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Convergence and innovation in export quality and the world income distribution

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Abstract

Previous research has documented a strong correlation between countries' income levels and the quality of their export goods. Given the evidence of fast unconditional convergence in export quality, this raises the question how to reconcile these stylized facts with a stable world income distribution.

This paper is the first to document why cross-country export quality convergence within products does not entail aggregate export quality convergence across countries. In fact, the latter is absent because the country-product-specific residual after accounting for export quality convergence is biased in favor of high-income countries' exports. To document this pattern of export quality dynamics and assess its aggregate implications, we construct bilateral export quality estimates for 122 countries and 2,700 manufacturing goods.

Furthermore, we show that the key explanation for this country-product-specific 'quality innovation residual' is the fact that high-income countries are more capital abundant and financially developed and export goods that are better aligned to their human capital endowments, all of which are correlated with export quality innovation.

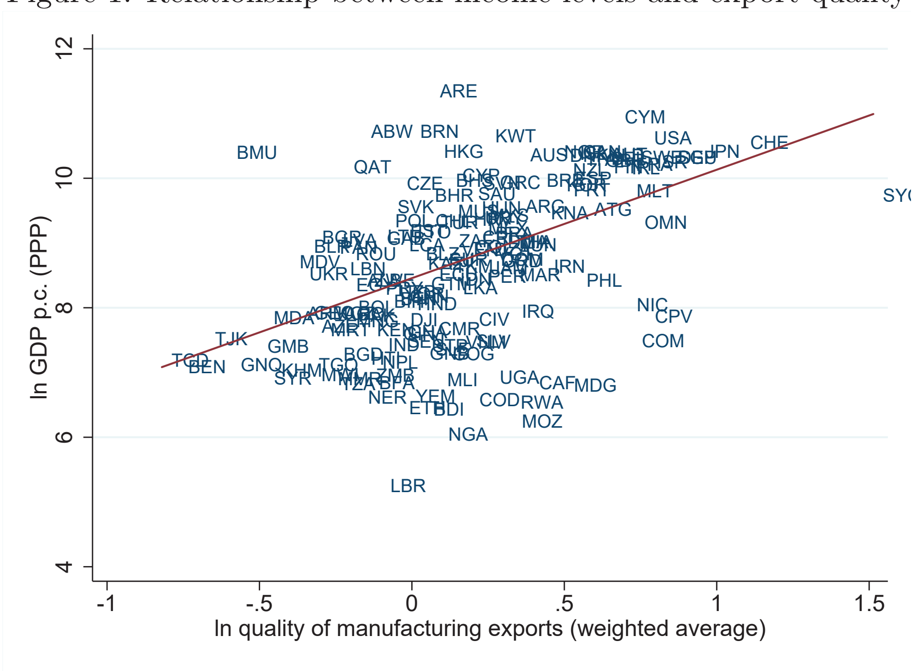
Keywords: export quality, convergence, export upgrading, quality ladders

JEL classification: F14, F43, O11, L15

1 Introduction

Seminal contributions in international economics have documented that countries at higher income levels increasingly specialize into high-quality product varieties across different sectors. Results by Schott (2004), for example, suggest that capital- and skill-abundant countries, instead of specializing across industries, use their endowment structure to produce varieties that are, on average, qualitatively superior. The correlation between export quality and income levels has been confirmed by various studies since (e.g. Hummels and Klenow, 2005; Feenstra and Romalis, 2014; Cusolito and Maloney, 2018) and is also depicted in figure 1 for the quality measure we construct in this paper.

Figure 1: Relationship between income levels and export quality



Previous studies have suggested unconditional convergence in export quality, usually at fast pace (Hwang, 2006; Krishna and Maloney, 2011; Hallak and Schott, 2011; Tian, 2017; Henn et al., 2020). Their estimates suggest that an export product will close half of the gap to any reference product of different quality within approximately 10 years. Given the tight empirical relationship between aggregate export quality and income, how can such fast unconditional convergence in export quality be reconciled with a relatively stable distribution of incomes across countries?[1] While some factors may blur the link from export quality convergence to cross-country income convergence, the relationship between product quality and development plays a key role in the seminal literature (e.g. Grossman and Helpman, 1991b; Aghion and Howitt, 1992; Fajgelbaum

[1]See, for example, Acemoglu and Ventura (2002) and Johnson and Papageorgiou (2020).

et al., 2011; Acemoglu et al., 2012), which clearly calls for a reconciliation of the empirically observed regularities about export quality, convergence, and development.

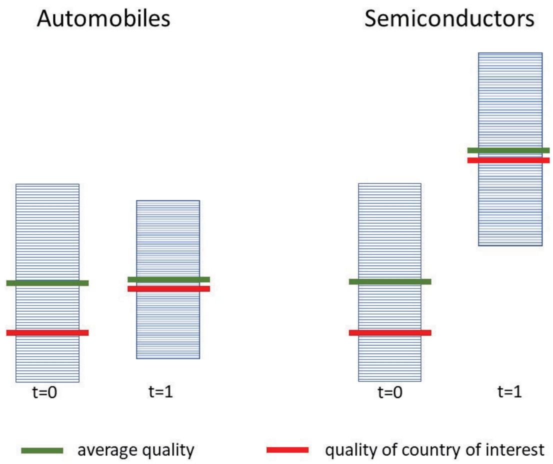
In this paper, we highlight that convergence is only one factor governing the dynamics of export quality. To illustrate the mechanisms working against convergence that we have in mind, consider a case with two goods: automobiles and semiconductors. Suppose, that in the initial period ($t = 0$), the quality ladders for both products are identical. This situation is depicted in figure 2, where each line within the quality ladder could be thought of as representing a country. The country we are interested in is depicted by a highlighted (red) line and starts at a low quality level of 1/3 in the quality ladders of both products. Over the next period (until $t = 1$), quality convergence takes place in both products. This is reflected by a narrowing of the quality ladders and the fact that our exporting country of interest has closed one fourth of the gap towards the frontier. However, there are two additional channels at work. Obviously, the whole quality ladder for semiconductors in figure 2 has moved up considerably over time, e.g. due to a sector-specific technology shock. Countries that are mostly exporting at the lower quality spectrum in each product may benefit from quality convergence within those products. But if they are at the same time specialized in products that show a less favorable overall development in their quality ladder (here: the automotive sector), their export portfolio is biased against products with more favorable quality developments which on an aggregate level would work against within-product quality convergence. We call this a 'portfolio' (or 'quality ladder') effect and show that it is indeed working in favor of high-income countries, although with a magnitude that does not make up for quality convergence within products.[2] The second aspect that the previous literature has neglected is the fact that convergence (and product-specific dynamics) does not fully explain export quality dynamics: after the convergence and and 'portfolio' effects depicted in figure 2 have materialized, more than half of the variation in export quality developments are still unexplained. Accordingly, we call this variation an 'innovation residual', where 'innovation' may be interpreted in a sense of targeted technical innovation effort or in a stochastic sense.

We show in this paper that this product-country-specific innovation residual of export quality dynamics is not random but systematically biased in favor of richer countries. From an economic perspective, this is reasonable because imitation and innovation in quality may be present at the same time and in a dynamic equilibrium with growth, imitation should not dim the incentives

[2] A similar idea of heterogeneity in dynamics across quality ladders has been investigated in the theoretical (closed economy) endogenous growth literature (Grossman and Helpman, 1991b; Sorger, 2011) but has been largely neglected in empirical studies on export quality dynamics. The only exception we are aware of is tentative evidence by Krishna and Maloney (2011) showing that despite export quality convergence, OECD countries seem to export products with more favorable overall quality dynamics.

for innovation.[3] Statistically, this reflects the fact that the zero unconditional expectation of a residual does not imply a conditional expectation of zero for a specific exporting country.

Figure 2: Illustrative example of convergence and quality ladder effects



We further explore potential drivers of the innovation residual that is unexplained by convergence and product-specific developments. We show that residual innovation is higher in sectors where exporting countries specialize (as measured by revealed comparative advantage), for exporting countries that are more financially developed, and for exports to countries at higher income levels. Moreover, factor endowments matter: residual export quality improves faster for products that are well-aligned with the exporting countries' skill endowment (measured by years of schooling) and for capital-abundant exporting countries. Those findings contain a Ricardian flavor of specialization, are in line with the notion that export quality innovation requires access to finance (Krishna et al., 2020), and add a dynamic perspective to the previous literature that suggests that importer income and exporters' factor endowments relate to export quality (Schott, 2004; Hallak, 2006; Alcalá, 2016).[4]

Our findings are derived from a measure of export quality which extends the idea of Khandelwal et al. (2013) to a bilateral setting. This allows us to link products to country characteristics of importers and exporters, which is necessary to explore the described mechanisms. For our quality estimation, we mainly rely on CEPII's BACI data set, which provides bilateral trade flows

[3]Grossman and Helpman (1991a) and Acemoglu et al. (2012) elaborate on this idea with product quality in a closed economy setting. See also the early theoretical literature about international product cycles and North-South trade of different qualities (Krugman, 1979; Flam and Helpman, 1987).

[4]From a broader perspective, this aspect also links our study to Acemoglu and Zilibotti (2001); Bernard et al. (2007); Acemoglu et al. (2012), and Lectard and Rougier (2018).

at the 6-digit level. To be consistent with earlier studies, we focus on the manufacturing sector, comprising approximately 2,700 products after deletion of homogeneous goods, and focus on the decade before the global financial crisis.

Our quantitative results are summarized as follows: convergence of quality within export products is an important force for quality dynamics, as suggested by the previous literature. Our estimates suggest that it takes on average 10 years to close half of the gap in quality to any reference frontier. Modest differences in convergence speed are not systematically biased against developing countries. Thus, this convergence channel on aggregate works in favor of developing countries: a doubling of the income level (per capita, in PPPs) is associated with a slowdown of aggregate export quality improvements by 1.1 percentage points p.a. At the same time, the portfolio and innovation effect work in the opposite direction: for those channels, a doubling of the income level is associated, respectively, with a 0.1 and 1.7 percentage point p.a. increase in aggregate export quality. Taken together, those effects imply that despite convergence of quality within export goods there is no relationship between initial aggregate export quality and subsequent aggregate improvements in export quality on the country level, and that aggregate quality improvements are – if anything – positively correlated with income levels. This pattern is fully consistent with a stable world income distribution in the presence of a strong relationship between export quality and development.

Our findings link the empirical trade literature on export quality dynamics to the macroeconomic growth literature of quality ladders and are a particularly relevant contribution from a development angle: so far, an important policy conclusion of the literature has been that developing countries can use 'automatic escalators' of convergence within certain industries (see, for example, Lederman and Maloney, 2012, for export quality and Rodrik, 2013, for productivity in manufacturing). Our study highlights that this conclusion can be premature: even if welfare-relevant indicators in sub-parts of the economy convergence across countries, this does not entail convergence in the aggregate welfare-relevant indicator across countries.[5] This is of utmost policy importance because it highlights the complex interaction between sectoral and horizontal (factor market) policies (see Maloney and Nayyar, 2018, for a broader discussion). On the one hand, contries can indeed use 'automatic escalators' of quality convergence and perform broad horizontal policies in the area of financial development without much sectoral focus. On the other hand, our results

[5]For example, Rodrik (2013) finds convergence of productivity in different manufacturing sub-sectors across countries (see also Klein, 2019). Our results highlight that this needs not necessarily entail cross-country convergence in aggregate manufacturing productivity because productivity trends across sub-sectors or country-sector specific productivity shocks may be systematically biased against low-productivity countries. This does not seem to be the case in Rodrik (2013), as he also documents unconditional convergence in aggregate manufacturing. However, his implied convergence speed slows down with increasing level of aggregation (from -0.031 at the 4-digit level to -0.023 in aggregate manufacturing, see his table II), confirming the relevance of our argument.

highlight that such a sectoral perspective also matters: they show a complex interaction of export quality improvements with specialization patterns and the appropriateness of countries' factor endowments and products factor intensities. Moreover, modest differences in quality innovation across products suggest that it indeed matters what a country exports (Hausmann et al., 2007; Hidalgo and Hausmann, 2009). Overall, our results thus support a wise combination of development-oriented factor and sector policies (e.g. Lin, 2011).

The remainder of this paper is organized as follows: section 2 reviews the previous literature on export quality convergence and presents a simple framework that helps to illustrate why the evidence for cross-country export quality convergence within products does not need to entail aggregate export quality convergence across countries. Section 3 discusses key contributions to the estimation of export quality and particularly outlines the approach of Khandelwal et al. (2013) that we apply to bilateral trade data for quality estimation in our study. The section also explains the data we put to this framework for quality estimation and provides some descriptive statistics of our newly constructed quality measure. In section 4, we apply the framework from section 2 to our newly constructed export quality measures. We particularly document robust convergence in export products' quality and that residual innovation is biased in favor of high-income countries. Since both factors work in the opposite direction, we show that no convergence in countries' aggregate export quality takes place. In section 5, we further investigate potential factors driving residual innovation and show that the key factor distinguishing high-income from lower-income countries for overall export quality dynamics is factor appropriateness. In section 6, we put potential contributors to overall quality dynamics into perspective and provide a final assessment of the different forces potentially driving export quality across high- and low-income countries. Section 7 concludes and further elaborates on the relation of our findings to the literature and future research.

2 Export quality dynamics: a macro framework and related literature

Previous studies such as Hwang (2006); Krishna and Maloney (2011); Hallak and Schott (2011); Tian (2017); and Henn et al. (2020) have documented rapid and widespread unconditional convergence in the quality of exported goods across countries, using different measures for export quality that we discuss in section 3. They usually rely on a seemingly conventional convergence regression of the form

$$\Delta \ln \Lambda_{pit} = \rho \ln \Lambda_{pi,t-1} + \varepsilon_{pit}, \tag{1}$$

where Λ is a measure for export quality and the subscripts p, i, and t indicate different export products (usually on a 4-10 digit level of aggregation), exporting countries, and time periods, respectively. In this setting, the parameter ρ governs the speed of (log-linear) convergence in a products' quality across countries. We refer to the case $\rho < 0$ as quality convergence within products.[6] Economically, this *convergence effect* can be motivated through catch-up factors, e.g. driven by demonstration and imitation effects, and is usually estimated to be in the vicinity of -0.04 to -0.10.[7] Most authors have thus concluded that export quality across countries converges, with the policy implication that developing countries can make use of 'automatic escalators' (see particularly Lederman and Maloney, 2012).

This interpretation assumes the residual export quality dynamics beyond the convergence term $\rho \ln \Lambda_{pi,t-1}$ to be of purely stochastic nature. In other words, ε_{pit} is assumed to exhibit no systematic correlation with country fundamentals or the relevance of product p in countries' export share. However, those conditions need not be fulfilled, with dramatic consequences for economic interpretation. For example, it is possible that certain products may experience more favorable overall dynamics in their quality ladders, for example, due to technological progress in a sector or changes in demand for certain products' quality and that those products rank more prominently in high-income countries' export portfolio or that the residual quality dynamics ε_{pit} are otherwise positively correlated with countries' development level. To understand this possibility in more detail, we define $\varepsilon_{pit} \equiv \alpha_{pt} + a_{pit}$ and re-write equation (1) for the dynamics of export quality as:

$$\Delta \ln \Lambda_{pit} = \rho \ln \Lambda_{pi,t-1} + \alpha_{pt} + a_{pit}, \tag{2}$$

where α indicates a *quality ladder effect*, reflecting the possibility that products may experience different overall dynamics in their quality ladders and a is a product-country-specific quality effect. While this *residual innovation effect*

[6] It is worth to notice that we assume ρ it to be homogeneous across products and countries. Although this assumption can be relaxed, we consider it meaningful given our empirical results and to illustrate the main mechanism we aim to highlight.

[7] Obviously, this coefficient is influenced by the scaling of the dependent variable.

may to some extent capture purely stochastic shocks, it also allows for the possibility that countries experience systematic product-specific innovations. For example, a new (product-specific) technology that is not factor-neutral may benefit particularly those countries endowed with the technology-using factor. Recent work by Alcalá (2016) also suggests such a systematic relationship between countries' specialization patterns and export quality.[8]

Both effects, the quality ladder dynamics α and the innovation residual a may have severe implications for the overall quality dynamics of a country's exports because what matters from a macroeconomic perspective is the *aggregate quality dynamic* of a country's export basket, defined as:

$$\Delta_{agg} \ln \Lambda_{it} = \sum_p s_{ip} \; \Delta \ln \Lambda_{pit}, \tag{3}$$

where s_{ip} indicates the share of good p in the exports of country i.[9] It is straightforward but instructive to highlight that this aggregate quality dynamic is the sum of the aggregate convergence effect, the aggregate quality ladder effect which we consider a (static) 'portfolio effect' at the aggregate level (because it varies by exporting country i only due to variation in the initial export shares s_{ip}), and the aggregate innovation residual:

$$\Delta_{agg} \ln \Lambda_{it} = \underbrace{\rho \sum_p s_{ip} \; \ln \Lambda_{pi,t-1}}_{\substack{\text{agg convergence} \\ \text{effect}}} + \underbrace{\sum_p s_{ip}\alpha_{pt}}_{\substack{\text{portfolio} \\ \text{effect}}} + \underbrace{\sum_p s_{ip}a_{ipt}}_{\substack{\text{agg innovation} \\ \text{residual}}} \; . \tag{4}$$

We refer to the case of faster improvement in aggregate quality for countries with lower initial quality, $\text{Cor}(\Delta_{agg} \ln \Lambda_{it}, \; \sum_p s_{ip} \; \ln \Lambda_{pi,t-1}) < 0$, as *aggregate export quality convergence* across countries.

The key contribution of our paper is to highlight why convergence in product quality, $\rho < 0$, does not necessary imply *aggregate* export quality convergence and to quantitatively assess the factors governing this relationship, which are highlighted by equation (4): First, countries exporting higher-quality products in the first place may be specialized in products with more favorable overall quality dynamics. In other words, initial aggregate export quality $\sum_p s_{ip} \ln \Lambda_{pi,t-1}$

[8]While co-existence of convergence and innovation may be intuitive from economic perspective, it may be more confusing from a stochastic perspective that we also take in section 4 and where innovation reflects a residual. In this setup it may be helpful to understand that the product-country-specific quality effects has zero expectation, $\mathbf{E}(a_{pit}) = 0$, but a non-zero conditional expectation, $\mathbf{E}(a_{pit}|p, i) \neq 0$.

[9]Note that we use initial shares in our analysis and do neither account for entry or exit of products (see section 7). In other words, we calculate aggregate export quality dynamic using fixed export shares (and dropping exiting products).

may be positively correlated with the 'portfolio' term $\sum_p s_{ip}\alpha_{pt}$. Second, countries at higher export quality may on aggregate realize more favorable residual innovation, conditional on quality convergence. In other words, initial aggregate export quality $\sum_p s_{ip} \ln \Lambda_{pi,t-1}$ may be positively correlated with the residual innovation term $\sum_p s_{ip} a_{ipt}$.

To date, economic theory and previous empirical research give little guidance on the direction and relative magnitude of those factors. Our paper highlights that the portfolio effect and, particularly, the aggregate residual innovation effect actually work against the aggregate convergence effect and are large enough to offset the latter.

3 Estimation of export quality: review and methodology

Early studies to measure export quality relied on raw unit values (e.g. Aiginger, 1997; Schott, 2004). The contributions by Hwang (2006) and Krishna and Maloney (2011) on export quality convergence also followed this approach. However, it requires strong assumptions for unit values to be a valid measure for export quality.[10] For our purpose, a key limitation is that unit values may reflect increased producer factor prices. Countries' income increases that also raise production costs may thus be misinterpreted as export "quality" upgrading. In this case, exporting countries will however lose market shares, especially in the context of high elasticities of substitution (as suggested by Feenstra and Romalis, 2014). This rationale is used by subsequent studies that attempt to disentangle price from quality effects: for a given export price, differences in demand must reflect product quality.

For example, the approach of Hallak and Schott (2011) relates export unit values with information about global demand for a country's products taken from their trade balance: "among countries with identical export prices, the country with the higher trade balance is revealed to possess higher product quality." Their approach estimates quality from trade balances for the whole manufacturing sector and for more disaggregated subsectors but remains limited to 2-digit sectors and 43 countries. The demand-side intuition that higher export unit values reflects quality if demand remains constant is also used by Khandelwal (2010) but his approach requires data on market shares of imports relative to corresponding domestic varieties, which are not available for many countries.

[10] See Szczygielski and Grabowski (2012) and Trenczek and Wacker (2019) for a more comprehensive discussions on the issue. Raw unit values are still in use to gauge quality in recent studies such as Harding and Javorcik (2012) and Alcalá (2016). Feenstra and Romalis (2014) conclude that "much of the variation in unit values is explained by quality".

Other methods to control for the fact that unit values capture factor costs of the exporter that are unrelated to quality model the supply side of the economy more explicitly. An example is the approach first applied by Hallak (2006) and used by Henn et al. (2020) to construct and analyze a comprehensive bilateral data set of export quality for 166 countries over the period 1962-2014 on a modified SITC 4-digit (835 products) and the BEC 3-digit level.[11]

Feenstra and Romalis (2014) and Tian (2017) take a more structural approach to combine the demand with the supply side. The former model a supply-side effect of heterogeneous-quality firms that works in the opposite direction as the demand-side intuition: as demand rises, less efficient exporting firms enter into the market, which produce at lower quality. Taking both opposing effects into account, they find for 185 countries at the 4-digit SITC level "that much of the variation in unit values is explained by quality." Tian (2017) uses a gravity model of trade that is consistent with firms' quality heterogeneity and identifies product quality as an unexplained part of export value when factors such as trade frictions, input costs, or productivities are accounted for. This raises quite high demands for data so that the analysis is restricted to twelve 2-digit manufacturing sectors in 19 OECD countries for the period 1995-2006.[12] However, Feenstra and Romalis (2014) caution that estimates for quality in such comprehensive structural models "are very sensitive to proxies chosen for important model variables, whether it be population as the proxy for the number of firms or the manufacturing trade balance as a measure of demand."

3.1 The approach of Khandelwal et al. (2013)

This cautionary note leads us to aim for a quality measure that can be compiled for a large set of countries at a disaggregated product level and which is relatively intuitive in the sense that it avoids a 'black box' treatment of initial unit values. In our view, an approach pioneered by Khandelwal et al. (2013) is suited best to fulfill this purpose and has been widely used in the literature to estimate export quality (Martin and Mejean, 2014; Bas and Strauss-Kahn, 2015; Fan et al., 2015).[13] It assumes that consumers obtain utility from certain products p. Within each product category there are different varieties, indexed ζ, which are associated with a certain quality $\Lambda(\zeta)$. These varieties can be substituted for each other, with an elasticity $\sigma_p > 1$. The associated constant elasticity of

[11] After being normalized relative to the 90th percentile in the relevant product-year, those estimates are then also aggregated to higher levels by trade values and normalized again. In our view, this aggregation is problematic because it will aggregate quite different products under unclear welfare assumptions.

[12] It is worth highlighting that in the study of Tian (2017), beta-convergence in quality on the sectoral level, and particularly when controlling for country fixed effects, is faster than on the overall manufacturing level. This highlights the potential role of the export portfolio as it suggests that countries converge within product categories but not as much towards overall higher-quality export portfolios.

[13] The cited studies use this approach for exporting firms. In our context, one can hence think of variety ζ as an average variety exported by firms of the respective country.

substitution (CES) utility function leads to a demand function

$$q(\zeta) = p(\zeta)^{-\sigma} P^{\sigma-1} Y \Lambda(\zeta)^{\sigma-1} \tag{5}$$

for each variety, where q is the quantity consumed, $p(\zeta)$ is the observed price for variety ζ, and P and Y are the overall price index and expenditure of the respective market. Equation (5) captures the intuition that increases in quality should be positively related to demand, holding prices and income constant.

Taking logs and indexing each variety ζ by its respective exporting and importing countries i and j at period t (such that ζ can be interpreted as the average variety exported by firms of country i to country j in period t) yields the demand system

$$\ln q_{pijt} = -\sigma_{pj} \ln p_{pijt} + (\sigma_{pj} - 1) \ln P_{jt} + \ln Y_{jt} + (\sigma_{pj} - 1) \ln \Lambda_{pijt}. \tag{6}$$

In this setting, a product $p \times$ exporter $i \times$ import market j triplet (at period t) can be seen as a 'variety'. Each product p is hence vertically differentiated by varieties of different quality. The linear form of equation (6) allows estimating quality from price data (unit values). An empirical challenge in this setting is the fact that equation (5) is a general demand function while the empirical estimation of equation (6) raises the question about the relevant market for this demand. In other words, it must be clarified for which price and income level P and Y to control for, which is non-trivial since it is unclear to what extent imports compete with domestic varieties.

Approaches based on Khandelwal et al. (2013) usually assume that the importer-level variables P_{jt} and Y_{jt} can be approximated with fixed effects α_{jt}. This sweeps out any substitutability with domestic varieties as long as it does not vary over time in a systematic manner across products. While appropriate in their difference-in-difference setting, this approach is not feasible in our case for two related reasons. First, the time-dimension in those fixed effects centers the quality measure, which is essentially the residual of equation (6), for each year around 0. This means that by construction there will be no aggregate quality dynamics which we aim to study. Second, the importer-dimension of the fixed effects sweeps out average quality by importer. In other words, quality dynamics would always be constructed for a given product in a given import market. Since our goal is to understand aggregate quality dynamics of exporting countries, for which the composition of import partners matters, this will again defeat the purpose of our study. Instead, we hence estimate the following regression equation separately for each 4-digit SITC Rev.2 product group:

$$\ln q_{pijt} + \sigma_{pj} \ln p_{pijt} = \alpha_p + \beta_1 \sigma_{pj} \ln P_{jt} + \beta_2 \ln\left(\frac{M_{jt}}{P_{jt}}\right) + \beta_3 \ln\left(\frac{M_{jt}}{Y_{jt}}\right) + \epsilon_{pijt}, \tag{7}$$

where P is an aggregate import price index, M/P is real aggregate import demand, and M/Y is aggregate import penetration.

This specification assumes that the overall import sector is the relevant demand for product p in market j.[14] Controlling for P and the aggregate real demand term M/P are then straightforward.[15] Since import demand for a product p, however, will also depend on the availability of domestic substitutes, we further control for import penetration M/Y.[16] Finally, the product-fixed effect α_p accounts for the fact that absolute qualities are not necessarily comparable across product categories. One can then retrieve the residual of equation (7) to calculate

$$\ln \hat{\Lambda}_{pijt} = \hat{\epsilon}_{pijt}/(\sigma_{pj} - 1) \tag{8}$$

as a measure for quality. This reflects the idea that holding prices and most important demand shifters constant, higher demand must be associated with higher quality. "Quality" in this framework hence captures several aspects of products that consumers value, which can be technical product characteristics as well as, for example, branding aspects.

It is important to understand that $\mathbf{E}(\hat{\epsilon}_{pijt}) = 0$ and the inclusion of product fixed effects in equation (7) furthermore leads to a product quality estimate that will on average for each product be 0 over both periods. In other words, our quality measure is relative to an 'average' of all export-import relationships within each product over both periods.[17] However, the average of a product's quality may change between periods. Since any changes in product quality are relative to the mean and expressed in log terms, they are in proportionate terms and can hence be meaningfully compared for different products.

We follow this approach because of its intuitive appeal: it avoids 'black box' results for quality estimates that are difficult to retrace. This results from the fact that the method can easily be linked to the use of unit values in earlier studies. To see this, note that solving equation (6) for Λ implies that a 1 percent increase in observed prices p, which are unit values, is associated with a $\sigma/(\sigma - 1) > 0$ percent increase in quality, ceteris paribus. This term converges

[14] Taking aggregate price and demand indicators would capture many more aspects of an economy, including non-traded domestic goods and services.

[15] Note that equation (6) implies that $\beta_1 = \beta_2 = 1$, so that we could also subtract it on the left hand side of the equation. However, since our equation is only an approximation, we prefer estimating β_1 and β_2. Moreover, this approach circumvents where to level P.

[16] This assumes that there are no product-specific differences in the availability of domestic substitutes, at least not within the 4-digit product groups at which equation (7) is estimated. The latter assumption is also implicit in Khandelwal et al. (2013) but their importer-year fixed effects are more flexible in sweeping out differences over 4-digit domestic substitutability. The approach of Khandelwal (2010) is most precise in this regard but requires detailed data on import penetration by product which for his application to US imports are available on the 5-digit level but this is not the case for many other importing countries.

[17] Other studies such as Krishna and Maloney (2011) and Henn et al. (2020) define 'quality' relative to a frontier, which essentially is just another form of within-product normalization. A difference, however, is that their normalization is conducted for each year.

towards 1 for large σ, which is consistent with the approach of using unit values as a proxy for quality within a product group p if one subscribes to the notion that consumers find it easy to substitute different varieties (i.e. qualities) of a product, because in this case there will be a 1:1 relation between proportionate changes in unit values and product quality. Arguably, our approach is somewhat less flexible to control for non-quality factors in import demand than Khandelwal et al. (2013) but given data limitations for the broad set of countries we aim to study, we are confident that it is the best approach one can come up with for the objective of our study. Moreover, it should be highlighted that the main argument of our paper is irrespective of a precise measurement of export quality, although the precision at which quality is measured can certainly influence the quantitative magnitudes of the convergence, portfolio, and innovation effect.

3.2 Data for quality estimation

Our data source for the quantities and prices in equation (7) is the BACI data set compiled by CEPII (Gaulier and Zignago, 2010). It provides bilateral trade quantities, normalized to tons, and respective prices (as unit values) down to the 6-digit HS92 classification (about 4,800 goods). It is based on UN COMTRADE data and has several advantages over other data sets used in the literature.[18]

For our analysis of export quality dynamics, we focus on the decade 1995/97 to 2005/07. This is motivated by the fact that this period was characterized by rapid globalization and many developments that are now inherent features of the global trade system: it is the decade following WTO creation and where many formerly planned economies joined the world trade system. Truncating our analysis in the mid-2000s avoids capturing effects of the global financial crisis and the trade collapse it triggered. To smooth out annual variations in unit values, which can be substantial for bilateral data, we take the average of the years 1995-97 as our starting value and the average of the years 2005-07 as our endpoint.[19] Furthermore, we follow previous studies and focus on the manufacturing setcor (SITC Rev. 2 codes 5-8). We delete homogeneous products for which there is no scope for quality differentiation.[20]

Since unit values can take on quite extreme values, we delete outliers as follows: We drop observations with a unit value above (or equal to) the 100-fold

[18]For example, while most studies in the literature rely on unit values of exports towards the US, the BACI data set provides bilateral trade data that is checked for consistency in the sense that generally import data is used (and CIF subtracted) but double-checked with export data of the respective trade partner. In case of discrepancies, more weight is given to the country with the higher statistical capacity and reliability. Moreover, the BACI data set transforms all export quantities into tons and thus makes them comparable across sectors. Finally, the 6-digit classification allows for a finer disaggregation than several previous studies that have used unit values for non-US trade partners (mostly on the 4-digit level).

[19]Note that BACI reports no zero values, because that would inflate the size of the dataset. Zero trade flows are hence recorded as missings.

[20]This concerns all goods that fall into the category of being 'traded on organized exchange' according to the 'conservative' classification of Rauch (1996).

of the median unit value in a given 6-digit category. Similarly, we drop observations that are below (or equal to) 1 % of the respective median unit value. Furthermore, for a given country within a 6-digit category, we drop observations that are above (or equal to) the 10-fold of the median unit value of that 6-digit category of that exporter. Similarly, we drop observations that are below (or equal to) 10 % of this respective median unit value.

For the elasticity of substitution σ, we use the estimates from Feenstra and Romalis (2014). They differ from those of Broda and Weinstein (2006) and Broda, Greenfield, and Weinstein (2006) which are used in most other studies of that literature.[21] A key advantage from our perspective is their availability down to the 4-digit (instead of 3-digit) level.[22] They are common for all countries and years, which is consistent with Khandelwal et al. (2013) who also use one elasticity for the whole textiles and clothing sector in the US, the European Union, and Canada.[23] It is also consistent with our aim to work at the finest product disaggregation level available with most countries possible since the elasticities of Broda and Weinstein (2006) are only available for 73 countries. Quantitatively, the elasticities of Feenstra and Romalis (2014) are somewhat higher than those of Broda and Weinstein (2006), which the authors attribute to a wider coverage of countries, less susceptibility to measurement error, and the explicit inclusion of quality differentiation into their model. To limit the risk of outliers from imprecise estimation, we truncate σ at 45, which is roughly at the 90th percentile.[24] Consistent with the fact that we observe substitution elasticities at the 4-digit level, we also perform estimation of equation (7) on the 4-digit level.

Values for the aggregate import price index P, imports M, and output Y are taken from the Penn World Tables (PWT9.0; series pl_m, $(-1)\times$csh_m, cgdpo, see Feenstra et al., 2015) and averaged over the years 1995-97 and 2005-07, respectively. We also use PWT to compile per capita GDP (in PPPs; rgdpe/pop), which is presented at several instances of this paper.

Finally, it is worth remembering that the inclusion of fixed effects for each 6-digit product centres the quality around zero within each 6-digit product and export quality of each country will be relative to this position.

[21] Martin and Mejean (2014) are an exception and use the elasticities of substitution later published in Imbs and Mejean (2015) which are available at the 3-digit ISIC (Revision 2) level.

[22] This also mitigates heterogeneity bias in the elasticities due to aggregation (see Imbs and Mejean, 2015).

[23] Similarly, Fan et al. (2015) simply rely on different elasticities of substitution in the range $\sigma \in [5, 10]$ in some of their specifications.

[24] This approach is not uncommon, Khandelwal (2010) for example excludes elasticities of substitution above the 90th percentile.

3.3 Some descriptives

Table 4 in Appendix A provides summary statistics of the quality estimates (together with other variables). As mentioned, export quality estimates are roughly centered around 0 by construction (since they are the transformed residual of equation (7)). We generally create about 3.9 and 5.6 million observations for the first and second period, respectively. For 2.8 million of them, we have overlapping observations so that we can calculate changes over our decade of analysis. We lose another 0.1 million observations due to lack of control variables for our main specifications. The remaining 2.7 million observations, for which summary statistics are reported, belong to 122 exporting countries and amount to 94.2% (84.5%) of the overall export value recorded in the 3.9 (5.6) million observations at the beginning (end) of our sample period (which includes a total of 162 countries but is already cleaned of homogeneous and non-manufacturing goods and outliers). A list of exporting countries in the sample can be found in table 7 in Appendix A. Across all products in the sample, the 5th and 95th percentile indicate a range of roughly 20% to 450% of the respective average quality (equivalent to a range from approximately -1.5 to 1.5 in logs).

Moving to quality changes, which we annualized, they were 0.2% on average. This may sound surprisingly small but remember that this is an unweighted average of all observed varieties. Given that several important developing and emerging economies increasingly entered the world market with low-quality competitive pricing strategies since the early 1990s, this value does not sound entirely implausible. Also note that once one weights quality developments with the share each product has in countries' export portfolio, the average quality increase amounts to 18.2% p.a. This already indicates, that there are substantial differences in quality improvement across products. An (unweighted) distribution of the quality changes is also reported in figure 8 in Appendix C.

To assess the correlation between our export quality measure and exporters' income levels, we aggregate the former on the country level (weighted by its export value). Figure 1 shows the correlation of this aggregate manufacturing export quality measure with per capita income levels for 162 countries (not limited by availability of covariables). Table 11 in Appendix C reports the corresponding regression results for those countries and the 122 countries in the final sample. These results indicate that a 1% increase in a country's average export quality is associated with a 1.7 (2.1) % increase in its GDP p.c. for the respective 162 (122) countries, with an associated R-squared of 25 (35) %. Overall, these results leave us confident to have produced a meaningful proxy for export quality and re-iterate the finding of a positive correlation between development and country's export quality in the previous literature.

4 Export quality dynamics and aggregate implications: empirical results

In this section, we first demonstrate that quality convergence within products is a robust and widespread phenomenon. We then focus on different quality trends across 6-digit products and in the product-country-specific residual innovation term and show that both of them are positively correlated with exporting countries' income levels. Especially the latter one counterbalances the within-product quality convergence on an aggregate level. We finally explore what could drive this positive correlation between quality dynamics and exporting countries' development level.

4.1 Patterns of export quality convergence

For our export quality convergence analysis we start with a seemingly conventional convergence equation, which is a stochastic extension of the processes for quality dynamics we specified in section 2:

$$\Delta \ln \hat{\Lambda}_{ijpt} = \rho_{ip} \ln \hat{\Lambda}_{ijp,t-1} + \alpha_{pi} + \gamma_j + X_{ijpt}\theta + \varepsilon_{ijpt}, \tag{9}$$

and where $\Delta \ln \hat{\Lambda}_{ijpt}$ is the annualized percentage change in export quality of a given product p at the 6-digit level exported by country i to country j, $\ln \hat{\Lambda}_{ijp,t-1}$ is the respective initial log quality of that product, and ε_{ijpt} is an error term. The coefficient ρ captures convergence (for $\rho < 0$). Its potential subscripts ip indicates that convergence speed may differ across exporting countries and/or products (or higher-level sectors). The constant α captures average changes in export quality across varieties and can similarly be indexed with exporter- and/or product-specific effects. γ_j is a potential importer fixed effect and other potential covariables (such as gravity variables) can be captured in X_{ijpt}.

As Hwang (2006) points out, equation (9) can be interpreted as the reduced form representation of an economy where firms make investment decisions to raise quality but face rising imitation costs as they come closer to the frontier. Depending on the exact formulation, this cost structure might be different across industries and countries (and e.g. depend on fixed investment costs for R&D, property rights, the market form).

Note that in the presence of a product fixed effects α_p, the convergence term ρ only captures convergence *within* products' quality. Because of the normalization of our quality measure via product fixed effects in equation (7) and since changes are in percentages, we would not expect those fixed effects to make much of a difference for estimated convergence speed. In statistical terms, the normalization within products through equation (7) largely sweeps out systematic correlation between $\ln \hat{\Lambda}_{ijp,t-1}$ and products which may otherwise lead to biased estimates of ρ.

The inclusion of fixed effects is hence rather a matter of economic interpretation. Since it is our aim to explain differences in export quality dynamics by product- and exporter-specific features, we will opt for a sparse inclusion of fixed effects in our baseline models because they would remove the variation in export quality dynamics we ultimately aim to explain.

Accordingly, the first column of table 1 reports a specification without any fixed effects. One observes a highly significant convergence parameter in the vicinity of -0.07. As discussed, the inclusion of product-fixed effects (column 2) and additional exporter- and importer-fixed effects (column 1 in table 5 in Appendix A) does not considerably change this estimate. Neither does the inclusion of standard bilateral gravity variables (column 3 of table 1). Our simple specification explains about 40 % of variation in export quality, highlighting the pre-eminent role of convergence. The convergence parameter estimate of -0.07 implies a half-life of 9.6 years[25] and is similar in magnitude to estimates in Hwang (2006) and Tian (2017), who use different concepts to gauge export quality but a similar regression framework.[26]

A common econometric concern for such convergence regressions is the possibility that the precision of measurement has increased over time. Even if true export quality remains unchanged over time, higher measurement error for observed quality in the first period could result in a $\hat{\rho} < 0$ because the overall distribution of quality would 'converge' towards their true values despite the absence of convergence in an economic sense. We assess this possibility by regressing quality changes on end (instead of initial) levels of quality. Assuming that there is no convergence but quality is more precisely measured in the final period, this should produce either an insignificant result (if quality is measured perfectly in the final period), or a negative parameter (if measurement quality improves while the true distribution is stable). Column 2 of table 5 in Appendix A instead shows a positive coefficient, rejecting the idea that our convergence results are driven by any plausible type of measurement error.

Overall, there is hence clear evidence of convergence within products in our newly constructed export quality measure. As Appendix B illustrates, this convergence pattern is extremely widespread across sectors/products but still exhibits some differences in convergence speed. However, two possibilities may withhold developing countries from benefiting from this feature: country-specific features that lead to a slower convergence speed in developing countries[27] or the

[25] Calculated as $-\ln(2)/\ln(1+\rho)$.

[26] Results in the studies by (Krishna and Maloney, 2011; Hallak and Schott, 2011; Henn et al., 2020) are not possible or straightforward to compare.

[27] Despite the fact that export quality positively correlates with income levels, industrialized countries still export considerable lower-quality varieties. It could be the case that industrialized countries manage to converge particularly fast in those varieties, e.g. because of high

Table 1: Baseline convergence regression results

VARIABLES	(1) No FEs	(2) Baseline	(3) Gravity
initial ln $\hat{\Lambda}$	-0.0675***	-0.0668***	-0.0772***
	(5.89e-05)	(5.86e-05)	(6.22e-05)
distance			9.20e-08***
			(1.54e-08)
com. colonizer			0.00382***
			(0.000361)
com. language			-0.000659***
			(0.000153)
Constant	0.00583***	0.00577***	-0.0619***
	(4.84e-05)	(4.80e-05)	(0.00336)
Observations	2,712,223	2,712,223	2,712,223
R-squared	0.380	0.395	0.451
Product FE	No	6-digit	6-digit
Exporter FE	No	No	Yes
Importer FE	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

possibility that convergence is mainly present in products/sectors that are typical for highly industrialized countries.

The first possibility can be rejected because if we interact the convergence parameter ρ in equation (9) with exporting countries' income level, the estimated interaction term shows a positive sign. This suggests that, on average, developing countries achieve faster convergence speed for export quality than industrialized ones. These results are reported and quantitatively assessed in appendix B.1 and show that country-specific convergence speeds cannot reconcile quality convergence with a stable distribution of incomes across countries.

Our analysis further reveals that quality convergence is very widespread across products and sectors, refuting the possibility that convergence is only achieved for products that are more likely to be exported by industrialized countries. In appendix B.2, we provide a comprehensive analysis of heterogeneity in convergence dynamics across sectors and products. Among other exercises, we estimate product-specific convergence parameters for each 6-digit product containing at least 30 bilateral observations. Out of the 2,654 products that fulfill this criterion, the mean convergence parameter is -0.068 (with a standard deviation of 0.011), and none of them is positive (maximum -0.012). Except

absorptive capacities (such as a highly skilled workforce).

for one, all coefficient estimates are statistically different from 0 (t-statistic ≤ -1.96). We found some differences in convergence speed across sectors, with fastest convergence in the machinery and transport equipment sector and slowest convergence in chemicals but these differences in speed, which may reflect higher entry costs in certain industries, are not enough to constitute a potential disadvantage for developing countries.

4.2 Residual and product specific innovation: what are their aggregate implications?

The previous literature on export quality convergence has ignored the possibility that the residual of a seemingly conventional convergence regression like (9) may be biased in favor or higher-income countries and that products with more favorable overall quality dynamics may rank more prominently in the export portfolio of those higher-income countries. To explore the aggregate implications of this possibility and to put quantitative flesh to the bones of the framework spelled out in in section 2 we estimate the relevant parameters in the regression

$$\Delta \ln \hat{\Lambda}_{ijpt} = \rho \ln \hat{\Lambda}_{ijp,t-1} + \alpha_p + a_{ijpt}, \tag{10}$$

and investigate the relationship of the product-specific quality ladder effects α_p and residual innovations a with exporting countries' income level and export shares s_i.[28] While the portfolio effect that aggregates differences in quality ladder dynamics is defined exactly as in equation (4), we alter the definitions of the aggregate convergence effect and aggregate innovation effect to facilitate the fact that equation (10) includes an importer-specific dimension. This leaves us with the following definitions for the three effects studied, where s_{ijp} indicates the share of an importer-product combination jp for exporting country i:

$$\begin{aligned} agg\ convergence\ effect_i &= \rho \sum_p \sum_j s_{ijp} \ln \hat{\Lambda}_{ijp,t-1} \\ portfolio\ effect_i &= \sum_p s_{ip}\alpha_p \\ agg\ innovation\ residual\ effect_i &= \sum_p \sum_j s_{ijp} a_{ijp} \end{aligned}$$

Those aggregate effects are regressed on and plotted against exporters log GDP per capita levels in table 2 and figure 3, respectively.

[28] To avoid incidental parameter problems for the fixed effect we are interested in, we limit the sample to 6-digit products containing at least 30 bilateral observations. Compared to the baseline regression in column 1 of table 1, this lowers the sample by 371 observations. Results are reported in column 3 of table 5 in Appendix A. The distribution of the 2,654 product quality fixed effects α_p from equation (10) is depicted in figure 9 in Appendix C. They are approximately normally distributed with an inter-quartile range from -0.9 to 0.7 percentage point annual changes in export quality.

Table 2: Aggregate quality components vs. exporting countries' GDP p.c.

	(1)	(2)	(3)
VARIABLES	agg convergence effect	portfolio effect	agg innovation residual
log GDP p.c.	-0.0111***	0.000823***	0.0169***
	(0.00162)	(0.000307)	(0.00250)
Constant	0.0884***	-0.00645**	-0.167***
	(0.0143)	(0.00286)	(0.0229)
Observations	122	122	122
R-squared	0.352	0.047	0.275

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The picture that emerges from this analysis is clear and indicates a strong residual innovation force operating against the within-product convergence effect. On aggregate, this within-product convergence effect operates in favor of lower-income countries, as indicated in the first panel of figure 3 and column (1) of table 2, reflecting that they start out at lower export qualities. However, the two other forces operate into opposite direction. Particularly, residual innovation shows a strong positive correlation with exporters' income levels. The magnitude of this effect is large enough to offset lower-income countries' advantages from the convergence effect: while a doubling of GDP per capita is associated with 1.1 percentage point slower quality improvements from convergence, it is associated with 1.7 percentage point faster quality innovation (see columns 1 and 3 of table 2). Both effects bear a relevant correlation with exporting countries' development level, as indicated by the R-squared of 0.35 and 0.27, respectively. The portfolio effect additionally works against convergence but its estimated magnitude is relatively small: convergence within products is more than 10 times as important for aggregate export quality dynamics than the divergence effect due to different product dynamics and export shares, and the latter shows a rather low overall correlation with development levels, with an R-squared of 0.05.

The combination of these individual effects leads to the absence of convergence in *aggregate* export quality across countries, which is shown in the left panel of figure 4. The depicted linear regression line essentially exhibits a slope of 0. Export quality convergence is thus a driving force for quality dynamics within products but not relevant to explain aggregate export quality dynamics across countries. Particularly, aggregate export quality dynamics are no candidate for reshuffling the global income distribution across countries at a macroeconomic level: the relationship between aggregate quality changes and income levels, depicted in the right panel of figure 4 is, if anything, positive. This explains why a stable income distribution can be reconciled with convergence in exported goods' quality, despite the strong link between income levels and export quality.

Figure 3: Aggregate quality components vs. development levels

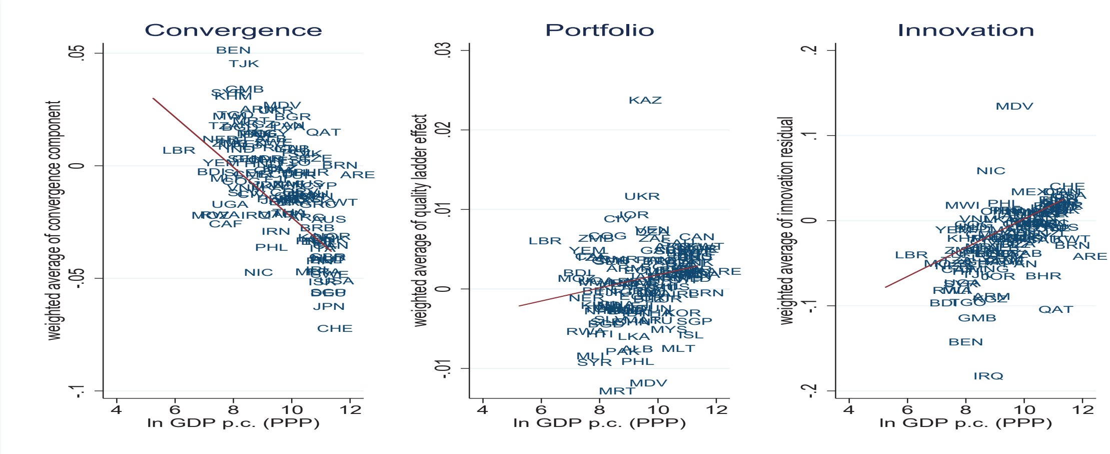
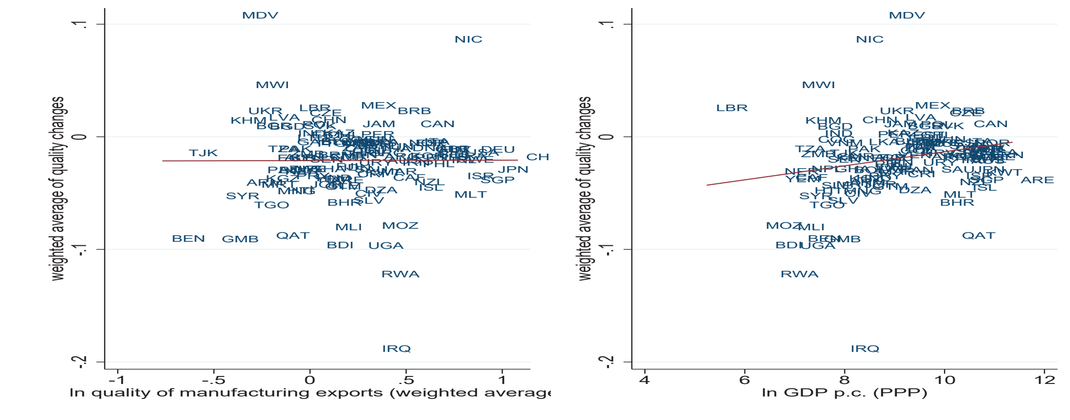


Figure 4: Aggregate quality changes vs. initial and development levels



5 Potential drivers of residual innovation

Given the importance that residual innovation plays in our results, it is natural to ask about its potential drivers. While we refer a detailed causal analysis of this question to further analysis, we analyze some correlates in this section.

As highlighted by Alcalá (2016), the two main approaches to the determinants of quality in trade are the factor-endowments approach (e.g., Schott, 2004) and an income-demand approach (e.g., Hallak, 2006; Fajgelbaum et al., 2011)[29], to which Alcalá (2016) adds a complementary Ricardian approach. Additionally, Krishna et al. (2020) stress the relevance of financial development for export quality upgrading. This suggests to investigate the following potential correlates of export quality innovation:

1. To capture the role of factor endowments for export quality innovation, we use a *factor appropriateness index for capital* (FAI_c), which relates the factor intensity of a product to the endowment structure of the exporting country. To do so, we use data constructed by Shirotori et al. (2010), which provides revealed factor intensities for approximately 5,000 exported products (HS 6-digit level) as well as information on exporting countries' physical capital stock per worker. Formally, the index is then defined as:

$$FAI_{c,ipt} = \frac{(K/L)_{pt}}{K_{it}/L_{it}},$$

where $(K/L)_{pt}$ is the revealed capital intensity of a product p in period t as provided by Shirotori et al. (2010).[30]

The idea of factor appropriateness driving quality innovation is motivated by two considerations. First, a product that is well-aligned to the factor endowments of a country (i.e. an FAI close to 1) allows and creates incentives for countries' product-specific innovation. Second, following the idea of Acemoglu et al. (2012), innovation in a product may first be capital- (or skill-) intensive, before is becomes increasingly standardized. This implies that countries exporting products that are too capital- (or skill-)intensive given their endowments (i.e. an FAI $>$ 1), will have a disadvantage in innovation activities for that product. In other words, the FAI may to some extent reveal a 'functional specialization' in exports (Timmer et al.,

[29] The income-demand effect in Fajgelbaum et al. (2011) operates through a home market effect. Instead, we focus in this section on the foreign income-demand for quality because investigating the role of home market income for export quality would be tautological in our setting: it would lead to the conclusion that richer countries have more favorable quality dynamics because they are richer.

[30] The idea of this index is hence similar to the PRODY by Hausmann et al. (2007) that reflects the typical income level associated with a product and is constructed as a weighted average of the per capita GDP of countries exporting that product. For the FAI, the factor intensity is used instead of the income level.

2018), where a lower FAI may suggest more scope for innovation-relevant activities (such as R& D).[31]

2. In the same vein, we use a *factor appropriateness index for skills* or human capital (FAI_s), which uses average years of schooling instead of the physical capital stock. Otherwise, the construction and intuition is identical to the FAI_c.

3. If one thinks that innovation results from specific tasks (such as R&D) that are capital- or skill-intensive, the absolute capital or skill endowments of a country should matter. We hence also investigate average years of schooling and physical capital stock per worker (K/L) to our regressions (both taken from Shirotori et al., 2010).

4. Besides from fostering capital accumulation, *financial development* may have an additional effect on export quality by financing innovation (see Krishna et al., 2020) Therefore, we include the financial development index developed by Sahay et al. (2015), which summarizes how developed financial institutions and financial markets are in terms of their depth, access, and efficiency. Besides from its methodological appeal (including the availability of sub-indices) a key reason why we opted for this index of financial development was its wide availability (covering over 180 countries).

5. The idea of the 'Linder hypothesis' that higher-income countries import higher-quality varieties is well-studied in the literature (e.g. Hallak, 2006; Crinò and Epifani, 2012). From a dynamic perspective, we add *importer income* per capita, taken from PWT 9.0 (series rgdpe/pop), to explore the possibility that exporting to higher-income markets creates additional learning spillovers beyond those already captured in the convergence term.

6. To capture the Ricardian intuition of Alcalá (2016), we additionally add a *revealed comparative advantage* index (RCA), which relates the share of a product in a country's export basket to the product's share in total world trade. Formally:

$$RCA_{ipt} = \frac{X_{ipt}/\sum_p X_{ipt}}{\sum_i X_{ipt}/\sum_i \sum_p X_{ipt}},$$

   where X indicates exports. A comparative advantage is 'revealed' if RCA>1 and indicates that exporter i over-proportionally specializes in the export of that product (compared to other countries).

   The intuition for this term is twofold: First, RCA may reveal countries' endowment factors beyond capital or skills that are advantageous

[31]Unfortunately, the functional specialization measure by Timmer et al. (2018) is only available for 40 countries, on a rather aggregated level (35 industries), which does not allow us to formally test this idea.

for product-specific innovation, which could be certain managerial skills or institutions (e.g. Costinot, 2009). Second, increased specialization in a product may lead to learning-by-doing externalities and (potentially external) economies of scale.

All of these variables are taken from the beginning of the sample period and most of them are included in natural logarithms. We additional take the square of our factor appropriateness and RCA measures because one could expect those effects to be non-linear (e.g., to have a maximum effect around 1, i.e. 0 in logs). Note that we do not include any type of fixed effects as they would sweep out the type of variation we aim to explore. For the same reason, we also do not include exporter income levels in our regressions, although we show that our results are not driven by its omission.

The results of our exploratory analysis are reported in table 3. The first column focuses on the product-exporter measures (appropriateness and specialization) and also includes importer GDP. It confirms the role that factor appropriateness, especially for capital, plays for residual quality innovation.[32] After including capital/worker, financial development, and school attainment, capital appropriateness is no longer statistically significant, however (column 2). Since the square of revealed comparative advantage and years of schooling are also insignificant those variables are dropped in our preferred specification reported in column (3) of table 3.[33] Our results suggest that exporting products that are too skill-intensive given a country's endowment structure is negatively associated with residual innovation. This relationship strengthens with the skill-intensity of the product, as indicated by the squared negative term.[34] Moreover, countries experiencing higher residual innovation are more capital abundant. Those findings are consistent with the intuition of the (closed economy) model by Acemoglu et al. (2012) that quality innovation first requires (human) capital and that the product can only be produced with less capital and skill intensity after some standardization and imitation process (which is then reflected in convergence).Additionally, financial development seems to foster export quality innovation beyond supporting capital accumulation. This is also intuitive as innovation requires upfront investments and thus access to finance (Krishna et al.,

[32]Due to collinearity in the factor appropriateness indices and to facilitate interpretation, we separately evaluate the appropriateness indices for capital and skills and drop the squared terms, respectively, in table 12 in appendix C.

[33]Given the skewness of the capital stock, we also considered including it in log terms, which made it more difficult to discriminate between a model with capital appropriateness and the log capital stock since both fell slightly short of the 10 % level of statistical significance (possibly due to high multicollinearity). If capital stock is included in log terms in our preferred specification it is statistically significant at the 1 % level (results available upon request). In appendix C, we show that the quantitative implications of an alternative specifications with capital appropriateness (instead of capital stock) leads to similar conclusions.

[34]Because of potential non-linearity in the factor appropriateness variables, we also applied a non-parametric local regression smoothing technique (lowess). Results are reported in figure 10 in appendix C.

2020).[35] Note that both, capital stock and financial development, do not merely reflect exporting countries' income levels: they remain statistically significant after controlling for exporter GDP (see last column of table 12 in appendix C). Countries also find it easier to increase export quality in products they specialize in, as indicated by the positive coefficient for revealed comparative advantage. Economically, this could reflect some 'learning by doing' externalities. Importer GDP per capita is also positively correlated with our innovation residual, suggesting that the pressure for quality innovation may be higher in high-income markets or that there are particular learning effects in those markets.

To assess the economic relevance of those potential drivers of residual innovation, column (4) of table 3 reports standardized beta coefficients. One can see that the potential relevance of all variables is of a similar level of magnitude, although capital abundance and financial development seem to be the most relevant ones for explaining the variation in our innovation residual. This finding about the relative economic relevance of variables is also illustrated by an analysis of variance in table 6 in the appendix. Note that the overall power of the model to explain the observed variation in residual innovation appears rather modest, as indicated by an R-squared of about 4%. As will become apparent in the next section, however, those factors explain the structure in variation that is economically relevant: differences in those factors between high- and low-income countries translate into a magnitude of export quality dynamics that is sufficient to offset the within-product export quality convergence that low-income countries enjoy.

6 The opposing factors of overall export quality dynamics reconciled

After we have studied the relevance of export quality convergence against its opposing factors of a portfolio effect and residual innovation and its correlates, we can now put these factors into perspective for a final overall assessment of the different forces potentially driving quality dynamics across high- and low-income countries. As opposed to the analysis in section 5, we now look at overall quality dynamics $\Delta \ln \Lambda$ instead of the innovation residual a and include a measure of product sophistication, the PRODY, into our analysis.[36] A higher PRODY indicates that this product is more likely to be exported by higher-income countries. The intuition for including this product-specific variable is to capture

[35] To further explore the potential relevance of financial development, we replaced financial development by the 'financial markets' and 'financial institutions' sub-indices from Sahay et al. (2015) in our regression. When jointly included, both of them are statistically significant and contribute a similar degree to explaining the variation in residual innovation. Results are available upon request.

[36] We take the PRODY for 1997 as provided by CEPII (Jarreau and Poncet, 2012) based on the idea of Hausmann et al. (2007).

Table 3: Correlates of residual innovation

VARIABLES	(1) *i-p* focus	(2) full	(3) preferred	(4) std beta
$\ln(\text{FAI}_c)$	-0.00970***	-0.00216		
	(0.00235)	(0.00235)		
$\ln(\text{FAI}_s)$	-0.00676	-0.00923**	-0.0100**	-0.0431
	(0.00618)	(0.00405)	(0.00393)	
$\ln(\text{FAI}_c)^2$	-8.36e-05	-0.000248		
	(0.000841)	(0.000824)		
$\ln(\text{FAI}_s)^2$	-0.0145**	-0.00979*	-0.0101**	-0.0264
	(0.00580)	(0.00567)	(0.00438)	
ln(RCA)	0.00163***	0.00155***	0.00157***	0.0439
	(0.000250)	(0.000227)	(0.000222)	
$\ln(\text{RCA})^2$	-4.82e-05*	-1.01e-06		
	(2.89e-05)	(2.14e-05)		
imp ln(GDP pc)	0.00285***	0.00328***	0.00335***	0.0458
	(0.000612)	(0.000586)	(0.000604)	
K/L		7.61e-08*	9.64e-08**	0.0786
		(4.20e-08)	(3.73e-08)	
Financial devt		0.0382***	0.0368**	0.0784
		(0.0135)	(0.0141)	
Yrs of schooling		-0.000457		
		(0.000835)		
Constant	-0.0255***	-0.0537***	-0.0600***	
	(0.00659)	(0.00874)	(0.00753)	
Observations	2,711,852	2,710,094	2,710,094	2,710,094
R-squared	0.032	0.039	0.038	0.038

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

the faster improvements in quality dynamics in products typically exported by higher-income countries. It hence captures some aspects of our portfolio effect. This leaves us with the following equation to describe export quality dynamics:

$$\begin{aligned}\Delta \ln \hat{\Lambda}_{ijp} \quad = \quad & a + \rho \ln \hat{\Lambda}_{ijp,t-1} + \beta_1 \ln(PRODY)_p + \beta_2 \ln(FAI_s)_{ip} + \\ & \beta_3 \ln(FAI_s)^2_{ip} + \beta_4 \ln(RCA)_{ip} + \beta_5 \ln Y_j + \beta_6 K/L_i + \\ & \beta_7 \text{ fin devt}_i + \varepsilon_{ijpt}. \end{aligned} \tag{11}$$

After obtaining the parameter estimates for equation (11), we multiply them with the average values of the right-hand-side variables for low-, middle- and high-income countries (see table 8 in the appendix for all values and parameters).[37] This provides us with predicted dynamics of export quality for the 'typical manufacturing export good' of those country groups.

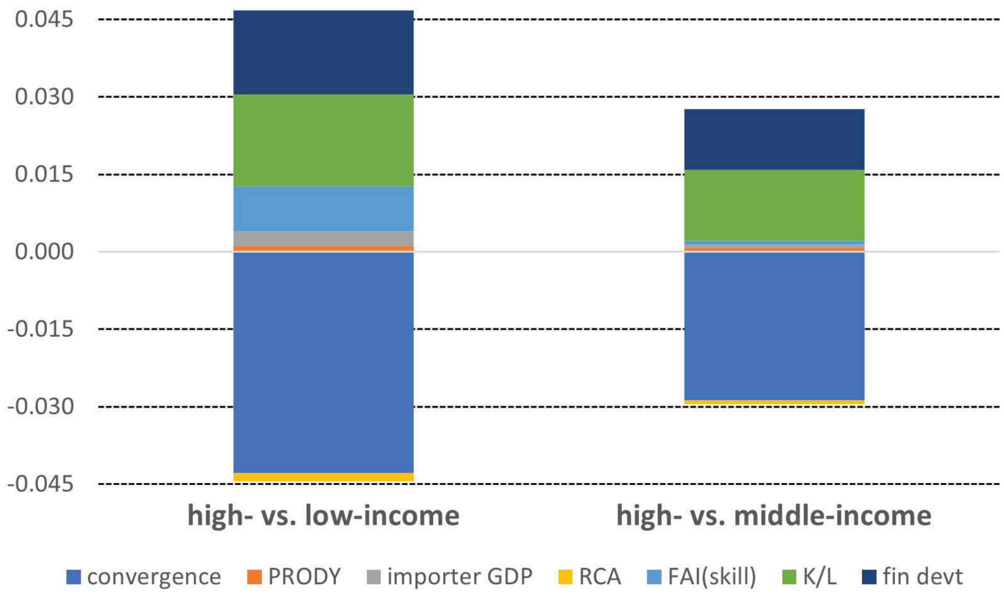
The results are graphically displayed in figure 5 and illustrate why aggregate export quality of lower-income countries does not converge towards higher-income countries. As one can see, convergence leads to a 4.3 percentage points slower growth in export quality of high-income compared to low-income countries due to the fact that low-income countries tend to start at lower initial export quality levels and thus catch up. This 'advantage of backwardness' is outweighed, however, by three key opposing factors: high-income countries are more capital abundant and more financially developed than low-income countries and they export products that are more appropriate to their skill endowments. Since all three factors are positively associated with faster growth in export quality they jointly make up for the export quality convergence that low-income countries enjoy. Also considering the other factors included in equation (11), which appear less relevant, our model suggests that there is virtually no difference in the average developments of aggregate export quality between low- and high-income countries, despite fast export quality convergence within products. This is fully consistent with the stylized fact presented in figure 4 that aggregate export quality changes are largely uncorrelated with income levels.[38]

We do not claim that those effects are causal in the sense that fostering capital accumulation or financial development will necessarily lead to faster export quality improvements. The key message of our results is illustrative: to

[37] Low-, middle-, and high-income countries refer to the lowest third, mid-third, and highest third of countries ordered by income p.c. level. See table 7 in Appendix A. For the mean values of covariables we weight observations for each country with their percentage in the respective country's export portfolio and take the unweighted average over all countries in an income group.

[38] Our model specified in equation (11) suggests that overall export quality in high-income countries increases 0.2 percentage points faster than in low-income and 0.2 percentage points slower than in middle-income countries. Appendix C presents a different specification, where the explanatory variables suggest a 1.3 percentage point faster increase of export quality of high-income compared to low-income countries.

Figure 5: Contributors to differences in export quality dynamics between country groups



highlight potential channels how export quality convergence is counteracted by other dynamic factors in export quality and to gauge if these effects are potentially large enough to outweigh the effects of quality convergence. Although the exact results obtained should be taken with a grain of salt, they suggest that this may potentially be the case.

7 Conclusion

In this paper, we have highlighted that convergence in goods' export quality across countries does not imply convergence of countries' aggregate export quality. In fact, our paper is the first to demonstrate that the distribution of aggregate export quality across countries is stable. This finding explains how previous findings of quality convergence in export goods can be reconciled with a stable world income distribution, despite the strong link between export quality and income levels. Furthermore, our results suggest that the key explanation why developing countries lack export quality innovation may be their lower capital abundance and financial development levels as well as their tendency to export goods that require too much human capital given their skill endowment.

This finding is consistent with the view that quality innovations are capital- and skill-intensive and that the 'advantages of backwardness' through imitation and convergence can only be reaped after a process of standardization (Acemoglu et al., 2012). This is further consistent with the point raised by Grossman and Helpman (1991a) that in a dynamic equilibrium with growth, imitation should not dim the incentives for innovation, and with the idea of international product cycles in North-South trade (Krugman, 1979; Flam and Helpman, 1987) and the underlying concept of trade in tasks (Timmer et al., 2018). More disaggregated empirical work will be needed to better understand those dynamics and its contributing factors.

Our findings also have considerable policy implications because they suggest that the existence of (unconditional) convergence in export products' quality does not mean that developing countries can simply use the 'automatic escalators' of convergence. On the other hand, our findings also suggest clear limits to defying comparative advantage by picking the 'best products' for exports. The results and discussion in section 5 suggest that moving towards capital- and skill-intensive goods without an appropriate endowment structure will leave less (human) capital for important innovation activities, which weighs on quality improvements. Hence, a clever mix of sectoral and horizontal policies is needed and future theoretical work may help to further model the resulting policy trade-offs.

In ongoing work, we aim to extent our findings in two directions. First, the focus on convergence in the quality of export goods by definition precludes the possibility to study the important dynamics of entry and exit and systematic export portfolio changes. We study those patterns of quality dynamics from a macroeconomic portfolio perspective in related work but focused on a product-perspective in this paper to highlight the channels of product quality dynamics that work against quality convergence within products. Second, our work builds on the extensive literature on quality in final goods gross exports. Given that many economies heavily rely on imported intermediates, a key challenge in future work will be to investigate and better understand at which part of the value chain countries' contribution to quality actually takes place.

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A Appendix A

Table 4: Summary statistics of variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Δ ln $\hat{\Lambda}$	0.00	0.1	-0.76	0.8	2,712,223
initial ln $\hat{\Lambda}$	0.08	0.92	-4.85	5.32	2,712,223
ln (RCA)	-0.38	2.17	-12.88	15.96	2,712,223
ln(PRODY)	9.5	0.44	6.89	10.46	2,712,223
ln(FAI$_c$)	-0.1	1.00	-3.84	5.43	2,712,223
ln(FAI$_s$)	-0.04	0.33	-1.61	2.65	2,712,223
exp ln (GDP pc)	9.85	0.82	5.25	11.35	2,712,223
imp ln (GDP pc)	9.39	1.06	5.25	11.35	2,712,223
K/L	119,650	63,410	658	215,175	2,712,223
Fin devt	0.50	0.17	0	0.87	2,710,465

Table 5: Convergence regression results: robustness

	(1)	(2)	(3)
VARIABLES	Country FEs	Endvalue	Baseline T≥30
initial ln $\hat{\Lambda}$	-0.0771***		-0.0668***
	(6.22e-05)		(0.000235)
ln $\hat{\Lambda}$ end period		0.0606***	
		(6.76e-05)	
Constant	-0.0619***	-0.00497***	0.00577***
	(0.00336)	(5.24e-05)	(1.96e-05)
Observations	2,712,223	2,712,223	2,711,852
R-squared	0.451	0.283	0.378
Product FE	6-digit	6-digit	6-digit
Exporter FE	Yes	No	No
Importer FE	Yes	No	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Analysis of variance for innovation residual

VARIABLES	(1) Table 3 col 1	(2) Table 3 col 3
ln(RCA)	31.02	31.07
ln(RCA)^2	0.44	
ln(FAI$_c$)	101.09	
ln(FAI$_s$)	6.24	20.16
ln(FAI$_c$)^2	0.03	
ln(FAI$_s$)^2	15.06	9.99
imp ln(GDP pc)	24.76	33.91
K/L		49.75
Financial development		53.26
Observations	2,711,852	2,710,094
R-squared	0.032	0.038

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Sample countries by income group

low-income	Obs	middle-income	Obs	high-income	Obs
Armenia	114	Albania	735	Argentina	14,873
Bangladesh	4,641	Algeria	363	Australia	39,633
Benin	159	Belize	109	Austria	72,691
Bolivia	913	Brazil	39,230	Bahrain	742
Cambodia	848	Bulgaria	12,975	Barbados	995
Cameroon	800	Chile	8,489	Belgium	94,950
China	115,029	Colombia	11,141	Brunei Darussalam	376
Congo, Rep.	134	Costa Rica	4,404	Canada	46,656
Cote d'Ivoire	2,179	Croatia	9,227	Cyprus	3,035
El Salvador	3,338	Ecuador	2,343	Czech Republic	43,516
Gambia, The	54	Egypt, Arab Rep.	7,534	Denmark	60,741
Ghana	724	Estonia	8,066	Finland	36,999
Haiti	198	Fiji	427	France	155,905
Honduras	1,854	Gabon	210	Germany	182,173
India	69,973	Guatemala	5,332	Greece	21,118
Jordan	2,232	Indonesia	31,408	Hungary	28,357
Kenya	3,287	Iran, Islamic Rep.	3,579	Iceland	1,381
Kyrgyz Republic	90	Jamaica	908	Ireland	22,301
Malawi	325	Kazakhstan	266	Israel	17,916
Mali	193	Latvia	5,969	Italy	166,065
Mongolia	159	Lithuania	9,658	Japan	94,857
Mozambique	124	Malaysia	36,017	Korea, Rep.	68,115
Nepal	1,484	Mauritius	2,869	Kuwait	799
Nicaragua	692	Mexico	29,154	Malta	1,617
Niger	205	Morocco	7,444	Netherlands	102,334
Pakistan	9,285	Panama	9,836	New Zealand	9,738
Paraguay	611	Peru	4,780	Norway	29,293
Rwanda	70	Philippines	15,059	Portugal	33,146
Senegal	1,065	Poland	31,218	Qatar	371
Sierra Leone	64	South Africa	20,849	Saudi Arabia	8,698
Syrian Arab Republic	2,381	Sri Lanka	5,409	Singapore	44,771
Tajikistan	127	Thailand	50,635	Slovak Republic	17,247
Tanzania	460	Trinidad and Tobago	3,292	Slovenia	19,605
Togo	710	Tunisia	6,190	Spain	95,996
Uganda	456	Turkey	53,507	Sweden	73,366
Vietnam	7,970	Ukraine	9,922	Switzerland	73,139
Yemen, Rep.	83	Uruguay	2,317	United Arab Emirates	16,052
Zambia	325	Venezuela, RB	4,057	United Kingdom	156,034
		Zimbabwe	1,754	United States	166,447
	233,356		456,682		2,022,048

Table 8: Calculation of implied effects

		variable means			implied effects			Δ btw high- and ... income	
	Coef.	low-income	middle-income	high-income	low-income	middle-income	high-income	Δ high- vs. low	Δ high vs. middle
convergence	-0.075	-0.132	0.058	0.443	0.010	-0.004	-0.033	-0.043	-0.029
ln(RCA)	0.002	1.997	1.542	1.081	0.003	0.003	0.002	-0.002	-0.001
ln(PRODY)	0.002	8.988	9.165	9.563	0.018	0.018	0.019	0.001	0.001
ln(FAI_s)	-0.006	0.585	0.058	-0.110	-0.003	0.000	0.001	0.004	0.001
ln(FAI_s)^2	-0.014	0.342	0.003	0.012	-0.005	0.000	0.000	0.005	0.000
imp ln(GDP pc)	0.003	9.169	9.870	10.048	0.030	0.033	0.033	0.003	0.001
K/L	0.000	7,440	36,461	133,021	0.001	0.005	0.019	0.018	0.014
Fin devt	0.047	0.131	0.228	0.480	0.006	0.011	0.022	0.016	0.012

B Appendix B: Convergence heterogeneity

B.1 Does export quality of low-income countries converge slower?

Given some, though modest, differences in convergence speed across products and product-country factors, we explore the opportunity if lower-income countries' export quality converges slower. This could reflect the fact that their export portfolios over-proportionally include products that experience somewhat slower convergence and hence potentially reconcile export quality convergence with a stable income distribution across countries.

To test for this hypothesis, we allow the convergence parameter in our regression to depend on the exporter's income level:

$$\Delta \ln \hat{\Lambda}_{ijpt} = \rho_0 \ln \hat{\Lambda}_{ijp,t-1} + \rho_1 \ln GDP_i \times \ln \hat{\Lambda}_{ijp,t-1} + \alpha_p + \gamma_j + X_{ijpt}\theta + \varepsilon_{ijpt}. \tag{12}$$

Note that we opt for a specification without any fixed effects or control variables in the baseline because we want those effects to be reflected in the parameter estimate for the income levels. The result in column 1 of table 9 indicate that export quality convergence is actually faster for lower-income countries and slows down with increasing income levels of the exporter. The quantitative implication of this heterogeneity is negligible: when moving from a log-income level of 9.4 to 10.4 (the IQR in observations), the implied quality convergence coefficient slows down from -0.074 to -0.072. Nevertheless, this result is clear evidence that lower-income countries do not suffer from any factors that slow down their quality convergence. Once one additionally includes the covariables lnPRODY, lnRCA, lnRCA^2, lnFAI$_c$, lnFAI$_c^2$, lnFAI$_s$, lnFAI$_s^2$, and interactions of them with the convergence term (column 2), the convergence slowdown for higher-income countries becomes even more pronounced. But as in the case of additionally including product- and importer-fixed effects (column 3), the quantitative implications are negligible.[39]

B.2 Heterogeneity in convergence dynamics across sectors and products

In this section, we investigate the possibility that convergence speed differs across certain product types or sectors, which could hold back developing countries in their convergence if they are particularly specialized in exporting those goods. Column 1 of table 10 shows the results for the different 1-digit manufacturing sectors (which are dummy variables that are then interacted with initial

[39] Since the clear unit of analysis in this case is the exporting country, we performed a robustness check for the specification in column 1, where we weighted each observation with its share in the respective exporter's export basked and clustered standard errors on the exporting country level. The interaction between exporter income and initial export quality is still positive (0.0036) and statistically significant at the 10% level (t-statistic 1.88).

Table 9: Convergence heterogeneity by exporter income level

VARIABLES	(1) Baseline	(2) Baseline	(3) Baseline
initial ln $\hat{\Lambda}$	-0.100***	-0.105***	-0.107***
	(0.000721)	(0.00170)	(0.00167)
exp ln(GDP pc)	0.0204***	0.0148***	0.00879***
	(6.49e-05)	(0.000184)	(0.000254)
initial ln $\hat{\Lambda}$ × exp ln(GDP pc)	0.00274***	0.00428***	0.00293***
	(7.30e-05)	(0.000218)	(0.000215)
Constant	-0.195***	-0.186***	-0.0987***
	(0.000644)	(0.00137)	(0.00269)
Observations	2,712,223	2,712,223	2,712,223
R-squared	0.404	0.408	0.434
Other controls/interactions	No	Yes	Yes
Product FE	No	No	6-digit
Exporter FE	No	No	No
Importer FE	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

quality). Sector 5 (chemicals) is the reference category and the negative additional convergence coefficient for the other sectors suggests that export quality in those sectors converges significantly faster, particularly so in sector 7 (machinery and transport equipment). Robustness checks of this specification with product-fixed effects and additional exporter- and importer-fixed effects lead to quantitatively similar results and imply that the half-life in the chemical sector is about 25% longer than for machinery and transport equipment. Results are available upon request.

Another way to investigate cross-product and cross-sector heterogeneity in convergence is to run the simple convergence equation

$$\Delta \ln \hat{\Lambda}_{ijpt} = \rho \ln \hat{\Lambda}_{ijp,t-1} + a + \epsilon_{ijpt}, \quad (13)$$

product by product and investigate the obtained convergence coefficients. We perform this regression for every product containing at least 30 bilateral observations. Out of the 2,654 products that fulfill this criterion, the mean convergence parameter is -0.068 (with a standard deviation of 0.011), and none of them is positive (maximum -0.012). Except for one, all coefficient estimates are statistically different from 0 (t-statistic ≤ -1.96). The kernel density estimate of those parameter estimates in figure 6 in appendix B.2 shows that these 2,654 product-specific convergence parameter estimates are approximately normally distributed. Figure 7 plots the same kernel density by sector. Consistent with

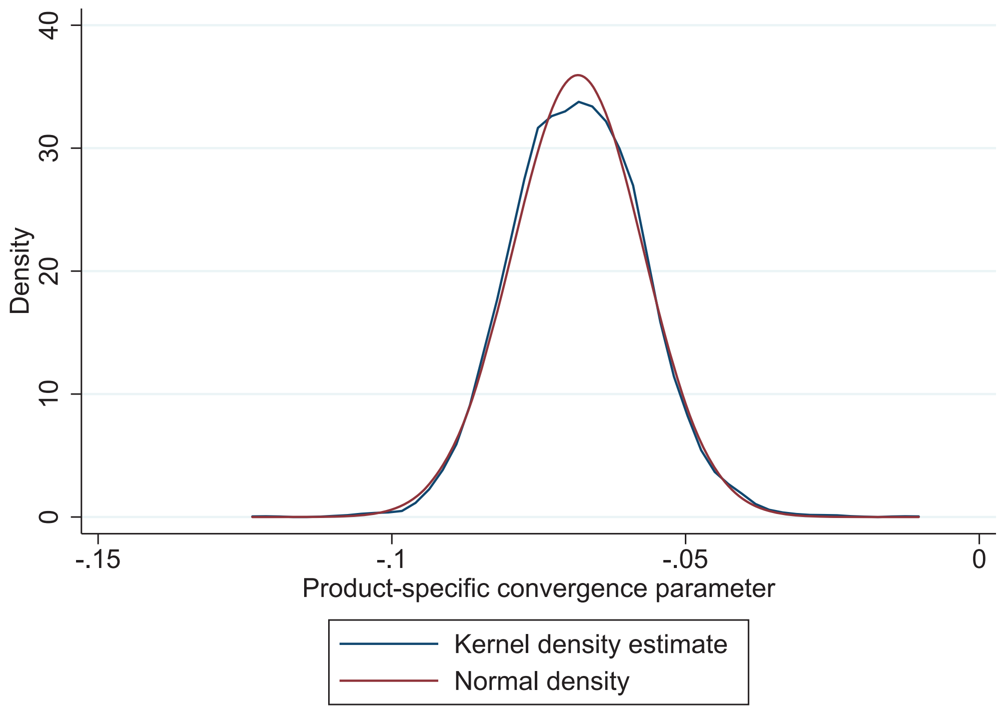
Table 10: Convergence heterogeneity by sectors and PRODY

VARIABLES	(1) No FEs	(2) PRODY	(3) PRODY & FEs
initial ln $\hat{\Lambda}$	-0.0585***	-0.0613***	-0.0961***
	(0.000235)	(0.00128)	(0.00123)
SITC Rev.2 1-digit sector = 6	-0.00672***		
	(0.000211)		
SITC Rev.2 1-digit sector = 7	-0.00558***		
	(0.000207)		
SITC Rev.2 1-digit sector = 8	-0.0125***		
	(0.000210)		
SITC=5 $\times$ initial ln $\hat{\Lambda}$	0		
	(0)		
SITC=6 $\times$ initial ln $\hat{\Lambda}$	-0.00430***		
	(0.000262)		
SITC=7 $\times$ initial ln $\hat{\Lambda}$	-0.0139***		
	(0.000253)		
SITC=8 $\times$ initial ln $\hat{\Lambda}$	-0.00952***		
	(0.000259)		
ln(PRODY)		0.00711***	
		(0.000110)	
ln(PRODY) $\times$ initial ln $\hat{\Lambda}$		-0.000645***	0.00199***
		(0.000135)	(0.000129)
Constant	0.0133***	-0.0617***	-0.0625***
	(0.000191)	(0.00104)	(0.00336)
Observations	2,712,223	2,712,223	2,712,223
R-squared	0.383	0.381	0.451
Product FE	No	No	6-digit
Exporter FE	No	No	Yes
Importer FE	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

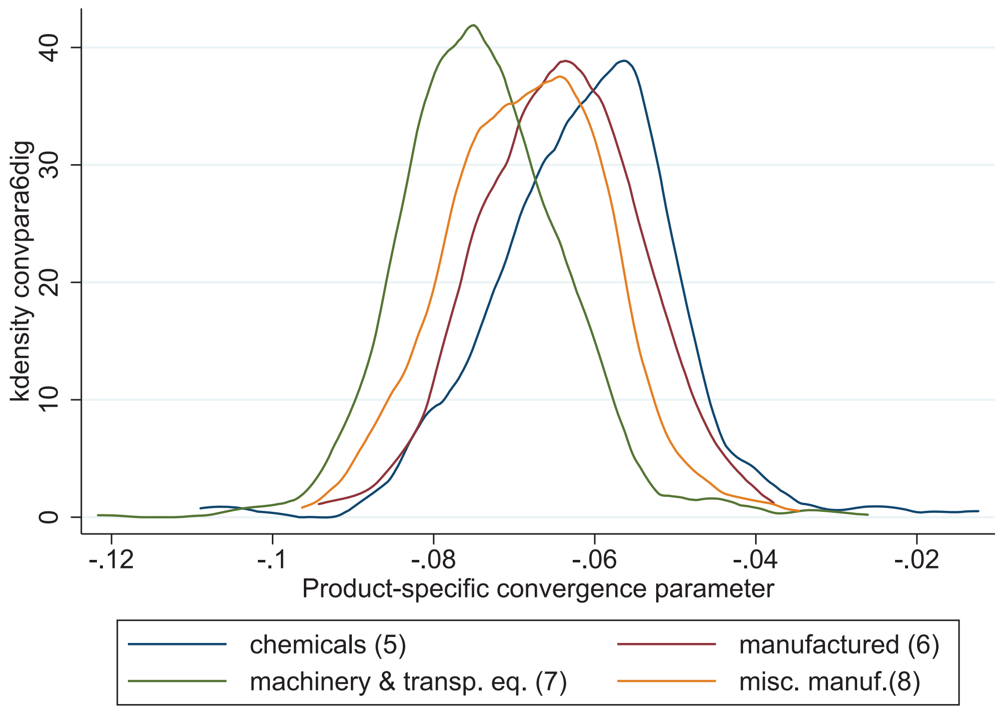
the results in table 10, export quality convergence is estimated to be fastest in the machinery and transport equipment sector and slowest in chemicals.

Figure 6: KDE of product-specific convergence parameter



Those differences in the speed of export quality convergence may reflect higher entry costs in certain industries, e.g. due to upfront fixed investment or R&D, such that more sophisticated goods are potentially shielded from easy catch-up. To further explore this issue, we interact our convergence coefficient in equation (9) with the log of PRODY, a measure of product sophistication. There is some evidence that convergence speed slows down at higher product sophistication, as the negative interaction term between PRODY and initial quality in column 3 of table 10 indicates. This finding, however, depends on the inclusion of product-fixed effects, as one can see from comparison with column 2. In either case, the differences are economically negligible because the implied difference in half-life when moving from the 25th to the 75th percentile of lnPRODY is less than 1%.

Figure 7: KDE of product-specific convergence parameter, by sector



C Appendix C: Additional results

Table 11: Correlations between average export quality and GDP p.c.

VARIABLES	(1) exp ln(GDP pc)	(2) exp ln(GDP pc)
aggregate ln $\hat{\Lambda}$	1.675***	2.121***
	(0.212)	(0.192)
Constant	8.457***	8.467***
	(0.0891)	(0.0984)
Observations	162	122
R-squared	0.251	0.352
Note	all countries	final sample

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 8: Distribution of Quality Changes

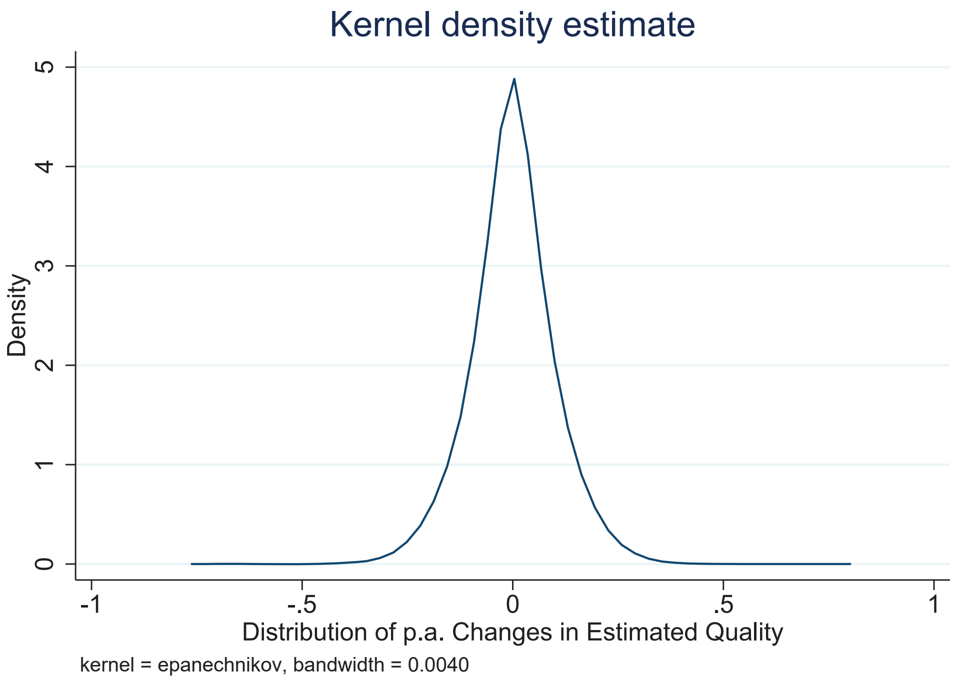
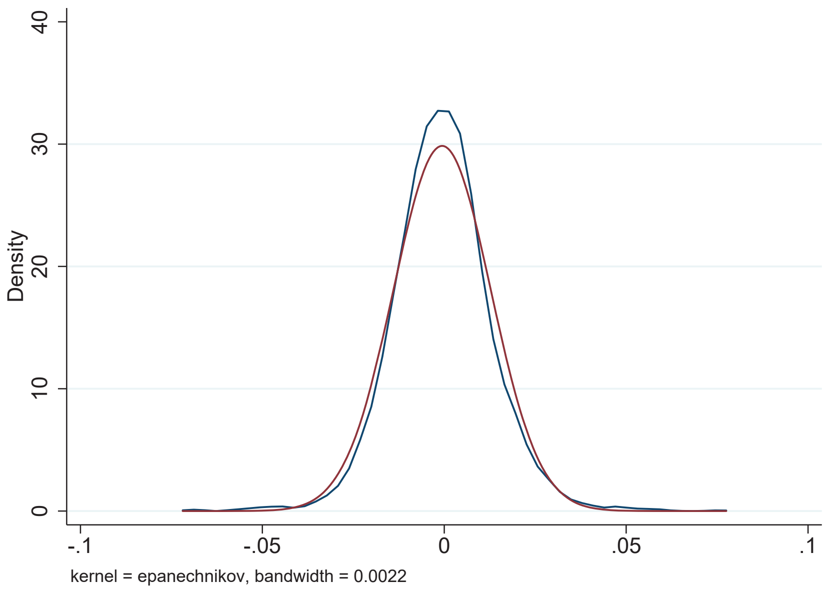


Figure 9: Density of product quality fixed effects



Additional results for section 5

Table 12: Correlates of residual innovation (additional results)

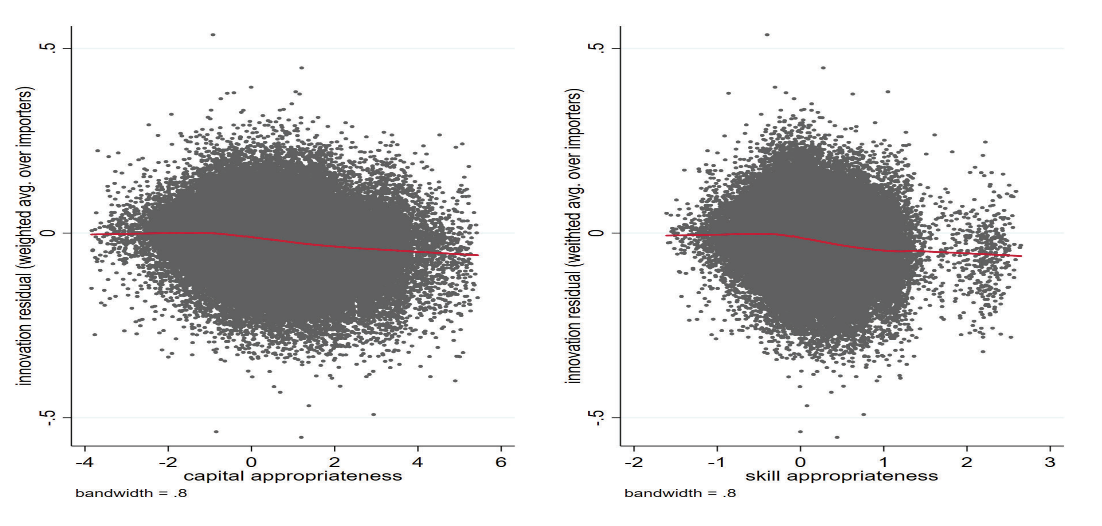
VARIABLES	(1) capital	(2) skills	(3) linear only	(4) incl Yi	(5) endowmts	(6) incl Yi
$\ln(\mathrm{FAI}_c)$	-0.0113***		-0.0103***	-0.00444**		
	(0.00145)		(0.00201)	(0.00214)		
$\ln(\mathrm{FAI}_s)$		-0.0276***	-0.00789	-0.00522		-0.0103***
		(0.00401)	(0.00575)	(0.00667)		(0.000185)
$\ln(\mathrm{FAI}_c)^2$	-0.00109			0.000893		
	(0.000753)			(0.00101)		
$\ln(\mathrm{FAI}_s)^2$		-0.0187***		-0.0108**		-0.0104***
		(0.00574)		(0.00534)		(0.000255)
imp ln(GDP pc)	0.00288***	0.00286***	0.00278***	0.00315***	0.00352***	0.00334***
	(0.000652)	(0.000652)	(0.000630)	(0.000581)	(0.000617)	(4.38e-05)
ln(RCA)	0.00171***	0.00166***	0.00184***	0.00179***		0.00156***
	(0.000244)	(0.000277)	(0.000265)	(0.000224)		(2.16e-05)
$\ln(\mathrm{RCA})^2$	-4.91e-05	-7.33e-05**		-2.29e-05		
	(2.96e-05)	(2.93e-05)		(3.26e-05)		
exp ln(GDP pc)				0.00951**		-0.000654***
				(0.00401)		(0.000145)
K/L					1.14e-07***	1.01e-07***
					(4.16e-08)	(1.51e-09)
Financial devt					0.0390**	0.0375***
					(0.0156)	(0.000414)
Yrs of schooling					0.000922	
					(0.000853)	
Constant	-0.0262***	-0.0249***	-0.0268***	-0.123***	-0.0742***	-0.0545***
	(0.00694)	(0.00747)	(0.00661)	(0.0382)	(0.00858)	(0.00131)
Observations	2,711,852	2,711,852	2,711,852	2,711,852	2,710,094	2,710,094
R-squared	0.031	0.025	0.031	0.035	0.035	0.038

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Because of potential non-linearity in the essential factor appropriateness variables, we also apply a non-parametric local regression smoothing technique (lowess).[40] The results depicted in figure 10 confirm an overall negative relationship between the innovation residual and products' relative demand for capital and skills, which gains momentum around an FAI of 0 (in logs). The break around 0 affirms that export quality innovation suffers from producing goods with a higher capital or skill demand than corresponds to the country's endowment structure. Note that there is considerable variation in this residual innovation and that factor appropriateness can only explain a small fraction of it but the magnitude implied by the FAI is indeed economically relevant: for a low capital FAI_c, corresponding to products using less capital than the country's endowment structure suggests, export quality innovation is about average (close to 0). For products that are much more capital intensive than the country's endowment structure suggests, e.g. an FAI_c around 5, figure 10 suggests that residual innovation grows by about 5 percentage points slower.

[40]We perform this analysis to the weighted sum of innovation residuals over importers, $\sum_j s_j a_{pij}$ because of the dimensionality curse in those non-parametric techniques.

Figure 10: Innovation residual and factor appropriateness (lowess)



Alternative setup for section 6

Alternative to the setup to study the different forces potentially driving quality dynamics across high- and low-income countries in section 6, we provide a robustness check where we focus on factor appropriateness and allow for heterogeneities in convergence speed. Specifically, we allow quality convergence to depend on PRODY, the exporter-product-specific variables studied in section 5 and importer GDP. This leaves us with the following equation to describe export quality dynamics:

$$\begin{aligned}\Delta \ln \hat{\Lambda}_{ijp} \quad = \quad & \beta_1 \ln(PRODY)_p + \beta_2 \ln Y_j + \sum_{m=1}^{2} \Big(\beta_{2+m} \ln(RCA)_{ip}^m + \\ & \beta_{4+m} \ln(FAI_c)_{ip}^m + \beta_{6+m} \ln(FAI_s)_{ip}^m \Big) + \\ & \ln \hat{\Lambda}_{ijp,t-1} \times \Big[\rho_0 + \rho_1 \ln(PRODY)_p + \rho_2 \ln Y_j + \\ & \sum_{m=1}^{2} \Big(\rho_{2+m} \ln(RCA)_{ip}^m + \rho_{4+m} \ln(FAI_c)_{ip}^m + \\ & \rho_{6+m} \ln(FAI_s)_{ip}^m \Big) \Big] + a + \varepsilon_{ijpt}. \end{aligned} \tag{14}$$

The results of this regression are reported in table 13 and table 14 provides detailed accounts of the calculations for the different country groups. Results are graphically summarized in figure 11. As one can see, in this alternative scenario, convergence leads to a 4 percentage points faster growth in export quality in low-income compared to high-income countries, after taking into account all heterogeneity interactions in equation (14), due to the fact that low-income countries tend to start at lower initial export quality levels. This 'advantage of backwardness' is outweighed by other factors which in this alternative model setup even leads to an overall faster growth in export quality for 'typical exports' of high-income countries. The largest part of this effect is explained by the fact that higher-income countries apparently produce goods that are much more aligned with their physical (and to some extent human) capital endowments. Low-income countries, in contrast, typically export goods that are much more skill- and particularly more capital-intensive than their factor endowment structure calls for. The negative effect of defying comparative advantage leads to a 4.3 percentage points lower growth in export quality for low-income countries relative to high-income countries. Additionally, high-income countries benefit from higher quality growth in more sophisticated products that they typically export. The importance of importer GDP and RCA are comparably negligible. Overall, this means that average export quality in high-income countries grows 1.3 percentage points faster than in low-income countries despite the presence of fast export quality convergence within products. For middle-income countries, the convergence effect somewhat dominates the other dynamics such that those countries experience a 0.7 percentage points faster growth rate in export quality than high-income countries. This is still a considerable reduction compared to the impetus that unconditional quality convergence suggests.

Figure 11: Contributors to differences in export quality dynamics between country groups (alternative model)

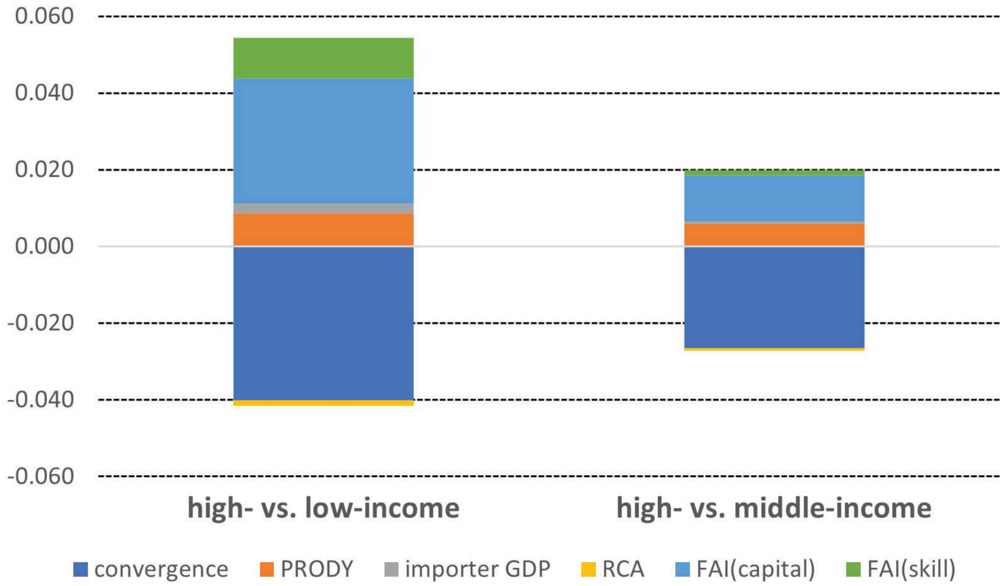


Table 13: Alternative model for export quality dynamics

VARIABLES	(1)
ln(RCA)	0.00182***
	(2.30e-05)
ln(PRODY)	0.0150***
	(0.000127)
$\ln(\text{RCA})^2$	-8.50e-05***
	(5.84e-06)
$\ln(\text{FAI}_c)$	-0.0131***
	(8.40e-05)
$\ln(\text{FAI}_s)$	-0.00861***
	(0.000224)
$\ln(\text{FAI}_c)^2$	0.000294***
	(4.54e-05)
$\ln(\text{FAI}_s)^2$	-0.0138***
	(0.000355)
imp ln(GDP pc)	0.00278***
	(4.65e-05)
initial ln $\hat{\Lambda}$	-0.0930***
	(0.00161)
ln(RCA) $\times$ initial ln $\hat{\Lambda}$	0.00158***
	(2.83e-05)
ln(PRODY) $\times$ initial ln $\hat{\Lambda}$	0.000906***
	(0.000155)
$\ln(\text{RCA})^2$ $\times$ initial ln $\hat{\Lambda}$	2.36e-05***
	(6.94e-06)
$\ln(\text{FAI}_c)$ $\times$ initial ln $\hat{\Lambda}$	-0.00263***
	(0.000100)
$\ln(\text{FAI}_s)$ $\times$ initial ln $\hat{\Lambda}$	0.00595***
	(0.000271)
$\ln(\text{FAI}_c)^2$ $\times$ initial ln $\hat{\Lambda}$	0.000690***
	(4.92e-05)
$\ln(\text{FAI}_s)^2$ $\times$ initial ln $\hat{\Lambda}$	-0.0116***
	(0.000387)
imp ln(GDP pc) $\times$ initial ln $\hat{\Lambda}$	0.00132***
	(5.40e-05)
Constant	-0.163***
	(0.00133)
Observations	2,712,223
R-squared	0.407
Product FE	No
Exporter FE	No
Importer FE	No

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Calculation of implied effects

	Coef.	**variable means** low-income	middle-income	high-income	**implied effects** low-income	middle-income	high-income	Δ btw high- and ... income low	middle
ln(RCA)	0.002	1.997	1.542	1.081	0.004	0.003	0.002	-0.002	-0.001
ln(PRODY)	0.015	8.988	9.165	9.563	0.135	0.138	0.144	0.009	0.006
$\ln(\text{RCA})^2$	0.000	3.986	2.377	1.168	0.000	0.000	0.000	0.000	0.000
$\ln(\text{FAI}_c)$	-0.013	2.229	0.542	-0.387	-0.029	-0.007	0.005	0.034	0.012
$\ln(\text{FAI}_s)$	-0.009	0.585	0.058	-0.110	-0.005	-0.001	0.001	0.006	0.001
$\ln(\text{FAI}_c)^2$	0.000	4.967	0.294	0.149	0.001	0.000	0.000	-0.001	0.000
$\ln(\text{FAI}_s)^2$	-0.014	0.342	0.003	0.012	-0.005	0.000	0.000	0.005	0.000
imp ln(GDP pc)	0.003	9.169	9.870	10.048	0.025	0.027	0.028	0.002	0.000
initial ln $\hat{\Lambda}$	-0.093	-0.132	0.058	0.443	0.012	-0.005	-0.041	-0.053	-0.036
initial ln $\hat{\Lambda}$ $\times$...									
...ln(RCA)	0.002	-0.263	0.090	0.478	0.000	0.000	0.001	0.001	0.001
...ln(PRODY)	0.001	-1.185	0.533	4.233	-0.001	0.000	0.004	0.005	0.003
...$\ln(\text{RCA})^2$	0.000	-0.526	0.138	0.517	0.000	0.000	0.000	0.000	0.000
...$\ln(\text{FAI}_c)$	-0.003	-0.294	0.032	-0.171	0.001	0.000	0.000	0.000	0.001
...$\ln(\text{FAI}_s)$	0.006	-0.077	0.003	-0.048	0.000	0.000	0.000	0.000	0.000
...$\ln(\text{FAI}_c)^2$	0.001	-0.655	0.017	0.066	0.000	0.000	0.000	0.000	0.000
...$\ln(\text{FAI}_s)^2$	-0.012	-0.045	0.000	0.005	0.001	0.000	0.000	-0.001	0.000
...imp ln(GDP pc)	0.001	-1.209	0.574	4.448	-0.002	0.001	0.006	0.007	0.005