Importing Technology

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Abstract

We look at disaggregated imports of various types of equipment to make inferences on cross-country differences in the composition of equipment investment. We make three contributions. First, we document strikingly large differences in investment composition. Second, we explain these differences as being based on each equipment type's degree of complementarity with other factors whose abundance differs across countries. Third, we show that the composition of capital has the potential to account for some of the large observed differences in TFP across countries. [Keywords: Equipment Imports, R&D, Appropriate Technology, TFP; *JEL* Codes E22, E23, F1, O11.]

1 Introduction

$Y = F(K, L)$ is equation (1) in virtually all papers that attempt to explain income differences across countries (development accounting). This is appropriate: differences in capital and labor explain a large fraction of the dispersion in income. It has also long been recognized that factor "L" can usefully be disaggregated in order to enhance the explanatory power of F for Y. Hence, distinctions between "raw labor" and "human capital"; or between "skilled labor" and "unskilled labor," have been successfully introduced in attempts to understand differences in income. In this paper, we propose to begin exploring an analogous disaggregation of factor "K". Specifically, we break down overall capital in nine equipment categories (from computers to motor vehicles).[1]

Direct measures of the quantities of equipment installed in a country by type are, of course, not available. However, recent research by Eaton and Kortum (2001) has shown that most of the world's capital is produced in a small number of R&D-intensive countries, while the rest of the world generally imports its equipment. This suggests that, for most countries, imports of capital of a certain type are an adequate proxy for overall investment in that type of equipment. This stylized fact (which we confirm in our data set), motivates our empirical approach and, for the most part, is a maintained assumption throughout our paper.

Our first contribution is to show that there is enormous cross-country variation in the *composition* of K: different types of equipment constitute widely varying fractions of the overall capital stock across countries. For example, *for each of our nine equipment categories,* the share in total investment in 1995 has minima in the low single digits, and maxima that vary between 20 percent and 80 percent! The standard deviations of investment shares are always large relative to the cross-country means. (Skip ahead to Table 2 for more details).

This staggering variation in the composition of K raises two natural questions: (i) what explains cross-country differences in the shares of investment devoted to different types of equipment? and (ii) can these differences in capital composition help fill the large unexplained cross-country gaps in labor productivity?

To address these questions we write down a simple model of investment in heterogenous types of capital. The model suggests that a capital-type share in total

[1]For examples of development-accounting exercises see, among several others, Mankiw, Romer, and Weil (1992), Klenow and Rodriguez (1997), Hall and Jones (1999), Hendricks (2002), and Caselli and Coleman (2002).

investment depends on its intrinsic efficiency (reflecting embodied technology), as well as on the degree to which it is complementary with other inputs whose abundance may vary across countries. For example, computers may be more complementary with human capital than other types of capital, leading to the prediction that human-capital abundant countries will devote a larger share of their investment to computers.

When we implement this insight empirically, we find that the intrinsic efficiency of equipment differs across equipment types: holding the supply of complementary factors constant, a dollar spent on one type of capital delivers more efficiency units than a dollar spent on another. Furthermore, we uncover clear patterns of differential complementarity between equipment types and other country characteristics: cross-country differences in human capital, institutions, composition of GDP, financial development, and other factors have considerable explanatory power for differences in the composition of K. In addition, both the intrinsic efficiency, and the patterns of complementarity of different equipment types, can be rationalized with data on the R&D intensity of the industries that produce them: equipment types coming out of high R&D industries are generally more complementary with factors that one would expect to be more relevant for the adoption of new technology.

With these empirical results at hand, we return to the model to ask whether capital composition should matter for differences in income. The model shows that the overall contribution of capital to income can be broken down into a "quantity" and a "quality" term, where the latter reflects the composition of K. While the quantity term is the one conventionally included in development-accounting exercises, the latter has hitherto been overlooked. Conventional development accounting finds a huge role for mysterious "TFP differences." Our capital-quality term could in theory whittle down this unexplained component. When we perform a tentative version of the development–accounting exercise that takes capital composition into account we find that variation in capital quality has the potential to enhance our ability to explain TFP differences.

Besides contributing to the development-accounting research agenda, this paper is at the cross-roads of several other literatures. Since it tells a story where most countries acquire embodied technologies through capital imports from the world technological leaders, it directly adds to a series of contributions on cross-country technology diffusion.[2] In this line of research, the paper is especially closely related to

[2] E.g. Grossman and Helpman (1991), Barro and Sala-i-Martin (1995), and Aghion and Howitt (1998) on the theory side, and Coe and Helpman (1995), Coe, Helpman and Hoffmeister (1997),

Caselli and Coleman (2001), who study the determinants of computer diffusion across countries. As in that paper, the main idea here is to look at equipment imports as measures of technology adoption by "follower" countries. This paper, however, generalizes the analysis to a larger number of equipment types – adding up to the total stock of equipment. Furthermore, in this paper we ground the empirical work into a theoretical model of investment in heterogeneous equipment types, and this allows us to more neatly map some of the empirical results into parameters describing the intrinsic efficiency and factor-complementarity of various types of capital, and to relate these parameters to the R&D intensity of the industries where that capital is produced.[3]

We also add to previous evidence on the role of R&D in enhancing the efficiency units embodied in capital. Wilson (2002), for example, uses US data to compute measures of R&D embodied in different types of capital. He then constructs an industry-level index of the R&D content of the overall capital stock employed by different industries, and shows that an industry's TFP is increasing in this measure of the technology embodied in the capital it uses. Part of our paper builds on this approach: essentially, we look at a country's (as opposed to an industry's) capital composition by R&D content, and relate this composition to the country's overall productivity.

The paper is also clearly related to the tradition on embodied technical change, which emphasizes differences in the efficiency units delivered by different vintages of capital.[4] Particularly close here are those papers that, a la Jovanovic and Rob (1997), attempt to improve the success of the development-accounting exercise through vintage effects. Effectively, this is equivalent to breaking down K by vintage, while maintaining the assumption that within a vintage capital is homogeneous. The difference here, of course, is that we do not break down K by vintage but by type, i.e. we relax the within-vintage homogeneity assumption. While this has not been previously done in the development-accounting literature, this *is* best practice in the growth accounting literature.[5]

Keller (1998), Eaton and Kortum (1999), Xu and Wang (1999), Caselli and Coleman (2001), Barba Navaretti, Schiff, and Soloaga (2003), and Comin and Hobijn (2003) on the empirical side – see Keller (2001) for additional references and a survey of this literature. See also Hall and Khan (2003) for a broad introduction to the literature on technology adoption.

[3] Our results on computers are consistent with the results in Caselli and Coleman (2001).

[4] Solow (1960), Greenwood, Hercowitz, and Krusell (1997), and Jovanovic and Rob (1997), inter many alia.

[5] E.g. Jorgenson, Gollop, and Fraumeni (1987), and Young (1995).

We emphasize differences in the patterns of complementarity between different types of equipment and various other factors that differ by country. Since we think of different types of equipment as embodying different technologies, this also implies that we provide direct evidence in support of theories of appropriate technology.[6] In these theories, countries with different factor endowments optimally choose different technologies. In our setting this shows up in the composition of the capital stock by equipment type. Finally, we indirectly contribute to the literature on the composition of international trade flows.[7]

We start the rest of the paper with a simple model of investment in heterogeneous types of capital (Section 2). This model delivers predictions on the share of each type of capital in total investment, and in Section 3 we show how these predictions can be turned into an empirical model. Section 4 describes the data, and Section 5 presents empirical results on the composition of a country's investment. Our model also generates predictions on the relationship between the composition of investment and per-capita income: Section 6 investigates this relationship and assesses the potential role of capital quality in filling the large gap in income differences that is still left after accounting for quantity. Section 7 summarizes the results.

2 Theory

Imagine that in country i final output Y^i is produced combining various intermediate inputs, x_p^i, according to the CES production function[8]

$$Y^i = B^i \left[\sum_{p=1}^{P} \left(x_p^i \right)^{\gamma} \right]^{\frac{1}{\gamma}} \qquad \gamma < 1,$$

where B is a disembodied total factor productivity term. Intermediate-good p is produced combining equipment and labor:

$$x_p^i = A_p^i \left(L_p^i \right)^{1-\alpha} \left(K_p^i \right)^{\alpha} \qquad 0 < \alpha < 1, \tag{1}$$

[6] Examples: Atkinson and Stiglitz (1969), Diwan and Rodrick (1991), Basu and Weil (1998), Acemoglu and Zilibotti (2001), and Caselli and Coleman (2002).

[7] See Hummels and Klenow (2002) for a recent decomposition of trade flows and further references to the literature.

[8] Production functions such as this one have been the staple of recent developments in growth theory.

where K_p^i (L_p^i) measures the quantity of equipment (labor) used to produce intermediate-input p, and A_p^i is the productivity of sector p.

Our key assumption is that capital is heterogeneous: there are P distinct types of capital, and each type is product specific, in the sense that intermediate p can only be produced with capital of type p. In other words, an intermediate in our model is identified by the type of equipment that is used in its production. For example, for equipment-type "trucks," the corresponding intermediate good x (say, "road transportation") is the one obtained by combining workers with trucks. For equipment-type "computers," the corresponding intermediate good is "computing services," etc. Hence, our intermediates do not easily map into industries or sectors (computers are used in most industries), but rather into the various types of activities (transport, computing, etc.) required to generate output within each sector. The assumption that $\gamma < 1$ implies that – in producing aggregate output – all these activities are imperfect substitutes.

For simplicity and in order to focus on the novel contribution of the paper, we assume here that labor is homogeneous within a country, though its quality can vary across countries, as we detail below. In the empirical work we will explore relaxations of this assumption. The x production function allows for capital-labor substitutability. This feature is not very important but it facilitates linking up our model with the development-accounting literature.

The productivity term A_p^i is both country, i, and product, p, specific. To understand its interpretation it is essential first to clarify that – due to the nature of our data – K_p^i is measured in US dollars, i.e. it is the US-dollar value of the capital stock of type p. The idea behind country variation is that equipment of type p may be more complementary with the endowments of country i. In this sense, different types of capital may be more or less appropriate for different countries.[9]

Product variation in A allows for the possibility that one dollar spent on equipment of type p may deliver different amounts of efficiency units if instead spent on type p'. For example, the embodied-technology content of good p may be greater because the industry producing equipment of type p is more R&D intensive.[10]

[9] In order to make sure that cross-country differences in K_p^i measure physical differences in installed capital we need to assume that the law of one price holds. This is plausible, since we know that most capital is imported from a few world producers. If the law of one price does not hold, cross-country differences in A_p^i may also reflect price differences.

[10] Since, for simplicity, we have written an aggregate production function that is symmetric in the

Our empirical work will allow us to learn about how A^i_p varies systematically with i and with p, and what this implies for furthering our understanding of cross-country differences in Y.[11]

Since the K^i_ps are measured in dollars, we can write:

$$\sum_p K^i_p = K^i,$$

where K^i is the dollar value of the capital stock, which we take as given.[12] We assume that labor is fully mobile across types of capital, and denote by $L^i = \sum_p L^i_p$ the aggregate labor supply. Note that in equilibrium this economy will feature aggregate constant returns to scale in K^i and L^i (see below).

Since labor is perfectly mobile across the production processes p, producers in all sectors face a horizontal labor supply schedule with wage w^i. Furthermore, if investors allocate their dollars so as to arbitrage away differences in the rental rate of capital, producers face a common user cost r^i. Define $\xi^i_p = K^i_p/K^i$ as the share of capital-type p in the aggregate capital stock. Under our assumptions, in equilibrium we have

$$\xi^i_p = \frac{\left(A^i_p\right)^{\frac{\gamma}{1-\gamma}}}{\sum_j \left(A^i_j\right)^{\frac{\gamma}{1-\gamma}}}. \tag{2}$$

This expression (derived in the appendix) simply states that investment tends to concentrate on the equipment types that feature the highest embodied efficiencies, but this is counterbalanced to some extent by the diminishing returns to each intermediate input produced with those equipment types (because $\gamma < 1$).

This result should also clarify why in equilibrium different equipment types can deliver different amounts of efficiency units per dollar. If $\gamma = 1$ (perfect substitutability among capital types), then in each country all the investment will be concentrated

services provided by different types of capital, product variation in A^i_p may also reflect differences in the varous capital types' shares in aggregate output.

[11] Our formulation is reminiscent of a popular version of the vintage-capital model, in that each type (vintage) of capital is combined with a certain amount of labor to produce some input into (or, in vintage models: some portion of) final output. As in those models, we could have written the producton function in a more specifically "capital augmenting" way, such as $x^i_p = \left(L^i_p\right)^{1-\alpha}\left(A^i_p K^i_p\right)^{\alpha}$, but of course with Cobb-Douglas technologies the two formulations are equivalent.

[12] Since differences in disembodied productivity affect all sectors equally, and the model is symmetric in all other respects, endogenizing the investment rate would not change any of the formulas we use in the empirical analysis.

on the highest-efficiency type of capital. In contrast, with imperfect substitutability, investors will be willing to hold a diversified portfolio of types, even if the intrinsic efficiency of the various types differ. However, more efficient types will be held in larger proportions. While we do not model the conditions under which the capital is produced (in some foreign country) it is easy to imagine situations where the price of an efficiency unit would vary across types. For example, this will arise if capital is produced under perfect competition, so that price equals marginal cost, and the cost of producing one unit of efficiency differs across types. Alternatively, the degree of monopoly power could vary across equipment producing sectors (in the equipment-producing country).

We can also look at the implications of our assumptions for aggregate income. Using results in the appendix it is possible to write aggregate output as

$$Y^i = B^i \left(K^i\right)^{\alpha} \left(L^i\right)^{1-\alpha} \left[\sum_p \left(A_p^i\right)^{\gamma} \left(\xi_p^i\right)^{\gamma}\right]^{\frac{1}{\gamma}},$$

where the last term is an index of the quality of the capital stock. We can think of this representation as breaking down the contribution of investment to output as a *quantity* (K) vs. *quality* (the expression in square brackets) decomposition. Substituting from (2) this decomposition can be alternatively stated as :

$$Y^i = B^i \left(K^i\right)^{\alpha} \left(L^i\right)^{1-\alpha} \left[\sum_p \left(A_p^i\right)^{\frac{\gamma}{1-\gamma}}\right]^{\frac{1-\gamma}{\gamma}}. \tag{3}$$

The last section of the paper will further discuss this decomposition and the implications of our results for this kind of development-accounting exercise.

3 Empirical Specification

The main focus of the empirical analysis is equation (2), where the share of capital of type p in country i's total capital is related to the efficiency level of type p in country i relative to the efficiency of total capital in country i. Our general approach will be to make assumptions on the determinants of the A_p^is, and test these assumptions by estimating equation (2).

Before getting into the details, however, we need to acknowledge a limitation in our ability to map data to theory. Specifically, while we argue that we have fairly accurate information on the composition across equipment types of the dollar value of investments each country makes, we cannot accurately measure the dollar value of the *stocks* each country has. In order to convert the flows into stocks, we would need longer investment time series.[13] We will therefore proxy for ξ_p^i using investment in capital of type p as a share of total investment. This would be strictly correct only if there was full depreciation of capital in one year. Though full depreciation in one year is clearly unrealistic, both some robustness checks we performed, and some of the features of our empirical results, lead us to retain confidence in the conclusions we obtain. We explain this in Section 5.

There are P (nine in our case) equations (2), one for each equipment type. Since the ξ_p^is sum to one, these equations are linearly dependent. Hence, we divide the equations for types 2 through P by the equation for type 1, obtaining the $P-1$ equations:[14]

$$\frac{\xi_p^i}{\xi_1^i} = \frac{\left(A_p^i\right)^{\frac{\gamma}{1-\gamma}}}{\left(A_1^i\right)^{\frac{\gamma}{1-\gamma}}}, \qquad \text{for } p = 2, ..., P. \tag{4}$$

It is immediately clear, therefore, that we can only make inferences on the ratios A_p^i/A_1^i, i.e. on the relative productivity of different types of capital in country i. Without loss of generality, therefore, we normalize $A_1^i = 1$, which essentially just redefines A_p^i as what was A_p^i/A_1^i up to this point.

For the purposes of obtaining an empirical specification, we conjecture that A_p^i depends on a series of country and product characteristics as follows:

$$A_p^i = A_p \prod_c \left(z_c^i\right)^{\delta_{c,p}}. \tag{5}$$

In this equation, A_p is a product-specific productivity term that applies in all countries (the *intrinsic* efficiency of this type of capital relative to type 1). z_c^i is the value of characteristic c in country i relative to the average value for the world. It captures the abundance or scarcity of characteristic c in country i. $\delta_{c,p}$ measures the degree of complementarity between equipment of type p and characteristic c. For example, c could be human capital. If $\delta_{c,p} = 0$ there is no complementarity between human capital and physical capital of type p: brute force is all that is needed to operate this

[13] As well as product-specific physical depreciation rates, and product-specific price deflators, which tend in general to be somewhat controversial.

[14] Notice that $\frac{\xi_p^i}{\xi_1^i} = \frac{K_p^i}{K_1^i}$. Thus, we refer to the equation in (4) as *relative imports equations.*

type of equipment. Instead, if $\delta_{c,p}$ is large, p is a highly skill-complementary type of capital.[15] Because of our normalization, the δs capture complementarity between country-characteristic c and capital-type p relative to the complementarity between c and product-type 1.

Notice that the productivity of capital-type p in a particular country will equal that type's *intrinsic* efficiency under either of two conditions: (1) if the capital type is neither complementary nor substitutable with every characteristic, or (2) if the country is neither abundant nor scarce (compared to the rest of the world) in every characteristic. One should be clear, then, that the "intrinsic efficiency" of capital type p, as we define it, is the average efficiency across the world. Note that though it is independent of any one country's vector of characteristics, it does take into account the level of these characteristics in the world at any point in time.

Besides human capital, some other possible characteristics c that may complement different capital types differently are: *Inward* foreign direct investment (FDI) as a share of aggregate investment, where a high δ would denote a comparative advantage by foreign corporations in importing and installing this type of capital; *Outward* FDI (as a share of investment), since – as pointed out by Feenstra (1998) – outward FDI may be a mechanism for acquiring intangible assets such as technical knowledge (a high δ would then indicate that having outward FDI may bring in knowledge which is complementary to this type of capital); The degree of protection of property rights, where a high δ implies that investing in this type of capital is more profitable when property rights are well protected;[16] The share of government in GDP, where a high δ signals that the government has a comparative advantage in operating this type of capital, or a unique demand for this capital; The shares of private GDP accounted for by different sectors, such as services or agriculture, which allows for sector-specificity of the capital types p, and hopefully controls for demand factors that may confound the interpretation of A_p^i; Measures of financial development, where a high δ may mean that external financing is comparatively more important for investing in this capital

[15] This discussion assumes that there is a representative worker with the average level of human capital. We explore alternative assumptions below.

[16] Although there are subtle issues of interpretation. If the protection of property rights – particularly intellectual property rights – confers some monopoly power to the would-be importer, the effect on the import share of capital types that are particularly complementary with property-right protection may actually fall. In our empirical work we distinguish between intellectual property rights and property rights more generally.

type; Geographical characteristics, that may pick up differences across countries in the relative transport costs of different types of capital. In addition, to partially account for other omitted country characteristics we control for per-capita income.

It may seem odd, particularly to trade economists, that an equation explaining relative imports of a good, be it equipment or otherwise, does not contain variables representing the importing country's abundance in the factors used most intensively to produce that good. A Heckscher-Ohlin-Vanek type of model (e.g., Leamer (1984)) would predict that a country would import relatively more of those goods that tend to be produced by the factor inputs in which the country is scarce (compared to the rest of the world). Our relative imports equation is based on the premise that the types of imported goods we are interested in, namely equipment, cannot be produced domestically by most countries. Such countries do not have those factors (or, perhaps more realistically, those technologies) required to produce equipment and hence these factors play no role in the composition of equipment imports.

Substituting (5) and the above normalizations into (4), we get:

$$\frac{\xi_p^i}{\xi_1^i} = (A_p)^{\frac{\gamma}{1-\gamma}} \prod_c \left(z_c^i\right)^{\delta_{c,p}\frac{\gamma}{1-\gamma}}. \tag{6}$$

One possible reduced-form implementation of this equation is to estimate, separately for each p,

$$\frac{\xi_p^i}{\xi_1^i} = \beta_p \prod_c \left(z_c^i\right)^{\beta_{c,p}} \varepsilon_p^i, \tag{7}$$

where β_p and $\beta_{c,p}$ are parameters to be estimated, and ε_p^i is a mean-1 disturbance. In this specification, the interpretation of β_p is as $(A_p)^{\frac{\gamma}{1-\gamma}}$, and the interpretation of $\beta_{c,p}$ is as $\delta_{c,p}\gamma/(1-\gamma)$. For each type p, these regressions can be estimated with cross-country data on imports relative to type 1 and each of the country characteristics.

A more informative implementation may be to further model the terms A_p and $\delta_{c,p}$ as functions of capital type $p's$ characteristics. In particular, both A_p and $\delta_{c,p}$ may depend on the amount (or the intensity) of global research and development spending (R) that is embodied in capital-type p (relative to type 1). This suggests modeling A_p and $\delta_{c,p}$ as functions of R_p/R_1. In other words, the intrinsic efficiency of capital type p relative to type 1 is a function of the R&D embodied in each type; likewise for the relative complementarity of type p with characteristic c. For example, assuming

$A_p = a(R_p/R_1)^\sigma$ and $\delta_{c,p} = b\log(R_p/R_1)$ leads to an estimating equation:

$$\frac{\xi_p^i}{\xi_1^i} = a\left(\frac{R_p}{R_1}\right)^\phi \prod_c \left(z_c^i\right)^{\phi_c \log(R_p/R_1)} \varepsilon_p^i, \tag{8}$$

where the parameter ϕ estimates $\sigma\gamma/(1-\gamma)$ and ϕ_c estimates $b\gamma/(1-\gamma)$. The parameters ϕ and ϕ_c can be identified from a regression pooling types and countries.

The advantage of this second specification is that the coefficients now specifically identify the determinants of import shares as functions of the amount of technology embodied in capital, whereas the constants in the previous specification could be identifying effects on import shares coming from both technology and non-technology (e.g., demand) causes. The disadvantage, though, is that in the R&D regression we may be omitting determinants that are not captured by R&D. Furthermore, if the omitted factors are correlated with R&D, we may be assigning the contributions of these omitted factors to R&D.

Though the parameters in both of the above specifications could be identified with a single year of data, we additionally exploit time variation in order to estimate the parameters more precisely and test whether the intrinsic efficiency of a capital type (in the first specification) or the productivity of R&D (in the second specification) has changed over time.

The choice of estimation technique for equations (7) and (8) is not trivial. A seemingly natural approach would be to take logs on both sides of the equations and use ordinary least squares on the resulting linear model. As recently pointed out by Santos-Silva and Tenreyro (2003), however, using the log-linear version of multiplicative models has two potentially serious pitfalls. First, if some of the ξ_p^is are zero, as is not uncommon in trade data, there is a loss of perfectly good information. In addition, the loss of zero observations may potentially lead to sample-selection issues. Second, there is a strong presumption with trade data that the ε_p^is will be heteroskedastic, and Santos-Silva and Tenreyro show that in this case OLS estimates of the log-linear version of equations such as (7) and (8) can lead to severe bias in the coefficients. Hence, a non-linear method is called for, and these authors' propose a simple pseudo-maximum likelihood approach that performs very well in Monte Carlo experiments.[17] Pseudo maximum likelihood (PML) will be our method of choice, though we also report on

[17] This consists in assuming that the ε_p^is followed a generalized-Poisson distribution – with variance equal to the conditional expectation of the dependent variable – and performing maximum likelihood. To see why this works, here is the GMM interpretation. Given a model $y_i = \prod_k x_{ik}^{\beta_k}\varepsilon_i$, the moment

log-linear estimates when they differ substantially from those we obtain by PML.

4 Data

Our basic measurement strategy is motivated by evidence that for most countries a very large fraction of the stock of equipment is imported. For these countries, this allows us to measure ξ_p^i, or type-p investment share in total equipment investment, as type-p import share in total equipment import. We obtain the raw data for these import shares from Feenstra (2000). This data set provides bilateral imports and exports from over 100 countries at a very disaggregated level (generally the 4-digit SITC, Revision 2, level). To construct our investment shares, we first aggregate the bilateral import data to get total imports by importing country, for each of the 4-digit commodities. We then identify the 4-digit commodities that correspond to capital goods. Capital-good imports at the 4-digit level are then aggregated (if necessary) into 9 capital-type categories, to match the 9 capital-producing industries for which we have separate R&D-content data (described below). The nine capital-type categories are listed and described in Table 1. The import share ξ_p^i is imports of type p divided by total capital imports (note that this differs from total imports).[18]

Table 1 Here

conditions are $E\left[(y_i - \prod_k x_{ik}^{\beta_k})x_{ik}|x_{i1}, ..., x_{iK}\right] = 0$ for every k. The procedure recommended by Santos-Silva and Tenreyro estimates the β_ks by solving the set of equations $\sum_i (y_i - \prod_k x_{ik}^{\beta_k})x_{ik} = 0$, and is therefore equivalent to applying the method of moments by giving equal weight to all observations. This is the optimal GMM weighting scheme in the special case where $Var(\varepsilon_p^i|x_{i1}, ..., x_{ik}) = E(y_i|x_{i1}, ..., x_{ik})$, but the authors show that it continues to perform very well for a wide variety of alternative assumptions. In contrast, the more standard non-linear least squares estimator solves the system of equations $\sum_i (y_i - \prod_k x_{ik}^{\beta_k})x_{ik} \prod_k x_{ik}^{\beta_k} = 0$, i.e. it gives more weight to observations with a high conditional expectation for the dependent variable. Since high values for the dependent variable are typically associated with high variance, this is equivalent to giving more weight to more noisy observations. Consistent with this, non-linear least squares turns out to be much less efficient than Poisson maximum likelihood in Monte Carlo experiments.

[18] We have also repeated all our empirical exercises by only aggregating capital imports from the top 15 R&D producing countries, an exercise that may be more closely faithful to the spirit of the rest of the paper. There was no discernbible difference in results.

Data on R&D by industry, for the 15 primary R&D-performing countries in the world, are provided in the ANBERD database maintained by the OECD.[19] According to Coe and Helpman (1995), these 15 countries account for roughly 90% of the world R&D expenditures. A subset of nine of the industries in the R&D database are capital-good producers. To construct "world" R&D flows by capital-type (p), we aggregate R&D spending (in constant US dollars) across all countries by capital-good-producing industry. We then construct world R&D stocks by capital-type using a perpetual inventory accumulation of past flows and a depreciation rate of 15%.[20] Besides the R&D stock, in our empirical work we also experiment with two alternative measures of R&D intensity by capital-type. The first, which we call the "R&D flow intensity," is the world R&D flow into an equipment type divided by total sales of that type by the same 15 R&D-performing countries. The second measure, "R&D stock intensity," is the R&D stock divided by total sales. The sales data are from the UNIDO Industrial Statistics Database. The time span of overlapping coverage between the Feenstra, ANBERD, and UNIDO data sets is 1980 to 1997.

The means and standard deviations, by capital-type, of the capital (equipment) import shares are shown in Table 2, for two "representative" years. Also shown are the correlations between each equipment type's import share and real GDP per capita. We report separate statistics for the full sample of countries for which we have both capital-import and GDP per capita data, and for the sample we use in our relative imports regressions below. This latter sample excludes the 15 R&D-performing countries (as well as countries with incomplete data on the right-hand-side variables). According to the evidence presented by Eaton and Kortum (2001), identification of imports with investment is most legitimate for these non-R&D-performing countries.

Table 2 Here

The most important thing to note is that the standard deviations of the import shares are quite large relative to the means. The coefficients of variation (standard deviation divided by mean) are especially large for aircraft, other transportation equipment, and computers. These large coefficients of variation document that there is a great deal

[19] The 15 countries are Australia, Canada, Denmark, Finland, France, (unified) Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Great Britain, and USA.

[20] We initialize the R&D stock in 1973 as the 1973 R&D flow divided by the depreciation rate. The choice of a 15 percent depreciation rate is standard in the literature on R&D stocks.

of cross-country variation in the composition of capital. Looking at the raw correlations with per-capita income, it appears that poorer countries' capital stocks tend to have larger shares of fabricated metal products, non-electrical equipment, and other transportation equipment. Rich countries' investments, instead, are more skewed towards computing and accounting machinery, electrical and communication equipment, and professional goods.

An alternative method for identifying investment shares is to measure investment (by type) as imports minus exports plus gross domestic output. Data on exports by type are available from Feenstra (2000) while data on gross domestic output of each equipment type can be gleaned from the UNIDO data set. Unfortunately, the UNIDO data is much more limited in country coverage than our other data, leading to too small of a sample size for meaningful empirical work. Nevertheless, the investment shares computed combining the import data with production and export data tend to convey a roughly similar impression of high variance across countries. More importantly, as documented in Figure 1, the investment shares computed as imports plus output minus exports are highly correlated with the import shares we use in our regressions, especially for non-R&D performing countries.

Figure 1 Here

Aside from statistics characterizing import shares, Table 2 also shows the values in 1980 and 1995 of the three measures of embodied R&D. It is notable that the three measures of embodied R&D roughly agree on the ordering of capital types by embodied technology, especially in 1980. While this ordering has changed somewhat over time, the capital types which tend to embody the most R&D are consistently aircraft, communications equipment, computers, and professional goods, while fabricated metal products and non-electrical machinery seem to embody the least.

Data on country characteristics are obtained from a variety of sources. We measure human capital by the average years of education reported by Barro and Lee (2001).[21] Foreign direct investment, inward and outward, is from Lane and Milesi-Ferretti (2001). We look at two measures of property-right protection, one narrow, limited to intellectual property right protection (IPR), and the other broad, covering property rights in general. The former is an index compiled by Ginarte and Park (1997),

[21] Nothin changes when using Hall and Jones' (1999) index of human capital that takes into account evidence from Mincerian wage regressions.

while the latter is from various editions of the Fraser Institute's "Economic Freedom of the World." The sectorial composition of GDP (by industry and by government share) is from the World Bank's World Development Indicators, and so is our measure of financial development (M3 money supply as a fraction of GDP). To account for geographic characteristics that may induce type-specific transport cost differences we obtain an index of "remoteness" (essentially, geographical distance from the "rest of the world," where distances to other countries are weighted by GDP) from Santos-Silva and Tenreyro (2003). GDP per capita and aggregate investment (used to scale the FDI variables) are from the Penn World Tables, Mark 6.0 [Heston, Summers, and Aten (2002)]. Table 3 shows the means and standard deviations, for 1980 and 1995, of the country-characteristic variables we use in our empirical work. The statistics are computed using the regression sample we use for the relative imports regression below.[22]

Table 3 Here

The final data set is three dimensional. The panel is balanced in the capital-type dimension, but unbalanced in the year and country dimensions. The range of the year dimension is the 5-year intervals 1970-1995. We restrict our panel to 5-year intervals because many of the country characteristics are relatively slow moving over time. This recommends that we try to rely most heavily on cross-country variation to identify our parameters. There are between 38 and 40 countries in the panel, depending on which variables are to be included. This panel excludes the 15 R&D-performing countries because, as explained above, the correspondence between investment composition and import composition is best outside of these countries. Nevertheless, we did check to see if the regression results reported below are robust to including these countries. They are. In fact, the results change very little except the significance levels of a number of coefficients is increased, which is likely explained simply by the added number of observations.

Finally, note that though the observations in our panel have three dimensions, the only variables that vary by equipment type are R&D (which varies by type and year, but not country) and the capital import shares (which vary by all three dimensions).

[22] Specifically, we use the sample used in the final specifications of Tables 4 and 5. Note that the sample means reported in Table 3 are not the same as the "world" means we use to normalize z_c^i. The world mean for a characteristic is computed using the full sample of countries, including the R&D-performing countries, that have data for that characteristic.

5 Estimation Results

5.1 Type-by-Type Specification

In this sub-section we report the coefficients obtained by estimating equation (7) for each capital type. One of the nine types must act as numeraire, and we choose "Fabricated Metal Products" (ISIC 381) because Table 2 suggests this to be the type of capital that embodies the least amount of technology. Two of the three measures of R&D content rank this type last and the other measure ranks it second to last. "Fabricated Metal Products" consists of hand tools, cutlery, general hardware, metal furniture and fixtures, structural metal products, etc..

Table 4 Here

The results of these regressions are reported in Table 4. Panel A contains a baseline specification including a constant, human capital, inward and outward FDI, the government share in GDP, as well as the shares of industry (manufacturing, plus construction, mining, and utilities) and services (the omitted share is agriculture). The baseline specification also includes the "catch-all" control of per-capita GDP and a time trend. Panels B, C, D, and E further enrich the baseline specification by adding, incrementally, the measure of geographic remoteness, the proxy for financial development, a broad measure of property rights protection, and a measure of intellectual property rights protection.

Not surprisingly, as we add controls we lose precision in the estimates. This is partly because the number of coefficients to be estimated increases. Mostly, however, the loss of precision is due to the fact that the additional controls cover fewer countries and (especially) fewer periods, so that the overall sample size is considerably reduced. We will therefore emphasize results from Panel A, and comment on their robustness across other panels.

Recall that according to our model the constant term captures type-specific (and not country-varying) differences in intrinsic efficiency (relative to fabricated metal products). There is robust evidence of intrinsic inefficiency for computing and accounting equipment, electrical equipment, communication equipment, and aircraft: for these equipment types the constant is significantly negative in all specifications.[23] In the

[23] Since these regressions are estimated via PML, the intercepts actually correspond to $\log(\beta_p)$. Thus, a negative estimate implies $\beta_p = (A_p)^{\frac{\gamma}{1-\gamma}}$ is less than one, which implies A_p is less than one.

context of our model, this suggests that these capital goods, even though they are generally considered "high-tech," may actually be less productive than metal products for the average country, i.e. the country with average endowment of human capital, outward FDI, inward FDI, etc.. These capital goods may indeed require a country to have a relative abundance of complementary characteristics before they become more productive than hand tools, general hardware, and the other kinds of basic capital goods contained within the "Metal Products" type.[24]

Interestingly, however, investment shares in the same group of equipment types show substantial positive time trends, suggesting that their intrinsic efficiencies have risen, or equivalently, that the worldwide quantities have risen of those characteristics complementary to these capital types.

Inward FDI is related to lower investments in every other type of capital compared to metal products. This negative relationship is quite robust for most equipment categories. Though somewhat less robust, Outward FDI has generally symmetrical implications: higher imports of most types of capital, especially non-electrical equipment, computers, and aircraft. The government consumption share in GDP is negatively associated with non-electrical equipment, computers, and electrical equipment, with the relationship most robust for electrical equipment. The share of industry in GDP robustly predicts relatively more non-electrical equipment investment. Services' share of GDP is associated with less investment in Electrical Equipment and Communication Equipment, and with more investment in motor vehicles – though none of these relationships is very robust.

Remoteness clearly increases relative investment in computers, motor vehicles, and (most appropriately) communications equipment. Financial development appears to lead to relatively lower investment in non-electrical equipment, and greater in elec-

[24] The alternative interpretation of this result is that the constants reflect shares of different types of capital services in the aggregate production function. A variant of this alternative interpretation arises if there is a high degree of homogeneity of capital goods within these categories relative to that of metal products. Our model is predicated on the assumption that each capital type is a homogenous good and is used in the production of a homogenous input into the production of final output. Therefore each capital type has diminishing returns to scale, dictated by the parameter γ. If in fact a type category contains many varieties of capital goods, as is likely for metal products, it will not suffer the same degree of diminishing returns and will therefore be demanded in larger quantities. One could think of the degree of heterogeneity, or variety, in a capital-type as a feature of its intrinsic quality.

trical equipment. Broad property rights protection is positively related to investment in aircraft, professional goods, non-electrical, electrical and communication equipment. On the other hand, we find no evidence of a relationship between intellectual property rights and the relative demand for any particular type of capital.

According to our baseline specification human capital is complementary with computers, electrical equipment, communication equipment, motor vehicles and professional goods. These patterns are in accordance with a wealth of recent evidence that there is a high degree of complementarity between human capital and certain new technologies, such as computers, as well as with previous empirical studies of technology diffusion. However, these results are surprisingly non-robust: additional controls cause human capital to no longer be significant for any type of equipment (except communications equipment in the third specification). It is hard to say whether this reflects omitted-variable bias in the baseline specification, or an excessive loss of degrees of freedom in the subsequent, more demanding ones.[25]

Real income per capita has a positive relationship in the first two specifications with computers and electrical equipment, but this goes away once we add more characteristics.

Estimating the same set of regressions using Ordinary Least Squares (after taking logs of both sides of equation (7)) instead of Pseudo Maximum Likelihood yields very similar coefficient estimates (in terms of both sign and magnitude) but lower standard errors. Most importantly, human capital is found to be significant in the first three specifications for computers, electrical equipment, communications equipment, motor vehicles, aircraft, and professional goods.

5.2 Embodied R&D Specifications

In this section we pool the investments in all equipment types (always relative to metal products) to estimate equation (8). The explanatory variables, therefore, are an equipment type's R&D content, as well as a set of interaction terms between R&D content of the type and characteristics of the importing country. The results are reported in Table 5, where we estimate five specifications exactly analogous – in terms of the list of country characteristics progressively included – to the five type-by-type specifications of the previous subsection. The embodied R&D measure used in these

[25] When we tried splitting the human capital variable into various skill categories, we found a positive complementarity between post-secondary education and aircraft use.

regressions is the R&D flow intensity – i.e. worldwide current R&D spending divided by worldwide sales. It turned out that the results were not at all sensitive to the choice of the R&D variable.[26] Collectively these R&D regressions exploit fewer country-year data points than the type-by-type analogs because the data on output by equipment-producing industry, the denominator in R&D intensity, begins in 1980. However, this disadvantage is compensated by the fact that pooling across capital types increases the number of observations by a factor of 8.

Table 5 Here

In the regressions of Table 5, the log of an equipment type's relative R&D intensity is negatively associated with that type's investment share (always relative to metal products). This suggests that – for a country with characteristics at the same level as the worldwide average – equipment types embodying more R&D are relatively less efficient. The positive coefficient on the interaction term between R&D-intensity and a time trend, though, suggests that the efficiency of R&D-intensive equipment has been catching up with that of less R&D-intensive equipment. In other words, average efficiency has increased more rapidly for R&D-intensive types of equipment than other types. Both of these two effects are consistent with the results from the type-by-type regressions above, which found that equipment types generally considered "high-tech" were relatively less efficient, at the average level of characteristics, but their efficiency levels were increasing relative to other types.[27]

All of the other explanatory variables are interactions of R&D intensity with country characteristics. The coefficients are quite consistent with what one would expect given the results in Table 4 of the type-by-type regressions. The coefficient on the interaction between R&D intensity and inward FDI is robustly negative. In other words, FDI flows skew the composition of the capital stock towards low-tech types of equipment. This is somewhat surprising, and defies much common wisdom. In particular, FDI is often cited in policy circles as a key vehicle for technology transfer. Our results are inconsistent with this view. However, they are consistent with the view

[26]Results using the R&D stock or the R&D stock intensity are availble from the authors upon request.

[27]These results on R&D weaken the cogency of the interpretation according to which the constants in the previous regressions merely reflect differences in the shares of different equipment types in the aggregate production function, though we cannot rule out the posibility that these shares just happen to be negatively correlated with R&D intensity.

that FDI signals outsourcing of the production of low-tech goods to countries with cheap inputs. Furthermore, notice that – even if it does not affect high-technology transfer – FDI may still be highly beneficial to recipient countries if it increases the overall capital stock.

As in the type-by-type specifications, there seems to be symmetry between the roles of Inward and Outward FDI: Outward FDI is associated positively with the R&D intensity of imports. Perhaps Outward FDI is a means of acquiring technical knowledge that is then used with more high-tech equipment imports.

Another variable whose interaction with R&D content has robust predictive power for investment shares is remoteness: far away places import a relatively larger share of high-tech (or at least high R&D) equipment. The likely explanation for this finding is that high-tech equipment is "lighter," in a physical weight per dollar sense, so that remote locations will have a disproportionate demand for them. It may also be that remote countries demand relatively more computers and, of course, communications equipment (both high in R&D) to conduct business with other countries. Remote countries may also require more aircraft (also high in R&D) to trade goods and engage in face-to-face business with those in other countries.

Another robust result seems to be that a broad measure of property rights protection interacts positively with the R&D intensity of the types of equipment a country invests in. Perhaps high technology products are more costly to protect from looting, theft, or expropriation. It could also be that aircraft are driving this result: aircraft are very R&D intensive and property rights may be quite important for goods as expensive as aircraft. This result does not appear to be driven by broad property rights proxying for intellectual property rights: including a separate measure of IPR has no effect on the coefficient on broad property rights and IPR's coefficient itself is insignificant.

There is also evidence of a negative interaction between R&D intensity and the services share in GDP, and some evidence of a negative R&D-government share interaction. The Industrial Share and Financial Development play no significant role, and real per-capita income is not significant in three of the five specifications, perhaps indicating that we are not omitting some important determinant of a country's capital composition.

The results on human capital are, again, suggestive but inconclusive. In the first three columns the coefficient on the human capital-R&D interaction is large and significant, as one would expect. However, this result is not robust to the addition of broad property rights protection, an addition that causes a large decline in sample size.

Before concluding the discussion of our empirical estimates of equations (7) and (8) we briefly revisit the question of how well do investment shares proxy for capital shares. We make two points. First, we computed a crude measure of stocks of imported equipment via a perpetual inventory of past equipment imports, using depreciation rates derived from US. data, and assuming that equipment prices remained constant over our sample period. The regression results using these stocks were quite similar to those we have just reported. Second, the patterns of coefficients we obtain in our regressions are inconsistent with serious biases from using investment flows as proxies for stocks. High-tech capital types, such as computers, are likely to have higher depreciation rates than low-tech types, such as hand tools. Hence, assuming 100% depreciation will lead to an especially large underestimate of low-tech capital. In our type-by-type regressions, this would lead us to underestimate the intercept for low-tech capital types, and overestimate the intercept for high-tech capital. However, what we find is low intercepts for high-tech equipment types! Furthermore, the relative underestimation of low-tech capital, and overestimation of high-tech capital, will be worse for countries that are late (relative to the observation year) adopters of high-tech capital. If late adopters of high-tech capital have low values for our country characteristics, the coefficients on these characteristics will be biased towards zero. We conclude that our results would likely only become more pronounced if dollar-value equipment stocks could be more accurately measured.

There are only minor differences between the results obtained by Pseudo Maximum Likelihood, shown in Table 5, and those obtained by Ordinary Least Squares. For one thing, the coefficients on the government share and services share in GDP are never significantly different from zero in the OLS results. Also, GDP per capita is never significant in when we estimate via OLS, whereas it was significant in specifications B and C when we estimated via PML.

6 Implications for Development Accounting

Until now we have endeavored to identify the cross-country determinants of imports of capital-embodied technology. We have found that there are a number of country-specific factors that have a significant effect on the demand for capital of different types. In particular, these country-specific inputs and institutions affects how much a country invests in R&D-intensive capital goods. In this section we try to address the obvious question: does this matter for explaining productivity differences across countries?

The simple model we laid out in Section 2 suggests that the answer should be yes. In that section, we derived the equation (rewritten here in per-worker – denoted by lower case – terms)

$$y^i = B^i \left(k^i\right)^\alpha \left[\sum_p \left(A_p^i\right)^\gamma \left(\xi_p^i\right)^\gamma\right]^{\frac{1}{\gamma}}, \tag{9}$$

which suggests that differences in the composition of the stock of equipment, i.e. in the vector of the ξs, could have explanatory power for cross-country differences in output *over and above the explanatory power due to total capital*, k^i. We also showed that if one adds competitive assumptions, equation (9) becomes

$$y^i = B^i \left(k^i\right)^\alpha \left[\sum_p \left(A_p^i\right)^{\frac{\gamma}{1-\gamma}}\right]^{\frac{1-\gamma}{\gamma}}. \tag{10}$$

Given a measure of k^i, in development accounting one proceeds to estimate or calibrate α, and to then make inferences on the ability of observed differences in capital per worker to explain differences in cross-country income per worker. It typically turns out in these studies that observed capital stocks (even including human capital) leave a large fraction of the per-worker output variance unexplained, leading researchers in this field to embark in a quest for the "mystery capital," or other source of "TFP differences," that may fill the large gap in our understanding of income differences.

The two last equations indicate that, if different types of equipment deliver different amounts of efficiency units in different countries (because of differences in the relative abundance of complementary factors), then looking at capital "quantity" alone will give an incomplete measure of the contribution of the observed capital stock to output differences.[28]. More importantly, they suggest that "capital quality", or the

[28] Most development-accounting studies measure k^i by investment in "international-dollars" from the Penn World Tables (PWT), suitably aggregated over time with the perpetual inventory method. Since relative prices in international dollars are fairly close to US relative prices [Hill (2000)] investment as measured in PWT should differ from investment in US dollars by a roughly constant factor for all countries. Furthermore, the constant-international-dollar time aggregate should differ from the

terms in square brackets, may help fill some of the gap in our ignorance of what causes income differences.[29]

Implementing a development-accounting exercise based on equations (9) and/or (10) obviously requires knowledge of the vector of country-specific efficiency parameters A_p^i. But the A_p^is are exactly the objects we tried to estimate in the first part of the paper. In particular, given a set of country characteristics z_c^i, we have assumed $A_p^i = A_p \prod_c (z_c^i)^{\delta_{c,p}}$, and estimated the parameters A_p and δ_{cp}. We can therefore plug these numbers in equations (9) and (10) (in the former case, together with the observed ξ_p^is), and ask what fraction of the overall variance of income per worker does our capital-composition term explain.

An important caveat that must precede any further detail is that in performing this exercise we abandon the claim that the normalization $A_1^i = 1$ is "without loss of generality." We now take cross-country differences in A_p^i seriously as true differences in the absolute efficiency units embodied in capital of type p. The underlying (admittedly strong) economic assumption is that "fabricated metal products" – our numeraire – are equally productive in all countries (i.e. they have no particular pattern of complementarity or substitutability with country characteristics). Differences in capital quality are then due to differences in composition, as well as to differences in the efficiency of capital types other than fabricated metal products. We think that the very low R&D content of fabricated metal products, documented in Table 2, lends some credibility to this assumption.

With that caveat, we define $Q_i(\gamma, \alpha) = \left[\sum_p \left(A_p^i\right)^\gamma \left(\xi_p^i\right)^\gamma\right]^{\frac{1}{\gamma(1-\alpha)}}$ one possible measure of the "quality" of country i's capital stock. Then we can compute for different choices of α and γ the fraction of income variance explained by capital quality as

$$\frac{Var\{\log[Q_i(\alpha, \gamma)]\}}{Var[\log(y_i)]}.$$

As an alternative measure less affected by outliers, one can also look at the inter-

corresponding current-dollar one by (roughly) the US deflator. Hence, even though our equations call for measuring k^i in current US dollars, and development-accounting studies measure it in base-year international dollars, the two approaches should give very similar asessments of the contribution of capital "quantity" to income differences.

[29] On some of these questions it is actually possible to make some progress without disaggregating the capital stock. For example, Hsieh and Klenow (2002) decompose k into a component due to savings and one due to price levels of investment goods, and find that most of the explanatory power of k comes from prices.

percentile range, i.e. the ratio of the 90th to the 10th percentile of the distribution of Q, divided by the analogous ratio for the distribution of y.[30] We compute similar statistics for the alternative measure of quality, $Q_i'(\alpha,\gamma) = \left[\sum_p \left(A_p^i\right)^{\frac{\gamma}{1-\gamma}}\right]^{\frac{1-\gamma}{\gamma(1-\alpha)}}$. This alternative implementation would use exclusively the estimated A_p^is, and not the observed ξ_p^is.

Note that in the first half of the paper we have estimated the A_p^is in two ways: with type-by-type regressions in which A_p and the parameters δ_{cp} were constant, and with embodied R&D regressions in which A_p and δ_{cp} where functions of the R&D content of capital of type p. Hence, our proposed decomposition can be performed four ways: two ways of computing quality (using only the A_p^is or also the ξ_p^is), and two ways of estimating A_p^i.

Before presenting the results, it is worth making two additional comments on the nature of this exercise. First, even if the distribution of Q turns out be highly dispersed, so that quality "explains" a reasonably large fraction of the output variance, it may be that the correlation between Q and y is low. To address this concern we also report these correlations.

Second, by focusing exclusively on variation in Q_i, we are attributing *all* of the remaining variation in incomes to the term $B^i\left(k^i\right)^\alpha$. However, to the extent that this residual term covaries with Q_i, it may be legitimate to assign some of the covariance to the latter. For example, Klenow and Rodriguez-Clare (1997) compute the fraction of the variance in per-capita income explained by the observables, as the variance of the observables plus half of the covariance between observables and unobservables. From this perspective, therefore, we are reporting lower bounds on the fraction of the income variance explained by capital quality.

Table 6 Here

Our tentative decomposition results are reported in Table 6. In all experiments we hold α constant at 0.33. For γ, we try three different values: 0.25, 0.5, and 0.75. Also, for both the type-by-type and R&D regressions, we must decide on a particular specification to obtain A_p^i. We use the final, "full" specification of Tables 4 and 5.

In all cases our measure of the quality of capital shows a solid positive correlation with per-capita income. Figure 2 shows some of these correlations graphically (for

[30] See Caselli (2003) for a discussion of this approach to development accounting. In this section we use the full sample – including the 15 R&D producing countries. However, the estimated A_p and δ_{cp} continue to be those obtained in Section 5 from the non R&D-performing sample. We perform these calculations to data from the year 1990.

$\gamma = 0.75$). Unfortunately, however, it turns out that our measures of the amount of income variance explained by capital quality is exceedingly sensitive to the value of γ used. In fact, by choosing a suitably low value for γ it is possible to explain all of the variation in income with capital quality alone. The intuition is that, as we have seen, the vector of investment shares ξ varies tremendously across countries. Clearly, then, the less substitutable the capital types (the lower γ), the larger the effect of capital-composition on income differences. An additional shortcoming of the results is that the amount of variation explained is very sensitive to the measure of dispersion we use, with the inter-percentile range generally implying that capital quality explains a larger fraction of the variation in the data. These differences in results are clearly attributable to our small sample size.

A different approach to measuring quality would be to simply use equation (2), together with $A_1^i = 1$, to derive $Q_i''(\alpha, \gamma) = \left(\xi_1^i\right)^{\frac{-(1-\gamma)}{\gamma(1-\alpha)}}$. This is perhaps a more elegant approach. Furthermore, it has the obvious appeal that it does not require one to rely on the regression results: it can be performed on the "raw data." On the other hand, if the relationship in (2) is noisy, the approach based on the regression results may provide a cleaner way of extracting information about the A_p^is than just relying on the share of fabricated metal products. In any event, when we perform the development-accounting exercise using Q'' we draw roughly the same lessons as when we use Q or Q' (the correlations with income are slightly higher, and the ratios of log-variances and of inter-percentile ranges are slightly lower).

While these highly unstable results make it difficult to draw a clear conclusion, they at least suggest that capital-composition effects (what we called the quality of capital) have potential in enhancing our ability to account for cross-country income differences. Suppose they could account for 10 percent of the overall variance – a number that seems at least not implausible based on the evidence in Table 6. Development-accounting exercises using the standard measure of the real capital stock (that only accounts for quantity), as well as a measure of human capital, are typically unable to explain much more than 50 percent of the overall income variance. 10 percent attributable to capital-quality alone would be a large improvement on that!

7 Conclusions

Disaggregating capital into separate quantity and quality terms could be important for development accounting. We have showed that the quality of the capital stock differs with its composition. This is because different types of capital are intrinsically more or less efficient, and because they are complementary with different country characteristics. When differences in embodied efficiency are taken into account, the overall contribution of capital to cross-country income differences can increase substantially.

References

[1] Acemoglu, Daron, and Fabrizio Zilibotti. "Productivity Differences." Quarterly Journal of Economics 116, no. 2 (2001): 563-606.

[2] Aghion, Philippe, and Peter Howitt. Endogenous Growth Theory. Cambridge, MA: MIT Press, 1998.

[3] Barro, Robert J., and Xavier Sala-i-Martin. Economic Growth. New York, NY: McGraw-Hill, 1995.

[4] Basu, Susanto, and David N. Weil. "Appropriate Technology and Growth ." Quarterly Journal of Economics 113, no. 4 (1998): 1025-54.

[5] Caselli, Francesco, and John Coleman. "Cross-Country Technology Diffusion: The Case of Computers." American Economic Review Papers and Proceedings, May 2001.

[6] Caselli, Francesco, and John Coleman. "The World Technology Frontier." NBER Working Paper 7904 (2002).

[7] Coe, David T., and Elhanan Helpman. "International R&D Spillovers." European Economic Review 39, no. 5 (1995): 859-87.

[8] Comin and Hobijn (2003): "Cross-Country Technology Adoption: Making the Theory Face the Facts." Forthcoming, *Journal of Monetary Economics*

[9] Diwan, I., and Dani Rodrick. "Patents, Appropriate Technology, and North-South Trade." Journal of International Economics (1991).

[10] Eaton, Jonathan, and Samuel Kortum. "Trade in Capital Goods." European Economic Review 45, no. 7 (2001): 1195-235.

[11] Feenstra, Robert C (1998): "Facts and Fallacies about Foreign Direct Investment," February 1998. Published in Martin Feldstein, ed. International Capital Flows, University of Chicago Press and NBER, 1999, 331-350.

[12] Feenstra, Robert C. "World Trade Flows, 1980-1997." Mimeo (2000).

[13] Gera, Surendra, Wulong Gu, and Frank C. Lee. "Information Technology and Labour Productivity Growth: An Empirical Analysis for Canada and the United States." Canadian Journal of Economics 32, no. 2 (1999): 384-407.

[14] Ginarte, Juan C., and Walter G. Park. "Determinants of Patent Rights: A Cross-National Study." Research Policy 26, no. 3 (1997): 283-301.

[15] Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell. "Long-Run Implications of Investment-Specific Technological Change." American Economic Review 87, no. 3 (1997): 342-62.

[16] Grossman, Gene, and Elhanan Helpman. Innovation and Growth in the Global Economy. Cambridge, MA: MIT Press, 1991.

[17] Hall, B., and B. Khan (2003): "Adoption of New Technology," NBER Working Paper 9730.

[18] Hall, Robert E., and Charles I. Jones. "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" Quarterly Journal of Economics (1999): 83-116.

[19] Hendricks, Lutz. "How Important Is Human Capital for Development? Evidence From Immigrant Earnings ." American Economic Review 92, no. 1 (2002): 198-219.

[20] Heston, Alan, Robert Summers, and Bettina Aten. "Penn World Table Version 6.1." Center for International Comparisons at the University of Pennsylvania (CICUP) (2002).

[21] Hill, Robert J. (2000): "Measuring Substitution Bias in International Comparisons Based on Additive Purchasing Power Methods," *European Economic Review*, 44(1), 145-62, January.

[22] Hsieh, Chang-Tai, and Peter J. Klenow. "Relative Prices and Relative Prosperity." Mimeo (2002).

[23] Hummels, David, and Peter J. Klenow (2002): "The Variety and Quality of a Nation's Trade," NBER WP 8712.

[24] Hulten, Charles R. "Growth Accounting When Technical Change Is Embodied in Capital." American Economic Review 82, no. 4 (1992): 964-80.

[25] Jorgenson, Dale W., Frank M. Gollop, and Barbara M. Fraumeni. Productivity and U.S. Economic Growth. Cambridge, MA: Harvard University Press, 1987.

[26] Jovanovic, Boyan, and Rafael Rob. "Solow Vs. Solow." Working Paper, New York University (1997).

[27] Klenow, Peter J., and Andres Rodriguez-Clare. "The Neoclassical Revival in Growth Economics: Has It Gone Too Far? " NBER Macroeconomics Annual (1997).

[28] Keller, Wolfgang. "The Geography and Channels of Diffusion at the World's Technology Frontier." NBER Working Paper 8150 (2001).

[29] Keller, Wolfgang. "International Technology Diffusion," unpublished, University of Texas.

[30] Lane, Philip R., and Gian Maria Milesi-Ferretti. "The External Wealth of Nations: Measures of Foreign Assets and Liabilities for Industrial and Developing Countries." Journal of International Economics 55, no. 2 (2001): 263-94.

[31] Leamer, Edward E. Source of Comparative Advantage. Cambridge, MA: MIT Press, 1984.

[32] Mankiw, N. Gregory, David Romer, and David N. Weil. "A Contribution to the Empirics of Economic Growth." Quarterly Journal of Economics 107, no. 2 (1992): 407-37.

[33] Barba Navaretti, G., M. Schiff, and I. Soloaga (2003): "The Knowledge-Content of Machines: A New View on North-South Trade and Technology Diffusion, unpublished, Universitá degli Studi di Milano.

[34] Parente, Stephen L., and Edward C. Prescott. "Barriers to Technology Adoption and Development." Journal of Political Economy 102, no. 2 (1994): 298-321.

[35] Santos-Silva, Joao, and Silvana Tenreyro (2003): "Gravity-Defying Trade," Federal Reserve Bank of Boston, Working Paper 03-1.

[36] Solow, Robert M. "Investment and Technical Progress." Mathematical Methods in the Social Science. Editors Kenneth Arrow, Samuel Karlin, and Paul Suppes. Stanford, CA: Stanford University Press, 1960.

[37] Wilson, Daniel J. "Is Embodied Technological Change the Result of Upstream R&D? Industry-Level Evidence." 2002. Review of Economic Dynamics 5 (2) (April), pp. 342-362.

[38] Young, Alwyn. "The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience." 1995. Quarterly Journal of Economics 110, pp. 641-680.

Appendix: Derivation of Equation (2)

Here for notational convenience we drop the country superscripts i. In each intermediate process p the marginal product of labor is equal to the wage rate w, or

$$B(1-\alpha)\left(\sum_j x_j\right)^{\frac{1}{\gamma}-1} A_p^{\gamma} L_p^{(1-\alpha)\gamma-1} K_p^{\alpha\gamma} = w.$$

Solving for L_p, summing over all sectors, and imposing the market-clearing condition $\sum_p L_p = L$, we can solve for the wage w. Substituting back into the above equation we get

$$\lambda_p \equiv \frac{L_p}{L} = \frac{A_p^{\frac{\gamma}{1-(1-\alpha)\gamma}} K_p^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}}{\sum_j A_j^{\frac{\gamma}{1-(1-\alpha)\gamma}} K_j^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}} = \frac{A_p^{\frac{\gamma}{1-(1-\alpha)\gamma}} \xi_p^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}}{\sum_j A_j^{\frac{\gamma}{1-(1-\alpha)\gamma}} \xi_j^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}}.$$

We also have the condition that the marginal product of capital is equalized across sectors, or

$$\alpha\left(\sum_j x_j\right)^{\frac{1}{\gamma}-1} A_p^{\gamma} L_p^{(1-\alpha)\gamma} K_p^{\alpha\gamma-1} = r.$$

Dividing this by the pricing equation for labor we find the conventional result that the capital labor ratio is equalized across sectors:

$$\frac{K_p}{L_p} = \frac{K}{L},$$

which implies

$$\xi_p = \lambda_p.$$

Hence we must solve the system of equations

$$\xi_p = \frac{A_p^{\frac{\gamma}{1-(1-\alpha)\gamma}} \xi_p^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}}{\sum_j A_j^{\frac{\gamma}{1-(1-\alpha)\gamma}} \xi_j^{\frac{\alpha\gamma}{1-(1-\alpha)\gamma}}}.$$

Conjecturing that the solution takes the form $\xi_p = A_p^a / \left(\sum_j A_j^a\right)$ and substituting in the last equation one finds $a = \gamma/(1-\gamma)$, and hence the solution in the text.

Table 1. Description of Capital Type Categories

Capital-Type	ISIC code (Rev. 2)	Description
Fabricated Metal Products	381	Cutlery, hand tools, general hardware, metal furniture and fixtures, structural metal products, etc..
Non-electrical equipment	382-3825	Engines & turbines, agricultural machinery (including tractors, excluding metal tools), metal & wood-working machinery, industrial trucks, military ordinance (including tanks), etc..
Office, Computing, and Accounting Machinery	3825	Computers, calculators, typewriters, and other office equipment (excluding photo-copiers)
Electrical Equipment (excluding communications equipment)	383-3832	Electrical industrial machinery, electrical appliances, and other electrical apparatus
Communications equipment	3832	Semiconductors, wire & wireless telephone equipment, radio & TV sets, audio recording equipment, signalling equipment, radar equipment, etc..
Motor Vehicles	3843	Automobiles and related parts (excludes industrial trucks and tractors)
Other Transportation Equipment	3842+3844+3849	Railroad equipment, motorcycles & bicycles, wagons & carts, etc..
Aircraft	3845	Aircraft and related parts
Professional Goods	385	Measuring & controlling equipment, photographic & optical goods, and watches & clocks

Table 2. Statistics relating to Import Shares and R&D

Capital Type →	Fabricated Metal Products	Non-electrical equipment	Office, Computing, and Accounting Machinery	Electrical Equipment	Communi-cations equipment	Motor Vehicles	Other Transportation Equipment	Aircraft	Professional Goods
1980									
All Available Countries (N=155)									
Import Share Mean	0.095	0.240	0.025	0.123	0.096	0.247	0.056	0.048	0.071
Std. Deviation	0.043	0.096	0.023	0.049	0.053	0.091	0.065	0.068	0.036
min	0.0043	0.0336	0.0004	0.0449	0.0246	0.0107	0.0019	0.0002	0.0048
max	0.2421	0.6221	0.1108	0.3527	0.4290	0.5271	0.5168	0.5673	0.2304
corr. w/ income per capita	-0.1822	-0.2053	0.2542	0.12	0.1331	-0.0245	-0.1371	0.009	0.2116
Non-R&D Performing Sample Used in Our Regressions (N=33)									
Import Share Mean	0.082	0.264	0.022	0.124	0.103	0.230	0.045	0.057	0.071
Std. Deviation	0.035	0.060	0.012	0.041	0.068	0.077	0.027	0.066	0.029
min	0.034	0.078	0.007	0.049	0.044	0.055	0.017	0.002	0.044
max	0.429	0.361	0.051	0.228	0.429	0.358	0.141	0.297	0.205
corr. w/ income per capita	-0.117	-0.051	0.618	0.323	0.174	0.144	-0.509	-0.522	0.214
R&D Measures									
R&D Stock (billions of US $)	112	484	519	688	1220	923	30	1370	321
ranking:	*8*	*6*	*5*	*4*	*2*	*3*	*9*	*1*	*7*
R&D flow intensity	0.011	0.031	0.204	0.080	0.200	0.072	0.026	0.230	0.119
ranking:	*9*	*7*	*2*	*5*	*3*	*6*	*8*	*1*	*4*
R&D stock intensity	0.060	0.164	1.113	0.515	1.044	0.400	0.143	1.426	0.561
ranking:	*9*	*7*	*2*	*5*	*3*	*6*	*8*	*1*	*4*
1995									
All Available Countries (165)									
Import Share Mean	0.083	0.209	0.060	0.144	0.114	0.238	0.034	0.047	0.071
Std. Deviation	0.062	0.079	0.052	0.070	0.052	0.100	0.039	0.092	0.028
min	0.0121	0.0273	0.0063	0.0116	0.0111	0.0102	0.0022	0.0000	0.0125
max	0.5469	0.4790	0.4115	0.5851	0.3657	0.5545	0.3372	0.8842	0.2259
corr. w/ income per capita	-0.2479	-0.1364	0.532	0.2713	0.2004	-0.3207	-0.4079	0.1386	0.3261
Non-R&D Performing Sample Used in Our Regressions (40)									
Import Share Mean	0.057	0.242	0.062	0.157	0.125	0.218	0.023	0.041	0.074
Std. Deviation	0.023	0.087	0.035	0.079	0.056	0.093	0.012	0.042	0.028
min	0.023	0.052	0.013	0.085	0.068	0.042	0.007	0.001	0.037
max	0.122	0.479	0.185	0.445	0.356	0.393	0.067	0.216	0.196
corr. w/ income per capita	-0.114	-0.334	0.575	0.201	0.132	-0.090	-0.362	0.021	0.085
R&D Measures									
R&D Stock (billions of US $)	202	887	1170	848	2280	1810	57	1880	801
ranking:	*8*	*5*	*4*	*6*	*1*	*3*	*9*	*2*	*7*
R&D flow intensity (%)	0.007	0.024	0.074	0.035	0.077	0.034	0.036	0.178	0.096
ranking:	*9*	*8*	*4*	*6*	*3*	*7*	*5*	*1*	*2*
R&D stock intensity (%)	0.043	0.130	0.521	0.211	0.448	0.185	0.212	1.304	0.455
ranking:	*9*	*8*	*2*	*6*	*4*	*7*	*5*	*1*	*3*

Table 3. Summary Statistics for Independent Variables

Variable	1980 # of countries	1980 Mean	1980 Std. Dev.	1995 # of countries	1995 Mean	1995 Std. Dev.
Inward FDI divided by total investment (Inward FDI)	32	0.34569	0.52048	38	0.57475	0.69683
Outward FDI divided by total investment (Outward FDI)	32	0.00778	0.01754	38	0.06710	0.14134
Industrial sector's share of GDP (Industrial Share)	32	0.352	0.094	38	0.324	0.077
Service sector's share of GDP (Services Share)	32	0.484	0.088	38	0.550	0.088
Government's share of GDP (Gov't Share)	32	0.130	0.045	38	0.123	0.040
Intellectual Property Rights, ranges from 0 to 5 (IPR)	32	2.179	0.788	38	2.654	0.722
Average years of education for population 25 and over (Human Capital)	32	2.263	0.856	38	3.140	0.882
Percentage of pop. with some secondary education but no tertiary education (Secondary Ed.)	32	16.466	9.973	38	25.108	12.313
Percentage of pop. with less than secondary education (No Secondary Ed.)	32	78.922	11.144	38	64.266	14.873
Real GDP per capita (Income per Capita)	32	5345.062	3097.485	38	6987.000	5118.008
Remoteness	32	9037.303	1774.931	38	9219.273	2021.550
M3 as percent of GDP (Fin. Development)	32	40.930	18.083	38	51.152	25.562
scale of 0 to 10 (Property Rights)	32	4.940	2.018	n/a	n/a	n/a

Table 4. Type-by-Type Relative Imports Regression

	2	3	4	5	6	7	8	9
Variable	**Non-elec eqp**	**Computers**	**Elec Eqp**	**Comm Eqp**	**Other Transport**	**Motor Vehicles**	**Aircraft**	**Prof goods**
Panel A -- Dependent Variable = Relative Imports								
Intercept	1.665 **	-3.404 **	-1.426 **	-2.390 **	0.155	1.175 **	-3.712 **	-0.765
Time Trend	-0.221	2.693 **	2.045 **	2.870 **	-0.803	-0.041	3.518 **	0.864
Inward FDI	-0.120 **	-0.077	-0.061 **	-0.038	-0.111 **	-0.057 **	-0.159 **	-0.107 **
Outward FDI	0.028 **	0.035 *	0.017	0.002	0.019	0.001	0.053 **	0.011
Gov't Share	-0.324 **	-0.570 **	-0.450 **	-0.140	-0.205	-0.040	0.095	-0.285
Industrial Share	0.680 **	0.384	0.188	-0.384	0.451	0.337	-0.121	0.138
Services Share	-0.259	-0.253	-1.027 **	-0.827 *	0.556	0.676 *	-0.567	0.111
Human Capital	0.134	0.487 *	0.286 *	0.561 **	-0.043	0.248 **	0.142	0.417 **
Income Per Capita	-0.040	0.460 **	0.407 **	0.170	-0.403	-0.041	-0.230	0.114
Pseudo R2	0.108	0.168	0.134	0.103	0.031	0.026	0.112	0.056
N	205	205	205	205	205	205	205	205
# countries	40	40	40	40	40	40	40	40
Panel B -- Dependent Variable = Relative Imports								
Intercept	1.388 **	-4.428 **	-1.765 **	-3.026 **	0.044	0.512	-4.114 **	-1.186
Time Trend	0.025	3.557 **	2.340 **	3.417 **	-0.703	0.533	3.878 **	1.228
Inward FDI	-0.123 **	-0.113 **	-0.071 **	-0.057 *	-0.111 **	-0.066 **	-0.159 **	-0.114 **
Outward FDI	0.032 **	0.039 *	0.020 *	0.008	0.021	0.008	0.058 **	0.017
Gov't Share	-0.234 **	-0.298	-0.346 **	0.050	-0.168	0.166	0.237	-0.147
Industrial Share	0.611 **	0.202	0.120	-0.478 *	0.431	0.224	-0.242	0.036
Services Share	-0.368	-0.680	-1.149 **	-1.018 **	0.530	0.517	-0.796	-0.052
Human Capital	0.024	0.107	0.161	0.303	-0.091	-0.032	-0.035	0.243
Income Per Capita	-0.014	0.636 **	0.454 **	0.250 *	-0.400	0.017	-0.170	0.170
Remoteness	0.457 **	1.390 **	0.495 **	0.940 **	0.187	1.033 **	0.663	0.693 **
Pseudo R2	0.114	0.194	0.139	0.120	0.031	0.054	0.117	0.064
N	205	205	205	205	205	205	205	205
# countries	40	40	40	40	40	40	40	40
Panel C -- Dependent Variable = Relative Imports								
Intercept	1.270 **	-4.497 **	-1.078	-2.672 **	0.118	0.183	-3.710 **	-1.033
Time Trend	0.177	3.606 **	1.550 **	3.027 **	-0.828	0.856 *	3.452 **	1.068
Inward FDI	-0.123 **	-0.113 **	-0.077 **	-0.060 *	-0.110 **	-0.065 **	-0.163 **	-0.115 **
Outward FDI	0.034 **	0.040 *	0.009	0.004	0.019	0.012	0.053 **	0.015
Gov't Share	-0.175	-0.297	-0.559 **	-0.053	-0.214	0.260 *	0.142	-0.184
Industrial Share	0.631 **	0.220	0.066	-0.517 *	0.458	0.334	-0.382	0.004
Services Share	-0.396	-0.722	-0.952 **	-0.935 *	0.552	0.523	-0.753	-0.044
Human Capital	0.040	0.111	0.231	0.340 *	-0.112	-0.060	-0.001	0.274
Income Per Capita	0.009	0.628 **	0.343 **	0.213	-0.452	-0.011	-0.141	0.167
Remoteness	0.331	1.478 **	0.620 **	0.958 **	0.394	1.130 **	0.608	0.662 *
Fin. Development	-0.154 *	-0.018	0.510 **	0.240 *	0.119	-0.259 **	0.279	0.098
Pseudo R2	0.118	0.199	0.167	0.128	0.032	0.072	0.122	0.067
N	200	200	200	200	200	200	200	200
# countries	39	39	39	39	39	39	39	39

Table 4 (continued). Type-by-Type Relative Imports Regression

	2	3	4	5	6	7	8	9
Variable[a]	**Non-elec eqp**	**Computers**	**Elec Eqp**	**Comm Eqp**	**Other Transport**	**Motor Vehicles**	**Aircraft**	**Prof goods**
Panel D -- Dependent Variable = Relative Imports								
Intercept	1.339 **	-4.568 **	-1.030	-2.683 **	0.614	1.071	-6.102 **	-1.301
Time Trend	0.137	3.736 **	1.623 *	3.233 **	-1.315	-0.012	6.176 **	1.514
Inward FDI	-0.103 **	-0.095	-0.054	-0.031	-0.104 *	-0.055 **	-0.111 **	-0.082 **
Outward FDI	0.023 **	0.046 *	0.002	0.004	0.014	0.011	0.041 *	0.012
Gov't Share	-0.241	-0.362	-0.423 **	-0.029	-0.334	0.070	0.140	-0.112
Industrial Share	0.718 **	0.650	0.211	-0.427	0.585	0.344	-0.112	-0.036
Services Share	-0.201	-0.140	-0.656	-0.564	0.449	0.436	-0.114	-0.048
Human Capital	-0.079	0.000	0.075	0.211	-0.139	-0.007	-0.317	0.054
Income Per Capita	-0.046	0.320	0.186	0.031	-0.441	-0.043	-0.442	0.101
Remoteness	0.226	1.530 **	0.539	0.854 **	0.177	0.805 **	0.221	0.754
Fin. Development	-0.219 *	-0.086	0.276 *	0.046	0.128	-0.135	-0.048	-0.081
Property Rights	0.045 **	0.065	0.064 *	0.088 **	-0.007	0.014	0.170 **	0.088 **
Pseudo R2	0.112	0.168	0.102	0.103	0.039	0.042	0.154	0.068
N	142	142	142	142	142	142	142	142
# countries	39	39	39	39	39	39	39	39
Panel E -- Dependent Variable = Relative Imports								
Intercept	1.337 **	-4.852 **	-1.506 *	-2.902 **	0.803	1.101	-6.618 **	-1.804
Time Trend	0.057	3.763 **	1.936 **	3.120 **	-1.599	-0.140	6.615 **	1.718
Inward FDI	-0.103 **	-0.094	-0.042	-0.024	-0.109 *	-0.055 *	-0.098 **	-0.070 *
Outward FDI	0.018 *	0.036	-0.005	-0.013	0.007	0.007	0.042 *	-0.002
Gov't Share	-0.252 *	-0.352	-0.426 **	-0.059	-0.398	0.035	0.134	-0.111
Industrial Share	0.688 **	0.793	0.257	-0.332	0.507	0.331	-0.068	0.007
Services Share	0.189	0.948	-0.395	0.557	0.998	0.896 **	-0.281	0.672
Human Capital	-0.153	-0.160	-0.072	-0.052	-0.182	-0.063	-0.356	-0.210
Income Per Capita	0.047	0.525	0.187	0.250	-0.312	0.054	-0.540 *	0.222
Remoteness	0.245	1.597 **	0.665 *	1.014 **	0.140	0.826 **	0.311	0.936 **
Fin. Development	-0.283 **	-0.217	0.170	-0.128	0.098	-0.169	-0.081	-0.287
Property Rights	0.036	0.031	0.068 *	0.065	-0.029	-0.002	0.179 **	0.084 *
IPR	0.006	0.006	0.235	0.112	-0.059	-0.029	0.221	0.271
Pseudo R2	0.112	0.168	0.103	0.105	0.042	0.043	0.167	0.071
N	140	140	140	140	140	140	140	140
# countries	38	38	38	38	38	38	38	38

Note: For each of the country-specific factors above, the log of the factor is what is actually included in the regression.

Table 5. Embodied R&D Regressions

Dependent Variable → / Independent Variable ↓	1	2	3	4	5
	Relative Imports	Relative Imports	Relative Imports	Relative Imports	Relative Imports
Constant	1.847 **	1.856 **	1.848 **	1.735 **	1.685 **
LOG(R_P/R_1)	-0.663 **	-0.700 **	-0.705 **	-0.580 **	-0.660 **
Time Trend	0.008 **	0.010 **	0.010 **	0.008 **	0.009 **
Inward FDI	-0.036 **	-0.041 **	-0.042 **	-0.031 **	-0.029 **
Outward FDI	0.007 **	0.009 **	0.008 **	0.007 **	0.001
Industrial Share	0.032	-0.028	-0.027	0.074	0.149 *
Services Share	-0.254 **	-0.378 **	-0.355 **	-0.095	0.260 *
Gov't Share	-0.102 **	-0.024	-0.042	-0.031	-0.039
Human Capital	0.174 **	0.074 *	0.091 **	0.024	-0.063
Income per Capita	0.049	0.094 **	0.082 **	-0.052	0.002
Remoteness		0.375 **	0.383 **	0.302 **	0.349 **
Fin. Development			0.039	-0.027	-0.076 *
Property Rights				0.049 **	0.041 **
IPR					0.057
N	1176	1176	1136	824	808
# Countries	40	40	39	39	38

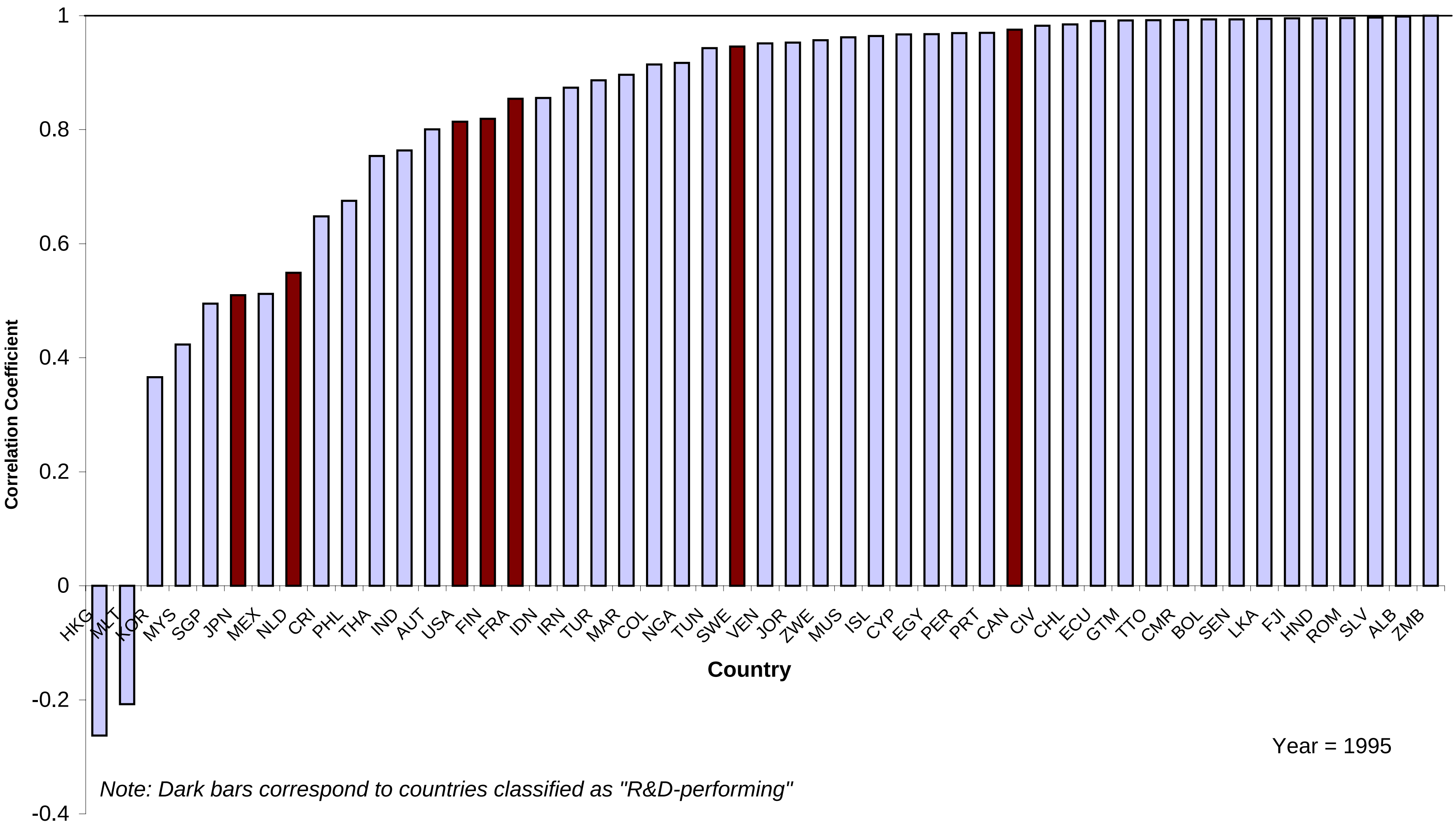
Note: For each of the country-specific factors above, it is the log of the factor interacted with log(R_p/R_1) that is included in the regression.

Table 6. Relationship between Capital Quality Measures and Income p.c. (1990 sample)

Quality Measure	Gamma	Ratio of Log-Variances	Ratio of 90-10 Interpercentile Ranges	Log-Correlation with Income p.c.
Q predicted by Type-By-Type Regression (from Table 4, panel E)	0.25	6.093	5.127	0.255
	0.5	0.695	0.723	0.248
	0.75	0.080	0.371	0.239
Q' predicted by Type-By-Type Regression (from Table 4, panel E)	0.25	5.967	4.794	0.260
	0.5	0.663	0.695	0.260
	0.75	0.074	0.365	0.260
Q predicted by Embodied R&D Regression (Table 5, row E)	0.25	4.997	4.921	0.261
	0.5	0.579	0.708	0.242
	0.75	0.069	0.377	0.223
Q' predicted by Embodied R&D Regression (Table 5, row E)	0.25	4.940	4.882	0.283
	0.5	0.549	0.699	0.283
	0.75	0.061	0.366	0.283

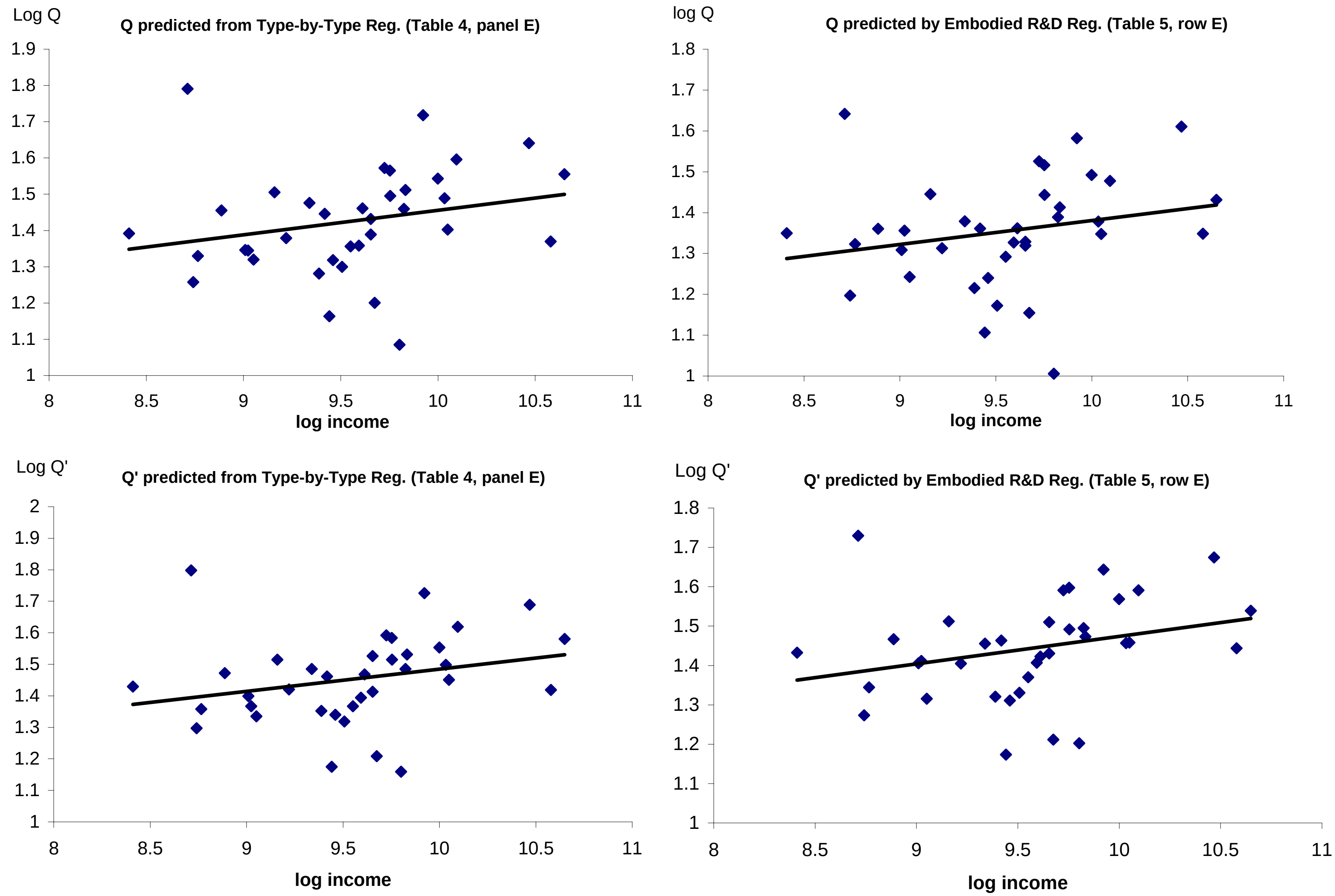
Note: Numerator in ratios corresponds to quality measure; denominator corresponds to income per capita.

Figure 1. Correlations between Import Shares and Investment Shares, by Country



Note: Dark bars correspond to countries classified as "R&D-performing"

Figure 2. Scatterplots of Quality Measure and Income per Capita (1990 sample)



Note: Q and Q' measures above are constructed assuming $\gamma = 0.75$.