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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 results are for 1500 A.D., we find that even technology as old as 1000 BC is associated with today's outcomes in some plausible specifications.

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Motivation

The study of economic development usually emphasizes 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 or the effects of the colonial regimes.[1] Is it possible that precolonial, preindustrial history also matters significantly for today's national economic outcomes?

This paper assembles a new dataset on the history of technology over 2500 years of history prior to the era of colonization and extensive European contacts. It finds 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). 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 surprisingly significant effects under plausible conditions for measures of technological sophistication going back to 1000 BC. Moreover, technological history is correlated not only with per capita income today but also population size and thus total GDP (not surprisingly, perhaps, since greater technological productivity could either support a larger population, or a higher income for the same size population, or both). We find these results largely continue to hold when we include continent dummies or geographic controls.

We do not have space in this paper to explore WHY technology in 1000 BC or 1500 AD still predicts outcomes today, a burning question on which we hope to gain insight from further research. A very simple explanation is that technological experience has an important effect on the ability to adopt the new technologies that have come along since the industrial revolution, but many other explanations are consistent with our results. An alternative is that technology is reflecting some very long run determinant of development, of which many have already been explored such as heritable culture (Guiso et al. 2006, Fernandez 2007, Spolaore and Wacziarg 2006), religious beliefs (Barro and McCleary 2006, 2003), ethnic fractionalization (Easterly and Levine 1997), intellectual traditions (Mokyr 2005), and ancient history of statehood (Bockette et al. 2002).[2] The recent emphasis on institutions also may be consistent with our results (e.g. Acemoglu, Johnson, and Robinson 2002), to the extent that institutions have very long run determinants. We will speculate further in the conclusion and suggest some avenues for exploration that we are pursuing in subsequent work to this paper.[3]

We are certainly aware that an attempt to collect technology data starting 3000 years ago and reach serious conclusions is audacious, if not crazy. We will certainly acknowledge the huge caveats inherent in such an exercise as we go along. We still think it worth doing because of the increased interest in the literature as to what very long run tendencies can tell us about the nature and history of economic development.

Another set of examples of such recent interest in the literature are several well known theories of very long run development. Kremer 1993 has a dynamic story for population (since 1 million BC!) in which better technology makes possible a larger population (a la Malthus), and a larger population yields more inventors to make further technological advances. The idea that larger populations cause better technology is a venerable one associated with such economists as Simon Kuznets, Esther Boserup, and Julian Simon. Boserup argued that population pressure induces innovation in a "necessity is the mother of invention" type argument. Kuznets and Simon emphasized that more people means more creators of (non-rival) ideas, which means better technology.. Galor and Weil 2000 (see also Galor 2005) have these features in a story of very long run development with the critical added feature that advances in technology raise the rate of return to human capital, which causes the dynamic process to eventually switch over from extensive growth (output and population growth at the same rate) to intensive growth (per capita income growth). Jones (2005) emphasizes even more the non-rival nature of technological ideas, which inevitably generates increasing returns to scale (also featuring the feedback loop between population and ideas). If societies evolve in isolation through many eons, those who started out ahead would be even further ahead in both population and income today.

Although we do not in this paper confirm any one particular long-run theory or mechanism, our results can be seen as a vindication for such long run theorizing about development (as well as for the empirical work stressing long run factors mentioned above) –at the very least as a complement rather than necessarily a substitute for the traditional emphasis on the last few decades.

Description of technology data set

The datasets presented in this paper measure the cross-country level of technology adoption for over 100 current countries in three historical periods: 1000 B.C., 0 A.D. and the pre-colonial period around 1500 A.D.[4] Each dataset acts as a "snap shot" in time, capturing the levels of technology adoption by country throughout the world. In each time period, we determine a country's level of technology adoption in five distinct sectors: communications, agriculture, military, industry, and transportation. By aggregating these values, we determine a country's overall level of technology adoption.

Technology adoption is measured on the extensive margin by documenting whether a country uses a particular technology at all, 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. It is much easier to document whether a technology is being used in a country (the extensive margin) rather then measuring the degree of its adoption (the intensive margin). 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.

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 justified since we are 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.

Our datasets are primarily influenced by the work that ethnologists such as George Murdock and others have done on cross-cultural analysis (Murdock 1967; Carneiro 1970; Tuden and Marshall 1972; Barry and Paxson 1971). Murdock and others were interested in compiling data on multiple cultures and comparing their traits using analytical methods.[5] A work that exemplifies this is "The Measurement of Cultural Complexity" (Murdock and Provost 1973). In that paper, 186 cultures are ranked by their level of cultural complexity. Cultural complexity was measured using ten variables; these variables included the type of transportation a culture uses, the level of political integration and urbanization of a culture, and the degree of technological specialization. Using these rankings, one can conclude that the Roman Empire was culturally more complex than the Masai of East Africa (Murdock & Provost 1973: 304).

Since our interests lie in technology adoption within a specific time period, the ethnographic data described above hold little value for our analysis. Therefore, we adapt the methodology used in the cross-cultural analysis work to develop our own technology adoption datasets. Murdock & Morrow (1970) in their work "Subsistence Economy and Supportive Practices", provide a detailed description of the methodology that is commonly used to code a cross-cultural dataset (Carneiro 1970; Tuden and Marshall 1972; Barry and Paxson 1971; Murdock and Wilson 1972). In their work, Murdock and Morrow use over 400 sources to evaluate 180 cultures. A team of researchers survey multiple sources for each culture, take detailed notes in the form of direct quotations, record page numbers of references, and then code and rank each culture. Inference is used by all of the authors to assist in their coding. In Carneiro's appendix to his dataset, he notes (1973: 854), "the presence of the trait, while not directly observable, may nevertheless be inferred from the presence of certain other traits which are themselves directly observable." All of our technology adoption datasets are coded following this described methodology.

The datasets for 1000 B.C. and 0 A.D. are derived from the "Atlas of Cultural Evolution" (Peregrine 2003), while we coded the dataset for 1500 A.D. in its entirety. We include a detailed discussion about each dataset in the following sections.

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. In each sector, we examine the same technologies for the two periods. The datasets for 1000 B.C. and 0 A.D. are based on Peter Peregrine's (2003) "Atlas of Cultural Evolution"[6] (henceforward abbreviated as "ACE"). In this work, Peregrine evaluates the traits (i.e. writing and records, agriculture, transportation, urbanization) of 289 prehistoric cultures that existed before 1000 A.D. following closely the same methodology as Murdock & Provost (1973).

The source for the coding of the "ACE" dataset is the *Encyclopedia of Prehistory* (Peregrine & Ember 2001a), which is a nine volume work that documents over 250 prehistoric cultures. *The Encyclopedia of Prehistory* was compiled from contributions of over 200 authors and covers every geographic region of the world (Peregrine & Ember 2001b:3). The *Encyclopedia of Prehistory* contains a profile of each prehistoric culture and summarizes the culture's environment, settlements, economy, and social political organization. Using the information from each profile, Peregrine codes the traits of each culture to construct the "ACE" dataset.

It is important to note that the "ACE" limits its survey to prehistoric cultures; prehistory refers to the time period that precedes written records (Rouse 1972: 3). Once a culture introduces written records, it is considered part of the historic period and excluded from the "ACE." Since written records were introduced at different times throughout the world, cultures have varying dates on when they entered the historic period. For example, China, Greece, and Mesopotamia had written records during the first millennium B.C. (Rouse 1972: 8) and are coded as historic regions in the "ACE" (Peregrine 2003). Since most of the world in both 1000 B.C. and 0 A.D. is prehistoric, the "ACE" provides data that covers most of the world. We then make inferences on the historic regions of the world at 1000 B.C. and 0 A.D. to complete our datasets.

The "ACE" provides us with data documenting the cultural traits of prehistoric societies; our task was to convert this data in order to measure each country's level of technology adoption. The "ACE" dataset contains four variables of particular interest: "Writing and Records," "Agriculture", "Technological Specialization", and "Land Transportation." We use these four variables to code the adoption of the technologies in communications, agriculture, industry, and transportation. Table 1 documents the concordance between the "ACE" and our technology adoption datasets.

Each of the variables in the "ACE" dataset takes on one of three values as shown in the first column of Table 1. For example, the variable "technology specialization," can take on one of three values: a "3" indicates that metalwork is done by a culture; a "2" indicates that pottery is produced by a culture, and a "1" signifies an absence of both metalworking and pottery. We take these values and convert them to signify the presence or absence of a technology. In our technology adoption dataset, the presence of a technology was awarded a "1" while the absence was awarded a "0".

Table 1: Coding Concordance Between "ACE" Dataset 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

Technology adoption in the agriculture sector is measured indirectly, as the "ACE" dataset did not code the actual technologies being used. We infer that the greater the role that agriculture plays in a culture's subsistence the more likely that advanced agricultural technologies were employed. The appendix contains a more detailed discussion on how the agriculture sector is coded.

An example of how we code a country 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 (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

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

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 level belongs to 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 level 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

Coding for the historic regions of the world in 1000 B.C. and 0 A.D. relied on a combination of inference and additional documentation. Cultures with written records were the most technologically sophisticated at the time. A survey of the historic regions during these periods confirms this assumption. In 1000 B.C., the historic regions include China, Egypt, Greece, and Mesopotamia, while in 0 A.D. the historic regions expand to encompass Western Europe and Persia. All of these regions had advanced civilizations that were highly innovative relative to the rest of the world. For example, by 1000 B.C., Egypt, China, Greece, and Mesopotamia had growing city populations which relied on high productivity agriculture (Scarre 1988:122,144; O'Brien 1999:30,36). Wheeled chariots were invented in Mesopotamia around 3000 B.C., and were used in Egypt, Greece, and China by 1000 B.C.(Encyclopedia Britannica 2006h). Jewelry and decorative ornaments constructed out of gold and silver are also evident in these cultures (Scarre 1988; O'Brien 1999). We therefore code the historic regions in our dataset as having the highest level of technology adoption in agriculture, communications, transportation, and industry.

The "ACE" did not contain any variables that correspond to 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 "ACE" dataset defined many cultures by the type of metals they were using for tools. Neolithic cultures are coded as having stone weapons, while Bronze and Iron Age cultures were coded as having bronze and iron weapons respectively. Prehistoric cultures not adequately described in the "ACE" dataset are coded through inference. Since the people of the New World did not use bronze until near the time of European contact, all countries in North and South America are coded as not having bronze or iron weapons in 1000 B.C. and 0 A.D (Diamond 1997:259; Kipfer 2000).

The historic regions of 1000 B.C. (Mesopotamia, Northern Africa, Greece, China) did not all use iron for weapons. We therefore differentiate iron producing regions from those that did not use the metal. Asia Minor and Mesopotamia are coded as using iron since the Hittites became major producers of iron in the 3rd millennium B.C. (Collis 1997:32; Kipfer 2000:257). Greece also had iron objects by 1200 B.C and is coded accordingly. The two most prominent historic regions not possessing iron technology by 1000 B.C. are Egypt and China. Both regions first used iron in the 6th century B.C. (Wager 1993; Lucas 1934:198). Egypt and China however both used bronze well before 1000 B.C. (Kerr & Wood 2004:7; Erman 1971: 461) and our dataset in 1000 B.C. reflects this.

The coding of historic regions in 0 A.D. proved much easier as iron technology had diffused throughout Europe, the Middle East, North Africa, and China during the 1st millennium B.C. (Kipfer 2000:258). We therefore code all historic regions as using iron weapons in the 0 A.D. dataset.

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. The technology adoption dataset for 1500 A.D. differs from the prehistoric datasets in that it is not based on an existing work. While the datasets for 1000 B.C. and 0 A.D. relied on the "ACE" (Peregrine 2003) for a preponderance of data, the dataset for 1500 A.D. is coded using over 170 source materials.

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 is 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 20 technologies in the four sectors other than agriculture vs. the eight 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.

Our technology datasets for 1500 A.D. involve surveying multiple sources (atlases, history books, journal articles) and determining whether a technology was used in a country. However, as with our datasets for 1000 B.C. and 0 A.D, the dataset for 1500 A.D. does include a proxy for the level of agricultural technology adoption.

We must of course stress that there are several possible weak links in the chain to go from the source material on old cultures to our dataset corresponding to today's nation states – such as the possibly tenuous link between ancient cultures and the territories of modern day nation states, and the possible errors of commission and omission on whether technologies are present given incomplete records, just to mention two. There also is likely to be selection bias in that more technologically advanced cultures are likely to leave better records.[7]

Despite these caveats, there are also important reasons to believe in the quality of our data. First, as we describe below, it builds on the methodological contributions of the existing literature. Second, it is based on a very extensive documentation described in detail in a separate appendix.[8] Third, it is much easier to code extensive than intensive measures of technology adoption for pre-colonial periods. The former is feasible, after a significant effort such as ours. The latter is just impossible. Third, as we shall see below, our technology adoption measures for 1500 A.D. are highly correlated to the technology adoption measures for 1000 B.C. and 0 A.D. from ACE. We find this supportive of the quality of our data given that they were constructed in a completely independent way. Finally, as we shall show below, the overall technology adoption measure is highly correlated to contemporaneous measures of the development of societies such as the urbanization rate. These arguments lead us to persist nevertheless in making the best of the always shaky nature of very old data in order to see whether our measures have any signal along with the noise.

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

The methodology for coding 1500 A.D. datasets follow the works mentioned previously by Murdock and Morrow (1970), Murdock and Provost (1973), Peregrine (2003), and Carneiro (1970). We rely on two principal inference techniques while coding the dataset: 1) technological continuity (Basalla 1988) and 2) temporal extrapolation (Murdock & Morrow 1970: 314). Technological continuity is the idea that innovations are a result of previous antecedents; innovations typically do not spontaneously arise without preexisting technologies.[9] Technological continuity allows us to infer that countries with advanced technologies also have more primitive ones. The use of military technology in 1500 A.D. illustrates this technique. Large warships with over 180 guns on deck were considered the pinnacle of military technology in 1500 A.D. (Black 1996). We find that many countries with large warships also had advanced land weapons such as muskets and field artillery. It is not unreasonable to assume a country must first acquire land-based arms technology before producing ships with large naval guns. Therefore, in cases such as Portugal and Germany, where large warships were present we infer that these countries also had advance land weaponry.

Temporal extrapolation is an inference technique we use in the 1500 A.D. dataset. This technique assumes that a technology maintains persistency over time. It is not unreasonable to assume that a technology that is adopted by a country at a certain point in time will continue to be in use in that country fifty to one hundred years later. Temporal extrapolation allows us to code countries where documentation for a specific technology is not available for 1500 A.D. When a technology's presence cannot be documented in a country in 1500 A.D., we look at preceding time periods. If a technology is used by a country before 1500 A.D. we infer that it was used during 1500 A.D. as well. An example of this is our coding of transportation technology in Turkey. We are able to document that the magnetic compass was in use in the Ottoman Empire by 1450. Using temporal extrapolation, we code Turkey as having the magnetic compass in the 1500 A.D. dataset. Clearly there are limits to this technique; the longer the extrapolation period, the less confidence we have in inferring if a technology was still being used. By consulting a very large number of sources, we have been able to code the 1500 A.D. data set based on information from the XVth century.[10]

Country concordance for the 1500 A.D. dataset follows the methodology we described in the introduction. We assume that a technology used by a civilization diffuses throughout the regions it controlled. An example is the Ottoman Empire. The Ottomans controlled a wide swath of territory during 1500 A.D., including but not limited to modern day Egypt, Libya, Greece, and Iraq. Technologies used by the Ottoman Empire were assumed to have diffused from Turkey to all the countries we cited as being under Ottoman control.

The following passages briefly describe the process of determining levels of technology adoption for the military, agriculture, communications, transportation, and industrial sectors. Further discussion on our coding methodology is in the appendix.

Military technology in 1500 A.D.

We measure a country's level of military technology adoption by documenting the presence of land and sea based weapons in a country. In total, we document the presence of eight variables for each country.

The variables that represent technology for land weaponry include: the presence of a standing army, the use of firearms, muskets, cavalry, and field artillery. Sea based weapons are measured by the presence of naval warships and their armaments. The types of sea based weapons we document are: warfare capable ships, ships with heavy naval guns, and heavy warships that have over 180 guns and weigh over 1500 tons.

Agricultural Technology in 1500 A.D.

As with the datasets for 1000 B.C. and 0 A.D., we use a country's primary form of subsistence (hunting and gathering, pastoralism, agriculture) as a proxy for technology adoption in 1500 A.D. This measure is rationalized by the fact that the adoption of some important agricultural technologies is necessary for a country to move from a hunter and gathering society to an agrarian one. In addition to this indirect measure, for those countries whose primary form of subsistence was agriculture, we also measure the adoption of plough cultivation.

Transportation Technology in 1500 A.D.

A country's level of transportation technology adoption is measured by the forms of naval and land based transportation. We examine six variables, four of which measure a country's naval technology, while the remaining two measure land-based technology. Land-based technologies include the wheel and animals used for transportation. Naval-based transportation technology adoption is measured by whether a country's seamen used magnetic compasses for navigation and the distances that a country's exploration fleet sailed.

Communications Technology in 1500 A.D.

We measure a country's adoption of communications technologies by examining the technologies used to disseminate written information. We directly measure these technologies by documenting in a country the presence of the following items: paper, books, woodblock printing tools, and movable type printing presses.

The technologies we document represent the stages that many countries went through as they developed their communications technology. By 1500 A.D., paper and books had diffused throughout most of Asia and Europe. These technologies were also adopted in parts of North Africa. More advanced technological countries adopted means of more rapid reproduction of written communication, such as the moveable type press.

Industrial Technology in 1500 A.D.

Industrial technology measures a country's adoption of metallurgical technology. We measure a country's extensive margin of technology adoption by documenting the presence of iron and steel production in the country.

By 1500 A.D., iron and steel were being produced in Europe, the Middle East, and East Asia. While iron was being used for tools throughout Africa in 1500 A.D., steel was not present in Sub-Saharan Africa before contact with the Europeans. Also, the technology used to produce iron and steel was not present in the New World until after European contact.

Descriptive statistics

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. The descriptive statistics for the technology adoption measures at the sector level are relegated to Table A2 in the appendix.

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	123	0.46	0.32	0	1

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. The decline in the average level of adoption in 1500 A.D. indicates that these technologies had diffused less than the technologies from ACE in 0 A.D.

An important question that the descriptive statistics can answer is how large is 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.[11] 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 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 fact that these ranges are the maximum possible signals a large cross-country dispersion in overall technology adoption.

Figures 1 through 3 and Table 4 explore the cross-country variation in the overall technology adoption level. Table 4 explores the variation across continents in overall technology adoption. Figures 1 through

3 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.

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	26	0.87	0.074	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	0.13
	Oceania	9	0.12	0.04	0	0.13

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

Figure 1: Overall technology adoption in 1000 B.C.

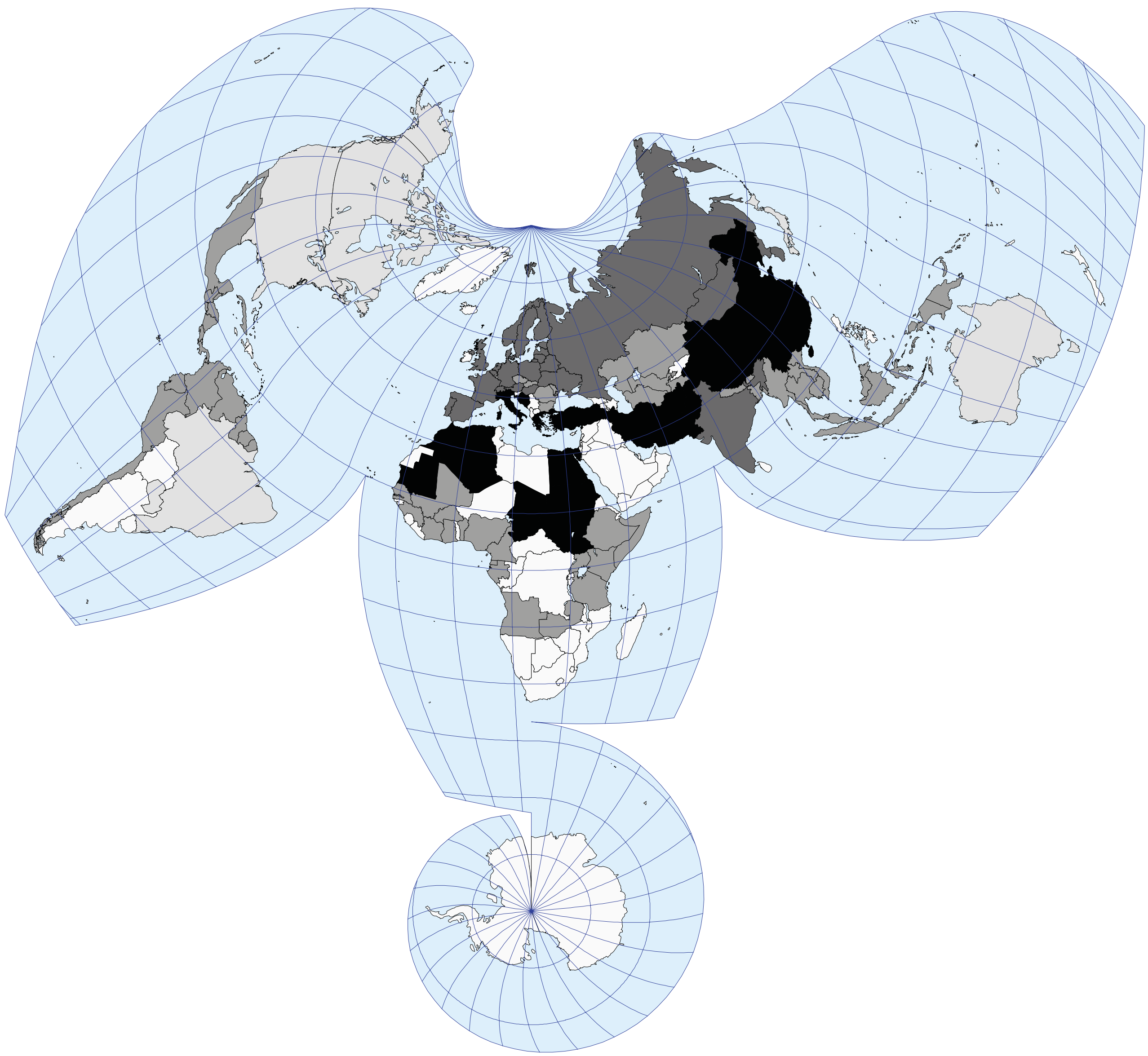


Figure 2: Overall technology adoption in 0 A.D.

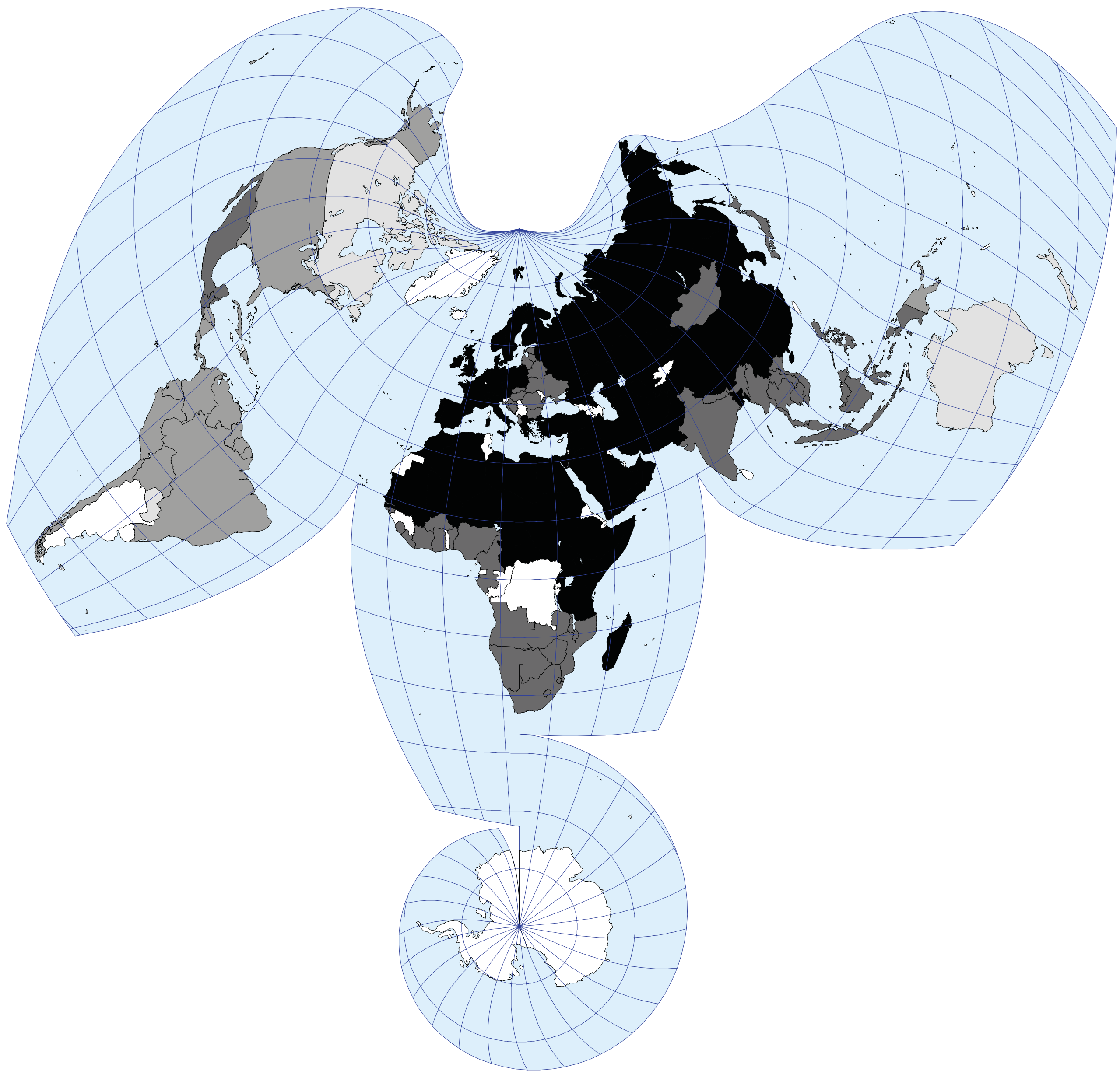
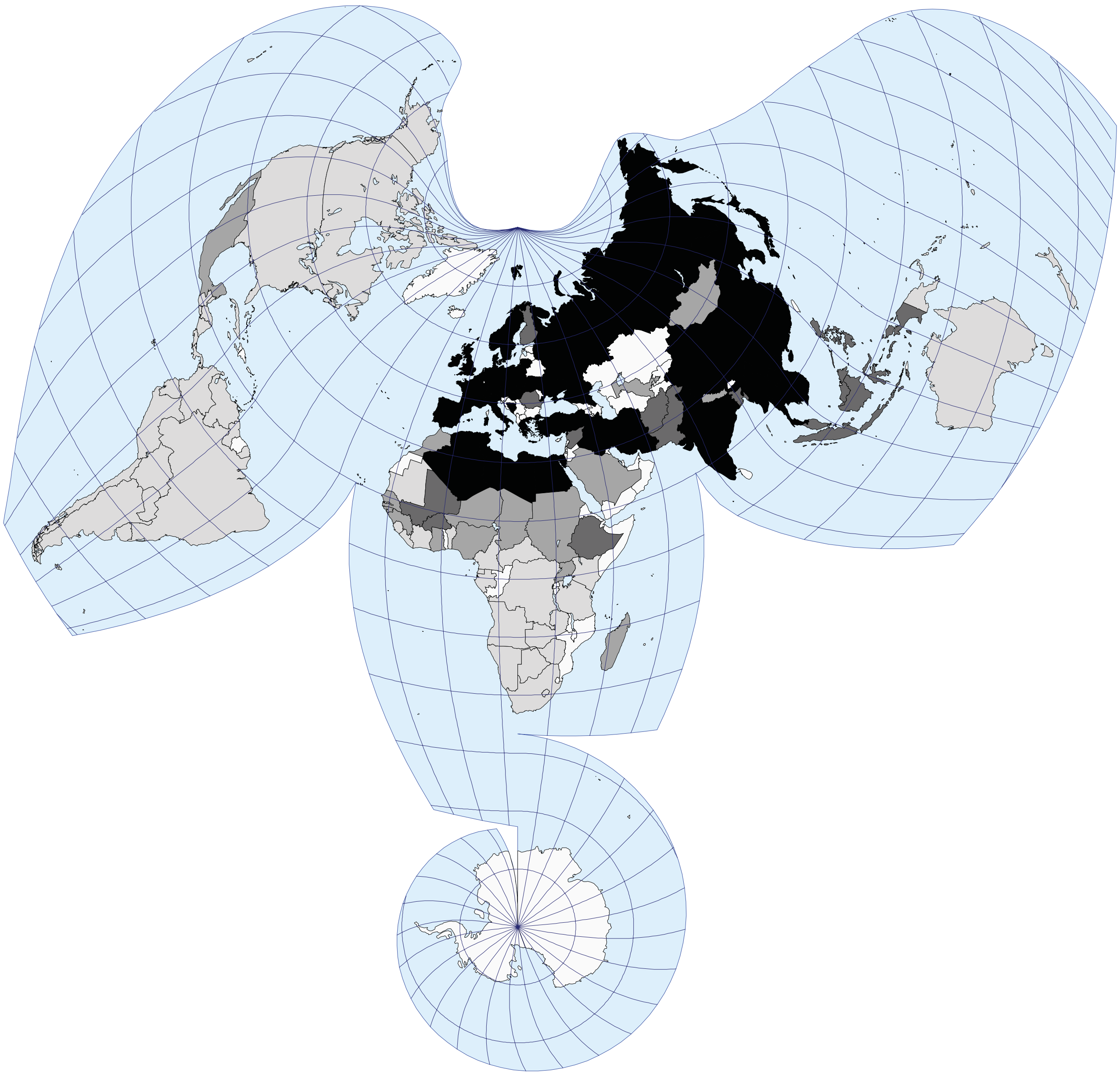


Figure 3: Overall technology adoption in 1500 A.D.



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.

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.

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. The average overall adoption levels in these empires are 0.7.

Technology history and current development

Without more delay, we turn next to the question that motivates our exploration. Namely, 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.

Table 6: 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	0.73				1.45		
	(1.96)				(3.05)		
in year 0		0.09				1.46	
		(0.23)				(2.83)	
in 1500AD			1.64				2.96
			(5.14)				(8.33)
Major European Involvement				1.83	2.47	2.83	3.22
				(12.08)	(10.78)	(8.18)	(12.86)
Minor European Involvement				0.16	0.63	0.82	1.43
				(1.05)	(2.72)	(3.23)	(5.9)
Constant	8.2	8.45	7.75	8.43	7.68	7.21	6.74
	(40.5)	(30.23)	(37.42)	(69.64)	(27.1)	(17.35)	(27)
N	105	124	107	130	105	124	107
R2	0.03	0	0.19	0.08	0.17	0.13	0.5

Note: t-statistics in parenthesis computed using robust standard errors.
Major European Involvement is a dummy that is 1 for the "Neo-Europes": US, Canada, New Zealand and Australia.
Minor European Involvement is a dummy that is 1 for areas of partial European settlement in Latin America, the Caribbean and southern Africa.

The first three columns of Table 6 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 4 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 4. 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 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.

Figure 4: Technology in 1500 and current development

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 4 we find the Neo-Europes. That is 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.

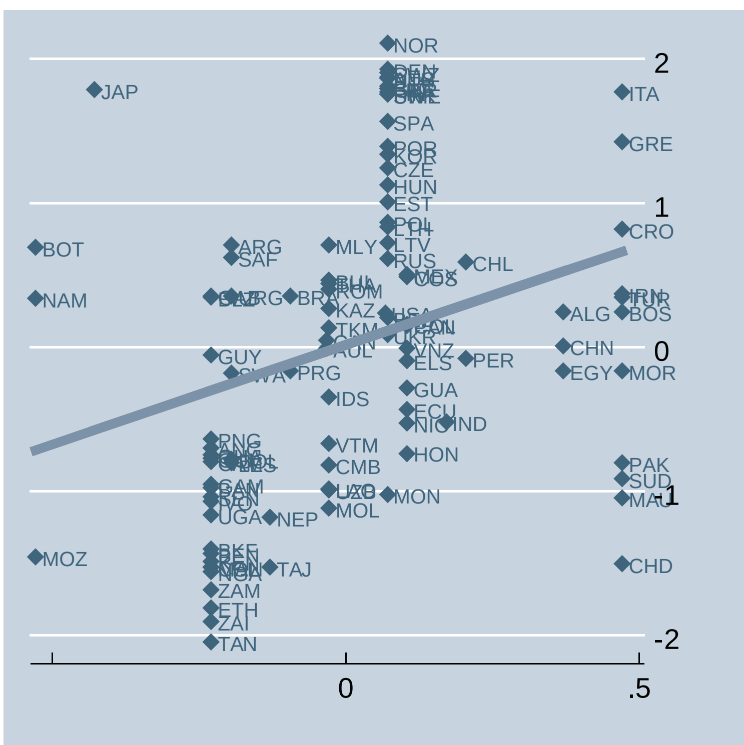
We would expect that the European settlers in the Spanish and Portuguese colonies and in the Neo-Europes affected quite dramatically the process of technology transfer (as well as other factors with which technology may be associated such as human capital accumulation and institutional development) in 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 1900 from Acemoglu, Johnson and Robinson (2001).[12] 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:

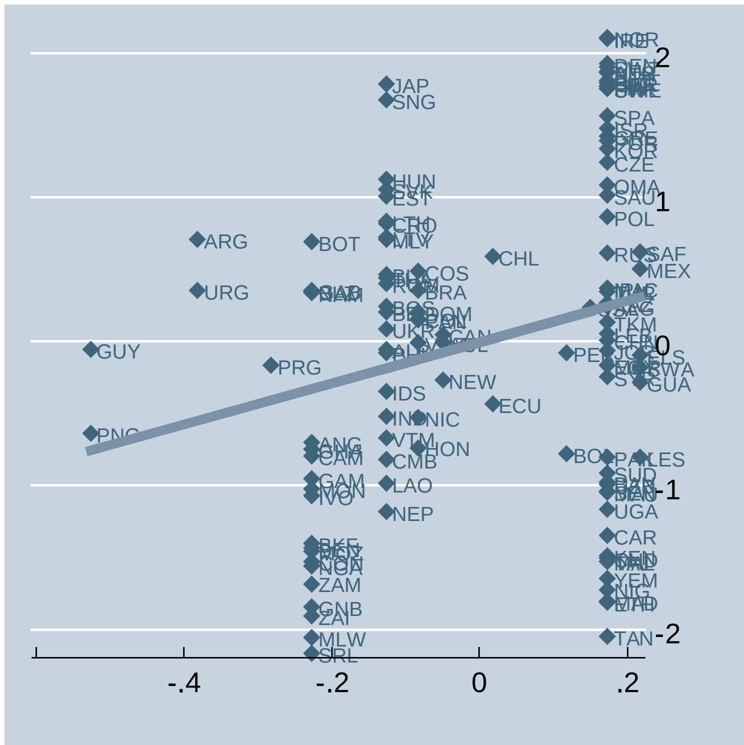
$$y_c = \alpha + \beta T_c + Major_c + Minor_c + u_c \qquad (2)$$

Figure 5: (Conditional) overall technology adoption in 1000 B.C. and (conditional) current development



Columns 5 through 7 in Table 6 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.

Figure 6: (Conditional) overall technology adoption in 0 A.D. and (conditional) current development



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. [13]Also, we continue to find significant correlations in important specifications (such as those already reported above, and more below) even when the European dummies are excluded.

Figure 7: (Conditional) overall technology adoption in 1500 A.D. and (conditional) current development

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.

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 Africa's poverty, compared to the usual emphasis of historians on the slave trade and colonialism.[14]

Figures 5 through 7 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.

Robustness and Discussion

Next we discuss the robustness and interpretation of the main fact uncovered in the previous section, that technology history is positively and strongly associated with current development.

A. Robustness

We start by exploring whether we are identifying the effect of historical technology on current development through the cross-continent variation of also through the within continent variation. To answer this question, the first three columns of Table 7 report the estimates of regression (2) when adding four continent dummies to the control set.

Table 7: 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	0.2			0.2			0.76		
	(0.5)			(0.24)			(1.59)		
in year 0		0.64			0.04			0.55	
		(1.51)			(0.09)			(1.15)	
in 1500AD			1.34			1.46			2.43
			(2.2)			(2.8)			(5.32)
Europe dummy	1.73	1.57	0.57						
	(7.91)	(5.22)	(1.06)						
Africa dummy	-0.32	-0.66	-1.12						
	(2.15)	(2.47)	(3.52)						
Asia dummy	0.44	0.39	-0.57						
	(1.63)	(1.2)	(1.27)						
America dummy	0.15	0.11	-0.24						
	(0.87)	(0.67)	(0.73)						
Distance to equator				3.9	4.14	2.91			
				(8.48)	(9.02)	(4.1)			
Tropical dummy							-1.02	-1.14	-0.45
							(4.82)	(5.81)	(1.99)
N	105	124	107	97	114	103	105	124	107
R2	0.58	0.61	0.66	0.54	0.45	0.6	0.35	0.34	0.52

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

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 3.8. We will see below that the association of ancient technology with modern *total* GDP and population are more robust to including continent dummies.

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 9 in Table 7 report the estimates of regression (2) after controlling for the distance to the Equator (columns 4 through 6) or whether the country is tropical (columns 7 through 9). 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 distance to the Equator or after including the tropical dummy. Again, we will see next that the association of ancient technology with modern total GDP and population is more robust to including geographic controls.

Studying whether more advanced technology also made higher population and higher total GDP feasible as well as higher per capita GDP is natural, given the population-technology models mentioned in the introduction. To answer this question we estimate the effect of primitive technology on the log of real GDP (*Yc*) and in the log of population (*Lc*), both in 2002, as indicated in regressions (4) and (5).

$$\log(Y_c) = \alpha + \beta T_c + u_c \tag{4}$$

$$\log(L_c) = \alpha + \beta T_c + u_c \tag{5}$$

Table 8a: Technology History, Current GDP, Population and Arable Land

Dependent Variable	Log GDP 2002			Log Population 2002			Log Arable Land		
	I	II	III	IV	V	VI	VII	VIII	IX
Overall Technology adoption level:									
in 1000BC	1.86			1.27			1.6		
	(2.68)			(2.4)			(2.66)		
in year 0		0.93			0.97			0.46	
		(1.45)			(2.13)			(0.73)	
in 1500AD			3.12			1.85			1.45
			(5.72)			(3.87)			(2.54)
Major and Minor european involvement dummies		NO			NO			NO	
N	105	124	107	114	136	118	110	132	114
R2	0.08	0.02	0.25	0.05	0.03	0.12	0.07	0	0.06

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

Table 8a reports the estimates of these specifications for the measures of overall technology adoption in each of the three periods. In columns 1 through 3 we observe that the measures of primitive technology in 1000 B.C. and in 1500 A.D. have a very significant positive effect on current GDP. The effect of technology adoption in 0 A.D. is positive but insignificant. Columns 4 through 6 show that countries with higher overall levels of historical technology adoption have higher population today. This is the case for each of the three measures of primitive technology. Unlike the regressions for per capita income, the coefficient on technology in 1000 BC for today's GDP and population is significant even without including the European settlement dummies, and 1500 AD also continues to be strongly significant without these dummies.

In columns 7 through 9 of Table 8a we estimate the effect of technology adoption history on land area by estimating the following regression:

$$\log(A_c) = \alpha + \beta T_c + u_c \tag{6}$$

where *Ac* is the arable land area. Our estimates show that the log of arable land area of today's nation states is also related to historical technology in that area. We interpret this as evidence that countries with more advanced technologies could conquer more land and/or could control more land more easily.

This could also be another mechanism by which advanced technology led to larger populations; conversely countries with larger populations, thanks to more advanced technology, could also conquer or settle more territory. Over the very long period that we are considering, the size of nations in both area and population is endogenous. Our results show that technology is one of the determinants of the size of nations. However, since both land area and population are endogenous and we lack good instruments, we cannot separate out the relationship between these two different dimensions of size.

Table 8b: Technology History, Current GDP, Population and Arable Land, European Influence Dummies

Dependent Variable	Log GDP 2002			Log Population 2002			Log Arable Land		
	I	II	III	IV	V	VI	VII	VIII	IX
Overall Technology adoption level:									
in 1000BC	2.85			1.74			2.25		
	(3.63)			(2.72)			(3.78)		
in year 0		3.19			2.1			1.91	
		(3.87)			(3.04)			(2.14)	
in 1500AD			5.2			2.86			2.66
			(11.11)			(4.69)			(4.14)
Major and Minor european involvement dummies		YES			YES			YES	
N	105	124	107	114	136	118	110	132	114
R2	0.21	0.16	0.53	0.09	0.09	0.21	0.21	0.1	0.2

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

Table 8b estimates specifications (4) through (6) adding the two European settlement dummies. This increases the effects (and makes all 3 dates significant) of technology adoption history on current GDP, on current population and on current arable land area. Hence, we conclude that historical technology adoption was associated with both a larger population and a higher average income.

We next check the robustness of this conclusion to controlling for the distance from the Equator which affected the significance of the ancient technology variables in the per capita income regressions. Columns 1 through 9 in Table 8c show that controlling for distance to Equator does not affect the strong positive effect of technology adoption history on current GDP, on current population, and on current land area. It is interesting to note that, while distance to Equator is positively and significantly associated with current GDP in the regressions where technology adoption history is measured at 1000 B.C. and 0 A.D., it is insignificantly associated with current GDP when technology adoption is measured in 1500 A.D. Similarly, while distance to Equator is insignificantly associated with current population in the regressions for technology adoption in 1000 B.C. and 0 A.D., it is negatively and significantly associated to current population when technology adoption is measured in 1500 A.D. We interpret these significant changes in the mechanism by which latitude affects current income per capita as a signal that the association of latitude and current development is not invariably causal and direct. In contrast, the association of technology adoption history with current GDP and population is robust to measuring technology in any of the three periods.

Table 8c: Technology History, Current GDP, Population and Arable Land, Distance from Equator

Dependent Variable	Log GDP 2002			Log Population 2002			Log Arable land		
	I	II	III	IV	V	VI	VII	VIII	IX
Overall Technology adoption level:									
in 1000BC	2.42			2.47			1.98		
	(2.68)			(3.18)			(3.07)		
in year 0		2.33			2.57			1.55	
		(2.78)			(3.49)			(1.77)	
in 1500AD			5.43			4.66			2.53
			(7.23)			(5.68)			(2.18)
Distance from Equator	2.96	3.5	-0.07	-0.52	-0.46	-3.2	1.38	2.1	0.44
	(2.56)	(4.33)	(0.08)	(0.6)	(0.71)	(3.06)	(1.56)	(2.46)	(0.27)
N	97	114	103	105	125	113	104	124	111
R2	0.3	0.28	0.54	0.13	0.11	0.3	0.23	0.15	0.2

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

Table 8d shows the regressions for total GDP, population, and land area when continent dummies are included. The association of ancient technology with these modern outcomes is much more robust to including continent dummies than the results with per capita income. This suggests that the legacy of ancient technology for these other aspects of the "wealth of nations" is not driven only by differences between continents.

Table 8d: Technology History, Current GDP, Population and Arable Land, Continent Dummies

Dependent Variable	Log GDP 2002			Log Population 2002			Log Arable land		
	I	II	III	IV	V	VI	VII	VIII	IX
Overall Technology adoption level:									
in 1000BC	1.45			1.59			1.59		
	(1.86)			(2.57)			(2.9)		
in year 0		2.14			1.45			0.95	
		(2.55)			(2.05)			(1.06)	
in 1500AD			4.5			3.07			2.55
			(5.71)			(3.69)			(3.52)
Continent Dummies		YES			YES			YES	
N	105	124	107	114	136	118	110	132	114
R2	0.37	0.38	0.56	0.21	0.14	0.43	0.33	0.16	0.31

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

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." Moreover, total GDP and population are correlated with land area, so this reverse causality could contaminate these results also. As one check on this potential problem, we include land area as a right hand side variable in these regressions (although there are still major concerns about endogeneity of land area). Table 9 shows that the same results hold for total GDP and population when we include land area. It is also possibly illuminating that per capita GDP today is uncorrelated with land area, 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). These results provide suggestive evidence that the results for GDP and Population are not driven by possible reverse causality between land area and ancient technology.

Table 9: Technology History, Current GDP and per capita GDP after controlling for arable land

Dependent Variable	Log GDP 2002			Log per capita GDP 2002			
	I	II	III	IV	V	VI	VII
Overall Technology adoption level:							
in 1000BC	1.46			1.43			
	(2.29)			(2.6)			
in year 0		2.11			1.47		
		(3.17)			(2.72)		
in 1500AD			4.06			3.37	
			(9.28)			(10.34)	
Log arable land area	0.79	0.63	0.52	-0.01	-0.03	-0.18	0.02
	(9.3)	(5.18)	(5.34)	(0.14)	(0.54)	(4.48)	(0.43)
Major and Minor european involvement dummies		YES			YES		NO
N	102	121	105	102	121	105	127
R2	0.61	0.49	0.74	0.17	0.13	0.8	0

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

To explore further the persistence of technology, 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.[15] 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 has now become the relevant margin to explain cross-country differences in technology.

The first three columns of Table 10 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. This remarkably high persistence of technological differences over 3000 years of human history reinforces the key finding of our paper. (It is also reassuring that the error rate on our technological measures is not disastrously high.)

Table 10: Effect of ancient technology on current technology

Dependent Variable				Current technology adoption					
Overall Technology adoption level:									
in 1000BC	0.18			-0.01			-0.02		
	(2.69)			(0.15)			(0.38)		
in year 0		0.24			0.03			0.16	
		(3.11)			(0.54)			(2.36)	
in 1500AD			0.44			0.21			0.15
			(8.17)			(2.6)			(2.05)
Distance from Equator				0.65	0.63	0.47			
				(7.57)	(8.01)	(3.72)			
Continent dummies	NO			NO			YES		
N	110	131	111	102	121	106	110	131	111
R2	0.23	0.24	0.51	0.56	0.55	0.52	0.62	0.6	0.66

Note: t-statistics in parenthesis
All regressions include major and minor European involvement dummies.

Columns 4 through 6 of Table 10 shows that from 1500 AD to the present, technology adoption is also highly persistent after controlling for the distance to the Equator , 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. Again, we think of this robust persistence of technology differences over very long periods as the main finding of this paper.

An important question is how our findings of technology and income persistence relate to the "reversal of fortune" finding of Acemoglu, Johnson, and Robinson (2002). As shown in Table 6 earlier and

Table 10 in this section, we found that there is a strong positive association between overall technology adoption in 1500 A.D. and current development/technology. Based on these results, we have found some kind of "persistence of fortune". When controlling for the European influence dummies we found that the effect of historical technology adoption in 1500 A.D. on current development for the former colonies becomes even more positive. However, the strong effect of the European influence dummies could themselves be capturing precisely the AJR story that European settlers brought good institutions that dramatically changed later "fortunes." We could alternatively interpret the dummies as representing technology transfer, but we do not really have strong enough evidence to contradict AJR's institutional interpretation. We plan to investigate this further in future work.

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." The most surprising part of the finding 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 with European contact and colonization. Even more surprising is that technology in 1000 BC and 0 AD has a significant correlation with modern outcomes in many specifications. While of course this finding is subject to standard caveats about the quality of data from ancient periods, the finding has important implications to the extent that it survives those caveats.

The burning question about our results is WHY do technology/income differences persist for such long periods. Is it that old technology is complementary to new technology, that technology is reflecting the effect of institutions, is it the positive technology-population feedback discussed in many recent papers, or is it one of the many other long-run factors previous empirical researchers have stressed? Exploring these many questions adequately would require a complete paper in itself, which we are presently pursuing.

We think our results might also provide food for thought to the policymakers and international institutions who seem to overemphasize the instruments under their control, with a seemingly 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. Our technology history only explained a partial share of the modern day variance of development outcomes, and even then may be proxying for some other very long run factor, and so history is obviously not *everything*. Yet our results show very old history displays a surprisingly high association with today's outcomes.

Endnotes

1. A notable, honorable, and famous exception is Jared Diamond (1997) *Guns, Germs, & Steel*, however, this work did not systematically test the effect of ancient technologies on modern incomes 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.

2. This list is far from exhaustive, just illustrative.

3. This is much debated in the economic history literature. Mokyr (1990, p. 169) stresses the importance of technology for growth but argues that technological experience has limited importance for new technology adoption: "It is misleading to think that nothing leads to technological progress like technological progress." Rosenberg and Birdzell (1987) also minimize the role of previous technological experience for explaining "how the West grew rich." Greene (2000) 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.

4. The 1500 A.D. dataset measures a country's level of technology adoption between 1500 A.D. to 1600 A.D. Also, technically speaking, there is no year 0 AD, as the calendar moves from 1 BC to 1 AD. We use the terminology anyway since people understand the concept of year 0 more readily than 1 BC or 1 AD.

5. See the Human Relations Area Files at Yale University for an extensive collection of source material for over 150 cultures.

6. 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.

7. Of course, in the presence of this bias, the resulting technology adoption measure would be highly correlated across with actual technology adoption.

8. And in even more detail in a second appendix available from the authors that documents the information used to code each technology for each country.

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

10. In many of the cases where we have used temporal extrapolation, we have also been able to document the presence of the technology during the XVIth century.

11. The exceptions to this rule are the measures of technology adoption in agriculture.

12. 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).

13. 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 regresors in column 8 of Table 6. We do not report these results here as Putterman and Weil (2007) have not yet made their data public (nor have we, waiting for more peer review).

14. 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.

15. In particular, these technologies are electricity (in 1990), internet (in 1996), pc's (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.

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