American Economic Journal: Macroeconomics 2 (July 2010): 65–97
http://www.aeaweb.org/articles.php?doi=10.1257/mac.2.3.65

Was the Wealth of Nations Determined in 1000 BC?†

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We assemble a dataset on technology adoption in 1000 BC, 0 AD, and 1500 AD for the predecessors to today's nation states. Technological differences are surprisingly persistent over long periods of time. Our most interesting, strong, and robust results are for the association of 1500 AD technology with per capita income and technology adoption today. We also find robust and significant technological persistence from 1000 BC to 0 AD, and from 0 AD to 1500 AD. The evidence is consistent with a model where the cost of adopting new technologies declines sufficiently with the current level of adoption. (*JEL* N10, O33, O47)

The emphasis of economic development practitioners and researchers is on modern determinants of per capita income such as quality of institutions to support markets, economic policies chosen by governments, human capital components such as education and health, or political factors such as 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., Robert Lucas 2000) or the effects of the colonial regimes. Is it possible that history as old as 1500 AD or older also matters significantly for today's national economic development? A small body of previous growth literature also considers very long run factors in economic development (Quamrul Ashraf and Oded Galor 2008; Valerie Bockstette, Areendam Chanda, and Louis Putterman 2002; Galor and David N. Weil 2000; Luigi Guiso, Paola Sapienza, and Luigi Zingales 2008; Charles Jones 2001; Michael Kremer 1993; Putterman and Weil 2008; Enrico Spolaore and Romain Wacziarg 2009; and Guido Tabellini 2007).

This paper explores these questions both empirically and theoretically. To this end, we assemble a new dataset on the history of technology over 2,500 years of history prior to the era of colonization and extensive European contacts. This is

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† To comment on this article in the online discussion forum, or to view additional materials, visit the articles page at http://www.aeaweb.org/articles.php?doi=10.1257/mac.2.3.65.

obviously an extremely ambitious undertaking, and the data we collect and estimate are subject to many caveats about methodology, accuracy, and representativeness. It is only because our measures are relatively crude and general (presence or absence of written language, the wheel, agriculture rather than hunting-gathering, iron tools, etc.) that this exercise is feasible at all. Subject to these caveats, we detect signs of technological differences between the predecessors to today's modern nations as long ago as 1000 BC, and we find that these differences persisted and/or widened to 0 AD and to 1500 AD (which will be the three data points in our dataset, with 1500 AD estimated from a different collection of sources than 1000 BC and 0 AD). The persistence of technological differences from one of these three "ancient history" data points to the next is high, as well as robust to controlling for continent dummies and other geographic factors.

Our principal finding is that the 1500 AD measure is a statistically significant predictor of the pattern of per capita incomes and technology adoption across nations that we observe today. The finding is much stronger when we base the old technology measure on a population-weighted average of the technology of the places of origin of the current population, using migration data from Putterman and Weil (2008). Our finding that "old technology matters" is similar to Putterman and Weil's (2008) result that the history of statehood and the timing of the transition to agriculture matters. We find that these results for 1500 AD continue to hold when we include continent dummies and geographic controls. Technology in 1000 BC and 0 AD is sometimes significant as a predictor of income and technology today, but these associations are not robust (however, these earlier dates do robustly predict technology in 1500 AD).

Two questions naturally follow up our findings. First, what mechanisms propagated historical shocks that affect the history of technology adoption into the present? Second, what do our findings teach us about existing growth models? There is nothing about the empirical results that makes causality automatic from past technology to present outcomes, and different models could suggest some causal or noncausal mechanisms. To illuminate these questions, we present a very simple framework in which the new technology adoption is a function of some combination of the strength of complementarity to old technology and the return to adopting new technology. Depending on the strength of this complementarity, 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. However, the alternative hypothesis is that the return to new technology adoption has been systematically and persistently higher in some places than in others. Our simple model also helps us think about alternative hypotheses that may generate the observed importance of historical technology adoption on current development. (We will reference the relevant literature when we present the model.)

To discern between our hypothesis and these hypotheses, we exploit the cross-sectoral variation in technology adoption. We find the same persistence in technology adoption when calculated only within sectors after removing the country average adoption level in the period and country-sector fixed effects (hence controlling for any factors that operate at a country-wide level such as institutions).

This evidence provides support to the hypothesis that the technology adoption dynamics—in which the cost of adopting new technology falls with the stock of previous technology—are one of the mechanisms that generates the propagation uncovered in the data.

Economic historians have long debated the importance of past technology adoption for the adoption of subsequent technologies, especially what triggered the Industrial Revolution in Europe. Joel Mokyr (1990, 169) and Nathan Rosenberg and L. E. Birdzell, Jr. (1986) argue that technological experience is a long way from being a sufficient condition for the "European miracle," stressing the earlier technological lead of China. Mokyr (1990, 164) also notes how many technological advances petered out throughout history without leading to a permanent stream of innovation. Kevin 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.

However, while economic historians disagree on an initial technology advantage as a sufficient cause of the Industrial Revolution, their description of technology history reaches a consensus on many mechanisms that cause past technology to have an effect on future technology. (There is no contradiction here—past technology could matter, and yet not be sufficient to explain why Europe, and not China, experienced the Industrial Revolution, which could also depend on other factors such as institutions and values.) Specifically, they provide many case studies of technological innovation to document mechanisms that support the assumption of our model that a higher initial technology level lowers the cost of adopting new technologies (or in a few cases, raises the benefits of new technologies).

In Table 1, we list the surprisingly long list of such mechanisms detailed by economic historians (although some of the mechanisms are related to each other), along with many of the illustrative examples historians have given from technology history. The examples are skewed toward the Industrial Revolution and after since that is where historians have focused most of their energies and the historical record is most complete (although many Greek/Roman and medieval examples also appear). It is possible that some of the mechanisms only started to operate at the time of the Industrial Revolution. However, we think it is also possible that the Industrial Revolution was only a speeding up of technology dynamics (which we will discuss below), and that many of these dynamic mechanisms will apply to earlier technological eras. Finally, the technological dynamics probably are different today than they were over the long run covered by this study, as reflected in the fact that we are forced to use a measure of intensive technology adoption to capture interesting differences today, as opposed to the extensive margin (presence or absence of technologies) in the old historical measures for 1000 BC, 0 AD, and 1500 AD.

Our empirical methodology is very different from the case histories of the technology history literature. We don't claim it is superior. Indeed, it would be worth little unless we already had the rich literature of case studies to draw upon. Crude and mechanical as our measures will turn out to be, they do supply an additional method of testing the hypothesis of technology persistence. Clearly, one important barrier that may have prevented other researchers from implementing this strategy is the lack of a dataset. One of our contributions is to attempt to construct a dataset to

Table 1—Mechanisms for Persistence of Technology from Economic History Literature

Mechanism for technology persistence	Examples from economic history literature
Complementarities between existing technology and new technology (CT is "complementary to"). If a new technology is complementary to an old technology, then the cost of adopting the new technology is lower. The more technologies in the initial technology set, the more new technologies there will be that are complementary.	Cement masonry CT roads and aqueducts under Romans (Mokyr 1990, 19–20); Roman water lifting CT power transmission (gears, cams, chains) (Mokyr 1990, 21); medieval waterwheels CT grain mills (Rosenberg and Birdzell 1986, 154); medieval heavy plow CT fallow system CT draft animals feeding on fallow and fertilizing field CT horse collar and nailed horseshoe (Mokyr 1990, 32–35); compass CT astrolabe CT advances in astronomy CT oceangoing ships in fifteenth century (Mokyr 1990, 47; Rosenberg and Birdzell 1986, 72, 84); metallurgy CT Gutenberg press (Mokyr 1990, 48); new crops alfalfa and clover CT stall feeding of livestock CT animal fertilizer and abandonment of fallow system 1500–1750 (Mokyr 1990, 58); chain mail CT breastplates and armor for soldiers (Rosenberg and Birdzell 1986, 58); textile machinery CT chemical innovation on detergents, bleaches mordants, and dyes (David Landes 1969, 108).
Recombination of old technologies to make new technology. Many new technologies are novel combinations of old technologies. The greater the number of old technologies, the greater the number of possible combinations to make new technologies.	"the lever, the wedge and the screw, … the ratchet, the pulley, the gear, and the cant" used to make Greek/Roman war machines (Mokyr 1990, 21); salt preservation of meat and improved transportation in fifteenth century = long distance trade in cattle from rural areas to cities (Rosenberg and Birdzell 1986, 75–76); steam power + iron and steel metallurgy = factory machines (Rosenberg and Birdzell 1986, 146); steam engine + rails = railroad, refrigeration + steamships = long distance meat exports to Europe, electricity generation + conductors + meters + lamps = electric light (Rosenberg 1982, 58–59); germ theory + bactericidal molds + mass chemical production = penicillin (Mokyr 2002, 107); internal combustion engine + glider + propeller = airplane (Mokyr 2002, 114).
Feedback from technology to science. When techniques "work," this gives new evidence to scientists to test theories about why they work. Science will, in turn, be used to make further innovations in technique. "Science" should be defined very broadly beyond formal science to include general understanding of "laws of nature" or "the way the world is," making statements that are true or false. Technology is defined as the toolkit of "techniques," which are not "true or false," but simply "work."	Working machines to Galileo's general theory of machine principles (Mokyr 1990, 75); steam engine to thermodynamics (Mokyr 1990, 90; Rosenberg 1982, 14); food canning to bacteriology and germ theory of disease (Rosenberg and Birdzell 1986, 245); Wright brothers to aerodynamics (Mokyr 2005, Mokyr 2002, 96–97; Rosenberg 1982, 157), discovery of transistor to field of solid-state physics (Rosenberg 2000, 33); telegraph to mathematical physics (Mokyr 2002, 90).
Feedback from technology to lower access costs for knowledge. The more advanced are certain "access" technologies, the easier it is to obtain general scientific knowledge, which then lowers the cost of innovation and adoption.	Greek/Roman alphabetization, Arabic numerals, Gutenberg printing, nineteenth century innovation in paper and printing, lower transport costs for people and books, postal services, standard weights and measures, encyclopedias, ICT revolution (Mokyr 2002).
Spillover of technology from one sector to another. Technological ideas from one sector inspire new approaches to problems in other sectors.	Clockmaking and watchmaking beginning with medieval town clocks spillover to precision machining for factories in the Industrial Revolution (Rosenberg and Birdzell 1986, 148–150); Steam engine inventor Watt's background was in mining industry, which required knowledge of metallurgy, chemistry, mechanics, and civil engineering (Mokyr 1990, 162); spillover from petrochemical industry for auto fuel to plastics and synthetic fibers (Rosenberg 2000, 92).

(*Continued*)

TABLE 1—MECHANISMS FOR PERSISTENCE OF TECHNOLOGY FROM ECONOMIC HISTORY LITERATURE (*Continued*)

Mechanism for technology persistence	Examples from economic history literature
Economies of scale. Some technologies have fixed costs or internal economies of scale such that it is only worth adopting them at higher scale of operation of the economy. The greater initial technology is, the greater the scale of operation of the economy.	Larger oceangoing ships and expanding world trade in fifteenth century (Rosenberg and Birdzell 1986, 82–83); mechanical reaper (Paul A. David 1975); assembly line and interchangeable parts (Mokyr 2002).
Economies of scope of General Purpose Technologies (GPT). When a GPT is invented, it's payoff is greater, the more technologies in which it can be used. Hence, the greater initial technology is, the greater the payoff to a GPT.	Gutenberg printing press, ocean-going ships in fifteenth century, electric engine for factories in virtually all sectors and multiple home appliances (Rosenberg 1982, 78–79); ICT (Mokyr 2002, 112–113).
Feedback from technology to improved lab equipment. Improved lab equipment lowers the cost of scientific discovery, innovation, or adoption. The better existing technology is, the better the lab equipment.	Medieval optics made possible telescope and microscope (Rosenberg and Birdzell 1986, 58); instruments measuring time, distance, weight, pressure, temperature, Volta's battery, Petri dish (Mokyr 2005); advances in lens grinding to make better telescopes and microscopes (Mokyr 2002, 97–100).
Learning by doing. Much of technological progress consists of learning how to make old techniques work better through small adjustments, minor innovations, and adaptation to local circumstances.	Oceangoing ships since fifteenth century improved sailing efficiency and ship design until advent of steam power (Rosenberg and Birdzell, 263); coal required to generate kilowatt-hour of electricity fell drastically over the decades; semiconductors moved from a single transistor on a chip to more than a million such components (Rosenberg 1994, 14–15); high pressure steam engine design and transmission (Mokyr 2002, 84); transition from Bessemer to Siemens Martin steelmaking process (Mokyr 2002, 86–87).

explore these issues, even though such data construction faces huge challenges and is subject to large margins for error.

The rest of the paper is organized as follows. Section I presents the dataset. Section II uncovers the main findings and shows the robustness of these findings. Section III presents a simple model that rationalizes the facts and some extensions that yield some additional predictions that allow us to identify several competing hypotheses about the nature of the propagation mechanism. Section IV concludes.

I. Description of Technology Dataset

The historical datasets presented in this paper measure the cross-country level of technology adoption for over 100 countries in three periods: 1000 BC, 0 AD, and the pre-colonial period in 1500 AD. Each dataset acts as a "snap shot" in time, capturing the levels of technology adoption by country throughout the world. The earliest measures will obviously be crude, while 1500 AD will be based on a wider set of information.

Technology adoption is measured on the extensive margin by documenting whether a country uses a particular technology, not how intensively a particular technology is used. The 1000 BC measure is only possible because there is some record on which very basic technologies were used. For example, in the dataset for 1000

BC, we consider two transportation technologies: pack animals and wheeled 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 BC and 0 AD) to the early modern period (1500 AD) to reflect the evolution of the technology frontier.

Our focus on the extensive margin of technology adoption is obviously less ideal than also measuring the intensive margin of the extent of technology utilization, but we are constrained by data availability. 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). In addition, the extensive margin has arguably been up to the nineteenth century or so, an important margin to explain the cross-country variation in technology adoption (Anni-Maria Pulkki and Paul Stoneman 2006).

The technologies in our datasets 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) has some information content about the technological sophistication of economies in the distant past.

A related issue is that some sectors are more densely covered than others (i.e., for 1500 AD, we have eight technologies in military, but only two 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 (measured on the [0, 1] interval as explained below) 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 the borders of present day nations into concordance with the cultures and civilizations in 1000 BC, 0 AD, and 1500 AD. 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 AD. One difficult decision was how to treat cases where a country had multiple cultures within its borders during a certain time period. We opted to take the culture with the highest level of technology adoption to represent that country, which seems to follow from our goal of measuring the extensive margin of technology adoption in a country. For example, in 1000 BC, 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 BC.

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 that will be discussed below, 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.

Another big issue is what would happen when there are large changes in population composition on a territory due to large-scale migrations and conquest or extinction of previous groups. Does technology persist within places or within peoples? We will utilize the data on migrations from 1500 AD to 2000 AD recently constructed by Putterman and Weil (2008) to address this issue in the empirical work.[1]

Each dataset is constructed following the methodology used by George P. Murdock and other ethnologists (Murdock 1967; Robert L. Carneiro 1970; Arthur Tuden and Catherine Marshall 1972; Herbert Barry III and Leonora M. Paxson 1971). Each dataset is coded by a team of researchers surveying multiple sources reducing (but far from eliminating), in this way, the degree of measurement error. Researchers take detailed notes, including direct quotations, and using, when appropriate, two inference techniques: technological continuity (George Basalla 1988) and temporal extrapolation (Murdock and Diana O. Morrow 1970, 314).

Technological continuity stresses that innovations are a result of previous antecedents. Innovations typically do not spontaneously arise without preexisting technologies.[2] 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 AD. Large warships with over 180 guns on deck were considered the pinnacle of military technology in 1500 AD (Jeremy 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 50 to 100 years earlier is assumed to still be in use.[3] In addition, in most of the cases, we are able to document that the technology was present in 1550 AD. An example of this is the coding of transportation technology in 1500 AD Turkey. We code Turkey as having the magnetic compass in the 1500 AD dataset based on evidence that it was in use in the Ottoman Empire by 1450.

The datasets for 1000 BC and 0 AD are derived from the "Atlas of Cultural Evolution" (henceforth, abbreviated as "ACE"), (Peter N. Peregrine 2003), while

[1] This data only became available for this current version of the paper. In previous versions, we used dummy variables to indicate countries where there was major or minor replacement of the indigenous population by Europeans.

[2] See Basalla (1988, 30–57) for a number of case studies documenting technological continuity or technological evolution.

[3] This time frame rules out long-run technological regression such as the loss of some Roman achievements in medieval Europe or the Chinese ocean-going voyages to East Africa.

we coded the dataset for 1500 AD in its entirety. The ACE itself is based on the Encyclopedia of Prehistory (Peregrine and Melvin Ember 2001a, 2001b) whose compilation involved multiple data sources and more than 200 researchers. The 1500 AD dataset involved several researchers and over 200 sources. Of course, all this firepower is even more critical because constructing data based on fragmentary evidence from thousands of years ago is an enormous challenge.

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 rather than extrapolation. 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 attempted to document the presence or absence of technologies in each of the countries. Since in some occasions this has not been possible, in our empirical analysis we cluster the standard errors to take into account the correlation in the information used in the coding of technology.

Finally, there are further 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.

Both of these concerns are serious, but, in the end, we believe they do not invalidate our data. This conclusion is based on three reasons. First, 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 arguably 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 IIIC, 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 addresses country-level bias including biases in the reporting or collection of data.

A. *Technology Datasets for 1000 BC and 0 AD*

The datasets for 1000 BC and 0 AD measure the level of technology adoption for agriculture, transportation, communications, writing, and military for 113 and 135 countries, respectively. As Table 2 shows, we are asking some very basic questions. Was there written language, pack animals, the wheel, pottery or metalwork, or agriculture? Were tools stone, bronze, or iron? The "ACE" does not contain any variable that directly measures 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

TABLE 2—CODING CONCORDANCE BETWEEN "ACE" AND THE TECHNOLOGY ADOPTION DATASET

"ACE" dataset	Technology dataset for 1000 BC and 0 AD*
Writing and 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 percent 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

* 0 = indicates absence of technology, 1 = presence of technology.

development of more advanced weapons (Kenneth Macksey 1993, 216; Christopher Scarre 1988; John 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 (Oliver F. G. Hogg 1968, 19–22). The relevant data from the ACE, and how it is used, can be found in Table 2. The Appendix gives a specific country example of coding (Korea).

The ACE database gives very crude indicators of technology. There are many caveats. First, we were limited to measuring those technologies present in the ACE database. It omits other important technologies that we know varied in ancient times, such as the plough, mathematics, astronomy, or medicine. Second, we are assuming the same ranking of technologies for all, when in fact the "best" technology may depend on local circumstances.[4] Third, the ACE only covers cultures in "prehistoric areas," with the implication that all "historic areas" are at the highest technology level (an implication that we confirmed in correspondence with Peregrine, the author of the ACE). "Historic areas" (defined as the availability of written records on their history) were confined to Zhou China and the Greco-Roman world in 1000 BC. The later included Anatolia, the Fertile Crescent, the Arabian Peninsula, and Northern Africa. In 0 AD, the historic area had spread to Western Europe, most of China, and the Eurasian land corridor in between, as well as further south in the Horn of Africa

[4] A famous fact is that the Aztecs used wheels in toys for children, but not in productive activities. This may suggest local geography affects what is the "best" technology. However, it also may reflect complementarities to the absence of other technologies, like good roads, which would be more consistent with universal rankings of what is best.

and eastern Africa. This unfortunately suppresses the probably important variations in technology within the "historic area." The inclusion of parts of sub-Saharan Africa as implicitly being at the technological frontier in 0 AD may seem a little surprising, and coding it at the frontier may be a mistake. However, we follow the usual principle that exogenous error is better than subjective adjustment. Moreover, Peregrine and Ember 2001a (Volume 1) note that Africa is "fascinating in its diversity" and that "Ceramics, metals, writing, and monumental architecture were all developed. Trade links cut across the continent and into Southwest Asia" (Peregrine and Ember 2001a, xix). The omission of other technologies and the homogeneous treatment of the "historic area" would make the 1000 BC and 0 AD subject to random error and would bias the results against the persistence hypothesis. We also cluster the standard errors for the historic area to avoid biasing the standard errors of the estimated coefficients.

B. *Technology Dataset for 1500 AD*

The technology dataset for 1500 AD encompasses 113 countries and evaluates the level of technology adoption across the same 5 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 AD do not incorporate the technology transferred by Europeans to the rest of the world after European exploration began around 1500.

There are a larger number of sources covering the technology adoption patterns in 1500 AD than there are in 1000 BC or 0 AD. This allows us to collect adoption data for 24 technologies in the 4 sectors other than agriculture versus the 11 technologies covered in the datasets for 1000 BC and 0 AD. As a result, our estimate of the level of technology adoption in 1500 AD is likely to be more precise than for the earlier periods. Note that, as before, our measures attach equal weight to each of the five sectors, so our overall average is not biased toward sectors in which more technological information is available. So for example, more information is available on military technologies (8) than industrial technologies (2), but military and industry have equal weights in our overall index. For the same reason, closely related technologies within a sector that might risk "double counting" do not increase the weight of that sector in our overall index.

Table 3 presents the various technologies measured in 1500 AD.[5,6] We are still asking the same very basic questions, but the advance of the technological frontier since earlier epochs allows additional questions that capture more differentiation. Were there ocean-going ships, paper, printing, firearms, or artillery? The magnetic compass? Steel?

[5] 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.

[6] Our sectoral and overall technology adoption measures are robust to reasonable variations in the definition of new technologies. Collapsing heavy naval guns and large ships with +180 guns into a unique technology results in a measure of adoption in military with a correlation of 0.996 with our measure.

Table 3—Variables in the 1500 AD 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 and 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

C. *Current Technology*

To explore whether historical technology differences have "persisted" until current times, we construct a measure of current technology level based on Comin, Bart Hobijn, and Emilie Rovito (2008). This measure captures (one minus) the average gap in the intensity of adoption of ten major current technologies with respect to the United States. 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.

More specifically, for each technology, Comin, Hobijn, and Rovito (2008) measure how many years ago the United States last had the usage of technology "*x*" that country "*c*" currently has. We take these estimates and 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 and add one to obtain a measure of the average gap in the intensity of adoption with respect to the United States, whose adoption level is one, by construction.

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 century or so, the nature of technological change and diffusion has changed. The increased information flows, migrations, and decline in transportation costs have meant that the extensive margin of technology has diffused very quickly across countries. Therefore, the intensive margin of technology adoption is now the relevant margin to explain cross-country differences in technology today.

Since richer countries tend to demand more intensively new technologies, our measure of current technology adoption will be correlated with per capita GDP. However, as shown in Comin and Hobijn (2004), there are many other determinants of technology adoption above and beyond per capita income. Hence, it is informative to test a direct measure of current technology to assess the persistence of technology.

It is also worthwhile noting that the major technologies used to summarize the current state of technology belong to four of the sectors covered by the historical datasets (i.e., all but military). We shall take advantage of this feature of the data when estimating the persistence of technology within sectors in Section IIIC.

II. Data Analysis

A. *Cross-Country Dispersion in Technology*

Table 4 explores the variation across continents in overall technology adoption (the Appendix gives a listing of all individual countries in our sample). In all three historical periods, Europe and Asia present the highest average levels of overall technology adoption, while America and Oceania present the lowest, with Africa in between. In current times, the average adoption level is highest in Europe and Oceania (driven by Australia and New Zealand), followed by America, Asia, and Africa. The other statistics (standard deviation, min, and max) show that there is also substantial variation within continents, which will be important in our empirical work. We will also see that there is substantial cross-sectoral variation behind these averages as well.

Table 5 provides a more detailed comparison of the evolution of overall technology adoption in the most advanced countries. These countries correspond to four historical civilizations: Western Europe, China, the Indian civilization, and the Middle Eastern peoples. Western Europe includes Spain, Portugal, Italy, France, the United Kingdom, Germany, Belgium, and the Netherlands. The Indian civilization includes India, Pakistan, and Bangladesh. Finally, the Middle Eastern civilization

Table 4—Descriptive Statistics of Overall Technology Adoption by Continent

Continent	Observations	Average	SD	Min	Max
1000 BC					
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
0 AD					
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
1500 AD					
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
Current					
Europe	34	0.63	0.19	0.27	0.87
Africa	42	0.31	0.08	0.13	0.54
Asia	33	0.41	0.15	0.23	0.76
America	22	0.47	0.17	0.34	1
Oceania	3	0.73	0.32	0.36	0.92

Table 5—Average Overall Technology Adoption in Advanced Civilizations

Civilization	1000 BC	0 AD	1500 AD	Current
W. Europe	0.65	0.96	0.94	0.71
China	0.9	1	0.88	0.33
Indian	0.67	0.9	0.7	0.31
Arab	0.95	1	0.7	0.43

Note: Western Europe includes Spain, Portugal, Italy, France, United Kingdom, Germany, Belgium, and the 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.

includes Saudi Arabia, United Arab Emirates (UAE), Yemen, Oman, Iraq, Iran, Turkey, Syria, Lebanon, Jordan, Egypt, Libya, Tunisia, Algeria, and Morocco.

In 1000 BC, 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 levels are 0.67 and 0.65, respectively. In 0 AD, India and Western Europe catch up with China and the Middle Eastern empires. In 1500 AD, Western Europe has completed the transition and is the most advanced of the four great civilizations with an average overall adoption level of 0.94. China remains ahead of most countries with an overall adoption level of 0.88. The Indian and the Middle Eastern empires have fallen behind to 0.7. Today, the gap between Western Europe and the other three historical empires has widened considerably.

Table 6—Technology Measures and Contemporary Urbanization Estimates

Dependent variable: urbanization rate in	1000 BC	0 AD	1500 AD
Overall technology adoption level in 1000 BC	2.08		
	(10.48)		
Overall technology adoption level in 0 AD		1.69	
		(6.99)	
Overall technology adoption level in 1500 AD			8.04
			(2.57)
Distance from equator			
Observations	113	135	54
R^2	0.5	0.58	0.18

Notes: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology. All regressions include a constant.

Why do our historical 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 and produced most of the useful inventions? Basically, it is because what we are measuring is the adoption of technologies rather than the invention (i.e., by 1500, gunpowder was already adopted in Western Europe and most of the Arab world). Most historians agree that Europe had caught up to and surpassed the Islamic civilization sometime in the late Middle Ages. The Appendix details what differences in technology adoption affected the rankings the most, and also provides the country data.

The levels of historical technology adoption reported for the empires in Table 5 until 1500 AD 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 compared to the technological advantage of the historical empires compared to most of the rest of the countries in the world.

A final check on our technology adoption datasets is to correlate them with the contemporaneous urbanization rate. Daron Acemoglu, Simon Johnson, and James A. Robinson (2002) have also used the urbanization rate as a proxy for the development level for pre-modern periods. The urbanization rate for 1000 BC and 0 AD come from Peregrine's "ACE,"[7] while the urbanization rate for 1500 AD (paradoxically a much smaller sample) comes from Acemoglu, Johnson, and Robinson (2002). We find that there is a significant positive contemporaneous association between technology adoption history and the contemporaneous urbanization rates (Table 6). This provides some reassurance that our measures of technology adoption in pre-colonial times have some positive information content despite the huge challenge of estimating such data.

[7] 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; and 3 if it is larger than 400 persons.

Table 7A—Technology in 1500 AD as Function of Technology in 0 AD or 1000 BC

	Overall technology adoption level in 1500 AD									
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overall technology adoption level in 0 AD	0.782***		0.356***		0.614***		0.635***		0.691***	
	(8.36)		(5.75)		(7.14)		(7.58)		(6.15)	
Overall technology adoption level in 1000 BC		0.784***		0.242***		0.582***		0.584***		0.637***
		(5.55)		(4.92)		(3.50)		(3.43)		(3.25)
Europe dummy			0.520***	0.689***						
			(11.07)	(17.08)						
Africa dummy			0.00481	0.193***						
			(0.10)	(4.41)						
Asia dummy			0.368***	0.537***						
			(5.11)	(9.11)						
America dummy			−0.00448	0.0681*						
			(−0.34)	(1.90)						
Distance to equator					0.348	−0.0973	0.424	−0.118		
					(0.57)	(−0.27)	(0.82)	(−0.30)		
Distance to equator squared					0.590	1.280***	0.438	1.310**		
					(0.82)	(2.75)	(0.72)	(2.71)		
Landlocked							−0.0979***	0.0155	−0.101**	0.0104
							(−2.79)	(0.38)	(−2.50)	(0.22)
Tropical dummy									−0.249***	−0.215**
									(−3.09)	(−2.26)
Constant	−0.0624	0.128*	0.0296***	0.0182	−0.129	0.0881*	−0.129*	0.0860	0.146	0.299**
	(−0.90)	(1.70)	(2.85)	(0.56)	(−1.64)	(1.71)	(−1.79)	(1.62)	(1.46)	(2.13)
Observations	116	104	116	104	108	97	108	97	116	104
R^2	0.47	0.47	0.86	0.87	0.67	0.63	0.69	0.63	0.64	0.57

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

B. *Technology History and Current Development*

The aim of our admittedly extremely ambitious data collection exercise is to assess whether technological differences persist over long periods. Since the measures come from different independent sources, this will also be a check on whether the data contain a signal as well as noise. We first check the correlations among our three technology measures from 1000 BC, 0 AD, and 1500 AD. The correlation between 1000 BC and 0 AD is 0.62, which is not so surprising since these two estimates come from the same source. 1500 AD is an independent data collection exercise, however, so it is reassuring that the correlation between 1000 BC and 1500 AD, and between 0 AD and 1500 AD are also both high: 0.69 in both cases. Not only do these correlations suggest the data contains a signal as well as noise, it also gives some confirmation that technological differences persist over very long periods. Moreover, these associations are robustly significant controlling for a variety of fixed factors usually discussed in the long-run development literature, as shown in Tables 7A and 7B: continent dummies, distance from equator

Table 7B—Technology in 0 AD as Function of Technology in 1000 BC

Dependent variable	Overall technology adoption level in 0 AD (1)	(2)	(3)	(4)	(5)
Overall technology adoption level in 1000 BC	0.609***	0.325***	0.625***	0.662***	0.622***
	(5.10)	(4.84)	(4.88)	(5.74)	(5.12)
Europe dummy		0.536***			
		(5.98)			
Africa dummy		0.511***			
		(5.09)			
Asia dummy		0.531***			
		(5.96)			
America dummy		0.120			
		(1.63)			
Distance to equator			−0.392	−0.688	
			(−0.59)	(−1.17)	
Distance to equator squared			0.878	1.297	
			(0.93)	(1.54)	
Landlocked				0.168***	0.163***
				(3.79)	(3.84)
Tropical dummy					−0.0305
					(−0.56)
Constant	0.432***	0.135**	0.439***	0.420***	0.404***
	(4.56)	(2.63)	(3.45)	(3.81)	(3.89)
Observations	111	111	103	103	111
R^2	0.39	0.70	0.45	0.51	0.45

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8A—Ancient Technology Measures and Income and Technology Today

Dependent variables	Log income per capita in 2002 (1)	(2)	(3)	Current technology (4)	(5)	(6)
Overall technology adoption level in 1000 BC	0.747*			0.0851		
	(1.87)			(1.37)		
Overall technology adoption level in 0 AD		0.0895			0.0138	
		(0.19)			(0.14)	
Overall technology adoption level in 1500 AD			1.566***			0.221**
			(3.24)			(2.58)
Constant	8.196***	8.452***	7.786***	−0.590***	−0.557***	−0.655***
	(28.22)	(19.62)	(22.72)	(−13.60)	(−6.89)	(−12.22)
Observations	104	123	111	109	130	115
R^2	0.03	0.00	0.18	0.02	0.00	0.12

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 8B—Migration-Adjusted Technology Measures and Income and Technology Today

	Log income per capita in 2002			Current technology		
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Migration-adjusted technology level in 1000 BC	1.599***			0.211***		
	(3.45)			(3.3)		
Migration-adjusted technology level in 0 AD		2.303**			0.418**	
		(2.35)			(2.56)	
Migration-adjusted technology level in 1500 AD			3.261***			0.514***
			(6.76)			(6.87)
Constant	7.697***	6.602***	6.544***	−0.662***	−0.895***	−0.862***
	(23.46)	(8.65)	(18.6)	(−16.65)	(−7.85)	(−21.06)
Observations	104	123	111	109	130	115
R^2	0.12	0.11	0.5	0.07	0.12	0.4

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

and distance from equator squared, a dummy for landlocked, and a dummy for tropical climate.

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

$$y_c = \alpha + \beta T_c + u_c, \tag{1}$$

where current development, y_c, is measured either by the log of PPP adjusted per capita income in 2002 AD or by current technology adoption; T_c is the measure of historical technology; and u_c is the error term.

The first three columns of Table 8A report the estimates of regression (1) when y_c is per capita income in 2002 and T_c is measured successively by the overall adoption level in 1000 BC, in 0 AD and in 1500 AD (t-statistics are in parentheses). The technology adoption level in 1000 BC and in 0 AD is not significantly correlated with current development at the 5 percent level. Although technology at these ancient dates persisted into subsequent periods, as shown above, they do not have any meaningful role to directly explain outcomes today.

The overall technology adoption level in 1500 AD is positively and significantly associated with current income per capita. This R^2 indicates that this measure of technology in 1500 AD explains 18 percent of the variation in log per capita GDP in 2002. Changing from the maximum (i.e., 1) to the minimum (i.e., 0), the overall technology adoption level in 1500 AD is associated with a reduction in the level of income per capita in 2002 by a factor of 5.

The next three columns of Table 8 show that current technology is associated with historical technology adoption very much in the same way as current per capita income. The association between current technology and technology in 1000 BC or 0 AD is insignificant. However, there is a significant association between technology in

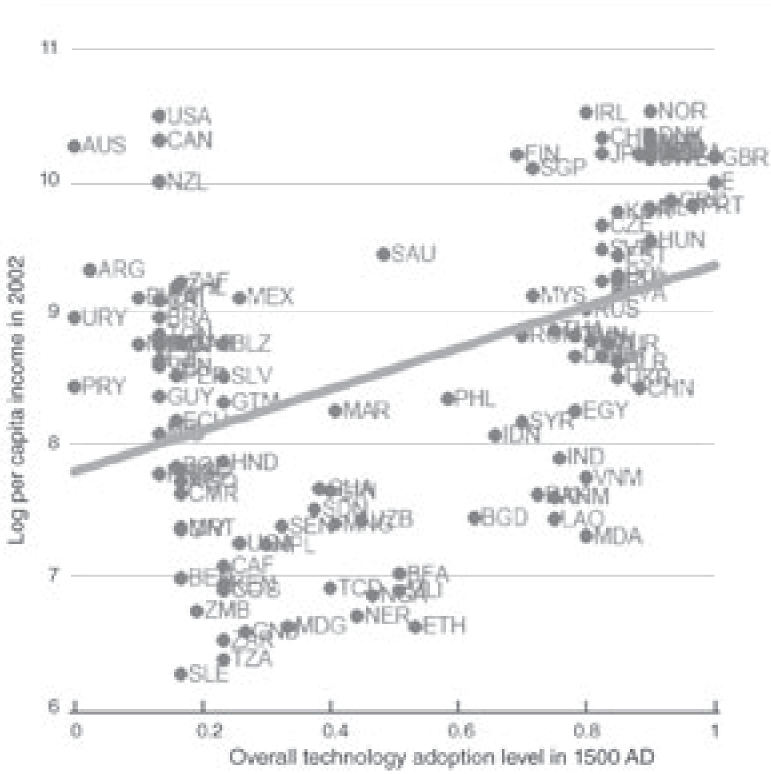

Figure 1. Technology in 1500 AD and Current Development

1500 AD (measured at the extensive margin) and current technology adoption (measured at the intensive margin). In particular, changing from the maximum (i.e., 1) to the minimum (i.e., 0), the overall technology adoption level in 1500 AD is associated with an increase in the time lag in the intensity of adoption with respect to the United States of 22 percent of the years since the invention of the technology. Figure 1 shows the simple scatter of per capita income today against technology in 1500 AD.

This paper does not address some well-known puzzles, such as the failure of China to capitalize earlier on its technological prowess (China (CHN) is below the regression line on the right, but it is more than offset by many other countries above the regression line for the same 1500 AD technology line), or the stagnation following the earlier technological prowess of the Islamic empire (Syria (SYR)and Egypt (EGY) are also below the regression line at about 1500 AD = 0.8, but again are offset by more numerous examples of rich countries today corresponding to this level). 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.

Much larger outliers than China or Islamic countries come from the Americas and Oceania. Latin American countries were behind the median country in the overall technology adoption level in 1500, but today they are middle income countries.

A similar case is South Africa (ZAF). Even more revealing, in the top left corner of Figure 1, we find the Neo-Europes, the United States, Canada, Australia, and New Zealand. These outliers are also influential observations, although the 1500 AD association is significant despite them. These were among the countries with the most primitive technology in 1500 AD, but are among the world's richest countries today. These cases likely have something to do with the partial or nearly complete replacement of the original inhabitants with European settlers. Large-scale European settlement was mainly a function of an exogenous event—the susceptibility of natives to European diseases, which created lightly inhabited fertile lands to be taken over by European settlers (Easterly and Ross Levine 2009). This raises the question of whether we were correct to identify the place as the unit of persistence, as opposed to peoples who may move and take their technology with them.

Fortunately, pathbreaking work by Putterman and Weil (2008) allows us to address this issue. Putterman and Weil's (2008) huge data collection exercise gives, for each country, the composition of its current population today by its origin country, taking into account migrations since 1500 AD. We then pre-multiply the vector of overall technology in 1500 AD by the origin matrix and enter the origin weighted measure of technology as the regressors in Table 8B. Instead of measuring the technology or income in a place today associated with 1500 AD technology in the same place, we are measuring the association of the place's technology today with the technology in 1500 AD of the places from where the ancestors of the current population came from.

This is straightforward for the 1500 AD technology measure. It is more problematic for the 1000 BC and 0 AD exercise, since we have no data on migrations before 1500 AD. It still seems of interest to correct the 1000 BC and 0 AD measures by the post-1500 migration matrix to test a peoples-rather-than-places technology persistence view. The post-1500 migrations are arguably the most consequential, since the discovery of the New World and the technological advances in oceangoing transport made wholesale replacement of low-technology people by high-technology people more likely than in earlier eras. We could assume either that pre-1500 migrations were random and orthogonal to the error term, or that they also tended to direct high-technology peoples to low-technology places (because of the ease of conquest and the high returns from applying more advanced technology to a previously underdeveloped land area). In the first case, the coefficient on 0 AD and 1000 BC would be unbiased. In the second case, the coefficient would be biased downward, making persistence look lower than it really was.

The results of the people-based technology measures are certainly stronger than the place-based measures. The measures from three different points in time of people-based old technology now all have significant predictive value for today's per capita income. Although 1000 BC and 0 AD are now significant, they still have a lot less explanatory power than 1500 AD, which continues to be our key result. Figure 2 shows the simple scatter plot between migration-adjusted technological heritage from 1500 AD and per capita income today. The result on long-run technological persistence is stronger overall if we base technology on people rather than places (the R^2 increases from 0.18 to 0.50). It is also reassuring that two very different exercises produce the same robust result for the association between technology in 1500 AD and per capita income today.

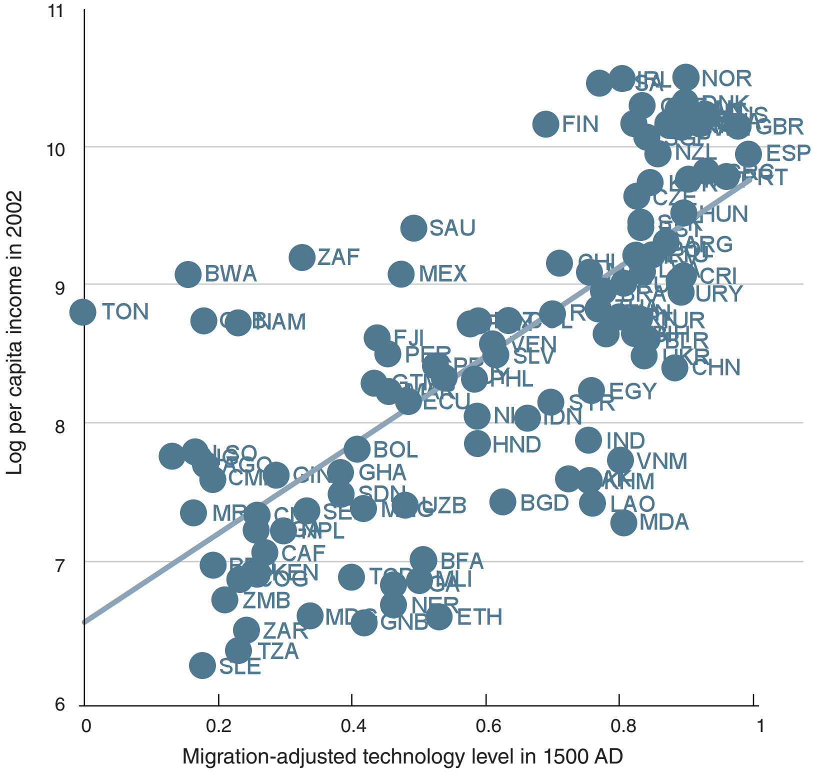

Figure 2. Scatterplot of Per Capita Income in 2002 against Migration-Adjusted Technology Heritage from 1500 AD

Our key 1500 AD result implies large magnitudes. Regressing income today on the migration-weighted index for 1500 AD, a coefficient of 3.261 implies that a movement from 0 to 1 is associated with an increase in per capita income today by a factor of 26.1. The log difference in per capita income today between Western Europe and sub-Saharan Africa is 2.59 (a factor of 13.3). This income difference is usually attributed to the post-1500 slave trade, colonialism, and post-independence factors in sub-Saharan Africa. The averages for Western Europe and sub-Saharan Africa on the migration-weighted technology index in 1500 AD are 0.923 and 0.303, respectively. The log per capita income difference today associated with that 1500 AD technology difference is $3.261 \times (0.923 - 0.303) = 2.023$ (a factor of 7.6). Thus, 78 percent of the log difference in income today between sub-Saharan Africa and Western Europe (2.023/2.59) is associated with the technology differences in 1500 AD.

If we do a horse race between the people-based and place-based measures, the former wins decisively, as shown in Table 9. The place-based technology actually has a negative sign, which is not robustly significant across all three periods (specifically not in the all-important 1500 AD result). Hence, we strongly confirm Putterman and Weil's (2008) seminal insight that history of peoples matters more than history of places (which they tested with places' history on antiquity

Table 9—Horse Race between Original and Migration-Adjusted Technology Indices

	Log income per capita in 2002			Current technology		
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Overall technology adoption level in 1000 BC	−1.640** (−2.34)			−0.304* (−1.73)		
Migration-adjusted technology level in 1000 BC	3.238*** (3.72)			0.516** (2.74)		
Overall technology adoption level in 0 AD		−1.214*** (−3.16)			−0.226** (−2.06)	
Migration-adjusted technology level in 0 AD		3.535*** (5.02)			0.648*** (4.30)	
Overall technology adoption level in 1500 AD			−0.459 (−1.31)			−0.117 (−0.98)
Migration-adjusted technology level in 1500 AD			3.658*** (6.48)			0.614*** (4.62)
Constant	7.589*** (23.35)	6.468*** (10.64)	6.529*** (18.57)	−0.681*** (−18.06)	−0.920*** (−10.44)	−0.865*** (−21.14)
Observations	104	123	111	109	130	115
R^2	0.16	0.16	0.51	0.12	0.19	0.42

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

of states and years of experience with agriculture). The same result shows up for technology history in our exercise. Hence, from now on in the paper, we will use the people-based measure of technology history for each country rather than the place-based measure.

We do not automatically infer that past technology CAUSES present income and technology. Although past technology history appears to matter for later income and technology, it may reflect an omitted third factor rather than a causal effect. We will not be able to decisively resolve which it is, although we will do two illustrative exercises at the end: one that tests the role of population size, and another that will show old technology still matters after controlling for fixed country-time factors.

To summarize, once we correct for post-1500 AD migration, the persistence of technology is a robust fact across each of our time periods up to the present: from 1000 BC to 0 AD, from 0 to 1500 AD, and from 1500 AD to the present. Our key result remains that development today is significantly related to technology differences in 1500 AD. Note, however, that our present measure of technology captures the intensive margin of technology adoption, while the three previous time periods captured the extensive margin. Although past technology history has mattered up until now because of the shift to the intensive margin it probably will matter differently in the future from what we have demonstrated for the past. Our results are likely more useful for understanding the history of today's technology differences than for predicting their future evolution.

Table 10—Technological Persistence after Removing Cross-Continent Variation

	Log income per capita in 2002			Current technology		
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Overall technology adoption level in 1000 BC	0.471 (0.86)			0.0272 (0.43)		
Overall technology adoption level in 0		1.446** (2.27)			0.345** (2.60)	
Overall technology adoption level in 1500 AD			2.211*** (4.56)			0.374*** (4.00)
Europe dummy	0.487 (0.54)	0.0353 (0.07)	−0.317 (−1.07)	0.00340 (0.02)	−0.149 (−1.24)	−0.164 (−1.63)
Africa dummy	−1.439 (−1.64)	−2.040*** (−3.85)	−1.401*** (−5.10)	−0.315 (−1.61)	−0.440*** (−3.81)	−0.309*** (−3.19)
Asia dummy	−0.792 (−0.90)	−1.138** (−2.34)	−1.159*** (−4.43)	−0.264 (−1.34)	−0.374*** (−3.41)	−0.360*** (−3.86)
America dummy	−0.246 (−0.28)	−0.617 (−1.29)	−0.678*** (−3.40)	−0.154 (−0.77)	−0.273** (−2.41)	−0.253** (−2.56)
Constant	8.794*** (9.84)	8.291*** (12.19)	8.051*** (26.70)	−0.385* (−1.95)	−0.523*** (−3.47)	−0.513*** (−4.59)
Observations	104	123	111	109	130	115
R^2	0.51	0.57	0.61	0.45	0.51	0.54

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

C. *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, Table 10 reports the estimates of regression (1) when the dependent variable is per capita income (first three columns) and current technology adoption (last three columns), and we add four continent dummies to the control set.

We extract two main conclusions from Table 10. First, much of the effect of technology history is detected from the cross-continent variation. Adding the continent dummies nearly eliminates the effect of overall technology adoption in 1000 BC on current development (column 1), and reduces, by approximately one-third, the effect of technology adoption in 0 AD (column 2) and in 1500 AD (column 3) on current development. The first effect of 1000 BC is no longer statistically significant, although 0 AD is. Second, the correlation between today (income or technology) and 1500 AD is robustly significant to continent dummies.

John Luke Gallup, Jeffrey D. Sachs, and Andrew D. Mellinger (1999) have argued that the latitude is an important determinant of income per capita, with the tropics at a disadvantage, and also that landlocked countries do worse. Robert E. Hall and Jones (1999); Acemoglu, Johnson, and Robinson 2002; Easterly and

Table 11A—Technological Persistence to Today's Income after Controlling for Geographic Variables

	Log income per capita in 2002					
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Migration-adjusted technology level in 1000 BC	−0.227 (−0.77)			0.348 (0.78)		
Migration-adjusted technology level in 0		0.157 (0.20)			0.971 (1.15)	
Migration-adjusted technology level in 1500 AD			1.770** (2.58)			2.590*** (4.09)
Distance to equator	4.287*** (2.90)	2.906 (1.45)	1.680 (0.68)			
Distance to equator squared	−0.526 (−0.24)	1.544 (0.60)	1.063 (0.32)			
Landlocked	0.897*** (−5.94)	0.823*** (−5.54)	0.646*** (−2.74)	0.752*** (−3.73)	0.745*** (−4.01)	−0.472* (−1.97)
Tropical dummy				1.154*** (−4.81)	1.145*** (−4.71)	−0.430 (−1.59)
Constant	7.615*** (30.61)	7.492*** (14.82)	6.969*** (25.41)	9.044*** (23.01)	8.414*** (10.93)	7.263*** (13.21)
Observations	97	114	104	104	123	111
R^2	0.54	0.51	0.60	0.36	0.37	0.54

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Levine 2003; and Dani Rodrik, Arvind Subramanian, and Francesco Trebbi (2004) argue that the effect of geography is through institutions. We do not need to resolve this issue for this paper, as we can just look at the reduced form. Tables 11A and 11B report the estimates of regressions for today's income and technology after controlling for the distance to the equator both with a linear and a quadratic term, or alternatively a dummy for the tropics, and also control for landlocked. As emphasized by the previous literature, there is some evidence for effects of geography (again we are agnostic whether it is direct or indirect).[8] Now, neither the results on 1000 BC and 0 AD are robust, but the results on 1500 AD for current income and technology are robust to these geographic controls. The coefficient on 1500 AD is, again, reduced compared to the bivariate specification. Now, an increase from 0 to 1 in the 1500 AD technology is associated with an increase in income today by a factor between 5.9 and 13.3.

Hence, our robust finding is that 1500 AD matters for current development, while the results on 1000 BC and 0 AD mattering for today's development are not robust. We still have the result that there is persistence in technology in the more ancient periods, from 1000 BC to 0 AD, and from 0 AD to 1500 AD, but the variation in

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

Table 11B—Technological Persistence to Today's Income after Controlling for Geographic Variables

	Current technology					
Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)
Migration-adjusted technology level in 1000 BC	−0.0520			−0.00958		
	(−1.09)			(−0.14)		
Migration-adjusted technology level in 0		0.122			0.233*	
		(0.96)			(1.84)	
Migration-adjusted technology level in 1500 AD			0.300***			0.396***
			(3.09)			(4.55)
Distance to equator	0.144	−0.0608	−0.433			
	(0.44)	(−0.18)	(−1.15)			
Distance to equator squared	0.860	1.068**	1.315**			
	(1.59)	(2.12)	(2.25)			
Landlocked	0.124***	0.108***	−0.0601	0.124***	0.111***	−0.0470
	(−4.65)	(−4.37)	(−1.64)	(−3.70)	(−3.60)	(−1.26)
Tropical dummy				0.203***	0.168***	0.0831
				(−5.01)	(−5.76)	(−1.64)
Constant	0.645***	0.736***	0.751***	0.422***	0.637***	0.740***
	(−23.24)	(−9.03)	(−17.41)	(−6.27)	(−6.30)	(−9.89)
Observations	101	120	107	109	130	115
R^2	0.52	0.49	0.56	0.31	0.32	0.43

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

technology unexplained by persistence over each long epoch is high enough to make the direct link from 1000 BC to the present much weaker than the link from 1500 AD to the present.

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 can only address this imperfectly since land area is also an endogenous variable, but we run two robustness checks (available in the Web Appendix as Table A1). First, per capita GDP today and current technology are uncorrelated with land area. Second, the correlation between historical technology adoption and either per capita GDP today or current technology remain unaffected by the land area control. So the association between contemporaneous technology and land area does not seem to reflect any dominant "sampling" effect of larger land area.

III. A Framework to Think about the Evolution of Technology

We present an elementary framework to help us think about alternative hypotheses and how to identify them in the data. We refer the interested reader to the working paper for a version with endogenous technology adoption which delivers the same predictions as this framework.

A. *Technology Adoption Dynamics*

Generations are indexed by t. Countries are indexed by c. Let A_{ct} denote the level of technology up to t. This measure could encompass either the extensive margin of technology adoption (i.e., the number of technologies available in the country) or the intensive margin of technology adoption (i.e., how many producers have adopted the available technologies). Technology evolves according to

$$A_{ct} - A_{ct-1} = A_{ct-1}^{\gamma} e^{\theta_{ct}} + \varepsilon_{ct}. \tag{2}$$

The term A_{ct-1}^{γ} reflects the complementarity between previous technology and new technology adoption discussed in the introduction and documented in Table 1. The strength of the complementarity is measured by the parameter γ. θ_{ct} is a parameter that varies with other factors that promote technology adoption besides the complementarity between old technology and new adoption or innovation. In the optimizing model, θ_{ct} captures the relative benefits and costs of adopting new technologies. ε_{ct} represents random noise, such as the likelihood of measurement errors that we have discussed at different points in this paper.

The long-run persistence of technology depends on the value of γ. Suppose for simplicity that θ_{ct} is the same for all c and t. Then if γ is larger than one, technology grows at an accelerating rate as the technology level rises in the long run. This would also apply across countries, so that more advanced countries will have faster growth, and there will be divergence. This may seem consistent with some historical facts, but (2) also implies growth would soon reach absurdly explosive levels if γ is larger than one, so this obviously cannot be a complete story. If γ is equal to one, A_{ct} grows endogenously in the long run at a stationary rate, as in the Solow model; there is technological persistence, but neither convergence nor divergence. Finally, if γ is smaller than one, A_{ct} grows at a decreasing rate in the long run as technology rises. Less advanced countries will grow faster than more advanced countries, and there will be convergence. Over very long periods of time, the effect of initial technology leads or lags will vanish if γ is smaller than one, while if it is greater than or equal to one, initial technology will matter even in the very long run. A finding that initial technology still has some effect on current technology after some very long time period is supportive of the view that γ is greater than or approximately equal to one.

Obviously, we do not believe in a mono-causal view that only past technology history matters; θ_{ct} will have *some* variance across countries and over time in response to other factors. The part of the variance that is uncorrelated with initial technology will dampen the correlation between initial technology and today's technology. The same is true for ε_{ct}, including measurement error. The longer the time period, subject to these two sources of variance, the weaker the effect of initial technology.

The patterns of persistence are that we find technology in 1500 AD to be a robust correlate of technology today, but not 1000 BC or 0 AD. This is suggestive of some combination of high variance of θ_{ct} or ε_{ct}, and a value of γ that is around unity. However, we also find 1000 BC and 0 AD to be robust correlates of 1500 AD, with relatively constant explanatory power and coefficients. This pattern could simply reflect the lower measurement error in the 1500 AD measure than in the previous measures.

B. *Persistent Technology Adoption Dynamics versus Persistent Omitted Variables*

An alternative view to the technological complementarity 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 $\gamma \approx 1$, we could have γ close to zero, and the persistence of historical adoption results from θ_{ct} being persistently higher in some places than in others in the very long run.

Several variables could, as discussed by other literature, be persistent and affect the return to technology adoption. The most prominent in the literature are population, institutions, culture and genetics.[9] More population, for example, could mean more inventors of ideas (Kremer 1993). Similarly, semi-endogenous growth models, e.g., Jones (1995, 1999, 2001, 2005), Samuel S. Kortum (1997), and Paul S. Segerstrom (1998), also have the feature that the force that ultimately keeps technology improving is the continuous expansion of the scale in the economy through population growth.[10] The reduced form of these models in technology alone would also predict technological persistence, and so this fact alone is not enough to assess the weight to be attached to different models. Similarly, other long lasting factors that make θ_{ct} persistently different between countries, such as values, norms, and culture (Guiso, Sapienza, and Zingales 2008; Tabellini 2007), experience with statehood (Bockstette, Chanda, and Putterman 2002), or genetic diversity or distance from other cultures (Ashraf and Galor 2008; Spolaore and Wacizarg 2009) would be consistent with our results.

It is possible to make progress in the identification of the source of persistence when there is historical data available on the persistent omitted variable that may affect the return to technology adoption. If that is the case, historical technology should not affect current development after controlling for the historical value of the other variable. For example, this follows from expression (2) after substituting in $\theta_{ct} = l_{ct}$, where l_{ct} is the log population.[11]

Table 12 reports the estimation results. 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. The sign on population is negative and significant in column 1, and negative and almost significant in column 2. This is inconsistent with an important role for historical population size determining future technology for this period. Column 3 also fails to find evidence for feedback from historical technology to current population size, which is another important part of technology-population models. This does not necessarily contradict the technology-population model in general, since the nation may not be the

[9] Acemoglu, Johnson, and Robinson 2002; Ashraf and Galor (2008); Hall and Jones (1999); Jones (2001); Mokyr (2005b); Spolaore and Wacziarg (2006). Lucas (2008) stresses openness to trade, which we could lump under "institutions" if we accept recent work that argues policies and institutions are not really separable.

[10] These models stress the effect of population through the supply of ideas with the increased number of thinkers. We can generate a similar population effect by having population affect our return to ideas (as it obviously does with nonrival ideas).

[11] As we show in the working paper (Comin, Easterly, and Gong 2006), this identification strategy is valid regardless of the influence from other countries technology in the adoption cost.

Table 12—Interaction between Technology and Population

	Current			1500 AD	
	Income	Technology	Population	Technology	Population
Dependent variables	(1)	(2)	(3)	(4)	(5)
Migration-adjusted technology level in 1500 AD	3.506***	0.545***	0.607		
	(8.75)	(6.87)	(1.39)		
(Log) population AD 1500	−0.150***	−0.0239*	0.738***		
	(−2.77)	(−1.96)	(16.36)		
Migration-adjusted technology level in 0 AD				0.541**	−0.740
				(2.43)	(−1.32)
(Log) population in 0 AD				0.0699***	0.831***
				(3.18)	(15.77)
Constant	6.378***	−0.884***	16.22***	0.158	1.628***
	(22.62)	(−21.71)	(57.11)	(0.75)	(3.21)
Observations	106	110	114	98	98
R^2	0.55	0.43	0.64	0.28	0.80

Note: t-statistics in parentheses computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

correct unit of observation for the population that adds to the idea stock (particularly as we approach the modern day when there was sharply lower communication and transport costs between nations). For us, the important point is simply that the coefficient on past technology is robust to controlling for historical population.

Since the modern period may have different dynamics than ancient periods, we conduct similar exercises with technology column 4 and population column 5 in 1500 AD as dependent variables and technology and population in 0 AD as independent variables. Now, we find a positive effect of population in 0 AD on technology for 1500 AD (consistent with population-technology models), and the size of the autoregressive coefficient on technology falls (compare with Table 7A). However, the effect of technology adoption in 0 AD on technology in 1500 AD is still significant after controlling for population in 0 AD.

We are inclined to interpret our findings as supporting a direct effect of old technology on new technology, even though there may also be some indirect effect through the population channel.

Of course, it is not possible to obtain historical data on all the potentially persistent factors that may affect historical technology adoption. Nevertheless, further progress can be made in the identification of the source of the persistence in technology adoption if the effect of these omitted factors (i.e., institutions, culture, and genetic endowment) on the return to technology adoption has an important symmetric component across sectors. That is, good institutions preserve property rights and induce agents to adopt new technologies in all sectors (covered by our dataset).

Under this sensible assumption, we can estimate γ by exploiting the large observed within country variation in technology adoption. As Table 13 shows, the

Table 13—Variation in Technology Adoption within Countries versus across Country

		SD across countries		SD of deviations of sector level technology from overall technology adoption within countries			
Period	Observations	Overall	Agriculture	Industry	Military	Transportation	Communications
1000 BC	114	0.28	0.35	0.18	0.16	0.22	0.23
0	136	0.28	0.25	0.18	0.26	0.24	0.32
1500 AD	125	0.32	0.2	0.19	0.13	0.12	0.17
Current	134	0.2	0.12	0.11	—	0.11	0.12

Notes: "SD across countries" is the cross-country standard deviation in overall technology adoption level. "SD of deviations of sector level technology from overall technology adoption within countries" is computed as follows: $\sigma(x_{sct} - x_{ct})$, where $\sigma(z)$ represents the standard deviation of z across countries, x_{sct} is the level of technology in sector s, country c, and period t, and x_{ct} denotes the overall adoption level in country c in period t, the average of the adoption levels by sector for country c in period t.

within-country variation across sectoral indices is large relative to the cross-country variation in the overall index (which is the average of the sectoral indices).

Formally, let technology adoption in sector s in country c in period t be denoted by a_{cst}. Then, we have the following law of motion for a_{cst}:

$$a_{cst} = \beta_{ct} + \beta_{cs} + \beta_{st} + \gamma\, a_{cst-1} + u_{cst}. \tag{3}$$

This regression includes a country effect (β_{ct}) that could be time-varying and that captures the evolution of country-specific factors, such as institutions, genes, population, and geography (i.e., θ_{ct}). It also includes a country-sector fixed effect (β_{cs}) that captures very persistent comparative advantage in adopting technologies in a given sector. Finally, (3) also includes a sector time-varying effect (β_{st}) that takes care, for example, of the fact that the technology adoption measures in the current period are a different concept and units, capturing the intensive margin.

The identification of γ presents the well-known challenge often encountered in convergence regressions of a lagged dependent variable. To solve this problem, we first difference equation (3) obtaining

$$a_{cst} - a_{cst-1} = \beta_{ct} - \beta_{ct-1} + \beta_{st} - \beta_{st-1} + \gamma\,(a_{cst-1} - a_{cst-2}) + \overline{u}_{cst} \tag{4}$$

and instrumenting $a_{cst-1} - a_{cst-2}$ with a_{cst-2}. If a_{cst-2} is uncorrelated with $\overline{u}_{cst}$, our estimate of γ will be unbiased. We are going to implement the IV regression of (4) for just one first difference with $t = 2000$ AD, $t - 1 = 1500$ AD and $t - 2 = 0$ AD. It seems a tenable assumption 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 the equation using data on the other four sectors in our dataset. Since, from our previous results, large scale population movements had an effect on the change of technology between 1500 AD and 2000 AD, we will use the migration-weighted technology indices (as in the exercises above) when estimating γ in (4).

Table 14 reports the estimates of γ with column 1 and without column 2 the country fixed effects. The main finding is that we observe significant estimates of γ in both specifications. There are several important implications from these estimates.

Table 14—Persistence of Technology Within

Dependent variable:	$Technology_{cst}$ (1)	(2)	(3)	(4)	(5)	(6)
$Technology_{cst-1}$	0.4***	0.29***	0.25***	0.25***	0.39***	0.28***
	(4.85)	(4.84)	(3.71)	(3.11)	(4.54)	(4.12)
Country time-varying effects	No	Yes	Yes	Yes	Yes	Yes
Sectors excluded other than military	—	—	Agri.	Com.	Transp.	Indust.
Observations	417	417	315	307	312	317
R^2	—	0.48	0.43	0.56	0.32	0.56

Notes: Panel regressions using (migration adjusted) technology level "a" in sector *s*, country *c* in year *t*. Most general regression is: $a_{cst} = \beta_{ct} + \beta_{cs} + \beta_{st} + \gamma\, a_{cst-1} + u_{cst}$, where β_{cs} is a country-sector fixed effect, β_{ct} is a country time-varying effect, β_{st} is a technology specific trend, and u_{cst} is the error term. Regressions are estimated in first differences instrumenting $Technology_{ctst-1} - Technology_{cst-2}$ by $Technology_{cst-2}$ to avoid the lagged dependent variable bias. Hence, the second-stage regression is $a_{cst} - a_{cst-1} = \beta_{ct} - \beta_{ct-1} + \beta_{st} - \beta_{st-1} + \gamma\,(a_{cst-1} - a_{cst-2}) + u_{cst}$ where $t = 2000$, $t - 1 = 1500$, and $t - 2 = 0$.

t-statistics in parenthesis computed using robust standard errors clustered to take into account the correlation in the information used in the coding of technology.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Recall that both of these regressions include country fixed effects in levels and country-sector fixed effects in levels. This is suggestive that 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, do not fully account for the persistence of technology (i.e., γ). There is an effect of old technology even after removing such country effects. In columns 3–6 of Table 14, we report the estimates of γ after eliminating successively one of the four sectors covered in our dataset. Recall that we have excluded the military technologies from this analysis. The coefficient estimates are somewhat lower than in the previous regressions of Technology in 2000 AD on migration-adjusted technology in 1500 AD (see Tables 8B, 10, and 11B), but still of nontrivial magnitude and statistically significant. The significance of the estimate of γ is not driven by any specific sector. This result is consistent with our simple framework, since the knowledge created when adopting a technology in a given sector is likely to reduce the costs of adopting subsequent technologies within the sector, but not so much in other sectors.

IV. Conclusions

The main finding of this paper is a simple one. Technology in 1500 AD is associated with the wealth of nations today. This is robust to including continent dummies and geographic controls, so it is not just driven by "Europe versus Africa" or "tropical versus temperate zones." There are two notable parts of the finding. The first is that technology as old as 1500 AD is a historical correlate of development when we consider that most historical discussions of developing countries start with post-1500 European contact and colonization. The second notable aspect of our finding is that the magnitude of the association between historical technology adoption and current development is nontrivial. In our baseline specification for migration-adjusted technology, 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 26. More realistically, after including a battery of controls, this multiple is still between 5.9 and 13.3.

In an effort toward understanding what drives this correlation, we have found suggestive results that technology is very persistent, that this persistence is not driven only by the persistence of population, and that it does not disappear when calculated only within sectors after removing the country average adoption level in the period and country-sector fixed effects (hence, controlling for any factors that operate at a country-wide level such as institutions). This evidence provides support to the hypothesis that the technology adoption dynamics, in which the cost of adopting new technology falls with the stock of previous technology, are one of the mechanisms that generates the propagation uncovered in the data.

Appendix

Example of Coding in 1000 BC and 0 AD

Korea was inhabited by the Mumun peoples in 1000 BC. The Mumuns had no tradition of either written or nonwritten 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 BC 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 percent 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 BC 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 1000 BC is 0.6.

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