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CARBON BORDER ADJUSTMENTS AND EXPORT DIVERSIFICATION ACROSS DEVELOPING MANUFACTURING ECONOMIES

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Abstract:

This analysis examines whether carbon intensity, manufacturing activity and foreign investment explain export diversification across developing manufacturing economies amid evolving environmental trade pressures. Using 176 annual observations from 15 economies during 2010 to 2021, the analysis applies ordinary least squares with economy and year fixed effects, clustered inference and sensitivity specifications. Carbon intensity exhibits a negative association with diversification, with a coefficient of −0.10864 and p value of 0.1887. Manufacturing activity also shows a negative association, with a coefficient of −0.00423 and p value of 0.3871, while foreign investment records a positive coefficient of 0.00110 and p value of 0.7453. None achieves statistical significance. Manufacturing majority estimates remain inconclusive, while alternative outcome specifications reveal directional sensitivity. These findings distinguish productive expansion from diversification across broad export categories, qualifying conventional structural transformation expectations. The analysis underscores the importance of measurement and economic heterogeneity, supporting differentiated industrial strategies, export monitoring and evidence based environmental trade assessments.

Key Words: Export Diversification; Carbon Intensity; Manufacturing Specialisation; Foreign Direct Investment; Panel Data Econometrics

1. Introduction:

The transition toward lower carbon production presents a structural challenge for developing manufacturing economies seeking to diversify their exports while maintaining international competitiveness. Carbon related trade measures can alter the relative costs of production and market access, potentially affecting economies whose export structures depend on established manufacturing capabilities and emissions intensive activities. Yet the relationship between carbon intensity and export diversification is not straightforward. Production systems with high emissions intensity may reinforce existing specialisation through accumulated infrastructure, capital and technological capabilities, while industrial expansion may create opportunities for additional export activities. Branger and Quirion (2014) demonstrate that the competitiveness implications of border carbon adjustments depend substantially on policy design and modelling assumptions, while Cosbey et al. (2019) identify important differences in how such measures may be implemented. These findings establish the importance of examining production characteristics and export structures together, but they do not determine whether economies with higher carbon intensity exhibit systematically different patterns of export diversification. Resolving this distinction matters because environmental trade assessments, industrial development strategies and export promotion policies require evidence on whether productive transformation is associated with broader export structures or reinforces existing specialisation.

Export diversification is closely connected to productive capabilities, economic development and international market integration, although its relationship with industrial expansion remains conditional. Hausmann and Hidalgo (2011) demonstrate that the structure of economic production reflects combinations of complementary capabilities, suggesting that diversification depends on the availability of knowledge, infrastructure and production networks. Cadot et al. (2011) identify a nonlinear relationship between development and export diversification, in which diversification can eventually give way to reconcentration. Parteka and Tamberi (2013) further establish that market access contributes to explaining export diversification beyond differences in income. Together, these studies indicate that expanding productive capacity does not necessarily produce a more balanced export composition. Their findings also expose an important measurement distinction: diversification across broad merchandise export categories is not equivalent to the development of additional products within an established manufacturing sector. This distinction becomes particularly relevant when manufacturing already represents the majority of merchandise exports, because further manufacturing expansion may strengthen the dominant export category even as production capabilities increase.

Carbon intensity introduces an additional dimension to this relationship through technological persistence and the allocation of productive resources. Carbon intensive production can depend on established technologies, specialised capital and infrastructure that are costly to replace or redirect toward alternative activities. Aghion et al. (2016) provide evidence that technological development responds to economic incentives while remaining influenced by previous innovation trajectories. This path dependence suggests that

emissions intensive production structures may be associated with persistent export specialisation. However, the relationship may also operate through productive expansion, as carbon intensive manufacturing can support intermediate inputs, industrial infrastructure and supplier networks that facilitate additional activities. Dechezleprêtre and Sato (2017) demonstrate that environmental regulation has heterogeneous competitiveness effects across sectors and institutional settings, challenging interpretations that assume uniform economic responses. Consequently, the expected negative relationship between carbon intensity and export diversification reflects a balance between technological persistence and opportunities for productive expansion. Carbon intensity itself measures emissions relative to economic output rather than regulatory stringency or exposure to carbon border charges. Its association with export composition therefore requires interpretation as a production characteristic rather than a direct measure of environmental trade policy.

Manufacturing activity provides a second explanation through industrial capabilities and productive specialisation. Manufacturing development can generate knowledge spillovers, supplier relationships and transferable skills that reduce the costs of entering related production activities. Neffke et al. (2011) demonstrate that industrial diversification follows technological relationships between existing and emerging activities, indicating that productive capabilities influence the direction of structural change. Nevertheless, expansion within manufacturing may increase the dominance of manufactured goods in aggregate merchandise exports rather than distribute export earnings more evenly across broad categories. Rodrik (2016) identifies substantial differences in industrialisation trajectories across developing economies, demonstrating that manufacturing development does not follow a uniform structural pattern. The relationship between manufacturing value added and broad export category diversification may therefore differ according to the initial composition of merchandise exports. Where manufactured products already exceed half of total merchandise exports, greater manufacturing activity may accompany stronger category concentration. This conditional expectation distinguishes productive diversification within manufacturing from diversification across manufacturing, agriculture, fuels and mineral exports.

Foreign direct investment represents a third potential influence through external financing, production knowledge and international commercial connections. Investment inflows may facilitate the development of additional export activities by expanding access to technology, supplier networks and foreign markets. Harding and Javorcik (2012) establish a relationship between investment promotion and export upgrading, suggesting that foreign investment can contribute to productive capability development. Havranek and Irsova (2011) identify productivity spillovers through relationships between foreign affiliates and domestic suppliers, although their magnitude varies across empirical settings. These mechanisms suggest that foreign investment may support diversification when domestic firms acquire capabilities that enable entry into additional export activities. However, foreign investment may also reinforce existing specialisation when capital flows concentrate in established sectors. Irsova and Havranek (2013) find that horizontal productivity spillovers depend on investor and domestic characteristics, with limited average effects across the reviewed evidence. Accordingly, aggregate foreign investment inflows cannot independently establish whether investment supports export diversification or strengthens existing production structures. The relevant empirical question concerns their conditional association with observed export composition.

The measurement of export diversification is central to distinguishing these competing explanations. Export diversification may describe the number of exported products, the distribution of export values across products or sectors, or changes in the sophistication and quality of exported goods. Cadot et al. (2013) demonstrate that these dimensions require careful conceptual and empirical differentiation. Henn et al. (2020) examine export quality as a distinct dimension of international trade performance, reinforcing the need to avoid treating export variety, composition and upgrading as interchangeable outcomes. This analysis measures broad export category diversification using the distribution of merchandise exports across manufactures, food, agricultural raw materials, fuels, and ores and metals. The recorded shares are normalised by their combined total, and diversification is calculated as one minus the sum of their squared normalised shares. Higher values indicate a more even distribution across the five categories. The effective number of export categories provides an alternative expression of the same distribution. This approach permits consistent comparisons of broad export composition while recognising that it does not measure product level entry, export sophistication or diversification within manufacturing.

The closest literature establishes important relationships between productive capabilities, development, environmental competitiveness and foreign investment, but the reviewed evidence does not resolve how carbon intensity, manufacturing value added and foreign investment jointly relate to broad export category diversification within developing manufacturing economies. Research on economic complexity and industrial relatedness explains how capabilities support productive expansion, while studies of export diversification identify nonlinear development patterns and the importance of market access. Environmental competitiveness research focuses primarily on regulatory design, production costs and sectoral exposure, whereas foreign investment research examines productivity spillovers and export upgrading. These contributions do not establish whether the three observed production and investment characteristics retain distinct conditional associations

with broad export category balance after accounting for economic development, trade integration, common annual changes and persistent economy differences. The unresolved issue is particularly relevant for manufacturing dominant export structures, where increasing industrial activity may coexist with greater concentration across broad merchandise categories. Addressing this gap requires an empirical framework that separates export composition from industrial upgrading and distinguishes observed associations from the causal effects of trade or environmental policies.

This study aims to examine the conditional relationships between carbon intensity, manufacturing value added, foreign direct investment inflows and broad export category diversification across selected developing manufacturing economies during 2010 to 2021. The central research question is whether these production and investment characteristics are systematically associated with the distribution of merchandise exports across broad categories after accounting for differences in economic conditions and persistent economy characteristics. Three specific objectives guide the analysis: to determine whether higher carbon intensity is associated with lower export diversification; to assess whether manufacturing value added is negatively associated with broad export category diversification when manufactured goods exceed half of merchandise exports; and to examine whether higher foreign direct investment inflows are associated with greater diversification. The manufacturing majority condition defines a theoretically relevant analytical subsample rather than an estimated interaction or mediation pathway. These objectives connect technological persistence, productive specialisation and external capability formation to observable differences in export composition without assuming that the proposed mechanisms are causally identified.

The empirical analysis integrates annual World Development Indicators observations for Bangladesh, Brazil, China, Egypt, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, the Philippines, South Africa, Thailand, Türkiye and Viet Nam. The documented frame contains 180 potential economy and year observations, of which 176 provide complete information for the analytical variables. The selected economies represent heterogeneous manufacturing and export structures rather than a statistically representative sample of all developing economies. Ordinary least squares estimation with economy and year fixed effects assesses conditional associations while controlling for GDP per capita, trade openness and GDP growth. Economy clustered standard errors account for within economy dependence, following Cameron and Miller (2015). The analytical design also recognises the limitations of fixed effects estimation for causal identification, as discussed by Imai and Kim (2019). Additional specifications examine manufacturing majority observations, an alternative diversification measure and balanced annual coverage. These comparisons assess the sensitivity of the findings to export composition, outcome transformation and sample coverage without attributing observed relationships to unmeasured carbon border adjustment policies.

The contribution of this analysis is to distinguish the relationship between productive expansion and broad export category balance from the broader processes of technological upgrading and industrial diversification. The empirical findings indicate that carbon intensity and manufacturing value added have negative baseline coefficients, while foreign direct investment has a small positive coefficient, but none of the three relationships achieves conventional statistical significance. The manufacturing majority specification likewise provides no statistically established negative manufacturing relationship, and sensitivity estimates reveal changes in coefficient direction and magnitude across outcome and sample definitions. These findings qualify interpretations that treat industrial expansion, foreign investment or carbon intensity as reliable standalone predictors of broad export diversification. Their relevance extends beyond the selected economies by clarifying the measurement and identification requirements for comparing productive transformation under changing environmental trade conditions. The remainder of the article presents the research hypotheses in Section 2, the data in Section 3, and the methods in Section 4. Section 5 presents the findings, Section 6 discusses their significance, and Section 7 sets out the conclusions and implications.

2. Theory, Conceptual Framework and Hypotheses Development:

This analysis links export diversification to productive capabilities, carbon intensity and investment conditions. Capability theory explains diversification through the knowledge, infrastructure and supplier networks that allow firms to produce additional goods. Hausmann and Hidalgo (2011) show how complementary capabilities shape national production structures. However, diversification does not increase uniformly with development. Cadot et al. (2011) identify diversification followed by reconcentration, while Parteka and Tamberi (2013) demonstrate that market access explains differences beyond income. These findings support a framework in which productive expansion can broaden exports or reinforce existing specialisation.

Carbon related trade constraints introduce a competitiveness mechanism. Differences in production emissions can affect the costs facing traded goods and influence incentives to retain or change production structures. Cosbey et al. (2019) explain how border carbon adjustment design connects carbon costs with international competitiveness. Branger and Quirion (2014) show that estimated competitiveness consequences depend on policy design and modelling assumptions. This analysis draws on that economic logic to examine associations between observed production characteristics and export composition.

Export diversification is operationalised as the evenness of exports across manufactures, food, agricultural raw materials, fuels, and ores and metals. The observed shares are normalised by their combined total. Diversification equals one minus the sum of their squared normalised shares. Higher values indicate a more balanced distribution across these five categories. Carbon intensity, manufacturing value added and foreign investment enter the framework as separate observed predictors.

Carbon intensity represents the emissions associated with generating a unit of economic output. Dependence on established carbon intensive technologies can tie capital, infrastructure and skills to existing activities. Such dependence can increase the costs of reallocating resources toward alternative production. The proposed mechanism therefore connects technological persistence with a less balanced export structure.

Evidence on directed technological change supports the relevance of technological persistence. Aghion et al. (2016) find that innovation responds to fuel prices while following firms' previous technological trajectories. Their findings indicate that accumulated capabilities can sustain existing production choices even when incentives change. Applied here, higher carbon intensity is expected to accompany lower diversification when established activities retain resources that could support alternative exports.

Industrial expansion provides a competing mechanism because carbon intensive production can support additional activities through infrastructure and intermediate inputs. Dechezleprêtre and Sato (2017) find heterogeneous competitiveness effects from environmental regulation, with aggregate effects generally smaller than effects in particular exposed sectors. The expected negative association therefore reflects a theoretical balance between technological persistence and productive expansion.

H1: Higher carbon intensity of GDP is associated with lower broad export category diversification.

Manufacturing value added captures the contribution of manufacturing production to GDP. Manufacturing expansion can support specialised suppliers, production knowledge and transferable skills. These connections can reduce the costs of entering related activities. Neffke et al. (2011) show that industrial diversification follows existing technological relationships, supporting the proposition that established capabilities influence subsequent productive expansion.

The expected relationship depends on the level at which diversification is measured. Additional manufactured products can broaden activity within manufacturing while increasing the dominance of manufactures in the five category export distribution. Where manufactures already exceed half of merchandise exports, further manufacturing expansion may therefore accompany lower broad category diversification. The observed manufactured export share provides a measurable boundary condition.

Manufacturing expansion also differs across development trajectories. Rodrik (2016) documents substantial variation in industrialisation opportunities and manufacturing performance across economies. Manufacturing value added should therefore not be interpreted as a universal indicator of export variety. The directional expectation concerns observations with an existing majority share of manufactured exports.

H2: Among observations where manufactures exceed half of merchandise exports, higher manufacturing value added as a share of GDP is associated with lower broad export category diversification.

Foreign direct investment inflows represent external investment relative to economic size. Foreign investors can introduce production knowledge, financing and commercial connections that help domestic firms develop export activities. These mechanisms can reduce entry barriers and spread export earnings across additional activities. Harding and Javorcik (2012) find evidence connecting investment promotion with export upgrading in developing economies, supporting the relevance of foreign investment to export capability formation.

Domestic supplier relationships provide a further transmission mechanism. Foreign affiliates can create demand for inputs and encourage suppliers to improve production practices. Havranek and Irsova (2011) find economically meaningful average productivity spillovers to suppliers, although effects vary across settings. The proposed diversification mechanism operates when these connections allow domestic firms to expand beyond the existing export core.

Foreign investment can also reinforce concentration when inflows favour established activities. Irsova and Havranek (2013) find that average horizontal productivity spillovers are approximately zero and depend on investor and domestic characteristics. A positive diversification association therefore cannot be assumed from investment inflows alone. The hypothesis expresses the expectation that capability expansion outweighs concentration within established activities.

H3: Higher foreign direct investment inflows as a share of GDP are associated with higher broad export category diversification.

The conceptual framework specifies three associations with broad export category diversification. Carbon intensity represents technological persistence, manufacturing value added represents productive specialisation, and foreign investment represents external capability formation. GDP per capita, GDP growth and trade as a share of GDP provide observed controls for development, economic conditions and international integration. The effective number of export categories provides an alternative expression of the same

distribution rather than an additional independent dimension. The hypotheses express theoretical expectations for empirical evaluation and allow contrary or statistically inconclusive results.

3. Data:

This analysis documents data provenance, establishes the analytical sample and translates the conceptual framework into observed variables. The procedures preserve source values, distinguish missing observations from zeros and support reproducible comparisons across economies.

3.1 Data Sources, Population, and Sample Construction:

The primary dataset combines eleven annual series from the World Bank's World Development Indicators through the Indicators API, version 2. Source observations, series identifiers and extraction URLs are preserved in the research workbook. The database catalogue identifier is 0037712. The extraction date is recorded separately from the observation period. A frozen database release identifier was not retained. Data use follows the applicable World Bank attribution licence and additional conditions attached to original providers.

The supplementary dataset contains 4,046 export records from the United Nations Comtrade database. These records describe exports to the world at the two-digit Harmonized System chapter level. The workbook retains the reported classification revision, export value and extraction URL. Supplementary records cover 42 economy and year combinations. Their incomplete coverage prevents their use as the primary estimation sample. Redistribution remains subject to United Nations Comtrade usage conditions.

The unit of analysis is an economy observed annually from 2010 to 2021. The documented frame comprises Bangladesh, Brazil, China, Egypt, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, the Philippines, South Africa, Thailand, Türkiye and Viet Nam. Fifteen economies observed over twelve years provide 180 potential observations. Export values and foreign investment inflows represent annual flows. Manufacturing value added, trade and investment shares express annual economic activity relative to their stated denominators.

The target population comprises developing economies with manufacturing activity and merchandise exports. The accessible frame is a purposive selection of fifteen economies rather than a verified population census. The analysis therefore makes conditional comparisons within the selected frame. Development and market access motivate comparative coverage, following Cadot et al. (2011) and Parteka and Tamberi (2013). Productive capabilities and industrial relatedness provide further reasons to compare heterogeneous production structures, as discussed by Hausmann and Hidalgo (2011) and Neffke et al. (2011). Rodrik (2016) establishes the relevance of distinguishing manufacturing trajectories across development settings. These arguments motivate the empirical setting without establishing population representativeness.

Four observations lack all five export category shares. They concern Bangladesh in 2014, 2019, 2020 and 2021. The complete analytical sample contains 176 observations across fifteen economies. Fourteen economies contribute twelve observations each, while Bangladesh contributes eight. The primary estimation panel is therefore unbalanced.

Table 1: Sample construction

Stage	Economies	Observations	Implemented Rule
Documented purposive frame	15	180	Annual coverage from 2010 to 2021
Excluded observations with missing export composition	1 affected	4 excluded	All five export shares unavailable
Integrated complete sample	15	176	Export components and all explanatory variables observed
Baseline specification	15	176	Contemporaneous variables with economy and year effects
Manufacturing majority specification	12	130	Manufactured exports exceed 50 percent of merchandise exports
Alternative outcome specification	15	176	Effective number of export categories
Balanced coverage sensitivity specification	14	168	Exclude Bangladesh and retain complete annual coverage

The baseline loses no additional observations through missing controls or estimator requirements. The manufacturing majority restriction excludes 46 observations from the complete sample. The balanced coverage check removes Bangladesh's eight retained observations. No lags or differences create further sample losses.

3.2 Data Integration, Cleaning, and Quality Assurance:

Integration uses the three letter economy identifier and reference year. Source observations additionally retain the indicator code, producing a unique economy, year and series key. Each series joins to the panel through a verified one to one relationship. The audit found no duplicate panel keys, duplicate source keys, unmatched source keys or discrepancies between panel values and corresponding source observations. Supplementary trade records also contain no duplicate economy, year, classification and chapter keys.

Raw observations remain separate from calculated outcomes. Numeric values retain their source units, while availability fields identify missing observations. This structure follows the data organisation principles described by Broman and Woo (2018). Preserved identifiers, extraction URLs and transformation records support traceability consistent with Wilkinson et al. (2016). Retaining original observations alongside executable calculations also supports the reproducibility principles discussed by Munafò et al. (2017).

All variables use the source reference year. No frequency conversion, currency conversion or additional inflation adjustment was applied. GDP per capita is supplied in constant 2015 US dollars. Carbon intensity uses kilograms of carbon dioxide equivalent per constant 2015 US dollar of GDP. Percentage variables retain the provider's original scale. Historical observations reflect revisions available at extraction rather than archived information sets available during each reference year.

Each export composition series contains four missing observations, producing twenty missing source cells across the same four Bangladesh years. Carbon intensity, manufacturing value added, foreign investment, GDP per capita, trade and GDP growth each contain 180 observed values. Missing export shares remain blank. No imputation, interpolation or replacement with zero was applied.

Complete observation selection does not establish that missingness is random. White and Carlin (2010) show that the relative performance of deletion and imputation depends on the missingness mechanism. Hughes et al. (2019) similarly caution against treating either approach as universally preferable. Excluded observations have mean GDP per capita of 1,507.59 US dollars, compared with 5,389.47 among retained observations. Mean trade shares are 32.52 and 66.52 percent, respectively. These differences identify a composition risk concentrated in one economy.

Quality checks confirmed finite analytical values, export shares between zero and 100, positive category denominators, positive GDP per capita and positive carbon intensity. Negative investment inflows and GDP growth were retained because they represent valid economic outcomes. Trade shares above 100 percent were retained because exports plus imports can exceed GDP. No observations were removed through trimming or winsorisation. Independently reconstructed diversification values matched the workbook calculations within numerical precision.

3.3 Variable Measurement, Construction, and Validation:

The principal outcome measures the distribution of merchandise exports across five broad categories. This concentration based approach distinguishes export composition from the number of individual products, consistent with the measurement distinctions reviewed by Cadot et al. (2013). It also differs from export quality, which concerns characteristics within product lines, as examined by Henn et al. (2020). Equation 1 normalises the recorded category shares:

$$q_{kit} = \frac{x_{kit}}{\sum_{j=1}^{5} x_{jit}}$$

Here, x_{kit} is the source percentage for export category k, economy i and year t. The index j enumerates the five categories. The resulting q_{kit} represents the category's share within their combined total. The five categories are manufactures, food, agricultural raw materials, fuels, and ores and metals. Normalisation ensures that their conditional shares satisfy:

$$\sum_{k=1}^{5} q_{kit} = 1.$$

Equation 3 defines export concentration:

$$H_{it} = \sum_{k=1}^{5} q_{kit}^{2} .$$

Here, H_{it} is the Herfindahl concentration index calculated across the five normalised export categories. Higher values indicate greater concentration. Equation 4 defines the principal diversification outcome:

$$D_{it} = 1 - H_{it}.$$

Here, D_{it} is broad export category diversification. Higher values indicate a more even distribution across the five categories. Equation 5 defines the alternative outcome:

$$N_{it} = \frac{1}{H_{it}}.$$

Here, N_{it} is the effective number of export categories. It expresses the observed concentration as an equivalent number of equally represented categories. The theoretical bounds are:

$$\frac{1}{5} \leq H_{it} \leq 1, \qquad 0 \leq D_{it} \leq \frac{4}{5}, \qquad 1 \leq N_{it} \leq 5.$$

The five source shares sum to between 70.2875 and 99.9999 percent of merchandise exports. Normalisation therefore measures the distribution within recorded categories without assigning unclassified trade to an invented residual category. The calculation requires all five components and applies the same

transformation across economies and years. Explicit denominators and aggregation rules address the construction concerns discussed by Greco et al. (2019).

The predictors remain separate observed measures. Carbon intensity describes national production emissions relative to output rather than environmental regulation. This distinction matters because regulatory competitiveness effects vary across activities and settings, as reviewed by Dechezleprêtre and Sato (2017). Foreign investment measures annual net inflows relative to GDP. It does not directly measure technology transfer or export upgrading, although Harding and Javorcik (2012) provide evidence connecting investment promotion with upgrading.

Table 2: Variable dictionary

Variable or Indicator	Analytical Role	Definition And Construction	Source and Identifier	Unit and Frequency	Transformation and Direction	Missing Value Rule	Coverage and Limitation
Broad export category diversification	Primary outcome	$D_{it} = 1 - H_{it}$	Calculated from the five WDI export series	Annual index	Higher values indicate greater category evenness	Require all five components	176 observations; broad export composition
Effective export categories	Alternative outcome	$N_{it} = H_{it}^{-1}$	Same five WDI export series	Annual effective count	Higher values indicate more effective categories	Require all five components	176 observations; alternative transformation of the same distribution
Manufactured exports	Outcome component and conditional sample criterion	Manufactured exports as a percentage of merchandise exports	WDI, TX.VAL.MANF.ZS.UN	Annual percent	Source level; values above 50 define the conditional sample	Preserve missing values	176 observations
Food exports	Outcome component	Food exports as a percentage of merchandise exports	WDI, TX.VAL.FOOD.ZS.UN	Annual percent	Normalised through Equation 1	Preserve missing values	176 observations
Agricultural raw material exports	Outcome component	Agricultural raw material exports as a percentage of merchandise exports	WDI, TX.VAL.AGRI.ZS.UN	Annual percent	Normalised through Equation 1	Preserve missing values	176 observations
Fuel exports	Outcome component	Fuel exports as a percentage of merchandise exports	WDI, TX.VAL.FUEL.ZS.UN	Annual percent	Normalised through Equation 1	Preserve missing values	176 observations
Ores and metals exports	Outcome component	Ores and metals exports as a percentage of merchandise exports	WDI, TX.VAL.MMTL.ZS.UN	Annual percent	Normalised through Equation 1	Preserve missing values	176 observations
Carbon intensity	Predictor	Carbon dioxide equivalent emissions relative to real GDP	WDI, EN.GHG.CO2.RT.GDP.KD	Annual kilograms per constant 2015 US dollar	Source level; higher values indicate greater carbon intensity	Require an observed value	180 available; 176 in baseline
Manufacturing value added	Predictor	Manufacturing value added as a percentage of GDP	WDI, NV.IND.MANF.ZS	Annual percent	Source level; higher values indicate greater manufacturing contribution	Require an observed value	180 available; 176 in baseline
Foreign direct investment	Predictor	Annual net investment inflows as a percentage of GDP	WDI, BX.KLT.DINV.WD.GD.ZS	Annual percent	Source level; negative values retained	Require an observed value	180 available; 176 in baseline; no sector allocation
GDP per capita	Control	Real GDP per person	WDI, NY.GDP.PCAP.KD	Annual constant 2015 US dollars	Source level	Require an observed value	180 available; 176 in baseline
Trade openness	Control	Exports plus imports as a percentage of GDP	WDI, NE.TRD.GNFS.ZS	Annual percent	Source level; values may exceed 100	Require an observed value	180 available; 176 in baseline

Variable or Indicator	Analytical Role	Definition And Construction	Source and Identifier	Unit and Frequency	Transformation and Direction	Missing Value Rule	Coverage and Limitation
GDP growth	Control	Annual percentage growth of real GDP	WDI, NY.GDP.MKTP.KD.ZG	Annual percent	Source growth rate; negative values retained	Require an observed value	180 available; 176 in baseline

Percentage variables retain the zero to 100 scale. A one unit change therefore represents one percentage point. No logarithmic transformation or standardisation was applied. The outcome and its component shares are not entered together as explanatory variables. The effective category count replaces diversification only in the alternative outcome specification.

Table 3: Descriptive statistics for the common estimation sample

Variable	Valid Observations	Mean	SD	Median	Minimum	Maximum
Broad export category diversification	176	0.4504	0.1846	0.4382	0.0811	0.7464
Effective export categories	176	2.0652	0.7793	1.7801	1.0883	3.9435
Carbon intensity	176	0.6825	0.2944	0.6142	0.2545	1.4900
Manufacturing value added	176	18.5075	5.2184	17.6893	10.3325	31.5624
Foreign investment inflows	176	2.2494	1.3640	2.0108	−0.8583	9.6810
GDP per capita	176	5,389.47	3,392.97	3,755.16	943.66	13,670.94
Trade openness	176	66.5205	38.6162	54.1024	22.7722	186.6758
GDP growth	176	4.1569	3.4647	4.7851	−9.5183	11.8111

Standard deviations use the sample denominator. Validation consists of source reconciliation, range checks, denominator checks and independent reconstruction of calculated outcomes.

3.4 Analytical Framework, Identification, and Reproducibility:

The implemented analysis estimates conditional associations within economies. Equation 7 specifies the baseline:

$$D_{it} = \alpha_i + \lambda_t + \beta_1 C_{it} + \beta_2 M_{it} + \beta_3 F_{it} + \gamma_1 P_{it} + \gamma_2 T_{it} + \gamma_3 G_{it} + \varepsilon_{it}.$$

Here, D_{it} is export diversification, C_{it} is carbon intensity, M_{it} is manufacturing value added, and F_{it} is foreign investment inflows. The controls P_{it}, T_{it} and G_{it} represent GDP per capita, trade openness and GDP growth. Economy effects are denoted by α_i, year effects by λ_t and the remaining disturbance by ε_{it}. The parameters $\beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3$ describe conditional slopes.

Ordinary least squares estimate Equation 7 with explicit economy and year indicators. All explanatory variables refer to the same year as the outcome. The baseline design matrix has full column rank and uses 176 observations. The reported associations use variation within economies after accounting for common year effects and the included covariates.

Inference uses economy clustered covariance estimates with the conventional CR1 finite sample adjustment. Tests use a student reference distribution with the number of economies minus one degree of freedom. This procedure accommodates dependence within economies, following Cameron and Miller (2015). The baseline contains fifteen clusters, while the manufacturing majority specification contains twelve. Pustejovsky and Tipton (2018) show why conventional cluster inference can remain sensitive to small cluster counts despite finite sample adjustments.

Economy effects absorb stable differences, while year effects absorb common annual shifts. They do not establish that explanatory variables are independent of unobserved changing conditions. Imai and Kim (2019) explain why fixed effects alone do not establish causal identification. Dependence across economies also differs from dependence within economies, as established by Cameron et al. (2011). Omitted changing confounders remain a threat to interpretation, consistent with Cinelli and Hazlett (2020). The coefficients are therefore interpreted as conditional associations rather than policy effects.

Three additional specifications were implemented. The manufacturing majority specification applies Equation 7 to the 130 observations where manufactured exports exceed 50 percent of merchandise exports. This is an observed sample condition rather than an estimated interaction. The alternative outcome specification replaces D_{it} with N_{it} while retaining the same 176 observations. The balanced coverage specification excludes Bangladesh and retains 168 observations across fourteen economies.

These checks are exploratory. The alternative outcome assesses sensitivity to scaling within the same export distribution, while the balanced panel assesses sensitivity to the economy with incomplete coverage. Neither provides independent causal validation. No observations were trimmed or eligibility thresholds revised after inspecting coefficient estimates.

The replication materials retain the variable dictionary, source reconciliation checks, missingness records, descriptive calculations and executable estimation code. An independent residualisation calculation reproduced the baseline slope estimates within numerical precision. Source definitions, annual timing, measurement scales and complete observation rules remain consistent across the documented specifications.

4. Methods:

This analysis employs a longitudinal panel framework to estimate conditional relationships between carbon intensity, manufacturing activity, foreign direct investment and broad export category diversification. The methodological approach combines two-way fixed effects estimation, economy clustered statistical inference and sensitivity specifications to assess the direction, magnitude and precision of the hypothesised associations. The design prioritises transparent measurement, consistent sample construction and reproducible estimation without attributing causal effects to observational relationships.

4.1 Research Design and Identification Strategy:

This analysis adopts a quantitative longitudinal research design using annual economy level observations from 2010 to 2021. The analytical objective is to estimate the conditional associations between three production and investment characteristics and export diversification across selected developing manufacturing economies. The unit of analysis is the economy year, while the principal outcome measures the evenness of merchandise exports across five broad categories. The explanatory variables comprise carbon intensity of GDP, manufacturing value added as a percentage of GDP and foreign direct investment inflows as a percentage of GDP. GDP per capita, trade openness and GDP growth provide additional controls for economic development, international integration and annual economic conditions.

The identification strategy exploits changes in explanatory variables within economies over time after accounting for persistent economy characteristics and common annual shocks. Economy fixed effects absorb time invariant differences in geography, historical production structures and other stable characteristics, while year fixed effects account for annual influences shared across the sample. The estimated coefficients therefore describe conditional within economy relationships rather than differences driven exclusively by cross sectional characteristics. This approach is consistent with the panel inference principles discussed by Cameron and Miller (2015), although fixed effects alone do not establish causal identification, as demonstrated by Imai and Kim (2019).

The conceptual framework evaluates three hypotheses. The first concerns a negative association between carbon intensity and export diversification, reflecting technological persistence and productive specialisation. The second examines a negative manufacturing relationship within observations where manufactured goods exceed half of merchandise exports. The third concerns a positive association between foreign investment and diversification through potential capability formation. The manufacturing majority condition defines an observed analytical subsample rather than a causal treatment, interaction effect or mediation mechanism.

Identification relies on sufficient within economy variation in the explanatory variables after accounting for year effects and observed controls. The documented baseline design matrix has full column rank, supporting estimation of the specified conditional coefficients. Nevertheless, changing institutional conditions, sectoral policies, investment allocation and technological developments may jointly influence production characteristics and export composition. Reverse causality and omitted time varying factors therefore remain possible. Cinelli and Hazlett (2020) establish the importance of unobserved confounding for interpreting observational estimates. Accordingly, this analysis treats all estimated relationships as conditional associations rather than causal effects of carbon border adjustments or other environmental trade measures.

4.2 Model Specification and Measurement Alignment:

The empirical specification follows the analytical framework and variable definitions documented in Table 2. Broad export category diversification is constructed from five recorded merchandise export shares, covering manufactures, food, agricultural raw materials, fuels, and ores and metals. Equation 1 normalises these shares by their combined total, while Equations 3 and 4 define export concentration and diversification. The effective number of export categories, defined in Equation 5, provides an alternative expression of the same distribution. This measurement strategy distinguishes broad export composition from product level variety and export quality, consistent with Cadot et al. (2013). The baseline econometric model is specified in Equation 7:

$$D_{it} = \alpha_i + \lambda_t + \beta_1 C_{it} + \beta_2 M_{it} + \beta_3 F_{it} + \gamma_1 P_{it} + \gamma_2 T_{it} + \gamma_3 G_{it} + \varepsilon_{it}.$$

Here, D_{it} denotes broad export category diversification for economy i in year t. C_{it} represents carbon intensity measured in kilograms of carbon dioxide equivalent per constant 2015 US dollar of GDP. M_{it} denotes manufacturing value added as a percentage of GDP, and F_{it} represents annual foreign direct investment net inflows as a percentage of GDP. The control variables P_{it}, T_{it} and G_{it} denote GDP per capita in constant 2015 US dollars, trade openness as a percentage of GDP and annual real GDP growth, respectively. Economy fixed effects are represented by α_i, year fixed effects by λ_t, and the regression disturbance by ε_{it}. The

parameters$\beta_1, \beta_2, \beta_3$represent the principal conditional slopes, while γ_1, $\gamma_2$and $\gamma_3$represent associations with the controls.

All explanatory variables enter contemporaneously with the dependent variable. The specification retains their original measurement scales without logarithmic transformation or standardisation. Consequently, a one unit increase in a percentage variable represents one percentage point, while the carbon intensity coefficient measures the associated index change per additional kilogram of carbon dioxide equivalent per constant dollar. The controls account for observed economic differences that may coincide with export composition, although contemporaneous adjustment does not eliminate the possibility that some controls respond to the same underlying economic processes as the explanatory variables.

The manufacturing majority specification applies Equation 7 to observations where manufactured exports exceed 50 percent of merchandise exports. This restriction evaluates the second hypothesis within its theoretically defined setting without introducing an unestimated interaction term. The alternative outcome specification replaces \(D_{it}\) with the effective number of export categories while preserving the explanatory structure. The balanced coverage specification retains Equation 7 but excludes the economy with incomplete annual export composition observations. These specifications permit comparisons of coefficient direction, magnitude and uncertainty across defined analytical conditions.

4.3 Sample Construction, Estimation and Statistical Inference:

The estimation sample follows the eligibility and integration procedures reported in Table 1. The documented sampling frame contains 15 developing manufacturing economies observed annually over twelve years, yielding 180 potential observations. Four Bangladesh observations lack the five export category shares required to construct the dependent variable. Their exclusion produces an unbalanced analytical panel of 176 observations, with fourteen economies contributing twelve observations and Bangladesh contributing eight. The manufacturing majority specification contains 130 observations across twelve economies, while the balanced coverage specification contains 168 observations across fourteen economies. The alternative outcome specification retains the complete analytical sample.

The analytical dataset integrates eleven World Development Indicators series using economy identifiers, reference years and source indicator codes. Source observations and calculated outcomes remain separately identifiable. Integration checks establish unique economy year keys, consistent source relationships and agreement between the integrated panel and corresponding source observations. Missing export shares remain unobserved rather than being replaced with zeros. No imputation, interpolation, trimming or winsorisation was applied. Negative foreign investment and GDP growth observations remain in the dataset because they represent valid economic values. The complete observation approach preserves directly observed measurements, although its interpretation depends on the distribution of missingness, as discussed by White and Carlin (2010) and Hughes et al. (2019).

Ordinary least squares estimate Equation 7 using explicit economy and year indicator variables. The estimator is appropriate for describing conditional linear associations in the observed panel and accommodates the additive fixed effect's structure. The baseline estimation uses 176 observations without additional losses from controls, lags or differencing. The reported coefficients are unweighted conditional estimates, and the design does not involve instrumental variables, treatment assignment or generated causal exposure measures.

Statistical inference uses economy clustered covariance estimates with the conventional CR1 finite sample adjustment. This approach allows arbitrary heteroskedasticity and within economy dependence under the clustering assumptions, following Cameron and Miller (2015). The baseline contains fifteen economy clusters, while the manufacturing majority and balanced coverage specifications contain twelve and fourteen clusters, respectively. Hypothesis tests use a student reference distribution with the number of economies minus one degree of freedom. Two-sided tests and 95 percent confidence intervals quantify uncertainty, with statistical significance evaluated at the 5 percent level.

The limited number of clusters requires cautious interpretation because conventional clustered inference may remain sensitive to small sample properties. Pustejovsky and Tipton (2018) demonstrate that finite sample corrections do not automatically eliminate inference problems when cluster counts are limited. Furthermore, clustering by economy addresses within economy dependence but does not independently establish robustness to all forms of cross economy dependence. Cameron et al. (2011) distinguish these dependence structures and their implications for covariance estimation. The reported inference therefore reflects the implemented economy clustering convention rather than a comprehensive correction for every possible dependence pattern.

4.4 Validation, Sensitivity Analysis and Reproducibility:

The analytical procedures begin with source reconciliation and verification of economy, year and indicator identifiers, followed by construction of the five category diversification measures. Complete observations are selected only after verifying the availability of the required export components and explanatory variables. The resulting analytical variables are checked for finite values, valid export percentage ranges, positive category denominators and consistency with source measurement units. Independently reconstructed

diversification values match the workbook calculations within numerical precision. These procedures support measurement traceability and reproducibility, consistent with Broman and Woo (2018) and Wilkinson et al. (2016).

Model validation includes verification that the baseline design matrix has full column rank and independent reproduction of the baseline slope coefficients through residualisation. The independent calculation matches the ordinary least squares estimates within numerical precision, confirming consistency between the fixed effects implementation and the corresponding partial regression calculation. This verification establishes computational agreement rather than causal identification or the absence of model misspecification.

Three exploratory sensitivity specifications assess consequential analytical choices. The manufacturing majority restriction evaluates the hypothesised manufacturing relationship within observations dominated by manufactured exports. The alternative outcome specification examines whether coefficient patterns depend on expressing the same export distribution as diversification or an effective category count. The balanced coverage specification evaluates sensitivity to excluding Bangladesh, whose missing export observations produce incomplete annual coverage. Each specification retains the same contemporaneous explanatory variables, controls and fixed effects structure, allowing differences to be interpreted in relation to the changed sample or outcome definition.

Sensitivity is evaluated through changes in coefficient direction, magnitude and statistical uncertainty rather than significance alone. The alternative outcome remains a transformation of the same underlying export distribution and therefore does not provide independent measurement validation. Similarly, the manufacturing majority specification changes sample composition without estimating a formal moderation effect, while the balanced coverage comparison does not establish that missing observations are random. These distinctions prevent the sensitivity analysis from being interpreted as evidence of causal robustness.

Reproducibility is supported by preserved source observations, indicator identifiers, extraction URLs, variable definitions, missingness records, descriptive calculations and executable estimation code. The documented workflow retains consistent annual timing, original measurement scales and sample eligibility rules across specifications. These practices follow the reproducibility principles discussed by Munafò et al. (2017). Taken together, the design provides a transparent assessment of conditional relationships between production characteristics, investment conditions and export composition, while preserving the distinction between statistically estimated associations and unobserved causal mechanisms.

5. Findings:

This analysis examines the relationships between carbon intensity, manufacturing activity, foreign direct investment and export diversification across developing manufacturing economies. The empirical assessment combines descriptive evidence with economy and year fixed effects regressions, using clustered inference to evaluate three hypotheses. Alternative outcome and sample specifications assess the stability of the estimated relationships and their implications for understanding export structures.

5.1 Sample Characteristics and Export Diversification Patterns:

The analytical sample comprises 176 annual observations from 15 developing manufacturing economies during 2010 to 2021. The initial sampling frame contained 180 observations, of which four Bangladesh observations were excluded because all five merchandise export category shares were unavailable. The resulting panel retains 12 annual observations for 14 economies and eight for Bangladesh. The manufacturing majority subsample contains 130 observations across 12 economies, while the balanced coverage sample contains 168 observations across 14 economies.

Export diversification measures the evenness of merchandise exports across manufactures, food, agricultural raw materials, fuels, and ores and metals. The index equals one minus the sum of squared category shares after normalisation within the five recorded categories. Higher values indicate greater diversification, while the effective number of export categories provides an alternative representation of the same distribution. This distinction follows the measurement concerns identified by Cadot et al. 2013 and Greco et al. 2019. The emphasis on productive capabilities and industrial composition is consistent with Hausmann and Hidalgo 2011, Neffke et al. 2011 and Rodrik 2016.

Table 4: Descriptive statistics of the analytical sample

Variable	N	Mean	SD	Minimum	Maximum
Export diversification	176	0.4504	0.1846	0.0811	0.7464
Effective export categories	176	2.0652	0.7793	1.0883	3.9435
Carbon intensity	176	0.6825	0.2944	0.2545	1.4900
Manufacturing value added	176	18.5075	5.2184	10.3325	31.5624
Foreign direct investment	176	2.2494	1.3640	−0.8583	9.6810
GDP per capita	176	5,389.47	3,392.97	943.66	13,670.94
Trade openness	176	66.5205	38.6162	22.7722	186.6758

GDP growth	176	4.1569	3.4647	−9.5183	11.8111

Note: SD denotes sample standard deviation. Carbon intensity is measured in kilograms of carbon dioxide equivalent per constant 2015 US dollar of GDP. GDP per capita is expressed in constant 2015 US dollars. Manufacturing value added, foreign direct investment, trade openness and GDP growth are expressed in percent. The diversification index and effective category count are calculated from five normalised export shares.

The mean diversification index of 0.4504 indicates substantial concentration within the recorded export categories, although its standard deviation of 0.1846 reveals considerable variation across observations. The effective category count averages 2.0652, indicating that the observed distribution corresponds to approximately two equally represented export categories. Its maximum of 3.9435 demonstrates that some economy and year combinations maintain considerably more balanced export structures.

Manufacturing contributes an average of 18.51 percent of GDP, while carbon intensity averages 0.6825 kilograms per constant dollar. Foreign direct investment inflows average 2.25 percent of GDP but include negative observations, indicating periods of net disinvestment. These differences establish meaningful variation in production characteristics and investment conditions, although descriptive distributions alone cannot establish the direction of the hypothesised relationships.

The five recorded export categories account for between 70.2875 and 99.9999 percent of merchandise exports before normalisation. Consequently, the diversification index measures balance within the observed categories rather than complete product level export variety. The four excluded observations also have lower average GDP per capita and trade openness than retained observations, introducing a potential composition limitation. These measurement and sample characteristics constrain the interpretation of the regression estimates.

5.2 Hypothesis Testing and Main Regression Findings:

This analysis estimates ordinary least squares regressions with economy and year fixed effects to identify conditional relationships between export diversification and the three explanatory variables. GDP per capita, trade openness and GDP growth enter as controls. Standard errors are clustered by economy using the CR1 finite sample adjustment, with statistical inference based on the number of economy clusters. This approach follows Cameron and Miller 2015, while the interpretation of conditional associations reflects the identification considerations established by Imai and Kim 2019 and Cinelli and Hazlett 2020.

Table 5: Main regression estimates for export diversification

Explanatory Variable	Coefficient	Clustered SE	95% CI	p Value
Carbon intensity	−0.10864	0.07863	−0.27728 to 0.05999	0.1887
Manufacturing value added	−0.00423	0.00473	−0.01438 to 0.00593	0.3871
Foreign direct investment	0.00110	0.00332	−0.00602 to 0.00822	0.7453
GDP per capita	−0.0000044	0.0000146	−0.0000358 to 0.0000270	0.7685
Trade openness	−0.00133	0.00094	−0.00334 to 0.00069	0.1796
GDP growth	−0.00003	0.00126	−0.00274 to 0.00268	0.9813

Model information	Value
Observations	176
Economies	15
R squared	0.9816
Adjusted R squared	0.9776
Economy fixed effects	Included
Year fixed effects	Included

Note: The dependent variable is the five-category export diversification index. SE denotes standard error and CI denotes confidence interval. Confidence intervals and two-sided p values use economy clustered CR1 covariance estimates with 14 degrees of freedom. Percentage variables enter in percentage point units. The reported R squared includes the contribution of economy and year fixed effects.

The estimated carbon intensity coefficient is −0.10864, indicating that an increase of 0.1 kilograms of carbon dioxide equivalent per constant dollar is associated with a 0.01086 reduction in the diversification index, conditional on the included controls and fixed effects. However, the confidence interval extends from −0.27728 to 0.05999 per unit, and the p value of 0.1887 exceeds the conventional 5 percent threshold. The estimated direction is consistent with the technological persistence mechanism examined by Aghion et al. 2016, but the evidence does not establish a statistically distinguishable negative relationship. H1 is therefore not statistically supported.

Manufacturing value added has a negative coefficient of −0.00423 in the complete sample. A one percentage point increase in manufacturing value added is associated with a 0.00423 reduction in diversification, holding the other variables constant. The confidence interval includes zero and the p value is 0.3871. This estimate describes the full sample and does not independently test the manufacturing majority hypothesis. The conditional analysis is reported separately below.

Foreign direct investment has a positive coefficient of 0.00110, implying a 0.00110 increase in diversification for each additional percentage point of investment inflows relative to GDP. The confidence interval ranges from −0.00602 to 0.00822, with a p value of 0.7453. Although the coefficient has the direction anticipated by the external capability formation argument of Harding and Javorcik 2012, the estimate is imprecise and does not establish a positive relationship. H3 is not statistically supported.

The control variables also lack statistically significant conditional associations at the 5 percent level. The model explains 98.16 percent of the total observed variation, including variation accounted for by the economy and year indicators. This high explanatory proportion does not establish causal identification or demonstrate that the three substantive predictors independently explain export diversification. The estimated coefficients provide conditional within economy associations after adjustment for common annual changes and observed covariates.

5.3 Conditional Manufacturing Effects and Robustness Assessment:

The manufacturing majority specification restricts estimation to observations where manufactured goods exceed 50 percent of merchandise exports. This restriction directly evaluates H2 within its defined empirical setting. The alternative outcome replaces the diversification index with the effective number of export categories, while the balanced coverage specification excludes Bangladesh to assess sensitivity to incomplete annual coverage.

The sensitivity analysis retains the same explanatory variables, controls and fixed effect's structure. Economy clustered inference remains appropriate for within economy dependence, although small cluster counts can affect test reliability, as demonstrated by Pustejovsky and Tipton 2018. The interpretation also recognises the distinction between within cluster and cross-sectional dependence discussed by Cameron et al. 2011. The alternative outcome follows the export measurement considerations of Cadot et al. 2013 and Greco et al. 2019, while the balanced coverage comparison addresses the complete observation selection concerns discussed by Hughes et al. 2019.

Table 6: Conditional and sensitivity regression estimates

Variable	Manufacturing Majority	Effective Categories	Balanced Coverage
Carbon intensity	0.00215	−0.26302	−0.12223
Clustered SE	0.07721	0.33224	0.07556
p value	0.9783	0.4418	0.1297
Manufacturing value added	−0.00325	−0.01511	−0.00675
Clustered SE	0.00454	0.01795	0.00624
p value	0.4886	0.4143	0.2991
Foreign direct investment	0.00378	−0.00118	0.00112
Clustered SE	0.00473	0.01432	0.00340
p value	0.4411	0.9353	0.7481
Observations	130	176	168
Economies	12	15	14
R squared	0.9697	0.9810	0.9788
Adjusted R squared	0.9613	0.9769	0.9741

Note: All specifications include GDP per capita, trade openness, GDP growth, economy fixed effects and year fixed effects. Standard errors use economy clustered CR1 covariance estimates. The manufacturing majority and balanced coverage specifications use the diversification index. The alternative outcome specification uses the effective category count. Reported p values are two sided.

Within the manufacturing majority sample, manufacturing value added has a coefficient of −0.00325, with a standard error of 0.00454 and a p value of 0.4886. Its 95 percent confidence interval extends from −0.01325 to 0.00674. A one percentage point increase in manufacturing value added is therefore associated with a 0.00325 reduction in the diversification index, but the estimate remains statistically inconclusive. H2 is not statistically supported, despite the negative coefficient matching its predicted direction.

The carbon intensity coefficient changes from −0.10864 in the baseline to 0.00215 in the manufacturing majority sample. This directional change indicates sensitivity to sample composition, although

neither estimate is statistically significant. Foreign direct investment retains a positive coefficient of 0.00378 in the restricted sample, but its p value of 0.4411 does not support a reliable positive association.

Replacing the diversification index with the effective category count produces negative coefficients for carbon intensity and manufacturing value added. Their p values of 0.4418 and 0.4143 indicates substantial uncertainty. The foreign investment coefficient changes sign to −0.00118, with a p value of 0.9353. Consequently, the positive investment relationship does not remain directionally consistent under the alternative outcome transformation.

The balanced coverage specification retains negative coefficients for carbon intensity and manufacturing value added and a positive coefficient for foreign investment. Carbon intensity becomes somewhat more negative at −0.12223, while manufacturing value added reaches −0.00675. Nevertheless, their respective p values of 0.1297 and 0.2991 remain above the 5 percent threshold. The foreign investment coefficient remains close to its baseline magnitude at 0.00112, with a p value of 0.7481.

Taken together, these comparisons show that the estimated relationships are sensitive to outcome definition and sample composition, particularly for carbon intensity and foreign investment. None of the three hypothesised relationships achieves conventional statistical significance across the implemented specifications. The sensitivity results therefore reinforce the need to distinguish theoretically plausible mechanisms from empirically established associations.

5.4 Hypothesis Assessment and Empirical Implications:

The hypothesis assessment applies a two sided 5 percent significance criterion, supported by coefficient direction, confidence intervals and sensitivity across specifications. This evaluation distinguishes consistency with theoretical expectations from sufficient statistical evidence.

Table 7: Summary of hypothesis testing

Hypothesis	Expected Relationship	Estimated Coefficient	p Value
H1: Carbon intensity and diversification	Negative	−0.10864	0.1887
H2: Manufacturing value added and diversification within manufacturing majority observations	Negative	−0.00325	0.4886
H3: Foreign investment and diversification	Positive	0.00110	0.7453

Note: H1 and H3 use the complete sample of 176 observations. H2 uses the manufacturing majority sample of 130 observations.

The results establish three empirical findings. First, higher carbon intensity is associated with lower diversification in the complete sample, but the estimated relationship is insufficiently precise to establish the hypothesised negative association. Second, manufacturing value added has a negative coefficient within manufacturing majority observations, yet the evidence does not distinguish this relationship from zero. Third, foreign investment inflows exhibit a small positive baseline coefficient without statistically reliable evidence of diversification gains.

The main contribution is the distinction between broad export category diversification and productive expansion within manufacturing. Manufacturing growth can coexist with greater specialisation across broad export categories because the index measures the distribution among five sectors rather than product variety within manufacturing. The estimates do not establish that manufacturing expansion causes concentration, but they clarify why the measurement level matters when evaluating structural diversification.

The findings also distinguish production carbon intensity from direct exposure to carbon border adjustment policies. The observed carbon variable measures emissions relative to GDP rather than border charges, regulatory compliance costs or policy treatment. Accordingly, the estimated relationship cannot be interpreted as an effect of carbon border adjustments on export diversification.

The evidence supports a limited but informative empirical conclusion. Across the selected developing manufacturing economies, carbon intensity, manufacturing value added and foreign investment do not exhibit statistically established conditional relationships with broad export category diversification under the implemented specifications. The coefficient directions provide partial consistency with the proposed mechanisms, but their uncertainty and sensitivity prevent stronger conclusions. The results identify the importance of export composition, measurement choice and economy heterogeneity for interpreting diversification patterns without attributing unobserved policy effects to the available data.

6. Discussion:

The central finding of this analysis is that carbon intensity, manufacturing activity and foreign direct investment do not exhibit statistically established relationships with broad export category diversification, despite coefficient directions that partly align with theoretical expectations. Table 5 indicates a negative carbon intensity coefficient of −0.10864 and a negative manufacturing coefficient of −0.00423, while foreign investment exhibits a positive but small coefficient of 0.00110. None reaches conventional statistical significance. These results challenge the assumption that productive expansion, carbon efficiency and

international investment translate predictably into more balanced export structures. Equation 7 distinguishes these conditional associations from persistent differences across economies and common annual changes. The contribution lies in identifying an important measurement distinction: manufacturing expansion may increase productive capabilities without increasing diversification across broad export categories. This distinction extends the structural transformation perspective of McMillan and Rodrik (2011), who demonstrate that the contribution of structural change to productivity differs across development settings. It also qualifies the relationship between economic complexity and productive capabilities discussed by Hidalgo and Hausmann (2009), without implying that the present analysis measures economic complexity directly. The findings suggest that aggregate export diversification cannot be treated as an interchangeable indicator of industrial development, technological upgrading or export sophistication.

The proposed mechanisms provide plausible explanations for the estimated relationships, but the empirical specification does not identify causal transmission pathways. Carbon intensity may reflect technological persistence and dependence on established production activities, while manufacturing value added may capture industrial specialisation and foreign investment may facilitate external capability formation. Equation 7 estimates these variables as separate contemporaneous predictors rather than sequential mediating processes. Consequently, the coefficients in Table 5 cannot establish whether technological persistence mediates industrial concentration or whether foreign investment changes diversification through technology transfer. This distinction matters because the literature identifies competing channels. Acemoglu et al. (2012) demonstrate theoretically how environmental policy can redirect technological development, while Costinot et al. (2012) show that production structures respond to underlying comparative advantage and resource allocation. Similarly, Javorcik and Spatareanu (2011) identify supplier linkages as a potential channel of foreign investment spillovers. The absence of a statistically reliable investment coefficient in the present analysis indicates that aggregate investment inflows alone provide insufficient evidence of capability diffusion into additional export categories. The theoretical implication is that production characteristics and investment conditions should not be interpreted as direct measures of the mechanisms through which diversification occurs.

The sensitivity results reveal that the direction of an estimated relationship can depend on the definition of diversification and the composition of the analytical sample. Table 6 shows that the carbon intensity coefficient changes from negative in the complete sample to slightly positive among manufacturing majority observations, whereas manufacturing value added remains negative across the reported specifications. Foreign investment changes from a positive baseline coefficient to a negative coefficient when diversification is expressed as the effective number of export categories. Because Equation 5 transforms the same underlying export distribution measured by Equation 4, this difference does not identify a separate economic pathway. Instead, it demonstrates that coefficient estimates can respond to nonlinear transformations of the dependent variable. The manufacturing majority restriction also changes the observed population rather than identifying an interaction effect. These distinctions contribute to debates on diversification measurement by showing why conclusions based on broad export shares require explicit attention to aggregation and sample boundaries. The evidence is consistent with the wider argument of Koren and Tenreyro (2013) that development and production structures involve changing patterns of specialisation, but it does not establish which productive channel dominates. No causal decomposition is identified, and the relative contribution of carbon intensity, manufacturing activity and foreign investment to diversification cannot be inferred from their coefficient magnitudes because their measurement scales differ.

The analysis also reveals structural and measurement constraints that influence how export diversification should be interpreted across developing manufacturing economies. The five recorded export categories account for between 70.2875 and 99.9999 percent of merchandise exports before normalisation. Accordingly, Equation 4 measures the balance among recorded categories rather than the complete distribution of exported products. This limitation is substantive because an economy can increase the number of manufactured products while maintaining a dominant manufacturing share in merchandise exports. The conditional estimate in Table 6 is consistent with this distinction, although its statistical uncertainty prevents a definitive relationship from being established. The exclusion of four Bangladesh observations further demonstrates how incomplete export composition data can alter analytical coverage, particularly when missing observations occur in an economy with relatively low income and trade openness. The balanced coverage results preserve the broad baseline coefficient directions, but they do not establish that sample selection is inconsequential. These findings reinforce the importance of distinguishing measurement coverage from economic diversification itself. They also connect with the concerns of Melitz and Redding (2014) regarding heterogeneous firm responses and trade adjustment, and with the evidence of Bernard et al. (2012) that aggregate trade patterns conceal substantial differences in firm and product composition. The implication is that broad sectoral indices are informative for comparing export structures but cannot independently reveal the product entry, firm adjustment or technological upgrading processes underlying those structures.

The international significance of these findings concerns the interpretation of structural transformation under changing environmental and trade conditions. Research on environmental regulation demonstrates that

competitiveness responses depend on sectoral exposure, technological adjustment and policy design rather than following a uniform relationship across economies. Dechezleprêtre and Sato (2017) identify heterogeneous competitiveness consequences, while Branger and Quirion (2014) show that the estimated implications of carbon border adjustments depend on the underlying policy and modelling assumptions. The present analysis contributes a complementary empirical perspective by examining carbon intensity alongside manufacturing activity and foreign investment within a common export composition framework. However, carbon intensity is not a measure of carbon border adjustment exposure, and the estimates cannot identify the consequences of introducing such measures. The weak and unstable conditional relationships suggest that global comparisons should distinguish emissions intensity, productive specialisation and actual trade policy exposure. For decision makers, this means that aggregate carbon intensity or investment inflows should not be used alone to predict diversification outcomes. Export strategies require separate monitoring of broad category balance and product level upgrading, while environmental trade assessments require direct measures of policy exposure and sectoral emissions. Future research can extend Equation 7 by incorporating verified policy exposure, sector specific production information and product level export transitions, allowing the competing mechanisms to be evaluated rather than inferred. The contribution of this analysis is therefore to establish the empirical limits of simple structural predictors and to clarify the measurement and identification requirements for explaining export diversification across developing manufacturing economies.

7. Conclusion and Implications:

The global transition toward sustainable production challenges the assumption that industrial expansion and international investment necessarily generate more diversified export structures. This analysis shows that the three examined structural relationships remain statistically inconclusive, while their estimated directions and magnitudes vary across analytical conditions. The central contribution is the distinction between expanding productive capabilities and achieving a more balanced distribution of export activities. Greater industrial development may coexist with specialisation, while external capital and technological characteristics do not independently establish diversification gains. These findings refine structural transformation theory by demonstrating the importance of measurement boundaries and economic heterogeneity when evaluating productive change. For policymakers, the evidence supports assessing industrial upgrading and export diversification as separate strategic objectives rather than assuming that progress in one guarantee improvement in the other. Trade and industrial authorities should monitor export composition alongside productive capacity, evaluate investment initiatives against observable diversification outcomes, and distinguish environmental competitiveness risks from actual policy exposure. Firms can similarly strengthen strategic planning by assessing market concentration, production flexibility and opportunities for related activities. Such evidence informed decisions can improve resource allocation and support economic resilience, although their wider social benefits require further evaluation.

The analysis is limited by its purposively selected economies, incomplete observations, broad category measurement and contemporaneous observational design. These boundaries provide opportunities to extend the framework using product level trade records, sectoral emissions, investment allocation and direct measures of environmental trade policy exposure. Longer longitudinal comparisons and explicit interaction models could determine whether existing industrial specialisation conditions subsequent diversification patterns. Mediation analysis and stronger identification strategies could examine technological adjustment and supplier relationships as potential transmission channels. Extending these comparisons across institutional and development settings would clarify the generalisability of the observed relationships and strengthen evidence for internationally relevant industrial and trade policy decisions.

References:

1. Acemoglu, D., Aghion, P., Bursztyn, L., & Hémous, D. (2012). The environment and directed technical change. American Economic Review, 102(1), 131-166. https://doi.org/10.1257/aer.102.1.131
2. Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124(1), 1-51. https://doi.org/10.1086/684581
3. Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2012). The empirics of firm heterogeneity and international trade. Annual Review of Economics, 4, 283-313. https://doi.org/10.1146/annurev-economics-080511-110928
4. Branger, F., & Quirion, P. (2014). Would border carbon adjustments prevent carbon leakage and heavy industry competitiveness losses? Insights from a meta-analysis of recent economic studies. Ecological Economics, 99, 29-39. https://doi.org/10.1016/j.ecolecon.(2013).12.010
5. Broman, K. W., & Woo, K. H. (2018). Data organization in spreadsheets. The American Statistician, 72(1), 2-10. https://doi.org/10.1080/00031305.(2017).1375989
6. Cadot, O., Carrère, C., & Strauss-Kahn, V. (2011). Export diversification: What's behind the hump? The Review of Economics and Statistics, 93(2), 590-605. https://doi.org/10.1162/REST_a_00078

7. Cadot, O., Carrère, C., & Strauss-Kahn, V. (2013). Trade diversification, income, and growth: What do we know? Journal of Economic Surveys, 27(4), 790-812. https://doi.org/10.1111/j.1467-6419.(2011).00719.x
8. Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. Journal of Human Resources, 50(2), 317-372. https://doi.org/10.3368/jhr.50.2.317
9. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. Journal of Business & Economic Statistics, 29(2), 238-249. https://doi.org/10.1198/jbes.(2010).07136
10. Cinelli, C., & Hazlett, C. (2020). Making sense of sensitivity: Extending omitted variable bias. Journal of the Royal Statistical Society: Series B, 82(1), 39-67. https://doi.org/10.1111/rssb.12348
11. Cosbey, A., Droege, S., Fischer, C., & Munnings, C. (2019). Developing guidance for implementing border carbon adjustments: Lessons, cautions, and research needs from the literature. Review of Environmental Economics and Policy, 13(1), 3-22. https://doi.org/10.1093/reep/rey020
12. Costinot, A., Donaldson, D., & Komunjer, I. (2012). What goods do countries trade? A quantitative exploration of Ricardo's ideas. The Review of Economic Studies, 79(2), 581-608. https://doi.org/10.1093/restud/rdr033
13. Dechezleprêtre, A., & Sato, M. (2017). The impacts of environmental regulations on competitiveness. Review of Environmental Economics and Policy, 11(2), 183-206. https://doi.org/10.1093/reep/rex013
14. Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. Social Indicators Research, 141(1), 61-94. https://doi.org/10.1007/s11205-017-1832-9
15. Harding, T., & Javorcik, B. S. (2012). Foreign direct investment and export upgrading. The Review of Economics and Statistics, 94(4), 964-980. https://doi.org/10.1162/REST_a_00226
16. Hausmann, R., & Hidalgo, C. A. (2011). The network structure of economic output. Journal of Economic Growth, 16(4), 309-342. https://doi.org/10.1007/s10887-011-9071-4
17. Havranek, T., & Irsova, Z. (2011). Estimating vertical spillovers from FDI: Why results vary and what the true effect is. Journal of International Economics, 85(2), 234-244. https://doi.org/10.1016/j.jinteco.(2011).07.004
18. Henn, C., Papageorgiou, C., Romero, J. M., & Spatafora, N. (2020). Export quality in advanced and developing economies: Evidence from a new data set. IMF Economic Review, 68(2), 421-451. https://doi.org/10.1057/s41308-020-00110-8
19. Hughes, R. A., Heron, J., Sterne, J. A. C., & Tilling, K. (2019). Accounting for missing data in statistical analyses: Multiple imputation is not always the answer. International Journal of Epidemiology, 48(4), 1294-1304. https://doi.org/10.1093/ije/dyz032
20. Imai, K., & Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? American Journal of Political Science, 63(2), 467-490. https://doi.org/10.1111/ajps.12417
21. Irsova, Z., & Havranek, T. (2013). Determinants of horizontal spillovers from FDI: Evidence from a large meta-analysis. World Development, 42, 1-15. https://doi.org/10.1016/j.worlddev.(2012).07.001
22. Javorcik, B. S., & Spatareanu, M. (2011). Does it matter where you come from? Vertical spillovers from foreign direct investment and the origin of investors. Journal of Development Economics, 96(1), 126-138. https://doi.org/10.1016/j.jdeveco.(2010).05.008
23. Koren, M., & Tenreyro, S. (2013). Technological diversification. American Economic Review, 103(1), 378-414. https://doi.org/10.1257/aer.103.1.378
24. McMillan, M. S., & Rodrik, D. (2011). Globalization, structural change and productivity growth. In M. Bacchetta & M. Jansen (Eds.), Making globalization socially sustainable (pp. 49-84). International Labour Organization and World Trade Organization.
25. Melitz, M. J., & Redding, S. J. (2014). Heterogeneous firms and trade. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), Handbook of international economics (Vol. 4, pp. 1-54). Elsevier. https://doi.org/10.1016/B978-0-444-54314-1.00001-X
26. Munafò, M. R., Nosek, B. A., Bishop, D. V. M., Button, K. S., Chambers, C. D., Percie du Sert, N., Simonsohn, U., Wagenmakers, E.-J., Ware, J. J., & Ioannidis, J. P. A. (2017). A manifesto for reproducible science. Nature Human Behaviour, 1(1), Article 0021. https://doi.org/10.1038/s41562-016-0021
27. Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. Economic Geography, 87(3), 237-265. https://doi.org/10.1111/j.1944-8287.(2011).01121.x
28. Parteka, A., & Tamberi, M. (2013). What determines export diversification in the development process? Empirical assessment. The World Economy, 36(6), 807-826. https://doi.org/10.1111/twec.12064

29. Pustejovsky, J. E., & Tipton, E. (2018). Small-sample methods for cluster-robust variance estimation and hypothesis testing in fixed effects models. Journal of Business & Economic Statistics, 36(4), 672-683. https://doi.org/10.1080/07350015.(2016).1247004
30. Rodrik, D. (2016). Premature deindustrialization. Journal of Economic Growth, 21(1), 1-33. https://doi.org/10.1007/s10887-015-9122-3
31. White, I. R., & Carlin, J. B. (2010). Bias and efficiency of multiple imputation compared with complete-case analysis for missing covariate values. Statistics in Medicine, 29(28), 2920-2931. https://doi.org/10.1002/sim.3944
32. Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.-W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., . . . Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. Scientific Data, 3, Article 160018. https://doi.org/10.1038/sdata.(2016).18