreciate at an obsolescence rate (Griliches, 1980; Hall et al., 2010; Alston et al., 2011). Accordingly, contemporary public spending measures may show limited association with current TFP even when long-run effects are positive, particularly when spending is tilted toward activities with long gestation periods. This has two implications. First, if public services affect productivity primarily through knowledge accumulation, the contemporaneous coefficient on broad public spending categories may be biased toward zero. Second, specifications that incorporate lag structures or knowledge stock measures should better capture the long-run productivity contributions of R&D and related public goods.

This framework motivates the following hypothesis:

Hypothesis 1: Support instruments that operate primarily through broad price wedges and distorting market signals are expected to be negatively associated with TFP, reflecting losses in allocative efficiency and weaker incentives for innovation and restructuring.

Hypothesis 2: Less distortionary budgetary transfers can be positively associated with TFP when they relax credit, insurance, or information constraints and accelerate technology adoption; the magnitude and sign of the association are expected to be sensitive to coupling and targeting.

Hypothesis 3: Public goods, particularly R&D, are expected to raise TFP over longer horizons through knowledge accumulation. Consequently, contemporaneous spending measures may understate productivity impacts, whereas knowledge stock or lagged specifications should better capture long-run effects.

The following section describes the main variables of the model, i.e. the agricultural productivity, the agricultural support, the stock of public knowledge, the control variables, and the external instrument variable used to address the endogeneity of the model.

3. Data and variables

3.1 Sample construction and panel structure

The empirical analysis uses an unbalanced country-level annual panel of 17 Latin American and Caribbean (LAC) countries over the period 1995–2023: Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Guatemala, Jamaica, Mexico, Panama, Peru, Paraguay, and Uruguay. Country selection was determined by the intersection of three data requirements: (i) availability of total factor productivity (TFP) indices from USDA-ERS for the full sample period; (ii) coverage of at least ten consecutive years in the Agrimonitor database, a threshold we consider necessary to identify dynamic relationships under System GMM estimation; and (iii) availability of the full set of macroeconomic, institutional, and climate controls. Countries with shorter Agrimonitor coverage windows (such as Bahamas, Barbados, Suriname, Haiti, and Trinidad and Tobago) appear in some descriptive figures for reference but are excluded from the estimation sample.

The panel is unbalanced as a result of heterogeneous Agrimonitor coverage across countries (Conroy et al., 2024). Table B.1 in the appendix reports, for each country, the years covered and the number of country-year observations used in estimation. On average, we observe 18.9 country-year cells, or 65% of the 493 potential observations. We do not impute missing observations. The System GMM estimator accommodates unbalanced panels through

the use of all available moment conditions at the country level; when forward orthogonal deviations (see Appendix A) span a gap in the data, the corresponding moments are dropped.

Agricultural productivity data are compiled from USDA-ERS (October 2024 release) and from complementary sources described below. Measures of agricultural policy support are obtained from the Agrimonitor database, the IDB-led initiative that extends the OECD producer support estimate (PSE) methodology to non-OECD countries in LAC (Conroy et al., 2024). Climate variables are derived from the Copernicus ERA5 reanalysis (Berg et al., 2018). Macroeconomic and institutional controls are compiled from the World Development Indicators (WDI), the Worldwide Governance Indicators (WGI), and International IDEA.

3.2 Agricultural productivity

Because TFP measurement requires strong assumptions on the aggregation of heterogeneous inputs and outputs, we use two alternative indices that differ in their treatment of prices, weights, and the set of inputs considered. Cross-index agreement strengthens the interpretation of our results, and divergences help localize which methodological assumptions drive specific findings. The indices are:

- *The USDA index,* which follows a Törnqvist-type aggregation approach based on four primary inputs, land, labor, capital, and materials, with cost-share weights that vary by decade (USDA-ERS, 2024; Fuglie, 2015). We use the October 2024 release of the USDA-ERS international agricultural productivity database.
- *The Färe–Primont index,* which is a non-parametric, multiplicatively complete productivity index that satisfies all standard axioms of index number theory (O'Donnell, 2012). It is constructed using a common reference technology, which makes it fully transitive and therefore suitable for multilateral comparisons across countries and time periods. It considers five inputs and is constructed by the authors using USDA-ERS and FAOSTAT (October 2024) data, with shadow prices derived from DEA techniques. Appendix C describes the construction of the index in detail, reports its implied aggregation weights and validates it against the USDA-ERS series.

3.3 Agricultural support variables

Agricultural policy support is measured using indicators derived from the producer support estimate (PSE) methodology. The PSE framework decomposes total government support to agriculture into conceptually distinct channels. Market Price Support (MPS) captures the implicit transfer arising from the gap between domestic and reference international prices for commodities, multiplied by production levels, and therefore reflects support delivered through price-distorting policies such as tariffs, export restrictions, and administered prices. Direct Transfers (DT) refer to explicit budgetary transfers to producers

based on output, area, animal head, income, or input use. The Producer Support Estimate (PSE) aggregates both channels, representing total support received directly by producers. The General Services Support Estimate (GSSE) encompasses public expenditures benefiting the sector as a whole rather than individual producers, including agricultural R&D, health and inspection services, rural infrastructure, marketing, and public storage. Finally, the Consumer Support Estimate (CSE) captures transfers to or from consumers through food subsidies or price distortions, and the Total Support Estimate (TSE) consolidates all three components: PSE, GSSE, and CSE. Although CSE is included in the TSE aggregate, it is not analyzed as a separate regressor in the empirical specifications, as our focus is on the supply-side channels through which policy support may affect agricultural productivity.

We additionally define Budget Support as the sum of DT and GSSE, capturing actual fiscal expenditures on agriculture as distinct from implicit MPS transfers. This decomposition allows us to separate distortionary support channels (MPS) from non-distortionary ones (DT, GSSE), an empirically relevant distinction given the heterogeneous effects on productivity predicted by the literature (Anríquez et al., 2016; Piñeiro et al., 2020).

All support variables are expressed as a share of agricultural GDP, measured as agricultural value added from the WDI, to ensure cross-country comparability. This normalization scales policy intensity relative to the size of each country's agricultural sector and mitigates concerns about mechanical correlation with sector size.

3.4 Stock of agricultural public knowledge

Public R&D expenditures produce productivity gains only gradually, as new technologies are developed, validated, disseminated, and adopted. A contemporaneous R&D flow variable would therefore substantially understate the role of research. Following the distributed-lag tradition in the agricultural productivity literature (Alston et al., 2009; Fuglie, 2018; Lachaud and Bravo-Ureta, 2021), we construct a stock of agricultural public knowledge as a gamma-weighted accumulation of past R&D flows.

Let $R_{i,t}$ denote real public agricultural R&D expenditure in country i and year t, obtained from van Dijk et al. (2025). The stock of agricultural public knowledge, $K_{i,t}$, is defined as:

$$\log(K)_{it} = \sum_{j=0}^{J} \varpi_j \log(R)_{t-j} + \xi_t \qquad (5)$$

where the weights ϖ_j follow a discretized gamma distribution of shape φ and scale ψ:

$$\varpi_j = \frac{(j-g+1)^{\left(\frac{\varphi}{1-\varphi}\right)}\psi^{(j-g)}}{\sum_{j=0}^{J}\left[(j-g+1)^{\left(\frac{\varphi}{1-\varphi}\right)}\psi^{(j-g)}\right]}, \quad J \geq j > g \qquad (6)$$

The gamma weighting scheme produces a flexible lag profile in which weights can rise initially, peak at an intermediate lag, and then decline—consistent with the empirical pattern of agricultural innovation adoption and obsolescence (Alston, 2018; Baldos et al., 2019; Lachaud, 2025). The weights are normalized to sum to unity ($\sum_{j=0}^{J} \varpi_j = 1$), ensuring that $\log(K)_{i,t}$ can be interpreted as a proper weighted average of past log R&D expenditures. Two design choices are required. First, the lag length J is selected empirically using an auto-regressive distributed lag (ARDL) procedure applied to the full model, which identifies J = 14 as the optimal truncation. Second, the shape and scale parameters (φ, ψ) are selected via a grid search over 81 combinations, evaluated on the basis of (i) the Akaike and Bayesian Information Criteria (AIC/BIC), and (ii) the consistency of the resulting lag profile with the adoption and depreciation patterns documented for agricultural R&D (Fuglie, 2018) and, specifically for the Latin American context, with Lachaud (2025). The final values (φ = 0.8, ψ = 0.4) jointly minimize AIC/BIC among the candidates considered and produce a lag profile peaking at lags 3–4, in line with the technology-adoption timing reported in this literature.

Figure 1 displays the resulting lag profile together with two alternative parameterizations: (φ = 0.75, ψ = 0.5) and (φ = 0.7, ψ = 0.65). The preferred parameterization places peak weight on lags 3–4 and assigns substantial but declining weight to lags up to 14, which is consistent with the adoption cycle of agricultural technologies documented in Fuglie (2018).

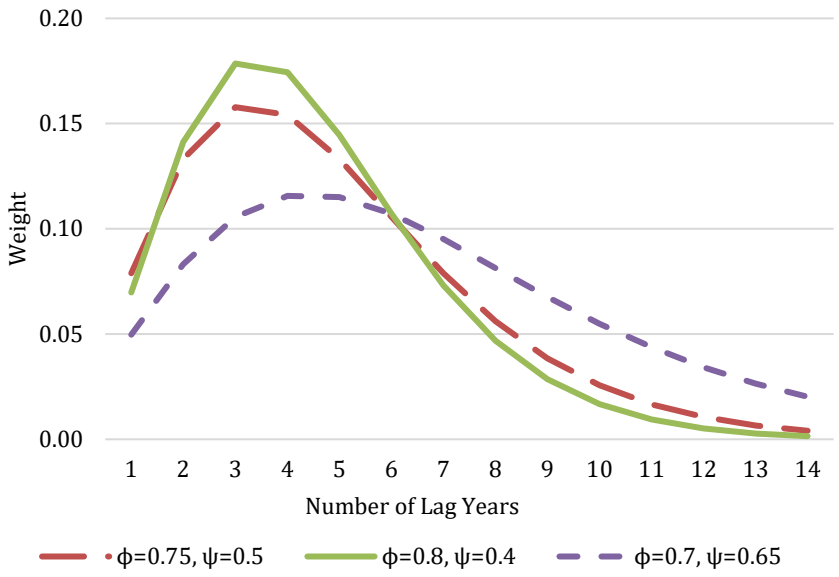


Figure 1. Gamma lag distribution for the construction of the stock of agricultural public knowledge

The stock variable, normalized by agricultural GDP, enters the empirical specification in natural logarithms, allowing the associated coefficient to be interpreted as the elasticity of TFP with respect to the accumulated knowledge stock.

3.5 Control variables

We include three groups of controls intended to absorb country-specific conditions that may simultaneously affect TFP and the allocation of agricultural support.

We include climate control variables constructed from the Copernicus ERA5 reanalysis (Berg et al., 2018), a 0.25° × 0.25° daily gridded product. We compute two annual country-level variables: (i) total annual precipitation (mm), aggregated from the grid to national boundaries using cropland area weights; and (ii) the number of extreme heat days per year, defined as days on which the country-average daily maximum temperature exceeds the 1961–1990 country-specific historical mean of the same calendar day by at least two standard deviations. Climate controls capture direct production shocks that would otherwise confound the relationship between policy support and productivity, as governments often respond to adverse weather events with emergency transfers.

We also include macroeconomic control variables such as trade openness (the sum of exports and imports as a share of GDP, WDI), and the annual consumer price inflation (WDI). Trade openness captures the transmission of international price signals and the pace of technology diffusion, consistent with the theoretical channel by which trade conveys embodied technology across borders (Eaton & Kortum, 2002) and with empirical evidence linking trade openness to total factor productivity growth (Miller & Upadhyay, 2000). Inflation is treated as potentially endogenous in specifications involving MPS, PSE, or TSE, because price-level dynamics enter mechanically into the measurement of these support categories. In specifications involving DT, GSSE, Budget Support, or the knowledge stock, inflation is treated as exogenous.

Finally, we include an institutional quality control variable. This is proxied by the Control of Corruption indicator from the WGI, expressed as a country percentile rank. Corruption has been shown to distort the allocation of public resources and undermine agricultural productivity in developing countries (Bulte et al., 2007), consistent with the broader evidence that corruption reduces growth by lowering investment and misallocating public resources (Mauro, 1995).

3.6 External instrument: rural voter turnout

To achieve identification of the causal effect of agricultural support on TFP, we exploit an external instrument: the rural voter turnout index. The economic rationale is grounded in the political economy of agricultural policy (Krueger, 1974; Swinnen, 2018; Anderson, 2009): rural constituencies that are both numerous and politically engaged exert greater pressure on legislators to enact and sustain agricultural support programs than constituencies that are large but politically inactive or small but politically engaged. The interaction form of RVT captures precisely this joint condition.

The rural voter turnout index, $RVT_{i,t}$, is defined as the interaction of the rural population share and national parliamentary voter turnout:

$$RVT_{i,t} = RuralShare_{i,t}\ x\ Turnout_{i,t} \qquad (7)$$

where $RuralShare_{i,t}$ is the share of the population living in rural areas in country i and year t (WDI), and $Turnout_{i,t}$ is the voter turnout rate at the most recent parliamentary election, sourced from the International IDEA Voter Turnout Database (IDEA, 2024).

Rural voter turnout shifts policymakers' incentives to allocate resources toward agriculture: higher rural turnout raises the marginal electoral return to rural targeted policies, increasing the equilibrium level of support (Swinnen, 2018). Conditional on controls for macroeconomic conditions, climate shocks, and institutional quality, rural turnout is not expected to shift the agricultural production frontier directly in the short run.

Because parliamentary elections in most LAC countries occur at intervals of 3–5 years, we linearly interpolate turnout between election years and carry the last observed value forward for years after the most recent election. This interpolation preserves the cross-country and across-election variation required for identification. The rural voter turnout index captures the political weight of rural constituencies in the formation of agricultural policy: the product rises when rural populations are both large and politically engaged. The instrument's relevance, exclusion restriction, and the diagnostic tests used to assess its validity are discussed in Section 4.3.

3.7 Descriptive statistics

Table 1. Descriptive statistics

Variable	Unit	N	Mean	Std. Dev.	Min	Max
Panel A: Outcome Variables						
TFP USDA	Index	493	93.11	16.75	45.74	155.99
TFP Färe–Primont	Index	493	95.55	22.59	50.70	217.20
Panel B: Policy Support Variables						
Total Support Estimate	USD mn / agricultural GDP	330	14.43	18.44	-45.03	64.86

Producer Support Estimate	USD mn / agricultural GDP	330	10.97	17.73	-46.81	62.55
Market Price Support	USD mn / agricultural GDP	330	7.56	17.02	-47.85	59.09
Budget Support	USD mn / agricultural GDP	330	6.34	4.04	0.00	18.95
Direct Transfers	USD mn / agricultural GDP	330	3.41	3.08	0.00	14.81
General Services Support Estimate	USD mn / agricultural GDP	330	2.93	1.79	0.00	9.17
Stock of Agricultural Public Knowledge	Log	476	17.70	1.82	14.14	21.76
Panel C: Control Variables						
Annual Precipitation	Millimeters	493	1,739.37	798.61	477.40	4,169.92
Extreme Heat Days	Number of days per year with temperature shocks	493	35.13	41.16	0.00	313.00
Trade Openness	Ratio of total exports and imports of goods and	493	61.43	26.35	13.94	169.19

	services to GDP (% of current US$)					
Inflation	Annual consumer price inflation (%)	487	7.37	10.96	-7.11	133.50
Log agricultural GDP (constant 2017 US$)	Log	493	22.24	1.42	18.46	25.38
Control of Corruption	Country percentile rank of political institutions	425	44.66	20.95	1.06	92.45
Panel D: External Instrument						
Rural Voter Turnout	Interaction of rural population and voter turnout in parliamentary elections	493	19.99	10.11	4.02	47.52

Note: Total Support Estimate, Producer Support Estimate, Market Price Support, Direct Transfers, General Services Support Estimate, and Budget Support are normalized by agricultural GDP. N reflects data availability for each variable (1995–2023, 1995–2022 for the R&D stock). The effective System GMM estimation sample is smaller (321 observations for the agricultural support specifications, with a similar reduction for the R&D stock specification) due to the lags required to construct internal GMM instruments; see regression tables for the exact N per specification. The stock of agricultural public knowledge is reported as the log of its level, as used in the error correction models; in the System GMM specifications (Table 3) it enters as the log of the stock normalized by agricultural GDP (N = 476, mean −4.53, s.d. 0.80, min −7.00, max −3.05). Log agricultural GDP enters only the error correction models of Section 5.3, as a short-run control in first differences.

Table 1 reports descriptive statistics for the variables used in the analysis. Panel A presents the two TFP indices used as outcome variables (USDA-ERS and Färe–Primont), both available for the full sample period. Panel B reports the variables of interest, each entering a

separate System GMM specification. TSE, PSE, and MPS take negative values in a subset of country-years, reflecting periods of implicit taxation of agriculture—typically associated with export restrictions or price controls—rather than support. DT and GSSE, consisting of budgetary transfers, are non-negative by construction; Budget Support, their sum expressed as a share of agricultural GDP, is reported separately. Coverage of the six Agrimonitor-sourced variables (N=330) is lower than the rest of the panel due to gaps in Agrimonitor's country-year coverage, and the effective GMM estimation sample is smaller still (N=321) once the lag structure required for internal instruments is imposed. The stock of agricultural public knowledge, used in its own specification, is available through 2022 rather than 2023, with an analogous reduction applying to its GMM sample.

Panel C summarizes the control variables (climate, trade openness, inflation, and control of corruption); trade openness exceeds 100% for countries such as Panama and Paraguay, small and highly open economies within the sample, and inflation exhibits a long right tail reflecting episodes of high inflation in countries such as Argentina. Finally, Panel D reports rural voter turnout, the external instrument used in the System GMM estimation.

3.8 Descriptive patterns of main variables

First, agricultural productivity has grown substantially in LAC since 1995 but has shown signs of deceleration in recent years. Figure 2 illustrates this pattern, plotting the two TFP indices over the period 1995–2023. Both indices agree on a period of sustained and strong growth between 1995 and 2010. After 2010, trajectories begin to diverge: the USDA index continues growing robustly, with a notable acceleration toward 2023, while the Färe–Primont, by contrast, exhibits a sharper contraction around 2020–2021, followed by a recovery to its pre-pandemic level by 2023. These divergences across indices are consistent with their different weighting structures and aggregation approaches and motivate the use of multiple TFP measures throughout the empirical analysis.

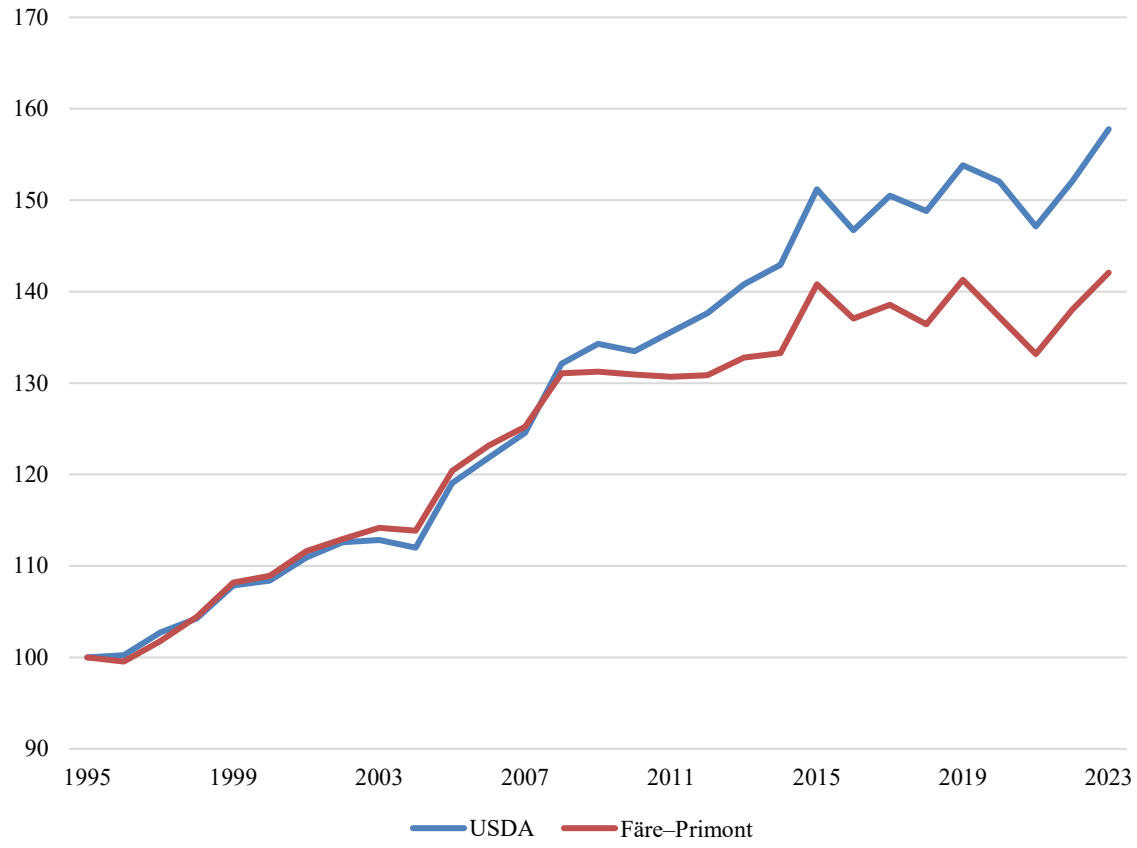


Figure 2. Agricultural Productivity Indices for Latin America and the Caribbean

Second, total agricultural support as a share of agricultural GDP varies widely across LAC. Figure 3 shows that Jamaica, Barbados, Panama and Trinidad and Tobago exceed 40% of agricultural GDP, whereas Argentina exhibits negative total support (reflecting implicit taxation of producers through export restrictions). The LAC regional average stands at 18%, well below the levels observed in Canada, the European Union, and the United States (approximately 25%, 37%, and 54% respectively).

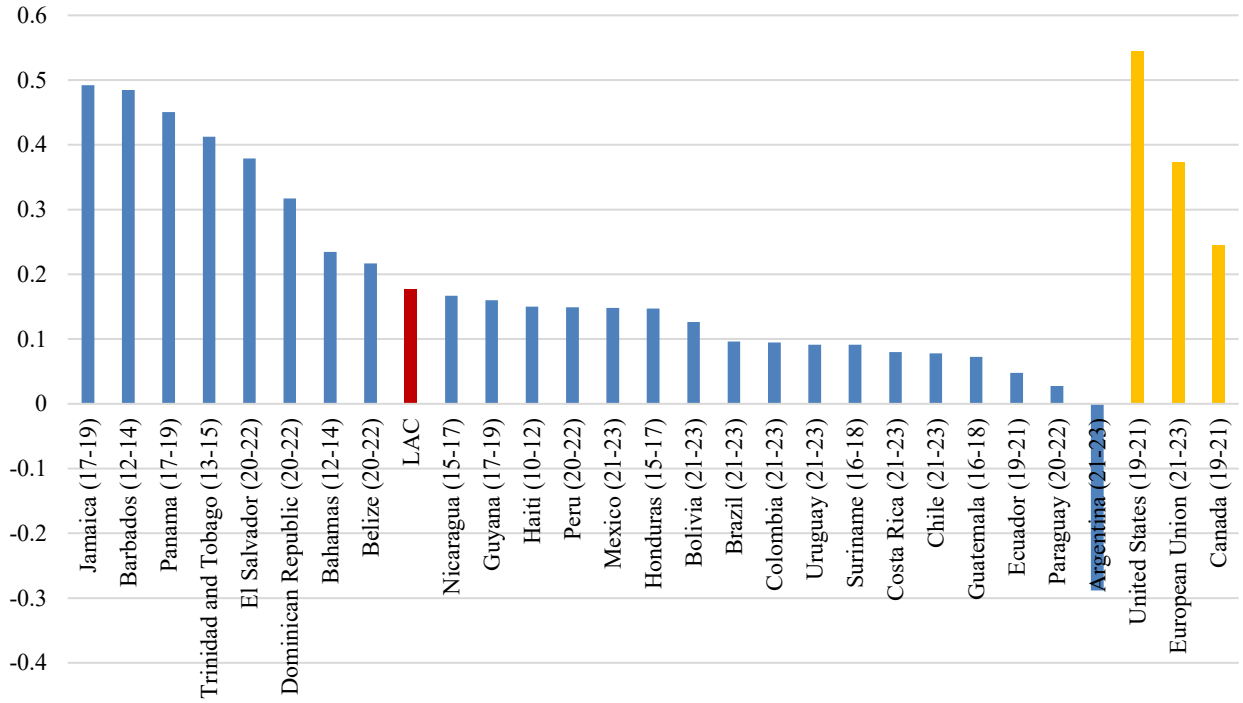


Figure 3. TSE as a percentage of agricultural GDP, average of last three years available until 2023

Source: Own elaboration using Agrimonitor and World Bank datasets.

Third, the composition of producer support in LAC is heavily tilted toward MPS. Figure 4 shows that at the regional level, 73% of PSE is delivered through MPS and only 27% through direct transfers. This composition contrasts with the OECD benchmarks (Canada, the EU, and the US), where MPS accounts for less than half of PSE. Only Uruguay, Chile, and Paraguay exhibit MPS shares below 50% within LAC.

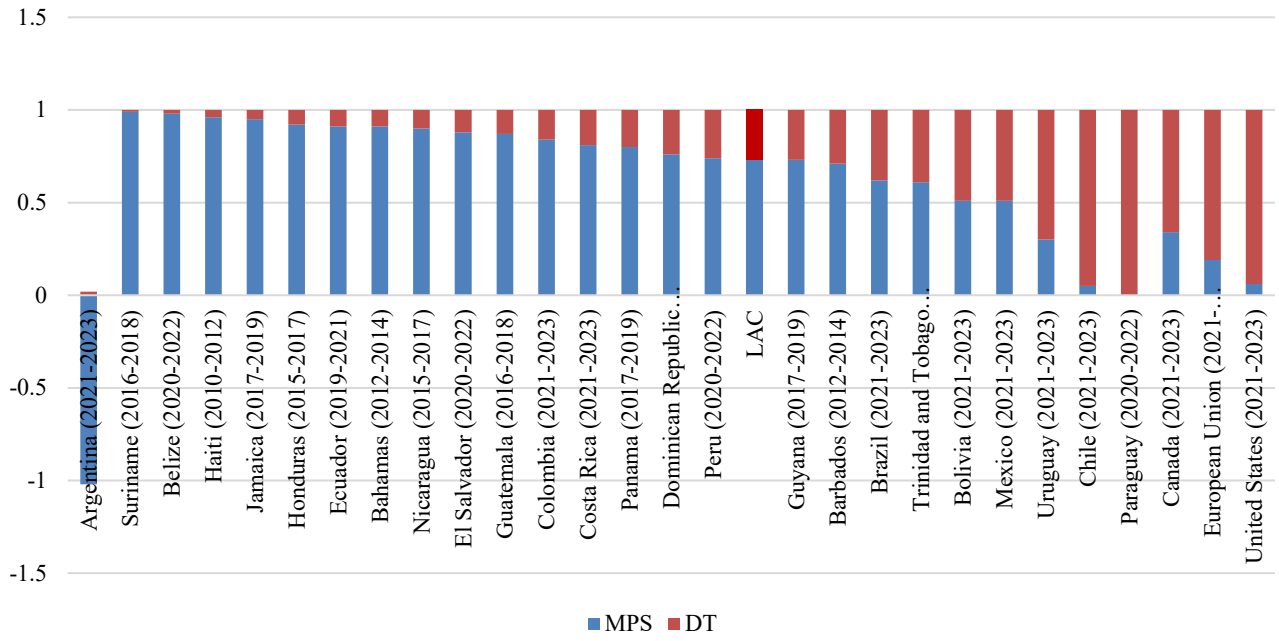


Figure 4. PSE components (MPS and DT) until 2023
Source: Own elaboration using Agrimonitor dataset.

4. Methods

Our objective is to quantify the effect of agricultural support policies on agricultural productivity, allowing for the dynamic nature of TFP, and for the potential endogeneity of support policies with respect to productivity outcomes. This section presents the estimating equation (4.1), the sources of endogeneity we need to address and the motivation for our choice of System GMM (4.2), the moment conditions used in estimation (Appendix A), and the identifying assumptions for the external instrument (4.3).

4.1 Model specification

We estimate a dynamic panel model using the System GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998), which is a suitable approach when there is a lagged dependent variable among the regressors, there are endogeneity issues, there are unobserved fixed effects, the number of individuals (N) is large, while the number of time periods (T) is relatively small. The general equation can be expressed as follows:

$$TFP_{i,t} = \alpha \cdot TFP_{i,t-1} + \beta' X_{i,t} + \gamma \cdot SE_{i,t} + t + \varepsilon_{i,t} \qquad (8)$$

where $TFP_{i,t}$ is one of our alternative TFP indices for country i in year t; the lagged dependent variable $TFP_{i,t-1}$ captures the persistence of agricultural productivity; $SE_{i,t}$ is one of the agricultural support variables (TSE, PSE, MPS, DT, GSSE, or Budget Support), expressed as a share of agricultural GDP; $X_{i,t}$ is the vector of control variables (precipitation,

extreme heat days, trade openness, inflation, control of corruption); and $\varepsilon_{i,t}$ is the idiosyncratic error term. Country fixed effects η_i are not included as regressors but are instead eliminated through the forward orthogonal deviations transformation (Arellano and Bover, 1995), which subtracts from each observation a weighted average of all future observations for the same unit, thereby removing time-invariant unobserved heterogeneity without introducing the finite-sample bias associated with the inclusion of country dummies in dynamic panel models. Year fixed effects are similarly excluded: in a System GMM framework, each time dummy requires a dedicated instrument column and including a full set of $T-1$ dummies would generate more instruments than cross-sectional units ($N = 17$), violating the necessary condition for valid inference and inducing the instrument proliferation problem documented by Roodman (2009). The linear time trend t is included instead as a parsimonious alternative that captures common secular trends in agricultural productivity while preserving the validity of the moment conditions.

The parameter of interest is γ, interpretable as the effect of a one-percentage-point increase in a given support measure (as a share of agricultural GDP) on the TFP index. Common LAC-wide shocks are partially absorbed by the linear time trend *t* and by the control variables in $X_{i,t}$, particularly trade openness and inflation, though we acknowledge this may not fully capture the idiosyncratic timing and magnitude of each episode, and interpret γ with this caveat in mind.

We estimate Equation (8) separately for each support category. TSE, PSE, and their components are definitionally related (TSE = PSE + GSSE + CSE; PSE = MPS + DT), and joint inclusion would induce exact multicollinearity. The parallel specifications capture the total association between each policy channel and TFP, not the marginal effect conditional on the remaining channels—a distinction we emphasize in the interpretation of results.

Also, a second specification is estimated for the effect of public agricultural R&D. In this specification, $SE_{i,t}$ is replaced by $log(K)_{i,t}$, and both TFP indices are transformed into natural logarithms, so that γ is interpretable as the elasticity of TFP with respect to the accumulated stock of agricultural public knowledge.

4.2 Identification strategy and estimator choice

A within-group or OLS estimation of Equation (8) faces four sources of endogeneity. First, unobserved country-specific factors, such as the quality of agricultural extension networks, land tenure security, long-run investment culture, and institutional trust, may simultaneously determine TFP and the political allocation of support. While the forward orthogonal deviations transformation removes the time-invariant component of these unobservables, time-varying confounders remain a concern. Second, reverse causality arises because governments may respond to agricultural performance by adjusting support levels.

Political economy models predict both directions: governments may increase support for lagging sectors (political insurance; Swinnen, 2018) or for successful ones (rent capture; Krueger, 1974), and either mechanism generates correlation between $SE_{i,t}$ and the error term. Third, contemporaneous shocks, such as a severe drought, may simultaneously depress TFP and trigger emergency transfers, inducing a mechanical negative correlation between $SE_{i,t}$ and $\varepsilon_{i,t}$. Fourth, the inclusion of the lagged dependent variable $TFP_{i,t-1}$ induces Nickell bias (Nickell, 1981) under within-group estimation. Although the bias is of order *1/T* and vanishes asymptotically, with at most 28 annual observations per country (19 on average) it remains non-negligible when the autoregressive coefficient α is close to unity, as is typical for productivity series.

We address these concerns jointly by estimating Equation (8) using the System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), which dominates plausible alternatives on three grounds. Within-group estimation yields inconsistent estimates of α in finite T, which in turn contaminates the estimate of γ. The Anderson–Hsiao (1981) IV estimator provides consistent but inefficient estimates, discarding moment conditions available under conditional homoskedasticity and producing large standard errors in short panels. The Arellano–Bond (1991) difference GMM estimator uses all available lags as internal instruments for the first-differenced equation, but when the autoregressive coefficient is close to unity, lagged levels become weak instruments for subsequent first differences, resulting in severe finite-sample bias (Blundell and Bond, 1998).

System GMM augments the first-differenced equation—here implemented via forward orthogonal deviations (Arellano and Bover, 1995)—with a levels equation in which lagged first differences of the endogenous variables serve as instruments for their contemporaneous levels. Under the additional identifying assumption that first differences of the endogenous variables are uncorrelated with the unobserved country-specific component removed by the transformation, the levels equation introduces additional moment conditions that substantially increase instrument strength and estimator efficiency. System GMM has become the standard estimator for dynamic panels (Roodman, 2009a, 2009b), and is well suited to our setting: while the sample spans up to $T = 29$ years, Agrimonitor coverage varies considerably across countries, with an average of approximately 19 periods available for the agricultural support variables, reinforcing the finite-T motivation for the System GMM approach over alternatives that require long time series.

We restrict the lag range to *s = 2, 3* to mitigate instrument proliferation (Roodman, 2009b). We additionally apply the collapse option to the instrument matrix, which reduces the dimension of the moment set without discarding information by constructing a single instrument for each lag distance rather than one per (lag distance × time period) combination. The total number of instruments is kept below the number of cross-sectional units n = 17, the standard rule-of-thumb ceiling. The only exception is the robustness check with a pandemic

dummy (Appendix E, Table E.2), in which the instrument count equals the number of countries.

All exogenous controls, such as climate variables, trade openness, and control of corruption, enter the instrument matrix as standard instruments for themselves. Inflation is treated as endogenous in specifications involving MPS, PSE, or TSE, because price-level dynamics enter mechanically into the measurement of these support categories; in the remaining specifications, inflation is treated as exogenous. The lag depth of the internal instruments varies across specifications: specifications involving MPS, PSE, and TSE use lags 2 and 3, while the direct transfers specification extends the lag range to 2 through 4. This extension is motivated by two considerations. First, the diagnostic tests, in particular the Difference-in-Hansen test for the exogeneity of the rural voter turnout instrument, perform better under the broader lag range. Second, treating inflation as exogenous in the direct transfers specification frees instrument slots, allowing the inclusion of a third lag while keeping the instrument count below the ceiling of $N = 17$, so that the TSE, PSE, MPS and direct transfers specifications contain 16 instruments each, while the GSSE, budget support and R&D stock specifications, which use lags 2 and 3 and treat inflation as exogenous, contain 14.

All specifications are estimated by two-step feasible GMM with the Windmeijer (2005) finite-sample correction for standard errors. The two-step estimator uses a consistent estimate of the moment-condition weighting matrix obtained from the first step and achieves asymptotic efficiency relative to one-step GMM. The Windmeijer correction addresses the well-documented downward bias in two-step standard errors that arises in small samples. Standard errors are additionally clustered at the country level to account for within-country serial correlation not fully captured by the dynamic structure of the model.

4.3 Identification via the external instrument

The external moment condition $E[RVT_{i,t} \cdot (\eta_i + \varepsilon_{i,t})] = 0$ requires two identifying assumptions. The first is relevance: $RVT_{i,t}$ must be correlated with the endogenous regressor $SE_{i,t}$, conditional on the remaining instruments and controls. Section 3.6 sets out the political economy rationale for this condition.

The second assumption is exogeneity: $RVT_{i,t}$ must affect TFP only through its effect on $SE_{i,t}$, conditional on the controls in $X_{i,t}$. The main threat to this assumption is that rural political participation may be correlated with broader rural development, such as road density, educational attainment, and financial access, that could affect agricultural productivity directly. We address this concern in three ways. First, the control vector includes trade openness, inflation, institutional quality, and climate shocks, which jointly absorb a substantial portion of the channels through which rural development could affect productivity

in the short run, particularly those correlated with macroeconomic and institutional conditions. Second, by restricting $RVT_{i,t}$ to enter exclusively in the levels equation, we impose a single, more conservative moment condition that is easier to defend theoretically than the alternative of including it in both equations. Third, the slow-moving dimension of rural development, which might plausibly violate the exclusion restriction, is partially absorbed by the forward orthogonal deviations transformation, which removes time-invariant unobserved heterogeneity. The remaining within-country variation in $RVT_{i,t}$ is driven primarily by turnout variation across elections conditional on a slowly-evolving rural share, which is less directly connected to contemporaneous productivity shocks.

We acknowledge that no IV strategy can rule out exclusion restriction violations definitively. Our confidence in the identification derives from the combination of the theoretical grounding of the relevance channel, the consistency of the sign of the estimated γ for the disaggregated support measures across two methodologically distinct TFP indices, and the battery of diagnostic tests reported for every specification in Section 5.

For every specification we report four standard System GMM diagnostics. The Arellano–Bond AR(1) and AR(2) tests assess first- and second-order serial correlation in the FOD-transformed residuals. By construction, AR(1) should reject, as the FOD transformation mechanically induces first-order correlation, whereas AR(2) should fail to reject if the underlying idiosyncratic error $\varepsilon_{i,t}$ is serially uncorrelated—the condition required for the validity of the moment conditions. The Hansen J-test assesses the joint validity of the full instrument set; our collapsed instrument matrix with lag depth (2, 3) is designed to keep the instrument count moderate and the test informative (Roodman, 2009b). The Difference-in-Hansen test evaluates the additional moment condition introduced by the levels equation, and in particular the exogeneity of $RVT_{i,t}$ with respect to $\eta_i + \varepsilon_{i,t}$; rejection would invalidate this moment condition and reduce the estimator to difference GMM. Although the Difference-in-Hansen test has well-known limitations in small samples (Bowsher, 2002; Roodman, 2009b), the test does not reject the exogeneity of the external instrument at the 5% level in any of the specifications of Tables 2 and 3 except the GSSE specification under the Färe–Primont index, which provides reassurance regarding instrument validity while calling for additional caution in interpreting the GSSE estimate. We additionally report the instrument count alongside $N = 17$ as a rule-of-thumb diagnostic, verifying that it remains below the number of cross-sectional units in all specifications of Tables 2 and 3.

5. Findings

5.1 Aggregate support and its composition

The findings indicate that broader measures of agricultural support are not positively associated with productivity. Table 2 shows that TSE exhibits a negative association with agricultural productivity under the Färe–Primont index, where the coefficient falls just short of statistical significance at the 10% level, while under the USDA index the estimate is close to zero and not statistically significant. In magnitude, the estimate implies that a 1 percentage point increase in TSE as a share of agricultural GDP is associated with a reduction in TFP of 0.14 points under the Färe–Primont index. The difference in sign between the two indices is not unusual for aggregate measures of support, given that USDA and Färe–Primont rely on different aggregation procedures and weighting schemes, which can amplify or attenuate broad composition effects. These results suggest that higher aggregate support to the agricultural sector is not systematically associated with higher productivity, aligned with the idea that disaggregation is relevant to understanding what is behind the aggregate results.

A similar pattern arises for PSE. The estimated coefficient is negative and statistically significant at the 10% level under the Färe–Primont index, while under the USDA index it is close to zero and not statistically significant. Quantitatively, a 1 percentage point increase in PSE as a share of agricultural GDP is associated with a reduction in TFP of 0.16 points under the Färe–Primont index. As with TSE, the divergence between the two indices is consistent with the fact that aggregate measures of producer support bundle heterogeneous instruments whose contribution to productivity is not captured uniformly across productivity measures.

When we disaggregate producer support, the results reveal that its pattern is driven primarily by MPS. The estimated coefficient is negative under both productivity indices and statistically significant at the 5% level under the Färe–Primont index. A 1 percentage point increase in MPS is associated with a decline in TFP of 0.21 points under the Färe–Primont index. The estimate for the USDA index is also negative, although it is not statistically significant. This pattern is consistent with the view that support operating through price distortions may reduce productive efficiency.

The findings provide tentative evidence of a positive association between direct transfers and productivity, although the result is not robust across productivity indices. The estimated coefficients are positive under both indices, and the USDA estimate is statistically significant at the 10% level, while the Färe–Primont estimate is of similar magnitude but imprecisely measured. This pattern points towards a possible short-run productivity contribution, but the lack of precision under Färe–Primont prevents drawing a robust conclusion. One possible explanation is that direct transfers include policy instruments with potentially heterogeneous effects on production decisions and input use. Some forms of direct

transfers may relax financial constraints and facilitate productive investment, while others may operate mainly through income stabilization rather than productivity enhancement.

The results for GSSE are also not supportive of a positive short-run productivity effect. Both estimated coefficients are negative and not statistically significant. This finding differs from much of the existing literature, which generally reports positive productivity effects from expenditures on research and development, infrastructure, extension services, and other general services. Several explanations may account for the absence of a positive short-run effect. First, these categories of expenditure tend to affect productivity gradually, so their effects may materialize only over a longer horizon than the one captured in the baseline specification. Second, GSSE expenditures are often lumpy and discontinuous, which complicates the alignment of contemporaneous flows with their productive contribution. Finally, the quality of targeting and implementation of these programs is known to vary substantially across LAC countries, which may attenuate or even reverse their short-run association with productivity.

A negative point estimate could in principle also reflect reverse causality that the instruments do not fully remove, for instance, governments expanding spending on infrastructure, sanitary services or research in response to productivity downturns, or the crowding out of private investment. Two pieces of evidence bound these alternatives (Appendix D). First, we find no evidence of a counter-cyclical response of GSSE. In fixed-effects regressions of GSSE on lagged TFP growth, the coefficient on growth in the previous year is positive in all specifications, and significant in those estimated in changes and, under USDA, also in levels at the 10% level. Feedback of this kind would bias the contemporaneous coefficient upward, not downward, and therefore cannot account for a negative estimate. Second, the estimates are too imprecise to distinguish a small negative effect from zero. The 95% confidence intervals range from −1.49 to 0.89 under USDA and from −1.86 to 1.43 under Färe–Primont, and replacing contemporaneous GSSE with its first lag, or with the average of its first three lags, yields small coefficients that are far from significant. We therefore read the GSSE result as a null short-run association rather than as evidence of a negative effect. Crowding out of private investment cannot be tested with the aggregate data available, and its assessment would require micro-level evidence.

A similar conclusion applies to budget support, defined as the sum of direct transfers and GSSE. The estimated coefficients are positive under both TFP indices, but neither is statistically significant. Although the precision of the estimates is limited, the fact that the signs are consistently positive is suggestive and contrasts with the negative coefficients obtained for TSE, PSE, and MPS under the Färe–Primont index. As with GSSE, the absence of a precisely estimated coefficient should not necessarily be interpreted as evidence of no effect, but rather as an indication that the productivity gains associated with these less

distortionary forms of support may be weak in the short run or may emerge only with substantial lags.

Table 2. Effect of agricultural policy support on TFP

Type of support variable	USDA	Färe–Primont
Total Support Estimate (TSE)		
Coefficient	0.014	**-0.144**
(Std. error)	(0.069)	**(0.089)**
No. instruments	16	16
AR(1) p-value	0.009	0.044
AR(2) p-value	0.532	0.381
Hansen test (p)	0.651	0.556
Difference-in-Hansen (p)	0.292	0.241
Producer Support Estimate (PSE)		
Coefficient	0.011	**-0.158***
(Std. error)	(0.076)	**(0.085)**
No. instruments	16	16
AR(1) p-value	0.009	0.050
AR(2) p-value	0.528	0.396
Hansen test (p)	0.547	0.439
Difference-in-Hansen (p)	0.293	0.227
Market Price Support (MPS)		
Coefficient	-0.071	**-0.207****
(Std. error)	(0.109)	**(0.105)**
No. instruments	16	16
AR(1) p-value	0.010	0.046
AR(2) p-value	0.469	0.382
Hansen test (p)	0.349	0.465
Difference-in-Hansen (p)	0.161	0.238
Direct transfers		
Coefficient	**0.312***	0.283
(Std. error)	**(0.188)**	(0.335)
No. instruments	16	16
AR(1) p-value	0.010	0.061
AR(2) p-value	0.523	0.411
Hansen test (p)	0.713	0.300
Difference-in-Hansen (p)	0.853	0.199
General Services Support Estimate (GSSE)		
Coefficient	-0.298	-0.217
(Std. error)	(0.607)	(0.838)
No. instruments	14	14
AR(1) p-value	0.010	0.040
AR(2) p-value	0.530	0.363

Hansen test (p)	0.546	0.164
Difference-in-Hansen (p)	0.279	0.047
Budget support		
Coefficient	0.350	0.196
(Std. error)	(0.275)	(0.199)
No. instruments	14	14
AR(1) p-value	0.013	0.043
AR(2) p-value	0.523	0.364
Hansen test (p)	0.679	0.385
Difference-in-Hansen (p)	0.613	0.713

Notes: Significance: *** p<0.01, ** p<0.05, * p<0.1. No. countries: 17, no. observations: 321.

These findings suggest that the relationship between agricultural support and productivity depends importantly on the composition of support. The most consistent result is the negative association between MPS and TFP, which appears with the same sign under both productivity indices. Broader aggregate measures, such as TSE and PSE, also tend to be negatively associated with productivity under the Färe–Primont index, although the estimates under the USDA index are close to zero and not statistically significant. On the other hand, direct transfers and budget support display positive but less robust associations, and GSSE does not show a positive contemporaneous effect in either specification. Thus, these findings suggest that the productivity implications of agricultural support depend less on the total volume of support than on the policy instruments through which that support is delivered.

The absence of a robust contemporaneous effect of GSSE on productivity does not necessarily imply that expenditure on public goods is unimportant for agricultural performance. A large literature has documented positive effects of public investments, particularly in research and development, infrastructure, extension, and related services, on agricultural productivity (Ludeña, 2010; Bravo-Ortega and Lederman, 2004; Anríquez et al., 2016). As we explained before, one possible explanation for the weak GSSE results is that these expenditures affect productivity only with substantial lags. In order to explore this possibility, we conduct a complementary analysis focusing on agricultural public R&D, one of the core components of public services.

5.2 Effect of R&D

For this analysis, we construct a stock of agricultural public knowledge from past R&D expenditures using a modified gamma lag structure, following the literature on delayed and cumulative R&D effects (Alston et al., 2009; Fuglie, 2018). The resulting variable, expressed in logarithmic form, captures the accumulated contribution of past public research investments rather than contemporaneous expenditures alone. Figure 1 in the Data section presents the alternative gamma lag distributions used to characterize the time profile of knowledge accumulation and depreciation, while Table 3 reports the estimates obtained using

the baseline dynamic panel specification. This exercise relies on a different data source from the one used in the main GSSE analysis, allowing for a longer time series and more consistent cross-country information on public agricultural R&D expenditures.

The results in Table 3 provide evidence of a positive association between the stock of agricultural public knowledge and TFP. The estimated coefficient is positive under both productivity indices, and the relationship is statistically significant at the 1% level for the USDA index, for which a 1 percent increase in the stock of agricultural public knowledge is associated with an increase in TFP of 0.022 percent. The coefficient for the Färe–Primont index is also positive, although it is not statistically significant at conventional levels. These results are consistent with the view that agricultural R&D contributes to productivity growth, even if the estimates vary across productivity measures.

Table 3. R&D and TFP

R&D variable	USDA	Färe–Primont
Log. stock of agricultural public knowledge	**0.022*** **	**0.024**
(Std. error)	**(0.007)**	**(0.017)**
No. instruments	14	14
AR(1) p-value	0.011	0.026
AR(2) p-value	0.418	0.514
Hansen test (p)	0.550	0.302
Difference-in-Hansen (p)	0.456	0.079

Notes: Significance: *** p<0.01, ** p<0.05, * p<0.1. No. countries: 17, no. observations: 454.

Whereas aggregate GSSE expenditures do not display a robust contemporaneous association with TFP in the baseline regressions, the R&D exercise suggests that this important component of public services may affect productivity through a longer-term accumulation process. This distinction is economically meaningful. R&D is unlikely to generate immediate productivity gains, as its effects depend on knowledge creation, diffusion, and adoption, all of which unfold gradually over time. As a result, regressions based on current support flows may understate the contribution of public goods expenditures whose returns materialize after several years.

Some variation across TFP indices is not surprising in this context, since each measure is constructed using different aggregation methods and therefore captures productivity dynamics somewhat differently. For this reason, coefficient magnitudes and levels of statistical significance need not coincide exactly across specifications. What is more informative is that the estimated relationship between the stock of public agricultural

knowledge and productivity is positive under both indices, which strengthens the interpretation that the long-run contribution of agricultural R&D is likely to be economically relevant, aligned with the literature on this topic.

Section 5.3 complements these estimates with an error correction model that characterizes the long-run equilibrium relationship between accumulated knowledge and agricultural productivity. Its three specifications reveal a consistent pattern: public agricultural knowledge has a positive long-run effect on TFP in both the LAC and the OECD samples.

5.3 Complementary analysis

The System GMM estimates reported above capture the short-run association between agricultural support policies and TFP, exploiting within-country variation in policy allocations while addressing endogeneity through internal and external instruments. However, by design, the System GMM framework does not distinguish between short- and long-run dynamics, nor does it explicitly model the adjustment process toward a long-run productivity equilibrium. This limitation is particularly consequential for agricultural R&D, whose returns materialize only gradually through the accumulation of knowledge stocks (Alston et al., 2009; Fuglie, 2018; Lachaud and Bravo-Ureta, 2021).

To address this, we estimate an Error Correction Model (ECM) using the Pooled Mean Group (PMG) estimator developed by Pesaran, Shin, and Smith (1999), alongside the Mean Group (MG) estimator of Pesaran and Smith (1995) as a less restrictive alternative. The PMG estimator accommodates heterogeneous short-run dynamics across countries while imposing homogeneity of the long-run cointegrating vector, whereas the MG estimator allows both short- and long-run coefficients to vary freely across countries. The choice between the two is guided by the Hausman specification test in each sample. By modeling TFP and the R&D stock as cointegrated I(1) processes, the ECM avoids the potential spurious regression concerns that arise when estimating levels relationships in dynamic panels with persistent series and does not require an external instrument for identification. The System GMM and the ECM are therefore complementary rather than redundant: the former identifies the causal effect of policy support on productivity using exogenous variation in rural voter turnout and is well suited for short panels, while the latter characterizes the long-run equilibrium relationship between accumulated knowledge and agricultural productivity by exploiting the time-series properties of the data.

5.3.1 Data and specification

The key variable of interest is the log of the stock of agricultural public knowledge, $\log(K)_{it}$, constructed following the same procedure described in Section 3. The stock is built as a gamma-weighted sum of past R&D expenditures, with shape parameter $\varphi = 0.8$ and

scale parameter $\psi = 0.4$ selected via grid search, and underlying R&D expenditure data drawn from van Dijk et al. (2025) for both samples. The lag length, however, is allowed to differ across samples: a 14-year window is used for the LAC sample, consistent with the main analysis, while both 14-year and 10-year windows are estimated for the OECD sample to assess sensitivity to the assumed knowledge maturation horizon, a dimension that may differ systematically between research systems in advanced and developing economies.

An important methodological departure from the System GMM analysis concerns the normalization of the knowledge stock. In the main analysis, the stock is normalized by contemporaneous agricultural GDP, consistent with the treatment of all other policy support variables. In the ECM specifications, we use the unnormalized stock of knowledge as the key regressor (Coe & Helpman, 1995), for two reasons. First, normalizing a cumulative stock variable by contemporaneous agricultural GDP imposes the implicit restriction that the long-run coefficient on agricultural GDP equals minus one, a restriction empirically rejected in our data. Second, agricultural GDP is confirmed as I(0) in the OECD sample (IPS: *W-t-bar* = −2.823, $p = 0.002$) and I(1) in the LAC sample (IPS: *W-t-bar* = −1.040, $p = 0.149$), which precludes its inclusion in the long-run cointegrating vector for at least one sample. We therefore include the logarithm of agricultural GDP as a short-run control in first differences in both samples, a symmetric treatment that absorbs contemporaneous fluctuations in sector size without contaminating the long-run relationship of interest.

The dependent variable is the log USDA TFP index, as the Färe–Primont index used in the main analysis is not available for the full set of the OECD sample. The specification includes annual precipitation, extreme heat days, trade openness, institutional quality, and inflation as additional controls, all entering in first differences given their I(0) classification. The model is estimated separately for the 17 LAC countries in the main analysis and the full set of 38 OECD member countries, which includes four LAC-OECD members (Chile, Colombia, Costa Rica, and Mexico).

5.3.2 Unit root and cointegration tests

We verify the order of integration of all variables using the Im-Pesaran-Shin (IPS) and Fisher-type panel unit root tests, applying both with and without a linear time trend as appropriate. Results are reported in Table B.2. For the LAC sample, both $\log(TFP)_{it}$ and $\log(K)_{it}$ are confirmed as I(1): the Fisher test in levels with trend fails to reject the null of a unit root for both variables (Pm = −0.353, $p = 0.638$ and Pm = 1.219, $p = 0.112$, respectively), while first differences strongly reject the null (Pm: $p < 0.01$ for both). With the exception of log agricultural GDP, which is I(1) in the LAC sample (Table B.2, Panel B), all remaining control variables are confirmed as I(0) and therefore enter only the short-run dynamics; log agricultural GDP itself enters in first differences in both samples, as detailed below.

For the OECD sample, the Fisher test in levels with trend confirms I(1) for $\log(TFP)_{it}$ (Pm = −0.200, $p = 0.579$) and for the 14-year stock of knowledge $\log(K)_{it}$ (Pm = 1.429, $p =$

*0.07*7). For the 10-year stock of knowledge, the Fisher test in levels yields mixed evidence: two of the four statistics reject the null of a unit root, while the inverse normal and inverse logit statistics, which are more robust to cross-sectional heterogeneity in large panels, fail to reject ($p = 0.32$8 and $p = 0.18$1, respectively). Given the heterogeneity of the OECD sample, we follow the latter and classify $\log(K_{10})_{it}$ as I(1), consistent with the strong rejection of a unit root in first differences for both stock variables (Pm: $p < 0.00$1 for both). Log agricultural GDP is confirmed as I(0) in the OECD sample (IPS: *W-t-bar* = −2.823, $p = 0.00$2) and enters the short-run dynamics in both samples for symmetry.

Panel cointegration between $\log(TFP)_{it}$ and $\log(K)_{it}$ is assessed using the Pedroni (1999, 2004), Kao (1999), and Westerlund (2007) tests, with results in Table B.3. For LAC (14-year R&D stock), two of three Pedroni statistics reject the null of no cointegration (Phillips-Perron $t = -4.273$, $p < 0.001$; ADF $t = -5.273$, $p < 0.001$), while the Modified Phillips-Perron statistic does not ($p = 0.092$); the Westerlund variance ratio additionally rejects at the 5% level ($p = 0.012$). The Kao test does not reject for this sample ($p = 0.131$). For OECD, the evidence is considerably stronger and fully consistent across both stock specifications: all three Pedroni statistics, the Kao Augmented Dickey-Fuller statistic, and the Westerlund variance ratio reject the null at the 1% level under the 14-year specification (Modified Phillips-Perron $t = -4.708$; Phillips-Perron $t = -11.387$; ADF $t = -11.509$; Kao ADF $t = 4.040$; Westerlund variance ratio = −4.546; all $p < 0.00$1), with virtually identical results under the 10-year specification (Modified Phillips-Perron $t = -4.370$; Phillips-Perron $t = -11.393$; ADF $t = -11.465$; Kao ADF $t = 4.477$; Westerlund variance ratio = −4.509; all $p < 0.00$1). Across all three specifications, these results provide sufficient evidence of a long-run cointegrating relationship to proceed with ECM estimation.

5.3.3 Results

Table 4 reports PMG and MG long-run estimates alongside the Hausman test for all three specifications. The Hausman test fails to reject coefficient homogeneity for the LAC sample (*chi2(1)* = 0.88, $p = 0.34$9), supporting the PMG estimator. For the OECD sample, the test is borderline at both lag specifications (lag 14: *chi2(1)* = 2.64, $p = 0.10$4; lag 10: *chi2(1)* = 3.03, $p = 0.08$2), suggesting genuine heterogeneity in the long-run R&D-productivity relationship across advanced economies, reflecting differences in research systems, institutional capacity, and integration into international knowledge networks, and pointing to the MG estimator as the preferred choice. The error correction term is negative and statistically significant across all specifications, confirming a stable long-run TFP equilibrium in both samples.

Table 4. PMG and MG Estimates: Long-run Effect of Agricultural Public Knowledge Stock on TFP

Models	Model 1: LAC	Model 2: OECD	Model 3: OECD

	PMG	MG	PMG	MG	PMG	MG
Lag structure	**14 years**		**14 years**		**10 years**	
Long-run coefficient						
Log R&D stock	**0.079*** (0.007)**	-4.852 (5.260)	-0.005 (0.011)	0.571 (0.355)	0.008 (0.010)	**0.538* (0.304)**
Short-run dynamics						
ECT	**-0.278*** (0.094)**	-0.372*** (0.102)	-0.263*** (0.047)	**-0.352*** (0.047)**	-0.280*** (0.046)	**-0.386*** (0.046)**
Diagnostics						
Hausman test (p-value)	0.349		0.104		0.082	
Preferred estimator	PMG		MG		MG	
N countries	17	17	38	38	38	38
N observations	436	436	951	951	951	951

*Notes: Standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All specifications include trade openness, institutional quality, precipitation, extreme heat days, inflation, and log agricultural GDP as short-run controls in first differences. The preferred estimator is selected based on the Hausman test.*

a. LAC sample (Model 1)

Under PMG, the long-run elasticity of agricultural TFP with respect to the public knowledge stock is positive and highly significant ($p < 0.001$), implying that a 1% increase in the cumulative R&D stock is associated with a 0.079% increase in long-run TFP. The error correction term ($p = 0.003$) implies that approximately 28% of any deviation from the long-run equilibrium is corrected annually. These findings are consistent with the System GMM results in Section 5.2 and with the broader literature on delayed returns to public agricultural research in developing countries (Fuglie, 2018; Lachaud and Bravo-Ureta, 2021).

b. OECD sample with 14-year lag (Model 2)

When the same lag structure used for LAC is applied to OECD, the long-run coefficient is positive but insignificant under the preferred MG estimator ($p = 0.107$). This suggests that a 14-year maturation horizon, while appropriate for the applied and adaptive research that dominates LAC systems, may be insufficient to capture the longer return profile of the more basic and pre-competitive research that characterizes OECD agricultural systems. The error correction term ($p = 0.000$) confirms long-run equilibrium dynamics.

c. OECD sample with 10-year lag (Model 3)

Reducing the lag to 10 years yields a positive and significant long-run coefficient under MG ($p = 0.077$), consistent with the hypothesis that agricultural innovations in OECD countries reach their productivity impact more rapidly due to more developed research infrastructure, stronger extension systems, and faster technology diffusion channels (Fuglie, 2018; Alston et al., 2023). The error correction term ($p = 0.000$) implies a faster adjustment speed than in LAC, consistent with the more dynamic nature of OECD agricultural systems.

The three specifications reveal a consistent pattern: public agricultural knowledge has a positive long-run effect on TFP in both LAC and OECD, but the maturation horizon differs across development contexts: 14 years in LAC, reflecting slower technology adoption and predominantly applied research, and 10 years in OECD, reflecting faster innovation cycles and more efficient knowledge diffusion (Alston et al., 2023; Fuglie, 2018). These findings reinforce the central conclusion of the paper: sustained investment in public agricultural R&D is a high-return policy instrument in LAC, supported by both the causal short-run evidence from the System GMM and the long-run equilibrium dynamics documented here.

This complementary analysis points to the importance of adopting a longer-term perspective when evaluating the productivity effects of public support in agriculture. The results suggest that the contribution of public expenditures may depend not only on the type of support, but also on the horizon over which their effects are measured. In particular, distortionary support instruments such as market price support are more closely associated with lower productivity in the short run, while investments in public agricultural knowledge appear to be linked to higher productivity through gradual and cumulative channels.

As with the previous results, these estimates should be interpreted with caution. Each regression is estimated separately and therefore captures the relationship between a specific policy variable and TFP without jointly modeling the full set of agricultural support instruments. This modeling choice is deliberate. The support categories examined in the paper are not fully independent from one another, given that some are broad aggregates, while others are components of those aggregates by construction. Therefore, including them simultaneously would generate substantial multicollinearity and complicate the interpretation of individual coefficients, since the estimated effect of one instrument would be conditional on other highly related forms of support. Therefore, when we estimate the regressions separately, we provide a more transparent characterization of how each policy instrument is associated with productivity, and the exercise remains informative, as it suggests that different forms of support may affect productivity through distinct mechanisms and over very different time horizons. Section 5.5 shows, however, that market price support and direct transfers can be estimated jointly without exact collinearity, and that the differential pattern documented here is preserved in that joint specification.

5.4 Measurement considerations and limitations

Several measurement issues bear on the interpretation of results and are acknowledged in this section.

The analysis operates at the national level, which imposes two related limitations. First, aggregate TFP may mask important within-country heterogeneity—including intra-sectoral resource reallocation, farm-level productivity dispersion, and differential policy incidence across producer types. Second, the Agrimonitor indicators capture policy design and fiscal allocation rather than effective resource utilization on the ground: funds budgeted are not necessarily disbursed, and disbursed funds are not necessarily used productively. As a result, the estimated coefficients combine the effects of policy design and implementation and cannot separate the two. Both limitations are imposed by data availability, as comparable micro-level productivity and policy measures are not available across the 17 countries in our sample, and the estimated coefficients should be understood as average country-wide responses rather than structural parameters of a farm-level production function.

Cross-country TFP comparability is constrained by the heterogeneous underlying data and methodological assumptions embedded in each index. We address this concern by employing two alternative indices, USDA and Färe–Primont, and treat qualitative agreement across indices as the primary criterion for the credibility of our conclusions. Appendix C documents the construction of the Färe–Primont index and validates it against the published USDA-ERS series, and Section 5.5 reports formal tests of the equality of the estimates across the two indices. Climate variables are spatially aggregated from gridded reanalysis data to national boundaries using cropland area weights. Measurement error is likely to be more severe in geographically heterogeneous countries such as Peru, Chile, and Mexico, potentially biasing the corresponding coefficients toward zero. Finally, although the System GMM estimator accommodates unbalanced panels, moment conditions that span data gaps are dropped, and the resulting reduction in efficiency is concentrated in countries with shorter Agrimonitor coverage.

5.5 Robustness checks

This section examines three aspects of the robustness of the main results: whether the estimates differ significantly across the two productivity indices, whether they are driven by the pandemic years, and whether the differential association of market price support and direct transfers with TFP survives a joint specification. Appendix E reports the corresponding estimates.

Equality of the estimates across indices: Several results are statistically significant under one productivity index but not under the other. To assess whether these differences are themselves significant, we test the null hypothesis that the coefficient of each support measure is the same in the USDA and Färe–Primont equations. Because both equations are estimated

on the same countries and years, the two estimators are correlated; we estimate this correlation from the country-level contributions to each two-step GMM estimator and combine it with the Windmeijer-corrected standard errors of Tables 2 and 3 to compute a Wald statistic for the difference. Table E.1 shows that equality is not rejected at the 5% level for any support measure. The largest differences, for TSE and PSE, both have p-values of 0.12, the p-value for MPS is 0.24, and for direct transfers, GSSE, budget support and the R&D stock it exceeds 0.5. The divergences across indices in Table 2 therefore reflect differences in precision rather than statistically distinguishable effects.

Pandemic years: The Färe–Primont index contracts more sharply than the USDA index in 2020–2021 (Figure 2). Adding a dummy for 2020 and 2021 to every specification leaves the estimates close to those of Tables 2 and 3 (Table E.2). Under Färe–Primont, TSE, PSE and MPS remain negative and are significant at the 5% level (−0.155, −0.169 and −0.210), while under USDA they remain close to zero. The R&D stock remains positive under both indices, significant at the 1% level under USDA but not under Färe–Primont ($p = 0.17$), and the direct transfers coefficient under USDA is of similar size but no longer significant ($p = 0.15$). The dummy itself is negative and of similar size under both indices: between 1.0 and 2.0 index points under USDA and between 1.3 and 2.4 under Färe–Primont in the support specifications, and 2.5% and 2.6% in the R&D stock specification. Controlling for the pandemic shock therefore does not reduce the differences between the estimates under the two indices. Consistently, 2020 and 2021 account for only 4% of the squared differences between the annual growth rates of the two indices in the estimation sample (Appendix C).

Joint specification of MPS and direct transfers: Because PSE is the sum of MPS and direct transfers, the two components can enter the same equation without exact collinearity, which allows us to test whether their differential association with TFP survives mutual control. To keep the instrument count below the number of countries, the internal instruments for MPS and direct transfers use the second lag only; we report one version in which inflation is treated as endogenous (16 instruments) and one in which it is treated as exogenous (15 instruments). Table E.3 shows that MPS remains negative in all four combinations of index and specification and is significant in two of them: at the 5% level under Färe–Primont when inflation is treated as endogenous (−0.184) and at the 10% level under USDA when inflation is treated as exogenous (−0.121). Direct transfers remain positive in all four (between 0.47 and 0.62), although they are not significant in any. The difference between the two coefficients is between 0.61 and 0.74 TFP points per percentage point of agricultural GDP, and the test of equality yields p-values between 0.11 and 0.19. The joint specification therefore preserves the pattern of the separate regressions: market price support remains negatively associated with TFP once direct transfers are controlled for, while direct transfers remain positively but imprecisely associated with it.

6. Conclusions and policy implications

This paper examines the relationship between agricultural support policies and TFP in LAC using alternative productivity indices and dynamic panel estimators. Three main findings emerge from the analysis. First, broader measures of support, such as TSE and PSE, are not positively associated with productivity in a robust way. Second, the most consistent negative association is found for MPS, suggesting that support operating through price distortions may weaken productive efficiency. Third, less distortionary categories of support, such as direct transfers and GSSE, do not display robust positive contemporaneous effects in the baseline specifications. At the same time, the complementary analysis of agricultural public R&D indicates that some forms of public expenditure may contribute positively to productivity when their effects are examined over a longer horizon and through accumulated knowledge stocks rather than contemporaneous expenditure flows.

These findings suggest that aggregate measures of agricultural support alone may not adequately capture its relationship with productivity, highlighting the importance of considering the composition of support. This point is particularly relevant in LAC, where MPS and other broad transfers continue to account for a large share of producer support. According to Agrimonitor (2025), the MPS represents, on average, 73% of producer support in the region. Only Uruguay, Chile, and Paraguay report MPS levels below half of their PSE, with Uruguay at 30%, Chile at 5% and Paraguay effectively at 0%, while Argentina exhibits negative MPS, implying support for consumers rather than producers. The results are consistent with the view that reducing reliance on distortionary price-based support, while strengthening the design and effectiveness of alternative policy instruments, could contribute to a more productivity-oriented agricultural policy framework.

At the same time, the results do not support the conclusion that all non-price-based support is systematically productivity enhancing in the short run. The estimates for direct transfers are positive under both productivity indices and marginally significant under USDA, but the lack of precision under Färe–Primont prevents drawing a robust conclusion. A similar situation applies to GSSE in the baseline specifications, where the coefficient is negative but imprecisely estimated under both indices and is better read as a null short-run association (Section 5.1). This suggests that the effects of these categories likely depend on policy design, targeting, implementation quality, and the horizon over which outcomes are evaluated. Direct transfers may still play an important role in the presence of liquidity constraints, uninsured shocks, or information frictions, but the results indicate that their productivity effects should not be assumed ex ante. Likewise, expenditures grouped under GSSE may include heterogeneous interventions whose returns may differ substantially in timing and magnitude, and may also be affected by crowding out, lumpiness, or variable implementation quality that dampen their short-run association with productivity.

The complementary analysis of agricultural public R&D provides an important finding as well. Although aggregate GSSE does not display a robust contemporaneous association with productivity, the stock of agricultural public knowledge is positively associated with TFP under both productivity indices and statistically significant under the USDA index. This pattern is consistent with the idea that at least part of the contribution of public support operates through long-run accumulation channels. In particular, expenditures on research are unlikely to generate immediate productivity gains, since their effects depend on processes of knowledge creation, diffusion, and adoption that unfold gradually over time. From this perspective, the absence of a strong contemporaneous GSSE effect should not necessarily be interpreted as evidence that public goods expenditures are unproductive, but rather as an indication that their benefits may materialize with substantial lags.

This interpretation has direct implications for policy design. If different support instruments operate through distinct channels and over different horizons, then the composition of agricultural support becomes central. Measures aimed at immediate income stabilization or short-run relief may serve objectives that are different from those intended to raise long-run productivity. In addition, public investments in research, extension, infrastructure, and related services may be more appropriately assessed from a medium to long-run perspective rather than on the basis of contemporaneous expenditure and productivity relationships alone. The results therefore highlight the importance of examining not only the overall level of agricultural support, but also its composition, objectives, and the time horizons over which different instruments may influence productivity.

The regional evidence on R&D allocation also suggests substantial scope for such reallocation. Brazil and Ecuador devote 94% and 81% of their GSSE, respectively, to R&D and agricultural knowledge, whereas the corresponding share is 11% in Bolivia, 9% in Panama and 7% in Peru (Figure B.1). These differences highlight substantial heterogeneity in the composition of public agricultural expenditures across the region and underscore the importance of assessing whether current allocations to research and innovation are aligned with countries' productivity challenges and investment priorities.

This heterogeneity also highlights an opportunity to reassess spending priorities within agricultural support policies. Countries allocating a relatively small share of public agricultural expenditures to research and innovation could examine whether greater investment in these areas would be consistent with their productivity objectives and existing institutional capacities. The positive long-run association between agricultural public knowledge and TFP identified in the complementary analysis provides additional support for considering R&D within these policy discussions. Although the strength and statistical significance of the estimated relationships vary across specifications and samples, the findings are broadly consistent with the literature emphasizing the potential long-term productivity benefits of sustained public agricultural research. However, the estimated relationships do not

directly quantify the productivity gains from specific budget reallocations, which would require further country-specific analysis.

More broadly, the findings highlight the limits of relying exclusively on support indicators to assess policy effectiveness. These indicators are indispensable for tracking the composition and incidence of support, but they are less informative about causal effects on productivity. A natural implication is that support accounting frameworks should be complemented by more systematic impact evaluations of specific policy instruments. Approaches based on counterfactuals can help identify which interventions generate measurable productivity gains, under what conditions, and over what horizons. This is especially important in a setting where different forms of support may affect productivity through very different mechanisms, some immediate and others cumulative.

Finally, the conclusions of the paper should be interpreted in light of the empirical design. Each support category is examined separately, and the estimates therefore capture average associations rather than the full effects of jointly determined policy portfolios. A joint specification of market price support and direct transfers yields the same differential pattern, although the difference between the two coefficients is imprecisely estimated (Section 5.5). In addition, some variation across productivity indices remains, which reinforces the need for caution in interpreting individual coefficients too mechanically. Formal tests, however, do not reject the equality of the estimates across the two indices (Section 5.5). Even so, the qualitative patterns are informative. The evidence points consistently to a less favorable productivity role for distortionary price support, while offering a more nuanced assessment of non-distortionary instruments, whose contribution appears to depend critically on composition, timing, and implementation. For the region, this suggests that improving agricultural productivity is likely to require not only changes in the level of support, but also a reconsideration of the policy instruments through which that support is delivered.

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Appendix A

Moment conditions and forward orthogonal deviations

System GMM jointly estimates Equation (8) transformed into forward orthogonal deviations (FOD) and Equation (8) in levels. The FOD transformation (Arellano and Bover, 1995) eliminates η_i by subtracting from each observation a weighted average of all available future observations within the same unit. Unlike first-differencing, FOD preserves the first observation of each unit and does not propagate gaps in unbalanced panels. This is a meaningful advantage in our setting, where Agrimonitor coverage differs across countries. We denote the FOD-transformed error by $\varepsilon_{i,t}$. The moment conditions are as follows:

For the FOD-transformed equation:

$$E\left[TFP_{i,t-s} \cdot \varepsilon^*_{i,t}\right] = 0 \qquad s = 2,3 \tag{9}$$

$$E\left[SE_{i,t-s} \cdot \varepsilon^*_{i,t}\right] = 0 \qquad s = 2,3 \tag{10}$$

For the levels equation:

$$E\left[\Delta TFP_{i,t-1} \cdot \left(\eta_i + \varepsilon_{i,t}\right)\right] = 0 \tag{11}$$

$$E\left[\Delta SE_{i,t-1} \cdot \left(\eta_i + \varepsilon_{i,t}\right)\right] = 0 \tag{12}$$

$$E\left[RVT_{i,t} \cdot \left(\eta_i + \varepsilon_{i,t}\right)\right] = 0 \tag{13}$$

Equations (11) and (12) use lagged first differences as internal instruments for the contemporaneous levels. Equation (13) introduces the external instrument $RVT_{i,t}$ exclusively in the levels equation, exploiting cross-country variation in rural political engagement to identify the effect of agricultural support on TFP. This restriction is more conservative than including $RVT_{i,t}$ in both equations, as it imposes a single moment condition whose validity is assessed via the Difference-in-Hansen test, discussed in Section 4.3.

Appendix B

Table B.1. Country coverage and sample observations 1995–2023

Country	ISO3	Observations	Coverage (%)
Argentina	ARG	23	79.3
Belize	BLZ	12	41.4
Bolivia	BOL	18	62.1
Brazil	BRA	28	96.6
Chile	CHL	28	96.6
Colombia	COL	28	96.6
Costa Rica	CRI	28	96.6
Dominican Republic	DOM	17	58.6
Ecuador	ECU	16	55.2
Guatemala	GTM	13	44.8
Jamaica	JAM	14	48.3
Mexico	MEX	28	96.6
Panama	PAN	10	34.5
Peru	PER	13	44.8
Paraguay	PRY	16	55.2
El Salvador	SLV	14	48.3
Uruguay	URY	15	51.7
Total		321	65.1

Notes: The sample period is 1995–2023 (29 potential years per country) based on Agrimonitor (Conroy et al., 2024) availability. Coverage (%) is calculated as observations / 29. † The unbalanced structure reflects heterogeneous Agrimonitor coverage across countries. The public knowledge stock variable $\log(K)_{it}$, drawn from van Dijk et al. (2025), is available for all 17 countries over 1995–2022 and does not contribute to the unbalanced structure of the panel.

Table B.2. Panel Unit Root Tests

Panel A: Key Variables of Interest — Fisher-type ADF Test

Variable	Levels		First differences		Order of integration
	Pm	p-value	Pm	p-value	
LAC sample (N = 17)					
$\log(TFP)_{it}$	-0.353	0.638	4.391	0.000	I(1)
$\log(K^{14})_{it}$	1.219	0.112	2.402	0.008	I(1)
OECD sample (N = 38)					
$\log(TFP)_{it}$	-0.200	0.579	8.237	0.000	I(1)
$\log(K^{14})_{it}$	1.429	0.077	5.182	0.000	I(1)
$\log(K^{10})_{it}$	4.311	0.000	6.703	0.000	I(1) †

†† For $\log(K_{10})_{it}$, the Modified inverse chi-squared statistic (Pm) rejects the null of a unit root in levels, but the inverse normal ($Z = -0.445$, $p = 0.328$) and inverse logit ($L^* = -0.912$, $p = 0.181$) statistics — which are more robust to cross-sectional heterogeneity with large N — fail to reject. Given the heterogeneity of the OECD sample, we follow the latter and classify $\log(K_{10})_{it}$ as I(1), consistent with the strong rejection of a unit root in first differences ($Pm = 6.703$, $p < 0.001$).

Panel B: Control Variables — Im-Pesaran-Shin Test (no trend)

Variable	LAC (N = 17)		OECD (N = 38)		Order of integration
	W-t-bar	p-value	W-t-bar	p-value	
Log agricultural GDP	-1.040	0.149	-2.823	0.002	I(1) in LAC; I(0) in OECD
Trade openness	-1.619	0.053	-4.887	0.000	I(0)
Control of corruption	-1.376	0.084	-2.038	0.021	I(0)
Precipitation	-15.814	0.000	-19.314	0.000	I(0)
Extreme heat days	-5.357	0.000	-15.081	0.000	I(0)
Inflation	-9.429	0.000	-7.243	0.000	I(0)

Notes: The Fisher-type test is based on augmented Dickey-Fuller regressions with 4 lags (Maddala and Wu, 1999). Pm denotes the Modified inverse chi-squared statistic. The IPS test uses lag length selected by AIC with a maximum of 4 lags (Im, Pesaran, and Shin, 2003). H_0: all panels contain a unit root. † For $\log(K_{10})_{it}$, the Fisher test in levels rejects H_0, which may reflect reduced persistence of the shorter-window stock rather than genuine stationarity; the test in first differences strongly rejects H_0 ($p < 0.001$), supporting I(1) classification.

Table B.3. Panel Cointegration Tests: $\log(TFP)_{it}$ and $\log(K)_{it}$

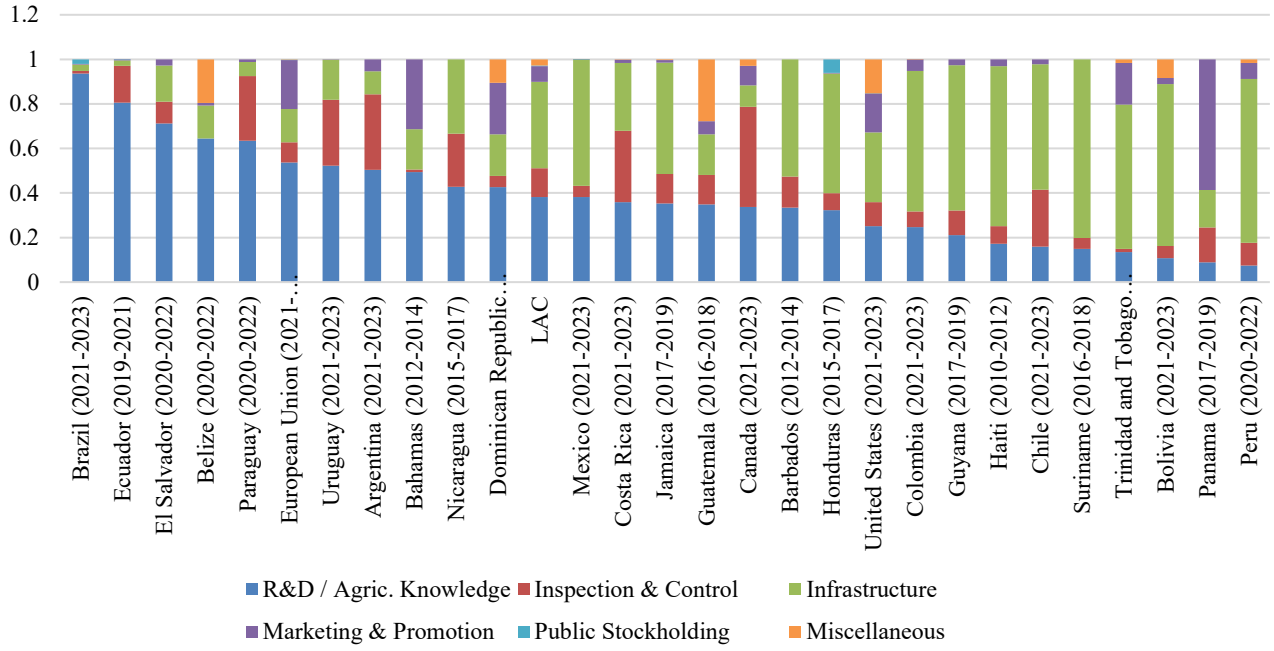
	LAC (N = 17)		OECD (N = 38), K_{it}^{14}		OECD (N = 38), K_{it}^{10}	
	Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Pedroni (1999, 2004)						
Modified Phillips-Perron t	-1.332	0.092	-4.708	0.000	-4.370	0.000
Phillips-Perron t	-4.273	0.000	-11.387	0.000	-11.393	0.000

	LAC (N = 17)		OECD (N = 38), K_{it}^{14}		OECD (N = 38), K_{it}^{10}	
Augmented Dickey-Fuller t	-5.273	0.000	-11.509	0.000	-11.465	0.000
Kao (1999)						
Modified Dickey-Fuller t	0.597	0.275	1.043	0.149	1.505	0.066
Dickey-Fuller t	0.168	0.433	0.918	0.179	1.316	0.094
Augmented Dickey-Fuller t	1.121	0.131	4.040	0.000	4.477	0.000
Unadjusted modified DF t	0.125	0.450	-0.666	0.253	-0.804	0.211
Unadjusted Dickey-Fuller t	-0.209	0.417	-0.426	0.335	-0.576	0.282
Westerlund (2007)						
Variance ratio	-2.259	0.012	-4.546	0.000	-4.509	0.000

Notes: All tests assess cointegration between $\log(TFP)_{it}$ and $\log(K)_{it}$. The Pedroni (1999, 2004) test includes panel means and a linear time trend with lag length selected by AIC. The Kao (1999) test includes panel means without trend. The Westerlund (2007) test is the variance ratio statistic. H_0: no cointegration. ***, **, and * indicate rejection of H_0 at the 1%, 5%, and 10% significance levels, respectively.

Within GSSE, the allocation to R&D varies dramatically across countries. Figure B.1 shows that Brazil and Ecuador devote more than 80% of GSSE to R&D, and Peru only around 7%. Given the theoretical importance of R&D in driving long-run productivity growth, these disparities are likely to be economically consequential.

Figure B.1. GSSE components (R&D, agricultural health, infrastructure, marketing, public storage and others) until 2023



Source: Own elaboration using Agrimonitor dataset.

Appendix C

Construction and validation of the Färe–Primont index

C.1 Data

The index is computed for 25 LAC countries observed annually over 1961–2023 (1,575 country-year observations): Argentina, the Bahamas, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, Uruguay and Venezuela. Quantities are taken from the USDA-ERS International Agricultural Productivity database, the same source as the USDA index. The output vector y_{it} contains (i) crop output and (ii) livestock and fisheries/aquaculture output, both measured at constant prices as reported by USDA-ERS. The input vector x_{it} contains land, labor, capital, fertilizer and animal feed. Series are rescaled by constant factors for numerical conditioning; the index is invariant to these changes of units. All 1,575 observations are pooled into a single reference technology, so that every country-year is evaluated against the same frontier. The 17 countries used in the regressions are a subset of this sample.

C.2 Aggregation weights

Let $\bar{x}$ and $\bar{y}$ denote the sample means of the input and output vectors. For each observation (i,t), input shadow prices are obtained from the input-oriented DEA problem in multiplier form under variable returns to scale,

$$\theta_{it} = \max u'\bar{y} - \omega \quad \text{s.t.} \quad v'x_{it} = 1; \quad u'\bar{y} - v'x_{js} - \omega \le 0 \text{ for all } (j,s); \quad u, v \ge 0 \qquad (C1)$$

and output shadow prices from the output-oriented problem

$$1/\delta_{it} = \min v'\bar{x} - \psi \quad \text{s.t.} \quad u'y_{it} = 1; \quad v'\bar{x} - u'y_{js} - \psi \ge 0 \text{ for all } (j,s); \quad u, v \ge 0 \qquad (C2)$$

In (C1), all observations are compared at the common, representative output level $\bar{y}$, so that each input bundle is evaluated relative to the input bundles observed in the sample; analogously, in (C2) all output bundles are compared at the representative input level $\bar{x}$. The normalized shadow prices are $p_{it} = v^*_{it}/\theta_{it}$ and $q_{it} = \delta_{it}u^*_{it}$, which are the gradients of the input and output distance functions at the evaluated points, so that $p_{it}'x_{it} = 1/\theta_{it}$ and $q_{it}'y_{it} = \delta_{it}$. The aggregation weights are their sample averages, $\bar{p} = (NT)^{-1}\sum_{i,t} p_{it}$ and $\bar{q} = (NT)^{-1}\sum_{i,t} q_{it}$, which define the aggregate input and output quantities and the productivity index:

$$X_{it} = \bar{p}' x_{it}, \quad Y_{it} = \bar{q}' y_{it}, \quad TFP_{it} = Y_{it}/X_{it}, \quad FP_{it} = 100 \cdot TFP_{it}/TFP_{i,2015} \qquad (C3)$$

The index used in the paper is the variable-returns-to-scale version; the non-increasing-returns version is numerically identical, and the constant-returns version differs by at most 0.09 index points. The linear programs are solved with the CBC solver through PuLP. DEA multipliers need not be unique; re-solving the programs with a different solver (HiGHS) yields an index with a correlation of 0.997 with the baseline and a mean absolute difference of 1.9 index points.

C.3 Properties and relation to O'Donnell (2012)

Given that the weights $\bar{p}$ and $\bar{q}$ are common to all observations, X and Y are linear aggregator functions, and the resulting index is multiplicatively complete and transitive and satisfies the identity and proportionality axioms (O'Donnell, 2012). Our construction shares this defining feature of the Färe–Primont index—fixed aggregator functions common to all observations—but derives the weights differently from O'Donnell's (2012) implementation, which evaluates the input and output distance functions once, at a representative observation: our weights are obtained by comparing each input (output) bundle with all observed bundles at the representative output (input) level, in the spirit of the benefit-of-the-doubt approach to constructing composite indices (Cherchye et al., 2007), and are averaged over all observations, so that they do not depend on a single point of the frontier.

Table C.1 reports the value shares implied by our weights at the sample-mean quantities, together with the USDA-ERS cost and revenue shares. Our weights give 57.5% of the output weight to crops, close to the 58% share of crops in the USDA-ERS output aggregate. On the input side, they place more weight on capital and fertilizer and less on land than the USDA-ERS cost shares.

Table C.1. Value shares implied by the aggregation weights (percent, at sample-mean quantities)

Aggregation weights	Land	Labor	Capital	Fertilizer	Feed	Crops	Livestock & fisheries
Baseline Färe–Primont (this paper)	12.7	31.0	36.9	15.7	3.8	57.5	42.5
USDA-ERS	20.5	34.7	26.4	11.6	6.8	58.2	41.8

Notes: Shares are evaluated at the sample means of inputs and outputs (25 LAC countries, 1961–2023). USDA-ERS: average LAC cost shares over 1961–2023 for inputs, and share of crops in gross agricultural output at constant prices at sample-mean quantities for outputs.

C.4 Validation against the USDA-ERS index

The USDA-ERS index is an externally produced and widely used benchmark, constructed with a different method (Törnqvist aggregation with market-based cost and

revenue shares). Over the full sample of 25 countries and 1961–2023, the correlation between the two indices is 0.89 both in levels and in annual growth rates; in the 330 country-years of the estimation sample (the 17 estimation countries in the years covered by Agrimonitor, before the lags required by the GMM estimator are imposed) it is 0.89 in levels and 0.90 in growth rates (growth rates are observed for 325 of them). Across the 17 estimation countries, the correlation of average annual TFP growth over 1996–2023 is 0.92, and the correlation of annual growth rates within countries ranges from 0.78 (Mexico) to 0.98 (Colombia and Paraguay) (Table C.3). Both indices display the same broad chronology—fast growth in the 1960s, slower growth in the 1970s and 1980s, stronger growth in 2001–2010 and a deceleration after 2010—although the Färe–Primont index shows faster growth in 1991–2010 and a sharper slowdown in 2011–2023 (Table C.2).

The divergence between the indices is concentrated in a few observations. Belize alone accounts for 55% of the sum of squared differences between the annual growth rates of the two indices in the estimation sample, followed by Argentina (8%) and the Dominican Republic (5.5%); by year, 2022 accounts for 34%, while 2020 and 2021 together account for 4%.

Table C.2. Average annual TFP growth by decade, 17 estimation countries (percent)

Period	USDA-ERS	Färe–Primont
1962–1970	1.91	1.44
1971–1980	0.98	0.96
1981–1990	1.07	1.07
1991–2000	1.02	1.48
2001–2010	1.36	1.74
2011–2023	1.04	0.68

Notes: Pooled mean of annual growth rates over country-years in each period; 17 countries in the estimation sample.

Table C.3. Country-level comparison of the two indices

Country	Avg. growth USDA (%)	Avg. growth FP (%)	Corr. of annual growth	Share of squared divergence (%)
Argentina	-0.14	-0.59	0.90	8.0
Belize	-0.83	-0.02	0.89	55.3
Bolivia	0.84	1.70	0.95	2.0
Brazil	2.63	2.04	0.94	1.9
Chile	2.93	1.70	0.97	3.5
Colombia	0.32	0.26	0.98	0.5
Costa Rica	-0.20	-0.27	0.89	3.9
Dominican Republic	3.10	3.79	0.89	5.5
Ecuador	2.18	2.33	0.95	2.3
Guatemala	1.42	1.82	0.81	2.5
Jamaica	0.02	0.49	0.87	1.9

Country	Avg. growth USDA (%)	Avg. growth FP (%)	Corr. of annual growth	Share of squared divergence (%)
Mexico	3.35	3.04	0.78	2.9
Panama	-0.40	-0.29	0.89	0.8
Peru	2.28	2.56	0.95	1.4
Paraguay	1.01	1.17	0.98	2.3
El Salvador	0.68	1.21	0.95	1.2
Uruguay	-1.36	-2.35	0.95	4.2

Notes: Average annual growth and correlation of annual growth rates over 1996–2023. Share of squared divergence: contribution of each country to the sum of squared differences between the annual growth rates of the two indices, computed over the 325 country-years of the estimation sample in which both growth rates are observed.

Appendix D

GSSE: reverse causality and lagged effects

Table D.1 regresses GSSE, and its annual change, on the first two lags of TFP growth, with country fixed effects and the control variables of Equation (8). If governments raised GSSE in response to productivity downturns, the coefficients on lagged growth would be negative. The coefficient on growth in the previous year is instead positive in all four regressions, significant at the 5% level in the regressions in changes and at the 10% level for USDA in levels, while the coefficient on growth two years earlier is close to zero. Table D.2 replaces contemporaneous GSSE in the System GMM specification of Table 2 with its first lag and with the average of its first three lags; the coefficients are small relative to their standard errors and none is significant.

Table D.1. Does past TFP growth predict GSSE? Fixed-effects estimates

	GSSE, USDA	GSSE, Färe–Primont	ΔGSSE, USDA	ΔGSSE, Färe–Primont
TFP growth, t−1	0.0127* (0.0062)	0.0051 (0.0073)	0.0286** (0.0132)	0.0268** (0.0100)
TFP growth, t−2	0.0058 (0.0090)	-0.0054 (0.0136)	-0.0003 (0.0128)	-0.0058 (0.0149)
Joint test, p-value	0.082	0.222	0.080	0.030
Observations / countries	311 / 17	311 / 17	300 / 17	300 / 17

Notes: Within (fixed-effects) estimates with standard errors clustered by country in parentheses; TFP growth in percent, computed within the 1995–2023 sample. Controls: control of corruption, trade openness, inflation, annual precipitation, extreme heat days and a linear trend. Significance based on t(16): *** p<0.01, ** p<0.05, * p<0.1.

Table D.2. System GMM estimates with lagged GSSE

	USDA	Färe–Primont
GSSE, t−1	-0.097 (0.488)	-0.047 (0.448)
Observations / instruments	319 / 14	319 / 14
Mean of GSSE, t−1 to t−3	-0.151 (0.506)	-0.332 (0.373)
Observations / instruments	285 / 14	285 / 14

Notes: System GMM with the specification and instrument structure of the GSSE column of Table 2 (lags 2–3); Windmeijer-corrected standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix E

Robustness checks

Table E.1. Tests of equality of the coefficients across productivity indices

Support variable	Difference FP − USDA (s.e.)	Correlation of estimators	p-value
Total Support Estimate (TSE)	-0.158 (0.101)	0.19	0.120
Producer Support Estimate (PSE)	-0.169 (0.109)	0.09	0.120
Market Price Support (MPS)	-0.136 (0.117)	0.40	0.244
Direct transfers	-0.030 (0.370)	0.08	0.937
General Services Support Estimate (GSSE)	0.081 (0.833)	0.37	0.923
Budget support	-0.154 (0.277)	0.35	0.579
Log. stock of agricultural public knowledge	0.002 (0.014)	0.55	0.906

Notes: Wald test of H_0: $\gamma_{FP} = \gamma_{USDA}$ for each support measure. The variance of the difference combines the Windmeijer-corrected standard errors of Tables 2 and 3 with the correlation between the two estimators, estimated from the country-level contributions to each two-step GMM estimator. Specifications as in Tables 2 and 3.

Table E.2. Adding a pandemic dummy for 2020–2021

Support variable	USDA		Färe–Primont	
	Coefficient	Dummy 2020–2021	Coefficient	Dummy 2020–2021
Total Support Estimate (TSE)	0.020 (0.074)	-1.063 (1.155)	-0.155** (0.078)	-2.003* (1.191)
Producer Support Estimate (PSE)	0.016 (0.081)	-1.017 (1.236)	-0.169** (0.081)	-1.689 (1.171)
Market Price Support (MPS)	-0.067 (0.104)	-1.248 (1.454)	-0.210** (0.096)	-1.735 (1.126)
Direct transfers	0.270 (0.187)	-1.652* (0.879)	0.277 (0.356)	-1.282 (1.383)
General Services Support Estimate (GSSE)	-0.301 (0.606)	-2.014* (1.136)	-0.196 (0.934)	-2.385** (1.091)
Budget support	0.330 (0.272)	-1.465 (1.243)	0.208 (0.213)	-1.271 (1.205)
Log. stock of agricultural public knowledge	0.025*** (0.008)	-0.025*** (0.008)	0.026 (0.019)	-0.026*** (0.009)

Notes: System GMM estimates with the specifications of Tables 2 and 3, adding a dummy equal to one in 2020 and 2021, which enters as a regressor and as an IV-style instrument in both equations. Coefficient: coefficient of the support measure, as in Tables 2 and 3. Dummy 2020–2021: coefficient of the pandemic dummy, in index points (in logarithms for the R&D stock). The dummy raises the number of instruments to 17 for TSE, PSE, MPS and direct transfers, equal to the number of countries, and to 15 for GSSE, budget support and the R&D stock. AR(2) p-values range from 0.35 to 0.51 and Hansen p-values from 0.17 to 0.70. The Difference-in-Hansen test rejects the exogeneity of the external instrument at the 5% level only for GSSE and the R&D stock under Färe–Primont (p = 0.043 and 0.034). Windmeijer-corrected standard errors in parentheses. No. countries: 17; no. observations: 321 (454 for the R&D stock). *** p<0.01, ** p<0.05, * p<0.1.

Table E.3. Joint specification of market price support and direct transfers

	USDA, inflation endogenous	USDA, inflation exogenous	FP, inflation endogenous	FP, inflation exogenous
Market Price Support (MPS)	-0.136 (0.117)	-0.121* (0.068)	-0.184** (0.082)	-0.116 (0.092)
Direct transfers	0.470 (0.486)	0.507 (0.394)	0.533 (0.424)	0.620 (0.466)
Difference DT − MPS (s.e.)	0.606 (0.467)	0.627 (0.397)	0.718 (0.467)	0.735 (0.504)
Test of equality, p-value	0.194	0.114	0.125	0.145
No. instruments	16	15	16	15
AR(2) p-value	0.469	0.466	0.353	0.360
Hansen test (p)	0.527	0.445	0.582	0.374
Difference-in-Hansen (p)	0.116	0.106	0.630	0.406

Notes: MPS and direct transfers enter the same System GMM equation, with the controls and external instrument of Table 2. Internal instruments: lags 2–3 of the lagged dependent variable and lag 2 of MPS, direct transfers and, when treated as endogenous, inflation. Windmeijer-corrected standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. No. countries: 17, no. observations: 321.

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