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Education and the evolution of comparative advantage

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ABSTRACT

We analyze the evolution of comparative advantage in 1,240 products from 49 low- and middle-income countries between 1995 and 2015. We show that countries with high education levels were more successful in developing comparative advantage in products unrelated to those they already exported. This effect is strongest for non-core products. In contrast, these countries did not develop comparative advantage in products that were intrinsically complex or education-intensive. These results are robust to corrections for specification errors, for institutional, infrastructure, and FDI-related factors, for regional specialization patterns, for key shifts in global trade rules, and for each economy's degree of industrial dynamism prior to 1995. These findings suggest that the key role of education when seeking to develop new industries is to help a country learn to manage unfamiliar challenges, and so overcome path dependence.

1. Introduction

One of the most important empirical findings of the last fifteen years has been the robust relationship between an economy's complexity and its economic success. Countries that produce a more complex mix of products experience higher rates of economic growth, less severe downturns and lower inequality (Hausmann et al., 2006; Saviotti and Frenken 2008; Felipe and Hidalgo, 2015; Hausmann et al. 2014; Hartmann et al. 2017; Pinheiro et al. 2018). Governments and economists have therefore long struggled with the question of how to achieve a complex product mix. The key difficulty for developing countries is that complex products tend to be unrelated to those that these countries already produce, so that they draw on new capabilities that these countries do not have (Frenken et al. 2007). This makes it difficult for developing countries to learn to produce complex products (Hidalgo et al. 2007). A common perception from country and industry case studies is that a well-educated workforce is helpful (Freeman 1995; Booth and Snower 1996; Newfarmer et al. 2009). However, the literature has not established how education changes a country's product mix. Does it facilitate the development of industries that produce unrelated products, complex products, or, as factor-proportions theories suggest, educated-labor-intensive products?[1]

History suggests that the matter deserves careful consideration. Starting in the 1950s, Japan, then Asia's New Industrializing Economies, and later the Southeast Asian economies and China, invested significantly in education, while opening up new export markets and accelerating growth (World Bank 1993; Wang & Wei 2010). The United States' success in diversifying and upgrading its industrial base through most of the 20th century also required significant expansions in education (Goldin and Katz, 2009). The industrial successes of Germany, Finland and Switzerland are similarly credited in part to their historically solid human capital achievements (Freeman 1995; Dahlman et al. 2006; Polasek et al. 2010). And yet, several counterexamples suggest that even if education is necessary for upgrading a country's production and export structures, it may not suffice, if the existing product mix is unrelated to the target industries. The Philippines enjoyed a long-standing educational advantage over much of Southeast Asia, while many countries in the Middle East and North Africa have more

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[1] This paper uses standard definitions: *Capabilities* is shorthand for productive knowledge and practices embedded in individuals, firms, industries, supply chains, and institutions (Hausmann et al. 2014). Industries relying on overlapping capabilities (or inputs) are said to be *related* to each other (Hidalgo et al. 2018). *Path dependence* means a tendency to develop new industries that are related to existing industries (Bahar et al. 2019). More *complex products* require more capabilities.

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educated populations than most of South Asia - and yet their industrial development does not compare favorably. Or to take another example, Bangladesh's product mix became ever more concentrated in garments as the country's education level increased rapidly. How education interacts with the existing product mix to facilitate the development of new industries is therefore an open empirical question.

This question requires an answer for three reasons. The first is that theory suggests that education could be important for developing new comparative advantages. The complexity literature and related work rooted in evolutionary theories (Nelson and Winter 1982; Hausmann et al. 2014; Stiglitz and Greenwald 2014) regard the acquisition of tacit knowledge through learning by doing and the translation of knowledge across related domains to be key processes by which new capabilities are developed. Educated workers can speed up learning by doing and the expansion of industries through knowledge transfer between firms (Hausmann and Rodrik 2003), and permit the translation of knowledge across less related domains (Florida, 2002). In addition, education is thought to enhance actors' abilities to respond to emerging opportunities (Schultz 1975) – abilities that are crucial to the building of new industries.

The second reason is that while education, particularly high-quality education, has been shown statistically to promote economic growth (Krueger and Lindahl 2001; Hanushek and Woessmann 2008), the mechanism underlying this relationship has not been clearly established. It is therefore useful to examine whether helping shift towards core products – the set of products that are most complex and related to others – might be such a mechanism. Suggesting such a connection, previous studies argue that the effects of education on development are most likely contingent on the composition of economic activity (Pritchett 2006).

Finally, some authors credit education with facilitating export-driven growth in East Asia (World Bank 1993; Hobday 1995; Stiglitz 1996). However, this evidence comes from case studies, and these authors do not provide statistical evidence that education transforms the product mix. Meanwhile, others studying this history are more skeptical of education's role (Booth 1999; Asian Development Bank 2007; Chang 2012; Studwell 2013).

This paper therefore examines the role of education in the evolution of comparative advantage using export data for 1240 different goods for 49 low- and middle-income countries between 1995 and 2015. In particular, we test three hypotheses, each about a role that education could play in altering a country's export mix – which, we assume, reflects its industrial strengths. First, motivated by the theory of economic complexity, we ask whether countries whose workforces were more educated in 1995 were more likely to develop comparative advantage by 2015 in products that were *unrelated* to those they exported with comparative advantage in 1995 (i.e., whether they developed strengths in "unfamiliar" products). Second, motivated by the same theory, we ask whether countries with high education levels in 1995 were more likely to develop comparative advantage in products that are *intrinsically more complex*. The third hypothesis derives from trade theory and is that education expansions should shift the export mix towards *more education-intensive products*.

Our key finding is that countries whose workforces were more educated in 1995 were indeed more likely to move towards unfamiliar products. We also provide evidence that, as might be expected, good quality basic education and high primary attainment facilitate movements towards unfamiliar peripheral products (those that are least complex and least related to other products), but not towards unfamiliar core products. There is at best weak evidence to support the second hypothesized role of education, and none at all to support the third. We apply a two-step procedure which confirms that the lack of support for the latter two hypotheses is not driven by errors in the measurement of education or its change over time – but rather, by the fact that countries' specialization patterns did not shift very much towards either complex or education-intensive products. We also demonstrate that our results are robust to errors in specification or operationalization; to biases owing to omitted variables related to institutional quality, infrastructure, FDI-receipt or regional specialization patterns; to changes in global trade rules affecting garments and textiles; to the exclusion of China from our sample; and to the fact that countries that underwent fast industrial development prior to 1995 tended to have both higher educational attainment in 1995, and more rapid industrial development between 1995 and 2015. Education's estimated effects on changes to the export mix also grow as the time for these changes to occur increases. While the instruments required to produce fully credible causal estimates of the effects of education on comparative advantage are not available, the robustness of our results to every alternative explanation and their increasing strength over time suggest that they do provide a useful qualitative indication of the causal connections involved. The primary role of education in industrial development, at least among those we examine, is to help navigate the unfamiliar.

Several previous studies suggest that the topic is worth exploring. Ciccone and Papaioannou (2009) show that countries that had more highly educated workers and those that expanded education faster did experience more rapid employment growth in skill-intensive industries. Agosin et al. (2012) show that more educated countries are better able to maintain a diverse export mix in the face of terms-of-trade shocks. Jetter and Ramírez Hassan (2015) show that primary education attainment is a strong Bayesian predictor of national export diversification. Coniglio et al. (2018) inquire after a range of factors associated with unrelated diversification, and show that two crude proxies for education - scientific publication and educational expenditures - are associated with the development of unfamiliar industries in developing countries. Pinheiro et al. (2022) show that the average relatedness of the products in which a country acquires comparative advantage tends to fall with several indicators of economic development, including a human capital index.

The current paper, by maintaining a sharp focus on the role of education in the development of new industrial specializations,[2] adds to this literature in several ways. First, we introduce an econometric specification that can be used to run a horse race between different roles that education (or, indeed, any other national variable) can play in shaping the evolution of comparative advantage. Second, we apply this specification to examine these roles empirically. Our findings suggest that high education levels are helpful for promoting unrelated diversification, but not for shifting into more complex products (controlling for their relatedness). We also show that there is no evidence that educational expansions promote the expansion of education-intensive industries (as is usually predicted by factor proportions models). Third, we examine the effects of education of different levels, and of the quality of education, on shifts in comparative advantage. Fourth, we establish the robustness of these effects of education to a wide range of identification challenges. And finally, we show that education promotes unrelated diversification into peripheral products, but not into core products.

Although the most successful cases of industrialization in developing countries, with the exception of China, predate 1995 (Felipe et al. 2019), we study the period 1995–2015 for three reasons. First, there is much more competition between nations for footholds in tradable industries

[2] Our focus is on whether countries' specializations shift towards unfamiliar, complex and education-intensive products. It is of course possible that such shifts in specialization patterns could occur even as a country specializes in fewer products. The relationships between education and national measures of diversification and complexity have been analyzed elsewhere, but are difficult to interpret (Hausmann et al. 2007; Hausmann et al. 2014; Mehta & Felipe 2014).

now than in the past, so results from recent times are more relevant for policy. Second, the effectiveness of education should depend not only upon the quantity of schooling obtained, but also on its quality. We proxy for this using cognitive skills measures derived from international standardized tests that are only available beginning in the late 1990s. Third, trade policies vary less across countries after the structural-adjustment era.

The remainder of this paper is structured as follows: We discuss theory and introduce our specification and hypothesis tests in Section 2. We describe our data and variable definitions in Section 3 and our results in Section 4. Section 5 offers auxiliary analyses that clarify the interpretation and implications of our findings. Section 6 concludes. Several robustness tests are provided in our supplementary materials.

2. Theory and econometric specification

This section discusses a range of theoretical approaches that connect education to the development of new industrial specializations in developing economies. The discussion generates a set of testable hypotheses.

2.1. Theory

Education can facilitate developing countries' acquisition of new comparative advantage in three ways.[3] It can reduce production costs in an industry by increasing productivity, either by facilitating faster diffusion of knowhow to local producers from the industry's global technology frontier (Nelson and Phelps 1966) or from early domestic innovators to imitator firms (Hausmann and Rodrik 2003), or by facilitating learning-by-doing (see comments in, e.g., Arrow 1962; Lucas 1988). An increased endowment of educated labor also leads to the expansion of educated-labor-intensive industries which grow to fully employ these human resources – the well-known Rybczynski effects (Leamer 1984). And, education can facilitate entrepreneurship, enabling firms to expand into or become established in new industries (Schultz 1975).

These theories are generic in that they discuss the role of education without reference to which industries exist or are to be developed. In contrast, the literature on industrial diversification emphasizes that developing different types of industries poses different challenges, and that existing industries can be helpful springboards for launching new ones (Frenken et al. 2007; Hidalgo et al. 2007; Hausmann et al. 2014). These studies emphasize that the chances of success in a new industry depend upon the relatedness of the products produced by the new industries to those produced by the existing industries (Hidalgo et al. 2007; Hidalgo et al. 2018), and the complexity of the products produced by the new industries (Hidalgo and Hausmann 2009). It follows that the role of education is likely to depend upon these attributes as well.

Three findings from this diversification literature are important for this paper: First, already-existing industries in low-income countries tend to produce less-complex products, so that core products tend to be unrelated to those that these countries already produce (Hidalgo et al. 2007).

Second, it is much more common for an economy to develop new industries that produce products that are related to those it already produces. In other words, industrial development tends to be 'path dependent', especially for less developed economies (Hidalgo et al. 2007; Pinheiro et al. 2022). Path dependence arises because productive knowledge must often be acquired through learning-by-doing and because supplies of specialized factors and raw material inputs are unlikely to exist unless other industries that require them exist as well (Stiglitz and Greenwald 2014). As a consequence, before becoming capable of producing complex, core products, developing countries must usually develop a series of related, stepping stone industries. Skipping the development of such stepping stone industries and moving directly into unrelated industries is sometimes referred to as 'leapfrogging', and is rare (Hobday 1995).

Third, industrializing economies that escape path dependence by developing unrelated complex industries often experience development booms (Hausmann et al. 2014; Pinheiro et al. 2018). This is because these new industries, being unrelated to the existing export mix, both require, and facilitate – thorough learning-by-doing, the development of new sets of capabilities. These new capabilities then enhance productivity in new and existing products.

Why might education facilitate unrelated diversification and the development of more complex industries?

There are several reasons to think that education facilitates unrelated diversification. It is well known that multinational companies tend to have greater demand for skills and to hire more educated labor than do domestic firms (Hakkala et al. 2014; Alfaro-Urena et al. 2019), and that education aids in entrepreneurship (Van der Sluis et al. 2008). Neffke et al. (2011) show that foreign firms and entrepreneurs promote unrelated diversification. Together, these results suggest that education promotes unrelated diversification by facilitating entrepreneurship and attracting outside firms with new knowhow. Indeed, the finding that education, by promoting entrepreneurship, facilitates unrelated diversification, resonates well with early human capital theory. Schultz (1975) theorized that education may help entrepreneurs to recognize and exploit disequilibrium opportunities. Young industries and those less related to existing industries are likely to offer more disequilibrium opportunities, given that competition in their input and output markets tend to be thinner. A further mechanism is emulation: if early entrants are active in establishing the viability of unrelated industries, educated labor can play a vital role in expanding those new industries by transferring knowhow from the entrant to other firms (Hausmann and Rodrik 2003). Finally, education can enhance creativity – the ability to redeploy knowledge used in some domains to solve problems in other domains (Florida 2002). Such redeployments of knowledge are obviously critical for unrelated diversification. In other words, education can help to navigate the unfamiliar.

Conversely, education could facilitate related rather than unrelated diversification. This is because organizations learn by doing. As organizations learn how to make a given product by producing others that are related to it (Posner 1961; Grossman and Helpman 1995), education that increases the effectiveness of this learning-by-dong is likelier to promote related diversification than unrelated diversification. And, if experimentation in unrelated industries is limited, then educated workers, through emulation, may expand production of related products (e.g., see the discussion of Bangladeshi experience in Hausmann and Rodrik 2003).

It follows that education will tend to promote unrelated diversification when it helps overcome unfamiliar challenges by promoting creativity, capacity to exploit disequilibria, entrepreneurship and cross-regional collaboration; and related diversification if it simply speeds up learning by doing.

The argument that education facilitates the development of industries that make complex products is straightforward. Complex products involve more knowledge than less-complex products, and education helps acquire knowledge. Thus, if two countries with differing educational endowments have an identical initial industrial mix, the

[3] Given that developing countries typically diversify by learning to produce existing products and to apply existing production techniques, we do not discuss education's role in R&D in new products and techniques. See Viotti (2002).

more educated country is likely to develop new comparative advantage in a more complex set of products than is the less educated country (e.g., see the model of Hausmann et al. 2007).

The above discussion of education's role in industrial change is rooted in the complexity and evolutionary literature and emphasizes learning. As noted, factor-proportions theories of trade take a general equilibrium approach, predicting that education expansions will lead to an expansion of industries that intensively employ educated labor relative to industries that do not (the Rybczynski effect).

2.2. Econometric specification

To examine these ideas, we estimate linear probability models on a pooled sample of products (indexed by p) and countries (indexed by c, replacing Home and ROW). Our specification is motivated by the preceding arguments regarding education in relation to the relatedness, complexity and education-intensity of new industries. Our main specification is:

$$\begin{aligned} CA_{c,p,1} &= \alpha_c + \alpha_p + f(RCA_{c,p,0}) + \beta_F F_{c,p,0} + \beta_{EF} E_{c,0} F_{c,p,0} \\ &+ \gamma_{ET} E_{c,0} T_{p,0} + \delta_{EE} el_p \Delta Yrs_c + \delta_{KE} kl_p \Delta kl_c + e_{c,p,1} \end{aligned} \tag{1}$$

$RCA_{c,p,t} = (X_{c,p,t}/X_{c,t})/(X_{p,t}/X_t)$ is Balassa's (1965) index of revealed comparative advantage at time t, where X denotes exports. $CA_{c,p,1} \equiv I\{RCA_{c,p,1} \geq k\}$ is an indicator that country c had a comparative advantage in product p in subsequent period 1. Our baseline results use $k = 1$. Discretizing RCA in this way sacrifices variation in the dependent variable, but this is standard in the literature because it solves a range of econometric problems, and because varying the value of k allows us to check whether results are driven by differences in RCA around particular values (Bahar et al. 2014; Bahar et al. 2019).[4]

Our initial and subsequent time periods (*0* and *1*) are 1995 and 2015. $E_{c,0}$ captures country c's initial education level; $T_{p,0}$ is a measure of product p's intrinsic complexity. $F_{c,p,0}$ measures the relatedness of product p to country c's existing product mix, and we refer to it henceforth as their "familiarity" with product p. Terms involving these variables capture learning dynamics. To capture Rybczynski effects due to the accumulation of education and capital, products' initial intrinsic education intensity (el_p) and capital intensity (kl_p) are interacted with the national growth rates between 1995 and 2015 of the supplies of these factors, relative to labor. This captures the effects of factor accumulation on the acquisition of comparative advantage. To render the coefficients readily interpretable, all RHS variables other than familiarity are normalized to have a mean of zero and a standard deviation of one.

Country fixed effects allow for national traits conducive the acquisition of more comparative advantages, while product fixed effects capture traits that make it more difficult to develop comparative advantage in some products than in others.

We correct for lagged RCA to control for long-run drivers of trade patterns, such as history and geography, as well as the availability of human and physical capital prior to $t = 0$.[5] Unlike studies of long-run determinants of the level of comparative advantage, which provide powerful confirmation of the long-run role of factor endowments effects (Eaton and Kortum 2002; Chor 2010), controlling for lagged RCA means that our coefficients capture the relationship between the independent variables and medium-run *changes in* comparative advantage.

This specification permits us to test our three hypotheses regarding the role of education. First, if high education levels encourage the development of comparative advantage in unfamiliar products (those unrelated to a country's existing product mix), β_{EF} will be negative. Alternately, if education simply increases the effectiveness of learning by doing for familiar industries, β_{EF} will be positive. Second, higher education levels may predispose countries to develop comparative advantage in more complex products, in which case, γ_{ET} should be positive. Third, under a factor-proportions framework, acquiring more education should help countries gain comparative advantage in education-intensive products, so that $\delta_{EE} > 0$.

The model also permits us to examine whether countries tend to develop comparative advantage in familiar products. We will conclude that this is, on average, the case for a country with initial education level $E_{c,0}$ if $\beta_F + \beta_{EF} E_{c,0} > 0$. Thus, a positive β_F indicates that a country endowed with average education $(E_{c,0} = 0)$ experienced path dependence. Conversely, $\beta_F + \beta_{EF} E_{c,0} < 0$ indicates that a country with education level $E_{c,0}$ tended to move into unfamiliar products.

We measure education as a vector whose dimensions include quality and quantity, with quantity decomposable into contributions from primary, secondary, and college attainment. This permits us to test hypotheses regarding the roles of these dimensions of education in industrial development. To examine whether and how the role of education varies across type of product, we also re-estimate this specification on subsamples of core and peripheral products.

The estimated interaction coefficients reflect differences in the characteristics of the target products in which RCA is most often developed between more and less educated countries. They provide causal estimates of education's effect on the character of the export mix only if those differences are not explained by omitted variables that vary across country-product dyads. Reverse causation is unlikely because the dependent variable is measured 15–20 years after the independent variables. As suitable instruments for education and familiarity are unavailable, we will check that our findings are robust to the inclusion of a wide variety of omitted country-product-level variables. To ensure they are robust to the omission of variables capturing institutional or infrastructure quality, openness to FDI, or industrial dynamism pre-1995, we estimate specifications that interact proxies for these national characteristics with familiarity and with product complexity. Finding, as we do, that our results are robust to this, to the exclusion of products and one country (China) for which the global trade rules changed, and to several other potential sources of error, suggests that they do provide insight into education's role in industrial diversification.

[4] RCAs are non-negative, often zero, and strongly right-skewed, suggesting that a corner solution model would be required if we treated them as continuous. Identification of these models relies on untestable distributional assumptions, and the product fixed effects required by theory raise incidental parameters problems in a maximum likelihood context (Cameron & Trivedi 2005). Corner solution models also yield nonlinear conditional expectations functions, which complicates hypothesis testing (Wooldridge 2002). Log-linearizing RCA, as required by the exponential Churdle model results in findings being driven by differences close to RCA=0, while using an inverse hyperbolic sin transformation would implicitly assume that starting to export a product poses similar challenges to increasing exports in an already exported product. In contrast, linear probability models are consistent and easy to interpret (Angrist & Pischke 2008). To ensure that our findings are not specific to the dynamics of comparative advantage around $RCA_{c,p,t1} = 1$, we follow Bahar et al. (2014) in estimated the model after discretizing around $RCA_{c,p,t1} =$ 0.5, 0.8 and 2 (see Supplementary Table A4).

[5] The lagged RCA correction takes the form: $f(RCA) = f_0 * I\{RCA = 0\} + f_1 * [1 - I\{RCA = 0\}]g(RCA)$, where $g(RCA) = \ln(RCA)$ when $RCA > 0$ and $g(RCA) = m$ when $RCA = 0$. This specification makes allowance for the possibility that exporting any of a product has different effects on the likelihood of future comparative advantage than does having a high-RCA in it. Our coefficient estimates are invariant to the value chosen for the constant m by construction. Log-linearizing the non-zero values is recommended by the q-q plot of ln(RCA) (Supplementary Figure A1). We have also run our main regressions using a hyperbolic sine function in place of g(), but this is restrictive and does not alter our main results.

3. Data and measurement

We use CEPII data on countries' exports, between 1995 and 2015, of 1240 goods classified by 4-digit Harmonized System (1992) codes, elaborated by The Growth Lab at Harvard, (2019a).

Our main analysis excludes countries with per capita incomes in 1995 above \$19,000. We do so because these countries had already developed comparative advantage in many core products by 1995 (Fig. 1), making it difficult for them to establish comparative advantage in many more core products during the period of our study. As advanced economies are among the most educated in the world, including them in the main analysis would lead to underestimates of the role of education among countries still attempting to move into the core of the global economy. Indeed, when we run our main regressions (those appearing in Table 2) on a sample of only these rich countries, the coefficient on the interaction between education and familiarity is statistically insignificant and very small, while the other education interactions remain insignificant (not shown, for brevity).

The main variable limiting our sample size is the quality of education. Hanushek and Woessman (2009, henceforth, H&W) carefully calibrate and splice together the results of several international standardized mathematics and science tests administered to 15 year-olds to produce a cross-sectional dataset of the average cognitive skills of a student in each country by the late 1990s. This calibration is performed relative to a group of OECD countries that took multiple tests over time. Altinok et al. (2018) use slightly different criteria and procedures to assemble an imbalanced panel of student cognitive skills for these and other countries between 1965 and 2012, and use these to derive a cross-sectional dataset. In addition to affording greater country coverage, these cross-sectional estimates are arguably more reliable than the H&W estimates for countries whose standardized test performances differ most from the OECD countries that H&W use in their calibrations, but capture conditions in slightly later years. Our main sample includes 49 countries appearing in Altinok et al.'s cross-sectional dataset, 35 of which also appear in H&W, and our results are robust to switching to the H&W measures (see Section 4.3.1.).

We measure countries' average years of schooling in 1995 and 2015 using data from Penn World Tables (PWT, Feenstra et al. 2015). Data on primary, secondary and college attainment rates in 1995 in the population aged 15 and above come from Barro and Lee (2010, henceforth B&L).

We define the relatedness between products p and q by their "proximity", $\varphi_{p,q} \equiv \min\left[\Pr\left(RCA_{c,p} \geq 1 | RCA_{c,q} \geq 1\right),\ \Pr\left(RCA_{c,q} \geq 1 | RCA_{c,p} \geq 1\right)\right]$. Proximate products are presumed to rely on similar capabilities. We measure familiarity using "density", which measures how related a product is to the country's export basket. This is calculated as $F_{c,p} \equiv \sum_{q \neq p}\left(CA_{c,q}\varphi_{p,q}\right) / \sum_{q \neq p}\left(\varphi_{p,q}\right)$, and must lie between zero and one (Hidalgo et al. 2007). Our measures of RCA and density are drawn from the CEPII trade data as prepared by the Harvard Growth Lab, and were calculated using all countries in that dataset.

Let M be a C x P matrix with each element equal to $CA_{c,p}$. We measure complexity, $T_{p,0}$, by the product complexity index (PCI_p), which utilizes information in M and a recursive method to assign higher scores to those products that are exported with comparative advantage by fewer countries (uniqueness), especially when those countries' exports are themselves diverse (Hausmann et al. 2014, p. 24).

We infer how intensive each product is in the use of factor Z using $Z_p \equiv \sum_c\left(RCA_{c,p,0} Z_{c,0}\right) / \sum_c\left(RCA_{c,p,0}\right)$, where $Z_{c,0}$ denotes nations' endowments of the factor. We create three measures of the educated-labor-content of products (el_p) in this way. First, when $Z_{c,0}$ is national average years of schooling, estimated from Penn World Tables, we obtain the measure Yrs_p. Second, when it is the share of a country's population aged 15+ that completed college, taken from B&L's country data, we obtain $Coll_p$. Finally, when it is high-schoolers' cognitive skill levels, using H&W's country data, we get Cog_p. These measures are modeled on $ProdY_c$, an early measure in the complexity literature

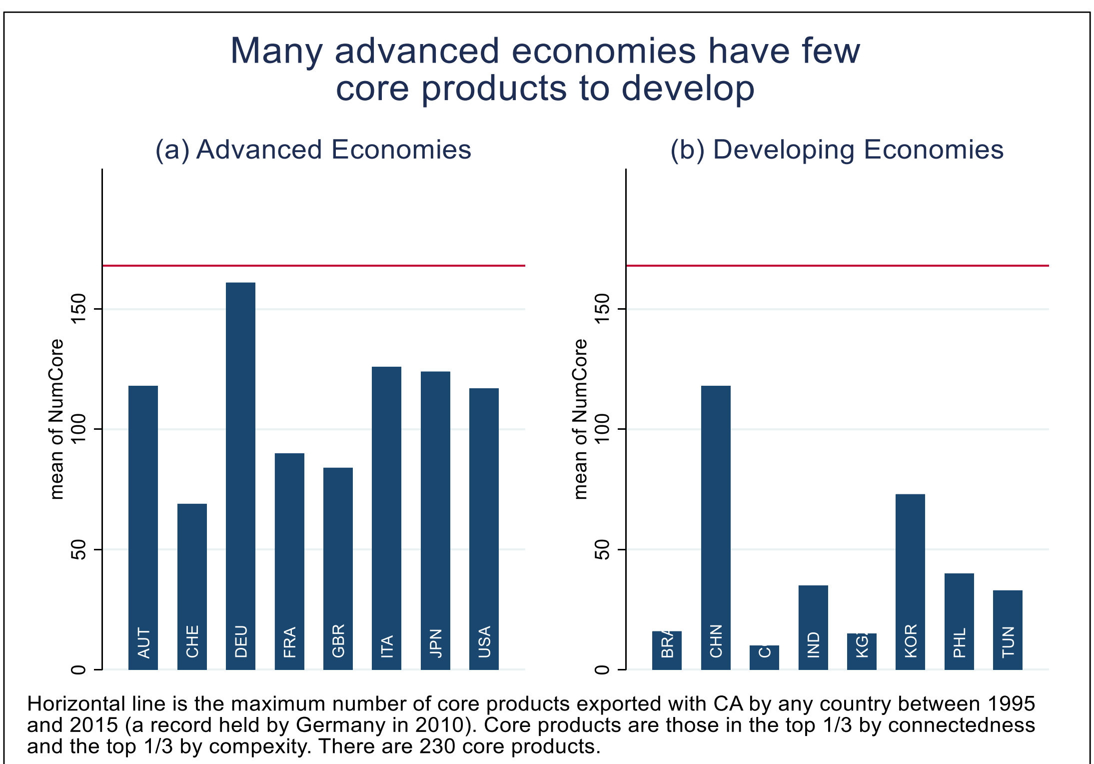

Fig. 1. Why we drop advanced economies.

Table 1
Summary Statistics.

	Observations	Mean	SD	Minimum	Maximum
Country-level variables					
Quantity (Average Years of Schooling)	49	7.11	2.35	2.16	11.39
Education Quality A (Altinok et al., 2018)	49	494.39	75.07	282.24	652.62
Education Quality B (Hanushek & Woessman, 2009)	35	4.27	.58	3.09	5.34
Primary (Primary Attainment, aged 15+)	48	73.13	17.08	36.21	98.03
Secondary (Secondary Attainment, aged 15+)	48	33.32	16.65	4.81	76.70
College (College Attainment, aged 15+)	48	5.88	4.19	.58	19.35
ΔYrs_c (Change in Average Years of Schooling)	49	2.31	.76	.50	4.55
ΔQuality A (Change in Edu Quality A)	22	9.81	30.02	−36.60	63.47
Δkl_c (Change in Capital:labor ratio)	44	.55	.44	−0.51	2.02
Product-level variables					
PCI (Product Complexity Index, 1995)	1240	0.00	1.00	−2.93	2.84
PCI (Product Complexity Index, 2015)	1240	.00	1.00	−3.39	3.01
Yrs_p (Average years of schooling across product exporters)	1240	8.73	1.30	3.13	12.35
Cog_p (Average education quality across product exporters)	1240	4.75	.22	3.89	5.20
$Coll_p$ (Average college attainment across product exporters)	1240	8.07	1.73	3.20	15.58
ProdKL (K/L averaged across product exporters)	1240	−9.49	.74	−13.11	−6.66
$ProdY_p$ (Average GDP across product exporters, 1995)	1240	15,509	7387	175	47,422
$ProdY_p$ (Average GDP across product exporters, 2015)	1240	21,980	10,980	395	76,409
Country-Product-level variables					
RCA (1995)	60,760	1.20	9.24	0	868.77
RCA (2015)	60,760	1.18	9.19	0	1243.06
CA = *I*(RCA_2015>=1}	60,760	.17	.37	0	1
ΔRCA (Change in Export RCA, 1995–2015)	60,760	−0.03	9.23	−867	476
Familiarity (1995)	60,760	.16	.09	.00	.70

Note: All country-level and product-level variables will be normalized to have a mean of zero and standard deviation of one when used in regressions.

(Hausmann et al., 2007), which captured a product's complexity by the average real per capita GDP of the countries with a comparative advantage in it (i.e., $Z_{c,0} = GDP_{c,0}$). We create each of these measures using data capturing conditions as close to 1995 as possible. We also use this procedure and PWT data on each country's ratio of capital to employment to measure products' relative capital intensities, kl_p.[6] The same PWT data are used directly to measure log-changes between 1995 and 2015 in countries' average years of schooling(ΔYrs_c) and capital per worker (Δkl_c).

Next, we define the connectedness of each product as the sum of its proximities to all other products: $C_q \equiv \sum_{n \neq q} \varphi_{n,q}$. We classify products as "core" if they are in the top tercile of the distributions of both connectedness and *PCI* and "peripheral" if they are in the bottom tercile of both distributions. To illustrate: most unprocessed agricultural and mined commodities, human hair, jute fibers and electric power are revealed to be peripheral; jet engines, x-ray machines, watch movements, optical devices and machine tools are core products; and paper, electric shavers, hats, copper wire and wine are in-between. In our data set of 1240 products, 230 are core and 232 are peripheral. The remaining 778 are in-between.

The control variables used in this paper include multiple measures of the quality of countries' institutions and infrastructure (listed in the note to Table 4), as well as the average of their FDI/Exports and FDI/GDP ratios between 1995 and 2015 (drawn from the World Development Indicators, WDI). Finally, we use three proxy measures of countries' industrial dynamism prior to 1995, explained in Section 4.3.3.

Table 1 provides summary statistics. Usefully, the countries in our sample differ widely in educational attainment and quality, and RCAs in many industries (country-product dyads) demonstrate significant changes between 1995 and 2015.[7]

4. Results

4.1. Regression analysis

Table 2 builds up our baseline estimates of specification (1). Columns (1) and (2) include only terms involving relatedness and complexity. Column (1) measures the quantity of education in 1995 by average years of schooling, while Column (2) measures it by the proportions of the population aged 15+ that completed primary, secondary and college education. Column (3) includes only the explanatory variables suggested by a factor abundance approach. As we do not have attainment rates by schooling level in 2015, or time series for most countries on changes in education quality, we focus on the effects of changing average years of schooling. The three-way interaction allows that increasing years of schooling would be more supportive of the development of comparative advantage in education-intensive products if that education is of a high quality. Columns (4) and (5) combine the two sets of coefficients. Other than familiarity and the $f(RCA_{c,p,0})$ terms, every variable entering the table, whether on its own or interacted, is normalized to have a mean of zero and standard deviation of one.

As expected, the coefficients on the lagged dependent variable indicate positive relationships between the probability of comparative advantage in 2015, and having both, non-zero and larger RCAs, in 1995.[8]

We use country-clustered standard errors throughout this paper. These standard errors are very conservative, given that we have not sampled a small number of countries from a large universe, but rather

[6] It is possible that the use of such revealed factor-intensity measures in trade regressions could yield spurious positive results by construction: it should not be surprising if educated countries learned to produce "education-intensive products", which are defined as those products that highly educated countries produce. However, this paper does not report such positive results – we find roughly no relationship between factor endowments and the development of comparative advantage in products intensive in those factors.

[7] The development of comparative advantages in different types of products are summarized in Supplementary Table A1, Fig. 2 and Fig. 3.

[8] Post-estimation calculations of $P(RCA_{p,t1} \geq 1 | RCA_{p,t0} > 0)$ and a kernel-weighted estimate of the same (Supplementary Figure A2) confirm that this is a (nearly) monotonic positive relationship.

Table 2
Main regression results.

	Economic Complexity		Heckscher-Ohlin-Vanek	Both	
	(1)	(2)	(3)	(4)	(5)
Corrections for lagged RCA					
I{RCA in 1995=0}	−0.203*** (0.013)	−0.199*** (0.013)	−0.263*** (0.016)	−0.202*** (0.014)	−0.195*** (0.014)
[1 - I{RCA in 1995=0}] **ln*(RCA in 1995)	0.049*** (0.002)	0.049*** (0.002)	0.066*** (0.003)	0.050*** (0.002)	0.050*** (0.002)
Familiarity	2.214*** (0.180)	2.310*** (0.166)		2.238*** (0.190)	2.332*** (0.178)
Familiarity x Quantity	−0.649*** (0.166)			−0.633*** (0.160)	
Familiarity x Quality A	0.181 (0.157)	0.004 (0.181)		0.114 (0.132)	−0.078 (0.162)
Familiarity x Primary		−0.372 (0.260)			−0.448 (0.269)
Familiarity x Secondary		−0.076 (0.165)			0.065 (0.184)
Familiarity x College		−0.110 (0.202)			−0.139 (0.211)
PCI x Quantity	−0.024** (0.010)			−0.028** (0.012)	
PCI x Quality A	0.028*** (0.008)	0.023*** (0.008)		0.021** (0.010)	0.015* (0.008)
PCI x Primary		−0.011 (0.010)			−0.014 (0.011)
PCI x Secondary		−0.020* (0.010)			−0.016 (0.012)
PCI x College		0.006 (0.010)			0.001 (0.010)
Δkl_c x kl_p			−0.002 (0.008)	0.007 (0.004)	0.006 (0.005)
ΔYrs_c x Yrs_p			−0.002 (0.004)	−0.006 (0.005)	−0.005 (0.005)
Quality A x Yrs_p			0.023*** (0.005)	0.009** (0.004)	0.010** (0.004)
ΔYrs_c x Quality A x Yrs_p			−0.006 (0.008)	0.002 (0.009)	0.001 (0.008)
Country Fixed Effects	✓	✓	✓	✓	✓
Product Fixed Effects	✓	✓	✓	✓	✓
Observations	60,760	59,520	54,560	54,560	53,320
R-squared	0.266	0.266	0.242	0.264	0.264
R-Squared from a restricted regression, excluding all education terms		0.261	0.239		0.259

Note: Estimates based on linear probability specification (Eq. (1)). Country-clustered standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Restricted regressions in columns (2) and (5) use the same sample as the regressions in columns (1) and (4).

attempted to include every low and middle-income country for which the relevant data are available (Abadie et al. 2017). We report in the text on any results that are qualitatively altered by the use of unclustered robust standard errors.

The results in Table 2 show that a high quantity of education is associated with overcoming unfamiliarity. The positive significant coefficient on familiarity indicates that the average country (one with average education quality and quantity) is much more likely to develop comparative advantage in products that are more familiar to it. The negative sign on the familiarity-quantity interaction is consistent with more education helping countries develop comparative advantage in relatively unfamiliar products. Evidence of this effect is strongest for primary school, and when using unclustered standard errors, the p-value on the interaction between familiarity and primary attainment is effectively zero. Together, these results suggest that learning-by-doing is important, and that education promotes unrelated diversification by helping countries to cope with unfamiliar challenges.

In contrast to this evidence that a higher *quantity* of education – most likely primary education – was associated with developing comparative advantage in less familiar products, there is no evidence of such an association with a high *quality* of education, conditional on quantity. This suggests that what matters for overcoming unfamiliarity under general circumstances are the foundational skills delivered by a universal basic education.[9]

To understand the magnitude of this effect of education quantity, consider two products and two countries. Assume, for each product, that its lagged RCA and familiarity are the same in both countries, but that one product is 0.20 points (roughly two standard deviations, Table 1) more familiar than the other product in both countries. Also assume that both countries have average education quality, that country A has average education quantity, and that country B's years of schooling are one standard deviation higher than the mean. The estimates in column (4) then indicate that in country A the probability of comparative advantage in 2015 is 45 p.p. higher in the more familiar product than in the unfamiliar product. However, in country B, this probability will only be 32 percentage points higher in the more familiar product. This 13 p.p. difference attributable to education is sizeable compared to the 17 p.p. mean probability of comparative advantage.[10] On the other hand, despite this large effect of education quantity, there are no countries in our sample with enough years of schooling to eliminate path dependence (i.e., there are no countries for which 2.238 – 0.633*Quantity $\leq$ 0).

The results in Table 2 paint a mixed picture regarding the hypothesis that education helps develop comparative advantage in more complex products. Higher average years of schooling in 1995 are associated with developing comparative advantage in *less* complex products, while higher quality education is associated with developing comparative advantage in *more* complex products. Moreover, the magnitude of these relationships is small. The effect of school quality on comparative

[9] These results do not imply that education quality is unimportant for overcoming path dependence. Cognitive skills and years of schooling are positively correlated, and high-quality schooling may push years of schooling higher. When we re-run the estimates in Table 2 excluding all terms involving average years of schooling, education quality is associated with stronger movements towards unfamiliar products. Results are produced in our replication code.

[10] In country A the difference in probability of comparative advantage is 0.2*2.238 = 0.448. In B it is 0.2*(2.238-0.633) = 0.321.

Table 3
Regressions in subsamples of core and peripheral products.

	Core Products			Peripheral Products		
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	2.924***	2.901***	3.058***	2.099***	2.280***	2.360***
Familiarity x Quantity		−0.655**			−0.862***	
Familiarity x Quality A		0.500	0.099		−0.306	−0.502*
Familiarity x Primary			−0.047			−0.753**
Familiarity x Secondary			−0.317			0.191
Familiarity x College			0.124			−0.155
PCI x Quantity		−0.023*			−0.023**	
PCI x Quality A		0.015	0.012		−0.012*	−0.015**
PCI x Primary			−0.027**			−0.031***
PCI x Secondary			−0.015			−0.002
PCI x College			0.016			0.005
Δkl_c x kl_p	0.006	0.010	0.006	0.012***	0.016***	0.016***
ΔYrs_c x Yrs_p		0.005	0.004		−0.004	−0.005
Quality A x Yrs_p		0.011	0.011		0.009*	0.011**
ΔYrs_c x Quality A x Yrs_p		0.013	0.008		0.003	0.001
Country Fixed Effect	✓	✓	✓	✓	✓	✓
Product Fixed Effect	✓	✓	✓	✓	✓	✓
Corrections for Lagged RCAs	✓	✓	✓	✓	✓	✓
Observations	10,120	10,120	9890	10,164	10,164	9933
R-squared	0.257	0.260	0.259	0.319	0.330	0.331

Note: Estimates from linear probability model, Eq. (1). Core (peripheral) products are in the top (bottom) tercile by both connectivity and complexity. Significance using country clustered standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

advantage in complex products is roughly 1/3 the size of the effect of school quantity on comparative advantage in unfamiliar products.[11]

Regressions (4)-(5) provide no significant evidence that increases in education shift countries towards education-intensive products. The point estimates suggest that countries with larger increases in average years of schooling between 1995 and 2015 tended to develop comparative advantage in *less* education-intensive products. They also do not support the possibility that increasing years of schooling shifts comparative advantage towards education-intensive products more reliably in countries with higher quality education. Reconfirming this null result, Regression (3) drops all terms involving relatedness and complexity ($F_{c,p,0}$ and $T_{p,0}$), allowing all accumulation of comparative advantage to be explained only by factor accumulation, and shows that expansions in education quantity are still unrelated with movements towards education-intensive products.

Table 2 also reports R-squared statistics for models that restrict the coefficients on all education terms to be zero in order to assess education's explanatory power. Allowing that education could be useful for overcoming unfamiliarity, product complexity or education-intensity adds very little to model R-squared.[12] In combination with the large and statistically significant coefficient on the interaction between familiarity and education quantity, this indicates that education is useful for overcoming unfamiliarity, but that past specialization patterns, product characteristics and country characteristics are still the main measured determinants of subsequent specialization patterns.

4.2. *Core and peripheral products*

Table 3 presents results on the subsets of core and peripheral products.[13] Our main result, that countries with higher average years of schooling were substantially more likely to develop comparative advantage in unfamiliar products, holds for both subsets.

However, there are four differences between core and peripheral products. First, primary attainment is associated with learning to produce unfamiliar peripheral products, but this is not the case for core products. Second, while countries with higher quality education exhibit a slight tendency to develop comparative advantage in unfamiliar peripheral products, this is reversed for core products.[14] Third, capital accumulation is significantly associated with movement towards capital-intensive products among peripheral products, but not among core products. Fourth, the effects of familiarity are larger among core products than among peripheral products. All of these results suggest that it is harder to develop comparative advantage in core products than in peripheral products, and that general education is particularly important for moving up lower rungs of the product ladder.

4.3. *Robustness checks*

Instruments for education and familiarity do not exist. To ensure that our results are not misleading, we have verified that they are robust to errors in specifying key variables, to the inclusion of other plausible explanatory factors, to sample-exclusions selected to capture changes in institutions governing global trade, and to problems akin to reverse causation that would arise if industrial dynamism causes countries to invest in education.

[11] Consider two products two standard deviations apart in complexity, and two countries one standard deviation apart in education quality but with the same years of schooling. Holding all other variables constant across products and countries, the difference between the probabilities of comparative advantage in the more and less complex products would be 4.2 p.p. (=0.021*2*1) greater in the better educated country. Compare this to the 13 p.p. effect of school quantity in unfamiliar products.

[12] For example, R-squared rises from 0.2614 to 0.2664 when the four education-related terms in column (1) are added. In a linear probability model, R-squared captures the difference in the predicted probabilities of "success" – in our case, a comparative advantage in the product – between observed cases of success and failure (Gronau 1998).

[13] Results for in-between (neither core nor peripheral) products closely resemble those in Table 2, and are produced in our replication code.

[14] When using unclustered standard errors, the coefficients on the familiarity-quality interaction for core products in columns (2) and (3) have p-values of 0.082 and 0.138. The analogous p-values in the peripheral regressions (5) and (6) are 0.016 and 0.000.

Table 4
Robustness to controls for institutions, infrastructure and FDI.

	Control Variable								
	Contracts (1)	Infrastructure (2)	Days (3)	Internet (4)	Regulatory Quality (5)	Rule of Law (6)	FDI/ Exports (7)	FDI/GDP (8)	Principal Component (9)
Familiarity	2.286***	2.349***	2.213***	2.300***	2.281***	2.311***	2.345***	2.283***	2.625***
Familiarity x Control Variable	−0.026	0.044	0.042	0.071	0.288	−0.065	0.271**	0.065	−0.184
Familiarity x Quantity	−0.640***	−0.652***	−0.624***	−0.724***	−0.713***	−0.637***	−0.619***	−0.660***	−0.894***
Familiarity x Quality A	0.083	0.089	0.121	0.096	0.059	0.112	0.080	0.094	0.097
PCI x Control Variable	0.000	0.002	−0.001	0.011	0.018***	0.010	−0.003	−0.006	−0.001
PCI x Quantity	−0.030*	−0.032**	−0.028**	−0.044***	−0.034***	−0.028**	−0.025**	−0.024*	−0.082***
PCI x Quality A	0.023	0.023*	0.021**	0.026**	0.018*	0.017	0.019*	0.020**	0.064***
Δkl_c x kl_p	0.006	0.006	0.006	0.006	0.006	0.007	0.007*	0.007	0.004
ΔYrs_c x Yrs_p	−0.008	−0.008*	−0.006	−0.011**	−0.006	−0.006	−0.006	−0.006	−0.027**
Quality A x Yrs_p	0.010*	0.010**	0.009**	0.007	0.009**	0.009**	0.009**	0.009**	0.012
ΔYrs_c x Quality A x Yrs_p	0.000	0.001	0.002	0.004	0.003	0.003	0.002	0.002	0.006
Country Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Corrections for Lagged RCAs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	43,400	47,120	53,320	48,360	54,560	54,560	54,560	54,560	22,320
R-squared	0.271	0.273	0.264	0.274	0.266	0.265	0.265	0.265	0.303
F-test	4.834	7.241	6.275	6.008	6.019	6.891	8.691	7.981	17.658
Prob>*F*	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: All control variables have been normalized to have a mean of zero and standard deviation of 1. FDI, exports and GDP were originally in nominal values, drawn from World Development Indicators (WDI). Infastructure and institutional controls appearing in the table are: an index of sanctity of contract from the 2001 Growth Competitiveness Index (GCI); index of infrastructure quality from the 2004 Global Competitivess Index; days to open a business in 2003 from World Bank's Doing Business Surveys (DBS); Internet users as percent of the population in 1995 from the International Telecommunications Union; and measures of regulatory quality and rule of law in 2000 from World Bank's World Governance Indicators. Control variables that do not appear in the table yield the same qualitative results as those shown in the table, and are: roads per square kilometer in 2005 (WDI); number of procedures to open a business in 2003 (DBS); and indices of ICT infrastructure and freedom from corruption in 2001 (GCI). The control variable in Column (9) is the first principal component of all 10 institutional and infracstructural variables. The estimation is based on a linear probability model (Eq. (1)). Significance using country-clustered standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.1. *Errors in the specification of key variables*

There has been some debate over how to measure national education quality, given concerns regarding the cross-county and inter-test comparability of international mathematics and science test results. Hanushek and Woessmann (2009) are conservative in this regard, producing estimates for a smaller set of countries than do Altinok et al. (2018). Supplementary Table A2 shows that re-estimating the regressions in Table 2 for a smaller number of countries using the Hanushek and Woessmann (2009) measures does not alter the results qualitatively.

It is also possible that PCI_p does not capture the aspects of product complexity that education is most helpful for overcoming. To see whether this accounts for the weak estimated effects of education on the complexity of the emerging export mix, Supplementary Table A3 replaces PCI_p with six different proxy measures for complexity. Columns (2)-(5) use Yrs_p, $Coll_p$, Cog_p and $ProdY_p$ measured in 1995, while columns (6) and (7) use PCI_p and $ProdY_p$ measured in 2015.[15] Once again, the results from Table 2 are confirmed. This is reassuring. However, attenuation due to mismeasurement of product complexity and education-intensity is still possible, given that our 1240-product trade classification could obscure intra-industry trade in tasks or sub-categories of products that have very different levels of complexity and factor intensity.[16]

Supplmenentary Table A4 confirms that changing the RCA threshold for establishing comparative advantage leaves the results from Table 2 qualitatively unchanged as well.

[15] We do not use measures of the education-intensity of products derived from the 2015 export record to avoid recoding false positives for mechanical reasons. See Footnote 6.

[16] We are grateful to an anonymous referee for highlighting this possibility, which we are unable to address with the data available.

4.3.2. *Other possible explanatory variables*

Our findings do not appear to result from a spurious correlation between education and other national characteristics that shape diversification paths.

Institutions, infrastructure and FDI are thought to be important contributors to the development of industrial knowhow (Lall 1992; Felker et al. 2013; Crescenzi et al. 2015). They are also correlated with education. Table 4 reports several regressions, each of which controls for interactions with the PCI and familiarity, of a country-level measure of institutional quality, infrastructure and/or openness to FDI. We ran 13 such regressions, each with a different country-level control variable, but show only 10 of them in Table 4. The other three are qualitatively similar and available on request. When added, none of these controls changes our findings regarding the role of education. Only two of the 26 introduced interaction terms are statistically significant: high quality regulatory institutions predict movement towards complex products, and countries receiving more FDI relative to their exports were more likely to develop comparative advantage in products with which they were already familiar.

Spillovers of knowledge and supply-chains across geographically close countries are also known to influence comparative advantage (Caniëls and Verspagen 2001; Bahar et al. 2014; Bahar et al. 2019). Supplementary Table A5 checks whether our findings are driven by the omission of such neighborhood effects. Each regression in that table corrects for a weighted average of the familiarity with product *p* of every country other than home country *c* in 1995, or for a weighted average of their RCAs in product *p*. The weights are the inverse of each country's geographic distance from *c* (Mayer and Zignago 2011). Adding these variables and their interactions with education changes none of our results.

Table 5
Correcting for prior industrial dynamism.

	Measure of Prior Industrial Dynamism Used					
	Real GDPPC Growth Rate		Labor Productivity Growth Rate		First stage coefficients on familiarity & PCI	
	(1)	(2)	(3)	(4)	(5)	(6)
Familiarity	2.280***	2.585***	2.393***	2.549***	2.054***	2.084***
Familiarity x Quantity	−0.802***		−0.668***		−0.679***	
Familiarity x Quality A	−0.107	−0.103	0.021	0.007	0.134	−0.060
Familiarity x Primary		−0.677*		−0.491**		−0.370
Familiarity x Secondary		0.130		−0.068		0.102
Familiarity x College		−0.134		−0.178		−0.190
Familiarity x Dynamism (1975–95)	0.833*	0.757	0.355	0.250	−0.004	−0.067
Familiarity x Dynamism (1985–95)	−0.584	−0.686	−0.273	−0.356	−0.159***	−0.125**
PCI x Quantity	−0.031***		−0.020		−0.018*	
PCI x Quality A	−0.009	−0.019	0.010	0.004	0.019*	0.010
PCI x Primary		−0.010		−0.006		0.004
PCI x Secondary		−0.030*		−0.015		−0.008
PCI x College		0.014		−0.000		−0.007
PCI x Dynamism (1975–95)	0.042**	0.055**	0.012	0.013	0.102	0.112
PCI x Dynamism (1985–95)	0.002	−0.007	0.011	0.011	0.668***	0.678***
Δkl_c x kl_p	0.005	0.003	0.005	0.005	0.005	0.004
ΔYrs_c x Yrs_p	−0.013***	−0.007**	−0.010**	−0.007	−0.014***	−0.012**
Quality A x Yrs_p	0.006	0.007	0.006	0.006	0.006	0.005
ΔYrs_c x Quality A x Yrs_p	0.001	−0.000	−0.002	−0.000	−0.007	−0.001
Country Fixed Effects	✓	✓	✓	✓	✓	✓
Product Fixed Effects	✓	✓	✓	✓	✓	✓
Corrections for Lagged RCAs	✓	✓	✓	✓	✓	✓
Observations	33,480	32,240	38,440	37,200	42,160	40,920
R-squared	0.313	0.313	0.293	0.292	0.294	0.292

Note: GDP per capita data are from World Development Indicators. Labor productivity is from Penn World Tables. First stage coefficients in Columns (5) and (6) are explained in Section 4.4.3. Coefficients are estimates from a linear probability model of comparative advantage in 2015 (Eq. (1)). Significance using country-clustered standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Changes in international trade rules could create omitted variables biases. It is infeasible to control for all changes in global trading rules and bilateral trade agreements, much less to account for their endogeneity to trade patterns. However, Supplementary Table A6 shows that our results are not driven by two of the largest such changes. Excluding China from our analysis changes nothing qualitatively, indicating that our statistical results are not driven arithmetically by changes in China's industrial mix following its WTO accession in 2001.[17] Excluding textiles and garments also leaves our qualitative results unchanged, indicating that they are not driven by the phaseout of the multifiber arrangement and its successor Agreement on Textiles in 2005.

4.3.3. *Correcting for countries' intrinsic industrial dynamism*

We now consider the possibility that education predicts post-1995 diversification because countries that are intrinsically dynamic (due to their political settlement, for instance; Acemoglu and Robinson 2012; Studwell 2013) also tended to invest in education. If so, our results could be spurious, reflecting bias due to the omission of a measure of intrinsic dynamism.

The regressions in Table 5 check our results from Table 2 for robustness to the inclusion of interactions of such dynamism measures with familiarity and product complexity. We utilize four alternative measures of each country's dynamism in each of two prior time periods, 1975–1995 and 1985–1995. In columns (1) and (2) we proxy for intrinsic dynamism using each country's annualized rate of per-capita GDP growth during 1975–1995 and during 1985–1995. In columns (3) and (4) we use annualized labor-productivity growth from both periods to proxy for intrinsic dynamism. The regressions in columns (5) and (6) employ two different proxies for intrinsic dynamism. To arrive at these two proxies, we first ran separate regressions for each country for 1975–1995 and for 1985–1995, of comparative advantage on product familiarity and complexity using the specification in Section 5, Eq. (2) and SITC export data (The Growth Lab at Harvard, 2019b). The negative of the resulting coefficient on familiarity and the coefficient on complexity from these prior periods capture pre-existing tendencies for countries to develop comparative advantage in, respectively, unfamiliar and complex products. We then interacted each period's negative $\widehat{\beta}_c$ with familiarity and each period's $\widehat{\gamma}_c$ with complexity.

As in Table 4, adding these interaction terms ensures that the coefficients on our education interactions capture the effects of education on related diversification and diversification towards complex products *net of* the effects of prior dynamism on the evolution of the product mix between 1995 and 2015. We use proxies from two periods, even though this complicates the interpretation of these dynamism-interactions, to net out a lot of such variation.

The correlations between the number of years of schooling in 1995 and these four measures of dynamism in 1985–1995 are: 0.195 (with per-capita GDP growth), 0.133 (with labor-productivity growth), 0.408 (with negative $\widehat{\beta}_c$), and −0.237 (with $\widehat{\gamma}_c$). Only the third of these correlations, between prior $\widehat{\beta}_c$ and number of years of schooling in 1995, is statistically significant at even the 10% level. Correlations between years of schooling and these measures from 1975 to 1995 are even smaller. This suggests that our results in Table 2 were not biased by the omission of measures of prior dynamism. This suggestion is confirmed by the fact that the coefficients on the education interactions in Table 5 and Table 2 are qualitatively the same.

We focus on columns (5) and (6), which use measures of dynamism that directly measure prior tendencies to shift towards unfamiliar and complex products. As expected, the coefficients on the dynamism interactions in these regressions confirm that countries whose export

[17] This strategy does not rule out the possibility that China's WTO entry altered other countries' patterns of comparative advantage.

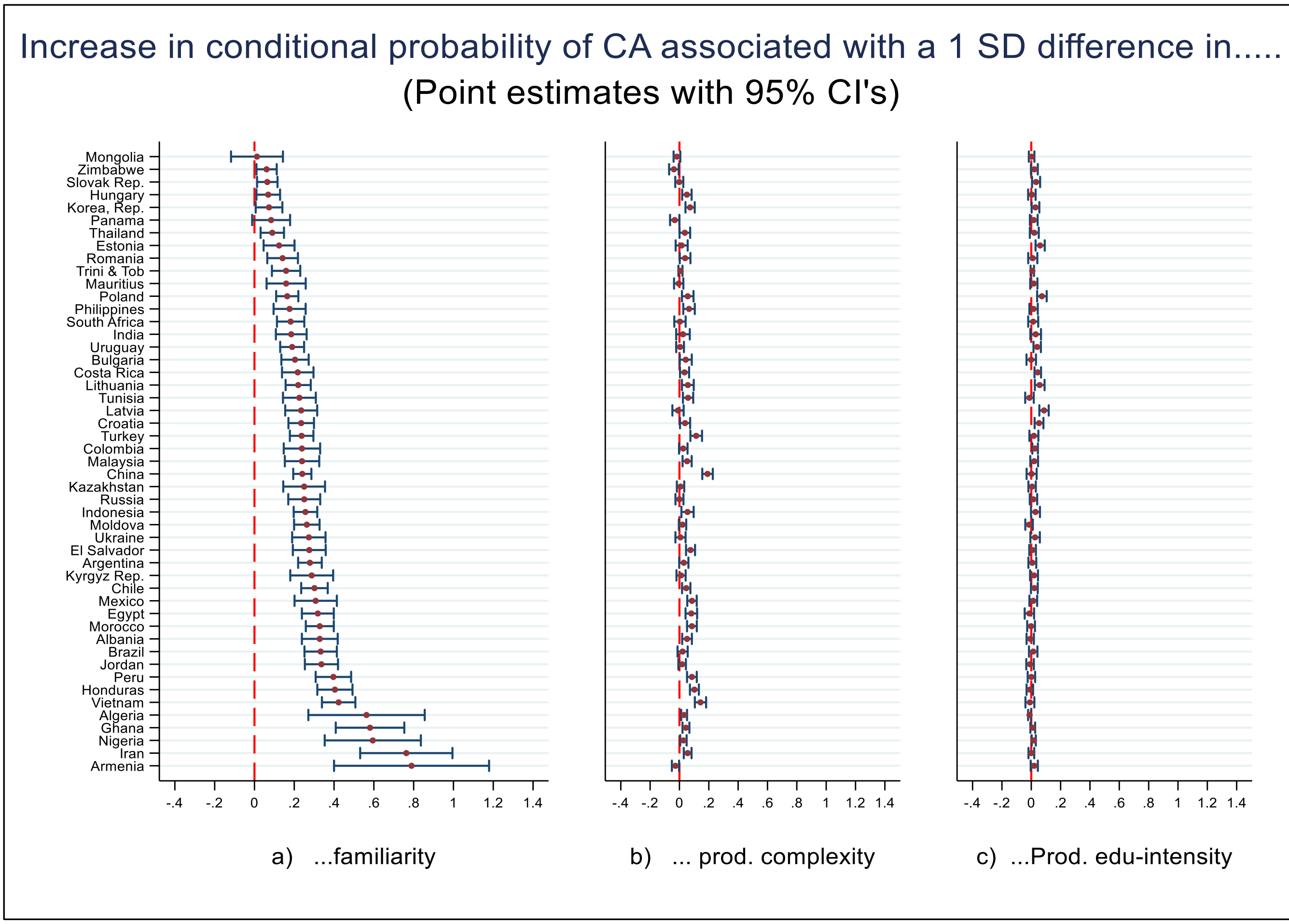

Fig. 2. Describing the evolution of comparative advantage.
Note: All three coefficients for a given country are estimated from a single regression, estimating Eq. (2). Separate regressions are run for each country. Countries in each graph are ordered by the point estimates in Panel (a).

mixes were more dynamic prior to 1995 were more likely to move into unfamiliar and complex products between 1995 and 2015. Moreover, the role of college and especially primary attainment in overcoming familiarity appears much stronger once these corrections are made.

4.3.4. *Timing considerations*

Our results so far suggest that the key barrier to industrial change is path dependence, and that the key role of education is to reduce this path dependence by speeding up learning. Path dependence is, by definition, stronger in the short term, and learning takes time. Our preferred explanation therefore suggests that the effect of initial familiarity on the subsequent export mix should be smaller, and education's tendency to reduce this path dependence, should be larger, the more time elapses between the initial and subsequent time period. Both predictions are clearly borne out in Supplementary Table A7, which shows that education's effects strengthen as the time interval is gradually expanded from 5 to 20 years.

5. Discussion: does education help the monkey jump?

We use the analogy introduced by Hidalgo et al. (2007) to discuss our results. Imagine a forest consisting of trees (products), and groups of monkeys (countries) fanning out through this forest by jumping from tree to tree (developing comparative advantage in different products). A group of monkeys will find it more difficult to jump to trees located at a greater distance from those it has already populated (these products are unfamiliar to the country). Taller trees (complex or education-intensive products) offer more nutritious fruit, but the monkeys will find it challenging to reach them. This is for two reasons: the branches of taller trees are high up (the products are intrinsically difficult to produce); and taller tress cluster in the core of the forest, far from its periphery where the monkeys initially live.

Our results so far indicate that more educated groups of monkeys reached more distant trees. They also indicate that, if two stands of trees were equally far from a group's starting positions, the more educated groups were not systematically more likely to move to the taller stand, even though it is more nutritious. Why is this so?

We begin to narrow down the possibilities using a two-stage statistical decomposition of the education-interaction terms in Eq. (1). The decomposition reveals whether the coefficients on those interactions are large (β_{EF}) and small (γ_{ET} and δ_{EE}) because there is more variation across countries in their tendencies to move towards distant trees than towards tall trees, or because education accounts for a larger share of the variation in tendencies to reach distant trees than of the variation in tendencies to reach tall trees.

In the first stage, we estimate the following simplified linear probability model on 49 separate country samples of 1240 products each:

$$CA_{c,p,1} = \alpha_c + f\left(RCA_{c,p,0}\right) + \beta_c F_{c,p,0} + \gamma_c T_{p,0} + \delta_c el_p + u_{c,p} \tag{2}$$

The coefficients tell us whether country c tended to develop comparative advantages in products that were more familiar ($\beta_c > 0$), complex ($\gamma_c > 0$) and education-intensive ($\delta_c > 0$). Bigger estimates of β_c indicate that its monkeys had more difficulty reaching more distant

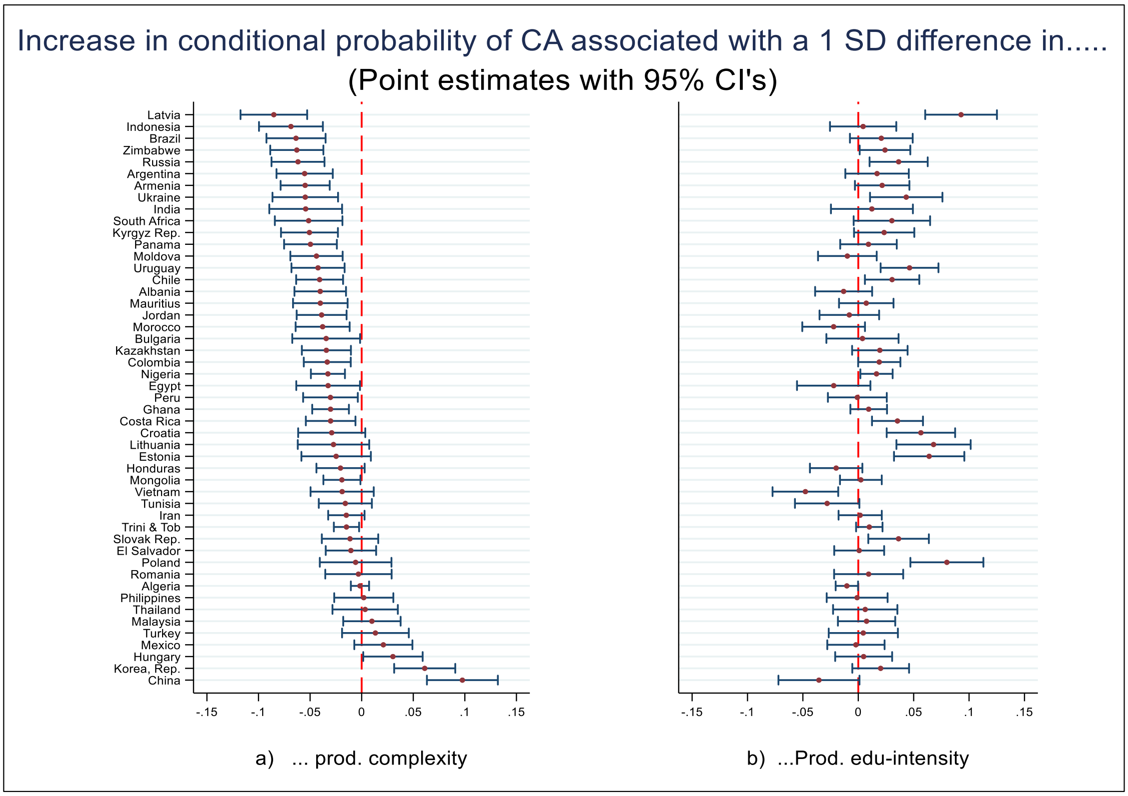

Fig. 3. Describing the evolution of comparative advantage, unconditional on familiarity.
Note: All three coefficients for a given country are estimated from a single regression, estimating Eq. (2). Separate regressions are run for each country. Countries in each graph are ordered by the point estimates in Panel (a).

trees. Bigger values for γ_c or δ_c indicate that its monkeys had more success in reaching taller trees. We normalize $F_{c,p,0}$, $T_{p,0}$ and el_p to have means of zero and standard deviations of one so that the magnitudes of their coefficients can be compared. In the second stage we regress the first stage coefficients on education, to ask whether tendencies to reach far away and tall trees are stronger for more educated groups of monkeys.[18]

The first-stage estimates (Fig. 2) show that success in reaching far-away products varies a lot across countries (Panel a), but that success in reaching more sophisticated products does not (Panels b and c). The β_c coefficients range from roughly zero (in Korea, Hungary) to 0.75 (Iran and Armenia), with Malaysia offering a median estimate of 0.27. The median countries' γ_c and δ_c coefficients are much smaller (0.040 and 0.015, respectively). In the second stage, regressions of the first-stage coefficients (β_c, γ_c and δ_c) on years of initial schooling and education quality respectively yield R^2 coefficients of 0.15, 0.25 and 0.22, indicating that education explains *less* (not more) of the variation in β_c than in γ_c and δ_c. Thus, one should not be surprised that education is unhelpful for shifting an economy's comparative advantages towards complex and education-intensive products because nothing appears to have been helpful in this way - those shifts are small.

These results also imply that our null effects (education does not help to reach the tall trees) are not due to errors in the measurement of education or its change over time.[19] Even if education, when properly measured, would have explained all the variation in γ_c and δ_c (i.e. the second-stage R^2 statistics would be 1), this variation is so limited (Figs. 2b and 2c) that education would not explain much of the variation in comparative advantage (i.e., γ_{ET} and δ_{EE} would still be small). Also, mismeasured education should have attenuated our estimates of β_{EF} – which remain large, and led to low second-stage R^2 statistics.

Our negative results on progress towards sophisticated products are obtained from regressions that control for the familiarity of these products to the country. Of course, policy-makers should also take an interest in outcomes *unconditional* on the familiarity of the target products. Did countries shift towards core products at all, and did education help to push them in this direction? Fig. 3 shows that when the familiarity term is dropped from Equation (2) (β_F is restricted to zero), some two-thirds of our countries tended to develop CA in *less* complex products, climbing down the complexity ladder. Together with Fig. 2, which shows that very few countries shifted towards the less complex among *equally familiar* products, this indicates that the unfamiliarity of complex products has indeed made them harder to reach. To consider whether more educated countries were more likely to move to tall trees unconditional on familiarity, Supplementary Table A8 re-estimates the regressions in Table 2 without the familiarity terms. It finds no evidence to suggest that education helped in this way.

To summarize: Tall trees (complex products) are hard to reach. This is partly because they are located far from the monkeys (complex products are unfamiliar in developing countries).[20] Education facilitates leaps to more distant trees (it helps overcome unfamiliarity, Table 2). However, education does not help countries to actually get to the tall trees (Table A8). Rather, education empowered the monkeys to cover longer distances, while failing to help them adjust their direction and

[18] Validating this two-stage approach to explaining our main estimates, the coefficients in these second-stage regressions are of the same signs and roughly the same magnitudes of those in Table 2, Column (4). These results, available in our replication code, hold using both OLS and WLS in the second stage.

[19] This is analogous to the argument of Krueger and Lindahl (2001) that such attenuation biases obscure the benefits of education for economic growth.

[20] Most of the within-country correlations between familiarity and the pci and between familiarity and education-intensity are around negative 0.70.

head towards the tall trees (Table 2), and so most countries headed away from the tall trees (Fig. 3).

6. Conclusions

We have analyzed the relationship between education and the evolution of comparative advantage among low- and middle-income countries. We found strong evidence consistent with education helping countries develop comparative advantage in unfamiliar products – products that are unrelated to those in which they already have comparative advantage. In contrast, more educated countries were not much more likely to develop comparative advantage in complex products, and countries whose education endowments grew more were not more likely to develop comparative advantage in education-intensive products. Taken together, these results are more obviously supportive of an approach to the development of comparative advantage that emphasizes relatedness between products than of a Heckscher-Ohlin-Vanek approach. The relatedness approach emphasizes that the process is evolutionary, with productive capabilities developing in path dependent fashion. Education's main contribution to the process, it appears, is to reduce this path dependence by facilitating longer leaps into previously unfamiliar products.

While there are no plausible instruments for our key independent variables, several types of auxiliary evidence suggest that these results should be taken seriously. They are robust to many changes in specification, to changes in time interval over which specializations can emerge, to changes in how product complexity is operationalized, to some changes in global trade rules, and to corrections for national, institutional, infrastructural, and FDI-related variables. We also find that primary education and education of a higher quality is most strongly associated with overcoming the unfamiliarity of peripheral products, but not of core products. This finding is consistent with the widely accepted idea that core products require the acquisition of more capabilities, and also with the idea that quality basic education is important for amassing basic capabilities. Perhaps most importantly, our results are *not* explained by the fact that the most educated countries in 1995 tended to be a little more dynamic in the prior decades.

While these results draw attention to what education can do, we caution that education differences account for rather little of the cross-country variation in industrialization paths. Education variables have limited explanatory power overall, and while education is associated with less path dependence, it does not eliminate it. Even the most educated countries would, other things equal, tend to develop comparative advantage in products that are related to those they already produce. This path-dependence suggests that industrial development needs to be partly a deliberate process, with governments facilitating the development of a series of stepping-stone industries that the economy can traverse on its way to developing strengths in core products. Our findings suggest that investments in education allow the stepping stones to be spaced a little further apart.

Author statement

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CRediT authorship contribution statement

Jesus Felipe: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Hongyuan Jin:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – review & editing. **Aashish Mehta:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Replication code and data are available at https://www.global.ucsb.edu/people/aashish-mehta.

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Supplementary materials

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