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ORIGINAL ARTICLE

Aiding Higher Education with Export Expansion in the Developing World

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Abstract

The recent change towards advanced technologies favors skill-intensive labor, motivating workers to upgrade their educational achievements to the tertiary level. However, workers in many developing countries cannot exploit the opportunity for premium wages in skill-intensive sectors owing to insufficient education facilities and resources. In such contexts, aid to education provides a capacity-building tool to eliminate the insufficiency but is often unsuccessful. Using theories of trade and human capital, this study argues that complementarity between education aid and skill-intensive manufactured exports creates a synergistic effect in upgrading educational achievements by rectifying both structural and incentive constraints. Through extensive data analysis, the result demonstrates that skill-intensive exports enhance aid's effectiveness in increasing tertiary school enrollment, whereas neither exports nor aid alone significantly affect enrollment. It further shows that the aid–export complementarity is less relevant in low-income countries, whereas skill-intensive exports alone promote education upgrading in developed countries via the Stolper–Samuelson effect.

Keywords: Higher education; human capital; technological change; skill-intensity; development aid

1. Introduction

Trade is intrinsically related to education. In particular, export expansion represents firms' demand to hire additional labor capable of handling the specific modes of technology and thus motivates workers to pursue education to acquire the appropriate skills for employment. While an array of studies have explored the relationship between trade and education based on relative skill intensity,[1] few have paid sufficient attention to the asymmetry between the groups of developing countries that have made phenomenal progress in tertiary education enrollment since the early 1990s and those that have experienced stagnant growth.[2] Furthermore, the tertiary education enrollment rate increase for the former group is inconsistent with the

[1]The literature on the relationship between trade and education is substantial; notable ones include Findlay and Kierzkowski (1983), Levin and Raut (1997), Hickman and Olney (2011), Atkin (2016), Blanchard and Willmann (2016), Greenland and Lopresti (2016), Blanchard and Olney (2017), Li (2018), and Li et al. (2019).

[2]The World Bank (2021, 18) reported that countries in the Latin America–Caribbean and East Asia–Pacific regions made phenomenal progress in terms of their enrollment rates in tertiary schools; the average rate increased to approximately 50% in 2018 from 10% in 1978, whereas countries in Sub-Saharan Africa had a stagnant average enrollment rate of approximately 10%.

Heckscher–Ohlin (HO)-based models that indicate the rationality of having lower educational achievements for workers in developing countries where low-skilled labor is abundant.[3]

The current study seeks to fill this research gap, considering two stylized facts with important implications for the relationship between trade and education in developing countries. The first fact pertains to the production technology that has changed, not only in developed countries but also in an increasing number of developing countries, towards more skill-intensive methods owing to the spread of information, communication, and automation technologies across countries (World Bank, 1994, 2002, 2021; Berman et al., 1998; Berman and Machin, 2000; Behar, 2016). This change favors high-skilled workers by providing them with premium wages, contradicting the conventional view of skill-neutral technological change (Berman et al., 1998; Acemoglu, 2003). Such technological change, known as skill-biased technological change (SBTC), creates demand for skill-intensive labor and incentivizes workers in both developed and developing countries to pursue tertiary education to seek employment in skill-intensive sectors.

The second stylized fact considered here is that even though skill-intensive labor is in greater demand, workers in many developing countries cannot exploit the technological change owing to difficulty in upgrading their educational achievements to the tertiary level critical for skill-intensive work. This is because both financial insufficiency and bureaucratic inefficiency, persistent features of many developing countries, have created structural constraints on higher education. Studies showed that education aid, a prominent external policy intervention to reduce such constraints, has mixed results in promoting educational achievements (Asiedu and Nandwa, 2007; Dreher et al., 2008; Birchler and Michaelowa, 2016; Masino and Niño-Zarazúa, 2016; World Bank, 2021). Such inconclusive evidence on aid effectiveness runs counter to the fact that the importance of education aid is widely recognized by many donor governments and multilateral aid organizations and was reflected in United Nations' programs, including the World Declaration on Education for All in 1990, Millennium Development Goals in 2000, and Sustainable Development Goals in 2015. By 2018, tertiary education, including post-secondary technical and managerial training, had become the main recipient sector, attracting approximately 40% of education aid budgets by members of the Development Assistance Committee (DAC) of the Organization for Economic Cooperation and Development (OECD).[4] The gap between aid concentration on tertiary education and uncertain effectiveness suggests that the educational facilities and resources funded by the aid are underused and fail to stimulate higher educational achievements, leaving many workers with low achievements in low-skilled work (Heyneman and Lee, 2016; Masino and Niño-Zarazúa, 2016; Miningou, 2019). The prevalence of low educational achievements across developing countries is seemingly congruent with the insight from the HO-based models but is essentially inconsistent with these models because it occurs under technological and structural conditions that differ from the assumptions underlying the models. Taken together, these stylized facts imply an inconsistency between the technological change demanding higher skills and the constraints preventing education upgrading in developing countries.

This study draws on the theories of trade and human capital development to analyze how this inconsistency can be overcome. It argues that skill-intensive manufactured exports, which derive from trade and investment openness, create aggregate demand for high-skilled labor. This motivates workers to improve their abilities to handle advanced technologies to earn premium wages in skill-intensive sectors. To accomplish this, workers leverage the higher education facilities funded by aid. Without such aid, they may forego skill improvement owing to the structural

[3]See Findlay and Kierzkowski (1983) and Levin and Raut (1997) for HO-based models that link trade and education. See Hickman and Olney (2011), Atkin (2016), Greenland and Lopresti (2016), and Blanchard and Olney (2017) for empirical studies.

[4]The author's calculation based on data from the OECD (2022).

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constraints associated with higher education and remain content with lower achievements and lower wages in low-skilled sectors. In contrast, without skill-intensive exports, workers may be discouraged from using the education facilities and resources funded by aid. Therefore, the aid–export complementarity is key to creating a synergistic effect for upgrading educational achievements by simultaneously eliminating the structural and incentive constraints on higher education.

To evaluate the above argument, this study analyzes panel data on the experiences of 87 middle-income developing countries, from 1995 to 2019, when an increasing number of developing countries entered the World Trade Organization (WTO) system for trade liberalization with the expansion of tertiary education enrollment. Using a system generalized method of moments (GMM) estimator for linear dynamic panel data models, the study demonstrates that skill-intensive manufactured exports enhance the effectiveness of education aid in increasing tertiary school enrollment, whereas neither skill-intensive exports nor education aid alone significantly affect enrollment. An extended analysis shows that aid–export complementarity is pertinent to middle-income countries and less relevant to low-income countries in which change to advanced technology is limited. In contrast, education upgrading in developed countries occurs via the Stolper–Samuelson effect whereby workers respond to an increasing demand for high skills in conjunction with skill-intensive exports by taking advantage of the countries' rich tertiary education facilities and resources.

This study makes two important contributions to the literature on trade and education. First, while Blanchard and Olney (2017) showed that skill-intensive exports are sufficient for increasing the years of schooling, including tertiary enrollment, in the sample of both developed and developing countries, this study is the first to suggest that, particularly in developing countries, skill-intensive exports alone are insufficient; they need to be complemented by education aid to offset structural constraints on tertiary schooling. Second, while existing education aid studies, including Kremer (2003) and Masino and Niño-Zarazúa (2016), focus on merit scholarships and participatory school management as domestic incentives for schooling, this study shows that skill-intensive exports provide an external incentive that is more relevant to post-graduation wages that rational individuals wish to increase and complement aid in increasing tertiary enrollment. In summary, this study is novel as it reveals that tertiary enrollment expansion in developing countries requires both supply-side capacity-building assistance and demand-side material incentives, which have received limited attention in the literature on trade and that of aid, respectively.

The rest of this paper is structured as follows. First, it reviews extant studies on the effects of education aid and trade on school choices. From a critical literature review, it formulates an hypothesis for aid–export complementarity. Second, the empirical section evaluates the hypothesis in middle-income countries, and compares it with low- and high-income countries. The concluding section summarizes the findings and presents the limitations of the study and directions for future research.

2. Literature Review and Hypothesis Development

2.1 Human Capital Accumulation for Development and the Role of Aid

Education affects post-graduation employment. In his path-breaking study on human capital, Becker (1994) articulates that the incentives to acquire education include a time-discounted function of the expected wages associated with schooling, tuition, and other opportunity costs. Such wages reflect the valuation of human capital, including individual characteristics such as intelligence, ability, skill, experience, and competence, which are nurtured through education that helps one adapt to technological change (Lucas, 1988; Romer, 1990; Barro, 2013; Hanushek and Woessmann, 2015).

Despite the importance of technological change, the supply-side capacity of tertiary education for skill improvement varies between countries. Numerous studies on development show that an insufficient education infrastructure and resources in the average developing country is a serious issue. For instance, Masino and Niño-Zarazúa (2016) argue that much of the insufficiency has a domestic origin, including budgetary constraints for large underserved populations, weak bureaucratic capacity to manage policies, varied needs and interests that complicate the pursuit of an education policy, and social norms and economic conditions that impede higher education.

One way to rectify the structural causes of the insufficiency is to provide capacity-building assistance to improve the education infrastructure, including learning materials and teacher training in the relevant countries (Asiedu and Nandwa, 2007; Dreher et al., 2008; Birchler and Michaelowa, 2016). Recent studies, cited below, on educational development focus on education aid as a crucial capacity-building intervention to address the insufficiency and analyze its effects on educational achievement and income. The studies are categorized into two types: (1) macro statistical studies that utilize panel data on aid expenditures to assess the effects on school enrollment and economic growth (Asiedu and Nandwa, 2007; Dreher et al., 2008; Birchler and Michaelowa, 2016) and (2) randomized controlled trials or quasi-experiments to assess the impact of educational interventions on educational achievement and future income (Duflo, 2001; Kremer, 2003; Glewwe et al., 2014).

A multitude of studies have pursued either of the types by employing different models and data. Although the findings are mixed, the following general patterns emerge. First, as concluded by Masino and Niño-Zarazúa (2016), there are difficulties, such as addressing structural constraints and improving supply-side capacities, in obtaining education aid for the physical infrastructure, learning materials, and teacher training. However, education aid can more effectively improve education quality when complemented with demand-side incentive programs, such as school vouchers, merit-based scholarships, and community participation. Second, while education aid has a positive effect on primary school enrollment, it has a much weaker effect on enrollment at higher school levels that are crucial for human capital under technological change (Michaelowa and Weber, 2008). This is at odds with the fact that aid for higher education accounts for a large part of total education aid budgets (Michaelowa and Weber, 2008; Birchler and Michaelowa, 2016). A major reason for such ineffectiveness may be that the incentive constraint becomes more severe as the education level goes up, owing to the higher tuition and opportunity costs and greater structural constraints. This implies that the intensity of incentive constraints is an inverse function of personal income, which Kremer (2003) and Masino and Niño-Zarazúa (2016) find can be rectified through domestic incentive programs comprising merit scholarships and school vouchers.[5]

2.2 Trade as an Incentive for Skill Enhancement

Besides domestic programs, Findlay and Kierzkowski (1983) and Blanchard and Olney (2017) argue that manufactured exports provide a powerful external incentive for skill enhancement, which is more relevant to the post-graduation wages that rational individuals wish to maximize. This is because the manufacturing sector employs many workers who specialize in specific tasks at various stages of production. Findlay and Kierzkowski (1983) developed an HO-based model, which links the skill intensity of a country's exports to educational investment by individuals. Their model conceptualizes education choices by clarifying how trade influences relative prices and the returns on skill or wages through the Stolper–Samuelson effect. For instance, if a country has a comparative advantage in producing skill-intensive manufactured products under open trade, the relative prices of such products will rise. This relative price increase will augment the relative demand for higher skills and the skilled wage premium, which will induce more individuals to invest in higher education, further enhancing the skill-intensive sector's productivity.

[5]Antràs et al. (2017) demonstrate that domestic redistributive programs can rectify income inequality arising from skill asymmetries under open trade. Education aid addressed in this study is expected to play a similar role.

By contrast, if a country has a comparative advantage in labor-intensive or low-skilled production, trade openness will increase the demand for low-skilled labor, hence discouraging higher education not required for low-skilled work.[6]

However, an increasing number of empirical studies (e.g., Berman et al., 1998; Berman and Machin, 2000; Goos et al., 2014; Behar, 2016; Pi and Zhang, 2018) show that shifts to advanced technologies (personal computers, automated packaging, and other capital goods) that favor high skills have occurred in developed countries and have gradually been affecting (middle-income) developing countries, thus raising the demand for skilled labor in both regions. Shapiro and Mandelman (2021) show that premium wages for higher skills have risen in both developed and developing countries, thus stimulating the growth of skilled labor on a global scale.[7] These empirical findings reject a naïve interpretation of the Stolper–Samuelson effect based on factor endowment, which posits that trade openness increases the returns to unskilled workers in developing economies with abundant low-skilled labor.

2.2.1 Impact of Skill-Biased Technological Change

The recent technological change appears to be skill-biased because it increases the relative demand for high-skilled labor, refuting the conventional view of skill-neutral technology. This technological change, or SBTC, affects a multitude of industrial sectors, including labor-intensive sectors, in high- and middle-income countries. At least three hypotheses have been advanced to model pathways through which SBTC traverses across countries and affects skill intensity.

Acemoglu (2003) develops a model of endogenous technological change based on the HO theorem in which he argues that trade openness enhances the demand for high-skilled labor under the assumption of production with abundant factors complementary to high-skilled labor. This is because trade openness intensifies international competition and motivates firms to efficiently produce goods through skill-intensive sectors. In developing countries, this technological change may take the form of increased imports of widely accessible technologies that require skilled labor. Trade liberalization increases the demand for skilled labor by reducing the prices of the relevant capital goods, and hence, increasing their imports.

The second hypothesis, advanced by Epifani and Gancia (2008), relies on oligopolistic competition, rather than perfect competition assumed in the HO theorem. It predicts that an increase in trade volume involves skill-intensive production, because trade expands the market size of an economy and accelerates increasing returns. In relative terms, output increases more rapidly in skill-intensive sectors that exploit economies of scale and raise the relative wage of high-skilled labor. Thus, trade openness combined with the availability of technology may increase the relative demand for high-skilled labor through increasing returns in skill-intensive sectors, even in developing countries.

Feenstra and Hanson (1997) advance the third hypothesis in which they focus on foreign direct investment based on the assumption that the production of final goods can be split into intermediate stages with varying skill intensities. To minimize the production costs, firms rationally outsource some of the production processes at intermediate stages to foreign locations, including developing countries. This outsourcing strategy becomes possible when the countries open their markets through the liberalization of trade and investment. When the production that is shifted abroad uses advanced technology and requires skill-intensive labor, the outsourcing strategy increases the average skill intensity of production and skill premium wages in the developing countries.

[6]Atkin (2016) found that the expansion of job opportunities in export sectors increased the high school dropout rate during the period of rapid trade liberalization in Mexico. Similarly, Li et al. (2019) demonstrate that trade liberalization in China is reducing the completed years of schooling owing to the expansion of job opportunities in low-skilled sectors.

[7]Country-specific studies provide evidence for the relationship between technological change and educational achievement. Li (2018) demonstrates that the composition of skills in export affects school choices in China; high-skilled export shocks raise both high school and college enrollment, while low-skill export shocks reduce both. Heath and Mobarak (2015) find that female school enrollment in Bangladesh increases with manufacturing growth in the garment industry.

2.2.2 Education Aid

The three hypotheses conceptualize the pathways to skill enhancement based on the assumption that sufficient education infrastructure and resources exist and enable workers to shift from a low- to a high-skilled labor force in accordance with technological change.[8] However, the realization of an incentive for acquiring high skills depends on the supply-side education capacity in which developed and developing countries sharply diverge. This asymmetry is due to the insufficiency of the supply-side capacity in developing countries, which education aid seeks to rectify. The improved school facilities and resources, funded by aid, can respond to the demand for higher education that results from high-skilled manufactured exports through some of the pathways modeled in the hypotheses. Motivated to improve their skills to attain premium wages, workers and their families pressure the recipient countries' governments to efficiently use education aid to enhance school facilities and services by removing bureaucratic inefficiency as another structural constraint. Therefore, a combination of both high-skilled exports and education aid is key to creating demand- and supply-side impetuses for tertiary education in developing countries. This argument is operationalized into the following testable hypothesis:

> *Hypothesis: High-skilled manufactured exports increase the effectiveness of education aid in improving tertiary education enrollment in developing countries.*

3. Empirical Analysis

3.1 Model

To test the hypothesis, an empirical model was constructed to account for the levels of tertiary education enrollment in developing countries under varying quantities of education aid and high-skilled manufactured exports. The model is expressed as follows:

$$TEE_{it} = \alpha_0 + \alpha_1 TEE_{it-1} + \alpha_2 AID_{it-1} \cdot HSE_{it-1} + \alpha_3 AID_{it-1} + \alpha_4 HSE_{it-1} + \alpha_5 LSE_{it-1} + \alpha_6 AGE_{it-1} + \boldsymbol{X}_{it-1}\boldsymbol{\beta} + D_i + u_{it}.$$

3.1.1 Dependent Variable

The model accounts for the logarithm of TEE_{it}, which is the tertiary education enrollment in middle-income country i in year t, measured as the gross enrollment ratio for tertiary (higher) education for both sexes (%). It focuses on tertiary education because it nurtures cognitive capacity, which is crucial for skill-intensive work (World Bank, 1994, 2002, 2021). Further, it provides workers in four out of six developing regions with higher rates of return to investment in higher education than other levels of schooling (Montenegro and Patrinos, 2014).

My study does not use the years of schooling, the main dependent variable in the study by Blanchard and Olney (2017), because it cannot distinguish higher- from lower-levels of education, crucial for evaluating the hypothesis. Instead, the current study focuses on tertiary school enrollment in middle-income countries that have been experiencing SBTC that creates demand for skill-intensive labor.[9] By comparison, low- and high-income countries are analyzed to evaluate differences from middle-income countries. The data on the tertiary enrollment variable, created by the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics, were drawn from the *World Development Indicators*, the World Bank's

[8]Kremer and Holla (2009) demonstrate that supplying information on how earnings rise with education can increase schooling.

[9]The analysis used the World Bank's classification of countries based on gross national income in 2019 – the final year of the sample. Given that gross national income usually increases over time, setting the benchmark year earlier would bias hypothesis testing because some of the sample countries became high-income countries during the estimation period.

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(2022) database.[10] The UNESCO data are available from 1990 for a sufficiently large number of developing countries. The enrollment data were linearly interpolated to fill in missing values and were logged to correct for a positively skewed distribution owing to a disproportionate number of developing countries with low tertiary school enrollment ratios. For robustness, the model was estimated for the unlogged data, which yielded the coefficient estimates that do not alter the interpretation of the result based on the logged data reported in the text, although the level of statistical significance was lower owing to the remaining skewedness in the unlogged data, and the estimated coefficient of the lagged dependent variable exceeded unity (see Table 4A for the estimates of the unlogged data).

3.1.2 Independent Variables

The model evaluates the hypothesis by analyzing to what extent TEE_{it} is affected by the complementarity between education aid and exports. The key independent variable is the interaction term, denoted by $AID_{it-1} \cdot HSE_{it-1}$. The former is the logarithm of education aid to post-secondary (or tertiary) school committed by all DAC donors (bilateral and multilateral) to country i in year $t-1$ to model the nonlinear relationship between school enrollment and education aid (Miningou, 2019), while the latter is the logarithm of skill-intensive (or high-skilled) manufactured exports (USD) to the rest of the world by country i in year $t-1$.

The coefficient of the interaction term α_2 measures the extent of the aid–export complementarity regarding tertiary-level achievement in country i. Hence, α_2 is used to evaluate the hypothesis predicting a positive effect of the aid–high-skilled export complementarity on tertiary enrollment. AID_{it-1} and HSE_{it-1} are separately entered into the model to capture the marginal effects of aid and high-skilled exports on tertiary enrollment.

Regarding donors, this study focuses on OECD/DAC member countries because they have been more mindful of Education for All than non-DAC donors and created the international development targets in 1996, which were then converted to the Millennium Development Goals (Carbonnier et al., 2014). Non-DAC donors began to allocate aid in the mid-2000s, much later than DAC donors, and the share of education aid by the former is much smaller than that by the latter.

Other trade-related variables in the model are LSE_{it-1} and ARE_{it-1}, low-skilled manufactured exports and agricultural exports, respectively, both of which are likely to reduce tertiary enrollment by increasing the demand for low skills at the expense of high skills. All these terms are lagged by one year to capture a delayed effect on school choices. Additionally, the model includes the lagged dependent variable to capture persistence in enrollment. The variable also removes time-specific fixed effects from the model (see the result of the relevant test in Appendix 3A). The data on exports and education aid are elaborated as follows.

Trade data are from the COMTRADE dataset created by the United Nations Conference on Trade and Development (United Nations Statistics Division, 2022). This dataset reports country-level exports in nominal US dollars by 4-digit SITC industry, which are used to construct the independent variables. Following Blanchard and Olney (2017), the analysis uses three distinct components of exports: agriculture, low-skilled manufactures, and high-skilled manufactures. Agricultural exports are calculated as the sum of the exports in SITC industries 0, 1, 2, and 4, whereas manufactured exports are the sum of exports in SITC industries 6, 7, and 8. These manufacturing industries are divided into low- and high-skilled ones, using the classification scheme by Blanchard and Olney (2017) with respect to the contents of skill and technology. Agricultural

[10]The World Bank defines gross enrollment ratio as 'the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown' (https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SE.TER.ENRR). The ratio may exceed 100% or the population of the age group that officially corresponds to the level of education, if there is late enrollment, early enrollment, or repetition (https://datahelpdesk.worldbank.org/knowledgebase/articles/114955-how-can-gross-school-enrollment-ratios-be-over-100). No adjustment was made on the data for the empirical analysis to maintain the original measurement.

exports are reported as being homogenous in the COMTRADE dataset, and viewed as undifferentiated by skill in this study, with the qualification that the estimated effects might conceal potential skill heterogeneity in agricultural trade.

To collect data on the education aid by DAC members, this study used the Creditor Reporting System (CRS) provided by the OECD (2022). In the CRS categorization, education aid includes programs on education policy and administration, school facilities and equipment, teacher training, and educational research that contribute to building education infrastructure. The CRS offers aggregate data on education aid for all school levels, including post-secondary or tertiary level, and disaggregate aid data for various school levels from 1995. The data on post-secondary education aid were used to estimate the model, as the most relevant aid series for the hypothesis. For robustness, the data on total education aid were used to reestimate the model. This is because education is cumulative in the sense that higher-level achievement requires lower-level schooling (Birchler and Michaelowa, 2016). The estimate of the key coefficient with total education aid (see Table 4A) was consistent with that based on post-secondary education aid reported in the text and a bit smaller because a part of the total aid is spent for a portion of students who reach the tertiary level.

3.1.3 Control Variables

The model includes control variables: $\boldsymbol{X}_{it-1}$. The lack of data limits the set of time-variant country-specific control variables because relatively few data series cover the countries and years on education, trade, and aid. Blanchard and Olney (2017) note that, for this reason, the specification needs to maximize sample size by including the most relevant controls. Following Blanchard and Olney (2017), the baseline specification in the current study includes total (real) imports, population, nominal gross domestic product (GDP), and death rate per 1,000 people, sourced from the World Development Indicators (WDI) provided by the World Bank, except for the share of immigrants in the population. The data on immigration are available only in five-year intervals, and thus, are removed from the model to maintain a significant sample size.[11] A sensitivity analysis was conducted to check the robustness of the estimation by including less available additional control variables, education expenditure, foreign direct investment inflow, democratic level, government effectiveness, regulatory quality, and the rule of law, and treating them as endogenous.[12] The estimates with the additional variables are reported in Table 4A and do not alter the interpretation of the aid–export complementarity in the main text.[13]

3.2 Estimation Procedures

The model was estimated for 1995–2019 based on panel data covering 87 middle-income countries that were merged from the datasets for the variables cited earlier. Although data availability was restrictive, the estimation period represents an era in which tertiary education enrollment steadily increased in the developing world. Hence, the effect can be estimated.[14] The model has potential endogeneity biases because aid and high-skilled manufactured exports affect tertiary enrollment, while the enrollment affects aid and the exports. Hence, to account for endogeneity, the two-step system GMM estimator with panel data was used (Blundell and Bond, 1998). This estimation technique is appropriate for reducing sample bias in the panel data that include all 87

[11]Another reason for removing the immigrant variable from the model was that it was uncorrelated with school enrollments and years of schooling in the study by Blanchard and Olney (2017).

[12]The data on all these variables were drawn from the WDI dataset, except for democracy (polity2), which was taken from the Integrated Network for Societal Conflict Research (2022).

[13]Some of the equations suffer from misspecifications perhaps due to missing data.

[14]See Table 1A for the descriptive statistics of the variables and Appendix 2A for the list of the middle-income countries covered in the analysis.

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countries exceeding the sample period of 24 years.[15] Kiviet et al. (2017) note that, owing to the flexibility of GMM, it is difficult to make a reasonable choice from the numerous implementation options available in the estimator. To overcome this problem, a sequential selection procedure was adapted from Kiviet (2020) and Kripfganz (2019) and is elaborated in Appendix 3A.

The specification determined through the selection procedure eliminates the unobserved country-specific fixed effects, D_i, by first differencing, while instrumenting the lagged dependent variable, TEE_{it-1}, with the second-lagged first differences, that are highly correlated with the lagged dependent variable but uncorrelated with the error term, u_{it}.[16] It further instruments the endogenous variables with the second-lagged first differences that are orthogonal on the fixed effects. The two-step system GMM estimator entails a system of two equations comprising the differenced and level models with additional moment conditions, to improve efficiency with a collapsed instrument matrix (Roodman, 2009).

3.3 Estimation Results

3.3.1 Main Finding

Table 1 lists the system GMM estimates of the model.

In column (1) of Table 1, the GMM estimates of the interactive model demonstrate that the most important coefficient, α_2, for the interaction term between higher education aid and high-skilled manufactured exports is positive and significant at the 95% confidence level. The direction and significance of the coefficient estimate in column (1) are consistent with those in the alternative estimation techniques – difference GMM and difference two-stage least squares (2SLS) – and less so with difference ordinary least squares (OLS), while the magnitude and efficiency are greater in the system GMM than in the difference GMM, as argued by Blundell and Bond (1998) (see Table 5A for the estimates of the alternative techniques). These results render empirical support to the hypothesis that the aid–export complementarity has a synergistic effect in increasing tertiary enrollment.

In contrast, the estimated marginal effect of education aid in column (1) is negative, meaning that education aid has a reducing effect on tertiary enrollment in the countries where high-skilled exports are zero. This is perhaps because these countries have relatively backward production technology and abundant low-skill-intensive labor, prompting the governments to use aid money in accordance with such factor endowment, for instance, to construct tertiary school buildings with low-skill-intensive workers, rather than to hire competent instructors and acquire library books. Thus, contrary to the stated goal, the higher education aid reduces tertiary enrollment by augmenting demand for low-skill-intensive labor at the expense of skill-intensive labor.

In addition, the estimated marginal effect of high-skilled manufactured exports is insignificant without aid and aid–export interaction. This means that even if high-skilled exports occur, the tertiary education facilities and resources not funded by aid remain insufficient and could not attract an enrollment increase. This adds further empirical support to the hypothesis that, on average, high-skilled exports need to be complemented by education aid to create a positive effect on tertiary enrollment in middle-income countries.

The lower panel of Table 1 provides test statistics on the system GMM estimation. In all cases, the Arellano–Bond test statistics for AR(1) and AR(2)-type serial correlation in all equations suggest that there is first-order serial correlation in the differenced residuals, but there is no second-order serial correlation. The Sargan–Hansen J-test reports the p-values for the null hypothesis of the validity of the over-identifying restrictions. In all specifications, the p-values

[15]The difference GMM estimator proposed by Arellano and Bond (1991) is likely to suffer from small sample bias when it is used for the panel data, characterized as being short and wide, and the dependent variable is highly persistent (Alonso-Borrego and Arellano, 1999).

[16]Time effects were statistically insignificant and removed from the model for parsimony. See Appendix 3A for this result.

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Table 1. Effect fo high-skilled manufactured exports on the effectiveness of education aid in increasing tertiary school enrollment

Regressors	(1) Interactive	(2) Additive	(3) No Aid
Lagged dependent variable	0.820***	0.786***	0.800***
	(0.107)	(0.230)	(0.0817)
Higher education aid*high-skilled manufactured exports	0.00964**		
	(0.00487)		
Higher education aid	−0.174**	0.00967	
	(0.0876)	(0.0105)	
High-skilled manufactured exports	−0.0160	0.00967	0.0109
	(0.0152)	(0.0146)	(0.0166)
Low-skilled manufactured exports	0.0356	0.0297	0.0539
	(0.0242)	(0.0541)	(0.0400)
Agricultural exports	−0.0151	−0.0171	−0.0320
	(0.0296)	(0.0359)	(0.0469)
GDP	0.0465	0.0774	0.00776
	(0.0777)	(0.133)	(0.159)
Real imports	0.0141	0.0380	0.0990
	(0.0350)	(0.0882)	(0.107)
Population	−0.181	−0.249	−0.249**
	(0.125)	(0.256)	(0.107)
Death rate	−0.191	−0.109	−0.111
	(0.165)	(0.270)	(0.226)
Constant	2.573**	2.456	3.573
	(1.197)	(2.014)	(2.821)
Observations	1,297	1,297	1,464
Arellano–Bond test statistic for AR(1)	0.013	0.066	0.020
Arellano–Bond test statistic for AR(2)	0.175	0.264	0.217
Sargan–Hansen over-identification J-test (p-value)	0.596	0.173	0.093
Windmeijer under-identification test (p-value)	0.000	0.001	0.000

Notes: All equations are estimated via a two-step system GMM estimator (Blundell and Bond, 1998). All regressors are logged and lagged by 1 year. The robust standard errors are calculated by applying the Windmeijer (2005) finite-sample correction to the two-step GMM estimator; ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The Arellano–Bond test statistics for AR(1) and AR(2)-type serial correlation in the first differenced residuals are from Arellano and Bond (1991). The Sargan–Hansen over-identification test is from Sargan (1958) and Hansen (1982). The Windmeijer under-identification test is from Windmeijer (2018).

do not reject the null hypothesis. Further, the p-values of the under-identification test by Windmeijer (2018) reject the null that the instruments are under-identified.

The variants of the GMM model in Table 1 were compared to confirm the validity of the aid–export complementarity. The comparison used model selection criteria known as the Andrews and Lu (2001) model and moment selection criteria (MMSC). Particular attention was paid to the Bayesian (BIC) and Hannan–Quinn information criteria (HQIC), which subtract a bonus term from the over-identification test statistic and reward fewer coefficients for a given number

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Table 2. Model comparison: Andrews and Lu model and moment selection criteria

Model	Number of Moments	Number of Parameters	MMSC-AIC	MMSC-BIC	MMSC-HQIC
Model 1: Interactive	21	11	−11.6722	−36.4456	−21.9526
Model 2: Additive	19	10	−5.2264	−27.5224	−14.4787
Model 3: No aid	17	9	−4.4773	−27.2707	−13.9527

Notes: The numbers of the models correspond to the column numbers in Table 1. The preferred model is selected using the Andrews and Lu model and moment selection criteria (MMSC) based on likelihood selection criteria (Akaike [AIC], Bayesian [BIC], and Hannan–Quinn [HQIC] information criteria) (Andrews and Lu, 2001).

of moment conditions. Table 2 reports the results of the model comparison and shows that the interactive model has smaller BIC and HQIC values than both the additive and no-aid models and is, therefore, superior. This means that the aid–export complementarity is an integral part of the data generating process on tertiary education enrollment in middle-income countries affected by SBTC through high-skilled exports.

3.3.2 Coefficient Consistency

To assess consistency in the estimated extent of the aid–export interaction, the GMM estimation of the interactive model in column (1) of Table 1 was used to construct a graph. Figure 1 plots the average marginal effects of high-skilled manufactured exports on tertiary enrollment conditioned

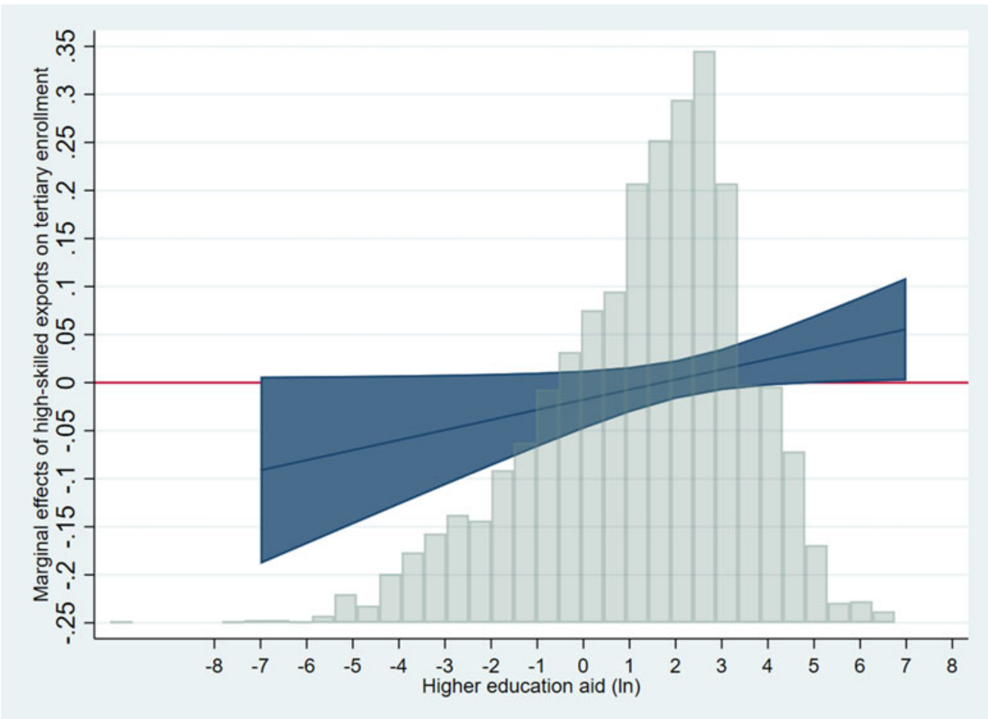

Figure 1. Marginal effects of high-skilled manufactured exports on tertiary education enrollment conditioned by education aid.

Notes: The graphs are created from the system GMM estimation of the interaction model reported in column (1) of Table 1. CIs represent the upper and lower 95% confidence intervals. The bars indicate the distribution of aid to post-secondary education.

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by education aid. In the figure, the positively shaped line, sandwiched by the upper and lower 95% confidence intervals, indicates that the marginal effect of high-skilled exports on enrollment increases in accordance with the amount of aid. The histogram indicates the distribution of aid as the moderating variable, to evaluate the sensitivity of the interaction model to the range of the

Table 3. Effect of skill-intensive manufactured exports on tertiary education enrollment: low- and high-income countries

Regressors	(1) Low Income Interactive	(2) Low Income No Aid	(3) High Income No Aid
Lagged dependent variable	1.229***	1.228***	0.835***
	(0.124)	(0.146)	(0.0647)
Higher education aid*high-skilled manufactured exports	0.00618		
	(0.00700)		
Higher education aid	−0.102		
	(0.113)		
High-skilled manufactured exports	0.0169	0.0101	0.0361***
	(0.0242)	(0.0320)	(0.0126)
Low-skilled manufactured exports	−0.0257	−0.0339	−0.0432***
	(0.0235)	(0.0215)	(0.0154)
Agricultural exports	−0.0181	−0.0284	−0.00228
	(0.0357)	(0.0428)	(0.0112)
GDP	−0.139	−0.151	−0.0823***
	(0.0980)	(0.120)	(0.0308)
Real imports	0.0299	0.0284	0.0958***
	(0.0463)	(0.0941)	(0.0334)
Population	0.195*	0.194*	0.133**
	(0.114)	(0.108)	(0.0660)
Death rate	0.273	0.0867	0.0269
	(0.334)	(0.408)	(0.0605)
Constant	−0.568	0.624	0.351
	(1.705)	(2.794)	(0.352)
Observations	302	311	1,077
Arellano–Bond test statistic for AR(1)	0.016	0.018	0.004
Arellano–Bond test statistic for AR(2)	0.619	0.901	0.192
Sargan–Hansen over-identification J-test (*p*-value)	0.609	0.290	0.101
Windmeijer under-identification test (*p*-value)	0.042	0.034	0.003

Notes: All equations are estimated via a two-step system GMM estimator (Blundell and Bond, 1998). All regressors are logged and lagged by one year. The robust standard errors are calculated by applying the Windmeijer (2005) finite-sample correction to the two-step GMM estimator; ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The Arellano–Bond test statistics for AR(1) and AR(2)-type serial correlation in the first differenced residuals are from Arellano and Bond (1991). The Sargan–Hansen over-identification test is from Sargan (1958) and Hansen (1982). The Windmeijer under-identification test is from Windmeijer (2018).

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moderating variable. The estimated slope indicates that a 10% increase in high-skilled exports leads to an approximately 0.1% change in tertiary enrollment across various values of aid: $100 \cdot (1.1^{0.0964} - 1) \approx 0.1$. Comparison of the histogram and the confidence intervals suggests that significance occurs at relatively large volumes of aid to reflect the fact that large financial resources are required to improve higher education to attract enrollment. This again demonstrates that aid needs to complement high-skilled exports to increase tertiary enrollment.

3.3.3 Low- and High-Income Countries

By extension, the GMM model was estimated for low- and high-income countries, expecting major differences from middle-income countries. In low-income countries, aid is unlikely to increase tertiary enrollment because demand for skill-intensive labor is weak in the absence of significant technological change (Berman et al., 1998; Behar, 2016). By contrast, high-income countries, which rarely receive education aid, have rich tertiary education facilities and resources through which workers can relatively easily upgrade their educational achievements in response to aggregate demand for skill-intensive labor owing to high-skilled exports.

The results of the GMM estimation are reported in Table 3 and consistent with expectations. Columns (1) and (2) report the estimates for low-income countries in which neither the aid–export complementarity nor high-skilled exports are correlated with tertiary enrollment. Column (2) shows that, in high-income countries, the effect of high-skilled exports on tertiary enrollment is positive and significant. The test statistics on the lower panel of Table 3 indicate that the GMM estimation is valid in all cases.

The results in Tables 1 and 3 together suggest that the aid–export complementarity is most pertinent in middle-income countries but absent from low-income countries. High-income countries provide the case in which skill-intensive exports alone promote higher educational achievements via the Stolper–Samuelson effect. The difference lies in the availability of sophisticated education facilities and resources and access to advanced production technologies, both of which are insufficient in low-income countries; therefore, the aid–export complementarity cannot have a significant effect on tertiary enrollment.

4. Conclusion

Higher education contributes to economic growth via adaptation to technological advancement. This holds under the recent SBTC that provides premium wages for skill-intensive labor trained through tertiary education. However, precise mechanisms for promoting tertiary-level schooling are poorly understood, and this is particularly pertinent to developing countries with various constraints on educational achievements. This study demonstrates that a combination of high-skilled manufactured exports and aid to education creates a significant synergistic effect in terms of supporting tertiary school enrollment by simultaneously reinforcing supply-side capacity and providing a demand-side impetus for higher skills. This aid–export complementarity is relevant to middle-income countries with access to education aid and advanced technologies via trade and investment openness, whereas it is still inconsequential in low-income countries without sufficient accesses. Therefore, the result suggests that the recent technological change in favor of high skills creates another source of development asymmetry and aid ineffectiveness that plague low-income countries.

Despite the novel finding, this study has several limitations. First, it did not demonstrate the origins of access to advanced technology in middle-income countries that creates the initial high-skilled manufactured exports for aggregate demand for skill-intensive labor, the key to differentiate between middle- and low-income regions (Li, 2018). It relied on the assumption that such access comes from trade and investment openness. Second, the study focused on the positive effect of tertiary education on human capital accumulation but overlooked its potential adverse effect in increasing income inequality, which aggravates political instability and economic growth

(Alesina and Perotti, 1996). Not all students are competent enough to attend college even if the demand for high skills and education aid is present. Students with low competence who are not direct beneficiaries of the aid–export complementarity would remain low-skilled with lower wages. The resulting increase in income inequality would destabilize political systems in low-income countries where income redistribution and constitutional safeguards are weak at best.

To avoid the vagaries of political instability, policymakers would avoid market openness and forego opportunities for technological change and human capital development or use the risk of political instability as an excuse for market closeness. Hence, it is important to provide less competent students with remedial school programs to prevent increases in income inequality and facilitate market openness for human capital development under political stability.[17] Therefore, future research should consider multifaceted perspectives to shed light on the complexity of education problems intrinsically related to trade and development.

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Appendix

Table 1A. Descriptive statistics for middle-income countries

Variables	Obs	Mean	SD	Min	Max
Tertiary education enrollment	1297	2.8946	.91562	−.58503	4.7293
Aid to post-secondary education	1292	2.0955	1.9789	−6.2664	6.7539
High-skilled manufactured exports	1217	19.955	3.0863	5.9691	28.035
Low-skilled manufactured exports	1217	20.358	2.9136	6.3706	27.312
Agricultural exports	1221	20.982	2.0034	12.733	25.622
GDP	1297	24.072	2.0132	19.015	30.29
Real imports	1297	5.4106	0.74044	3.5763	7.7931
Population	1297	16.357	1.9251	11.545	21.065
Death rate	1297	1.972	0.35399	0.9999	3.0255

Notes: See the text for the definitions and data sources of the variables.

Appendix 2A. List of developing (medium-income) countries

Armenia, Angola, Argentina, Azerbaijan, Bosnia and Herzegovina, Bangladesh, Benin, Brazil, Bhutan, Botswana, Belarus, Belize, Republic of Congo, Cote d'Ivoire, Cameroon, China, Colombia, Costa Rica, Cuba, Cape Verde, Djibouti, Dominican Republic, Algeria, Ecuador, Egypt, Fiji, Gabon, Grenada, Georgia, Ghana, Guatemala, Guyana, Honduras, Indonesia, India, Iraq, Iran, Jamaica, Jordan, Kenya, Kyrgyz, Cambodia, Comoros, Kazakhstan, Laos, Saint Lucia, Sri Lanka, Lesotho, Libya, Morocco, Moldova, Myanmar, Mongolia, Mauritania, Maldives, Mexico, Malaysia, Namibia, Nigeria, Nicaragua, Nepal, Peru, Papua New Guinea, Philippines, Pakistan, Paraguay, Yugoslavia, Senegal, Suriname, Sao Tome and Principe, El Salvador, Thailand, Turkmenistan, Tunisia, Turkey, Tanzania, Ukraine, Uzbekistan, Saint Vincent and the Grenadines, Venezuela, Vietnam, Vanuatu, Samoa, South Africa, Zambia, and Zimbabwe (87 countries)

Appendix 3A. Specification search procedures

This appendix outlines the sequential approach to identify a valid specification for the two-step system GMM estimation that was adapted from Kiviet (2020) and Kripfganz (2019). The search led to the identification of the specification that treats all regressors as endogenous and uses a system of equations in first differences and levels. Further, the instruments employed in

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the levels equations are the second-lagged first-differences of the endogenous series, while those used in the differenced equation are the second-lagged levels of the endogenous series. The search followed five steps:

Step 1. Time effects were examined. As the coefficients were insignificant, they were removed to reduce instrument count. Standard level instruments and robust standard errors were also chosen (Windmeijer, 2005).

Step 2. As recommended by Roodman (2009), the models were curtailed and collapsed to prevent instrument proliferation from biasing estimates to select the valid subsets of instruments through three specification tests in steps 3 and 4.

Step 3. The first test was conducted with the Arellano–Bond statistics for AR(1) and AR(2)-type serial correlation in the differenced residuals. A valid set of instruments requires first-order serial correlation in the differenced residuals, but not second-order correlation. Second, the Sargan–Hansen J-test was used to determine the validity of the over-identifying restrictions. Third, the under-identification test by Windmeijer (2018) was used to ascertain whether the instruments could sufficiently account for the endogenous variables, with H_0 being at the p-value < 0.05.

Step 4. Passing the under-identification test would likely result in failing the over-identification test. Given the tension between under- and over-identification, the Andrews and Lu (2001) MMSC was used for model selection. A pragmatic approach was to select the preferred specification that was within reasonable ranges for both over- and under-identification test statistics and minimize the MMSC criteria.

Step 5. Having correctly specified the GMM estimator, the incremental over-identification test was used to examine additional moment conditions for the level model (Kiviet, 2020).

Alternative specifications considered in the search included one that defines population and death rate as predetermined or weakly exogenous, and another that defines both as strictly exogenous, while the remaining controls are endogenous in both the specifications. The results of selection based on the MMSC criteria showed that the original specification is superior to the two alternatives (See Table 6A). The same sequential procedure was used to establish the best specifications for low- and high-income countries, which are presented in Table 3. The results were still sensitive to specifications, although they are consistent with theory, and a systematic selection procedure was used.

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Table 4A. Sensitivity analysis

Regressors	(1) Unlogged Dependent Variable	(2) Total Education Aid	(3) Expenditure & FDI	(4) Democratic Level	(5) Government Effectiveness	(6) Regulatory Quality	(7) Rule of Law
Lagged dependent variable	1.138***	0.858***	0.811***	1.006***	0.866***	0.879***	0.868***
	(0.0468)	(0.0655)	(0.107)	(0.0290)	(0.0797)	(0.0846)	(0.0947)
Education aid*high-skilled manufactured exports	0.0900*	0.00673*	0.0113**	0.00344**	0.0234**	0.0243**	0.0260**
	(0.0523)	(0.00352)	(0.00506)	(0.00167)	(0.00995)	(0.0103)	(0.0112)
Education aid	−1.708*	−0.110*	−0.206**	−0.0638*	−0.431**	−0.451**	−0.475**
	(1.009)	(0.0649)	(0.0920)	(0.0330)	(0.186)	(0.193)	(0.209)
High-skilled manufactured exports	−0.0846	−0.0119	−0.0130	−0.0137*	−0.0416	−0.0467*	−0.0435
	(0.174)	(0.0127)	(0.0219)	(0.00824)	(0.0259)	(0.0254)	(0.0294)
Low-skilled manufactured exports	0.0107	0.0418*	0.0326	0.0243**	0.0166	0.0197	0.0170
	(0.164)	(0.0222)	(0.0280)	(0.0113)	(0.0141)	(0.0140)	(0.0153)
Agricultural exports	−0.389	−0.0648	−0.0125	−0.0757***	0.0217	0.0199	0.0149
	(0.506)	(0.0441)	(0.0334)	(0.0220)	(0.0460)	(0.0483)	(0.0616)
GDP	−1.789	−0.0189	0.0531	0.0290	−0.130*	−0.129**	−0.203*
	(1.214)	(0.0656)	(0.0865)	(0.0255)	(0.0726)	(0.0649)	(0.107)
Real imports	−0.165	0.0141	0.0107	−0.00409	0.0491	0.0463	0.109*
	(0.461)	(0.0473)	(0.0304)	(0.0168)	(0.0390)	(0.0397)	(0.0595)
Population	1.949*	−0.133*	−0.159	0.0119	−0.0305	−0.0327	0.0518
	(1.051)	(0.0745)	(0.108)	(0.0295)	(0.0859)	(0.0843)	(0.101)
Death rate	−4.360**	−0.174	−0.145	−0.108	−0.158	−0.192	−0.0440
	(2.215)	(0.154)	(0.153)	(0.0697)	(0.115)	(0.147)	(0.133)
Education expenditure			−0.0181				
			(0.0491)				

(*Continued*)

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Table 4A. (*Continued.*)

Regressors	(1) Unlogged Dependent Variable	(2) Total Education Aid	(3) Expenditure & FDI	(4) Democratic Level	(5) Government Effectiveness	(6) Regulatory Quality	(7) Rule of Law
Foreign direct investment inflow			−0.00510				
			(0.00484)				
Democratic level				0.000468			
				(0.00398)			
Government effectiveness					0.0916		
					(0.0890)		
Regulatory quality						0.0496	
						(0.0971)	
Rule of law							0.285**
							(0.136)
Constant	27.59	3.979***	2.544**	0.710	4.041***	4.148***	4.107**
	(17.81)	(1.436)	(1.022)	(0.557)	(1.176)	(1.019)	(1.648)
Observations	1,316	1,308	1,202	1,142	1,083	1,083	1,083
Arellano–Bond test statistic for AR(1)	0.006	0.003	0.017	0.003	0.013	0.015	0.0161
Arellano–Bond test statistic for AR(2)	0.734	0.168	0.177	0.814	0.007	0.010	0.0139
Sargan–Hansen over-identification J-test (*p*-value)	0.598	0.410	0.601	0.545	0.879	0.788	0.893
Windmeijer under-identification test (*p*-value)	0.250	0.102	0.011	0.062	0.003	0.033	0.000

Notes: All equations are estimated via a two-step system GMM estimator (Blundell and Bond, 1998). All regressors are logged and lagged by one year. The robust standard errors are calculated by applying the Windmeijer (2005) finite-sample correction to the two-step GMM estimator; ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The Arellano–Bond test statistics for AR(1) and AR(2)-type serial correlation in the first differenced residuals are from Arellano and Bond (1991). The Sargan–Hansen over-identification test is from Sargan (1958) and Hansen (1982). The Windmeijer under-identification test is from Windmeijer (2018).

Table 5A. Alternative estimation techniques

Regressors	(1) Dif–GMM	(2) Dif–OLS	(3) Dif–2SLS
Lagged dependent variable	0.712***	0.293***	0.599***
	(0.148)	(0.0470)	(0.119)
Education aid*high-skilled manufactured exports	0.00471*	0.00155*	0.00148**
	(0.00265)	(0.000819)	(0.000730)
Education aid	−0.0845*	−0.0256	−0.0241
	(0.0507)	(0.0165)	(0.0147)
High-skilled manufactured exports	−0.0131	−0.00967	−0.00932*
	(0.0168)	(0.00618)	(0.00487)
Low-skilled manufactured exports	0.0458***	0.00189	0.00667
	(0.0161)	(0.00509)	(0.00542)
Agricultural exports	−0.00802	−0.00901	−0.0156
	(0.0329)	(0.0126)	(0.0172)
GDP	0.0499	0.0255	0.0356
	(0.108)	(0.0225)	(0.0247)
Real imports	0.00952	0.00886	−0.0134
	(0.0804)	(0.0179)	(0.0200)
Population	0.324	0.118	0.0713
	(0.255)	(0.217)	(0.172)
Death rate	0.0602	−0.0681	−0.0888
	(0.213)	(0.0674)	(0.0646)
Constant	−6.313	0.0295***	0.0160***
	(5.022)	(0.00480)	(0.00505)
Observations	1,297	1,139	1,134
R-squared		0.152	
Arellano–Bond test statistic for AR(1)	0.029		
Arellano–Bond test statistic for AR(2)	0.137		
Sargan–Hansen over-identification J-test (*p*-value)	0.275		
Windmeijer under-identification test (*p*-value)	0.004		
Keibergen–Paap under-identification test (*p*-value)			0.013

Notes: All regressors are logged and lagged by one year. Dif–GMM is the difference GMM proposed by Arellano and Bond (1991). Dif–OLS is the first-difference ordinary least squares (OLS) estimation. Dif-2SLS is the first-difference second-stage least squares (2SLS) estimation with the second lagged dependent variable being an instrument. Robust standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. The Arellano–Bond test statistics for AR(1) and AR(2)-type serial correlation in the first differenced residuals are from Arellano and Bond (1991). The Sargan–Hansen over-identification test is from Sargan (1958) and Hansen (1982). The Windmeijer under-identification test is from Windmeijer (2018). The Keibergen–Paap under-identification test is from Kleibergen and Paap (2006).

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Table 6A. Specification search

Model	Number of Moments	Number of parameters	MMSC-AIC	MMSC-BIC	MMSC-HQIC
Model 1: Endogenous	21	11	−11.6722	−36.4456	−21.9526
Model 2: Predetermined	18	11	−9.0866	−26.428	−16.2829
Model 3: Exogenous	18	11	−8.8085	−26.1499	−16.0048

Notes: All equations are estimated via a two-step system GMM estimator (Blundell and Bond, 1998). All regressors are logged and lagged by one year. Endogenous = All regressors are endogenous. Predetermined = The population and death rate variables are predetermined. Exogenous = The population and death rate variables are exogenous. The preferred model is selected using the Andrews and Lu model and moment selection criteria (MMSC) based on likelihood selection criteria (Akaike [AIC], Bayesian [BIC] and Hannan–Quinn information criteria [HQIC]) (Andrews and Lu, 2001).

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