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From Gutenberg to Google: The Internet Is Adopted Earlier if Ancestors Had Advanced Information Technology in 1500 AD

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THE INTERNET IS ADOPTED EARLIER IF ANCESTORS HAD ADVANCED INFORMATION TECHNOLOGY IN 1500 AD

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Abstract

Individuals with ancestry from countries with advanced information technology in 1500 AD, such as movable type and paper, adopt the internet faster than those with less advanced ancestry. The analysis illustrates persistence over five centuries in information technology adoption in European and U.S. populations. The results hold when excluding the most and least advanced ancestries, and when accounting for additional deep roots of development. Historical information technology is a better predictor of internet adoption than current development. A machine learning procedure supports the findings. Human capital is a plausible channel as 1500 AD information technology predicts early 20th century school enrollment, which predicts 21st century internet adoption. A three-stage model including human capital around 1990, yields similar results.

JEL codes: O33, D13, D83, J24, N70, Z13

Keywords: internet; technology diffusion; information technology; intergenerational transmission; printing press

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1 Introduction

Curiosity, the desire for more knowledge, could be harder to account for than the desire for material advantage, the basic motivation of the *homo economicus*. Yet, curiosity is at the heart of sustained economic growth as productivity increases require new knowledge. Prior to the industrial revolution, productivity increases were one-off events, while after the revolution productivity increases became complementary and sustained. This marks a unique turn in human history, and as Mokyr (2016) writes, it may take a confluence of factors to explain. One essential input was the printing press as the agent of change ushering in the Enlightenment (Eisenstein, 1979) and instrumental for the development of the scientific method, as well as the diffusion and persistence of the Industrial revolution.[2] Technology shifts can have long-term effects, see for example, Atkeson and Kehoe (2007) and Boerner and Severgnini (2019).

Johannes Gutenberg's invention in the mid-15th century, the printing press, uses movable type and paper to mass-produce books. This paper finds that the printing press remains an important influence five centuries later leaving its imprint on the current digital information revolution. The adoption of the internet is studied, and its adoption may measure curiosity in two ways. First, adopting new technology is a measure of curiosity, learning a new tool. Second, the nature of the internet as an information and communications technology makes it directly related to curiosity in the technology's application since information and communication are inputs to new knowledge. Moreover, the approach focuses on the intergenerational transmission of human capital. It avoids concerns with potentially omitted spatial

[2] The ability to print books generated the largest advance in accessing knowledge in the past millennia, Mokyr (2002, 2005) argues. Book production positively predicts preindustrial economic development (Dittmar, 2011). The Enlightenment was the first knowledge economy (Jacob, 2014), which fostered a positivist scientific culture separated from normative demands by churches and kings. The scientific method of reproducible experiments coupled with the Baconian idea that knowledge should be useful led to a dual feedback between theoretical and applied science. The interplay between propositional and prescriptive knowledge, as Mokyr (2002) labels them, may have been essential for propelling the Industrial revolution beyond its initial phase.

correlations, as the individuals studied reside in locations different from their ancestors exposed to the year 1500 AD technology.

The main finding in this paper is that the internet is adopted earlier by those with ancestors who had highly developed information technology in the year 1500 AD. It indicates that the early availability of printed books has fostered curiosity persisting in the current day. A machine learning procedure reaffirms the importance of 1500 AD information technology for predicting internet adoption among a large set of potential predictors.

Technology is the engine of growth in the Solow model and the most important force in lifting the standard of living over time and across countries.[3] The role of formal institutions for growth is emphasized in part of the literature, for example, Parente and Prescott (1994), while another strand focuses on informal institutions, see Algan and Cahuc (2010). Another example is Acemoglu, Johnson, and Robinson (2001, 2002) who emphasize the importance of institutions brought by European colonizers, while Glaeser et al. (2004) argue that the role of formal institutions cannot be distinguished from the human capital brought by the colonizers. This paper studies technology adoption holding formal institutions constant, through within country comparisons, and focuses on the role of human capital (broadly defined to include, for example, curiosity) or informal institutions transmitted across generations by migrants.[4]

Migration is an important aspect of the analysis in several respects. First, studying the internet adoption of children of immigrants makes it possible to hold formal institutions constant through the inclusion of fixed effects. The individuals compared are born and reside in the same country where they face the same institutional environment. Second, the main explanatory variable, information technology in the year 1500 AD in the ancestral country, is adjusted to account for population movements from the year 1500 to 2000. This ancestry adjusted value reflects the

[3] See for example Grossman and Helpman (1991).

[4] The paper will hence not speak to the relative importance of informal versus formal institutions.

experience of ancestors of today's populations, not the characteristics of the place, in the year 1500. This adjustment makes a big difference for countries that have experienced large population changes, as shown by Putterman and Weil (2010) who created the matrix of population movements. Moreover, Putterman and Weil (2010) show that the ancestry adjustment substantially improves the predictive power of historical factors in explaining current development, implying greater importance of population characteristics (over place characteristics).[5] Third, studying children of immigrants traces the migration argument directly, that individuals bring human capital with them to new environments and transmit the knowledge across generations, underlying the strong results where migration adjusted factors are important in the literature mentioned above.

Smartphones are ubiquitous today and it may seem as though everyone is constantly connected to the internet. Yet, a majority of Europeans, 54%, never used or had no access to the internet in 2004. This share had dropped to one in three in 2010. One in five used the internet every day in 2004 and this fraction had more than doubled to 45% six years later. 64% of Americans had internet access at home in 2006, which had increased to 82% in 2014.[6] The internet adoption rates differ systematically, both in Europe and the U.S., with the historical technology of their ancestors.

Children of immigrants are compared within the same birth country. Individuals whose ancestors had more developed information technology in 1500 AD use the internet more than those with less advanced ancestors. The main analysis is done in

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[5]Other papers have also found that the ancestry adjustment produces stronger estimates. Comin, Easterly, and Gong (2010) find the technology levels persist over millennia and that 1500 AD technology predicts current development. The genetic diversity that Ashraf and Galor (2013) find has an inverted U-shaped relationship with development is also ancestry adjusted. Chanda, Cook, and Putterman (2014) find that the estimated sign on historical development, for predicting current development, changes from negative to positive when the migration adjustment is applied. Spolaore and Wacziarg's (2013) extensive review article reproduce many of these findings.

[6] The U.S. internet access of 64% in 2006 lines up very closely with Europe where 34% report they did not have internet access in 2006.

30 European countries, but the predictive power of historical information technology is also seen in the U.S.

The finding that historical information technology among the ancestors predicts internet use holds when accounting for historical development and the diffusion of other technologies historically. Geography, genetic diversity, and other deep roots of development factors do not alter the result. The findings are not driven by the most or least developed ancestries. Historical technology is a stronger predictor of internet adoption than current development. While the current development of the ancestral country predicts internet use it only does so as long as historical information technology is excluded from the model. 1500 AD information technology is a strong predictor of internet use also when accounting for the current development in the ancestral country.

The 1500 AD information technology data is not directly measuring the printing press but component technologies underlying the press. The four measured technologies are the use of movable block printing, the use of paper, the use of books, as well as woodblock printing.[7] Movable type had been used in China centuries earlier than Gutenberg put them into his press. Also, paper and books (as well as woodblock printing) were in use in different parts of the world by 1500 AD. The technology index made up of these components is hence not Eurocentric.

The historical literature indicates that the ability to print books leads to an expansion in human capital.[8] First, the elite gets access to more knowledge and the development of the scientific method yields more knowledge.[9] Contrasting the importance of upper tail human capital, average human capital appears unimportant in the early industrial revolution (see for example, Allen 2003 and Galor 2005). Yet,

[7] The year 1500 AD technology data are from Comin, Easterly, and Gong (2010).
[8] See for example Eisenstein (1979).
[9] Squicciarini and Voigtländer (2015) document the importance of this upper tail human capital as the diffusion of the French industrialization is predicted by subscriptions to the *Encyclopédie*, a compilation of scientific and technological advances. Mokyr (2016) discusses how the Republic of Letters, an elite network of scientists and intellectuals, produced and disseminated knowledge during the Enlightenment.

at some point general human capital might gain importance as technologies become more complex, and more educated workers are needed in production.

Evidence presented below indicates that the early ability to print books yielded advances in general human capital four centuries later. The ability to print books in 1500 AD strongly predicts primary school enrollment in the year 1920, providing a link between the early ability to print books and general human capital. In the second stage, 1920 primary schooling predicts internet adoption. This two-stage model illustrates that printing, as practiced by Gutenberg, predicts general human capital almost one century before the dawn of Google, human capital that in turn, predicts internet adoption. This illuminates a link from the turn of the 16th century information technology to early 20th century average human capital to 21st century internet adoption. The results are similar when the human capital measure is the average years of schooling around 1990. Moreover, a three-stage model, with historical information technology in the first stage, linking 1920 human capital to 1990 human capital yields similar results for internet adoption; human capital is a mediator for the persistence of information technology adoption. The findings provide evidence that skill begets skill over the centuries and that human capital is a plausible mechanism explaining the relationships operating over half a millennium. This could be one explanation behind the persistence of fortune, or lack thereof, in many parts of the world; the human capital promoting technology adoption exhibits complementarities across generations and centuries.

The paper proceeds as follows. The next section discusses the empirical specifications, followed by a section presenting the data. The results are presented in section 4, and the last section concludes.

2 Data

The European Social Survey (ESS) provides the individual data. Data from the second to fifth rounds of the ESS are used.[10] The survey asks about the country of birth of

[10] See Table A1 for the participating countries in each round. The main outcome variable, internet use, is not included in later rounds.

the respondent as well as the country of birth of both parents.[11] This information allows me to identify children of immigrants and from which countries their parents originate. Studying 30 countries of residence for children of immigrants reduces the concern that the results are driven by conditions of one particular country. Individuals with ancestry from 76 countries are studied. This reduces the concern that the results are particular to a small number of ancestral backgrounds.

The sample includes individuals born in the country of residence (where the interview is conducted), who have at least one parent born abroad (in a country different from the interviewed individual's birth country). To reduce noise from small migrant groups, there is a requirement that at least five mothers and fathers originate from each ancestral country to be included in the analysis. There is also a requirement that there is data on internet use as well as ancestral country technologies in 1500 AD. The restrictions result in 76 ancestral countries.

The summary statistics are presented in Table A2. The children of immigrants are similar to the general population on observables. Their mean age is somewhat lower, which may account for their slightly higher education and internet use.

2.1 Internet Use

The following question captures internet use. "Now, using this card, how often do you use the internet, the World Wide Web or e-mail - whether at home or at work - for your personal use?" The categories for the answers are "No access at home or work," "Never use," "Less than once a month," "Once a month," "Several times a month," "Once a week," "Several times a week," and "Every day." The answers for the first two categories ("No access" and "Never use") are coded as 1 in a joint category. The following categories are coded by rising digits from 2 ("Less than once a month") to 7 ("Every day"), so a higher value captures more frequent use. The results are similar if each category is coded with a separate digit (in particular coding "No access" as 0).

[11] Parental birth country is not available in the first round. The fifth round is the last to include the question about internet use. Extensive documentation of the data is available at http://ess.nsd.uib.no/.

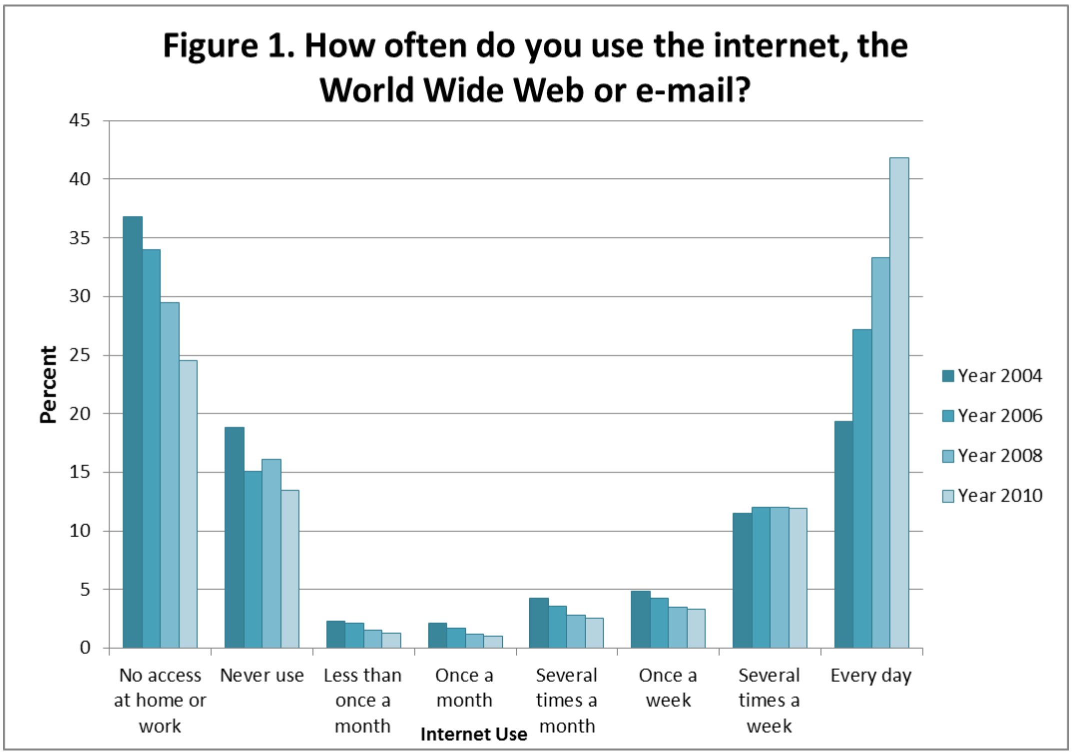
The distribution of internet use, by survey wave, is plotted in Figure 1. There is a clear trend over time from the left to the right of the distribution, where all of the increase is driven by a higher fraction of people using the internet every day. The trend points to the importance of including year fixed effects in the analysis.

2.2 Ancestral country technology in 1500 AD

The historical data set on technologies in five sectors used here was collected by Comin, Easterly, and Gong (2010). The focus of this study is on information technology, but there is also data on technologies in agriculture, industry, transportation, and the military.

Each technology measure includes several components and is expressed as an index between 0 and 1. The information technology measure in 1500 AD has four components; indicators for the use of movable block printing, the use of paper, the use of books, and the use of woodblock printing.[12] The agricultural technology takes on one of four values depending on the primary form of subsistence; the lowest value is assigned to hunting and gathering, and the highest value is given to plow cultivation.

[12] Information technology and communications technology are used interchangeably throughout the paper.



The remaining three measures are based on indicators for the use of different technologies (as is the case with information technology). Industrial technology has two components; the presence of steel and/or iron in a civilization. Transportation technology has six components; having ships capable of crossing oceans (three such components), the compass, the wheel, and horse powered vehicles. Military technology has eight components, including having a standing army, muskets, and field artillery. The focus for all technology measures is on the migration adjusted technologies reported by Comin, Easterly, and Gong (2010). The adjustment is made based on the migration matrix describing population movements from 1500 AD to the current time produced by Putterman and Weil (2010). The measures capture what technologies the ancestors of the current population in a country were exposed to in 1500 AD. The variation in the historical technology variables stems from two sources; the technologies at use in a particular place and the population movements to and from that place (the migration adjustment).

If only one parent is an immigrant, the ancestral technology level is given by the value in the immigrant parent's birth country. If both parents are immigrants the ancestral technology level is the average across the parents. The ancestral countries and the level of information technology in the year 1500 AD (migration adjusted) are presented in Appendix Table A3.

2.3 Ancestral country characteristics

Apart from historical technologies in the ancestral countries, there is a wide array of controls used in the long run development literature. First is a range of geographical characteristics of the ancestral country. These include distance to equator, latitude, temperature, precipitation, and if the country is landlocked. Also accounted for are the percentage arable land, the land suitability for agriculture, years since the Neolithic revolution, and the percent at risk of malaria. The data sources are the data sets posted by Comin, Easterly, and Gong (2010) as well as Ashraf and Galor (2013).

The predicted genetic distance from Ashraf and Galor (2013) is also included. The migration adjusted value, based on the Putterman and Weil (2010) migration matrix, is used. To account for 1500 AD development, the population density is used. An additional measure is state history in 1500 AD, which accounts for historical experience with an organized political body.[13] These are established measures of early development in the literature, see for example, Putterman and Weil (2010) and Chanda, Cook, and Putterman (2014).

To account for current economic development, the natural logarithm of gross domestic product (GDP) per capita is used. The values are taken from the World Development Indicators provided by the World Bank and refer to the 2000s. An additional measure of current development used is life expectancy at birth; also this measure is from the World Development Indicators.

Data on primary school enrollment rates in the year 1920 across countries is from Benavot and Riddle (1988). The data is on the population enrolled in primary school

[13] Both 1500 AD population density and state history are as in Chanda, Cook, and Putterman (2014). The migration adjusted, accounting for population movements since 1500 AD, are used but results are very similar using unadjusted values.

as the percentage of the relevant school age population. Data on average years of schooling in 1985-95 is as in Chanda, Cook, and Putterman (2014).

2.4 Individual control variables

The ESS includes a wide set of individual controls. Age, gender, marital status, education, employment status, income, and religious affiliation are observed. Marital status is captured by two dummies for married and never married, with widowed and divorced being the excluded category. Education is captured by one dummy for tertiary (university) degree and above, and one dummy for upper secondary as the highest attained degree. Lower education is the excluded category. One dummy captures individuals who are out of the labor force (students, not employed and not looking for work, and retired), and another dummy for unemployed who look for work. The employed is the omitted category. Income is measured by income decile, based on the country specific income distribution. I create one dummy for the bottom three deciles, Low Income, and one dummy for the middle four deciles, Middle Income. There are two dummies for being a Catholic or a Protestant. All other religious denominations are in the excluded category.

2.5 Time spent watching TV

Part of the analysis considers another outcome variable; time spent watching TV. It is captured by the following question: “On an average weekday, how much time, in total, do you spend watching television?” Answers are coded into eight categories with values 0 through 7; “None”, “Less than 0,5 hour”, “0,5 hour to 1 hour”, “More than 1 hour, up to 1,5 hours”, “More than 1,5 hours, up to 2 hours”, “More than 2 hours, up to 2,5 hours”, “More than 2,5 hours, up to 3 hours”, and “More than 3 hours”.

2.6 Use of the internet to make phone calls

In rounds three and four of the ESS (collected in 2006 and 2008), there is a question if the respondent uses the internet for telephone calls at home. If the individual uses the internet to make phone calls, the indicator variable takes on the value 1 and 0 otherwise. About one in five individuals makes calls over the internet.

2.7 U.S. data

The General Social Survey (GSS) is used for U.S. data.[14] Three dependent variables are examined. The first question is, “Do you have access to the Internet in your home?” and the second “Do you personally ever use a computer at home, at work, or at some other location?” Both these are answered with a “Yes,” coded as 1, or “No,” coded as 0. The third question asks, “On the average day, about how many hours do you personally watch television?”[15] Answers range from 0 to 24. Individual characteristics age and gender are included, as well as fixed effects for 9 regions and all survey years. Ancestry is determined through the variable “ethnic” asking, “From what countries or part of the world did your ancestors come?” There are 28 ancestries matched to ancestral information technology, mostly European countries but also China, India, Mexico, and Canada. The sample is second and higher generations immigrants, that is, individuals born in the U.S. who have foreign ancestry. GSS summary statistics are found in Appendix Table A2.

3 Empirical specification

Internet use among children of immigrants is related, within the birth country, to historical technology in the ancestral country. The approach addresses reverse causality in two ways. First, the historical technology is measured centuries before the current era. Second, technology is measured in a different context than the individual lives. The internet use of an individual could hardly determine the technology available in a different country centuries ago. Moreover, the ancestral technology variation is separated from the historical and institutional characteristics of the birth country, which are captured by the country fixed effect. The main analysis is ordered Logit regressions of the following form:[16]

$$\text{Internet\_Use}^{*}_{icat} = \beta_0 + \beta_1 \text{1500AD\_Tech}_a + \beta_2 \text{X}_{iat} + \gamma_{ct} + \varepsilon_{icat} \qquad (1)$$

[14] The cumulative 1972-2014 GSS data file, release 5, is available at http://gss.norc.org/.

[15] The internet question is available in the five rounds since 2006, the computer question in six rounds (2000-2004, 2010-2014), and the TV watching question in 24 rounds (since 1975, except 1976, 1984, and 1987).

[16] The results are robust to using the ordered Probit estimator or a linear ordinary least squares (OLS) model.

$\text{Internet\_Use}^*_{icat}$ captures a latent and continuous measure of the internet use by individual i, born and residing in country c with at least one parent born in country a, and a≠c, in period t. Observed internet use is in ordered categories such that

$$\text{Internet\_Use}_{icat} = j \quad if \quad \theta_{j-1} < \text{Internet\_Use}^*_{icat} < \theta_j$$

where $\theta_0 = -\infty, \theta_k = \infty$, and j=1, 2, …, k. The probability of a given observation is given by

$$Pr(\text{Internet\_Use}_{icat} = j)$$

$$= Pr\big(\theta_{j-1} < \beta_0 + \beta_1 \text{1500AD\_Tech}_a + \beta_2 \text{X}_{iat} + \gamma_{ct} + \varepsilon_{icat} < \theta_j\big)$$

$$= F\big(\theta_j - XB\big) - F\big(\theta_{j-1} - XB\big)$$

where $XB \equiv \beta_0 + \beta_1 \text{1500AD\_Tech}_a + \beta_2 \text{X}_{iat} + \gamma_{ct}$. In the ordered Logit version the error term is logistically distributed and $F(z) = 1/(1 + e^{-z})$. In the ordered Probit the error is normally distributed and $F(\cdot)$ is the normal distribution. The linear ordinary least squares model estimates (1) with observed internet use as the dependent variable.

The model is estimated using a sample of second generation immigrants. The average level of ancestral historical technology, $\text{1500AD\_Technology}_a$, is common to all individuals with a parent born in country a.[17] X_{iat} captures individual demographic and economic controls as well as additional ancestral country characteristics that may affect internet use. The country of residence-by-year fixed effects are denoted by γ_{ct}, and ε_{icat} is the error term. The standard errors are clustered by the parent's birth country.[18]

[17] If both parents are immigrants and they are born in different countries then the ancestral country value is the average across both parents.

[18] The clustering is based on the mother's birth country if she is an immigrant. If the mother is native the clustering is based on the father's birth country. Hence, the clustering is conservative in the sense that it is based on only one country also in cases when the parents are born in different countries.

Individual and ancestral country controls are accounted for in X_{iat}. The inclusion of the country-by-year fixed effects γ_{ct} means that I account for the institutional structure and all other unobserved differences which apply to all residents in country c and year t. It also means that the variation used to identify the estimate on ancestral historical technology is to compare the internet use of second generation immigrants within each country of residence and year relative to the characteristics in their countries of ancestry.[19] The country-by-year effects account for level differences between countries and non-linear time trends within each country.[20]

4 Results

4.1 Baseline results

The baseline results are presented in Table 1. First, I introduce information technology in 1500 AD in the ancestral country (or countries if both the parents are immigrants). The estimate on ancestral information technology is positive and highly significant, as seen in specification 1 of Table 1. It shows that historical information technology predicts internet adoption. This first specification only accounts for the most exogenous individual characteristics; age, age squared, and gender, as well as country-by-year fixed effects.

Adding a wide set of individual controls does not change the estimate on historical information technology. The second specification adds individual controls, marital status, education, labor market status, income, and religion dummies. The estimate remains similar to the earlier specification but is now more precisely estimated, see column 2 of Table 1. Several of the individual controls are highly correlated with internet adoption. Most likely to adopt the internet are the young, highly educated, high income earners, labor force participants, and those not Catholic. The associations with age, education, labor force participation, and income are hardly

[19] For example, the comparison is if individuals with more developed ancestry born in France have higher internet use than those born in France with less developed ancestry.

[20] A more parsimonious model with country and year fixed effects yields similar results. Fernandez (2010) provides a more detailed discussion of the method.

surprising. Yet, the results indicate that the predictive power of historical information technology does not operate through these channels.

The final column of Table 1 uses the same control variables as in the second column, but the estimation is conducted with OLS rather than the ordered Logit in the previous columns. The results in the third column of Table 1 are very similar to the ordered Logit results in the second column. Using the linear OLS model does not produce noticeably different results than the non-linear model that accounts for the ordinal nature of the dependent variable. The results in Table 1 are very similar when using a full set of age fixed effects instead of the second order polynomial.

The estimated coefficient is quantitatively significant. An increase in the ancestral historical information technology of one standard deviation corresponds to the effect of being two years younger or moving two deciles higher in the middle of the income distribution. Internet use has a strong age gradient. One standard deviation increase in historical information technology corresponds to changing from Russian to UK ancestry, or from Brazilian to Portuguese ancestry.

There could be a concern of regional differences within countries with, for example, internet access. Very similar results are obtained using regional fixed effects to make within region comparisons rather than within country variation, indicating that this is not an issue. The results are also robust to accounting for the mother's and father's education. The point estimate on historical information technology is slightly lower, but not significantly so, when the mother's education is included. This provides a slight indication that some of the effect could work through the mother's education. Higher parental education is associated with higher internet adoption.

These results also point to an important role of parental education as a driver of internet use. High education, both of the mother and the father transmit into higher internet use beyond the effect of the individual's education and other controls. Policy promoting higher education could hence have a pay-off in increasing information technology use both in the current and future generations.

4.2 Other 1500 AD technologies

Information technology is, of course, not the only technology in 1500 AD. Comin, Easterly, and Gong (2010) built a data set with technologies in four additional areas; agriculture, industry (metal working), transportation, and the military. Information technology could correlate with these other technologies, which could be the driving force behind internet adoption. The historical technologies are considered one at a time in Table 2.

The historical information technology is entered in the first column of Table 2 as the baseline specification (from column 2 of Table 1). The estimate is positive and highly significant. The second measure is agricultural technology in 1500 AD; the estimate is positive and significant at the 5% level, as seen in column 2 of Table 2. There is hence evidence that agricultural technology promotes internet adoption, complementing other findings of the importance of historical agricultural technology for current outcomes such as Michalopoulos, Putterman, and Weil (2015). The industrial technology is included in the third column of Table 2 but the positive estimate is not significant at conventional levels.

Transportation technology is examined in the fourth column of Table 2. The point estimate is negative but not significant. Military technology is included in column 5 of Table 2. The point estimate is positive but not significant.

All five technology measures are included jointly in the sixth column of Table 2. Accounting for population density in 1500 AD, a common measure of historical development, yields very similar estimates in the seventh column. The point estimate on information technology is similar to the baseline specification and remains strongly significant. This indicates that accounting for the other technologies does not rival the influence of historical information and that the identifying variation is independent of the other four technology areas. The agricultural technology estimate is a bit lower in magnitude and only significant at the 10% level in the joint model. Additionally, in the joint specification transportation technology is estimated to have a significant predictive power over internet adoption but with a negative sign. This could indicate substitutability between information and transportations technology. Yet, the transportation technology result is not robust to a more parsimonious model such as in column 4 of Table 2, that is, transportation technology does not significantly predict internet use independently.

Considering the variation in transportation technology conditional on highly developed information technology, most of Europe (that had advanced information technology) had an average level of transportation technology in 1500, as captured by using the wheel, horse powered vehicles, and the compass (with index values around 0.5). The other half of the transportation technology index comprises three measures of ocean crossing capabilities. Such ship technologies were limited to the naval superpowers at the time; Spain, the UK, and Portugal. The results indicate that ancestry from these naval empires does not predict faster internet adoption compared to other European ancestries.

4.3 Geography and other deep roots of development

The existing literature has argued that geography and land characteristics are important to explain long run development. Hypotheses of the deep roots of development go far back. Montesquieu (1748) made an early argument for the importance of geography, that the temperate climate of England was most conducive to progress. More recent research has reinforced the role of geography in predicting development; see, for example, Sachs (2001). Hibbs and Olsson (2004) and Olsson and Hibbs (2005) find that geographic factors which predict the timing of the Neolithic revolution, the transition from hunting and gathering to agriculture, also predict income and the quality of institutions currently. Another strand of the literature focuses on the importance of the Neolithic revolution; Diamond (1997) presents the arguments. Agriculture enabled larger and more complex societies, a prerequisite for specialization, innovation, and growth. [21]

It is possible that these geographic and other deep factors work through the technology adoption channel, at least in part. To examine this hypothesis, a range of

[21] Also see the review by Spolaore and Wacziarg (2013) as well as Ashraf and Galor (2011).

deep factors in the ancestral country is added to the baseline model. These are the distance to the equator, latitude, percentage of arable land, land suitability for agriculture, average temperature, and average precipitation.

The estimate on historical information technology is slightly higher in this model, as seen in column 1 of Table 3. The average temperature is strongly related to internet use, being significant at the 1% level. The point estimate is negative implying that those with ancestry from warmer countries adopt the internet slower than those with colder ancestry. This could be seen as providing some support for Montesquieu's (1748) hypothesis that a warm climate is a barrier to development. Note though that it is not the temperature where the individual lives that predicts behavior (it is part of the country fixed effect) but how it predicts the behavior of the descendants from such conditions who live in a different environment. Moreover, latitude has a negative estimate that is significant at the 5% level indicating that ancestry from countries more to the south predicts later internet adoption. There is some evidence, at the 10% level, that less land suitable for agriculture predicts faster internet adoption.

Three additional ancestral country factors are added in the next specification; a dummy for a landlocked country, years since the Neolithic revolution (in logs), and risk of malaria. The point estimate on historical information technology increases again and is highly significant, as seen in column 2 of Table 3. Both temperature and latitude retain their significance. The risk of malaria is significant at the 10% level, yet it is not a robust predictor, as seen in the next column.

The third specification adds the predicted genetic diversity and its square (migration adjusted) in the ancestral country. Ashraf and Galor (2013) found a strong inverted U-shaped relationship between genetic diversity and development. There is no significant evidence of a U-shaped relationship between genetic diversity and internet adoption; see column 3 of Table 3.[22]

[22] If only the linear term for genetic diversity is included it is insignificant.

The point estimate on historical information technology is higher still in this specification, almost double the magnitude compared to the baseline model. Additional strong predictors of internet adoption are ancestral country temperature and latitude, both with negative estimates. Accounting for the variables in the deep roots to development literature does not rival the predictive power of historical information technology; it rather makes the relationship stronger.

4.4 Current and past development

Current development in the ancestral country predicts internet adoption among children of immigrants. Economic development, measured by the logarithm of GDP per capita, in the ancestral countries is included in a model with the baseline individual controls as well as country-by-year fixed effects. The estimate on current economic development is positive and significant, as seen in column 1 of Table 4. Ancestry from currently more developed countries predicts internet adoption among children of immigrants.

Information technology in 1500 AD in the ancestral countries is added to the model in the next specification. The predictive power of historical technology is positive and significant as before. Interestingly, the point estimate on economic development shrinks by over 80% and is now insignificant. Information technology from five centuries ago is a better predictor of internet adoption than current economic development.

1500 AD technology predicts current economic development across countries, as reported by Comin, Easterly, and Gong (2010). The results in Table 4 indicate that the intergenerational transmission of information technology adoption operates through channels not captured by economic development.

A further check on the predictive power of current development is to use a health based measure; life expectancy at birth. Ancestral country life expectancy predicts internet adoption, as seen in column 3 of Table 4. When 1500 AD information technology is added to the model the estimate on life expectancy drops close to zero while historical technology is of similar magnitude and significance as before.

Historical technologies other than information technology were studied in Table 2. Other dimensions of historical development could be transmitted across generations and influence internet use. Two widely used historical development measures are examined, population density and state history in 1500 AD.[23] The two dimensions of historical development yield insignificant estimates, while 1500 AD information technology is strongly significant, as seen in specification 5 of Table 4. It is hence historical information technology and not economic or political development that predicts internet adoption.[24]

Both the two measures of current development and the two measures of 1500 AD development are included in column 6 of Table 4. 1500 AD information technology remains strongly significant, and a somewhat larger point estimate than the baseline, while all four measures of current and historical development are insignificant. Communication technology from five centuries ago is a better predictor of internet adoption than current and historical development.

The influence of historical information technology is also robust when accounting for ancestral country trust (as well as the individual's expressed trust). Trust has been found to be an important determinant of development, see for example Algan and Cahuc (2010).[25] The results are also robust to accounting for ancestral country individualism. Gorodnichenko and Roland (2017) argue that individualism is an important factor behind development.

4.5 Variable selection via LASSO and Elastic Net

To examine if the results are influenced by the particular grouping of the variables, I apply two mechanical variable selection operators on the full set of 20 ancestral

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[23] Population density is a measure of economic development in the Malthusian era. State history measures experience with an organized state discounted back in time from 1500 AD, as defined by Putterman and Weil (2010). Both population density and state history are migration adjusted.

[24] Neither population density nor state history in 1500 AD predicts internet adoption when estimated in separate models (corresponding to column 1 of Table 4 but with a historical development measure).

[25] Trust is also transmitted across generations and has been found to influence health, see for example Ljunge (2014a, b).

variables in Tables 2 through 4. Least Absolute Shrinkage and Selection Operator (LASSO) is an estimator that adds a penalty to the usual sums of squares objective in OLS.[26] The penalty is the sum of the absolute values of the estimated coefficients in the model. The absolute values introduce "corners" in the optimization, which may produce zero estimates for several coefficients. The parameter lambda assigns the relative weight to the penalty term so a higher value of lambda promotes a model with more coefficients being set to zero. [27]

The dependent variable used is the internet use after partialing out the baseline socio-economic controls and the country-by-year fixed effects.[28] The model is estimated for 100 values of lambda. The preferred model is the lambda with the smallest mean squared error (of the objective function), where 10 fold cross-validations have been performed. That model selects five ancestral factors out of the 20 examined, that is, five estimates are non-zero while the remaining 15 are set to zero. The five factors (in the order selected by LASSO) are: information technology in 1500 AD, genetic diversity, agricultural technology in 1500 AD, transportation technology in 1500 AD, and risk of malaria. That 1500 AD information technology is the first variable selected indicates that it is the most important for explaining internet use among the 20 ancestral factors.[29]

The elastic net operator is applied as an additional check on the results. The elastic net combines the penalty functions of LASSO and ridge regression. The penalty function in ridge regression is the sum of squared estimates. Equal weight is assigned to the LASSO and ridge regression penalties (alpha=.5). The elastic net selects the same five variables as LASSO, indicating robustness in variable selection

[26] The variable selection operators discussed in this section are based on linear models.

[27] LASSO can shrink the original model as several estimates may be set to zero, contrasting with for example OLS where all estimates tend to be non-zero. A more thorough discussion is found in for example Hastie, Tibshirani, and Freidman (2009) or the Matlab documentation.

[28] The partialing is done in order to limit the variable selection to the ancestral factors.

[29] Current GDP per capita in the ancestral country is selected as the 14th variable.

across methods.[30] 1500 AD information technology is selected first also by the elastic net operator.

4.6 Restricting the sample by the historical technology level

One concern might be that the result is driven by those with the most advanced ancestry. Those with the most advanced technologies in 1500 AD tend to be the most developed now, see Comin, Easterly, and Gong (2010). To examine the sensitivity, the sample is limited by restricting the ancestral country information technology in 1500 AD. The first column of Table 5 excludes those with the highest ancestral communication technology (that is, a value of 1). This excludes Western European countries with homogenous populations (such as the Nordic countries and Greece), as well as China, Japan, and Korea. The estimate on ancestral information technology remains significant and similar in magnitude to the baseline.

The historical technology is restricted to be less than 0.95 in column 2 of Table 5. This sample cut excludes ancestry from all Western European countries. The point estimate on historical technology remains strongly significant. The point estimate is a bit higher, but confidence intervals overlap with estimates from other models. The sample is cut further by limiting historical technology to be less than 0.9. This excludes ancestry from most Eastern European countries (although some Eastern European countries, such as Poland and Lithuania, were highly developed). The estimate on historical information technology is still strongly significant as seen in column 3 of Table 5, and the point estimate is similar to the previous specification. The results are hence robust to excluding historically highly developed ancestries.

Next, the sample is cut to exclude the least developed nations. The restrictions that ancestral country historical technology is at least 0.4 and 0.5 are imposed in columns 4 and 5, respectively, in Table 5. The estimates on historical technology remain strongly significant and similar in magnitude to the previous two specifications. The results are robust to excluding the ancestries that were least developed historically.

[30] The preferred model is the lambda with the smallest mean squared error among the 100 lambdas examined.

The last specification excludes both the most developed ancestries, restricted to be less than 0.95, and the least developed ancestries, restricted to be at least 0.5. The estimate on historical information technology is strongly significant, as seen in column 5 of Table 5. The point estimate doubles in magnitude compared to the previous specification, indicating a very strong relationship in this middle range, although the confidence interval is also quite wide.

4.7 Earlier and later internet adopters, resisters, and every day users

In this section, the influence of historical information technology is estimated using the first two waves of the survey and the last two waves, respectively. For both the earlier and later period both the bottom end of the distribution, the resisters, and the top end, the everyday users, are examined.

The usual internet use variable with seven categories is the dependent variable in columns 1 and 2 of Table 6. The first column estimates the baseline model on the first two waves of data (collected in 2004 and 2006), and the second column studies the last two waves (collected in 2008 and 2010). The point estimate on historical technology is slightly larger in the later period, but it is hard to discern any significant difference across the periods. The predictive power of historical technology seems uniform over the earlier and later periods.

The next three columns study a different dependent variable defined as a dummy variable that takes on the value one if the individual has no internet access or never use the internet. It is an indicator of internet resisters and captures the laggards in internet adoption. The point estimate in the full sample is negative, as expected, and significant at the 5 percent level, as seen in column 3 of Table 6. The point estimate is higher in magnitude in the earlier period, as indicated in columns 4 and 5 of Table 6, but it is hard to see a significant difference across periods.

Individuals always using the internet are the focus of the last three specifications of Table 6. An indicator is created for individuals who use the internet every day (it takes on the value one if using every day, otherwise it is zero). The estimates on historical technology are positive and highly significant in the full sample as well as the earlier and later periods, as seen in columns 6 through 8 of Table 6. The point estimate is slightly higher in the later period, but the overall impression is that the estimates are similar across periods.

Table 6 illustrates that the influence of historical information technology is present both in the earlier and the later periods. Moreover, the historical influence operates both at the bottom and top ends of the internet adoption distribution; both resisters and every day users are predicted by the ancestral influence.

4.8 Mother's and father's influence

This section examines the influence of ancestral technology through influences from the mother and father separately. The first sample includes all native born children with an immigrant mother. The internet adoption of the individual is then related to 1500 AD information technology in the mother's birth country, along with the baseline individual controls as well as country-by-year fixed effects.

There is a positive and significant estimate on 1500 AD information technology in the mother's birth country, as seen in column 1 of Table 7. The second column considers the immigrant father sample; native born individuals with a father born in a different country. The estimate on the father's side is also positive and significant. Although the point estimate is higher on the mother's side, there is no evidence of significant differences across mothers and fathers in the predictive power of historical technology on internet adoption.

4.9 Time spent watching TV and internet phone calls

One alternative use of one's time is to watch TV. The TV may represent old information technology compared to the internet. This section analyzes how historical information technology in the ancestral country predicts the time spent watching TV.

Individuals with ancestry from countries with more developed information technology in 1500 AD spend less time in front of the TV, compared to those with less advanced ancestry, as seen in column 1 of Table 8. This is the outcome of the model that accounts for a wide range of personal characteristics as well as country and time fixed effects.

The results illustrate how historical information technology predicts the shift away from the old toward the new information technology; it predicts a move from TV toward the internet. The estimate is quantitatively significant. A one standard deviation increase in the ancestral information technology corresponds to the effect of having an upper secondary education compared to less education, or the effect of being three years younger. Among the controls, time spent watching TV is decreasing in education, labor force attachment, and income, while it is increasing in age.

Further evidence on technology adoption comes from the survey question asking if the individual uses the internet to make phone calls. The question is only asked in two survey rounds, hence reducing the sample size substantially and consequently providing less precision in the estimates.

The estimation gives some evidence of faster technology adoption in this dimension among those with more advanced historical information technology ancestry. The point estimate is positive and significant at the 10% level, as seen in the second column of Table 8.

4.10 U.S. evidence

The patterns found in European countries above are also found in the U.S., even though the U.S. data only includes 28 ancestries. Individuals with ancestry from populations with high information technology in the year 1500 are more likely to have internet access at home, as seen in specification 1 in Table 9. They are also more likely to use computers, as the result in column 2 of Table 9 shows.[31] There is hence evidence that information technology is transmitted across many generations also in the U.S. context. Americans with high information technology ancestry also spend significantly less time watching TV, as was the case with Europeans, as seen in

[31] This result relates to the diffusion of computers studied by Caselli and Coleman (2001), Goolsbee and Klenow (2002), and Skinner and Staiger (2007).

column 3 of Table 9. The findings indicate that information technology adoption has deep roots both in Europe and the U.S.

The data on watching TV covers the time before the spread of the internet, which makes it possible to study the timing of the historical information technology's predictive power. Google was started in January 1996,[32] and that year is used to split the sample into the pre-Google era 1975-1994 and the Google era 1996-2014 (the last year of the survey; there was no survey in 1995). The model is estimated separately in these sub-samples of roughly similar size.

The predictive power of historical technology for time spent watching TV is driven by behavior in the Google era. The estimate in the Google era in column 5 of Table 9 is strongly significant and almost three times the magnitude of the estimate in the pre-Google era that is insignificant at conventional levels, as seen in column 4 of Table 9. This provides further evidence for the interpretation that individuals with high technology ancestry adopt the new information technology, the internet, and shift out of the old technology, TV, faster than those with less advanced ancestry as the TV estimate is only significant in the period when the internet is available.

4.11 Human capital as a channel

How can the estimated influence of information technology in 1500 AD persist five centuries to predict internet adoption in the 21st century? The printing press might have induced a culture of education and curiosity, propagated both by social institutions and through intergeneration transmission in families. The ability to print books cheaply is, as argued by Eisenstein (1979), an important factor behind the Enlightenment, which Jacob (2014) describes as the first knowledge economy. Mokyr (2002, 2005) argues that the feedbacks between practical and theoretical knowledge is what sustained the Industrial revolution. Although the initial phases of the Industrial revolution may have depended heavily on "upper tail" human capital, as studied by Squicciarini and Voigtländer (2015), at some point average human capital may have become important. Primary school enrollment is a measure of

[32] The source is https://en.wikipedia.org/wiki/Google, retrieved on February 19th, 2018.

average human capital in the early 20th century. Average years of schooling in the late 20th century are another measure of average human capital. Both are studied below in two and three-stage models.

4.11.1 Two-stage models

First, focusing on primary schooling in 1920, I relate it both to internet adoption and 1500 AD information technology. Primary schooling in the year 1920 in the ancestral country predicts internet adoption among children of immigrants almost one century later as seen in column 1 of Table 10.

1500 AD information technology strongly predicts 1920 primary schooling in the ancestral country, as seen in column 2 of Table 10, which provides new evidence on the proliferation of primary schooling and complements Gallego's (2010) study of historical predictors of schooling. This specification is the first stage of a two-stage model where historical information technology predicts 1920 schooling, which in the second stage is related to internet adoption.

The second stage estimates are reported in column 3 of Table 10, where ancestral 1920 primary schooling is instrumented with 1500 AD information technology. The point with the two-stage model is not to argue for an unbiased causal effect of 1920 primary schooling on internet adoption, the exclusion restriction could be too strong for such an interpretation, but to illustrate a causal chain. Human capital is a plausible mechanism for persistent influences. Table 10 provides evidence in support of such an interpretation, reducing the five centuries of persistence in the baseline model into one step over four centuries and a second step over one century.

The model illustrates a channel through which historical technology may influence current internet adoption. 1500 AD information technology predicts human capital formation four centuries later, and early 20th century education predicts 21st century internet adoption. Is there evidence that information technology works through channels beyond human capital? Following Acharya, Blackwell, and Sen (2015), this is examined through a model where both 1920 human capital and 1500 AD information technology is included. As 1500 AD information technology is not significant, once the mediator human capital is accounted for, it indicates that there is no other significant omitted channel through which historical information technology affects internet adoption. The estimates are reported in column 4 of Table 10.

The evidence on the human capital channel also applies to a more recent measure; average years of schooling between 1985 and 1995. The lower panel of Table 10 presents the results. Ancestral country average schooling predicts internet use in the reduced form model in specification 5. 1500 AD information technology strongly predicts averages schooling in the first stage regression in specification 6. The second stage estimate in column 7 yields a positive and highly significant estimate on years of schooling. There is no evidence of 1500AD information technology working through other channels as it is not significant in specification 8. Following Acharya, Blackwell, and Sen (2015), it indicates that human capital is a sufficient mechanism to understand the persistence across five centuries.

4.11.2 Three-stage models

The two human capital channels examined separately in Table 10 are linked to each other. The three-stage model shows that 1500 AD information technology predicts 1920 primary school enrollment, as in the two-stage model above, in the first stage.[33] The second stage adds a new link to the chain; it shows that 1920 primary school enrollment (instrumented with historical information technology) predicts average years of schooling 1985-95. The more recent human capital measure is a strong predictor of internet adoption in the third stage, where 1920 human capital instruments for human capital seven decades later.

The results are robust to accounting for current and historical development. Current GDP per capita (in log) is included in the third stage (where it does not post-date the

[33] The three stage models are estimated with systems GMM accounting for clustering on parental birth country. The dependent variable is residualized internet use after accounting for individual characteristics and country-by-year fixed effects.

dependent variable). Historical economic and political development, as measured by 1500 AD population density and state history, are accounted for in all three stages.

Interestingly, the estimate on current economic development is negative. It indicates that non-human capital dimensions of development could slow internet adoption. The estimate on average years of schooling triples in magnitude, which indicates that when holding economic development constant the human capital dimensions becomes more important (although it is hard to make strong claims as standard errors increase as well). The historical population density and state history variables are not significant in any stage.

5 Conclusion

The evidence presented suggests the persistence of information technology adoption across half a millennia. The persistence is found among families who migrate and the inclination to adopt new technology is transmitted across generations. How could there be persistence across five centuries?

The printing press could be the most important invention of the past millennium. The press made possible the dissemination of knowledge on a previously unparalleled scale. Books store the cumulative experiences of people. Having early access to this technology could shape people to become curious, and this curiosity could be taught to children across many generations. These inclinations may also shape schooling institutions, which could reinforce the intergenerational transmission. Children with greater curiosity may be more prone to adopt new technologies like the internet.

Examples of long term persistence of human capital within populations include the literacy of Jews explored by Botticini and Eckstein (2012). They describe how religion mandated Jews to read very early, a skill with low productivity until new urban occupations appeared centuries later. A related argument for Protestants, where everyone should be able to read the Bible, is made by Becker and Woessmann

(2009), who find that literacy correlates with distance to Wittenberg. Clark (2014) shows that in prestigious occupations surnames persist over centuries illustrating persistence of economic status within families.[34] Long term persistence of traits within populations has hence been shown in other domains; new is the evidence of long persistence in information technology adoption. Moreover, examining information technology adoption sheds some light on what fosters curiosity, an essential ingredient behind sustained growth, as argued by Mokyr (2016).

Two and three-stage models indicate that human capital is a mediator. Historical information technology predicts school enrollment in 1920, which in turn predicts internet adoption. Average years of schooling around 1990 are also seen as a mediator in a corresponding model. Moreover, historical technology and human capital in 1920 and 1990 are linked to internet adoption in a three-stage model. This provides evidence of human capital as a mechanism through which information technology adoption persists across centuries.

The approach of relating the internet adoption of children of immigrants to ancestral technology in 1500 AD puts reverse causality concerns to rest. The internet use of an individual could hardly affect the technologies available in the ancestral country five centuries earlier. Omitted variables remain a concern, of course, as one can never be certain that all relevant variables have been included. Yet, there are a few reasons why one might think omitted variables are not detrimental to the analysis. First, the robust result is specific to the cultural transmission of information technology, from the 1500 AD level to internet use the past decade. The point estimate on historical information technology is basically unchanged when accounting for four other types of technology as well as historical economic and political development. This provides some assurance that it is not historical technology or development in general that predicts internet use. Yet, it could be some unmeasured technology in 1500 AD that is behind the result that I have not been able to include due to data limitations, a technology that would have to be strongly correlated with information technology

[34] Barone and Mocetti (2016) find persistence of earnings by surname over six centuries in tax records from Florence.

but not with the other technologies or level of development. Second, the analysis has included a wide range of factors examined in the deep roots of development literature. A couple of these factors come in as significant predictors, temperature and latitude, but they do not rival the predictive power of historical information technology. It is impossible to know if the literature has accounted for the most important factors. Still, given the state of the literature, most of the relevant factors have been accounted for. Third, the result is also robust to accounting for the current level of development in the ancestral country. If omitted factors have driven current development and this is behind the internet adoption, these factors are accounted for. This provides some assurance that the result is not driven by factors behind current development. Still, one cannot be sure there are not omitted historical factors related to other dimensions of current development that are behind the result. Moreover, machine learning methods select historical information technology as the most important factor in explaining internet adoption.

The analysis shows that the result is not due to a two (or three) point structure of the data, such as highly developed ancestries compared to the least developed (and the middle). The results hold when excluding the most developed, the least developed, and both the most and least developed ancestries.

The results should not be interpreted as deterministic. An unfavorable ancestry does not mean that individuals necessarily lag in internet adoption. Far from all variation is explained by historical ancestral factors; there is certainly variation within ancestral groups. Moreover, there is a broad increase in internet adoption over time in the sample and applies to all groups. The ancestry result is rather a prediction of timing. Individuals with less developed ancestry tend to adopt the internet later than those with highly developed ancestry, on average.

Studying the internet may be of interest as a modern example of information technology adoption and its determinants. Internet use could also affect productivity. Forman, Goldfarb, and Greenstein (2012) find evidence that internet use leads to wage growth across U.S. cities. Akerman, Gaarder, and Mogstad (2015) find that broadband expansion improved productivity among skilled workers. This evidence suggests that internet adoption could be one channel through which economic development is promoted. The evidence presented here could illustrate one specific channel through which historical technology affects current development.

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Table 1. Historcal information technology and internet use. Baseline results.

Dependent variable: Internet use

Model:	Ordered Logit	Ordered Logit	OLS
	(1)	(2)	(3)
Information technology	**0.655**	**0.635**	**0.473**
in 1500 AD, ancestral country	(0.279)**	(0.226)***	(0.193)**
Age	0.015	-0.039	-0.071
	(0.011)	(0.014)***	(0.013)***
Age squared/100	-0.079	-0.020	0.015
	(0.011)***	(0.013)	(0.014)
Female	-0.379	-0.359	-0.287
	(0.064)***	(0.053)***	(0.043)***
Married		0.055	0.050
		(0.082)	(0.071)
Never married		0.164	0.124
		(0.099)*	(0.104)
Upper secondary		0.375	0.327
		(0.115)***	(0.109)***
College or university		1.475	1.442
		(0.088)***	(0.086)***
Out of the labor force		-0.244	-0.350
		(0.065)***	(0.059)***
Unemployed		-0.145	-0.233
		(0.092)	(0.099)**
Low income		-0.791	-0.817
		(0.076)***	(0.082)***
Middle income		-0.234	-0.242
		(0.051)***	(0.052)***
Catholic		-0.216	-0.247
		(0.070)***	(0.068)***
Protestant		-0.131	-0.081
		(0.081)	(0.061)
Country-by-year fixed effects	Yes	Yes	Yes
Observations	11516	11516	11516

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' The models in the first two columns are estimated using ordered logit, while the third column is estimated with ordinary least squares (OLS). The sample is children of immigrants with at least one immigrant parent. Communications technology refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The information technology measure is migration adjusted to capture population movements since 1500 AD. Low income is a dummy for the bottom three deciles. Middle income is a dummy for the middle four deciles. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 2. Internet use and historical technology in five sectors.

Dependent variable: Internet use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Information technology	0.635					0.571	0.585
in 1500 AD, ancestral country	(0.226)***					(0.202)***	(0.221)***
Agricultural technology		0.528				0.402	0.406
in 1500 AD, ancestral country		(0.246)**				(0.235)*	(0.233)*
Industrial technology			0.537			0.147	0.138
in 1500 AD, ancestral country			(0.412)			(0.339)	(0.332)
Transportation technology				-0.274		-0.828	-0.825
in 1500 AD, ancestral country				(0.246)		(0.218)***	(0.213)***
Military technology					0.270	0.183	0.195
in 1500 AD, ancestral country					(0.210)	(0.139)	(0.157)
Population density							-0.012
in 1500 AD, ancestral country							(0.038)
Invidual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11516	11516	11516	11516	11516	11516	11516

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' The models are estimated using ordered logit. The sample is children of immigrants with at least one immigrant parent. The technology measures refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. All historcal measures are migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 3. Internet use, historical technology, and geography.

Dependent variable: Internet use

	(1)	(2)	(3)
Information technology	0.772	0.814	0.913
in 1500 AD, ancestral country	(0.277)***	(0.297)***	(0.314)***
Distance to equator,	-0.822	-0.295	-0.387
ancestral country	(0.521)	(0.509)	(0.549)
Latitude,	-0.005	-0.006	-0.006
ancestral country	(0.002)**	(0.003)**	(0.002)**
Percentage of arable land,	0.005	0.003	0.003
ancestral country	(0.003)	(0.003)	(0.003)
Land suitability for agriculture,	-0.107	-0.105	-0.107
ancestral country	(0.061)*	(0.063)*	(0.061)*
Average temperature,	-0.027	-0.024	-0.025
ancestral country	(0.007)***	(0.007)***	(0.007)***
Average precipitation,	0.002	0.002	0.002
ancestral country	(0.001)	(0.001)	(0.002)
Landlocked		-0.003	-0.027
ancestral country		(0.100)	(0.110)
Years since Neolithic revolution (log),		0.155	0.117
ancestral country		(0.113)	(0.109)
Percent at risk of malaria,		0.486	0.416
ancestral country		(0.241)**	(0.276)
Predicted genetic diversity,			-144.468
ancestral country			(93.379)
Predicted genetic diversity squared,			101.857
ancestral country			(65.025)
Invidual controls	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes
Observations	10273	10273	10273

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' The models are estimated using ordered logit. The sample is children of immigrants with at least one immigrant parent. Communications technology refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The historical variables, information technology, years since the Neolithic revolution and genetic diversity, are migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 4. Current and historical development.

Dependent variable: Internet use

	(1)	(2)	(3)	(4)	(5)	(6)
Information technology		0.652		0.915	0.571	0.817
in 1500 AD, ancestral country		(0.263)**		(0.353)***	(0.219)***	(0.289)***
GDP per capita (log), currently,	0.127	0.020				0.075
ancestral country	(0.055)**	(0.055)				(0.081)
Life expectancy, currently,			0.014	-0.011		-0.019
ancestral country			(0.007)**	(0.010)		(0.014)
Population density in 1500 AD,					0.047	0.053
ancestral country					(0.042)	(0.045)
State history in 1500 AD,					-0.438	-0.333
ancestral country					(0.282)	(0.286)
Invidual controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10970	10970	11165	11165	11505	10959

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' Information technology refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The historical measures are migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Robustness to outliers; restricting the main regressor's range.

Dependent variable: Internet use						
Restriction on information	< 1	< 0.95	< 0.90			< 0.95
technology in 1500 AD				> 0.4	> 0.5	> 0.5
(ranges from 0 to 1)	(1)	(2)	(3)	(4)	(5)	(6)
Information technology	0.537	0.813	0.884	0.774	0.812	1.587
in 1500 AD, ancestral country	(0.223)**	(0.362)**	(0.408)**	(0.248)***	(0.323)**	(0.560)***
Invidual controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9842	4393	4228	11407	10792	3669

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' Information technology refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The information technology measure is migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 6. Earlier and later internet adopters, resisters, and every day users.

Dependent variable:	Internet use		Never use internet			Every day user		
Years:	2004-2006	2008-2010	2004-2010	2004-2006	2008-2010	2004-2010	2004-2006	2008-2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information technology	0.526	0.693	-0.487	-0.622	-0.379	0.716	0.636	0.759
in 1500 AD, ancestral country	(0.286)*	(0.231)***	(0.238)**	(0.347)*	(0.249)	(0.227)***	(0.309)**	(0.228)***
Invidual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5202	6314	11516	5202	6314	11516	5202	6314

Notes: The dependent variable in columns 1-2 is Internet Use, which ranges from 1, 'no access'/'never use' to 7, use 'every day.' The dependent variable in columns 3-5 is an indicator of never using or having no acces to internet. The dependen variable in columns 6-8 is an indicator for using the internet every day. The models in columns 1-2 are estimated using ordered logit, while columns 3-8 are estimated with logit. The sample is children of immigrants with at least one immigrant parent. Information technology refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The information technology measure is migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 7. Influences on the mother's and father's side.

Dependent variable: Internet use		
Sample:	Immigrant mother	Immigrant father
	(1)	(2)
Information technology	0.864	
in 1500 AD, mother's birth country	(0.215)***	
Information technology		0.603
in 1500 AD, father's birth country		(0.255)**
Invidual controls	Yes	Yes
Country-by-year fixed effects	Yes	Yes
Observations	7489	7825

Notes: The dependent variable is Internet Use, which ranges from 1, 'no access,'/'never use' to 7, use 'every day.' Information technology refer to the parent(s) birth country. Column 1 restricts the sample to children of immigrants with an immigrant mother and relates internet use to historical technology in the mother's birth country. Column 2 does the corresponding analysis for those with an immigrant father. The information technology measure is migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 8. Time spent watching TV and internet phone calls.

Dependent variable:	Time spent watching TV	Use the internet to make phone calls
	(1)	(2)
Information technology in 1500 AD, ancestral country	-0.344	0.424
	(0.161)**	(0.240)*
Invidual controls	Yes	Yes
Country and year fixed effects	Yes	Yes
Observations	11481	5401

Notes: The dependent variable in column (1) is Time spent wathching TV, which ranges from 0, 'no time at all,' to 7, use 'more than 3 hours.' The model is estimated using ordered logit. The dependent variable in column (2) is an indicator if the respondent uses the internet for phone calls at home, which takes on the value 1 if used and 0 otherwise. The model is estimated using logit. The sample is children of immigrants with at least one immigrant parent. The technology measure refer to the parent(s) birth country. If both parents are immigrants it is the average over both parents, if only one parent is an immigrant it is the value from the immigrant parent's birth country. The technology measure is migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data is from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 9. Information technology use in the U.S.

Dependent variable:	Internet at home (1=yes, 0=no)	Use computer (1=yes, 0=no)	TV watching, hours	TV watching, hours	TV watching, hours
Time period:			1975-2014	1975-1994	1996-2014
	(1)	(2)	(3)	(4)	(5)
Information technology in 1500 AD, ancestral country	1.627	2.301	-1.132	-0.611	-1.722
	(0.593)***	(0.730)***	(0.403)***	(0.470)	(0.405)***
Individual controls (exogenous)	Yes	Yes	Yes	Yes	Yes
Year and region fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3221	5414	18742	10658	8084

Notes: The dependent variable in column (1) is an indicator if the individual has internet access at home. In column (2) the dependent variable is an indicator if the individual uses a computer. In column 3 the dependent variable is the number of hours of TV the individual wathces per day. All specifications study second and higher generation immigrants and estimates the predictive power of 1500 AD information technology in the ancestral country. Individual controls include age, age squared, and gender. Region of residence and year fixed effects are included in all specifications. There are 9 regions. Data is the General Social Survey. Standard errors in parenthesis, which allow for clustering on the ancestral country. Ordered logit models estimated. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 10. Human capital as a mechanism; two stage models.

Panel A				
Dependent variable:	Internet use	Primary school enrollment 1920	Internet use	Internet use
Model:	OLS	First stage	Second stage	OLS
	(1)	(2)	(3)	(4)
Primary school enrollment 1920 (log),	0.108		0.117	0.095
ancestral country	(0.043)**		(0.051)**	(0.045)**
Information technology		4.553		0.102
in 1500 AD, ancestral country		(0.605)***		(0.220)
F-statistic for exclusion of the instrument		56.6		
Invidual controls	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes
Observations	7192	7192	7192	7192
Panel B				
Dependent variable:	Internet use	Avg. years of schooling 1985-95	Internet use	Internet use
Model:	OLS	First stage	Second stage	OLS
	(5)	(7)	(8)	(6)
Average years of schooling 1985-95 (log),	0.322		0.373	0.263
ancestral country	(0.115)***		(0.143)***	(0.136)*
Information technology		1.294		0.141
in 1500 AD, ancestral country		(0.177)***		(0.215)
F-statistic for exclusion of the instrument		53.3		
Invidual controls	Yes	Yes	Yes	Yes
Country-by-year fixed effects	Yes	Yes	Yes	Yes
Observations	10879	10879	10879	10879

Notes: The dependent variable in columns 1 and 3 is Internet Use, which ranges from 1, 'no access'/'never use' to 7, use 'every day.'The dependent variable in column 2 is primary school enrollment in 1920 in the ancestral country (in percent). Column 1 is an OLS regression of internet use on 1920 school enrollment. Column 2 is the first stage of a 2SLS where 1920 school enrollment is regressed on historical information technology. Column 3 reports the second stage where internet use is regressed on 1920 school enrollment (log) in the ancestral country, where school enrollment is instrumentet with 1500 AD information technology in the ancestral country. Ancestral country variables are averages over both if both parents are immigrants; if only one parent is an immigrant it is the value from the immigrant parent's birth country. The information technology measure is migration adjusted to capture population movements since 1500 AD. Individual controls include age, age sq., gender, education, martial and labor force status, income, and religion. Data are from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

Table 11. Three stage models.

Dependent variable:	Internet use	Avg. years of schooling 1985-95	Primary school enrollment 1920	Internet use	Avg. years of schooling 1985-95	Primary school enrollment 1920
	Third stage	Second stage	First stage	Third stage	Second stage	First stage
	(1)	(2)	(3)	(4)	(5)	(6)
Average years of schooling 1985-95 (log), ancestral country	0.301 (.100)***			0.974 (.369)***		
Primary school enrollment 1920 (log), ancestral country		0.281 (0.0288)***			0.290 (0.038)***	
Information technology in 1500 AD, ancestral country			5.08 (0.843)***			4.18 (0.899)***
GDP per capita (log), currently, ancestral country				-0.275 (0.126)**		
Population density in 1500 AD, ancestral country				0.038 (0.057)	-0.013 (0.043)	0.250 (0.153)
State history in 1500 AD, ancestral country				0.457 (0.517)	-0.438 (0.249)	-0.748 (1.01)
Observations	7,125	7,125	7,125	6,916	6,916	6,916

Notes: The dependent variable in columns 1 and 4 is residualized internet use after accounting for the baseline individual characteristics as well as country-by-year fixed effects. The dependent variable in columns 2 and 5 is average years of schooling 1985-95 in the ancestral country (in log). The dependent variable in columns 3 and 6 is primary school enrollment in 1920 in the ancestral country (in log). Each model, columns 1 to 3 and 4 to 6, is estimated using systems GMM allowing for clustering on parental birth country. Ancestral country variables are averages over both parents if both parents are immigrants; if only one parent is an immigrant it is the value from the immigrant parent's birth country. The information technology measure is migration adjusted to capture population movements since 1500 AD, as is the population density and state history in 1500 AD. Individual controls used for residualizing internet use include age, age sq., gender, education, martial and labor force status, income, and religion. Data are from the second to fifth waves of the European Social Survey. Standard errors in parenthesis. Standard errors allow for clustering on the parent's birth country. Significance stars, * p<0.1, ** p<0.05, *** p<0.01.

7 Appendix Tables

Table A1. Countries Participating in the ESS by Survey Round.

	Survey Round:					
Country	1	2	3	4	5	6
Austria	X	X	X			
Belgium	X	X	X	X	X	X
Bulgaria			X	X	X	X
Croatia				X	X	
Cyprus			X	X	X	X
Czech Republic	X	X		X	X	X
Denmark	X	X	X	X	X	X
Estonia		X	X	X	X	X
Finland	X	X	X	X	X	X
France	X	X	X	X	X	X
Germany	X	X	X	X	X	X
Greece	X	X		X	X	
Hungary	X	X	X	X	X	X
Ireland	X	X	X	X	X	X
Israel	X			X	X	X
Italy	X	X				X
Latvia			X	X		
Lithuania				X	X	X
Luxembourg	X	X				
Netherlands	X	X	X	X	X	X
Norway	X	X	X	X	X	X
Poland	X	X	X	X	X	X
Portugal	X	X	X	X	X	X
Romania			X	X		
Russian Federation			X	X	X	X
Slovakia		X	X	X	X	X
Slovenia	X	X	X	X	X	X
Spain	X	X	X	X	X	X
Sweden	X	X	X	X	X	X
Switzerland	X	X	X	X	X	X
Turkey		X		X		
Ukraine		X	X	X	X	X
United Kingdom	X	X	X	X	X	X

Notes: Data from the European Social Survey (ESS). The ESS round 6 cumulative file is used . Round 1 does not include information on parental birth country. Internet use is not included in round 6.

Table A2. Summary statistics.

	Children of immgrants sample		General population sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Internet use	4.37	2.72	3.68	2.74
Age	43.9	17.86	47.9	18.7
Female	0.540	0.498	.542	.498
Married	0.478	0.500	0.532	0.499
Never married	0.330	0.470	0.271	0.444
Upper secondary degree	0.512	0.500	0.455	0.498
College/university degree	0.302	0.459	0.249	0.432
Out of labor force	0.446	0.497	0.483	0.500
Unemployed	0.045	0.208	0.038	0.192
Low income	0.222	0.416	0.254	0.435
Middle income	0.303	0.460	0.299	0.458
Catholic	0.210	0.407	0.309	0.462
Protestant	0.081	0.273	0.126	0.332
Time spent watching TV	4.15	2.13	4.35	2.04
Use the internet to make phone calls	2.15	1.11	2.39	1.27
Ancestral country variables:				
Information tech in 1500 AD	0.860	0.193		
Agricultural tech in 1500 AD	0.951	0.155		
Industrial tech in 1500 AD	0.966	0.115		
Transportation tech in 1500 AD	0.542	0.141		
Military tech in 1500 AD	0.784	0.219		
Primary school enrollment 1920 (%)	48.6	30.4		
Primary school enrollment 1920 (%), log	3.42	1.27		
Average years of schooling 1985-95	7.98	2.18		
Average years of schooling 1985-95, log	2.03	0.34		
GDP per capita (log), currently	9.51	0.83		
Population density in 1500 AD	2.05	1.32		
State history in 1500 AD	0.531	0.224		
Distance to equator	0.504	0.119		
Latitude	44.0	15.0		
Percentage of arable land	25.6	14.5		
Land suitability for agriculture	-1.18	0.97		
Average temperature	8.93	7.79		
Average precipitation	59.1	29.6		
Landlocked	0.111	0.310		
Years since Neolithic revolution (log)	8.73	0.28		
Percent at risk of malaria	0.028	0.131		
Predicted genetic diversity	0.734	0.010		
U.S. data				
Internet at home	0.721	0.449		
Use computer	0.718	0.450		
Hours spent watching TV	3.01	2.40		
Age	46.0	17.6		
Female	0.565	0.496		
Comm. tech in 1500 AD (ancestral)	0.962	0.089		

Notes: Data from the European Social Survey, rounds 2 through 5. U.S. data from the General Social Survey, rounds from 1977 through 2014. The children of immigrants sample refers to individuals born in the country of residence whose mother and/or father is born in a different country. The U.S. data include native born individuals who report foreign ancestry.

Table A3. Countries of ancestry and historical information technology.

Country	Information tech year 1500 AD, ancestral country	Country	Information tech year 1500 AD, ancestral country	Country	Information tech year 1500 AD, ancestral country
Afghanistan	.5257732	Germany	.9865	Norway	1
Algeria	.5	Ghana	.5	Pakistan	.5
Angola	.02	Greece	1	Peru	.3568789
Argentina	.9219936	Guinea-Bissau	.5	Philippines	.75
Australia	.9632284	Hong Kong	.99075	Poland	1
Austria	.992	Hungary	.9964817	Portugal	.9924902
Bangladesh	.5	India	.5	Romania	.9971374
Belarus	.97125	Indonesia	.51	Russia	.758794
Belgium	.99	Iran	.74375	Senegal	.5065327
Bosnia and Herzegovina	1	Iraq	.5031779	Slovakia	.9980443
Brazil	.7920666	Ireland	.9994245	South Africa	.19675
Canada	.9341387	Italy	.9989899	Spain	.9961863
Chile	.6626473	Japan	1	Sweden	1
China	1	Kenya	.0665	Switzerland	.9949749
Colombia	.5849613	Latvia	.925	Syria	.5
Congo	0	Libya	.5	Thailand	.57
Côte d'Ivoire	.2119839	Lituania	.9825	Tunisia	.5
Croatia	.9977309	Madagascar	.503	Turkey	.5391753
Cuba	.7308366	Malaysia	.63625	Ukraine	.953
Czech Republic	1	Mali	.49	United Kingdom	.9707737
Denmark	.996	Malta	.9987469	United States	.8389535
Egypt	.5	Marocco	.537	Uruguay	.9268312
Estonia	.935	Moldova	.7800602	Uzbekistan	.7575
Ethiopia	.5	Netherlands	.9805539	Venezuela	.557492
Finland	1	New Zealand	.8705821	Vietnam	.75625
France	.9718593	Nigeria	.5		

Note: Information technology in year 1500 AD is measured between 0 and 1. The index is based on indicators for the existence of movable type, the use of paper, the use of books, and woodblock printing. Values are migration adjusted to account for population movements since 1500 AD. The source is Comin, Easterly, and Gong (2010).