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Climate-Related Development Finance and Structural Transformation: Evidence on Technology and Labor Markets in Developing Economies

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Abstract

Climate-related development finance is expected to support low-carbon investment, technological diffusion, and economic adjustment, yet it remains unclear whether these processes translate into broader structural transformation. This paper examines associations between climate-related development finance, technological transformation, and labor-market restructuring in developing economies over 2010–2021. Using an unbalanced country-level panel dataset, we distinguish between mitigation- and adaptation-related finance and construct two formative directional indices capturing green-digital technological transformation and changes in occupational and sectoral employment structures. Two-way fixed-effects models are complemented by robustness tests, moderation analysis, and country-cluster bootstrap estimates of an indirect finance–technology–labor association. The results provide no robust evidence of the hypothesized positive transmission sequence. Neither mitigation nor adaptation finance is positively associated with technological transformation. The technology–labor association is statistically indistinguishable from zero but imprecisely estimated, while the direct finance–labor estimates are also statistically insignificant in the available labor-market sample. Institutional quality provides only suggestive evidence of conditioning, and advanced skills do not significantly moderate labor-market adjustment. A three-year lag and alternative positive-weighting checks do not alter the substantive finance–technology conclusion. Labor-data coverage is substantially narrower and compositionally selective, limiting external validity for the labor-market results. Overall, the results highlight a disconnect between financial mobilization and detectable broad country-level structural change within the measures, period, and empirical design considered here.

Keywords: climate-related development finance; technological transformation; labor-market transformation; developing economies; green transition; structural transformation

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1. Introduction

Climate finance is central to the international response to climate change, especially in developing economies that face high investment needs alongside tighter fiscal, technological, and institutional constraints. However, mobilizing finance is not the same as transforming an economy. Climate-related projects may deliver renewable energy, resilient infrastructure, or technical assistance without producing changes large enough to alter national technological and employment structures. The central question, therefore, is

whether greater climate-related development finance is systematically associated with broader structural transformation.

Existing research documents important links between green or climate finance, renewable energy, innovation, and entrepreneurship, while the technology and green-transition literatures emphasize changes in skills, tasks, occupations, and worker reallocation (Mohan & Morris, 2024; Hou et al., 2023; Tyros et al., 2023; Acemoglu & Restrepo, 2019). Institutional quality and domestic capabilities also shape whether finance translates into innovation and adoption. These strands are closely related but are usually examined separately rather than as a common finance-technology-labor transmission process.

This separation matters in developing economies. Financial resources may support specific technologies without generating broad diffusion; technological adoption may change productivity or task content before occupational and sectoral employment shares respond; and institutions and skills can condition both stages (Tsomb, 2026; Adu & Ramfol, 2025). The transmission from finance to structural change is therefore an empirical question rather than a mechanical consequence of higher financial flows.

This paper tests whether climate-related development finance is associated with technological transformation and whether technological transformation is subsequently associated with labor-market restructuring. It also examines a direct finance-to-labor relationship, institutional quality, and advanced skills as conditioning factors, as well as an indirect finance-to-labor pathway through technology. The conceptual sequence is climate-related development finance → green-digital technological transformation → labor-market transformation.

The empirical analysis uses an annual country-level panel covering 2010–2021, considering data availability. The population of inference is defined ex ante using the World Bank's historical income classifications, retaining economies whose modal classification over the period is low-income, lower-middle-income, or upper-middle-income. This yields a primary population of 135 developing economies before model-specific missing observations are accounted for. Because the availability of technological and labor-market data differs substantially across countries and years, the resulting panel is unbalanced, and the effective estimation sample varies across equations.

Climate-related development finance is measured using the OECD Development Assistance Committee Rio Markers database. Mitigation- and adaptation-related commitments are considered separately because the two objectives can operate through different channels and because an individual development-cooperation activity can carry both markers. The measures should be interpreted as the value of development-finance activities for which mitigation or adaptation is identified as a principal or significant objective, rather than as exact accounting measures of climate-specific expenditure. The baseline specification uses per-capita commitments expressed in constant prices, transformed to accommodate the highly skewed distribution and genuine zero observations, and lagged by one year.

To capture technological transformation, the paper constructs a Green-Digital Technological Transformation Index (GDTI) combining two dimensions with relatively broad cross-country coverage: renewable electricity as a share of total electricity output and Internet use as a share of the population. The renewable-electricity component captures changes in the composition of the electricity generation mix, as a rising share of renewable generation reflects the displacement of conventional generation sources within total electricity output (International Energy Agency [IEA], 2026). The digital component captures broad connectivity and diffusion capacity. Access to high-quality digital infrastructure supports the diffusion and adoption of digital technologies, making connectivity an enabling condition for technological transformation rather than a technology-specific outcome in itself (OECD, 2026). The GDTI is therefore constructed as a transparent equal-weight formative index

rather than as a latent measure, and its components are also examined separately in the robustness analysis.

The main estimates use country and year fixed effects, with country-clustered standard errors, and are interpreted as conditional within-country associations rather than causal treatment effects. Robustness checks address alternative definitions of finance, two- and three-year lags, alternative positive weighting of the GDTI, index components, heterogeneous trends, first differences, income-group heterogeneity, nonlinearities, and extensive versus intensive margins. Dynamic GMM is retained only as an endogeneity diagnostic because no numerically stable specification emerged. Additional diagnostics assess the composition and precision of the substantially smaller labor-market estimation sample.

The results do not support a systematic positive finance–technology–labor transmission sequence. Neither mitigation nor adaptation finance is robustly positively associated with the GDTI; the estimated GDTI–LMTI association is statistically indistinguishable from zero but comparatively imprecise; direct finance-to-labor relationships and bootstrap indirect associations are also statistically insignificant. Institutional moderation is positive in baseline models but not robust to more demanding time controls, while advanced skills do not significantly moderate the technology–labor relationship.

These findings require careful interpretation. They do not establish that climate-related development finance is ineffective, that technological change has no labor-market consequences, or that economically meaningful effects are absent. The labor-market relationships are estimated with substantially more limited coverage than the finance–technology relationship, and countries entering the final labor-market estimation sample differ systematically from excluded countries on several observable characteristics. Precision also varies across labor equations: the GDTI–LMTI estimate is particularly uncertain, whereas the direct finance–LMTI estimates are more informative for moderate standardized associations. The results, therefore, indicate that, for the developing economies, period, measures, and empirical design considered here, the hypothesized positive relationships do not emerge as systematic country-level patterns. The distinction between absence of evidence for a proposed link and evidence of no effect is maintained throughout.

The paper contributes by integrating finance, technology, and labor-market restructuring into a single framework; distinguishing mitigation from adaptation finance; examining institutions and advanced skills as conditioning mechanisms; and explicitly testing an indirect technology channel. The contribution does not depend on confirming every hypothesis: locating where a theoretically plausible transmission sequence fails to emerge is itself informative about the conditions required for structural transformation.

Section 2 develops the literature review, framework, and hypotheses. Section 3 presents the data and empirical strategy; Section 4 presents the results and robustness analysis; Section 5 presents the discussion, policy implications, and limitations; and Section 6 presents the conclusions.

2. Literature Review and Hypotheses

2.1. Climate-Related Development Finance and Technological Transformation

Climate-related development finance can support technological change by easing financing constraints, sharing risk, and supporting deployment, demonstration, and complementary capacity (Mondal et al., 2026). These mechanisms are especially relevant in developing economies. However, their effects depend on what is financed, technological maturity, absorptive capacity, and the extent to which successful projects diffuse beyond their initial setting.

Warren (2020) highlights blind spots in international climate finance, particularly for demonstration, pilot implementation, and hard-to-abate sectors. He argues for stronger

links between research, demonstration, technical assistance, and subsequent concessional and private finance. Higher financial volumes may therefore fail to produce broad transformation when portfolios do not support additional innovation, replication, or diffusion.

Empirical evidence is generally positive but heterogeneous. Hou et al. (2023), using data from 53 countries and regions, find that green finance supports renewable energy development through investment and technological innovation, with stronger effects where green finance systems and environmental regulation are more developed.

More recent evidence focused specifically on developing economies reaches a similar conclusion. Nguyen et al. (2025) examine foreign financial investment in renewable energy and find that it improves clean-energy access, electricity access, and renewable-electricity output in developing countries. Their dynamic-panel estimates also indicate that several of these effects persist over time. However, the effects differ across regions and country characteristics, including fossil-fuel dependence, economic growth, and foreign-capital intensity. Nghiem et al. (2026), using data for 76 developing countries, likewise identify a long-run relationship between green finance and renewable energy. These studies support the view that finance can contribute to the energy transition. However, they also illustrate that the strength of the relationship depends on the type of finance, the outcome considered, and the economic context.

Green-finance studies also support an innovation channel. Bai and Lin (2023) find that the development of green finance promotes green technological innovation among Chinese listed firms. These results establish a plausible mechanism but concern domestic green-finance systems rather than international climate-related development finance.

Evidence directly related to climate finance, rather than broader green finance measures, is more mixed. Adu and Ramfol (2025) analyze 23 Sub-Saharan African countries over 2011–2022 using System-GMM and find a negative direct relationship between climate finance and innovation, while institutional quality has a positive effect and improves the conditional relationship between climate finance and innovation. Tsomb (2026), using a dynamic panel of 42 developing countries, also finds that the effect of climate finance on green innovation is conditional rather than uniformly positive. Human capital has a threshold effect, and the composition of human capital matters: technical, ICT, and environmental specializations are more conducive to green innovation than a broad increase in formal human capital alone. Together, these studies suggest that climate finance may contribute to technological transformation only when complementary institutional and human-capital conditions are sufficiently developed (Tsomb, 2026).

Climate finance and green finance should therefore not be treated as equivalent (Khan et al., 2022). The former covers a broad set of mitigation- and adaptation-related development activities, whereas many green-finance measures capture domestic credit, investment, or financial development. Evidence on one is informative about mechanisms but does not directly establish the effect of the other.

The outcome variable also matters. Much of the existing empirical literature focuses on renewable energy consumption, renewable electricity output, green patents, firm-level innovation, or emissions (Leippold & Yu, 2026). These are important but relatively specific outcomes. The GDTI used in this study deliberately asks a broader question. It combines renewable-electricity penetration with economy-wide digital connectivity not because Internet use is itself a climate technology, but because digital connectivity is an enabling infrastructure for data exchange, monitoring, information services, coordination, and the diffusion of digital applications that increasingly support mitigation and adaptation. The World Bank's Green Digital Transformation framework similarly treats digital foundations and tools as relevant to climate action, while emphasizing that the digital and green transitions are distinct and must be strategically connected (World Bank, 2023). The digital

component should therefore be interpreted as a measure of general technological diffusion capacity, not as a direct indicator of climate-specific digital innovation (Qin et al., 2026). This broader construction raises the empirical threshold: finance may successfully support a renewable-energy project or a sector-specific digital application without producing a sufficiently large country-level change in both dimensions of the index (Hassan et al., 2026).

Overall, the literature supports a positive finance-technology expectation but repeatedly points to heterogeneity, complementary institutions and human capital, and diffusion limits. These considerations motivate the first link in the conceptual framework.

2.2. Technological Change and Labor-Market Transformation

Technological change affects labor markets through productivity, skills, tasks, and sectoral reallocation (Ross et al., 2024). Its net effect depends on whether technologies complement or substitute for workers, create new tasks, and whether workers can move across occupations and sectors.

The skill-biased technological change literature provides a central foundation. Acemoglu (2002) shows how technical change can respond to the relative supply of skills, while Acemoglu and Autor (2011) emphasize the interaction of skills and tasks. Technologies that complement highly educated workers can increase their relative demand while reducing demand for workers concentrated in substitutable tasks (Mondolo, 2022).

Cross-country evidence confirms that these effects vary across settings. Nogueira and Afonso (2018), using 30 OECD countries, find that both SBTC and international trade matter for skill-based wage inequality, with their relative importance varying across country groups. Nogueira and Madaleno (2023) likewise find that technological change and education are associated with wage differentials across skill groups.

A task-based perspective provides a more granular explanation of these effects. Rather than assuming that technology substitutes for entire occupations, this literature focuses on the tasks performed within jobs (Mondolo, 2022). Routine tasks are particularly susceptible to codification and automation, while non-routine cognitive and interpersonal tasks tend to be more complementary to advanced technologies (Autor et al., 2003). This framework helps explain employment polarization: technological change can increase demand for high-skill occupations, reduce demand for routine middle-skill occupations, and leave some non-routine service occupations comparatively less exposed. Michaels et al. (2014) provide cross-country evidence that the growth of information and communication technology is associated with shifts in labor demand toward highly educated workers and away from middle-educated workers, reinforcing the connection between technological diffusion and changes in the structure of employment.

The displacement effect of technology, however, is only one side of the adjustment process. Acemoglu and Restrepo (2019) distinguish between automation, which reallocates tasks from labor to capital, and the creation of new tasks in which labor has a comparative advantage. Automation can reduce labor demand through a displacement effect even when it raises productivity, whereas new tasks can reinstate labor in production. Their empirical decomposition for the United States indicates that weaker employment growth in recent decades is associated with an acceleration in displacement, particularly in manufacturing, and a weaker reinstatement effect. This distinction is important for our framework because technological transformation does not imply a predetermined employment outcome. Its labor-market effect depends on whether the technologies being adopted primarily substitute for existing tasks, complement workers, or generate sufficiently important new tasks and activities.

The green transition adds sectoral reallocation. Low-carbon activities can expand while carbon-intensive production contracts, creating jobs in some sectors and displacement in

others (International Labor Organization, 2023a). The key issue is whether workers possess the skills and mobility needed to access new opportunities. Tyros et al. (2023) document large cross-country differences in green-skill endowments and the capacity to move from brown to green jobs. Many workers have transferable skills, but production workers often require more reskilling, and workers in highly automatable occupations face larger barriers. Accordingly, renewable and digital technologies can expand without an immediate change in occupational or sectoral employment, as skill mismatches, geographic immobility, institutional frictions, or the capital intensity of new technologies may slow adjustment.

The literature, therefore, supports an expected positive technology-labor relationship while making clear that adjustment can be heterogeneous and slow (Chan & Bheekee, 2026). This motivates the second link in the framework.

2.3. Climate-Related Development Finance and Labor-Market Transformation

Direct empirical evidence on the labor-market effects of climate finance remains limited and points to potentially heterogeneous outcomes (Zhao et al., 2025). Climate-related finance may generate employment-related effects through investment and entrepreneurial activity. Mohan and Morris (2024), for example, find a positive relationship between climate finance and entrepreneurship in developing countries, while also documenting important heterogeneity in fossil-fuel-exporting economies. More direct labor-market evidence is provided by Zhao et al. (2025), who find that climate finance is associated with lower female labor-force participation across 92 developing countries, with stronger effects for mitigation finance. These findings suggest that the labor-market consequences of climate finance need not be uniformly positive and may depend on the type of finance, the sectors affected, and country-specific economic conditions (Zhao et al., 2025; Mohan & Morris, 2024).

One mechanism operates through entrepreneurship and business formation. Mohan and Morris (2024) provide direct cross-country evidence for developing economies and find a strong positive association between climate finance and entrepreneurial activity. Their estimates indicate that a 10% increase in climate finance is associated with a close-to-2% increase in entrepreneurship, and the positive relationship remains evident when adaptation and mitigation finance are examined separately. Nonetheless, the authors also identify important heterogeneity: the interaction between climate finance and fossil-fuel-export dependence is negative. This result is relevant to labor-market transformation because entrepreneurship can create new firms and employment opportunities. However, the capacity of climate finance to stimulate this process depends on the recipient economy's productive structure.

Recent evidence also points to potential improvements in labor-market inclusion. Ko et al. (2026) examine 46 African countries from 2011 to 2021 and analyze whether climate-finance inflows are associated with the share of young people not in employment, education, or training. Using panel models with Driscoll–Kraay corrections and IV–GMM, they find a statistically significant negative association between climate finance and youth NEET (Not in Education, Employment, or Training) rates that is robust across several specifications. Their study provides evidence that climate finance can be associated with improved labor-market inclusion among a particularly vulnerable group. At the same time, youth NEET is a specific social outcome and does not directly measure the sectoral or occupational restructuring of employment. It therefore demonstrates one possible labor-market benefit without establishing that climate finance generates broad structural transformation.

Firm-level evidence points in the same positive direction for some employment outcomes. Sun et al. (2025), using Chinese A-share listed firms and city- and province-level climate-finance indices for 2008–2023, find that stronger climate-finance development is associated with higher enterprise employment. Their mechanism analysis suggests that

climate finance can increase employment by encouraging R&D, digital transformation, and risk hedging, thereby reducing firms' capital–labor ratios and agency costs. This evidence is useful because it provides a direct link between climate finance, technological behavior, and labor demand. However, the setting differs from international development finance: the climate-finance measure captures local financial development within China rather than OECD Rio-marked flows to developing-country recipients. The findings therefore support a plausible mechanism but cannot be treated as direct evidence for the CRDF (Climate-Related Development Finance) measure used in this study.

The relationship is not uniformly positive. Zhao et al. (2025) analyze a panel of 92 developing countries and find that women's labor-force participation declines as climate finance increases. The negative association is stronger for mitigation finance and for finance directed toward infrastructure and multisector activities, and it is more pronounced in countries facing greater risk and economic uncertainty. The authors also identify gender norms and unequal access to resources as factors that can prevent women from benefiting from climate-financed economic change. This study is particularly important because it shows that aggregate climate investment can coexist with adverse distributional effects in the labor market. A transition that creates activity or employment in some sectors or groups may still reduce opportunities for others.

Li et al. (2025) further show a nonlinear relationship between climate finance and labor income share among Chinese listed firms, reflecting competing channels through debt-default risk and labor-capital allocation. Employment quantity, labor income share, job quality, and worker composition can therefore respond differently.

Together, these studies show that climate finance can affect labor markets through entrepreneurship, firm expansion, inclusion, and factor allocation, but effects vary across countries, firms, and demographic groups.

This heterogeneity is directly relevant to the outcome used in the present study. The LMTI is designed to capture structural labor-market transformation rather than employment growth alone. It combines two conceptually distinct but jointly relevant dimensions of a low-carbon structural transition: occupational upgrading, represented by a larger employment share in higher-skill occupations, and sectoral reallocation, represented by a smaller employment share in selected carbon-exposed sectors. This distinction is consistent with evidence showing that the green transition involves both changes in skill requirements and the reallocation of workers across occupations and between emission-intensive and greener activities (OECD, 2024a; Tyros et al., 2023). Neither dimension is sufficient on its own. A climate-financed investment may create jobs without increasing the share of high-skill jobs, or reduce employment in a carbon-exposed industry without generating occupational upgrading. Conversely, finance may support entrepreneurship or other economic activities without materially changing national occupational and sectoral employment shares. The LMTI should therefore be interpreted as a transparent summary of the direction of structural reallocation, not as a measure of job quality or as implying that every higher-skill job is green or that every job in the selected sectors is carbon-intensive. Indeed, substantial heterogeneity in the environmental characteristics of jobs exists both across and within sectors (Tyros et al., 2023). Direct evidence on whether climate-related development finance generates broad occupational and sectoral reallocation at the country level remains limited.

2.4. Institutional Quality as an Enabling Condition

Institutions shape how climate-related investments are selected, implemented, monitored, and scaled. Government effectiveness, regulatory quality, rule of law, and control of corruption can reduce uncertainty, improve execution, and limit inefficient use of resources, making institutional quality a plausible enabling condition.

Browne (2022) emphasizes that international climate finance inherits governance challenges from development finance and that recipient-country authority and institutional arrangements affect how resources are delivered. The same commitment can therefore generate different outcomes depending on domestic coordination and implementation capacity.

A broader innovation literature provides strong support for the idea that institutional quality affects technological outcomes. Chen et al. (2024) examine 72 countries over 1996–2017 and find that the effect of green innovation on energy efficiency depends on institutional quality. Their threshold estimates indicate that green innovation reduces energy intensity only after countries exceed a minimum level of institutional quality. The authors link this result to the protection of property rights, enforcement capacity, and the institutional environment surrounding investment in green technologies. This evidence is important because it suggests that institutions need not merely exert an independent effect on technological change; they can alter the effectiveness with which technological innovation translates into environmental and productive outcomes.

The interaction between institutions and finance has been examined more directly in recent climate-finance research. Adu and Ramfol (2025) analyze 23 Sub-Saharan African countries between 2011 and 2022 using System-GMM. They find a negative direct association between climate finance and innovation, a positive association between institutional quality and innovation, and, crucially, a positive conditional effect: as institutional effectiveness improves, the relationship between climate finance and innovation becomes more favorable. This is one of the studies most directly related to the moderation mechanism examined in the present paper, as it treats institutional quality not merely as a control variable but as a condition that affects the finance–innovation relationship.

Several channels are plausible: stronger institutions can reduce policy uncertainty, improve procurement and monitoring, strengthen environmental regulation, and facilitate coordination among governments, firms, financial institutions, and development partners. Weak institutions can instead raise transaction costs and slow implementation and replication.

Institutions are not sufficient for transformation, however. Their effects depend on the level of development, technological capability, infrastructure, finance, and human capital. The empirical hypothesis, therefore, concerns whether institutions strengthen the finance-technology association, not whether institutions alone generate transformation.

The literature consequently supports institutional quality as a plausible, context-dependent moderator of climate-finance effectiveness.

2.5. Skills, Technological Change, and Labor-Market Adjustment

Skills shape how technological change translates into labor-market outcomes. New technologies alter tasks and relative productivity, creating demand for capabilities that may be scarce in the existing workforce. When workers possess complementary and transferable skills, technological change can support occupational upgrading; when they do not, adjustment costs and bottlenecks increase.

The SBTC literature provides the basic mechanism: technologies that are complementary to highly qualified labor raise the relative demand for such labor. Nogueira and Madaleno (2023) show that SBTC and education remain associated with wage differentials across OECD countries, underscoring the role of labor-supply composition and adaptability.

Green technologies sharpen this issue because they require technical, engineering, scientific, digital, and managerial capabilities. OECD/Cedefop (2014) emphasizes that green skills are needed across sectors and that education, training, and transferable skills are integral to movement from contracting to expanding activities.

Recent evidence confirms that this reallocation capacity varies considerably across countries and occupations. Tyros et al. (2023) construct task-based indicators of green skills for a large group of OECD and non-OECD EU countries and find substantial differences in the supply of green skills and in the potential to reallocate workers from brown to green jobs. For many brown occupations, workers possess skills that are broadly transferable to green employment, but production workers often face larger reskilling needs. The authors also find that workers in highly automatable occupations generally lack the skills required for an easy transition into green jobs. The green transition can therefore create opportunities without automatically absorbing workers displaced by other forms of technological change.

The broader OECD evidence reaches a similar conclusion. The OECD Skills Outlook 2023 argues that environmental and digital transitions are outpacing the adaptation of education and training systems. Limited participation in adult learning constrains workers' ability to reskill and reduces their capacity to move from contracting sectors and occupations to expanding ones as economies become greener. The report also stresses that workers need skills that allow them to work alongside new technologies and realize their productivity potential (OECD, 2023b). In a related assessment, the OECD identifies anticipating changes in skill needs as essential to avoid bottlenecks in the green transition and to connect labor market information with employment, career guidance, education, and adult learning policies (OECD, 2023a).

Advanced educational attainment should therefore not be equated with transition-specific capability. Technical and vocational qualifications, ICT and engineering skills, environmental expertise, and occupation-specific experience may matter more directly than broad educational categories. This limitation is particularly relevant in developing economies, where training systems, retraining finance, and worker mobility may be weaker. Technology can therefore diffuse while high-skill jobs remain concentrated in a small set of firms or locations. Just-transition policy reinforces the same point: active labor-market measures, reskilling, and income support can facilitate adjustment to green investment and policy changes (International Labor Organization, 2023b).

The role of skills may also be nonlinear. If technological change requires a minimum stock of specialized competencies, modest increases in general human capital may have little effect until a sufficient capability threshold is reached. Recent evidence on climate finance and green innovation supports this possibility: Tsomb (2026) finds that the effect of climate finance on green innovation in developing countries depends on human-capital thresholds and that technical, ICT, and environmental specializations are particularly relevant. Although this study focuses on innovation rather than labor-market adjustment, it reinforces the broader idea that the composition and level of skills can condition the effectiveness of green technological change.

The literature, therefore, supports skills as a plausible moderator of the technology-labor relationship while warning that advanced education is only a coarse proxy for transition readiness.

2.6. Research Gap, Conceptual Framework, and Hypotheses

The literature provides substantial evidence on separate links involving climate finance, technology, and labor markets, but much less on the complete country-level transmission chain. Finance can support renewable energy and innovation, technology can alter skills and tasks, and climate finance can affect specific employment outcomes. However, these relationships are rarely tested within a common framework.

This separation creates an important empirical gap. Studies such as Hou et al. (2023) and Nguyen et al. (2025) show that finance can support renewable energy development, while Mohan and Morris (2024) and Ko et al. (2026) identify relationships between climate

finance and specific economic or labor market outcomes. At the same time, the task-based literature shows that technological change can displace some tasks, create others, and alter the composition of labor demand (Acemoglu & Restrepo, 2019), while the green-skills literature demonstrates that the ability of workers to move from brown to green jobs varies substantially across occupations and countries (Tyros et al., 2023). What remains less clear is whether these relationships form a systematic country-level sequence in developing economies: whether climate-related development finance is associated with broad technological transformation, whether that transformation is associated with labor-market restructuring, and whether technology acts as a transmission channel between finance and labor-market outcomes. This distinction between project- or outcome-specific effects and economy-wide transformation is central. Successful projects can coexist with little movement in broad national technology or employment indicators.

A second gap concerns the conditions under which the transmission process may be stronger or weaker. Recent studies suggest that institutional quality can alter the relationship between climate finance and innovation (Adu & Ramfol, 2025), while green technological outcomes may depend on institutional thresholds and development conditions. Similarly, evidence on green skills shows that technological and environmental transitions depend on the transferability and availability of relevant competencies rather than on technology alone (Tyros et al., 2023). Human-capital thresholds may also affect the capacity of climate finance to foster green innovation (Tsomb, 2026). These findings imply that finance, technology, institutions, and skills should not be treated as independent drivers. They are potentially complementary elements of a broader transformation process.

The framework, therefore, contains three core links: CRDF to technological transformation, technology to labor-market transformation, and a direct CRDF-to-labor relationship. Institutional quality moderates the first link and advanced skills the second.

It also allows an indirect finance-to-labor pathway through technology. Because finance may fail to diffuse and technological change may combine displacement with new-task creation (Acemoglu & Restrepo, 2019; Warren, 2020), the complete sequence is an empirical proposition rather than an assumption. This gives the proposed transmission sequence a clear empirical interpretation before the results are observed. If one stage fails to appear in aggregate data, the pattern can identify where broader transmission may be constrained without implying that individual projects are ineffective.

The conceptual sequence can be summarized as follows:

Climate-Related Development Finance → Green-Digital Technological Transformation → Labor-Market Transformation

Institutional Quality moderates the first link; Advanced Skills moderate the second link; CRDF may also have a direct link to labor-market transformation.

The hypotheses derived from this framework are stated below. H1–H5 correspond to the direct and moderating relationships developed in Sections 2.1–2.5. H6 captures the indirect transmission mechanism that links the first two stages of the framework.

H1. *Higher climate-related development finance is associated with greater technological transformation in developing economies.*

H2. *Greater green-digital technological transformation is associated with greater labor-market transformation in developing economies.*

H3. *Higher climate-related development finance is associated with greater labor-market transformation in developing economies.*

H4. *Institutional quality positively moderates the relationship between climate-related development finance and technological transformation, such that the association is stronger in countries with higher institutional quality.*

H5. *Advanced skills positively moderate the relationship between green-digital technological transformation and labor-market transformation, such that the association is stronger in countries with a higher share of advanced-skilled labor.*

H6. *Climate-related development finance is indirectly associated with labor-market transformation through green-digital technological transformation in developing economies.*

H6 is a transmission hypothesis about an indirect association, not a causal mediation claim. The empirical test asks whether the data are consistent with an indirect pathway from climate-related development finance to labor-market transformation through the GDTI. Because the design is observational and sequential ignorability cannot be established, the product-of-coefficients exercise is interpreted only as evidence on an indirect transmission association.

3. Data and Methodology

3.1. Sample and Data Sources

This study uses an annual country-level panel to examine whether climate-related development finance is associated with technological and labor-market transformation in developing economies. The analytical period is 2010–2021. The database combines four main sources: the OECD Development Assistance Committee (DAC) Rio Markers database for climate-related development finance; the World Bank's World Development Indicators (WDI) for technological and macroeconomic variables; the Worldwide Governance Indicators (WGI) for institutional quality; and ILOSTAT for occupational, sectoral-employment, and educational data. The master database contains 153 recipient-economy codes and up to 1836 country-year observations before the final population rule and model-specific data requirements are applied.

The population of inference is defined ex ante as developing economies rather than as the full set of aid recipients. To ensure that the definition is reproducible over time as countries move between income groups, we use the World Bank's historical analytical income classifications (World Bank, 2026). For each economy, the annual World Bank classification is recorded for every year from 2010 through 2021, and the modal category over the twelve-year window is assigned as the economy's period classification. Economies whose modal classification is low income (LIC), lower-middle income (LMC), or upper-middle income (UMC) are retained in the primary sample; economies classified as high income (HIC) are excluded. Codes without an official World Bank income classification for the study period are not assigned to a category ad hoc and are excluded from the primary sample. No modal ties arise in the classification window. This procedure yields 135 developing economies before model-specific missing observations are accounted for.

The income rule is deliberately based on the historical classification rather than on a country's current income group. Applying a single current classification retrospectively would misclassify economies that crossed income thresholds during the sample period. The modal rule provides a stable period-level population definition while preserving the World Bank's official annual classifications. The broader recipient-economy dataset is retained only for audit and sensitivity purposes and is not the population used to evaluate the main hypotheses.

The final estimation panel is unbalanced because source coverage differs markedly across variables. Technological and macroeconomic indicators are available for a much larger set of country-years than harmonized occupational and sectoral labor-market data. The effective sample, therefore, varies across equations. We report the number of observations and countries for every model rather than imposing a single complete-case sample on the entire analysis. A common sample is imposed only where it is required by the statistical design, most notably for the two paths used to calculate the indirect effect in the transmission analysis.

3.2. Climate-Related Development Finance

The main explanatory variables measure development finance, separately for climate change mitigation and adaptation. The term climate-related development finance (CRDF) is used throughout the paper because the OECD Rio-marker framework identifies whether mitigation or adaptation is a principal or significant objective of a development-cooperation activity, rather than the exact monetary amount attributable exclusively to the climate objective. A principal marker indicates that the climate objective is fundamental to the design of the activity, whereas a significant marker indicates that it is an important, but not principal, objective. The CRDF variables should therefore be interpreted as the value of development-finance activities carrying a mitigation or adaptation objective, rather than as accounting measures of climate-specific expenditure.

The baseline measure includes activities marked as either principal or significant for the relevant climate objective. Mitigation and adaptation are constructed and estimated separately. This distinction is necessary because the same development-cooperation activity may carry both markers, so adding the two categories could double-count activities with dual climate objectives. The underlying commitment values are expressed in millions of constant 2024 US dollars.

For each climate objective c, where c ∈ {M, A} denotes mitigation (M) or adaptation (A), the commitment reported for country i in year t is converted into constant-2024-US-dollar per-capita terms as:

$$CRDF^{pc,c}_{i,t} = \frac{CRDF^{c}_{i,t} \times 10^{6}}{Pop_{i,t}} \quad (1)$$

where $CRDF^{c}_{it}$ is the reported commitment amount in millions of constant 2024 US dollars, and $Pop_{i,t}$ is the total population.

The resulting per-capita variables contain genuine zero observations and have strongly right-skewed distributions in the study data. To reduce the influence of the upper tail while retaining zero-valued observations, the baseline measure is transformed as:

$$LCRDF^{*c}_{i,t} = \ln\left(1 + CRDF^{pc,c}_{i,t}\right) \quad (2)$$

Accordingly, $LCRDF^{c}_{i,t}$ denotes the natural logarithm of one plus per-capita climate-related development finance for climate objective c. The addition of one ensures that observations with zero CRDF remain defined after the logarithmic transformation.

The baseline regressions use the one-year lag, $LCRDF^{c}_{i,t-1}$. The lag reflects the empirical premise that a financial commitment and subsequent technological deployment or labor-market adjustment need not occur contemporaneously. It should not be interpreted as implying that one year represents a unique or universal implementation horizon, since the time between commitment, project execution, technological deployment, and any subsequent structural response may differ across activities and countries. Two- and three-year lags are therefore examined as robustness checks on timing. These checks extend the short-run window without claiming to identify the full project-specific implementation horizon.

An additional robustness specification restricts CRDF to activities for which mitigation or adaptation is coded as the principal objective. This provides a narrower measure of climate-related development finance while preserving the distinction between the two climate objectives.

3.3. Measuring Technological Transformation

Technological transformation is represented by two dimensions, both of which are observable with reasonably broad cross-country coverage: changes in the composition of electricity generation and the diffusion of digital connectivity. The green component is renewable electricity output as a percentage of total electricity output (WDI code EG.ELC.RNEW.ZS; World Bank, n.d.-c). This indicator measures the share of total electricity generation produced from renewable sources. It is therefore used here to capture changes in the composition of the electricity generation mix rather than installed renewable capacity or the adoption of any individual technology (International Energy Agency [IEA], 2026).

The digital component is the percentage of the population using the Internet (WDI code IT.NET.USER.ZS; World Bank, n.d.-b). Internet use is interpreted here as a broad indicator of digital connectivity and of the infrastructure through which digital technologies can diffuse, rather than as a direct measure of any particular digital technology (OECD, 2024b). This interpretation is deliberately limited: the indicator does not directly measure artificial intelligence, firm-level digitalization, digital monitoring and verification systems, or climate-specific digital innovation. The separate component regressions reported in the robustness analysis are therefore important because they allow the green and digital dimensions to be examined independently rather than assuming that the composite index captures a common response.

Each component is standardized over the pooled estimation database using:

$$z(X_{it}) = \frac{X_{it} - \bar{X}}{s_X}, \tag{3}$$

where $\bar{X}$ and s_X denote the pooled mean and standard deviation of the variable. The baseline Green-Digital Technological Transformation Index (GDTI) is the equal-weight mean of the standardized renewable-electricity and Internet-use components:

$$GDTI_{it} = \frac{z(RENEW_{it}) + z(INTERNET_{it})}{2} \tag{4}$$

The GDTI is a formative directional index. Renewable-electricity penetration and Internet use are treated as distinct dimensions that jointly define the empirical concept of green-digital transformation; they are not assumed to be interchangeable manifestations of a single latent construct. In the complete two-component sample, the components are weakly and negatively correlated ($r = -0.149$). A principal-component diagnostic reinforces this interpretation: PC1 explains 57.5% of joint variance and assigns opposite signs to renewable electricity and Internet use (loadings of approximately -0.707 and $+0.707$, up to arbitrary sign orientation). Its absolute correlation with the equal-weight GDTI is only 0.026. PC1 therefore captures a contrast between the two dimensions rather than the intended directional construct, in which increases in both contribute positively. In this application, the PCA score is therefore not substantively equivalent to the formative construct defined in the study. Equal positive weighting is retained for transparency and reproducibility, and 60/40 and 40/60 positive-weight alternatives are examined as sensitivity checks.

An extended index is used as a sensitivity check by adding high-technology exports as a percentage of manufactured exports (WDI code TX.VAL.TECH.MF.ZS):

$$GDTI3_{it} = \frac{z(RENEW_{it}) + z(INTERNET_{it}) + z(HTECH_{it})}{3} \tag{5}$$

This three-component measure is not used as the baseline because high-technology exports reflect the technological composition of manufactured exports rather than domestic technological adoption, and they have weaker country-year coverage.

3.4. Measuring Labor-Market Transformation

Labor-market transformation is measured through two structural dimensions: the occupational composition of employment and employment in selected carbon-exposed sectors. The occupational component uses ILOSTAT data classified under ISCO-08. High-skill employment is defined as employment in Major Group 1 (Managers), Major Group 2 (Professionals), and Major Group 3 (Technicians and Associate Professionals), measured as a share of total employment (International Labor Organization, n.d.). ISCO-08 identifies these as distinct major occupational groups, but the resulting measure should not be interpreted as a direct measure of educational attainment, green skills, or digital skills.

The occupational share is defined as:

$$HS_{it} = 100 \times \frac{EMP_{it}^{M1} + EMP_{it}^{M2} + EMP_{it}^{M3}}{EMP_{it}^{TOT}} \quad (6)$$

The second component measures the employment share in selected carbon-exposed sectors, using the ISIC Revision 4 classification. The included sections are Mining and Quarrying (B), Manufacturing (C), Electricity, Gas, Steam and Air-Conditioning Supply (D), and Transportation and Storage (H):

$$CE_{it} = 100 \times \frac{EMP_{it}^{B} + EMP_{it}^{C} + EMP_{it}^{D} + EMP_{it}^{H}}{EMP_{it}^{TOT}} \quad (7)$$

This is an employment-based exposure proxy, not an emissions measure. The selected ISIC sections contain activities with heterogeneous carbon intensities, and the labor dataset does not provide harmonized annual emissions per worker at the detailed industry level for the countries in the sample. The variable is therefore used to capture a sectoral dimension of the employment structure, with that limitation explicitly maintained in the interpretation of the results.

The two components are standardized and combined into the Labor-Market Transformation Index (LMTI):

$$LMTI_{it} = \frac{z(HS_{it}) - z(CE_{it})}{2} \quad (8)$$

Higher values indicate, by construction, a labor-market structure with a larger employment share in Managers, Professionals, and Technicians, and in Associate Professionals, and a smaller share in the selected carbon-exposed sectors. The index is formative and directional. It does not imply that every movement toward higher-skill employment is green, nor that every job in the selected sectors is carbon-intensive. For this reason, the occupational and sectoral components are also estimated separately in the robustness analysis.

3.5. Institutional Quality and Advanced Skills

Institutional quality is measured using four dimensions of the World Bank's Worldwide Governance Indicators (WGI): Control of Corruption, Government Effectiveness, Regulatory Quality, and Rule of Law. These indicators capture distinct but closely related aspects of the institutional environment relevant to policy implementation, regulatory capacity, legal enforcement, and the management of public resources.

To place the four governance indicators on a common scale within the estimation sample, each component is standardized as:

$$Z_{k,it} = \frac{X_{k,it} - X_k}{S_k} \quad (9)$$

where $X_{k,\,it}$ denotes governance dimension k for country i in year t, while X_k and S_k denote, respectively, its sample mean and standard deviation. The institutional-quality index is then constructed as the equal-weight mean of the four standardized components:

$$IQ_{it} = \frac{Z_{cc,it} + Z_{GE,it} + Z_{RQ,it} + Z_{RL,it}}{4} \tag{10}$$

where CC, GE, RQ, and RL denote Control of Corruption, Government Effectiveness, Regulatory Quality, and Rule of Law, respectively. Higher values of IQ_{it} therefore indicate stronger institutional quality relative to the study sample.

The equal-weight construction was checked against a principal-component representation using the same four governance variables. A principal component analysis based on their correlation matrix and the 1607 country-year observations with complete information shows that the first principal component explains 84.3% of their joint variation. The corresponding first-component loadings are very similar across the four indicators: approximately 0.499 for Control of Corruption, 0.506 for Government Effectiveness, 0.490 for Regulatory Quality, and 0.505 for Rule of Law. The first principal-component score is also almost perfectly correlated with the equal-weight standardized index in absolute value ($|r| > 0.999$). These diagnostics indicate that the four measures share a strong common dimension and that the equal-weight index retains essentially the same information while remaining more transparent and straightforward to reproduce.

Advanced skills are measured using ILOSTAT information on educational attainment. The variable $Skills_{it}$ denotes the share of the relevant population in country i classified as having advanced education in year t. Because the empirical analysis uses advanced skills as a conditioning variable and in interaction terms, the measure is standardized over the available study observations as:

$$SKILLSZ_{it} = \frac{SKILLS_{it} - \overline{SKILLS}}{S_{SKILLS}} \tag{11}$$

where $\overline{SKILLS}$ and S_{SKILLS} denote the sample mean and standard deviation of the advanced-skills measure, respectively. Higher values of $SKILLSZ_{it}$ therefore indicate a greater prevalence of advanced educational attainment relative to the study sample.

This variable should be interpreted as a measure of broad advanced educational attainment rather than of transition-specific capabilities. It does not directly identify technical, environmental, ICT, vocational, or occupation-specific skills that may be particularly relevant to green and digital transformation. This limitation is maintained explicitly in the interpretation of the skills interaction. Institutional quality and advanced skills are included in the empirical framework as conditioning variables rather than as outcome measures.

3.6. Control Variables

The baseline models include five macroeconomic controls from the World Development Indicators. GDP per capita at purchasing power parity in constant 2021 international dollars (NY.GDP.PCAP.PP.KD; World Bank, n.d.-a) enters in logarithmic form and captures differences in development and productive capacity. Real GDP growth (NY.GDP.MKTP.KD.ZG) controls for short-run macroeconomic conditions. Trade openness is measured as the sum of exports and imports of goods and services, both expressed as percentages of GDP. Urban population as a percentage of total population (SP.URB.TOTL.IN.ZS) controls for urbanization, and annual population growth (SP.POP.GROW) captures demographic change. Total population (SP.POP.TOTL) is also used in constructing the per-capita climate-finance measures.

The control set is intentionally parsimonious. It covers broad macroeconomic and structural conditions that can move alongside technological and labor-market change with-

out saturating the model with closely related covariates or variables that may themselves form part of the transmission mechanism being studied.

3.7. Empirical Strategy

The primary estimator is a two-way fixed-effects model with country and year fixed effects, with standard errors clustered at the country level. The analysis is designed to estimate conditional within-country associations rather than causal treatment effects. Country fixed effects remove time-invariant observed and unobserved country characteristics, while year fixed effects absorb shocks and trends common to all countries in a given year. Clustering at the country level allows the regression errors to be arbitrarily correlated within an economy over time.

The first equation tests the relationship between climate-related development finance and technological transformation:

$$GDTI_{it} = \alpha_i + \lambda_t + \beta_k CRDF^k_{i,t-1} + \gamma' X_{it} + \varepsilon_{it}, \qquad k \in \{M, A\} \tag{12}$$

Here, α_i denotes country fixed effects, λ_t year fixed effects, and X_{it} the vector of macroeconomic controls. Mitigation and adaptation are estimated in separate equations because they represent different climate objectives, and because individual activities can be marked for both. The coefficient is identified from changes in CRDF within a country over time after conditioning on the included controls and common year effects.

The second equation tests whether technological transformation is associated with labor-market transformation:

$$LMTI_{it} = \alpha_i + \lambda_t + \theta GDTI_{it} + \gamma' X_{it} + \varepsilon_{it} \tag{13}$$

The third equation estimates the direct finance-labor relationship:

$$LMTI_{it} = \alpha_i + \lambda_t + \delta_k CRDF^k_{i,t-1} + \gamma' X_{it} + \varepsilon_{it} \tag{14}$$

These equations provide the main tests of H1, H2, and H3. The separate mitigation and adaptation specifications are treated as two empirical implementations of the same conceptual hypothesis rather than as newly numbered sub-hypotheses.

To examine the proposed finance-technology-labor transmission channel, CRDF and GDTI are included jointly in the labor-market equation:

$$LMTI_{it} = \alpha_i + \lambda_t + b\, GDTI_{it} + c'_k CRDF^k_{i,t-1} + \gamma' X_{it} + \varepsilon_{it} \tag{15}$$

For each finance category, path a is estimated using the CRDF-to-GDTI equation, and path b is estimated using the labor-market equation above. Both paths are estimated on the same complete-case sample. The indirect effect is:

$$IE_k = a_k \times b \tag{16}$$

Inference for the indirect effect IE_k is based on 5000 country-cluster bootstrap replications. Countries, rather than individual country-year observations, are resampled so that the within-country dependence structure is preserved. Percentile and bias-corrected and accelerated (BCa) confidence intervals are reported. This procedure avoids relying on the normal approximation underlying the Sobel test. Given the observational design, the result is interpreted as evidence for or against an indirect transmission association, not as proof of causal mediation.

Institutional quality is tested as a moderator of the finance-technology relationship:

$$GDTI_{it} = \alpha_i + \lambda_t + \beta_k CRDF^k_{i,t-1} + \eta IQ_{it} + \phi_k\left(CRDF^k_{i,t-1} \times IQ_{it}\right) + \gamma' X_{it} + \varepsilon_{it} \tag{17}$$

The coefficient φ_k on the interaction term $CRDF^k_{i,t-1} \times IQ_{it}$ indicates whether the association between CRDF and technological transformation changes systematically with institutional quality. Advanced skills are examined analogously in the technology-labor equation:

$$LMTI_{it} = \alpha_i + \lambda_t + \theta GDTI_{it} + \kappa ADVSKILL_{it} + \psi(GDTI_{it} \times ADVSKILL_{it}) + \gamma' X_{it} + \varepsilon_{it} \quad (18)$$

Variables entering interaction terms are centered or standardized before the product term is formed so that lower-order coefficients remain interpretable. H4 and H5 are assessed using the interaction terms, together with the corresponding robustness tests, rather than from a single baseline *p*-value.

The fixed-effects estimates should not be read as experimental causal effects. The allocation of climate-related development finance is not random and can respond to vulnerability, institutional capacity, donor priorities, project pipelines, domestic climate policy, or other time-varying conditions. Country and year fixed effects remove important sources of confounding, but they cannot eliminate all time-varying omitted factors or reverse causality. The language used throughout the empirical analysis, therefore, refers to associations and within-country covariation.

3.8. Robustness, Identification, and Endogeneity Diagnostics

The robustness strategy is organized around the main threats to interpretation rather than around statistical significance. The first set of checks concerns measurement. A Principal-only measure replaces the Principal plus Significant Rio-marker definition; the GDTI is estimated separately from its renewable-electricity and Internet components and is also reconstructed as an extended three-component index that includes high-technology exports; and the LMTI is decomposed into its high-skill occupational component and its selected carbon-exposed-sector component. These exercises test whether a particular component or definition drives the conclusions drawn from the composite indices.

The second set concerns timing and heterogeneous trends. The climate-finance variables are re-estimated with two- and three-year lags. Country-specific linear trends are added to allow economies to follow different underlying trajectories. Region-by-year fixed effects and income-group-by-year fixed effects absorb shocks that vary systematically across geographic and development groups, and combined region- and income-group time effects provide an even more demanding check. First-difference specifications examine whether the results depend on the fixed-effects level formulation.

The third set examines heterogeneity and functional form. The baseline relationships are estimated separately across the LIC, LMC, and UMC groups defined by the same modal World Bank classification used to construct the primary sample. Quadratic CRDF terms are used to examine possible nonlinear relationships, but turning points are interpreted only where the linear and quadratic terms form a statistically coherent and substantively plausible pattern. Extensive- and intensive-margin specifications distinguish between the presence of positive CRDF and the amount of finance conditional on receiving a positive amount. Because access indicators can be weakly identified when within-country status changes are rare, the number of access switches is audited directly. It is used to judge whether an apparently precise access coefficient is substantively credible.

Potential endogeneity was also examined using dynamic panel GMM, but the GMM results are not used as inferential evidence in the final specification. We estimated a deliberately parsimonious diagnostic battery based on System-GMM and Difference-GMM, using collapsed internal instruments and tightly restricted lag windows to limit instrument proliferation (Arellano & Bond, 1991; Blundell & Bond, 1998; Roodman, 2009). The battery included one-step System-GMM, two-step specifications with lag-2 and lag-3 internal instruments, a reduced standard-IV matrix, forward orthogonal deviations, and Difference-GMM.

Across all 25 diagnostic models, the estimated moment covariance matrix remained singular, and the software required a generalized inverse. Importantly, this singularity cannot be mechanically attributed to the correlation between mitigation and adaptation CRDF ($r = 0.671$): the two finance measures are never entered jointly in the relevant GMM equations, the warning appears in both the mitigation-only and adaptation-only specifications, and it also appears in the H2 dynamic specification, which contains neither CRDF measure. The warning also persists with deliberately restricted instrument sets, generally well below the number of country groups. These diagnostics point to a broader rank/numerical-identification problem in the available unbalanced dynamic-panel moment structure, rather than to simple collinearity between the two climate-finance measures or to conventional instrument proliferation. An aggregate measure formed by summing mitigation and adaptation is not used as a corrective because activities may carry both Rio markers, so a simple sum can double-count dual-marked finance and would not constitute a clean alternative exposure measure. Several focal coefficients also changed sign across otherwise defensible variants. Because no numerically clean dynamic specification emerged under the pre-specified parsimonious designs, GMM is treated strictly as an endogeneity diagnostic and is not used to support or reject any hypothesis.

The final inferential architecture is therefore straightforward. H1–H5 are evaluated primarily using two-way fixed-effects models and associated robustness checks; H6 is evaluated using the same-sample country-cluster bootstrap indirect effect. Dynamic GMM is disclosed for transparency, but does not enter the main evidential chain. This choice was fixed after the diagnostic battery and was not based on whether any particular specification was statistically significant.

4. Empirical Results

4.1. Descriptive Statistics and Preliminary Evidence

Table 1 reports descriptive statistics for the developing-economy sample. The panel remains unbalanced because the underlying sources differ substantially in country-year coverage. Technological indicators are available for a much larger part of the sample than the harmonized occupational and sectoral employment series used to construct the LMTI. This difference in coverage carries over to the model-specific estimation samples rather than being resolved by imposing a single complete-case panel across all specifications.

Table 1. Descriptive statistics.

Variable	N	Mean	SD	Min	Max
GDTI	1487	−0.0242	0.6420	−1.2313	2.0192
LMTI	459	−0.0578	0.5436	−1.4394	1.7413
Mitigation CRDF (t − 1)	1474	1.4649	1.2820	0.0000	7.3532
Adaptation CRDF (t − 1)	1474	1.5771	1.3239	0.0000	7.4120
Institutional quality	1607	−0.1221	0.8449	−2.3404	2.0893
Advanced skills	660	−0.0595	0.9733	−1.5447	3.7263
Log GDP per capita	1533	8.9084	0.8580	6.8957	10.4832
GDP growth (%)	1574	3.1685	6.2822	−50.3385	86.8267
Trade openness	1473	75.2878	35.7144	0.0000	347.7203
Urban population (%)	1608	50.3864	20.2134	10.9843	92.1180
Population growth (%)	1608	1.4986	1.4038	−6.6464	9.9923

Notes: Statistics use all available observations within the developing-economy sample. CRDF is expressed as ln(1 + constant-2024-USD per capita) and lagged by one year in the main models.

Within the developing-economy sample, the GDTI is available for 1487 country-year observations and the LMTI for 459. The two lagged climate-finance measures display substantial variation, while institutional quality and advanced skills also vary markedly across countries and over time. The unconditional correlation (Table 2) between GDTI and LMTI is positive but modest ($r = 0.175$). Lagged mitigation and adaptation finance are only weakly correlated with the GDTI, whereas the two finance measures are more strongly correlated with each other ($r = 0.671$). This provides an additional practical reason for estimating mitigation and adaptation separately in the main equations.

Table 2. Selected pairwise correlations.

Pair	Correlation	Pairwise N
GDTI—LMTI	0.175	441
Mitigation CRDF(t − 1)—GDTI	0.067	1360
Adaptation CRDF(t − 1)—GDTI	0.015	1360
Mitigation—Adaptation CRDF	0.671	1474
Institutional quality—GDTI	0.312	1487
Advanced skills—LMTI	0.369	420

Notes: These are unconditional pairwise correlations and are reported only as descriptive evidence; they do not control for country effects, common year shocks, or macroeconomic covariates.

4.2. Climate-Related Development Finance and Technological Transformation

The first set of models evaluates whether climate-related development finance is associated with broad green-digital technological transformation (Table 3). In the mitigation specification, the coefficient on lagged CRDF is −0.0098, and the adaptation coefficient is −0.0150. Both equations use 1219 observations from 122 countries. Neither estimate is statistically different from zero at conventional levels, and neither has the positive sign predicted by H1. The baseline evidence, therefore, does not support a systematic positive within-country relationship between either category of climate-related development finance and the GDTI.

Table 3. The two main two-way fixed-effects estimates.

Hypothesis	Relationship	Coefficient	Cluster SE	*p*-Value	N	Countries
H1 (mitigation)	Mitigation CRDF(t − 1) → GDTI	−0.0098	0.0063	0.120	1219	122
H1 (adaptation)	Adaptation CRDF(t − 1) → GDTI	−0.0150	0.0104	0.149	1219	122
H2	GDTI → LMTI	−0.0311	0.1062	0.769	398	62
H3 (mitigation)	Mitigation CRDF(t − 1) → LMTI	0.0071	0.0119	0.548	403	65
H3 (adaptation)	Adaptation CRDF(t − 1) → LMTI	0.0187	0.0136	0.170	403	65

Notes: All models include log GDP per capita, GDP growth, trade openness, urban population share, population growth, country fixed effects, and year fixed effects.

The magnitude and sign of these coefficients should not be read as evidence that climate finance reduces technological transformation. The estimates are imprecise, and the confidence intervals implied by their standard errors include effects close to zero. The relevant conclusion is narrower: after controlling for country fixed effects, year fixed effects, and the pre-specified macroeconomic covariates, the data do not provide evidence of the positive average relationship proposed in H1.

4.3. Technological and Labor-Market Transformation

H2 examines whether within-country changes in the GDTI are associated with changes in the LMTI. The estimated coefficient is −0.0311 (cluster SE = 0.1062; $p = 0.769$), based on 398 observations from 62 countries. The 95% confidence interval is approximately [−0.239, 0.177]. The estimate is therefore statistically indistinguishable from zero, but the interval remains wide enough that economically meaningful associations in either direction cannot be ruled out. H2 is consequently not supported in the available sample, but the result should be interpreted as imprecise evidence rather than as evidence of no technology-labor relationship.

4.4. Direct Relationship Between Climate-Related Development Finance and Labor-Market Transformation

The direct mitigation coefficient is 0.0071 (cluster SE = 0.0119; $p = 0.548$), and the adaptation coefficient is 0.0187 (cluster SE = 0.0136; $p = 0.170$), with 403 observations from 65 countries in each specification. Their approximate 95% confidence intervals are [−0.016, 0.030] and [−0.008, 0.045], respectively. Neither estimate is statistically distinguishable from zero. The direct H3 intervals are appreciably narrower than the H2 interval, so these equations are more informative about moderate direct associations, although they do not establish the absence of an effect. H3 is therefore not supported in the available labor-market sample, while external validity remains constrained by labor-data coverage.

4.5. Technological Transmission Channel

The transmission hypothesis is assessed using a common complete-case sample, so that the two component paths are estimated from the same country-year observations. This avoids attributing an indirect effect to differences in sample composition across the finance-to-technology and technology-to-labor equations. The final common sample contains 388 observations from 62 countries for both mitigation and adaptation.

For mitigation (Table 4), path a is −0.0054 and path b is −0.0188, producing an indirect association of 0.000102. The country-cluster bootstrap standard error is 0.001280, the percentile 95% confidence interval is [−0.001776, 0.003562], and the bias-corrected and accelerated (BCa) interval is [−0.001725, 0.003707]. The bootstrap p-value is 0.810. For adaptation, path a is −0.0144 and path b is −0.0124, giving an indirect association of 0.000179; the BCa 95% interval is [−0.002439, 0.006364] and the bootstrap p-value is 0.922. Both intervals include zero. The analysis, therefore, does not detect the proposed indirect transmission pattern in the available common sample. Given the observational design, narrower labor-market coverage, and uncertainty in the component paths, this result is not interpreted as evidence that an indirect relationship is absent.

Table 4. Same-sample country-cluster bootstrap indirect effects.

Finance	Path a	Path b	Indirect	Boot. SE	Percentile 95% CI	BCa 95% CI	*p*-Value	N	Countries
Mitigation	−0.0054	−0.0188	0.000102	0.001280	[−0.001776, 0.003562]	[−0.001725, 0.003707]	0.810	388	62
Adaptation	−0.0144	−0.0124	0.000179	0.001818	[−0.003669, 0.004163]	[−0.002439, 0.006364]	0.922	388	62

Notes: The indirect effect is a × b. Inference is based on 5000 country-cluster bootstrap replications. The exercise is interpreted as evidence of an indirect transmission association, not as causal mediation.

4.6. Conditioning Effects of Institutional Quality and Advanced Skills

The baseline institutional-quality interactions are positive and statistically significant in the developing-economy sample. The mitigation CRDF × institutional-quality coefficient is

0.0177 (Table 5), while the adaptation interaction is 0.0228. On their own, these estimates are consistent with the idea that the finance-technology relationship becomes more favorable as institutional quality improves. The robustness analysis below, however, shows that this pattern is not stable once differential technological trajectories are controlled more aggressively. H4 is therefore treated as suggestive at baseline rather than as a robustly supported hypothesis.

Table 5. Baseline conditioning effects.

Hypothesis	Interaction	Coefficient	Cluster SE	*p*-Value	N	Countries
H4 (mitigation)	Mitigation × institutional quality → GDTI	0.0177	0.0073	0.015	1219	122
H4 (adaptation)	Adaptation × institutional quality → GDTI	0.0228	0.0085	0.007	1219	122
H5	GDTI × advanced skills → LMTI	0.0231	0.0502	0.645	359	56

Notes: The interaction variables are centered or standardized as described in Section 3. Statistical significance in the baseline H4 equations is not treated as sufficient evidence of robust moderation.

The corresponding skills interaction is clearly weaker. The coefficient on GDTI × Advanced Skills in the LMTI equation is 0.0231, using 359 observations from 56 countries. There is therefore no evidence that the broad advanced-education measure systematically strengthens the relationship between green-digital technological transformation and labor-market restructuring. H5 is not supported.

4.7. Robustness Analysis

4.7.1. Alternative Finance Definitions, Lag Structure, and Index Components

The main conclusions are not sensitive to a more restrictive definition of climate-related development finance, longer short-run lags, or alternative positive weighting of the GDTI (Table 6). Restricting finance to principal objective activities leaves the adaptation estimate insignificant and produces a marginally significant mitigation coefficient with a negative sign, contrary to H1. With a two-year lag, mitigation remains insignificant, and adaptation is close to conventional significance but negative. Extending the lag to three years again yields insignificant GDTI coefficients (mitigation: beta = −0.0104, $p = 0.137$; adaptation: beta = −0.0089, $p = 0.203$) and near-zero, insignificant LMTI coefficients (mitigation: beta = 0.0036, $p = 0.765$; adaptation: beta = 0.0012, $p = 0.932$). Thus, the baseline null pattern is not attributable solely to the use of a one-year lag, although the longer lag further reduces the effective labor-market sample.

The weighting diagnostic leads to the same substantive conclusion. Re-estimating H1 with 60% renewable electricity/40% Internet and 40% renewable electricity/60% Internet produces mitigation coefficients of −0.0090 ($p = 0.165$) and −0.0106 ($p = 0.094$), and adaptation coefficients of −0.0159 ($p = 0.178$) and −0.0141 ($p = 0.126$), respectively. None produces the positive association predicted by H1. The PCA diagnostic is not used as a replacement index because, with weak negative component correlations, PC1 assigns opposite signs to the two dimensions, thereby changing the meaning of the formative construct rather than merely reweighting it.

Alternative definitions of the transformation indices lead to similar conclusions. Replacing the baseline GDTI with the three-component extended index yields a negative technology-to-labor coefficient (−0.1470), but the estimate is not statistically significant. Decomposing the LMTI also provides no evidence that the aggregate result reflects offsetting relationships across its two components. The GDTI is not significantly associated with either the share of high-skill employment or employment in the selected carbon-exposed sectors. Mitigation and adaptation finance are likewise not significantly associated with the share of high-skill employment. The absence of a significant relationship at the aggregate

level, therefore, does not appear to conceal statistically detectable relationships in these underlying labor-market dimensions.

Table 6. Measurement and timing robustness.

Relationship	Coefficient	SE	*p*-Value	N	Countries
Principal-only mitigation -> GDTI	−0.0112	0.0065	0.084	1219	122
Principal-only adaptation -> GDTI	−0.0078	0.0061	0.203	1219	122
Lag t − 2 mitigation -> GDTI	−0.0104	0.0070	0.137	1103	122
Lag t − 2 adaptation -> GDTI	−0.0163	0.0085	0.053	1103	122
Lag t − 2 mitigation -> LMTI	−0.0030	0.0160	0.849	384	65
Lag t − 2 adaptation -> LMTI	0.0073	0.0133	0.584	384	65
extended GDTI -> LMTI	−0.1470	0.1123	0.190	370	60
GDTI -> high-skill share	−0.5253	0.7781	0.500	468	74
Mitigation -> high-skill share	−0.0787	0.1123	0.483	482	78
Adaptation -> high-skill share	0.0319	0.0983	0.746	482	78
GDTI -> carbon-exposed-sector share	0.1889	0.8664	0.827	510	77
Mitigation -> renewable component	−0.0059	0.0085	0.493	1260	123
Adaptation -> renewable component	−0.0184	0.0178	0.300	1260	123
Mitigation -> Internet component	−0.0150	0.0083	0.072	1266	124
Adaptation -> Internet component	−0.0122	0.0082	0.137	1266	124
Lag t − 3 mitigation -> GDTI	−0.0104	0.0070	0.137	984	122
Lag t − 3 adaptation -> GDTI	−0.0089	0.0070	0.203	984	122
Lag t − 3 mitigation -> LMTI V5	0.0036	0.0122	0.765	355	62
Lag t − 3 adaptation -> LMTI V5	0.0012	0.0140	0.932	355	62
GDTI 60% renewable/40% Internet: mitigation	−0.0090	0.0065	0.165	1219	122
GDTI 60% renewable/40% Internet: adaptation	−0.0159	0.0118	0.178	1219	122
GDTI 40% renewable/60% Internet: mitigation	−0.0106	0.0064	0.094	1219	122
GDTI 40% renewable/60% Internet: adaptation	−0.0141	0.0092	0.126	1219	122

Notes: All rows use the developing-economy sample, subject to model-specific data availability. The component regressions are included to make the behavior of the formative indices transparent.

Estimating the GDTI components separately provides a further check on the composite result. Neither mitigation nor adaptation finance is significantly associated with the renewable-electricity component. For Internet use, the mitigation coefficient is negative (−0.0150) and marginally significant at the 10% level, whereas the adaptation coefficient is also negative (−0.0122) but statistically insignificant. The component-level estimates, therefore, provide no evidence of the positive technological response predicted by H1. More importantly, the statistically insignificant aggregate GDTI result does not appear to be masking a strong positive association with either its green or digital component.

4.7.2. Heterogeneous Time Dynamics and First Differences

More demanding controls for time-varying heterogeneity reinforce the baseline interpretation. The mitigation-to-GDTI coefficient remains insignificant when controlling for country-specific linear trends, income-group-by-year effects, combined region- and income-group-specific time effects, and first differences. The region-by-year estimate is

negative and significant, but it does not provide the positive relationship predicted by H1. Adaptation-to-GDTI is insignificant across all corresponding specifications.

The same stability is evident in the labor-market equations. The GDTI remains statistically insignificant in the LMTI equation when the models include country-specific trends, region-by-year effects, income-group-by-year effects, combined group-specific time effects, or are estimated in first differences. In the first-difference specification, the coefficient is close to zero (−0.0015) and statistically insignificant (Table 7). The direct mitigation and adaptation coefficients are likewise statistically insignificant across these alternative specifications. The persistence of these results indicates that the baseline null findings are not sensitive to alternative controls for differential time patterns across countries, regions, and income groups.

Table 7. Selected heterogeneous-time and first-difference checks.

Relationship	Specification	Coefficient	SE	*p*-Value	N	Countries
Mitigation -> GDTI	country trends	−0.0085	0.0072	0.237	1219	122
Mitigation -> GDTI	region income year	−0.0103	0.0068	0.132	1140	113
Mitigation -> GDTI	first difference	−0.0051	0.0040	0.202	1081	121
Adaptation -> GDTI	country trends	−0.0046	0.0070	0.515	1219	122
Adaptation -> GDTI	region income year	−0.0106	0.0119	0.373	1140	113
Adaptation -> GDTI	first difference	−0.0009	0.0045	0.850	1081	121
GDTI -> LMTI	country trends	−0.0164	0.1440	0.909	398	62
GDTI -> LMTI	region income year	−0.0505	0.1097	0.645	383	60
GDTI -> LMTI	first difference	−0.0015	0.0705	0.983	296	47
Mitigation -> LMTI	country trends	−0.0044	0.0063	0.485	403	65
Mitigation -> LMTI	region income year	−0.0027	0.0115	0.813	389	63
Mitigation -> LMTI	first difference	−0.0032	0.0053	0.543	298	49
Adaptation -> LMTI	country trends	0.0069	0.0084	0.416	403	65
Adaptation -> LMTI	region income year	0.0118	0.0170	0.489	389	63
Adaptation -> LMTI	first difference	0.0118	0.0073	0.106	298	49

Notes: The table reports the most demanding and directly comparable checks. Region-by-year and income-group-by-year estimates lead to the same substantive interpretation and are retained in the estimation archive.

4.7.3. Robustness of the Institutional Interaction

The institutional interaction is the only statistically significant baseline result, so it is subjected to a more demanding stability check. The baseline evidence is concentrated in the digital component, where the interactions are positive and statistically significant for both mitigation (0.0211) and adaptation (0.0333) (Table 8). This result, however, is not robust to alternative controls for heterogeneous time patterns. Once country-specific trends are introduced, the interaction coefficients fall to 0.0016 for mitigation and −0.0068 for adaptation, and neither remains statistically significant. The interactions are also statistically insignificant under region-by-year effects, income-group-by-year effects, combined group-specific time effects, and first-difference specifications. The baseline evidence of institutional moderation should therefore be interpreted as suggestive rather than as a stable feature of the data.

This loss of significance is not a minor change in precision around an otherwise stable estimate. The interaction coefficients themselves shrink sharply and, in some specifications, change sign. The evidence is therefore consistent with the baseline interaction partly

reflecting heterogeneous technological trajectories rather than a stable conditioning effect of institutional quality. For this reason, H4 is not classified as supported despite the significant baseline coefficients.

Table 8. Digital-component robustness of institutional moderation.

Finance	Specification	Interaction Coef.	SE	*p*-Value	N	Countries
Mitigation	year	0.0211	0.0089	0.017	1266	124
Mitigation	country trends	0.0016	0.0058	0.776	1266	124
Mitigation	region income year	0.0007	0.0101	0.945	1187	115
Mitigation	first difference	0.0024	0.0031	0.434	1138	124
Adaptation	year	0.0333	0.0124	0.007	1266	124
Adaptation	country trends	−0.0068	0.0078	0.385	1266	124
Adaptation	region income year	−0.0009	0.0132	0.947	1187	115
Adaptation	first difference	0.0024	0.0048	0.619	1138	124

Notes: These estimates refer to the Internet-use component, where the baseline institutional interaction is concentrated. They are not full-GDTI interaction estimates.

4.7.4. Income-Group Heterogeneity and Nonlinearity

Splitting the sample by income group does not reveal a clear pattern in the relationship between climate finance and technological transformation. In the GDTI equations, none of the mitigation or adaptation coefficients (Table 9) is statistically significant for the LIC, LMC, or UMC groups. In the labor-market equations, the only statistically significant result is the mitigation coefficient for LIC economies (0.1313). However, this estimate is based on only 29 observations across seven countries, making the result too fragile to support a broader conclusion about income-group differences. The corresponding adaptation coefficient is not significant, and neither type of climate finance is significant for the LMC or UMC groups.

Table 9. Income-group heterogeneity.

Outcome	Finance	Group	Coefficient	SE	*p*-Value	N	Countries
GDTI	Mitigation	LIC	0.0090	0.0182	0.621	273	28
GDTI	Mitigation	LMC	−0.0159	0.0105	0.131	507	50
GDTI	Mitigation	UMC	−0.0037	0.0060	0.536	439	44
GDTI	Adaptation	LIC	0.0095	0.0098	0.329	273	28
GDTI	Adaptation	LMC	−0.0235	0.0245	0.336	507	50
GDTI	Adaptation	UMC	−0.0005	0.0085	0.954	439	44
LMTI	Mitigation	LIC	0.1313	0.0647	0.042	29	7
LMTI	Mitigation	LMC	0.0140	0.0229	0.542	186	32
LMTI	Mitigation	UMC	−0.0112	0.0088	0.202	188	26
LMTI	Adaptation	LIC	−0.0554	0.1802	0.759	29	7
LMTI	Adaptation	LMC	0.0283	0.0265	0.287	186	32
LMTI	Adaptation	UMC	0.0004	0.0109	0.971	188	26

Notes: The LIC labor-market equations are based on very small samples and are treated as exploratory. No isolated subgroup coefficient is used to overturn the full-sample conclusion.

The quadratic specifications (Table 10) also provide little evidence of a nonlinear relationship. In the GDTI equation, the linear adaptation term is negative and statistically significant (−0.0385), while the squared term is only marginally significant. The squared mitigation term is not significant. In the LMTI equations, neither quadratic term is statistically significant. Overall, these results are weak and vary across outcomes, providing no clear evidence of a threshold or U-shaped relationship between climate finance and technological transformation.

Table 10. Quadratic specifications.

Outcome	Finance	Linear Beta	*p*	Squared Beta	*p*	Turning Point	N	Countries
GDTI	Mitigation	−0.0303	0.063	0.0049	0.137	3.086	1219	122
GDTI	Adaptation	−0.0385	0.030	0.0055	0.095	3.482	1219	122
LMTI	Mitigation	0.0080	0.785	−0.0002	0.968	19.203	403	65
LMTI	Adaptation	−0.0472	0.334	0.0153	0.220	1.548	403	65

Notes: Turning points are reported for completeness but are not interpreted substantively where the quadratic term is not precisely estimated.

4.7.5. Extensive and Intensive Margins

The extensive/intensive-margin exercise separates access to any positive climate-related development finance from the amount received among positive observations. Several extensive-margin coefficients are large and statistically significant. The mitigation access coefficient is negative (Table 11), while the adaptation access coefficient is positive. The corresponding intensive-margin coefficients are small and statistically insignificant. These extensive-margin estimates are not used to revise the baseline hypothesis assessment because identification of access status relies on very few within-country switches.

Table 11. Extensive- and intensive-margin estimates.

Finance	Margin	Coefficient	SE	*p*-Value	N	Countries
Mitigation	Extensive	−0.2100	0.0368	<0.001	403	65
Mitigation	Intensive	0.0080	0.0119	0.500	402	65
Adaptation	Extensive	0.2424	0.0974	0.013	403	65
Adaptation	Intensive	0.0167	0.0139	0.231	400	65

Notes: Joint access-plus-intensity equations lead to the same qualitative interpretation. The access coefficients should be read together with the switch audit reported in the text.

The access results are not treated as reliable evidence for H3 because their within-country identification is extremely thin. In the complete labor-market sample, mitigation access status changes only twice, both transitions occurring in a single country, while adaptation access status changes only four times across two countries. With so few switches, apparently precise fixed-effects access coefficients can be dominated by a handful of transitions. The access exercise is therefore retained as a diagnostic of data structure rather than as evidence of a causal or structural extensive-margin effect.

4.7.6. Dynamic-Panel Diagnostic

Dynamic GMM was examined as an endogeneity diagnostic rather than as part of the main inferential strategy. A pre-specified battery of 25 parsimonious specifications was estimated, covering one-step and two-step System-GMM, deeper-lag instruments, a reduced standard IV matrix, forward orthogonal deviations, and Difference-GMM. Every

specification produced a singular estimated covariance matrix of moments and required a generalized inverse. The warning persisted despite instrument counts generally being well below the number of country groups. It also occurred when mitigation and adaptation were entered separately and in the H2 specification, which contains neither a financial measure. The singularity, therefore, cannot be explained mechanically by the correlation between mitigation and adaptation in the CRDF, nor can it be attributed simply to conventional instrument proliferation. Taken together, the diagnostics indicate a broader rank/numerical-identification problem in the moment structure available for this unbalanced panel.

The dynamic coefficients were also not sufficiently stable for substantive interpretation: several focal estimates changed sign across otherwise defensible variants. Although AR(2) and the Hansen tests often failed to reject, these diagnostics do not resolve the singular covariance problem. In keeping with the decision rule established before the diagnostic battery was evaluated, no GMM specification is selected ex post. The dynamic exercise is therefore disclosed for transparency, but is not used to support or reject the hypotheses.

4.7.7. Labor-Market Coverage and Precision

Because harmonized labor-market data are substantially less complete than the technology indicators, we assessed whether countries entering the final H3 estimation sample differ systematically from the remaining economies in the predefined Option A population. The diagnostic is conducted at the country level to avoid treating repeated country-year observations as independent. The final H3 sample contains 65 countries; 70 of the 135 eligible developing economies are not included in the final direct labor-market regressions. Countries in the labor sample have higher average log GDP per capita, institutional quality, GDTI, mitigation CRDF, and GDP growth. Differences are small for adaptation, CRDF, trade openness, and urbanization. Low-income economies are substantially underrepresented among included countries. These comparisons establish observable compositional differences, not the direction or magnitude of any selection bias in the unobserved labor outcomes.

Precision diagnostics complement the coverage analysis (Table 12). H2 has an approximate 95% confidence interval of $[-0.239, 0.177]$, which is sufficiently wide that economically meaningful associations in either direction cannot be ruled out. The direct H3 estimates are more precise: the approximate 95% confidence interval is $[-0.016, 0.030]$ for mitigation and $[-0.008, 0.045]$ for adaptation. These intervals show that the GDTI-LMTI equation is materially less informative about small-to-moderate associations than the direct finance-LMTI equations. Accordingly, the null labor-market estimates are not interpreted uniformly: H2 is explicitly described as imprecise, while H3 is described as more informative but still constrained in external validity by labor-data coverage.

Table 12. Labor-market coverage and precision diagnostics.

Diagnostic	Included	Excluded	SMD/95% CI	*p*-Value	Coverage
Log GDP per capita (country mean)	9.157	8.651	SMD = 0.618	0.001	65/63
Institutional quality (country mean)	0.137	−0.368	SMD = 0.637	<0.001	65/69
Mitigation CRDF (country mean)	1.666	1.279	SMD = 0.395	0.024	65/69
Adaptation CRDF (country mean)	1.687	1.543	SMD = 0.138	0.426	65/69
GDTI (country mean)	0.183	−0.208	SMD = 0.707	<0.001	65/68
GDP growth (country mean)	3.723	2.583	SMD = 0.422	0.015	65/68
Income-group composition	LIC 10.8%	LIC 34.3%	chi-square = 11.46	0.003	65/70

Table 12. *Cont.*

Diagnostic	Included	Excluded	SMD/95% CI	*p*-Value	Coverage
Regional composition	—	—	chi-square = 9.98	0.076	65/70
H2: GDTI -> LMTI	beta = −0.0311	SE = 0.1062	95% CI [−0.239, 0.177]	0.769	N = 398; countries = 62
H3: mitigation -> LMTI	beta = 0.0071	SE = 0.0119	95% CI [−0.016, 0.030]	0.548	N = 403; countries = 65
H3: adaptation -> LMTI	beta = 0.0187	SE = 0.0136	95% CI [−0.008, 0.045]	0.170	N = 403; countries = 65

Notes: Country-level comparisons use country means over available 2010–2021 observations to avoid treating repeated country-year observations as independent. SMD denotes standardized mean difference; *p*-values for continuous variables are from Welch unequal-variance tests, while income-group and regional composition use Pearson chi-square tests. For descriptive country-characteristic rows, the final column reports the number of countries with non-missing information in the included and excluded groups, respectively; these counts can be below 65 and 70 because coverage differs by variable. For H2 and H3, the final column reports regression observations and contributing countries. These diagnostics show observable differences in sample composition; they do not, by themselves, establish econometric selection bias.

4.8. Overall Assessment of the Hypotheses

The full set of estimates yields an appropriately differentiated assessment of the conceptual framework (Table 13). H1 is not supported in the available large-sample estimates for either mitigation or adaptation finance. For H2, no statistically detectable GDTI–LMTI association is found, but inference is limited by comparatively low precision and narrow labor-data coverage. H3 likewise yields no statistically detectable direct association in the available labor-market sample. However, these estimates are more informative about moderate standardized associations than H2 and remain subject to external validity constraints. H4 is suggestive in baseline specifications but not robust to more demanding time controls. H5 yields no statistically detectable moderation in the available labor sample. H6 yields no statistically detectable indirect association, and its interpretation is constrained by the same labor-data coverage and by the observational nature of the component paths.

Table 13. Final hypothesis assessment.

Hypothesis	Relationship	Assessment
H1	CRDF -> technological transformation	Not supported in the available large-sample estimates
H2	GDTI -> labor-market transformation	No statistically detectable association; inference limited by precision and labor-data coverage
H3	CRDF -> labor-market transformation	No statistically detectable association in the available labor sample; external validity limited by coverage
H4	Institutional quality moderates CRDF -> technology	Suggestive in baseline specifications; not robust to more demanding time controls
H5	Advanced skills moderate technology -> labor	No statistically detectable moderation in the available labor sample
H6	Indirect CRDF -> technology -> labor association	No statistically detectable indirect association; inference limited by labor-data coverage

Notes: Mitigation and adaptation are estimated separately within H1, H3, H4, and H6. Hypothesis decisions reflect the complete pattern of baseline and robustness evidence.

The robustness analysis does not reveal a coherent alternative pattern hidden behind the baseline estimates. The few coefficients that reach conventional significance are either of the opposite sign to the relevant hypothesis, confined to a very small subgroup, weakly estimated in nonlinear models, or identified from too few within-country switches to carry substantive weight. The empirical conclusion is therefore based on the consistency of the full evidence set rather than on isolated *p*-values.

5. Discussion

5.1. Main Findings and the Finance-to-Transformation Puzzle

The evidence does not support a systematic finance-technology-labor transmission sequence. Neither mitigation nor adaptation finance is positively associated with the GDTI across the main specifications; GDTI is not significantly associated with LMTI; direct finance-to-labor relationships and bootstrap indirect effects are unsupported. H4 is positive only in baseline models and loses robustness under stronger controls for heterogeneous technological trajectories.

The strength of this conclusion is not identical across all links in the framework. The finance-to-technology result is estimated on a substantially larger sample and remains consistently non-positive across a wide set of alternative specifications. The technology-to-labor and direct finance-to-labor equations, by contrast, rely on much smaller labor-market samples and are correspondingly less precise. Their non-significance should therefore be interpreted as an absence of evidence for the hypothesized positive associations, not as precise evidence that economically meaningful effects are impossible. This distinction is important because the paper's empirical contribution rests on the pattern in the full evidence set rather than on a mechanical reading of individual *p*-values.

This pattern motivates a finance-to-transformation puzzle: greater financial mobilization is not systematically accompanied by broad, measurable changes in national technology and employment structures in the data examined here. This is a descriptive interpretation of the aggregate empirical pattern, not evidence that climate finance is ineffective or that it has an established causal mechanism. Transformational change may require scale, depth, persistence, and complementary capabilities beyond those required for successful project delivery (Weiss et al., 2026).

Narrower effects can still coexist with this aggregate pattern. Mohan and Morris (2024) find positive effects on entrepreneurship, and Ko et al. (2026) report lower youth NEET rates. Such outcomes may occur without changing national occupational and sectoral employment shares. The results, therefore, provide no systematic evidence for the proposed aggregate transmission sequence; they do not show that climate finance is ineffective.

5.2. Why Climate-Related Development Finance May Not Translate into Technological Transformation

One explanation is measurement. OECD Rio markers identify climate objectives at the activity level, so reported CRDF is climate-related rather than a direct measure of climate-specific expenditure (OECD, 2024a). Higher recorded finance need not map one-for-one into the technological dimensions captured by the GDTI.

A second issue is scale. GCF frameworks distinguish project impact from paradigm shift and emphasize replication, scale, and enabling environments (Green Climate Fund, n.d., 2023). Financing an intervention and producing country-level technological transformation are therefore different stages.

Aggregation reinforces this distinction. A local renewable project may add capacity without materially changing the national electricity mix, while climate-financed digital tools may be valuable without affecting national Internet penetration. Component regressions confirm that the GDTI result does not conceal a strong positive response in either dimension.

Diffusion also depends on local capabilities. Greenwood and Warren (2022) highlight behavioral and contextual constraints on technology adoption, while Browne (2022) emphasizes governance challenges in international climate finance.

Our institutional interaction is consistent with this possibility, but is not robust. Adu and Ramfol (2025) report a more favorable finance-innovation relationship under stronger

institutions, yet our interaction becomes small and insignificant under more demanding time controls.

Timing may also attenuate the estimates because commitments can precede procurement, construction, operation, and diffusion by several years. One-, two-, and three-year lag specifications do not reveal a stable positive relationship, providing no evidence that the baseline pattern is driven solely by an excessively short one-year lag. These aggregate checks, nevertheless, cannot rule out longer or project-specific implementation horizons.

5.3. Why Technological Change May Not Translate into Labor-Market Transformation

The technology-labor link is estimated less precisely because harmonized labor data are sparse. Within that sample, neither the aggregate index nor its components provide evidence for H2.

This finding should not be interpreted as evidence that green or digital technologies have no labor-market consequences. Technological adoption can first alter productivity, capital intensity, work organization, and the task content of existing jobs, while changes in occupational and sectoral employment shares occur more slowly. Labor reallocation may also be constrained by geographic mismatch, differences in skill requirements, and the adjustment costs faced by workers moving across occupations, sectors, and regions (Tyros et al., 2023; OECD, 2024b). The GDTI and LMTI, therefore, capture distinct stages of adjustment rather than two dimensions that should necessarily move together within the same short time horizon.

Tyros et al. (2023) show that brown-to-green mobility depends on the transferability of skills and that production and highly automatable occupations often require substantial reskilling.

This also helps interpret the insignificant GDTI × Advanced Skills interaction. Advanced education is a broad proxy, whereas Tsomb (2026) finds that technical, ICT, and environmental specialization matter for climate-finance-related innovation.

The LMTI should also be interpreted narrowly. It is a directional structural index: higher values reflect a larger share of employment in Managers, Professionals, and Technicians and Associate Professionals, with a smaller share in selected carbon-exposed sectors. These dimensions are intended to capture occupational upgrading and sectoral reallocation, not overall labor-market welfare or job quality. Changes in wages, informality, working conditions, gender participation, regional employment, task content, and worker-to-worker or job-to-job transitions can occur without large movements in the national shares entering the index. This measurement boundary helps reconcile the aggregate null result with studies that find effects on more specific labor outcomes and is another reason not to interpret H2 or H3 as evidence that labor-market consequences are absent.

5.4. Institutions and Skills as Enabling Conditions

Institutions and human capital remain plausible enabling conditions, but the data do not identify either as a robust moderator. Institutional interaction is significant only in baseline models, whereas advanced skills do not significantly moderate the technology-labor relationship.

Existing studies nevertheless support their theoretical relevance: Adu and Ramfol (2025) emphasize institutions, Tsomb (2026) specialized human capital, and Tyros et al. (2023) skill transferability. Broad country-level proxies may therefore conceal the specific capacities that matter for implementation and reallocation.

Institutions and skills may also operate jointly: public agencies need administrative and technical capacity, firms need adoption capabilities, and workers need task-relevant skills. Simple linear interactions cannot capture these complementarities.

The relevant question is therefore whether finance, governance, and human capital combine sufficiently to move projects from approval to implementation, implementation to diffusion, and diffusion to durable changes in production and employment. The present estimates do not identify that mechanism causally.

5.5. Implications for Climate Finance and Just-Transition Policy

The results do not imply that climate finance should be reduced; they show that financial volume alone is an incomplete indicator of structural transformation, especially when labor-market estimates are comparatively imprecise.

Project appraisal can therefore separate financial mobilization from transformation potential. The GCF investment framework already assesses paradigm-shift potential alongside impact, ownership, and effectiveness (Green Climate Fund, n.d.), encouraging attention to replication, scale, and persistence.

Implementation capacity and country ownership also matter. The GCF Readiness Strategy seeks to strengthen the enabling environments through which developing countries convert climate priorities into catalytic investment (Green Climate Fund, 2023). Our results do not establish a causal institutional mechanism, but they provide no basis for treating finance as independent of implementation capacity.

Where employment effects are explicit objectives, technological investment should be accompanied by attention to skills, job matching, and adjustment. ILO just-transition guidance links employment policy, social protection, skills, and social dialogue to the transition process (International Labor Organization, 2015, 2023b).

Monitoring should likewise distinguish project outputs from intermediate and structural outcomes. Installed capacity, infrastructure, or training are meaningful outputs but are not equivalent to economy-wide diffusion or labor reallocation.

More broadly, the results point to a transmission-oriented approach: financial scale matters, but transformation depends on how finance translates into implementation, technological additionality, diffusion, specialized capabilities, and worker adjustment.

5.6. Limitations and Research Agenda

The analysis estimates conditional within-country associations; it does not identify causal effects. Country and year fixed effects, along with richer time controls, cannot remove all time-varying confounding, donor allocation responses, reverse causality, or anticipation. Dynamic GMM was explored, but singular moment-covariance matrices and unstable focal coefficients prevented its use for inference.

Measurement uncertainty begins with the climate-finance variable itself. The OECD Rio marker methodology identifies whether mitigation or adaptation is the principal or significant objective of a development cooperation activity. However, for bilateral flows, it does not directly determine the exact amount of expenditure attributable to the climate objective within each marked activity (OECD, 2024b). Restricting the measure to principal-objective finance yields a more conservative definition and serves as a robustness check, but it does not fully resolve this issue. A more detailed assessment would distinguish among sectors, financial instruments, providers, project objectives, and implementation channels. It would also benefit from linking commitments to actual disbursements and to identifiable stages of project implementation, since the value and timing of a commitment need not closely correspond to resources deployed on the ground.

The GDTI combines renewable-electricity penetration with general digital connectivity, two distinct dimensions that capture only part of climate-relevant technological change. Their weak negative correlation reinforces the interpretation of the GDTI as a formative directional index rather than a latent scale. In this application, PCA produces a contrast

between the dimensions rather than a substantively equivalent representation of the formative construct. At the same time, alternative positive 60/40 and 40/60 weights leave the finance–technology conclusion unchanged. More granular measures of storage, efficiency, electrification, industrial decarbonization, and climate-specific digital adoption would nevertheless strengthen the technology analysis.

The LMTI is similarly partial. ISCO-08 Major Groups 1–3 capture occupational categories commonly associated with higher skill requirements, not direct measures of educational attainment, task content, or green skills (International Labor Organization, 2012). Its selected carbon-exposed-sector component is an employment-based sectoral exposure proxy rather than an emissions measure: the selected sectors encompass heterogeneous activities, and harmonized annual sector-level emissions-per-worker data with coverage comparable to the labor panel are unavailable in the assembled dataset. Introducing a partial emissions-intensity diagnostic for only a subset of countries or sectors could therefore change the estimation sample and the construct being evaluated rather than provide a like-for-like validation of the LMTI. The index also omits wages, job quality, informality, gender, regional displacement, task content, and worker transitions. It should consequently be interpreted as a directional indicator of occupational upgrading and sectoral employment reallocation, not as a comprehensive measure of green jobs, job quality, or economy-wide labor-market welfare. More detailed occupational, wage, emissions, task, and worker-level data would provide a richer picture.

The interpretation of the labor-market results is further constrained by data availability and sample composition. The final direct finance–LMTI equations use 403 observations from 65 countries, compared with 1219 observations from 122 countries in the finance–GDTI equations. A country-level coverage diagnostic shows systematic observable differences between the 65 countries entering the final H3 labor sample and the 70 developing economies that do not: included countries have higher average log GDP per capita, institutional quality, GDTI, and mitigation CRDF, while low-income economies account for 10.8% of included countries versus 34.3% of excluded countries. Income-group composition differs significantly (chi-square = 11.46, $p = 0.003$), whereas regional composition differences are weaker (chi-square = 9.98, $p = 0.076$). These diagnostics do not establish econometric selection bias or reveal how the missing labor outcomes would behave. However, they show that labor data availability is not observationally neutral across the target population, thereby limiting external validity. Precision also varies across labor equations: H2 has a wide confidence interval and limited ability to exclude economically meaningful associations, whereas the direct H3 estimates are relatively more informative about moderate standardized effects. Greater access to harmonized labor-force microdata, establishment-level information, and subnational datasets would enable a more representative and precise study of worker and firm adjustment.

Advanced educational attainment is an imperfect proxy for transition-specific capability. Skill content and transferability may matter more than aggregate education (Tsomb, 2026; Tyros et al., 2023). Future work should incorporate green, STEM, ICT, and vocational skills, occupational tasks, and firm-level shortages.

A further limitation arises from the level of aggregation and the timing of the data. Effects that are economically important at the level of a project, firm, sector, or region may be too concentrated to appear in national averages. At the same time, the year in which a financial commitment is recorded may be separated by several years from procurement, construction, operation, technological diffusion, and eventual labor-market adjustment. The one-, two-, and three-year lag structures examined in the aggregate panel cannot capture this sequence in detail. Linking geocoded climate-finance projects to local technology adoption, firms, and employment would bring the analysis closer to the mechanisms through which

finance may contribute to structural change. Clearly dated project phases would make it possible to distinguish commitment, implementation, completion, and subsequent diffusion. Future causal work could examine pre-specified eligibility rules or allocation thresholds using quasi-experimental designs, or donor-side climate-finance supply shocks interacted with predetermined recipient exposure to donors in a shift-share framework. Such strategies would require explicit tests of relevance and careful defense of the exclusion restriction; they are proposed as identification candidates rather than assumed-valid instruments. These approaches would be preferable to treating additional lags of an aggregate country panel as a substitute for exogenous variation.

Future research should therefore focus on where the finance-to-technology and technology-to-labor links strengthen or fail, and how project characteristics, institutions, and specialized skills interact. More granular evidence on firms, workers, sectors, and places would reveal distributional effects that national structural indicators cannot capture.

6. Conclusions

This paper examined whether climate-related development finance is associated with a broader sequence of technological and labor-market transformation in developing economies, while considering institutions and advanced skills as conditioning factors and technology as a possible indirect channel.

The evidence does not support a systematic transmission sequence. Neither mitigation nor adaptation finance shows a robust positive association with the GDTI, and this conclusion is stable across the main robustness checks. This finance-to-technology link is the most precisely estimated part of the analysis.

The evidence involving labor-market transformation requires differentiated caution. The GDTI–LMTI coefficient is statistically indistinguishable from zero but has a wide confidence interval, so economically meaningful associations in either direction cannot be excluded. The direct mitigation- and adaptation-finance coefficients are also statistically insignificant and are comparatively more precise for moderate standardized associations. However, labor-market coverage is substantially narrower and compositionally selective: only 65 countries are included in the final direct labor equations, and low-income economies are underrepresented relative to the target population. The bootstrap indirect associations through technological transformation are likewise statistically indistinguishable from zero. These results should therefore be read as a failure to detect the hypothesized positive labor-market relationships in the available sample, not as evidence that such relationships are absent.

Institutional quality strengthens the finance-technology relationship only in baseline specifications and is therefore suggestive rather than robust. Advanced skills do not significantly moderate the technology-labor relationship, although broad educational attainment may be too coarse to capture transition-specific capabilities.

The central implication is that financial mobilization and structural transformation are empirically distinct outcomes. Climate finance can generate useful project-, sector-, or group-level outcomes without necessarily producing changes large or persistent enough to be detected in national technological and employment structures over the observed horizon. The resulting finance-to-transformation puzzle is an interpretation of the aggregate pattern documented here, not a claim that climate finance is ineffective.

The contribution lies in testing the finance-technology-labor sequence within a single framework rather than assuming that relationships documented separately form a complete process. The results show that transformation cannot be inferred from financial volumes alone.

For policy and evaluation, this favors distinguishing commitments and project outputs from later diffusion and labor-market adjustment. Implementation capacity, technological additionality, specialized skills, and worker adjustment are relevant parts of that transmission process, although the present design does not identify an optimal policy combination.

These conclusions remain subject to the limits of an observational country-level design. The analysis does not identify causal effects of individual interventions, the technological and labor-market indices capture only selected dimensions of structural change, and the smaller labor-market sample limits precision. Project-level, sectoral, local, or longer-run effects may therefore remain hidden in national annual data. More granular information on project implementation, technologies, firms, workers, and specialized skills, combined with stronger identification strategies, would provide a more direct test of the mechanisms examined here.

For the developing economies, period, and measures examined here, larger aggregate climate-related development-finance flows are not systematically associated with the proposed finance-technology-labor transformation sequence. This does not rule out project-level, sector-specific, or longer-run effects. It shows that financial mobilization should not be treated as equivalent to structural transformation and motivates more granular research into the mechanisms linking the two.

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