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# High-income export destinations, quality and wages☆

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ABSTRACT

This paper establishes a link between the income level of the destination countries and the level of average wages in the exporting country across the world economy. We use cross-country panel data to set up an instrumental variable model of high-income export destinations and wages. We find robust evidence that, worldwide, industries that ship products to high-income destinations do pay higher average wages. Our IV results indicate this is a causal relationship. We also explore the operating mechanisms, and find robust evidence in support of a dual link. First, industries that ship products to high-income destination export higher quality goods (as measured by the average unit value of exports within industries). This is because high-income countries demand high-quality products. Second, the provision of quality is costly and requires more intensive use of higher-wage skilled labor. As a result, the production of higher quality products at the industry level creates a wage premium and conduces to higher average industry wages.



## 1. Introduction

The destination of exports is becoming an important element in modern trade theories (Bernard et al., 2011; Melitz and Redding, 2014). The underlying idea is that differing features of importing countries affect the choices made by producers in exporting countries. Thus, the destination of exports can be a determinant of a country's outcomes. Among those features, a prominent theme in recent models is quality. Countries differ in the way they value quality, with richer, more developed countries valuing high quality products more than poor, less developed countries. This creates a demand for quality products, especially in high-income destinations. Accessing these markets to meet this demand requires quality upgrades. Those exporters willing to do this need to modify the production process and become more intensive in skilled labor. This creates a demand for skills that translates into higher average wages in origin countries. There is, in effect, a mechanism linking high-income export destinations, quality and wages, that works through quality valuation and quality provision. Support for the quality valuation and quality provision mechanisms is provided by Verhoogen (2008) and Brambilla et al. (2012). Verhoogen (2008) introduces a model linking exports, quality and wages and reports supporting evidence from Mexican exports. Brambilla et al. (2012) elaborate upon this idea and establish a link between high-income destinations, quality, skill utilization, and wages.

In this paper, our main objective is to establish a causal link between the income level of destination countries and the level of average wages in exporting countries across the world economy. Our goal is to generalize the results for Mexico (Verhoogen, 2008) and Argentina (Brambilla et al., 2012). To do this, we use cross-country panel data to set up an instrumental variable model of high-income export destinations and wages. We utilize the trade and production database compiled by Nicita and Olarreaga (2007) on exports and wages across industries and countries. We merge these data with per capita GDP to build a measure of the average income across destinations of an industry's exports. For each industry–source-country pair, we calculate the export-share weighted average of per capita GDP across destinations. We then study whether the average per capita GDP across destinations is significantly correlated with the average wage paid by firms in the industry. To deal with endogeneity issues in the export-share weights, we estimate bilateral trade regressions at the industry level using country characteristics and bilateral exchange rates as regressors (Brambilla et al., 2012; Park et al., 2010). These regressions allow us to build an instrument defined as the average income across destinations computed

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using the predicted (instead of the observed) export-share weights (Frankel and Romer, 1999; Feyrer, 2013; Irwin and Terviö, 2002).[1]

We find robust evidence that, worldwide, industries that ship products to high-income destinations do pay higher average wages. Our IV results indicate this is a causal relationship. We also explore the operating mechanisms, and find robust evidence in support of the dual link advanced above. First, industries that ship products to high-income destinations export higher quality goods (as measured by the average unit value of exports within industries). This is because high-income countries demand high-quality products. Second, the provision of quality is costly and requires more intensive use of skilled labor. As a result, the production of higher quality products at the industry level conduces to higher average industry wages. We find that these relationships are stronger in high-income source countries than in less-developed countries because the latter may lack the firm capabilities and worker skills needed to produce higher quality products. Moreover, we find that these links are stronger in industries with a higher scope for product differentiation and quality upgrades.

We also report evidence of the inequality-trade link postulated by Fajgelbaum et al. (2011). Specifically, we find that industries that ship products to more unequal economies pay higher average wages because they ship higher quality goods. This channel, however, is not strong enough to offset the main finding of the paper. Conditioning on both average income and average inequality across destinations of an industry's exports, the effect of average per capita GDP remains positive and statistically significant, while the inequality mechanism loses explanatory power. Overall, the mechanism operates via a demand for quality created by income and its distribution across the population.

Our results are also useful to substantiate the claim in Manova and Zhang (2012) about the role of inputs in modern trade models. Their stylized facts suggest that more successful exporters use higher quality inputs to produce higher quality goods across different destinations. In our framework, higher quality inputs are captured by higher skills, as in Verhoogen (2008) or Brambilla et al. (2012). Sutton (2007) argues that the production of higher quality incurs higher costs because of the need to in turn utilize higher quality inputs, which are more expensive. Kugler and Verhoogen (2012) find support for this argument among Colombian firms. Brambilla et al. (2014) use Chilean data to unveil the link between different skilled tasks (engineers versus administrative workers) and the provision of quality. Bastos et al. (2014) find that exporters to high-income countries sell higher quality products (as in Brambilla et al., 2012) and this requires higher quality inputs (as in Kugler and Verhoogen, 2012).

An important contribution of our paper is to provide general results that complement and reinforce the existing literature. Many papers find support for either the quality valuation or the quality provision mechanisms. The fact that richer countries demand higher quality products can be explained with non-homothetic preferences. Using aggregate product-level bilateral trade data, Hallak (2006) is one of the first authors to document the positive correlation between export unit values and the level of income of the country of destination. More recent studies, such as Baldwin and Harrigan (2011) and Johnson (2012), also find positive correlations between export unit values and the income of the destination country. Using firm-level data, Manova and Zhang (2012) show that Chinese exporting firms do indeed charge higher prices in richer markets. Similar evidence is reported by Bastos and Silva (2010), for the case of Portuguese exporters, and Görg et al. (2010), for the case of Hungarian exporters.

The evidence in support of the quality provision mechanism is more scant. Schott (2004) explores U.S. import unit values and reports higher unit values for varieties originating in capital- and skill-abundant countries. Moreover, exporting countries that become more skill- and capital-abundant with time experience increases in unit values relative to other exporters. He also finds that richer countries tend to export higher quality products. Hummels and Klenow (2005) show that quality differentiation is needed to explain differences in unit values and show that these unit values positively correlate with the per capita income of the exporting country. In much of the literature, the quality provision originates in productivity differences. Melitz (2003) presents the standard model of trade with heterogeneous firm productivity and Crozet et al. (2012) present a quality interpretation of this model. Baldwin and Harrigan (2011) and Johnson (2012) both incorporate productivity differences as a source of comparative advantage in high quality products. More productive firms can afford to cover the fixed cost (and also the plausibly higher marginal cost) of producing high quality products, and enjoy higher profits due to higher prices. Often, however, the implicit mechanism is left unexplored.

There are at least three additional attempts at identifying both the quality valuation and the quality provision angles. Hallak (2010) documents that trade is more intense among countries with similar income per capita, thus confirming the Linder hypothesis. The Linder conjecture also needs a quality provision link, because the prediction is about bilateral trade and requires a demand and a supply mechanism. However, Hallak (2010) adopts a reduced-form approach whereby there is a positive association between income and quality supply. Fajgelbaum et al. (2011) set up a model in which quality valuation arises from non-homothetic preferences so that richer countries have a higher quality demand. In addition, the structure of preferences is such that more unequal economies will also have a higher relative demand for quality products. In turn, the model features a home-market effect which predicts that richer countries and more unequal countries will have a comparative advantage in higher quality goods. Under plausible conditions, but not always, richer countries will export high quality products and import low quality products, even within categories of goods. Caron, Fally, and Markusen (2014) establish a positive correlation between the income elasticity of a good and its skilled-labor intensity. This implies that richer countries demand and produce higher quality goods and, as a consequence, trade between rich countries is more intense than trade between rich and poor countries (especially in higher quality goods).

The remainder of this paper is organized as follows. In Section 2, we present a general theoretical framework that summarizes various related trade models of exports and quality. In Section 3, we describe the data used for the analysis and we introduce our basic finding and the underlying mechanisms. In Section 4, we describe the identification strategy and we present the main results. In Section 5, we produce additional evidence in support of the mechanisms. Section 6 concludes.

## 2. Theory: high-income exports, quality and wages

The premise of this paper is that there is a link between the income level of the markets of destination of exports and the level of average wages paid in an industry. The underlying mechanism is that high-income countries demand quality, and that the supply of quality is intensive in skilled labor and commands higher wages. In this section, we lay out a partial equilibrium model of export destinations, quality and wages. The model encompasses a large class of related models in the literature, which we review along the way.

### 2.1. Set-up

Consider a differentiated good $j$ with quality $\theta_j$ and price $p_j$. The demand function for this good is $x(p_j, \theta_j)$, conditional on income and on the prices of all the other goods. Consider a firm in a monopolistic

[1] Our approach builds on micro-based models of heterogeneous firms that we test using cross-country industry data (instead of firm-level data). There is a substantial literature that adopts a similar strategy. Helpman et al. (2004), Helpman et al. (2008), Baldwin and Harrigan (2011), Johnson (2012), and Manova (2013), among others, develop models of heterogeneous firms and use similar cross-country, cross-sector data to test their predictions. Hallak (2006), Hallak (2010) and Fieler (2011), also among many others, use bilateral trade flows to estimate detailed micro-based trade theories.

competition framework that faces this demand function. The firm has to choose the quality $\theta_j$ of the good and its selling price. In line with the literature, the total cost of producing the physical units depends on quantities as well as on the quality of the good. The cost function is $C_j(x_j, \theta_j)$. There may also be a separate cost of producing quality (that is independent of quantities), $\tilde{F}_j(\theta_j)$. Firm $j$ maximizes profits

$$\pi_j = p_j x\left(p_j, \theta_j\right) - C_j(x_j, \theta_j) - \tilde{F}_j(\theta) - F_j, \tag{1}$$

where $F_j$ is a fixed cost of production or of entering a market.

### 2.2. Preferences

The literature imposes some restrictions on this general framework. First, the demand function takes a logit (Verhoogen, 2008; Fajgelbaum et al., 2011; Brambilla et al., 2012) or a quality-adjusted CES specification (Bastos et al., 2014; Feenstra and Romalis, 2012; Hallak, 2006, 2010; Johnson, 2012; Kugler and Verhoogen, 2012).[2] For our purposes, both demand systems deliver the same results and, in what follows, we adopt the logit model. The utility that individual $h$ in destination $d$ derives from the consumption of variety $j$ is given by

$$U^d_{hj} = \alpha\left(y^d\right)\theta^d_j - p^d_j + \epsilon^d_{hj}, \tag{2}$$

where $y^d$ is income in destination $d$ and $\epsilon_{hj}$ is a random deviation that follows a type-I extreme value distribution. As in Verhoogen (2008), the parameter $\alpha(y^d)$ captures quality valuation. Quality valuation is increasing in income ($\alpha'(y^d) > 0$) as consumers in high income countries are willing to pay more for a good of a given quality. This is the quality valuation mechanism.

The multinomial–logit aggregate demand function is

$$x^d\left(p^d_j, \theta^d_j\right) = \frac{M^d}{W^d}\exp\left(\alpha\left(y^d\right)\theta^d_j - p^d_j\right), \tag{3}$$

where $M^d$ is the number of consumers in country $d$, or market size, and $W^d$ is an index that summarizes the characteristics of all available products in that market (i.e., $W^d = \sum_{d \in Z^d}(\alpha^d\theta^d_z - p^d_z)$, where $Z^d$ is the set of available products).[3]

### 2.3. Technology

The second restriction usually imposed by the literature is that the production technology is such that physical output is produced under constant marginal costs. We can thus work with a marginal cost function $c_j(\theta_j)$ that depends on quality, with $c_j'(\theta_j) > 0$ and $c_j''(\theta_j) > 0$. This function differs (slightly) across papers and we indicate those differences throughout the discussion.

In the source country, there are $J$ firms producing differentiated products under monopolistic competition. Each firm can ship its product to multiple destinations. At this point, to simplify the analysis, we assume that there are no fixed costs of producing quality, that is $\tilde{F}_j(\theta) = 0$. There are, however, fixed costs to reach markets which are common to all firms and all destinations, $F \geq 0$. As in Verhoogen (2008), we further assume that firms run separate production lines for different qualities and that they can choose prices $p^d_j$ and quality $\theta^d_j$ at each destination market separately. Separability of production together with constant marginal costs implies that the decisions on entry, quality choice and price are not interrelated across markets. We can thus write the profit function for a destination $d$ as:

$$\pi^d_j = \left[p^d_j - c_j\left(\theta^d_j\right)\right]x^d\left(p^d_j, \theta^d_j\right) - F, \tag{4}$$

The first order conditions for profit maximization are:

$$p^d_j = 1 + c_j\left(\theta^d_j\right), \tag{5}$$

$$\alpha\left(y^d\right) = \frac{c_j'\left(\theta^d_j\right)}{p^d_j - c_j\left(\theta^d_j\right)}. \tag{6}$$

The intuition is straightforward. First, firms charge a constant markup over marginal costs. Second, given the optimal markup, optimal quality in a given market requires equating the marginal costs of quality provision with the quality valuation $\alpha$.

Differentiating the first order conditions it is easy to show that

$$\frac{d\theta^d_j}{dy^d} = \frac{\alpha'\left(y^d\right)}{c_j''\left(\theta^d_j\right)} > 0, \tag{7}$$

$$\frac{dp^d_j}{dy^d} = \frac{\alpha'\left(y^d\right)c_j'(\theta_j)}{c_j''(\theta_j)} > 0. \tag{8}$$

These results establish that higher income countries, which value quality more ($\alpha'(y^d) > 0$), induce firms to optimally deliver higher quality products, $d\theta^d_j/dy^d > 0$. In turn, these products can be sold at a higher price, $dp^d_j/dy^d > 0$. Note that the assumption $c_j''(\theta_j) > 0$, i.e., marginal costs increase sufficiently quickly with product quality, is crucial for the result.

To better characterize the solution, we need to describe the function $c_j(\theta_j)$. Some authors directly parameterize the cost function. In Johnson (2012), Crino and Epifani (2012), and Hallak and Sivadasan (2013), $c(\theta) = \kappa\theta^\beta$. In Flam and Helpman (1987) and Hummels and Klenow (2005), $c(\theta) = \kappa e^{\theta/\beta}$. Verhoogen (2008), followed by Bastos et al. (2014), Brambilla et al. (2012), Feenstra and Romalis (2012), and Kugler and Verhoogen (2012), provides microfoundations for these specifications. The basic idea is that the production of quality requires higher quality inputs (including labor and intermediate inputs) that are more costly to purchase. Since we are interested in wages and skill utilization, we model this idea as follows.

The production of one unit of physical output requires $1/\ell$ units of labor. Workers are heterogeneous in skills or ability, $S$. Thus, a higher ability worker can produce $\ell$ units of physical output, but of a higher quality $\theta$. To model quality production, there are different options in the literature. Assume, for instance, that quality is produced with skilled labor $S$, combined with "capability" or "caliber" $\lambda$ (Kugler and Verhoogen, 2012; Hallak and Sivadasan, 2013) as follows:

$$\theta_j = \lambda_j S^\sigma_j, \tag{9}$$

where the parameters $\lambda$ and $\sigma$, both positive, determine the returns to skills in quality production. Eq. (9) delivers a positive relationship between the production of quality $\theta_j$ and the level of skill utilization $S_j$.

To attract higher skilled workers firms face an upward sloping wage schedule as in Verhoogen (2008). We work with a simple functional form

$$S_j = w^\xi_j, \tag{10}$$

where $w_j$ is the wage rate offered to skill level $S_j$ and $\xi > 0$ governs the responsiveness of the skill level to the offered wage. Eq. (10) can be interpreted as a reduced-form representation of an efficiency-wage

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[2] Antoniades (2015) adapts the linear demand system in Melitz and Ottaviano (2008) to a vertical differentiation framework.

[3] Alternatively, the CES demand is $x = (\theta^{\iota(y^d)(\rho-1)}p_j^{(-\rho)}I)/P$, where $I$ is income, $P$ is the CES price index, and $\rho$ is the elasticity of substitution. Here, $\iota(y^d)$ plays the role of $\alpha(y^d)$: a higher $\iota$ implies a higher quality valuation and $\iota'(y^d) > 0$ so that richer countries value quality more than poor countries.

model or a profit sharing model. Eqs. (9) and (10) establish the quality provision mechanism: the production of quality requires skills and skilled workers are paid higher wages.For a firm, the cost of producing one unit of output of quality $\theta_j$ is the cost of hiring $1/\ell$ workers of skill $S_j$ at the wage $w_j$. Using Eqs. (9) and (10), the marginal cost of producing a physical unit of good $j$ is

$$c_j(\theta_j) = \frac{1}{\ell}\left(\frac{\theta_j}{\lambda_j}\right)^{\frac{1}{\xi\sigma}}, \tag{11}$$

with $c' > 0$ and $c'' > 0$, provided $\sigma\xi < 1$, that is, provided quality does not rise too rapidly with skills, and skills do not rise too rapidly with wages. Eq. (11) resembles the cost structure assumed by Crino and Epifani (2012), Hallak and Sivadasan (2013), and Johnson (2012).[4]Firms can in principle differ in physical output productivity $\ell$, and in capability $\lambda$. To simplify the analysis we assume firms are heterogeneous only in capability $\lambda$, although adding firm heterogeneity in a second dimension is straightforward.

Under the specification in Eqs. (9), (10) and (11), the choices of firm $j$ with productivity $\lambda_j$ shipping to destination market $d$ are:

$$\theta_j^d = \theta\left(\lambda_j, y^d\right) = \lambda_j\left(\xi\sigma\lambda_j\ell\alpha\left(y^d\right)\right)^{\frac{\xi\sigma}{1-\xi\sigma}}; \tag{12}$$

$$p_j^d = p\left(\lambda_j, y^d\right) = 1 + \frac{1}{\ell}\left(\xi\sigma\lambda_j\ell\alpha\left(y^d\right)\right)^{\frac{1}{1-\xi\sigma}}; \tag{13}$$

$$S_j^d = S\left(\lambda_j, y^d\right) = \left(\xi\sigma\lambda_j\ell\alpha\left(y^d\right)\right)^{\frac{\xi}{1-\xi\sigma}}; \tag{14}$$

$$w_j^d = w\left(\lambda_j, y^d\right) = \left(\xi\sigma\lambda_j\ell\alpha\left(y^d\right)\right)^{\frac{1}{1-\xi\sigma}}. \tag{15}$$

Fig. 1 depicts the mechanisms (using Eqs. (9), (10), (12) and (13), for a given $\lambda$, and assuming $\alpha(y^d) = \ln y^d$ for illustration purposes). On the upper-right panel, we plot the function $\alpha(y^d)$, which slopes upward. On the upper-left, we plot $p$ and $\theta$ as a function of $\alpha$. This establishes the quality valuation mechanism: higher income countries value quality more and this induces firms to deliver higher quality products at a higher price. On the bottom-left panel, we map the optimal $\theta$ to skill utilization $S$ and wages $w$. This establishes the quality provision mechanisms. Quality is costly, and firms must pay higher wages to attract high-skilled workers. Finally, on the bottom-right panel, we plot the link between the income level of the destination market and the wage.

### 2.4. Implications for wages at the country-industry level

The mechanisms just described represent the decision of a firm facing varying income levels in different destination markets. If we observed in the data firm- and destination-specific outcomes, we could empirically test the validity of Eqs. (12)–(15). Manova and Zhang (2012), Bastos and Silva (2010), and Görg et al. (2010), for instance, show that export prices charged by the same firm are increasing in the income level of the country of destination.

It is difficult, however, to find data with firm- and destination-specific wages—our variable of interest in this paper. In general, wage data are available at the firm level or, as in our case, at the industry level. To derive testable predictions in these cases, we need to formalize entry decisions into each destination market, which in turn give rise to

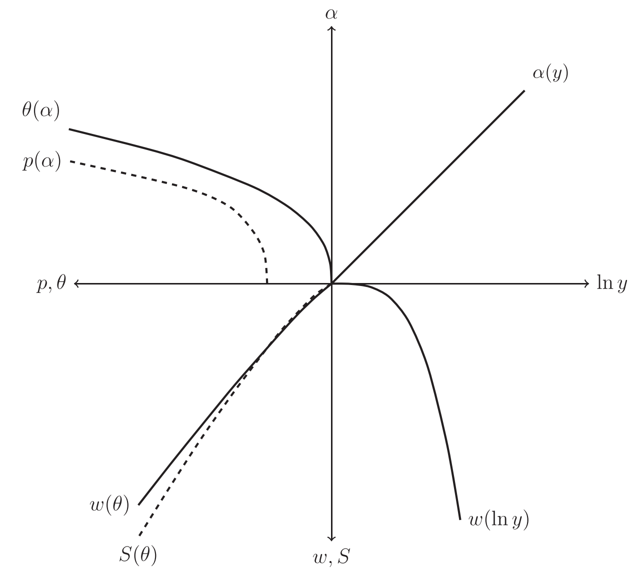


**Fig. 1.** High-income exports and wages. Quality valuation and quality provision mechanisms. Notes: numerical solution to models (12), (13), (14), and (15), assuming $\alpha(y_d) = \ln y_d$. Parameter values $\sigma = 0.8$, $\xi = 0.9$, $\ell = 1$, $\lambda = 1$. Upper-right panel: function $\alpha(y^d)$, the valuation of quality as a function of income. Upper-left: optimal price and quality as a function of $\alpha$. This is the quality valuation mechanism: higher income countries value quality more and this induces firms to deliver higher quality products at a higher price. Bottom-left panel: skill utilization and wages, as a function of $\theta$. This is the quality provision mechanisms. Quality is costly, and firms must pay higher wages to attract high-skilled workers. Bottom-right panel: link between the income level of the destination market and the wage.

compositional effects. To enter a given market of destination $d$, firm variable profits in that market need to be greater or equal to the fixed cost $F$. This means that only firms with capability $\lambda_j$ above a threshold $\lambda^{d*}$ enter market $d$. Using Eq. (4) and the first order condition (5), the threshold capability is defined by

$$x\left(\lambda^{d*}, y^d\right) - F = 0. \tag{16}$$

Since $x$ is increasing in the income of the destination market $y^d$, if a firm enters market $d$, it will also enter all markets $d'$ with $y^{d'} > y^d$.

With firm-level wage data, the theory can be tested as follows. First, we need to aggregate outcomes up to the firm level. Using wages as an example, firm level wages are an average of Eq. (15), weighted by the participation of each destination in employment

$$\tilde{w}(\lambda_j) = \sum_{d \in D_j} \frac{x(\lambda_j, y^d)}{X(\lambda_j)} w\left(\lambda_j, y^d\right), \tag{17}$$

where $D_j$ is the set of destinations served by firm $j$ including the domestic market, and $X$ is total firm output.[5] Second, we compare firm wages after changes in firm exposure to high-income export destinations. In Eq. (17), changes in exposure are captured by changes in the shares $x(\lambda_j, y^d)/X(\lambda_j)$. For modeling purposes, we assume at this point that destinations $d$ are subject to demand shocks $a^d$ so that we can write quantity demanded as $x = x(\lambda, y^d, a^d)$. These shocks can include shocks to national income, exchange rate shocks, or trade cost shocks. A positive demand shock in destination $d$ thus creates an increase in the share of destination $d$.[6] We

[4] There are variants of this framework in the literature. If the production function is $\theta = \lambda\sigma \ln S_j$, then $c(\theta) = \frac{\kappa}{\ell} e^{\theta_j/\lambda}$, where $\kappa = e^{\frac{1}{\sigma\xi}}$. This is the cost structure in Flam and Helpman (1987) and Hummels and Klenow (2005). Alternatively, the log-supermodular production function of Kugler and Verhoogen (2012) is $\theta_j = [\lambda_j^\sigma + S_j^\sigma]^{\frac{1}{\sigma}}$, where $\sigma < 0$ is the degree of complementarity among inputs and a higher $\sigma$ (in absolute value) implies a higher level of complementarity between capability and skills. The marginal cost of producing a physical unit of good $j$ is $c(\theta) = \frac{1}{\ell}[\theta_j^\sigma - \lambda_j^\sigma]^{\frac{1}{\xi\sigma}}$.

[5] Because of the fixed coefficients technology the participation in employment is equal to the participation in output.

[6] To better illustrate the result, we assume that these shocks $a^d$ do not affect the choice of quality directly. This is analogous to Verhoogen (2008) and Brambilla et al. (2012), who work with exchange rate shocks that do not affect the quality valuation of a country.

denote the vector of shocks across all destinations by $\alpha$. The impact on firm-level wages is:

$$\frac{\partial \tilde{w}(\lambda_j, a)}{\partial a^d} = \frac{1}{X(\lambda_j, a)} \frac{\partial x(\lambda_j, y^d, a^d)}{\partial a^d} \left( w\left(\lambda_j, y^d\right) - \tilde{w}(\lambda_j, a) \right). \tag{18}$$

Suppose we observe that an increase in the share of destination $d$ is associated with an increase in firm average wages. Then, the derivative implies that the wage of destination $d$ is indeed higher than the average firm wage, that is $w(\lambda_j, y^d) - \tilde{w}(\lambda_j) > 0$. More generally, the theory predicts we should observe a positive derivative (i.e., an increase in firm wages) for firms that become more exposed to higher income export destinations. Brambilla et al. (2012) exploit an exchange rate shock to show that exogenous shifts in export destinations indeed affect firm average wages in the direction predicted by the theory.

To test the empirical predictions of our model worldwide, for which we have industry level data for a large set of source countries, we need to further aggregate the model predictions up to the industry level. This means aggregating across firms and entails compositional effects that we need to discuss carefully. Using the zero-profit entry condition, we can construct measures of average variables at the industry level (we omit industry subindexes) by aggregating over both destinations and firms. The distribution of capabilities $\lambda$ is characterized by a cdf $G$ and density $g$, which are the same across firms. Using wages as an example, the average industry wage is

$$\overline{w}(a) = \sum_{d \in D} \frac{X_I^d(a^d)}{X_I(a)} \int_{\lambda^{d*}}^{\infty} \frac{w(\lambda_j, y^d)}{1 - G\left(\lambda^{d*}\right)} dG(\lambda_j) \tag{19}$$

where $X_I$ is total industry output, $X_I^d$ is industry output sold at destination $d$, and thus $X_I^d/X_I$ is the share of destination $d$ in total industry output. We can again exploit exogenous changes in participation of the different destinations to test the theory. Taking derivatives with respect to the demand shocks $a^d$ in destination $d$

$$\begin{aligned}\frac{\partial \overline{w}}{\partial a^d} &= \frac{1}{X_I} \frac{\partial X_I^d}{\partial a^d} \left( \int_{\lambda^{d*}}^{\infty} \frac{w(\lambda_j, y^d)}{1 - G\left(\lambda^{d*}\right)} dG(\lambda_j) - \overline{w} \right) + \\ &+ \frac{X_I^d}{X_I} \frac{g\left(\lambda^{d*}\right)}{1 - G\left(\lambda^{d*}\right)} \frac{\partial \lambda^{d*}}{\partial a^d} \left( \int_{\lambda^{d*}}^{\infty} \frac{w(\lambda_j, y^d)}{1 - G\left(\lambda^{d*}\right)} dG(\lambda_j) - w\left(\lambda^{d*}, y^d\right) \right).\end{aligned} \tag{20}$$

The first term is analogous to Eq. (18) and indicates that if we observe that the average industry wage goes up together with the share of destination $d$ in industry output it must mean that the wage of destination $d$ is higher than the average industry wage, which is consistent with the theory as long as $d$ is a high income country. The second term adds a compositional effect. As sales to market $d$ become larger, more firms find it profitable to pay the fixed costs to enter this destination, in other words, the cutoff $\lambda^{d*}$ (derived in Eq. (16)) goes down. The new exporting firms are lower capability firms and pay lower wages, thus bringing down industry wages. This second effect works in the opposite direction of the first effect. The theoretical predictions are consequently ambiguous. However, an empirical finding that industry wages are increasing in exogenous increases in exports to high income countries supports the quality valuation and provision mechanisms in our model, as they are consistent with a setting in which the first effect of the derivative (firm-level increases in wages) is positive and dominates the second effect (low wage firms entering export markets).[7]

In principle, it is possible to consider scenarios where shocks also affect the choice of quality (and price) directly. For example, consider an exogenous increase in the quality valuation parameter $\alpha$ of a high-income destination $d$. A change in $\alpha^d$ can be a source of shocks included in $a^d$, but it creates additional mechanisms in Eq. (20). Incumbent firms choose to increase quality destined to this market and this raises average industry wages. In turn, entrants, even though they are less capable and ceteris paribus depress average wages, can also choose higher quality, compensating (partially or totally) the negative compositional effect above. Expression (20) is stronger because it ignores these additional mechanisms, which, if supported by the data, only reinforce the predictions of the theory.

To end, we should note that, in our model, market size per se does not affect the choice of quality. The quality valuation and the firm quality decision depend on the destination market's per capita income and not on its total income. This is in part because of the demand framework we adopted and in part because we ruled out fixed costs in quality production. If market size determines quality, the entry cutoff as well as the compositional effects become much more complicated to assess.

## 3. Data

We now set out to show that the mechanisms outlined in the theory operate in a cross-section of countries across the world. Our main source of data is the “Trade, Production and Protection” database put together by Nicita and Olarreaga (2007). The cross-country data include information on export values and export quantities, production, value added, employment, wages, and number of establishments for 28 manufacturing industries corresponding to the 3-digit level of the International Standard Industrial Classification (ISIC), Revision 2. The database is available at the World Bank trade website (www.worldbank.org/trade).

We combine the Nicita and Olarreaga data with supplementary data on country characteristics from the World Development Indicators. These characteristics include per capita GDP, GDP, population, bilateral exchange rates, and inequality measures such as the Gini coefficient and the share of income held by different quintiles of the population. Our database covers a total of 82 countries from 1990 to 2000. The data appendix provides more details.

The starting point of our analysis is the correlation between the average income across export destinations and the level of wages. Using the Nicita and Olarreaga (2007) data, for each source country we calculate the average industry wage as the ratio of total industry wage bill to total employment. Let $w_{ic}$ be the average wage in industry $i$ in country $c$. To construct a measure of exposure to high income destinations we compute the average income across export markets. Let $GDPpc_d$ be the per capita GDP of destination country $d$ in 1990 (the first year of data) and let $s_{icdt}$ be the share of destination $d$ in exports of industry $i$ of source country $c$.[8] We define the average income of an industry's exports as:

$$g_{ict} = \ln\left( \sum_d s_{icdt} * GDPpc_d \right). \tag{21}$$

Average income thus varies by industry, source country, and year through differences in the export-share weights. The top-left panel in Fig. 2 uncovers our basic finding, the positive correlation between the log of the average wage paid in industry $i$ in country $c$ and the average income across export destinations. The correlation is estimated non-parametrically using a local weighted kernel regression. The graph suggests that, on average, industry wages are increasing in the average income across export destinations. Note that, in (21), we keep the per capita GDP of destination country $d$ fixed at the 1990 level, thus treating $GDPpc_d$ as a predetermined feature of the trade partners. We do this explicitly to capture differences in wages for industries with varying

[7] Whereas a negative empirical finding would be ambiguous in terms of the support provided to the theory.

[8] Note that shares are defined as the participation in export value, not units (as the theory suggests). We opted for the export value weight specification because it is consistent with more general structures of technology (e.g., different labor input requirements, linear technology in output production and so on). Also, due to lack of comparable data we exclude domestic production in the computation of the shares.

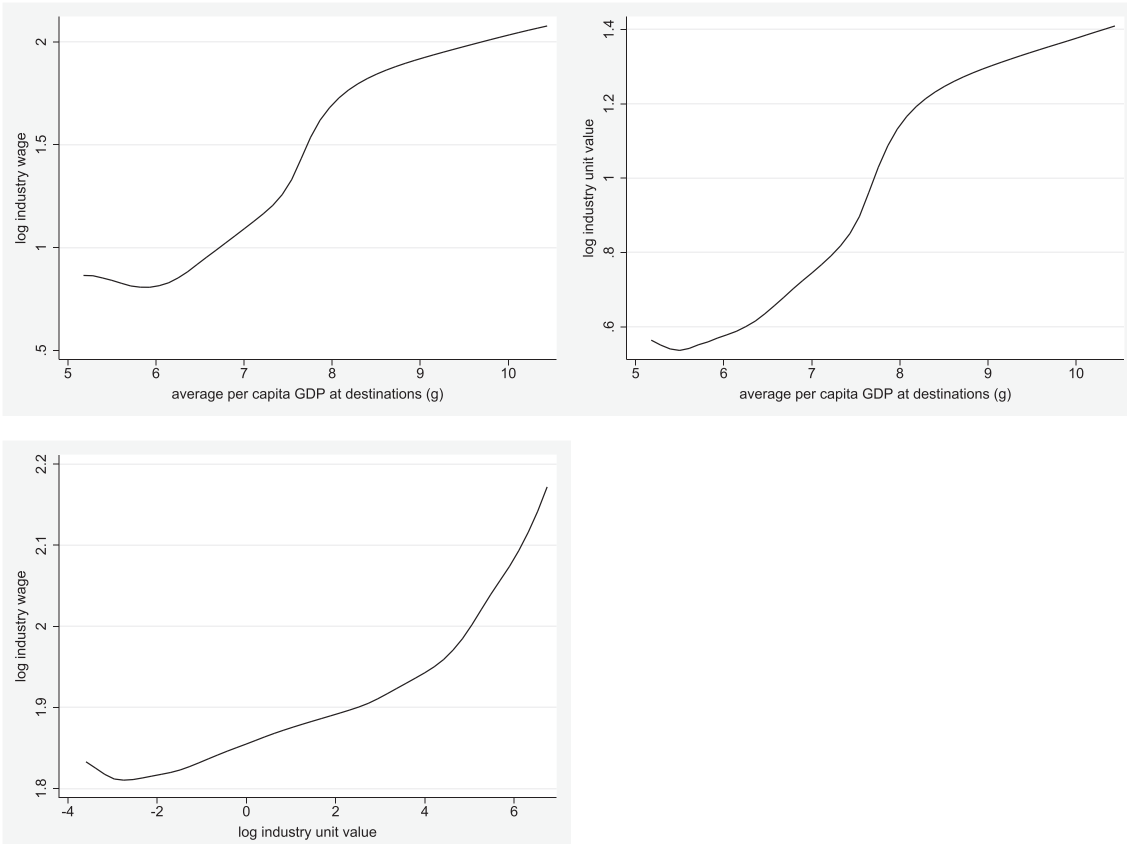


**Fig. 2.** Basic correlations. Average wages, average per capita GDP across export destinations, and average unit values. Notes: univariate non-parametric correlations. Top-left: average wage and average per capita GDP across destinations; Top-right: average unit value of exports and average per capita GDP across destinations; Bottom: average wage and average unit value. All variables are in logs and vary at the country-of-origin-industry-year level.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

exposure to different destinations. Below, we also explore models where the level of income of the destination countries varies across time, so that $g_{ict} = \ln(\sum_d s_{icdt} * GDPpc_{dt})$. None of our results are affected by this alternative definition of $g$.

As we showed in the model, this link operates via a two-part mechanism. The quality valuation mechanism links high-income exports with demand for quality. The quality provision mechanism links quality production with skill utilization and wages. Both mechanisms are supported in our data. To document the quality valuation mechanism, the trade data in Nicita and Olarreaga's database allows us to build measures of export quality with export unit values, the ratio of export values to export quantities.[9] Prima-facie evidence that exports to high-income countries are of higher quality is in the top-right panel of Fig. 2, which shows a positive correlation between average export unit values and income across destinations. This link originates from a higher demand for quality in higher-income countries.

Finally, to document the basic correlation behind the quality provision mechanism, we estimate a non-parametric regression between average industry wages and export unit values. In the bottom panel of Fig. 2, we show that this correlation is positive. The provision of higher quality is more costly, in part because quality upgrades are intensive in skilled labor, which is more expensive. We thus interpret the correlation between quality and wages as indicative of a positive correlation between quality and skills.

[9] This is a widespread, albeit imperfect, measure of average quality. See for example Schott (2004), Hummels and Klenow (2005) or Hallak (2006). Khandelwal (2010) and Hallak and Schott (2011) discuss and estimate demand-based measures of quality.

Before moving to the econometric analysis, we should note here an alternative potential explanation for the links postulated by our theory and the correlations found in the data. This explanation also implies a dual link, but one of a different nature. Firstly, heterogeneous firms may follow a strategy of price discrimination across markets and charge higher markups and earn higher profits in high-income countries (as shown by De Loecker and Warzynski, 2012). Secondly, firms may engage in a profit-sharing strategy with their workers because of efficiency wages and fair wages reasons (Abowd and Lemieux, 1993; Blanchflower et al., 1996; Egger and Kreickemeier, 2009; Egger and Kreickemeier, 2012; Helpman et al., 2010; Amiti and Davis, 2011; Helpman et al., 2014.) As a result, firms that export to higher income countries pay on average higher wages.

## 4. Econometric model and results

In this section, we econometrically explore these mechanisms more carefully. We start by studying the empirical causal link between export destinations and wages and then discuss the evidence in support of the quality valuation and provision mechanisms.

### *4.1. Export destinations and wages*

We begin the analysis with the following regression specification for wages:

$$\log w_{ict} = \gamma^1 g_{ict} + \mathbf{x}'_{ict}\beta^1 + \phi^1_t + \phi^1_{ic} + u^1_{ict}, \tag{22}$$

**Table 1**
Wages and per capita GDP across export destinations. OLS-FE estimation.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Average p/c GDP | 0.0412*** | 0.0479*** | 0.0404*** | 0.0450*** | 0.0372*** |
| | (0.0142) | (0.0139) | (0.0142) | (0.0143) | (0.0126) |
| Log origin p/c GDP | | 1.167*** | | 1.056*** | 1.170*** |
| | | (0.0753) | | (0.0788) | (0.0714) |
| Log industry exports | | | 0.000178** | −8.67e−05 | −1.55e−05 |
| | | | (7.27e−05) | (6.95e−05) | (6.12e−05) |
| Log industry output | | | | 0.134*** | 0.0221 |
| | | | | (0.0197) | (0.0177) |
| Productivity | | | | | 0.204*** |
| | | | | | (0.0230) |
| Observations | 12,850 | 12,850 | 12,850 | 12,331 | 11,382 |
| $R^2$ | 0.016 | 0.079 | 0.017 | 0.116 | 0.217 |
| Origin-industry groups | 1757 | 1757 | 1757 | 1719 | 1575 |

Note: dependent variable is average wage. Controls in all columns: origin-industry effects, year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *. Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

where log $w_{ict}$ is the log of the average wage paid in industry $i$ in country of origin $c$ at time $t$, $g_{ict}$ is the export-share weighted average per capita GDP across destination markets (as defined in Eq. (21)), $\mathbf{x}_{ict}$ is a vector of controls that varies across several specifications, $\phi_t^1$ are year fixed-effects, $\phi_{ic}^1$ are country of origin-industry fixed effects, and $u_{ict}^1$ is the error term. For our purposes, the main regressor in Eq. (22) is $g_{ict}$, and we are mostly interested in $\gamma^1$. In all specification throughout the paper, the standard errors are clustered by industry–source-country.

The baseline OLS–FE results are in Table 1.[10] In column 1, we report the basic correlation between wages and income across export destinations conditional only on the fixed effects $\phi_t^1$ and $\phi_{ic}^1$. The coefficient is positive and significant. An industry with average income across destinations that is 10% higher pays on average 0.412% higher wages. Note that this simple model includes year effects, so that any aggregate shock is accounted for, as well as origin-industry effects, so that time-invariant characteristics of an industry in a given country (such as certain technological characteristics or policies that remain constant) are also accounted for. This result is robust to the inclusion of various important controls. In column 2, we add the log of the per capita GDP of the origin country. Higher income implies a higher domestic demand and thus higher wages. The level of per capita GDP also accounts for differential country effects across time, such as periods of booms or crises. In column 3, we exclude per capita GDP but include the log of industry exports. In this regression, both average per capita GDP across destinations and industry exports appear positive and statistically significant. As in Brambilla et al. (2012), adding the level of exports, on top of the income level of destination markets, is conceptually important. The positive coefficient on $g$ implies that, conditional on a level of exports, those industries with a higher composition of high-income exports pay higher average wages. This finding is robust to the inclusion of per capita GDP in the country of origin, log industry exports and log industry output (column 4), where $\hat{\gamma}_1 = 0.0450$.

The results so far can be confounded by productivity shocks. The argument is that more productive firms may be able to both explore high-income destinations markets and pay higher wages (perhaps sharing a fraction of the additional profits created by the productivity shocks). To control for this, we add output per worker which is a direct measure of labor productivity in column 5. The results are not affected: $\gamma^1 = 0.0372$ remains positive and statistically significant.

As pointed out by Brambilla et al. (2012), even after controlling for all these effects, there might still be unobserved confounding factors. In particular, our main regressor $g_{ict}$ is built using the share of an industry's exports destined to different destinations, and these shares could be endogenous. Within industries, firm attributes such as unobserved productivity or cost shocks that are not captured by labor productivity directly can create upward biases. By contrast, industries that are more susceptible to the presence of unions may be subject to stronger labor regulations and may be less productive, and this can make them less likely to export, especially to high-income countries. Still, unions would force them to pay high wages on average (Galiani and Porto, 2010). This would create a downward bias in the OLS–FE specification. In addition, exports are also associated with imports, within firms and within industries (Bernard et al., 2007). Assume quality production requires imported inputs, and that these rise wages, for example because high quality inputs are complements of skilled labor. This can bias our results up. By contrast, imported machines may replace skilled labor in quality production and bias results down. Further, exports and imports may be more likely to occur in industries with a heavier presence of multinational corporations that may split skilled tasks across subsidiaries and be more likely to imports goods to be sold domestically, thus hiring less workers and paying lower wages, on average. Finally, the presence of measurement error in export exposure to different destinations can create a downward bias in the OLS estimates (Brambilla et al., 2012).

We deal with the endogeneity issue by estimating the model with instrumental variables. To do this, we need to find instruments that are able to (partly) explain the shares of industry $i$'s exports to country $c$ for all industries $i$ and all countries $c$. This means the instruments need to (partly) explain the patterns of global trade. We do this by combining ideas from the literature. Frankel and Romer (1999) and Feyrer (2013), among others, instrument trade in growth regressions with predictions of the volume of trade of country $c$ based on exogenous factors such as geography, distance, or time-varying air transportation costs.[11] Brambilla et al. (2012), Park et al. (2010), and Revenga (1992), among others, use partners' exchange rates as instruments. Here, since we need predictions for trade shares to each country's export destinations, we propose to use bilateral exchange rates to explain trade export shares in the following model:

$$s_{icdt} = \delta_i e_{cdt} + \nu_{it} + \nu_{icd} + \epsilon_{icdt}, \tag{23}$$

[10] These results are thus the linear version of the plot in Fig. 2, conditional on covariates.

[11] This approach has been adopted and improved by numerous authors. The geography-based instrument can fail if there are time-invariant country characteristics that are correlated with trade and growth simultaneously. To deal with this, Feyrer (2013) uses a time-variant measure of geography given by changing costs in transportation. Felbermayr and Gröschl (2013) work with the interaction of the occurrence of natural disasters (volcano eruptions, earthquakes, floods) and geographical variables. See also Hall and Jones (1999), Irwin and Terviö (2002), Alcalá and Ciccone (2004), Noguer and Siscart (2005), Frankel and Rose (2005), Rodriguez and Rodrik (2001).

**Table 2**
Predicting export shares. F-test.

| ISIC | Observations | Exchange rate | *t*-Test | *F*-Test | *p*-Value |
|---|---|---|---|---|---|
| 311 | 54,514 | −.0003081** | 2.32 | 6.44 | 0 |
| 313 | 27,750 | −0.0005431 | 0.82 | 8.25 | 0 |
| 314 | 14,628 | −0.0011346 | 0.71 | 12.03 | 0 |
| 321 | 53,653 | −.0004286** | 2.49 | 7.07 | 0 |
| 322 | 36,726 | 0.0000389 | 0.18 | 5.09 | 0 |
| 323 | 32,091 | −0.0002422 | 1.09 | 6.43 | 0 |
| 324 | 20,299 | −.0014037*** | 2.73 | 583.1 | 0 |
| 331 | 35,961 | −.0004324* | 1.75 | 93.2 | 0 |
| 332 | 30,876 | −0.0003432 | 1.16 | 6.33 | 0 |
| 341 | 41,557 | −.0005853*** | 3.61 | 1918 | 0 |
| 342 | 37,130 | −.0013117*** | 4.64 | 8.91 | 0 |
| 351 | 51,957 | 7.31E−06 | 0.05 | 9.97 | 0 |
| 352 | 50,481 | −0.0003492 | 1.52 | 12.06 | 0 |
| 353 | 27,871 | −.0012818*** | 3.31 | 395.97 | 0 |
| 354 | 12,411 | −.0039314*** | 3.03 | 857.05 | 0 |
| 355 | 38,506 | 0.0000308 | 0.14 | 5685.17 | 0 |
| 356 | 39,930 | −.0004563** | 2.20 | 359.15 | 0 |
| 361 | 27,154 | −.0006605** | 2.18 | 1228.04 | 0 |
| 362 | 34,413 | 0.0000955 | 0.39 | 12.18 | 0 |
| 369 | 36,178 | 0.0002915 | 0.94 | 10.29 | 0 |
| 371 | 40,137 | 0.0000266 | 0.15 | 10.79 | 0 |
| 372 | 34,232 | −0.0002386 | 1.10 | 613.94 | 0 |
| 381 | 51,331 | −.0003225*** | 2.61 | 409.98 | 0 |
| 382 | 50,489 | −0.0000567 | 0.46 | 7.37 | 0 |
| 383 | 46,758 | −.0004196** | 2.07 | 7.8 | 0 |
| 384 | 42,195 | −.0003788** | 2.01 | 1804.87 | 0 |
| 385 | 39,005 | −.000454** | 2.08 | 16.56 | 0 |
| 390 | 37,719 | −.000497** | 2.33 | 140.37 | 0 |

Note: regressions of export shares on real bilateral exchange rates, year effects, and origin–destination fixed effects run at the ISIC 3-digit industry level. Table displays industry code, exchange rate coefficient and *t*-test, and *F*-statistic and associated *p*-value.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

where, as before, $s_{icdt}$ is the share of exports of good $i$ from country $c$ to destination $d$ at time $t$. The regressor $e_{cdt}$ is the real bilateral exchange rate between country $c$ and country $d$, $v_t$ are year effects, and $v_{cd}$ are origin–destination fixed effects. This regression is run separately for each industry $i$, which allows us to incorporate flexibility into the model. Bastos et al. (2014) use an instrument which is very similar to ours, in the sense that they predict export shares of Portuguese firms using exogenous exchange rate movements.

It is important to note that we do not need to estimate a fully specified structural model of trade. We need a good prediction for the trade export shares, i.e., we need instruments that are correlated with our endogenous regressor $g$. To give a sense of the results from Eq. (23), we report in Table 2, for each of the 28 manufacturing industries in our sample, the coefficient and $t$-statistic of the bilateral exchange rates as well as the $F$ test of joint significance associated with the estimation of Eq. (23) by OLS–FE. We find that bilateral exchange rates are statistically significant in 15 out of the 28 industries and that the $F$ statistic is high in all sectors. This means that, for all ISIC sectors, the shares are predicted with sufficient precision, which helps with the statistical properties of our IV strategy. Note that there are differences in the $t$- and $F$ statistics across sectors but, as we show in the first stage below, the model has sufficient power to identify the impacts of interest. In other words, the model fits better in some sectors than in others, but the overall fit is good. This helps in establishing a strong correlation between our instrument and the endogenous regressor, which we can formally test with the first stage results, as we do next.

After estimating Eq. (23) separately for each industry, we predict the flow of trade $\hat{s}_{icdt}$ and then, for each $i$ and $c$, we build our instrument for $g$ as

$$\hat{g}_{ict} = 1\left(\sum_d \hat{s}_{icdt} * GDPpc_d\right). \tag{24}$$

**Table 3**
Wages and per capita GDP across export destinations. IV estimation.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) First stage results* | | | | | |
| Predicted Average p/c GDP | 0.309*** | 0.309*** | 0.310*** | 0.311*** | 0.310*** |
| | (0.0213) | (0.0214) | (0.0214) | (0.0217) | (0.0241) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| $R^2$ | 0.202 | 0.202 | 0.202 | 0.202 | 0.194 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *B) Second stage results* | | | | | |
| Average p/c GDP | 0.0986** | 0.131*** | 0.0935** | 0.136*** | 0.0902** |
| | (0.0437) | (0.0434) | (0.0440) | (0.0434) | (0.0384) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| $R^2$ | 0.011 | 0.068 | 0.013 | 0.106 | 0.210 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *C) Second stage results: robustness* | | | | | |
| Average p/c GDP | 0.0989** | 0.127*** | 0.0938** | 0.130*** | 0.0868** |
| | (0.0427) | (0.0425) | (0.0429) | (0.0422) | (0.0376) |

Note: dependent variable is average wage. Main regressor: Average per capita GDP across destinations. Instrument: Average per capita GDP across destinations computed using predicted export shares as weights. Panels A and B: Average p/c GDP is computed as a weighted average of the per capita GDP in 1990. Panel C: Average p/c GDP is computed as a weighted average of per capita GDP at time *t*. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

Finally, we estimate the wage model (22) by IV–FE using $\hat{g}_{ict}$ as defined in Eq. (24) as the instrument for $g$.

Our findings are reported in Table 3. In Panel A, we show the first stage results. The columns in these regressions correspond to the same specifications of the baseline OLS–FE model in Table 1. In all of them, we find a strong positive correlation between the instrument and the endogenous regressor and this correlation is always statistically significant. In Panel B, we show the IV results from the second stage. Again, in all specifications, $g$ has a statistically strong positive causal effect on wages.[12] These results confirm the finding that industries in which exports are destined to high income destinations pay higher average wages. In the preferred specification in column 5, on average, an increase in 10% in the average per capita GDP across destinations causes average wages in the industry to increase by 0.902%.[13] The findings in Brambilla et al. (2012) and Verhoogen (2008), which apply to Argentine and Mexican firms, hold, on average, for a wider cross-section of countries.

At the bottom of Table 3, we report the second-stage results using a variant of $g$ in which the per capita GDP of destination countries is allowed to change over time. This has no substantial effect on the results, which remain virtually unchanged. Our preferred model is, however, the one that keeps destination per capita GDP constant at their pre-sample level, because it provides a better test of our theory. Changes in per capita GDP due to booms or slowdowns in trade partners could affect wages in source countries due to market size effects, for instance, or, alternatively, may not affect quality valuation if preferences are determined according to long-run permanent income. The model that exploits exogenous changes in exposure to high-income destinations is

[12] Note that asymptotically it is not necessary to correct the standard errors on the second stage regression for the fact that the instrument is estimated (although there might be biases in small sample, of course). See Wooldridge (2001).

[13] Note that this implies a downward bias in the OLS estimates. As argued above, and as in Brambilla et al. (2012), this bias can be created by various factors, such as political economy forces (for instance, industry unionization the raises wages and hinders exports) and measurement error in export exposure.

**Table 4**
Wages and per capita GDP across export destinations. Alternative IV estimation.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) First stage results* | | | | | |
| Predicted average p/c GDP | 0.543*** | 0.543*** | 0.562*** | 0.570*** | 0.566*** |
| | (0.0337) | (0.0337) | (0.0343) | (0.0343) | (0.0372) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| $R^2$ | 0.241 | 0.241 | 0.251 | 0.254 | 0.250 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *B) Second stage results* | | | | | |
| Average p/c GDP | 0.0733** | 0.0917*** | 0.0823** | 0.0923*** | 0.0912*** |
| | (0.0329) | (0.0322) | (0.0320) | (0.0322) | (0.0295) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| $R^2$ | 0.014 | 0.075 | 0.015 | 0.113 | 0.208 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *C) Second stage results: robustness* | | | | | |
| Average p/c GDP | 0.0755** | 0.0907*** | 0.0847*** | 0.0903*** | 0.0871*** |
| | (0.0323) | (0.0319) | (0.0315) | (0.0318) | (0.0289) |

Note: analogous to Table 3 using an alternative instrument, in which export shares are computed from predicted export flows. Controls in all columns: origin-industry effects, year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

**Table 5**
Operating mechanisms. Unit values and per capita GDP across export destinations.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) OLS–FE* | | | | | |
| Average p/c GDP | 0.149*** | 0.153*** | 0.148*** | 0.154*** | 0.130*** |
| | (0.0299) | (0.0297) | (0.0299) | (0.0309) | (0.0326) |
| Observations | 12,850 | 12,850 | 12,850 | 12,331 | 11,382 |
| $R^2$ | 0.018 | 0.026 | 0.019 | 0.026 | 0.023 |
| Origin-industry groups | 1757 | 1757 | 1757 | 1719 | 1575 |
| *B) IV second stage* | | | | | |
| Average p/c GDP | 0.229*** | 0.250*** | 0.221*** | 0.234*** | 0.166** |
| | (0.0768) | (0.0765) | (0.0763) | (0.0794) | (0.0819) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| $R^2$ | 0.014 | 0.021 | 0.016 | 0.023 | 0.023 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *C) Alternative IV second stage* | | | | | |
| Average p/c GDP | 0.152** | 0.164** | 0.166*** | 0.164** | 0.114* |
| | (0.0649) | (0.0638) | (0.0637) | (0.0646) | (0.0662) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| $R^2$ | 0.017 | 0.025 | 0.017 | 0.026 | 0.022 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |

Note: dependent variable is average unit value. Main regressor: Average per capita GDP across destinations. Panel A: OLS regressions. Panel B: IV regressions; instrument is average per capita GDP computed using predicted export shares; first stage is the same as Table 3. Panel C: IV regressions; instrument is average per capita GDP computed using predicted export flows; first stage is the same as Table 4. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

arguably a cleaner test of the quality mechanism. Nevertheless, as shown, our results are quite robust.

To end, we explore results from an alternative version of the instrument. Instead of running an auxiliary regression of export shares, we set up a model of trade with export flows (as opposed to shares) as the dependent variable. Export shares are then built using the predicted export flows. The advantage of this regression is that the predicted shares are bounded between 0 and 1 and sum to 1. From an IV statistical viewpoint, since IV models need not be fully specified, the distinction should not be relevant and it is not in practice. We report results using the alternative instrument in Table 4. Panel A shows statistically strong first-stage results. Panel B shows that the IV impacts are positive and statistically significant in all five specifications. Moreover, the differences in the magnitude of the IV results are negligible. In the full model of column 5 for instance, the IV coefficient is 0.0912, which is almost exactly the same as the coefficient in Table 3, 0.0902. In Panel C, we report robustness results using the version of exposure $g$ that allows destination per capita GDP to vary over time. Results are very similar to those in our previous specifications.

### *4.2. The operating mechanisms*

We now investigate the operating mechanisms, the link between export quality and high-income exports, on the one hand, and the link between quality and wages, on the other. For the first of these mechanisms, we use a regression model analogous to Eq. (22) with quality on the left-hand side instead of wages, given by

$$\log uv_{ict} = \gamma^2 g_{ict} + \mathbf{x}'_{ict}\beta^2 + \phi^2_t + \phi^2_{ic} + u^2_{ict}, \tag{25}$$

where $uv$ is the average unit value in industry $i$, country of origin $c$, and time $t$. In this model, for similar reasons as in Eq. (22), the shares of export destinations can be endogenous. We thus estimate the models by both OLS–FE and IV–FE using the same instrument $\hat{g}$ as before. Results are in Table 5. Looking first at the OLS–FE results (Panel A, at the top), we find that, pooling all countries, the average per capita GDP across destinations is positively associated with average unit values. The results are robust to the inclusion of all the other previous controls, namely, log per capita GDP at origin (column 2), log industry exports (column 3), log industry output (column 4), and log industry productivity (column 5). Our IV results, in Panel B, confirm the causal link.[14] In all five specifications, high-income export destinations lead to higher quality at the industry level. These impacts are always statistically significant. Using the preferred estimates in column 5, unit values are on average around 1.66% higher in industries in which the average income across destinations is 10% higher. These results are thus consistent with the intuition that industries oriented to higher income destinations produce, on average, higher quality products.[15] For additional robustness, we also run the IV model with the alternative instrument built using predicted flows. The results are in Panel C and support the linkage between high-income export destinations and quality.

Turning to the link between quality, skills and wages, the model is

$$\log w_{ict} = \gamma^3 \log uv_{ict} + \mathbf{x}'_{ict}\beta^3 + \phi^3_t + \phi^3_{ic} + u^3_{ict}. \tag{26}$$

For completeness, we report estimates of this model with OLS–FE at the top of Table 6. We uncover a positive correlation between the average quality in an industry and the average wage paid by the industry (Panel A). The estimates are always positive (column 1 to 5) and statistically significant.

However, to be consistent with our interpretation, we need to argue that this association is caused by the fact that the production of higher quality products requires skills, and that skilled workers are paid higher wages than unskilled workers used more intensively in lower quality industries. While we do not have information on skill utilization in the data, we can establish this link more strongly by estimating Eq. (26) with instrumental variables (so as to rule out, for instance, the likely scenario in which exogenous shocks to wages lead to higher unit values because of pass-through from cost to prices). In this case, the endogenous variable, the log of the unit value, can also be instrumented with the predict average per capita GDP of an industry destinations.

[14] The first stage results are the same as in Table 3 and are not reported here.
[15] These results are not affected when the per capita GDP of destination countries in $g$ changes over time.

**Table 6**
Operating mechanisms. Wages and unit values.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) OLS–FE* | | | | | |
| Average UV | 0.0421*** | 0.0295*** | 0.0414*** | 0.0289*** | 0.0184*** |
| | (0.00836) | (0.00809) | (0.00830) | (0.00800) | (0.00686) |
| Observations | 12,850 | 12,850 | 12,850 | 12,331 | 11,382 |
| $R^2$ | 0.018 | 0.078 | 0.019 | 0.115 | 0.215 |
| Origin-industry groups | 1757 | 1757 | 1757 | 1719 | 1575 |
| *B) IV first stage* | | | | | |
| Predicted average p/c GDP | 0.339*** | 0.337*** | 0.339*** | 0.342*** | 0.342*** |
| | (0.0151) | (0.0150) | (0.0151) | (0.0155) | (0.0169) |
| Observations | 12,387 | 12,387 | 12,387 | 11,873 | 10,935 |
| $R^2$ | 0.221 | 0.226 | 0.221 | 0.228 | 0.216 |
| Origin-industry groups | 1743 | 1743 | 1743 | 1707 | 1549 |
| *C) IV second stage* | | | | | |
| Average UV | 0.0929*** | 0.0832*** | 0.0892*** | 0.0790*** | 0.0459** |
| | (0.0256) | (0.0268) | (0.0256) | (0.0262) | (0.0184) |
| Observations | 12,387 | 12,387 | 12,387 | 11,873 | 10,935 |
| $R^2$ | 0.011 | 0.069 | 0.013 | 0.109 | 0.211 |
| Origin-industry groups | 1743 | 1743 | 1743 | 1707 | 1549 |
| *D) Alternative IV second stage* | | | | | |
| Average UV | 0.0772*** | 0.0530*** | 0.0778*** | 0.0483*** | 0.0342*** |
| | (0.0180) | (0.0186) | (0.0180) | (0.0185) | (0.0126) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| $R^2$ | 0.015 | 0.075 | 0.016 | 0.115 | 0.212 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |

Note: dependent variable is average wage. Main regressor: Average unit value. Panel A: OLS regressions. Panels B and C: IV regressions; instrument is average per capita GDP computed using predicted export shares. Panel D: IV regressions; instrument is average per capita GDP computed using predicted export flows; first stage not shown. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

**Table 7**
Wages and inequality across export destinations.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) Gini* | | | | | |
| Average inequality | 0.0595** | 0.0757*** | 0.0625** | 0.111*** | 0.111*** |
| | (0.0281) | (0.0285) | (0.0285) | (0.0364) | (0.0328) |
| Average inequality | 0.0205** | 0.0222** | 0.0210** | 0.0201* | 0.00665 |
| | (0.00979) | (0.0100) | (0.00977) | (0.0106) | (0.00725) |
| Average p/c GDP | 0.126** | 0.161*** | 0.121** | 0.163*** | 0.0980** |
| | (0.0512) | (0.0515) | (0.0512) | (0.0511) | (0.0416) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *B) Ratio quintile shares* | | | | | |
| Average inequality | 0.0588** | 0.0765** | 0.0622** | 0.116*** | 0.118*** |
| | (0.0300) | (0.0310) | (0.0306) | (0.0427) | (0.0410) |
| Average inequality | 0.0167* | 0.0186** | 0.0173* | 0.0146 | 0.00163 |
| | (0.00907) | (0.00925) | (0.00907) | (0.0104) | (0.00712) |
| Average p/c GDP | 0.121** | 0.156*** | 0.116** | 0.154*** | 0.0920** |
| | (0.0504) | (0.0506) | (0.0505) | (0.0499) | (0.0409) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |

Note: dependent variable is average Wage. Main regressor is the average level of inequality at export destinations. Panel A: inequality is measured with the Gini coefficient. Panel B: inequality is measured with the ratio of the income share of the fifth to the first quintiles. The instrument is the average inequality of destination countries using predicted export shares as weights. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

This is because of the statistical association found in Eq. (25), the first link in our proposed mechanism.[16]

Our IV results are reported in Table 6. The first stage results (Panel B) confirm a strong predicted power of the instrument, as expected. The second stage results (Panel C) uncover a link between quality and wages. In specification 5, for instance, in an industry with 10% higher average unit value, wages are 0.459% higher. This result suggests a positive link between quality production and skill utilization, which implies a more intensive use of high-wage skilled workers at the industry level. Note that since wages and unit values are endogenous outcomes of the firms' profit maximization problem, the correct interpretation of these results is that, given an exogenous shift in exports to higher income markets, firms choose to produce higher unit values (higher quality) goods and that this choice requires higher wages. To wrap up, Panel D shows that similar results are obtained when we use the alternative instrument.

## 5. Robustness and additional supporting evidence

In this section, we provide additional supporting evidence in favor of both the quality valuation and the quality provision mechanisms. We carry out various direct tests of the quality valuation argument and we present additional facts from the data that are consistent with both mechanisms.

### 5.1. Inequality, distance, and destination market size

In our hypothesis, the link between income across export destinations and the level of wages hinges on a higher quality demand in richer countries due to non-homothetic preferences and an inherent quality valuation that depends on income. However, the link between high income exports and quality products may be driven by other forces. Consider first the role of the income distribution. In the model of Section 2, it is implicitly assumed that all individuals in a given country of destination share the same income level. If we elaborate on this model and add differences in income across individuals, as in the model of Fajgelbaum et al. (2011), the demand for quality may also be generated by a set of trading partners with more unequal income distributions. Under some conditions, thus, more unequal economies will display a larger demand for high quality products. This prediction can in turn be tested empirically as further supporting evidence of the quality valuation mechanism. To explore this idea, we build a measure of the average inequality level of an industry's exports using the Gini coefficient in place of the per capita GDP of the destination country in Eq. (21):

$$h_{ict} = \sum_d s_{icdt} * Gini_d. \tag{27}$$

Here, $h_{ict}$ is the export-share weighted average of the destinations Gini and a higher $h$ implies higher average inequality across export destinations. We create an instrument for $h$ using predicted shares, and we estimate the wage model (22) with instrumental variables. The results are in Table 7. In Panel A, we show regressions using the average Gini, with instruments for $h$ and without conditioning on $g$. In all the specifications, a higher average inequality of an industry's export destinations leads to higher industrial wages. We then add $g$, the average income level across export destinations and we instrument it as well. Two results emerge. First, the average level of income across destinations still appears positive and significantly associated with wages. We can conclude that the non-homothetic quality valuation effect remains relevant in explaining the mechanism. Second, the inequality channel survives in

[16] Note that the instrument is actually the predictions of the log of the unit value from the first stage regression of log $uv$ on $\hat{g}$. In the linear model, this is the same as using $\hat{g}$ directly in the IV estimation.

**Table 8**
Wages and distance to export destinations.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) Distance in km* | | | | | |
| Average distance | 0.198** | 0.204** | 0.187* | 0.245** | 0.0508 |
| | (0.0915) | (0.0937) | (0.105) | (0.107) | (0.0900) |
| Average p/c GDP | 0.0645 | 0.0994** | 0.0764* | 0.0923** | 0.156*** |
| | (0.0396) | (0.0393) | (0.0403) | (0.0412) | (0.0339) |
| Average distance | 0.121 | 0.0840 | 0.0827 | 0.117 | −0.167* |
| | (0.0990) | (0.103) | (0.121) | (0.124) | (0.0977) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *B) Non-contiguous exports* | | | | | |
| Share non-contiguous dest. | 0.0879 | 0.0859 | 0.0595 | 0.105 | 0.0117 |
| | (0.0617) | (0.0604) | (0.0710) | (0.0703) | (0.0587) |
| Average p/c GDP | 0.0608* | 0.0779** | 0.0660* | 0.0800** | 0.0846*** |
| | (0.0352) | (0.0340) | (0.0339) | (0.0324) | (0.0307) |
| Share non-contiguous dest. | 0.0489 | 0.0358 | 0.0132 | 0.0473 | −0.0450 |
| | (0.0533) | (0.0521) | (0.0623) | (0.0630) | (0.0540) |
| Observations | 12,333 | 12,333 | 12,333 | 11,819 | 10,878 |
| Origin-industry groups | 1738 | 1738 | 1738 | 1700 | 1542 |

Note: dependent variable is average Wage. Main regressor: log average distance to export destinations (Panel A) and the share of exports to non-contiguous destinations (Panel B). Variables are constructed at the origin-industry-year level. The instruments are the average distance and share of non-contiguous destinations using predicted export shares as weights. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

**Table 9**
Wages and market size across export destinations.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) GDP* | | | | | |
| GDP | 0.0526** | 0.0621*** | 0.0516** | 0.0647*** | 0.0362** |
| | (0.0214) | (0.0215) | (0.0214) | (0.0218) | (0.0176) |
| Average p/c GDP | 0.106* | 0.117* | 0.0877 | 0.115* | 0.108* |
| | (0.0623) | (0.0626) | (0.0634) | (0.0644) | (0.0564) |
| GDP | 0.00694 | 0.0115 | 0.0138 | 0.0150 | −0.00999 |
| | (0.0267) | (0.0271) | (0.0267) | (0.0285) | (0.0215) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *B) Population* | | | | | |
| Population | 0.101* | 0.123** | 0.0903 | 0.127** | 0.0300 |
| | (0.0545) | (0.0565) | (0.0549) | (0.0568) | (0.0399) |
| Average p/c GDP | 0.102*** | 0.116*** | 0.0996** | 0.120*** | 0.104*** |
| | (0.0394) | (0.0390) | (0.0396) | (0.0399) | (0.0358) |
| Population | 0.0381 | 0.0515 | 0.0287 | 0.0540 | −0.0302 |
| | (0.0427) | (0.0448) | (0.0428) | (0.0447) | (0.0310) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |

Note: dependent variable is Average Wage. Main regressor: destination market size. Panel A: market size is measured with the log average aggregate GDP of export destinations. Panel B: market size is measured with the log average population at destinations. Variables are constructed at the origin-industry-year level. The instruments are average GDP and average population using predicted export shares as weights. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

all specifications except the last (column 5). We can conclude that the inequality effect of Fajgelbaum et al. (2011), while indeed present in the data, is somewhat weaker across the world economy.

For completeness and robustness, we re-do the analysis using the ratio of the share of income in the upper quintile to the share of income in the lower quintile as a measure of inequality (instead of the Gini). For each industry, these ratios are weighted using export shares. The results, in Panel B of Table 7, are robust to this specification.

For our second experiment, consider the role of the geographic location of export destinations.[17] An alternative explanation for differences in quality across export destinations is the "shipping the good apples out" mechanism. With unitary transport costs that do not depend on quality and price, an increase in transport costs distorts relative prices in favor of higher quality goods. This means that, because they are more costly to reach, firms will tend to ship higher quality products to more distant destinations. If on average distance is associated with high income, the empirical predictions of the shipping-the-good-apples-out mechanism would be the same as the quality-valuation mechanism. To separate both effects we build a measure of average distance of an industry's exports, in a manner analogous to average per capita GDP and average inequality

$$D_{ict} = \ln\left(\sum_d s_{icdt} * Dist_{cd}\right), \tag{28}$$

where $Dist_{cd}$ is the distance in kilometers between countries $c$ and $d$. We create an instrument for $D$ using predicted export shares and we test whether average distance explains wages.

The IV results are in Table 8, Panel A. There are two specifications. In the first specification we do not control for average per capita GDP and find that average distance causes higher wages, although the coefficient is not significant in the preferred model (column 5). In the second specification we control for average per capita GDP and we find that higher average per capita GDP causes higher wages but that average distance does not. These results are consistent with the quality-valuation hypothesis and do not provide support to the shipping-the-good-apples-out hypothesis. The significant coefficients in the first specification could be due to the fact that distance is indeed correlated with higher income.

In Panel B we work with an alternative definition of average location of exports. We compute the share of exports to non-contiguous

[17] See also Bastos et al. (2014).

**Table 10**
High-income export destinations. Impacts by industry.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) Log wage* | | | | | |
| Average p/c GDP * high | 0.141** | 0.156*** | 0.135** | 0.172*** | 0.150*** |
| | (0.0597) | (0.0587) | (0.0601) | (0.0600) | (0.0565) |
| Average p/c GDP * low | 0.0882 | 0.112 | 0.0798 | 0.102 | 0.0163 |
| | (0.0673) | (0.0688) | (0.0671) | (0.0659) | (0.0492) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *B) Average unit value* | | | | | |
| Average p/c GDP * high | 0.239** | 0.249*** | 0.231** | 0.235** | 0.197** |
| | (0.0936) | (0.0931) | (0.0925) | (0.0982) | (0.0950) |
| Average p/c GDP * low | 0.221* | 0.236* | 0.208 | 0.217* | 0.105 |
| | (0.130) | (0.129) | (0.130) | (0.130) | (0.141) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |
| *C) Log wage* | | | | | |
| Average UV * high | 0.0955*** | 0.0737** | 0.0883*** | 0.0723** | 0.0664** |
| | (0.0301) | (0.0311) | (0.0307) | (0.0309) | (0.0262) |
| Average UV * low | 0.122*** | 0.106** | 0.117*** | 0.0981** | 0.0143 |
| | (0.0453) | (0.0486) | (0.0446) | (0.0463) | (0.0214) |
| Observations | 12,418 | 12,418 | 12,418 | 11,901 | 10,954 |
| Origin-industry groups | 1744 | 1744 | 1744 | 1707 | 1549 |

Note: same regressions as in Tables 3 to 6 but adding an interaction with a scope for differentiation dummy for different industries. High-scope industries are industries with unit values above the median unit value. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

**Table 11**
High-income export destinations. Impact by source-country.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *A) Log wage* | | | | | |
| Average p/c GDP * rich | 0.290*** | 0.364*** | 0.275*** | 0.376*** | 0.174*** |
| | (0.0910) | (0.101) | (0.0911) | (0.0992) | (0.0581) |
| Average p/c GDP * poor | 0.0122 | 0.0275 | 0.0124 | 0.0205 | 0.0547 |
| | (0.0496) | (0.0479) | (0.0496) | (0.0478) | (0.0487) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *B) Average unit value* | | | | | |
| Average p/c GDP * rich | 0.559*** | 0.607*** | 0.534*** | 0.543*** | 0.456*** |
| | (0.155) | (0.163) | (0.152) | (0.149) | (0.158) |
| Average p/c GDP * poor | 0.0807 | 0.0906 | 0.0809 | 0.0856 | 0.0431 |
| | (0.0883) | (0.0862) | (0.0884) | (0.0945) | (0.0968) |
| Observations | 12,167 | 12,167 | 12,167 | 11,665 | 10,733 |
| Origin-industry groups | 1724 | 1724 | 1724 | 1686 | 1530 |
| *C) Log wage* | | | | | |
| Average UV * rich | 0.163*** | 0.148*** | 0.158*** | 0.152*** | 0.0792*** |
| | (0.0336) | (0.0362) | (0.0334) | (0.0357) | (0.0189) |
| Average UV * poor | −0.0273 | −0.0285 | −0.0281 | −0.0444 | −0.0163 |
| | (0.0367) | (0.0354) | (0.0366) | (0.0325) | (0.0375) |
| Observations | 12,387 | 12,387 | 12,387 | 11,873 | 10,935 |
| Origin-industry groups | 1743 | 1743 | 1743 | 1707 | 1549 |

Note: same regressions as in Tables 3 to 6 but adding an interaction with an income-level dummy for the source country. Poor source countries are countries in the bottom 20% of the world income distribution. Specifications in columns (1) to (5) include the same controls as columns (1) to (5) in Table 1. All columns include origin-industry effects and year effects. Standard errors clustered at origin-industry level. Significance at 1%, 5% and 10% levels indicated by ***, ** and *.
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

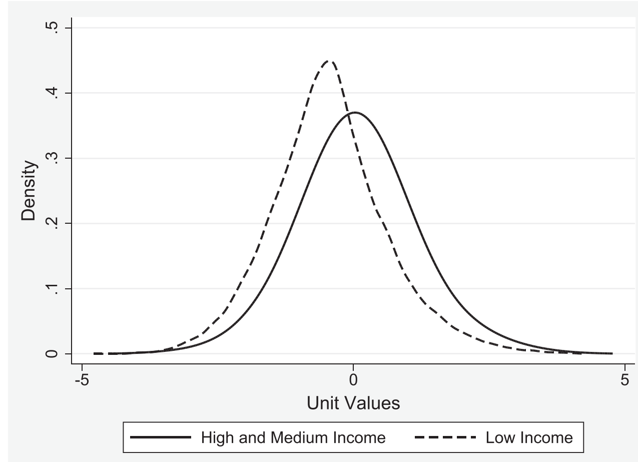


**Fig. 3.** Distribution of unit values in rich and poor source-countries. Notes: non-parametric density estimates of average unit values for richer countries (middle-income and rich countries) and poor countries (lower-income and low-income countries).
Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

destinations, and, as before, we construct the instrument using predicted shares. We again find that higher average per capita GDP causes higher wages but that exports to non-contiguous destinations do not.

In a third experiment, we explore another competing explanation for our findings. In countries with higher market size, firms may extract higher rents (Melitz and Ottaviano, 2008) which can then be shared with the workers (under efficiency wage constraints and profit sharing mechanisms). If richer countries in terms of per capita GDP are also countries with higher market size, the theory of quality valuation and quality provision may lose supportive power from the data. As with the distance theory, we can test this directly by controlling for measures of market size in our IV regressions. We do this in Table 9. As before, we first run the model without including the average per capita GDP of the destination countries. In Panel A, market size is measured with average aggregate GDP (define analogously to $g$). We find that average industry wages are indeed higher in industries that ship to larger economies. However, when average GDP and average per capita GDP are included simultaneously in the regression, only per capita GDP remains statistically significant. Similar but stronger results are reported in Panel B, where we measure market size with population.

### 5.2. Industry scope for quality differentiation

We can also assess the theory by inspecting whether the results are stronger among industries with high scope for quality differentiation. If quality valuation is one of the mechanisms underlying the results, the impacts documented here should be stronger in industries where firms can exploit the valuation of quality to a larger degree. We test this idea by running our regressions after splitting industries into two groups, high and low scope for quality differentiation, and adding interaction terms with average per capita GDP across destinations. To define the two industry groups we first compute, for each industry, the variance in unit values across source and destination countries. We then compute, across industries, the average variance in unit values. Industries with high scope for quality differentiation are those with variance in unit values above the mean.[18] Let $H_i$ be the associated indicator dummy (equal to 1 for high-scope industries). The regression model is

$$\log w_{ict} = \gamma_0^1 g_{ict}(1-H_i) + \gamma_1^1 g_{ict} * H_i + \mathbf{x}_{ict}^{'}\beta^1 + \phi_t^1 + \phi_{ic}^1 + u_{ict}^1, \qquad (29)$$

where we expect $\gamma_1^1$ to be positive and statistically significant and, also, $\gamma_0^1$ not to be statistically significant. For the IV model, the instruments are the predicted average per capita GDP across destinations computed using predicted exports shares as weights, interacted with the industry group dummies $H_i$ and 1-$H_i$. Results are reported in Table 10. In Panel A, we find that the link between high-income destinations and industry wages is indeed stronger in industries with higher scope for differentiation. In fact, the coefficients are positive and statistically significant among high-scope industries, while they are not statistically significant in industries with low scope for differentiation. We also find evidence of the mechanisms. In Panel B, unit values are increasing in income across destinations among high-scope industries, but not so much among low-scope industries. In Panel C, average wages are positively linked to unit values and, especially in our most complete specification (column 5), this holds among high-scope industries rather than among low-scope industries.

### 5.3. Origin country income

Additional evidence to support the mechanisms can be presented by recognizing that the theory of high-income export destinations need not hold for all countries. In particular, we argue here that these mechanisms are more likely to operate in middle-income and rich countries than in poorer, less developed countries. On the demand side, even though richer countries demand on average high quality products, they can also consume low quality products if there is dispersion in income (with low income individuals consuming lower quality products than high income individuals). On the supply side, the distribution of technical capability and skills need not be the same across source countries. Poor countries may not be endowed with the sufficient stock of firm capability and worker skills needed to satisfy higher quality demand in richer countries. Thus, the high income country import demand for lower quality products may be disproportionately supplied

[18] We find similar results if we use the median instead of the mean as the high variance cut-off.

**Table 12**
Unit value dispersion and income level at origin.

| | Average unit value | | S. deviation unit values | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Richer country dummy | 0.300*** | | 0.438*** | |
| | (0.0912) | | (0.0999) | |
| Log origin p/c GDP | | 0.180*** | | 0.197*** |
| | | (0.0278) | | (0.0324) |
| Observations | 13,000 | 13,000 | 12,947 | 12,947 |
| $R^2$ | 0.720 | 0.742 | 0.510 | 0.524 |

Note: regressions of dispersion in export unit values (at the industry level) and the level of income of the origin country. Significance at 1%, 5% and 10% levels indicated by ***, ** and *. Data from the "Trade, Production and Protection" database of Nicita and Olarreaga (2007) and World Development Indicators.

by poorer source countries because of sorting. As a result, the link between the average income of export destinations and quality may fail for poorer countries. In this case, the mechanism linking quality production and skill utilization (wages), while present, may not be strong enough to appear in the data.[19] The findings in Caron et al. (2014) are consistent with this argument.

As before, our strategy to further explore this idea is to separate countries by income level and test whether the mechanisms outlined above hold for richer rather than poorer countries. To do this, we split countries of origin into two groups, middle-income and rich countries and lower-income countries. This latter group includes countries at the bottom 20% of the world income distribution.[20] Results are in Table 11. In panel A, we find that the average per capita GDP across destinations has a positive impact on average wages only in richer countries. These impacts are larger than before, and always statistically significant. We infer that middle-income and rich countries exporting to high-income destinations do indeed pay higher wages, on average, but poorer, less developed countries pay roughly the same average wage irrespective of the destination of exports.[21] This is because poorer countries sell roughly the same quality at all destinations or, if they sell higher quality abroad, it is not a dominant force. This is revealed in panel B of Table 11, where we find a positive and statistically significant impact of the average per capita GDP across destinations on average unit values only in richer countries. Lastly, we report in panel C the link between average unit values and average log wages. This link is positive, once again, only in richer countries. These findings support the contention that the provision of quality requires more expensive skills thus leading to higher average wages.

To end, we gauge additional support to the claim that the theory of high-income export destination applies more strongly in richer countries than in less developed countries by looking at quality dispersion and at wage dispersion across countries and products. The distribution of quality can illustrate whether, in a given industry, richer countries produce higher quality products; and it can also show whether richer countries produce more diverse products in terms of quality, selling high unit value products in high-income destinations and lower unit value products in lower-income countries, while poorer countries tend to export more homogeneous lower quality products.

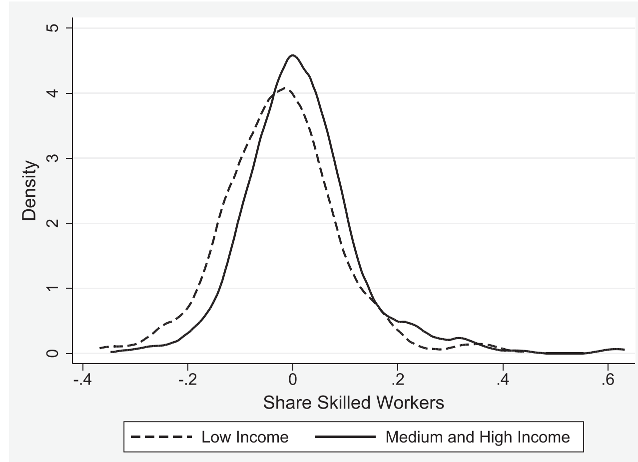


**Fig. 4.** Distribution of the share of skilled workers in middle-income and low-income source-countries. Notes: non-parametric density estimates of share of skilled workers in total employment for middle-income and low-income countries. Data from the Enterprise Surveys of the World Bank. See http://www.enterprisesurveys.org/. The richest countries in our classification are not included in the figure as they are not covered by the Enterprise Surveys.

Fig. 3 shows the distribution of unit values for the two groups of countries, middle-income and rich countries vis-à-vis low-income countries. We observe that the density of unit values in poorer countries is indeed shifted to the left, thus indicating lower mean unit values. In addition, the density of unit values in richer countries has thicker tails, thus indicating more dispersion. These observations hold on average as well. In column 1 of Table 12, we regress the average unit value of an industry on a high-income country dummy. The estimate is positive and highly statistically significant. This indicates that, in fact, high-income countries produce on average higher quality products than low-income countries. In column 2, we replace the dummy with the (log) per capita GDP of the origin country and find a positive and highly significant coefficient on the variable as well. In column 3, we regress the standard deviation of the unit values on the high-income country dummy. This relationship is also positive and significant. Column 4 reveals similar results when the high-income dummy is replaced by per capita GDP. This means that, within industries, richer countries tend to produce relatively less similar products.

A similar analysis for the dispersion of skills and wages can help illustrate the failure of the quality provision mechanism in poor countries. The Nicita and Olarreaga (2007) data, however, only report average industrial wages. We therefore switch to data from the World Bank's Enterprise Surveys.[22] These are firm-level surveys that allow us to compute, for a wide array of developed countries both the average industry wage and its standard deviation. In addition, the survey includes information on skilled and unskilled employment, which allows us to calculate the share of a firm's skilled workers in its total labor force.

Fig. 4 shows the distribution of these shares for the group of low-income countries and a subset of the middle-income countries.[23] As expected, the density of skilled shares for richer countries lies to the right, thus suggesting higher skilled utilization, on average. The right tail is also wider, thus suggesting more variance in skilled shares. This is consistent with the argument that richer countries produce more disperse varieties of products with more diverse skill utilization. We can also look at this with simple regressions of various measures of skilled

[19] In medium and high income countries it is reasonable to assume that there are low capability firms that sell low quality products to low income consumers in the domestic country and that export to low income markets.

[20] In our sample, lower-income countries are Armenia, Azerbaijan, Bangladesh, Bolivia, Cameroon, Cote d'Ivoire, Ecuador, Egypt, Ethiopia, Honduras, India, Indonesia, Iran, Kenya, Kyrgyzstan, Malawi, Moldova, Morocco, Nepal, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, and Tanzania.

[21] The UNIDO data cover formal sectors and thus miss informal/unregistered sectors that comprise a large share of employment in poorer countries (see for instance McCaig and Pavcnik, 2014). Consequently, reported average wages in these countries will be overstated (because informal wages are likely lower than formal wages) while export exposure tends to be more accurately measured (because small, informal, firms do not export). This might help explain low or even negative coefficients on the poor-dummy interactions in our regressions.

[22] These data are gathered by the World Bank. They can be accessed at http://www.enterprisesurveys.org/.

[23] The Investment Climate Survey covers only developing countries. In consequence, the richest countries in our classification are not surveyed. This is, however, not a shortcoming because the evidence we show works even for this more conservative comparison.

**Table 13**
Skill dispersion and income level at origin.

| | Average skilled share | | S. deviation skilled share | | S. deviation log wages | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Richer country dummy | 0.0391*** | | 0.0102** | | 0.117*** | |
| | (0.00695) | | (0.00452) | | (0.0340) | |
| Log p/c GDP origin | | 0.0182*** | | 0.000649 | | 0.0541*** |
| | | (0.00377) | | (0.00250) | | (0.0184) |
| Observations | 1088 | 1088 | 865 | 865 | 1101 | 1101 |
| $R^2$ | 0.216 | 0.209 | 0.093 | 0.088 | 0.087 | 0.085 |

Note: regressions of dispersion in skill utilization (at the industry level) and the level of income of the origin country. Significance at 1%, 5% and 10% levels indicated by ***, ** and *. Data from the Enterprise Surveys and World Development Indicators.

dispersion and the level of income of the country of origin. Results are in Table 13. Column 1 shows a positive correlation between average skilled shares and a country income-level indicator dummy, while column 2 shows a similar correlation with the log of per capita GDP. Column 3 and 4 uncover similar positive correlations between the standard deviation of the skilled shares and income. Finally, in columns 5 and 6, the dependent variable is the standard deviation of the (log) wage (relative to the mean) paid across industries. This is also a measure of dispersion in skills, if skilled workers earned higher wages. The results show that the positive correlations with country of origin income persist. Overall, thus, we interpret this evidence as an indication that higher income countries utilize a more disperse set of skill levels, within industries, which is consistent, again, with the notion that higher income countries produce more disperse qualities, within industries.

## 6. Conclusions

In this paper, we have set out to explore whether the income level in destination markets affects the average wage paid by exporters. The available evidence in support for the contention that exporting to high-income destinations conduces to higher equilibrium wages originates in case studies for Argentina and Mexico. Using cross-country panel data, we have provided systematic worldwide evidence to strongly support the maintained hypothesis: industries that are more exposed to high-income export destinations indeed pay higher wages, on average. We have also found evidence in favor of the operating mechanisms identified in the literature. On the one hand, the quality valuation mechanism suggests that higher-income countries demand higher quality, because consumers value quality and have a higher willingness to pay for it. On the other hand, the quality provision mechanism suggests that quality production requires higher quality inputs, in particular higher skilled labor, which are more expensive, and in particular commands higher wages. With this view, our results highlight the importance of quality in explaining the export wage premium and the welfare of a country's workforce.

The theory does not seem to apply for all countries, but rather for middle- to high-income countries. This is because poorer countries may face domestic constraints that impede the operation of the quality provision mechanism. For example, firm productivity in less developed countries may be bounded and this may limit the scope of quality production. Also, a skewed distribution of skills can create shortages of high skilled workers thus limiting quality production as well. These constraints could in turn be the result of frictions and distortions. With this view, our results illustrate additional implications of market imperfections on country's well-being and of policy to further enhance the development of poor economies.

## Appendix A. Data appendix

This Appendix briefly describes the Trade, Production and Protection database. Many more details on the data can be found in Nicita and Olarreaga (2007). The database includes annual data on trade flows (exports and imports), domestic production (output, value-added, employment, etc.), and trade protection (tariffs and non-tariff barriers) for 100 countries over the period 1976 to 2004. Due to some missing data, in the paper we use information for 82 countries, spanning the 1990–2000 period. The data is disaggregated into 28 manufacturing sectors, corresponding to the 3-digit level of the International Standard Industrial Classification (ISIC), Revision 2.

The source of domestic production related data is the United Nations Industrial Development Organization (UNIDO). The database includes information on output, value added, gross fixed capital formation, wage bill, number of establishments, and number of employees for each of the 28 manufacturing sectors. As pointed out by Nicita and Olarreaga (2007), UNIDO makes a great effort to standardize the data and make it comparable across countries and years. The panel is not balanced, because data may be missing for some countries/sectors/years.

The source of trade data is the COMTRADE database kept by the United Nations Statistic Division (UNSD). This data have been converted into the ISIC Revision 2 classification using concordance tables (see Jon Havemand website). Trade data contains exports and imports information, in both quantity and volume. While coverage is very complete, there are some missing observations

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