Does complexity explain the structure of trade?[1]

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Abstract

This paper analyzes whether complexity, measured by the number of skilled tasks that are performed in production, explains countries' commodity trade structure. We modify Romalis (2004) model to incorporate advantage differences in complexity across commodities together with differences in the number of mistakes made by workers in the production process in developed and developing countries as a source of comparative advantage. Our model predicts that the share of developed countries in world trade increases with products' complexity. Empirical tests confirm this prediction. Moreover, we find that complexity complements the explanation provided by skill-intensity on countries' commodity trade structure.

Key words: complexity, skill-intensity, factor proportions, trade structure, specialization.

JEL classification: F11, F12, F14

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1. Introduction

One of the features of the globalization process is the increasing number of firms located in developing countries engaged in international markets, and the emergence of the so-called emerging markets champions. Moreover, some of these firms are able to compete in skill-intensive activities with firms located in developed countries. For example, among services, some skill-intensive activities, such as medical diagnoses or software development, are outsourced to developing countries. Among manufactures, we also observe some developing countries' firms capturing substantial market shares in skill-intensive products, such as pesticides or electrical equipment.[2]

The increasing number of firms located in developing countries competing in skill-intensive activities does not fit well into the factor proportions theory of trade. According to this theory, developing countries should specialize in goods and services that make intensive use of the factor of production in which they are relatively well endowed: unskilled labor. In this paper we offer a novel explanation for the pattern of trade between developed and developing countries, an explanation that accommodates the growing presence of southern firms in some skill-intensive activities. We contend that complexity, defined as the number of skilled tasks that are performed in production, offers a complementary description of the pattern of trade between developed and developing countries.

Goods and services differ in their level of complexity. For example, among goods, the number of different skilled tasks needed to produce an aircraft is much larger than the number of skilled tasks needed to produce a bicycle. Among services there are also large differences in complexity. For example, the number of different skilled tasks needed to provide the services of a business school is much larger than the number of different tasks needed to run a barbershop. Usually, there is a correlation between the skill-intensity of a product or service, measured by the share of skilled workers in total employees, and its complexity level. However, there are cases in which a large skill-intensity does not imply a high level of complexity. For example, some of the goods and services where we observe an increasing presence of developing countries' firms (pesticides, electrical equipment, medical diagnoses or software writing) are characterized by a high degree of skill-intensity, but by a low degree of complexity.

Building on this concept, we contend that developed countries have comparative advantage in complex goods, whereas developing countries have comparative advantage in less complex goods. The advantage of developed countries in complex goods stems from the fact that small differences in workers' skills are magnified when a large number of skilled workers performing different tasks are combined in production. As average skills are higher in developed than in developing countries, productivity differences between the former and the latter will increase with the complexity of goods. In contrast, when products or services do not require complex production processes, differences in productivity are not magnified, and developing countries might compete in them. Hence, it is not only the intensity, but also the number of skilled tasks what determines developed countries' comparative advantage.

The contribution of this paper is to formalize these ideas, developing a model that incorporates differences in the number of mistakes made by workers in developed and developing countries, differences in complexity across commodities and monopolistic competition. The model predicts that developed countries share in trade will increase with the complexity of goods. This prediction receives ample support in the empirical analysis. Moreover, we show that complexity provides a better explanation of countries' trade structure than the one offered only by skill intensity. Both the model and the empirical analysis take into account the possibility for vertical fragmentation of the production process and the tradability of tasks.

This paper is related to several strands of the literature. First, it is linked to the literature that has worked on the concept of complexity and its influence on productive specialization. In particular, we draw the concept of complexity from Kremer (1993) and place it in a general equilibrium two-country model. Kremer defines complexity as the number of activities that might go wrong during the production process and influence the value of the product as a whole. In his model there are differences in skills across workers, where skills are defined as the probability a worker will successfully complete a task. One prediction of the model is that countries with more skilled workers will produce more complex goods. However, Kremer does not test his model empirically.

Costinot (2009) also defines complexity as the number of tasks that are required to produce a good. However, there are major differences between his work and ours. On the theoretical side, in Costinot's model the comparative advantage of high-wage countries in complex products stems from better contract enforcement in these countries; in contrast, in our model, high-wage countries comparative advantage stems from higher labor productivity, due to the lower number of mistakes made in the production process. On the empirical side, although Costinot defines complexity as the number of tasks involved in production, he measures it by the average training that a worker needs to participate in production. In contrast, we measure complexity directly as the number of tasks involved in production. In addition to that, the number of industries and countries included in our study is much larger.[3] Finally, we also compare the relative contributions of complexity and skill-intensity to explain countries' commodity trade structure.

Hidalgo and Hausmann (2009) also introduce the concept of complexity to understand the differences between high-wage and low-wage countries. They define complexity as the number of capabilities or intangible skills required to manufacture a good. These authors argue that the set of capabilities that are available in developed countries is much larger than in developing countries. If complex products require the combination of a large number of capabilities, it will be more probable to find the whole set of the required capabilities in developed than in developing countries. However, developing countries may still have comparative advantage in those activities that require a small range of skill-intensive capabilities. In contrast to Hidalgo and Hausmann (2009), in our model high-wage country's comparative advantage in complex goods does not stem from a larger variety of capabilities, but from higher labor productivity, which is magnified when a larger number of tasks are combined in production. In addition, Hidalgo and Hausmann calculate complexity following a different methodology, based on an iterative process that combines the number of products that a country exports (diversity) and the number of countries that export a product (ubiquity). Hidalgo and Hausmann (2009) observe that complexity predicts well a country's income level and growth; however, they do not study whether complexity explains countries' trade structure.

This paper is also related to recent studies that examine the pattern of international trade between developed and developing countries, and particularly, to Romalis (2004). This author develops a model to analyze how differences in factor proportions influence the commodity structure of trade. His model predicts that countries relatively well endowed with skilled labor will have a larger share in the world production and trade of skill-intensive goods. As predicted by the model, he shows that the share of developed countries in US imports is increasing in the skill-intensity of goods. Our paper complements Romalis' analysis showing that complexity also plays a substantial role in determining the pattern of trade between developed and developing countries. Our paper is also related with recent studies, such as Nunn (2007), Morrow (2010) and Chor (2010), which analyze the role of factor proportions theory and other forces, such as productivity and institutional differences, in explaining the commodity trade pattern in samples that combine developed and developing countries.

Finally, this paper is also related to recent literature where trade is described as an exchange of tasks, rather than as an exchange of goods. Grossman and Rossi-Hansberg (2008) develop a model to explain which tasks are offshored by firms and which tasks are performed in-house. They also analyze the consequences on reducing the costs of offshoring on domestic factor rewards. Other authors have analyzed which tasks are more likely to remain in developed countries, and which tasks have a higher risk of being offshored to developing countries (Autor et al., 2003; Blinder, 2009; Autor, 2010). These authors show that routine and impersonal tasks are easier to offshore to developing countries. In the paper, we analyze how the tradability of tasks might influence the predictions of the model, and the empirical analyses control for the possibility of offshoring less complex tasks to developing countries.

The rest of the paper is organized as follows. The next section develops the model. Section 3 presents the empirical model and the data and Section 4 comments the results of the econometric analyses. Section 5 concludes.

2. The Model

We modify the model developed in Romalis (2004) in order to analyze the relationship between a country's average skills and its share in the world production of complex goods. Romalis develops a model based on the factor proportions theory, where countries differ in their relative endowments of skilled and unskilled workers, and products differ in their skill-intensity. The model predicts that countries relatively well endowed in skilled workers should capture a larger share in the world production and trade of skill-intensive goods. In contrast, in our model differences across countries do not stem from differences in factor endowments but from the number of mistakes that workers make in production (Kremer, 1993). In particular, we assume that there is only one factor of production, labor, and that northern workers make fewer mistakes than southern workers. The lower number of mistakes is explained by the higher level of human capital per worker in the North than in the South. On the other hand, in our model products are not differentiated by skill-intensity but by their complexity level, defined as the number of workers performing different tasks that participate in the production process. The North will be more efficient than the South in the production of all products. However, northern countries advantage increases with the complexity of goods. Hence, northern countries develop comparative advantage in complex products and southern countries develop comparative advantage in less complex products. Substituting the factor proportion source of comparative advantage by a technological source of comparative advantage, and following the analytical steps taken in Romalis, we can derive a prediction on the relationship between a country's average human capital and its share in the world production and trade of complex goods.

To reach this prediction, we assume that there are M countries in the North and M countries in the South. As explained above, there is only one factor of production, labor. The differences between northern and southern countries stem from the number of mistakes that workers make in the production process, which are larger in the latter than in the former. We also assume that the number of mistakes is the same for each worker within a country. There is a continuum of industries z in the interval $[1, n]$. The index z ranks industries by their complexity level, defined as the number of workers performing different tasks that participate in production. Industries with a higher z are more complex.

Preferences are identical for all consumers in all countries. At the industry level, consumers have Cobb-Douglas preferences, so a fixed amount of income (bY) is spent in each industry z. Within each industry, firms are able to differentiate their products without any cost, and consumers enhance their utility consuming a larger set of varieties. Based on these assumptions, the demand for variety i of industry z depends on the price of variety i relative to a price index, and the expenditure in industry z:

$$q^D(z,i) = \frac{\hat{p}(z,i)^{-\sigma}}{\int_{i' \in I(z)} \hat{p}(z,i)^{1-\sigma}\, di'} bY \qquad (1)$$

where $I(z)$ denotes the set of varieties in industry z and σ the elasticity of substitution between varieties, which is greater than one. $\hat{p}(z,i)$ denotes the price of variety i paid by consumers. For varieties produced in other countries this price includes transport costs, which have the iceberg form, where τ units should be shipped for 1 unit to arrive ($\tau \geq 1$).

It is convenient to define the ideal price index $G(z)$:

$$G(z) = \left[\int_{i \in I(z)} \hat{p}(z,i)^{1-\sigma} di\right]^{\frac{1}{1-\sigma}} \quad (2)$$

The varieties of industry z consumed in a northern country can be produced domestically, in other northern countries or in southern countries. If we mark southern varieties with an asterisk and drop the industry notation, the ideal price index G can be expressed as:

$$G = [np^{1-\sigma} + (M-1)n(p\tau)^{1-\sigma} + Mn^*(p^*\tau)^{1-\sigma}]^{\frac{1}{1-\sigma}} \quad (3)$$

where p is the factory gate price set by a northern firm and n the number of varieties. The revenue of a typical northern firm can be expressed as:

$$pq^s = bY\left(\frac{p}{G}\right)^{1-\sigma} + (M-1)bY\left(\frac{p\tau}{G}\right)^{1-\sigma} + MbY\left(\frac{p^*\tau}{G}\right)^{1-\sigma} \quad (4)$$

The supply side of the model is inspired in the Kremer (1993) O-ring production function. Each variety requires the combination of different tasks that are performed simultaneously. To keep the model simple, we assume that each worker performs only one task and each task only requires one worker. Varieties belonging to different industries differ in the number of tasks required to manufacture them: varieties belonging to more complex industries require more tasks than varieties belonging to less complex industries. Each worker performs a task with a probability γ to perform it correctly. For example, $\gamma = 1$ means that the worker always performs the task correctly. As all tasks are needed to produce the good, if $\gamma = 0$ the production process stops and output equals zero. As northern workers have more human capital than southern workers their γ is larger. For simplicity, we assume that all tasks are subject to failure.

If firms are risk-neutral, production of variety i in industry z can be expressed as,

$$q^s(z,i) = \frac{L_{zi}}{z}\gamma^z, where\ L_{zi} \geq z\ \ and\ \ L_{zi}\ is\ a\ multiple\ of\ z \tag{5}$$

where L_{zi} represents the number of workers that participate in the production of variety i in industry z. As all tasks should be performed for the product to have full value, and workers carry out their tasks simultaneously, the product of γ represents the percentage of occasions where all workers involved in production perform their task correctly. The index z, which measures the level of complexity, also denotes the number of workers that participate simultaneously in the production process.

If production involves a fixed cost α, total costs can be expressed as

$$TC(q^s(z,i)) = \left(\alpha + \frac{q^s(z,i)z}{\gamma^z}\right)w \tag{6}$$

where w denotes the wage of workers in northern countries. As there is monopolistic competition, firms maximize their profits establishing a constant mark-up over marginal costs.

$$p(z) = \frac{\sigma}{\sigma-1}\frac{zw}{\gamma^z} \tag{7}$$

Based on equation (7), we can express the relative price of industry's z variety i in the North as:

$$\tilde{p}(z) = \frac{p(z)}{p^*(z)} = \frac{w}{w^*}\frac{\gamma^{*z}}{\gamma^z} \tag{8}$$

Note that as $\gamma^{*z} < \gamma^z$ the relative price in the North is decreasing in z ($\tilde{p}' < 0$): the higher the complexity of the good the lower the relative price of northern varieties.

As explained in Romalis (2004), using equations (3) and (4), and their analogues for the South, it is possible to solve for partial equilibrium in industry z. As long as there is no complete specialization, these solutions lead to an equation that establishes a link between the share of northern firms in z-industry's world revenues (v) and the relative price of northern goods:

$$v = \frac{Y}{W}\left[\frac{-p^{-\sigma}\tau^{1-\sigma}MF\left(\frac{Y^*}{Y}+1\right)+\tau^{2-2\sigma}M^2\frac{Y^*}{Y}+F^2}{-(p^{-\sigma}+\tilde{p}^{-\sigma})\tau^{1-\sigma}MF+\tau^{2-2\sigma}M^2+F^2}\right] \qquad (9)$$

where W is total world income ($W=M(Y+Y^*)$) and F is the quantity a northern firm sells in all northern markets divided by its domestic sales ($F=1+(M-1)\tau^{1-\sigma}$).

Equation (9) establishes a relationship between a higher human capital per worker and a larger share in the production and trade of complex goods. Northern workers are on average more productive than southern workers. As higher human capital per worker raise the probability of completing a task correctly, northern countries are more productive than southern countries in all products. However, because tasks should be performed simultaneously, the advantage of northern countries will be higher in those products that require a large number of tasks. Hence, given a relative wage, the price of varieties in the North relative to the South will decrease with the complexity of goods. As countries have the same preferences and there is full employment, northern countries will specialize in more complex products and, hence, will capture a larger share of the world revenue and trade of these products.

In the model, we have assumed that tasks are performed simultaneously. However, in reality, we observe industries where the production process is carried out sequentially: some workers perform a set of tasks and obtain an intermediate product, which is later manipulated by other workers.[4] If tasks are performed sequentially, the production process can be fragmented into different countries. Fragmentation of the production process may lead to violation of the model predictions. An example can illustrate this point. A mobile phone is a good which incorporates highly complex components that are manufactured in northern countries, but whose assembly is performed in southern countries (Xing, 2011). A mobile phone can be considered as a complex good, because a large number of different tasks are involved in the manufacturing of the electronic components, and in assembly. Our model predicts that the higher the complexity of the good the larger the share of northern countries in world production and trade. However, due to the offshoring of the assembly stage, southern countries will command a large share of the final trade of mobile phones, a complex product, contradicting the predictions of the model. The problem is that while the developing country activity—assembly services—is not complex, neither trade nor product complexity is measured at the level of the stage of the production process. In the empirical analyses, we will control for goods that incorporate complex components, but whose final assembly is performed in southern countries.

3. Empirical model and data

In this section we derive our empirical model and describe the construction of the variables used in the model as well as the data sources. We complete the section with a simple graphical analysis to examine the relationship between product complexity, industry skill-intensity and countries' commodity trade structure. The results of the econometric analyses are presented in the next section.

As Romalis (2004) points out, the predictions of the theoretical framework explained above are particularly sharp with respect to trade. As explained above, as consumers in all countries have the same preferences, and complex goods are relatively cheaper in northern countries, the share of northern countries in another country's imports should increase with the complexity of goods. To present this idea formally, we calculate the share of a northern country's firms in another northern country's total imports of commodity z:

$$x_{ijz} = \frac{n_z b_z Y \left(\frac{p\tau_z}{G(z)}\right)^{1-\sigma}}{(M-1)n_z b_z Y \left(\frac{p\tau_z}{G(z)}\right)^{1-\sigma} + M n_z^* b_z Y \left(\frac{p\tau_z}{G(z)}\right)^{1-\sigma}} \qquad (10)$$

Rearranging,

$$x_{ijz} = \frac{1}{(M-1) + M\frac{n^*}{n}\tilde{p}^{\sigma-1}} \qquad (11)$$

Equation (11) establishes an inverse relationship between the share in imports and the relative price. By equation (8) the relative price of northern firms decreases with the level of complexity. Hence, we expect a positive relationship between a northern country's share in imports and commodity's complexity.[5]

The regression equation to test this prediction can be expressed as

$$x_{ijz} = \beta_0 + \beta_1 z + u_{ijz} \qquad (12)$$

where x_{ijz} is the share of northern country i in northern country's j total imports of commodity z. The term z also denotes the complexity level, defined as the number of different tasks that are performed in production; u_{ijz} is the error term.

Estimation of equation (12) demands detailed industry-level bilateral imports data. At present, data meeting these characteristics is only available for merchandise and, hence, we have to exclude services from the analysis. This represents a limitation for our study. As explained in the introductory section, services provide examples of developing countries specializing in the supply of skill-intensive, but low-complexity activities. Hence, it would have been interesting to test whether these examples are isolated facts, or they also constitute a pattern for the services sector.

To calculate goods' complexity level we use data collected in a northern country: USA. The indicator of the complexity of goods comes from the Occupational Employment Statistics (OES) survey of the U.S. Bureau of Labor Statistics (www.bls.gov/oes). The OES uses a sample of 1.2 million establishments that operate in manufacturing and services to estimate how workers are distributed across occupations. The OES follows the Standard Occupational Classification (SOC), which distinguishes 801 different occupations. We consider that each occupation corresponds to a different task. In our theoretical model the complexity of a good is defined as the number of tasks subject to mistakes involved in the production process. To identify the tasks subject to mistakes we look to the skill-level required to produce the task, and assume that only skilled tasks are subject to failure. Hence, we measure complexity by the number of skilled tasks required to produce a good. We consider as skilled occupations those included between SOC category 11 and SOC category 29: management and other occupations that involve an intensive use of scientific and technical knowledge. At the end of this section, we use an alternative complexity measure to test the robustness of the empirical results. The OES database classifies good following the NAICS 4-digit classification (85 manufacturing sectors).

Imports data come from the BACI database. This database, developed by CEPII, reconciles the exporter and importer declarations on value and quantity at the HS 6-digit level provided by the United Nations Statistical Division Comtrade database for the period 1995-2007 (Gaulier and Zignago, 2010). Imports data is transformed to the NAICS classification followed by OES, using correspondence tables in Pierce and Schott (2012).

In the empirical analyses we assess the relative contributions of complexity and skill-intensity to explain countries' commodity trade structure. This latter variable is proxied by the share of non-production workers in total employment. Data on the share of non-production workers is obtained from the US Economic Census for the years 2002 and 2007. Hence, we restrict our empirical analysis to these years.

As explained before, to perform a valid estimation of the model, we should control for goods whose final assembly is performed in southern countries. This control is especially important when the highly complex components and the final good belong to the same 4-digit NAICS industry. To identify these industries we draw on recent work by Koopman et al. (2012) on the share of processing exports in Chinese exports, the most important assembler among southern countries.[6] Processing exports happen when materials and intermediate parts are imported from abroad with favorable tariff treatment, and after assembly, are exported as final goods. The share of processing exports is a good metric to identify industries where the final assembly of goods that incorporate complex components is carried out in developing countries. This metric encapsulates all the factors, such as the transportability of intermediate parts or the low complexity of the task that might explain why developing countries perform the last assembly process.

Koopman et al. (2012) find that the largest share of processing exports was found in electronic computers, cultural and office equipment, telecommunication equipment, cultural and office equipment, and household audiovisual apparatus industries. These industries, as we shown later, are characterized by a high complexity level. In the econometric analyses, we will introduce the share of processing exports as an independent variable to control for the bias that final assembly in developing countries might introduce in the estimations. We expect the coefficient for processing exports to be negative, as high-wage countries share in complex goods should be lower the higher the probability of performing the last assembly stage in developing countries. Appendix 1 provides the summary statistics and data sources of all the variables used in the paper.

Figure 1 presents the relationship between products' complexity and the share of northern countries in US total imports for the year 2007. As shown in the figure, there is a strong positive relationship between both variables: the share of northern countries is larger the higher the complexity of the good. We also observe that there is a large variation in complexity across industries. The lowest complexity level is found in NAICS code industry 3161, leather and hide tanning and finishing, where only three skill tasks are performed. In contrast, the industry with a larger number of skilled tasks (101) is NAICS code 3345, navigational, measuring, electro-medical and other instruments manufacturing.

In Figure 2, we analyze the relationship between the share of northern countries in US exports and skill-intensity, measured by the share of non-production workers in total employment. As predicted by the factor proportions theory, the share of northern countries rises with products' skill-intensity. We also observe that there is a large

Figure 1. Share of northern countries in US imports and products' complexity, 2007

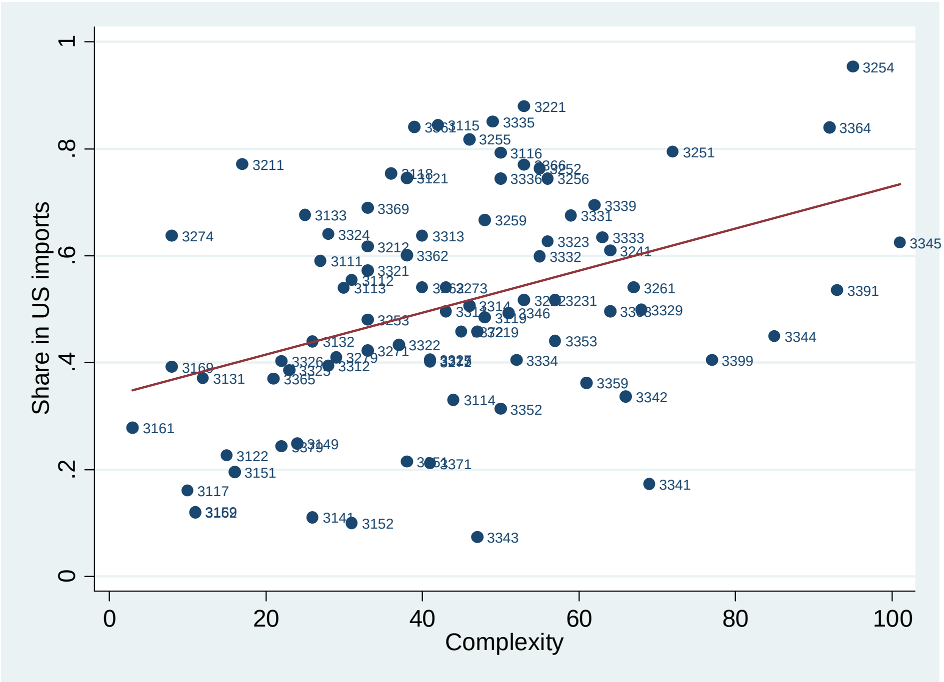
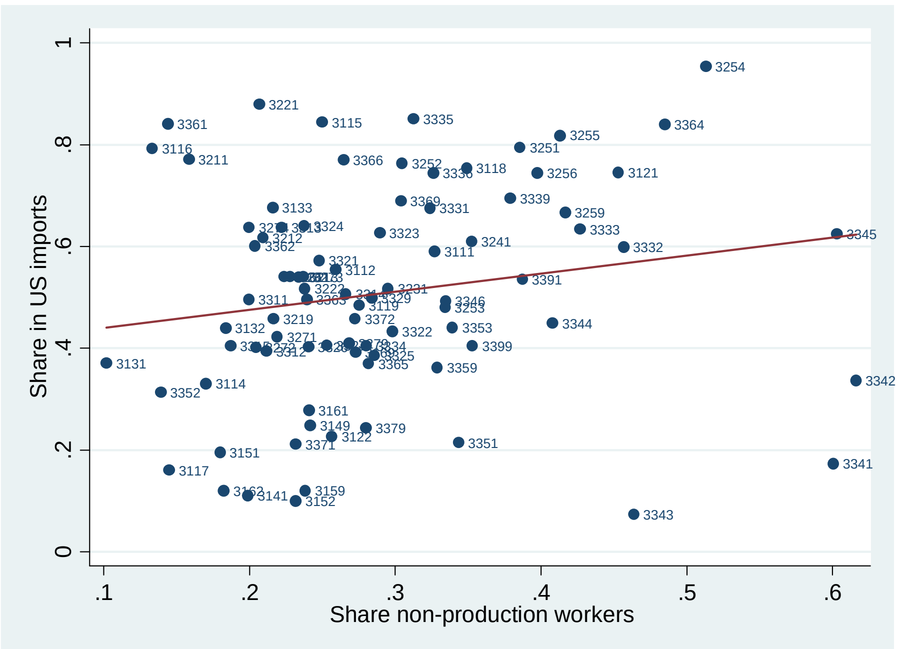


Figure 2. Share of northern countries in US imports and products' skill-intensity, 2007



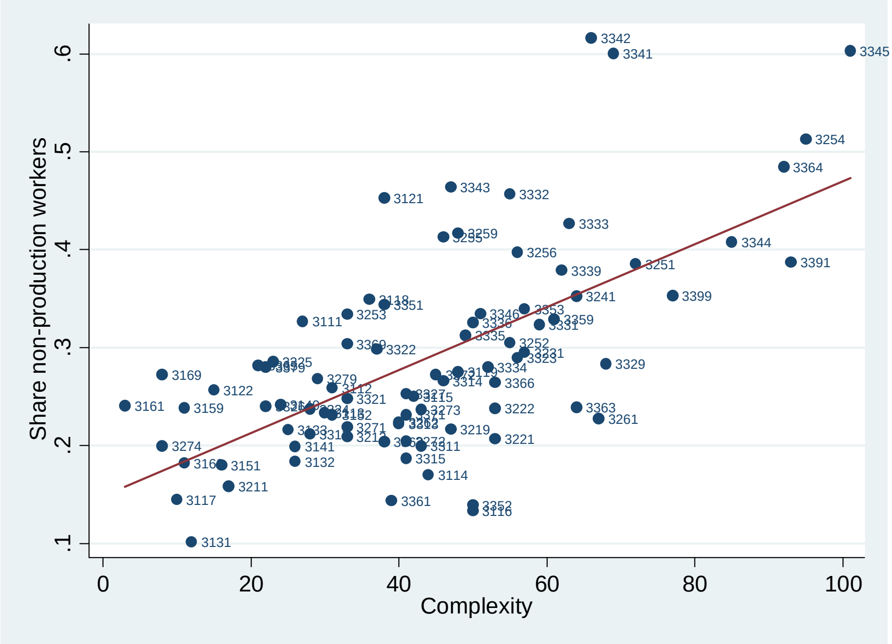
variation in skill-intensity across industries. The lowest skill-intensity is found in fiber, yarn and thread mills (code 3131), where the share of nonproduction workers is 10%; the highest skill level is found in communications equipment manufacturing (code 3342), where the share of nonproduction workers is above 60%.

Finally, Figure 3 shows the relationship between complexity and skill-intensity. We can see that there is a positive relationship between both variables: industries with a large number of skilled tasks also have a large share of non-production workers in total employment. The correlation between complexity and skill-intensity is 0.64, and skill-intensity explains 40% of the variation in complexity across industries. However, we also observe that there are substantial differences in skill-intensity for a given complexity level. For example, plastic product manufacturing (NAICS 3261) and communication equipment manufacturing (NAICS 3342) have almost the same complexity: 67 and 66 respectively. However, skill intensity in communication equipment manufacturing (62% of non-production workers) is almost three times larger than in plastic product manufacturing (23% of non-production workers). This variation in skill-intensity allows to test whether, as argued in this paper, complexity also plays a significant role in determining countries' trade commodity structure. The econometric analyses presented below aim to answer this question.

4. Econometric Analysis

Our estimates of equation (12) are distributed in two main sets. In the first set, we aggregate all northern countries imports for each manufacturing industry. In the

Figure 3. Relationship between skill-intensity and complexity, 2007



second set, we estimate equation (12) with industry-level bilateral imports data. In each set, equation (12) is estimated for three different samples. First, to compare our results with Romalis (2004), we consider the US as the reference northern country. We estimate whether the share of other northern countries in US imports increases with the complexity of the good. We consider northern countries as those with a GDP per capita equal or above 50 per cent of the US GDP per capita in year 2002. Second, we calculate the share of northern countries in each northern country's imports, and estimate the equation pooling all observations.[7] Finally, as equation (12) is symmetric for non-northern countries, we also estimate the model pooling observations on import share for both northern and southern countries.[8] Table 1 presents the results of the first set of econometric estimates. For each sample, we perform five different regressions. First, import shares are regressed on products' complexity; second, we regress import shares on skill-intensity and, third, we include both complexity and skill-intensity as independent variables in the regression. In the fourth regression, we

Table 1. Regression results on the relationship between the share of northern countries imports, complexity and skill-intensity. Aggregated northern country imports. Years 2002 and 2007

Panel A	**Importer: U.S.**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.420		0.436	0.490	0.554
	(0.107)***		(0.133)***	(0.118)***	(0.124)***
Skill-intensity		0.420	-0.043	0.145	0.030
		(0.250)*	(0.273)	(0.226)	(0.255)
Share of				-0.271	-0.227
processing exports				(0.088)***	(0.100)**
Observations	170	170	170	170	132
R-squared	0.185	0.089	0.185	0.272	0.309
Panel B	**Importer: Northern countries (26)**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.315		0.234	0.259	0.339
	(0.062)***		(0.080)***	(0.075)***	(0.087)***
Skill-intensity		0.473	0.225	0.314	0.149
		(0.146)***	(0.164)	(0.134)**	(0.150)
Share of				-0.128	-0.107
processing exports				(0.045)***	(0.046)**
Observations	4,420	4,420	4,420	4,420	3,432
R-squared	0.281	0.263	0.289	0.308	0.332
Panel C	**Importer: Northern and southern countries (70)**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.370		0.250	0.257	0.284
	(0.051)***		(0.060)***	(0.063)***	(0.073)***
Skill-intensity		0.600	0.335	0.359	0.257
		(0.124)***	(0.133)***	(0.119)***	(0.133)*
Share of				-0.035	-0.052
processing exports				(0.044)	(0.047)**
Observations	11,892	11,892	11,892	11,892	9,236
R-squared	0.300	0.291	0.314	0.315	0.322

Note: Complexity in hundreds. Standard errors clustered by industry in parentheses. Regressions in Panel A include year-specific dummy variables; regressions in Panel B and C include year-importer dummies. ***, **, *: statistically significant at 1%, 5% and 10% respectively.

introduce the share of processing exports to control for the probability that final assembly is performed in developing countries. Finally, in the fifth regression, to be as close as possible to the features of our model, we restrict the sample to narrow-defined manufacturing industries, removing those industries where natural resources play a major role in determining comparative advantage.[9] In all regressions, we pool observations for the years 2002 and 2007.

Table 1 Panel A presents the results when estimating the model with the US as the reference importer. As shown in Column 1, the complexity coefficient is positive and statistically significant. This result confirms the prediction of the model: the share of northern countries in US imports rises with the complexity of goods. According to this result, a one standard deviation increase in complexity leads to a 8 percentage points increase in the share of northern countries in US imports (0.420 * 0.188). In Column 2, we can see that the coefficient for skill-intensity is also positive and statistically significant. The coefficient, 0.42 is lower than that obtained by Romalis (1994: Table 8-Two factors): 0.93.[10] In this case, a one standard deviation increase in skill-intensity leads to a 4 percentage points increase in the share of northern countries in US imports (0.420*0.109). It is interesting to observe that the fit of the model is much higher when complexity is used as explanatory variable than when skill-intensity is used as explanatory variable. In Column 3, both complexity and skill-intensity are introduced in the regression. The coefficient for complexity remains positive and statistically significant; however, the coefficient for skill-intensity is statistically not significant. In Column 4, we introduce the share of processing exports to control for the likelihood that the final assembly process is performed in developing countries. As expected, the coefficient for the share processing exports is negative, as the share of northern countries in US imports becomes lower if the final assembly-task is performed in developing countries. The coefficient for complexity remains positive and statistically significant, and the coefficient for skill-intensity remains statistically not significant. We can see, as well, that the fit of the model improves substantially when the share of processing exports is taken into account. Finally, in regression (5) we remove from the sample those industries that are dependent on natural resources. We observe that the complexity coefficient becomes larger and remains statistically significant. This result confirms that complexity is especially relevant in industries where human capital is the most important productive factor in determining comparative advantage.

In Table 1 Panel B the dependent variable is the share of northern countries in total imports for each industry for a sample of 26 northern countries. Now, equation (12) includes year-importer fixed effects. Results are similar to those obtained in Panel A. The coefficients of complexity and skill-intensity are statistically significant when they enter independently (Columns 1 and 2). When they enter simultaneously, complexity is always positive and statistically significant. Skill-intensity is only statistically significant when we control for the share of processing exports. The coefficient on processing exports remains negative. In terms of magnitude, based on the coefficients presents in Column 4, a one standard deviation increase in complexity leads to a 5 percentage points increase in the share of northern countries in another northern country's imports (0.259*0.188); in the case of skill-intensity, a one standard deviation increase leads to a 3 percentage points increase in the share of northern countries (0.314*0.109).

Finally, in Table 1 Panel C the dependent variable is the share of northern countries in total imports for each industry for a sample of 26 northern countries and 44 southern countries. Now, complexity and skill-intensity are positive and statistically significant in all estimations. In this panel, the share of processing exports, although negative, is not statistically significant. According to the coefficients in Column 4, a one standard deviation in complexity increases the share of northern countries in a country's imports by 5 percentage points (0.257*0.188); in the case of skill-intensity, a one standard deviation raises the share of northern countries by 4 percentage points (0.359*0.109).

In the second set of regression analyses we use bilateral imports instead of aggregate imports. Now the dependent variable is the share of a northern country j in industry z imports by country i. In this specification, we introduce year-exporter-importer fixed effects. These fixed effects control for all the (gravity) variables that might influence the share of a northern country j in industry-z total imports by country i. As before, we estimate equation (12) for three different samples of importing countries: US only, 26 northern countries and 70 northern and southern countries. Table 2 presents the results. As shown in Table 2 Panel A, US imports from a northern country are positively associated with the complexity of the good. According to the coefficient in Column 1, a one standard deviation in complexity increases by 0.3 percentage points a northern country's share in US total imports (0.016*0.188). Skill-intensity is not statistically significant when entered simultaneously with complexity. As in Table 1 (aggregate imports), we also find using bilateral imports that the coefficient on share of processing exports is negative and statistically significant (column 4); in addition to that, the coefficient for complexity rises when we limit the sample to narrowly defined manufactures (column 5). When we expand the sample to 26 northern countries in Panel B the results are similar to those reported in Panel A. The only exception is that skill intensity is positive and statistically significant in Column 4. In

Table 2. Regression results on the relationship between the share of northern countries imports, complexity and skill-intensity. Bilateral imports (years 2002 and 2007).

Panel A	**Importer: U.S.**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.016		0.017	0.019	0.022
	(0.004)***		(0.005)***	(0.005)***	(0.005)***
Skill-intensity		0.017	-0.001	0.006	0.001
		(0.010)*	(0.010)	(0.009)	(0.010)
Share of				-0.011	-0.009
processing exports				(0.004)***	(0.004)**
Observations	4,210	4,210	4,210	4,210	3,283
R-squared	0.194	0.192	0.194	0.195	0.197
Panel B	**Importer: Northern countries (26)**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.012		0.009	0.010	0.014
	(0.003)***		(0.004)**	(0.003)***	(0.004)***
Skill-intensity		0.019	0.009	0.013	0.006
		(0.006)***	(0.007)	(0.006)**	(0.006)
Share of				-0.006	-0.004
processing exports				(0.002)***	(0.002)**
Observations	103,793	103,793	103,793	103,793	82,085
R-squared	0.608	0.608	0.608	0.608	0.626
Panel C	**Importer: Northern and southern countries (70)**				
	(1)	(2)	(3)	(4)	(5)
Complexity	0.014		0.008	0.009	0.011
	(0.003)***		(0.003)***	(0.003)***	(0.004)***
Skill-intensity		0.024	0.015	0.017	0.011
		(0.006)***	(0.006)**	(0.006)***	(0.006)*
Share of				-0.002	-0.002
processing exports				(0.002)	(0.002)
Observations	259,924	259,924	259,924	259,924	208,353
R-squared	0.544	0.544	0.545	0.545	0.576

Note: Complexity in hundreds. Standard errors clustered by industry in parentheses. Regressions in Panel A include year specific imports' origin country dummy variables; regressions in Panel B and Panel C include year-importer-exporter dummy variables. ***, **, *: statistically significant at 1%, 5% and 10% respectively.

Panel C we estimate equation (12) pooling the observations from northern and southern countries (70 countries). We find that both complexity and skill-intensity have a positive and statistically significant impact on the share of a northern country in a country's total imports. According to the coefficients in Column 4, a one standard deviation in the complexity of the product raises by 0.2 percentage points the share of an average northern country in another country's total imports (0.009*0.188); in the case of skill-intensity, a one standard deviation increase also leads to a 0.2 percentage increase in the share.

To sum up, our econometric analyses with both aggregated and bilateral imports confirm the predictions of the model on the positive relationship between complexity and the share of northern countries in imports.

To test the robustness of our benchmark results, we perform two sets of sensitivity analyses. The first set uses alternative indicators to proxy commodities' complexity level and skill-intensity. With respect to complexity, in the benchmark analysis it was built on the joint assumption that mistakes can only happen in skilled tasks and that all skilled tasks had the same probability of making mistakes. In the alternative complexity measure, we assume that mistakes can happen in all tasks but that the likelihood of making mistakes, and their impact in the product's final value, is related to the difficulty of the problems that have to be resolved in each task. To assess the difficulties faced by each occupation, we turn to the O*NET database, and draw information on how important the solving of complex problems is for each occupation. We assume that the higher the importance of solving complex problems the higher the probability of making mistakes. To calculate the new complexity measure (complexity 2) we add-up all occupations in each industry, weighting each task by the importance of solving complex problems in that task.[11]

With respect to skill-intensity, in the benchmark analysis it was proxied by the share of non-production workers in total employment. As suggested by previous authors, occupational data can provide an alternative proxy for skill-intensity (Autor et al., 2003; Winchester et al., 2006). Based on the data provided by the OES, we calculate a new measure of skill-intensity (skill-intensity 2) dividing the employment in skilled occupations (code 11 to 29) by total employment.

Table 3, presents the results of estimating the regressions with the alternative complexity and skill-intensity measures. We use the (aggregated) share of northern countries in total imports as the dependent variable. Table A3 in the appendix presents the results for bilateral data. As shown in Table 3, the results are very similar to those presented in Table 1. The alternative complexity measure is always positive and statistically significant. In Panels B and C, the alternative skill-intensity measure is also positive and statistically significant, confirming the complementary effect of complexity and skill intensity on country's pattern of trade.

As an additional sensitivity test, when building the benchmark complexity measure, we only add skilled tasks that overcome an employment threshold within the industry. This threshold is set at 0.1% of total employment in each occupation. Results are robust.[12]

In the second set of sensitivity analyses, we perform additional regression analyses based on the specification used by Chor (2010). Now the dependent variable is the log of z industry's exports from country i to country j. The independent variables include a set of country-level and industry-level interaction terms. The interaction

Table 3. Sensitivity analysis I. Alternative complexity and skill-intensity measures. Aggregated northern countries imports (years 2002 and 2007)

Panel A	**Importer: U.S.**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.240		0.248	0.236	0.253
	(0.047)***		(0.054)***	(0.054)***	(0.057)***
Skill-intensity 2		0.294	-0.055	0.209	0.249
		(0.253)	(0.224)	(0.221)	(0.241)
Share of processing exports				-0.229	-0.207
				(0.089)**	(0.098)**
Observations	170	170	170	170	132
R-squared	0.226	0.067	0.227	0.282	0.310

Panel B	**Importer: Northern countries (26)**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.144		0.123	0.117	0.138
	(0.035)***		(0.040)***	(0.039)***	(0.042)***
Skill-intensity 2		0.329	0.156	0.273	0.247
		(0.146)**	(0.137)	(0.130)**	(0.134)*
Share of processing exports				-0.102	-0.092*
				(0.046)**	(0.048)**
Observations	4,420	4,420	4,420	4,420	3,432
R-squared	0.268	0.236	0.274	0.284	0.319

Panel C	**Importer: Northern and southern countries (70)**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.150		0.100	0.098	0.110
	(0.036)***		(0.038)***	(0.037)***	(0.042)***
Skill-intensity 2		0.505	0.365	0.395	0.332
		(0.134)***	(0.130)***	(0.123)***	(0.121)***
Share of processing exports				-0.026	-0.045
				(0.043)	(0.046)
Observations	11,892	11,892	11,892	11,892	11,892
R-squared	0.272	0.278	0.296	0.297	0.309

Note: Complexity in logs. Standard errors clustered by industry in parentheses. Regressions in Panel A include year-specific dummy variables; regressions in Panel B and C include year-importer dummies. ***, **, *: statistically significant at 1%, 5% and 10% respectively.

terms include complexity forces, factor proportion forces, and institutional forces. To obtain the complexity interaction term we multiply our industry-level complexity measure and the exporter country's human capital endowment per worker. We expect this interaction term to be positive, because, according to our model, countries that are well endowed with human capital per worker make less mistakes and, hence, have comparative advantage in more complex goods. Factor proportion forces are captured by two interaction terms: industry's physical capital intensity multiplied by exporter country's physical capital endowment per worker, and industry's human capital intensity multiplied by the exporter country's human capital per worker. Based on the factor proportions theory, we also expect these interaction terms to be positive. Finally, institutional forces are captured multiplying the importance of relationship-specific investments in an industry and the exporting country's strength in enforcing the law. Following Nunn (2007), we also expect this interaction term to be positive, as exports of industries demanding relationship-specific investment will originate from countries were contracts are enforced. Algebraically:

$$\ln(X_{ijzt}) = \beta_C(z_{ct}h_{it}) + \beta_K(z_{kt}k_{it}) + \beta_H(z_{ht}h_{it}) + \beta_R(z_{rt}I_{it}) + \gamma_{it} + \gamma_{jt} + \gamma_{zt} + \gamma_{ij} \quad (13)$$

where X_{ijzt} denotes z-industry's exports from country i to country j at time t; z_{ct} , z_{kt} , z_{ht} and z_{rt} are product complexity, physical capital intensity, human capital intensity, and contract intensity of industry z at time t, respectively; h_{it} , k_{it} and I_{it} are the human capital endowment per worker (*skill abundance*), the physical capital endowment per worker (*capital abundance*), and the strength of the legal system in the exporter country at time t (*legal strength*), respectively. Finally, the specification includes year-exporter fixed effects (γ_{it}), year-importer fixed effects (γ_{jt}), industry-year fixed effects (γ_{zt}) and exporter-importer fixed effects (γ_{ij}).

In the new specification there are two new industry-level variables and three new country-level variables. Industry-level physical capital intensity (z_{kt}) comes from NBER-CES Manufacturing dataset. Contract intensity corresponds to the z_{rt} measure in Nunn (2007) and is calculated as the share (by value) of inputs that are not sold on an organized exchange, based on the "liberal" classification in Rauch (1999). Country-level physical capital abundance (k_{it}) comes from Jorgenson and Vu (2010) database and is calculated as the physical capital stock per worker. Country-level human capital abundance (h_{it}) comes from Barro and Lee (2010) and is calculated as the average years of schooling of the working age population. The strength of the legal system (I_{it}) comes from Gwartney, Hall, and Lawson (2010) and is calculated as an index from 0 to 1 that measures, among other things, the legal enforcement of contracts and the protection of property rights. When we combine the new sources of country-level data, we are left with 61 out of 70 countries that we used in the previous regressions.[13] Appendix A.1 provides summary descriptive of the variables.

Table 4 presents the results of the estimations. In Column (1) we include the interaction terms motivated by the factor proportions theory (physical capital and labor skill). As in Chor (2010), we find that both interaction terms are positive and statistically significant, confirming that countries well endowed in physical capital per worker and human capital per worker will export goods which make intensive use of these factors of production. In Column (2) we introduce our measure of industry-level complexity interacted with country-level human capital per worker. We can see that, as expected, the coefficient is positive and statistically significant. This result confirms our previous finding on the comparative advantage of countries well endowed in human capital per worker in complex goods. In Column (3), we introduce the institutional interaction term (industry contract relationship times country strength

Table 4. Sensitivity analysis II. Regressions using Chor (2010) specification. Dependent variable: log bilateral industry-level exports. Years 2002 & 2007.

	(1)	(2)	(3)	(4)
Capital intensity * capital abundance $z_{kt} * k_{it}$	0.050 (0.001)***	0.055 (0.001)***	0.057 (0.001)***	0.057 (0.001)***
Skill intensity * skill abundance $z_{ht} * h_{it}$	0.168 (0.014)***	0.035 (0.016)**	0.036 (0.016)**	0.038 (0.017)**
Complexity * skill abundance $z_{ct} * h_{it}$		1.735 (0.021)***	1.729 (0.022)***	1.894 (0.096)***
Contract intensity * legal strength $z_{rt} * I_{it}$			0.357 (0.084)***	0.375 (0.083)***
Complexity * legal strength $z_{ct} * I_{it}$				-0.521 (0.313)
Observations	243,776	243,776	243,776	243,776
Adjusted R-square	0.538	0.558	0.558	0.556

Note: In previous tables the dependent variable was (aggregated or bilateral) import shares. In Chor (2010) specification the dependent variable (log) bilateral imports. h_{it} , k_{it} and I_{it} are the human capital endowment per worker, the physical capital endowment per worker, and the strength of the legal system in the exporter country at time *t*, respectively; z_{ct} , z_{kt} , z_{ht} and z_{rt} are product complexity, physical capital intensity, human capital intensity, and contract intensity of industry *z* at time *t*, respectively. All regressions include exporter-year, importer-year, industry-year and exporter-importer fixed effects (not reported).

of the legal system) proposed by Nunn (2007). The coefficient is positive confirming that countries where the strength of the legal system is high will tend to export products that demand relation-specific investments.

Finally, in Column (4) we interact our industry-level complexity variable with the country-level strength of the legal system variable. We want to test whether, as predicted by our model, countries' higher participation in complex goods exports is related to human capital per worker; or, as found by Costinot (2009), higher participation is also related to the strength of the legal system. As shown in Column (4), the coefficient for the "complexity times human capital" variable remains positive and statistically significant, whereas the coefficient for the "complexity times strength of the legal system" variable is statistically not significant. This result confirms that, as predicted by our model, comparative advantage in complex goods is related to human capital per worker.

4. Conclusions

During the last years we observe an increasing number of firms located in developing countries competing with firms located in developed countries in skill-intensive products and services. This trend points out that skill-intensity is not sufficient to explain the trade pattern between developed and developing countries. In this paper, we argue that product complexity, measured as the number of skilled tasks that are performed in production, might also play a role in explaining trade patterns. We argue that developed countries have comparative advantage in activities that demand the coordination of a large number of skilled workers performing different tasks. This advantage stems from the fact that small differences in productivity are magnified when a large number of skilled activities should be combined. However, developing countries will be able to compete in skill-intensive goods or services if they do not demand complex production processes.

To formalize this idea we develop a model that incorporates differences in the number of mistakes made by workers between developed and developing countries and differences in complexity across commodities. The model predicts that the share of developed countries in world production increases with the complexity of goods. The empirical analyses provide ample support for this prediction. Moreover, we find that complexity complements the explanation provided by skill-intensity on country's commodity trade structure. Our analysis points out that both differences in technology and factor proportions are important to explain countries' trade pattern.

Appendix 1.

Table A1: Summary statistics and statistical sources

Aggregated import shares (N=11829)	Mean	S.D.	Min	Max	Source
share_north (%)	0.627	0.24	0.00	1.00	CEPII BACI
complexity (in hundreds)	0.425	0.19	0.03	1.01	US OES
skill intensity (%)	0.288	0.11	0.10	0.67	US Economic Census
complexity 2 (robustness)	1.840	0.37	0.39	2.51	US OES & US O*NET
skill 2 (%) (robustness)	0.153	0.12	0.03	0.70	US OES
share of processing exports (%)	0.366	0.25	0.01	0.97	Feenstra et al. (2010)
Bilateral import shares (N=259,924)					
share_north (%)	0.642	0.23	0.00	1.00	CEPII BACI
complexity (in hundreds)	0.440	0.19	0.03	1.01	US OES
skill intensity (%)	0.293	0.11	0.10	0.67	US Economic Census
complexity 2 (robustness)	1.865	0.36	0.39	2.51	US OES & US O*NET
skill 2 (%) (robustness)	0.159	0.12	0.03	0.70	US OES
share of processing exports (%)	0.376	0.25	0.01	0.97	Feenstra et al. (2010)
Bilateral export flows (N=243,776)					
exports (log)	6.290	3.10	0.00	17.66	CEPII BACI
log capital intensity * log capital intensity	48.035	9.56	19.22	84.19	NBER-CES dataset & Jorgenson-Vu dataset
log skill intensity * log human capital abundance	-1.734	1.52	-12.00	-0.46	US Economic Census & Barro-Lee (2010)
complexity * log skill abundance	0.931	0.43	0.04	2.60	US OES & Barro-Lee (2010)
contract intensity * legal strength	0.576	0.18	0.05	0.93	Nunn (2007) & Econ. Freedom Dataset (2010)
complexity * legal strength	0.286	0.15	0.01	0.91	US OES & Economic Freedom Dataset

Note: We include only observations with trade. In the sample with aggregated import shares there are 11900 potential observations (69 importers*85 industries*2 years). In the sample with bilateral import shares there are 821100 potential observations (70 importers*69 exporters*85 industries*2 years). In the sample with bilateral trade flows there are 622200 potential observations (61 importers*60 exporters*85 industries*2 years). All data refers to years 2002 and 2007 except Nunn (2007) with data for 1997 and Jorgenson and Vu dataset and Barro-Lee dataset with data for 2000 and 2005.

Table A2. Ranking of manufacturing industries by complexity in 2007

Naics code	Manufacturing industry name	complexity (number tasks)	skill intensity (%)	processing exports (%)	Naics code	Manufacturing industry name	complexity (number tasks)	skill intensity (%)	processing exports (%)
3161	Leather & Hide Tanning & Finishing	3	24.1	55.1	3115*	Dairy Product Man.	42	25.0	8.8
3169	Other Leather & Allied Product Man.	8	27.3	33.0	3273*	Cement & Concrete Product Man.	43	23.7	7.7
3274*	Lime & Gypsum Product Man.	8	20.0	4.6	3311	Iron & Steel Mills & Ferroalloy Man.	43	20.0	6.7
3117*	Seafood Product Preparation & Packaging	10	14.5	29.4	3114*	Fruit & Vegetable Preserving & Specialty Food	44	17.0	23.4
3159	Apparel Accessories & Other Apparel Man.	11	23.8	31.5	3372	Office Furniture (including Fixtures) Man.	45	27.2	34.6
3162	Footwear Man.	11	18.2	37.1	3255	Paint, Coating, & Adhesive Man.	46	41.3	39.1
3131	Fiber, Yarn, & Thread Mills	12	10.2	22.2	3314	Nonferrous Metal (exc. Aluminum) Production	46	26.6	19.7
3122*	Tobacco Man.	15	25.7	14.9	3219*	Other Wood Product Man.	47	21.7	18.7
3151	Apparel Knitting Mills	16	18.0	6.6	3343	Audio & Video Equipment Man.	47	46.4	92.6
3211*	Sawmills & Wood Preservation	17	15.8	18.8	3119*	Other Food Man.	48	27.5	15.5
3365	Railroad Rolling Stock Man.	21	28.2	63.3	3259	Other Chemical Product & Preparation Man.	48	41.7	23.1
3326	Spring & Wire Product Man.	22	24.0	7.7	3335	Metalworking Machinery Man.	49	31.3	16.8
3379	Other Furniture Related Product Man.	22	28.0	31.4	3116*	Animal Slaughtering & Processing	50	13.4	16.2
3325	Hardware Man.	23	28.6	21.8	3336	Engine, Turbine, & Power Transm. Equip. Man.	50	32.6	21.1
3149	Other Textile Product Mills	24	24.2	27.3	3352	Household Appliance Man.	50	13.9	71.1
3133	Textile, Fabric Finishing, Fabric Coating Mills	25	21.6	25.0	3346	Man. & Reproducing Magnetic & Optical Media	51	33.5	89.3
3132	Fabric Mills	26	18.4	22.4	3334	Ventilation, Heating, AirConditioning, Refrig.	52	28.0	53.2
3141	Textile Furnishings Mills	26	19.9	11.3	3221	Pulp, Paper, & Paperboard Mills	53	20.7	52.3
3111*	Animal Food Man.	27	32.7	5.2	3222	Converted Paper Product Man.	53	23.8	52.5
3312	Steel Product Man. from Purchased Steel	28	21.2	9.3	3366	Ship & Boat Building	53	26.5	90.2
3324	Boiler, Tank, & Shipping Container Man.	28	23.7	50.0	3252	Resin, Synthetic Rubber, Artific. Synthetic Fibers	55	30.5	63.1

Table A2 (cont.)

Naics code	Manufacturing industry name	complexity (number tasks)	skill intensity (%)	processing exports (%)	Naics code	Manufacturing industry name	complexity (number tasks)	skill intensity (%)	processing exports (%)
3279*	Other Nonmetallic Mineral Product Man.	29	26.8	10.5	3332	Industrial Machinery Man.	55	45.7	24.5
3113*	Sugar & Confectionery Product Man.	30	23.4	29.9	3256	Soap, Cleaning Compound, Toilet Preparation	56	39.7	38.4
3112*	Grain & Oilseed Milling	31	25.9	15.2	3323	Architectural & Structural Metals Man.	56	28.9	20.2
3152	Cut & Sew Apparel Man.	31	23.2	20.3	3231	Printing & Related Support Activities	57	29.5	51.7
3212*	Veneer, Plywood, Engineered Wood Products	33	20.9	11.4	3353	Electrical Equipment Man.	57	33.9	68.7
3253	Pesticide, Fertilizer & Other Agric. Chemicals	33	33.4	10.3	3331	Agriculture, Construction, & Mining Machinery	59	32.4	13.8
3271*	Clay Product & Refractory Man.	33	21.9	6.5	3359	Other Electrical Equipment & Component Man.	61	32.9	58.1
3321	Forging & Stamping	33	24.8	19.0	3339	Other General Purpose Machinery Man.	62	37.9	36.9
3369	Other Transportation Equipment Man.	33	30.4	26.4	3333	Commercial & Service Industry Machinery Man.	63	42.7	86.2
3118*	Bakeries & Tortilla Man.	36	34.9	44.4	3241	Petroleum & Coal Products Man.	64	35.2	49.7
3322	Cutlery & H&tool Man.	37	29.8	18.7	3363	Motor Vehicle Parts Man.	64	23.9	32.8
3121*	Beverage Man.	38	45.3	9.0	3342	Communications Equipment Man.	66	61.6	87.3
3351	Electric Lighting Equipment Man.	38	34.4	65.5	3261	Plastics Product Man.	67	22.8	42.9
3362	Motor Vehicle Body & Trailer Man.	38	20.4	26.4	3329	Other Fabricated Metal Product Man.	68	28.4	21.1
3361	Motor Vehicle Man.	39	14.4	28.1	3341	Computer & Peripheral Equipment Man.	69	60.0	95.9
3262	Rubber Product Man.	40	22.4	58.5	3251	Basic Chemical Man.	72	38.6	15.8
3313	Aluminum Production & Processing	40	22.2	14.7	3399	Other Miscellaneous Man.	77	35.3	56.7
3272*	Glass & Glass Product Man.	41	20.4	24.7	3344	Semiconductor & Other Electronic Components	85	40.8	88.9
3315	Foundries	41	18.7	1.4	3364	Aerospace Product & Parts Man.	92	48.5	20.6

Table A2 (cont.)

Naics code	Manufacturing industry name	complexity (number tasks)	skill intensity (%)	processing exports (%)
3327	Machine Shops; Screw, Nut, Bolts	41	25.3	9.9
3371	Household Furniture & Kitchen Cabinet	41	23.2	33.7
3391	Medical Equipment & Supplies Man.	93	38.7	36.4
3254	Pharmaceutical & Medicine Man.	95	51.3	14.4
3345	Navigational, Measuring, Medical, Control Instr.	101	60.3	82.7

Note: Complexity is the number of skilled tasks needed to produce a manufactured good. Skill intensity is the proportion of nonproduction workers in total employment in the industry. The share of processing exports is the percentage of processing exports in Chinese total exports. The symbol (*) indicates that the industry is relatively intensive in the use of natural resources.

The Internet links of the statistical sources used for construction of all the variables is: CEPII BACI International Trade Database at the Product Level (Gaulier & Zignano, 2010) http://www.cepii.fr/anglaisgraph/bdd/baci.htm. US Occupational Employment Statistics (OES), U.S. Bureau of Labor Statistics (www.bls.gov/oes). US Occupational Information Network (O*NET), US Department of Labor/Employment and Training Administration (USDOL/ETA) (http://www.onetonline.org/). US Economic Census 2002 and 2007 (www.census.gov/econ/census02 & www.census.gov/econ/census07). Feenstra et al. (2010) dataset on Chinese international trade data (www.internationaldata.org). NBER-CES Manufacturing Industry Database (http://www.nber.org/nberces/). Jorgenson and Vu dataset (http://scholar.harvard.edu/jorgenson/data). Barro and Lee dataset (Barro and Lee, 2010) (www.barrolee.com). Economic Freedom Dataset (Gwartney, Hall, and Lawson, 2010) http://www.freetheworld.com/datasets_efw.html. CEPII gravity dataset (Head. Mayer and Ries, 2010) (http://www.cepii.fr/anglaisgraph/bdd/gravity.htm). Industry-level data on the importance of relationship-specific investments (contract intensity) (Nunn, 2007) (http://www.economics.harvard.edu/faculty/nunn/data_nunn).

Appendix 2.

Table A3. Sensitivity analysis I with bilateral imports (year 2002 and 2007).

Panel A	**Importer: U.S.**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.010		0.010	0.010	0.010
	(0.002)***		(0.002)***	(0.002)***	(0.002)***
Skill-intensity 2		0.012	-0.002	0.008	0.009
		(0.010)*	(0.009)	(0.009)	(0.010)
Share of processing exports				-0.009	-0.008
				(0.004)**	(0.004)**
Observations	4,210	4,210	4,210	4,210	3,283
R-squared	0.195	0.191	0.195	0.196	0.198
Panel B	**Importer: Northern countries (26)**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.006		0.005	0.005	0.006
	(0.002)***		(0.002)***	(0.002)***	(0.002)***
Skill-intensity 2		0.013	0.006	0.011	0.010
		(0.006)**	(0.006)	(0.005)**	(0.006)*
Share of processing exports				-0.005	-0.004
				(0.002)**	(0.002)*
Observations	103,793	103,793	103,793	103,793	82,085
R-squared	0.608	0.607	0.608	0.608	0.626
Panel C	**Importer: Northern and southern countries (70)**				
	(1)	(2)	(3)	(4)	(5)
Complexity 2	0.006		0.004	0.004	0.004
	(0.002)***		(0.002)**	(0.002)*	(0.002)**
Skill-intensity 2		0.019	0.014	0.017	0.014
		(0.006)***	(0.006)**	(0.006)***	(0.006)**
Share of processing exports				-0.002	-0.003
				(0.002)	(0.002)
Observations	259,924	259,924	259,924	259,924	208,353
R-squared	0.544	0.544	0.544	0.544	0.576

Note: Complexity 2 in logs. See main text for a definition of complexity 2 and skill-intensity 2. Standard errors clustered by industry in parentheses. Regressions in Panel A include year-importer dummy variables; regressions in Panel B and Panel C include year-importer-exporter dummy variables. ***, **, *: statistically significant at 1%, 5% and 10% respectively.

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[2] The share of developing countries in world exports of pesticides and electrical equipment was 26% and 43% respectively in 2008. These shares have more than double since 1993 (Source: Own calculations using BACI database).

[3] Unfortunately it is not possible to make a direct comparison between both measures of complexity due to differences in industry classification and number of industries (20 in his paper and 85 in our paper).

[4] Costinot, Vogel and Wang (2011) develop a theoretical framework of sequential production processes.

[5] It is important to point out that the relative number of varieties (n/n^*) is an endogenous variable which decreases with the relative price in northern countries and increases with the relative size of northern countries (Romalis, 2004: 73).

[6] The share of processing exports on total Chinese exports is obtained from Chinese international trade data (Feenstra et al. 2010) for years 2002 and 2007.

[7] The countries included in this group are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong-Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovenia, South Korea, Spain, Sweden, Switzerland, United Kingdom and the United States.

[8] We include southern countries with at least a 0.1% participation in world trade in year 2002. The group is composed by Algeria, Argentina, Bangladesh, Belarus, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Czech Republic, Dominican Republic, Egypt, Guatemala, Hungary, India, Indonesia, Iran, Iraq, Kazakhstan, Kuwait, Lebanon, Lithuania, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Slovakia, South Africa, Thailand, Tunisia, Turkey, Ukraine, United Arab Emirates, Venezuela and Vietnam.

[9] The narrow definition of manufacturing industries excludes agricultural and mineral raw materials, food and beverages, wood products and non-metallic minerals.

[10] Romalis estimates the model using imports data for year 1998 and skill-intensity data for year 1992.

[11] Costinot, Oldensky and Rauch (2011) also combine the O*NET and the OES databases to calculate a measure of routineness at the industry level.

[12] Results not reported. They can be requested from the authors.

[13] Belarus, Dominica, Lebanon, Nigeria are not included in the Barro and Lee (2010) dataset. Arab Emirates United, Iraq, Kazakhstan, Kuwait and Saudi Arabia are not included in Jorgenson and Vu (2008) dataset.