Was the Wealth of Nations Determined in 1000 B.C.?*

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January 2008

Abstract

We assemble a dataset on technology adoption in 1000 B.C., 0 A.D., and 1500 A.D. for the predecessors to today's nation states. We find that this very old history of technology adoption is surprisingly significant for today's national development outcomes. Although our strongest and most robust results are for 1500 A.D., we find that even technology as old as 1000 BC matters in some plausible specifications. Although the data allow only some suggestive tests of rival hypotheses to explain long-run technological persistence, we find the evidence to be most consistent with a model of endogenous technology adoption where the cost of adopting new technologies declines sufficiently with the current level of adoption. The evidence is less consistent with a dominant role for population as predicted by the semi-endogenous growth models or for country-level factors like culture, genes or institutions

Keywords: Technology adoption, technology history, economic development.

JEL codes: O3, N7.

* We are thankful to Tobias Pfutze for comments and research assistance, to Tomoko Wada and Jason Zhan Shi for their research assistance, for comments, to Philippe Aghion, Michael Clemens, Rafael DiTella, Simon Gilgricht, Gene Grossman, Pete Klenow, Mike Kremer, Bob Lucas, Nathan Nunn, Peter Peregrine, Louis Putterman, Romain Wacziarg, David Weil and seminar/conference participants at Johns Hopkins, Brown, Harvard/MIT, HBS and to the NSF (Grant # SES-0517910) and the C.V. Starr Center for Applied Economics for their financial support.
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1. Motivation

Cross-country differences in per capita income in the pre-industrial world were significantly smaller than today. For example, according to Madison (2000), per capita income in the UK in 1500 AD was sixty-eight percent higher than in Mexico. In 2000, it was almost three times larger.

This observation has motivated two conclusions. First, that pre-industrial country conditions, and in particular, the technology adoption level, did not vary much across countries.[1] Second, that pre-industrial country conditions are almost irrelevant to understand current development dynamics. A consequence of these conclusions is the emphasis of economic development practitioners and students on modern determinants of per capita income like quality of institutions to support free markets, economic policies chosen by governments, human capital components such as education and health, or political factors like violence and instability.

Could this discussion be missing an important, much more long-run dimension to economic development? To the extent that history is discussed at all in economic development, it is usually either the divergence associated with the industrial revolution (e.g. Lucas, 2000) or the effects of the colonial regimes.[2] Is it possible that precolonial, preindustrial history also matters significantly for today's national economic development?

This paper explores these questions both empirically and theoretically. To this end, we assemble a new dataset on the history of technology over 2500 years of history prior to the era of colonization and extensive European contacts. The first significant finding is that there were important technological differences between the predecessors to today's modern nations as long ago as 1000 BC, and that these differences persisted to 0 AD and to 1500 AD (which will be the three data points in our dataset). Further, these precolonial, preindustrial differences have striking predictive power for the pattern of per capita incomes across nations that we observe today. Although our strongest results are for the detailed technology dataset we assemble for 1500 AD, we also find significant effects under plausible conditions for measures of technological sophistication going back to 1000 BC. We find that the results for 1500 AD largely continue to hold when we include continent dummies and geographic controls.

Two questions naturally follow up our findings. First, what mechanisms propagate historical shocks which affect the history of technology adoption into the present? Second, what do our findings teach us about existing growth models? To answer these question, we present a simple model where the stock of technologies adopted reduces the cost of adopting new technologies. Depending on the strength of this elasticity, historical technology adoption will or will not have a significant effect on the adoption of technologies that have come along since the industrial revolution and hence on current development. Hence, our empirical exploration provides an estimate for this elasticity.

[1] This conclusion is not necessarily true as follows from the work of Kremer (1993), Galor and Weil (2000) and Jones (2001, 2005) and Hansen and Prescott (2002). All these papers have Malthusian models where fertility increases with technology. In this context, countries may have significant differences in technology but very small differences in per capita income.

[2] A notable, honorable, and famous exception is Jared Diamond (1997) .

[4] Spolaore and Wacziarg (2006) have a fascinating exploration of the effect of genetic distance on log-income distance. They take genetic distance as a difference between all characteristics vertically transmitted from parents to

The model yields further predictions that we test. For example, we observe that technology adoption is extremely persistent, that historical technology predicts current technology and that once we control for current technology, historical technology does not predict current development.

Our simple model also helps us think about alternative hypothesis that may generate the observed importance of historical technology adoption on current development and, more importantly, it guides us in how to identify them in the data.

One such explanation is related to the idea that because of the fixed costs of improving technology (either through adoption or invention), the return to improving technology increases with population. This idea dates back to Simon Kuznets, and Julian Simon and has been formulated more recently by Kremer (1993), Galor and Weil (2000) and Jones (2001, 2005) and by the semi-endogenous models of Jones (1995), Kortum (1997), and Segerstrom (1998). According to this literature, historical technology should be related to historical population because it affected the return to adoption technology in the past. Further, since population is persistent, it should also affect the return to adopting technology in modern day societies. Hence, persistent differences in population size could explain the observed persistence in technology adoption.

To identify whether the persistence of technology results from the fact that technology is a powerful propagation mechanism or because population affects the return to technology adoption we just need to control for population in our regressions. We find that both the persistence of technologies and the effect of historical technology adoption on current development persist after controlling for historical population and for both historical and current population. Hence, our first exploration of the data is not consistent with a story in which population is a dominant determinant of the return to technology adoption and in which the persistence of population is driving the observed persistence of technology.

Other potential propagation mechanisms are institutions, culture or the genetic endowment.[4] To identify whether technology or these other factors are propagating historical shocks into the present, we exploit the cross-sector variation in technology adoption and explore whether the persistence of technology adoption holds after including country-year effects and country-sector fixed effects. We find not only that the persistence of technology holds also within sectors but that the magnitude of this effect is comparable to the estimated persistence before including country effects. Further, the persistence within sectors is not driven by any specific sector. In our view, these findings are an important challenge for the hypothesis that institutions, genes or culture are driving the persistence in adoption since these factors are likely to affect

children (not only genetic, but even more importantly cultural), and suggest that differences in these characteristics act as a barrier to technology/development diffusion . They find that countries populated by more genetically distant cultures also have more different per capita incomes. This finding is complementary to ours because genetic distance is very persistent and was determined in a distant past. It differs, however, in at least two respects. First, we explore the effects of technology adoption history on current development. Our left hand side variable has a direct effect on development, while genetic distance surely does not have a direct effect on development. It is a proxy for costs of transferring technology. Second, by exploring a relationship in levels we are able to preserve the transitivity of our measures. This is not the case when looking at distances.

symmetrically technology adoption across all sectors. However, it is quite natural to think that the knowledge from previous adoption experience has an important sector-specificity which would rationalize the within sector persistence in adoption.

In summary, what our findings teach us is that technology is remarkably persistent over the very long run, and that very significant inputs that shape the current cross-country distribution of per capita income were determined a long time ago and were likely to be propagated into the current times by the dynamics of technology adoption.

Our paper is clearly related to the influential book by Jared Diamond (1997) Guns, Germs, and Steel. One important thesis in Diamond's book is that current development is tied to ancient technologies. Diamond, however, does not systematically test the effect of ancient technologies on modern incomes or studies the propagation mechanisms as we will do here. Perhaps for that reason, the Diamond work did not change much the tendency of development economics to focus on the modern period or at most the colonial period. In a similar vein, historians have been debating the importance of past technology adoption for the adoption of subsequent technologies. Mokyr (1990, p. 169) and Rosenberg and Birdzell (1987) argue that technological experience has limited importance for new technology adoption. Greene (2000), instead, argues that, in the West, Greco-Roman dynamism was part of a long continuum from the European Iron Age to medieval technological progress and the industrial revolution. Of course, these arguments have been made based on anecdotal evidence. One of our contributions is to assemble a data set to explore more definitely these issues.

The rest of the paper is organized as follows. Section 2 presents the data set. Section 3 uncovers the main findings and shows their robustness. Section 4 presents a simple model that rationalizes the facts and some extensions that yield some additional predictions that allow us to identify several competing hypothesis about the nature of the propagation mechanism. Section 5 concludes.

2. Description of technology data set

The datasets presented in this paper measure the cross-country level of technology adoption for over 100 countries in three historical periods: 1000 B.C., 0 A.D. and the pre-colonial period in 1500 A.D. Each dataset acts as a "snap shot" in time, capturing the levels of technology adoption by country throughout the world.

Technology adoption is measured on the extensive margin by documenting whether a country uses a particular technology, not how intensively it is used. For example, in the dataset for 1000 B.C., we consider two transportation technologies: pack animals and vehicles. A country's level of technology adoption in transportation is then determined by whether vehicles and/or draft animals were used in the country at the time. The technologies that we examine change between the ancient period (1000 B.C. and 0 A.D.) to the early modern period (1500 A.D.) to reflect the evolution of the technology frontier.

Our focus on the extensive margin of technology adoption is motivated by data availability constraints and by its historical relevance. It is much easier to document whether a technology is being used in a country (the extensive margin) rather than measuring the degree of its adoption (the intensive margin).[5] In addition, the extensive margin has been up to 1875 or so a much more significant margin to explain the cross-country variation in technology adoption (Pulkki and Stoneman, 2006).

The technologies in our data sets are state of the art technologies (at the time) in productive activities (i.e. activities that entered GDP) and for which it has been possible to document its presence or absence for a wide range of countries. Of course, it is a very incomplete list since it does not cover all the significant frontier technologies available at the time. However, the number of technologies covered (12 for 1000 BC and 0 AD and 24 for 1500 AD) is sufficient to make precise inferences about the technological sophistication of economies in the distant past. More fundamentally, the criteria for including technologies in our analysis do not generate any bias in our results because they involve the closeness to the frontier in the distant past and are, a priori, independent of the current frontier.

A related issue is that some sectors are more densely covered than others (i.e. for 1500 AD we have 8 technologies in military but only 2 in metal working). To avoid overweighting sectors where we have been able to collect data on more technologies, we compute the average adoption rate in each sector and then compute the overall adoption level by averaging the sectoral adoption levels. We have also experimented with alternative aggregation approaches obtaining very similar results.

Since our main objective is to analyze the effects that historic technology adoption has on the current state of economic development, our datasets are partitioned using modern day nation states. We use the maps from the CIA's *The World Factbook* (2006) to put into concordance the borders of present day nations with the cultures and civilizations in 1000 B.C., 0 A.D. and 1500 A.D. For example, the technologies used by the Aztecs and their predecessors during pre-colonial times are coded as the ones used by Mexico in 1500 A.D. In cases where a country had multiple cultures within its borders during a certain time period, we take the culture with the highest level of technology adoption to represent that country. This technique is a direct consequence of our goal of measuring the extensive margin of technology adoption in a country. For example, in 1000 B.C. there were multiple cultures residing within Canada's modern day borders. The Initial Shield Woodland was the most technologically sophisticated of these cultures and we therefore use its level of technology adoption to represent Canada in 1000 B.C.

The use of the most advanced culture within a territory for a country's level of technology could induce a mechanical correlation between technology and country size (as measured either by population or land area). The larger the size, the more cultures are being sampled, which makes the maximum of all cultures higher. For population, this "mechanical" effect is really the Kuznets-Simon effect of population on technology mentioned in the introduction, if the most advanced technologies do indeed disseminate within the borders of what is today measured as a country. We will test for this effect in our empirics. For land area, this also could reflect a real economic phenomenon for the same reasons, but it would induce reverse causality between land area and technology. We will examine some simple tests as to whether this affects our results in the empirical section.

[5] It is well documented that the Chinese were using iron for tools by 0 A.D; what is more difficult to assess is the share of tools constructed from iron at the time.

Each dataset is constructed following the methodology used by George Murdock and other ethnologists (Murdock 1967; Carneiro 1970; Tuden and Marshall 1972; Barry and Paxson 1971). Each dataset is coded by a team of researchers surveying multiple sources reducing, in this way, the likelihood of measurement error. Researchers take detailed notes including direct quotations and using, when appropriate, two inference techniques: technological continuity (Basalla 1988) and temporal extrapolation (Murdock & Morrow 1970: 314).

Technological continuity stresses that innovations are a result of previous antecedents; innovations typically do not spontaneously arise without preexisting technologies.[6] We use this technique to infer that countries with advanced technologies in a particular sector also had more primitive ones. One example that illustrates this technique comes from the military technologies in 1500 A.D. Large warships with over 180 guns on deck were considered the pinnacle of military technology in 1500 A.D. (Black 1996). It is not unreasonable to assume that a country with heavily armed warships also had access to field artillery and muskets. Therefore, in Portugal and Germany, the presence of large warships was used to infer the use of both muskets and field artillery. Temporal extrapolation assumes that a technology maintains some level of persistence over time. A technology adopted fifty to one hundred years earlier is assumed to still be in use. In addition, in most of the cases, we are able to document that the technology was present in 1550. An example of this is the coding of transportation technology in 1500 Turkey. We code Turkey as having the magnetic compass in the 1500 A.D. dataset based on evidence that it was in use in the Ottoman Empire by 1450.

The datasets for 1000 B.C. and 0 A.D. are derived from the "Atlas of Cultural Evolution" [7] (henceforward abbreviated as "ACE"). (Peregrine 2003) while we coded the dataset for 1500 A.D. in its entirety. The ACE itself is based on the Encyclopedia of Prehistory (Peregrine & Ember 2001) whose compilation involved multiple data sources and over 200 researchers. The 1500 A.D. dataset involved several researchers and over 200 sources.

It is important to note that, in a majority of cases, the coding of technology adoption is based on direct evidence of the presence or absence of technologies in the countries. A relevant consideration could arise if we had a civilization covering various modern day countries and we did not have any source of evidence that the code for the civilization applies to all the individual countries. In this event, the standard errors for our regressions would be misleading. To avoid this problem, for 1500 AD, we have searched for documentation that allows us to determine the presence or absence on the countries that correspond to historical empires. For example, for the countries that composed the Ottoman empire in 1500, we have documented the presence or absence in each of the countries.

In a few cases, we have not been able to document directly the absence of some specific technology in a given country 'X'. In these cases, however, we have direct evidence of the absence of the technology is some neighboring country 'Y' that has been proven to dominate

[6] See Basalla (1988:30-57) for a number of case studies documenting technological continuity or technological evolution.

[7] Peregrine (2003) uses BP (Before Present) as the time variable when coding his datasets. We convert the BP time periods to either B.C. or A.D. Peregrine's 3000 BP dataset is used for our 1000 B.C. dataset and Peregrine's 2000 BP dataset is used for our 0 A.D. dataset.

technologically country 'X' at the time. This allows us to infer the absence of the technology in country 'X'.

An example of this is in our coding of communications in South America. We have little information about the diffusion of these technologies in 1500 AD in Brazil, Uruguay, Paraguay, and Colombia. Since the Incas were the most advanced civilization in South America during that time, any technologies absent from Inca civilization were assumed to be absent in the countries listed above. The Incas relied on Quipus (lengths of string knotted at intervals) for communications and had no written records (Scarre 1988:222; Encyclopedia Britannica 2006). This implies that the Incas did not have books or movable type printing. Using this geographic dominance argument, we infer that Brazil, Uruguay, Paraguay, and Colombia did not have these technologies either.

This geographic dominance argument might, however, have consequences on the computation of the standard errors in our regressions. Despite the few occasions where we have used the geographic dominance argument, we avoid this issue by clustering the errors around the areas of technological influence used to code the data. Further, we have checked that our results are robust to clustering the errors by continents.

Finally, there are two potential concerns in interpreting our data that we want to address directly. The first is that countries that were more advanced at the time were more likely to leave records. The second is that currently rich countries may be more likely to find remains that document the existence of technologies in the past.

We do not believe that either of these concerns has a significant influence on our data set. This conclusion is based on three reasons. First, remember that we use direct evidence of the absence of the technologies to code that the technology was not present in a country. That is, lack of evidence on the presence of the technology is not sufficient to code its absence. Second, modern day archeologists dig wherever they believe they can find remains regardless of the origin of the archeologists. Indeed, most of the main archeological discoveries are in developing countries and have been found by archeologists from developed economies. Finally, as we show in section 4.3, our findings about the persistence of technology adoption hold even when we include country (fixed and/or time varying) effects and exploit the cross-sectoral variation in technology adoption. That takes care of any country-level bias including biases in the reporting or collection of data.

2.1 Technology Datasets for 1000 B.C. and 0 A.D.

The datasets for 1000 B.C. and 0 A.D. measure the level of technology adoption for agriculture, transportation, communications, writing, and military on 113 and 135 countries respectively. The "ACE" does not contain any variable that measures directly the technologies used for military purposes. To assess a country's level of technology adoption for the military we use the "ACE" dataset to determine which metals were available for each culture. Metallurgy is integral for the development of more advanced weapons (Macksey 1993:216; Scarre 1988; Collis 1997:29). The progression from stone to bronze and finally iron corresponded to a progression of more powerful weapons; stone weapons were replaced by bronze swords and daggers; iron weapons were considerably stronger than their bronze predecessors (Hogg 1968:19-22). The relevant data from the ACE and how it is used can be found in table 1.

_________________ Insert Table 1 here _________________________

An example of how a country is coded in 1000 B.C. and 0 A.D will best illustrate our methodology.

Korea was inhabited by the Mumun peoples in 1000 B.C. The Mumuns had no tradition of either writing or non-written records. The Mumuns however did rely on agriculture as its primary form of subsistence and used pack animals for transportation. In addition the Mumuns produced metalwork and used bronze for tools but not iron (Rhee 2001). The coding for the Mumun entry in the "ACE" dataset (Peregrine 2003) therefore is:

Writing and Records = 1
Technology Specialization = 3
Land Transportation = 2
Agriculture = 3
Tools = 2

Based on this data, we code Korea in 1000 B.C. as:

Communication: Mnemonic or nonwritten records = 0; True Writing = 0
Industry: Pottery = 1; Metalwork = 1
Transportation: Pack or draft animals = 1; Vehicles = 0
Agriculture: 10% or more, but secondary = 1; Primary = 1
Military: Bronze weapons = 1; Iron weapons = 0

We aggregate the technology adoption measures at the sector level by adding all the individual technology measures in the sector and dividing the sum by the maximum possible adoption level in the sector. In this way, the sectoral adoption index is in the interval [0,1]. The overall adoption level in each country and time period is the average of the adoption level across sectors. Obviously, the overall adoption index also belongs to the interval [0,1].

The adoption levels in the four sectors just reported in Korea in 1000 B.C. are the following:

Communications = 0
Industry = 1
Transportation = 0.5
Agriculture = 1
Military = 0.5

And the overall level of technology adoption for Korea in 1000BC is 0.6.

2.2 Technology Dataset for 1500 A.D.

The technology dataset for 1500 A.D. encompasses 113 countries and evaluates the level of technology adoption across the same five sectors (agriculture, transportation, military, industry, and communications) as the previous datasets. Our technology measures outside Europe are estimated before European colonization. It is important to stress, therefore, that our technology measures in 1500 A.D. do not incorporate the technology transferred by Europeans to the rest of the world after European exploration began around 1500.

Obviously, there are a larger number of sources covering the technology adoption patterns in 1500 A.D. than in 1000 B.C. or 0 A.D. This allows us to collect adoption data for 24 technologies in the four sectors other than agriculture vs. the 11 technologies covered in the data sets for 1000 B.C. and 0 A.D. As a result, our estimate of the level of technology adoption in 1500 A.D. is likely to be more precise than for the earlier periods. Table 2 presents the various technologies measured in 1500 A.D.[8]

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3. Data analysis

3.1 Cross-country dispersion in technology

We start the data analysis by presenting in Table 3 some descriptive statistics for the overall technology adoption level in 1000BC, 0 A.D. and 1500 A.D.

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The increase in the cross-country average of the overall technology adoption level between 1000 B.C. and 0 indicates the diffusion of the technologies described in the ACE. Recall that the technology adoption data set for 1500 A.D. contains different technologies than the first two periods. Therefore, we should not compare the absolute level in 1500 AD with the previous levels.

Table 3 can help us explore how large was the cross-country dispersion in technology adoption. The binary nature of our measures of technology adoption for individual technologies provides two benchmarks to interpret the cross-country dispersion in technology adoption.[9] First, the maximum range for the average adoption level across countries is the interval [0,1]; 0 for a country that has not adopted any of the technologies and 1 for a country that has adopted all

[8] In our analysis we have experimented with some alternative aggregation schemes such as collapsing the technologies of ships capable of crossing the various oceans into just one technology without any significant change in our results.

[9] The exceptions to this rule are the measures of technology adoption in agriculture.

the technologies. Second, the maximum cross-country dispersion in adoption would occur when half of the countries have adopted all the technologies and the other half has adopted none. In this case the standard deviation of the average adoption level across countries would be 0.5.

In Table 3 we can observe how the range of the average adoption level across countries was [0, 1] in all three periods. The cross-country standard deviation in technology adoption was also very large. In all three periods, it was 60 percent of the maximum standard deviation.

Figures 1a through 1c and Table 4 explore further the cross-country variation in the overall technology adoption level. Table 4 explores the variation across continents in overall technology adoption. Figures 1a through 1c present a world map with the overall technology adoption level in each country and historical period. We use four colors to indicate technology adoption levels between 0 and 0.25, between 0.25 and 0.5, between 0.5 and 0.75 and between 0.75 and 1. Darker colors represent a higher overall technology adoption level. Missing values are represented in white.

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In all three periods, Europe and Asia present the highest average levels of overall technology adoption, while America and Oceania present the lowest, with Africa in between.

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A glimpse to the figures suffices to note that there is substantial variance in overall technology adoption both across and within continents. To make observation more precise, we decompose the cross-country variation in overall technology adoption between the variation within continents and the variation across between continents. In 1000BC, about 65 percent of the variance in overall technology adoption is due to variation within continents and 35 percent due to variation between continents. These proportions are reversed in 0 A.D. and in 1500 A.D. the share of total variance due to the between continent component rises to 78 percent.

Table 5 provides a more detailed comparison of the evolution of overall technology adoption in the most advanced countries. These countries correspond to four civilizations: Western Europe, China, the Indian civilization and the Middle Eastern peoples. Western Europe includes Spain, Portugal, Italy, France, United Kingdom, Germany, Belgium and Netherlands. The Indian civilization includes India, Pakistan and Bangladesh. Finally, the Middle Eastern civilization includes Saudi Arabia, UAE, Yemen, Oman, Iraq, Iran, Syria, Lebanon, Jordan, Egypt, Libya, Tunisia, Algeria and Morocco.

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In 1000 B.C. the Middle Eastern empires and China have an overall technology adoption level of 0.95 and 0.9 respectively, while in India and Western Europe the average adoption level are 0.67 and 0.65 respectively. In 0 A.D. India and Western Europe catch up with China and the Middle Eastern empires. In 1500 A.D. Western Europe has completed the transition and is the most advanced of the four great empires with an average overall adoption level of 0.94. China remains ahead of most countries with 0.88. But the Indian and the Middle Eastern empires have fallen behind to 0.7.

Why do our rankings differ from the view that ancient Europeans were barbarians, while China and the Middle East/Islamic civilizations were well in the lead for most of our sample period? Basically for two reasons. First, our measure is more comprehensive and it is less likely to be swayed by highly visible inventions like gunpowder in China. What we are measuring is the adoption of technologies rather than invention (i.e. by 1500 gunpowder was already adopted in Western Europe and most of the Arab world). Appendix 1 details what differences in technology adoption affected the most the rankings.

The usefulness of Table 5 goes beyond describing the relative evolution of technology in the major empires. Because our data collection exercise goes beyond a few case studies, we can put in perspective the relative dynamics of technology in the empires. In particular, the levels of technology adoption reported for the empires in Table 5 are all fairly high. Given the cross-country distribution of technology reported above, this implies that whether Europe is ahead of China or vice-versa is second order in the big scheme. The reality is that the technology is the modern-day countries that composed the historical empires was significantly above the rest of most of the rest of the countries in the world.

Underneath the overall technology adoption measures there is significant cross-country dispersion. To explore this, we subtract the country's overall technology adoption from its adoption level in each of the five sectors. Then, we compute the cross-country standard deviation of this variable to measure the within sector variation in technology adoption. Table 6 compares these measures to the cross-country dispersion in the overall technology adoption for each of the three periods we study.

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The main finding is that the within sector variation in technology adoption is approximately two thirds of the cross-country dispersion in overall technology. In section 4.3, we explore further the implications of this strikingly large heterogeneity in sectoral technology adoption.

A final check we conduct to show that our technology adoption data sets are sensible is to correlate them with the contemporaneous urbanization rate. Several authors[10] have use the urbanization rate as a proxy for development level specially for pre-modern periods such as the ones covered by our technology adoption data set.

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[10] Acemoglu, Johnson and Robinson (2002), for example.

The urbanization rate for 1000 B.C. and 0 A.D. come from Peregrine's "ACE",[11] while the urbanization rate for 1500 A.D. come from Acemoglu, Johnson and Robinson (2002). Table 7 reports the estimated contemporaneous effect of overall technology adoption on the urbanization rate. We find that there is a strong and positive contemporaneous association between technology adoption history and the contemporaneous urbanization rates. This provides further support for the quality of our measures of technology adoption in pre-colonial times.[12]

3.2 Technology history and current development

We turn next to studying whether centuries-old, pre-colonial technology history is correlated with development today. To answer this question, we estimate the following regression

$$y_c = \alpha + \beta T_c + u_c \qquad (1)$$

where y_c is the log of PPP adjusted per capita income in 2002 A.D., T_c is the measure of technology adoption and u_c is the error term.

The first three columns of Table 8 report the estimates of regression (1) when T_c is measured successively by the overall adoption level in 1000 B.C., in 0 and in 1500.A.D. (T-statistics are in parentheses.) The technology adoption level in 1000 B.C. is positively and significantly associated with the log of per capita GDP in 2002. Technology adoption in 0 A.D. is not significantly correlated to current development. The overall technology adoption level in 1500 A.D. is positively and significantly associated with current income per capita. This measure of technology in 1500 A.D. explains 18 percent of the variation in log per capita GDP in 2002.

In addition to being statistically significant, the effect is quantitatively large. Changing from the maximum (i.e. 1) to the minimum (i.e. 0) the overall technology adoption level in 1500 A.D. is associated with a reduction in the level of income per capita in 2002 by a factor of 5.

Figure 2 presents the scatter plot between overall technology adoption level in 1500 A.D. and current development. The positive relationship between these two variables is quite transparent. It is clearly not driven by outliers. In the bottom left quadrant of the plot we can see many African countries that had adopted very few of the technologies in our 1500 sample and that are quite poor today. European countries are in the top right corner.

Countries that roughly correspond to ancient empires such as Egypt, Iran, China, India, and Pakistan were middle-income countries in 2002 and had adopted between 70 and 90 percent of the technologies in our 1500 A.D. sample. These countries are slightly below the regression line in the bottom right quadrant of Figure 2. This paper does not address some well-known puzzles, such as the failure of China to capitalize earlier on its technological prowess, or the stagnation following the earlier technological prowess of the Islamic empire. These are very important

[11] Peregrine (2003) constructs a measure of the urbanization rate that can take three values. 1 if the largest settlement is smaller than 100 persons. 2 if it is between 100 and 399 persons. 3 if it is larger than 400 persons.

[12] The working paper version of this article shows that the positive contemporaneous association between overall technology adoption and the urbanization rate is robust to controlling for distance to the Equator.

puzzles that deserve (and have already attracted) their own literature, but we are concerned here with the global cross-country average relationship between old technology and modern income, and these counter-examples are not numerous enough to overturn the average global relationship.

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Latin American countries were behind the median country in the overall technology adoption level in 1500 but today they are middle income countries. This very likely has something to do with the long period of European settlement in Latin America, even though the European settlers were generally a minority of the population. Finally, in the top left corner of Figure 2 we find the Neo-Europes, the US, Canada, Australia and New Zealand. These were among the countries with most primitive technology in 1500 A.D. but are among the World's richest countries today. This is very likely due to the large-scale replacement of the original inhabitants with European settlers.

We would expect that the European settlers in the Spanish and Portuguese colonies and in the Neo-Europes affected quite dramatically the process of technology transfer (as well as other factors with which technology may be associated such as human capital accumulation and institutional development) in these countries during the colonial period. Another place where there was large scale (albeit still minority) European settlement was southern Africa. Of course, there could be technology transfer in any colonized nation, but the duration and intensity of the influence of the settlement processes in southern Africa, Latin America and the Neo-Europes suggest adding special controls. Further, the difference in the degree to which Europeans colonizers substituted for the local population justifies the distinction between the Neo-Europes and Latin America/southern Africa.

To formalize this intuition, we use the fraction of European settlers in total population in 1800 from Acemoglu, Johnson and Robinson (2001).[13] This fraction was over 90 percent for the Neo-Europes, between 15 percent and 65 percent for South Africa, Lesotho and Swaziland, and most countries in Latin America and the Caribbean, and below 15 percent for the rest of non-European countries.

Based on this, we create two dummies. The first captures predominant European settlers, and takes a value of one for the US, Canada, New Zealand and Australia and is zero for the rest of the countries. The second dummy reflects lesser European settler predominance than in the neo-Europes, and takes a value of one for the Latin American colonies of Spain and Portugal (see the appendix for a complete list), South Africa, Lesotho and Swaziland, and is zero otherwise. This yields the following regression equation:

$$y_c = \alpha + \beta T_c + Major_c + Minor_c + u_c \qquad (2)$$

[13] Similar results are obtained using the share of population from European descent in 1975 from Acemoglu, Johnson and Robinson (2001) or the fraction of European settlers 100 years after first settlement from Easterly and Levine (2006).

_______________ INSERT FIGURE 3 HERE_________________

Columns 5 through 7 in Table 8 report the estimates of equation (2) with T_c measured successively by the overall technology adoption level in 1000B.C., 0 and 1500 A.D.

_______________INSERT FIGURE 4 HERE_____________________

We find that the European settlement dummies have a significant positive relationship with current per capita income. Further, when including the European settlement dummies, the correlation between the overall technology adoption and current development increases. In particular, the effects of the technology adoption levels in 0 on current per capita income become statistically significant, and the effect of technology in 1000 BC and 1500 A.D. almost doubles. In other words, once we control for the most obvious historical example of replacement of the indigenous technology by technologies brought by new settlers, technology in ancient times becomes an even more significant predictor of per capita income today.

We acknowledge that there could have been other population migrations that transferred technology, and our singling out of the international European migration may be ad hoc, although it seems to us the primacy of European migration over the last 500 years is not really in doubt.

In any case, our results seem to hold for other population movements as well. We know from a collaborative exercise with David Weil that our findings hold also when we control more comprehensively for the international migration flows. Specifically, we use Putterman and Weil (2007)'s matrix which gives, for each country, the distribution of its current population by its origin. We then pre-multiply the vector of overall technology in 1500 AD by the origin matrix and find that the origin weighted measure of technology predicts current per capita income slightly better than the regressors in column 7 of Table 8. We do not report these results here as Putterman and Weil (2007) have not yet made their data public. Also, we continue to find significant correlations in important specifications (such as those already reported in Table 7) even when the European dummies are excluded.

_______________INSERT FIGURE 5 HERE_____________________

After including the settlement dummies, an increase in the overall adoption level from 0 to 1 in 1000 B.C. or in 0 A.D. is associated with an increase in income per capita in 2002 by a factor of 4. A similar increase in the overall adoption level in 1500 A.D. is associated with an increase in per capita income in 2002 by a factor of 19. This is half of the current difference in income per capita between the top and bottom 5 percent of the countries in the world. [14]

Similarly, 20 percent of the income difference between Europe and Africa is explained by Africa's lag in overall technology adoption in 1000 B.C., 8 percent is explained by the technology distance in 0 A.D., and 78 percent is explained by Africa's lag in overall technology adoption in 1500 A.D. This gives a very different perspective on Africa's poverty compared to the usual emphasis on modern governments. It also shifts backward in time the historical explanations for

[14] Table A1 shows the robustness of this finding to using as endogenous variable per capita income in earlier points in time. In particular, the table uses 1913, 1960 and 1990.

Africa's poverty, compared to the usual emphasis of historians on the slave trade and colonialism.[15]

Figures 3 through 5 display the scatter plots of the current income per capita and overall technology adoption after regressing these variables on the European influence dummies. These figures confirm the significant association between current development and historical technology after conditioning on the European influence dummies. Clearly, the strongest relationship holds between overall technology adoption in 1500 A.D. and current development.

3.3 Robustness

We explore the robustness of the findings encountered so far. We start by exploring whether we are identifying the effect of historical technology on current development through the cross-continent variation or also through the within continent variation. To answer this question, the first three columns of Table 9 report the estimates of regression (2) when adding four continent dummies to the control set.

We extract two main conclusions from columns 1 through 3. First, much of the effect of technology history is detected from the cross-continent variation. Adding the continent dummies eliminates the effect of overall technology adoption in 1000 B.C. on current development (column 1), and reduces by 60 percent the effect of technology adoption in 0 A.D. (column 2) and in 1500 A.D. (column 3) on current development. Only 1500 AD is still significant. The flip side of this is that a significant fraction of the effects of technology adoption history in 0 A.D. and 1500 A.D. on current development is driven by the within continent variation. In particular, the within continent variation in overall technology adoption in 1500 A.D. can still account for cross country variation in current income per capita by a factor of 4.5.[16]

_______________ INSERT TABLE 9 HERE _________________

Gallup, Sachs and Mellinger (1999) have argued that the latitude is an important determinant of income per capita, with the tropics at a disadvantage. Hall and Jones (1999), Acemoglu, Johnson, and Robinson 2002, Easterly and Levine 2003 and Rodrik et al. (2003) argue that the effect of tropical location is through institutions. Columns 4 through 6 in Table 9 report the estimates of regression (2) after controlling for the distance to the Equator. As emphasized by the previous literature, being far from the Equator tends to be associated with higher levels of current income per capita. Controlling for the latitude of countries, however, does not eliminate the strong positive effect of overall technology adoption in 1500 A.D. on current development. This effect remains statistically significant, though the association of technology adoption history on 1000 B.C. and in 0 A.D. on current development become insignificant after controlling for the

[15] There was some slave trade before 1500 A.D. across the Sahara and along the Indian Ocean. However, most accounts of the negative effects of the slave trade stress the Atlantic slave trade, which only became nontrivial after 1500 A.D.

[16] One interesting question is whether the effect of historical technology on current development works through a positive effect on total GDP or through a negative effect on current population. In the working paper we show that the relationship works entirely through the effect of technology on GDP. Indeed, historical technology also has a strong and robust relationship with current population, but the effect on current GDP is so large that more than compensates the effect on population.

distance to the Equator.[17] In columns 7 through 9 we additionally control for whether countries are land-locked reaching the same conclusions as in columns 4 through 6.

An interesting question is why the geography controls reduce the significance of historical technology adoption on current development. Of course, there are many possible explanations for this observation. One consistent with the model presented in section 4 is that geography affects the diffusion of technologies. Technologies diffuse faster within than across continents. Diamond (1997) advanced the hypothesis that certain technologies diffuse along latitudes. Finally, landlocked territories may be less exposed to newer technologies and hence adopt them later and/or less intensively.

_______________ INSERT TABLE 10 HERE _________________

As we have noted above, the association between land area and ancient technology could be reverse causality, since a larger land area contained a larger sample of cultures and technologies from which we are coding the "best." We conclude, however, that this is not a very significant concern based on two results reported in Table 10. First, per capita GDP today is uncorrelated with land area. Second, the correlation between historical technology adoption and per capita GDP today remains unaffected by the land area control. So the association between contemporaneous technology (as reflected in today's per capita GDP) and land area does not seem to reflect any dominant "sampling" effect (although this could have changed from ancient times).

4. A model of endogenous technology adoption and discussion

We next present a model that provides a simple rationalization for the facts uncovered so far. The model is also an effective tool to help us think about alternative hypothesis and how to identify them in the data.

4.1 Baseline model

Generations are indexed by t. Countries are indexed by c. Let A_{ct} denote the number of technologies adopted up to t. The representative agent in the country lives for one generation and decides how many new technologies to adopt during that period. The (gross) value he obtains from adopting ΔA_{ct} new technologies technology is

$$\pi_{ct} = \overline{\Theta}_{ct} \Delta A_{ct} \qquad (3)$$

where $\overline{\Theta}_{ct}$ is a potentially time-varying parameter.

The cost of adopting new technologies is given by the following function.

$$C_{ct} = b_{ct} \frac{(\Delta A_{ct})^{\gamma}}{A_{ct-1}} \qquad (4)$$

where b_{ct} may be time-varying and $\gamma \in [2, \infty)$ implying that the cost is increasing and convex in the number of new technologies adopted in the period. Note that, in this formulation, the cost

[17] Similar results hold when including a tropical dummy instead of the distance from the Equator.

of adoption declines with the stock of technologies previously adopted in the country. This is the case both because existing technologies reduce the physical cost of adopting the new technologies and because adopters learn from previous adoption experience. This learning may be formal (e.g. training) and/or informal (e.g. trial and error) but as a result of it, technological leaders are the first to adopt new technologies.

Optimal adoption of new technologies yields the following law of motion for A_{ct}.

$$\frac{\Delta A_{ct}}{A_{ct-1}} = \left(\frac{\Theta_{ct} A_{ct-1}^{1}}{A_{ct-1}^{\gamma-1}} \right)^{\frac{1}{\gamma-1}} \tag{5}$$

where

$$\Theta_{ct} \equiv \frac{\overline{\Theta}_{ct}}{\gamma b_{ct}} \tag{6}$$

To make further progress, it is useful to rewrite (5) using the log approximation around the deterministic steady state as follows:

$$a_{ct} = \frac{1}{\gamma-1}\theta_{ct} + \frac{1}{\gamma-1}a_{ct-1} \tag{7}$$

where $\theta_{ct} \equiv \log(\Theta_{ct})$ and $a_{ct} \equiv \log(A_{ct})$.

Iterating (7) back in time we obtain

$$a_{ct} = \sum_{\tau=1}^{t} \theta_{ct-\tau+1} \left(\frac{1}{\gamma-1} \right)^{\tau} + \left(\frac{1}{\gamma-1} \right)^{t} a_{c0} \tag{8}$$

We further assume that $\theta_{ct} = \alpha \theta_{ct-1} + \varepsilon_{\theta ct}$, where $E_0 \varepsilon_{\theta ct} = 0$, for t>0. Then, it follows that the expected level of technology adopted at t given the adoption history up to time 0 is

$$E_0(a_{ct}) = \frac{\alpha}{\gamma-1} \frac{\alpha^t - \left(\frac{1}{\gamma-1} \right)^t}{\alpha - \frac{1}{\gamma-1}} \theta_{c0} + \left(\frac{1}{\gamma-1} \right)^t a_{c0} \tag{9}$$

To derive the relationship between historical technology and current per capita income, we just need to assume that, at least in modern times, per capita income is determined by contemporaneous technology.[19] Formally,

$$y_{ct} = a_{ct} \tag{10}$$

Hence,

$$E_0(y_{ct}) = \frac{\alpha}{\gamma-1} \frac{\alpha^t - \left(\frac{1}{\gamma-1} \right)^t}{\alpha - \frac{1}{\gamma-1}} \theta_{c0} + \left(\frac{1}{\gamma-1} \right)^t a_{c0} \tag{11}$$

[19] This might not have been the case in pre-industrial societies where population is determined by Malthusian dynamics as in Kremer (1993), Galor and Weil (2000), Prescott and Hansen (2002) and Jones (2001, 2005), but it is a very reasonable assumption for modern societies.

This simple model delivers three testable predictions. First, since 't' is very large in our sample, the coefficient of a_{c0} in (11), $\left(\frac{1}{\gamma-1}\right)^t \rightarrow 0$ if $\left(\frac{1}{\gamma-1}\right)$<1. In other words, given the magnitude of 't', this coefficient can only be quantitatively different from zero if $\left(\frac{1}{\gamma-1}\right)$≈1.

Second, equation (9) implies that if $\left(\frac{1}{\gamma-1}\right)$≈1, there is persistence in technology adoption. That is, the technology adoption history helps predict current technology adoption. Third, the reason why technology adoption history can predict current development is because it can predict current technology. Therefore, after controlling for current technology historical technology adoption should not help us forecast current development.

These predictions can easily be tested with our data. To explore whether technology is persistent, we estimate the cross-country correlation of technology adoption across time periods.

__________________ INSERT TABLE 11 HERE ________________

As reported in Table 10, the correlation of the overall technology adoption level between 1000 B.C. and 0 is 0.62, between 0 A.D. and 1500 A.D. it is 0.71 and between 1000 B.C. and 1500 A.D. it is 0.68. This remarkably high persistence of technological differences over 2500 years of human history is an important finding of our paper. (It is also reassuring that the error rate on our technological measures is not disastrously high.)

We find instructive to make a quantitative assessment of this persistence. If 't' is measured in years, the autocorrelations estimated in the first column of Table 11 imply that when calibrated annually, $\left(\frac{1}{\gamma-1}\right) \geq 0.9995$.

We also observe this high persistence of technology adoption for the sector-level measures. The average correlation coefficient between the technology adoption in a sector in one period and in the subsequent period is around 0.5. Technology adoption is most persistent in military, industry and transportation. The lowest correlation is in communications between 1000 BC and 1500 AD. This latter correlation is still statistically significant at the 5 percent level. All the other correlations reported in Table 10 are significant at the 1/10000 level.

As shown in Table 12, this persistence is not driven by the geographical variables since it holds once we control for the continent, the latitude and whether the country is landlocked.

To explore whether the persistence of technology has 'persisted' until current times, we construct a measure of current technology level based on Comin, Hobijn and Rovito (2006). This measure captures (minus) the average gap in the intensity of adoption of ten major current technologies with respect to the US.[20] More specifically, for each technology, Comin, Hobijn and Rovito (2006) measure how many years ago did the United States last have the usage of technology ‘x’ that country ‘c’ currently has. We take these estimates, normalize them by the number of years since the invention of the technology to make them comparable across technologies, take the average across technologies and multiply the average lag by minus one to obtain a measure of the average intensity gap with respect to the US.

Note that this measure of current technology adoption differs from the historical measures in that it includes the intensive margin. This is the case because in the last 100 years or so, the first unit of technology has diffused very quickly across countries. Therefore, the intensive margin of technology adoption is the relevant margin to explain cross-country differences in technology.

The first three columns of Table 13 present the association between technology adoption in the three historical periods and current technology adoption. The main finding is that current technology is correlated with historical technology adoption in all three periods. As one would expect, the correlation is higher the more recent is the historical period.

_______________ INSERT TABLE 13 HERE _______________

Columns 4 through 6 of Table 13 shows that from 1500 AD to the present, technology adoption is also highly persistent after controlling for the distance to the Equator and being land-locked, although 1000 BC and 0 AD are not robust to this control. Lastly, controlling for continent dummies, the within-continent technology differences are also persistent for 0 and 1500 AD, although not for 1000 BC. The persistence of technology across the last 500 years, or the last 2000 years, is not just due to differences between continents.

________________ INSERT TABLE 14 HERE _________________

We conclude this exploration of the model predictions by investigating the third prediction, namely that the effect of historical technology adoption on current development operates through current technology adoption. Table 14 shows the strong positive association between current technology and development. Our measure of current technology alone, can account for 80 percent of the cross-country variation in current development. The importance and significance of this variable is robust to controlling for the distance to the equator and for the continent dummies.

In columns 4 through 8 of Table 14 we include our measure of overall technology adoption in 1500 AD as an additional control. However, its association with current development becomes insignificant once we control for current technology. This is the case even after including the European influence dummies (columns 7 and 8). Since technology 1500 AD was robust and significant in our previous regressions, we interpret this finding as evidence that the effect of historical technology on current development operates most robustly through the effect that historical technology adoption has on current technology adoption.

[20] In particular, these technologies are electricity (in 1990), internet (in 1996), pcs (in 2002), cell phones (in 2002), telephones (in 1970), cargo and passenger aviation (in 1990), trucks (in 1990), cars (in 1990) and tractors (in 1970) all in per capita terms.

4.2 Population

One interpretation of the findings so far is that technology is a very powerful propagation mechanism. That is, a variety of factors (e.g. institutions, geography shocks, luck,...) affect the return to adopting technology in the distant past and those historical technology adoption levels are propagated into the present through the effect that technology has on the agent's incentives to adopt subsequent technologies.

An alternative view, also consistent with the model presented above, is that the powerful propagation mechanism is not the dynamics of technology adoption but the dynamics of the return to adopting technology (θ_{ct}). That is, rather than having $\left(\frac{1}{\gamma-1}\right)$≈1, the persistence of historical adoption results from α≈1.

One variable that has been linked to the returns to adopting technology is population. Kremer (1993) and Jones (2001, 2005) develop models where this is the case because of the presence of fixed costs in the process of improving the technology. Similarly, semi-endogenous growth models (e.g. Jones (1995), Kortum (1997), Segerstrom (1998)) also have the feature that the force that ultimately keeps ignited the agents' incentives to improve technology is the continuous expansion of the scale in the economy. This literature, though, has not emphasized the cross-sectional implications of their models. However, when incorporating significant fixed costs of adopting technologies in the country - implied by the fact that some technologies are not adopted (Table 3)- into semi-endogenous growth models, they predict that the returns to adoption are increasing in the country's population.[21]

Our simple model can accommodate this insights by assuming that $\theta_{ct} = l_{ct}$, where l_{ct} is the log population and evolves according to $l_{ct} = n_c + l_{ct-1} + \varepsilon_{lct}$, $E_0 \varepsilon_{lct} = 0$, for t>0. Then, a_{ct} can be expressed as:

$$a_{ct} = \sum_{\tau=1}^{t} \left(n_c (t-\tau+1) + l_{c0} + \sum_{q=1}^{t-\tau+1} \varepsilon_{lcq} \right) \left(\frac{1}{\gamma-1} \right)^{\tau} + \left(\frac{1}{\gamma-1} \right)^{t} a_{c0} \qquad (12)$$

Over the long horizons we consider in this paper, $n_c \approx \frac{l_{ct} - l_{c0}}{t}$. Hence**,** (12 implies)

$$E_0(a_{ct}) = \left[\sum_{\tau=1}^{t} \frac{(t-\tau+1)}{t} \left(\frac{1}{\gamma-1} \right)^{\tau} \right] (l_{ct} - l_{c0}) + \left(\frac{1}{\gamma-1} \right)^{t} a_{c0} + \frac{1 - \left(\frac{1}{\gamma-1} \right)^{t}}{\gamma - 2} l_{c0} \qquad (13)$$

Expression (13) implies that if $\left(\frac{1}{\gamma-1}\right)$<1, historical technology should not predict current technology once we control for historical and current population. Further, failing to control for

[20] If this is not the case, then population simply cannot be the propagation mechanism that generates the persistence of the country's technology.

current and past population in our regressions may cause an upward bias in our estimate of $\left(\frac{1}{\gamma-1}\right)$ if the return to adopting technology, θ_{ct}, is higher in larger countries.

To identify whether the observed persistence of technology is driven by the omission of population in our regressions or because technology is a very powerful propagation mechanism, we just have to control for historical and current population in our baseline regression (2). Note that this identification strategy does not hinge in any way on the simplifying assumption that ζ=0. In other words, this test is valid regardless of the influence from other countries technology in the adoption cost. Table 15 and 16 report the results from such an exercise.

________________ INSERT TABLE 15 HERE _________________

The first three columns report the effect of technology and population in 1500 AD on current per capita income (column 1), current technology (column 2) and current population (column 3). The main finding is that the observed effect of historical technology on current development and current technology is robust to controlling for historical population. Indeed, the effect of historical population on current development is negative and significant. Both historical technology and population have positive significant effects on current population, although the significance of historical population is much higher.

We conduct similar exercises with technology (column 4) and population (column 5) in 1500 AD as dependent variables and technology and population in 0 as independent variables. Our findings are very similar to those reported in the first three columns of Table 15. Most significantly, the effect of technology adoption in 0 on technology in 1500 persists after controlling for population in 0.

________________ INSERT TABLE 16 HERE _________________

Expression (13) implies that to identify the propagation mechanism that generates the persistence of technology, we should control both for historical and for current population. Table 16 conducts this more proper test by including current population as control. Regardless of whether we use current development (column 1) or technology (column 2) as dependent variables, we still find that technology in 1500 AD has a strong and significant effect on current outcomes. Contrary to what expression (13) predicts, current population has a negative and significant effect on current development and technology. Population in 1500 has an insignificant effect. A shortcoming of this exercise is the endogeneity of current population, which we do not have a good means of addressing because of a lack of any obvious instrument.

In columns 3 and 4 of Table 16 we control further for the continent dummies. This reduces the magnitude of the coefficients but the effect of technology adoption in 1500 on current development and technology still remains significant.

These findings are suggestive that the returns to technology adoption are not primarily driven by population and that population dynamics are not the primary propagation mechanism that generates the observed effect of technology adoption history on current development.

4.3 Institutions, culture, genes

The literature has emphasized at least three more variables that are likely to affect the return to adopting technology and could be driving the observed persistence of technology. These are institutions, culture and genetics. If any of these variables affects historical technology adoption and is sufficiently persistent, its omission from our regression will bias the estimate of $\left(\frac{1}{\gamma-1}\right)$ and could rationalize the facts presented so far.

Common measures of institutions do not seem to be sufficiently persistent to cause any significant bias. Przeworski (2004) has calculated that the correlation of 'constraints on executive' for 59 countries from Polity IV from first year of independence to most recent year available is only .26. Similarly, we have estimated the cross-country correlation in the democracy variable from Polity IV in 2000 with the same variable in 1950 to be .33. It seems remarkable that these widely used measures of institutions are less persistent over a 50-year period than technology adoption over a 2500 year period.[22] (However, this is only one measure of institutions, and "deeper" measures of institutions may show much more persistence.) If institutions really do have low persistence, omitting historical institutions from our baseline regression should not bias our estimate of $\left(\frac{1}{\gamma-1}\right)$.

Further progress can be made in the estimation of $\left(\frac{1}{\gamma-1}\right)$ if we assume that, the effect of institutions, culture and genetic endowment on the return to technology adoption has an important symmetric component across sectors. affect symmetrically the return to technology adoption in different sectors of the economy. That is, once good institutions preserve property rights, agents adopt new technologies in all sectors (covered by our data set).[23] Under this sensible assumption, we can estimate $\left(\frac{1}{\gamma-1}\right)$ by exploiting the large observed within sector variation in technology adoption (see Table 6). This intuition is formalized with the following multi-sector extension of our baseline model.

Suppose that the profits and costs from adopting ΔA_{cst} new technologies technology in sector *s* are, respectively

$$\pi_{cst} = \overline{\Theta}_{cst} \Delta A_{cst} \tag{14}$$

$$C_{cst} = b_{cst} \frac{(\Delta A_{cst})^{\gamma}}{A_{cst-1}} \tag{15}$$

[22] We have not conducted a similar exercise for culture because we do not have a widely accepted measure of culture.
[23] Similarly, that the forces by which culture and genes affect technology adoption (e.g. higher willingness to experiment or higher I.Q.) are relevant to all the sectors covered in our data sets.

Note that in this formulation, the cost of adoption declines in the level of technology adopted in the sector. Then the optimal adoption of technology in sector *s* and country *c* implies the following law of motion for technology.

$$\frac{\Delta A_{cst}}{A_{cst-1}} = \left(\frac{\Theta_{cst} A_{cst-1}}{A_{cst-1}^{\gamma-1}} \right)^{\frac{1}{\gamma-1}} \tag{16}$$

where

$$\Theta_{cst} \equiv \frac{\overline{\Theta}_{cst}}{\gamma b_{cst}} = \Theta_{ct}^{I} * \Theta_{cs}^{S} * \Theta_{cst}^{S} \tag{17}$$

Let $\theta_{cst}^{S} \equiv \log(\Theta_{cst}^{S})$ be a zero mean, iid, term, $\theta_{ct}^{I} \equiv \log(\Theta_{ct}^{I}) = \alpha_I \theta_{ct-1}^{I} + \varepsilon_{Ict}$, where $E_0 \varepsilon_{Ict} = 0$ for t>0 and $\theta_{cs}^{S} \equiv \log(\Theta_{cs}^{S})$.

Then,

$$a_{cst} = \sum_{\tau=1}^{t} \left(\theta_{ct-\tau+1}^{I} + \theta_{cs}^{S} + \theta_{ct-\tau+1}^{S} \right) \left(\frac{1}{\gamma-1} \right)^{\tau} + \left(\frac{1}{\gamma-1} \right)^{t} a_{cs0} \tag{18}$$

and

$$E_0(a_{cst}) = \left[\frac{\alpha}{\gamma-1} \frac{\alpha^t - \left(\frac{1}{\gamma-1} \right)^t}{\alpha - \left(\frac{1}{\gamma-1} \right)} \right] \theta_{c0}^{I} + \left[\frac{1 - \left(\frac{1}{\gamma-1} \right)^t}{1 - \left(\frac{1}{\gamma-1} \right)} \right] \theta_{cs}^{S} + \left(\frac{1}{\gamma-1} \right)^{t} a_{cs0} \tag{19}$$

The empirical counterpart of equation (19) is

$$a_{cst} = \beta_{ct-1} + \beta_{cs} + \vartheta * a_{cst-1} + u_{cst} \tag{20}$$

This regression includes a country effect (β_{ct-1}) that could be time-varying and a country-sector fixed effect (β_{cs}). The identification of ϑ presents the well-known challenge often encountered in convergence regressions of a lagged dependent variable. To solve this problem we first difference equation (20) obtaining

$$a_{cst} - a_{cst-1} = \beta_{ct-1} - \beta_{ct-2} + \vartheta * (a_{cst-1} - a_{cst-2}) + \overline{u}_{cst} \tag{21}$$

and instrument $a_{cst-1} - a_{cst-2}$ with a_{cst-2} . If a_{cst-2} is uncorrelated with $\overline{u}_{cst}$ our estimate of ϑ should be unbiased. We are going to implement regression (21) with *t* = 2000AD, *t-1* = 1500 AD and *t-2* = 0 AD. We find it sensible that $\overline{u}_{cst} \equiv u_{cs2000} - u_{cs1500}$ is uncorrelated to the technology adoption level in 0 AD (i.e. 1500 years before).

In our list of current technologies we have no military technology. Hence, we estimate (21) using data on the other four sectors in our data set. Since, from our previous results, the European influence will have an effect on the growth of technology between 1500 and 2000, we control for the two European influence dummies when estimating ϑ in (21).

_________________ INSERT TABLE 17 HERE __________________

Table 17 reports the estimates of ϑ with (column 1) and without (column 2) the country fixed effects in the growth rates. There are several important implications from these estimates. The main finding is that we observe very large and significant estimates of ϑ in both specifications.

Recall that both of these regressions include country fixed effects in levels and country-sector fixed effects in levels. This is suggestive that extremely persistent factors that have remained constant over the last 500 years and which may or may not have affected asymmetrically technology adoption in the country - such as genes or geography- are not the primary drivers of the estimates of the persistence of technology (i.e. ϑ).

A second interesting observation is that the estimates of ϑ are virtually unaffected by the inclusion of the country-effects in the growth rates. These terms capture changes at the country level between 1500 and 2000 which affect symmetrically the adoption of technology across sectors (within the country). The fact that including these country effects in the regressions does not affect our estimate of ϑ (indeed it increases) is suggestive that omitted time-varying factors that have an important component which should affect the adoption of technology in many sectors in the economy – such as institutions – are not primarily driving the observed high persistence in technology adoption.[24] Note that this argument stands even if the omitted variable has a differential effect across sectors as long as it has a significant common component.

Because of potential cross-technology differences in diffusion not captured by our model, we explore the robustness of our estimates of ϑ to including technology-specific intercepts. As is clear from columns (3) and (4) of table 17, the significance of ϑ is unaffected. Interestingly, the similarity of the point estimates with and without country fixed-effects in the growth rates also persists after including technology-specific intercepts.

We conclude our empirical exploration of the sources of persistence in technology adoption by showing that the significance of ϑ is not driven by any single sector. In columns 5 through 8 of Table 17 we report the estimates of ϑ after eliminating successively one of the four sectors - recall that we have excluded the military technologies from this analysis- covered in our data set.

Two observations emerge from this exercise. First, the significance of the estimate of ϑ is not driven by any specific sector. Second, when comparing the estimates of ϑ obtained by exploiting the sectoral variation in technology adoption (e.g. columns 3-8 of Table 17) with the estimates we obtained when using the cross-country variation (e.g. columns 3, 6 and 9 of Table 13) it turns out that the former are not smaller than the later.

As argued above, this is hard to reconcile for theories where the mechanism that induces the persistence of technology has an important country component. Instead, this observation can be accounted for naturally by our simple theory since the knowledge created when adopting a technology is likely to reduce the costs of adopting subsequent technologies in the sector but not so much in other sectors.

Hence, we are inclined to conclude that the most natural explanation for the findings presented in this paper is that the dynamics of technology adoption are a very powerful propagation mechanism that transmits significant shocks of very diverse nature into the distant future. The

[24] We do not know whether the aspects of culture which are relevant for adoption of technology are fixed over a 500 year period or time varying, but in either case, they should be taken care off by one of the two arguments posed above.

primary feature of our model that predicts this result is that the cost of technology adoption is lower the higher is the previous stock of technology.

5. Conclusions

The main finding of this paper is a simple one: centuries-old technological history is associated with the wealth of nations today. This is largely robust to including continent dummies and geographic controls, so it is not just driven by “Europe vs. Africa” or “tropical vs. temperate zones.” There two most-surprising parts of the finding. The first is just how old the history can be and still be correlated with modern outcomes. Our most robust finding is that technology in 1500 AD is correlated with development outcomes today, itself remarkably old when we consider that most history discussions of developing countries start (at most) with European contact and colonization. The second most-surprising aspect of our finding is how large is the magnitude of the association between historical technology adoption and current development. In our baseline specification, going from having none to having adopted all the technologies available in 1500 AD is associated with an increase in current per capita GDP by a factor of 17. Even after including a battery of controls, this factor is over 5.

In an effort towards understanding what drives this surprising correlation, we have found suggestive results that technology is very persistent, that this persistence is not primarily driven by the persistence of population and that it does not diminish when exploiting the sectoral variation in technology adoption after removing the country average adoption level in the period and country-sector fixed effects. This evidence provides support to the hypothesis that the technology adoption dynamics are the mechanism that generates the propagation uncovered in the data.

Our findings are likely to have significant policy implications at least with respect to the immediacy of the effects of policies on development. The tendency of policymakers and international institutions to overemphasize the instruments under their control may have contributed to an excessive weight being placed on the behavior of modern-day governments and development strategies as a determinant of development outcomes. We do not claim that history is destiny. On the one hand, technology history only explained a partial share of the modern day variance of development outcomes, and so history is obviously not *everything*. On the other hand, in our model, technology just acts as a propagation mechanism of a variety of shocks. Hence, today's policies may have an effect on development but it may not be trivial to overturn the technological history of a nation and, in any case, it may take a significant amount of time before the effects of the policies show up in the development measures.

References

Acemoglu, D., S. Johnson and J. Robinson,(2002), “Reversal of Fortune: Geography and Institutions in the Making of the Modern World Income Distribution” *Quarterly Journal of Economics*, (November), v. 117, iss. 4, pp. 1231-94

Adshead, S.A.M. (1988) *China in World History.* New York: St. Margin's Press, Inc.

Barry, H. , III, & L.M. Paxson (1971) "Infancy and Early Childhood: Cross Cultural Codes 2," *Ethnology.* 10, pp. 466-508.

Basalla, G. (1988) *The Evolution of Technology.* Cambridge, United Kingdom: Cambridge University Press.

Black, J. (1996) *The Cambridge Illustrated Atlas of Warfare: Renaissance to Revolution 1492-1792.* Cambridge, United Kingdom: University of Cambridge.

Carneiro, R.L. (1970) "Scale Analysis, Evolutionary Sequences, and the Rating of Cultures" In: R. Naroll & R. Cohen eds. *A Handbook of Method in Cultural Anthropology.* Garden City, New York: The Natural History Press. pp: 834-871.

Collis, J. (1984) *The European Iron Age.* New York: Routledge.

Diamond, J. (1997) *Guns, Germs, & Steel.* New York: W.W. Norton & Company.

Easterly, W. and R. Levine (2003) “Tropics, germs, and crops: the role of endowments in economic development” Journal of Monetary Economics, 50:1, January 2003.

Encyclopedia Britannica (2006h) "chariot," Encyclopædia Britannica Online. http://search.eb.com/eb/article-9022532

Encyclopædia Britannica (2006) "Inca" Encyclopædia Britannica Online. 19 Aug. 2006 http://search.eb.com/eb/article-9042237

Erman, A. (1971) *Life in Ancient Egypt.* New York: Dover Publications Inc.

Gallup,J., J. Sachs, and A. Mellinger (1999) "Geography and Economic Development,", *International Regional Science Review*, Vol. 22, No. 2, pp. 179-232, August 1999.

Galor O., "From Stagnation to Growth: Unified Growth Theory", in P. Aghion and S. Durlauf, editors, *Handbook of Economic Growth*, 2005, 171-293.

Galor, O., and D.N. Weil (2000), “Population, Technology and Growth: From the Malthusian regime to the Demographic Transition”, *American Economic Review* 110: 806-828.

Greene, K. (2000). Technological Innovation and Economic Progress in the Ancient World: M.I. Finley Re-Considered. *The Economic History Review*, New Series, Vol. 53, No. 1 (Feb. 2000), pp. 29-59.

Hall, R. and C. Jones (1999) "Why Do Some Countries Produce So Much More Output per Worker than Others?", *Quarterly Journal of Economics*, February 1999, Vol. 114, pp. 83-116.

Hogg, O.F.G. (1968) *Clubs to Cannon, Warefare and Weapons before the introduction of Gunpowder.* London: Gerald Duckworth & Co. Ltd.

Jones, C.. “Growth and Ideas.”in P. Aghion and S. Durlauf, editors, *Handbook of Economic Growth*, 2005

Kerr, R. & N. Wood (2004) *Joseph Needham Science and Technology in China, Vol 5 Chemistry and Chemical Technology, Part XII: Ceramic Technology.* Cambridge, United Kingdom: Cambridge University Press.

Kipfer, B.A. ed. (2000) *Encyclopedic Dictionary of Archaeology.* New York: Lluwker Academic/Plenum Publishers.

Klenow, P. and A. Rodriguez-Clare (1997) "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" with Andrés Rodríguez-Clare, *NBER Macroeconomics Annual 1997*, B. Bernanke and J. Rotemberg ed., Cambridge, MA: MIT Press, 73-102

Kremer, M. “Population Growth and Technological Change: One Million B.C. to 1990,” *The Quarterly Journal of Economics*, Vol. 108, No. 3 (Aug., 1993), pp. 681-716.

Lucas, A. (1934) *Ancient Egyptian Materials & Industries*. London: Edward Arnold & Co.

Macksey, K. (1993) *The Penguin Encyclopeida of Weapons and Military Technology, Prehistory to the Present Day.* New York: Penguin Books USA.

McEvedy, C. and R. Jones (1978) *Atlas of World Population History* Penguin Books, London.

Mokyr, J. (1990) *The Lever of Riches: Technological Creativity and Economic Progress.* Oxford; New York; Toronto and Melbourne: Oxford University Press.

Mokyr, J. (2005) , The Intellectual Origins of Modern Economic Growth, The Journal of Economic History**,** VOLUME 65 JUNE 2005 NUMBER 2, 285-351.

Murdock, G.P. (1967) *Ethnographic Atlas.* University of Pittsburgh Press.

Murdock, G.P. & D.O. Morrow (1970) "Subsistence Economy and Supportive Practices" In: A. Spoher ed. *Ethnology,* 9. No. 3. pp: 302-330.

Murdock, G.P. & C. Provost (1973) "Measurement of Cultural Complexity" In: A. Tuden ed. *Ethnology*, 12, No. 4. pp: 379-392.

Murdock, G.P. & S.F. Wilson (1972) "Settlement Patterns and Community Organization," *Ethnology.* 11, pp. 254-295.

O'Brien, P.K. ed. (1999) *Atlas of World History.* New York: Oxford University Press.

Peregrine, P.N. (2003) "Atlas of Cultural Evolution" In:J.P. Gray ed. *World Cultures,*14, no. 3. pp: 1-75.

Peregrine, P.N. , & M. Ember eds. (2001a) *Encyclopedia of Prehistory.* Vols 1-8. New York: Kluwer Academic/Plenum Publishers.

Peregrine, P.N. , & M. Ember eds. (2001b) *Encyclopedia of Prehistory.* Vol 9.New York: Kluwer Academic/Plenum Publishers.

Pulkki, A.M., and P. Stoneman (2006) "International Diffusion of New Technologies: Intensive and Extensive Margins." Mimeo University of Warwick.

Rodrik, D. A. Subramanian, F. Trebbi (2004) "Institutions Rule: The Primacy of Institutions over Geography and Integration in Economic Development." *Journal of Economic Growth*, June 2004, v. 9, iss. 2, pp. 131-65

Rosenberg, N. and L.E. Birdzell Jr. *How the West Grew Rich: The Economic Transformation of the Industrial World*, Basic Books: New York, paperback reprint, 1987.

Rouse, I. (1972) *Introduction To Prehistory, A Systematic Approach.* New York: McGraw-Hill Book Company.

Scarre, C. ed. (1988) *Hammond Past Worlds The Times Atlas of Archaeology.* Maplewood, New Jersey: Hammond Inc.

Spolaore, Enrico and Romain Wacziarg, The Diffusion of Development, mimeo, Tufts and Stanford, March 2006

Tuden, A. & C. Marshall (1972) "Political Organization," *Ethnology.* 11, pp. 436-464.

Wager, D. B. (1993) *Iron and Steel in Ancient China.* New York: E.J. Brill.

Appendix 1

In Table 5 we document the progression of advanced civilizations (Western Europe, China, India, and the Arab Empire) from 1000 BC to the 16th century. Initially Western Europe lagged behind other civilizations but assumed technological leadership by 1500 AD. Western Europe initially started as the least technological sophisticated of the major advanced civilizations in 1000 B.C. It's lowly position was due to it's slower adoption of communications, transportation, and military technology.   Western Europe, with the exception of Italy, had not yet adopted written records for communication, vehicles for transportation, and iron weapons. Other advanced civilizations at the time, such as China and the Arab Empire already were using these technologies. However, by 0 A.D. Western Europe had adopted these technologies, and by 1500 A.D. it was the most technologically advanced civilization. Western Europe's ascendancy is primarily due to advances in transportation and military technology.. During the 16th century, Western Europe alone had expeditions across all major oceans. These journeys required adopting a number of shipbuilding and navigational technologies. Western Europe also was at the forefront in naval weapons. The navies of Western Europe deployed large warships (in excess of 1500 ton deadweight) with armaments of over 180 guns by the 16the century. Even advanced civilizations such as China and the Arab Empire had not yet adopted these advanced weapons.

Figure 2: Technology in 1500 and current development

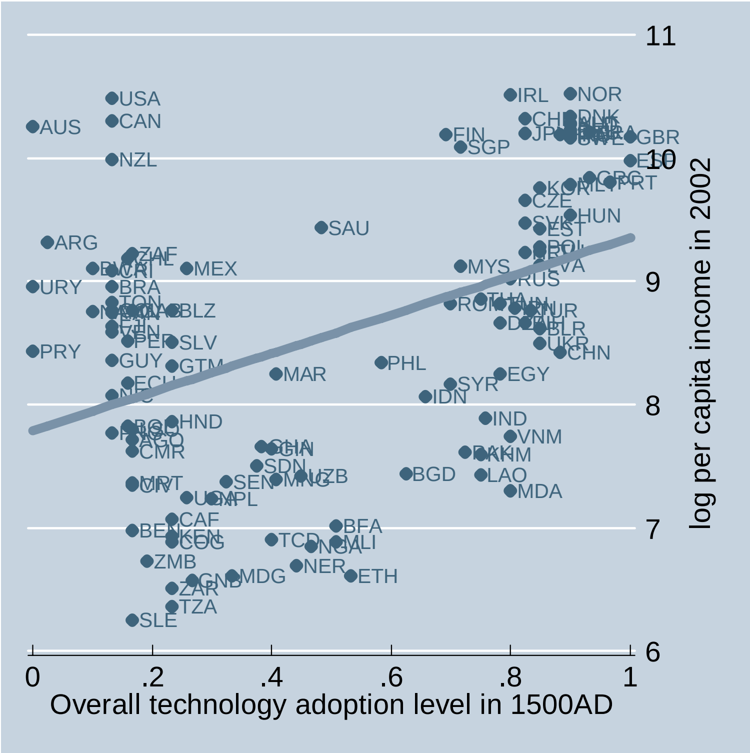

Figure 3: (Conditional) overall technology adoption in 1000 B.C. and (conditional) current development

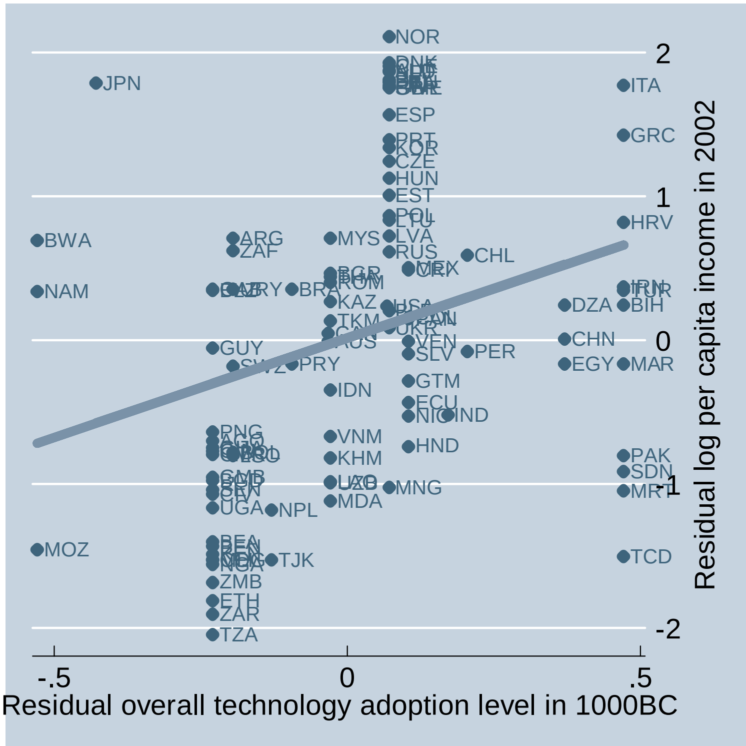

Figure 4: (Conditional) overall technology adoption in 0 A.D. and (conditional) current development

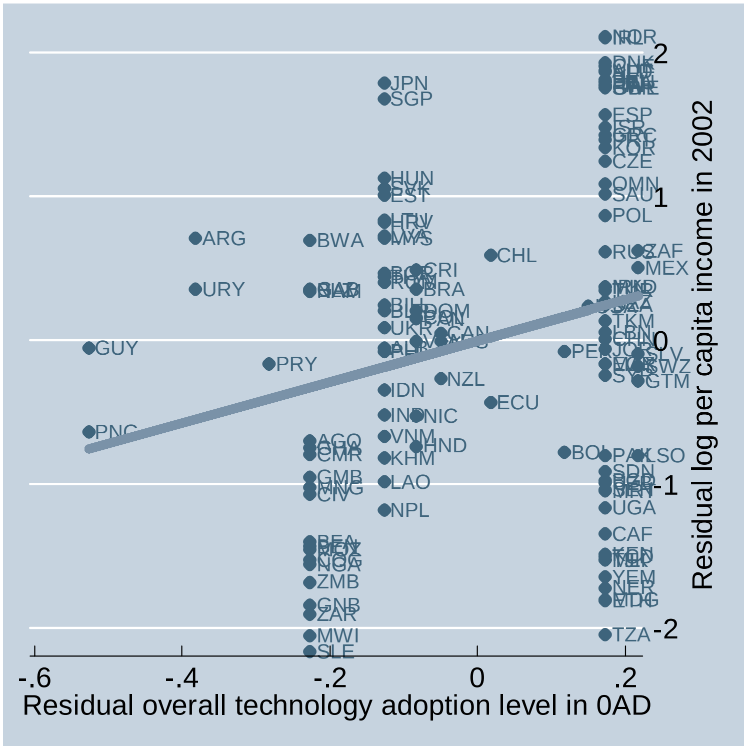

Figure 5: (Conditional) overall technology adoption in 1500 A.D. and (conditional) current development

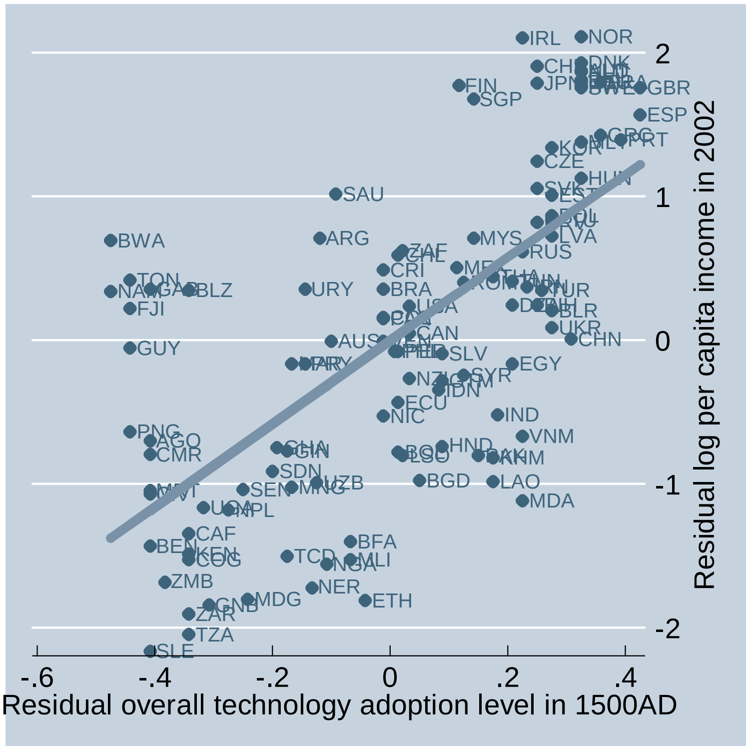

Table 1: Coding Concordance Between "ACE" and the Technology Adoption Dataset

"ACE" Dataset	Technology Dataset for 1000 B.C. & 0 A.D. (0 = indicates absence of technology, 1 = presence of technology)
Writing & Records	**Communication**
1 = None	
2 = Mnemonic or nonwritten records	0,1
3 = True Writing	0,1
Technological Specialization	**Industry**
1 = None	
2 = Pottery	0,1
3 = Metalwork (alloys, forging, casting)	0,1
Land Transport	**Transportation**
1 = Human Only	
2 = Pack or draft animals	0,1
3 = Vehicles	0,1
Agriculture	**Agriculture**
1 = None	0
2 = 10% or more, but secondary	1
3 = Primary	2
Military	**Military**
1 = Stone Tools	
2 = Bronze Tools	Bronze weapons: 0,1
3 = Iron Tools	Iron weapons: 0,1

Table 2: Variables in the 1500 A.D. dataset

Variable	Description	Values
	Military	
Standing Army	An organization of professional soldiers.	0,1
Cavalry	The use of soldiers mounted on horseback.	0,1
Firearms	Gunpowder based weapons	0,1
Muskets	The successor to the harquebus (the common firearm of European armies) was larger and a muzzle-loading firearm.	0,1
Field Artillery	Large guns that required a team of soldiers to operate. It had a larger caliber and greater range than small arms weapons.	0,1
Warfare capable ships	Ships that were used in battle are considered "warfare" capable.	0,1
Heavy Naval Guns	Ships required significant advances in hull technology before they were capable of carrying heavy guns.	0,1
Ships (+180 guns), +1500 ton deadweight	Large warships that only state navies had the capability of building.	0,1
	Agriculture	
Hunting & Gathering	The primary form of subsistence.	0
Pastoralism	The primary form of subsistence.	1
Hand Cultivation	The primary form of subsistence.	2
Plough Cultivation	The primary form of subsistence.	3
	Transportation	
Ships Capable of Crossing the Atlantic Ocean	Any ship that had successfully crossed the Atlantic Ocean.	0,1
Ships Capable of Crossing the Pacific Ocean	Any ship that had successfully crossed the Pacific Ocean.	0,1
Ships Capable of Reaching the Indian Ocean	Any ship that had reached the Indian Ocean from either Europe or the Far East.	0,1
Wheel	The use of the wheel for transportation purposes. The most common use was for carts.	0,1
Magnetic Compass	The use of the compass for navigation.	0,1
Horse powered vehicles	The use of horses for transportation.	0,1
	Communications	
Movable Block Printing	The use of movable block printing.	0,1
Woodblock or block printing	The use of woodblock printing.	0,1
Books	The use of books.	0,1
Paper	The use of paper.	0,1
	Industry	
Steel	The presence of steel in a civilization.	0,1
Iron	The presence of iron in a civilization.	0,1

Table 3: Descriptive statistics of Overall Technology Adoption

Period	Number Obs.	Average	Std. Dev.	Min	Max
1000BC	113	0.45	0.28	0	1
0	135	0.73	0.28	0	1
1500AD	130	0.48	0.32	0	1

Table 4: Descriptive statistics of Overall Technology Adoption by Continent

Period	Continent	Number Obs.	Average	Std. Dev.	Min	Max
1000BC						
	Europe	30	0.66	0.16	0.5	1
	Africa	34	0.36	0.31	0	1
	Asia	23	0.58	0.25	0.1	1
	America	24	0.24	0.12	0	0.4
	Oceania	2	0.2	0.14	0.1	0.3
0AD						
	Europe	33	0.88	0.15	0.7	1
	Africa	40	0.77	0.2	0.6	1
	Asia	34	0.88	0.15	0.6	1
	America	25	0.33	0.17	0	0.6
	Oceania	3	0.17	0.11	0.1	0.3
1500AD						
	Europe	32	0.86	0.07	0.69	1
	Africa	39	0.32	0.2	0.1	0.78
	Asia	25	0.66	0.19	0.07	0.88
	America	24	0.14	0.07	0	0.26
	Oceania	9	0.12	0.04	0	0.13

Table 5: Average Overall Technology Adoption in Advanced Civilizations

Civilization	1000BC	0 AD	1500 AD
W. Europe	0.65	0.96	0.94
China	0.9	1	0.88
Indian	0.67	0.9	0.7
Arab	0.95	1	0.7

Note: W. Europe includes Spain, Portugal, Italy, France, United Kingdom, Germany, Belgium and Netherlands. Indian Empire includes India, Pakistan and Bangladesh. Arab Empire includes Saudi Arabia, UAE, Yemen, Oman, Iraq, Iran, Syria, Lebanon, Jordan, Egypt, Libya, Tunisia, Algeria and Morocco

Table 6: Cross-country variation within technology vs. overall technology

		Std	Std. of deviations from overall tech.				
Period	N	Overall	Agriculture	Metal	Military	Transport.	Comm.
1000BC	113	0.28	0.35	0.18	0.16	0.22	0.23
0	136	0.28	0.25	0.24	0.18	0.26	0.32
1500AD	130	0.32	0.2	0.2	0.2	0.12	0.26

Note: std. stands for the cross-country standard deviation in overall level of technology adoption
Std of deviations from overall tech. stands for the cross-country standard deviation in technology adoption level in the sector after removing for each country the overall technology adoption level

Table 7: Urbanization rate and technology adoption history

Dependent Variable: Urbanization rate in	1000 B.C.	0 A.D.	1500 A.D.	1000 B.C.	0 A.D.	1500 A.D.
Overall Technology adoption level in 1000BC	2.08			1.96		
	(10.48)			(15.21)		
Overall Technology adoption level in 0		1.69			1.68	
		(6.99)			(7.39)	
Overall Technology adoption level in 1500AD			8.04			947
			(2.57)			(2.87)
Distance from Equator				0.39	0.16	-3.75
				(1.25)	(0.84)	(0.56)
N	113	135	54	106	126	51
R2	0.5	0.58	0.18	0.48	0.59	0.2

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include a constant

Table 8: Technology History and Current Development

Dependent Variable	Log Income per capita in 2002						
	I	II	III	IV	V	VI	VII
Overall Technology adoption level in 1000BC	0.75				1.45		
	(1.87)				(3.19)		
Overall Technology adoption level in 0		0.09				1.49	
		(0.19)				(1.84)	
Overall Technology adoption level in 1500AD			1.59				3.03
			(3.22)				(6.6)
Major European Involvement				1.76	2.47	2.85	3.31
				(8.33)	(8.41)	(8.18)	(11.43)
Minor European Involvement				0.1	0.62	0.86	1.51
				(0.51)	(2.17)	(1.87)	(4.84)
Constant	8.2	8.45	7.77	8.5	7.68	7.21	6.74
	(28.22)	(19.62)	(22.1)	(45.64)	(22)	(9.63)	(27)
N	104	123	110	110	105	123	110
R2	0.03	0	0.18	0.08	0.17	0.13	0.5

Note: t-statistics in parenthesis computed using clustered standard errors.
Major European Involvement is a dummy that is 1 for US, Canada, New Zealand and Australia.
Minor European Involvement is a dummy that is 1 mostly for Latin American, Caribean Countries and southern Africa.

Table 9: Primitive Technology and Current Development, Robustness

Dependent Variable	Log Income per capita in 2002								
	I	II	III	IV	V	VI	VII	VIII	IX
Overall Technology adoption level in 1000BC	0.21			0.2			0.76		
	(0.36)			(0.86)			(1.59)		
Overall Technology adoption level in 0		0.64			0.04			0.18	
		(1.6)			(0.09)			(0.46)	
Overall Technology adoption level in 1500AD			1.52			1.59			1.31
			(1.94)			(2.4)			(2.04)
Europe dummy	1.71	1.55	0.39						
	(9.28)	(3.77)	(.54)						
Africa dummy	-0.35	-0.69	-1.12						
	(1.75)	(2.33)	(2.27)						
Asia dummy	0.42	0.36	-0.54						
	(1.79)	(1.11)	(0.9)						
America dummy	0.18	0.14	-0.16						
	(1.05)	(0.93)	(0.53)						
Distance to equator				3.9	4.14	2.91	4.08	4.03	2.78
				(5.1)	(4.78)	(4.1)	(6.18)	(5.29)	(3.42)
Land-Locked							-0.81	-0.78	-0.69
							(6.81)	(5.62)	(3.25)
N	104	123	110	97	114	103	97	114	103
R2	0.58	0.61	0.62	0.54	0.51	0.58	0.62	0.58	0.63

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include major and minor European involvement dummies and a constant.

Table 10: Technology history, and per capita GDP after controlling for arable land

Dependent Variable	Log per capita GDP 2002			
	I	II	III	IV
Overall Technology adoption level in 1000BC		1.43		
		(2.83)		
Overall Technology adoption level in 0			1.51	
			(1.79)	
Overall Technology adoption level in 1500AD				3.38
				(7.37)
Log arable land area	0.02	-0.008	-0.03	-0.17
	(0.43)	(0.21)	(0.88)	(4.13)
Major and Minor european involvement dummies	NO		YES	
N	127	101	120	108
R2	0	0.17	0.14	0.55

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include a constant.

Table 11: Correlation of technology adoption measures over time

	Overall	Agri.	Military	Industry	Comm.	Transport.
Correlation (1000BC, 0AD)	0.62	0.39	0.51	0.39	0.32	0.64
p-value	0	0	0	0	0	0
Correlation (0AD, 1500 AD)	0.69	0.41	0.51	0.64	0.52	0.71
p-value	0	0	0	0	0	0
Correlation (1000BC, 1500AD)	0.69	0.42	0.69	0.66	0.24	0.6
p-value	0	0	0	0	0.017	0

Table 12: Correlation of technology adoption measures over time

Dependent Variable Overal technology adoption in:	0 A.D.	1500 A.D.	1500 A.D.	0 A.D.	1500 A.D.	1500 A.D.
Overall Technology Adoption in 1000 B.C.	0.66		0.58	0.33		0.28
	(5.36)		(2.9)	(4.84)		(3.43)
Overall Technology Adoption in 0 A.D.		0.66			0.36	
		(9.59)			(5.75)	
Distance from Equator	0.15	0.67	0.73			
	(1.1)	(4.44)	(3.41)			
Land-Locked	0.148	-0.11	0			
	(3.32)	(2.4)	(0.02)			
Continent dummies		NO			YES	
N	103	105	97	111	116	101
R2	0.48	0.7	0.62	0.7	0.86	0.88

Note: t-statistics in parenthesis computed using clustered standard errors.

Table 13: Correlation of technology adoption measures over time

Dependent Variable	Current technology adoption								
Overall Technology Adoption in 1000 B.C.	0.18			-0.06			-0.02		
	(2.71)			(1.1)			(0.32)		
Overall Technology Adoption in 0 A.D.		0.24			0.07			0.16	
		(2.14)			(1.2)			(1.76)	
Overall Technology Adoption in 1500 A.D.			0.45			0.18			0.17
			(6.47)			(1.83)			(2.18)
Distance from Equator				0.69	0.62	0.47			
				(6.00)	(5.73)	(3.07)			
Land-locked				-0.12	-0.11	-0.08			
				(6.06)	(5.95)	(2.41)			
Continent dummies		NO			NO			YES	
N	109	130	115	101	120	107	109	130	115
R2	0.23	0.25	0.5	0.62	0.6	0.63	0.62	0.6	0.63

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include major and minor European involvement dummies.

Table 14: Current technology and development

Dependent Variable:	(log) per capita income in 2002							
	I	II	III	IV	V	VI	VII	VIII
Current Technology adoption	5.16	4.47	4.57	4.9	4.42	4.51	4.55	4.83
	(22.42)	(16.27)	(16.31)	(17.6)	(13.38)	(11.55)	(14.34)	(11.49)
Overall Technology adoption level in 1500AD				0.44	0.16	0.74	0.57	0.78
				(1.63)	(0.51)	(1.17)	(1.23)	(1.37)
Distance from Equator		0.89			0.72		0.53	
		(3.05)			(1.66)		(1.36)	
Land-locked		-0.27			-0.33		-0.27	
		(2.11)			(2.47)		(2.48)	
Continent Dummies	NO	NO	YES	NO	NO	YES	NO	YES
European Influence Dummies	NO	NO	NO	NO	NO	NO	YES	YES
N	123	115	123	106	99	106	99	106
R2	0.8	0.81	0.83	0.83	0.85	0.86	0.88	0.87

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include a constant

Table 15: Population technology and development

		Current		1500 AD	
Dependent Variable:	Y/L	Technology	Population	Technology	Population
Overall Technology adoption level in 1500AD	3.35	0.49	0.69		
	(7.75)	(6.15)	(1.37)		
(Log) Population in 1500 AD	-0.16	-0.02	0.85		
	(3.13)	(1.67)	(19.95)		
Overall Technology adoption level in 0AD				0.69	0.48
				(6.11)	(1.7)
(Log) Population in 0AD				0.04	0.77
				(1.69)	(14.15)
N	105	110	115	98	98
R2	0.55	0.53	0.72	0.49	0.8

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include a constant. The regressions with current dependent variables include European influence dummies.

Table 16: Population technology and development

Dependent Variable:	Y/L	Current Technology	Y/L	Technology
Overall Technology adoption level in 1500AD	3.39	0.5	1.5	0.15
	(8.12)	(6.62)	(1.98)	(1.73)
(Log) Population in 2000 AD	-0.25	-0.05	-0.06	-0.015
	(2.19)	(2.94)	(0.52)	(0.76)
(Log) Population in 1500 AD	0.06	0.02	0	0.01
	(0.49)	(1.09)	0.01)	(0.61)
Continent Dummies	NO	NO	YES	YES
N	105	109	105	109
R2	0.58	0.57	0.68	0.69

Note: t-statistics in parenthesis computed using clustered standard errors.
All regressions include a constant and European influence dummies

Table 17: Peristence of Technology within sectors

Dependent Variable:	(log) $Technology_{cst}$ - (log) $Technology_{cst-1}$							
(log) $Technology_{cst-1}$ - (log) $Technology_{cst-2}$ *	0.95	0.85	0.31	0.41	0.17	0.27	0.46	0.34
	(7.66)	(7.39)	(4.67)	(5.47)	(2.55)	(3.07)	(4.54)	(4.64)
Country effects in growth rate	YES	NO	YES	NO	YES	YES	YES	YES
Country-Sector Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Technology-specific intercepts	NO	NO	YES	YES	YES	YES	YES	YES
Sectors excluded other than military	-	-	-	-	Agri.	Comm.	Transp.	Indust.
N	405	405	405	405	303	300	305	307
R2	-	-	0.4	0.35	0.38	0.45	0.18	0.53

Note: t-statistics in parenthesis computed using clustered standard errors. All regressions include a constant and European influence dummies.

* instrumented with log $technology_{cst-2}$

Table A.1: Primitive technology and current development, robustness checks

Dependent Variable: Log Income per capita in	1913			1960			1990		
	I	II	III	IV	V	VI	IV	V	VI
Overall Technology adoption level in 1000BC	-0.36			0.78			1.14		
	(0.62)			(2.32)			(2.28)		
Overall Technology adoption level in 0		1.08			1.27			1.35	
		(1.62)			(2.6)			(1.81)	
Overall Technology adoption level in 1500AD			2.14			1.87			2.98
			(4.91)			(4.85)			(6.47)
N	51	60	57	95	116	103	107	129	113
R2	0.18	0.28	0.4	0.17	0.18	0.4	0.14	0.12	0.5

Note: t-statistics in parenthesis computed using clustered standard errors.
Major and minor European inf;uence dummies included in all regressions.

Table A2: Average adoption level by sector in the Empires

Year	Empire	Sectors				
		Agriculture	Industry	Communications	Transportation	Military
1000 B.C.						
	W. Europe	1	1	0.125	0.5625	0.56
	China	1	1	1	1	0.5
	Indian	1	0.83	0.33	0.5	0.66
	Arab	1	1	1	1	0.75
0 A.C.						
	W. Europe	1	1	0.875	0.9375	1
	China	1	1	1	1	1
	Indian	1	1	0.66	0.83	1
	Arab	1	1	1	1	1
1500 A.D.						
	W. Europe	1	1	1	0.6875	0.968
	China	1	1	1	0.66	0.75
	Indian	1	1	0.5	0.55	0.458
	Arab	0.85	0.94	0.527	0.57	0.61

Note: W. Europe includes Spain, Portugal, Italy, France, United Kingdom, Germany, Belgium and Netherlands. Indian Empire includes India, Pakistan and Bangladesh. Arab Empire includes Saudi Arabia, UAE, Yemen, Oman, Iraq, Iran, Syria, Lebanon, Jordan, Egypt, Libya, Tunisia, Algeria and Morocco