RUHR
ECONOMIC PAPERS

When Development Finance Spurs Entrepreneurship: New Evidence from 5 Million Projects Using a Machine Learning Classifier

Sven Werner and Philipp A. Trotter

BERGISCHE UNIVERSITÄT WUPPERTAL
rwi

#1205

Imprint

Ruhr Economic Papers

Ruhr Economic Paper #1205 "When Development Finance Spurs Entrepreneurship: New Evidence from 5 Million Projects Using a Machine Learning Classifier"

Responsible Editor: Hendrik Jürges, University of Wuppertal

Jointly published by

RWI – Leibniz-Institut für Wirtschaftsforschung e.V.
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Bergische Universität Wuppertal, Schumpeter School of Business and Economics
Gaußstraße 20, 42119 Wuppertal, Germany

Series Coordination:
RWI Press Office, presse@rwi-essen.de, phone +49 (0) 201 8149-213
RWI – Leibniz Institute for Economic Research, Hohenzollernstr. 1–3, 45128 Essen, Germany
www.rwi-essen.de

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.
The Institute has the legal form of a registered association; Vereinsregister, Amtsgericht Essen VR 1784

ISSN 1864-4872 (online)
ISBN 978-3-96973-390-5
DOI https://dx.doi.org/10.4419/96973390

When Development Finance Spurs Entrepreneurship: New Evidence from 5 Million Projects Using a Machine Learning Classifier

Sven Werner[a] Philipp A. Trotter[b,a,c]

[a] Schumpeter School of Business and Economics, University of Wuppertal, 42119 Wuppertal, Germany.

[b] African Institute of Sustainable Energy and Systems Analysis (AISESA), Dakar, Senegal.

[c] Smith School of Enterprise and the Environment, University of Oxford, Oxford OX1 3QY, United Kingdom.

April, 03, 2026

Abstract

Development finance increasingly funds entrepreneurship in developing countries, but evidence of its impact on entrepreneurship is mixed. Existing studies analyze total development finance flows as entrepreneurship-specific development finance data did not previously exist. By training and validating a machine-learning classifier on development finance project descriptions (2000–2022; 5 million projects; 97% accuracy), we introduce a scalable, replicable measure of specific entrepreneurship-support development finance (ESDF). Crucially, this measure allows us to assess which entrepreneurship margins respond to development finance. In a 19-year panel of 50 developing countries, two-way fixed-effects regressions show that higher ESDF is associated with higher entrepreneurial intentions, while total development finance is not. ESDF is not significantly linked to early-stage entrepreneurial activity, however, suggesting conversion bottlenecks in current entrepreneurial processes.

Keywords

Entrepreneurship-support development finance, international assistance, entrepreneurial intentions, early-stage entrepreneurship, machine learning classification

Acknowledgements

Sven Werner and Philipp A. Trotter received funding from the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ). Philipp A. Trotter received funding from the Climate Compatible Growth programme by the UK government. The views expressed herein do not necessarily reflect the UK government's official policies.

Portions of the manuscript were copy edited for clarity and grammar using AI-based language tools (ChatGPT and Google Gemini). The authors reviewed and verified all edits and take full responsibility for the final content.

1 INTRODUCTION

Entrepreneurship is an important driver of development. It can expand livelihoods, employment, and household incomes particularly in developing countries (Haltiwanger et al., 2013; Valliere & Peterson, 2009). Further, entrepreneurial dynamism is often linked to innovation and aggregate growth (Audretsch, 2007; Stel et al., 2005; Urbano et al., 2019). As a result, development policy has increasingly treated entrepreneurship as a policy-relevant outcome.

A central channel to foster entrepreneurship in developing countries is development finance from bilateral and multilateral donors. These flows fund a wide range of activities, e.g., infrastructure, health initiatives, humanitarian relief. Increasingly, they also include programs that aim to support (prospective) entrepreneurs directly, such as entrepreneurial skills training, SME financing, and start-up accelerators (Manning & Vavilov, 2023; Sutter et al., 2019; WorldBank, 2013). In doing so, these interventions can alter the strategic entrepreneurship context in which entrepreneurs evaluate opportunities, mobilize resources, and decide between entrepreneurship and alternative livelihood strategies.

Motivated by the rising policy focus on entrepreneurship, a growing literature examines how development finance relates to macro-level entrepreneurship outcomes (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020). Yet, most macro studies rely on total development finance inflows as their key explanatory variable, even though policy interest often concerns entrepreneur-facing support. Consistent with this mismatch, findings based on aggregate inflows are not uniform: average relationships are often insignificant and reported associations vary by financier identity, finance type, and country circumstances such as shock exposure (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020). In order to reconcile these findings and better understand how entrepreneur-facing development finance shapes macro-level entrepreneurial dynamics in developing countries, three interlinked gaps need to be addressed:

First, existing research lacks a scalable and comparable way to identify which parts of development finance are explicitly aimed at supporting entrepreneurs across countries and time. Standard development finance datasets are organized around donors, instruments, and sectors, but whether a project targets entrepreneurs as a beneficiary group or policy objective is not consistently recorded and often cuts across these categories (OECD, 2024). As a result, we still know comparatively little about the magnitude, evolution, and cross-country distribution of entrepreneur-facing development finance.

Second, because entrepreneur-facing development finance is not directly observable, macro studies typically relate entrepreneurship outcomes to total development finance inflows grouping different types of support (Boudreaux et al., 2022; Moore et al., 2020). These types can affect entrepreneurial dynamics through distinct, and potentially opposing, channels. For example, some components may relax constraints for prospective entrepreneurs, while others may raise the opportunity cost of entrepreneurship by improving wage employment options (Poschke, 2013; Solomon et al., 2021). As a result, total development finance is a bundled construct whose estimated relationship with entrepreneurship is difficult to interpret as any specific policy-relevant margin. At the same time, this limitation cannot be addressed by relying on individual program evaluations alone. While project-level assessments can identify local mechanisms, they do not capture economy-wide spillover effects that are central to entrepreneurial dynamics, e.g., entrepreneurship support can increase the societal legitimacy of entrepreneurship (Bade, 2022), but it can also crowd out unsupported entrepreneurs (Cai & Szeidl, 2024). A macro-level approach is therefore needed to assess how entrepreneur-facing support relates to entrepreneurship once these broader spillovers are taken into account (Mohan & Morris, 2024).

Third, we lack macro-level evidence on which entrepreneurship margin responds to development finance interventions. Country-level entrepreneurship is not a single endpoint: shifts in entrepreneurial intentions need not translate mechanically into entrepreneurial entry (Gelderen et al., 2015; Kautonen et al., 2015). Distinguishing these margins matters for interpreting macro relationships and for policy design, because interventions can expand the pool of potential entrepreneurs without increasing early-stage activity if the conversion from intentions to entry remains constrained (Bade, 2022). Yet, macro studies often rely on a single entrepreneurship indicator, which obscures whether development finance primarily shapes upstream intentions or downstream entry and therefore limits what can be inferred about how development finance affects entrepreneurial dynamics.

In this paper we address these three gaps by introducing a new measure of entrepreneurship-support development finance (ESDF) and analysing whether such ESDF, as distinct from broader development finance (DF), is associated with country-level entrepreneurship margins (intentions vs early-stage activity). We develop and validate a supervised machine-learning text classifier that identifies DF projects that explicitly target entrepreneurs in their project descriptions. We apply the classifier to over five million development projects tracked in the OECD Creditor Reporting System (CRS) from 2000-2022 (Miric et al., 2023; Toetzke et al., 2022). Aggregating classified projects yields a country-year ESDF series that separates entrepreneur-facing disbursements from non-ESDF disbursements. Descriptively, we show that ESDF is a small but growing component of DF: ESDF disbursements have quintupled since 2000 from two to ten billion USD (constant 2022 USD) in 2022. Similarly, the share of total disbursements nearly doubled from 2-3% between 2000 and 2005 to 4-5% between 2018 and 2022.

We then link ESDF to entrepreneurship outcomes in a panel of 50 developing countries, combining DF flows with entrepreneurship indicators from the Global Entrepreneurship Monitor (GEM). We focus on two outcome margins: entrepreneurial intentions and early-stage entrepreneurial activity. Our baseline design estimates two-way fixed-effects panel regressions that relate within-country changes in entrepreneurship outcomes to within-country changes in ESDF and non-ESDF inflows, using a lag structure and standard macro controls. We complement this with targeted sensitivity checks and diagnostics for reverse causality. Our results show that total DF is not systematically associated with either entrepreneurial intentions or early-stage entrepreneurial activity. In contrast, ESDF is robustly positively associated with entrepreneurial intentions. However, we do not find a significant association between ESDF and early-stage entrepreneurial activity.

This study makes three contributions to the literature. First, we provide a measurement contribution by making ESDF observable at scale through a replicable measure derived from project texts

(Miric et al., 2023; Toetzke et al., 2022). This measure enables comprehensive global analysis of entrepreneurship-facing development support and can lay the foundation for further research and policy analysis at the intersection of DF and entrepreneurship. Also, this measure illustrates how artifical intelligence-based methods can expand entrepreneurship research (Harrison et al., 2023; Lévesque et al., 2022). Second, we clarify the existing contingent macro evidence by showing that an empirically relevant variation lies in ESDF rather than in total DF aggregates (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020). Our analyses of ESDF's influence on entrepreneurial dynamics at the macro-level complement existing micro-level program evaluations by accounting for general equilibrium effects of entrepreneurship-support programs (Mohan & Morris, 2024). Third, we contribute by adopting an entrepreneurial process lens to analyse the influence of entrepreneurship support (Ajzen, 1991; Krueger et al., 2000). Prior studies have identified conversion bottlenecks along the entrepreneurial process for individual entrepreneurs and in country-level dynamics, but often not analysed entrepreneurship support's influence on different margins along this process (Bade, 2022; Gelderen et al., 2015). We show that entrepreneurship support does not affect all stages of the entrepreneurial process equally and can raise entrepreneurial intentions while leaving realized entry largely unchanged at the country level. This implies that merely providing more financial support is not enough to increase early-stage entrepreneurship. To effectively increase entry, ESDF needs to address the binding conversion constraints from intentions to entry in the entrepreneur's ecosystem and consider positive and negative spillovers of the support programs.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes the ESDF measure construction and empirical strategy. Section 4 reports the results and robustness analyses. Section 5 discusses implications, limitations, and directions for future research.

2 THEORETICAL BACKGROUND AND HYPOTHESES

2.1 Entrepreneurship-support development finance

Entrepreneurship is widely treated as a development lever and, consequently, as a policy-relevant outcome (Sutter et al., 2017; WorldBank, 2013). It can expand livelihoods and employment and improve household income prospects (Haltiwanger et al., 2013; Valliere & Peterson, 2009), and at the aggregate level, entrepreneurial dynamism can contribute to innovation and growth (Audretsch, 2007; Stel et al., 2005; Urbano et al., 2019). Entrepreneurs may also create social and environmental welfare (Neumann, 2020). In developing countries, entrepreneurship encompasses heterogeneous forms, including a high share of activity in the informal sector and necessity-driven entrepreneurship, alongside technology-enabled high-growth start-ups (Kimmitt et al., 2020; Lay & Tafese, 2025; Welter et al., 2017). However, the development impact of entrepreneurship is not automatic: institutional conditions and the composition and quality of entrepreneurial activity shape whether entrepreneurship translates into economic performance and broader welfare (Neumann, 2020; Urbano et al., 2019).

Development finance is increasingly used to spur entrepreneurship in developing countries (WorldBank, 2013). Development finance, in general, comprises a heterogeneous set of instruments that differ in objectives, channels, and temporal horizons, rather than a single, uniform intervention (Bjørnskov, 2019; Clemens et al., 2012; Mavrotas & Ouattara, 2006). Many instruments target broad development levers, for example health (e.g., child vaccination and HIV prevention campaigns), education (e.g., school infrastructure, teacher capacity building), infrastructure (e.g., water and electricity supply), public administration (e.g., government capability building), and humanitarian aid (e.g., food provision during civil wars). In addition, DF supports economic activities across sectors (e.g., banking services, agricultural support, mining, construction, and tourism cooperation).

Across these activities, an increasing emphasis is placed on supporting entrepreneurs, as they can frame societal problems as opportunities and create new sources of value by recombining resources, building new organizational forms, and developing novel solutions (Alvarez & Barney, 2007; Doh et al., 2019). Yet current tracking practices for DF do not reflect this shift. Because entrepreneurship is a cross-cutting theme spanning sectors and goals, it is not tracked systematically.

In light of this limitation, prior studies have typically analyzed the relationship between total DF flows and entrepreneurial activity in developing countries. While these studies do not identify general associations between total DF and entrepreneurship, they document contingent relationships that vary by financier identity and finance type (e.g., bilateral versus multilateral; climate finance) and by context, such as shock exposure (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020).

Because total DF aggregates very different types of support, its implications for measured entrepreneurship rates are inherently ambiguous. Some components are unlikely to be directly linked to entrepreneurial activity with significant influence (e.g., vaccination campaigns for children), whereas others strengthen general conditions for economic activity (e.g., investments in infrastructure, human capital, and institutional quality). While such investments can provide a foundation for entrepreneurship (Ács et al., 2014; Autio et al., 2014; Stam & van de Ven, 2021), they can simultaneously expand wage-employment opportunities and increase the opportunity cost of entrepreneurship, especially for necessity-driven entrants (Poschke, 2013; Solomon et al., 2021). Development-financed activities, often implemented through public actors, may also crowd out private entrepreneurship (Faria et al., 2023; Islam, 2015). Moreover, broader development and institutional improvements can shift the composition of entrepreneurship away from informal and low-productivity self-employment toward fewer but more formal and higher-productivity ventures, muting changes in headline entrepreneurship rates (Baumol, 1996; Moore et al., 2020). Such compositional dynamics are consistent with non-linear relationships between development and entrepreneurial rates (Stel et al., 2005; Wennekers et al., 2010).

This ambiguity of total DF motivates a distinction between two broad categories of DF based on primary targets and program design when analyzing the relationship between DF and entrepreneurship.

The first category is entrepreneurship-support development finance (ESDF): programs that explicitly identify entrepreneurs (or prospective entrepreneurs) as a target group or objective, for instance, by facilitating venture founding, early operations, and venture quality with the intention to generate development impact (Manning & Vavilov, 2023). ESDF is entrepreneur-facing by design. It directly relaxes constraints that shape whether individuals can start and sustain ventures, for example by building entrepreneurial capabilities (skills training and business services) (Campos et al., 2017; McKenzie & Woodruff, 2014), providing resources (SME finance, start-up grants, microfinance, and intermediation) (Kersten et al., 2017; McKenzie, 2017), and expanding networks through accelerators and incubators (González-Uribe & Reyes, 2021; Lall et al., 2020). ESDF intervenes on the entrepreneurship margin itself rather than relying on broader development improvements to translate into entrepreneurship indirectly. Importantly, its effects need not be limited to direct beneficiaries. By generating legitimacy for entrepreneurship and contagion effects across entrepreneurs, ESDF can shift perceptions and behaviors among non-participants, implying that macro-level outcomes may reflect both direct and indirect exposure (Bade, 2022; Nanda & Sørensen, 2010). At the same time, country-level relationships of ESDF may be attenuated by general equilibrium effects (e.g., crowding out of competing entrepreneurs) and ecosystem constraints that ESDF does not address (Cai & Szeidl, 2024; Stam & van de Ven, 2021).

The second category is foundation development finance (foundation DF; non-ESDF): DF that does not explicitly target entrepreneurs as a beneficiary group. Rather than intervening on the entrepreneurship margin directly, foundation DF primarily builds general economic and institutional foundations—for example through financing and technical assistance for infrastructure, education, health, governance, and broad-based economic development—that may shape entrepreneurship only indirectly (Alesina & Dollar, 2000; Bjørnskov, 2019). This distinction is functional rather than normative. It reflects differences in program design and intended beneficiaries, not assumptions about which category is more effective. The key point is that the two categories implicate entrepreneurship through different pathways—direct versus indirect—so pooling them into a single total can obscure entrepreneurship-relevant mechanisms.

Taken together, this distinction highlights that total DF is a noisy predictor of entrepreneurship because it aggregates non-ESDF, whose effects are indirect and potentially offsetting, with ESDF, which is entrepreneur-facing by design. This motivates focusing on the composition of DF, and in particular the extent of ESDF.

Having distinguished entrepreneur-facing from foundation DF, we next consider which stage of the entrepreneurial process such support is most likely to shift.

2.2 Support along the entrepreneurial process

Entrepreneurship unfolds as a staged process in which individuals progress from consideration to intention formation, preparation, entry, and early venture operation, with attrition at each stage (Ajzen, 1991; Krueger et al., 2000). Analytically, two outcome margins are commonly distinguished: entrepreneurial intentions (the latent pool of potential entrants) and early-stage entrepreneurial activity (realized entry and initial operation) (Reynolds et al., 2005). A process perspective is useful at both the micro level—where individuals move across stages—and the macro level, where many individual transitions aggregate into population-level dynamics and can be shaped by social interaction and contagion (Bade, 2022).

A key implication is that intentions do not translate mechanically into entry. A large literature documents an intention-activity gap, showing that conversion depends on perceived behavioral control, action planning, self-regulation, and contextual constraints (Dileo & Pereiro, 2018; Gelderen et al., 2015; Kautonen et al., 2015).

For entrepreneurship-support programs, a central aim is therefore to expand the upstream pool of potential entrepreneurs and to ease conversion constraints so that intentions translate into activity with both margins shaping observed entrepreneurship rates (Liao et al., 2022; Souitaris et al., 2007). Yet prior macro-level analyses of DF and entrepreneurship have largely focused on downstream activity, leaving comparatively little evidence on how development-financed support shapes upstream stages of the entrepreneurial process at scale, including intentions (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020).

Examining intentions is particularly relevant when studying ESDF at the country level. In such settings, spillovers and contagion are salient: visible entrepreneurship-support initiatives can influence non-participants by legitimizing entrepreneurship and shifting perceived desirability and feasibility (Bade, 2022; Gelderen et al., 2015). Because such indirect exposure may affect large segments of the population, intentions can respond even when direct participation is limited. By contrast, converting activated intentions into realized early-stage activity typically requires additional complements (e.g., market access, regulatory navigation, operational capability, ecosystem capacity) and is therefore subject to stronger frictions and weaker spillovers in aggregate relationships (Dileo & Pereiro, 2018; Grilo & Thurik, 2005; Teixeira et al., 2018). As a result, ESDF is unlikely to affect intentions and early-stage activity to the same extent at the country level: ESDF should be more strongly associated with entrepreneurial intentions than with early-stage entrepreneurial activity, even when both associations are positive.

2.3 Hypotheses

Because total DF aggregates fundamentally different interventions—some unrelated to entrepreneurship and others with indirect, potentially offsetting implications for occupational choice and measured entrepreneurship—we do not expect a stable, systematic relationship between total DF inflows and country-level entrepreneurship outcomes.

Baseline expectation. *Total development finance is not systematically associated with country-level entrepreneurial intentions and early-stage activity.*

Our focus is therefore on ESDF, i.e., the entrepreneur-facing component of DF that directly reflects policymaker choices to directly support (prospective) entrepreneurs. Building on the mechanisms developed above, ESDF should expand the upstream pool of potential entrepreneurs, while the translation of intentions into early-stage activity remains subject to stronger frictions and complementary resource needs. Accordingly, ESDF should be more strongly associated with entrepreneurial intentions than with early-stage entrepreneurial activity.

Hypothesis 1 (H1). *Entrepreneurship-support development finance is positively associated with entrepreneurial intentions at the country level.*

Hypothesis 2 (H2). *Entrepreneurship-support development finance is positively associated with early-stage entrepreneurial activity at the country level, and this association is weaker than the association between ESDF and entrepreneurial intentions.*

3 RESEARCH METHODS

To analyse our hypotheses, we follow a four-step approach. Figure 1 presents an overview: First, we build on DF data from the OECD Creditor Reporting System (CRS) which contains project-level data on five million projects including textual descriptions. Second, to obtain a measure of ESDF, we develop a novel machine learning classifier which identifies those projects which explicitly aim to support entrepreneurs based on their textual descriptions. Further, we aggregate these ESDF and non-ESDF disbursements by country and year. Third, we then match the resulting DF data to entrepreneurial outcomes from the Global Entrepreneurship Monitor at the country level and to macro controls from the World Bank Development Indicators. Fourth, to test our hypotheses, we conduct two-way fixed-effects regressions and analyse the robustness of our findings to variations in the approach. These steps are detailed in the following.

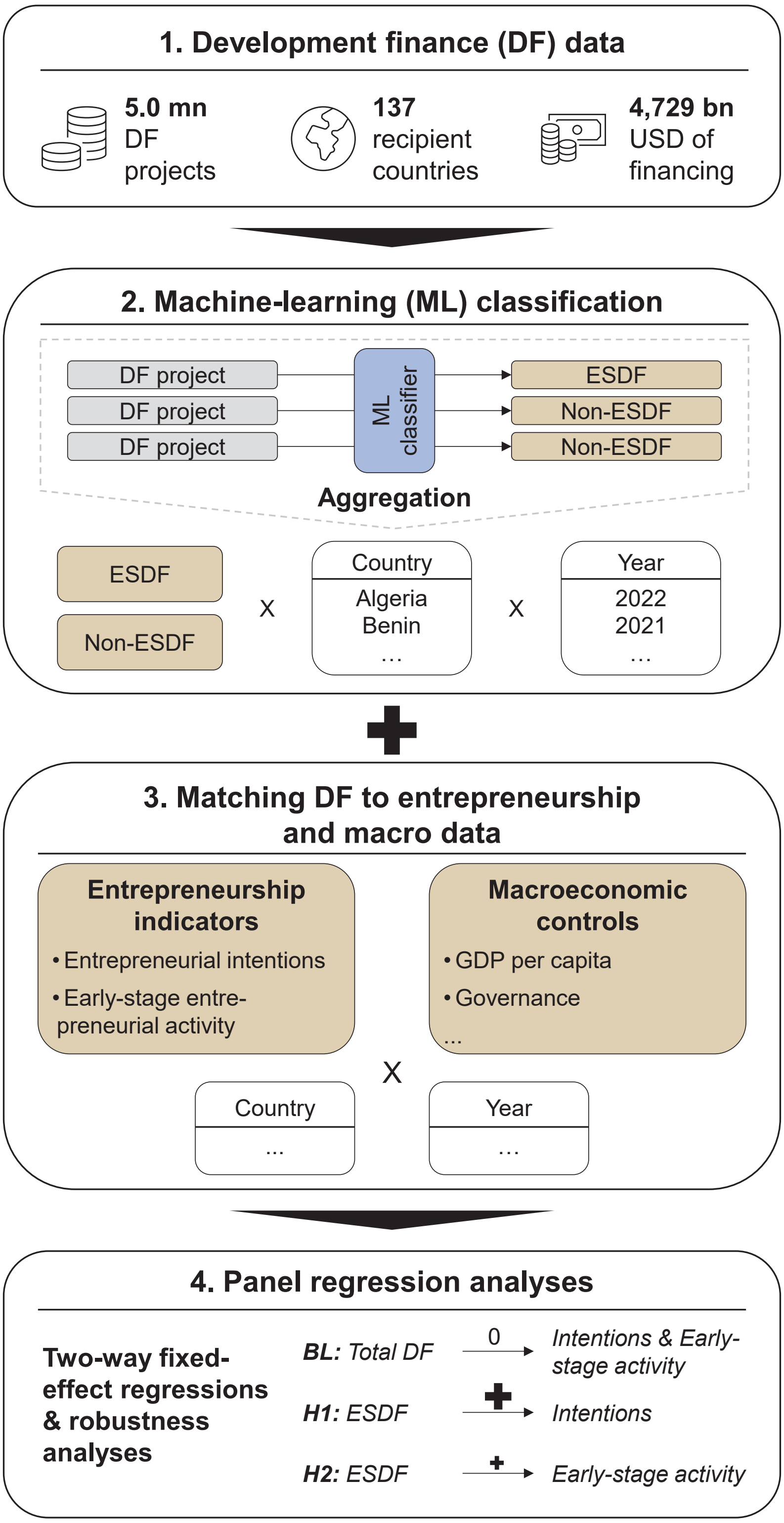

FIGURE 1 Machine-learning-based research method to analyse development finance and entrepreneurial outcomes

3.1 Measuring entrepreneurship-support development finance: Machine learning-based classification and validation

A central empirical barrier in the DF-entrepreneurship literature is that standard DF aggregates bundle heterogeneous interventions, many of which are not entrepreneur-facing and affect entrepreneurship through different mechanisms. We therefore construct a novel measure of ESDF by identifying, at scale, which development projects explicitly target entrepreneurs or prospective entrepreneurs. Following recent work that derives consistent and replicable DF measures by classifying project descriptions rather than relying on administrative tags (Toetzke et al., 2022), we implement a supervised text classifier that reads project descriptions and predicts whether each project qualifies as ESDF. We then aggregate predicted ESDF disbursements to the recipient country-year level to obtain a panel measure that separates entrepreneur-facing support from broader development spending. Following Toetzke et al. (2022), we allocate the full disbursement amount of a project to ESDF once it is classified as entrepreneurship supporting, as a percentage allocation cannot be meaningfully inferred from the textual description or metadata. As a result, ESDF disbursements reflect funding to projects that explicitly include an entrepreneurship-focused component, rather than a precise accounting of spending shares within multi-component projects. The design follows a transparent pipeline emphasized in previous literature scaling human-coded data using machine learning-based classification (Harrison et al., 2023; Hartmann et al., 2019; Miric et al., 2023): (i) assemble a harmonized data corpus of project descriptions; (ii) define ESDF with inclusion/exclusion rules; (iii) develop a machine learning classifier trained on hand-labeled training dataset; (iv) validate prediction performance of the classifier; and (v) convert project-level predictions into country-year ESDF measures used in the main analyses. The Online Appendix provides the full codebook (including edge cases and labeled examples), model implementation choices (hyperparameters and training procedure), and additional descriptive breakdowns. In addition, the code and data for the classifier are available online to enable replication, reuse and development for further research projects (Link: https://github.com/werner-sven/ml-classifier-entrepreneurship-support-development-finance).

3.1.1 Data

We draw on project-level records from the OECD CRS, a project-level repository widely viewed as the most comprehensive source on global DF (Toetzke et al., 2022). The data comprise 5,015,826 development projects from 2000 to 2022 financed by bilateral, multilateral, and private contributors. CRS records include a project title as well as short and long textual descriptions provided by contributing organizations, alongside structured metadata (e.g., donor, recipient, year, sector codes) and financial amounts.

Preprocessing follows established practice for CRS text classification (Stürenburg et al., 2025; Toetzke et al., 2022). For each project, we concatenate the title and all available description fields into a single input string. Further, we translate non-English descriptions into English using the Google Translate API.

3.1.2 Operationalizing entrepreneurship-support development finance

We defined ESDF as support programs that explicitly identify entrepreneurs (or prospective entrepreneurs) as a target group or objective. We operationalize this in the following way: A project is coded as ESDF if its textual description describes at least one component that explicitly mentions activities, programs, or objectives directly supporting potential, nascent, or established entrepreneurs or their ventures. Our definition of entrepreneurs builds on the definition by the Global Entrepreneurship Monitor (Reynolds et al., 2005) and includes business owners (e.g., start-up founders, owners of MSMEs, smallholder farmers who operate their own business), self-employed and those who are potential and nascent entrepreneurs (e.g., recipients of entrepreneurial skills training). Illustrative ESDF activities include entrepreneurship or self-employment training, grants or small-finance instruments directed at owners of MSMEs, mentoring and advisory services for small business owners, and incubation/acceleration or start-up support programs, policy support to ease business registration. As per our coding rule, entrepreneurship-support must be explicitly stated in the project description rather than inferred as an indirect downstream effect of broader development spending. Accordingly, broad economic growth initiatives, general private-sector or trade reforms without explicit entrepreneur focus, infrastructure projects, and financial inclusion or microfinance initiatives that do not name entrepreneurs as target group do not qualify as ESDF. We further operationalize this definition using a codebook presented in the Online Appendix.

3.1.3 Machine learning classification approach

We develop a machine learning classifier that identifies whether each development project qualifies as ESDF. Specifically, we fine-tune a pretrained bidirectional transformer language model (BERT) for this task. Transformer-based models are well suited for entrepreneurship-relevant boundary decisions because they capture meaning in context and reduce reliance on brittle keyword rules (e.g., distinguishing "start-up" as a general process, such as starting a donor-funded vaccination campaign, versus "start-up" as an entrepreneurial new business venture). This choice aligns with recent management methods guidance highlighting the advantages of embedding-based approaches (Miric et al., 2023), and it mirrors successful applications of transformer models to CRS descriptions in adjacent finance measurement for climate finance (Toetzke et al., 2022).

Following the stratified sampling logic used in CRS-based finance classification (Toetzke et al., 2022) and guidance on rare-class measurement (Miric et al., 2023), we construct a labeled set of 1,500 projects drawn from unique CRS project descriptions using a stratified design. Because ESDF is rare in the full CRS universe, we combine (i) 500 projects randomly sampled from the full CRS project universe with two targeted strata: (ii) 500 projects randomly retrieved from all projects featuring entrepreneurship-related keywords and (iii) 500 projects randomly drawn from entrepreneurship-adjacent CRS purpose codes (e.g., SME and business development categories). The used lists of keywords and purpose codes are presented and discussed in the Online Appendix. Stratified random sampling ensures sufficient representation of both ESDF and non-ESDF projects for supervised training and validation.

Trained human coders labeled each sampled project for its relevance to ESDF using a standardized codebook (see Online Appendix). When initial ratings were contested, we reviewed the project descriptions and coding decisions in detail and resolved discrepancies through discussion until we reached consensus. The resulting labeled dataset is available for download, supporting replication and enabling other researchers to review and evaluate the ESDF categorization used to train the classifier (Link: https://github.com/werner-sven/ml-classifier-entrepreneurship-support-development-finance). Sample labeled project descriptions are also included in the Online Appendix.

We then split the labeled data (stratified) into training (80%), evaluation (10%), and test (10%) sets. We fine-tune a BERT-family transformer (DistilBERT) across alternative configurations (e.g., learning rates, epochs, class weighting), while strictly holding out the test set (Miric et al., 2023). As false positive predictions are particularly harmful in our imbalanced class setting with comparably lower ESDF prevalence (Chawla, 2010), we then tune the threshold for classification to maximise precision on the evaluation set and select the model with the highest precision score based on the evaluation set, before measuring the final prediction performance on the held-out test data.

3.1.4 Prediction performance

For the selected model, we use the previously held-out test set to measure performance using accuracy, precision, recall, and F1, reported in Table 1. Reporting multiple metrics and reserving test data that the model never encounters during training follows established guidance for producing unbiased estimates of classifier effectiveness (Harrison et al., 2023; Hartmann et al., 2019; Miric et al., 2023). Because the labeled set is intentionally enriched with entrepreneurship-relevant and purpose-code-adjacent projects to balance the training data, its class prevalence and ambiguity differ from the CRS population. As a result, performance metrics from the held-out test split should be interpreted as reflecting a comparatively difficult, “stress-test” evaluation environment rather than as a direct estimate of population precision under the CRS base rate following Toetzke et al. (2022).

The selected classifier achieves 97% accuracy and an F1 score of 96%. We emphasize precision and recall because our downstream outcome is a financial aggregate: false positives inflate ESDF disbursements, while false negatives attenuate ESDF and bias estimated relationships toward zero.

TABLE 1 Performance of machine learning classifier on held-out test set for predicting ESDF

Metric	Explanation	Value
Accuracy	Share of all predictions that are correct	0.97
F1 (ESDF)	Balance of precision and recall for ESDF	0.96
Precision (ESDF)	Share of predicted ESDF that are truly ESDF	0.97
Recall (ESDF)	Share of true ESDF correctly predicted	0.95
Test set size (N)	Size of held-out test set	150
ESDF test prevalence (%)	Share of ESDF in the test data	44

Note: Pretrained language model fine-tuned on study data. Model was trained on the hand-labeled training set, tuned on the evaluation set, and performance metrics were calculated once on the untouched test set.

3.2 Panel data and variables

We construct a country-year panel that combines DF flows from the OECD CRS, entrepreneurial outcomes from the Global Entrepreneurship Monitor (GEM), and macroeconomic and institutional covariates from the World Bank.

3.2.1 Independent variables: ESDF and non-ESDF

Our independent variables capture the volume of DF received by a country in a given year. We rely on disbursements from bilateral and multilateral donors reported in the project-level CRS of the OECD. Reporting donors include members of the OECD Development Assistance Committee, as well as further donor countries that voluntarily report to the OECD for transparency purposes, and multilateral organizations totalling 119 donors. Similar to the definition of climate finance flows (Mohan & Morris, 2024), tracked DF disbursements contain both Official Development Assistance (ODA), a classification requiring a grant share of at least 10-45% depending on the income status of the recipient country, and Other Official Flows, which contain flows with lower grant proportions not qualifying as ODA.

For each recipient country-year, we aggregate our classified project-level disbursements (in constant 2022 USD) into two components: (i) ESDF, defined as disbursements predicted to support entrepreneurs according to our classifier (see details in the previous section), and (ii) non-ESDF, defined as flows not qualifying as ESDF, jointly summing to total DF. We exclude flows that are not allocable to specific recipient countries (e.g., regional projects without a recipient allocation). Between 2000 and 2022, 137 countries have been recipients of bilateral and multilateral DF tracked in the CRS. In addition, we construct complementary intensity metrics (ESDF per working-age population, ESDF as a share of total DF) and log transformations of flows using $ln(x+1)$. Because CRS net disbursements can, in a few instances, be negative (e.g., if total DF flows are dominated by repayments), we set negative DF values to missing in the log-based specifications, and test robustness to this approach using an inverse hyperbolic sine transformation preserving negative values.

Figures 2 and 3 summarize the resulting ESDF series. Figure 2 plots ESDF against non-ESDF over time to illustrate how entrepreneur-targeted spending co-moves with aggregate inflows. The global share of ESDF has roughly doubled from 2% in 2000-2005 to 4-5% in 2018-2022. At the same time, absolute ESDF disbursements have increased by five times from 2 to 10 billion USD following an increase in total DF. This amount compares to the total bilateral disbursements tracked in the CRS in 2022 of the United Kingdom (14 billion USD) and Canada (7 billion USD), who are the 5th and 6th largest bilateral donors globally.

Figure 3 documents cross-country heterogeneity in the share of ESDF as of total disbursements for 2020-2022 among DF recipient countries, highlighting how portfolio distribution between ESDF and non-ESDF differs.

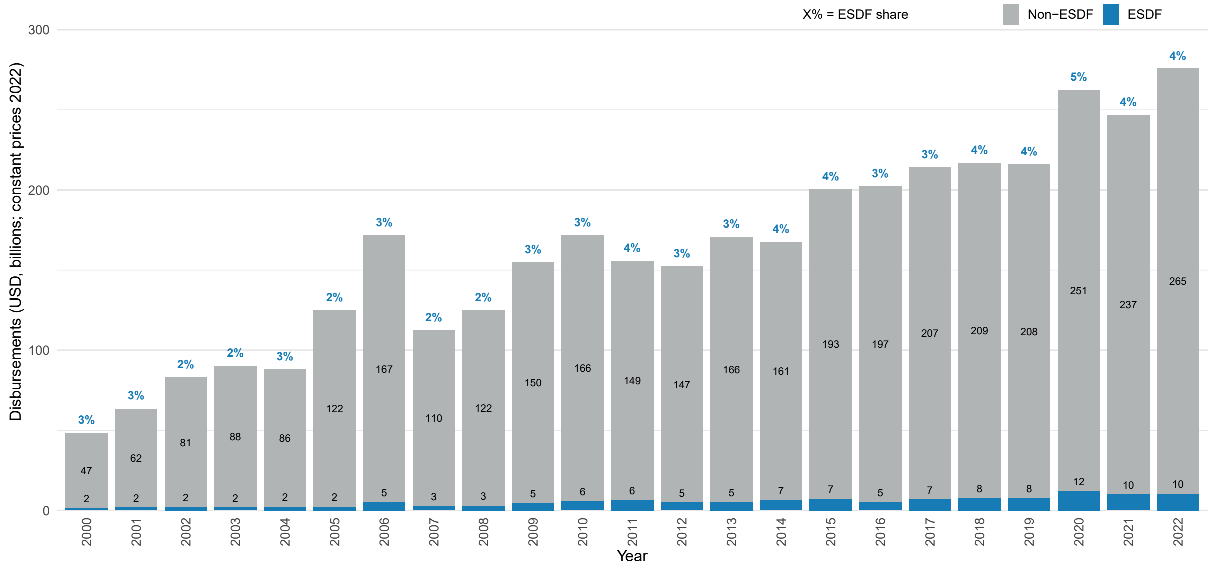

FIGURE 2 Global development finance portfolio structure 2000-2022: ESDF versus non-ESDF

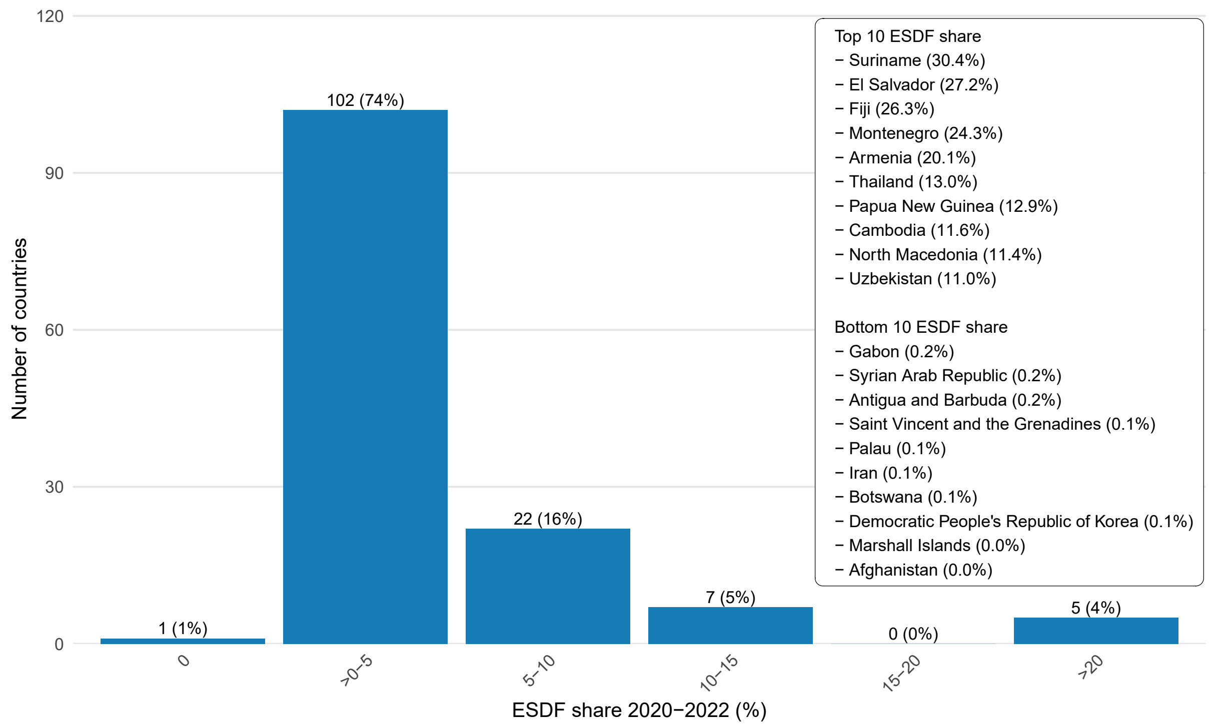

FIGURE 3 Distribution of ESDF share of total DF for 137 recipient countries 2020-2022 (figure excludes disbursements to regions not allocable to a country)

3.2.2 Dependent variables: entrepreneurial intentions and early-stage entrepreneurial activity

We focus on two closely related constructs that capture different stages of the entrepreneurial process: entrepreneurial intentions (latent entrepreneurship) and early-stage entrepreneurial activity (actual entry and early operation) (Bade, 2022; Gelderen et al., 2015). Entrepreneurial intentions reflect the share of adults (ages 18-64) who are not currently starting or running a new business but report an intention to start a business within the next three years. Early-stage entrepreneurial activity captures the share of adults (ages 18-64) who are actively involved in starting a business or who own and manage a new business.

Both measures are drawn from the Global Entrepreneurship Monitor (GEM) Adult Population Survey, a cross-national annual survey fielded with at least 2,000 respondents per participating country. GEM is widely used in entrepreneurship research and provides harmonized measures designed for cross-country comparability (Álvarez et al., 2013).

3.2.3 Control variables

We include a standard set of macroeconomic and institutional covariates that are related to both entrepreneurial outcomes and DF allocations (Moore et al., 2020). From the World Bank Development Indicators, we measure income level as GDP per capita (constant 2015 USD), because higher average income can relax individual-level financial constraints and increase the feasibility of entrepreneurial entry (Audretsch, 2007; Nyström, 2008) and also shapes donor priorities and the scale and composition of finance received (Peiffer & Boussalis, 2015). We capture business-cycle conditions using annual GDP growth (percent), which proxies demand conditions and opportunity costs that influence the timing of new venture creation (Moore et al., 2020) and can affect contemporaneous financing needs and donor responses (Dreher et al., 2024). We include market size measured by total population to account for differences in the scale of domestic demand and because population size is also related to the scale of DF flows (Fuchs et al., 2014).

We further control for net foreign direct investment inflows to proxy access to external capital, foreign market connections, and competitive dynamics that can affect both entrepreneurial opportunities and entry costs (Klapper et al., 2010) and may covary with DF inflows through broader patterns of international engagement (Peiffer & Boussalis, 2015). Trade openness, measured as total trade (exports + imports) as a share of GDP, captures integration into international markets and cross-border linkages that can expand opportunity sets for export-oriented and growth-oriented entrepreneurship (Coulibaly et al., 2018) and is likewise correlated with donor engagement and financing volumes (Fuchs et al., 2014). Finally, we include regulatory quality (mean-centered) from the Worldwide Governance Indicators as a proxy for the institutional environment that shapes the costs of starting and operating a business, including regulatory predictability and the burden of compliance (Bjørnskov & Foss, 2013; Dau & Cuervo-Cazurra, 2014), and that can influence donors' willingness to disburse and the form that finance takes (Dollar & Levin, 2006). In the main specification, we log-transform population and net FDI inflows using ln(1+x) to reduce skewness, with negative values for net FDI being set to missing.

3.2.4 Summary statistics

Table 2 reports summary statistics for the regression sample, which consists of country-year observations with complete data for the dependent variables, DF measures, and controls. The Online Appendix lists the countries included in the regression sample.

3.3 Empirical strategy

3.3.1 Estimation approach: Two-way fixed-effects

Our baseline specifications estimate two-way fixed-effects panel regressions that relate within-country changes in entrepreneurship outcomes to within-country changes in DF inflows (Imai & Kim, 2021; Wooldridge, 2010). Country fixed-effects absorb all time-invariant differences across countries (e.g., geography, constant institutional features, long-run development levels and constant cultural aspects), while year fixed-effects absorb common shocks and global trends that affect all countries in a given year (e.g., commodity cycles, global crises). We cluster standard errors by

TABLE 2 Summary statistics

Section	Variable	Mean	SD	P10	P50	P90
Dependent variables	Entrepreneurial intentions (in pp)	30.5	15.2	11.9	28.1	52.2
	Early-stage entrepreneurial activity (in pp)	16.1	8.3	6.6	14.4	27.5
Independent variables	Total DF (in mn USD)	2195.7	2404.9	256.2	1164.4	5822.2
	ln(Total DF)	7.1	1.2	5.5	7.1	8.7
	ESDF (in mn USD)	85.8	184.7	0.9	28.2	195.7
	ln(ESDF)	3.2	1.7	0.6	3.4	5.3
	Non-ESDF (in mn USD)	2109.9	2315.9	253.9	1106.4	5437
	ln(Non-ESDF)	7	1.2	5.5	7	8.6
	Total DF / WAP (in USD)	106.3	143.2	8	63.4	236.1
	ln(Total DF / WAP)	4	1.2	2.2	4.2	5.5
	ESDF / WAP (in USD)	4.4	9.4	0.1	1.2	9.7
	ln(ESDF / WAP)	1.1	1	0.1	0.8	2.4
	Non-ESDF / WAP (in USD)	102	139.5	7.8	60.4	231.2
	ln(Non-ESDF / WAP)	4	1.2	2.2	4.1	5.4
Controls	GDP per capita (in USD, constant 2015)	6278.7	3743.4	1683.4	5377.3	11772.4
	GDP growth (in pp)	4.5	3.3	0.9	4.7	8.5
	ln(Population)	17.3	1.6	15.1	17.3	19.2
	Regulatory quality	-0.1	0.6	-0.9	0	0.6
	ln(FDI)	22	2.3	20	22.1	24.2
	Trade openness (in pp of GDP)	66	32.5	35.1	58.2	115.1

Note: Summary statistics computed on the estimation sample of the baseline ESDF vs Non-ESDF model (outcome: intentions, model 2) with n=370. Absolute (level) DF variables are reported for reference only and are not used in the estimations.

country to allow for serial correlation in unobserved shocks within countries over time (MacKinnon et al., 2023).

We estimate the following specification separately for entrepreneurial intentions and early-stage entrepreneurial activity:

$$Y_{it} = \alpha + \beta DF_{i,t-2} + \gamma' X_{i,t-2} + \mu_i + \tau_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the entrepreneurial outcome in country i and year t. The DF term $DF_{i,t-2}$ is defined in two ways. First, as a baseline, it is a measure of total DF volume, $DF_{i,t-2} = \ln(\text{TotalDF}_{i,t-2})$. Second, we distinguish ESDF from foundation DF and set $DF_{i,t-2} = \left[\ln(\text{ESDF}_{i,t-2}),\ \ln(\text{non-ESDF}_{i,t-2})\right]$. Including both components ensures that the estimated association for ESDF is net of shifts in foundation DF, rather than reflecting changes in total DF volume.

The vector $X_{i,t-2}$ contains lagged controls, μ_i and τ_t are country and year fixed-effects, and ε_{it} is the idiosyncratic error term. All right-hand-side variables are lagged by two years to reflect that DF interventions typically require time to translate into entrepreneurship-relevant outcomes and to reduce mechanical simultaneity between outcomes and contemporaneous inflows (Mohan & Morris, 2024; Moore et al., 2020). Development finance variables are expressed in constant 2022 USD and transformed using $\ln(1 + x)$ to accommodate skewness and zero flows.

3.3.2 Robustness and sensitivity

The TWFE estimates provide a transparent baseline that leverages within-country variation while absorbing key confounds through controls and fixed-effects. Interpretation can nevertheless be threatened by (i) timing and outcome dynamics, (ii) endogeneity and reverse causality, and (iii) functional-form and outlier sensitivity. We therefore implement targeted sensitivity checks that map directly to these threats, with details reported in the Online Appendix.

First, to assess sensitivity to timing assumptions and gradual adjustment, we re-estimate the baseline models using one-year lags of the DF variables and controls (Moore et al., 2020). We also estimate a dynamic TWFE specification that adds the lagged dependent variable, $Y_{i,t-1}$, while retaining the two-year lag for DF and controls. Including $Y_{i,t-1}$ helps account for the strong persistence in entrepreneurship outcomes: countries with high (or low) entrepreneurial intentions or activity tend to remain high (or low) from one year to the next due to slow-moving capabilities, culture, and market structure (Bade, 2022). More generally, adding the lagged outcome is a standard way to capture dynamic adjustment and reduce sensitivity to unmodeled serial correlation in the outcome process (Feki & Mnif, 2016; Wilkins, 2018).

Second, to probe reverse causality and anticipatory donor responses, we implement a placebo lead test that augments the baseline specification with future DF (t+1) (Eggers et al., 2024). Under a causal interpretation of lagged DF effects, future inflows should not predict current entrepreneurship outcomes conditional on fixed-effects and the baseline lag structure. Evidence to the contrary would be consistent with feedback from entrepreneurship to subsequent DF or forward-looking allocation (Leszczensky & Wolbring, 2022).

Third, to assess whether our estimates are sensitive to skewness, zeros, or extreme DF disbursements, we re-estimate the baseline models under alternative transformation and scaling choices for DF flows. Specifically, we (i) winsorize lagged DF levels prior to applying the log transformation, (ii) replace logs with the inverse hyperbolic sine transformation (Mullahy & Norton, 2024), and (iii) scale DF by working-age population (WAP) before transformation to shift the DF measure from aggregate volume (holding population constant) to reflect DF exposure per capita.

Taken together, this empirical strategy leverages rich within-country variation over time while netting out a wide range of confounding factors through fixed-effects, lag structure, and standard macro-institutional controls. The sensitivity analyses are designed to directly interrogate the most salient threats to interpretation, including timing and persistence, anticipatory allocation and reverse causality, functional-form and outlier dependence, and therefore provide a disciplined set of diagnostics for the stability of the estimated relationships. These strategies cannot fully resolve endogeneity concerns because the design is not quasi-experimental, but they provide informative diagnostics and help assess how robust the estimated relationships are to key threats. Accordingly, we interpret the estimates as conditional associations that are more credible when they are stable across these targeted robustness checks.

4 RESULTS

4.1 Main results

Table 3 reports two-way fixed-effects estimates that relate entrepreneurship outcomes in country i and year t to DF inflows lagged by two years (i.e., $DF_{i,t-2}$), with controls also measured at $t-2$. Because the dependent variables are measured in percentage points (0-100), coefficients on $\ln(DF)$ can be interpreted as semi-elasticities: a 10% increase in DF is associated with approximately a 0.1β percentage-point change in the outcome, holding the included controls and fixed-effects constant.

Consistent with our baseline expectation, total DF is not statistically distinguishable from zero for either outcome. For entrepreneurial intentions (model 1), the estimate is −0.70 (SE 1.53). For early-stage entrepreneurial activity (model 3), the estimate is 0.38 (SE 0.62). Thus, the data do not indicate a robust association between total DF inflows (lagged two years) and either entrepreneurship outcome in these specifications.

Consistent with H1, entrepreneurship-support DF (ESDF) is positively and statistically significantly (at the 1%-level) associated with entrepreneurial intentions. In the ESDF-vs-non-ESDF decomposition (model 2), the ESDF coefficient is 1.94 (SE 0.52). For instance, a doubling in ESDF is associated with an increase in entrepreneurial intentions of $1.94 \times \ln(2) \approx 1.34$ percentage points two years later. Relative to the sample median share of entrepreneurial intentions of 28 percentage points, this corresponds to an increase of about $1.34/28.0 \approx 5\%$. Doubling ESDF implies an additional disbursement of $28 million USD (while holding non-ESDF and other controls constant) at the sample median. In the same model, the non-ESDF coefficient is −1.82 (SE 1.68) and is not statistically distinguishable from zero.

H2 predicted that ESDF is positively associated with early-stage entrepreneurial activity, but more weakly than with intentions. The estimated ESDF coefficient for early-stage entrepreneurial activity is statistically not distinguishable from zero. Accordingly, we do not find support for our hypothesis that ESDF is associated with early-stage entrepreneurial activity at the macro level. At the same time, the difference in results between intentions and activity is consistent with a larger association for intentions than for activity, as anticipated by H2. The corresponding non-ESDF estimate is 0.35 (SE 0.64) and is also statistically indistinguishable from zero.

TABLE 3 ESDF and entrepreneurial intentions and activity

	Entrepreneurial intentions		*Early-stage entrepreneurial activity*	
	Total DF	ESDF vs Non-ESDF	Total DF	ESDF vs Non-ESDF
	(1)	(2)	(3)	(4)
ln(Total DF)	-0.70		0.38	
	(1.53)		(0.62)	
ln(ESDF)		1.94***		-0.01
		(0.52)		(0.30)
ln(Non-ESDF)		-1.82		0.35
		(1.68)		(0.64)
GDP per capita (const. 2015 USD)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
GDP growth	0.21	0.16	-0.00	-0.00
	(0.25)	(0.23)	(0.13)	(0.13)
ln(Population)	21.50	24.01	13.43	13.38
	(25.36)	(26.95)	(14.45)	(14.48)
Regulatory quality	-3.45	-4.10	-0.81	-0.79
	(4.59)	(4.29)	(1.87)	(1.86)
ln(FDI)	-0.38	-0.40	-0.07	-0.07
	(0.31)	(0.33)	(0.11)	(0.11)
Trade openness	-0.18**	-0.16**	-0.00	-0.00
	(0.08)	(0.08)	(0.03)	(0.03)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Num. Countries	50	50	50	50
Num. Years	19	19	19	19
Num.Obs.	370	370	370	370
R2	0.730	0.741	0.768	0.768
R2 Within	0.078	0.115	0.027	0.027

Note: Two-way fixed effects (Country and Year). All DF variables and controls are lagged by 2 years. Standard errors clustered by country in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.2 Robustness

Table 4 summarizes a set of robustness checks that reestimate the ESDF-vs-non-ESDF specification under alternative timing, dynamic adjustment, functional-form, scaling, and sample definitions. Across all variants, the estimated ESDF association with entrepreneurial intentions remains positive and statistically significant. The ESDF coefficient ranges from about 1.20 (one-year lag) to 2.53 (per working-age population (WAP) scaling), with the baseline inference unchanged: higher ESDF is robustly associated with higher intentions. Further, also in line with the main specification, the corresponding ESDF estimates for early-stage entrepreneurial activity are generally not statistically distinguishable from zero.

TABLE 4 Robustness: ESDF and entrepreneurial intentions and activity (coefficient of ln(ESDF) for models (2) and (4))

Variant	Intentions	Early-stage activity
Lag 1 year	1.20** (0.48)	0.26 (0.28)
Dynamic FE-LDV	1.96*** (0.53)	0.30 (0.26)
DF Winsorization	1.90*** (0.53)	-0.04 (0.30)
IHS transformation	1.76*** (0.48)	-0.11 (0.29)
DF WAP (per working age population)	2.53*** (0.78)	0.08 (0.40)

Note: Each row reports the ln(ESDF) coefficient from the ESDF vs Non-ESDF model estimated separately for entrepreneurial intentions (model 2) and early-stage activity (model 4). The 'Dynamic FE-LDV' row additionally includes a lagged dependent variable (t-1). The IHS specification is estimated on a sample with 9 more observations as it is defined for negative values. All models include country and year fixed effects and the baseline control set (lagged consistently). Standard errors clustered by country in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

In more detail, varying the lag length to one year yields positive and statistically significant ESDF coefficients for intentions, consistent with the baseline two-year lag and suggesting that the main result is not sensitive to the exact adjustment horizon. For early-stage activity, the one-year lag estimator is statistically indistinguishable from zero, reinforcing that the relationship is much weaker for realized activity than for intentions, if existent at all.

Including the lagged dependent variable (Dynamic FE-LDV) leaves the ESDF coefficient for entrepreneurial intentions positive and statistically significant, suggesting that the baseline association is not merely an artifact of serial persistence in the outcome. The lagged dependent variable is itself strongly predictive of next-year intentions, consistent with substantial persistence in entrepreneurship outcomes. For early-stage entrepreneurial activity, the lagged outcome is likewise highly predictive of subsequent activity, but the ESDF coefficient remains small and statistically indistinguishable from zero, mirroring the baseline estimates (see Online Appendix for details).

To assess sensitivity to extreme DF realizations, we winsorize DF at the 1st and 99th percentiles prior to transformation and re-estimate the baseline specification. The ESDF coefficient for intentions remains positive and statistically significant, implying that the main finding is not driven by outliers; the early-stage activity estimate again remains statistically indistinguishable from zero.

Replacing $\ln(1+x)$ with the inverse hyperbolic sine transformation yields a very similar pattern: ESDF remains positively and significantly associated with intentions, while estimates for early-stage activity remain close to zero and imprecisely estimated. This indicates that the baseline results are not sensitive to the specific log functional form or to distributional features such as skewness, zeros and negatives.

Scaling DF by the working-age population (WAP), rather than using aggregate volumes while controlling for population size in the baseline), yields a slightly larger ESDF coefficient for intentions that remains highly significant. This suggests that the positive association persists when DF is interpreted as per-person exposure among the economically active population rather than total DF volume.

Finally, the placebo lead test yields no evidence that future DF inflows predict current entrepreneurship outcomes: lead coefficients are small and statistically indistinguishable from zero. This diagnostic provides no indication that the baseline findings are driven by reverse causality or anticipatory DF allocation. The test results are presented and discussed in detail in the Online Appendix.

5 DISCUSSION

This study examines whether DF is associated with country-level entrepreneurial dynamics while incorporating two theory-driven features: (i) development finance contains ESDF as well as broader foundation DF that shapes entrepreneurship only indirectly and can imply offsetting opportunity-cost and crowding-out channels (Faria et al., 2023; Poschke, 2013); and (ii) entrepreneurship unfolds as a staged process in which upstream intentions and downstream early-stage activity need not move together (Gelderen et al., 2015; Kautonen et al., 2015). Empirically, we find a consistent pattern. Total DF inflows are not systematically associated with either entrepreneurial intentions or early-stage entrepreneurial activity. In contrast, higher ESDF is robustly associated with higher entrepreneurial intentions, while its association with early-stage activity is not statistically distinguishable from zero. Taken together, these results are consistent with the idea that entrepreneur-facing support is most visible at the upstream activation margin, while the translation from intentions into entry remains constrained by conversion conditions at the country level.

5.1 Contributions to the entrepreneurship literature

First, we contribute to measurement by making entrepreneurship-support DF observable at scale. Existing cross-country work has typically relied on aggregate inflows because standard DF datasets do not systematically record whether projects explicitly target entrepreneurs as a beneficiary group or objective (OECD, 2024). Building on recent approaches that use texts as a consistent source of policy content, we introduce an ESDF construct derived in a consistent and replicable manner by applying a supervised machine-learning classifier to millions of unstructured project descriptions in the OECD CRS (Miric et al., 2023; Toetzke et al., 2022). This creates a country-year series that separates entrepreneur-facing disbursements from residual DF across countries and time. Because the measure is derived from routinely produced administrative text, it is updatable and extensible (e.g., to new years or narrower conceptualizations such as start-up growth support), and it provides a template for constructing additional entrepreneurship- and ecosystem-relevant measures from large scale unstructured text using machine-learning-based methods (Harrison et al., 2023; Lévesque et al., 2022; Shrestha & He, 2025).

Second, using this measure, we provide novel evidence on the influence of entrepreneurship-support on entrepreneurial dynamics. In the absence of such a measure prior work has focused on micro-level evaluations of individual entrepreneurship-support programmes and on the influence of total DF on entrepreneurship. Our work expands both streams.

We complement the large micro-evaluation literature by assessing whether entrepreneur-facing support is associated with country-level entrepreneurial dynamics once economy-wide spillovers and general-equilibrium forces are implicitly present in national aggregates while typically not in program evaluations (Bade, 2022; Mohan & Morris, 2024). In a macro setting, any association need not operate only through directly treated entrepreneurs: entrepreneur-facing initiatives can plausibly affect broader populations through information diffusion, perceived feasibility and desirability, role-model effects, and intermediary strengthening (Bade, 2022; Nanda & Sørensen, 2010).

Further, we highlight why evidence based on total DF can be ambiguous, showing that empirically relevant variation lies in entrepreneur-facing finance rather than in undifferentiated aggregates. Theory implies that pooling ESDF with non-ESDF finance yields a bundled exposure whose relationship with entrepreneurship is difficult to interpret: while ESDF is designed to relax constraints directly on (prospective) entrepreneurs (McKenzie & Woodruff, 2014; Quinn & Woodruff, 2019; Sutter et al., 2017), non-ESDF finance primarily strengthens broader foundations (e.g., infrastructure, human capital, governance) that may support entrepreneurship indirectly but can also raise the opportunity cost of entrepreneurship by expanding wage-employment options or shift the composition of entrepreneurship in ways that mute changes in headline entry rates (Poschke, 2013; Solomon et al., 2021).

Third, we contribute by bringing a staged, process-based perspective to the analysis of entrepreneurship-support on country-level entrepreneurial dynamics. The robust association between ESDF and entrepreneurial intentions alongside null associations with early-stage entrepreneurial activity is consistent with an intention-activity gap at the country level (Gelderen et al., 2015; Kautonen et al., 2015). This pattern aligns with the idea that intentions are a relatively fast-moving and spillover-sensitive margin, while realized entry depends on conversion conditions that are typically more structural and slower-moving (Bade, 2022; Dileo & Pereiro, 2018; Teixeira et al., 2018). Accordingly, our results suggest that ESDF may primarily expand the upstream pool of potential entrepreneurs, while constraints on translating that pool into entry remain binding at the country level. An important implication for future research is, therefore, to identify which entry constraints are binding in different contexts and to examine how ESDF can be designed and combined with complementary policy to relax them. Doing so requires linking micro-level mechanisms to macro-level outcomes: interventions may be effective for direct participants yet yield muted aggregate changes when general-equilibrium forces and policy interactions are taken into account, for example, when entrepreneur-facing support reshapes behavior beyond treated groups or when multiple programs complement (or negatively impact) each other.

5.2 Practical implications

Our findings have three implications for recipient-country policymakers, donors and development finance organizations, entrepreneurial ecosystem builders, and private investors and founders.

A first implication concerns measurement and management of DF. The study introduces a scalable approach to identify and track ESDF within heterogeneous DF portfolios. Using this approach it provides a global repository of 5 million DF projects identifying which support entrepreneurs.

This enables donors and recipient-country stakeholders to monitor the volume and distribution of entrepreneur-facing support across countries, regions, and sectors, rather than relying on aggregate DF totals. Such tracking can inform portfolio management by highlighting underfunded geographies or target groups, supporting benchmarking across organizations, and facilitating evidence-informed allocation decisions. Beyond internal steering, consistent ESDF measurement can improve cross-organizational coordination. Greater visibility over where entrepreneur-facing support is already concentrated can help reduce unintentional duplication, identify complementary partners, and inform where new programs are most needed.

More broadly, the measurement approach illustrates how machine-learning based classification can be used to detect and track cross-cutting policy objectives that are not systematically captured in existing project monitoring systems. This can support ex-post learning and accountability for themes that cut across sectors and instruments. In adjacent domains, such measurement may also be informative for private actors: rising ESDF levels may serve as an early indicator of pipeline expansion in specific regions where more entrepreneurial activity, that is potential investments, are to be expected.

A second implication concerns how DF is interpreted and managed when entrepreneurship is an explicit objective. The results indicate that aggregate DF volumes are a noisy influence on entrepreneurial dynamics because they bundle entrepreneur-facing initiatives with foundation-building investments whose implications for entrepreneurship are indirect and can be offsetting. For policymakers and donors, this implies that total DF is ill-suited as a key performance indicator when the goal is to foster entrepreneurship, and that weak aggregate associations between DF and entrepreneurship should not be interpreted as evidence that DF "does not work" for entrepreneurship. Instead, null or weak macro patterns may reflect that inflows were not entrepreneur-facing, or that general development improvements increased wage employment and opportunity costs, dampening headline entrepreneurship rates even as foundations improved.

These patterns motivate more granular theories of change that distinguish indirect, foundation-building pathways (e.g., institutions, infrastructure, education, market functioning) from direct, entrepreneur-facing pathways that relax constraints to entry and early operation. Effective entrepreneurship strategies are therefore likely to combine both: investments that strengthen the surrounding foundations in the entrepreneurial ecosystem and targeted programs that reduce binding frictions for founders and young ventures (Hess, Wurth, et al., 2025). Program design can also treat spillovers as a feature rather than an externality. Entrepreneur-facing initiatives may shape entrepreneurship beyond direct beneficiaries by generating legitimacy and diffusing information, practices, and networks into the wider ecosystem. Accelerator and ecosystem programs often pursue such broader reach through community events, founder communities, and investor engagement that strengthen local ecosystems beyond participants (Bade, 2026; Goswami et al., 2018; Hochberg & Fehder, 2015). Evaluations and performance management can therefore complement participant-level outcomes with ecosystem markers that capture broader reach, such as changes in founder registrations, mentor and investor network depth, or local service provider capacity. For founders and investors, these spillovers imply that entrepreneur-facing support can alter opportunity landscapes: ESDF-rich environments may increase access to knowledge and networks, while intensified support can also reshape competitive conditions as more potential entrants are activated (Cai & Szeidl, 2024).

A third implication is to adopt a staged view of entrepreneurship-support on outcomes that distinguishes activation from conversion. From a practical perspective, this suggests managing entrepreneurship as a funnel: tracking the size of the upstream pool (intentions), monitoring transitions into nascent activity and early-stage operation, and identifying where the greatest drop-offs occur. Different contexts may face different bottlenecks—for example limited entrepreneurial aspirations and feasibility perceptions, weak planning and self-regulation supports, financing gaps, market access constraints, regulatory frictions, or limited operational capabilities. A funnel perspective enables more targeted intervention selection by aligning program instruments with the specific bottleneck in the process.

The findings further suggest that entrepreneur-facing support is more readily reflected in upstream activation than in downstream realized activity at the macro level. This pattern is consistent with the idea that intentions and related feasibility perceptions can shift through both direct participation and indirect exposure, whereas entry and early operation require complementary conditions that ESDF does not fully address. For donors, development finance organizations, and ecosystem builders, this implies that moving from intention shifts to sustained increases in entry may require stronger emphasis on conversion constraints: improving program quality and fit to local bottlenecks as well as ensuring that entrepreneur-facing resources are sufficient for the transition into early operation. Portfolio design can therefore benefit from balancing programs that expand the upstream pool with programs that specifically facilitate conversion, reducing the risk of creating a large latent pool of potential entrepreneurs without addressing the barriers that prevent entry and early-stage survival.

5.3 Limitations and future research

Several limitations qualify inference and point to future work.

First, ESDF remains a bundle. Our construct aggregates heterogeneous entrepreneur-facing interventions across different target groups (e.g., potential versus incumbent entrepreneurs; livelihood/self-employment versus growth-oriented ventures), instruments (e.g., financing versus capacity building), and entrepreneurial ecosystems (e.g., least developed versus middle-income countries), while pooling all activity to the country-year level. This heterogeneity can attenuate estimated relationships and obscure meaningful differences in the design of entrepreneurship support. A natural next step is to further decompose ESDF by target group, instrument type, ecosystem context, and objective, and to test whether portfolio composition predicts differentiated entrepreneurship outcomes (e.g., opportunity versus necessity entrepreneurship, formality, growth expectations).

Second, our focus on explicitly ESDF also leaves bundled the large fraction of foundation DF. Foundational investments (infrastructure, human capital, institutional capacity, debt dynamics) can shape entrepreneurship through indirect and potentially offsetting channels (Solomon et al., 2021; Stam & van de Ven, 2021). Future research could trace which elements of foundation finance reshape entrepreneurial ecosystem components benefitting entrepreneurs and examine complementarities with direct entrepreneurship-support measures (Wang et al., 2022).

Third, conversion from intentions to activity and spillovers to indirect beneficiaries are not directly observed (Bade, 2022). While this macro level intentions-activity gap is consistent with conversion frictions and indirect ecosystem dynamics (where indirect beneficiaries may be more responsive on intentions than on realized activity), our macro design cannot isolate which mechanisms govern the translation from latent supply to realized entry, nor whether spillovers extend beyond direct beneficiaries. Future work can combine ESDF exposure with micro- or meso-level data (e.g. DF program participation and exposure, intermediary density, peer networks) to trace the pipeline from intentions to entry and to quantify spillovers beyond directly treated entrepreneurs (Cao & Shi, 2021; González-Uribe & Reyes, 2021).

Fourth, similar to other studies on the entrepreneurship development finance nexus, identification is associational (Boudreaux et al., 2022; Mohan & Morris, 2024; Moore et al., 2020). Although our two-way fixed-effects design, lag structure variations, reverse causality diagnostics and further robustness checks discipline interpretation, ESDF allocation may respond to unobserved country dynamics (reforms, shocks, political cycles) that also affect entrepreneurship within a country. Future research should pursue stronger designs by exploiting quasi-experimental variation in DF allocation (rule changes, funding windows, donor budgeting shocks), geocoded placement, discontinuities, or staggered rollouts that better separate selection from effects.

Finally, our country sample is constrained by data availability for entrepreneurship outcomes. Because GEM coverage is not universal and may over-represent countries with particular survey capacity or institutional characteristics, external validity to the full population of DF-recipient countries is not guaranteed (Reynolds et al., 2005). Extending the analysis to alternative entrepreneurship measures and broader country coverage is an important direction for future work. Subnational analyses may also be informative, as many DF efforts are spatially concentrated (e.g., in capital regions) and may therefore be less visible in national aggregates (Hess, Wahl, & Johnson, 2025).

Taken together, the study suggests that understanding how DF relates to entrepreneurship requires treating the distinct components of development finance seperatley and viewing its impact along the entrepreneurship process. Doing so reveals that entrepreneur-support development finance, a small but growing share of development finance, is consistently associated with entrepreneurial intentions, while realized entry appears more tightly governed by conversion conditions and complementary ecosystem inputs.

REFERENCES

Ács, Z. J., Autio, E., & Szerb, L. (2014). National systems of entrepreneurship: Measurement issues and policy implications. *Research Policy*, *43*, 476–494.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211.

Alesina, A., & Dollar, D. (2000). Who gives foreign aid to whom and why? *Journal of Economic Growth*, *5*, 33–63.

Alvarez, S. A., & Barney, J. B. (2007). Discovery and creation: Alternative theories of entrepreneurial action. *Strategic Entrepreneurship Journal*, *1*, 11–26.

Álvarez, C., Urbano, D., & Amorós, J. E. (2013). GEM research: Achievements and challenges. *Small Business Economics*, *42*, 445–465.

Audretsch, D. B. (2007). Entrepreneurship capital and economic growth. *Oxford Review of Economic Policy*, *23*, 63–78.

Autio, E., Kenney, M., Mustar, P., Siegel, D., & Wright, M. (2014). Entrepreneurial innovation: The importance of context. *Research Policy*, *43*, 1097–1108.

Bade, M. (2022). Conversion and contagion in entrepreneurship: A cross-country analysis. *Strategic Entrepreneurship Journal*, *16*, 207–239.

Bade, M. (2026). Ecosystem conditions and the efficacy of entrepreneurial support organizations: Moderating effects on venture entry. *Strategic Entrepreneurship Journal*, *in press*.

Baumol, W. J. (1996). Entrepreneurship: Productive, unproductive, and destructive. *Journal of Business Venturing*, *11*, 3–22.

Bjørnskov, C. (2019, September). Types of foreign aid. In N. Dutta & C. R. Williamson (Eds.), *Lessons on foreign aid and economic development: Micro and macro perspectives* (pp. 33–61). Springer International Publishing.

Bjørnskov, C., & Foss, N. (2013). How strategic entrepreneurship and the institutional context drive economic growth. *Strategic Entrepreneurship Journal*, *7*, 50–69.

Boudreaux, C. J., Jha, A., & Escaleras, M. (2022). Weathering the storm: How foreign aid and institutions affect entrepreneurship activity following natural disasters. *Entrepreneurship: Theory and Practice*, *46*, 1843–1868.

Cai, J., & Szeidl, A. (2024). Indirect effects of access to finance. *American Economic Review*, *114*, 2308–51.

Campos, F., Frese, M., Goldstein, M., Iacovone, L., Johnson, H. C., McKenzie, D., & Mensmann, M. (2017). Teaching personal initiative beats traditional training in boosting small business in West Africa. *Science*, *357*, 1287–1290.

Cao, Z., & Shi, X. (2021). A systematic literature review of entrepreneurial ecosystems in advanced and emerging economies. *Small Business Economics*, *57*, 75–110.

Chawla, N. V. (2010). Data mining for imbalanced datasets: An overview. In O. Maimon & L. Rokach (Eds.), *Data Mining and Knowledge Discovery Handbook* (pp. 875–886). Springer, Boston, MA.

Clemens, M. A., Radelet, S., Bhavnani, R. R., & Bazzi, S. (2012). Counting chickens when they hatch: Timing and the effects of aid on growth. *The Economic Journal*, *122*, 590–617.

Coulibaly, S. K., Erbao, C., & Mekongcho, T. M. (2018). Economic globalization, entrepreneurship, and development. *Technological Forecasting and Social Change*, *127*, 271–280.

Dau, L. A., & Cuervo-Cazurra, A. (2014). To formalize or not to formalize: Entrepreneurship and pro-market institutions. *Journal of Business Venturing*, *29*, 668–686.

Dileo, I., & Pereiro, T. G. (2018). Assessing the impact of individual and context factors on the entrepreneurial process. A cross-country multilevel approach. *International Entrepreneurship and Management Journal*, *15*, 1393–1441.

Doh, J. P., Tashman, P., & Benischke, M. H. (2019). Adapting to grand environmental challenges through collective entrepreneurship. *Academy of Management Perspectives*, *33*, 450–468.

Dollar, D., & Levin, V. (2006). The increasing selectivity of foreign aid, 1984–2003. *World Development*, *34*, 2034–2046.

Dreher, A., Lang, V., & Reinsberg, B. (2024). Aid effectiveness and donor motives. *World Development*, *176*, 106501.

Eggers, A. C., Tuñón, G., & Dafoe, A. (2024). Placebo tests for causal inference. *American Journal of Political Science*, *68*, 1106–1121.

Faria, J. R., Ogura, L., Prado, M., & Boudreaux, C. J. (2023). Government investments and entrepreneurship. *Small Business Economics*, *61*, 1657–1670.

Feki, C., & Mnif, S. (2016). Entrepreneurship, technological innovation, and economic growth: Empirical analysis of panel data. *Journal of the Knowledge Economy*, *7*, 984–999.

Fuchs, A., Dreher, A., & Nunnenkamp, P. (2014). Determinants of donor generosity: A survey of the aid budget literature. *World Development*, *56*, 172–199.

Gelderen, M. V., Kautonen, T., & Fink, M. (2015). From entrepreneurial intentions to actions: Self-control and action-related doubt, fear, and aversion. *Journal of Business Venturing*, *30*, 655–673.

González-Uribe, J., & Reyes, S. (2021). Identifying and boosting "gazelles": Evidence from business accelerators. *Journal of Financial Economics*, *139*, 260–287.

Goswami, K., Mitchell, R. J., & Bhagavatula, S. (2018). Accelerator expertise: Understanding the intermediary role of accelerators in the development of the Bangalore entrepreneurial ecosystem. *Strategic Entrepreneurship Journal*, *12*, 117–150.

Grilo, I., & Thurik, R. (2005). Latent and actual entrepreneurship in Europe and the US: Some recent developments. *The International Entrepreneurship and Management Journal*, *1*, 441–459.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *The Review of Economics and Statistics*, *95*, 347–361.

Harrison, J. S., Josefy, M. A., Kalm, M., & Krause, R. (2023). Using supervised machine learning to scale human-coded data: A method and dataset in the board leadership context. *Strategic Management Journal*, *44*, 1780–1802.

Hartmann, J., Huppertz, J., Schamp, C., & Heitmann, M. (2019). Comparing automated text classification methods. *International Journal of Research in Marketing*, *36*, 20–38.

Hess, S., Wahl, A., & Johnson, A. R. (2025). Measuring entrepreneurial ecosystems across levels: A district approach. *Small Business Economics*, *65*, 1617–1649.

Hess, S., Wurth, B., Stam, E., Giones, F., Fini, R., Cavallo, A., Wahl, A., Bosma, N., Theodoraki, C., Chabaud, D., Brem, A., & Kuckertz, A. (2025). The future of entrepreneurial ecosystems research: Toward a policy-oriented research agenda. *Journal of Business Venturing Insights*, *23*, e00538.

Hochberg, Y. V., & Fehder, D. C. (2015). Accelerators and ecosystems. *Science*, *348*, 1202–1203.

Imai, K., & Kim, I. S. (2021). On the use of two-way fixed effects regression models for causal inference with panel data. *Political Analysis*, *29*, 405–415.

Islam, A. (2015). Entrepreneurship and the allocation of government spending under imperfect markets. *World Development*, *70*, 108–121.

Kautonen, T., van Gelderen, M., & Fink, M. (2015). Robustness of the theory of planned behavior in predicting entrepreneurial intentions and actions. *Entrepreneurship Theory and Practice*, *39*, 655–674.

Kersten, R., Harms, J., Liket, K., & Maas, K. (2017). Small firms, large impact? A systematic review of the SME finance literature. *World Development*, *97*, 330–348.

Kimmitt, J., Muñoz, P., & Newbery, R. (2020). Poverty and the varieties of entrepreneurship in the pursuit of prosperity. *Journal of Business Venturing*, *35*, 105939.

Klapper, L., Amit, R., & Guillén, M. (2010). Entrepreneurship and firm formation across countries. In J. Lerner & A. Schoar (Eds.), *International differences in entrepreneurship* (pp. 129–158). University of Chicago Press.

Krueger, N. F., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. *Journal of Business Venturing*, *15*, 411–432.

Lall, S. A., Chen, L. W., & Roberts, P. W. (2020). Are we accelerating equity investment into impact-oriented ventures? *World Development*, *131*, 104952.

Lay, J., & Tafese, T. (2025). Africa's emergent tech sector: Characteristics and development implications. *Africa Spectrum*, *60*, 106–126.

Leszczensky, L., & Wolbring, T. (2022). How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. *Sociological Methods and Research*, *51*, 837–865.

Lévesque, M., Obschonka, M., & Nambisan, S. (2022). Pursuing impactful entrepreneurship research using artificial intelligence. *Entrepreneurship: Theory and Practice*, *46*, 803–832.

Liao, S., Javed, H., Sun, L., & Abbas, M. (2022). Influence of entrepreneurship support programs on nascent entrepreneurial intention among university students in China. *Frontiers in Psychology*, *13*, 955591.

MacKinnon, J. G., Nielsen, M. Ø., & Webb, M. D. (2023). Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics*, *232*, 272–299.

Manning, S., & Vavilov, S. (2023). Global development agenda meets local opportunities: The rise of development-focused entrepreneurship support. *Research Policy*, *52*, 104795.

Mavrotas, G., & Ouattara, B. (2006). Aid disaggregation and the public sector in aid-recipient economies: Some evidence from cote D'Ivoire. *Review of Development Economics*, *10*, 434–451.

McKenzie, D. (2017). Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition. *American Economic Review*, *107*, 2278–2307.

McKenzie, D., & Woodruff, C. (2014). What are we learning from business training and entrepreneurship evaluations around the developing world? *The World Bank Research Observer*, *29*, 48–82.

Miric, M., Jia, N., & Huang, K. G. (2023). Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents. *Strategic Management Journal*, *44*, 491–519.

Mohan, P., & Morris, D. (2024). Climate finance spillovers and entrepreneurship in developing countries. *Strategic Entrepreneurship Journal*, *18*, 475–501.

Moore, E. M., Dau, L. A., & Doh, J. (2020). Does monetary aid catalyse new business creation? Analysing the impact of global aid flows on formal and informal entrepreneurship. *Journal of Management Studies*, *57*, 438–469.

Mullahy, J., & Norton, E. C. (2024). Why Transform Y? The pitfalls of transformed regressions with a mass at zero. *Oxford Bulletin of Economics and Statistics*, *86*, 417–447.

Nanda, R., & Sørensen, J. B. (2010). Workplace peers and entrepreneurship. *Management Science*, *56*, 1116–1126.

Neumann, T. (2020). The impact of entrepreneurship on economic, social and environmental welfare and its determinants: A systematic review. *Management Review Quarterly*, *71*, 553–584.

Nyström, K. (2008). The institutions of economic freedom and entrepreneurship: Evidence from panel data. *Public Choice*, *136*, 269–282.

OECD. (2024). Development co-operation report 2024: Tackling poverty and inequalities through the green transition. *Development Co-operation Report*, *2024*.

Peiffer, C., & Boussalis, C. (2015, October). Determining aid allocation decision-making: Towards a comparative sectored approach. In B. M. Arvin & B. Lew (Eds.), *Handbook on the Economics of Foreign Aid* (pp. 45–63). Edward Elgar Publishing Ltd.

Poschke, M. (2013). Who becomes an entrepreneur? Labor market prospects and occupational choice. *Journal of Economic Dynamics and Control*, *37*, 693–710.

Quinn, S., & Woodruff, C. (2019). Experiments and entrepreneurship in developing countries. *Annual Review of Economics*, *11*, 225–248.

Reynolds, P., Bosma, N., Autio, E., Hunt, S., Bono, N. D., Servais, I., Lopez-Garcia, P., & Chin, N. (2005). Global entrepreneurship monitor: Data collection design and implementation 1998-2003. *Small Business Economics*, *24*, 205–231.

Shrestha, Y. R., & He, V. F. (2025). Integrating multimodal data and machine learning for entrepreneurship research. *Strategic Entrepreneurship Journal*, *in press*.

Solomon, S., Bendickson, J. S., Liguori, E. W., & Marvel, M. R. (2021). The effects of social spending on entrepreneurship in developed nations. *Small Business Economics*, *58*, 1595–1607.

Souitaris, V., Zerbinati, S., & Al-Laham, A. (2007). Do entrepreneurship programmes raise entrepreneurial intention of science and engineering students? The effect of learning, inspiration and resources. *Journal of Business Venturing*, *22*, 566–591.

Stam, E., & van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics*, *56*, 809–832.

Stel, A. V., Carree, M., & Thurik, R. (2005). The effect of entrepreneurial activity on national economic growth. *Small Business Economics*, *24*, 311–321.

Stürenburg, F., Forster, K., Banholzer, N., Toetzke, M., Harttgen, K., & Feuerriegel, S. (2025). Tracking funding disparities in global health aid with machine learning. *medRxiv*, 2025.06.20.25329993.

Sutter, C., Bruton, G. D., & Chen, J. (2019). Entrepreneurship as a solution to extreme poverty: A review and future research directions. *Journal of Business Venturing*, *34*, 197–214.

Sutter, C., Webb, J., Kistruck, G., Ketchen, D. J., & Ireland, R. D. (2017). Transitioning entrepreneurs from informal to formal markets. *Journal of Business Venturing*, *32*, 420–442.

Teixeira, S. J., Casteleiro, C. M. L., Rodrigues, R. G., & Guerra, M. D. (2018). Entrepreneurial intentions and entrepreneurship in European countries. *International Journal of Innovation Science*, *10*, 22–42.

Toetzke, M., Stünzi, A., & Egli, F. (2022). Consistent and replicable estimation of bilateral climate finance. *Nature Climate Change*, *12*, 897–900.

Urbano, D., Aparicio, S., & Audretsch, D. B. (2019). Institutional antecedents of entrepreneurship and its consequences on economic growth: A systematic literature analysis. *International Studies in Entrepreneurship*, *41*, 15–56.

Valliere, D., & Peterson, R. (2009). Entrepreneurship and economic growth: Evidence from emerging and developed countries. *Entrepreneurship and Regional Development*, *21*, 459–480.

Wang, H., Zhao, T., Cooper, S. Y., Wang, S., Harrison, R. T., & Yang, Z. (2022). Effective policy mixes in entrepreneurial ecosystems: A configurational analysis in China. *Small Business Economics*, *60*, 1509–1542.

Welter, F., Baker, T., Audretsch, D. B., & Gartner, W. B. (2017). Everyday entrepreneurship—a call for entrepreneurship research to embrace entrepreneurial diversity. *Entrepreneurship: Theory and Practice*, *41*, 311–321.

Wennekers, S., Stel, A. V., Carree, M., & Thurik, R. (2010). The relationship between entrepreneurship and economic development: Is it u-shaped? *Foundations and Trends in Entrepreneurship*, *6*, 167–237.

Wilkins, A. S. (2018). To lag or not to lag?: Re-Evaluating the use of lagged dependent variables in regression analysis. *Political Science Research and Methods*, *6*, 393–411.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. The MIT Press.

WorldBank. (2013). World Bank Group support for innovation and entrepreneurship: An independent evaluation.

Online appendix

CONTENTS

A1 DETAILS ON MACHINE LEARNING CLASSIFICATION APPROACH

A1.1 Codebook for human labeling

The following depicts the codebook given to human hand-coders as guidance to label project descriptions.

Coding guide for classification of entrepreneurship-support programs in CRS development projects

The goal of this codebook is to identify development finance projects from the OECD Creditor Reporting System that support entrepreneurship in recipient countries.

Identification of entrepreneurship-support (ES) programs

The coder shall identify in column "ES" the type of the program:

1. Entrepreneurship support (code as 1) OR

2. No entrepreneurship support (code as 0)

Definitions, coding guidelines and examples can be found below.

1) Entrepreneurship support

A project offers entrepreneurship support if its description explicitly mentions activities, programs, or objectives that support potential, nascent, or established entrepreneurs/their ventures, or that explicitly support entrepreneurship in general without targeting a specific entrepreneur.

The following count as (potential) entrepreneurs (non-exhaustive): micro and small enterprises/businesses/ventures (MSMEs/SMEs); start-ups; farmers/fishers operating their own business (e.g., smallholder farmers or farmer cooperatives); self-employed; aspiring entrepreneurs; people receiving entrepreneurial skills training.

Examples of programs (code as 1):

- Training, grants, funding, microfinance, mentoring, incubation/acceleration, support for start-ups, new businesses, entrepreneurs, small business owners, or the self-employed, MSMEs
- General initiatives targeting entrepreneurship such as accelerators, incubators
- Policy/regulatory reforms that ease business registration or starting a business
- Entrepreneurial skills training for self-employment
- Capacity building for smallholder farmers as owners of their farm

2) No Entrepreneurship support

All programs that do not qualify as A. The below examples list borderline cases that are not entrepreneurship.

Examples (code as 0):

- General economic growth initiatives
- Project promoting savings accounts/mobile money broadly (households + firms)
- General microfinance projects without specific mentioning of entrepreneurs as target group
- Infrastructure development (unless explicitly for entrepreneurship, e.g., entrepreneurial zones)
- Broad employment programs and vocational training (unless a defined component targets self-employment/starting a business)
- Broad private sector development/trade/institutional reforms without explicit entrepreneur focus

Closing remarks

In ambiguous cases, the coder may request review by marking "REVIEW_NEEDED" with 1. Even then, provide a complete best-guess classification for the row.

A1.2 Example project descriptions

The following project descriptions provide illustrative examples of the text used both for human hand-coding and for training the machine learning classifier. Each description concatenates the project title, short description, and long description as reported in the CRS, following (Toetzke et al., 2022). Project texts are reproduced verbatim from CRS records and may contain original spelling and formatting errors. Human coders assigned labels solely based on this concatenated description to ensure the same information basis as used for fine-tuning the language model. The ESDF and non-ESDF labels shown are taken from the human-labeled gold standard dataset.

Examples of ESDF projects

Boost Africa - EIB Component ; BOOST AFRICA - EIB COMPONENT ; The aim of the Action is to enable and enhance entrepreneurship and innovation across Africa in a commercially viable way and to address a current gap in the Sub-Saharan market, by providing early stage venture capital paired with skills development.

Catalyzing Women's Entrepreneurship - Creating a Gender-Responsive Entrepreneurial Ecosystem ; Catalyzing Women's Entrepreneurship - Creating A Gender -Entrepreneurial ECOSYSTEM/Promote female entrepreneurship - Creation of an eco ; The Project Aims to Advance Women's Economic Empowerment and Contribute to Poverty Reduction in the Asia-Pacific Region (South Asia, Southeast Asia and the South Pacific). It is designed to add up the particular challenge that women-obned micro, small and medium-Sized Enterprises Face in Growing Their Businesses, Including Access to Finance and New Technologies. It is designed to include women's access to capital through innovative funding mechanisms and women entrepreneurs' Use of business development services and financial technologies. The Project Supports The Development of Gender-Responsible Policies and Programs for Business Development and Investment.Project Activities Included: (1) Technical Assistance To Support Innovative Financing Mechanisms To Developed Targeted Products for Women Entrepreneurs, Including Bonds, Impact Investment Funds and Finnish Technology Platforms, (2) Advisory support and Capacity Building for Policymakers On Regulatory Frameworks for Digital Finance, (3) Training for Women Entrepreneurs On Using Information and Communications Technologies to Plan, Manage and Grow their Busines, and (4) Training for Policymakers On Developing, Implementing and Monitoring Gender-Resferent Entrepreneurship and Developing Initiatives and Developing ENABLING POLICY FRAMEWORKS FOR INNOVATIVE FINANCE MENHANISMS.

Children and Young people: from the street to self-employment ; CHILDREN AND YOUNG PEOPLE: FROM THE STREET TO SELF-EMPLOYMENT ; The initiative tries to create joint mutual aid groups made up of children and young people rescued from the street, by leading and training them to become small business cooperatives. The project consists in activities located in the Democratic Republic of Congo, that is suffering from instability, conflicts and social disorder, it focuses its activities in North Kivu and Tanganvika Provinces and, particularly, in the cities of Bukavu, Ulvira, Goma, Baraka, Kelemie.

Baring India Private Equity Fund II LP ; BARING INDIA PRIVATE EQUITY FUND II LP ; Expanding access to finance for the SME sector, upgrading corporate governance and financial discipline in portfolio companies and supporting incumbent management teams in unlocking the full value of their businesses are all major contributors to the development of entrepreneurial skills so vital for economic growth

---

Empowering Palestinian women to participate in digital entrepreneurship (PWpower) ; EMPOWERING PALESTINIAN WOMEN TO PARTICIPATE IN DIGITAL ENTREPRENEURSHIP (PW-POWER) ; To strengthen the participation of women and girls in the labor market in the field of technology in Palestine. The focus is placed on women who are studying in colleges or universities, already working in the field of technology or those who want to retrain.

Integrated approach to economic recovery of the agricultural and entrepreneurial sector in rural areas ; Integrated economic raising approach to the agricultural and entrepreneurial sector in rural areas ; Encouragement of the economic recovery of farmers and small rural entrepreneurs

Examples of Non-ESDF projects

Expanding Private Participation in Infrastructure Program, Subprogram 1 ; EXPANDING PRIVATE PARTICIPATION IN INFRASTRUCTURE PROGRAM, SUBPROGRAM 1 ; The program will assist the government in meeting its targeted infrastructure investment rate, including public and private spending. This will be achieved by supporting sequenced reforms aimed at stepping up private investment in infrastructure through the promotion of public–private partnership (PPP) projects. In close alignment with the Philippine Development Plan (PDP), 2011–2016, the program supports initiatives aimed at (i) strengthening government financial support to PPPs, (ii) expanding and efficiently implementing the pipeline of PPP projects, and (iii) strengthening legal and regulatory frameworks for PPPs.

P209 - Volunteering - Senegal - International Solidarity Volunteering (VSI) - DEFAP ; P209 - Volunteering - Senegal - International Solidarity Volunteer (VSI) - Defap ; P209 - Volunteering - Senegal - International Solidarity Volunteering (VSI) - DEFAP: www.defap.fr - Productive sector (including Mico -Projets, Tourism, Crafts, Support for the creation of activities ...) - The support of the Ministry to International Trade and Solidarity Volunteering is complementary to the support provided to civil society, allowing actors to mobilize volunteers Their actions of development and humanitarian action. Initiation volunteer (LIF): International Solidarity Youth Programs (JSI) and Ville Vie Vacances Internationale (VVV-SI) allow the intercultural meeting of groups of young

French people with other young people around the realization of international solidarity projects abroad.

Poverty Reduction Support Operations 4 ; POVERTY REDUCTION SUPPORT OPERATIONS 4 ; The Fourth Poverty Reduction Support Operation (PRSO) for Georgia will provide supplemental budget support to the Government to help efforts to sustain implementation of the PRSO program in the face of unanticipated budget constraints associated with the August 2008 conflict. The PRSO reform program focuses on four critical reform pillars: (i) strengthening public sector accountability, efficiency, and transparency, (ii) improving electricity and gas sector services, (iii) improving the environment for private sector development, and (iv) improving social protection, education, and health care services. The reforms aim at developing a dynamic and competitive private sector as the main engine of growth, with the state playing a supportive role by providing basic public goods and services. These development strategies, reflected in Georgia's poverty reduction strategy paper (PRSP), have served the country well. Driven by rapidly rising foreign direct investment (FDI) flows of about 1.5 billion per year, which translated into domestic investment of 28 percent of gross domestic product (GDP), GDP growth averaged 10.5 percent per year over the last three years and reached 12.4 percent in 2007. During the same period, inflation was on average 8.7 percent per year, though it accelerated to 11 percent in 2007. Private capital inflows financed the large external current account deficit while international reserves increased from 881*millionin*2006*to*1,361 million in 2007, and to 1,550 million by end-July 2008 (or about 2.6 months of imports). At the same time, external debt declined from 46 percent of GDP in 2003 to 16.7 percent in 2007.THIS WILL INVOLVE AN INITIAL 2 YEAR PHASE OF 2.5 MILLION, AND A SUBSEQUENT 2 YEAR EXTENSION VALUED AT $1.5 MILLION FOLLOWING A REVIEW OF PHASE 1.

---

for support of the Advocacy Accelerator ; FOR SUPPORT OF THE ADVOCACY ACCELERATOR ; Programme: Gender Equity & Governance > Global Reproductive Equity > FP/RH and Global Development. Description: This grant to Amref Health Africa will provide flexible support for the

Advocacy Accelerator (AAC), a pan-African platform that stimulates locally driven advocacy by engaging advocates, technical assistance providers, and donors. The AAC aims for a strengthened advocacy ecosystem with better coordination among country-based advocates capable of implementing effective advocacy strategies leading to change in government policies and development practice. During the grant period, the AAC will bolster its internal operations as it transitions to an independent organization and continues to consolidate its activities to support African health and development advocates to achieve greater impact. (Strategy: Global Reproductive Equity)

Economic Governance Technical Assistance and Capacity Building ; ECONOMIC GOVERNANCE TECHNICAL ASSISTANCE AND CAPACITY BUILDING ;

A1.3 Model training and evaluation

In this section, we summarize implementation choices for training, selecting, and performance measurement of the ESDF classifier. Full code is available online (Link: https://github.com/werner-sven/ml-classifier-entrepreneurship-support-development-finance).

Training and threshold tuning on the evaluation set. We fine-tune a BERT-family transformer model for binary sequence classification (ESDF versus non-ESDF) on the hand-labeled training data. To assess robustness, we train a small set of candidate model configurations that vary standard fine-tuning choices (e.g., learning rate, number of epochs, batch size, regularization/class weighting). After training, we tune the probability threshold used to convert model scores into a binary ESDF label. We sweep thresholds on the evaluation set and select the threshold that maximises precision to avoid excessive bias from false positives in our rare class setting (Chawla, 2010). Candidate models are then evaluated across metrics using the common evaluation split (not the test split). Table 5 summarizes evaluation performance for the candidate models on the evaluation set. Across hyperparameters, all models indicate a very high accuracy of greater than

95%. We choose model (1) as our main model (hyperpara.meters: learning rate: 2e-5, batch size: 8, epochs 10) based on comparison of precision given our rare class setting. Note that threshold-tuning on the evaluation set creates some risk of overfitting for the performance metrics calculated based on the same evaluation set. Therefore, we focus our discussion of the performance of the model on the strictly held-out test data (see below).

Performance on held-out test and confusion matrix. For the selected model and using the tuned threshold, we report final accuracy, precision, recall, and F1 in the main text based on the held-out test split. In addition, Figure 4 reports the confusion matrix on the held-out test set to transparently show the classifier's error profile (true positives/negatives and false positives/negatives) at the chosen threshold.

TABLE 5 Performance of machine learning classifier candidates on the evaluation split for predicting ESDF.

Model	distilbert-base-uncased lr=2e-5, bs=8, ep=10	distilbert-base-uncased lr=2e-5, bs=16, ep=10	distilbert-base-uncased lr=3e-5, bs=8, ep=10
Accuracy	0.95	0.97	0.95
F1 (ESDF)	0.94	0.96	0.94
Precision (ESDF)	1.00	1.00	1.00
Recall (ESDF)	0.89	0.92	0.88
Threshold (τ)	0.918	0.533	0.989

Note: Models were trained on the hand-labeled training split. "lr" refers to learning-rate, "bs" to batch size and "ep" to epochs. Thresholds were tuned on the evaluation split to maximize precision (ESDF); reported metrics are computed at the tuned τ on the same evaluation split. The test split remains untouched.

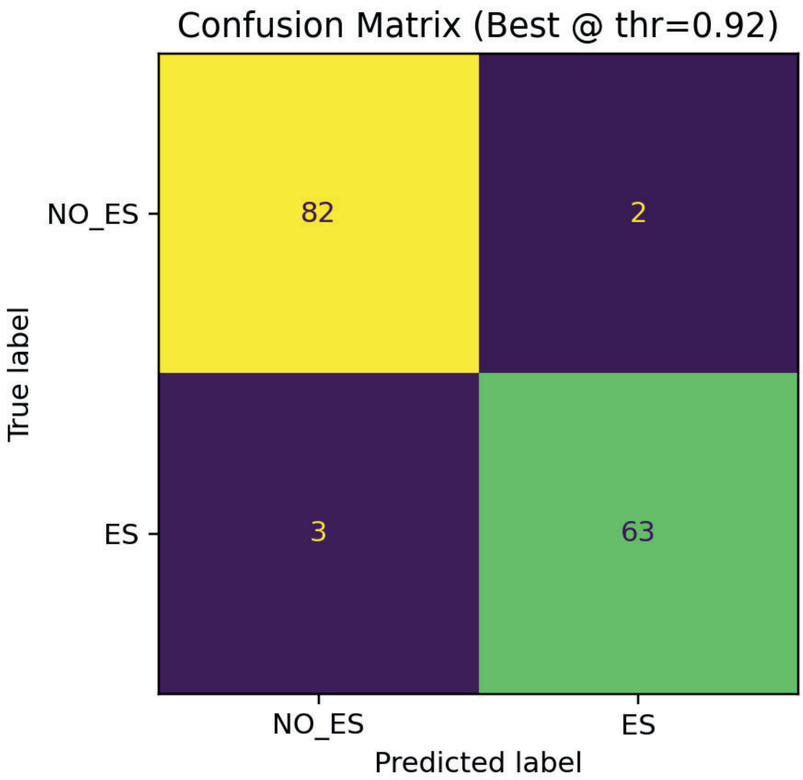

FIGURE 4 Confusion matrix: Performance of selected ESDF classifier based on held-out test set

A2 COUNTRY DISTRIBUTION OF ANALYSIS

Table 6 lists all countries included in the estimation sample for the baseline ESDF versus non-ESDF specification on entrepreneurial intentions. Countries enter the sample in years for which entrepreneurial intentions are observed and for which all required lags of the explanatory and control variables are available. Country names are followed by the number of observations in brackets. The sample is primarily reduced by the limited availability of GEM measures—especially for entrepreneurial intentions and early-stage entrepreneurial activity in developing countries.

TABLE 6 Countries in estimation sample

Algeria [4]	Egypt [10]	Pakistan [4]
Argentina [16]	El Salvador [2]	Panama [12]
Belarus [2]	Georgia [2]	Peru [14]
Belize [2]	Ghana [3]	Philippines [4]
Bolivia [3]	Guatemala [12]	Serbia [3]
Bosnia and Herzegovina [8]	India [13]	South Africa [16]
Botswana [4]	Indonesia [8]	Sudan [2]
Brazil [19]	Iran [14]	Thailand [12]
Burkina Faso [4]	Jordan [4]	Tunisia [4]
Cameroon [3]	Kazakhstan [7]	Türkiye [10]
Chile [14]	Lebanon [5]	Uganda [6]
China (People's Republic of) [15]	Madagascar [3]	Uruguay [12]
Colombia [16]	Malaysia [10]	Venezuela [3]
Costa Rica [3]	Mexico [12]	Viet Nam [4]
Croatia [8]	Morocco [8]	West Bank and Gaza Strip [3]
Dominican Republic [4]	Namibia [2]	Zambia [3]
Ecuador [11]	North Macedonia [7]	

Note: List of countries included in the estimation sample of the baseline ESDF vs Non-ESDF model (outcome: intentions, model 2). Country names are followed by the number of observations in brackets.

A3 ROBUSTNESS AND SENSITIVITY

A3.1 Dynamic fixed-effects robustness (FE-LDV)

As an additional robustness check, we estimate a dynamic version of our baseline TWFE model that adds the lagged dependent variable while retaining the two-year lag structure for DF and controls:

$$Y_{it} = \alpha + \rho Y_{i,t-1} + \beta DF_{i,t-2} + \gamma' X_{i,t-2} + \mu_i + \tau_t + \varepsilon_{it}. \tag{2}$$

Including $Y_{i,t-1}$ explicitly captures serial persistence in entrepreneurship outcomes and reduces sensitivity to slow-moving dynamics and residual serial correlation that could otherwise load onto the DF coefficient (Wilkins, 2018). While dynamic fixed-effects estimators can exhibit finite-T (Nickell) bias, the bias declines with T; with 19 years in our panel, any remaining bias is likely modest, making the specification informative as a robustness exercise (Nickell, 1981; Wilkins, 2018).

The analysis indicates substantial persistence in both outcomes: ρ is tightly estimated at approximately 0.45-0.49 for intentions and 0.28-0.29 for activity. Conditional on this persistence, the association between ESDF and intentions remains positive and statistically significant for ESDF (1.96; SE=0.53), consistent with the baseline TWFE estimates of the main analysis. The coefficient for influence of DF on early-stage activity are small and statistically insignificant across dynamic specifications also in line with the results of the main analysis.

The number of observations falls from 370 in the baseline TWFE models to about 250 in the FE-LDV models because the dynamic specification requires additional lag availability: $Y_{i,t-1}$ must be observed and (in our baseline structure) DF and controls are measured at $t-2$. Consequently, the FE-LDV results are based on a stricter set of country-years with sufficiently complete and consecutive information, and should be interpreted as a robustness check on this more restricted sample.

TABLE 7 Dynamic fixed-effects robustness (FE-LDV; lagged DV t-1; DF and controls lagged 2 years)

	Intentions (FE-LDV)		*Early-stage activity (FE-LDV)*	
	Total DF	ESDF vs Non-ESDF	Total DF	ESDF vs Non-ESDF
	(1)	(2)	(3)	(4)
Lagged dependent variable (t-1)	0.49***	0.45***	0.29***	0.28***
	(0.07)	(0.07)	(0.09)	(0.09)
ln(Total DF)	-0.93		-0.44	
	(1.39)		(0.63)	
ln(ESDF)		1.96***		0.30
		(0.53)		(0.26)
ln(Non-ESDF)		-1.66		-0.53
		(1.43)		(0.63)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Num. Countries	36	36	36	36
Num. Years	18	18	19	19
Num.Obs.	249	249	254	254
R2	0.827	0.836	0.819	0.820
R2 Within	0.292	0.330	0.133	0.138

Note: Dynamic two-way fixed effects (Country and Year) models including a lagged dependent variable (t-1). DF and controls are lagged by 2 years. Standard errors clustered by country in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

A3.2 Placebo lead test

To diagnose reverse causality and anticipatory DF allocation, we conduct a placebo treatment test that asks whether *future* DF predicts *current* entrepreneurship after conditioning on the baseline lag structure and fixed-effects (Eggers et al., 2024). The intuition is that, under the maintained causal ordering (DF affecting entrepreneurship with lags), DF realized in $t+1$ should have no causal effect on Y_{it}; however, if donors respond to (observed or anticipated) changes in entrepreneurship, or if other violations of exogeneity generate feedback from Y to subsequent DF, then future DF may spuriously correlate with current outcomes (Leszczensky & Wolbring, 2022).

We augment the baseline ESDF decomposition model by adding a one-year lead of ESDF and non-ESDF while keeping the baseline lag-2 DF terms and lag-2 controls:

$$\begin{aligned} Y_{it} = \alpha &+ \beta_1 \ln(\text{ESDF}_{i,t-2}) + \beta_2 \ln(\text{non-ESDF}_{i,t-2}) \\ &+ \theta_1 \ln(\text{ESDF}_{i,t+1}) + \theta_2 \ln(\text{non-ESDF}_{i,t+1}) \\ &+ \gamma' X_{i,t-2} + \mu_i + \tau_t + \varepsilon_{it}. \end{aligned} \tag{3}$$

The placebo parameters of interest are θ_1 and θ_2. Under the identifying assumptions of the baseline design, these coefficients should be approximately zero (Eggers et al., 2024).

The results of the placebo test (Table 8) indicate that future DF flows are not associated with current entrepreneurship outcomes (i.e., θ_1 and θ_2 are small and statistically indistinguishable from zero). This provides no indication that our baseline estimates are driven by reverse causality or anticipatory DF allocation. At the same time, consistent with the interpretation of placebo tests, this evidence is best viewed as a diagnostic that raises (or lowers) concern about specific violations rather than as a definitive validation of the design (Eggers et al., 2024).

TABLE 8 Placebo lead test (future DF and current entrepreneurship)

	Intentions	*Early-stage activity*
	Placebo lead t+1	Placebo lead t+1
	(1)	(2)
ln(ESDF (t+1))	-0.50	-0.05
	(0.88)	(0.33)
ln(Non-ESDF (t+1))	-0.32	0.64
	(1.51)	(0.82)
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Num. Countries	50	50
Num. Years	19	19
Num.Obs.	367	367
R2	0.740	0.768
R2 Within	0.116	0.030

Note: Each model includes the baseline lag-2 ln(ESDF) and ln(Non-ESDF) terms and the baseline lag-2 control set, plus a lead (t+1) of ln(ESDF) and ln(Non-ESDF) as placebo terms. Two-way fixed effects (Country and Year). Standard errors clustered by country in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

ONLINE APPENDIX REFERENCES

Chawla, N. V. (2010). Data mining for imbalanced datasets: An overview. In O. Maimon & L. Rokach (Eds.), *Data Mining and Knowledge Discovery Handbook* (pp. 875–886). Springer, Boston, MA.

Eggers, A. C., Tuñón, G., & Dafoe, A. (2024). Placebo tests for causal inference. *American Journal of Political Science*, *68*, 1106–1121.

Leszczensky, L., & Wolbring, T. (2022). How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. *Sociological Methods and Research*, *51*, 837–865.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*, 1417–1426.

Toetzke, M., Stünzi, A., & Egli, F. (2022). Consistent and replicable estimation of bilateral climate finance. *Nature Climate Change*, *12*, 897–900.

Wilkins, A. S. (2018). To lag or not to lag?: Re-Evaluating the use of lagged dependent variables in regression analysis. *Political Science Research and Methods*, *6*, 393–411.