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Capital imports composition, complementarities, and the skill premium in developing countries☆

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ABSTRACT

We study how the composition of capital imports affects relative demand for skill and the skill premium in a sample of developing economies. Capital imports per se do not affect the skill premium; in contrast, their composition does. While imports of R&D-intensive capital equipment raise the skill premium, imports of less innovative equipment lower it. We estimate that R&D-intensive capital is complementary to skilled workers, whereas less innovative capital equipment is complementary to unskilled labor—which explains the composition effect. This mechanism has substantial explanatory power. Variation in tariffs, freight costs and overall barriers to trade, over time and across types of capital, favors imports of skill-complementary capital over other types. We calculate that reductions in barriers to trade increase inequality substantially in developing countries through the composition channel.

1. Introduction

The concurrent rise in trade flows and increase in the skill premium in several developing countries are the two of the most striking economic phenomena of the 1980s and 1990s (Goldberg and Pavcnik, 2007), and have prompted many economists to ask: Is there a causal relationship between the two? And if so, what is the mechanism? The failure of standard Heckscher–Ohlin theory to explain distributional changes across skill groups in developing countries has shifted focus to more nuanced forms of competition in the final goods space, or to other channels through which globalization may affect factor prices.[1,2]

In this paper we empirically study a new channel: Variation in the composition of capital equipment imports. While other papers highlight the role of capital imports under the assumption of capital–skill complementarity (Griliches, 1969) within structural quantitative trade models (Burstein et al., 2013; Parro, 2013), this paper is the first to test the mechanism directly, in a sample of developing countries. We find that capital imports per se do not affect the skill premium; rather, it is the *composition* of capital imports that matters. While imports of R&D-intensive capital equipment raise the skill premium, imports of less innovative capital equipment actually lower the skill premium.

As Fig. 1 illustrates, a high ratio of R&D-intensive capital relative to less innovative capital imports (henceforth, the capital import ratio) is associated with larger increases in the skill premium, while the overall

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[1] See Feenstra and Hanson (1996), Zhu and Trefler (2005), Yeaple (2005), Zeira (2007), Verhoogen (2008), Bustos (2011), Burstein and Vogel (2012), Harrigan and Reshef (2012) and Bonfatti and Ghatak (2013). Harrison et al. (2011) provide a recent survey.

[2] The failure to detect the Stolper–Samuelson effects in skill abundant countries, let alone in unskilled abundant countries, together with scant evidence of industry reallocations due to trade liberalization, has prompted many researchers to abandon the trade explanation altogether and focus on technological explanations, for example Berman et al. (1994) and Machin and Van Reenen (1998). However, see also Bernard and Jensen (1997) for evidence on the importance of trade-induced changes in demand for skill and reallocations across plants within industries.

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level of capital imports does not matter (as we illustrate below). A shift in the composition of imports towards R&D-intensive capital shifts the composition of investment in developing countries, and hence the composition of the capital stock towards more skill-complementary capital, and increases demand for skill. The explanatory power of this mechanism in our sample of developing countries is economically large: An increase in the capital import ratio from the first to the third quartile increases the change in the skill premium by two-thirds of the corresponding inter-quartile change, all else equal. This is the first contribution of this paper. We then investigate why this is the case.

We find that only R&D-intensive capital equipment is complementary to skilled labor; in contrast, we find that less innovative capital equipment is complementary to unskilled labor. To our best knowledge, we are the first to empirically document that some types of capital are more complementary to unskilled workers. Acemoglu (2002) suggests an explanation for why this is the case: An increase in the supply of skilled labor in industrial economies, which occurred during the same period that we study, "directs" more innovation and resources (read: R&D expenditures) towards developing skill-complementary machines, and relatively less towards machines that are complementary to unskilled workers (the "market size effect").[3]

In the model of Acemoglu (2003) technology firms in less developed countries copy blueprints of machines from developed countries (at some cost), produce them domestically, and sell to final goods producers. If the ability to successfully copy is not available or is not optimal, then importing machines from developed countries is another way to obtain the technology that they embody. Our work focuses on this channel of embodied technology diffusion. Indeed, developing countries import much of their equipment, which originates mostly in developed, skill abundant countries (Eaton and Kortum, 2001); therefore, we can treat capital imports as a good measure of investment in developing countries (Caselli and Wilson, 2004). We present detailed evidence that supports this argument. Therefore, it is reasonable to infer the characteristics of capital investment in developing economies based on data from developed economies.

Finally, we ask *whether* trade liberalization generally increases the skill premium. The capital composition mechanism described above only tells us *how* trade liberalization *may* increase the skill premium. In this context, the question is whether trade liberalization shifts the distribution of capital imports towards more skill-complementary equipment. We provide evidence that is consistent with this.

We show that tariffs and freight costs dropped more for skill-complementary capital imports than for unskilled-complementary capital imports. We also show that bilateral trade resistance fell differentially for skilled-complementary equipment relative to unskilled-complementary capital imports—both for our sample of developing countries and more generally. The increase in the import ratio through this mechanism alone increases the change in the relative wage of skilled workers in our sample of developing countries by 1–1.2% *per year*, which is about one third of the inter-quartile change.

This paper contributes to three broad strands of literature: Trade liberalization and changes in relative demand for skill; capital–skill complementarity; and the effect of computers on relative demand for skill.

First, we provide empirical evidence for a new mechanism that links trade liberalization and relative factor demand in developing countries—through the composition of capital imports. Caselli and Wilson (2004) document broad cross-country variation in the composition of capital imports by R&D intensity. They link this composition to differences in total factor productivity. Coe and Helpman (1995) and Acharya and Keller (2009) investigate the role of aggregate imports in facilitating R&D spillovers and technology transfers. None of these studies address changes in relative demand for skill and distributional consequences. Burstein et al. (2013) and Parro (2013) assume that aggregate capital is complementary to skill, but do not test whether this is indeed the case, nor do they allow for different types of capital with different complementarities.

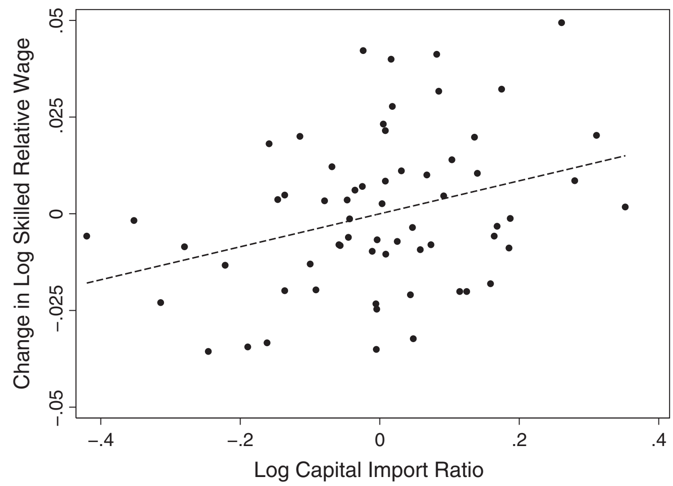

Fig. 1. Wage inequality and the composition of capital imports, 1983–2000. Notes: The figure displays the partial correlation between changes in log skilled relative wage, defined as the wage of non-production workers to production workers, and the capital import ratio, defined as the ratio of R&D-intensive capital equipment imports relative to less innovative capital equipment imports. We control for the change in skill abundance, country and period fixed effects, total capital imports divided by GDP, and shifts in the skill intensity of export shares; as in Table 6, column 3, the slope is 0.04 and the partial R^2 is 0.11.

Our work is also related to Koren and Csillag (2012), who show how imports of machines increase the wages of workers whose occupations are particularly complementary to those machines. While their estimates focus on micro, within-worker effects in Hungary alone, we address relative demand shifts for the entire economy, in 21 developing countries. Zhu and Trefler (2005) offer an elegant general equilibrium model and show how trade liberalization may increase demand for skill in developing countries through shifts in the composition of exports towards skill intensive goods. We exploit similar data in our analysis, and find that our mechanism is independent of theirs. We also demonstrate that the capital imports composition mechanism is a stronger mechanism for affecting the skill premium.

We highlight the effects of trade liberalization through the input side of production. For example, Amiti and Konings (2007) study how greater access to inputs increases productivity, and Goldberg et al. (2010) show how this may have an effect on growth in the number of products produced. Amiti and Davis (2012) find that trade liberalization increases average wages at firms that import more intermediate inputs in Indonesia, and offer a fair-wage mechanism to explain their findings. However, all these papers do not investigate distributional effects. Our work can help explain the results in Amiti and Cameron (2012), who find that imports of intermediate inputs tend to lower skill premia within firms in Indonesia.[4] Amiti and Cameron (2012) do not study complementarities of intermediate inputs with skilled and unskilled labor, and their results are confined to firms that actually import. While our results pertain to the entire economy, we conjecture that similar forces (composition of imported intermediate inputs in conjunction with complementarities) drive their results. Saravia and Voigtländer (2012) argue that high quality intermediate inputs substitute for skilled workers, but that the quality gains at the firm output level increase returns to employing skilled workers. In contrast to all these studies, we focus on aggregate, economy-wide relative demand effects that are not confined to importing firms alone. Thus, while our approach is less forensic in nature, we capture broader implications.

[3] Similar ideas are investigated in Galor and Moav (2000), but the framework in Acemoglu (2002) is more closely related to ours. Both are reminiscent of historical accounts of innovation and demand for skill in Goldin and Katz (2008).

[4] Indonesia is not one of the countries in our sample.

The second strand of literature to which we contribute studies capital–skill complementarity. Since the seminal work of Griliches (1969) it has become standard to assume that capital is complementary to skilled labor. Several studies adopt this framework in order to address questions on economic growth, trade, and inequality.[5] This body of work uses aggregate measures of capital; in contrast, we show that complementarities vary systematically at disaggregated levels. Our analysis reveals that it is the most innovative, R&D-intensive capital that is complementary to skilled workers, while other types of capital are in fact complementary to the unskilled. These results are robust to different definitions of skill. This can help explain the lack of robustness in previous attempts to test the aggregate capital–skill complementarity hypothesis, e.g., Duffy et al. (2004): Differences in the composition of capital across countries and over time may render the overall characterization of complementarity elusive.

Finally, our work is also related to the literature on computers and demand for skill. We find that the R&D-intensive, skill-complementary capital is, to a first approximation, mostly composed of information and communication technology (ICT) equipment. The work of Autor et al. (1998), Bresnahan et al. (1999), and Autor et al. (2003) all indicate that this type of equipment raises relative demand for skilled labor, although their empirical results focus on the U.S. Michaels et al. (2011) study the effect of ICT capital deepening on polarization of labor demand in developed countries. They find that ICT deepening reduces relative demand for medium-skilled workers, while increasing relative demand for high skill workers.[6] While we take advantage of similar distinctions between types of capital in some of our specifications, we investigate in greater detail the pattern of complementarities across more disaggregate types of capital, relate this pattern to R&D intensity, and find that other types of capital are actually complementary to unskilled labor—a new result. In addition, we apply our results to imports in developing countries.

After introducing the framework that underpins our analysis in Section 2, in Section 3 we document the strong effect of the composition of capital imports on the skill premium. In Section 4 we show that more R&D-intensive capital equipment is complementary to skilled labor, and that less innovative capital equipment is complementary to unskilled labor. Section 5 argues that trade liberalization increases inequality through the composition channel. Section 6 concludes.

2. Analytical framework

In this section we lay out a simple analytical framework to help organize the discussion. Since we are considering developing countries, we ignore the possibility to produce capital goods domestically, but allow them to import capital goods, whose prices are given internationally. We make an Armington assumption and let the final goods be differentiated by country of production. We ignore balanced trade considerations, since these are not essential to the analysis here.

There are two types of capital—C and K (think computers and tractors, respectively)—and two types of labor—skilled H and unskilled L. The aggregate production function for the economy is

$$Q = \left[\delta X^{\frac{\sigma-1}{\sigma}} + (1-\delta) Y^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where

$$X = H^{\beta} C^{1-\beta}$$

$$Y = L^{\beta} K^{1-\beta},$$

$\beta \in (0,1)$ and $\sigma > 1$. The only critical assumption here is that each type of capital is more complementary to one type of labor than with the other: C with H—and K with L. Any production function that maintains this property will suffice. We devote Section 4 to justifying this assumption. Although not a necessary assumption, this production function exhibits the same degree of complementarity between C and H as that between K and L, and equal expenditure shares. Allowing elasticities and βs to vary across X and Y complicates the discussion without providing additional insight. In fact, our estimates in Section 3 and in Section 4 are broadly consistent with this symmetry.[7] Estimates of the aggregate elasticity of substitution between H and L in the literature are typically above unity; this implies $\sigma > 1$.[8]

Workers supply labor—both H or L—inelastically. Denote the wage of skilled labor by w_H and the wage of unskilled labor by w_L. Denote the price of capital as r_j for $j \in \{C,K\}$. Competitive factor markets imply that factors are paid the value of their marginal product.[9]

Some algebra (see the Appendix) yields

$$\omega = \frac{\delta}{1-\delta}\left(\frac{H}{L}\right)^{-\frac{\sigma-\beta(\sigma-1)}{\sigma}}\left(\frac{C}{K}\right)^{\frac{(1-\beta)(\sigma-1)}{\sigma}}, \tag{1}$$

where $\omega \equiv w_H/w_L$. Holding constant C/K, greater skill abundance H/L reduces the relative wage of skilled labor ω. Holding constant H/L, a greater C/K ratio also increases ω as long as $\sigma > 1$.[10] Eq. (1) also shows that the overall quantity of capital $C + K$ is not important for determining ω: Only the composition matters.

Taking logs of Eq. (1) we have

$$\ln \omega = \kappa - \alpha \ln\left(\frac{H}{L}\right) + \lambda \ln\left(\frac{C}{K}\right), \tag{2}$$

where $\kappa = \ln[\delta/(1-\delta)]$, $\alpha = 1-\beta(\sigma-1)/\sigma$, and $\lambda = (1-\beta)(\sigma-1)/\sigma$. Taking differences of Eq. (2) yields

$$\Delta \ln \omega = -\alpha \Delta \ln\left(\frac{H}{L}\right) + \lambda \Delta \ln\left(\frac{C}{K}\right). \tag{3}$$

In the empirical counterpart to Eq. (3) we include country fixed effects (e.g., due to variation in changes in industrial structure δ) and other controls. We also include time effects to deal with common unobserved trends (e.g., disembodied technological change).

Before turning to the empirical analysis we make the following observation. An alternative interpretation of Q is utility over a skill intensive good X and a skill un-intensive good Y. This would open the door to production and export composition effects that are reminiscent of

[5] For example, Stokey (1996) and Krusell et al. (2000) and the aforementioned Burstein et al. (2013) and Parro (2013).

[6] For evidence on polarization and for the "routinization" hypothesis see Goos and Manning (2007) for the U.K., Autor et al. (2006) for the U.S., Harrigan et al. (2015) and Goos et al. (2009) for European and other developed countries.

[7] In Tables 6 and 7 the coefficients to skill-complementary and unskilled-complementary capital equipment are very similar in absolute value, with some tendency towards Y. Applying the latter point to the model further supports the proposed mechanism, making this a simplifying feature. Acemoglu (2002) also makes this assumption to streamline his model.

[8] The elasticity of substitution between H and L in the current framework is $\sigma / [\sigma - \beta(\sigma - 1)]$. If this is greater than unity, then so is σ, given $\beta \in (0,1)$. For the U.S., Katz and Murphy (1992) estimate an aggregate elasticity of substitution between college and high-school graduates at 1.4. More recent estimates are reported by Heckman et al. (1998) at 1.44, and Krusell et al. (2000) at 1.67. Despite estimating an elasticity of substitution in services at less than one, Reshef (2013) estimates an aggregate elasticity (that takes into account substitution across sectors, not just within) above one.

[9] The model is static, so we ignore capital depreciation. This does not affect our empirical analysis, unless depreciation rates vary systematically across countries and over time with changes in relative wages, which is unlikely. In the empirical implementation we control for time fixed effects, which absorb, inter alia, common time-varying depreciation.

[10] When $\sigma < 1$ a strong complementarity between X and Y changes the direction of the effect. Take the extreme case of $\sigma = 0$, i.e., fixed proportions in X and Y. An increase in C/K increases the relative supply of X/Y, but since there is no substitution we do not need as much X and hence demand for skilled labor falls.

Table 1
Capital goods classifications, R&D intensity and complementarity.

A. ISIC classifications		
	R&D intensity rank	Estimated complementarity in OECD data
Aircraft equipment (3845)	1	Skilled labor
Office, computing, and accounting machinery (3825)	2	Skilled labor
Communication equipment (3832)	3	Skilled labor
Professional goods (385)	4	–
Electrical equipment, excluding communication (383 *without* 3832)	5	Unskilled labor
Motor vehicles (3843)	6	–
Non-electrical equipment (382 *without* 3825)	7	Unskilled labor
Other transportation equipment (3842, 3844, 3849)	8	Unskilled labor
Fabricated metal products (381)	9	Unskilled labor
B. EU-KLEMS classifications		
	EU-KLEMS ICT classification	Estimated complementarity in EU-KLEMS data
Computing equipment	ICT	Skilled labor
Communication equipment	ICT	Skilled labor
Software	ICT	Skilled labor
Transportation equipment	Non-ICT	Unskilled labor
Machinery	Non-ICT	Unskilled labor

Notes: R&D intensity rank by ISIC, rev.2 (numbers in parentheses) in 1980 is from Caselli and Wilson (2004). This ranking is based on their estimates of world R&D expenditures divided by world sales for each capital good; it is the same whether R&D flows or stocks (perpetual inventory method) are used. See the Appendix for more detailed descriptions of ISIC capital classifications. We allocate EU-KLEMS ICT classifications to the ISIC classification based on the EU-KLEMS documentation. See O'Mahony and Timmer (2009) for documentation of the EU-KLEMS database. The degree of complementarity with skilled or unskilled labor is from the authors' baseline estimation.

Zhu and Trefler (2005) (henceforth, ZT)—but for different reasons and through a different mechanism. We shut down this channel in our framework because our analysis leads us to believe that the mechanism highlighted in ZT is not tightly related to ours. There are two reasons for this.

First, using data from EU-KLEMS (O'Mahony and Timmer (2009)), we find that changes in empirical counterparts of C and K contribute little to changes in relative demand for skill via changes in industrial composition alone, net of within-industry changes in skill intensity. This is done by multiplying the contribution of each type of capital to different industries' overall growth times industry skill intensity, and aggregating using industry weights in the beginning of the sample (see details in the Appendix and in Table A2). Moreover, it seems that K contributes just as much to increases in skill intensity through the industry composition channel as C does.[11] Second, the changes in export shares towards skill intensive goods in ZT (their Δz) are negatively correlated with the composition of capital imports (see Table A1). If an increase in demand for skilled labor is reflected in a shift in the composition of exports, then the correlation should have been in the opposite direction. This may not be surprising, since ZT examine only changes in the manufacturing export shares, while capital imports can affect the entire economy, not only the tradable sector. In the empirical implementation we control for Δz in all specifications.

3. Capital imports and the skill premium: 1983–2000

In this section we demonstrate that the composition of capital imports explains changes in skill premia in developing countries, whereas overall capital imports do not. We focus on the 1980s and 1990s, during which many developing countries—and specifically the ones in our sample—liberalized their international trade regimes.[12]

3.1. Data

Since we do not have empirical equivalents for C and K for developing countries, we rely on imports of capital to approximate changes in capital stocks, i.e., investment. This is a reasonable assumption for the developing countries in our sample, since they import most of their capital during our period of interest. We document this fact in detail in Section 3.2 below, as well as the tight correlation between imports and "implied investment" (defined below).

All trade data are from Feenstra et al. (2005). We break down total capital imports (M) into imports of R&D-intensive capital (M_H), and imports of relatively R&D-unintensive capital (M_L). Capital goods are defined as ISIC rev.2 category 38, "Manufacture of Fabricated Metal Products, Machinery and Equipment". R&D intensity ranking of capital goods in 1980 is taken from Caselli and Wilson (2004) and are briefly described in Table 1. Their ranking of nine types of equipment is based on estimates of world R&D expenditures divided by world sales for each capital good; it is the same whether R&D flows or stocks (perpetual inventory method) are used. M_H includes five of the most R&D-intensive capital equipment, while M_L includes the remainder least R&D-intensive capital equipment. This division is based on the estimated complementarity levels to skilled and unskilled labor, as demonstrated in Section 4 below. Our empirical equivalents of C and K are R&D-intensive and R&D-unintensive capital, respectively.

We merge import data with data on changes in relative skilled wages. We follow and extend Zhu and Trefler's (2005) methodology, encompassing the most comprehensive sample of developing countries for which there are data on relative skilled wages in the time sample of

[11] It is not surprising that non-ICT capital contributes just as much as ICT capital through this channel, since non-ICT capital is a much larger share of capital stocks. Berman et al. (1994) calculate that only 30% of the skill intensity increase in U.S. manufacturing in the 1980s is due to changes in industry composition. Our calculation is consistent with this.

[12] For instance, data from the World Bank's World Development Indicators (available at: http://data.worldbank.org/data-catalog/world-development-indicators) reveal that the average increase between 1980–1999 in the share of total trade in GDP for all countries in our sample is approximately 40%, having several countries more than doubling their trade share during this period, including Argentina, India, Mexico, Thailand, and the Philippines. Goldberg and Pavcnik (2007) provide evidence on trade-liberalizing policy changes during our period of interest in some of the countries in our sample, including Argentina, Mexico, India, and Hong Kong.

Table 2
Descriptive statistics.

	Mean	Median	Std. Dev.	Min.	Max.	25th percentile	75th percentile
$\Delta\ln(w_H/w_L)$	−0.003	−0.002	0.033	−0.093	0.071	−0.021	0.015
$\Delta\ln(H/L)$	0.043	0.032	0.053	−0.128	0.158	0.012	0.066
Δz	0.005	0.000	0.032	−0.065	0.156	−0.010	0.014
ln(import ratio)	−0.012	−0.038	0.425	−0.988	0.759	−0.317	0.290
ln(aggregate capital imports/*GDP*)	−9.513	−9.610	0.896	−11.348	−7.193	−10.031	−9.083
ln(R&D intensive capital imports/*GDP*)	−10.234	−10.384	0.952	−12.313	−7.958	−10.865	−9.620
ln(R&D un-intensive capital imports/*GDP*)	−10.222	−10.249	0.896	−11.827	−7.819	−10.829	−9.874
Δln(FDI)	0.068	0.083	0.407	−2.002	1.976	−0.003	0.183
$\Delta\ln(GDP/POP)$	0.045	0.054	0.080	−0.174	0.234	−0.001	0.092
ΔIndustrial share	−0.006	−0.002	0.036	−0.101	0.112	−0.025	0.008
ΔGovernment share	0.005	−0.007	0.099	−0.124	0.701	−0.026	0.018
ΔServices share	0.005	0.008	0.021	−0.062	0.043	0.000	0.016
ΔFinancial development	0.018	0.021	0.079	−0.230	0.301	−0.002	0.051
ΔIPR-protection	0.039	0.000	0.084	−0.240	0.284	0.000	0.066
$\Delta\ln(K)$	0.039	0.036	0.029	−0.005	0.115	0.021	0.048

Notes: The sample includes 63 observations, covering 21 developing countries over the period of 1983–2000. $\Delta\ln(w_H/w_L)$ is the change in the logarithm of skilled relative wage in manufacturing; $\Delta\ln(H/L)$ is the change in logarithm of aggregate relative supply of skill; Δz is the shift in export shares to high income OECD countries; ln(import ratio) is the logarithm of the ratio of R&D-intensive capital imports to R&D-unintensive capital imports; ln(capital imports/*GDP*) is the logarithm of capital imports (for the R&D intensive, unintensive, and the overall aggregated group) normalized by GDP; Δln(FDI) is the change in the logarithm of the average US FDI (2005 prices). $\Delta\ln(GDP/POP)$ is the change in the logarithm of GDP per capita. ΔIndustrial, ΔGovernment and ΔServices share are the changes in the logarithm of the sectoral value added shares in GDP. ΔFinancial-development is the change in the logarithm of M3 money supply as a fraction of GDP. ΔIPR-protection is the change in the Intellectual Property Rights Protection Index from Ginarte and Park (1997), updated by Park (2008). IPR-protection data are available every 5 years, so we linearly interpolate between observations within a country. $\Delta\ln(K)$ is the change in the logarithm of total real capital stock (Penn World Tables, mark 8.0); capital stock data is not available for Algeria. All variables in levels are averages within change periods, while all variables in changes are annual changes. For further details on countries in the sample, data construction and sources, see the Appendix.

interest. These are based on the availability of wages for non-production (skilled) and production workers in manufacturing from the International Labor Organization's occupational wage database. In addition to using a maximized sample, this has the advantage of direct comparability to ZT's results, with the difference of adding Hungary to the sample (for which data was previously unavailable). The sample includes 63 observations covering 21 developing countries in 1983–2000, and is an unbalanced panel due to data availability.[13] Although the sample is relatively small, this is the best data and most relevant sample. Despite the small sample size, the estimates are precise and robust.

We use the relative wage of non-production to production workers as our measure of skilled relative wages $\omega = w_H/w_L$.[14] We compute the shift towards more skill-intensive exports within a given period Δz, exactly as described in Zhu and Trefler (2005).[15] ZT argue that Δz can help explain changes in wage inequality; we examine below the relative importance of ZT's mechanism versus capital imports composition. Our measure of aggregate relative supply of skilled labor (skill abundance) (H/L) uses data from Barro and Lee (2013). Skilled workers H have at least secondary education and unskilled workers L have less than that level of education. Educational attainment data are available every 5 years, so we linearly interpolate between observations within a country.

We use the following ancillary control variables. From the World Bank's World Development Indicators: Government, services and industrial shares in value added; a measure of financial development (M3/GDP); GDP and population. We use data on foreign direct investment (FDI) position of U.S. multinational firms in the countries in our sample from the Bureau of Economic Analysis. We use the intellectual property rights protection index (IPR) from Ginarte and Park (1997), updated by Park (2008); these data are available every 5 years, so we linearly interpolate between observations within a country. Finally, we use the total capital stock data from the Penn World Tables, mark 8.0.[16]

Table 2 reports descriptive statistics for the main variables of interest. During the sample (a period of trade liberalization) the relative wage of skilled workers increased for half of the countries, while the other half experienced decreasing relative wage; overall, changes in w_H/w_L are roughly split between positive and negative changes. The log of the import ratio (M_H/M_L) is on average −0.012, which implies that R&D-intensive capital imports are approximately equivalent in value relative to R&D-unintensive capital imports ($e^{-0.012} \approx 0.99$).

Importantly, we find a relatively weak and statistically insignificant correlation between $\Delta\ln(H/L)$ and $\ln(M_H/M_L)$. This is important because, as we discuss below in more detail, the potential endogeneity of $\Delta\ln(H/L)$ does not bias the estimator of the coefficient to $\ln(M_H/M_L)$. In other words, it is reasonable to assume conditional mean independence for $\ln(M_H/M_L)$ with respect to $\Delta\ln(H/L)$.

3.2. Imports and investment

In this section we make two important points: First, that capital imports account for most of the investment in the sample of countries that we examine; and second, that capital imports are strongly correlated with investment. Before doing so, we describe the distribution of capital imports and changes thereof.

Table 3, Panel A reports the distribution of capital imports. The sample is restricted to the unbalanced panel that is described above and in greater detail in the Appendix. There is substantial variation in these shares across countries in our sample. On average, the shares of M_H, and M_L are 48.4%, and 51.6%, respectively. Panel B documents substantial variation across countries in the changes in these shares. On average, the share of M_H increases by 0.5% points *per year*, offset by a commensurate decrease in the share of M_L; capital imports become

[13] The criterion for being considered a developing country is having real GDP per capita below $14,000 in 1980. The countries in the sample are: Algeria, Argentina, Barbados, Bolivia, Central African Republic, Cyprus, Honduras, Hungary, Hong Kong, India, South Korea, Sri Lanka, Madagascar, Mauritius, Mexico, the Philippines, Singapore, Thailand, Trinidad and Tobago, Uruguay, and Venezuela. See the Appendix for the years in which each country is observed.

[14] Proxying skill by "non-production" is problematic, though it is common practice by necessity. Berman et al. (1994) show that for the United States, the production/non-production worker classification is a good proxy for skilled and unskilled workers. In our estimation of complementarities below we entertain other definitions of skill.

[15] See the Appendix for details on the construction of Δz, which we extended (following ZT's methodology) to 2000.

[16] Penn World Tables, mark 8.0 is available at the University of Groningen, http://citaotest01.housing.rug.nl/febpwt/Home.mvc.

Table 3
Capital import shares and changes in capital import shares.

		R&D intensity rank										
		1	2	3	4	5	6	7	8	9	1+2+3+4+6	5+7+8+9
		Capital type										
		Aircraft equipment	Office, computing, and accounting machinery	Communication equipment	Professional goods	Electrical equipment, excluding communication	Motor vehicles	Non-electrical equipment	Other transportation equipment	Fabricated metal products	M_H	M_L
A. Average capital import shares												
Algeria	1985–1992	0.019	0.026	0.052	0.070	0.158	0.160	0.370	0.020	0.125	0.328	0.672
Argentina	1991–1995	0.024	0.091	0.146	0.065	0.157	0.250	0.181	0.031	0.055	0.577	0.423
Barbados	1985–1995	0.007	0.078	0.096	0.060	0.210	0.286	0.156	0.002	0.106	0.527	0.473
Bolivia	1991–1997	0.028	0.036	0.095	0.037	0.132	0.267	0.284	0.009	0.112	0.463	0.537
Central African Republic	1987–1993	0.013	0.058	0.078	0.033	0.081	0.409	0.226	0.021	0.081	0.591	0.409
Hong Kong	1983–1997	0.017	0.098	0.203	0.170	0.302	0.049	0.094	0.018	0.049	0.537	0.463
Cyprus	1983–2000	0.054	0.051	0.143	0.072	0.120	0.326	0.135	0.007	0.092	0.646	0.354
Honduras	1983–1997	0.043	0.036	0.082	0.045	0.132	0.248	0.292	0.011	0.111	0.454	0.546
Hungary	1995–2000	0.003	0.152	0.168	0.055	0.270	0.140	0.130	0.013	0.069	0.517	0.483
India	1986–1997	0.093	0.068	0.062	0.129	0.190	0.061	0.334	0.025	0.040	0.412	0.588
Korea	1983–1997	0.057	0.074	0.078	0.116	0.313	0.036	0.281	0.006	0.038	0.362	0.638
Madagascar	1983–1995	0.031	0.041	0.061	0.053	0.091	0.315	0.300	0.025	0.082	0.501	0.499
Mauritius	1983–2000	0.132	0.041	0.110	0.129	0.099	0.170	0.225	0.013	0.082	0.582	0.418
Mexico	1990–1997	0.015	0.072	0.107	0.063	0.292	0.170	0.179	0.008	0.093	0.428	0.572
Philippines	1983–1999	0.049	0.070	0.080	0.047	0.396	0.097	0.202	0.014	0.045	0.343	0.657
Singapore	1985–1997	0.044	0.158	0.150	0.078	0.356	0.034	0.132	0.007	0.041	0.464	0.536
Sri Lanka	1983–1997	0.058	0.038	0.112	0.052	0.137	0.226	0.237	0.062	0.078	0.486	0.514
Thailand	1984–1995	0.037	0.094	0.083	0.061	0.246	0.146	0.257	0.016	0.059	0.421	0.579
Trinidad and Tobago	1985–1996	0.073	0.053	0.056	0.060	0.112	0.192	0.363	0.001	0.089	0.434	0.566
Uruguay	1985–1995	0.010	0.060	0.123	0.067	0.127	0.353	0.207	0.014	0.040	0.613	0.387
Venezuela	1984–1997	0.008	0.059	0.080	0.068	0.133	0.269	0.314	0.017	0.053	0.483	0.517
Average across countries		0.039	0.069	0.103	0.073	0.193	0.200	0.233	0.016	0.073	0.484	0.516
B. Average annual changes in capital import shares												
Algeria	1985–1992	−0.003	0.001	0.008	0.005	0.010	−0.007	−0.005	−0.003	−0.006	0.004	−0.004
Argentina	1991–1995	0.004	−0.005	−0.007	−0.006	−0.006	0.016	0.002	−0.005	0.005	0.003	−0.003
Barbados	1985–1995	−0.001	0.003	0.000	0.002	−0.029	0.020	0.006	0.000	−0.002	0.025	−0.025
Bolivia	1991–1997	0.008	0.001	0.023	−0.002	0.000	−0.015	−0.012	−0.001	−0.001	0.014	−0.014
Central African Republic	1987–1993	0.001	0.003	0.003	−0.003	−0.003	0.002	0.002	−0.001	−0.005	0.008	−0.008
Hong Kong	1983–1997	−0.001	0.006	0.007	−0.009	0.002	0.000	0.000	−0.001	−0.004	0.003	−0.003
Cyprus	1983–2000	0.002	0.003	−0.001	−0.004	−0.001	0.003	−0.001	0.000	−0.002	0.004	−0.004
Honduras	1983–1997	−0.001	0.002	0.001	−0.003	−0.002	0.009	−0.003	−0.001	−0.004	0.009	−0.009
Hungary	1995–2000	0.000	0.011	0.005	−0.007	0.028	−0.011	−0.006	−0.009	−0.011	−0.002	0.002
India	1986–1997	0.003	0.007	0.003	0.003	0.002	0.001	−0.017	−0.002	0.001	0.016	−0.016
Korea	1983–1997	−0.001	0.002	−0.004	0.002	0.010	−0.002	−0.005	−0.001	−0.001	−0.004	0.004
Madagascar	1983–1995	0.001	0.004	0.008	−0.001	−0.004	0.008	−0.012	−0.001	−0.002	0.020	−0.020
Mauritius	1983–2000	0.006	0.004	0.003	−0.006	−0.001	0.005	−0.008	0.000	−0.003	0.011	−0.011
Mexico	1990–1997	−0.004	−0.005	−0.003	−0.002	0.035	−0.016	−0.010	−0.002	0.006	−0.029	0.029
Philippines	1983–1999	−0.003	0.007	0.000	−0.001	0.014	−0.004	−0.008	−0.001	−0.003	−0.002	0.002
Singapore	1985–1997	−0.004	0.010	−0.001	−0.001	0.004	−0.001	−0.004	0.000	−0.003	0.002	−0.002
Sri Lanka	1983–1997	−0.002	0.007	0.001	0.000	−0.001	−0.003	0.003	0.001	−0.006	0.004	−0.004
Thailand	1984–1995	0.001	0.004	−0.002	−0.002	0.009	−0.002	−0.009	−0.001	0.001	−0.001	0.001
Trinidad and Tobago	1985–1996	−0.004	0.002	−0.002	−0.001	0.000	0.004	0.000	0.000	0.002	−0.001	0.001
Uruguay	1985–1995	−0.001	0.001	−0.004	0.002	−0.002	0.011	−0.008	0.002	−0.002	0.010	−0.010
Venezuela	1984–1997	0.000	0.004	0.003	−0.001	0.000	−0.001	−0.004	−0.001	0.001	0.005	−0.005
Average across countries		0.000	0.003	0.002	−0.002	0.003	0.001	−0.005	−0.001	−0.002	0.005	−0.005

Notes: In Panel A import capital shares are computed as shares in total capital imports and averaged over the sample used for the regressions in Tables 5–8. Country samples are noted next to each country. In Panel B average annual changes in capital import shares are computed as the share in the last year minus the share in the first year divided by the number of years for each country. Averages over all countries are reported below country data. Import data are from Feenstra et al. (2005).

Table 4
Import and net import shares in implied investment.

	H		*L*		All	
	Imports	Net imports	Imports	Net imports	Imports	Net imports
Algeria	–	–	–	–	–	–
Argentina	0.35	0.27	0.30	0.25	0.33	0.26
Barbados	1.06	0.87	0.61	0.19	0.76	0.45
Bolivia	0.98	0.94	0.84	0.83	0.90	0.87
Central African Republic	0.91	0.89	0.79	0.78	0.85	0.83
Hong Kong	1.71	0.55	0.76	0.42	1.02	0.48
Cyprus	1.07	0.95	0.55	0.47	0.80	0.71
Honduras	0.95	0.94	0.56	0.54	0.69	0.67
Hungary	0.58	0.00	0.70	0.11	0.62	0.05
India	0.14	0.09	0.11	0.04	0.12	0.06
Korea	0.28	−0.16	0.27	0.05	0.25	−0.01
Madagascar	0.89	0.87	0.72	0.71	0.78	0.77
Mauritius	0.99	0.71	0.67	0.64	0.83	0.68
Mexico	1.11	−0.93	1.26	0.24	1.14	−0.16
Philippines	1.07	0.08	1.05	0.05	1.28	−0.18
Singapore	0.84	−0.05	0.86	0.38	0.94	0.20
Sri Lanka	0.95	0.88	0.82	0.75	0.88	0.81
Thailand	0.86	0.34	0.49	0.31	0.58	0.33
Trinidad and Tobago	0.81	0.79	0.60	0.57	0.68	0.65
Uruguay	0.68	0.50	0.39	0.34	0.53	0.42
Venezuela	0.44	0.38	0.39	0.34	0.41	0.36
Average	0.85	0.45	0.65	0.40	0.73	0.42

Notes: This table reports average shares of imports and net imports (= imports − exports) in implied investment for two types of capital goods and for their sum, where implied investment = output + imports − exports. Capital types are: H = high R&D intensity (ranks 1, 2, 3, 4, 6), skill-complementary; L = low R&D intensity (ranks 5, 7, 8, 9), unskilled-complementary; All = $H + L$. Import data correspond to this classification exactly; output data do not distinguish aircraft equipment from other transportation equipment, which are included in group L. Output data are from UNIDO and trade data are from Feenstra et al. (2005). The sample is the same as that in the inequality regressions, but due to UNIDO data limitations the sample is not full for all countries; in particular, there are no output data for Algeria.

Table 5
Correlation between capital imports and implied investment.

	H		*L*		All	
	Investment type					
	Imp.	Net imp.	Imp.	Net imp.	Imp.	Net imp.
Algeria	–	–	–	–	–	–
Argentina	0.87	0.96	−0.12	0.24	0.64	0.81
Barbados	0.96	0.97	−0.45	0.58	0.31	0.71
Bolivia	0.98	1.00	1.00	1.00	0.99	1.00
Central African Republic	0.94	0.95	0.70	0.71	1.00	1.00
Hong Kong	0.99	1.00	0.99	0.98	1.00	0.99
Cyprus	0.96	1.00	0.98	0.98	0.97	0.99
Honduras	1.00	1.00	0.97	0.97	0.99	0.99
Hungary	0.97	−0.94	0.98	0.99	0.99	0.51
India	0.89	0.41	0.66	−0.01	0.82	0.13
Korea	0.97	−0.71	0.98	−0.42	0.99	−0.75
Madagascar	0.95	0.93	0.95	0.94	0.94	0.93
Mauritius	1.00	0.99	0.99	0.99	1.00	0.99
Mexico	0.57	0.43	0.97	0.98	0.83	0.40
Philippines	0.97	−0.40	0.70	0.29	0.81	0.06
Singapore	1.00	−0.89	0.88	0.89	1.00	0.98
Sri Lanka	0.99	0.99	0.99	0.98	1.00	0.99
Thailand	0.82	−0.01	0.92	0.94	0.91	0.86
Trinidad and Tobago	0.87	0.88	0.49	0.54	0.70	0.72
Uruguay	0.78	0.92	0.96	0.97	0.88	0.94
Venezuela	0.91	0.88	0.79	0.85	0.88	0.88
Average	0.92	0.50	0.76	0.71	0.88	0.70

Notes: This table reports pairwise correlation coefficients between implied investment and imports of capital goods or net imports of capital goods for two types of capital goods and for their sum. Implied investment = output + imports − exports. Net imports = imports − exports. Capital types are: H = high R&D intensity (ranks 1, 2, 3, 4, 6), skill-complementary; L = low R&D intensity (ranks 5, 7, 8, 9), unskilled-complementary; All = $H + L$. Import data correspond to this classification exactly; output data do not distinguish aircraft equipment from other transportation equipment, which are included in group L. Output data are from UNIDO and trade data are from Feenstra et al. (2005). The sample is the same as that in the inequality regressions, but due to UNIDO data limitations the sample is not full for all countries; in particular, there are no output data for Algeria.

more R&D intensive and more skill-complementary over time. Over the period 1983–2000 there is a shift of 8.5 percent points towards M_H.

We now assess the importance of capital imports in "implied investment", which we define as domestic absorption of capital equipment

$$I = Y + M - X,$$

where Y is output, M are imports and X are exports. Output data on capital equipment are from UNIDO (2013), and are available at the 2-digit ISIC rev.3 classification. The 2-digit classification allows aggregating up to the two main groups that are also used for imports and exports. The only mismatch is for aircraft equipment, which cannot be separated from "other transport equipment", and is allocated to Y_L. [17] The main limitation of the UNIDO data is that country and year coverage are sparse for our sample. Another limitation is that part of "implied investment" of capital goods may be, in fact, absorbed by households as durable goods.[18] Nevertheless, the data are informative. We match import data to output data for all possible observations.

Table 4 reports the share of imports in implied investment, M/I. On average, M_H and M_L are 83% and 64% of H-type and L-type investments respectively, with the notable outliers of Korea and India (which produce and export much of this equipment). Overall, imports are 72% of investment. We also report shares of net imports (=$M - X$) in investment. Net imports can help offset the effect of importing intermediate inputs that are assembled and then exported, when both flows fall within the same classification. The shares of net imports in investment are necessarily lower (especially for Mexico, due to the maquiladora sector), but they are still substantial, especially for H-type investment.

Next, we turn to the correlation of imports with implied investment. Table 5 reports pairwise correlation coefficients between the two types of implied investment and capital imports or net imports, of the respective kind. In addition, the table reports correlations of total investment with total capital imports or net imports. By and large, imports and net imports are highly correlated with investment. The exceptions occur for countries that are big exporters of capital of a particular type, where net imports are negatively correlated with investment. This is a consequence of output being strongly correlated with exporting for these cases. For example, Korea is a big exporter of all capital types; India exports L-type, but not H-type capital. The regression results in the next two sections are robust to the exclusion of these countries.

Overall, the evidence implies that capital imports are a good approximation for investment. It is likely to be particularly good for H-type investment, since developing countries rely much more on imports of R&D-intensive capital, relative to R&D-unintensive capital.

3.3. Capital imports and the skill premium: OLS estimates

We now turn to testing our main hypothesis. Eq. (3) implies a relationship between changes in relative skilled wages $\omega = w_H/w_L$ and changes in the ratio of skill-complementary to unskilled-complementary capital (C/K), but not with overall levels of capital ($C + K$). We approximate changes in C/K with the import ratio. Changes in $\ln(C/K)$ do not map precisely into $\ln(M_H/M_L)$. Therefore, we

[17] The relevant 2-digit ISIC rev.3 categories are: 28 Fabricated Metal Products, 29 Machinery and Equipment n.e.c., 30 Office, Accounting And Computing Machinery, 31 Electrical Machinery and Apparatus, 32 Radio, Television and Communication Equipment, 33 Medical, Precision and Optical Instruments, 34 Motor Vehicles, Trailers, Semi-trailers, and 35 Other Transport Equipment. Y_H includes 30 + 32 + 33 + 34, and Y_L includes 28 + 29 + 31 + 35.

[18] For example, "Office, Accounting and Computing Machinery" (ISIC 3825) may include computers for personal use; "Motor Vehicles" (ISIC 3843) may include cars for personal use.

Table 6
Capital import composition and the skill premium, 1983–2000.

A. Baseline results (OLS and TSLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $\Delta\ln(w_H/w_L)$					
	Estimator					
	OLS	OLS	OLS	OLS	TSLS	TSLS
$\Delta\ln(H/L)$	−0.001	0.006	0.005	0.006	0.005	0.008
	(0.16)	(0.13)	(0.14)	(0.14)	(0.09)	(0.09)
$\ln(M_H/M_L)$		0.04***	0.04***		0.05***	
		(0.01)	(0.01)		(0.02)	
$\ln(M/GDP)$	−0.006		−0.01		−0.01	
	(0.02)		(0.01)		(0.02)	
$\ln(M_H/GDP)$				0.036**		0.05*
				(0.01)		(0.03)
$\ln(M_L/GDP)$				−0.048***		−0.06**
				(0.02)		(0.03)
Δz	0.45***	0.47***	0.51***	0.51***	0.52***	0.53***
	(0.13)	(0.14)	(0.15)	(0.15)	(0.12)	(0.67)
Observations	63	63	63	63	63	63
No. of countries	21	21	21	21	21	21
Degrees of freedom	35	35	34	34	34	34
R-squared, within	0.24	0.31	0.32	0.32	0.68	0.67

B. First-stage results for TSLS

	(5)	(5)	(6)	(6)
Dependent variable	$\ln(M_H/M_L)$	$\ln(M/GDP)$	$\ln(M_H/GDP)$	$\ln(M_L/GDP)$
$\ln M_H M_L$_gravity	0.98***	0.19		
	(0.03)	(0.19)		
$\ln M$gdp_gravity	0.007	0.44***		
	(0.02)	(0.13)		
$\ln M_H$gdp_gravity			0.92***	0.13
			(0.23)	(0.23)
$\ln M_L$gdp_gravity			−0.28	0.48*
			(0.25)	(0.25)
Instrument strength statistics				
Shea's partial R-squared	0.88	0.27	0.3	0.27
Partial R-squared	0.98	0.3	0.44	0.39
F-statistic	573.26	8.3	18.55	8.01

Notes: All specifications include country and period fixed effects. Standard errors clustered by country in parentheses. The dependent variable is $\Delta\ln(w_H/w_L)$, the change in the logarithm of skilled relative wage. Main explanatory variables: $\Delta\ln(H/L)$ is the change in logarithm of relative supply of skill; $\ln(M_H/M_L)$ is the logarithm of the ratio of R&D-intensive capital imports to R&D-unintensive capital imports; $\ln(M/GDP)$ is the logarithm of aggregate capital imports divided by GDP, and similarly for M_H, and M_L. Δz is the shift in export shares as in Zhu and Trefler (2005). $\ln M_H M_L$_gravity, $\ln M_H$gdp_gravity, $\ln M_L$gdp_gravity, and $\ln M$gdp_gravity are the import ratio, R&D-intensive, R&D-unintensive, and aggregate imports instruments, respectively. All variables in levels are averages within periods, while all variables in changes are annual changes. See the Appendix for further details on countries in the sample, data construction and sources.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

experiment with several specifications: We use each type of capital imports as a ratio to GDP, to population and to the total capital stock, or simply in logs. We also estimate specification not in logs. The results are not sensitive to these changes and are reported in the Appendix.

We estimate the empirical counterpart to Eq. (3),

$$\Delta\ln\omega_{it} = \lambda\ln\left(\frac{M_H}{M_L}\right)_{it} + \theta\ln\left(\frac{M}{GDP}\right)_{it} + \alpha\Delta\ln\left(\frac{H}{L}\right)_{it} + \eta\Delta z_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \tag{4}$$

where γ_i and δ_t are country and period fixed effects, respectively, that are included in all specifications. We always include Δz_{it} in order to compare our mechanism to that in (Zhu and Trefler, 2005). Due to data constraints the change intervals (Δ) are not all perfectly aligned and are of different lengths, so country-specific intervals are grouped into five periods (t), and changes are annualized. On average, each country is observed in three periods; in the Appendix we list all country-specific intervals and common periods. We normalize overall capital imports by GDP. Variables not in changes are averaged within the period in order to be consistent with the annualized changes.

The coefficients of interest are λ and θ. Our hypothesis is that $\lambda > 0$ and $\theta = 0$.

Table 6 reports the results of estimating Eq. (4); we start with OLS and then in Section 3.4 we report TSLS estimates. Column 1 shows that the overall capital imports are not associated with changes in inequality, and column 2 shows that the import ratio is positively correlated with increases in the relative skilled wage.

Column 3 delivers the main message of this section: Even in the presence of overall capital imports, only the composition matters for changes in relative skilled wages, as we observe a positive and statistically significant coefficient to the latter in conjunction with a statistically insignificant one to the former. The partial R^2 of the import ratio in this regression is 0.11 (this is the regression underlying Fig. 1). The explanatory power of the import ratio is economically large: An increase from first to third quartiles increases the change in the skill premium by two-thirds of the corresponding inter-quartile change, all else equal. The equivalent change in Δz has roughly half of this effect.[19]

Column 4 shows that both the numerator M_H and the denominator M_L of the import ratio have explanatory power, in opposite directions. The coefficients to $\ln(M_H/GDP)$ and $\ln(M_L/GDP)$ are precisely estimated, and are relatively similar in absolute value, which is consistent with our assumption on the output elasticities and shares (β) in Section 2 above.

3.3.1. Robustness checks for the capital composition mechanism

In Table 7 we check the robustness of our results to adding a set of ancillary control variables (OLS estimates). If multinationals are important actors that import equipment, and employ superior disembodied technology that is also skill biased, then omitting their activity may induce a bias to the estimator of the coefficient to the import ratio. Note that both premises need to be true in order to create bias. In order to guard against this potential bias we add FDI position of U.S. multinational firms in the target country. If economic development is itself a skill-biased process that also increases incentives for more skill-complementary imports, then this would again induce bias; therefore we control for GDP per capita. Next, we add shares in value added of the industrial (manufacturing), government and services sectors. These may capture the effect of structural change on the skill premium. We also add a proxy for financial development (M3 money supply divided by GDP) to capture the ability to finance investment. We add the IPR protection index to correct for potential bias if exporters are less likely to export R&D-intensive equipment to countries that do not enforce IPR, which in turn have inherently less demand for skill.[20] We control for the aggregate real capital stock, in order to show that the capital import composition mechanism operates independently of total net investment, not only independently of total capital imports.[21] Due to data limitations, adding these variables reduces the sample size.

Overall, the results in Table 7 indicate that adding these control variables, either in changes—which we think is the more appropriate specification—or in levels (averages within periods), does not affect the main conclusion of this section. The point estimates of λ do not change much and overall retain their precision. Only when we add all control variables in levels, the estimates become less precise, but this is hardly surprising since we are left with only 20 degrees of freedom. In contrast, it is reassuring that the estimates remain precise in all other specifications, where regressors are added one at a time.

Table 8 reports additional checks of the composition mechanism (OLS estimates). First, it is possible that capital is imported only to be used as an input into producing and exporting goods that fall within the same broad classification. This can happen due to the relatively high level of aggregation. In order to address this concern we add interaction terms for four countries that export significant amounts of capital goods: India, Korea, Mexico, and the Philippines.[22] The results in columns 1 and 2 show no differential effect for these four countries, and the main effects do not change much.

Second, unobserved quality of capital imports may be a complementary mechanism to ours. If high income countries produce high quality products—overall, or within R&D ranks—and it is only high quality equipment that is complementary to skilled labor, then the results may be driven by imports from high income countries.[23] In order to address this concern we identify the six largest capital exporters in our period of interest, based on Eaton and Kortum (2001): France, Germany, Italy, Japan, United Kingdom, and the United States. These are also high income countries that, presumably, produce high quality equipment. We construct separate capital import variables for flows originating in these six major producers and for flows that originate elsewhere, and fit specification that are similar to the baseline results in Table 6.

Overall, the results in columns 3–8 in Table 8 do not indicate that the baseline results in Table 6 are driven by quality differentiation. In columns 3–4 we use only imports from countries other than the six major exporters (denoted "rest" in Table 8); in columns 5–6 we use only imports that originate from the six major exporters. These results are very similar to the baseline results in columns 3 and 4 of Table 6. In columns 7 and 8 we include capital imports originating from both types of sources. In column 7 both coefficients to overall capital imports are small and statistically insignificant.[24] Although there is a large drop in the coefficient to the import ratio from high income countries, strong collinearity among the regressors prevents separate identification.

Finally (results are reported in the Appendix), the estimates of the main specifications of columns 3 and 4 of Table 6 are virtually unchanged, both in magnitude and statistical significance, if we normalize capital imports by population or total capital stock, rather than by GDP, or do not normalize at all. This is because capital imports have sufficient independent variation across countries and time, over and above their relationship to country size.

3.4. Capital imports and the skill premium: TSLS estimates

One potential concern in estimating Eq. (4) is endogeneity. For example, technological shocks that are not Hicks-neutral or are sector-specific may drive up both demand for skilled labor and imports of specific types of equipment. Another concern is omitted variable bias. For example, some intermediate inputs may be associated with specific imported equipment; if these inputs must be imported, and if they have systematic patterns of complementarity that correlate with those of capital equipment, then they can bias the estimator.[25] Although we try to address these concerns with the ancillary control variables in Table 7, they remain a threat to the internal validity of our estimates. An additional potentially endogenous variable in Eq. (4) is $\Delta\ln(H/L)$. We stress that since $\Delta\ln(H/L)$ is statistically uncorrelated with $\ln(M_H/M_L)$, any bias in the estimator of the coefficient to $\Delta\ln(H/L)$ does not affect the estimator of the coefficient to $\ln(M_H/M_L)$.

We construct the following instruments for capital imports, which are inspired by the methodology of Frankel and Romer (1999). As they do, we exploit exogenous geographic variation that affects bilateral trade flows—in our case dyadic distance—to construct instruments for trade flows by country—in this case imports. We estimate the following equation for capital type H and L and for all capital imports separately for each importer, country and year:

$$\ln M_{oit} = \alpha_{it} + \delta_{it} \ln DISTANCE_{oi} + \varepsilon_{oit}, \tag{5}$$

where M_{oit} is capital imports of type H and L or all capital imports, from origin country o to destination country i in year t, and $DISTANCE_{oi}$ is the distance (great circle) from o to i. Here α_{it} captures destination–year specific effects, and δ_{it} allows the effect of distance to vary by destination

[19] For Δz $0.5 \times [0.014 - (-0.010)] = 0.012$, and for the log import ratio $0.04 \times [0.290 - (-0.317)] = 0.024$; these represent 67% and 33% of the inter-quartile change in $\Delta\ln\omega$ of $0.036 = [0.015 - (-0.021)]$.

[20] FDI, sectoral shares, financial development and intellectual property rights protection are also used by (Caselli and Wilson, 2004) as explanatory variables for capital imports.

[21] Results are similar if instead of capital K we use the capital-output ratio K/Y, $\ln(K/Y)$ or $d\ln(K/Y)$. The results are available by request.

[22] These countries have a correlation of less than 0.5 between net imports and implied investment; see Table 5.

[23] For quality-differentiation of exports by income see Schott (2004) and Hummels and Klenow (2005). Koren and Csillag (2012) and Saravia and Voigtländer (2012) differentiate between domestic and imported machines and intermediate inputs, respectively. They do not differentiate among sources of imports.

[24] This result is the same when we drop the import ratios from high income and other countries.

[25] To the extent that this is true, one can interpret our estimates as inclusive of this secondary effect. We do not include imports of intermediate inputs in Eq. (4) for two reasons. First, it is not obvious how to estimate complementarities for intermediate inputs: They are variable inputs, not quasi-fixed, and therefore without price data we cannot classify them by degree of complementarity. Second, the bulk of intermediate inputs is produced and supplied domestically, as many studies point out, for example Amiti and Cameron (2012). Therefore, imported inputs do not satisfy our identifying assumption, that imports are a good measure of flows of total usage (in our case, investment).

Table 7
Capital import composition and the skill premium, additional controls, 1983–2000.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable	$\Delta\ln(w_H/w_L)$																	
$\Delta\ln(H/L)$	−0.00	−0.01	0.01	−0.03	0.01	0.00	−0.01	0.02	−0.03	0.04	−0.00	−0.02	−0.03	−0.02	0.00	−0.00	0.01	−0.07
	(0.145)	(0.127)	(0.155)	(0.137)	(0.149)	(0.135)	(0.126)	(0.154)	(0.146)	(0.144)	(0.129)	(0.140)	(0.142)	(0.142)	(0.131)	(0.111)	(0.143)	(0.109)
$\ln(M_H/M_L)$	0.05***	0.03*	0.05***	0.04***	0.04***	0.04***	0.03**	0.04**	0.03*	0.04**	0.04***	0.05***	0.03**	0.04**	0.04**	0.04**	0.04**	0.04
	(0.014)	(0.015)	(0.009)	(0.013)	(0.013)	(0.014)	(0.018)	(0.015)	(0.017)	(0.016)	(0.013)	(0.014)	(0.014)	(0.017)	(0.015)	(0.018)	(0.014)	(0.031)
$\ln(M/GDP)$	−0.01	−0.02	−0.02	−0.01	−0.01	−0.01	−0.00	0.00	0.01	−0.02	−0.01	−0.03*	−0.00	−0.01	−0.01	−0.00	−0.01	−0.04
	(0.018)	(0.018)	(0.013)	(0.019)	(0.018)	(0.017)	(0.024)	(0.019)	(0.024)	(0.015)	(0.017)	(0.016)	(0.020)	(0.018)	(0.018)	(0.020)	(0.017)	(0.039)
Δz	0.49***	0.50***	0.60***	0.50***	0.49***	0.45***	0.37*	0.49***	0.39	0.51***	0.49***	0.71***	0.50***	0.50***	0.51***	0.46**	0.51***	0.69***
	(0.157)	(0.150)	(0.165)	(0.167)	(0.152)	(0.139)	(0.183)	(0.158)	(0.273)	(0.149)	(0.154)	(0.145)	(0.166)	(0.165)	(0.138)	(0.173)	(0.155)	(0.172)
	Control variables in changes									Control variables in levels								
ln(FDI)	−0.01								−0.02*	−0.01								−0.02
	(0.008)								(0.010)	(0.008)								(0.014)
$\ln(GDP/POP)$		0.13*							0.09		0.01							0.05**
		(0.066)							(0.070)		(0.014)							(0.023)
Financial development			0.09						0.04			−0.03						−0.05
			(0.057)						(0.083)			(0.018)						(0.035)
Industrial share				0.12					0.34				−0.05					0.03
				(0.156)					(0.229)				(0.055)					(0.171)
Services share					0.10				0.44*					0.06				0.12
					(0.240)				(0.249)					(0.096)				(0.218)
Government share						0.08***			0.04						−0.03			−0.03
						(0.024)			(0.035)						(0.028)			(0.043)
IPR-protection							0.09		0.03							0.03***		0.02
							(0.052)		(0.057)							(0.011)		(0.016)
$\ln(K)$								−0.62	−1.12**								−0.01	−0.04
								(0.452)	(0.468)								(0.030)	(0.053)
Observations	63	63	57	59	59	63	60	61	52	63	63	59	59	59	63	60	61	53
No. of countries	21	21	19	20	20	21	20	20	17	21	21	20	20	20	21	20	20	18
Degrees of freedom	34	34	30	31	31	34	32	32	20	34	34	31	31	31	34	32	32	20
R-squared, within	0.35	0.38	0.42	0.34	0.33	0.39	0.32	0.35	0.58	0.36	0.34	0.41	0.34	0.34	0.35	0.38	0.33	0.58

Notes: OLS estimates. All specifications include country and period fixed effects. Standard errors are clustered by country in parentheses. The dependent variable is $\Delta\ln(w_H/w_L)$, the change in the logarithm of skilled relative wage. Main explanatory variables: $\Delta\ln(H/L)$ is the change in logarithm of relative supply of skill; $\ln(M_H/ML)$ is the logarithm of the ratio of R&D intensive capital imports to R&D-unintensive capital imports; $\ln(M/GDP)$ is the logarithm of aggregate capital imports divided by GDP. Δz is the shift in export shares as in Zhu and Trefler (2005). ln(FDI) is the logarithm of the average US FDI (2005 prices). $\ln(GDP/POP)$ is the logarithm of real GDP per capita; industrial, government and services shares are the sectoral value added shares in GDP (all in logarithms); ln(financial development) is the logarithm of M3 money supply divided by GDP; the IPR protection index is the Intellectual Property Rights Protection Index from Ginarte and Park (1997), updated by Park (2008). IPR-protection data are available every 5 years, so we linearly interpolate between observations within a country. $\ln(K)$ is the logarithm of total real capital stock (Penn World Tables, mark 8.0); capital stock data is not available for Algeria. All variables in levels are averages within periods, while all variables in changes are annual changes. See the Appendix for further details on countries in the sample, data construction and sources.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 8
Capital import composition and the skill premium, inspecting alternative mechanisms, 1983–2000.

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Separate effects for significant capital exporters: India, Korea, Mexico, and the Philippines (IKMP)		Excluding capital imports from six largest high-income capital producers		Only capital imports from six largest high-income capital producers		Separate capital imports from six major high-income capital producers from all the rest	
$\Delta\ln(H/L)$	0.00	0.00	−0.08	−0.09	0.01	0.01	−0.08	−0.08
	(0.145)	(0.145)	(0.123)	(0.122)	(0.150)	(0.150)	(0.131)	(0.130)
$\ln(M_H/M_L)$	0.04**							
	(0.017)							
$\ln(M/GDP)$	−0.01							
	(0.018)							
$\ln(M_H/GDP)$		0.034*						
		(0.019)						
$\ln(M_L/GDP)$		−0.04**						
		(0.020)						
$\ln(M_H/M_L) *$ IKMP	0.02							
	(0.046)							
$\ln(M/GDP) *$ IKMP	−0.01							
	(0.023)							
$\ln(M_H/GDP) *$ IKMP		0.02						
		(0.048)						
$\ln(M_L/GDP) *$ IKMP		−0.03						
		(0.046)						
$\ln(M_H/M_L)$, rest			0.04***				0.04**	
			(0.012)				(0.017)	
$\ln(M/GDP)$, rest			−0.01				−0.01	
			(0.014)				(0.025)	
$\ln(M_H/M_L)$, high income					0.03**		0.01	
					(0.013)		(0.025)	
$\ln(M/GDP)$, high income					−0.01		−0.00	
					(0.019)		(0.026)	
$\ln(M_H/GDP)$, rest				0.04**				0.034*
				(0.014)				(0.017)
$\ln(M_L/GDP)$, rest				−0.05***				−0.045*
				(0.014)				(0.022)
$\ln(M_H/GDP)$, high income						0.03**		0.005
						(0.013)		(0.018)
$\ln(M_L/GDP)$, high income						−0.04**		−0.005
						(0.019)		(0.031)
Δz	0.53***	0.53***	0.55***	0.55***	0.49***	0.49***	0.55***	0.55***
	(0.184)	(0.184)	(0.159)	(0.156)	(0.147)	(0.148)	(0.163)	(0.161)
Observations	63	63	63	63	63	63	63	63
No. of countries	21	21	21	21	21	21	21	21
Degrees of freedom	32	32	34	34	34	34	32	32
R-squared, within	0.33	0.33	0.43	0.43	0.3	0.3	0.43	0.43

Notes: OLS estimates. All specifications include country and period fixed effects. Standard errors are clustered by country in parentheses. The dependent variable is $\Delta\ln(w_H/w_L)$, the change in the logarithm of skilled relative wage. Main explanatory variables: $\Delta\ln(H/L)$ is the change in logarithm of relative supply of skill; $\ln(M_H/M_L)$ is the logarithm of the ratio of R&D-intensive capital imports to R&D-unintensive capital imports; $\ln(M/GDP)$ is the logarithm of aggregate capital imports divided by GDP, and similarly for M_H, and M_L. Δz is the shift in export shares as in Zhu and Trefler (2005). In Regressions 1 and 2 we add interactions with a dummy variable IKMP that indicates any of the significant exporters of capital in our sample of developing countries: India, Korea, Mexico, and the Philippines. In Regressions 3 and 4 we exclude capital imports from the following six major, high-income, producers: France, Germany, Italy, Japan, the United Kingdom, and the United States. In Regressions 5 and 6 we separate imports from the six major, high-income, producers from all the rest. All variables in levels are averages within periods, while all variables in changes are annual changes. See the Appendix for further details on countries in the sample, data construction and sources.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

and year. We estimate Eq.(5) separately for each i and t. We then compute predicted values based on $\hat{\delta}_{it} \ln DISTANCE_{oi}$ and aggregate them to obtain $(\widehat{M}_H)_{it}^{gravity}$, $(\widehat{M}_L)_{it}^{gravity}$, and $(\widehat{M})_{it}^{gravity}$.[26] By replacing true values with these "gravity-predicted", we construct instruments for $\ln(M_H/M_L)_{it}$, $\ln(M_H/GDP)_{it}$, $\ln(M_L/GDP)_{it}$, and $\ln(M/GDP)_{it}$.

Note that we are not interested in estimating the causal effect of distance in Eq. (5). Instead, we wish to use exogenous variation in distance in order to extract exogenous variation to be used as an instrument that satisfies the exclusion restrictions. In the Appendix we show that omitted variables in Eq. (5) are unlikely to threat the exogeneity of the instruments, thus calculated. This depends on whether the covariance of such omitted variables with distance across origin countries varies systematically with omitted variables in Eq. (4), or with $\Delta\omega_{it}$ directly. While impossible to prove or disprove, it is difficult to think of omitted variables with such properties.

Columns 5 and 6 of Table 6 report the IV estimates. In all specifications we treat all capital imports as endogenous and instrument for them. The second stage results show that the magnitudes of the coefficients of interest increase somewhat, and consequently their explanatory power. For example, a one standard deviation increase in the import ratio now increases the change in the skill premium by

[26] Distance data are from CEPII, http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=6. We first take exponents of the distance-predicted values $\widehat{M}_{oit} = e^{\widehat{\ln M_{oit}}}$, then sum over all origins $\widehat{M}_{it} = \sum_o \widehat{M}_{oit}$. We neglect terms that multiply $e^{\widehat{\ln M_{oit}}}$ (for example, $e^{\frac{1}{2}\hat{\sigma}_\varepsilon^2}$, if ε is distributed normal) because they are constant and, therefore, when we take logs and use as instruments they will be absorbed by fixed effects in the first stage.

approximately two-thirds of a standard deviation, significantly more than Δz.[27]

In Panel B of Table 6 we report first stage estimates and statistics. The signs of the coefficients to the instruments are as expected, having a strong positive effect on the corresponding type of capital imports. Overall, the instruments are strong: The Shea (1997) partial R^2 are large and not substantially lower than the usual partial R^2. Although not an appropriate statistic when there is more than one endogenous instrumented variable (Stock and Yogo, 2002), we report the partial F-stat and find it reasonably high in all cases.

To summarize, we find that the composition of capital imports matters, not the overall quantity. These results hold both when using OLS and TSLS estimators, and also survive a battery of other robustness checks. Imports of R&D-intensive equipment are associated with increases in the skill premium; imports of less innovative capital equipment are associated with decreases in the skill premium. In the next section we explain why this is the case.

4. Complementarity of capital to skilled and unskilled labor

In this section we explain why the capital import ratio explains changes in the skill premium. Since Griliches (1969), capital is considered complementary to skilled labor. With some reservations about robustness, other studies generally confirm the capital–skill complementarity hypothesis.[28] However, these studies (including Griliches') investigate complementarity to aggregate measures of capital; they do not consider the composition of capital. In this section we establish that R&D-intensive capital equipment is complementary to skilled labor, while less innovative capital equipment is complementary to unskilled labor.[29] To be precise, when we say that a type of capital is complementary to a class of workers, this is a relative statement. For example, R&D-intensive capital equipment is more complementary to skilled labor than to unskilled labor.

The estimation employs data from the EU-KLEMS data set (O'Mahony and Timmer, 2009), which includes mostly high income countries. The complementarity estimates in these data are relevant for developing countries, which import most of their capital equipment (as we establish above) from high income countries (as shown in Eaton and Kortum, 2001). The validity of this exercise for developing countries also relies on similarity in responses to relative demand for skill in different settings. We therefore estimate these responses using two definitions of skilled labor, one of which is more relevant for developing countries.

We follow the standard methodology and estimate a skilled labor share equation, e.g., as in Berman et al. (1994). Assume a translog cost function where there are four inputs: Skilled and unskilled labor, and two types of capital. If capital is quasi-fixed, skilled and unskilled labor are variable factors, and production exhibits constant returns to scale, then cost minimization yields the following relationship

$$S = \alpha + \beta \ln\left(\frac{w_H}{w_L}\right) + \gamma_1 \ln\left(\frac{K_1}{Y}\right) + \gamma_2 \ln\left(\frac{K_2}{Y}\right), \tag{6}$$

where S denotes the wage bill share of skilled labor, w_H and w_L are wages of skilled and unskilled labor, K_1 and K_2 are two types of capital, and Y denotes output. Details on the derivation are in the Appendix. The γ_j coefficients indicate the type and magnitude of complementarity with skilled labor: $\gamma_j > 0$ implies stronger complementarity to skilled labor, while $\gamma_j < 0$ implies stronger complementarity to unskilled labor.

We estimate versions of Eq. (6) by capital type,

$$S_{it} = \beta \ln\left(\frac{w_H}{w_L}\right)_{it} + \gamma_j \ln\left(\frac{K_j}{Y}\right)_{it} + \gamma_{-j} \ln\left(\frac{K_{-j}}{Y}\right)_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{7}$$

where K_j is capital of type j and K_{-j} captures the sum of all other capital types. Here α_i and δ_t are country and year fixed effects, respectively. The fixed effects capture, inter alia, unobserved disembodied non-neutral technological change. We estimate Eq. (7) using two independent sources of data on capital stocks: EU-KLEMS and OECD. Although the categories of capital are broad (five or nine groups), and may include sub-categories that are more, or less, complementary to skill, the classification is informative and captures important qualitative differences.

4.1. Complementarity estimates using the EU-KLEMS data

Our first set of estimates uses an unbalanced panel of 14 countries in 1970–2005 from the EU-KLEMS data set. The EU-KLEMS data set reports data on capital stocks for five distinct capital groups (j): (1) Computing equipment, (2) communication equipment, (3) software capital, (4) transport equipment, and (5) machinery. First we estimate Eq. (7) separately for each capital group. Then we aggregate into two groups: ICT (information and communication technology capital, groups 1–3) and non-ICT (groups 4–5); see Table 1. Finally, we also estimate Eq. (7) using the total capital stock.[30]

The EU-KLEMS disaggregates workers into three groups: High skilled, medium skilled, and low skilled. The definition of high skilled workers is consistent across countries, and implies at least a university-equivalent bachelor's degree. The definitions of the other two groups vary somewhat across countries, but are consistent over time within a country. Medium skilled workers do not attain a university-equivalent bachelor's degree, but complete high-school and possibly a non-university vocational degree; low skilled workers do not complete high school. We use two definitions of skill in the implementation of Eq. (7): High (narrow definition), and high + medium (broad definition). This facilitates two goals. First and foremost, the broad definition is more relevant for developing countries. Second, it allows checking the robustness of the complementarity results.[31] Wage bill shares for all three groups are given in the data directly. Wages are given by wage bills divided by hours worked. We follow standard methodology and estimate Eq. (7) by TSLS, instrumenting for the capital shares using their values in the previous period. Results are not sensitive to the number of lags included. We report standard errors using country level clustering.

The results in Table 9 show a clear pattern: On one hand, computing equipment, communication equipment, and software capital are complementary to skilled workers; on the other hand, transport equipment, and machinery are complementary to unskilled workers. When the ICT and non-ICT capital groups are included, we confirm the results for their subcomponents: ICT capital is complementary to skilled workers; non-ICT capital is complementary to unskilled workers. These results

[27] For Δz 0.52 × 0.032 = 0.0166, and for the log import ratio 0.05 × 0.425 = 0.0212; these represent 50% and 64% of the standard deviation of $\Delta \ln\omega$ (0.033).

[28] See Fallon and Layard (1975), Bergstrom and Panas (1992) and Duffy et al. (2004).

[29] This in itself can help explain the sensitivity of the results in Duffy et al. (2004): The composition and, hence, overall degree of complementarity of capital is not the same across countries in their panel.

[30] See the Appendix for details on the sample used in the complementarity estimation. In the Appendix we also report shares of capital types in the aggregate capital stock, and changes thereof, for each country in the sample.

[31] Duffy et al. (2004) find the international empirical evidence in favor of the capital–skill complementarity hypothesis at the aggregate level most convincing when skilled workers are defined broadly, as high + medium.

Table 9
Capital complementarity to skilled and unskilled labor, EU-KLEMS data, 1970–2005.

	Dependent variable: Wage bill share of skilled workers						
	Capital type						
	Computing equipment	Communication equipment	Software	Transport equipment	Machinery	–	Total
A. Narrow definition of skilled labor: University-equivalent tertiary education							
	0.21***	0.14*	0.19***	−0.43***	−0.51***		0.23***
	(0.03)	(0.08)	(0.05)	(0.09)	(0.12)		(0.03)
ICT (groups 1, 2 and 3)						0.19***	
						(0.06)	
Non-ICT (groups 4 and 5)						−0.54***	
						(0.12)	
Observations	345	345	345	345	345	345	345
No. of countries	14	14	14	14	14	14	14
B. Broad definition of skilled labor: At least high-school							
	0.07***	0.16***	0.04***	−0.11***	−0.09***		0.09***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)		(0.01)
ICT (groups 1, 2 and 3)						0.12***	
						(0.02)**	
Non-ICT (groups 4 and 5)						−0.14***	
						(0.02)	
Observations	345	345	345	345	345	345	345
No. of countries	14	14	14	14	14	14	14

Notes: This table reports TSLS estimates of $\gamma 1$ in the regression $S = \beta * \ln(w_H/w_L) + \gamma 1 * \log(\text{capital\_}j / \text{output}) + \gamma 2 * \log(\text{capital\_}{-j} / \text{output}) + \varepsilon$, for different capital types j, where capital_j is the total capital stock net of capital_j. S is the wage bill share of skilled workers and w_H/w_L is the relative wage of skilled to unskilled workers. Positive coefficients indicate complementarity to skilled workers; negative coefficients indicate complementarity to unskilled workers. Instruments to capital shares are their 1-period lagged values; all first stage results report F-statistics for weak instruments an order of magnitude greater than 10. All regressions include time and country fixed effects. Data: EU KLEMS. Standard errors in parentheses are clustered at the country level.
*** p < 0.01.
** p < 0.05.
* p < 0.1.

hold whether we use the narrow or the broad definition of skill. Since the year fixed effects add little explanatory power, fitting Eq. (7) without them yields virtually the same results. Taking changes in Eq. (6) and estimating the resulting equation by TSLS with country fixed effects—using lagged variables in changes as instruments—yields remarkably similar results.[32]

In the last column of Table 9 we also estimate that the aggregate capital stock is complementary to skilled labor. We find it comforting that we can replicate previous findings. This should not be confused with the results in Section 3: The composition of the aggregate capital stock and investment in countries in the EU-KLEMS sample—which are mostly developed economies—is much more R&D intensive, with a higher share of ICT, relative to the sample of developing countries that we examine above. Moreover, developed economies import a much smaller share of their capital investment.

4.2. Complementarity estimates using OECD data

We wish to estimate Eq. (7) using the nine groups—classified by R&D intensity—that are used above in Section 3, but the EU-KLEMS data on capital stocks are not classified according to ISIC.[33] Since there are no readily available capital stocks that are classified by ISIC, we estimate these using OECD data.[34]

The OECD data include production Y, imports M, and exports X, by ISIC in 1970–2005. This allows estimating implied investment I for each of the nine *capital* groups

$$I_{g,t} = Y_{g,t} + M_{g,t} - X_{g,t},$$

where $g = 1, 2, \ldots, 9$ denotes R&D intensity rank. We then use the perpetual inventory method to estimate capital stocks

$$K_{g,t+1} = (1 - \delta_g) K_{g,t} + I_{g,t}.$$

We estimate capital stocks in the initial year by type as

$$K_{g,0} = \frac{I_{g,0}}{\delta_g}.$$

Depreciation estimates by capital type δ_g are from Fraumeni (1997), and are based on U.S. data.[35] We estimate Eq. (7) using the same methodology and data as above, except that we use our estimated capital stocks by R&D intensity.[36]

Table 10 reports the complementarity estimation results, which largely confirm the results in Table 9. The most R&D-intensive capital types (aircraft equipment, office, computing and accounting machinery, communication equipment) are complementary to skilled labor. Of the other six relatively less R&D-intensive capital types, four (electrical equipment excluding communication, non-electrical equipment, other

[32] These results are reported in the Appendix.
[33] Based on the EU-KLEMS documentation, it is not obvious as to how to map all nine disaggregate ISIC capital types into the EU-KLEMS classification or even into broad ICT and non-ICT groups.
[34] OECD data from *StatsExtract* data are available at: http://stats.oecd.org/.
[35] These are the same depreciation rates that are used in the EU-KLEMS for construction of capital stocks by group.
[36] The sample for which we calculate capital stocks using OECD data is reported in the Appendix, where we also report shares of capital types in the aggregate capital stock, and changes thereof, for each country in the sample.

Table 10
Capital complementarity to skilled and unskilled labor, imputed capital stocks.

Dependent variable: Wage bill share of skilled workers											
R&D intensity rank	1	2	3	4	5	6	7	8	9	–	–
Capital type	Aircraft equipment	Office, computing, and accounting machinery	Communication equipment	Professional goods	Electrical equipment, excluding communication	Motor vehicles	Non-electrical equipment	Other transportation equipment	Fabricated metal products	–	Total
A. Narrow definition of skilled labor: University-equivalent tertiary education											
	0.41***	0.13***	0.23***	0.11	−0.46***	−0.05	−0.53***	−0.48***	−1.11***		0.44***
	(0.06)	(0.06)	(0.05)	(0.09)	(0.04)	(0.04)	(0.19)	(0.09)	(0.17)		(0.07)
K_H (R&D ranks 1, 2, 3, 4 and 6)										0.58***	
										(0.05)	
K_L (R&D ranks 5, 7, 8 and 9)										−0.82***	
										(0.11)	
Observations	305	305	305	305	305	305	305	305	305	305	305
No. of countries	17	17	17	17	17	17	17	17	17	17	17
B. Broad definition of skilled labor: At least high-school											
	0.17	0.13***	0.14***	0.01	−0.21***	0.16**	−0.09	−0.28***	−0.59***		0.24***
	(0.15)	(0.04)	(0.05)	(0.08)	(0.05)	(0.08)	(0.18)	(0.07)	(0.19)		(0.08)
K_H (R&D ranks 1, 2, 3, 4 and 6)										0.32***	
										(0.12)	
K_L (R&D ranks 5, 7, 8 and 9)										−0.35***	
										(0.09)*	
Observations	305	305	305	305	305	305	305	305	305	305	305
No. of countries	17	17	17	17	17	17	17	17	17	17	17

Notes: This table reports TSLS estimates of $\gamma 1$ in the regression $S = \beta * \ln(w_H / w_L) + \gamma 1 * \log(\text{capital\_}j / \text{output}) + \gamma 2 * \log(\text{capital\_}{-j} / \text{output}) + \varepsilon$, for different capital types j, where capital_$-j$ is the total capital stock net of capital_j. S is the wage bill share of skilled workers and w_H/w_L is the relative wage of skilled to unskilled workers. Positive coefficients indicate complementarity to skilled workers; negative coefficients indicate complementarity to unskilled workers. Instruments to capital shares are their 1-period lagged values; all first stage results report F-statistics for weak instruments an order of magnitude greater than 10. All regressions include time and country fixed effects. All data except capital stocks are from the EU KLEMS. Capital stocks are imputed perpetual inventory method; see text for details. Standard errors in parentheses are clustered at the country level.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

transportation equipment, fabricated metal products) are complementary to unskilled labor. The Spearman rank correlation between the complementarity coefficient and the R&D rank is −0.95 (p-value = 0.0001). Motor vehicles and professional goods are not more complementary to either class of labor when using the narrow definition of skill. However, the results using the broad definition of skill make us decide to include the latter two types of capital in M_H in the import composition estimation in Section 3 above.

When we aggregate the R&D-intensive, skill-complementary, capital groups (K_H), and the R&D-unintensive, unskilled-complementary, capital groups (K_L), we confirm the results for their subcomponents: K_H is complementary to skilled workers and K_L is complementary to unskilled workers. These results are similar when we use the broad definition of skill (high + medium).

Overall, using several specifications and data sources, we find strong evidence for capital–skill complementarity for R&D-intensive, innovative capital types; we find that less innovative and relatively R&D-unintensive equipment is complementary to unskilled labor. This is the reason that the composition of capital imports (which stands in for investment), and not the overall quantity, affects the skill premium.

5. Trade liberalization and changes in the composition of capital imports

We argue above that an increase in the share of R&D-intensive, skill-complementary capital in total capital imports increases relative demand for skilled labor and therefore raises the skill premium. During 1983–2000, a period of trade liberalization in the sample of developing countries that we study, the share of M_H in our sample increases by 3.5% on average, commensurate with an equal drop in the share of M_L—and there is significant variation in this change across countries. However, this does not necessarily imply that trade liberalization increases the skill premium through this channel. This is a difficult question to answer, but in this section we provide some evidence that is consistent with this hypothesis.[37]

The mechanics of trade liberalization work through changes in domestic relative prices of M_H versus M_L. Using the framework of Section 2 we can derive an approximation for $\ln(M_H/M_L)$ as (see the Appendix)

$$\Delta \ln\left(\frac{C}{K}\right) = \rho\Delta \ln\left(\frac{H}{L}\right) - \varphi\Delta \ln\left(\frac{r_C}{r_K}\right),$$

where r_C/r_K is the price of C relative to K, $\rho = \beta(\sigma - 1) / [\sigma - (1 - \beta)(\sigma - 1)] > 0$ and $\varphi = \sigma / [\sigma - (1 - \beta)(\sigma - 1)] > 0$. We decompose each capital import price r_j into four components: A "free on board" (FOB) price at the source r_j^*, ad valorem tariffs τ_j, specific

[37] Alfaro and Hammel (2007) argue that in the same period that we study stock market liberalizations are associated with increases in imports of capital equipment. This channel is complementary to liberalization in goods trade—both reduce the cost of purchasing capital equipment abroad. The question here is whether the effect of these reforms is greater on M_H versus M_L. Larrain (2013) argues that capital account liberalization in industrialized countries increased inequality by making available external funding for capital investment. He does not distinguish between different types of capital, but finds stronger effects in industries that exhibit stronger aggregate capital–skill complementarity and more external finance reliance. However, the estimated magnitudes are small. In contrast, we focus on the mechanism, in a set of less-developed countries.

(transportation) freight costs $\tilde{f}_j$, and other ad valorem trade barriers b, so that

$$\frac{r_C}{r_K}=\frac{\left(r_C^*+\tilde{f}_C\right)(1+\tau_C)(1+b_C)}{\left(r_K^*+\tilde{f}_K\right)(1+\tau_K)(1+b_K)}=\frac{r_C^*}{r_K^*}\cdot\frac{(1+f_C)(1+\tau_C)(1+b_C)}{(1+f_K)(1+\tau_K)(1+b_K)}, \quad (8)$$

where $f_j \equiv \tilde{f}_j / r_j^*$ is the ad valorem equivalent freight cost. Although freight costs are usually denominated in specific (per unit, not per value) terms in the real world, a more meaningful way to analyze their impact on trade flows is to transform them into ad valorem terms (see Hummels and Skiba, 2004; Hummels, 2007). Most countries, with few exceptions, apply tariffs to the transport-inclusive CIF (cost, insurance and freight) price of a product, as in Eq. (8). In the Appendix we report separate results for 12 countries who do not follow this rule, and instead apply tariffs to FOB prices.[38]

We demonstrate that $1 + f_j$, $1 + \tau_j$ and the product of $(1 + f_j)(1 + \tau_j)(1 + b_j)$ all fall proportionately more for M_H versus M_L—both in a broad set of countries, and in our sample of developing economies, where data permits testing this—all of which reduce r_C/r_K, given r_C^*/r_K^*. We keep the exposition of results to a minimum; full statistical outputs are available upon request.

5.1. Tariffs on M_H fall proportionately more relative to M_L

We start by demonstrating that on average, $1 + \tau_C$ falls proportionately more than $1 + \tau_K$, i.e., their ratio falls. We use tariff data from the TRAINS data set in 1988–2010, which gives us 2826 observations over 169 countries.[39] We fit the following regression

$$\ln\left(1+\tau_{it}^j\right)=\delta_1 t+\delta_2\left[I_{(j\in M_H)}\cdot t\right]+\delta_3 I_{(j\in M_H)}+\alpha_i+\varepsilon_{it}, \quad (9)$$

where i is a country, and $j \in \{M_H, M_L\}$ indicates that a product is either in the M_H or M_L capital import group, and α_i is a country fixed effect. We cluster standard errors by country. Developing countries are underrepresented in TRAINS, but less so over time; therefore t denotes time since country i enters the data set, which takes into account evolving coverage. We cluster standard errors by country in order to take this into account.

The point estimate of δ_1 is -0.004 and the point estimate of δ_2 is -0.001, both statistically significant at the 1% level. Tariffs fall over time, but tariffs on M_H more so. Over the sample, $\delta_2 = -0.001$ translates into a relative reduction of 0.022. We also fit specifications similar to Eq. (9) with time dummies instead of linear time trends. Those regressions confirm the previous conclusion, but also illustrate that the drop is driven mostly by countries with long representation (large t).[40]

5.2. Transport costs of M_H fall proportionately more relative to M_L

We now use data from Hummels (2007) on ad valorem freight costs for shipments into the U.S. 1983–2004, and demonstrate that transportation costs fall more for M_H than for M_L (i.e., $1 + f_C$ falls proportionately more than $1 + f_K$). We also find that effect is stronger for shipments by air relative to shipments by sea. In these data, the share of air shipments for M_H doubles from 20.5% in 1983 to 41% in 2004. The share of air shipments for M_L fluctuates around 45%.

We fit the following regression

$$\begin{aligned}\ln\left(1+f_j\right)=&\ \delta_1 t(j)+\delta_2\left[I_{(j\in M_H)}\cdot t(j)\right]+\delta_3 I_{(j\in M_H)}+\gamma\ln(w/v)_j\\&+\alpha_{s(j)}+\varepsilon_j,\end{aligned} \quad (10)$$

where j is a shipment, $j \in \{M_H, M_L\}$ indicates that a product is either in the M_H or M_L capital import group, and $w/v =$ denotes the weight per dollar value of shipment. Here $\alpha_{s(j)}$ is a fixed effect for all shipments j imported from source s (which absorbs the effect of distance, inter alia), and $t(j)$ indicates that shipment j is observed in year t. In the estimation we weigh observations by shipment value and cluster standard errors by source country. When we estimate Eq. (10) for sea shipment we also control for the share of containerized trade in the shipment. We fit Eq. (10) using data on shipments of capital goods, of which 220,568 are by air and 181,159 are by sea. We weigh observations by value, because we are interested in inferences about total value by import type, not average shipment (results are qualitatively similar without weighting).

For air shipments, the point estimate of δ_1 is -0.0005 and the point estimate of δ_2 is -0.0005, both statistically significant at the 1% level.[41] Air freight costs fall over time, but at double the rate for M_H. Over the sample, $\delta_2 = -0.0005$ translates into a relative reduction of 0.0105. For sea shipments, the point estimate of δ_1 is -0.0006 and the point estimate of δ_2 is -0.0003, both statistically significant at the 1% level.[42] Sea freight costs fall over time, but faster for M_H. Over the sample, $\delta_2 = -0.0003$ translates into a relative reduction of 0.0063. We also fit specifications similar to Eq. (10) with time dummies instead of linear time trends. Year fixed effects can absorb better global changes in fuel prices. Those regressions confirm the previous conclusion, but also show that the relative reductions happen continuously over time.

5.3. Barriers to trade for M_H fall relative to M_L

Finally, we demonstrate that bilateral barriers to trade for M_H fall relative to M_L. The data on tariffs do not have good coverage of developing countries, and the data on freight costs pertain only to U.S. imports, so the following exercise helps paint a more complete picture.

We estimate the following gravity equation

$$\begin{aligned}m_{sit}^j=&\ \beta_1 t+\beta_2 I\left(m_{sit}^j\in M_H\right)+\beta_3\left[I\left(m_{sit}^j\in M_H\right)\cdot t\right]+\left(\chi_s^0+\chi_s^1\cdot t\right)\\&+\left(\eta_i^0+\eta_i^1\cdot t\right)+\varepsilon_{sit}^j,\end{aligned} \quad (11)$$

where m_{sit}^j are log capital imports from source s to importer i in time t of capital type $j \in \{M_L, M_H\}$; and $I(m_{sit}^j \in M_H)$ indicates whether m_{sit}^j is of type M_H $(=1)$ or not $(=0)$. Exporter and importer fixed effects—χ_s^0 and η_i^0—and exporter and importer-specific time trends—$\chi_s^1 \cdot t$ and $\eta_i^1 \cdot t$—respectively, capture levels and trends in demand conditions in the importer countries and in technology in the source country. It is important to see that the latter ensure that β_1, β_2 and β_3 are identified only by bilateral variation in barriers to trade. Here β_1 captures overall trends, and β_2 captures the permanent differential level of bilateral

[38] These 12 countries are: Afghanistan, Australia, Botswana, Canada, Democratic Republic of the Congo, Lesotho, Namibia, New Zealand, Puerto Rico, South Africa, Swaziland, and the United States. In these countries, which we call the "FOB sample", tariffs are applied to the FOB (free on board) price, exclusive of freight costs. See http://export.customsinfo.com/ and http://export.gov/logistics/eg_main_018142.asp. We thank Robert Feenstra for this reference.

[39] TRAINS (Trade Analysis and Information System) data downloaded from http://wits.worldbank.org/wits/.

[40] Time dummies for M_H become increasingly large, negative and statistically significant from 8 years in the sample and on.

[41] If we drop $\ln(w/v)$ the point estimates of δ_1 and δ_2 both become -0.0006 respectively.

[42] If we drop $\ln(w/v)$ and the containerization indicator the point estimates of δ_1 and δ_2 become -0.0005 and -0.0004, respectively.

barriers to trade for M_H. The coefficient of interest is β_3, which captures the differential change in bilateral barriers to trade for M_H. This coefficient absorbs the differential trend in the effect of all bilateral trade impediments (inter alia, distance, language, colonial ties, tariffs and freight costs).

We estimate Eq. (11) by OLS, clustering standard errors by country-pair, using import data in 1984–1999, for 157 countries (136,786 observations).[43] We estimate $\beta_3 = 0.0126$ (highly statistically significant), which indicates that bilateral barriers to trade fall for M_H relative to M_L. When we restrict the importers to the set of developing countries that we study above in Section 3 (with no restriction on exporters), we estimate $\beta_3 = 0.017$ (highly statistically significant).

These results are confirmed when we estimate gravity equations separately for each year in 1984–1999 (which is the most appropriate way to do this; see Head and Mayer, 2014):

$$m_{si}^j = \beta \cdot I\left(m_{si}^j \in M_H\right) + \chi_s + \eta_i + \varepsilon_{si}^j. \tag{12}$$

The increase over time in β is gradual and its trajectory over time is virtually the same as the estimate of β_3 in Eq. (11). We also estimate Eq. (12) with a Heckman correction for sample selection along the lines of Helpman et al. (2008), using their common religion index as an excluded variable in the selection equation. This increases the magnitude of the coefficients to $I(m_{si}^j \in M_H)$ somewhat, but hardly affects their trend over time. To summarize, bilateral barriers to trade for M_H fall relative to M_L, regardless of how we estimate this.

What do these estimates imply for changes in inequality in developing countries? The estimate $\hat{\beta}_3 = 0.017$ implies an increase in $\ln M_H - \ln M_L = \ln (M_H / M_L)$ of 0.255 from 1984 to 1999, which, given $\hat{\lambda} = 0.04$ (OLS) translates into an annual increase in w_H/w_L of approximately 1.02% *per year*; if we use $\hat{\lambda} = 0.05$ (TSLS), the implied annual increase in w_H/w_L is 1.224%, which is about one third of the inter-quartile change (see Table 2). Thus, differential reductions in bilateral trade resistance for developing countries have a large effect on changes in relative wages of skilled workers in these countries. According to Eq. (8), the remainder can be attributed to changes in supply conditions, namely the drop in the relative price of skill-complementary equipment versus other capital.[44]

6. Conclusion

Empirical investigations of episodes of trade liberalization usually do not find large effects on the skill premium. One reason is that these studies focus on traded *final* goods (e.g., Bustos, 2011; Verhoogen, 2008; Zhu and Trefler, 2005) or intermediate inputs (e.g., Amiti and Cameron, 2012; Feenstra and Hanson, 1996), and typically focus on mechanisms that directly affect only the traded sector. In this paper we show that the composition of capital imports has strong explanatory power for changes in the skill premium in a sample of developing countries. In addition, we argue that trade liberalization can shift the distribution of capital imports in a way that increases the skill premium. Thus, we provide a novel explanation for the increase in the skill premium in developing countries that liberalized trade.

We find that when the composition of capital imports is more R&D intensive, the skill premium increases, whereas when it is less R&D intensive the skill premium falls. This is because R&D-intensive capital is complementary to skilled labor, whereas R&D-unintensive capital is complementary to unskilled labor. To our best knowledge, we are the first to argue that some types of capital are more complementary to unskilled workers. The composition of imports has a first order effect on the composition of capital stocks in developing countries, because they import most of their capital and produce little of it domestically. The composition of imports largely determines the composition of investment, and, in turn, the capital stock. This is why the capital import ratio—a measure of import composition—has such strong explanatory power. We estimate that an increase in the import ratio from the first to the third quartile increases the rate of change in the skill premium by two thirds of the inter-quartile difference.

We argue that trade liberalization has shifted the distribution of import composition towards more skill-complementary capital. First, tariff reductions and reductions in freight costs have been larger, on average, for skill-complementary equipment. In addition, bilateral trade barriers fall more rapidly for imports of skill-complementary equipment relative to unskilled-complementary equipment. This shifts the composition of capital imports towards skill-complementary equipment—and causes an increases in the skill premium. We estimate that this effect is equivalent to about a third of the inter-quartile difference in changes in the skill premium.

Our results highlight the importance of the composition of imports, not just aggregate quantities. While we focus here on capital imports, we believe that the mechanism that we investigate—composition together with patterns of complementarities—can help explain results in other papers (e.g., Amiti and Cameron, 2012). In addition, the importance of composition raises concerns for the validity of estimates of the contribution of capital imports to increases in the skill premium in quantitative trade models that have no role for composition. Since the composition of capital imports varies across countries, so does the effective complementarity of aggregate capital imports. Such quantitative analyses—in particular, Burstein et al. (2013) and Parro (2013)—can be modified to take into account capital import composition, together with the pattern of complementarities that we uncover. This can lead to a better understanding of the role of capital imports in affecting the distribution of the gains from trade.

Appendix A. Detailed descriptions of ISIC capital goods classifications

Capital goods are defined as ISIC rev.2 category 38, "Manufacture of Fabricated Metal Products, Machinery and Equipment". Here we list capital goods from the highest to the lowest R&D intensity based on Caselli and Wilson (2004) with corresponding ISIC in parentheses:

1. Aircraft equipment (3845): Aircraft and related parts.
2. Office, computing, and accounting machinery (3825): Computers, calculators, typewriters, and other office equipment (excluding photocopiers).
3. Communication equipment (3832): Semiconductors, wire and wireless telephone equipment, radio and TV sets, audio recording equipment, signaling equipment, radar equipment.
4. Professional goods (385): Measuring and controlling equipment, photographic and optical goods, and watches and clocks.
5. Electrical equipment, excluding communication equipment (383 *without* 3832): Electrical industrial machinery, electrical appliances, and other electrical apparatus.
6. Motor vehicles (3843): Automobiles and related parts (excludes industrial trucks and tractors).
7. Non-electrical equipment (382 *without* 3825): Engines and turbines, agricultural machinery (including tractors, excluding metal tools), metal and wood-working machinery, industrial trucks, military ordinance (including tanks).
8. Other transportation equipment (3842, 3844, 3849): Railroad equipment, motorcycles and bicycles, wagons and carts.
9. Fabricated metal products (381): Cutlery, hand tools, general hardware, metal furniture and fixtures, structural metal products.

[43] See the Appendix for the list of countries in the sample.

[44] Of course, this is less relevant for countries that also produce much of the capital that they use.

Table A1
Correlation matrix; import composition and relative wages.

	$\Delta\ln(w_H/w_L)$	$\Delta\ln(H/L)$	ln(import ratio)	ln(aggregate capital imports/GDP)	ln(R&D intensive capital imports/GDP)	ln(R&D un-intensive capital imports/GDP)	Δln(FDI)	$\Delta\ln(GDP/POP)$	ΔIndustrial share	ΔGovernment share	ΔServices share	ΔFinancial development	ΔIPR protection	$\Delta\ln(K)$	Δz	$\ln M_H M_L$_gravity	lnMHgdp_gravity	$\ln M_L$gdp_gravity	lnMgdp_gravity
$\Delta\ln(w_H/w_L)$	1																		
$\Delta\ln(H/L)$	0.03	1																	
ln(import ratio)	0.04	−0.15	1																
ln(aggregate capital imports/GDP)	0.13	0.13	0.13	1															
ln(R&D intensive capital imports/GDP)	0.13	0.09	0.35	0.97	1														
ln(R&D un-intensive capital imports/GDP)	0.12	0.16	−0.10	0.97	0.90	1													
Δln(FDI)	0.25	−0.12	−0.38	0.37	0.27	0.46	1												
Δln(GDP/POP)	0.16	−0.11	0.25	0.61	0.63	0.55	0.55	1											
ΔIndustrial share	0.31	0.03	−0.42	0.18	0.07	0.28	0.52	0.31	1										
ΔGovernment share	0.00	−0.03	0.12	−0.15	−0.12	−0.18	−0.32	0.03	0.00	1									
ΔServices share	0.12	−0.08	0.40	0.46	0.54	0.35	0.26	0.69	−0.26	0.11	1								
ΔFinancial development	0.25	0.09	0.16	0.60	0.60	0.55	0.16	0.60	0.24	0.25	0.46	1							
ΔIPR-protection	−0.08	0.24	−0.20	0.37	0.30	0.42	0.09	0.36	0.17	0.16	0.17	0.16	1						
$\Delta\ln(K)$	0.27	0.13	−0.40	0.45	0.32	0.54	0.11	0.52	0.14	−0.01	0.17	0.17	0.10	1					
Δz	0.23	−0.01	−0.35	0.27	0.17	0.36	0.36	0.05	−0.10	0.16	0.32	0.09	0.49	0.16	1				
$\ln M_H M_L$_gravity	0.04	−0.08	0.99	0.12	0.36	−0.15	0.11	0.23	−0.20	0.02	0.00	0.05	−0.03	−0.34	−0.32	1			
$\ln M_H$gdp_gravity	0.03	0.05	0.65	0.61	0.74	0.44	0.15	0.17	−0.03	−0.24	−0.07	0.05	−0.03	−0.13	−0.05	0.61	1		
$\ln M_L$gdp_gravity	0.04	0.13	0.37	0.67	0.73	0.57	0.15	0.10	0.06	−0.29	−0.05	0.02	−0.09	0.03	0.03	0.35	0.9219	1	
$\ln M$gdp_gravity	0.03	0.11	0.52	0.62	0.72	0.48	0.17	0.12	−0.01	−0.27	−0.05	0.02	−0.07	−0.06	−0.03	0.50	0.9674	0.98	1

Notes: The sample includes 63 observations, covering 21 developing countries over the period of 1983–2000. $\Delta\ln(w_H/w_L)$ is the change in the logarithm of skilled relative wage in manufacturing; $\Delta\ln(H/L)$ is the change in logarithm of aggregate relative supply of skill; Δz is the shift in export shares to high income OECD countries; ln(import ratio) is the logarithm of the ratio of R&D-intensive capital imports to R&D-unintensive capital imports; ln(capital imports/GDP) is the logarithm of capital imports (for the R&D intensive, unintensive, and the overall aggregated group) normalized by GDP; Δln(FDI) is the change in logarithm of the average US FDI (2005 prices). $\Delta\ln(GDP/POP)$ is the change in the logarithm of GDP per capita. ΔIndustrial, ΔGovernment, ΔServices share are the changes in the logarithm of the sectoral value added shares in GDP. ΔFinancial-development is the change in the logarithm of M3 money supply as a fraction of GDP. ΔIPR-protection is the change in the Intellectual Property Rights Protection Index from Ginarte and Park (1997), updated by Park (2008). IPR-protection data are available every 5 years, so we linearly interpolate between observations within a country. $\Delta\ln(K)$ is the change in the logarithm of the total capital stock (Penn World Tables, mark 8.0); capital stock data is not available for Algeria. $\ln M_H M_L$_gravity, $\ln M_H$_gravity, and $\ln M_L$_gravity, and $\ln M$_gravity are the import ratio, R&D-intensive, R&D-unintensive, and aggregate import instruments, respectively. All variables in levels are averages within change periods, while all variables in changes are annual changes. For further details on countries in the sample, data construction and sources, see the Appendix.

Table A2
Contribution of ICT and non-ICT capital to changes in demand for skill.

	Employment share		Wagebill share	
	ICT	Non-ICT	ICT	Non-ICT
A. Annualized percent contribution to aggregate skill intensity				
EU15	0.17	0.40	0.16	0.36
Japan	0.12	0.41	0.12	0.42
South Korea	0.03	0.22	0.03	0.23
U.S.	0.05	0.13	0.05	0.13
Czech Republic	0.03	0.06	0.03	0.05
Hungary	0.08	1.36	0.05	1.40
B. Annualized percent contribution to skill intensity in manufacturing				
EU15	0.05	0.04	0.05	0.04
Japan	0.02	0.03	0.02	0.04
South Korea	0.02	1.00	0.02	1.05
U.S.	0.01	0.02	0.01	0.02
Czech Republic	0.04	0.23	0.04	0.25
Hungary	0.24	1.57	0.31	1.91

Notes: The table reports annualized percent point contributions of ICT and non-ICT capital to changes in skill intensity through industry growth, the net of changes in skill intensity within industries. Sample for EU15, Japan, South Korea and the U.S. is 1983–2000. Sample for Czech Republic and Hungary is 1995–1999. See the Appendix for details on the exact calculations made.

Table A3
Capital import composition and the skill premium, 1983–2000, alternative specifications.

	$\Delta\ln(w_H/w_L)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	No normalization		Normalize by population		Normalize by total capital stock		No logs	
$\Delta\ln(H/L)$	0.01	0.01	0.00	0.00	0.00	0.00	0.03	−0.01
	(0.129)	(0.129)	(0.127)	(0.127)	(0.129)	(0.129)	(0.15)	(0.15)
$\ln(M_H/M_L)$	0.04***		0.04***		0.04**			
	(0.014)		(0.014)		(0.014)			
$\ln(M)$	0.00							
	(0.012)							
$\ln(M/POP)$			0.00					
			(0.011)					
$\ln(M/K)$					0.00			
					(0.013)			
$\ln(M_H)$		0.04**						
		(0.015)						
$\ln(M_L)$		−0.04**						
		(0.015)						
$\ln(M_H/POP)$				0.04***				
				(0.014)				
$\ln(M_L/POP)$				−0.04**				
				(0.015)				
$\ln(M_H/K)$						0.04***		
						(0.014)		
$\ln(M_L/K)$						−0.04**		
						(0.017)		
M_H/M_L							0.03***	
							(0.01)	
M/GDP							−0.03	
							(0.118)	
M_H/GDP								0.49***
								(0.162)
M_L/GDP								−0.59*
								(0.31)
Δz	0.47***	0.47***	0.47***	0.47***	0.46***	0.46***	0.49***	0.51***
	(0.147)	(0.147)	(0.146)	(0.147)	(0.147)	(0.148)	(0.14)	(0.14)
R-squared, within	0.315	0.315	0.316	0.316	0.319	0.319	0.316	0.29
No. of countries	21	21	21	21	20	20	21	21
Degrees of freedom	35	35	35	35	33	33	35	35
Observations	63	63	63	63	61	61	63	63

Notes: All specifications include country and period fixed effects. Standard errors clustered by country in parentheses. ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. The dependent variable is $\Delta\ln(w_H/w_L)$, change in the logarithm of skilled relative wage. Main explanatory variables: $\Delta\ln(H/L)$ is the change in logarithm of relative supply of skill; $\ln(M_H/M_L)$ is the logarithm of the ratio of R&D-intensive capital imports to R&D-unintensive capital imports; $\ln(M)$ is the logarithm of aggregate capital imports, and similarly for M_H, and M_L; division by POP means normalization by population, division by K means normalization by total capital stock (Penn World Tables, mark 8.0). In the latter case data is not available for Algeria. Δz is the shift in export shares as in Zhu and Trefler (2005). All variables in levels are averages within periods, while all variables in changes are annual changes. See the Appendix for further details on countries in the sample, data construction and sources.

Table A4
Capital stock shares and changes in capital stock shares, five equipment groups, EU KLEMS data.
Data is from the EU KLEMS data set (O'Mahony and Timmer, 2009).

Capital type		Computing equipment	Communication equipment	Software	Transportation equipment	Machinery	ICT capital (Computers + Communication + Software)	Non-ICT Capital (Transportation + Machinery)
A. Average capital stock shares								
Australia	1970–2005	0.065	0.062	0.033	0.530	0.309	0.161	0.839
Austria	1976–2005	0.042	0.065	0.014	0.691	0.188	0.122	0.878
Czech Republic	1995–2005	0.129	0.051	0.016	0.626	0.178	0.196	0.803
Denmark	1970–2005	0.070	0.013	0.035	0.591	0.291	0.118	0.882
Finland	1970–2005	0.025	0.053	0.044	0.597	0.281	0.121	0.879
Germany	1970–2005	0.046	0.071	0.029	0.656	0.198	0.146	0.854
Italy	1970–2005	0.023	0.069	0.019	0.712	0.176	0.112	0.888
Japan	1970–2005	0.044	0.063	0.028	0.647	0.218	0.135	0.865
Netherlands	1970–2005	0.056	0.074	0.036	0.565	0.270	0.165	0.835
Portugal	1995–2005	0.163	0.052	0.018	0.544	0.222	0.233	0.767
Slovenia	1995–2005	0.100	0.175	0.023	0.550	0.152	0.298	0.702
Sweden	1993–2005	0.054	0.072	0.080	0.644	0.149	0.207	0.793
United Kingdom	1970–2005	0.050	0.033	0.050	0.634	0.233	0.133	0.867
United States	1970–2005	0.052	0.090	0.046	0.596	0.216	0.188	0.812
Average		0.066	0.067	0.034	0.613	0.220	0.167	0.833
B. Changes in capital stock shares								
Australia	1970–2005	0.366	−0.007	0.079	−0.288	−0.149	0.437	−0.437
Austria	1976–2005	0.204	0.045	0.040	−0.315	0.027	0.288	−0.288
Czech Republic	1995–2005	0.108	0.007	−0.003	−0.176	0.063	0.113	−0.112
Denmark	1970–2005	0.337	0.011	0.090	−0.319	−0.119	0.438	−0.438
Finland	1970–2005	0.096	0.190	0.080	−0.210	−0.155	0.366	−0.366
Germany	1970–2005	0.153	0.053	0.046	−0.092	−0.160	0.252	−0.252
Italy	1970–2005	0.112	0.019	0.031	−0.100	−0.063	0.163	−0.163
Japan	1970–2005	0.117	0.057	0.051	−0.163	−0.060	0.224	−0.223
Netherlands	1970–2005	0.291	0.024	0.075	−0.316	−0.074	0.390	−0.390
Portugal	1995–2005	0.250	0.025	0.015	−0.249	−0.041	0.289	−0.289
Slovenia	1995–2005	0.068	−0.176	0.043	0.034	0.030	−0.064	0.064
Sweden	1993–2005	0.054	0.021	−0.022	0.017	−0.069	0.052	−0.052
United Kingdom	1970–2005	0.262	0.080	0.067	−0.273	−0.136	0.409	−0.409
United States	1970–2005	0.257	0.082	0.108	−0.310	−0.137	0.447	−0.447
Average		0.191	0.031	0.050	−0.197	−0.075	0.272	−0.272

Notes: In Panel A capital stock shares are computed as shares in total nominal capital stock and averaged over all available years. In Panel B changes in capital stock shares are computed as the share in the last year minus the share in the first year. Samples are noted next to each country. Averages over all countries are reported below country data.

Table A5
Capital complementarity to skilled and unskilled labor, EU-KLEMS data, 1970–2005—regressions in changes.

	Dependent variable: Change in wage bill share of skilled workers						
	Capital type						
	Computing equipment	Communication equipment	Software	Transport equipment	Machinery	–	Total
A. Narrow definition of skilled labor: University-equivalent tertiary education							
	0.21***	0.38***	0.32***	−0.49***	−0.51***		0.43***
	(0.002)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
ICT (groups 1, 2 and 3)						0.29***	
						(0.004)	
Non-ICT (groups 4 and 5)						−0.48***	
						(0.01)	
Observations	331	331	331	331	331	331	331
No. of countries	14	14	14	14	14	14	14
B. Broad definition of skilled labor: At least high-school							
	0.05***	0.13***	0.07***	−0.14***	−0.11***		0.13***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.004)		(0.01)
ICT (groups 1, 2 and 3)						0.09***	
						(0.001)	
Non-ICT (groups 4 and 5)						−0.14***	
						(0.002)	
Observations	331	331	331	331	331	331	331
No. of countries	14	14	14	14	14	14	14

Notes: This table reports TSLS estimates of $\gamma1$ in the regression $\Delta S = \beta * \Delta\ln(w_H / w_L) + \gamma1 * \Delta\log(\text{capital\_}i / \text{output}) + \gamma2 * \Delta\log(\text{capital\_}{-i} / \text{output}) + \Delta\varepsilon$, for different capital types i, where capital_$-i$ is the total capital net of capital_i. S is the wage bill share of skilled workers and w_H/w_L is the relative wage of skilled to unskilled workers. Δ is the first difference operator. Positive coefficients indicate complementarity to skilled workers; negative coefficients indicate complementarity to unskilled workers. Instruments for capital shares are their 1-period lagged values (both in changes); all first stage results report F-statistics higher than 1000. All regressions include country fixed effects. Data: EU KLEMS. Standard errors in parentheses are clustered at the country level. ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table A6
Capital stock shares and changes in capital stock shares, nine equipment groups, OECD data.

R&D intensity rank:		1	2	3	4	5	6	7	8	9	1 + 2 + 3 + 4 + 6	5 + 7 + 8 + 9
Capital type:		Aircraft equipment	Office, computing, and accounting machinery	Communication equipment	Professional goods	Electrical equipment, excluding communication	Motor vehicles	Non-electrical equipment	Other transportation equipment	Fabricated metal products	M_H	M_L
A. Average capital stock shares												
Austria	1995–2005	0.006	0.030	0.104	0.071	0.407	0.172	0.039	0.021	0.150	0.382	0.618
Belgium	1995–2005	0.018	0.022	0.072	0.083	0.305	0.281	0.034	0.012	0.172	0.477	0.524
Czech Republic	2001–2005	0.009	0.051	0.091	0.099	0.404	0.177	0.039	0.012	0.119	0.427	0.573
Finland	1980–2005	0.016	0.040	0.116	0.068	0.523	0.078	0.034	0.012	0.113	0.318	0.682
France	1978–2005	0.053	0.040	0.064	0.065	0.378	0.170	0.060	0.009	0.161	0.392	0.609
Germany	1980–2005	0.022	0.043	0.054	0.137	0.343	0.206	0.047	0.009	0.139	0.462	0.538
Hungary	1992–2005	0.004	0.043	0.136	0.087	0.440	0.154	0.035	0.007	0.094	0.424	0.576
Italy	1980–2005	0.027	0.030	0.092	0.110	0.242	0.163	0.053	0.020	0.263	0.422	0.578
Japan	1986–2005	0.011	0.065	0.167	0.102	0.217	0.280	0.029	0.001	0.128	0.626	0.374
Korea	1994–2005	0.011	0.031	0.287	0.092	0.228	0.199	0.049	0.009	0.094	0.620	0.380
Netherlands	1985–2005	0.032	0.049	0.165	0.065	0.229	0.181	0.040	0.018	0.220	0.492	0.508
Poland	1996–2005	0.011	0.049	0.100	0.098	0.270	0.226	0.057	0.018	0.173	0.483	0.517
Slovenia	1995–2005	0.005	0.049	0.083	0.116	0.191	0.247	0.053	0.016	0.240	0.500	0.500
Spain	1980–2005	0.017	0.053	0.072	0.102	0.198	0.277	0.048	0.020	0.213	0.521	0.479
Sweden	1980–2005	0.030	0.048	0.102	0.089	0.256	0.246	0.056	0.018	0.154	0.515	0.485
United Kingdom	1980–2005	0.065	0.082	0.096	0.086	0.191	0.236	0.063	0.015	0.165	0.566	0.434
United States	1980–2005	0.070	0.063	0.123	0.074	0.155	0.287	0.060	0.012	0.156	0.617	0.383
Average		0.024	0.046	0.113	0.091	0.293	0.211	0.047	0.014	0.162	0.485	0.515
B. Changes in capital stock shares												
Austria	1995–2005	0.008	0.000	−0.027	0.005	−0.029	0.052	0.002	0.011	−0.007	0.028	−0.023
Belgium	1995–2005	0.000	0.002	0.016	−0.009	−0.021	−0.025	0.004	−0.001	0.042	−0.022	0.024
Czech Republic	2001–2005	0.001	0.002	−0.009	−0.011	−0.003	0.015	−0.006	0.003	0.008	0.001	0.002
Finland	1980–2005	0.011	0.010	0.146	−0.040	0.020	−0.055	−0.010	−0.010	−0.032	0.047	−0.032
France	1978–2005	0.032	0.009	0.001	0.005	−0.085	0.086	−0.014	0.006	−0.022	0.071	−0.115
Germany	1980–2005	0.006	0.009	−0.012	−0.062	0.111	0.053	−0.036	0.000	−0.050	−0.006	0.025
Hungary	1992–2005	−0.001	−0.015	0.090	0.029	0.001	0.020	−0.062	−0.001	−0.062	0.059	−0.124
Italy	1980–2005	0.014	0.023	−0.022	0.006	−0.018	0.036	0.010	−0.006	−0.015	0.032	−0.028
Japan	1986–2005	0.003	0.021	0.085	−0.023	−0.051	0.027	−0.023	0.004	−0.040	0.045	−0.111
Korea	1994–2005	0.011	0.045	0.097	0.026	−0.036	−0.031	−0.018	−0.007	0.022	0.079	−0.040
Netherlands	1985–2005	−0.028	0.007	−0.003	0.005	0.025	0.047	−0.032	0.011	0.046	0.014	0.050
Poland	1996–2005	0.001	0.005	0.018	−0.007	−0.066	0.020	−0.009	−0.007	0.047	0.017	−0.035
Slovenia	1995–2005	0.002	−0.010	0.013	0.014	−0.030	−0.065	−0.004	−0.004	0.083	−0.036	0.045
Spain	1980–2005	0.008	0.013	−0.010	−0.030	−0.031	0.117	−0.013	0.000	−0.055	0.067	−0.099
Sweden	1980–2005	−0.005	0.008	0.027	−0.049	−0.092	0.125	0.021	−0.001	−0.034	0.060	−0.106
United Kingdom	1980–2005	0.007	0.041	0.007	−0.019	−0.054	0.073	0.001	−0.006	−0.051	0.054	−0.111
United States	1980–2005	−0.027	0.018	0.040	−0.018	−0.039	0.086	−0.007	−0.007	−0.047	0.053	−0.099
Average		0.003	0.011	0.027	−0.010	−0.023	0.034	−0.011	−0.001	−0.010	0.033	−0.046

Notes: In Panel A capital stock shares are computed as shares in total nominal capital stock and averaged over all available years. In Panel B changes in capital stock shares are computed as the share in the last year minus the share in the first year. Samples are noted next to each country. Averages over all countries are reported below country data. Capital stock data was aggregated according to the classification in Table 1 based on data from OECD. Stocks are calculated by perpetual inventory method, using capital type-specific depreciation. Investment of each capital type is given by $I = Y - X + M$, where Y is output, X are exports and M are imports (data from OECD). See the main text for complete details.

Appendix B. Data

B.1. Inequality regressions

B.1.1. Sample

The sample is an unbalanced panel covering 1983–2000 with varying time periods for each country, based on data availability for wage data, and builds on, and extends, the sample of Zhu and Trefler (2005). All countries in this sample have real GDP per capita in 1980 below $14,000 in 1980 dollars. The sample is further restricted by data availability.

List of countries and intervals: Algeria (1985–1989, 1990–1992), Argentina (1991–1993, 1993–1995), Barbados (1985–1989, 1990–1993, 1993–1995), Bolivia (1991–1994, 1994–1997), Central African Republic (1987–1989, 1991–1993, 1993–1997), Cyprus (1983–1986, 1986–1989, 1990–1993, 1993–1997, 1997–2000), Honduras (1983–1987, 1990–1993, 1993–1997), Hungary (1995–1998, 1998–2000), Hong Kong (1983–1985, 1985–1989, 1991–1994, 1994–1997), India (1986–1989, 1990–1994, 1994–1997), South Korea (1983–1986, 1986–1989, 1991–1993, 1993–1997), Sri Lanka (1983–1985, 1985–1988, 1990–1993, 1993–1997), Madagascar (1983–1987, 1994–1995), Mauritius (1983–1985, 1985–1989, 1990–1993, 1993–1997, 1997–2000), Mexico (1990–1993, 1993–1997), the Philippines (1983–1986, 1986–1989, 1990–1994, 1995–1999), Singapore (1985–1989, 1991–1993, 1993–1997), Thailand (1984–1986, 1991–1995), Trinidad and Tobago (1985–1988, 1990–1996), Uruguay (1985–1989, 1990–1993, 1993–1995) and Venezuela (1984–1986, 1986–1989, 1990–1997).

Since the intervals do not perfectly overlap for all countries, we group country-specific intervals into five periods. Each interval was classified to the period with which it has the largest overlap. These are: 1983–1986 (10 country observations), 1986–1989 (14 country observations), 1990–1993 (16 country observations), 1993–1997 (19 country observations), and 1997–2000 (4 country observations). On average, each country is observed in three periods. These periods underlie the time fixed effects in all estimations of Eq. (4).

B.1.2. Variable definitions

Change in the logarithm of skilled relative wage, Δlnω: Defined as the wage ratio of manufacturing workers in non-production occupations (managers, professionals, technicians, and clerks) to manufacturing workers in production occupations (craft workers, operators, and laborers). Source: International Labour Organization.

Change in logarithm of relative supply of skill (skill abundance), Δln(H/L): Relative supply of skill is measured by the ratio of skilled to unskilled population, aged 25 and above. The skilled group is defined as those having at least secondary education. Source: (Barro and Lee, 2013).

Shift in export shares, Δz: Consider the area under the cumulative distribution function of export shares to OECD countries with 1980 real GDP per capita exceeds $14,000 (in 1980 dollars), where industries are ranked by their skill intensity. Δ*z* is the difference in this area between the last and first year in each period. More formally, rank all industries for some country by skill intensity (based on the ratio of non-production workers to production workers) and normalized to 1. Define this rank as $r \in [0,1]$. The export share of each industry in time *t* is $x_t(r)$, where only exports to OECD countries with real GDP per capita in 1980 above $14,000 in 1980 dollars. $\Delta z_t = \int_0^1 \int_0^r x_t(s) ds dr - \int_0^1 \int_0^r x_{t-1}(s) ds dr$. Source: Zhu and Trefler (2005).

GDP, Population, Industrial/Government/Services share (value added shares in GDP): Source: World Bank, World Development Indicators.

Aggregate capital stocks Source: Penn World Tables, Version 6.1 (Heston et al., 2012).

Intellectual property rights protection index: This index characterizes strongly that patent rights are protected. It is constructed using a coding scheme applied to national patent laws, examining five distinct categories. Source: Ginarte and Park (1997), updated by Park (2008).

Financial development: M3 money supply as a fraction of GDP. Source: World Bank, World Development Indicators.

B.1.3. Data from Feenstra et al. (2005)

Imports of R&D-intensive capital: Imports of R&D-intensive capital are averaged within each time interval. R&D-intensive capital is an aggregated group that includes the following ISICs: computing equipment (3825), communication equipment (3832) aircraft equipment (3845), motor vehicles (3843), and professional goods (385).

Imports of R&D-unintensive capital: Imports of R&D-unintensive capital are averaged within each time interval. R&D-unintensive capital is an aggregated group that includes the following ISICs: fabricated metal products (381), non-electrical equipment (382 without 3825), electrical equipment (383 without 3832), and other transportation equipment (3842, 3844, 3849).

Aggregate capital imports: Imports of aggregate capital are averaged within each time interval. Aggregate capital is an aggregated group that includes all nine capital groups.

The capital import ratio: The capital import ratio is defined as imports of R&D-intensive capital (averaged within each time interval) divided by R&D-unintensive capital (averaged within each time interval).

Capital goods are defined as ISIC rev.2 category 38, “Manufacture of Fabricated Metal Products, Machinery and Equipment”.

B.2. Complementarity estimation samples

Data on capital stocks from the EU-KLEMS data set are available for 14 countries: Australia (1970–2005), Austria (1976–2005), Czech Republic (1995–2005), Denmark (1970–2005), Finland (1970–2005), Germany (1970–2005), Italy (1970–2005), Japan (1970–2005), Netherlands (1970–2005), Portugal (1995–2005), Slovenia (1995–2005), Sweden (1993–2005), the United Kingdom (1970–2005) and United States (1970–2005).

The sample for which we are able to compute capital stocks according to the classification in Table 1 includes 17 countries: Austria (1995–2005), Belgium (1995–2005), Czech Republic (2001–2005), Finland (1980–2005), France (1978–2005), Germany (1980–2005), Hungary (1992–2005), Italy (1980–2005), Japan (1980–2005), Korea (1994–2005), Netherlands (1985–2005), Poland (1996–2005), Slovenia (1995–2005), Spain (1980–2005), Sweden (1980–2005), the United Kingdom (1980–2005) and the United States (1980–2005).

B.3. Gravity estimation sample, 1984–1999

Afghanistan, Albania, Algeria, Angola, Argentina, Australia, Austria, Bahamas, Bahrain, Bangladesh, Barbados, Belgium-Lux, Belize, Benin, Bermuda, Bhutan, Bolivia, Brazil, Brunei, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cayman Islds., Central Africa, Chad, Chile, China, Colombia, Comoros Islds., Congo, Costa Rica, Cote D'Ivoire, Cuba, Cyprus, Denmark, Djibouti, Dominican Rep., Ecuador, Egypt, El Salvador, Eq. Guinea, Ethiopia, Fiji, Finland, Fm. Czechoslovakia, Fm. USSR, Fm. Yugoslavia, France, French Guiana, Gabon, Gambia, Germany, Ghana, Greece, Greenland, Guadeloupe, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Kiribati, Korea DPR, Korea Rep., Kuwait, Laos, Lebanon, Liberia, Libya, Madagascar, Malawi, Malaysia, Maldives, Malta, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Netherlands, Neth. Antilles, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Reunion, Romania, Rwanda, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Solomon Islds., Somalia, South Africa, Spain, Sri Lanka, Mali, St. Kitts and Nevis, Sudan, Surinam, Sweden, Switzerland, Syria, Taiwan, Thailand, Togo, Trinidad-Tobago, Tunisia, Turkey, Turks and Caicos, Uganda, the United Kingdom, United Arab Em., United Rep. Tanzania, the United States, Uruguay, Venezuela, Vietnam, Yemen, Zambia and Zimbabwe.

Appendix C. Derivations for the analytical framework section

There are two types of capital—*C* and *K* (think computers and tractors, respectively)—and two types of labor—skilled *H* and unskilled *L*. The aggregate production function is given by

$$Q = \left[\delta X^{\frac{\sigma-1}{\sigma}} + (1-\delta) Y^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where

$$X = H^{\beta} C^{1-\beta}$$
$$Y = L^{\beta} K^{1-\beta},$$

$B \in (0,1)$ and $\sigma > 1$.

Workers supply labor—either *H* or *L*—inelastically. Denote the wage of skilled labor by w_H and the wage of unskilled labor by w_L. Denote the price of capital as r_j for $j \in \{C,K\}$. Competitive factor markets imply that factors are paid the value of their marginal product:

$$\frac{\partial Q}{\partial H} = \frac{\sigma}{\sigma-1}[\cdot]^{\frac{\sigma}{\sigma-1}-1}\delta\frac{\sigma-1}{\sigma}X^{\frac{\sigma-1}{\sigma}-1}\beta\frac{X}{H} = \beta\delta Q^{\frac{1}{\sigma}}X^{\frac{\sigma-1}{\sigma}}H^{-1} = w_H$$

$$\frac{\partial Q}{\partial C} = \frac{\sigma}{\sigma-1}[\cdot]^{\frac{\sigma}{\sigma-1}-1}\delta\frac{\sigma-1}{\sigma}X^{\frac{\sigma-1}{\sigma}-1}(1-\beta)\frac{X}{C} = (1-\beta)\delta Q^{\frac{1}{\sigma}}X^{\frac{\sigma-1}{\sigma}}C^{-1} = r_C$$

$$\frac{\partial Q}{\partial L} = \frac{\sigma}{\sigma-1}[\cdot]^{\frac{\sigma}{\sigma-1}-1}(1-\delta)\frac{\sigma-1}{\sigma}Y^{\frac{\sigma-1}{\sigma}-1}\beta\frac{Y}{L} = \beta(1-\delta)Q^{\frac{1}{\sigma}}Y^{\frac{\sigma-1}{\sigma}}L^{-1} = w_L$$

$$\frac{\partial Q}{\partial K} = \frac{\sigma}{\sigma-1}[\cdot]^{\frac{\sigma}{\sigma-1}-1}(1-\delta)\frac{\sigma-1}{\sigma}Y^{\frac{\sigma-1}{\sigma}-1}(1-\beta)\frac{Y}{K}$$
$$= (1-\beta)(1-\delta)Q^{\frac{1}{\sigma}}Y^{\frac{\sigma-1}{\sigma}}K^{-1} = r_K.$$

The relative wage of skilled workers is

$$\omega \equiv \frac{w_H}{w_L} = \frac{\delta X^{\frac{\sigma-1}{\sigma}}H^{-1}}{(1-\delta)Y^{\frac{\sigma-1}{\sigma}}L^{-1}} = \frac{\delta}{1-\delta}\left(\frac{H^\beta C^{1-\beta}}{L^\beta K^{1-\beta}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{H}{L}\right)^{-1}$$

$$= \frac{\delta}{1-\delta}\left(\frac{H}{L}\right)^{-\frac{\sigma-\beta(\sigma-1)}{\sigma}}\left(\frac{C}{K}\right)^{\frac{(1-\beta)(\sigma-1)}{\sigma}},$$

as in the main text. In order to derive the expression for C/K we start with

$$\frac{r_C}{r_K} = \frac{\delta X^{\frac{\sigma-1}{\sigma}}C^{-1}}{(1-\delta)Y^{\frac{\sigma-1}{\sigma}}K^{-1}} = \frac{\delta}{1-\delta}\left(\frac{H^\beta C^{1-\beta}}{L^\beta K^{1-\beta}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{C}{K}\right)^{-1}$$

and

$$= \frac{\delta}{1-\delta}\left(\frac{H}{L}\right)^{\frac{\beta(\sigma-1)}{\sigma}}\left(\frac{C}{K}\right)^{\frac{(1-\beta)(\sigma-1)-\sigma}{\sigma}},$$

which gives

$$\frac{C}{K} = \left(\frac{\delta}{1-\delta}\right)^{\frac{\sigma}{\sigma-(1-\beta)(\sigma-1)}}\left(\frac{H}{L}\right)^{\frac{\beta(\sigma-1)}{\sigma-(1-\beta)(\sigma-1)}}\left(\frac{r_C}{r_K}\right)^{-\frac{\sigma}{\sigma-(1-\beta)(\sigma-1)}}.$$

Taking logs and then first differences gives the equation used in the main text.

Here we show that $\sigma-(1-\beta)(\sigma-1)>0$ for $\beta \in (0,1)$ and $\sigma>0$, regardless of whether σ is greater than unity or not. For $\sigma>1$ we have a positive fraction, $(1-\beta)$, times a positive number smaller than σ, $(\sigma-1)$, which together give $(1-\beta)(\sigma-1)<\sigma$. When $\sigma<1$ the product $(1-\beta)(\sigma-1)<\sigma$, but then deducting a negative number from a positive one remains positive.

Appendix D. Contribution of changes in capital stocks to changes in relative demand for skill via changes in industry sizes

We draw on the EU-KLEMS data set. For each country and industry in the data set we collect the following variables for 1983–1997 (the sample in the main analysis):

- The percent contribution to value added growth of two classes of capital—ICT (c_i) and non-ICT capital (n_i)
- The change in employment share of some industry i within a country (Δl_i)

In addition, we collect data on two measures of skill intensity in the initial year 1983: wage bill shares of skilled labor (s) and employment shares of skilled labor (e).

The predicted contributions of each capital type to change in the economy-wide skill intensity in production *through industry growth alone* are

$$C = \sum_i c_i \Delta l_i s_i$$

$$N = \sum_i n_i \Delta l_i s_i,$$

for ICT and non-ICT capital, respectively. This calculation does not take into account the effect of changes in capital stocks on skill intensity by virtue of uneven complementarities, which is the focus of this paper. The assumption that underpins the validity of these calculations are constant returns to scale industries, since we are using contributions to value added growth c_i and n_i for employment growth. This assumption is not difficult to admit.

We divide C and N by aggregate skill intensity in the initial year, multiply by 100 and divide by the number of years over which they are computed—this gives us annualized percent point contributions to changes in skill intensity through this channel. We compute these both using s and using e. The levels tell us how important this channel is. Comparing C to N tells us which type of capital contributed to economy skill intensity more, via changes in production patterns. The results are summarized in Table A2.

We find that—through this specific channel—the contributions of ICT and non-ICT to increases in skill intensities are small. We also find that non-ICT capital contributes just as much to increases in skill intensity, if not more.

Appendix E. Exogeneity of instruments

Denote log values in lower case. Then Eq. (5) becomes

$$m_{oit} = \alpha_{it} + \delta_{it} dist_{oi} + \varepsilon_{oit}. \tag{13}$$

Here $dist_{oi}$ may be exogenous, but the OLS estimator of δ_{it} may be biased. The exogeneity of the predicted values of this regression may be violated if the OLS estimator of δ_{it} varies systematically with omitted variables in Eq. (4), or with $\Delta\omega_{it}$ directly.

Suppose that there is an omitted variable in Eq. (13). Rewrite Eq. (13) as

$$m_{oit} = \alpha_{it} + \delta_{it} dist_{oi} + u_{oit} + \gamma x_{oit}, \tag{14}$$

where u is an orthogonal error and x is an omitted variable, possibly correlated with $dist$. Fix i and t. The OLS estimator of δ_{it} in Eq. (13) is

$$\hat{\delta}_{it} = \delta_{it} + \gamma\frac{\sum_o\left(dist_{oi}-\overline{dist}_i\right)(x_{oit}-\overline{x}_{it})}{\sum_o\left(dist_{oi}-\overline{dist}_i\right)^2} + \frac{\sum_o\left(dist_{oi}-\overline{dist}_i\right)u_{oit}}{\sum_o\left(dist_{oi}-\overline{dist}_i\right)^2}, \tag{15}$$

and the probability limit is

$$\text{Plim } \hat{\delta}_{it} = \delta_{it} + \gamma\frac{cov(dist_{oi}, x_{oit}|i,t)}{var(dist_{oi}|i)}. \tag{16}$$

We could also have γ vary along i and t, but this is sufficient to illustrate the potential for bias. Recall that we use $\hat{\delta}_{it} dist_{oi}$ to construct the instruments. If the second term in Eq. (16) varies systematically by i and t in a way that is correlated with omitted variables in Eq. (4), or with $\Delta\omega_{it}$ directly, then we may have concerns for exogeneity of the instruments. Note that this requires more than the existence of such a covariance; it means that the covariance between distance and x across origin countries varies systematically over i and t. While impossible to prove or disprove, it is difficult to think of omitted variables with such properties.

Appendix F. Derivation of complementarity equation

Let there be two types of capital, k_1 and k_2, which are quasi-fixed, and let there be two variable inputs: Skilled and unskilled labor, h and l, respectively (what follows extends to additional variable and/or quasi-fixed inputs). In this case, variable costs are given by $c = w_h \cdot h + w_l \cdot l$. If h and l are the argmin of costs, then c is the cost function. The logarithm of c can be approximated by a translog cost function:

$$\begin{aligned}\ln(c) &= \alpha_h \ln(w_h) + \alpha_l \ln(w_l) + \alpha_{k_1} \ln(k_1) + \alpha_{k_2} \ln(k_2) + \alpha_y \ln(y) + \\ &+ \frac{1}{2}\left[\begin{array}{l}\beta_{hh} \ln(w_h)^2 + \beta_{hl} \ln(w_h)\ln(w_l) + \beta_{lh} \ln(w_l)\ln(w_h) + \beta_{ll} \ln(w_l)^2 \\ +\beta_{k_1k_1} \ln(k_1)^2 + \beta_{k_2k_2} \ln(k_2)^2 + \beta_{yy} \ln(y)^2\end{array}\right] \\ &+ \gamma_{hk_1} \ln(w_h)\ln(k_1) + \gamma_{hk_2} \ln(w_h)\ln(k_2) + \gamma_{hy} \ln(w_h)\ln(y) \\ &+ \gamma_{lk_1} \ln(w_l)\ln(k_1) + \gamma_{lk_2} \ln(w_l)\ln(k_2) + \gamma_{ly} \ln(w_l)\ln(y) \\ &+ \gamma_{k_1k_2} \ln(k_1)\ln(k_2) + \gamma_{k_1y} \ln(k_1)\ln(y) + \gamma_{k_2y} \ln(k_2)\ln(y),\end{aligned}$$

where y is output. Symmetry implies $\beta_{hl} = \beta_{lh}$.

By Shephard's lemma, $\partial c / \partial w_h = h$, so that the cost share of skilled labor is

$$S \equiv \frac{w_h h}{c} = \frac{\partial \ln(c)}{\partial \ln(w_h)} = \frac{\partial c}{\partial w_h}\frac{w_h}{c}.$$

Using this in the translog we get

$$S = \alpha_h + \beta_{hh} \ln(w_h) + \beta_{hl} \ln(w_l) + \gamma_{hk_1} \ln(k_1) + \gamma_{hk_2} \ln(k_2) + \gamma_{hy} \ln(y).$$

By linear homogeneity of cost with respect to prices, cost shares are homogenous of degree zero; therefore $\beta_{hh} + \beta_{hl} = 0$. By linear homogeneity of the production function we have $\gamma_{hk_1} + \gamma_{hk_2} + \gamma_{hy} = 0$ (increasing all inputs by the same factor increases output by same factor, but this should not affect the cost share). Using these two properties gives

$$S = \alpha + \beta \ln\left(\frac{w_h}{w_l}\right) + \gamma_{k_1} \ln\left(\frac{k_1}{y}\right) + \gamma_{k_2} \ln\left(\frac{k_2}{y}\right),$$

which is used in the main text.

Appendix G. Trade liberalization and changes in the composition of capital imports: FOB sample

We now address the few cases where tariffs are applied to FOB (free on board) prices, exclusive of freight costs. Denote the countries for which this rule applies as the "FOB sample": Afghanistan, Australia, Botswana, Canada, Democratic Republic of the Congo, Lesotho, Namibia, New Zealand, Puerto Rico, South Africa, Swaziland, and the United States. See http://export.customsinfo.com/ and http://export.gov/logistics/eg_main_018142.asp. We thank Robert Feenstra for this reference.

In these cases, Eq. (8) becomes

$$\frac{r_C}{r_K} = \frac{r_C^*(1+\tau_C) + \tilde{f}_C + \tilde{b}_C}{r_K^*(1+\tau_K) + \tilde{f}_K + \tilde{b}_K} = \frac{r_C^*}{r_K^*} \cdot \frac{1+\tau_C + f_C + b_C}{1+\tau_K + f_K + b_K}, \tag{17}$$

where $b_j \equiv \tilde{b}_j / r_j^*$ is the ad valorem equivalent distance related cost, and f_j is defined above. Our findings above pertain to this case as well, but we can say something more here. If tariffs, transportation and distance-related costs are lower for R&D-intensive capital imports, then a blanket drop in tariffs at the same rate will also reduce r_C/r_K. To see this, write Eq. (17)

$$\left.\frac{r_C}{r_K}\right|_{\Delta\tau=0} = \frac{r_C^*}{r_K^*} \cdot \frac{1+\tau_C + \Delta\tau + f_C + b_C}{1+\tau_K + \Delta\tau + f_K + b_K}$$

and take the derivative with respect to $\Delta\tau$

$$\left.\frac{\partial}{\partial\Delta\tau}\frac{r_C}{r_K}\right|_{\Delta\tau=0} = \frac{r_C^*}{r_K^*} \cdot \frac{(\tau_K + f_K + b_K) - (\tau_C + f_C + b_C)}{(1+\tau_K + f_K + b_K)^2}.$$

This derivative is positive if $(\tau_K + f_K + b_K) > (\tau_C + f_C + b_C)$. Contemplating an equal *percent point* drop in tariffs for both K and C is meaningful if the absolute difference between them before liberalization is not too large—which is what we observe. This is consistent with a larger drop in percent terms in $1 + \tau_C$ versus $1 + \tau_K$ found above, since we find $\tau_C < \tau_K$. We now show that this is indeed the case. As above, we keep the exposition of results to a minimum; full statistical outputs are available upon request.

First, we estimate that τ_C is smaller than τ_K in the FOB sample. Using the same TRAINS tariff data and definitions above, we fit fixed effects regressions

$$\tau_{it}^j = \beta I(j \in M_H) + \alpha_i + \delta_t + \varepsilon_{it}, \tag{18}$$

where α_i is a country fixed effect and δ_t is a year fixed effect. We cluster standard errors by country. We estimate $\beta = -1.77\%$ and highly statistically significant. If we only consider the first year in the sample for each country (i.e., $t = 1$), then we find $\beta = -2.6\%$.

Second, we estimate that freight costs are lower for R&D-intensive capital transported via sea, but the opposite is true for shipments via air. Sea shipments are the bulk of shipment value in the U.S. import data, 64% on average throughout the period. Using the same ad-valorem freight data used above to estimate Eq. (10), we fit regressions of the type

$$f_j = \beta I_{(j \in M_H)} + \gamma \ln(w/v)_j + \alpha_{s(j)} + \delta_{t(j)} + \varepsilon_j, \tag{19}$$

where $\alpha_{s(j)}$ is a source s fixed effect for all shipments j imported from source s, and $\alpha_{t(j)}$ is a time fixed effect for all shipments j that are observed in year t (which absorbs global changes in fuel prices). In the estimation we weigh observations by shipment value and cluster standard errors by source country. When we estimate Eq. (19) for sea shipment we also control for the share of containerized trade in the shipment. We estimate, with high precision, that $\beta = -0.33$ percent points for sea shipments, but $+0.23$ percent points for air shipments. When we do not weigh observations by value, we estimate, with high precision, that $\beta = -1.27$ percent points for sea shipments and -2.1 percent points for air shipments.

Finally, we estimate that bilateral barriers to trade are lower for M_H relative to M_L. We estimate the following gravity equations separately for each year in 1984–1999 (which is the most appropriate way to do this; see Head and Mayer, 2014):

$$m_{si}^j = \beta \cdot I\left(m_{si}^j \in M_H\right) + \chi_s + \eta_i + \varepsilon_{si}^j,$$

where m_{sit}^j are log capital imports from source s to importer i of capital type $j \in \{M_L, M_H\}$; and $I(m_{si}^j \in M_H)$ indicates whether m_{si}^j is of type M_H ($=1$) or not ($=0$). Exporter and importer fixed effects—χ_s and η_i—respectively, capture demand conditions in the importer countries and technology in the source country. It is important to see that the latter ensure that β is identified only by bilateral variation in barriers to trade for M_H. This coefficient absorbs the differential effect of all bilateral trade impediments (inter alia, distance, language, colonial ties, tariffs and freight costs).

We estimate this equation by OLS, clustering standard errors by country-pair, using import data in 1984–1999, both for 157 countries (136,786 observations) and for the twelve countries in the FOB sample (12,786 observations). In both samples and in every year we find that $\beta < 0$; on average across years $\hat{\beta} = -0.179$ for the entire sample, and for the FOB sample $\hat{\beta} = -0.164$ on average, which indicates that bilateral trade resistance falls for M_H is lower than M_L on average.

We also estimate the gravity equation with a Heckman correction for sample selection along the lines of Helpman et al. (2008), using their common religion index as an excluded variable in the selection equation. This increases the magnitude of the coefficients to $I(m_{si}^{j} \in M_H)$, but hardly affects their trend over time. To summarize, bilateral barriers to trade are lower for M_H relative to M_L, regardless of how we estimate this.

Appendix H. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdeveco.2015.07.011.

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