Journal of Economic Growth
https://doi.org/10.1007/s10887-023-09224-w

Trade and economic growth: Does the sophistication of traded goods matter?

P. Niluka S. P. Ekanayake[1] · **Jakob B. Madsen**[1] · **Tushar Bharati**[1]

Accepted: 1 February 2023
© The Author(s) 2023

Abstract
Since the appearance of the seminal paper of Frankel and Romer (Am Econ Rev 89(3): 379–399, 1999), 'Does trade cause growth?', the impact of aggregate trade openness on income has been controversial. This research shows that the type of product that is traded has first-order effects, while overall trade intensity has second-order effects on per capita income because of (i) the hierarchical structure of learning-by-doing in products with different levels of sophistication of the production processes; and (ii) the fertility and education effects of trade specialization following the quantity–quality tradeoff framework of Galor and Mountford (Am Econ Rev 96(2): 299–303, 2006). Using data on trade disaggregated by the level of technological sophistication of the production process for 223 countries over the period 1962–2019, we find that (1) the effects of foreign trade on income differ widely across technology categories; (2) high-tech trade has permanent growth effects; and (3) a significant fraction of the impact of trade on income is mediated through education and fertility.

Keywords Trade · Economic growth · Technology · Learning-by-doing · Quantity–quality tradeoff

JEL Classification F14 · F43 · J13 · O11 · O33

1 Introduction

The effect of trade on per capita income has long been controversial. While most economic theories point toward positive income effects of trade, early empirical evidence was plagued by reverse causality and omitted variable bias (see, for discussion of the earlier

✉ Jakob B. Madsen
jakob.madsen@uwa.edu.au

P. Niluka S. P. Ekanayake
niluka.pereraekanayake@uwa.edu.au

Tushar Bharati
tushar.bharati@uwa.edu.au

[1] Department of Economics, University of Western Australia, 35 Stirling Highway, Crawley, WA 6009, Australia

Published online: 04 April 2023

literature, Sachs & Warner, 1995a; Wacziarg & Welch, 2008). To better address causality, Frankel and Romer (1999) proposed an instrumental variable identification strategy using the gravity equation based on geographic characteristics to predict bilateral trade between countries. However, the results based on their identification strategy remain mixed and sensitive to the choice of data, model specification, and the inclusion of confounding factors (Rodriguez & Rodrik, 2000; Irwin & Terviö, 2002; Ortega & Peri, 2014; Deij et al., 2021).[1]

In this paper, we show that the use of aggregate trade data in per capita income regressions, as is typical in the existing literature, obscures the effects of trade openness. We hypothesize that the effects of trade on income depend on the sophistication of the traded goods. With aggregate data, the conflicting effects on income of trade in products of different levels of sophistication tend to cancel each other out, rendering the overall impact sensitive to sample selection. Thus, the composition of trade has first-order effects on income, whereas the effects of aggregate trade on income are of second order.[2]

Following the literature on the hierarchical structure of learning-by-doing, as outlined in the next section, we posit that trade in high-tech goods has positive productivity effects, while trade in low-tech agricultural products has negative productivity effects. Exports and imports of high-tech products are likely to promote R&D and production efficiency through scale effects, technology diffusion, and better quality of intermediate goods (Buera & Oberfield, 2020; Coe & Helpman, 1995; Grossman & Helpman, 1995; Madsen, 2007; Rivera-Batiz & Romer, 1991). Furthermore, by increasing returns to education, high-tech trade stimulates investment in human capital formation; thus, promoting future innovations. This virtuous cycle of human capital investment, innovation, and technology diffusion can set countries on a high-growth path (Galor & Mountford, 2006, 2008; Galor, 2022). Specializing in the production of unsophisticated products with low income elasticities and little scope for learning-by-doing, by contrast, entrenches countries in low-growth traps (Young, 1991).

This line of reasoning finds indirect support from history. Williamson (2013), argues that the first globalization wave over the period 1850–1913 was a main factor behind the Great Divergence. The industrial core benefited from scale economies and specialization in manufacturing production, while the periphery countries specialized in commodity production that resulted in deindustrialization, rent seeking, and excessive adverse income consequences of marked commodity price volatility.

Galor and Mountford (2008) suggest that, during the early industrialization period, trade enhanced the specialization of industrial economies in sophisticated production, which induced a rise in demand for skilled labor. This expedited the demographic transition in these economies, increased investment in human capital formation, and caused sustained growth in income per capita. Countries that specialized in unskilled non-industrial production directed their gains from trade towards population growth, which slowed down their transition to sustained growth.

To test the learning-by-doing hypothesis, we begin by examining the effect of trade openness decomposed into product categories with different levels of sophistication on

[1] Wacziarg (2001) uses an alternative methodology that exploits the policy component of trade shares to measure trade policy openness, and documents a positive effect of trade openness on economic growth.

[2] The literature in this field often uses the terminology ‘growth effect of trade’ even though the studies almost always estimate the effect of trade openness on income levels. Throughout the paper, we make a clear distinction between level and growth effects. We use level effects to refer to the changes in income per capita due to trade. Growth effect refers to the change in growth in per capita income due to trade.

income per capita. Our analysis uses annual bilateral trade data from 223 countries covering the period 1962–2019. Following the model in Young (1991), we rank traded goods by the level of technological sophistication of their production process. We use the classification from Lall (2000) to categorize goods into (i) agricultural products (AG), (ii) mining and quarrying (MQ), (iii) low-tech (LT) manufacturing, and (iv) high-tech (HT) manufacturing. To account for endogeneity, we use the identification strategy of Frankel and Romer (1999) in which trade openness is instrumented by the sum of bilateral trade predicted by geographic factors from the gravity equation. We extend the Frankel–Romer model by allowing for time-varying trade distance-resistance by ships and aircraft, as suggested by Feyrer (2019), and interact all the other geographic predictors in the gravity equations with year fixed effects to allow for dynamics in the role of these factors. Several checks for the validity of the exclusion restriction support our identification strategy. The identification strategy is detailed in Sect. 3.2.

While the learning-by-doing model of Young (1991) goes a long way in explaining the effects of differentiated trade on income, it does not directly explain our finding that specialization in low-tech manufacturing promotes growth despite its meagre learning-by-doing potential. This is not because the hierarchical model is at fault, but because specialization in low-tech manufacturing influences the tradeoff between fertility and education through the opportunity costs of childbearing and the gender wage gap. A crucial ingredient missing from the learning-by-doing model in explaining the impact of foreign trade on income is that specialization in low-tech manufacturing can promote the fertility transition and the associated increase in the investment in education following the quantity–quality (QQ) tradeoff framework. To this end, we incorporate fertility and education into the analysis following the research of Galor and Mountford (2008). Based on the QQ-tradeoff, Galor and Mountford (2008) show that the gains from trade in advanced countries have been directed towards investment in education, while these gains have been channeled towards population growth in developing countries.

There are three reasons to introduce the QQ-tradeoff framework into the analysis. First, trade specialization is the mechanism through which hierarchical learning-by-doing influences growth and, as such, it does not give an independent role for trade-induced increases in women's labor market opportunities and reductions in the gender wage gap that will enhance human capital formation and promote growth. This means that low-tech manufacturing reduces income because of low learning-by-doing opportunities. However, since low-tech manufacturing is dominated by female-labor-intensive production, such as in textiles, toys, and food processing, an expansion of low-tech manufacturing reduces the gender wage gap, which in turn reduces fertility and promotes education (Galor & Weil, 1996; Madsen et al., 2020). Recent research shows that the fertility transition in today's advanced countries, which started around 1870, was pivotal for the productivity expansion in the 20th century and for the Great Divergence (Dalgaard & Strulik, 2013; Galor & Weil, 2000; Galor & Mountford, 2008; Madsen et al., 2020).

Second, the fertility and education effects of decomposed trade are strong joint robustness checks of the leaning-by-doing model of Young (1991) and the QQ-tradeoff model of Galor and Mountford (2008). In the strongest case scenario, all estimated import and export elasticities with respect to categorized trade are consistent across the two models. As will become apparent in the empirical section, the underlying fertility and education effects of trade are crucial for understanding the dichotomy between the export and import elasticities in the income regressions. Third, the feed-back effects from fertility and education to growth, however, cannot easily be captured by reduced form income regressions because it takes years before the growth effects of a fertility reduction are borne out due to time spent in the education system, on-the-job learning by doing, and the time it takes for young age cohorts to replace older workers that exit the labor market.

Our theory and empirical methodology builds on a number of earlier studies.[3] The studies closest to ours are Coe and Helpman (1995), Coe et al. (1997), Madsen (2007), Galor and Mountford (2008), Kim and Lin (2009), and Ang et al. (2015). Using data for advanced countries, Coe and Helpman (1995) and Madsen (2007) find significant positive associations between the R&D stocks of trading countries and total factor productivity. However, they do not address causality. Coe et al. (1997) find positive productivity effects of R&D knowledge spillovers from advanced to developing countries based on FE-OLS regressions. Using the identification strategy of Frankel and Romer (1999) and aggregate trade data, Kim and Lin (2009) show that aggregate international trade benefits advanced countries but harms developing countries.

For fertility and education, the studies closest to ours are Schultz (1985), Galor and Mountford (2008), Edmonds et al. (2010), Chakraborty (2015), Atkin (2016), Blanchard and Olney (2017), Anukriti and Kumler (2019), and Bignon and García-Peñalosa (2021). Galor and Mountford (2008) find that while aggregate trade increases education and reduces fertility in the OECD countries, it has the opposite effect in non-OECD countries. Schultz (1985) argues that the grain invasion from the New World in the second half of the 19th century caused an increase in the butter-rye price ratio and led to the fertility transition in Sweden because it gave females a comparative advantage in the labor market. Related to the study of Schultz, Bignon and García-Peñalosa (2021) demonstrate that the escalating tariffs on cereals in 1892 in France increased the prices of agricultural products relative to prices of manufactures, which in turn reduced the incentive to invest in the quality of children. The common thread running through these studies is that the effects of trade on education and fertility depend crucially on how they influence the returns to investment in human capital.[4]

The remainder of the paper is organized as follows. In the next section, we summarize the relevant theoretical literature on the macroeconomic effects of trade decomposed into technology categories. Section 3 sets out our empirical strategy and discusses the data. We present our main findings on the effect of trade on income in Sect. 4, and the trade effects on fertility and education in Sect. 5. Section 6 derives the quantitative effects of decomposed trade for income, fertility and education, and Sect. 7 concludes the paper.

[3] Schultz (1985), Young (1991), Galor and Weil (1996), Frankel and Romer (1999), Yanikkaya (2003), Galor and Mountford (2008), Feyrer (2009), Edmonds et al. (2010), Andersen and Dalgaard (2011), Ortega and Peri (2014), Ang et al. (2015), Chakraborty (2015), Atkin (2016), Blanchard and Olney (2017), Pascali (2017), Anukriti and Kumler (2019), Feyrer (2019), Deij et al. (2021), and Bignon and García-Peñalosa (2021).

[4] Blanchard and Olney (2017) estimate the distinctive effects of *exports* decomposed into agricultural products, low-skill manufacturing and high-skill manufacturing on the educational attainment of the population over 15 years of age for a large sample of countries. However, there are important differences between their and our study. First, Blanchard and Olney (2017) use educational attainment as the outcome variable which is problematic because it is a predetermined stock variable. For example, the primary educational attainment of a 40-year-old is determined 30 years earlier when she did her education. The time-lag is 90 years for a 100-year-old. Using a stock for a flow variable, raises serious concerns about their identification strategy. Second, the omission of imports in the estimates of Blanchard and Olney (2017) misses out crucial insights into the overall effects of trade on income as shown below. Third, unlike Blanchard and Olney (2017), we examine the effect of trade on fertility, which we believe is an important piece in understanding gains from trade. Fourth, we use trade information from a larger set of countries and for a longer period.

2 The nexus between trade and growth: winners and losers

Gains from specialization, scale effects and knowledge-diffusion have been stressed in the literature on trade and income (Buera & Oberfield, 2020). Initial gains from trade can originate in countries specializing in the products they hold a comparative advantage in; however, this alone cannot explain the longer-term income consequences of trade. In this section, we review the theoretical literature on (i) the positive productivity effects of trade; (ii) the negative productivity effects of trade; and (iii) the indirect productivity effects of trade mediated through the QQ-tradeoff.

2.1 Winners: positive growth effects of trade

Initial income gains from international trade originate in countries specializing in the products they hold a comparative advantage in. Over time, however, trade and growth/income are linked through R&D externalities, scale effects and creative destruction. Given that R&D is the core growth engine in endogenous growth models, interactions with the outside world will result in technology transmissions through the channels of imports and exports. A large literature has found positive effects of imports of R&D-intensive intermediate products on income, such as machinery and equipment (Coe & Helpman, 1995; Madsen, 2007). Hence, implementation of machinery imported from an R&D-intensive producer will automatically increase the productivity of the importing country (Coe & Helpman, 1995; Grossman & Helpman, 1991). Related to this, an expansion of international trade raises the expected profitability of R&D investment because a larger market renders it easier to recoup the sunk costs associated with R&D intensive projects (Dinopoulos & Segerstrom, 1999; Grossman & Helpman, 1991; Rivera-Batiz & Romer, 1991). This need not be a zero-sum game because the shifts in resources from production to R&D increases the long-run rate of innovation and productivity growth in all trading countries.

A trade-induced dynamic selection mechanism additionally promotes economic growth because low productivity, less competitive firms exit the market; thus, allowing for cross-firm resource reallocation from less to more productive firms (Hsieh & Klenow, 2009). Furthermore, selection on productivity shifts the productivity distribution of incumbent firms upwards and leads to technology diffusion (Sampson, 2016). As technology diffusion raises average productivity, low-productivity firms become even more unprofitable, which generates further selection. In equilibrium, the positive feedback from technology diffusion and selection results in endogenous growth driven by the dynamic selection mechanism (Sampson, 2016). As discussed in the next subsection, the downside of this efficiency gain is that the within-country variation of firms in terms of efficiency is likely to be lower than the between-country variation, suggesting that a reduction in trade barriers may not benefit all countries equally.

2.2 Losers: negative productivity effects of trade openness

The direct benefits of trade discussed above start with increased R&D and innovation and lead to diffusion of better technology. But the adoption of new technology requires complementary skilled labor (Acemoglu & Zilibotti, 2001; Basu & Weil, 1998). The stock of and investment in human capital is often low in developing countries, which constrains technology adoption. Often, these developing countries end up specializing in the production of unsophisticated products that have limited prospects for revolutionary innovations, technology spillovers and productivity growth; thus, trapping them at low levels of income.

More formally, Young (1991) shows that industry-specific productivity advances are functions of not only the productive activity in that industry, but also of spillovers of learning-by-doing to other industries. Young (1991) ranks products hierarchically by the level of technological sophistication of the production process. Assuming learning-by-doing in production is bounded for every product by the level of technological sophistication of the production process, he shows that the development of new productive technologies initially leads to rapid learning-by-doing. As the productive capacity of these new technologies is exhausted, learning-by-doing slows down. To prevent the productivity advances from slowing down, new technical processes need to be introduced. In the absence of technological adoption, which in turn depends on complementary inputs, their static comparative advantage leads these economies to specialize in products in which gains from learning-by-doing have been largely exhausted. Countries with the prerequisites for technological diffusion, on the other hand, specialize in products in which learning-by-doing has strong momentum.

Along the same lines, Redding (1999) shows that the productivity gain may be short-lived for producers of unsophisticated goods with little promise of learning-by-doing. If producers fail to fully internalize the learning-by-doing potential of production relative to their trading partners, free trade will induce dynamic welfare losses for them. Hausmann et al. (2007) argue that poor countries tend not to gain from trade because entrepreneurs in these countries face considerable cost uncertainty when they plan to produce a new product. This deters them from undertaking the production of new products.

In related work, Matsuyama (1992) shows that exogenous increases in agricultural productivity in closed economies releases labor to manufacturing and, consequently, promotes industrialization. In open economies, however, the link between agricultural productivity and economy-wide growth is negative. Countries with low arable land-labor ratios tend to have the initial comparative advantage in manufacturing. These countries specialize in manufacturing production and, at the same time, become net importers of agricultural products and raw materials. Manufacturing productivity increases over time because of learning-by-doing, a feature that is absent in the agricultural sector. Furthermore, increasing trade openness amplifies this effect by directing domestic demand for newer products to high-income elasticity sectors in rich countries (Matsuyama, 2019).

2.3 Effects on education and fertility

Galor and Mountford (2006, 2008) take the hierarchical model of Young (1991) a step further by showing that countries with a comparative advantage in unskilled intensive agricultural production end up in a high-fertility regime with low investment in education because the returns to education are low. Conversely, when a country with comparative advantages in skill-intensive production opens up for trade, the skill premium increases and the country moves up the QQ-schedule. Historically, since the industrial core countries specialized in production of relatively sophisticated products, the pre-WWI globalization wave promoted fertility transitions in these countries, while the periphery countries were trapped in a high fertility regime (Galor & Mountford, 2008).

The Galor and Mountford (2006, 2008) model is complementary to the learning-by-doing model of Young (1991), essentially because of a direct positive link between the skill premium (returns to education) and technological sophistication of production.

Another important feature of the Galor and Mountford (2006, 2008) model is the central role of the gender wage gap in the QQ-tradeoff decision through the job opportunities and wages of females. While the skill premium channel implies a positive relationship between technological sophistication and income, the nexus between women's relative wages and trade sophistication depends on the complementarity between women's employment opportunities and the production process. For example, the opportunities of females can be used as a potential explanation for why the newly industrialized countries escaped their low-income equilibrium (see Corollary 3 in Galor and Mountford, 2008). Starting from a low-income level in the 1950s and 1960s, the emerging low-tech manufacturing production of textiles, standardized consumer goods, and food processing in East Asia, for example, increased the job opportunities for females relative to males. This, in turn, reduced the gender wage gap and fertility. The reduced fertility gave increased opportunity for parents to invest more in each child, as predicted by the QQ-tradeoff framework. As shown theoretically and empirically by Madsen et al. (2020), the gender wage gap affects fertility and education by increasing the female opportunity costs of fertility.

3 Estimation strategy and data

3.1 Estimation strategy

To investigate the macroeconomic effects of categorized trade, we consider, as outcome variables, the level and growth of per capita income, fertility and education. The modelling strategies for each of these outcome variables are detailed in the subsections below.

3.1.1 Income and growth models

The estimation models for the level and the growth in per capita income are stochastically specified as follows:

$$\ln Y_{it} = \alpha_0 + \alpha_1 \ln T_{it}^{AG} + \alpha_2 \ln T_{it}^{MQ} + \alpha_3 \ln T_{it}^{LT} + \alpha_4 \ln T_{it}^{HT} + \Xi_{it}, \tag{1}$$

$$\begin{aligned} \ln Y_{it} = \beta_0 + \beta_1 \ln Y_{i,t-1} + \beta_2 \ln T_{it}^{AG} + \beta_3 \ln T_{it}^{MQ} \\ + \beta_4 \ln T_{it}^{LT} + \beta_5 \ln T_{it}^{HT} + \Xi_{it}, \end{aligned} \tag{2}$$

$$\Delta \ln Y_{it} = \zeta_0 \ln T_{it}^{AG} + \zeta_1 \ln T_{it}^{MQ} + \zeta_2 \ln T_{it}^{LT} + \zeta_3 \ln T_{it}^{HT} + \Xi_{it}, \tag{3}$$

where $\Xi_{it} = \iota_1 \ \ln \ Pop_{it} + \iota_2 \ Inst_{it} + \mathbf{Z}_{it}\zeta' + \kappa_r + \kappa_t + \epsilon_{it}$; Y_{it} is GDP per capita in country i in year t; Pop_{it} is population; $Inst_{it}$ is institutions; T^{AG}, T^{MQ}, T^{LT}, and T^{HT} are trade in agricultural products, mining and quarrying trade, low-tech and resource-based manufacturing (low-tech for shorthand) trade, and high- and medium-tech (high-tech for shorthand) trade, as shares of GDP, respectively; $\mathbf{Z}$ is a vector of controls; κ_r and κ_t are region- and time-effects; and ϵ_{it} is the stochastic error term.

The regional dummies, κ_r, are based on the World Bank's classification that accounts for time-invariant regional effects, such as distance from the equator and land size. We opt for regional-effects instead of country-effects in the baseline regressions because the variation in trade patterns, especially in the short to medium run, typically varies across, and not within, countries (see the Online Appendix Table A1). Our results are consistent, although less efficient, when we replace region fixed effects with country effects (see the Online Appendix Table A19). To simplify the presentation, we combine trade in high-tech and medium-tech manufacturing under the high-tech category. Medium-tech products, which include motor vehicles and machinery manufacturing, are sufficiently sophisticated to be classified as high-tech manufacturing products. Another simplification is the exclusion from Eq. (1) of trade in miscellaneous goods, which make up only 1.3% of the GDP for an average country. However, miscellaneous goods are included in total trade. In Online Appendix Table A10, we show that relaxing these two assumptions does not change our conclusions.

The level of population affects income through two opposing forces when examining trade-income dynamics. In their cross-country estimates, Frankel and Romer (1999) include population because more populous countries tend to be more open to trade than countries with small populations. Thus, population in cross-section estimates captures between-country population trade effects. However, in our panel specification, the within-country variation in the population additionally captures the population growth drag due to diminishing returns introduced by land, oil and mineral resources as fixed factors of production. In this context, note that population has a growth as well as a level effect in per capita income, as shown in the Online Appendix Section A2.1. Following the predictions of the Solow model, we extend the income models with the population growth and the investment-income ratio in the robustness section.

Several control variables are considered in the robustness section. Of these, the most important controls are immigration and foreign direct investment (FDI) because, like trade, these are sources of interlinkages and spillovers effects, and trade may capture the effects of immigration and FDI on the outcome variables. Ortega and Peri (2014), for example, find that the coefficients of trade openness are rendered insignificant once immigration is allowed for in their income model, suggesting that the coefficient of trade captures the effects of immigration on income in the OLS regressions and, therefore, that the Frankel–Romer exclusion restriction is violated in the first-stage IV regressions. Like trade, immigration is endogenous and, therefore, instrumented to ensure that the coefficients of trade are not biased due to endogeneity of immigration. Immigration and FDI are not included in the baseline regressions because they reduce the sample size significantly.

To reduce the influence of random and cyclical fluctuations, we follow the growth literature and estimate our models using 5-year averages of the annual observations. In Online Appendix Table A9, we show that our results are robust to using semi-decennial, decennial, and semi-centennial averages. We log transform all variables to reduce the influence of outliers.

Following the literature on growth and trade, we use the level and the growth in per capita income as the outcome variables. Total factor productivity, TFP, is not used as the regressand in the baseline regressions because (1) the available TFP estimates are limited to mostly high- and some middle-income countries, potentially introducing a country selection bias; (2) the existing estimates of TFP are highly problematic and potentially misleading;[5] and (3) we want to capture the trade-effects on income through investment, education, labor

[5] In the absence of data on mining and land rent, the population growth drag is not factored out of the TFP estimates in the PWT. This implies that the agricultural product trade-induced population growth through the QQ-tradeoff channel increases TFP when the population growth drag is not allowed for in the TFP

force participation, efficiency, and technological progress; not only through the technology channel as is implied by TFP-regressions. As shown and discussed in the Online Appendix, although the principal results are the same regardless of whether TFP or per capita income is used as the outcome variable, the economic effects of trade are larger when income is used as the outcome variable (see Online Appendix Table A6).

Equation (1) is a static income model, which is by far the dominant specification used in the literature on trade and growth following Frankel and Romer (1999) (see, for a review of the literature, Deij et al., 2021). This specification implies that a change in trade openness of product type k has a one-off permanent effect on income. Numerous empirical studies have derived distinctive theoretical implications of the learning-by-doing effects of passive learning (see, for an overview, Thompson, 2010). These studies find declining cost-quantity relationships over time, as shown by Thompson (2010). If learning is dominantly passive, then productivity growth is invariably bounded and too much passive learning may, under certain circumstances, lead to stagnation (Thompson, 2010). The dynamic specification given by (2) allows for a lagged adjustment in response to changes in the regressors and, therefore, for more persistent effects of trade on income than model (1). Model (3) tests for potential permanent growth-effects of trade for product category k, while (2) tests for persistent but not permanent growth-effects of trade for all product categories, jointly.

When a distinction between passive and active learning is made, trade in some types of products may have persistent or even permanent growth effects if they promote active learning, where active learning is a goal-directed activity, such as investment in R&D and, hence, is distinct from passive learning. The knowledge derived from R&D embodied in these products accumulates over time, continually pushing the TFP frontier outwards. To see how R&D and, hence, potentially trade in high-tech products, feed into the growth process, consider the growth in knowledge or TFP, denoted as g_A, which is governed by the following ideas production function (Ha & Howitt, 2007; Madsen, 2010):

$$g_A = \dot{A}/A = \lambda (X/Q)^{\sigma} A^{\phi - 1}, \qquad Q \propto L^{\beta},\ \ 0 < \sigma \leqslant 1,\ \ \phi \leqslant 1, \tag{4}$$

where X is a measure of innovative activity, such as R&D and patents; Q is product variety; β is the coefficient of product proliferation; ϕ is returns to scale in knowledge; λ is a research productivity parameter; and σ is a duplication parameter, which is zero if all innovations are duplications and one in the absence of duplicated innovations.

The first-generation endogenous growth theory of Romer (1990) predicts that $\phi = 1$ and $\beta = 0$; Schumpeterian growth models predict that $\phi = 1$ and $\beta = 1$; and semi-endogenous growth models predict that $\phi < 1$ and $\beta = 0$. Innovative activity has permanent growth effects if $\phi = 1$. Henceforth, the ratio of X and Q will be referred to as research intensity. Empirically, Ang and Madsen (2015) find that the null hypothesis of $\phi = 1$ and $\beta = 1$ cannot be rejected at conventional significance levels for the advanced countries.

Equation (4) provides two important insights. First, assuming that $\beta = 1$, and that the complexity of new innovations is proportional to labor productivity, it is trade-intensity, T^k, and not trade volume, τ^k_{ijt}, that matters for per capita income growth. Second, T^k has permanent growth effects if it enhances the knowledge stock (level of technology) in the

Footnote 5 (continued)

estimates; thus, it results in a significantly positive bias in the coefficients of agricultural trade elasticity. Furthermore, TFP is a highly problematic proxy for technology because capital accumulation is, to a large degree, driven by investment-specific technological progress that spurs capital accumulation by reducing the user cost of capital and, consequently, reduces TFP, when in fact it should have increased it (Greenwood & Krusell, 2007).

same fashion as R&D intensity by advancing the quality of final products and the technology embodied in intermediate inputs. The knowledge stock, A, increases permanently at a constant rate if ϕ is equal to one, as is assumed in first-generation endogenous growth models and Schumpeterian second-generation growth models. Long-lasting growth effects result from T^k if ϕ is close to one.

According to the learning-by-doing model, high-tech trade is predicted to put productivity on an upward trajectory, a growth-effect that may be long-lasting or even permanent, depending on scale effects in the ideas production function. The growth-effects of specialization in low-tech manufacturing and agriculture, by contrast, are bounded. For countries in which the majority of the population is trapped in the Malthusian regime, an increase in trade in agricultural products leads to a one-off reduction in per capita income provided that per capita income exceeds subsistence, otherwise the effect is zero. If per capita income is pulled below the subsistence level by a trade-induced increase in fertility, the fertility rate subsequently declines and eases the population growth drag until the initial per capita income level is reestablished. While a large fraction of the countries in the world today have completed the fertility transition, the majority of countries started their fertility transition after 1962. Using the data collected by Dalgaard et al. (2021), only 60 of the 177 countries they consider started the fertility transition before 1962.

3.1.2 Education and fertility

To the extent that trade affects income through the QQ-tradeoff following the Galor and Mountford (2008) hypothesis, fertility and education regressions are powerful robustness checks of the income regression results because education and fertility have stochastic properties that are different from income and are determined by different factors. If the trade in different product categories has long-term income consequences through fertility and human capital formation, the income-regression results should be mirrored in fertility and gross enrollment rate (GER) regressions.

To investigate the effects of trade across product categories on fertility and education, we estimate the following two models:

$$\begin{aligned} GER_{it} = {} & \kappa_0^e + \kappa_1^e \ln T_{it}^{AG} + \kappa_2^e \ln T_{it}^{MQ} + \kappa_3^e \ln T_{it}^{LT} + \kappa_4^e \ln T_{it}^{HT} \\ & + \kappa_5^e \ln Pop_{it} + \kappa_6^e \, Inst_{it} + \kappa_7^e \ln Comp_{it} + \kappa_r^e + \kappa_t^e + \epsilon_{it}^e, \end{aligned} \tag{5}$$

$$\begin{aligned} \ln TFR_{it} = {} & \eta_0^f + \eta_1^f \ln T_{it}^{AG} + \eta_2^f \ln T_{it}^{MQ} + \eta_3^f \ln T_{it}^{LT} + \eta_4^f \ln T_{it}^{HT} \\ & + \eta_5^f \ln Pop_{it} + \eta_6^f \, Inst_{it} + \eta_7^f \, CMR_{it} + \eta_r^f + \eta_t^f + \epsilon_{it}^f, \end{aligned} \tag{6}$$

where GER is gross enrollment rates; $Comp$ is the number of compulsory school years; CMR is the crude mortality rate (deaths per 1000 population); and TFR is the total fertility rate, measured as the average number of children born to a woman over her lifetime conditional on the contemporaneous age-specific fertility rates throughout her lifetime. Here, GER is estimated as the weighted average of primary (7/17), secondary (5/17), and tertiary (5/17) gross enrollment rates, with figures in parentheses denoting relative weights that signify years of education at each level. GERs are measured as the fraction of the population of schooling age that is enrolled in primary, secondary or tertiary education.

Although the fertility and education decisions are made simultaneously in the QQ-model, we have kept trade unlagged as in the other models for expositional simplicity and because the education decision is also contemporaneously affected by trade. For example, if the returns to education (including the costs of education) have changed between the time of the child's birth and the time at which the child enters education, then, if possible, the parents may revise the number of additional children they previously planned. Furthermore, access to credit to fund education may have changed between the time of birth and the time of education (Galor & Weil, 1996). Estimates with lagged trade variables, which are presented in the Online Appendix Table A17, give results that are almost identical to the estimates without lagged trade.

3.2 Identification

The coefficients of the trade variables included in Eqs. (1)–(3) and (5)–(6) are unlikely to be unbiased when the OLS estimator is applied for the following reasons: First, per capita income and GERs may affect the level and the composition of trade. For example, countries with high income and school enrollment, are more likely to trade in high-tech products than low-income countries, thus, resulting in a positive feedback effect from income and GERs to high-tech trade and vice versa for fertility. Second, the attenuation bias is likely to be large for trade because of significant misreporting in trade flows, as evidenced by large discrepancies in bilateral mirror flows, even when CIF/FOB factors are corrected for (Farhad, 2020). Third, the coefficients of trade may be biased due to unobserved confounders that are correlated with trade. Fourth, trade openness may be endogenous because immigration, among other controls, is omitted from the model.

As our primary identification strategy for trade openness, we use a dynamic version of the Frankel and Romer (1999) IV strategy where bilateral trade levels, predicted by the gravity model, are used to instrument observed trade openness. For immigration, we also use a gravity model for identification, but without geographic variables as shown below. As will become apparent in the discussion in Sect. 4.2.1, comparison between estimates of the gravity models for trade and immigration give important information on whether or not the exclusion restriction for trade is violated.

Based on the instruments used by Frankel and Romer (1999), the following gravity model is estimated separately for total exports, E, total imports, M, and total trade, T, (i.e., the sum of total exports and total imports) for each product category:

$$\begin{aligned}\ln(\tau^k_{ijt}/GDP_{it}) = {} & \beta_0 + \beta^N_t \ln N_{it} + \beta^A_t \ln A_{it} + \beta^{Ai}_t \ln D^{Air}_{ij} \\ & + \beta^S_t \ln D^{Sea}_{ij} + \beta^N_{2t} \ln N_{jt} + \beta^A_{2t} \ln A_{jt} \\ & + \beta^L_t (L_i + L_j) + \beta^B_t B_{ij} + \beta^{BAi}_t B_{ij} \ln D^{Air}_{ij} \\ & + \beta^{BS}_t B_{ij} \ln D^{Sea}_{ij} + \beta^{BN}_t B_{ij} \ln N_{it} \\ & + \beta^{BN}_{2t} B_{ij} \ln N_{jt} + \beta^{BA}_t B_{ij} \ln A_{it} + \beta^{BA}_{2t} B_{ij} \ln A_{jt} \\ & + \beta^{BL}_t B_{ij}(L_i + L_j) + \gamma_i + \gamma_j + \gamma_t + \varepsilon_{ijt},\end{aligned} \tag{7}$$

where GDP_{it} is the nominal GDP of country i in year t; τ^k_{ijt} is the bilateral trade in product category k between country i and j; N_{it} and N_{jt} are the population sizes of countries i and j; A_{it} and A_{jt} are the land areas of countries i and j; D^{Sea}_{ij} and D^{Air}_{ij}, are the sea distance and the great circle distance between countries i and j; $\beta^L_t \left(L_i + L_j\right)$ takes the value of '2' if both trading partners are landlocked, '1' if only one of the two countries is landlocked, and '0' if none of the countries are landlocked. B_{ij} is a dummy variable that takes the value of one if the two trading countries share a common land border, and zero otherwise. γ_i, γ_j, and γ_t are reporter country, partner country, and time fixed effects. All nominal variables are denominated in USD.

We use the approach of Pascali (2017) and Feyrer (2019) by allowing the coefficients of the following time-invariant variables to vary over time: air and sea distance, land area, common border, and landlockedness. Sea distance and air distance are included in Eq. (7) to cater for (1) the increasing share of transport by air and a corresponding reduction in the share of sea transport in total trade measured in values; and (2) the cross-country variation in transport mode depending on geographic distance, product composition of trade, and other geographic characteristics, such as ruggedness. For the estimations of the gravity models, we use the Poisson Pseudo-Maximum-Likelihood (PPML) estimation technique (Silva & Tenreyro, 2006). Finally, the standard errors are clustered at the trading country pair level. In Online Appendix Table A4, we show that the results remain almost identical when we replace region or country fixed effects by country-pair fixed effects or by country-year fixed effects for both trading partners.

Our decision to interact the time-invariant geographic factors with time dummies, incorporates the empirical insights from various studies. Hummels (2007), for example, documents that the cost of air freight per ton fell by a factor of ten over the period 1955–2004, while ocean freight rates were generally flat over the 1952–1972 period and rose with oil prices through the 1980s. Feyrer (2019) points out that this led to an increase in air freight and a corresponding reduction in ocean freight, implying that the resistance to trade due to air and sea distances between countries changed over time. This change is likely to have affected trade across product categories differently. Mining and quarrying as well as agricultural products still continue to be transported via sea, while high-tech products are increasingly transported via air (see Feyrer, 2019, for a detailed breakdown for the United States). Similarly, we allow the coefficients of land areas, landlockedness, and common border to vary over time due to oil price shocks, time-variation in communication and transport technology, etc.

As instruments for bilateral migration flows, we use various proxies for the cultural proximity between country pairs, following Bahar and Rapoport (2018). Unlike Ortega and Peri (2014), we do not use geographical instruments for both trade and migration because overlapping instruments lead to a violation of the exclusion restriction if the common instruments capture effects in the trade equation that should be attributed to migration and vice versa.[6] We estimate the following gravity model for migration:

$$\begin{aligned}\ln(Mig_{ijt}/Pop_{it}) = \mu_{1t}(\mathrm{ComCol})_{ij} + \mu_{2t}(\mathrm{ColCol})_{ij} + \mu_{3t}(\mathrm{ComRel})_{ij} + \mu_{4t}(\mathrm{OfLang})_{ij} \\ + \mu_{2t}(\mathrm{SpLang})_{ij} + \mu_{6t}\ln N_{it} + \mu_{7t}\ln N_{jt} + \mu_r + \mu_j + \varepsilon_{ijt},\end{aligned} \tag{8}$$

where Mig_{ijt} migration is the stock of residents in country i born in country j; $(\mathrm{ComCol})_{ij}$ indicates whether the two countries had at least one common colonizer in the past;

[6] FDI is included in the structural model as another network variable; however, it cannot be instrumented using bilateral instruments for our world sample since bilateral FDI flows are only available for the OECD countries and cover only a limited time span. As one of the few studies investigating the determinants of FDI from the gravity equation, Kahouli and Maktouf (2015) find that FDI is determined by factors that are quite different from the geographic determinants of bilateral trade used here. Kahouli and Maktouf (2015), find that FDI is predominantly determined by inflation (negative) and internet users (positive) in the host country. Geographic distance and sharing a common border were either insignificant or had conflicting signs across their models. Furthermore, the coefficients of trade, shared language and colonial links were almost all insignificant.

$(\text{ColCol})_{ij}$ is a dummy taking the value of one if one of the countries was colonized by the other, and zero otherwise; $(\text{ComRel})_{ij}$ is a dummy variable taking the value of one for country pairs having at least one common religion; $(\text{OfLang})_{ij}$ is a dummy taking the value of one for country pairs having at least one common official language, and zero otherwise; and $(\text{SpLang})_{ij}$ is a dummy taking the value of one for country pairs having at least one common language spoken by at least 9% of the population, and zero otherwise.

Finally, we use the predictions from Eqs. (7) and (8) to construct the instruments for trade and immigration:

$$\hat{T}^k_{it} = \sum_{i \neq j} \exp^{\hat{\beta}' X^k_{ijt}}, \tag{9}$$

$$\hat{M}_{it} = \sum_{i \neq j} \exp^{\hat{\mu}'Z_{ijt}}, \tag{10}$$

where $\mathbf{X}_{ijt}$ and $\mathbf{Z}_{ijt}$ are vectors of right-hand side variables in Eq. (7) and Eq. (8).

3.3 Exclusion restrictions

A question is whether the exclusion restrictions for the instruments are plausibly satisfied. To check for any evidence against the validity of the exclusion restriction we take the following steps:

First, as key growth transmitters through global interactions, we include immigration and FDI ratios in the second-stage regressions in the robustness section. If the coefficients of trade change significantly when these controls are included in the model, the exclusion restriction is violated because instrumented trade captures the impact of immigration and FDI on the outcome variable.

Second, in the robustness section, we estimate the baseline model in which out-of-sample bilateral trade relationships are used to form the instrument. In other words, the instrument for trade openness, Eq. (9), includes predictions for all potential bilateral trade relationships for our whole country sample. For example, if there is no reported trade in the technology group k between Congo and New Zealand, then a value of zero is entered into Eq. (9). In the out-of-sample predictions, the predicted values generated from the gravity model are included in the instrument. As shown by Deij et al. (2021), this gives consistent results regardless of whether the absence of reported trade is due to no trade, misreported data entry, or that the data are not published.

Why is it important to include out-of-sample predictions in the instrument set as a check for the exclusion restrictions? Deij et al. (2021) show that a serious violation of the exclusion restriction may occur if only observed bilateral trade relationships are used to form the trade instrument. They show that the coefficient of overall trade openness becomes significantly positive in a sample in which the bilateral trade flows are randomly generated when the instrument is generated from in-sample predictions. This is because the number of bilateral trade flows recorded in the data is a positive function of per capita income. Most bilateral trade flows in poor countries, for example, are either missing, misreported, or zero, while the reverse is true for advanced countries, thus, artificially creating an instrument for trade openness that is increasing in income regardless of whether such a relationship exists.

Third, we estimate the immigration gravity model using the same geographic characteristics as instruments for migration as we use for trade to check the extent to which migration and trade are determined by the same geographic characteristics. Coefficient similarity between the two models indicates potential violations of the exclusion restrictions for both instruments because it increases the likelihood that bilateral flows of any type are captured by common geographic characteristics.

Fourth, we use several implicit checks of the plausibility of the exclusion restriction in the estimates below. For example, if the IV estimates of the fertility and the education models are consistent with those of the income-regressions, then it is more likely that the instruments are not capturing non-trade related effects on income, fertility and education because these variables are largely determined by the same factors. Furthermore, in the North–South trade section, we check whether the baseline results are determined by the income level of the country rather than production specialization. To this end, we estimate the baseline model for the South-South and South-all trade. If the results for the South-South and South-all trade are consistent with the baseline regressions, then this is evidence against the possibility that the instruments are correlated with unobserved factors that simultaneously determine income and trade.

3.4 Data

We use annual bilateral trade data from 1962 to 2019 from the UN-COMTRADE database, classified using the Standard International Trade Classification (SITC).[7] We then categorize each SITC product code into one of the following five categories: high-tech manufacturing (HT), low-tech manufacturing (LT), mining and quarrying products (MQ), agricultural products (AG), and miscellaneous products (MS). To achieve this, we follow the United Nations' classifications of products based on R&D intensity (see Lall, 2000, for documentation). This classification based on SITC revision 2 closely follows the ISIC Revision 3 technology intensity definition (OECD, 2003).

Table 1 presents some examples of the commodities included in each category. The complete classification is reported in Table A2. The classification is intuitive and shows the pyramid of the sophistication of the products. High-tech goods require large amounts of highly specialized and skilled labor. In comparison, production of low-tech goods, such as textiles, toys, footwear, and processed food, can be done almost entirely by unskilled labor.

The data on GDP at current prices in USD, GDP per capita (constant 2010 USD), weighted gross enrollment rate (GER), population, GDP growth, consumer price index, official exchange rates (LCU per USD, period average), and the total fertility rates are from the World Development Indicators (World Bank, 2020). Information on land area and bilateral air distances are from the CEPII database (Conte & Mayer, 2021). Information on sea distance is obtained from the CERDI Sea Distance Database that contains bilateral maritime distances between 227 countries (Bertoli et al., 2016). Information on bilateral migration and country-level FDI are sourced from World Bank (2020).

As a proxy for institutional quality, we use the judicial constraints on the executive (variable *v2x_jucon*) from the V-Dem database. The measure is constructed as a response to the

[7] The data available from the UN-COMTRADE database used SITC revision 1 codes from 1962 to 1975 and SITC revision 2 codes from 1976 to 2019. We convert data from all years into SITC revision 2 codes before splicing them.

Table 1 Examples of traded goods by degree of technological sophistication

1. Agricultural products (AG)—examples	3. Low-tech products (LT)—examples
Live animals for food Fresh or frozen meat Milk and cream Fresh and preserved eggs, birds Fresh, chilled, and frozen fish	Agro-based manufacturing: preserved or prepared meat, fish, vegetables Other-resource based manufacturing: metal ores, glass, clay refractory Low-tech manufacturing: textiles, garments, footwear, handbags, paper, glassware, pottery, rails, iron and steel castings, toys, sporting goods, musical instruments
2. Mining and Quarrying (MQ)—examples	**4. High-tech products (HT)—examples**
Crude petroleum Lignite and peat coal Chemicals excluding pharmaceuticals Natural and manufactured gas Silver, platinum, nickel, aluminum, lead, zinc	Medium-tech: passenger motor vehicles, lorries, special motor vehicles, synthetic fibers, railway coaches, explosives, steam boilers, internal combustion piston engines High-tech: radioactive materials, pharmaceutical products, steam engines, turbines, aircraft, optical instruments, television receivers, data processing machine parts

The classification follows Lall (2000). Please refer to Online Appendix Table A2 for details on the SITC product codes included in each category

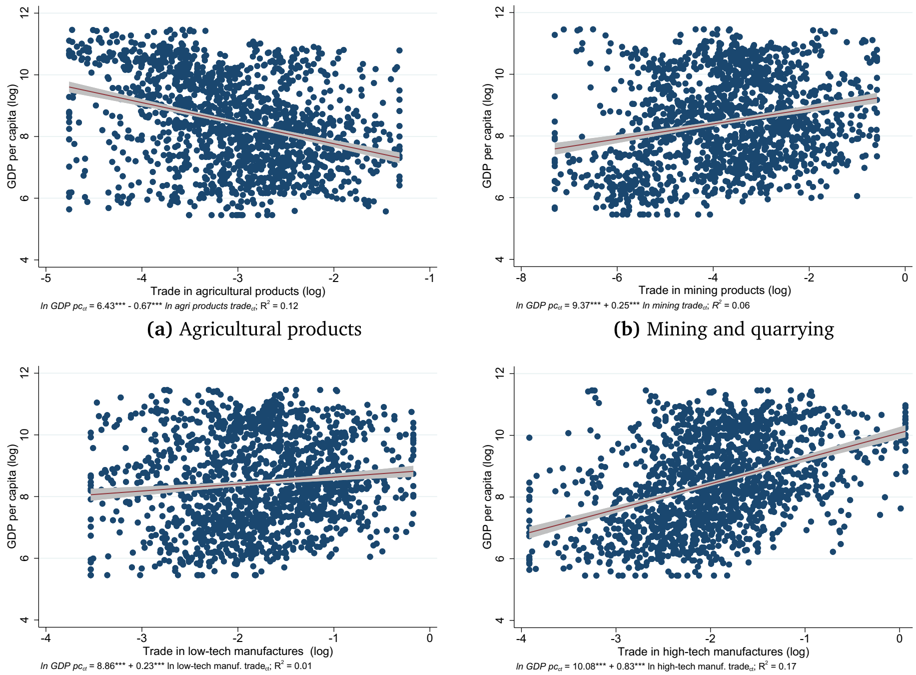
question: To what extent does the executive respect the constitution and comply with court rulings, and to what extent is the judiciary able to act in an independent fashion? and is measured on a continuous scale between 0 and 1, where ‘0’ denotes the least respect for the constitution and court rulings and ‘1’ denotes the highest level of respect. The advantages of using the V-Dem database over other comparable data is that it has the largest country coverage of the available institutional quality indicators. More importantly, *v2x_jucon* is based on detailed analyses by many experts with knowledge of the institutional landscape of individual countries.[8] Online Appendix Table A1 reports the summary statistics for the variables used.

3.5 Association between trade openness and per capita GDP

Figure 1 displays the relationship between per capita GDP and the trade-income ratio by product categories measured in 5-year averages.[9] As in the baseline models, we consider agricultural products, mining, low-tech manufacturing and high-tech manufacturing. Graphs with trade decomposed into imports and exports are presented in Online Appendix Figures A1 and A2. Consistent with the discussion in Sect. 2, Fig. 1a shows that the association between trade in agricultural products and GDP per capita is negative because specialization in agricultural products offers limited potential for

[8] Currently, the project employs investigators with detailed knowledge of the institutional landscape for individual countries distributed over five principal investigators, 22 project managers, 33 regional managers, over 100 county coordinators, and more than 3700 country experts, underscoring a highly sophisticated construction process.

[9] To deal with extreme observations, we winsorize the data at the first and 99th percentile. Values below the first (above the 99th) percentile of the variables of interest are recoded to the first (99th) percentile value.



(a) Agricultural products

(b) Mining and quarrying

(c) Low-technology manufactures

(d) High-technology manufactures

Fig. 1 Trade in different product categories and GDP per capita. *Sources*: Bilateral SITC 3-digit level annual trade data from the UN-COMTRADE database and GDP per capita, (constant 2010 USD) from World Bank (2020) for the years 1962–2019

innovation and technology diffusion and little incentive to invest in human capital. The positive association between income and trade in mining and quarrying products in Fig. 1b is somewhat surprising. The learning-by-doing prospects in mining are limited, and resource-rich countries have often been found to have poor institutions Sachs and Warner (1995b). However, as shown in Online Appendix Table A12, the positive growth effects of specializing in mining disappear when the top oil-rich countries are excluded from the sample; that is countries for which oil exports account for more than 50% of total merchandise exports.

Trade in low-tech manufacturing products has a slight positive association with GDP per capita in the Fig. 1c. Below, we show that the direction of this relationship becomes significantly negative once confounding variables and, particularly, unobserved heterogeneity are controlled for. Finally, Fig. 1d shows a positive association between trade in high-tech products and income, which, as we will see, is robust to a battery of checks. This is not surprising. High-tech products afford greater scope for, learning-by-doing, technological diffusion, and could start a virtuous cycle of human capital formation, lower fertility, and increasing innovation, thus promoting long-term growth.

4 Estimation results: the level of income

In this section we present OLS and IV regression results as well as estimates with categorized trade shares. Only the qualitative results are discussed in this section. The economic effects are summarized and discussed in Sect. 6.

4.1 OLS regressions

Table 2 presents the income regressions using OLS. The association between income and total trade, total imports, and total exports is reported in columns (1), (3), and (5). The overall association is weak: The positive association between exports and income is counterbalanced by the negative correlation between income and imports. When trade is decomposed by the degree of sophistication in columns (2), (4), and (6), the coefficients of imports and exports of agricultural products are significantly negative, particularly for exports, suggesting a negative specialization effect, where we measure specialization as net export (exports–imports), and low learning-by-doing opportunities for agricultural products.[10]

For low-tech manufacturing products, there is a significant negative association between trade in low-tech manufacturing products and income. From this result, it is tempting to conclude that trade in low-tech manufacturing products is bad for productivity and economic development. While this is true at the global level, it is not true for the individual country that specializes in low-tech production. A problem associated with inferences based on imports and exports bundled together is that it disguises potential specialization effects of trade. When trade is decomposed into exports and imports, we find that some countries gain while other lose. For low-tech imports, the coefficient is significantly more negative than that of exports, suggesting significant positive effects of net exports of low-tech products on income. But when imported, low-tech goods, such as textiles, are unlikely to promote productivity growth because they do not enter the production process as productivity-enhancing intermediate goods. Therefore, they do not have any positive technological externalities. Instead, imports of low-tech manufacturing products crowd out female-intensive low-tech production. This in turn promotes fertility because it crowds out domestic low-tech manufacturing that consists predominantly of textile and food processing; industries that are traditionally highly female labor-intensive (see, e.g., Galor and Weil, 1996; Galor, 2022). For example, Moon (2019) finds that the increasing job opportunities in the low-tech sector was the main driver of the almost three-fold increase in the female labor force participation rate in Bangladesh over the period 1991–2016. Since the full income-effects of fertility transitions take several decades to materialize (Madsen et al., 2020), most of the income-effects derived from the estimates in Table 2 are likely to reflect the productivity gains associated with the transition from agriculture to low-tech manufacturing.

For high-tech products, both imports and exports have a significantly positive impact on TFP, suggesting that it is overall trade in high-tech products that matters for income, not specialization effects, because of the positive technological externalities. High-tech

[10] The significantly negative income-effects of specialization in agricultural products may partly explain why the Latin American countries, with a markedly high share of agricultural product exports in total income, have experienced incredibly low growth during the last century.

Table 2 The effect of trade on GDP per capita, by product category (OLS estimates, 1962–2019)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (Real GDP per capita)					
	Total trade		Imports		Exports	
Ln T^{TT}	0.041		− 0.253*		0.184**	
	(0.113)		(0.145)		(0.072)	
Ln T^{AG}		− 0.569***		− 0.153*		− 0.283***
		(0.083)		(0.091)		(0.042)
Ln T^{MQ}		0.144***		0.044		0.071***
		(0.040)		(0.059)		(0.020)
Ln T^{LT}		− 0.454***		− 1.055***		− 0.107**
		(0.155)		(0.152)		(0.054)
Ln T^{HT}		0.503***		0.745***		0.190***
		(0.162)		(0.200)		(0.035)
Ln (*Pop*)	− 0.050	− 0.211***	− 0.111*	− 0.255***	− 0.046	− 0.126***
	(0.050)	(0.046)	(0.057)	(0.057)	(0.049)	(0.040)
Inst	1.602***	1.589***	1.621***	1.592***	1.581***	1.464***
	(0.248)	(0.211)	(0.238)	(0.215)	(0.248)	(0.216)
R-squared	0.589	0.705	0.598	0.664	0.605	0.705
Mean of DV	8.37	8.37	8.38	8.38	8.37	8.39
# of countries	168	168	168	168	168	168
Observations	1415	1413	1405	1403	1404	1375

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are 5-year non-overlapping averages. All specifications control for year and region fixed effects

imports, such as instruments and sophisticated machinery and equipment, increase the production potential directly through three channels: Production chains; investment in machinery and equipment that is more productive than the existing capital stock; and technology diffusion that increases the quality and the variety of the manufactured products. These strong effects of high-tech trade on TFP and per capita income are consistent with the findings of Coe and Helpman (1995) and Madsen (2007), and likely derive from positive learning-by-doing effects, scale effects, and an increasing production share of high-value-added, high-tech manufactures.

Turning to the control variables, the coefficients of institutional quality are all significantly positive while those of population are negative, indicating that the country-size effect of trade (between variation) is dominated by the population growth drag (within variation). The dominant population drag effect is consistent with the results in Online Appendix Table A11, in which the coefficients of population are insignificant for the North (25% richest countries), but highly significantly negative for the South (75% of countries with the lowest income), which is consistent with our prior that the population growth drag should be significantly more pronounced in the South than the North because the agriculture, oil and mining shares in total GDP are much larger in the South than in the North.

In sum, the estimates in Table 2 suggest that per capita income is not strongly correlated with overall trade openness because conflicting growth effects of trade in different product categories counterbalance each other. Instead, it is the composition of trade on product category and the direction of trade that matter for income. For high-tech products, imports as well as exports affect income positively, while positive specialization effects are derived from low-tech trade. For mining and agricultural products, significant effects on income derive from exports, but not imports.

4.2 IV regressions

Before turning to the second-stage estimates for Eq. (1), we present the estimation results from the gravity models for trade and immigration with the intention to gain insights into the plausibility of the exclusion restrictions.

4.2.1 Gravity models

The focus parameters of the estimates of the gravity model for categorized trade openness and immigration are presented in columns (1)–(6) in Table 3. First, consider the estimates of the trade models. As predicted by theory, the coefficients of air (great circle) distance are significantly negative regardless of time-period and product type. The air distance elasticity of trade has increasingly become negative for manufacturing products over time, a result that is consistent with the finding of Feyrer (2019). The increasingly negative magnitude of the coefficient of air distance for manufacturing products, however, does not necessarily mean that the air transport costs have increased over time. Instead, an increasing preference for fast delivery may have increased the tendency to trade with countries in close vicinity as part of the value chain or, more likely, that the use of air transportation has increased disproportionately more over short than long distances. While the air distance resistance has increased over time for manufacturing products, there is no significant trend in T^{AG} and T^{MQ}, which is unsurprising since air transport is not a realistic option for most of these products. Although fresh fruit and some vegetables are increasingly transported by air, the dominant agricultural traded commodities still have a low ratio of value-added to weight, such as cereals, wine, livestock, long-life dairy products, and frozen meat.

The coefficients of sea distance are all negative, but are significant only for T^{AG} and T^{MQ} over the periods 1988–2019 and 1978–2012, respectively. The statistical insignificance of the resistance terms for manufactured goods may indicate that the great circle distance (air distance) also captures the resistance associated with land transport via rail and trucks - modes of transport used extensively for trade in manufacturing products within Europe. Trade in high-tech goods is much more sensitive to air distance relative to sea distance compared to trade in agricultural products, low-tech goods and mining products. This is consistent with the data from the US. According to Feyrer (2019), the fraction of goods transported by air in 2001 was substantially higher for high value-to-weight products, such as pharmaceuticals, instruments, and electronics than for low value-to-weight products.

Turning to the estimates of the gravity model for immigration in the last column in Table 3, the coefficients of the dummies of the cultural variables are all significantly positive at the 1% level for all years, suggesting that close cultural links are important determinants of the destination country chosen by immigrants. Furthermore, there is no clear trend in the coefficients of the cultural variables.

Table 3 Gravity estimates for trade and immigration

	(1)	(2)	(3)	(4)	(5)	(6)		(7)
	T_{it}^{k} as % of GDP, where k = [...]							Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*		
Ln D_{ij}^{Air}× I(1962-1967)	− 0.892***	− 0.852***	− 1.181***	− 0.852***	− 0.774***	− 1.353***	ComCol× I(1962-1970)	1.634***
	(0.098)	(0.115)	(0.271)	(0.121)	(0.109)	(0.189)		(0.219)
Ln D_{ij}^{Air}× I(1968-1972)	− 1.069***	− 0.795***	− 1.738***	− 0.999***	− 0.784***	− 1.460***	ComCol × I(1971-1980)	1.720***
	(0.102)	(0.102)	(0.269)	(0.101)	(0.104)	(0.260)		(0.232)
Ln D_{ij}^{Air}× I(1973-1977)	− 0.864***	− 0.897***	− 0.386	− 0.951***	− 0.837***	− 1.306***	ComCol × I(1981-1990)	1.800***
	(0.095)	(0.101)	(0.293)	(0.104)	(0.093)	(0.217)		(0.206)
Ln D_{ij}^{Air}× I(1978-1982)	− 0.872***	− 0.946***	− 0.392	− 0.978***	− 0.799***	− 1.076***	ComCol × I(1991–2000)	1.792***
	(0.086)	(0.146)	(0.211)	(0.113)	(0.086)	(0.297)		(0.201)
Ln D_{ij}^{Air}× I(1983-1987)	− 0.947***	− 0.685***	− 0.636**	− 1.167***	− 0.920***	− 1.070***	ComCol × I(2001–2010)	1.653***
	(0.073)	(0.133)	(0.223)	(0.091)	(0.073)	(0.230)		(0.198)
Ln D_{ij}^{Air}× I(1988-1992)	− 0.869***	− 0.640***	− 0.439**	− 1.061***	− 0.799***	− 1.397***	OfLang × I(1962-1970)	1.082***
	(0.072)	(0.113)	(0.153)	(0.092)	(0.067)	(0.248)		(0.291)
Ln D_{ij}^{Air}× I(1993-1997)	− 0.962***	− 0.765***	− 0.741**	− 1.099***	− 0.873***	− 1.213***	OfLang × I(1971-1980)	0.928***
	(0.066)	(0.085)	(0.227)	(0.080)	(0.059)	(0.165)		(0.274)
Ln D_{ij}^{Air}× I(1998–2002)	− 1.070***	− 0.900***	− 0.723***	− 1.219***	− 1.027***	− 1.182***	OfLang × I(1981-1990)	0.798**
	(0.057)	(0.081)	(0.144)	(0.068)	(0.063)	(0.147)		(0.247)
Ln D_{ij}^{Air}× I(2003–2007)	− 1.082***	− 0.871***	− 0.561***	− 1.177***	− 1.148***	− 0.942***	OfLang × I(1991–2000)	0.637**
	(0.051)	(0.074)	(0.117)	(0.068)	(0.054)	(0.140)		(0.229)
Ln D_{ij}^{Air}× I(2008–2012)	− 1.092***	− 0.880***	− 0.647***	− 1.212***	− 1.153***	− 1.079***	OfLang × I(2001–2010)	0.732**
	(0.051)	(0.069)	(0.118)	(0.068)	(0.050)	(0.145)		(0.241)
Ln D_{ij}^{Air}× I(2013–2017)	− 1.194***	− 0.966***	− 0.887***	− 1.288***	− 1.226***	− 1.255***	ComRel × I(1962-1970)	2.757***
	(0.057)	(0.069)	(0.177)	(0.072)	(0.052)	(0.139)		(0.300)

Table 3 (continued)

	(1) T_{it}^{k} as % of GDP, where k = [...]	(2)	(3)	(4)	(5)	(6)		(7) Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*		
Ln $D_{ij}^{Air}\times$ I(2018–2019)	− 1.224***	− 0.924***	− 0.921***	− 1.298***	− 1.276***	− 1.271***	ComRel× I(1971-1980)	3.143***
	(0.057)	(0.076)	(0.178)	(0.071)	(0.055)	(0.137)		(0.309)
Ln $D_{ij}^{Sea}\times$ I(1962-1967)	− 0.101	− 0.100	0.255	− 0.168	− 0.193	0.132	ComRel× I(1981-1990)	3.159***
	(0.086)	(0.086)	(0.249)	(0.102)	(0.104)	(0.181)		(0.265)
Ln $D_{ij}^{Sea}\times$I(1968-1972)	0.065	− 0.177*	0.971**	− 0.101	− 0.120	0.142	ComRel× I(1991–2000)	3.196***
	(0.097)	(0.084)	(0.314)	(0.087)	(0.090)	(0.188)		(0.260)
Ln $D_{ij}^{Sea}\times$ I(1973-1977)	− 0.180	− 0.105	− 0.236	− 0.289*	− 0.144	0.050	ComRel × I(2001–2010)	2.884***
	(0.113)	(0.083)	(0.238)	(0.126)	(0.081)	(0.158)		(0.275)
Ln $D_{ij}^{Sea}\times$ I(1978-1982)	− 0.168*	− 0.103	− 0.463**	− 0.144	− 0.121	− 0.018	SpLang × I(1962-1970)	1.199***
	(0.068)	(0.095)	(0.161)	(0.086)	(0.072)	(0.238)		(0.297)
Ln $D_{ij}^{Sea}\times$ I(1983-1987)	− 0.117	− 0.219	− 0.483**	0.024	− 0.065	− 0.093	SpLang × I(1971-1980)	1.293***
	(0.061)	(0.113)	(0.161)	(0.077)	(0.059)	(0.178)		(0.275)
Ln $D_{ij}^{Sea}\times$ I(1988–1992)	− 0.180**	− 0.270**	− 0.627***	− 0.068	− 0.168**	0.080	SpLang × I(1981–1990)	1.223***
	(0.059)	(0.094)	(0.116)	(0.077)	(0.057)	(0.198)		(0.266)
Ln $D_{ij}^{Sea}\times$ I(1993–1997)	− 0.179**	− 0.250***	− 0.348*	− 0.163**	− 0.162**	− 0.111	SpLang ×l(1991–2000)	1.321***
	(0.055)	(0.072)	(0.168)	(0.063)	(0.053)	(0.109)		(0.252)
Ln $D_{ij}^{Sea}\times$ I(1998–2002)	− 0.133**	− 0.254***	− 0.396***	− 0.085	− 0.091	− 0.257*	SpLang × I(2001–2010)	1.289***
	(0.045)	(0.065)	(0.108)	(0.051)	(0.053)	(0.128)		(0.264)
Ln $D_{ij}^{Sea}\times$ I(2003–2007)	− 0.122**	− 0.252***	− 0.406***	− 0.116*	− 0.032	− 0.397***	ColCol × I(1962–1970)	1.364***
	(0.040)	(0.058)	(0.098)	(0.050)	(0.041)	(0.101)		(0.221)
Ln $D_{ij}^{Sea}\times$ I(2008–2012)	− 0.123**	− 0.284***	− 0.442***	− 0.100*	− 0.003	− 0.245*	ColCol × I(1971–1980)	1.554***
	(0.040)	(0.053)	(0.092)	(0.050)	(0.039)	(0.110)		(0.248)

Table 3 (continued)

	(1) T_{it}^{k} as % of GDP, where k = [...]	(2)	(3)	(4)	(5)	(6)		(7) Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*		
Ln $D_{ij}^{Sea}\times$ I(2013–2017)	− 0.003	− 0.181**	− 0.241	− 0.016	0.096*	− 0.043	ColCol × I(1981–1990)	1.628***
	(0.046)	(0.055)	(0.137)	(0.055)	(0.044)	(0.113)		(0.223)
Ln $D_{ij}^{Sea}\times$ I(2018–2019)	0.030	− 0.201**	− 0.123	− 0.016	0.134**	0.078	ColCol × I(1991–2000)	1.496***
	(0.047)	(0.065)	(0.153)	(0.054)	(0.046)	(0.127)		(0.221)
							ColCol × I(2001–2010)	1.286***
								(0.211)
R^2	0.56	0.41	0.27	0.47	0.72	0.30		0.44
# of country pairs	33,985	33,985	33,985	33,985	33,985	33,985		37,830
Observations	229,690	229,690	229,690	229,690	229,690	229,690		189,150

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, clustered at the country-pair level. All trade and income variables are 5-year non-overlapping averages. All models include the log of population in the reporting country and the partner country. In addition to distance, the gravity regressions for trade include the following geographic variables: a dummy variable that takes the value of one if the reporter and the partner are landlocked, and zero otherwise; a dummy variable indicating whether two countries share a common border; land area of the two countries; and the interaction of these variables with year dummies. We also include reporter, partner, and year fixed effects

Table 4 Gravity estimates for trade and immigration using only geographic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	T_{it}^{k} as % of GDP, where k = [...]						Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*	
Ln D_{ij}^{Air}× I(1962–1970)	− 1.001***	− 0.903***	− 1.205***	− 0.998***	− 0.842***	− 1.566***	− 1.669***
Ln D_{ij}^{Air}× I(1971–1980)	− 0.934***	− 0.940***	− 0.467	− 0.991***	− 0.859***	− 1.467***	− 1.892***
Ln D_{ij}^{Air}× I(1981–1990)	− 1.021***	− 0.813***	− 0.466*	− 1.196***	− 1.033***	− 1.664***	− 1.865***
Ln D_{ij}^{Air}× I(1991–2000)	− 1.060***	− 0.867***	− 0.767***	− 1.199***	− 1.019***	− 1.387***	− 1.926***
Ln D_{ij}^{Air}× I(2001–2010)	− 1.147***	− 0.909***	− 0.558***	− 1.271***	− 1.249***	− 1.260***	− 1.846***
Ln D_{ij}^{Sea}× I(1962–1970)	− 0.017	− 0.081	0.273	− 0.081	− 0.112	0.235	− 0.045
Ln D_{ij}^{Sea}× I(1971–1980)	− 0.100	− 0.044	− 0.182	− 0.232*	− 0.094	0.256	− 0.008
Ln D_{ij}^{Sea}× I(1981–1990)	− 0.102	− 0.200*	− 0.574***	− 0.002	− 0.039	0.268	0.019
Ln D_{ij}^{Sea}× I(1991–2000)	− 0.113*	− 0.233***	− 0.302*	− 0.083	− 0.084	−0.113	0.025
Ln D_{ij}^{Sea}× I(2001–2010)	− 0.079	− 0.247***	− 0.445***	− 0.059	0.048	− 0.209	0.007
Ln A_i× I(1962–1970)	− 0.027	− 0.079	− 0.140	− 0.082	0.016	− 0.208*	− 0.530***
Ln A_i× I(1971–1980)	− 0.044	− 0.010	− 0.252*	− 0.067	− 0.020	− 0.198*	− 0.554***
Ln A_i× I(1981–1990)	− 0.045	0.012	− 0.114	− 0.062	− 0.070	− 0.137	− 0.585***
Ln A_i× I(1991–2000)	− 0.028	0.026	− 0.029	− 0.059	− 0.044	− 0.098	− 0.590***
Ln A_i× I(2001–2010)	0.010	0.056	− 0.016	− 0.021	0.004	− 0.160	− 0.606***
Ln A_j× I(1962–1970)	0.235*	0.308**	0.876***	− 0.109	− 0.581***	− 0.180	0.263*
Ln A_j× I(1971–1980)	0.232*	0.303**	0.985***	− 0.134	− 0.620***	− 0.224	0.229*
Ln A_j× I(1981–1990)	0.215*	0.269**	0.992***	− 0.158	− 0.610***	− 0.199	0.269*
Ln A_j× I(1991–2000)	0.231*	0.292**	0.963***	− 0.108	− 0.618***	− 0.233	0.274*
Ln A_j× I(2001–2010)	0.260**	0.336***	1.002***	− 0.091	− 0.577***	− 0.216	0.274*
$(L_i + L_j)$× I(1962–1970)	− 1.101	− 1.771	0.270	− 1.706	− 1.297	− 1.661	− 4.113***
$(L_i + L_j)$× I(1971–1980)	− 1.315	− 1.599	− 0.692	− 1.773	− 1.463	− 2.034	− 4.252***
$(L_i + L_j)$× I(1981–1990)	− 1.289	− 1.683	− 0.592	− 1.931	− 1.522	− 1.716	− 4.202***

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	T_{it}^{k} as % of GDP, where k = [...]						Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*	
$(L_i + L_j)\times$ I(1991–2000)	− 1.153	− 1.320	− 0.653	− 1.693	− 1.626	− 0.940	− 4.154***
$(L_i + L_j)\times$ I(2001–2010)	−1.140	−1.482	−0.396	−1.805	−1.562	−0.750	−4.290***
Border × I(1962–1970)	3.492**	4.569**	− 9.306*	4.861***	6.307***	3.108	− 0.858
Border × I(1971–1980)	1.994*	4.271***	− 4.461*	2.059*	3.857**	2.263	− 2.538
Border × I(1981–1990)	− 0.577	1.696	− 6.014**	0.374	0.850	0.966	− 2.727
Border × I(1991–2000)	− 0.124	1.398	− 4.770*	0.470	1.241	− 0.689	− 2.978
Border × I(2001–2010)	− 0.305	1.385	− 4.694*	0.688	0.250	− 0.627	− 1.820
Border × Ln $D_{ij}^{Air}\times$ I(1962–1970)	− 0.025	0.689**	2.757***	− 0.573*	− 0.862*	0.153	1.105***
Border × Ln $D_{ij}^{Air}\times$ I(1971–1980)	− 0.503**	0.671**	− 0.069	− 0.549**	− 0.686*	− 0.987**	1.160**
Border × Ln $D_{ij}^{Air}\times$ I(1981–1990)	0.185	0.562*	0.161	0.285	0.261	− 0.634	1.280***
Border × Ln $D_{ij}^{Air}\times$ I(1991–2000)	− 0.096	0.123	− 1.242*	− 0.036	0.176	− 0.842*	1.281***
Border × Ln $D_{ij}^{Air}\times$ I(2001–2010)	0.060	0.056	− 1.499**	− 0.008	0.587**	− 0.728*	1.300***
Border × Ln $D_{ij}^{Sea}\times$ I(1962–1970)	0.072	0.050	− 0.136	0.159	− 0.012	− 0.038	0.038
Border × Ln $D_{ij}^{Sea}\times$ I(1971–1980)	0.135	− 0.100	− 0.076	0.314*	0.192	0.019	− 0.045
Border × Ln $D_{ij}^{Sea}\times$ I(1981–1990)	0.022	− 0.079	0.287	− 0.006	0.054	− 0.087	0.027
Border × Ln $D_{ij}^{Sea}\times$ I(1991–2000)	0.042	0.074	0.204	0.077	− 0.022	0.258	0.034
Border × Ln $D_{ij}^{Sea}\times$ I(2001–2010)	0.024	0.227*	0.390*	0.060	− 0.130	0.268	0.129
Border × Ln $A_i\times$ I(1962–1970)	− 0.106	− 0.232***	− 0.554***	−0.028	0.034	− 0.019	− 0.136
Border × Ln $A_i\times$ I(1971–1980)	0.071	− 0.193***	0.142	0.043	0.094	0.281**	− 0.022
Border × Ln $A_i\times$ I(1981–1990)	0.024	− 0.094	0.003	− 0.024	0.049	0.144	− 0.085
Border × Ln $A_i\times$ I(1991–2000)	0.038	0.011	0.065	0.010	0.033	0.194	− 0.088
Border × Ln $A_i\times$ I(2001–2010)	− 0.006	− 0.015	0.116	0.004	− 0.063	0.159	− 0.103

Table 4 (continued)

	(1) T_{it}^{k} as % of GDP, where k = [...]	(2)	(3)	(4)	(5)	(6)	(7) Mig/Pop
	TT	*AG*	*MQ*	*LT*	*HT*	*MS*	
Border × Ln A_j× I(1962–1970)	− 0.019	− 0.307***	− 0.583**	0.105	0.398***	− 0.168	− 0.014
Border × Ln A_j× I(1971–1980)	0.130*	− 0.228***	− 0.185	0.150*	0.348***	0.154	− 0.004
Border × Ln A_j× I(1981–1990)	0.091	− 0.080	− 0.232*	0.105	0.208	0.225	− 0.023
Border × Ln A_j× I(1991–2000)	0.200*	0.003	0.387	0.207**	0.294**	0.237	−0.014
Border × Ln A_j× I(2001–2010)	0.184**	− 0.005	0.380*	0.191**	0.292***	0.217	− 0.138
Border ×($L_i + L_j$)× I(1962–1970)	0.427*	1.320***	− 0.138	0.618***	0.206	0.569	0.093
Border ×($L_i + L_j$)× I(1971–1980)	0.870***	0.974***	1.853***	0.845***	0.204	1.279***	0.292
Border ×($L_i + L_j$)× I(1981–1990)	0.945***	1.443***	1.573**	0.999***	0.304*	0.961*	− 0.008
Border ×($L_i + L_j$)× I(1991–2000)	0.748***	0.899***	0.951**	0.721***	0.600***	0.669**	− 0.130
Border ×($L_i + L_j$)× I(2001–2010)	0.680***	0.961***	0.933**	0.779***	0.523***	0.493	0.004
Border × Ln N_{it}	− 0.111	− 0.265***	− 0.020	− 0.070	−0.112	− 0.253**	− 0.130
Border × Ln N_{jt}	− 0.017	0.103	0.357**	− 0.110	− 0.233***	0.202	− 0.100
R^2	0.54	0.43	0.320	0.49	0.67	0.40	0.53
# of country pairs	32,420	32,420	32,420	32,420	32,420	32,420	39,284
Observations	95,237	95,237	95,237	95,237	95,237	95,237	196,420

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, clustered at the country-pair level, are not reported here for brevity, but are available on request. All trade and income variables are measured in 10-year intervals for the sample period 1962–2010. We also include reporter, partner, and year fixed effects

To check for the validity of the exclusion restrictions of the instruments used for trade, we regress the gravity model for immigration using the same instruments as those used for trade (Table 4). Since immigration data are available at 10-year intervals over the period 1962–2010, we use similar interval data in all columns of Table 4. Although the sample size is slightly different from Table 3, the results are almost identical when only overlapping data are used.

Remarkably, the coefficients of trade and immigration are, except for great circle distance, close to being orthogonal. Since the number of coefficients of great circle distance make up less than 10% of the total number of coefficients, this result suggests that the lion's share of the identifying variation in the instrument for trade satisfies the exclusion restriction. Complementary to this, the baseline IV results, which are presented in the next sub-section, remain almost unaltered if the baseline second-stage regressions are based on instruments in which the great circle distance is excluded from the gravity regression (see, Online Appendix Table A5). From these results, we can conclude that the exclusion restriction in the baseline trade model is unlikely to be violated due to immigration effects; i.e., it is unlikely that the instruments for trade in the gravity models capture immigration effects.

Table 5 The effect of trade on GDP per capita, by product category (2SLS estimates, 1962–2019)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (Real GDP per capita)					
	Total Trade		Imports		Exports	
Ln T^{TT}	0.098		− 0.415*		0.304***	
	(0.175)		(0.230)		(0.110)	
Ln T^{AG}		− 0.691***		− 0.017		− 0.332***
		(0.122)		(0.166)		(0.054)
Ln T^{MQ}		0.165***		0.022		0.094***
		(0.062)		(0.095)		(0.030)
Ln T^{LT}		− 0.868***		− 1.539***		− 0.237***
		(0.191)		(0.259)		(0.081)
Ln T^{HT}		0.924***		0.984***		0.296***
		(0.160)		(0.311)		(0.059)
Ln (*Pop*)	− 0.049	− 0.285***	− 0.152***	− 0.321***	− 0.043	− 0.168***
	(0.052)	(0.051)	(0.067)	(0.071)	(0.049)	(0.040)
Inst	1.594***	1.506***	1.628***	1.597***	1.553***	1.337***
	(0.254)	(0.213)	(0.235)	(0.220)	(0.257)	(0.234)
Mean of DV	8.38	8.38	8.38	8.38	8.38	8.40
# of countries	162	162	162	162	162	162
Observations	1388	1386	1378	1376	1377	1348

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are 5-year non-overlapping averages. All specifications control for year and region fixed effects. The first-stage *F*-stats for all excluded instruments are ≥ 165.28

4.2.2 Second-stage regressions

The second-stage results are presented in Table 5. The Sanderson-Windmeijer *F*-tests for excluded instruments, derived from the first-stage results presented in the Online Appendix Table A3, are highly significant in all cases, suggesting that the relevance criteria are satisfied. For brevity, we report the lowest *F*-stat across all specifications in the notes to each of the 2SLS tables. The principal results in Table 5 are consistent with our findings from the OLS regressions. The coefficients of high-tech goods, are consistently significantly positive for total trade, imports and exports. The coefficients of low-tech manufacturing are both significantly negative for imports and exports, however, the net specialization effect, as signified by net exports, is significantly positive, hence indicating an associated crowding out effect on female-intensive manufacturing and the trickle-down effects on fertility, as shown below. Finally, the coefficient of exports of agricultural products is significantly negative, while that of mining products is significantly positive.

4.2.3 Why are the trade effects larger for 2SLS than OLS?

Based on the Frankel and Romer (1999) framework, the literature generally finds that the 2SLS coefficients for trade openness in the income regressions are significantly larger than the OLS estimates. This raises the possibility that the exclusion restriction is violated. Frankel and Romer (1999), for example, find the 2SLS coefficient of trade openness to be 226% higher than that of the OLS coefficients (from their Table 3, columns (1) and (2)). In our estimates, the sum of the absolute value of the 2SLS coefficients of the four trade categories of imports (exports) are 28% (47%) higher than the OLS estimates, suggesting a markedly smaller discrepancy than that of Frankel and Romer (1999).

The 2SLS-OLS discrepancy in our estimates is likely to be caused by an attenuation bias in the OLS estimates because misreporting in foreign trade is rampant due to misclassification of products and country of origin/destination, tariff (tax) avoidance, smuggling, hoarding of foreign currency, etc. Farhad (2020), for example, estimates a lower bound of 30% in misreported world trade, suggesting a potentially large attenuation bias in the OLS estimates. Furthermore, the coefficients of trade openness in the OLS estimates are biased towards -1 because of the inverse relationship between the outcome variable (per capita income) and the denominator of trade openness.

4.3 Categorized trade shares and income

In this section, we report the effects of the trade share on income for each product category in total trade instead of using the share of trade in total income as regressors. There are two reasons for using distribution of trade shares as regressors. First, the coefficients of product-type trade shares are relatively shielded from feed-back effects from the dependent variable if the exclusion restriction in the IV-estimates is violated. If the exclusion restriction in the baseline regressions is violated, then we would expect the principal results in this subsection to differ from the baseline results, since the distribution of trade into product categories is determined by geographic characteristics that differ from product-type trade openness in the gravity model estimates. Second, the trade-share estimates provide direct information on the impact of a mean-preserved switch from trade in one type of product to another on income.

Table 6 The effects of changes in trade composition on GDP per capita (2SLS estimates, 1962–2019)

	(1)	(2)	(3)
	Ln(Real GDP per capita)		
	Total Trade	Imports	Exports
Ln T^{TT}	− 0.361*	− 0.543**	− 0.145
	(0.184)	(0.248)	(0.119)
Ln (T^{AG}/T^{TT})	− 0.693***	− 0.494*	− 0.334***
	(0.121)	(0.250)	(0.051)
Ln (T^{MQ}/T^{TT})	0.098	− 0.106	0.076*
	(0.091)	(0.121)	(0.045)
Ln (T^{LT}/T^{TT})	− 1.007***	− 2.902***	− 0.276**
	(0.270)	(0.627)	(0.108)
Ln (T^{HT}/T^{TT})	0.726***	− 0.315	0.241***
	(0.233)	(0.615)	(0.072)
Mean of DV	8.38	8.38	8.40
# of countries	162	162	162
Observations	1387	1377	1349

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are 5-year non-overlapping averages. Share of each product category is calculated for total trade/imports/exports by dividing trade in each category by the value of total trade so that the shares add up to 100. Miscellaneous trade is not presented. All specifications control for log of population; the institutional quality of the country; year and region fixed effects. The first-stage F-stats for all excluded instruments are ≥ 90.40

The trade-share regressions are reported in Table 6. The signs and statistical significance of the trade share variables are approximately similar to those of the baseline estimates; thus, again, suggesting that the exclusion restrictions in the IV baseline estimates are plausibly satisfied. Note that the interpretation of the coefficients and their statistical significance are in relative terms (e.i., effects of changing the composition of traded

Table 7 Income effects of a 1-percentage point switch in trade from one category to another

To category	Total Trade				Imports				Exports			
	From category											
	AG	MQ	LT	HT	AG	MQ	LT	HT	AG	MQ	LT	HT
AG	1				1				1			
MQ	4.87	1			5.28	1			1.95	1		
LT	2.30	− 2.57	1		− 2.01	− 7.30	1		0.65	− 1.30	1	
HT	7.13	2.26	4.83	1	5.28	0.00	7.30	1	2.58	0.62	1.93	1

The income effect for each category i is estimated as $\frac{\alpha^i}{share_i} - \frac{\alpha^j}{share_j}$, where $\alpha^i(\alpha^j)$ is the estimated effect of trade in product category $i(j)$ and $share_i$ and $share_j$ are the average shares of product categories i and j in total trade/imports/exports. The coefficients that are statistically insignificant are set to zero products on income) instead of the usual absolute terms because it is a zero-sum game in which trade shares add to one. To ensure that the shift from one to another product is mean-preserving, we need to use the semi-elasticities so the coefficients can be interpreted as percentage points.

Table 7 presents the effect on income of a decrease in the trade share of one category by 1-percentage point, matched with an increase in the trade share of another category by 1-percentage point. In the estimates, statistically insignificant coefficients from Table 6 are set to zero. As expected, increasing the share of high-tech products in total trade at the expense of any other product category is associated with a significant increase in income. An effect of 7.3% on income obtains from a 1-percentage point increase in the high-tech import share matched by a 1-percentage point reduction in the import share of low-tech products: High-tech imports result in positive knowledge spillovers, while the reduction in low-tech imports increases domestic production of low-tech female-intensive products.

Since many countries cannot easily make a switch to high-tech production, a realistic alternative is to switch from specialization in agricultural production to specialization in low-tech production. If this results in a 1-percentage point shift in (1) exports of agricultural to low-tech products; and (2) a reduction in imports of low-tech matched by an increase in the imports of agricultural products, then income increases by 0.65% + 2.01% = 2.66%. Since the low-tech sector predominantly uses unskilled labor and the labor supply from the agricultural sector in many poor countries is elastic, a large boost in low-tech production is not only feasible, it also has a significantly positive effect on income—not least because the marginal productivity of agricultural labor tends to be low in poor countries.

4.4 Controlling for immigration and FDI

As argued in Sect. 3, immigration and FDI are potentially important confounders because, together with trade, they represent international networks of knowledge externalities. Table 8 displays the results from the baseline model extended with immigration and FDI (columns (4)–(6)). For comparative purposes, we reproduce the results from the baseline specification with a smaller sample in columns (1)–(3), since, as stated, the bilateral migration flows are available for a smaller set of countries and a shorter time span than the trade variables. When FDI and immigration are controlled for in columns (4)–(6), the parameter estimates of the trade variables are close to those of the baseline regressions in the first three columns. We obtain similar results if the Frankel–Romer instruments are used for immigration instead of the cultural instruments, as shown in Online Appendix Table A14. These results suggest that the trade variables in the baseline regressions do not capture the effects of immigration or FDI flows on income. In other words, these results do not give any evidence against the exclusion restriction in the baseline IV regressions in the sense that the geography-specific instruments are not capturing the income-effects of immigration. These results corroborate our findings in Sect. 4.2.1 where it is shown that the geographic determinants of trade and immigration are dissimilar.

Turning to the new confounders in Table 8, the coefficients of immigration are significantly positive, the coefficients of FDI are insignificant, and the coefficients of the distance from the equator are positive but generally not significant. When going from aggregate to decomposed trade openness, the coefficients of immigration drop by 30%, on average (Online Appendix Table A14), suggesting that decomposed trade is an important control variable when the economic effects of immigration are assessed. To put the relative importance of immigration and trade into perspective, a one standard deviation increase

Table 8 2SLS estimates of trade and immigration (1962–2010)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Real GDP per capita)					
	w/o FDI and migration controls			with FDI and migration controls		
	Total trade	Imports	Exports	Total trade	Imports	Exports
Panel A: all products						
Ln T^{TT}	0.142	– 0.323	0.301***	0.089	– 0.349**	0.221**
	(0.174)	(0.223)	(0.115)	(0.140)	(0.174)	(0.103)
Ln (*FDI*/*GDP*)				– 0.011	0.055	– 0.038
				(0.059)	(0.061)	(0.064)
Ln (*Mig*/*Pop*)				0.310***	0.315***	0.294***
				(0.062)	(0.062)	(0.063)
Mean of DV	8.21	8.22	8.22	8.22	8.23	8.23
# of countries	161	161	161	159	159	159
Observations	590	585	586	555	551	552
Panel B: by product categories						
Ln T^{AG}	– 0.715***	0.108	– 0.323***	– 0.650***	0.221	– 0.302***
	(0.114)	(0.183)	(0.056)	(0.119)	(0.176)	(0.059)
Ln T^{MQ}	0.188***	– 0.088	0.104***	0.154**	– 0.125	0.083**
	(0.066)	(0.112)	(0.033)	(0.064)	(0.102)	(0.033)
Ln T^{LT}	– 0.801***	– 1.998***	– 0.198**	– 0.739***	– 1.811***	– 0.175**
	(0.162)	(0.367)	(0.081)	(0.174)	(0.343)	(0.080)
Ln T^{HT}	0.933***	1.690***	0.263***	0.795***	1.451***	0.186***
	(0.162)	(0.421)	(0.061)	(0.155)	(0.366)	(0.062)
Ln (FDI/GDP)				0.050	0.018	0.035
				(0.056)	(0.072)	(0.050)
Ln (*Mig*/*Pop*)				0.187***	0.240***	0.204***
				(0.055)	(0.057)	(0.054)
Distance from equator				0.010	0.015**	0.008
				(0.006)	(0.007)	(0.007)
Mean of DV	8.21	8.22	8.24	8.22	8.23	8.25
# of countries	161	161	160	159	159	158
Observations	589	585	570	555	551	537

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are 10-year non-overlapping averages. All models include the log of population; the institutional quality of the country; distance from the equator; and year and region fixed effects. The gravity equation for immigration is extended by the cultural proximity variables of Bahar and Rapoport (2018). The first-stage *F*-stats for excluded instruments are ≥ 26.08

in high-tech trade results in a 14.4% increase in income, while for immigration, the figure is 2.2%. For low-tech, a one standard deviation increase in net exports, results in a 10.1% increase in income (exports effect of LT × SD of LT exports - imports effect of LT × SD of LT imports = −0.175 × 0.062 − (−1.811) × 0.062, where SDs are taken from Online Appendix Table A1), again suggesting that trade is potentially much more influential than immigration for income.

Table 9 Dynamic income estimates (1962–2019)

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Ln (Real GDP per capita)			Ln (Real GDP per capita)		
	Total trade	Imports	Exports	Total trade	Imports	Exports
Ln T^{AG}	− 0.005	0.010	0.002	− 0.025**	0.009	− 0.008
	(0.010)	(0.014)	(0.005)	(0.011)	(0.014)	(0.005)
Ln T^{MQ}	− 0.003	0.005	− 0.003	0.002	0.005	− 0.000
	(0.005)	(0.007)	(0.003)	(0.005)	(0.007)	(0.003)
Ln T^{LT}	0.023	− 0.000	0.007	− 0.003	− 0.030	− 0.000
	(0.016)	(0.023)	(0.008)	(0.020)	(0.026)	(0.009)
Ln T^{HT}	0.027*	0.039**	0.013**	0.055***	0.057***	0.022***
	(0.016)	(0.017)	(0.006)	(0.018)	(0.019)	(0.007)
Ln (Real GDP per capita$_{(t-1)}$)				0.970***	0.980***	0.970***
				(0.007)	(0.006)	(0.007)
Ln (*Pop*)	0.012**	0.012**	0.004	0.003	0.006	− 0.001
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Inst	0.000	0.006	− 0.017	0.046*	0.037	0.024
	(0.022)	(0.022)	(0.025)	(0.025)	(0.025)	(0.026)
Mean of DV	0.09	0.09	0.09	8.41	8.41	8.43
# of countries	161	161	161	161	161	161
Observations	1279	1270	1246	1279	1270	1246

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are 5-year non-overlapping averages. All specifications control for year and region fixed effects. The first-stage F-stats for all excluded instruments are $\geq$ 282.81

4.5 Dynamic income effects

The results of estimating Eqs. (2) and (3) are presented in Table 9. In the first three columns where per capita income growth is the dependent variable, the coefficients of high-tech trade are all significantly positive, while the coefficients of the other trade variables are insignificant. These results are intuitive. Only trade in high-tech products has permanent growth effects because these products embody new technologies and are associated with or stimulate R&D through cut-throat competition and creative destruction. On the import side, the constant inflow of high-tech intermediate products that are superior to previous vintages, such as machinery, and information and communication technology, improves the efficiency of the production process by delivering a flow of investment-specific technological progress that continually increases the efficiency of production. The significance of this channel in the growth process is evidenced by Greenwood and Krusell (2007), who find that investment-specific technological progress is responsible for approximately half of the technological progress in the US. Adding to this, measured from the expenditure side, imports of high-tech consumables and investment products enhance income as the products get cheaper.

High-tech exports may promote growth by allowing for scale effects in R&D through larger markets, increased sales by existing R&D intensive firms, international technology-diffusion, and creative destruction of low R&D intensive and unproductive firms

(Grossman & Helpman, 1991; Rivera-Batiz & Romer, 1991). Quantitatively, a 1-percentage point increase in high-tech imports is associated with a 43% ($\hat{\beta}_{HT} \times 100/(Mean\ DV) =$ 0.039 × 100/0.09) increase in the change of income, suggesting that trade in high-tech products is a significantly positive determinant of growth. The corresponding number for high-tech exports is a 14% increase in the change of income. Overall, only high-tech trade openness promotes growth driven by exports as well as imports, as predicted by Schumpeterian learning-by-doing models. This result is also consistent with the Schumpeterian growth framework in which R&D is normalized with income to filter out the horizontal innovations (product variety) of R&D (see, e.g., Peretto, 1998; Ha and Howitt, 2007).

Next, consider the results in columns (4)–(6), where the lagged dependent variable is included as a regressor. The coefficients of high-tech exports and imports are again significantly positive and the coefficients of lagged income are 0.98 (imports) and 0.97 (exports), suggesting that high-tech trade has highly persistent effects on income but, statistically, non-permanent growth effects; however, since the lagged coefficient is biased downward due to the Nickel bias, we cannot conclude that the coefficient of lagged income is significantly below one. More importantly, since the model imposes the same adjustment lag structure on all the regressors, the coefficients of lagged income are dragged down by the short-term impact of the non-high-tech variables.

The coefficients of the non-high-tech variables, population and, to a large extent, institutions on total trade, are insignificant. This does not mean that income is unaffected by these variables, but that their effects on income are not persistent. In fact, a lagged dependent variable specification is a problematic specification in most situations (Keele & Kelly, 2006). If residual serial correlation is present, as here, the lagged dependent variable causes the coefficients of explanatory variables to be biased towards zero. In other words, a lagged dependent variable that is trended renders the coefficient estimates insignificant in most circumstances.

Finally, the estimates in this section give credibility to our identification strategy. Had instrumented trade captured non-trade externalities stemming from migration and FDI, then it is highly unlikely that we would have found permanent growth effects of only high-tech trade since it is inconceivable that the average migrant or average unit of FDI will set an economy on a permanent growth trajectory.

4.6 Robustness checks

Our principal results are robust to a battery of checks, which are presented and discussed in depth in the Online Appendix. The main results can be summarized as follows. First, in the Online Appendix Table A4, we show that the results are robust to the inclusion of country-pair or bilateral country-year fixed effects in the gravity estimates. Second, we follow the recommendation of Deij (2018) by including all possible *ij* combinations in Eq. (7) even if the trade between two countries is zero or unrecorded. The results, reported in Online Appendix Table A7, are almost identical to the baseline regression results, suggesting that the exclusion restriction is not violated due to a systematic relationship between income and observed non-zero bilateral trade across countries and goods.[11] Third, we estimate Eq. (1) in five, ten, and 60-year first-differences to check whether the baseline results are driven by unobserved cross-country heterogeneity or trends that the dependent and independent

[11] Table A8 presents the findings from the corresponding specifications for education and fertility.

variables have in common (Table A9). Except for the absolute magnitudes of the coefficients, the results are largely consistent with the 2SLS baseline level-regressions. Fourth, decomposing low-tech trade into non-food low-tech manufacturing and natural resource manufacturing (food processing), and high-tech into medium high-tech and advanced high-tech does not change the principal results (see Online Appendix Table A10).

Finally, we replace regional fixed effects with country effects to gain insight into the extent to which the results are robust to the elimination of the cross-country identifying variation in the data. We regress the models in 1-year frequencies because the within identifying variation in the data is significantly reduced by the 5-year time-aggregation when country effects are allowed for. Online Appendix Table A19 reports results for (1) the baseline regression without country-effects but with regional effects in 5-year intervals (columns (1)–(4)); (2) the baseline regression in 1-year intervals with country effects (columns (5)–(8)); and (3) the baseline regression in 1-year intervals with regional effects (columns (9)–(12)). The coefficients from the regressions with regional effects in 5-year and in 1-year estimates are almost identical, suggesting that the baseline results are not driven by time-aggregation. Turning to the estimates with country effects, the results concur with those of the baseline regression for trade in low- and high-tech, but their effects on income are muted compared to those of the baseline regressions. Conversely, trade in agricultural products has a stronger negative impact on income when the between-country variation is eliminated. Consistent with the baseline regressions, mining imports have positive effects on income as we should expect since commodities are essential inputs in manufacturing production. The effects of commodity exports, however, have turned negative when country dummies are included in the estimates; a result which is not surprising since the positive effects on income are driven by the large commodity producers that enrich themselves with high rents.

5 Trade effects on education and fertility

5.1 Full-sample estimates

The results of estimating Eq. (5) (gross enrollment rates) for all countries are presented in the first three columns in the upper panel of Table 10. For brevity, we only show the second-stage IV-regressions since the relevance criteria are satisfied by a large margin, where the lowest F-test for exclusion restrictions is presented in the notes to the tables. The coefficients of high-tech imports and exports are significantly positive, significantly negative for exports of agricultural products, and significantly positive for net exports of low-tech manufacturing products, where the latter is driven by the negative effects from imports. These results are consistent with the baseline income estimates in that imports and exports of high-tech products both have positive effects on enrollment, while it is net exports of low-tech products that promotes education.

The coefficient of mining exports is significantly positive, suggesting that mining exports may not be as detrimental for economic development as is often expressed in the natural resource curse literature. This result is consistent with Gollin et al. (2016) who finds a significant causal positive effect running from mineral and fuel resource exports to urbanization. This is because a large fraction of the export earnings is spent on urban non-tradables, which in turn draws rural labor into the urban centers. The mineral-induced urbanization increases education because access to education is substantially easier in

Table 10 The effect of trade on education and fertility

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted gross enrollment rate			Log (Total fertility rate)		
	Total trade	Imports	Exports	Total trade	Imports	Exports
Panel A: all countries						
Ln T^{AG}	−1.788***	0.389	−0.881***	0.169***	0.005	0.080***
	(0.548)	(0.653)	(0.261)	(0.015)	(0.021)	(0.007)
Ln T^{MQ}	1.042***	0.287	0.469***	0.011	−0.047***	0.013***
	(0.312)	(0.360)	(0.145)	(0.008)	(0.011)	(0.004)
Ln T^{LT}	−1.112	−5.585***	0.074	−0.075***	0.072**	−0.029**
	(0.933)	(1.284)	(0.488)	(0.027)	(0.036)	(0.011)
Ln T^{HT}	1.511**	3.601***	0.690***	−0.167***	−0.094***	−0.091***
	(0.713)	(1.076)	(0.260)	(0.025)	(0.030)	(0.008)
Ln (*Pop*)	−0.512**	−0.960***	−0.277	−0.007	0.010	0.011**
	(0.216)	(0.299)	(0.178)	(0.006)	(0.008)	(0.005)
Inst	3.730***	2.860***	3.223***	−0.287***	−0.321***	−0.178***
	(0.848)	(0.932)	(0.865)	(0.029)	(0.029)	(0.030)
Ln (Compulsory School Years)	1.365	2.089**	0.810			
	(0.962)	(1.017)	(0.988)			
Crude death rate				0.009***	0.008***	0.003
				(0.002)	(0.002)	(0.002)
Mean of DV	24.41	24.44	24.52	1.13	1.12	1.11
# of countries	143	143	141	164	164	164
Observations	739	736	729	1445	1435	1403
Panel B: countries that started the fertility transition after 1962						
Ln T^{AG}	−2.914***	0.036	−1.224***	0.199***	0.030	0.090***
	(0.608)	(0.877)	(0.323)	(0.020)	(0.025)	(0.010)
Ln T^{MQ}	1.286***	0.031	0.569***	0.015*	−0.029**	0.013***
	(0.328)	(0.432)	(0.172)	(0.009)	(0.012)	(0.004)
Ln T^{LT}	−0.960	−6.280***	−0.083	−0.042	0.155***	−0.016
	(1.059)	(1.545)	(0.531)	(0.036)	(0.039)	(0.014)
Ln T^{HT}	2.508***	5.620***	0.840***	−0.252***	−0.262***	−0.092***
	(0.796)	(1.197)	(0.281)	(0.032)	(0.036)	(0.010)
Ln (*Pop*)	−0.728**	−1.167***	−0.592**	0.002	0.027***	0.012*
	(0.311)	(0.373)	(0.269)	(0.008)	(0.009)	(0.007)
Inst	2.129*	0.624	1.520	−0.107***	−0.112***	−0.027
	(1.189)	(1.250)	(1.181)	(0.036)	(0.034)	(0.036)
Ln(Compulsory School Years)	−0.349	1.212	−0.761			
	(1.068)	(1.112)	(1.036)			
Crude death rate				0.005	0.004	0.004
				(0.003)	(0.003)	(0.003)
Mean of DV	21.60	21.63	21.73	1.37	1.37	1.36
# of countries	92	92	90	110	110	110
Observations	428	425	420	915	905	881

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are measured in 5-year non-overlapping averages. All specifications control for year and region fixed effects. The first-stage F-stats for excluded instruments are ≥ 58.85

urban centers than in the rural areas. Gollin et al. (2016), for example, find that urban enrollment rates are independent of mineral exports, implying that an expansion of mineral exports increases the level of education at the country level.

The results of estimating the fertility model, Eq. (6), are presented in the last three columns of the upper panel of Table 10. The Sanderson-Windmeijer tests suggest that the instrument relevance criteria are satisfied in all cases. Like the income and education estimates, we find differentiated fertility-effects of decomposed trade: The coefficient of exports of agricultural products is significantly positive, the coefficients of exports and imports of high-tech manufacturing goods are both significantly negative, and the coefficient of low-tech manufacturing exports (imports) is negative (positive). These results are largely mirror-images of the income and the enrollment regressions and suggest (1) that the QQ-tradeoff is a potentially important channel through which trade transmits to income; and (2) that the differential trade-effects found in the baseline income regressions are not driven by violations of the exclusion restrictions.

Remarkably, the coefficient of mining exports is significantly positive in the fertility regression, deviating from the mirror image scenario in which the coefficient should have the sign opposite to that of the income and the gross enrollment estimates. This ostensible contradiction, however, is intuitive and consistent with the QQ-framework. The income increase in the oil-rich countries is not fueled by a fertility transition as a result of increasing returns to education, noting that Gollin et al. (2016) finds that the returns to education are negatively related to mineral exports. Instead, high mining revenue increases the government's ability to fund education.

Next, consider the controls. As predicted by standard models, the coefficients of crude death rates are significantly positive in the fertility regressions because parents target having a certain number of children that survive to adulthood. Good institutions have significantly positive effects on education and significantly negative effects on fertility, essentially because they provide inexpensive educational opportunities for the school age-population. For population, almost all the coefficients are significantly negative in the enrollment as well as fertility estimates. The negative impact of population on education is through the income-reducing population growth drag, which in turn reduces investment in human capital, essentially because the government education budget is constrained by the income tax revenue.

The result that exports of low-tech manufacturing goods put downward pressure on fertility and promote education is consistent with the fertility model of Galor and Mountford (2008), because females have a comparative advantage in employment opportunities in low-tech manufacturing. As shown by Do et al. (2016) and Madsen et al. (2020), the fertility decision, in addition to the returns to human capital, depends on the relative opportunities of females vis-à-vis males, as reflected in the gender wage gap. From the onset of the Industrial Revolution as well as today, females have always dominated employment in the textile and the food processing industries - industries that dominate low-tech manufacturing (Galor, 2022). Similarly, Do et al. (2016) show theoretically and empirically that countries with a comparative advantage in female-labor-intensive goods have a comparatively lower fertility rate because the opportunity costs of children are higher in those countries. This reasoning gains support from the income and school enrollment regressions in which per capita income is negatively affected by imports of these goods because they crowd out the job opportunities of females.

5.2 Estimates for countries that started the fertility transition after 1962

While the effects of low-tech manufacturing on education and fertility in the estimates in the top panel in Table 10 are consistent with the model of Galor and Mountford (2008), the absolute values of the parameters are likely to be watered down by countries that have completed the fertility transition partly because of the low identifying variation in the data coming from fertility. To cater for this, we exclude the countries that started the fertility transition before 1962 from the sample in the estimates in the lower panel in Table 10.

While the principal results for the estimates for fertility and education in the lower panel are the same as those of the baseline regressions in the top panel, two results stick out: First, the coefficients of exports and imports, particularly, of high-tech trade are significantly larger those that of the full-sample estimates. A potential reason for this result is that the returns to education derived from investment in imported high-tech products is larger in poor than in rich countries that rely significantly less on imported investment goods than poor countries. An increase in investment in imports of high-tech products will increase the skill-premium and, therefore, the returns to education, since skilled labor is plausibly more complementary to high-tech machinery and equipment capital than unskilled labor. Second, the absolute values of the low-tech net export elasticities on education and fertility are significantly larger than their full-sample counterparts, suggesting that the positive effects of specialization on income in low-tech production through the channels of education and fertility are substantial for countries that started their fertility transition after 1962.

5.3 Robustness checks of the fertility and enrollment models

We include immigration and FDI in the enrollment and fertility regressions, see Online Appendix Table A15. The parameter estimates of categorized trade are all almost identical to those of the baseline gross enrollment and fertility regressions, providing further support to the Galor and Mountford (2008) model in which trade drives the QQ-tradeoff through the incentive structure. As a further check on the validity of the exclusion restrictions in the fertility and enrollment regressions, we undertake out-of-sample estimates (Online Appendix Table A8). The results are almost identical to those of the baseline regression, suggesting that the exclusion restriction is not violated due to a systematic relationship between fertility or education and the observed non-zero bilateral trade across countries and goods.

5.4 Is trade transmitted to income through fertility and education?

Next, we conduct a mediation analysis to verify the role of fertility and gross enrollment as pathways through which trade transmits to income and to quantify the relative importance of these two transmission channels. Mathematically,

Table 11 Mediation analysis: Direct and indirect effects

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Real GDP per capita)					
	Imports			Exports		
	Direct effect	via TFR	via GER	Direct effect	via TFR	via GER
T^{AG}	0.007	−0.142***	−0.236***	−0.253***	−0.024**	−0.089***
	(0.119)	(0.028)	(0.033)	(0.063)	(0.011)	(0.014)
T^{MQ}	−0.101	0.077***	0.081***	0.095***	−0.007**	0.011*
	(0.064)	(0.014)	(0.015)	(0.025)	(0.003)	(0.006)
T^{LT}	−1.160***	−0.007	−0.154***	−0.219***	0.018**	−0.003
	(0.234)	(0.025)	(0.041)	(0.080)	(0.008)	(0.020)
T^{HT}	0.882***	0.272***	0.574***	0.209***	0.045**	0.218***
	(0.196)	(0.048)	(0.070)	(0.056)	(0.020)	(0.019)

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, clustered at the country level. All trade and income variables are 5-year non-overlapping averages. All specifications additionally control for log of population and institutional quality as well as year and region fixed effects. We use the *gsem* command in Stata to estimate the structural equation model laid out in Eq. (11) and calculate bootstrapped standard errors for the indirect effect using the process described in Preacher and Hayes (2004)

$$\frac{\text{dGDP pc}}{\text{dTrade}} = \frac{\partial\text{GDP pc}}{\partial\text{Trade}} + \frac{\partial\text{GDP pc}}{\partial\text{Fertility}}\frac{\partial\text{Fertility}}{\partial\text{Trade}} + \frac{\partial\text{GDP pc}}{\partial\text{Education}}\frac{\partial\text{Education}}{\partial\text{Trade}}, \tag{11}$$

where the first right-hand-side term represents the direct effect of trade on income, while the other two terms represent the impacts on income that are mediated by fertility and education. We estimate the indirect effects as the product of the direct effect of trade on fertility (education) and the direct effect of fertility (education) on income (Sobel, 1982). Following Preacher and Hayes (2004), we calculate bootstrapped standard errors for the indirect effect.

Table 11 reports the direct effect of trade on income per capita as well as the indirect effect via fertility and education.[12] A 10% increase in total trade of agricultural products reduces GDP by 9.3% (10(0.496 + 0.186 + 0.248)), of which 4.7% (10(0.186 + 0.248)/0.93) is through an increase in fertility or a reduction in gross enrollments. For trade in agricultural products, most of the effects on income are mediated through fertility and education, where the indirect effects account for 100% (imports) and 31% (exports). The indirect effects of trade in mining and low-tech products via education and fertility are small relative to the direct effects, but the results are consistent with the baseline results: Low-tech product specialization increases income by reducing fertility and increasing enrollment. This is in line with the results in the previous two sub-sections: Low-tech production tilts the QQ-tradeoff in favor of education at the expense of fertility.

[12] These are calculated using the coefficients of association between the independent variables, the mediator, and the dependent variable in Eq. (11) reported in Table A20.

For high-tech trade, a significant fraction of the total effects is mediated through fertility and education. In case of imports, 49% of the total effect (=(0.272 + 0.574)/(0.882 + 0.272 + 0.574)) is transmitted through fertility and education. For exports, this corresponding fraction is 56% (=(0.045 + 0.218)/(0.209 + 0.045 + 0.218)). Moreover, the mediating effects of fertility and education are likely to increase over time since they take several decades before the full effects on income are borne out. Overall, the results indicate that a significant fraction of the effects of trade on income is mediated through the QQ-mechanism, particularly for high-tech and agricultural products.

6 Quantitative effects of trade on income, education and fertility

Thus far, we have concentrated on the qualitative effects on trade. In this section, we focus on the economic effects of trade on per capita income, education and fertility. Table 12 summarizes the key baseline IV parameter estimates (top panel) and the associated semi-elasticities (bottom panel). The full elasticities can be read from the replications of the baseline estimates in the top panel; however, semi-elasticities are emphasized here because they are independent of the level of trade openness for each trade category.

The table provides two striking insights. First, taking the average of the semi-elasticities for total trade openness of product categories weighted by their trade share results in an overall negative effect of trade on income, which may explain the controversy in the literature as to whether the effects of trade on income are positive. Second, the absolute values of the semi-elasticities are high for trade in high-tech, low-tech and agricultural products, suggesting that trade can be a blessing or a curse depending on the composition of the trade.

Next, consider two counterfactual experiments, where the first is relevant mostly for poor countries and the other is relevant for rich countries. Based on the semi-elasticities, a simultaneous one-percentage point reduction in imports of low-tech manufactured products and exports of agricultural products so that the trade balance remains unaffected, results in a 35% (19.7 + 15.1) increase in income. This change can be achieved by a switch from specialization in agricultural production to low-tech manufacturing production, often achieved through employment-induced migration from the rural to the urban sector. For education, this switch increases enrollments by 111% (39.2 + 71.4). To find the long-run income-effects of education, we use the steady state conditions of the Solow model. In steady state, there is a one-to-one relationship between enrollment rates and per capita income when the income share of capital is set to 0.30 and the income share of human capital is set to 0.35 (see, for derivations, Mankiw et al., 1992). Thus, the 111% increase in GERs yields an effect on income of 111%. This impact on income is approximately three times that of the direct impact on income (see the estimates in the first four columns in Table 12). The long-term effects on income mediated by education are not fully captured by the income regressions because of the long-delayed income response of education. The full economic effects of an increase in enrollment rates of the cohort of children at the age of six, for example, will be borne out with a long lag. Suppose that the enrollment rates at the primary level increase permanently from 40 to 50%. This will first affect growth when the graduated students enter the labor market. In addition, it will take a further 50 years before the entire labor force is fully replaced by cohorts with 50% enrollment rates.

For fertility, a trade balance neutral 1-percentage point reduction in exports of agricultural products matched by a reduction in imports of low-tech manufacturing products, reduces fertility by 4.5%. The consequences of this fertility change on income cannot

Table 12 The effect of trade on income, education, and fertility

Category k =	Ln(Real GDP per capita)				Weighted GER				Ln(TFR)			
	AG	MQ	LT	HT	AG	MQ	LT	HT	AG	MQ	LT	HT
Second stage coefficient												
Ln T^k	− 0.691***	0.165***	− 0.868***	0.924***	− 1.788***	1.042***	− 1.112	1.511**	0.169***	0.011	− 0.075***	− 0.167***
	(0.122)	(0.062)	(0.191)	(0.160)	(0.548)	(0.312)	(0.933)	(0.713)	(0.015)	(0.008)	(0.027)	(0.025)
Ln IM^k	− 0.017	0.022	− 1.539***	0.984***	0.389	0.287	− 5.585***	3.601***	0.005	− 0.047***	0.072**	− 0.094***
	(0.166)	(0.095)	(0.259)	(0.311)	(0.653)	(0.360)	(1.284)	(1.076)	(0.021)	(0.011)	(0.036)	(0.030)
Ln EX^k	− 0.332***	0.094***	− 0.237***	0.296***	− 0.881***	0.469***	0.074	0.690***	0.080***	0.013***	− 0.029**	− 0.091***
	(0.054)	(0.030)	(0.081)	(0.059)	(0.261)	(0.145)	(0.488)	(0.260)	(0.007)	(0.004)	(0.011)	(0.008)
Semi-elasticities												
T^k	− 17.275	4.108	− 6.582	8.062	− 45.142	25.940	NA	13.183	4.267	NA	− 0.569	− 1.457
IM^k	NA	NA	− 19.673	12.269	NA	NA	− 71.393	44.899	NA	− 3.339	0.920	− 1.172
EX^k	− 15.091	3.602	− 4.419	8.601	− 39.163	17.973	NA	20.051	3.556	0.498	− 0.541	− 2.644

*,**,*** denote 10%, 5%, and 1% levels of significance, respectively. Robust standard errors, in parentheses, are clustered at the country level. All trade and income variables are measured in 5− year non-overlapping averages. All specifications control for year and region-fixed effects. Data for this table are drawn from Table 5 and Table 10

easily be assessed as we need to know the preference parameters and the size of the population growth drag to find the mapping between fertility and income. Despite this, the absolute values of the semi-elasticities for fertility appear to be comparatively low, partly because the absolute values of the semi-elasticities are pulled down by the rich countries, as discussed in Section A2.2. Another reason for the ostensibly low fertility effect vis-à-vis enrollment rates, is statistical: A 100% increase in GERs starting at 10% for a low-income country corresponds to a 10-percentage point increase in GERs, while a 10% reduction in the fertility rate of six live births, translates into a 10-percentage point decrease in the scale from zero to six, assuming that the maximum total fertility rate is six. Overall, this counterfactual shows that well-designed industry and trade policies can have marked income consequences for developing countries with an abundance of low-skilled females working in the agricultural sector.

As the other counterfactual exercise, consider a trade-balance-preserving one-percentage point increase in high-tech imports plus exports. This results in a contemporary income increase of 21%, which is amplified over time by the persistent growth effects as shown in Sect. 4. In contrast to low-tech and agricultural production, the gain from a high-tech strategy does not derive from specialization in high-tech net exports because of the externalities associated with high-tech imports, as discussed above. For education and fertility, the high-tech trade-expansion results in a 65% increase in enrollment rates and a 3.8% reduction in the fertility rate.

7 Discussion and concluding remarks

Classifying traded goods into various categories according to their degree of sophistication, we find that imports and exports of high-tech manufactured goods have significantly positive effects on income and education and negative effects on fertility, while the reverse results are found for exports of agricultural products. Furthermore, consistent with the predictions of the learning-by-doing model and second-generation Schumpeterian endogenous growth theory, we show that trade in high-tech products has permanent growth effects.

In an apparent contradiction of the predictions of the learning-by-doing model, we, furthermore, find a robust positive effect on income of specialization, measured by net exports, in low-tech manufacturing, such as textile production and food processing, particularly for developing countries that have not completed their fertility transition. This result does not imply that specialization in low-tech production directly promotes learning-by-doing because it is an insufficient channel through which the economy is brought into a persistent growth trajectory. Instead, female-intensive low-tech manufacturing changes the QQ-tradeoff in favor of lower fertility and more education as low-skilled female labor is drawn into the urban labor force, as predicted by the model of Galor and Mountford (2008). This route of development was taken by the South-East Asian miracle economies in the 1960 s when they expanded low-tech manufacturing production of textiles and standardized consumer goods. Since then, these economies have moved up the technology ladder to become medium to large-scale producers of high-tech products.

Our findings have significant implications for cross-country income inequality and economic development. First, since trade in high-tech products is concentrated in the advanced countries, the globalization of trade since the 1960s has benefited growth in the rich countries more than countries below the technology frontier. This has resulted in an increasing income gap between rich and poor countries because of the persistent effects on income derived from high-tech trade. Thus, the expansion of trade in high-tech products is a trade-off between cross-country inequality and income growth at the world level. Second, the influence of trade on per capita income and income growth cannot be considered in isolation from the QQ-tradeoff mechanism: Not only because education and fertility are key channels through which trade transmits to income, but also because the QQ-tradeoff is strongly complementary to the learning-by-doing model in understanding the economic effects of trade.

Third, large economic dividends derive from low-tech female-intensive manufacturing production in countries that have not completed or initiated their fertility transition; typically, these are countries with a large low-skilled rural female labor force. In poor countries that cannot easily switch to high-tech production in the short- or medium-term, a realistic alternative is to switch from specialization in agricultural production to specialization in low-tech production: A 1-percentage point switch will result in a 2.66% increase in per capita income in the short-run and a further increase induced through the QQ-tradeoff. However, to reach a stage at which the economy moves into a permanent growth trajectory requires that the opportunities gained from low-tech production are used to promote high-tech production.

This brings us back to the first fundamental question whether trade causes (labor) productivity. For overall trade, it depends. For countries trading in high-tech products the answer is unambiguously affirmative regardless of whether it is imports or exports. For trade in low-tech products, the answer is ambiguous. Countries that have not completed their fertility transition gain from trade in low-tech manufacturing if they specialize in low-tech production. While trade in high-tech products benefit all involved trading partners, specialization in low-tech is beggar-thy-neighbor at the global level unless the expansion in low-tech production in developing countries crowds out low-tech production in countries that have completed the fertility transition. For agricultural production, trade unambiguously drags income down at the world and country levels.

To the second fundamental question, does trade cause *growth*, the answer is 'yes' provided that trade consists of high-tech products because of positive growth externalities through higher R&D-productivity that continually expand the domestic technology frontier. Thus, while the growth impact of trade at the global level is significantly positive due to the strong growth externalities from high-tech trade, it will also continually widen the income gap between countries with a high high-tech trade-intensity relative to countries with low high-tech trade-intensity. However, low-income countries that embark on a low-tech trade strategy that is used as a stepping stone to strengthen the trade in high-tech products, such as East and Southeast Asia, may be able to catch up to the technology frontier countries.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10887-023-09224-w.

Acknowledgements Helpful comments and suggestions from seminar participants at the University of Western Australia and, particularly, four anonymous referees are gratefully acknowledged. Jakob B. Madsen acknowledges financial support from the Australian Research Council (DP170100339; DP220102557).

Author contributions All authors contributed equally to the study.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions.

Data availability The data that support the findings of this study are available from the corresponding author upon request.

Code availability The code that supports the findings of this study is available from the corresponding author upon request.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Acemoglu, D., & Zilibotti, F. (2001). Productivity differences. *The Quarterly Journal of Economics, 116*(2), 563–606.

Andersen, T. B., & Dalgaard, C.-J. (2011). Flows of people, flows of ideas, and the inequality of nations. *Journal of Economic Growth, 16*(1), 1–32.

Ang, J. B., & Madsen, J. B. (2015). What drives ideas production across the world? *Macroeconomic Dynamics, 19*(1), 79–115.

Ang, J. B., Madsen, J. B., & Robertson, P. E. (2015). Export performance of the Asian miracle economies: The role of innovation and product variety. *Canadian Journal of Economics, 48*(1), 273–309.

Anukriti, S., & Kumler, T. J. (2019). Women's worth: Trade, female income, and fertility in India. *Economic Development and Cultural Change, 67*(3), 687–724.

Atkin, D. (2016). Endogenous skill acquisition and export manufacturing in Mexico. *American Economic Review, 106*(8), 2046–85.

Bahar, D., & Rapoport, H. (2018). Migration, knowledge diffusion and the comparative advantage of nations. *The Economic Journal, 128*(612), F273–F305.

Basu, S., & Weil, D. N. (1998). Appropriate technology and growth. *The Quarterly Journal of Economics, 113*(4), 1025–1054.

Bertoli, S., Goujon, M., & Santoni, O. (2016). *The CERDI-Seadistance Database*. Dataset Zenodo. https://doi.org/10.5281/zenodo.46822

Bignon, V., García-Peñalosa, C. (2021). The toll of tariffs: Protectionism, education and fertility in late 19th century France. Centre for Economic Policy Research Discussion Paper DP16069. Retrieved 06 Oct 2022 from https://repec.cepr.org/repec/cpr/ceprdp/DP16069.pdf

Blanchard, E. J., & Olney, W. W. (2017). Globalization and human capital investment: Export composition drives educational attainment. *Journal of International Economics, 106*, 165–183.

Brambilla, I., Lederman, D., & Porto, G. (2012). Exports, export destinations, and skills. *American Economic Review, 102*(7), 3406–38.

Buera, F. J., & Oberfield, E. (2020). The global diffusion of ideas. *Econometrica, 88*(1), 83–114.

Chakraborty, T. (2015). Trade liberalization in a traditional society: Implications for relative female survival. *World Development, 74*, 158–170.

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review, 39*(5), 859–887.

Coe, D. T., Helpman, E., & Hoffmaister, A. W. (1997). North-south R&D spillovers. *The Economic Journal, 107*(440), 134–149.

Conte, P. C., & Mayer, T. (2021). The CEPII Gravity Database. CEPII: Paris, France. http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.asp.

Dalgaard, C. J., Madsen, J. B., & Strulik, H. (2021). Physiological constraints and the transition to growth: Implications for comparative development. *Journal of Economic Growth*, *26*(3), 241–289.

Dalgaard, C.-J., & Strulik, H. (2013). The history augmented Solow model. *European Economic Review, 63*, 134–149.

Deij, S., Madsen, J. B., & Puzzello, L. (2021). When are instruments generated from geographic characteristics in bilateral relationships invalid? *Journal of Applied Econometrics, 36*(4), 437–452.

Deij, S. M. (2018). *Does Globalization Cause Growth?* Ph.D. thesis, Monash University.

Dinopoulos, E., & Segerstrom, P. (1999). A Schumpeterian model of protection and relative wages. *American Economic Review, 89*(3), 450–472.

Do, Q.-T., Levchenko, A. A., & Raddatz, C. (2016). Comparative advantage, international trade, and fertility. *Journal of Development Economics, 119*, 48–66.

Edmonds, E. V., Pavcnik, N., & Topalova, P. (2010). Trade adjustment and human capital investments: Evidence from Indian tariff reform. *American Economic Journal: Applied Economics, 2*(4), 42–75.

Fajgelbaum, P. D., & Khandelwal, A. K. (2016). Measuring the unequal gains from trade. *The Quarterly Journal of Economics, 131*(3), 1113–1180.

Farhad, M. (2020). Essays in political economy of international trade. PhD dissertation, University of Western Australia. Retrieved 31 Oct 2021.

Feyrer, J. (2009). Distance, trade, and income: the 1967–1975 closing of the Suez Canal as a natural experiment. NBER Working Paper No. 15557.

Feyrer, J. (2019). Trade and income: Exploiting time series in geography. *American Economic Journal: Applied Economics, 11*(4), 1–35.

Frankel, J. A., & Romer, D. H. (1999). Does trade cause growth? *American Economic Review, 89*(3), 379–399.

Galor, O. (2022). *The Journey of Humanity: The Origins of Wealth and Inequality*. Penguin Random House.

Galor, O., & Mountford, A. (2006). Trade and the great divergence: The family connection. *American Economic Review, 96*(2), 299–303.

Galor, O., & Mountford, A. (2008). Trading population for productivity: Theory and evidence. *The Review of Economic Studies, 75*(4), 1143–1179.

Galor, O., & Weil, D. N. (1996). The gender gap, fertility, and growth. *American Economic Review, 86*(3), 374–387.

Galor, O., & Weil, D. N. (2000). Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond. *American Economic Review, 90*(4), 806–828.

Gollin, D., Jedwab, R., & Vollrath, D. (2016). Urbanization with and without industrialization. *Journal of Economic Growth, 21*(1), 35–70.

Greenwood, J., & Krusell, P. (2007). Growth accounting with investment-specific technological progress: A discussion of two approaches. *Journal of Monetary Economics, 54*(4), 1300–1310.

Grossman, G. M., & Helpman, E. (1991). *Innovation and Growth in the Global Economy*. MIT Press.

Grossman, G. M., & Helpman, E. (1995). Technology and trade. In G. M. Grossman & K. Rogoff (Eds.), *Handbook of International Economics* (Vol. 3, pp. 1279–1337). Elsevier.

Ha, J., & Howitt, P. (2007). Accounting for trends in productivity and R&D: A Schumpeterian critique of semi-endogenous growth theory. *Journal of Money, Credit and Banking, 39*(4), 733–774.

Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of Economic Growth, 12*(1), 1–25.

Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics, 124*(4), 1403–1448.

Hummels, D. (2007). Transportation costs and international trade in the second era of globalization. *Journal of Economic Perspectives, 21*(3), 131–154.

Irwin, D. A., & Terviö, M. (2002). Does trade raise income? Evidence from the twentieth century. *Journal of International Economics, 58*(1), 1–18.

Kahouli, B., & Maktouf, S. (2015). The determinants of FDI and the impact of the economic crisis on the implementation of RTAs: A static and dynamic gravity model. *International Business Review, 24*(3), 518–529.

Kandilov, I. T. (2009). Do exporters pay higher wages? Plant-level evidence from an export refund policy in Chile. *The World Bank Economic Review, 23*(2), 269–294.

Keele, L., & Kelly, N. J. (2006). Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis, 14*(2), 186–205.

Kim, D.-H., & Lin, S.-C. (2009). Trade and growth at different stages of economic development. *Journal of Development Studies, 45*(8), 1211–1224.

Lall, S. (2000). The technological structure and performance of developing country manufactured exports, 1985–98. *Oxford Development Studies, 28*(3), 337–369.

Madsen, J. B. (2007). Technology spillover through trade and TFP convergence: 135 years of evidence for the OECD countries. *Journal of International Economics, 72*(2), 464–480.

Madsen, J. B. (2010). The anatomy of growth in the OECD since 1870. *Journal of Monetary Economics, 57*(6), 753–767.

Madsen, J. B., Islam, M. R., & Tang, X. (2020). Was the post-1870 fertility transition a key contributor to growth in the West in the twentieth century? *Journal of Economic Growth, 25*(4), 431–454.
Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics, 107*(2), 407–437.
Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory, 58*(2), 317–334.
Matsuyama, K. (2019). Engel's law in the global economy: Demand-induced patterns of structural change, innovation, and trade. *Econometrica, 87*(2), 497–528.
Moon, M. (2019). Status of female labour force participation in Bangladesh: Trend and factors. *World Applied Sciences Journal, 37*(5), 361–367.
OECD. (2003). *OECD Science*. Technology and Industry Scoreboard: OECD Publishing, Paris.
Ortega, F., & Peri, G. (2014). Openness and income: The roles of trade and migration. *Journal of International Economics, 92*(2), 231–251.
Pascali, L. (2017). The wind of change: Maritime technology, trade, and economic development. *American Economic Review, 107*(9), 2821–2854.
Peretto, P. F. (1998). Technological change and population growth. *Journal of Economic Growth, 3*(4), 283–311.
Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers, 36*(4), 717–731.
Redding, S. (1999). Dynamic comparative advantage and the welfare effects of trade. *Oxford Economic Papers, 51*(1), 15–39.
Rivera-Batiz, L. A., & Romer, P. M. (1991). Economic integration and endogenous growth. *The Quarterly Journal of Economics, 106*(2), 531–555.
Rodriguez, F., & Rodrik, D. (2000). Trade policy and economic growth: A skeptic's guide to the cross-national evidence. *NBER Macroeconomics Annual, 15*, 261–325.
Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5, Part 2), S71–S102.
Sachs, J. D., & Warner, A. (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity, 1995*(1), 1–118.
Sachs, J. D., & Warner, A. (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity, 1995*(1), 1–118.
Sampson, T. (2016). Dynamic selection: An idea flows theory of entry, trade, and growth. *The Quarterly Journal of Economics, 131*(1), 315–380.
Schultz, T. P. (1985). Changing world prices, women's wages, and the fertility transition: Sweden, 1860–1910. *Journal of Political Economy, 93*(6), 1126–1154.
Silva, J. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics, 88*(4), 641–658.
Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology, 13*, 290–312.
Thompson, P. (2010). Learning by doing. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the Economics of Innovation* (Vol. 1, pp. 429–476). Elsevier.
Verhoogen, E. A. (2008). Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector. *The Quarterly Journal of Economics, 123*(2), 489–530.
Wacziarg, R. (2001). Measuring the dynamic gains from trade. *The World Bank Economic Review, 15*(3), 393–429.
Wacziarg, R., & Welch, K. H. (2008). Trade liberalization and growth: New evidence. *The World Bank Economic Review, 22*(2), 187–231.
Williamson, J. G. (2013). *Trade and Poverty: When the Third World Fell Behind*. MIT Press.
Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.
World Bank (2020). World Development Indicators (WDI) 2020. World Bank Publications.
Yanikkaya, H. (2003). Trade openness and economic growth: A cross-country empirical investigation. *Journal of Development Economics, 72*(1), 57–89.
Young, A. (1991). Learning by doing and the dynamic effects of international trade. *The Quarterly Journal of Economics, 106*(2), 369–405.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.