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Comparative Advantage, Complexity, and Volatility

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Abstract

Less developed countries tend to experience higher output volatility, a fact that is in part explained by their specialization in more volatile sectors. This paper proposes theoretical explanations for this pattern of specialization – with the complexity of the goods playing a central role. Specifically, less developed countries with lower institutional ability to enforce contracts, or alternately, with low levels of human capital will specialize in less complex goods which are also characterized by higher levels of output volatility. We provide novel empirical evidence that less complex industries are indeed more volatile.

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1 Introduction

Understanding the sources of volatility is an important quest in economics. In a seminal paper, Lucas (1988) observed that, over long horizons, fluctuations in rates of growth are likely to be more substantial in less developed countries, suggesting a link between a country's level of economic development and its volatility. Indeed, as Figure 1 illustrates, the negative relationship between a country's level of development and aggregate volatility is quite pronounced. Analyzing the sources of this differential aggregate volatility across countries, Koren and Tenreyro (2007) and Tapia (2012) show that an important proximate explanation for the higher output volatility in developing countries is their production specialization in more volatile sectors. Figure 2 depicts the weighted average volatility of the sectors in which a country specializes against the level of development. More developed countries tend to specialize, on average, in less volatile sectors.

At the same time, several recent empirical studies have suggested that openness to international trade plays an important role in determining economic volatility (see, e.g., Rodrik 1998, Krebs, Krishna and Maloney 2010, di Giovanni and Levchenko 2009, di Giovanni and Levchenko 2012). While the empirical literature has variously suggested links between a country's level of development, pattern of production specialization, trade, and economic volatility, the reasons for these patterns are not well understood − that is, a coherent theoretical explanation linking these factors is, as yet, lacking.

This paper develops a theoretical framework in which openness to international trade leads to specialization in more volatile sectors in poorer countries − consistent with the empirical findings of Koren and Tenreyro (2007) mentioned above. In our framework, the central concept driving the linkage between trade openness, specialization, and volatility is the complexity of goods being produced. Complexity is defined as the number of different inputs required for the production of one unit of the good (as in Becker and Murphy 1992).

We show that sectoral output volatility depends on the complexity of goods produced in that sector. This is because when individual inputs to production are subject to shocks, the volatility of output will depend on how many such inputs there are. In particular, the more complex goods are less volatile, as the production in a sector that uses many inputs will be less affected, on average, by shocks to any particular input (a point also emphasized by Koren and Tenreyro 2012). By contrast, the volatility of a good that uses very few inputs will be more affected by the shocks to each individual input.

Starting from this technological characterization of industries in terms of their product complexity, we model two mechanisms through which less developed countries come to exhibit comparative advantage in the less complex – and therefore more volatile – goods. The first, building on Blanchard and Kremer (1997) and Levchenko (2007), relies on differences in the quality of contract enforcement. The more complex the production process, the greater is the number of parties to production, and the greater is the number of contracts that it requires. This implies that the relative loss of output due to imperfect contract enforcement is greater in the more complex sectors in countries with worse institutions, generating comparative advantage.

The second approach, building on Costinot (2009), relies on the differences in human capital endowments across countries and the optimal division of labor in production. In this second mechanism, the scope of the division of labor in production is determined endogenously as a function of the complexity of goods. Countries with higher levels of human capital per worker have a comparative advantage in the more complex goods because higher human capital allows each worker to learn more of the necessary production tasks (as we discuss in detail below). While we use the theoretical frameworks of Blanchard and Kremer (1997) and Costinot (2009) as building blocks of our analysis, neither of these important papers is concerned with the question of economic volatility, which is the focus of the present analysis.

Thus, openness to international trade moves less developed countries towards the production of less complex and more volatile goods. This is the main theoretical result obtained in the paper. The relationship between economic development and volatility in our framework is then driven by two mechanisms: the specialization in less complex goods by less developed countries and the greater volatility of goods with lower complexity. The first theoretical prediction – that less developed economies will specialize in less complex goods – is supported by several recent empirical studies. For instance, Levchenko (2007) has shown that countries with worse institutions have relatively higher export shares in goods with low product complexity − with complexity measured as the number of intermediates required for production in each sector. Similarly, Costinot (2009) has found that less developed countries specialize in less complex goods, with complexity measured as the average learning cost that a worker must pay in each sector before becoming productive. Finally, Nunn (2007) has demonstrated that less developed countries specialize in industries requiring less "relationship-specific" investments in their production – which could also be interpreted as industries with a lower degree of product complexity. Chor (2010) carries out a comprehensive empirical investigation by including these and other determinants of comparative advantage jointly in the analysis, and shows that they are all relevant for explaining trade patterns. By way of illustration of these results, Figure 3 shows that there is a pronounced positive relationship between the average complexity of a country's specialization pattern and the level of development: richer countries tend to specialize in more complex goods.

The second theoretical mechanism on which our paper relies − that less complex goods are characterized by greater volatility − has not previously been analyzed empirically in the literature. In this paper, we provide the first evidence regarding this relationship. Using U.S. sectoral production data from the NBER Productivity Database, we calculate industry-level volatility measures for some 460 4-digit SIC87 sectors over the period 1970-1997. Consistent with the theoretical results, we focus on the volatility of physical output rather than total sales or value added. We combine the volatility data with empirical measures of product complexity computed from the U.S. Input-Output tables. Our results demonstrate that there is a strong negative relationship between complexity and volatility, with complexity alone explaining some 18% of the variation in the actual volatility found in the data. The results are robust to a number of additional controls (such as factor intensity and sector-level elasticity of substitution), detrending methods, time periods, complexity measures, and removing outliers.

In sum, this paper contributes to the literature on economic development and international trade, by linking the patterns of comparative advantage with volatility. In our framework, production specialization in more volatile sectors takes place in poorer countries and emerges naturally from differences in complexity of goods and in the productivity of input factors across countries. The theoretical predictions are consistent with stylized empirical facts.

The rest of the paper is organized as follows. Section 2 describes the theoretical framework and derives the main results. Section 3 provides empirical evidence on the complexity-volatility link. Section 4 concludes.

2 Modeling Complexity, Volatility, and Comparative Advantage

We present below two theoretical mechanisms through which less developed countries come to exhibit comparative advantage in the less complex – and therefore more volatile – goods. The first, building on Blanchard and Kremer (1997) and Levchenko (2007), relies on differences in the quality of contract enforcement. The second approach, building on Costinot

(2009), relies on the differences in human capital endowments across countries and the optimal division of labor. We now consider each of these mechanisms in turn.

2.1 Intermediate Inputs and the Contracting Environment

Consider an economy with a large number of industries, each characterized by the number of intermediates z required for production, $z \in (0, \overline{z}]$. For simplicity, we assume that the final output in industry z is produced with a Leontief production function

$$q_z = \min(q(1), .., q(s), .., q(z)), \tag{1}$$

where $q(s)$ is the quantity of intermediate good s that goes into production of the final good, $s = 1, ..., z$. There is one factor of production, L, and a large number of ex-ante identical potential intermediate goods producers. These hire labor to produce intermediates with a linear production function $q(s) = l$. Both the intermediate and the final goods sectors are competitive.

Final good producers in a sector requiring z inputs contract with z intermediate goods producers to deliver the inputs. The country's contracting environment is imperfect. In particular, after the intermediates have been contracted for by the final goods producer, each intermediates producer reneges on the project with some probability $1 - \rho$. When this happens, the entire project yields the output of zero. The value of ρ captures the level of institutional quality in the country. The higher it is, the more unlikely an intermediate input producer is to renege. As a result, for a given level of investment into each intermediate good production, the final output is given by

$$\min\left(l(1), ..., l(z)\right). \tag{2}$$

with probability ρ^z, and zero with probability $1 - \rho^z$.

Since all intermediate goods producers are ex ante identical and enter symmetrically into the production function, the final goods producer contracts for the same level of investment/employment for each intermediate. Therefore, the expected final output per worker is given by $\frac{\rho^z}{z}$ in industry z. Thus, output per worker depends on the complexity, z, of the good, and the quality of institutions ρ. Note that expected output per worker decreases in z at any level of institutional quality ρ. This is a result in the spirit of the O-ring theory of Kremer (1993) and the complementarity model of Jones (2011): the more steps the good requires, the higher is the chance that something will go wrong. If the inputs are "essential" as they are with a Leontief production function, the lower is the expected output. Note that in a model with multiple goods, this also implies that more complex goods command higher prices. While we are not aware of empirical studies of such a relationship in the data, the prediction appears *prima facie* sensible and intuitive.[1]

In this setting, less complex goods – that is, goods with lower z – are more volatile. The overall output per worker is $\frac{1}{z}$ with probability ρ^z and zero with probability $1-\rho^z$. Therefore, the variance of output per worker is given by $\frac{1}{z^2}\rho^z\left(1-\rho^z\right)$. We state the following Lemma, proved formally in Appendix B:

Lemma 1 ***(Complexity and Volatility in the Imperfect Contracting Model)*** *The variance of output per worker decreases in z:* $\frac{d}{dz}Var\left(\frac{\rho^z}{z}\right) < 0$.

This result is intuitive: the fewer inputs to production there are, the greater is the (marginal) impact of an individual input on the overall output. Thus, the behavior of an individual input more closely approximates the behavior of the total output. By contrast, with a large number of inputs, the total output is determined by a combination of a large

[1] It is well documented that more developed countries export goods with higher unit values. Since both in the theoretical model and in the data more developed countries export the more complex goods, in this respect the model appears consistent with the data.

number of uncorrelated shocks, and is thus less volatile.[2,3]

2.2 Imperfect Contracting and Comparative Advantage

Now suppose there are two countries, North and South. While we do not model contract enforcement explicitly, we assume that a better contracting environment in a country implies that the probability that someone reneges $(1-\rho)$ is lower there. Without loss of generality, let us assume that the North has a more efficient contracting environment. Thus, $\rho_N > \rho_S$.

We can map this setting into the Ricardian model of Dornbusch, Fischer and Samuelson (1977). Denote by $a^N(z) = \frac{z}{\rho_N^z}$ the unit labor requirement for good z in the North, and similarly in the South. Then, the relative unit labor requirement for good z in the two countries is:

$$A(z) = \frac{a^S(z)}{a^N(z)} = \left(\frac{\rho_N}{\rho_S}\right)^z. \tag{3}$$

Does an efficient contracting environment create comparative advantage? That is, is the North relatively more productive in goods with higher z? The derivative of this ratio of productivities with respect to z is:

$$\left(\frac{\rho_N}{\rho_S}\right)^z \log\left(\frac{\rho_N}{\rho_S}\right) > 0. \tag{4}$$

We have just proved the following result:

Lemma 2 ***(Comparative Advantage in the Imperfect Contracting Model)*** *The North has comparative advantage in goods with higher z: $\frac{dA(z)}{dz} > 0$.*

[2] Note that the assumption of zero output in case of default is not important for the results. Alternatively, we could assume that even when the supplier reneges successfully, the final goods producer can force it to deliver a fraction δ of the contracted quantity of the intermediate good. In that case, the total output per worker is $\frac{\delta}{z}$ when no supplier defaults, and the variance of output is simply $\frac{1}{z^2}\rho^z(1-\rho^z)(1-\delta)^2$. It is clear that all the results carry over to this case.

[3] Note that the only shock, and thus the only volatility in this model comes from the possibility that an input supplier reneges on the delivery of the good. This assumption is not crucial: the result above extends to the case in which there is both a reneging shock and a genuine productivity shock, as long as the two are uncorrelated for each supplier.

The North is indeed relatively more productive in high-z goods.

The preceding theoretical framework, while admittedly highly stylized, serves to illustrate two key ideas. First, output volatility is driven by product complexity. And second, better (worse) contracting environments can therefore generate comparative advantage in less (more) volatile goods. If we expect the efficiency of the contracting environment to improve with development, we obtain specialization in more volatile goods in less developed countries – consistent with the empirical findings of Koren and Tenreyro (2007) discussed above.

What is the role of the Leontief production function assumption for these results? Lemma 1 – volatility decreasing with the number of inputs – is clearly much more general, in the sense that it applies under other elasticities of substitution between inputs. It is present, for instance, in the opposite extreme case with perfect substitute inputs, as well as intermediate elasticities of substitution. Koren and Tenreyro (2012) develop this idea further. Indeed, assuming extreme complementarity actually stacks the cards against finding this relationship: more substitutable inputs imply possibilities for diversification across inputs (in the extreme case of perfect substitutability this simply becomes the Law of Large Numbers), which makes the result that more inputs means lower volatility even more straightforward.

Where the Leontief-type structure is really necessary is to generate comparative advantage: contractual frictions have to compound with complexity, so that not only is the country with better institutions more productive in every good, but it is *relatively* more productive in the more complex goods. It is this aspect of the model that relies on the Leontief assumption. This type of physical environment is quite typical in models with incomplete contracts (Blanchard and Kremer 1997, Caballero and Hammour 1998, Levchenko 2007). The strict Leontief structure could be relaxed somewhat by adopting a more general production function for the total output conditional on delivery of all the inputs, but assuming that if just one input supplier reneges, the total output is still zero.

2.3 Human Capital and the Division of Labor

Our second modeling approach, based on Costinot (2009), relies on the differences in human capital endowments across countries and the optimal division of labor in the production of final goods. As in the previous section, more complex final goods require a larger number of intermediate inputs to be supplied or, as interpreted here, a larger number of different tasks to be performed. It is assumed that each of the tasks necessary for the production of the final good requires some fixed labor costs to be incurred. As in Costinot (2009), dividing up the tasks among a larger number of workers generates gains from specialization – fewer tasks taken on by a single worker implies lower fixed costs incurred per worker, thereby raising output per worker. On the other hand, since workers are subject to random productivity shocks, complementarity in production implies that the expected level of output is lower with a larger number of workers.[4] In the analysis that follows, we see how the trade-off between these two forces determines optimal team size used in production (and thus unit production costs) as a function of complexity. Then we will examine how, in this context, countries with high human capital workers have comparative advantage in the production of more complex goods.

Once again, consider an economy with many goods indexed by $z \in (0, \bar{z}]$. Each good is produced with a Leontief technology requiring z tasks to be performed. Let $s \in (0, z]$ denote a particular task that must be performed in order to produce good z, and let $q(s)$ be the quantity of task s. Then, the total output of good z, q_z, is given by

$$q_z = \min_{s \in (0,z)} q(s). \tag{5}$$

The economy is populated by L workers, each with productivity h. There are fixed costs associated with performing each task s. In particular, a worker must first spend 1 unit of

[4]This point has been emphasized recently by Jones (2011).

labor learning to perform each task. Let N be the team size that characterizes production of a good with complexity z. The first question we ask is what is the team size that maximizes output per worker in sector z.

With a team of size N, each team member specializes in $\frac{z}{N}$ tasks, and allocates her endowment of labor equally to each of them. Therefore, after paying the fixed cost to learn these tasks, each worker has $h-\frac{z}{N}$ units of labor to spend on production. Hence, each worker is able to dedicate $\frac{h-\frac{z}{N}}{\frac{z}{N}}$ units of labor to each task.

After paying the fixed costs, each worker receives a productivity shock ε, affecting her performance of each task equally. Therefore, the worker's actual output is

$$q(s) = \left(\frac{hN}{z} - 1\right)\varepsilon \tag{6}$$

of each task s. Plugging equation (6) into (5), it is immediate that the total output of this team is $q_z = \left(\frac{hN}{z} - 1\right)\min_{n=1,\dots,N}\varepsilon_n$, while the output per worker is

$$\frac{q_z}{N} = \left(\frac{h}{z} - \frac{1}{N}\right)\min_{n=1,\dots,N}\varepsilon_n. \tag{7}$$

Note that, holding team size fixed, output per worker is higher, the greater the human capital level h and the lower the complexity of the good being produced z. This is as is expected. Furthermore, output per worker is a function of the random productivity shocks faced by workers. What is the team size that maximizes output per worker in this setting? Assume that the shocks are uncorrelated across workers. The expected output per worker is then equal to

$$E\left(\frac{q_z}{N}\right) = \left(\frac{h}{z} - \frac{1}{N}\right)E(\varepsilon_{(1)}), \tag{8}$$

where $\varepsilon_{(1)} \equiv \min_{n=1,\dots,N}\varepsilon_n$ is the first order statistic associated with the sample of N outcomes of a random variable ε_n across the workers in a team (see Appendix A).

For the sake of tractability, assume for now that the shocks to workers are distributed $\varepsilon\ \sim$Uniform$(0,1)$. This assumption has the advantage of leading to a simple closed-form solution for the optimal team size. In particular, the expected output per worker with team size N is equal to (see eq. A.4): $\left(\frac{h}{z} - \frac{1}{N}\right)\frac{1}{N+1}$. Following Costinot (2009), this expression can be used to find the optimal team size N_z in a sector with complexity z:

$$N_z = \text{argmax}_N \left(\frac{h}{z} - \frac{1}{N}\right)\frac{1}{N+1}. \tag{9}$$

The first-order condition is given by:

$$\frac{1}{N^2}\frac{1}{N+1} + \left(\frac{h}{z} - \frac{1}{N}\right)\left(\frac{1}{(N+1)^2}\right) = 0. \tag{10}$$

Straightforward manipulation gives the optimal team size in sector z of:

$$N_z = \frac{z}{h}\left(1 + \sqrt{1 + \frac{h}{z}}\right). \tag{11}$$

The optimal team size increases in the complexity of the good, z, and decreases in the worker productivity h. Optimal team size increases with complexity due to the gains from specialization that are obtained when the necessary tasks are divided up among a larger number of workers. The higher is the level of human capital, the costlier a low productivity draw becomes, and thus optimal team size falls in h. As we will see, the relationship we have established between optimal team size, complexity and human capital will be important in determining the pattern of comparative advantage.

Though the model of the division of labor and team size follows Costinot (2009), the key tension that pins down the optimal team size is different in our paper. In Costinot (2009), the tension is between greater division of labor and the resulting higher per worker productivity on the one hand, and imperfect contract enforcement: the more workers are in a team, the greater is the probability that at least one of them reneges. In our setup, the tension is between division of labor and the greater possibility of an adverse productivity shock that an individual worker may experience, in a production setting characterized by strong complementarities, a mechanism inspired by Jones (2011). Note also that though we choose to follow Costinot's terminology and call the team members "workers," the model will not change if we think of N as intermediate inputs suppliers instead.

The first result we would like to establish is that in this setting more complex goods are also less volatile. Going back to the expression for output per worker (7), it is immediate that the volatility of output per worker is given by:

$$Var\left(\frac{q_z}{N}\right) = \left(\frac{h}{z} - \frac{1}{N}\right)^2 Var(\varepsilon_{(1)}). \tag{12}$$

We state the counterpart of Lemma 1 for this model:

Lemma 3 ***(Complexity and Volatility in the Division of Labor Model)*** *The variance of output per worker decreases in z:* $\frac{d}{dz}Var\left(\frac{q_z}{N}\right) < 0$.

The proof is provided in Appendix B. We should note that the result in Lemma 3 depends in an important way on the property that the variance of the first order statistic (the minimum of a random sample) decreases in the sample size. Though this property appears intuitive, there are no finite sample general results in statistics about how the variance of the first order statistic behaves as the sample size increases. However, it can be confirmed using direct calculation that this variance indeed decreases in the sample size for some important distributions such as the uniform (as in this paper), exponential, Pareto, and Fréchet. This gives us some confidence that our main results are not excessively driven by the particular distributional assumptions that we adopt.

A related result is that *in each sector* z, a country with lower productivity of workers experiences lower volatility. This is because higher productivity implies lower team size, which in turn increases the volatility of output.

2.4 Human Capital Differences and Comparative Advantage

Suppose now that there are two countries, North and South. The only difference between them is that the North's workers are more productive: $h^N > h^S$. Following Costinot (2009), we map this model into the Ricardian framework of Dornbusch et al. (1977), by considering the unit labor requirements in each good z in the two countries. The average labor requirement of a unit of the good z in the North is:

$$a^N(z) = \frac{h^N}{\left(\frac{h^N}{z} - \frac{1}{N_z^N}\right)\frac{1}{N_z^N+1}} = \frac{zh^N N_z^N(N_z^N+1)}{(h^N N_z^N - z)}, \tag{13}$$

and similarly in the South. Therefore, the ratio of relative unit labor requirements is given by:

$$A(z) = \frac{a^S(z)}{a^N(z)} = \frac{h^S N_z^S(N_z^S+1)(h^N N_z^N - z)}{h^N N_z^N(N_z^N+1)(h^S N_z^S - z)}. \tag{14}$$

In order to establish the direction of comparative advantage, we must ascertain whether the schedule $A(z)$ is increasing or decreasing. Taking the derivative with respect to z, and applying the envelope theorem, we obtain:

$$A'(z) = \frac{\frac{\partial a^S}{\partial z}a^N - a^S\frac{\partial a^N}{\partial z}}{\left(a^N\right)^2}. \tag{15}$$

Evaluating the partial derivatives with respect to z based on equation (13) and simplifying, $A'(z)$ becomes:

$$A'(z) = \frac{h^S N^S(N^S+1)}{(h^S N^S - z)^2 h^N N^N(N^N+1)}\left(h^N N^N - h^S N^S\right). \tag{16}$$

Therefore, the sign of this derivative is the same as the sign of $\left(h^N N^N - h^S N^S\right)$. Using equation (11), it is immediate that $\left(h^N N^N - h^S N^S\right) > 0$, and therefore the North has a comparative advantage in the more complex goods, as expected. We summarize the discussion above in the following Lemma:

Lemma 4 ***(Comparative Advantage in the Division of Labor Model)*** *The North has comparative advantage in goods with higher z:* $\frac{dA(z)}{dz} > 0$.

The intuition for this result is straightforward: When workers have higher human capital, they spend a smaller fraction of their time learning, and so unit labor requirements are lower. Importantly, this reduction is not uniform across goods. In the more complex sectors, learning costs are more important and the decrease in unit labor requirements is larger. As a result, the country with workers with greater human capital is relatively more efficient in the more complex industries.

2.5 Trade Equilibrium

We now specified the pattern of comparative advantage $A(z)$ in two ways: by relying on contract enforcement (equation 3), and human capital differences (equation 14). In order to close the model, we must specify agents' preferences. Assume, following Dornbusch et al. (1977), that all agents have identical Cobb-Douglas preferences, so that each good receives a constant share of expenditure. Let $\omega = \frac{w^N}{w^S}$ be the relative wage between the two countries. There exists a cutoff $\tilde{z}$, such that

$$\omega = A(\tilde{z}). \tag{17}$$

Let $S(\tilde{z})$ be the share of income spent on Southern goods. Then, the trade balance condition is given by

$$\omega = \frac{h^S L^S \left[1 - S(\tilde{z})\right]}{h^N L^N S(\tilde{z})}. \tag{18}$$

The equilibrium specialization pattern is illustrated in Figure 4. Equations (17) and (18) jointly determine the equilibrium pair $(\omega, \tilde{z})$. It is immediate that the South produces goods $(0, \tilde{z})$, while the North produces goods $(\tilde{z}, \bar{z})$. As such, the South ends up in the less complex industries in which production is the most volatile for each firm.

Though these models are of course much too stylized to explain the observed differences in per capita income across countries, we can circle back to the empirical facts motivating the paper, which are about how specialization in volatile and complex sectors is related to per capita income. The relative per capita incomes in equilibrium are given by equation (17), and since the price levels are the same in the two countries, equation (17) also gives the ratio of the real per capita incomes. Thus, a necessary condition for the country with better institutions or higher human capital to have higher per capita income is that at the cutoff value $\tilde{z}$, $A(\tilde{z}) > 1$. A sufficient condition is that at every z, $A(z) > 1$, that is, the country with better institutions or higher human capital has an absolute advantage in every good. This sufficient condition is easily verified in both models, and thus it is indeed the case that the higher-income country exports more complex and less volatile goods.[5]

3 Empirical Evidence

There are two crucial pieces of evidence that we must bring to bear to support the theory proposed above. The first is that poorer countries do indeed specialize in less complex goods. This result has been established recently in a series of studies. Levchenko (2007) shows that countries with worse institutions – which are essentially the less developed countries – have relatively higher export shares in goods with low product complexity. In that study, measures of product complexity at sector level are constructed using the Input-Output tables for the United States, and by examining how many intermediates each sector requires to produce. Costinot (2009) provides similar results using an alternative measure, which is the average learning cost that a worker must pay in each sector before she becomes productive. Nunn (2007) constructs a measure of contract intensity by combining the U.S. Input-Output table data with a classification of intermediate goods industries into those that require relationship-specific investments and those that do not. Nunn finds that less developed countries specialize in industries that do not rely on relationship-specific investments, which could be another way of capturing industries with a low z in the model above.

[5] It is immediate from (3) that the imperfect contracting model satisfies the sufficient condition. The easiest way to see that the human capital model satisfies the sufficient condition is to differentiate the expression for $a(z)$ in (13) (dropping the N-superscript) with respect to h, applying the envelope theorem.

Finally, Chor (2010) includes these and other determinants of comparative advantage jointly in the analysis, and shows that they are all relevant for explaining trade patterns. Since the finding that less developed countries specialize in less complex goods is well established in the literature, we do not revisit it in this paper (beyond depicting this pronounced pattern in Figure 3), and refer the reader to the papers above.

The second crucial element is the negative relationship between complexity and volatility at sector level. On this score, we are not aware of any existing empirical evidence. In this section, we use data on the actual complexity and volatility of the U.S. manufacturing sectors to demonstrate that complexity is a robust and highly significant predictor of volatility. The empirical strategy is focused on testing the predictions of the model for physical output, rather than total sales as is typical in the literature. This is important because predictions of the model regarding total sales would depend more heavily on assumptions on preferences.

In order to demonstrate the conditional correlation between product complexity and output volatility while controlling for other industry characteristics, we fit the following relationship on the cross-section of sectors using OLS:

$$\text{StDev}_i = \alpha + \beta \text{ImpliedStDev}(z)_i + \gamma \mathbf{X_i} + \epsilon_i,$$

where i indexes sectors, StDev_i is the standard deviation of output in sector i, $\text{ImpliedStDev}(z)_i$ is the standard deviation of that sector's output implied by its complexity z, and $\mathbf{X_i}$ is a vector of other sectoral characteristics used as controls.

3.1 Data

Industry-level data on volatility come from the NBER Productivity Database that reports information on 459 manufacturing sectors in the U.S. at the 4-digit SIC87 classification. We compute output per worker using data on total shipments and employment in each sector. Total output is deflated using sector-specific deflators provided in the database, ensuring that we capture the volatility of quantities. Because the level of real output per worker exhibits a trend, we compute the time series of the growth rate of output per worker for each sector, and take the standard deviation over time for the period 1970-1997. Taking growth rates is the simplest way of detrending the data. To check robustness of the results, we also HP-filter the output per worker series in each sector, and compute the volatility of the deviations from the HP-filtered trend. Following the recommendation of Ravn and Uhlig (2002), we set the HP filter parameter to 6.25, since the data are at the annual frequency. Output per worker data may be contaminated by the time variation in the use of inputs or other factors of production. Thus, we compute the volatility of two alternative series: value added per worker, and Total Factor Productivity (TFP). The sector-specific TFP series is available in the same database. For both of these, we compute the standard deviation of the growth rate of the series, though the HP-filtering procedure delivers the same results.

Data on product complexity come from the U.S. Input-Output Tables for 1992, and have been previously used by Cowan and Neut (2007) and Levchenko (2007). In particular, in this exercise we use the total number of intermediates in production as a proxy for product complexity z in the model above. It turns out that the number of intermediates ranges from 16 to 160, a tenfold difference. Table 1 reports the summary statistics for both complexity and the actual volatility (standard deviation of output per worker growth) of the sectors in our data. Table 2 reports the top 10 most and least complex sectors, according to the total number of intermediates used.

Using the variation in actual product complexity in place of z in the model, we can compute the optimal team size N from equation (11), and as a result the volatility in each sector from equation (B.2). The resulting standard deviation of output as a function of product complexity z is depicted in Figure 5. Volatility is decreasing in complexity.[6]

[6]The relationship between complexity and volatility would be similar if we instead computed implied

3.2 Results

Is the standard deviation of a sector as implied by its complexity a robust predictor of the actual volatility in that sector? Figure 6 presents the scatter plot of the standard deviation of output per worker growth against the implied volatility of output per worker constructed based on our model. There is a robust positive relationship between the two variables.

Table 3 presents the regression results. All throughout, we report the standardized beta coefficients, obtained by first demeaning all the variables and normalizing each to have a standard deviation of 1. Thus, the regression coefficients correspond to the number of standard deviations change in the left-hand side variable that would be due to a one standard deviation change in the corresponding independent variable. The four panels differ only in the measure of actual volatility used on the left-hand side. Panel A uses standard deviation of output per worker growth; Panel B, the volatility of deviations from HP trend; Panel C, volatility of value added per worker; Panel D, standard deviation of TFP growth. Column 1 reports the results of a bivariate regression of the actual on the implied volatility. The positive relationship is very pronounced: with the exception of the deviations from the HP trend series, the t-statistics on the coefficient on the implied volatility are in the range of 5-7, and the R^2's of the bivariate regressions are as high as 0.18.

Column 2 controls for other sector characteristics, such as raw materials intensity, capital intensity, and skill intensity, constructed based on Romalis (2004). As we can see, after controlling for other sector characteristics, the coefficient of interest in Panel B goes from being insignificant to significant at the 1% level, while the rest of the results are virtually unchanged. Finally, column 3 removes the outliers in terms of actual volatility, and still

volatility using the imperfect contracting model of section 2.1. All of the results are virtually unchanged under this alternative approach, so we do not report the full set of results based on the imperfect contracting model to avoid unnecessary repetition. To compute the variance, we choose the value of $h = 20$. We checked the robustness using all values of h between 1 and 200, and while h affects the level of the implied variance of output, the statistical significance of the results is unchanged.

finds that the relationship of interest is quite strong and statistically significant.[7] Finally, it may be that what we are picking up are differences in the elasticity of substitution across goods. For instance, Kraay and Ventura (2007) argue that developing countries are more volatile because they specialize in goods that have a higher elasticity of substitution. We use data from Broda and Weinstein (2006) to check whether sectoral volatility is systematically correlated with elasticity. Column 4 in each panel reports the results. Because the Broda-Weinstein data are in a different industrial classification, we lose 10 of the the sectors due to an imperfect concordance. Controlling for it the elasticity of substitution leaves the main results completely unchanged.

The control variables tend to come in with the expected sign. Sectors with the higher raw material intensity and with higher capital intensity tend to be more volatile. The coefficient on the elasticity of substitution is positive, and significant in two out of four specifications. Plausibly, sectors with higher elasticity of substitution are also more volatile. Perhaps a bit more surprisingly, sectors with higher skill intensity also tend to be more volatile. Two points are worth noting in this respect. First, the model is silent on this issue, since all the workers are the same and all the sectors in the theoretical model have the same "skill intensity." Second, the coefficient on skill intensity represents the conditional correlation, after controlling for complexity and other covariates. Indeed, it turns out that when omitting implied volatility from the right-hand side, skill intensity is actually negatively (but insignificantly) correlated with volatility. There is no strong *prima facie* case to expect a particular sign, especially after conditioning on the other correlates of sectoral volatility.

We now assess whether this relationship is robust to a number of additional alternative left- and right-hand side measures and samples. As mentioned above, the results are robust to

[7] More precisely, we drop the top 5% most volatile sectors, according to each corresponding measure of volatility. Alternatively, we also dropped the top 5% of most volatile sectors according to the Implied Volatility (i.e., the RHS variable), and the results were fully robust.

constructing the implied volatility based on the imperfect contracting model instead. Column 1 of Table 4 presents the results, computing implied volatility under the assumption that $\rho = 0.9$ (i.e., the probability a supplier reneges is 10%). The coefficient magnitude and the explanatory power of the implied volatility measure is virtually identical.[8] In constructing the implied volatility, in the baseline procedure we use the total number of intermediate inputs in each industry. However, it could be that some inputs in some industries have minuscule usage, and thus should not really be counted as adding to complexity. We thus computed an alternative measure for the number of intermediates, that only counts inputs whose share in the total input usage is at least at the 10th percentile of all the non-zero entries in the IO matrix. This truncating procedure in effect drops the bottom 10% of all input usages. Predictably, the range of the number of inputs across industries shrinks somewhat: while the unrestricted measure ranges from 16 to 160, the restricted measure ranges from 16 to 109. The two have a correlation of 0.8. Column 2 of Table 4 presents the main result while using the restricted measure of the number of inputs to construct implied volatility. The results are fully robust to this alternative approach.

Rather than use the data on the number of intermediate inputs to compute sectoral volatility as implied by the model, we can also assess whether actual volatility is positively correlated with measures of product complexity directly. The rest of Table 4 presents the results of estimating the relationship between actual volatility and various indicators of product complexity. Following Cowan and Neut (2007) and Levchenko (2007), we use a number of variables, all constructed using the 1992 Benchmark Input-Output Table for the United States. Column 1 regresses volatility on the number of intermediates used in production. Column 2 used the Herfindahl index of intermediate goods shares; Column 3, the Gini coefficient of intermediate use, columns 4 and 5 the shares of the 10 and 20 largest intermediate

[8]The results are robust to a wide variety of values of ρ, from $\rho = 0.1$ (90% probability of reneging) to $\rho = 0.99$ (1% probability of reneging).

inputs in the total input use. These variables have been used in the literature to measure product complexity. They may be preferable to simply using the number of intermediates if intermediate input use is dominated by one or two inputs (high concentration) and all the other intermediates are used very little. In that case what really matters to the final good producer is the relationship it has with the largest one or two suppliers. The scope for and consequences of reneging by suppliers of minor inputs is probably much smaller than by important suppliers. Thus, simply taking the number of intermediates may give excessive weight to insignificant input suppliers and overestimate the effective product complexity. Note that complexity increases in the number of intermediates, but decreases in all the other indicators. Thus, in columns 4 through 7 we should expect positive coefficients. We can see that with the exception of column 4, all the coefficients are significant at the 1% level. The coefficient on the Herfindahl index is not significant, but nonetheless enters with the expected sign.

We next check whether the main result is sensitive to the sample period and the detrending method, and whether it is confined to the U.S. data. Columns 1 and 2 of Table 5 compute sectoral volatility on the pre- and post-1984 periods respectively. This may be important because 1984 is widely seen as the onset of the Great Moderation, with lower volatility throughout the economy for the following 2 decades. It is clear that the relationship between complexity and volatility is equally significant and possesses a similar magnitude in both periods. In the baseline results, when HP-detrending the data we used a parameter of 6.5, recommended for annual data by Ravn and Uhlig (2002). To see whether the results are sensitive to this choice, we used the parameter of 100 instead. Column 3 of Table 5 presents the results. It is clear that the basic relationship is not driven by the HP-detrending parameter.

Finally, it remains an open question whether the relationship between complexity and volatility we demonstrated thus far in the U.S. data holds in a large set of other countries. Unfortunately, data availability does not permit us to carry out an analysis in a cross-section of countries at the same level of disaggregation (∼450 sectors). However, we can carry out this exercise based on the UNIDO sectoral production database, which reports data at the 3-digit ISIC level of disaggregation (28 sectors) over the period 1970-1999 for about 60 countries. The data and specification come from di Giovanni and Levchenko (2009), which can be consulted for further details. Implied volatility and factor intensity measures are concorded from the SIC to the ISIC classification. The results are reported in column 4 of Table 5. It is clear that the basic relationship between product complexity and sectoral volatility holds even in this large sample of countries, and even at the much coarser level of sectoral disaggregation. An additional question is whether this relationship holds in both high- and low-income countries. We estimated the specification in column 4 for the OECD and non-OECD samples separately, and the relationship is quite similar in both groups of countries, both in the size of the coefficient and in the level of significance. Those results are not reported in order to conserve space, but are available upon request.

We conclude that in a large sample of sectors, variation in complexity does play a significant role in explaining sectoral volatility, which is a key building block of our theory.

4 Conclusion

Recent literature has made important advances in understanding the patterns of macroeconomic volatility across countries. It is well known that poorer countries experience higher volatility. Koren and Tenreyro (2007) and Tapia (2012) demonstrate that part of the higher volatility in developing countries can be accounted for by the fact that they produce on average in more volatile sectors.

What can explain this puzzling observation? In this paper, we argue that international trade plays an important role. In particular, recent literature emphasized that poorer countries tend to export goods that are less complex (Levchenko 2007, Costinot 2009). Since these goods use fewer intermediates, shocks to each intermediate input are more important for production (a point also emphasized by Koren and Tenreyro 2012). Therefore, less complex goods tend to be more volatile. Comparative advantage in less complex goods, that could arise from institutional quality or productivity differences, drives specialization in more volatile industries by developing countries.

There is one aspect of our argument for which there is no extant empirical evidence. Namely, it has not been demonstrated previously that less complex goods are indeed more volatile. In the last section of the paper we use data on the actual complexity of sectors in the United States to construct the volatility of each industry based on our model. We then relate this implied volatility to the actual volatilities of sectors observed in the data, and show that there is a robustly significant relationship: less complex industries are indeed more volatile.

Appendix A Order statistics

Suppose that $\varepsilon_1, ..., \varepsilon_N$ is a random sample of size N drawn from a distribution with pdf f_ε and cdf F_ε. The first order statistic is defined as $\varepsilon_{(1)} \equiv \min_{n=1,...,N} \varepsilon_n$, that is, it is the minimum value in this random sample. The distribution of $\varepsilon_{(1)}$ can be derived as follows. The cdf of this variable is given by:

$$F_{\varepsilon_{(1)}}(x) = P(\min_{n=1,...,N} \varepsilon_n < x) = 1 - P(\min_{n=1,...,N} \varepsilon_n > x) = 1 - (1 - F_\varepsilon(x))^N. \tag{A.1}$$

Correspondingly, the pdf of $\varepsilon_{(1)}$ is obtained by differentiating the cdf:

$$f_{\varepsilon_{(1)}}(x) = N(1 - F_\varepsilon(x))^{N-1} f_\varepsilon(x). \tag{A.2}$$

As an example, suppose that $\varepsilon \sim$Uniform$(0, 1)$. The pdf of ε is $f_\varepsilon(x) = 1$, and the cdf is $F_\varepsilon(x) = x$. Then, the pdf of the first order statistic is

$$f_{\varepsilon_{(1)}}(x) = N(1 - x)^{N-1}. \tag{A.3}$$

Using integration by parts, it is straightforward to establish that in this case, the expectation and the variance of $\varepsilon_{(1)}$ are given by:

$$E(\varepsilon_{(1)}) = \frac{1}{N+1} \tag{A.4}$$

$$Var(\varepsilon_{(1)}) = \frac{N}{(N+1)^2(N+2)}. \tag{A.5}$$

These results will be useful in the main text.

Appendix B Proofs

B.1 Proof of Lemma 1

Proof: Taking this derivative directly,

$$\begin{aligned} \frac{d}{dz} Var\left(\frac{1}{z}\varepsilon_{(1)}\right) &= -\frac{2}{z^3}\rho^z\left(1 - \rho^z\right) + \rho^z\left(1 - 2\rho^z\right)\ln\rho\frac{1}{z^2} \\ &= \frac{\rho^z}{z^2}\left[\ln\rho\left(1 - 2\rho^z\right) - \frac{2}{z}\left(1 - \rho^z\right)\right]. \end{aligned}$$

Rearranging, the Proposition holds if and only if:

$$\frac{1-2\rho^z}{1-\rho^z}\ln\rho^z < 2.$$

When $\rho \in (0,1)$ and $z \geq 1$, it is always the case that $\rho^z \in (0,1)$. Therefore, the result necessary for the proposition obtains if

$$\frac{1-2\rho}{1-\rho}\ln\rho < 2 \qquad \forall\rho \in (0,1)\,.$$

We now show that this is condition holds by proceeding in two steps. First, we show that the function $f(\rho) = \frac{1-2\rho}{1-\rho}\ln\rho$ is monotonically increasing throughout the interval $\rho \in (0,1)$. And second, we show that the supremum of this function, which obtains when $\rho \to 1$ is less than 2, satisfying this required condition.

Differentiating $f(\rho)$:

$$\begin{aligned}
\frac{d}{d\rho}\left[\frac{1-2\rho}{1-\rho}\ln\rho\right] &= \frac{1-2\rho}{1-\rho}\frac{1}{\rho} + \ln\rho\left[\frac{-2(1-\rho)-(-1)(1-\rho)}{(1-\rho)^2}\right] \\
&= \frac{1-2\rho}{1-\rho}\frac{1}{\rho} + \frac{\ln\rho}{(1-\rho)^2} \\
&= \frac{(1-2\rho)(1-\rho)-\rho\ln\rho}{(1-\rho)^2\rho} \\
&= \frac{(1-\rho)^2-\rho(1-\rho)-\rho\ln\rho}{(1-\rho)^2\rho} \\
&= \frac{1}{\rho} - \frac{(1-\rho)+\ln\rho}{(1-\rho)^2}.
\end{aligned}$$

Thus, this derivative is positive if $(1-\rho)+\ln\rho < 0$. It is immediate that $\lim_{\rho\to 0}(1-\rho+\ln\rho) = -\infty$ and $\lim_{\rho\to 1}(1-\rho+\ln\rho) = 0$. Therefore, if this function is monotonic for $\rho \in (0,1)$, it is everywhere less than 0, as required. Taking the derivative of this function,

$$\frac{d}{d\rho}\left[1-\rho+\ln\rho\right] = -1 + \frac{1}{\rho} > 0 \qquad \forall\rho \in (0,1).$$

This establishes that $f(\rho) = \frac{1-2\rho}{1-\rho}\ln\rho$ is monotonically increasing in the interval $(0,1)$. We now show that its supremum is less than 2. The supremum obtains as $\rho \to 1$.

$$\begin{aligned}
\lim_{\rho\to1}\left[\frac{1-2\rho}{1-\rho}\ln\rho\right] &= \lim_{\rho\to1}(1-2\rho)\lim_{\rho\to1}\left[\frac{\ln\rho}{1-\rho}\right] \\
&= (-1)\lim_{\rho\to1}\frac{\ln\rho}{1-\rho} = -\lim_{\rho\to1}\frac{\frac{1}{\rho}}{-1} = 1 < 2,
\end{aligned}$$

where the last equality comes from applying l'Hôpital's Rule. This completes the proof. ■

B.2 Proof of Lemma 3

Proof: Using the optimal value of N in equation (11), the term in parentheses simplifies to:

$$\left(\frac{h}{z}-\frac{1}{N}\right)^2 = \frac{1+\frac{h}{z}}{N^2}. \tag{B.1}$$

Using equation (A.5) from the Appendix, the variance becomes:

$$Var\left(\frac{q_z}{N}\right) = \left(1+\frac{h}{z}\right)\frac{1}{N(N+1)^2(N+2)}. \tag{B.2}$$

To establish that the variance decreases in good complexity z, evaluate its derivative with respect to z:

$$\frac{d}{dz}Var\left(\frac{q_z}{N}\right) = \frac{\partial}{\partial z}Var\left(\frac{q_z}{N}\right) + \frac{\partial}{\partial N}Var\left(\frac{q_z}{N}\right)\frac{dN}{dz}. \tag{B.3}$$

Evaluating each of these subcomponents separately, it is indeed the case that $\frac{d}{dz}Var\left(\frac{q_z}{N}\right) < 0$.

■

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Table 1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
Complexity (z)	77.0	25.2	16	160	459
Actual volatility	0.080	0.040	0.027	0.339	459

Notes: Complexity is the number of intermediates used in production, calculated based on the U.S. I-O matrix. Actual volatility is the standard deviation of real output per worker growth, 1970-1997, calculated based on the NBER Productivity Database.

Table 2. Most and Least Complex Sectors

SIC Code	Sector Name	Number of Intermediates
	Least Complex Sectors	
2429	Special product sawmills, n.e.c.	16
3263	Semivitreous table and kitchenware	17
3151	Leather gloves and mittens	17
3131	Footwear cut stock	21
3292	Asbestos products	22
3142	House slippers	24
2397	Schiffli machine embroideries	24
3259	Structural clay products, n.e.c.	28
2441	Nailed wood boxes and shook	29
2121	Cigars	29
	Most Complex Sectors	
3728	Aircraft parts and equipment, n.e.c.	120
2865	Cyclic crudes and intermediates	122
281	Industrial Inorganic Chemicals	122
3585	Refrigeration and heating equipment	122
3731	Ship building and repairing	125
3812	Search and navigation equipment	136
3721	Aircraft	138
308	Miscellaneous Plastics Products	139
3714	Motor vehicle parts and accessories	148
3711	Motor vehicles and car bodies	160

Notes: This table reports the most and least complex sectors, with complexity measured by the number of intermediates used in production, calculated based on the U.S. I-O matrix.

Table 3. Actual and Implied Volatility

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Panel A: Dep. Var.: Standard Deviation of Output per Worker Growth				*Panel B: Dep. Var.: Standard Deviation of Output per Worker Deviation from HP Trend*			
Implied Volatility	0.426***	0.447***	0.343***	0.445***	0.043	0.145***	0.092***	0.143***
	(0.064)	(0.071)	(0.044)	(0.071)	(0.040)	(0.039)	(0.024)	(0.039)
Raw Materials Intensity		0.261***	0.243***	0.219**		1.105***	0.631***	1.071***
		(0.100)	(0.067)	(0.102)		(0.114)	(0.052)	(0.118)
Capital Intensity		0.084	0.116**	0.069		0.661***	0.438***	0.650***
		(0.071)	(0.052)	(0.072)		(0.076)	(0.043)	(0.076)
Skill Intensity		0.118*	0.045	0.088		0.336***	0.139***	0.306***
		(0.069)	(0.051)	(0.069)		(0.074)	(0.028)	(0.079)
Elasticity				0.085*				0.096**
				(0.047)				(0.044)
Observations	459	459	436	449	459	459	436	449
R^2	0.18	0.2	0.16	0.21	0.00	0.32	0.41	0.33
Sample	Full	Full	No Outliers	Full	Full	Full	No Outliers	Full
	Panel C: Dep. Var.: Standard Deviation of Value Added per Worker Growth				*Panel D: Dep. Var.: Standard Deviation of TFP Growth*			
Implied Volatility	0.300***	0.330***	0.234***	0.328***	0.426***	0.489***	0.316***	0.489***
	(0.059)	(0.072)	(0.029)	(0.072)	(0.084)	(0.092)	(0.049)	(0.093)
Raw Materials Intensity		0.642***	0.366***	0.622***		0.466***	0.197***	0.448***
		(0.111)	(0.051)	(0.119)		(0.103)	(0.065)	(0.106)
Capital Intensity		0.184***	0.138***	0.175***		0.303***	0.178***	0.302***
		(0.055)	(0.037)	(0.055)		(0.070)	(0.050)	(0.073)
Skill Intensity		0.181***	0.097**	0.165***		0.245***	0.091*	0.226***
		(0.053)	(0.041)	(0.055)		(0.072)	(0.051)	(0.066)
Elasticity				0.039				0.063
				(0.039)				(0.055)
Observations	459	459	436	449	459	459	436	449
R^2	0.09	0.26	0.26	0.26	0.18	0.23	0.15	0.24
Sample	Full	Full	No Outliers	Full	Full	Full	No Outliers	Full

Notes: Standardized beta coefficients reported throughout. Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variables are standard deviations computed over the period 1970-1997. *Implied Volatility* is the standard deviation of a sector implied by its complexity as in equation (12), where complexity is measured as the number of intermediates used by a sector, from the U.S. Input-Output matrix. *raw material intensity*=(value of raw material inputs)/(value of raw material inputs+value added); *capital intensity*=[1-(total compensation)/(value added)]*(1-raw material intensity); *skill intensity*=[(nonproduction workers)/(total employment)]*(1-capital intensity)*(1-raw material intensity), all computed based on the NBER Productivity Database. *Elasticity* is the elasticity of substitution between varieties in a given SIC sector (source: Broda and Weinstein 2006).

Table 4. Robustness: Alternative Measures of Implied Volatility or Complexity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Standard Deviation of Output per Worker Growth							
Implied Volatility (contract enforcement model)	0.432***						
	(0.077)						
Implied Volatility (min input usage cutoff)		0.473***					
		(0.071)					
Number of Intermediates			-0.300***				
			(0.056)				
Herfindahl Index				0.121			
				(0.087)			
Gini Coefficient					0.319***		
					(0.057)		
Share of 10 Largest Intermediates						0.253***	
						(0.056)	
Share of 20 Largest Intermediates							0.358***
							(0.065)
Raw Materials Intensity	0.247**	0.247**	0.161	-0.009	-0.04	-0.045	-0.039
	(0.099)	(0.098)	(0.116)	(0.141)	(0.125)	(0.128)	(0.123)
Capital Intensity	0.068	0.092	0.012	-0.083	-0.079	-0.089	-0.082
	(0.069)	(0.068)	(0.081)	(0.083)	(0.082)	(0.084)	(0.080)
Skill Intensity	0.092	0.137**	0.073	-0.025	0.075	0.037	0.098
	((0.069)	(0.068)	(0.072)	(0.073)	(0.068)	(0.071)	(0.067)
Observations	459	459	459	459	459	459	459
R^2	0.20	0.22	0.10	0.03	0.09	0.06	0.11

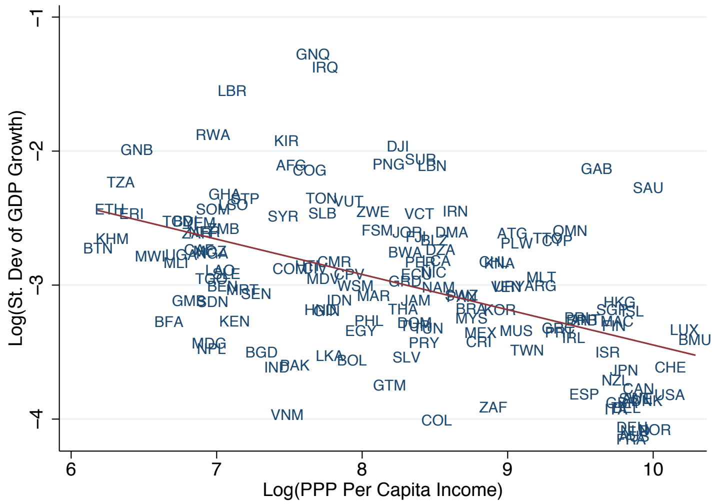
Notes: Standardized beta coefficients reported throughout. Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variables are standard deviations computed over the period 1970-1997. *Implied Volatility (contract enforcement model)* is the standard deviation of a sector implied by its complexity in the contract enforcement model. *Implied Volatility (min input usage cutoff)* is the standard deviation of a sector implied by its complexity as in equation (12), but imposing a minimum usage cutoff before being counted as an intermediate. *Number of Intermediates* is the number of intermediates used in production; Herfindahl Index is the Herfindahl index of intermediate input use; Gini Coefficient is the Gini coefficient of the intermediate input use. Share of 10 and 20 Largest Intermediates are shares in of the top 10 or 20 intermediate inputs in the total intermediate input use. *raw material intensity*=(value of raw material inputs)/(value of raw material inputs+value added); *capital intensity*=[1-(total compensation)/(value added)]*(1-raw material intensity); *skill intensity*=[(nonproduction workers)/(total employment)]*(1-capital intensity)*(1-raw material intensity), all computed based on the NBER Productivity Database.

Table 5. Robustness: Alternative Samples, Detrending Procedures, and Datasets

	(1)	(2)	(3)	(4)
Implied Volatility	0.313***	0.437***	0.101***	0.123***
	(0.053)	(0.095)	(0.029)	(0.021)
Raw Materials Intensity	0.443***	0.086	0.954***	0.131**
	(0.093)	(0.106)	(0.117)	(0.061)
Capital Intensity	0.124*	0.055	0.586***	-0.009
	(0.065)	(0.076)	(0.082)	(0.036)
Skill Intensity	0.099*	0.113	0.337***	0.059*
	(0.056)	(0.076)	(0.091)	(0.030)
Log(Trade/Output)				0.223***
				(0.029)
Log(Initial Output)				0.189***
				(0.035)
Country FE				yes
Observations	459	459	459	1579
R^2	0.18	0.18	0.23	0.50
Sample	Pre-1984	Post-1984	Full, HP(100)	UNIDO

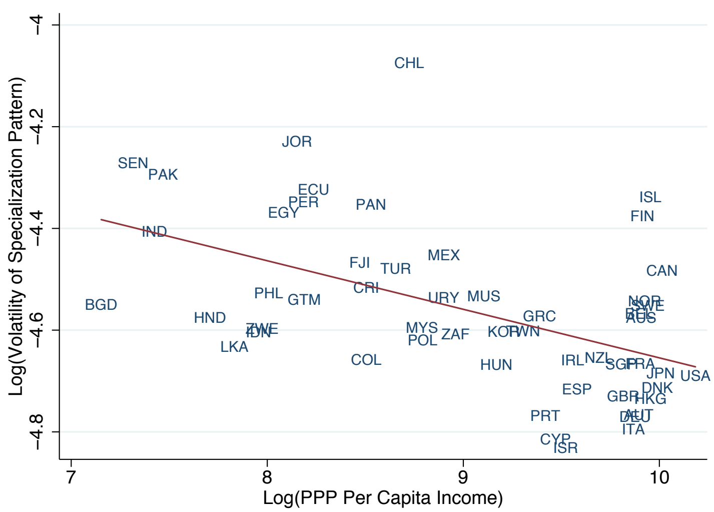
Notes: Standardized beta coefficients reported throughout. Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variables are standard deviations computed over the period 1970-1997. *Implied Volatility* is the standard deviation of a sector implied by its complexity as in equation (12), where complexity is measured as the number of intermediates used by a sector, from the U.S. Input-Output matrix. *raw material intensity*=(value of raw material inputs)/(value of raw material inputs+value added); *capital intensity*=[1-(total compensation)/(value added)]*(1-raw material intensity); *skill intensity*=[(nonproduction workers)/(total employment)]*(1-capital intensity)*(1-raw material intensity), all computed based on the NBER Productivity Database. *Log(Trade/Output)* is the log of the ratio of imports plus exports to total output in a sector. *Log(Initial Output)* is the log of the beginning-of-period output in a sector. The last column reports estimates based on a multi-country sample of the 3-digit ISIC manufacturing data from UNIDO.

Figure 1. Volatility and Development, 1970-2000



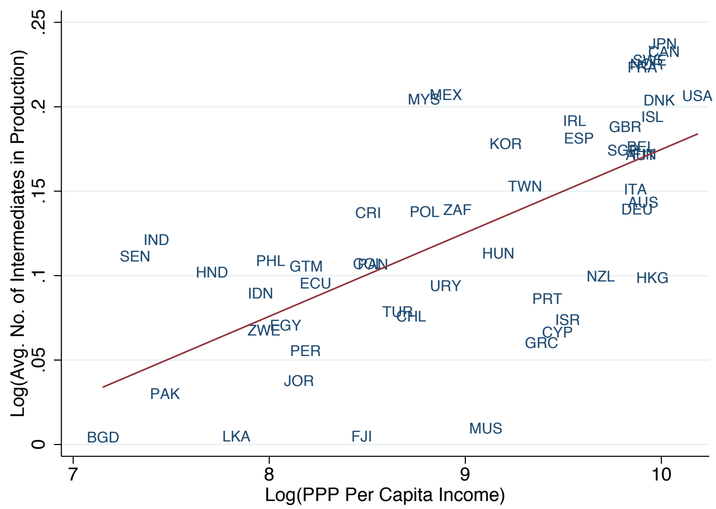
Notes: This figure displays the relationship between per capita income and the standard deviation of per capita GDP growth, in natural logs. Source: Penn World Tables.

Figure 2. Level of Development and Specialization in Volatile Sectors, 1970-2000



Notes: This figure displays the relationship between per capita income and the weighted average variance of the specialization pattern constructed following the methodology of Koren and Tenreyro (2007), in natural logs. Source: Penn World Tables and UNIDO.

Figure 3. Level of Development and Specialization in Complex Sectors, 1970-2000



Notes: This figure displays the relationship between per capita income and the weighted average number of intermediates used in production, with the weights equal to output shares. Source: Penn World Tables and UNIDO.

Figure 4. Pattern of Production and Trade

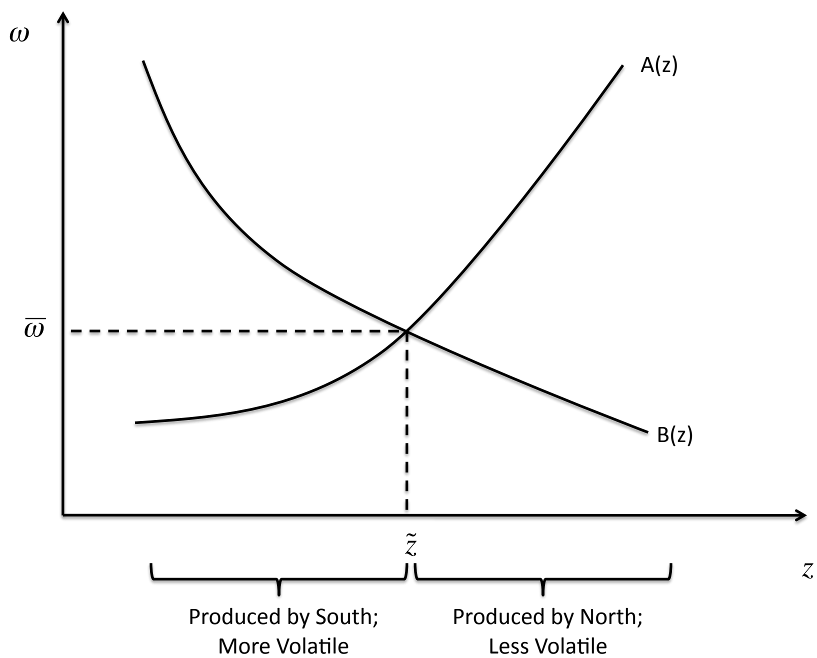
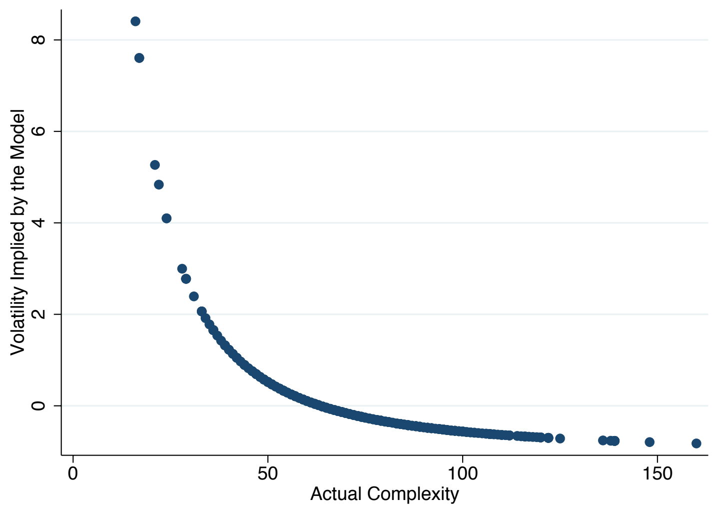
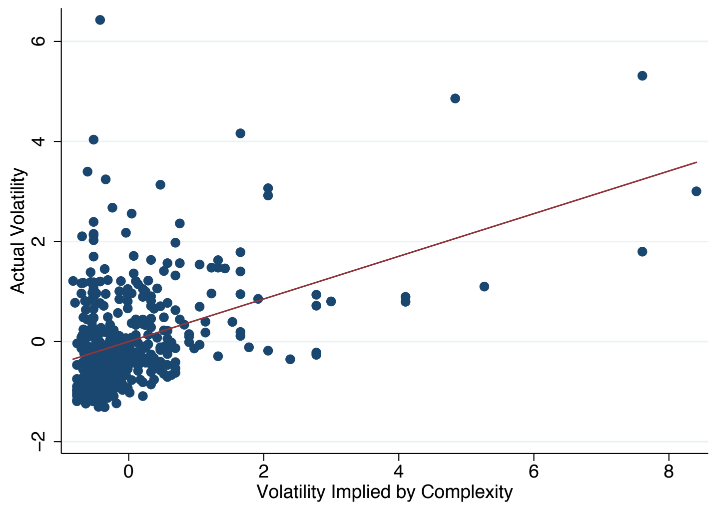


Figure 5. Volatility as a Function of Product Complexity: Model



Notes: This figure displays the relationship between the number of intermediate inputs in production (z) and volatility of output per worker, as implied by theory. *Actual Complexity* is the number of intermediate inputs used in a 4-digit SIC sector, calculated from the 1992 U.S. Input-Output Tables. It ranges from 16 to 160.

Figure 6. Actual Volatility and Volatility Implied by Product Complexity



Notes: *Actual Volatility* is the standard deviation of output per worker growth of a 4-digit SIC manufacturing sector in the United States over the period 1970-1997, sourced from the NBER Productivity database. *Volatility Implied by Complexity* is the standard deviation of output per worker implied by the theory, given the number of intermediate inputs used in that sector. The number of intermediates used in each 4-digit SIC sector is computed using the 1992 U.S. Input-Output Tables.