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CROSS-COUNTRY TECHNOLOGY DIFFUSION: THE CASE OF COMPUTERS

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ABSTRACT

We use data on imports of computer equipment for a large sample of countries between 1 970 and 1990 to investigate the determinants of computer-technology adoption. We find strong evidence that computer adoption is associated with higher levels of human capital and with manufacturing trade openness vis-a-vis the OECD. We also find evidence that computer adoption is enhanced by high investment rates, good property rights protection, and a small share of agriculture in GDP. Finally, there is some evidence that adoption is reduced by a large share of government in GDP, and increased by a large share of manufacturing. After controlling for the above-mentioned variables, we do not find an independent role for the English- (or European-) language skills of the population.

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1 Introduction

It has long been recognized that increases in technical efficiency play a critical role in long-term growth. For high-income countries this has led researchers to focus attention on the R&D process. For low-income countries – which are presumed to operate inside the technological frontier – an additional source of efficiency gains is to be found in the adoption of technologies already developed in technologically advanced countries.[1] Yet not much is known empirically on the determinants of technology adoption. This paper presents a case study of the diffusion of computer technology around the World. In particular, it tries to identify variables that predict adoption of computers in a panel of countries.

Computers make for an ideal case study of technology diffusion. First, they have been introduced recently, i.e. after or in conjunction with the inception of the relevant data collection processes. This allows us to catch the process from its very beginning. Second, computers constitute a clear case of embodied technology: a country cannot adopt computer technology without physically installing computers. Hence, a measure of the computing capacity installed is a direct measure of technology adoption. In contrast, it is very hard to measure the diffusion of technologies that are disembodied.

Of course direct measures of investment in computing equipment do not exist for large enough a number of countries and long enough a time span.[2] However, we argue that measures of **imports** of computing equipment are likely to be adequate proxies of such investments. This is because most countries in the World simply do not have a computer-making industry – and this was especially true at the beginning of the diffusion stage. For these countries, the capacity installed is the capacity imported. In other words, technology diffusion takes place through imports of the equipment embodying the technology.

We have detailed data on imports of computer equipment for virtually all countries in the World, starting in 1970. Hence, this paper will use panel data to seek to empirically characterize the determinants of imports of computers across countries. Our strongest findings are that computer adoption is associated with high levels of human capital, and with manufacturing trade openness vis-a-vis the OECD. We also find considerable evidence that computer adoption is enhanced by good property rights protection, high rates of investment per worker, and a small share of agriculture in GDP. There is also some evidence for a negative role of the size of government, and a positive role of the share of manufacturing in GDP.

[1] Macroeconomic evidence that poor countries operate inside the technology frontier can be found in (among others) Francesco Caselli, Gerardo Esquivel and Fernando Lefort (1996), Peter Klenow and Andres Rodriguez-Clare (1997), Robert Hall and Charles Jones (1999), and Caselli and John Coleman (2000).

[2] The UNDP has a data set with stock of personal computer for the 1990s. Jong-Wha Lee (2001) has examined these data and –consistent with our results – has found a strong role for human capital.

After controlling for the above-mentioned variables, we do not find an independent role for the English- (or European-) language skills of the population. The quantitative importance of these findings, as well as their theoretical interpretation, is discussed in the concluding section.

2 Data on Computer Imports

The focus of our analysis is computer investment per worker. We measure aggregate computer investment by imports of computer equipment. Almost all countries in the World report detailed information on their bilateral trade flows by very disaggregated product or commodity to the United Nations. These detailed trade flow data have been made available by Robert Feenstra, Robert Lipsey, and Harry Bowen (1997). This paper focuses on imports of automatic data processing machines and units thereof; magnetic and optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, n.e.s.. In practice, this variable measures imports of assembled computers, as well as imports of key components, such as central processing units, memory chips, storage devices, and peripherals.[3] We focus on the period 1970-1990, which essentially covers the beginning and the coming of age of the computer revolution. Information on computer imports is available on 155 countries, though the country coverage for most of our empirical work will shrink because of limitations in the covariates we use. We express the import data in per-worker terms by dividing aggregate computer imports by the labor force, as measured by the World Bank (1999).

We believe computer imports per worker to be an adequate measure of computer investment per worker for a large majority of the countries in the World. Simply put, the computer industry is well known to be highly concentrated internationally, with a handful of countries providing most of the World's computer output. For this reason, computer imports and computer investment are probably very closely associated. A check of this idea based on computer exports per worker gives a somewhat ambiguous response. The percentage of countries in the sample with no reported computer exports falls from 58% in 1970 to 13% in 1990. Hence, a sizeable fraction of the sample appear to be exporting some computers – perhaps suggesting the existence of a domestic computer industry, after all – especially in the

[3]The computer-import variable is category 752 in the UN data set. It includes the following sub-categories (for which separate data is available): Analogue and hybrid (analogue/digital) data processing machines (7521); Complete digital data processing machines, comprising in the same housing the central processing unit and at least one input unit and one output unit (7522); Complete digital central processing units; digital processors consisting of arithmetical, logical, and control elements (7523); Digital central (main) storage units, separately consigned (7524); Peripheral units, including control and adapting units (connected directly or indirectly to the central unit) (7525); and Off-line data processing equipment, n.e.s. (7528).

later period of coverage. However, inspection of the data reveals that most of the positives are trivial in amount – suggesting to us that almost certainly these exports reflect re-exports or statistical anomalies.

In order to deal with the ambiguous message from the export data, in our empirical work we work with three data sets of computer adoption. The first data set proxies computer adoption with computer imports and uses the full sample. The second uses the same adoption variable, but limits the sample to those countries with no reported computer exports. This is clearly overkill, as it excludes some countries that cannot be plausibly deemed to produce their computers domestically. But any alternative cut-off criteria would be arbitrary, and this stringent criterion allows us to check the robustness of the results from the full sample.[4] The third data set uses production data from UNIDO (2000) to construct an adoption variable based on the formula: adoption = production+imports-exports. One shortcoming of this (otherwise ideal) adoption variable is that the production data pertain to a somewhat broader category of equipment, namely Office, Computing, and Accounting Machinery (OCAM), so its identification with computer adoption is not as tight.[5] More distressingly, the country coverage is quite limited. Furthermore, time coverage for these data for a reasonable number of countries only starts in the 1980s. The important point, however, is that, as it will be seen, some key results are fairly similar in the three samples.

Table 1 reports summary statistics of computer imports per worker in selected years for the three samples. The table attests to the very large differences across countries within each period. Most variables are reported in current-dollar levels, and should therefore not be used for intertemporal comparisons. The only exception is the log-variance, which should be roughly unit-free, and is perhaps suggestive of some reduction in dispersion over time – perhaps a sign that Mr. Clinton's "digital divide" may be shrinking (at least among countries). To provide an additional preliminary look at the data, Figure 1 plots the log of computer imports per worker against the log of per capita income (from Heston and Summers, 1994) in selected years. In this figure each country's position is marked by its three-digit World Bank code name. Lowercase letters identify countries with positive reported exports of computers. Uppercase letters identify countries with no reported computer exports (i.e. our Non-Exporting Sample). Not all countries in the figure report data on the covariates we will use in the empirical work. A list of countries included in the regressions is reported in

[4] One problem with the import data is that they are not f.o.b., i.e. the values reflect in part insurance and freight. However, neither are they c.i.f. In practice, the reported values are somewhere between f.o.b. and c.i.f. See Feenstra, Lipsey, and Bowen (1997). It is not clear at this stage how to fix this problem.

[5] The OCAM production variable is category 3825 in the UNIDO (2000) dataset, which adopts an ISIC classification. Information provided by UNIDO itself allows to determine that concordance with the trade data requires to aggregate categories 751 (Office Machines), 752 (our computer variable), and 759 (parts for 751 and 752) in the latter.

the Appendix, together with their World Bank codes and the raw computer-import data.

Table 1: Computer Imports: Summary Statistics

	Mean	Log Std. Dev.	Min.	Median	Max.	No. of Obs.
Full Sample						
1970	0.784	2.458	0	0.106	8.286	119
1975	3.432	2.698	0	0.539	29.492	120
1980	14.006	2.463	0	1.792	126.216	133
1985	26.749	2.328	0	2.532	277.624	133
1990	60.463	2.313	0.008	5.424	1132.616	133
Non-Exporting Sample						
1970	0.203	2.093	0	0.035	4.081	69
1975	0.764	2.663	0	0.158	5.156	56
1980	2.983	2.178	0	0.456	25.114	62
1985	4.737	1.630	0.029	0.766	129.283	41
1990	4.268	1.876	0.065	1.894	22.750	17
OCAM Sample						
1985	76.928	2.226	-478.247	19.339	471.338	38
1990	216.862	2.161	-22.818	34.607	1108.104	41

Note: Computer imports per worker in current US dollars.

In using the current US-dollar value of computer-imports to compare computer adoption across countries at a given point in time we are implicitly assuming that computer prices obey purchasing power parity. Given the absolute absence of computer-price indices for all but a few countries we frankly admit we have no way of backing up this assumption. Even for the USA, the existing deflators are surrounded by considerable controversy, and different deflators behave wildly differently. For these reasons, in this paper we eschew inter-temporal comparisons: all our empirical work will handle intertemporal variation through time dummies which – assuming again that the law of one price holds – should absorb changes in the dollar price of computing power. We leave the study of intertemporal patterns of computer adoption to future work.

3 The Determinants of Diffusion

Our strategy to investigate the determinants of differences in computer-technology adoption is to look at a variety of regression results using specifications of the form

$$\log(I_{\mathsf{c}}^{\mathsf{it}}) = \alpha + \boldsymbol{\delta}^{\mathsf{t}}\beta + \mathsf{X}^{\mathsf{it}}\gamma + \eta^{\mathsf{i}} + u^{\mathsf{it}} \tag{1}$$

where $I_{\mathsf{c}}^{\mathsf{it}}$ is computer imports per worker (in current US dollars) in country i and year t, X^{it} is a set of explanatory variables, $\boldsymbol{\delta}^{\mathsf{t}}$ is a set of year dummies, η^{i} is a country effect, and u^{it} is independently and identically distributed among countries and years. All the variables we will include in the vector X are available at annual frequency, except for our measure of human capital, which is only available at 5-year intervals. Since this variable turns out to be a key determinant of computer adoption, our regressions are based on data for the years 1970, 1975, 1980, 1985, and 1990. Depending on the sample, the country coverage varies roughly between 40 and 90.[6]

In cross-country studies of this kind there is considerable controversy regarding the appropriate estimation technique, and in particular regarding the treatment of the country-specific term, η^{i}. The basic choice is between random effects (RE) and fixed effects (FE). The RE estimator is the most efficient but is consistent under the most stringent assumptions, i.e. that η^{i} is uncorrelated with the vector X^{it}. The FE estimator does not require this stringent assumption, but the country dummies absorb a lot of the variation in the data, making the estimator relatively inefficient. Our compromise solution in this "efficiency-consistency" trade off is to do a bit of both: we include a full set of regional dummies (fixed region effects) and treat the residual country effect as random (random country effect). In other words, we do assume that η^{i} is uncorrelated with X^{it}, but we include in the latter a full set of regional dummies. This technique is consistent if the part of the country effect that is orthogonal to the region effect is also orthogonal to the remaining elements of X^{it}. The advantage is that it is more efficient than the "fixed country effect" estimator. It is important to acknowledge, however, that when we apply the fixed country effect technique to the specification below we can identify virtually no significant explanatory variable.[7]

We treat the vector X^{it} as exogenous for $\log(I^{\mathsf{it}})$. Reverse causation is extremely unlikely to be a problem. For almost all countries in our samples computer adoption is

[6] In view of the fact that several countries report 0 imports of computers the log specification may seem to generate sample selection. It turns out, however, that none of the country-year observations with 0 computer imports has complete data on the set of explanatory variables we employ, so taking logs *per se* does not induce any additional censoring.

[7] The regional dummies are for: Sub-Saharan Africa; Latin America and Caribbean; Eastern Europe; Arab World; East Asia; Rest of Asia. In practice, the "omitted" region coincides almost perfectly with the OECD. See the appendix for more details on country-year coverage and regional assignments.

extremely limited between 1970 and 1990, and it is unlikely to have caused changes in any of the macroeconomic variables on the right hand side. For example, it is highly unrealistic that computer adoption may have impacted the supply of human capital in countries other than the most advanced – and even there it is doubtful, before 1990. That reverse causation is not a major concern does not of course rule out the possibility that we have induced bias in our estimates by omitting some important explanatory variable.

We start with regressions on the full sample of countries. We then restrict ourselves to the sub-sample with no reported computer exports. Finally, we check the robustness of our results on the OCAM Sample. Similarly, we start with a pooled (panel) specification, but we later present regressions run separately for the different years.

One word on our expositional strategy. In order to avoid repetitions, in documenting our results we proceed briskly and with a bare minimum of commentary. All matters of interpretation and relevance are deferred to the next (and concluding) section.

3.1 Full Sample

Table (2) reports the results from the all-country, all-year sample. The specification in Column I includes the basic set of explanatory variables that will be considered in this study: the log of real per-capita income; the log of real investment per worker; the share of agriculture in GDP; the share of manufacturing in GDP; the share of government spending in GDP; the extent of property-rights protection, as measured by an index – ranging from 1 to 10 – based on international surveys; the share of the population who speak English; human capital, as measured by the fraction of the labor force (over 15 years of age) who has at least a completed primary education; trade openness, as measured by the log of total imports per worker. Further details on these and the other data used in the paper are provided in the Appendix, which also lists the sources.[8] To conserve space, in the Tables we do not report the coefficients on the 5 year dummies and on the regional dummies. About the former we just note that they are as expected highly significant and growing very rapidly. On the latter we briefly report below.

In Column I the variables that have a statistically significant effect on computer adoption are per capita income (at the 10% level), investment per worker, the share of agriculture, human capital, and trade openness. Dropping the insignificant variables one at a time does not make any of the others become significant.

In Column II we further investigate the role of human capital by breaking this variable up into the share of the labor force who has attained primary schooling but went no further

[8] In the Appendix the reader can also find a Table of univariate regressions of the dependent variable on each of the explanatory variables used in this study, one at a time.

(including those who attended without completing it), the share who has attained secondary schooling (and went no further), and the share who has attained higher education (the latter two groups form the composite human-capital variable used in the previous specifications). Hence, the omitted group is the completely uneducated. The point estimates increase sharply from primary to secondary education, but level off (in fact, slightly drop) from secondary to higher education. Only the coefficient on the fraction attaining secondary education is significantly different from 0.[9,10]

We next further investigate the role of openness. In Column III we break down total import per worker by the identity of the trading partner – OECD vs non-OECD – and by the nature of the traded good – manufacturing goods versus non-manufacturing goods.[11] The result is that both origin and nature of the trade flows matter: only manufacturing imports from the OECD help predict computer adoption. We have subjected this result to a battery of checks by including alternative openness-related variables, such as (bilateral-trade weighted) distance from the leading World exporters, measures of FDI inflows, the black market premium, and the Sachs-Warner openness measure. None of these entered significantly in our regressions nor did its inclusion affect the significance of other variables.

We next investigated a separate role for exports. When we include (the log of) total exports per worker we obtain a significantly (at the 10% level) positive coefficient on this variable, and no substantive change in the coefficients or significance of other variables (Column IV). When we further break down exports by nature and destination the significant (at the 10% level) components are manufacturing exports to the OECD and non-manufacturing exports to non-OECD countries (Column V). In this last specification the negative coefficient on non-manufacturing imports from non-OECD countries becomes statistically significant (at the 10% level) and the significance of the coefficient on investment changes from the 5% to 10% level.

3.2 Non-Exporting Sample

The Full Sample we have analyzed so far undoubtedly includes some countries that are producers of computing equipment. For these countries, computer imports may not be an

[9]We also further broke down the labor force into finer education categories: primary school completed; secondary school attained but not completed; secondary school completed; higher education attained but not completed; higher education completed. There seems to be a broad monotonicity in the coefficients, although there is a sharp and puzzling drop from higher education achieved to higher education completed. Only the coefficients on secondary and higher education attained are statistically significantly different from 0.

[10]All the results are also essentially insensitive to looking at the corresponding shares for the labor force over 25 (instead of 25).

[11]More accurately, we treat as OECD members those countries that were members as of 1990 (this excludes Korea, Mexico, and the Eastern European members). We further exclude Turkey and include Israel.

adequate measure of computer adoption. In this subsection we examine a sub-sample of countries that report no computer exports whatsoever. We are virtually certain that these countries have no computer industry, so for this sub-sample the identification of computer imports with computer adoption should be very tight.

Our approach is to run the same exact set of regressions on the sub-sample as we did on the full sample. The results are reported in Table (3). The results are consistent with those of the full sample as regards investment per worker; human capital; and manufacturing imports from OECD countries. But they differ in the following respects: per-capita income, the share of agriculture, and any export variable are no longer significant predictors of computer adoption; the property rights variable takes on a significantly positive value in some (but not all) specifications; and, somewhat puzzlingly, imports of manufacturing from non-OECD countries are a significantly **negative** predictor of computer adoption (at the 10% level).

3.3 OCAM Sample

The Full Sample has ample country coverage, but underestimates computer adoption for those countries that have a substantial computer industry. The Non-Exporting Sample represents a radical but somewhat extreme solution to this problem. In this subsection we pursue an alternative solution, which is to focus on countries for which we have production data, so we can appropriately measure adoption as production plus net imports (i.e. imports minus exports). As discussed above, the price is a small country and time coverage (essentially only 1985 and 1990), as well as a less tight correspondence between the dependent variable – which now is OCAM – and the phenomenon we wish to explain. As for the Non-exporting Sample our strategy is to repeat the exact same battery of specifications. The results are reported in Table 4.

As in the Full Sample and in the Non-Exporting Sample, in the OCAM Sample human capital and manufacturing imports from the OECD are significantly positive predictors of computer adoption, though in the breakdown of the labor force by finer education groups the OCAM Sample attributes a much larger premium to higher education. The OCAM Sample agrees with the Full Sample (but disagrees with the Non-Exporting Sample) in identifying the share of agriculture as a negative predictor of computer adoption, and in not attributing any role to manufacturing imports from non-OECD countries. It agrees with the Non-Exporting Sample (and disagrees with the Full Sample) in assigning no predictive power to per-capita income, and – in the specifications with no export variables – in assigning a strong positive role to the protection of property rights. It differs from both in that investment per worker is not significant in the OCAM Sample, the share of manufacturing becomes significantly positive (from insignificant), and the share of government spending in GDP becomes significantly negative (from insignificant) – again in specifications not involving export variables.

3.4 Regressions by Year

Table (5) reports regression results separately for each of the years for which the human capital information can be constructed. The sample size becomes extremely small, especially for the early years (the binding constraint is the property rights indicator). Hence, we limit ourselves to reporting results including the Full Sample of countries. We also limit ourselves to reporting a somewhat parsimonious version of the specifications in the previous tables. Not surprisingly, the greatly diminished sample sizes make it difficult to identify the coefficients. The signs tend to be consistent with those from the pooled samples. Of the variables that had been significant in at least some of the pooled specifications only investment does not attain statistical significance in at least one year.

3.5 Regional Dummies

To conserve space we have not included in the foregoing tables the coefficients on the regional dummy variables. Yet such coefficients are of some interest in themselves, and in this sub-section we briefly report on their sizes and significance. The East Asian dummy is insignificant in the Full Sample and in the Non-Exporting Sample; it is strongly significantly negative in the OCAM Sample, with a coefficient of about -1, as well as in the 1990 regression (coefficient -0.5); but it is also significantly positive (coefficient 0.6) in the 1985 regression (and insignificant in the other regressions by year). The Latin American dummy tends to be significantly negative in the Full Sample (about -0.4) in the OCAM Sample (between -0.5 and -0.7), and in the 1990 regression (-0.4); but significantly positive in Column V for the Non-Exporting Sample (about 1.1) (and insignificant otherwise). The dummy for Sub-Saharan Africa is sometimes significantly positive in all samples (Full Sample: 0.7; Non-Exporting Sample: 1.2; OCAM Sample: 0.9; 1980 regression: 1.0). Otherwise it is insignificant. The Other Asian dummy is always significantly negative in the Full Sample (between -0.7 and -0.8) and in 1975 (-1.4) and insignificant in all other samples and periods. The Eastern European dummy tends to be significantly negative (-0.7 to -0.9) or insignificant when included. The Arab dummy tends to be significantly negative (between -0.7 and -0.8 in Full Sample, OCAM Sample, 1985 and 1990), or insignificant.

4 Discussion and Conclusions

We have presented a case study of the diffusion of computers across countries. One of the most robust findings is that high levels of educational attainment are important determinants of computer-technology adoption, even after controlling for a variety of other macroeconomic variables, including per-capita income. Human capital is important in the Full Sample, the Non-Exporting Sample, and the OCAM Sample. The effect is quantitatively substantial: in the full-sample and in the OCAM Sample a one-percentage-point increase in the fraction of the labor force who have better than primary education leads to an increase in computer investment per worker of roughly 1%. In the Non-Exporting Sample the response can be as large as 5%.

The finding of a robust and strong role for human capital in determining computer-technology adoption constitutes new confirmatory evidence that recent technological developments have had a skill-biased component. The presumption of a skill bias in information technology adoption is at the center of several attempts to explain recent wage dynamics in the US and in several other countries.[12] There exists some country-specific evidence of computer-skill complementarity in the USA, but in this paper we have shown that the complementarity is a world-wide phenomenon.[13] Unfortunately, this being a case study, we cannot say whether the key role played by human capital is specific to computers, or it extends to any new technology.[14,15]

Another very robust result is that computer investment responds positively to a country's openness to manufacturing imports from the OECD. In the Full Sample, a 10% increase in manufacturing imports per worker from the OECD leads to a roughly 6% increase in com-

[12] See, e.g., Alan Krueger (1993), David Autor, Lawrence Katz and Alan Krueger (1998) Daron Acemoglu (1998), Francesco Caselli (1999), Oded Galor and Daniel Tsiddon (1997), and Jeremy Greenwood and Mehmet Yorukoglu (1997). Mark Doms, Timothy Dunne, and Kenneth Troske (1997) show that manufacturing plants with relatively high skill intensity are more likely to adopt computers.

[13] See also Eli Berman, John Bound, and Stephen Machin (1998) for cross-country evidence of skill-biased technological change.

[14] In the literature one can find two views of the relationship between skills and technology. One view emphasizes "skill in adoption," and holds that an educated – and hence flexible – workforce is always a critical factor in the adoption of new technology. Another view focuses on "skill in use," and argues that certain technologies are inherently skill biased, i.e. complementary with educated workers. If the first view is correct, then adoption of any new technology depends on human capital; if the latter is correct, only adoption of skill-biased technologies depends on human capital. Furthermore, in the first view the role of human capital becomes less important over time, while in the second it remains important throughout. By performing more case studies of new technology diffusion, on data with improved time series comparability, it might be possible to exploit the above mentioned diferences in predictions to asess the relative importance of the two views.

[15] An alternative interpretation is that the complementarity between human capital and computers is in consumption (educated people derive utility from computers) rather than in production. As a partial check on this hypothesis we have re-run some of our specifications with an interaction term between the share of agriculture and the share of skilled labor. The coefficient is significantly negative. Hence, human capital is less conducive to computer adoption in countries with a relatively large share of agriculture. It seems to us that this supports a production over a consumption interpretation of the complementarity between human capital and computers.

puter investment per worker (10% in the Non-Exporting Sample, 4% in the OCAM Sample). The interpretation of this finding that is most consistent with the existing literature is that countries that import manufactures from the OECD benefit from a knowledge spillover. As people and products from the manufacturing industries of technologically advanced countries are the most likely to possess or reflect knowledge of computers, their uses and operations, exposure to such people and products allows other countries to learn about, and hence adopt, the new technology.[16] We should stress that imports of computers are always and everywhere a minuscule fraction of overall manufacturing imports from the OECD. Hence, it is emphatically *not* the case that the significance of manufacturing imports from the OECD is driven by computers being a component of such imports. The fact that in the Non-Exporting Sample imports of manufactures originating outside of the OECD are associated (albeit weakly) with *lower* propensities to invest in computers remains somewhat of a puzzle.

In the Full Sample and in the OCAM Sample there is some evidence (at the 10% level) of an effect from openness in the other direction, namely exports. One possible rationale for a role from exports is that traded goods, especially when directed to OECD countries, must satisfy standards of uniform quality, packaging, disclosure, and barcoding that can only be met through the application of computer technology. If this was the case, however, we would expect exports of manufacturing to OECD countries to explain most of the action as far as export variables are concerned. This variable is indeed significant at the 10% level in one instance, but so is exports of non-manufacturing goods to non-OECD countries. Overall, we think the export results are rather weak. The fact that the only trade-related variable that reliably predicts computer adoption is manufacturing imports from the OECD reinforces a knowledge-spillover interpretation.

Both in the Full Sample and in the Non-Exporting Sample computer adoption is strongly associated with high overall investment rates – for example because of high saving rates. In the Full Sample, a 10% increase in investment per worker leads to an increase in computer investment per worker in the 2 to 3% range. In the Non-Exporting Sample the estimates are in the 6-to-9% range. This result is perhaps not surprising, but it reminds us of an important lesson: when new technology is embodied in capital, high investment rates are a pre-condition to technology adoption.[17]

Both in the Full Sample and in the OCAM Sample we find that a large share of

[16] For models of trade and technology diffusion see, e.g., Gene Grossman and Elhanan Helpman (1991), Robert Barro and Xavier Sala-i-Martin (1995), and Philippe Aghion and Peter Howitt (1998). Also, see the related empirical work in David Coe and Helpman (1995), and Coe, Helpman, and Alexander Hoffmeister (1997).

[17] The literature on embodied technological progress is huge. Among recent contributions are Jeremy Greenwood, Zvi Hercowitz, and Per Krusell (1997), and Boyan Jovanovic and Rafael Rob (1998).

agriculture in GDP is associated with lower adoption of computers. In the Full Sample a one-percentage-point increase in the share of agriculture leads to a 2-to-3 percent decline in computer investment per worker (6 to 8% in the OCAM Sample). Unfortunately, the two samples disagree strongly on the question that is perhaps more interesting, i.e., whether there are differential effects on the relative shares of manufacturing and services: no in the Full Sample, yes in the OCAM Sample, where manufacturing appears to be more computer-friendly than services. The full-sample result is consistent with the view that computers are a general purpose technology, with a broad scope of applicability both in manufacturing and services.[18] The OCAM result points to more sector-specificity – at least at this level of aggregation – with a bias towards manufacturing.

In several specifications for the Non-Exporting Sample and especially for the OCAM Sample we find a role for the degree of property rights protection. This effect is not robust in specifications that include export variables, which suggests an interpretation in terms of omitted-variable bias. However, we also note that the Non-Exporting and OCAM Sample sizes are quite small, so that another interpretation could be that we have overstretched the degrees of freedom by including the export variables (which are almost never significant in these samples anyway). Because of this ambiguity, we do not dismiss the property-right result. When significant, the effect of property rights protection is large. The index is on a scale from 0 to 10 and a unit increase would lead to an increase in computer investment per worker in excess of 10% (in the OCAM Sample). To make this more concrete, moving from the first quartile to the median of the distribution of the property rights index requires a 2-point increase. It would be easy to rationalize a role for property rights in embodied technology adoption. Computers, for example, are relatively easy to confiscate, steal, or loot. Interestingly, however, the results suggest that property rights protection is important even after controlling for general investment. This might indicate that property rights protection has an impact on the composition of investment over and above its impact on the general level of investment.

Subject to the same caveats about the role of export variables, in the OCAM Sample we also find a strong negative effect on computer adoption from a large government share in GDP. A one-percentage-point increase in government spending as a share of GDP is associated with an increase in computer investment per worker of 2-to-3 percent. The result that large governments are bad for technology adoption would make a lot of sense: public bureaucracies are notoriously conservative and generally lack the incentives to seize new efficiency-enhancing opportunities. A country in which a larger share of economic activity is dominated by this inertia will be slower at embracing new technologies.

[18] See Helpman (1998) for a collection of contributions on GPTs.

In none of the three samples there is any evidence that particular foreign language skills are important determinants of technology adoption.

In terms of regional adoption performance a surprising result is that the Sub-Saharan Africa dummy is often significantly positive. Hence, relative to the OECD, Sub-Saharan Africa tends to adopt computers to an extent that is greater than what would be predicted by its human capital, outward openness, investment rate, etc. All the other regional dummies tend to have negative coefficients (when significant), and are therefore conditional underperformers – vis-a-vis the OECD – without a clear ranking among themselves.

In including per-capita income in our regressions we did not have in mind any specific causal mechanism. Rather, we thought of it as a (admittedly rudimentary) control for other possible determinants of technology adoption that data limitations (or limitations of imagination) prevented us from including. From this perspective, a fully successful case study of technology adoption should lead to specifications in which per-capita income is not statistically significant, as its continued significance signals that those additional determinants for whom per-capita income is a stand-in have not been fully identified. Since per-capita income has some (if weak) significant predictive power in our full sample, our list of determinants of computer adoption is conceivably still incomplete.

Besides identifying additional determinants, future work will have to answer several questions left open by the present contribution. Is the complementarity between computer adoption and human capital a sign of a long-run technical complementarity, or is it driven by the fact that skills are especially useful during the early stages of a technological change? What exactly is the role of property rights in technology adoption? Are large governments bad for technology adoption? Also, we have been unable to seek evidence on the role for learning externalities in computer adoption.[19] We believe that additional case studies of other episodes of international technology diffusion along the lines of the present work could be invaluable in starting to answering these questions.

[19] Austan Goolsbee and Peter Klenow (2000) p[resent evidence of network effects in the diffusion of home computers in the United States.

Appendix 1: data sources and definitions

For the dependent variables see the text.

Log Income Per Worker. PPP, from Robert Summers and Alan Heston (1994).

Log Investment Per Worker. PPP, from Summers and Heston (1994).

Agriculture Share in GDP. From World Bank (1999).

Manufacturing Share in GDP. From World Bank (1999).

Governemnt Spending Share of GDP. From Summers and Heston (1994).

Property Rights. This index is constructed by researchers at the Fraser Institute, (Jim Gwartney, Robert Lawson, and Dexter Samida, 2000), mainly using data from the International Country Risk Guide of the PRS Group. The index purports to provide an internationally comparable measure of the overall security of property rights and the quality of the legal structure. It takes values from 1 (least protection) to 10 (greatest protection). It is one of a broader set of measures of economic freedom developed by these authors. The property right index is itself an aggregate of three more specific measures of property rights and legal structure. The data (and the book) can be dowloaded at http://www.freetheworld.com/download.html. File V.xls reports the three sub-categories (A, B, and C) as well as the aggregate measure (V).

Fraction who Speak English. From Robert Hall and Charles Jones (1999).

Human Capital. Fraction of the labor force over 15 years of age that has completed primary school. From Robert Barro and Jong-Wha Lee (1993).

Primary Education, Secondary Education, Higher Education. Fractions of the labor force over 15 years of age who have some primary education but no secondary education, some secondary but not higher education, and some higher education, respectively. From Barro and Lee (1993).

Imports and Exports data. Obtained by summation over the relevant countries and categories from Feenstra, Lipsey, and Bowen (1997).

Appendix 2: country-year coverage of the three samples

See Table A.1.

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Table 2: Full Sample

	I	II	III	IV	V
Log Income Per-Worker	0.334*	0.341*	0.333*	0.219	0.119
	(0.197)	(0.199)	(0.190)	(0.197)	(0.198)
Log Investment Per-Worker	0.333**	0.322**	0.259**	0.251**	0.235*
	(0.124)	(0.125)	(0.123)	(0.121)	(0.124)
Agriculture Share in GDP	-0.028***	-0.028***	-0.028***	-0.027***	-0.022***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Manufacturing Share in GDP	0.001	0.001	0.005	0.005	0.002
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Gov. Spending Share in GDP	-0.012	-0.012	-0.012	-0.012	-0.012
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Property Rights (1-10)	0.043	0.044	0.035	0.036	0.032
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)
Fraction who Speak English	-0.042	-0.047	-0.079	-0.106	-0.089
	(0.223)	(0.224)	(0.214)	(0.208)	(0.217)
Human Capital	0.012**		0.012**	0.011**	0.010**
	(0.005)		(0.004)	(0.004)	(0.004)
Log Imports Per-Worker	0.546***	0.544***			
	(0.084)	(0.087)			
Primary Education		0.002			
		(0.004)			
Secondary Education		0.014**			
		(0.006)			
Higher Education		0.011			
		(0.010)			
Log MNF. Imp. from OECD PW			0.588***	0.550***	0.583***
			(0.129)	(0.129)	(0.132)
Log Non-MNF Imp. from OECD PW			0.079	0.020	0.006
			(0.131)	(0.133)	(0.130)
Log MNF Imp. From Non-OECD PW			-0.033	-0.049	-0.072
			(0.076)	(0.076)	(0.080)
Log Non-MNF Imp. from Non-OECD PW			-0.078	-0.080	-0.131*
			(0.070)	(0.069)	(0.072)
Log Exports Per-Worker				0.180*	
				(0.101)	
Log MNF Exp. to OECD PW					0.088*
					(0.045)
Log Non-MNF Exp. to OECD PW					0.031
					(0.072)
Log MNF Exp. to Non-OECD PW					0.066
					(0.054)
Log Non-MNF Exp. to Non-OECD PW					0.124*
					(0.064)
R^2	0.947	0.947	0.951	0.952	0.954
Number of Countries	89	89	89	89	89
Number of Observations	337	337	337	337	337

Note. Dependent Variable is the log of computer imports per worker in 1970, 1975, 1980, 1985, and 1990. Year dummies and a set of regional dummies were included in each regression. Estimation technique is Random Effect (RE). Standard errors in parenthesis. Statistical significance is denoted by * (10%), ** (5%), or ***(1%). MNF stands for "Manufacturing," and PW stands for "Per-Worker".

Table 3: Non-Exporting Sample

	I	II	III	IV	V
Log Income Per-Worker	-0.342	-0.314	-0.467	-0.512	-0.722
	(0.447)	(0.456)	(0.444)	(0.492)	(0.504)
Log Investment Per-Worker	0.859***	0.890***	0.666**	0.669**	0.925**
	(0.301)	(0.312)	(0.299)	(0.302)	(0.341)
Agriculture Share in GDP	-0.017	-0.017	-0.015	-0.015	-0.007
	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)
Manufacturing Share in GDP	-0.023	-0.020	-0.009	-0.010	-0.023
	(0.020)	(0.022)	(0.020)	(0.020)	(0.022)
Gov. Spending Share in GDP	0.006	0.011	0.011	0.011	0.016
	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)
Property Rights (1-10)	0.207**	0.203**	0.138	0.138	0.141
	(0.092)	(0.093)	(0.090)	(0.090)	(0.094)
Fraction who Speak English	0.344	0.221	0.040	0.033	0.367
	(1.123)	(1.226)	(1.134)	(1.144)	(1.178)
Human Capital	0.053***		0.057***	0.057***	0.041*
	(0.018)		(0.018)	(0.018)	(0.021)
Log Imports Per-Worker	0.041	0.012			
	(0.245)	(0.253)			
Primary Education		-0.001			
		(0.012)			
Secondary Education		0.064***			
		(0.021)			
Higher Education		0.013			
		(0.043)			
Log MNF. Imp. from OECD PW			0.956***	0.948**	0.876**
			(0.347)	(0.353)	(0.370)
Log Non-MNF Imp. from OECD PW			-0.366	-0.379	-0.325
			(0.384)	(0.391)	(0.420)
Log MNF Imp. From Non-OECD PW			-0.360*	-0.353*	-0.212
			(0.199)	(0.203)	(0.224)
Log Non-MNF Imp. from Non-OECD PW			-0.155	-0.162	-0.202
			(0.183)	(0.187)	(0.199)
Log Exports Per-Worker				0.052	
				(0.228)	
Log MNF Exp. to OECD PW					0.186
					(0.112)
Log Non-MNF Exp. to OECD PW					-0.021
					(0.187)
Log MNF Exp. to Non-OECD PW					-0.066
					(0.140)
Log Non-MNF Exp. to Non-OECD PW					-0.026
					(0.157)
R^2	0.887	0.889	0.905	0.906	0.910
Number of Countries	44	44	44	44	44
Number of Observations	87	87	87	87	87

Note. Dependent Variable is the log of computer imports per worker in 1970, 1975, 1980, 1985, and 1990. Year dummies and a set of regional dummies were included in each regression. Estimation technique is Random Effect (RE). Standard errors in parenthesis. Statistical significance is denoted by * (10%), ** (5%), or ***(1%). MNF stands for "Manufacturing," and PW stands for "Per-Worker".

Table 4: OCAM Sample

	I	II	III	IV	V
Log Income Per-Worker	-0.185	-0.207	-0.075	-0.335	-0.302
	(0.329)	(0.307)	(0.358)	(0.397)	(0.427)
Log Investment Per-Worker	0.118	0.086	-0.038	-0.176	-0.104
	(0.192)	(0.184)	(0.238)	(0.249)	(0.262)
Agriculture Share in GDP	-0.070***	-0.065***	-0.078***	-0.079***	-0.082***
	(0.013)	(0.013)	(0.014)	(0.015)	(0.019)
Manufacturing Share in GDP	0.038***	0.034***	0.045***	0.051***	0.052***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.013)
Gov. Spending Share in GDP	-0.022*	-0.028**	-0.023*	-0.017	-0.020
	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)
Property Rights (1-10)	0.131**	0.169***	0.122**	0.080	0.088
	(0.056)	(0.055)	(0.059)	(0.061)	(0.065)
Fraction who Speak English	0.165	0.103	-0.035	0.063	0.020
	(0.265)	(0.250)	(0.299)	(0.310)	(0.344)
Human Capital	0.013**		0.012**	0.015**	0.014**
	(0.005)		(0.006)	(0.006)	(0.007)
Log Imports Per-Worker	0.588***	0.657***			
	(0.101)	(0.101)			
Primary Education		0.005			
		(0.008)			
Secondary Education		0.003			
		(0.008)			
Higher Education		0.033***			
		(0.012)			
Log MNF. Imp. from OECD PW			0.425*	0.561**	0.418*
			(0.220)	(0.232)	(0.237)
Log Non-MNF Imp. from OECD PW			-0.052	-0.299	-0.179
			(0.246)	(0.283)	(0.280)
Log MNF Imp. From Non-OECD PW			0.159	0.052	0.134
			(0.142)	(0.153)	(0.161)
Log Non-MNF Imp. from Non-OECD PW			0.038	0.072	0.106
			(0.140)	(0.143)	(0.187)
Log Exports Per-Worker				0.356*	
				(0.196)	
Log MNF Exp. to OECD PW					0.095
					(0.109)
Log Non-MNF Exp. to OECD PW					0.153
					(0.161)
Log MNF Exp. to Non-OECD PW					-0.015
					(0.133)
Log Non-MNF Exp. to Non-OECD PW					0.018
					(0.159)
R^2	0.965	0.968	0.966	0.968	0.968
Number of Countries	4519	45	45	45	45
Number of Observations	72	72	72	72	72

Note. Dependent Variable is the log of OCAM adoption (production plus net imports) per worker in 1985 and 1990. Year dummies and a set of regional dummies were included in each regression. Estimation technique is Random Effect (RE). Standard errors in parenthesis. Statistical significance is denoted by * (10%), ** (5%), or ***(1%). MNF stands for "Manufacturing," and PW stands for "Per-Worker".

Table 5: Regressions by year

	1970	1975	1980	1985	1990
Log Income Per-Worker	0.972	-0.541	0.459	0.629**	0.150
	(0.783)	(0.772)	(0.409)	(0.269)	(0.191)
Log Investment Per-Worker	-0.033	0.488	0.260	0.071	0.032
	(0.702)	(0.514)	(0.247)	(0.176)	(0.133)
Agriculture Share in GDP	-0.070***	-0.051***	-0.026**	-0.023**	-0.018**
	(0.022)	(0.018)	(0.011)	(0.010)	(0.008)
Manufacturing Share in GDP	-0.002	0.008	0.004	0.007	0.012*
	(0.015)	(0.016)	(0.013)	(0.009)	(0.007)
Gov. Spending Share in GDP	0.015	-0.021	-0.018	-0.010	-0.018*
	(0.028)	(0.020)	(0.015)	(0.012)	(0.009)
Property Rights (1-10)	-0.084	0.050	0.138*	0.173***	0.041
	(0.111)	(0.088)	(0.070)	(0.053)	(0.043)
Fraction who Speak English	-0.357	-0.111	-0.303	-0.077	0.142
	(0.589)	(0.536)	(0.356)	(0.286)	(0.206)
Human Capital	0.013	0.015	0.014*	0.011	0.001
	(0.013)	(0.012)	(0.008)	(0.007)	(0.005)
Log Manuf. Imports from OECD Per-Worker	0.251	0.514**	0.811***	0.678***	0.750***
	(0.253)	(0.238)	(0.189)	(0.127)	(0.100)
Log Manuf. Imports from Non-OECD Per-Worker	0.061	0.044	-0.253*	-0.180*	0.119
	(0.191)	(0.189)	(0.135)	(0.101)	(0.079)
R^2	0.898	0.905	0.925	0.933	0.966
Number of Countries	43	45	77	89	83

Note. Dependent Variable is the log of computer imports per worker. A set of regional dummies was included in each regression. Estimation technique is Ordinary Least Squares (OLS). Standard errors in parenthesis. Statistical significance is denoted by * (10%), ** (5%), or ***(1%). MNF stands for "Manufacturing," and PW stands for "Per-Worker".

Table A.1: The Samples

Name	World Bank Code	Regional Dummy	Computer Imports per Worker in 1970	1975	1980	1985	1990	Years in NES	Years in OCAM S.
Algeria	DZA	Arab World	0.61	1.40	9.77	6.48	10.00	3	0
Bahrain	BHR	Arab World				80.65		0	0
Egypt	EGY	Arab World		0.09	0.84	1.45	2.71	3	2
Iran	IRN	Arab World		0.35	0.98	0.70	2.95	1	1
Jordan	JOR	Arab World				0.99	12.24	1	1
Kuwait	KWT	Arab World			36.24	67.88		0	1
Syria	SYR	Arab World			2.12	1.11	1.22	3	0
Tunisia	TUN	Arab World	0.17	0.70	1.60	2.76	16.55	1	0
Hong Kong	HKG	East Asia	0.39	2.77	19.94	105.29	292.15	0	2
Indonesia	IDN	East Asia	0.01	0.09	0.28	1.08	2.20	1	1
Malaysia	MYS	East Asia	0.20	0.66	3.64	17.70	31.72	0	2
Papua N. G.	PNG	East Asia				2.98	2.54	0	0
Philippines	PHL	East Asia	0.11	0.38	1.15	1.07	2.72	2	2
S. Korea	KOR	East Asia	0.03	0.53	5.82	16.77	55.58	0	2
Singapore	SGP	East Asia	2.05	7.24	52.38	211.18	1132.62	0	2
Thailand	THA	East Asia	0.04	0.14	0.32	2.35	6.45	0	1
Bulgaria	BGR	East Europe				4.37	5.22	0	0
Hungary	HUN	East Europe				6.06	24.56	0	0
Poland	POL	East Europe				2.53	6.34	0	0
Argentina	ARG	Lat. Am.	0.90	1.18	15.23	9.92	9.11	0	0
Barbados	BRB	Lat. Am.				26.50		0	0
Bolivia	BOL	Lat. Am.			0.39	1.65	2.47	3	0
Brazil	BRA	Lat. Am.	0.23	1.82	1.79	2.99	3.38	0	0
Chile	CHL	Lat. Am.	1.17	4.68	8.46	11.43	19.31	2	1
Colombia	COL	Lat. Am.	0.17	0.68	3.12	4.37	8.55	4	2
Costa Rica	CRI	Lat. Am.			1.42	1.67	22.75	3	0
Dom. Rep.	DOM	Lat. Am.			2.11	1.85	4.77	1	0
Ecuador	ECU	Lat. Am.	0.02	1.31	5.08	5.19	4.90	5	2
El Salvador	SLV	Lat. Am.			0.09	0.30	1.99	2	0
Guatemala	GTM	Lat. Am.			0.43	0.43	4.73	2	1
Guyana	GUY	Lat. Am.			0.61	0.30	3.21	0	0
Haiti	HTI	Lat. Am.			0.26	0.84		0	0
Honduras	HND	Lat. Am.			0.55	0.77	3.51	2	2
Jamaica	JAM	Lat. Am.			1.08	6.24	8.89	1	0
Mexico	MEX	Lat. Am.	0.45	1.23	6.48	7.20	15.55	1	1
Nicaragua	NIC	Lat. Am.			0.01	0.44	1.89	3	1
Panama	PAN	Lat. Am.			1.63	11.78	13.85	2	2
Paraguay	PRY	Lat. Am.			3.51	1.77	29.69	2	0
Peru	PER	Lat. Am.	0.27	1.23	2.50	4.61	4.05	2	2
Trin. and Tob.	TTO	Lat. Am.			13.64	23.59	14.71	0	1
Uruguay	URY	Lat. Am.			6.45	5.10	12.99	1	1
Venezuela	VEN	Lat. Am.	0.17	5.26	12.64	28.68	17.32	2	2

Note. In full sample a country-year data point is included when table entry is not missing. Dependent variable is log of table entry. Last two columns give the number of years in which the country was included in the Non-Exporting Sample (NES) and in the OCAM Sample, respectively. Table continues on next page.

Table A.1: The Samples (continued)

Name	World Bank Code	Regional Dummy	Computer Imports per Worker in 1970	1975	1980	1985	1990	Years in NES	Years in OCAM S.
Bangladesh	BGD	Other Asia			0.01	0.09	0.10	3	2
China	CHN	Other Asia				0.90	0.63	0	0
India	IND	Other Asia	0.00	0.02	0.02	0.10	0.33	0	2
Pakistan	PAK	Other Asia	0.04	0.02	0.12	0.41	1.08	1	1
Sri Lanka	LKA	Other Asia			0.30	0.97	1.49	1	1
Benin	BEN	Sub-Sahara			0.32	0.40	0.87	2	0
Cameroon	CMR	Sub-Sahara			1.33	1.95	1.93	0	0
Centr. Afr. Rep.	CAF	Sub-Sahara			0.10	0.10	1.13	2	0
Congo	COG	Sub-Sahara			1.63	3.96	5.93	2	0
Ghana	GHA	Sub-Sahara			0.14	0.39	0.79	1	1
Kenya	KEN	Sub-Sahara	0.05	0.18	0.35	0.76	0.95	2	0
Malawi	MWI	Sub-Sahara			0.12	0.57	0.44	0	0
Mali	MLI	Sub-Sahara			0.03	0.26	0.69	2	0
Mauritius	MUS	Sub-Sahara				1.79	22.57	1	0
Niger	NER	Sub-Sahara			0.35	0.26		2	0
Senegal	SEN	Sub-Sahara			0.97	1.40	4.52	0	1
Sierra Leone	SLE	Sub-Sahara				0.28	0.50	1	0
South Africa	ZAF	Sub-Sahara	1.63	6.52	25.76	25.07	20.57	0	1
Togo	TGO	Sub-Sahara			0.55	0.66	2.52	3	0
Uganda	UGA	Sub-Sahara			0.03	0.11	0.29	1	0
Zambia	ZMB	Sub-Sahara			0.67	2.45	2.19	0	0
Zimbabwe	ZWE	Sub-Sahara			0.24	1.62	3.74	1	0
Australia	AUS	none	4.18	15.46	53.82	122.49	200.35	0	2
Austria	AUT	none			63.14	82.42	236.46	0	0
Belgium	BEL	none	7.71	29.49	100.67	142.72	363.33	0	0
Canada	CAN	none	4.59	24.29	56.48	119.22	275.93	0	2
Cyprus	CYP	none				18.98	69.98	0	0
Denmark	DNK	none	6.62	22.85	78.28	122.03	261.03	0	1
Finland	FIN	none	2.08	19.55	56.62	95.57	209.96	0	2
France	FRA	none	4.60	15.51	59.53	84.89	198.79	0	0
Greece	GRC	none	0.60	0.87	6.08	12.18	42.62	2	2
Iceland	ISL	none	0.19	3.30	25.11	129.28	149.22	4	3
Ireland	IRL	none	1.38	7.86	95.82	277.62	451.44	0	0
Israel	ISR	none	4.08	1.19	57.62	144.15	158.77	1	0
Italy	ITA	none	2.26	9.68	38.27	58.74	150.83	0	1
Japan	JPN	none	0.51	3.19	11.28	16.29	44.86	0	2
Malta	MLT	none				18.26		0	0
Netherlands	NLD	none	8.29	29.15	117.22	210.69	689.84	0	2
New Zealand	NZL	none	3.20	17.18	41.30	109.71	160.85	0	0
Norway	NOR	none	1.70	16.75	79.89	174.98	263.80	0	2
Portugal	PRT	none	0.95	1.35	8.99	14.41	82.05	0	2
Spain	ESP	none	1.89	10.11	25.33	41.08	134.91	0	2
Sweden	SWE	none	3.14	24.61	85.81	144.08	290.21	0	2
Switzerland	CHE	none	5.37	25.67	126.22	202.68	563.57	0	0
Turkey	TUR	none	0.02	0.20	0.22	2.56	11.36	2	2
UK	GBR	none	2.28	10.66	60.20	117.84	257.67	0	2
USA	USA	none	1.12	1.88	8.33	55.07	126.56	0	2

Table A.2: Univariate Regressions

Variable	Coefficient	t-statistic
Log Income Per-Worker	1.991	42.878
Log Investment Per-Worker	1.244	40.140
Agriculture Share in GDP	-0.119	-34.734
Manufacturing Share in GDP	0.059	8.649
Gov. Spending Share in GDP	-0.076	-10.234
Property Rights (1-10)	0.639	19.596
Fraction who Speak English	2.638	7.235
Human Capital	0.083	19.268
Log Imports Per-Worker	1.405	57.617
Primary Education	0.031	5.449
Secondary Education	0.102	16.523
Higher Education	0.192	15.256
Log MNF. Imp. from OECD PW	1.322	56.306
Log Non-MNF Imp. from OECD PW	1.408	58.638
Log MNF Imp. From Non-OECD PW	1.233	45.375
Log Non-MNF Imp. from Non-OECD PW	1.131	43.125
Log Exports Per-Worker	1.280	54.640
Log MNF Exp. to OECD PW	0.824	50.287
Log Non-MNF Exp. to OECD PW	1.034	40.789
Log MNF Exp. to Non-OECD PW	0.749	42.024
Log Non-MNF Exp. to Non-OECD PW	1.023	39.386
East Asia	0.644	1.745
Lat. Am.	0.280	1.142
Sub-Sahara	-2.458	-12.273
Other Asia	-3.652	-9.064
East Europe	0.607	1.208
Arab World	-0.061	-0.204

Note. Dependent Variable is the log of computer imports per worker. Year dummies were included in each regression. Estimation technique is Ordinary Least Squares (OLS). MNF stands for "Manufacturing," and PW stands for "Per-Worker".

Figure 1: Computer Adoption and per Capita Income