

Smooth Transitions and Heterogeneous Regimes in Structural Transformation: Evidence from Technological Intensity

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Abstract: *This paper revisits the relationship between per capita income and technological-intensity structural transformation in manufacturing. It asks whether the income–cosphi relationship is better described by heterogeneous nonlinearity and smooth transition zones rather than by a common linear slope or hard income thresholds. Using a cross-country panel for 2014–2022, with a main sample of 482 observations from 65 countries and an expanded sample of 550 observations from 66 countries, the study employs two-way fixed effects as a benchmark, spline fixed-effects models as the main specification, threshold fixed-effects models as a heuristic tool, and a set of robustness checks including balanced versus unbalanced panels and Difference GMM. The results show that linearity is too restrictive. Nonlinear evidence is stronger in the main sample, the shape of the relationship differs between developed and developing economies, and threshold models do not support sharp breakpoints. Mechanism analysis further suggests that R&D conditions the nonlinear relationship more strongly than FDI. The paper contributes by reframing technological structural transformation as a nonlinear, heterogeneous, and conditional process rather than a universal income-threshold story.*

Keywords: Structural Transformation; Technological Intensity; Nonlinear Fixed Effects; Spline Regression; Threshold Effects; Innovation Capability

1. Introduction

Structural transformation has long been viewed as a central engine of long-run economic growth and income convergence, because development is not merely an expansion in aggregate output, but also a reallocation of labor and production toward activities with different productivity levels, learning potential, and technological content [1-4]. Recent studies have reinforced this core insight while also showing that contemporary development trajectories are more heterogeneous than earlier stylized narratives suggested [5-8]. In particular, newer contributions emphasize that structural transformation cannot be reduced to a one-way shift from agriculture to manufacturing and then to services; rather, it should be understood as a broader process involving industrial composition, productivity dynamics, labor reallocation, and spatial heterogeneity [5-7]. At the same time, recent evidence rejects the idea that manufacturing has lost its strategic importance for late development: manufacturing still matters for developing economies as a source of employment, capability formation, and catch-up, even if the contemporary pattern of industrialization differs from that of earlier periods [8, 9].

Yet most of this literature still studies structural transformation at a relatively aggregate level, focusing on broad sectoral shares or on the overall role of manufacturing in the economy. This leaves open a more specific question, which is central to this paper: how does development reshape the technological-intensity composition within manufacturing itself? This question matters because manufacturing is far from internally homogeneous. The OECD technology-intensity classification clearly distinguishes industries by technological content [10]. Importantly, this classification inherently encompasses IT-related manufacturing activities (e.g., computers, electronics, and optical products) within its high- and medium-high-technology categories, ensuring that digital

and ICT-driven structural shifts are implicitly captured in the analysis. Furthermore, Lall [11] long ago showed that export and production structures differ systematically by technological sophistication, with important implications for learning, spillovers, and long-run development performance. More recent work in economic complexity strengthens this view by treating growth, diversification, upgrading, resilience, and technological change as outcomes of underlying capability structures rather than of aggregate sectoral indicators alone [12-15]. Policy-oriented work from WIPO and UNCTAD similarly emphasizes that diversification into more sophisticated activities is path dependent, capability constrained, and conditioned by the productive structure already present in the economy [14], [16].

These insights point directly to a second gap in the empirical literature. Even when researchers acknowledge stage dependence or regime variation, empirical work often still gravitates toward interpretation in terms of either a common linear slope or a sharp threshold [4], [17]. Threshold estimation remains highly influential, and Hansen's fixed-effects threshold framework is still a classic reference for testing regime change in panel-data settings [18]. But the existence of a threshold estimator should not be conflated with evidence that economic relationships actually evolve through rigid and universal breakpoints. This is precisely why the smooth-transition tradition remains valuable: Gonzalez, Terasvirta, and van Dijk [19] developed panel smooth transition regression models for contexts in which coefficients evolve gradually rather than discretely. Recent surveys of structural transformation point in the same direction from a broader perspective, emphasizing gradual adjustment, heterogeneity, and context-specific pathways rather than a single deterministic development schedule [5-7]. For a paper focused on technological-intensity restructuring, this distinction is especially important, because it is difficult to argue that all economies should shift into a new technological regime at exactly the same income level across all countries and development stages.

A third gap concerns mechanisms. If the link between income and structural transformation is heterogeneous, income itself is unlikely to be the only determinant. The absorptive-capacity literature has long argued that accumulated knowledge bases and R&D effort shape the ability to recognize, assimilate, and exploit new knowledge [20]. Recent evidence continues to support this view. For example, Li and Du [21] show that absorptive capacity remains central to translating cross-border R&D linkages into innovation performance. At the same time, newer studies on FDI and structural transformation suggest that foreign investment can contribute to shifts toward more modern activities and more skill-intensive occupations, but typically in ways that depend heavily on local capabilities rather than through automatic upgrading [22, 23]. More broadly, both WIPO [14] and UNIDO [9] emphasize that innovation policy and industrial policy are effective only when they build on existing capabilities and help economies diversify into related, more sophisticated activities. In this perspective, countries at similar income levels may experience very different restructuring trajectories because their innovation systems, R&D effort, and absorptive capacity differ substantially.

Against this background, this paper shifts the focus away from the search for a single universal threshold and toward the identification of heterogeneous transition zones in the relationship between income and technological-intensity structural transformation. Instead of asking whether all countries cross the same hard breakpoint, the paper asks whether the income-*cosphi* relationship is nonlinear, whether its shape differs between developed and developing economies, and whether that nonlinear path is conditioned by domestic technological capability.

The distinctiveness of this study lies in its departure from the conventional search for a deterministic, "magic" income threshold. By bridging structural transformation literature with economic complexity, it offers a novel empirical framework demonstrating that technological restructuring is a smooth, capability-conditioned transition rather than an automatic byproduct of rising income. In doing so, the paper provides a more nuanced and empirically disciplined account of how domestic innovation bases dictate the trajectory of industrial upgrading across different stages of development.

2. Theoretical Framework and Measurement

This paper does not begin from the premise that every economy must cross the same universal income threshold in order to achieve technological restructuring. Instead, its conceptual foundation rests on a broader proposition: structural transformation is a staged but highly heterogeneous process. Accordingly, restructuring within manufacturing by technological intensity is unlikely to follow a single linear trajectory.

2.1 Structural Transformation as a Conditional Reallocation Process

From the classical literature to more recent contributions, long-run economic growth is understood not merely as a mechanical increase in output, but as an ongoing reallocation of productive resources toward sectors with higher productivity and greater learning potential [1-3]. Recent reviews reinforce this perspective while emphasizing that manufacturing continues to play a central role in many late-development strategies, even as the form of industrialization is changing under the influence of digital technologies and globalization [24-26]. Structural transformation, however, does not stop at the movement of labor from agriculture to industry. A more consequential step is the transformation of the internal structure of manufacturing itself. An economy may expand the industrial share of output while remaining concentrated in low-value-added processing segments. By contrast, movement toward more technology-intensive manufacturing branches carries substantially different long-run development implications, because it requires more complex knowledge systems and typically generates stronger spillovers [9-11].

2.2 The Logic of Nonlinearity and the Measurement of Technological Distance

Although transformation is staged, there is no theoretical reason to expect the relationship between income and technological restructuring to be linear. A more plausible interpretation is that this relationship is potentially nonlinear, because the constraints and mechanisms that drive industrial restructuring change across development stages. At low income levels, growth may mainly reflect scale expansion in low-technology or lower-middle-technology industries. As an economy enters the middle-income range, accumulated capabilities may accelerate restructuring, because absorptive capacity, learning, and movement into more complex segments improve. At very high income levels, the pace of transformation may slow, flatten, or change form as the economy approaches the technological frontier and part of the adjustment shifts toward knowledge-intensive services [12], [14], [16, 17]. This argument is consistent with the economic-complexity literature, which emphasizes the path-dependent nature of industrial upgrading. Countries tend to diversify into activities whose capability requirements are close to their existing productive base, while moves into more advanced technological sectors are often constrained by missing knowledge networks, skills, and complementary institutions [12-14], [27, 28]. If this reasoning is correct, income growth need not exert a constant marginal effect on technological restructuring; instead, the shape of the relationship is likely to vary across income ranges.

To operationalize this concept of structural change, the study does not rely on absolute sectoral shares. Instead, it measures “structural distance” through a cosine-similarity index (*cosphi*). Let S_{it} denote the value-added share vector for the four technology-intensity manufacturing groups (low, medium-low, medium-high, and high) for country i in year t , and let $S_{i,0}$ denote the structural vector in the base year. Similarity is then defined as follows:

$$\text{cosphi}_{it} = \frac{S_{it} \cdot S_{i,0}}{\|S_{it}\| \|S_{i,0}\|}, \quad (1)$$

Where:

- $S_{i,t}$ denotes the value-added share vector for the four technology-intensity manufacturing groups for country i in year t .
- $S_{i,0}$ denotes the corresponding structural vector in the base year.

By definition, *cosphi* takes values in the interval [0,1]. Lower values of *cosphi* indicate that the technological structure in year t is farther from the initial structure, implying a deeper degree of restructuring. The index is therefore used as a measure of technology-oriented structural distance rather than as an indicator of the absolute scale of production.

2.3 Heterogeneity and Conditioning Mechanisms: R&D versus FDI

The nonlinear trajectory outlined above does not unfold in a vacuum; it is conditioned by each economy's development position and internal capabilities. Catch-up-cycle arguments suggest that developing economies operate mainly through technology adoption, learning, and value-chain integration, whereas developed economies operate closer to frontier-innovation dynamics [9], [14], [16], [29]. This difference in development position makes it likely that transformation follows different shapes across the two groups. More importantly, income does not automatically generate structural transformation; it only creates the room for such

transformation to occur. Whether that room is actually converted into restructuring depends on absorptive capacity and the innovation base of the economy [20], [30]. In this sense, both endogenous R&D and FDI may condition the trajectory of technological restructuring, but through different channels. R&D reflects domestic knowledge creation and accumulation, whereas FDI reflects access to foreign technology, capital, and external linkages.

Recent empirical studies show that FDI spillovers do not arise automatically, but depend strongly on the absorptive capacity of firms and domestic production systems [22, 23], [31]. At the same time, a growing body of evidence suggests that indigenous innovation effort may play a more prominent role in deep catch-up processes, especially when the objective is not merely to expand production, but to move into more complex technological structures [21], [32]. The empirical question, therefore, is not whether only one of the two mechanisms matters, but which mechanism is more salient in altering the shape of the income-*cosphi* relationship.

2.4 Empirical Expectations

Building on the theoretical framework above, the study formulates three empirical expectations to be examined in the results section. First, the relationship between income growth and *cosphi* is likely to be nonlinear, generating smooth transition zones rather than a fixed slope or hard breakpoints [18, 19]. Second, the shape of this curve is expected to differ between developed and developing economies because the two groups face different transformation mechanisms [9], [14], [16], [29]. Third, endogenous technological capability, especially R&D, is expected to be the more salient conditioning mechanism, with a stronger capacity to alter the shape of the technological-transition path than FDI integration alone [20-22], [31, 32].

3. Methodology

3.1 Data and Sample Construction

The study uses a cross-country panel for 2014–2022 to examine the relationship between per capita income and technological-intensity structural transformation in manufacturing. The main estimation sample contains 482 observations from 65 countries, while an expanded sample of 550 observations from 66 countries is used for robustness checks. The dependent variable is *cosphi*, constructed from the cosine similarity between the technological structure of manufacturing in each observation year and the baseline structure. Due to the inverse nature of this index, lower values indicate a greater structural distance from the initial composition; consequently, a negative regression coefficient signifies deeper technological restructuring. It is worth noting that while *cosphi* mathematically measures structural distance rather than a unidirectional technological upgrading, within the context of development and catch-up growth, such significant structural departures are predominantly driven by shifts toward more advanced technological segments. The main explanatory variable is GDP per capita in natural logarithms. Baseline controls include FDI, trade openness, tertiary enrollment, R&D expenditure, high-tech exports, and, where available, the Global Innovation Index (GII).

Table 1. Sample Construction and Coverage

Sample layer	Observations	Countries	Period	Developed economies	Developing economies	Role in the study
Main estimation sample	482	65	2014-2022	342	140	Main sample used for the core empirical analysis
Robustness sample	550	66	2014-2022	373	177	Expanded sample used for sensitivity and robustness checks

The main sample is used for core estimation, while the expanded sample is used for sensitivity analysis under broader data coverage. Missing-data handling is intentionally conservative. The study does not interpolate or extrapolate *cosphi*. Invalid placeholder values are recoded as missing, and implausible observations are removed only where clearly necessary. Broader data coverage is used only for robustness checks and does not replace the main estimation sample.

3.2 Pre-Estimation Diagnostics and Cross-Sectional Dependence

Before estimating the main models, the study conducts pre-estimation diagnostics to assess cross-sectional dependence and the time-series properties of the core variables. This step is important because cross-country panels may be jointly affected by common technological, trade, or macroeconomic shocks, which can weaken inference based on conventional standard errors [33, 34].

Pesaran's CD test rejects the null of no cross-sectional dependence for both *cosphi* and log GDP per capita, indicating that countries in the sample do not evolve independently. Fisher-type panel ADF tests further show that *cosphi* is stationary in levels, whereas log GDP per capita is non-stationary in levels but becomes stationary after first differencing [35, 36]. The residual-based test is reported only as a supplementary check for long-run association and is not interpreted as formal cointegration evidence because the key variables display mixed orders of integration.

Table 2. Pre-estimation Diagnostics

Test	Variable	Statistic	p-value	Conclusion
Pesaran CD	<i>cosphi</i>	2.888	0.004	Cross-sectional dependence
Pesaran CD	log GDP per capita	81.961	<0.001	Cross-sectional dependence
Fisher ADF (level)	<i>cosphi</i>	566.117	<0.001	Stationary
Fisher ADF (level)	log GDP per capita	138.619	0.517	Non-stationary
Fisher ADF (first difference)	log GDP per capita	634.713	<0.001	Stationary
Residual-based long-run association check	FE residuals	525.009	<0.001	Evidence of long-run association in residuals

Note: Fisher ADF statistics are constructed by combining country-level ADF tests using Fisher's method. Because the key variables display mixed orders of integration, the residual-based test is reported only as a supplementary check for long-run association and is not interpreted as formal cointegration evidence. All static panel models are estimated with Driscoll–Kraay standard errors.

Given these diagnostics, all static panel models are estimated with Driscoll–Kraay standard errors [34], [37]. This choice makes inference more robust to cross-sectional dependence, serial correlation, and heteroskedasticity. At the same time, the analysis retains two-way fixed-effects specifications in levels, because the paper aims to evaluate the conditional shape of the income–*cosphi* relationship rather than to estimate a strict long-run equilibrium parameter. The reported coefficients are therefore interpreted as within-country conditional associations rather than as formal cointegration estimates.

3.3 Empirical Identification Strategy

Based on the data structure and the pre-estimation diagnostics discussed above, the study implements a three-step empirical identification strategy. The goal is not to impose a specific functional form on the relationship between income and technological structural transformation *ex ante*, but to move from a simple benchmark specification toward more flexible models in order to assess which type of relationship the data support more strongly. Accordingly, the paper begins with a linear two-way fixed-effects model as a benchmark, then turns to a spline specification as the main model for capturing nonlinear structure, and finally uses threshold models as an interpretive aid for delineating empirically meaningful transition ranges [18, 19], [38].

The overall analytical framework is visually summarized in Figure 1. The flow proceeds in three logical steps. First, it establishes a linear two-way fixed-effects model as a baseline to test the limits of a simple linear assumption. Second, it employs a spline fixed-effects specification as the core tool to map the underlying nonlinear structure. Finally, it incorporates a threshold fixed-effects model not to find absolute structural breakpoints, but as a supplementary heuristic device to delineate and interpret broad transition zones. This triangulated approach ensures that conclusions about structural heterogeneity are drawn from robust, complementary methods.

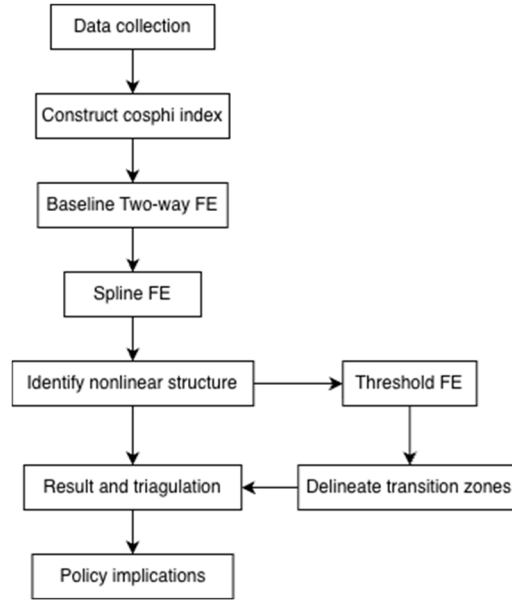


Figure 1. Empirical Identification Strategy

3.3.1 Step 1: Two-Way Fixed Effects as the Baseline

The first step in the empirical strategy is to estimate a linear two-way fixed-effects model, in which *cosphi* is regressed on per capita income and the baseline control set while absorbing time-invariant country heterogeneity and common shocks over time. The specification is as follows:

$$\text{cosphi}_{it} = \beta_1 \ln \text{GDPpc}_{it} + rX_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad , \quad (2)$$

where i indexes countries, t denotes years, X_{it} is the vector of control variables, α_i are country fixed effects, and λ_t are year fixed effects.

The role of this model is to provide an initial empirical benchmark for the income-*cosphi* relationship. In other words, the linear two-way fixed-effects specification is used to test whether a common income slope is sufficient to describe the data. If this specification already captures the variation in *cosphi* well, moving to nonlinear models would add little explanatory value. Conversely, if the linear model fits poorly or masks differences across country groups, that provides grounds for moving to more flexible specifications.

3.3.2 Step 2: Fixed-Effects Spline as the Main Specification

After establishing the linear benchmark, the study turns to a fixed-effects spline model as the paper's main specification. The reason for centering the analysis on splines is that both the data and the theoretical argument suggest that the income-*cosphi* relationship is unlikely to follow a fixed slope across the entire income distribution. At the same time, imposing a hard-threshold form or a fully segmented structure at the outset would be too strong relative to the available evidence. In this context, spline models allow the income-*cosphi* relationship to vary smoothly and continuously across income ranges without forcing the data to conform to sharp breakpoints [19], [38].

In general terms, the spline specification can be written as follows:

$$\text{cosphi}_{it} = \sum_{m=1}^M \theta_m B_m(\ln \text{GDPpc}_{it}) + \Gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad , \quad (3)$$

where $B_m(\cdot)$ denotes the spline basis functions constructed from log GDP per capita, and m captures the number of basis components needed to describe the curvature of the relationship.

Empirically, the study uses restricted cubic splines with knots placed at quantiles of the log GDP per capita distribution [38] (specifically, the spline is estimated with 4 degrees of freedom; the knots are placed at approximately the 0%, 33%, 67%, and 100% empirical quantiles of the log GDP per capita distribution in the main sample, corresponding roughly to 6.59, 9.46, 10.54, and 11.81). The spline is used as a flexible approximation to the functional form of the income-*cosphi* relationship rather than as a tool for identifying discrete thresholds. Within the paper's strategy, the fixed-effects spline serves as the formal model for

identifying the underlying nonlinear structure. The central conclusions about nonlinearity are drawn primarily from this specification, together with comparisons against the linear benchmark and higher-order parametric models. What matters here is that the spline fixed-effects model is used to map shape, not to claim the existence of a universal hard income threshold.

3.3.3 Step 3: Threshold Fixed Effects as a Tool for Delineating Transition Zones

After identifying the core nonlinear structure through the spline model, the study uses threshold fixed-effects models as an additional interpretive step. Here, the role of the threshold model is not to uncover absolute breakpoints in a strict econometric sense, but to help delineate ranges in the income distribution where the slope of the relationship may change meaningfully. In other words, threshold fixed effects are used as a heuristic tool for organizing information from the nonlinear functional form into income regions that are easier to interpret substantively.

A single-threshold specification can be written as follows:

$$\text{cosphi}_{it} = \beta_1 \ln \text{GDPpc}_{it} 1(\ln \text{GDPpc}_{it} \leq \tau) + \beta_2 \ln \text{GDPpc}_{it} 1(\ln \text{GDPpc}_{it} > \tau) + \Gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}, \quad (4)$$

where τ is the estimated threshold value, and $1(\cdot)$ is the indicator function. When extended to two thresholds, the model allows the data to be divided into three income regions with different slopes. In this paper, however, the estimated thresholds are not interpreted as universal and invariant income cutoffs, but only as suggestive ranges where the shape of the income-*cosphi* relationship may change.

Placing the threshold model in the third step and using it only as a supporting device has a clear methodological rationale. First, it helps the paper avoid over-interpreting threshold cutoffs as decisive structural discoveries, especially when formal threshold tests do not always provide sufficiently strong evidence for sharp breakpoints. Second, it ensures that any reported thresholds are read in conjunction with the spline results from the previous step - that is, as transition zones rather than as evidence of a hard-threshold mechanism. Threshold fixed effects are therefore used for interpretation, not for identifying the core structure of the paper. In short, the empirical identification strategy proceeds in three steps: a linear benchmark model, a fixed-effects spline model to identify the main nonlinear structure, and a threshold fixed-effects model to delineate transition zones in a supplementary interpretive sense. This design allows the paper to maintain methodological discipline while avoiding overly strong claims about hard thresholds and staying closer to what the current evidence actually supports.

3.4 Statistical Inference and Model-Comparison Criteria

Because the panel exhibits cross-sectional dependence, all static models are estimated with Driscoll–Kraay standard errors [34], [37]. This choice provides more reliable inference in the presence of cross-sectional dependence, serial correlation, and heteroskedasticity, all of which are common in cross-country panel data.

Model evaluation is based on a combination of statistical significance and model fit. The paper considers: (i) the significance of nonlinear components, (ii) the stability of signs and functional shapes across sample layers and country groups, and (iii) model-selection criteria that penalize complexity. Under this approach, a model is not preferred simply because it is more flexible, but because it provides a better description of the data after the cost of added complexity is taken into account.

For model comparison, the paper uses AIC, BIC, and RMSE [39, 40]. AIC and BIC are prioritized because they penalize additional parameters, whereas RSS tends to mechanically favor more flexible specifications. RMSE is retained as a supplementary indicator of in-sample prediction error. A model is treated as relatively preferred only when it improves penalized fit, shows meaningful nonlinear structure under Driscoll–Kraay inference, and yields a reasonably stable implied shape across alternative samples and country groups.

4. Data and Empirical Results

4.1 Descriptive Statistics and Preliminary Patterns

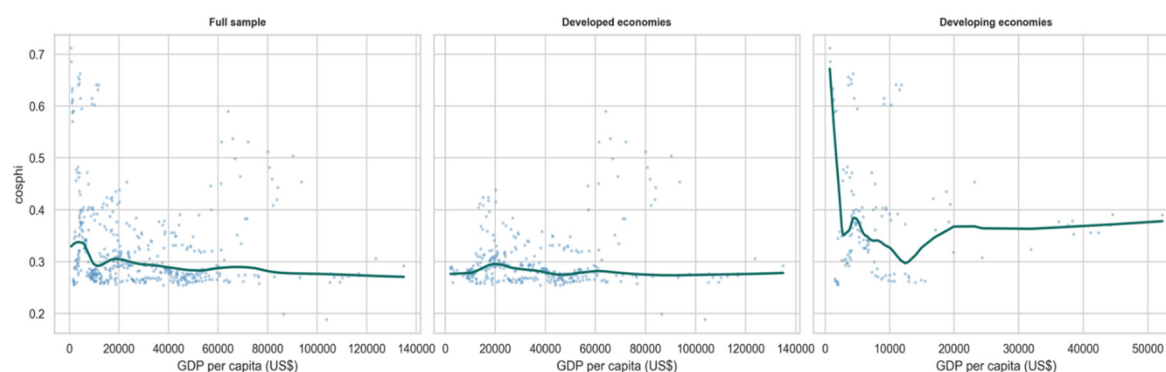
This section summarizes the main features of the data and uses LOWESS plots to provide an initial view of the relationship between income and technological structural transformation before turning to formal regression analysis. The purpose is descriptive: to assess whether the raw data are consistent with a simple linear relationship or instead suggest heterogeneity and nonlinearity across country groups.

Table 3. Descriptive Statistics

Variable	Full sample mean	Full sample SD	Developed mean	Developed SD	Developing mean	Developing SD
<i>cosphi</i>	0.327	0.090	0.300	0.054	0.394	0.120
GDP per capita	29,302.737	24,863.884	37,514.163	24,454.194	9,243.396	10,052.639
log GDP per capita	9.840	1.066	10.300	0.736	8.716	0.899
FDI	9.280	51.768	11.532	61.254	3.780	5.105
Trade openness	107.015	64.784	115.265	72.348	86.859	33.254
Tertiary enrollment	67.848	22.768	74.972	21.092	50.445	16.508
R&D expenditure	1.444	1.149	1.794	0.970	0.591	1.107
High-tech exports	14.849	10.591	16.224	9.269	11.489	12.702
GII	44.583	10.404	48.786	8.573	34.315	6.681

Table 3 shows clear differences between developed and developing economies, not only in income levels but also in indicators of technological and innovation capacity such as R&D expenditure, high-technology exports, and the GII. These differences suggest from the outset that a single common income slope may not adequately describe the full sample.

Figure 2 plots the LOWESS relationship between log GDP per capita and *cosphi* for the full sample and for the two country groups separately. The smoothed curves do not follow a stable linear pattern. Instead, the slope changes across income ranges and differs between developed and developing economies, indicating that the relationship between income and *cosphi* is unlikely to be uniform over the distribution.

**Figure 2.** LOWESS Relationship between Income and *cosphi*

The LOWESS plots also indicate that developing economies display more visible variation across income ranges, while the curve for developed economies is flatter in some regions and changes more gradually. Although these patterns are purely descriptive and do not yet control for other covariates or fixed effects, they provide an important preliminary signal: the raw income–*cosphi* relationship is not stably linear. Taken together, Table 3 and Figure 2 suggest two points that motivate the next sections: substantial heterogeneity across country groups and preliminary evidence of nonlinearity in the income–technological transformation relationship.

4.2 The Failure of the Linearity Assumption: Evidence from the Baseline Fixed-Effects Model

After documenting the preliminary patterns in the raw data, the next step is to assess whether a linear two-way fixed-effects specification is sufficient to characterize the relationship between income and technological structural transformation. In this paper, the baseline linear model is used only as an empirical benchmark against which more flexible nonlinear specifications are evaluated.

Table 4. Baseline Linear Two-way Fixed Effects Estimates

Variable	Full sample	Developed economies	Developing economies
log GDP per capita	-0.042*** (<0.001)	-0.050*** (<0.001)	-0.036** (0.013)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
DK-SE	Yes	Yes	Yes
Observations	482	342	140
Countries	65	42	23
Within R ²	0.026	0.017	0.030

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 shows that log GDP per capita carries a negative and statistically significant coefficient in the full sample as well as in both country groups. This indicates that, within countries and after controlling for country and year fixed effects, higher income is associated with lower values of *cosphi*. Regarding the control variables across all specifications, indicators such as trade openness, tertiary enrollment, and the Global Innovation Index (GII) generally exhibit expected signs but show varying degrees of statistical significance across different country groups. This variation is theoretically highly informative: it suggests that while human capital, global integration, and general innovation environments are essential macroeconomic foundations, their direct conversion into deep technological-intensity restructuring is not automatic. Instead, their effects are highly context-dependent and are likely mediated by the nonlinear dynamics of income and specific domestic capabilities, which justifies a deeper mechanism analysis.

At the same time, the baseline linear specification captures only an average conditional slope. Given its limited within- R^2 and its assumption of a constant slope within each sample, it is unlikely to represent the full shape of the income–*cosphi* relationship. Read together with the descriptive evidence and LOWESS patterns reported in section 4.1, the results suggest that a common linear slope is too restrictive.

The role of the baseline model is therefore diagnostic rather than definitive. It establishes that the average association between income and *cosphi* is negative, but it does not determine whether that relationship is stable across the income distribution or common across country groups. The next section therefore turns to nonlinear specifications to evaluate whether a more flexible functional form provides a better description of the data.

4.3 Mapping the Nonlinear Structure: Shape Evidence from the Spline Fixed-Effects Model

Having shown in section 4.2 that the baseline linear fixed-effects model captures only an average conditional slope in the income–*cosphi* relationship, the next step is to examine its shape using a more flexible specification. In this paper, the spline fixed-effects model serves as the main tool for mapping nonlinear structure, because it allows the slope of the relationship to vary smoothly across the income distribution.

Table 5. Model Comparison across Nonlinear Specifications

Dataset	Sample	Preferred model	AIC	BIC	RMSE	Adj. within R ²	Nonlinear Wald p-value
Verified main	Full sample	Cubic FE	-2169.814	-2132.213	0.0250	0.0285	0.003
	Developed economies	Cubic FE	-1563.873	-1529.360	0.0240	0.0148	0.032
	Developing economies	Quadratic FE	-614.976	-591.443	0.0254	0.0476	<0.001
Version robustness	Full sample	Linear FE	-2510.870	-2480.700	0.0244	0.0154	—
	Developed economies	Quadratic FE	-1712.553	-1681.181	0.0238	0.0098	0.149
	Developing economies	Cubic FE	-802.948	-774.363	0.0238	0.0321	<0.001

Table 5 compares linear and nonlinear specifications across sample definitions and country groups. The results show that nonlinear models improve the description of the data in several cases, especially in the main estimation sample. In that sample, cubic fixed effects are preferred for the full sample and for developed economies, whereas quadratic fixed effects are preferred for developing economies. In the expanded sample, however, the preferred specification varies across groups, and linear fixed effects become more competitive in the pooled regression. The implication is not that one nonlinear form dominates in every configuration, but that the relationship is unlikely to be adequately described by a single common linear slope.

To examine functional shape more directly, Figure 3 plots the spline partial effects with 95% confidence bands for the full sample and for the two country groups separately.

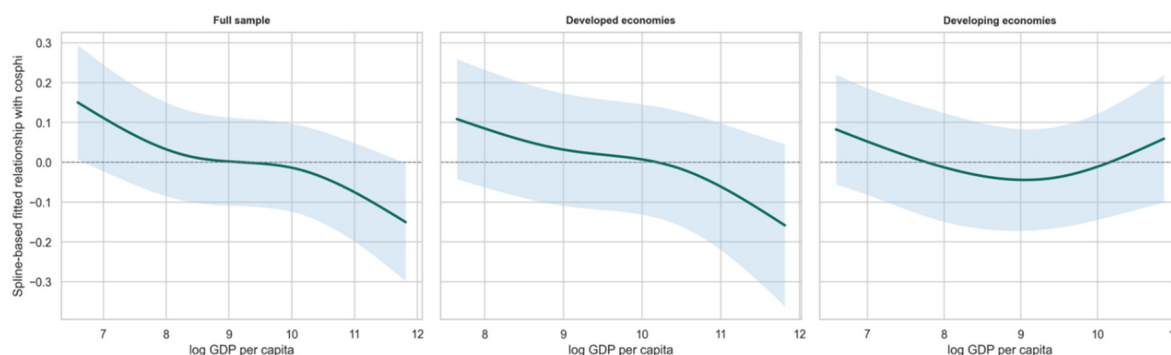


Figure 3. Spline Partial Effects with 95% Confidence Bands

Figure 3 shows that the income–*cosphi* relationship is nonlinear and differs across country groups. For the full sample and for developed economies, the spline curve tends to decline as income rises and becomes more strongly negative in the upper-income range. For developing economies, by contrast, the curve is more mildly nonlinear, declining through the low-to-middle range before turning slightly upward near the upper tail. Although the confidence bands widen at the extremes, especially for developing economies, the overall pattern remains inconsistent with a stable linear slope.

Taken together, Table 5 and Figure 3 support two conclusions. First, a common linear slope is too restrictive to characterize the income–*cosphi* relationship. Second, the nonlinear shape is heterogeneous across country groups. These results provide the basis for the next section, where threshold fixed-effects models are used as a supplementary device for organizing the nonlinear pattern into broader transition ranges.

4.4 Heterogeneity across Country Groups and Transition Zones

The spline results in the previous section show that the income–*cosphi* relationship is nonlinear, but also that its shape differs across country groups. This raises two related questions: whether the relationship follows different trajectories in developed and developing economies, and whether the observed variation should be interpreted as sharp regime breaks or as broader transition zones.

The spline curves suggest clear heterogeneity. In developed economies, the relationship becomes more clearly negative at higher income levels, indicating continued technological reorientation even in the upper-income range. In developing economies, by contrast, the curve is more mildly nonlinear, with stronger movement in the lower and middle parts of the income distribution and a weaker pattern near the top. The difference between the two groups therefore lies not only in average income levels, but also in the shape of the restructuring path itself.

To organize these nonlinear patterns more clearly, the paper next estimates threshold fixed-effects models. Their role here is limited: they are not used to identify exact structural income thresholds, but to provide a supplementary way of describing broader transition ranges in the income distribution.

Table 6. Threshold FE Estimates and Formal Threshold Tests

Panel A. Threshold Estimates					
Sample	Threshold 1 (USD per capita)	Threshold 2 (USD per capita)	Regime 1 slope	Regime 2 slope	Regime 3 slope
Full sample	32,653	53,996	-0.030	0.014	-0.070
Developed economies	50,566	61,627	-0.030	0.060	-0.104
Developing economies	2,578	12,715	0.007	-0.035	0.088

Panel B. Formal Threshold Tests for Sharp Breaks			
Sample	Test	LR statistic	Bootstrap p-value
Full sample	Single threshold vs. no threshold	12.481	0.840
	Two thresholds vs. one threshold	1.247	0.827
Developed economies	Single threshold vs. no threshold	14.350	0.654
	Two thresholds vs. one threshold	0.956	0.802
Developing economies	Single threshold vs. no threshold	5.829	0.443
	Two thresholds vs. one threshold	2.392	0.770

Table 6 shows that the estimated transition markers differ substantially across country groups. In developed economies, the implied cutoffs appear at much higher income levels than in developing economies, whereas in developing economies they arise much earlier in the distribution. At the same time, Hansen's bootstrap tests do not provide strong support for sharp threshold effects. The relatively high p-values in both the one-threshold and two-threshold tests indicate that the data do not support a strong interpretation in terms of precise or universal breakpoints. The estimated cutoffs should therefore be read as descriptive transition markers rather than exact structural thresholds.

Taken together, the spline and threshold results are more consistent with smooth and heterogeneous transition zones than with hard regime breaks. Threshold FE does not replace the spline evidence; it simply reorganizes the nonlinear pattern into broader income ranges that are easier to interpret substantively. The evidence in this section therefore supports two conclusions: the income–*cosphi* relationship differs meaningfully between developed and developing economies, and the relevant income ranges should be interpreted as heuristic transition zones rather than sharp structural thresholds.

4.5 Mechanisms of the Transition Zones

The previous sections show that the income–*cosphi* relationship is nonlinear and heterogeneous across country groups. A natural next question is whether this nonlinear structure is itself conditioned by the technological environment of the economy. To examine this possibility, the paper extends the spline fixed-effects model by interacting the spline basis of log GDP per capita with two mechanism variables, namely R&D expenditure and FDI. These interaction models are used to test whether the nonlinear shape identified earlier changes systematically with the economy's innovation capability and degree of foreign-capital integration.

Table 7. Mechanism-Conditioned Spline Models

Specification item	Spline × R&D	Spline × FDI
Joint test of interaction terms (p-value)	0.001	<0.001
AIC	-2169.149	-2160.810
BIC	-2114.836	-2106.497
ΔAIC relative to baseline spline	-3.354	4.985
ΔBIC relative to baseline spline	9.180	17.518
RMSE	0.02482	0.02504

Table 7 shows that the spline interaction terms are jointly significant in both the R&D and FDI specifications. However, the evidence is stronger for R&D. In the R&D case, the interaction model combines strong joint significance with an improvement in AIC relative to the baseline spline specification, indicating that endogenous innovation capability meaningfully conditions the nonlinear relationship. By contrast, although the FDI interactions are also jointly significant, the improvement in model fit is weaker. This difference is also visible in Figure 4, which plots the estimated income–*cosphi* relationship at low, median, and high levels of R&D. The figure shows that the shape of the relationship varies substantially with R&D intensity: at low R&D levels, *cosphi* starts higher and declines more sharply in the upper-income range; at median levels, the curve is flatter through the middle of the distribution; and at high R&D levels, the curve starts lower, rises through the low-to-middle range, and then declines again at higher income levels. The implication is that income does not operate through a universal restructuring path, but through a path conditioned by the economy's endogenous innovation capability.

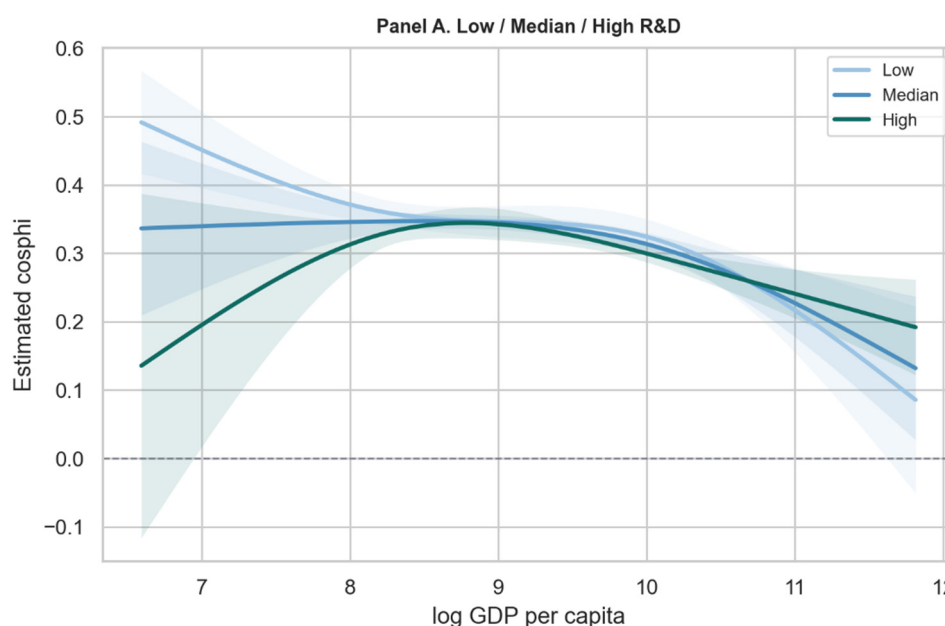


Figure 4. R&D-Conditioned Nonlinear Relationship between Income and *cosphi*

Taken together, the mechanism analysis suggests that the income–*cosphi* relationship is not only nonlinear and heterogeneous across country groups, but also conditional on the technological environment of the economy. Among the mechanisms considered, R&D provides stronger evidence than FDI that technological-intensity structural transformation depends on the ability to convert income growth into deeper technological restructuring. FDI still appears relevant, but its role is better interpreted as supplementary rather than central.

4.6 Robustness of the Results

To assess the credibility of the main findings, the paper conducts three robustness checks: sensitivity to sample construction, comparison between balanced and unbalanced panels, and a supplementary dynamic check using Difference GMM. The purpose is not to identify a single model that dominates in every configuration, but to examine whether the paper's central narrative of heterogeneous nonlinearity remains intact under alternative sample structures and estimation settings.

Table 8. Robustness to Sample Construction

Sample	Preferred model	AIC	BIC	RMSE
Main estimation sample / full sample	Cubic FE	-2169.814	-2132.213	0.02501
Main estimation sample / developed economies	Cubic FE	-1563.873	-1529.360	0.02395
Main estimation sample / developing economies	Quadratic FE	-614.976	-591.443	0.02541
Expanded sample / full sample	Linear FE	-2510.870	-2480.700	0.02437
Expanded sample / developed economies	Quadratic FE	-1712.553	-1681.181	0.02385
Expanded sample / developing economies	Cubic FE	-802.948	-774.363	0.02380

Table 8 shows that nonlinear evidence is stronger in the main estimation sample than in the expanded sample. In the main sample, cubic fixed effects are preferred for the full sample and for developed economies, while quadratic fixed effects fit better for developing economies. In the expanded sample, by contrast, linear fixed effects become more competitive in the pooled regression, and subgroup results are less uniform. This suggests that broader observational coverage does not remove the nonlinear signal altogether, but tends to weaken or diffuse it in pooled specifications. Additional checks using balanced panels do not overturn this pattern: the nonlinear structure remains broadly present, although the preferred functional form varies across sample versions. Taken together, these results indicate that sample construction matters for the clarity of the estimated relationship, but not in a way that reverses the paper's main conclusions.

Difference GMM is reported only as a supplementary dynamic check and is not used as a basis for the main inference. Although the dynamic specifications continue to suggest nonlinearity, diagnostic quality is uneven across samples, particularly because the pooled model yields a weak J-test result and the developing-country model shows an AR(2) problem. The dynamic evidence therefore does not replace the static fixed-effects results, but neither does it contradict the broader nonlinear pattern identified in the main analysis. Overall, the robustness checks reinforce three points: nonlinear evidence is strongest in the main estimation sample, the core pattern remains broadly present under alternative panel constructions, and the paper's central conclusions continue to rest on the static fixed-effects framework and complexity-penalized model comparison

5. Policy Implications

The empirical results suggest that technological-intensity structural transformation should not be understood as an automatic consequence of income growth or as a process governed by universal income thresholds. Instead, the evidence is more consistent with a conditional and heterogeneous transition process in which the effect of income depends on innovation capability, absorptive capacity, and stage of development. The policy implication is therefore not that countries simply need to reach a particular income level, but that they need the institutional and technological conditions that allow income growth to be translated into deeper restructuring.

For developing economies, the central policy priority is to strengthen the capacity to convert growth into substantive technological upgrading. The results indicate that these economies move through transition zones earlier in the income distribution, but that these zones do not guarantee automatic upgrading. Policy should therefore focus on higher education, R&D effort, absorptive capacity, and production linkages that support movement into more technology-intensive segments. The mechanism results further suggest that endogenous innovation capability matters more than FDI alone, implying that foreign-capital attraction is unlikely to be sufficient unless it is combined with domestic capability building.

For developed economies, the challenge is different. High income does not imply that technological restructuring is already complete or that it will continue automatically. Instead, the evidence points to continued restructuring in the upper-income range, but under conditions shaped by innovation-system quality, frontier R&D, and the ability to avoid structural inertia. Policy should therefore focus on sustaining advanced innovation ecosystems and renewing technological momentum rather than assuming that existing advantage will persist on its own. Taken together, the broader lesson of the paper is that industrial and innovation policy should be stage-sensitive and capability-sensitive, not organized around a "magic income threshold."

6. Conclusion

This paper examines whether the relationship between income and technological-intensity structural transformation in manufacturing is better described by a common linear slope, a hard income threshold, or a heterogeneous nonlinear structure across country groups. Using country-year panel data for 2014–2022, the analysis shows that a linear specification captures only an average conditional association and is insufficient to describe the full shape of the relationship between income and *cosphi*.

Three main findings emerge. First, nonlinear evidence is stronger in the main estimation sample than in the expanded sample, indicating that sample construction and data quality materially affect the clarity of the estimated relationship. Second, spline results show that the income–*cosphi* relationship is not stably linear and differs substantially between developed and developing economies. Third, threshold estimates are best interpreted as heuristic transition markers rather than as sharp structural breakpoints, because Hansen’s bootstrap tests do not provide strong support for hard thresholds.

The paper’s broader contribution is therefore not to identify a new income cutoff, but to reframe the income–structural transformation relationship as one characterized by heterogeneous transition zones. The results also indicate that this nonlinear structure is conditional rather than universal: R&D appears to be the more salient conditioning mechanism, while FDI plays a more limited supplementary role. Income should thus be understood not as a stand-alone force, but as one whose restructuring effect depends on each economy’s technological and innovation capability.

Several limitations should be acknowledged. The observation window remains relatively short for a topic involving structural and technological change, the results show some sensitivity to sample structure, and the mechanism analysis is limited to a narrow set of conditioning variables. Future research could extend the time dimension, develop richer measures of technological capability, and examine more closely the roles of innovation institutions, FDI composition, and global production-network positioning. Even so, the current evidence supports the view that technological-intensity structural transformation is best understood as a nonlinear, heterogeneous, and conditional process rather than as a common straight line or a set of universal hard thresholds.

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