Time for Growth

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Appendixes for online publication

Appendix A: Public mechanical clocks: An historical perspective

A1: Genesis of mechanical Clocks: Why Europe?

The roots of the first clocks have been widely debated in the literature since the devices first spread in medieval Europe instead of in the more technologically and culturally advanced regions, such as China or the Islamic World. The question of the initial invention is of potential interest in this paper because we relate the origins of clocks to the econometric instrument that is used in the empirical analysis. However, our main interest for the empirical study is the source of variation within Europe (i.e., why we find clocks earlier in some European cities than in others) and not a comparative analysis between different global regions.

The classic debate has been around the question of whether or not clocks can be directly linked to Chinese astronomical water clocks, perhaps intermediated via the Islamic world, where they are also found (Price (1956)), or if they were developed in Europe based on a rediscovery of classical Greek astronomical knowledge and Islamic expertise, but driven by an intrinsic European preference for time and punctuality that was very much rooted in the tradition of Cistercian monks (Landes (1983)). Whereas the astronomic technology link is plausible and may be valid for both arguments, a more direct interregional transmission explanation is problematic for two main reasons (as demonstrated by Landes (1983)): first, the necessary escapement mechanism that made the clock (universally) work in Europe was missing in China and the Islamic world; second, even once such a mechanism was invented and then made available in China or the Islamic world it was not adopted for several centuries (Cipolla (1967)). There was no obvious broad use of time or clocks in Chinese or Islamic culture.

Looking into the argument of the astronomical and astrological roots, it must be pointed out that the appearance of solar eclipses and other astronomic movements, as well as their cultural interpretation and building of machines, is not an exclusively medieval European phenomenon. Religious interpretations and further scientific studies can also be observed in Asia, the Islamic World, and many other cultures (Stephenson (1997) and Steele (2000)). In particular, the construction of several very advanced astronomic water clocks to study astronomy and astrology can be documented in the

medieval Islamic world and in medieval China (al Jazari (1206) and Cipolla (1967)). Additionally, the use of astrolabes to study eclipses and make astrological predictions has been documented (Schmidl (2018) and Thomann (2019)). Looking at some archaeological discoveries, we also find some suggestive links between astronomic events and prototypical machines for measuring time over the whole time of civilization.

As matter of example, by juxtaposing the number of total solar eclipses during ancient times with the location of the astrological heritage provided by the United Nations Educational Scientific and Cultural Organization (UNESCO),[1] we can observe several cases where ancient and more recent astronomical sites are located in areas of intense solar eclipse activities. Keeping in mind that this sample is not representative, we would refer to the examples of Stonehenge (Hawkings (1988)), the Stone Circle of Odry in Poland (Sadowski et al. (1993)), and the Navajo star ceiling in the US (Williamson (1984)). Two case studies are particularly striking. The first is related to the archaeological site located at Deir el-Bahri in Egypt. According to the archaeological interpretation of the discoveries of the Tomb of Senenmut at Western Thebes (Neugebauer and Parker (1988)), which is dated 1470 B.C., the ceiling of the heritage site depicts one of the oldest representations of the celestial firmament, which was inspired by the direct vision of celestial movements and very likely influenced by two total solar eclipses in the years 1522 B.C. and 1477 B.C. In addition, the problem of measuring the astronomical time explains the presence in the tomb of a monumental guideline for the construction of a water clock (*clepsydra*), which would be introduced later on introduced by the Egyptians to the Roman Empire (Sloley (1931)). The second example is related to the so-called *Antikythera* mechanism, which is dated 205 B.C. and was discovered from a shipwreck on the homonymous Greek island of Antikythera. Defined by Price (1959) as an "ancient Greek computer", this mechanism is a primordial clock-like mechanism that was used to calculate the motion of the stars and planet, and to predict eclipses during the eclipse cycle of 223 lunar months.

What makes medieval Europe different from other civilizations that led to the invention of the mechanical clock? Scholars such as North (1975) have shown that the invention of the escapement mechanism which first appeared in Europe, can be seen as a regional exogenous technology shock, since no historical source material from the first half of the 13th century anticipates such a mechanism. In addition, as outlined by Landes (1983) the known hydraulic water mechanisms in China or

[1]The information is available at `https://www3.astronomicalheritage.net/`

the Islamic world were more complicated in use than the escapement mechanism, and thus were less suitable for a general diffusion (i.e., water could freeze in the wintertime, and water clocks could not easily be positioned on towers). However, as discussed earlier, this explanation is insufficient because other cultures were not interested in building clocks or in a major diffusion of clocks (Cipolla (1967) and Landes (1983)). Thus the escapement mechanism was necessary, but not sufficient for the diffusion of the clock. Moreover, it is also difficult to argue that Europe was unparalleled in its cultural preferences for time and punctuality, given that this tendency only developed over time during the evolution of clocks themselves.[2] However, we cannot exclude that an initially small cultural difference might have facilitated the diffusion and use of clocks in Europe.

Medieval Europe differed from China and the Islamic World because it was comparatively scientifically backward and teeming with strong religious beliefs. This is supported by the fact that most of the reports on solar eclipses came from Europe and these European reports were based on chronicles and not scientific studies. In contrast, comparatively more scientific reports related to observations of eclipses can be found in Asia and the Islamic world (Stephenson (1997)). Also these reports had the purpose of creating judicial astrology and astronomic instruments. However, this information had a rather secrect character (Nakayama (1966)) and was not for the public. This might have reduced the incentives to create and diffuse big public astronomical clocks or astrological machines. On the contrary, the rather public debate (and strong tension) in Europe might have triggered the technological and cultural dynamics that we have described in this study. The widespread use of the astrolabe in Europe for astrological purposes and the further development of the astrolabe to measure time for predicting astrological constellations supports this argument (McCluskey (2000), Oestmann (2014), and Falk (2018)). Finally, the strong political fragmentation and independence of many European towns which led not only to economic competition, but also competition for ideas and scientific progress, might have had an impact on these dynamics and the diffusion of clocks in Europe compared to other global regions.

[2]Basic signaling clocks found in medieval European towns could also be found in China (Cipolla (1967)).

A2. Towns with solar eclipses, astronomic movements and the first public mechanical clocks

This section contains case studies, that document locations, where repeated solar eclipses were observed (as in Figure 1 of the main text), where astronomic programs related to solar eclipses were established, and finally where public mechanical clocks were built. Thus, it supports the correlation among the appearance of solar eclipses, astronomic programs related to solar eclipses, and the building of public mechanical clocks. A fine example is the papacy in Avignon. The popes had a strong interest in astronomy and solar eclipses, and they were surrounded by scientists with such expertise. Starting with Pope John XXII (1244-1334), who was advised by Cecco D'Ascoli, a professor of astronomy and medicine, and was factually advised by astrologers predicting political events. D'Ascoli worked on solar eclipses and in particular on the role of eclipses during the time of the crucifixion of Jesus (Thorndyke (1941) and Murphy (2015)). Later Pope Benedict XII (1285-1342) and Pope Clement VI (?-1352) were advised by the famous Jewish astronomer and astrologer Levi Ben Gerson who worked heavily on solar eclipses and witnessed a solar eclipse himself. He was also known for inventing astronomic instruments and refining the astrolabe. Pope Clement VI interested in Gerson's work and expertise supported the Latin translation of his book and also pushed a calendar reform based on his astronomic knowledge. A manuscript of the book also indicates that Gerson updated his manuscript with additional eclipse tables at the request of the later Pope Clement VI (Mancha (2006)). Pope Clement VI also supported Gersons work on juridical astrology. Building astronomic instruments including clocks was part of the papal agenda and the first public mechanical clock was built in 1353 in Avignon (Michele and De Derleke (1909) and Dohrn-van Rossum (1996)). This interest was continued by his successor Pope Innocent VI who had many astronomic instrument builders and clockmakers and built the first public clock in 1353 in Avignon.

The royal court in Perpignan (the seat of the King of Aragon), which is another example of a strong interest in astronomy and astrology, was the site of the construction of the first mechanical clock in a Spanish kingdom. The clock was built in 1356 and had been ordered by King Pedro IV (Perez-Alvarez (2013)). The King of Aragon supported the research and publication of astronomical work (Ryan (2011)). Solar eclipses and their predictions played an important role in this agenda; for instance, he allowed a treatise to be compiled on the calendar with an almanac of oppositions and conjunctions of

the sun and moon and predictions of eclipses for astrological analysis (Millas y Vallicrosa (1962)). In the chronicle of the history of the Aragon Kingdom, which was published in his name, past eclipses in the kingdom were mentioned (Nelson (1991)). It is also documented that the king had several astronomers and specialized metal workers at the court who developed and maintained his scientific instruments (Beeson (1971) and Perez-Alvarez (2013)). For instance, Jacob Ben David Bonet created the astronomical tables of Perpignan in 1361 (including tables for solar eclipses), and, built astronomical equipment for Pedro IV (1990, p. 26). To build the clock, he received support from one of the clockmakers from Pope Innocent VI in Avignon. His ongoing dedication to clocks, astronomy, and astrology can be found in an accompanying letter, which was sent with an astronomical clock in 1376 to his daughter, where he described all clock's astronomical and astrological functions in detail (Beeson (1971)).

Merton College in Oxford is a fine example of the importance of the role of astronomy/astrology and solar eclipses in universities. Oxford scholar and longstanding Merton College fellow, John Ashenden (?-1368) was one of the most important astrologers of his age and among the first to develop a scientific agenda to predict weather, plagues, and political events based on eclipses and planetary conjunctions (Carley (1992) and Nothaft (2016)). He was preceded by other scholars, such as Merton College graduate and later abbot and clock builder Richard Wallingford (1292-1336) who worked intensively on the calculation and prediction of solar eclipses. Given the strong interest at Merton College in astronomy and astrology (as part of theology studies), it comes as no surprise that a clock was already built in the late 13th century; after he left Merton College in 1327, Wallingford designed his famous astronomic clock in St Albans the same year, as documented by Beeson (1971) and North (2005). An interest and knowledge in St Albans related to astronomy/astrology and solar eclipses can already be derived from the 13th-century chronologist of St Albans, Matthew Paris (Lawrence-Mathers (2012)). Given this strong tradition, Nicholas of Lynn, a Carmelite friar working at Oxford, in 1386 was able to predict solar eclipses for the coming decades pretty accurately (Beard (2004)). Also Nicholas of Lynn related his astronomical studies to astrology, particularly to medical astrology.

In the city of Padua, Pietro d'Abano (1257-1316), who was an astrologist and professor of medicine, studied the impact of solar eclipses on medical conditions. Iacopo Dondi dall'Orologio (1290-1359), a later graduate from Padoa and friend of Pietro d'Abano and university professor of medicine and astronomy, created astronomical tables based on the Alphonsine tables, including solar eclipses. He

also built the first astronomical clock in Padua in 1344 at the request of the lord of the city. Padua became one of the most important centers for astrology in Europe starting in the late-13th and early-14th centuries, (e.g, Canova (2011)). Later Dondi also created the so-called *Astrarium*. This is an astronomical machine for astrology and was used by astrologers at the court of the duke of Milan (Addomine (2018)).

Appendix B: Tables and figures

Table B1: The diffusion of the mechanical clock in Europe before 1450.

	1400-1500			Entire sample		
Country	**City adopters**	**Cities in Bairoch**	**Percentage of adoption**	**City adopters**	**Cities Bairoch**	**Percentage of adoption**
Austria	2	9	22	2	17	12
Belgium	16	37	43	18	72	25
Czechia	2	5	40	8	22	36
Germany	54	134	40	68	245	28
France	36	92	39	65	341	19
Great Britain	11	63	17	13	174	7
Italy	49	149	33	65	407	16
Malta	0	1	0	1	1	100
Netherlands	15	36	42	18	62	29
Poland	5	21	24	9	56	16
Portugal	1	27	4	1	52	2
Romania	1	9	11	1	34	3
Slovakia	1	7	14	1	14	7
Slovenia	0	3	0	1	3	33
Spain	10	77	13	12	263	5
Sweden	1	18	6	1	20	5
Switzerland	13	15	87	13	19	68
Ukraine	1	57	2	1	57	2
Total	**218**	**760**	**29**	**298**	**1859**	**16**

Source: Authors' calculation based on the clock's dataset described in Section II of the main text. The first three columns are referred to the cities having population available either in 1400 or in 1500. Population data drawn from Bairoch et al. (1988). Only countries having at least one early mechanical clock reported.

Table B2: Descriptive statistics.

Variable	Mean	Standard deviation	Min	Max	N. of observations
Variables used in main regressions					
CLOCK	0.21	-	0.00	1.00	9,307
Population	13,700.65	38,760.37	1,000.00	2,240,000.00	9,307
Longitude	9.08	11.37	-16.61	142.55	9,307
Latitude	46.79	5.93	27.90	65.01	9,307
Atlantic	0.03	-	0.16	1.00	9,307
Calories	105857.12	-	29,628.22	177882.61	9,307
Potato	12,750.69	8,663.51	1.00	31,416.94	9,307
Land suitability	20,390.80	7,921.80	1.00	31,416.94	9,307
Ruggedness	16.19	10.02	1.07	47.29	9,307
Elevation (in m)	709.88	534.93	22.69	2,924.50	9,307
Eclipse	0.29	0.46	0.00	2.00	9,307
Variables used in additional regressions					
Mills	9.09	8.46	0.00	38.00	130
Ploughs	23.26	14.85	0.00	60.00	133
Press	0.15	-	0.00	1.00	9,307
*Cistercian*10	0.08	-	0.00	1.00	9,307
*Cistercian*40	0.54	-	0.00	1.00	9,307
Witch	0.19	1.18	0.00	19.00	9,307
Trials	0.16	0.52	0.00	5.00	9,307
University	0.07	-	0.00	1.00	9,307
Distance from first adopters (in km)	5.82	6.81	0.00	129.66	9,262
Distance from mines (in km)	3.29	4.72	0.01	108.35	9,307
Variables taken from Bosker et al. (2013) dataset					
Sea	0.21	-	0.00	1.00	5,360
River	0.55	-	0.00	1.00	5,360
Roman roads	0.24	-	0.00	1.00	5,360
Hub	0.24	-	0.00	1.00	5,360
Elevation (in m)	180.30	228.40	-4.00	2,234	5,360
Ruggedness	71.64	76.26	0.47	559.45	5,360
Bishop	0.31	-	0.00	1.00	5,360
Archibishop	0.09	-	0.00	1.00	5,360
University	0.07	-	0.00	1.00	5,360
Capital	0.04	-	0.00	1.00	5,360
Prince	0.36	-	0.00	1.00	5,360
Commune	0.37	-	0.00	1.00	5,360
Clockmakers, Pocket makers, and famous people					
Clock makers	2.39	94.91	0.00	8,391.00	22,040
Pocket makers (dummy)	0.04	-	0.00	1.00	9,307
Humanities	1.43	3.57	0.00	80.00	963
Arts	0.87	4.29	0.00	94.00	963
Science	0.37	2.05	0.00	45.00	963
State	0.78	2.78	0.00	56.00	963
Business	0.17	0.80	0.00	12.00	963
Precision	0.12	0.64	0.00	9.00	963

Source: Descriptive statistics of the variables considered in the econometric specifications. The description and sources of the variables are reported in Section II in the main text.

Table B3: Total and annular eclipses during the medieval period in Europe.

Date	Type	Duration in seconds	Path width in km
May 5th, 840	**Total**	**346**	**274**
March 24th, 852	**Annular**	**313**	**260**
October 29th, 878	**Total**	**110**	**250**
August 8th, 891	**Annular**	**342**	**211**
July 19th, 939	**Total**	**342**	**267**
May 17th, 961	**Annular**	**114**	**128**
December 22nd, 968	**Total**	**148**	**246**
October 21st, 990	Annular	489	644
January 24th, 1023	Total	180	276
June 29th, 1033	Annular	0.4	27
August 22nd, 1039	Annular	0.1	60
April 19th, 1064	Annular	238	208
February 16th, 1086	**Total**	**288**	**288**
September 23rd, 1093	Annular	123	101
December 25th, 1098	**Annular**	**533**	**483**
May 31st, 1109	Annular	311	140
August 11th, 1124	Total	199	259
August 2nd, 1133	Total	278	252
October 26th, 1147	Annular	251	207
January 26th, 1153	**Annular**	**413**	**367**
September 13th, 1178	Total	238	210
May 1st, 1185	Total	310	328
September 4th, 1187	Total	245	267
June 23rd, 1191	Annular	268	193
November 27th, 1201	Annular	376	302
February 28th, 1207	**Annular**	**272**	**232**
June 3rd, 1239	Total	318	313
October 6th, 1241	**Total**	**218**	**274**

Source: Espenak (2015). The eclipses marked in bold are the ones selected for constructing our instruments. Section II in the main text contains the criteria for our selection.

Table B4: OLS Regressions

	Dependent variable: $\ln POP$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CLOCK\cdot$								
$Year = 1200$	0.12	0.11	0.12	0.11	0.02	0.10	0.08	0.13
	(0.17)	(0.17)	(0.20)	(0.20)	(0.14)	(0.07)	(0.19)	(0.16)
$Year = 1300$	0.75***	0.67***	0.75***	0.67***	0.58***	0.46**	0.71***	0.74***
	(0.13)	(0.17)	(0.11)	(0.18)	(0.17)	(0.18)	(0.13)	(0.09)
$Year = 1400$	0.67***	0.62***	0.67***	0.62***	0.45***	0.46**	0.65***	0.66***
	(0.15)	(0.19)	(0.08)	(0.18)	(0.14)	(0.21)	(0.17)	(0.14)
$Year = 1500$	0.53***	0.47***	0.53***	0.47**	0.38**	0.38**	0.51***	0.52***
	(0.13)	(0.17)	(0.11)	(0.18)	(0.15)	(0.17)	(0.14)	(0.12)
$Year = 1600$	0.55***	0.50***	0.55***	0.50***	0.41***	0.38*	0.52***	0.50***
	(0.16)	(0.19)	(0.12)	(0.19)	(0.14)	(0.21)	(0.17)	(0.16)
$Year = 1700$	0.70***	0.63***	0.70***	0.63***	0.50***	0.40**	0.66***	0.63***
	(0.17)	(0.18)	(0.11)	(0.19)	(0.12)	(0.19)	(0.18)	(0.17)
$Year = 1750$	0.48***	0.40*	0.48***	0.40**	0.51***	0.43**	0.45***	0.43***
	(0.16)	(0.21)	(0.10)	(0.19)	(0.13)	(0.18)	(0.17)	(0.16)
$Year = 1800$	0.37**	0.27	0.37***	0.27	0.43***	0.42**	0.33*	0.32*
	(0.16)	(0.22)	(0.10)	(0.20)	(0.14)	(0.18)	(0.19)	(0.17)
$Year = 1850$	0.32*	0.21	0.32***	0.21	0.39**	0.35**	0.28	0.27
	(0.17)	(0.24)	(0.10)	(0.21)	(0.16)	(0.16)	(0.21)	(0.18)
Adjusted R^2	0.68	0.69	0.68	0.69	0.71	0.63	0.68	0.68
Control for coordinates	N	Y	N	N	N	N	N	N
Technological Space	Cistercian 10 km	Cistercian 10 km	Cistercian 10 km	Cistercian 10km	Cistercian 10 km	Cistercian 10 km	Cistercian 40 km	University 40 km
Sample	Entire	Entire	Entire	Entire	$POP \geq 5,000$	$POP \geq 10,000$	Entire	Entire
Distance cutoff (km)	1,000	1,000	500	-	1,000	500	1,000	1,000
N. of clusters	-	-	-	73	-	-	-	
N. of observations	9,307	9,307	9,307	9,184	6,933	3,367	9,307	9,307

Note: Estimation of equation (2) of the main text. All columns are controlled using the same regressors as column (3) in Table 2 of the main text. Standard errors corrected by spatial autocorrelation. Standard errors are robust and clustered by grids of 1,000× 1,000 km^2 in parentheses in column (4). All control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table B5: OLS Regressions: Reduced form

	Dependent variable: $\ln POP$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eclipse·								
$Year = 1200$	0.47*	0.50**	0.47**	0.50**	0.26		0.46*	0.45*
	(0.25)	(0.21)	(0.22)	(0.24)	(0.28)		(0.24)	(0.24)
$Year = 1300$	0.51**	0.55***	0.51**	0.55**	0.43*	0.15**	0.50**	0.50**
	(0.25)	(0.18)	(0.22)	(0.24)	(0.22)	(0.07)	(0.21)	(0.20)
$Year = 1400$	0.47**	0.52***	0.47**	0.52*	0.32	0.30**	0.47**	0.47**
	(0.24)	(0.17)	(0.23)	(0.28)	(0.21)	(0.12)	(0.23)	(0.23)
$Year = 1500$	0.68***	0.71***	0.68**	0.71**	0.41*	0.13	0.68***	0.68***
	(0.25)	(0.21)	(0.27)	(0.27)	(0.23)	(0.09)	(0.23)	(0.24)
$Year = 1600$	0.72***	0.72***	0.72***	0.72**	0.42**	0.18*	0.71***	0.71***
	(0.24)	(0.21)	(0.27)	(0.27)	(0.21)	(0.09)	(0.24)	(0.25)
$Year = 1700$	0.69***	0.71***	0.69**	0.71**	0.39	0.21**	0.67***	0.67***
	(0.22)	(0.20)	(0.27)	(0.28)	(0.24)	(0.09)	(0.21)	(0.21)
$Year = 1750$	0.54**	0.56***	0.54**	0.56**	0.32	0.17*	0.53**	0.53**
	(0.23)	(0.20)	(0.27)	(0.26)	(0.23)	(0.10)	(0.22)	(0.23)
$Year = 1800$	0.47*	0.55***	0.47*	0.55*	0.25	0.05	0.46**	0.46**
	(0.27)	(0.18)	(0.28)	(0.27)	(0.20)	(0.04)	(0.22)	(0.23)
$Year = 1850$	0.41	0.53***	0.41	0.53*	0.19	0.03	0.40*	0.40*
	(0.28)	(0.20)	(0.29)	(0.28)	(0.19)	(0.09)	(0.23)	(0.24)
Adjusted R^2	0.68	0.69	0.76	0.76	0.71	0.79	0.68	0.68
Control for coordinates	N	Y	N	N	N	N	N	N
Technological Space	Cistercian 10 km	Cistercian 10 km	Cistercian 10 km	Cistercian 10km	Cistercian 10 km	Cistercian 10 km	Cistercian 40km	University 40 km
Sample	Entire	Entire	Entire	Entire	$POP \geq 5,000$	$POP \geq 10,000$	Emtire	Entire
Distance cutoff (km)	1,000	1,000	500	-	1,000	500	1,000	1,000
N. of clusters	-	-	-	73				
N. of observations	9,307	9,307	9,307	9,184	6,933	3,367	9,307	9,307

Note: Estimation City and year fixed effects included in all regressions. All columns are controlled using the same regressors as column (3) in Table 2 of the main text. Standard errors corrected by spatial autocorrelation. Standard errors are robust and clustered by grids of 1,000× 1,000 km^2 in parentheses in column (4). All control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table B6: IV Regressions

	Dependent variable: $\ln POP$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CLOCK\cdot$								
$Year = 1200$	1.53	1.61	1.53	1.61	0.53	0.26	1.63	1.43
	(0.98)	(1.06)	(0.98)	(1.09)	(0.62)	(0.33)	(1.11)	(1.03)
$Year = 1300$	1.56***	1.84***	1.56**	1.84*	1.34***	0.99	1.66***	1.56***
	(0.59)	(0.70)	(0.77)	(1.02)	(0.35)	(0.73)	(0.60)	(0.60)
$Year = 1400$	1.32*	1.68*	1.32	1.68	0.88	1.69**	1.42	1.40
	(0.76)	(0.91)	(0.98)	(1.21)	(0.56)	(0.83)	(0.89)	(0.87)
$Year = 1500$	2.70***	2.56***	2.70**	2.56**	1.39***	0.85	2.76**	2.62**
	(0.97	(0.95)	(1.14)	(1.12)	(0.44)	(0.52)	(1.13)	(1.06)
$Year = 1600$	3.56	2.82**	3.56**	2.82**	1.94*	1.14*	3.60	3.51*
	(2.19)	(1.40)	(1.81)	(1.22)	(1.15)	(0.64)	(2.25)	(2.10)
$Year = 1700$	3.34**	2.74***	3.34**	2.74**	1.79*	1.46*	3.22**	3.20**
	(1.42)	(0.98)	(1.43)	(1.18)	(1.02)	(0.87)	(1.42)	(1.41)
$Year = 1750$	1.68*	1.66*	1.68	1.66	1.04*	1.11	1.77*	1.67
	(0.91)	(0.87)	(1.14)	(1.03)	(0.58)	(0.79)	(1.06)	(1.04)
$Year = 1800$	1.04	1.55*	1.04	1.55	0.06	0.48	1.15	1.03
	(0.78)	(0.84)	(1.14)	(1.15)	(0.43)	(0.43)	(0.84)	(0.90)
$Year = 1850$	0.30	1.42	0.30	1.42	-0.47	0.32	0.45	0.27
	(0.92)	(0.99)	(1.21)	(1.23)	(0.73)	(0.28)	(0.89)	(1.00)
Control for coordinates	N	Y	N	N	N	N	N	N
Technological Space	Cistercian	Cistercian	Cistercian	Cistercian	Cistercian	Cistercian	Cistercian	University
	10 km	10 km	10 km	10km	10 km	10 km	40 km	40 km
Sample	Entire	Entire	Entire	Entire	$POP \geq 5,000$	$POP \geq 10,000$	Entire	Entire
Distance cutoff (km)	1,000	1,000	500	-	1,000	500	1,000	1,000
N. of clusters	-	-	-	73				
N. of observations	9,307	9,307	9,307	9,184	6,933	3,367	9,307	9,307

City and year fixed effects included in all regressions. All columns are controlled using the same regressors as column (3) in Table 2 of the main text. Standard errors corrected by spatial autocorrelation. Standard errors are robust and clustered by grids of 1,000× 1,000 km^2 in parentheses in column (4). All control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table B7: First stage regression and partial F-test statistics.

	Dependent variable: $CLOCK \cdot T_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1200	1300	1400	1500	1600	1700	1750	1800	1850
Eclipse·									
$Year = 1200$	0.23***	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Year = 1300$	0.00	0.22***	0.01	0.01	0.02	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Year = 1400$	0.01	0.01	0.18***	0.01	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Year = 1500$	0.01	0.00	0.00	0.19***	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Year = 1600$	0.01	0.01	0.02	0.02	0.13***	0.03***	0.03**	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
$Year = 1700$	0.01	0.01	0.01	0.03**	0.02	0.13***	0.03**	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)	(0.01)
$Year = 1750$	0.01	0.01	0.02	0.02	0.02**	0.03**	0.13***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)	(0.01)
$Year = 1800$	0.01	0.01	0.02	0.02	0.02**	0.03***	0.03*	0.14***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
$Year = 1850$	0.01	0.01	0.01	0.02	0.02***	0.03**	0.03**	0.04***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Sanderson-Windmeijer multivariate F-test	18.87	59.75	15.83	55.42	29.51	15.71	27.30	55.77	58.25

First stage regression coefficients of $Eclipse \cdot Year$ of the specification reported in column (6) of Table 3 in the main text. City and year fixed effects included in all regressions. Standard errors are robust and clustered by grids of 1,000× 1,000 km^2 in parentheses. All of the control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively.

Table B8: Exogeneity test

Panel A.

Dep. variable:	*asinh mills*	*asinh plows*	*Printing press*	Cistercian 10 km	Cistercian 40 km	University	$\Delta \ln POP$ $1500-1400$	$\Delta \ln POP$ $1600-1500$	*Log Dist. to Wittenberg*	*Log Dist. to mines*	$\ln\left(1+\frac{Witches}{Pop_{1400}}\right)$	$\ln\left(1+\frac{Conflict}{Pop_{1500}}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Eclipse	-0.10	-0.13	0.05	0.02	0.07	0.01	0.17*	-0.04	-0.14	-0.11	0.00	0.00
	(0.34)	(0.33)	(0.04)	(0.04)	(0.06)	(0.03)	(0.10)	(0.03)	(0.13)	(0.21)	(0.00)	(0.00)
Adjusted R^2	0.34	0.40	0.48	0.19	0.64	0.18	0.21	0.26	0.99	0.05	0.16	
N. of observations	130	133	400	111	111	111	227	257	400	634	291	634

Panel B.

Dep. variable:	*Parliament*	*Bishop*	*Hub*	*Roman Road*	*Capital*	*Commune*
variable	(1)	(2)	(3)	(4)	(5)	(6)
Eclipse	-0.05	0.00	-0.02	-0.01	-0.04	0.03
	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
Adjusted R^2	0.73	0.44	0.41	0.27	0.14	0.67
N. of observations	387	387	387	387	387	387

Additional regressors: *Atlantic*, *Calories*, *Potato*, *Land Suitability*, *Ruggedness*, *Elevation*, initial population and a constant. Initial population not included in columns (1) and (2); *Longitude* and *Latitude* not included in column (8). Initial population level at year 1000 in column (3) , (4), and (5), at year 1300 in column (6), at year 1400 in column (7), at year 1500 in all the others. *aisnh* refers to the inverse hyperbolic sine function. Standard errors corrected by spatial autocorrelation within 100 km in column (1) , 200 km in column (2), and 1,000 km in all the others. Significance at the 90% confidence levels is indicated by *.

Table B9: IV regressions: Flexible differences-in-differences with alternative variables for clocks and instruments.

Dependent variable: $\ln POP$			
	Panel A: Reduced Form		
$VARIABLE:$	*Eclipses before*1000	*First Eclipse*	*First Eclipse*
	(1)	(2)	(3)
$VARIABLE \cdot$			
$YEAR = 1200$	0.65**	0.06**	0.06**
	(0.27)	(0.03)	(0.03)
$YEAR = 1300$	0.65**	0.06**	0.06**
	(0.28)	(0.03)	(0.03)
$YEAR = 1400$	0.57*	0.06*	0.06*
	(0.33)	(0.03)	(0.03)
$YEAR = 1500$	0.73**	0.09**	0.09**
	(0.30)	(0.03)	(0.03)
$YEAR = 1600$	0.71**	0.08**	0.08**
	(0.31)	(0.03)	(0.03)
$YEAR = 1700$	0.72**	0.08**	0.08**
	(0.32)	(0.03)	(0.03)
$YEAR = 1750$	0.51*	0.07**	0.07**
	(0.30)	(0.03)	(0.03)
$YEAR = 1800$	0.47	0.07**	0.07**
	(0.31)	(0.03)	(0.03)
$YEAR = 1850$	0.48	0.07**	0.07**
	(0.31)	(0.03)	(0.03)
	Panel B: Instrumental Variable		
$VARIABLE:$	*CLOCK*	*CLOCK*	$\ln(1 + Time\ CLOCK)$
$INSTRUMENT:$	*Eclipses before*1000	*First Eclipse*	*First Eclipse*
$VARIABLE \cdot$			
$YEAR = 1200$	1.78*	2.75	0.02
	(0.92)	(1.69)	(0.02)
$YEAR = 1300$	1.82*	2.23	0.02
	(0.95)	(1.67)	(0.02)
$YEAR = 1400$	1.42	2.23	0.03*
	(1.07)	(1.77)	(0.02)
$YEAR = 1500$	2.32**	3.57**	0.03*
	(0.97)	(1.76)	(0.02)
$YEAR = 1600$	2.19**	3.74*	0.02*
	(1.00)	(1.94)	(0.01)
$YEAR = 1700$	2.42**	3.70**	0.03*
	(1.07)	(1.82)	(0.02)
$YEAR = 1750$	1.07	2.03	0.02
	(0.98)	(1.67)	(0.02)
$YEAR = 1800$	0.83	2.56	0.02
	(1.04)	(1.78)	(0.02)
$YEAR = 1850$	0.87	2.66	0.02
	(1.07)	(1.88)	(0.01)
N. of clusters	73	73	73
N. of observations	9,173	9,184	9,173

New variables considered: $\ln(1 + Time\ CLOCK)$, where $Time\ CLOCK$ is the time of the clock if the clock is adopted before 1450 and 0 otherwise. $Eclipses before 1000$ is total number of overlapping eclipses before 1000. $Year\ first\ Eclipse$ is the year of the first of the multiple eclipses. Same control variables as in column (3) of Table 1 in the main text with all control variables are interacted by year dummies. Standard errors are reported in parentheses. Robust standard error clustered by grids of 500× 500 km^2. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table B10: First stage regression and partial F-test statistics with alternative instrument.

	Dependent variable: $CLOCK \cdot T_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1200	1300	1400	1500	1600	1700	1750	1800	1850
Eclipse									
$before$ 1000$\cdot$									
$YEAR = 1200$	0.25***	0.01	0.02***	0.02	0.01	0.02	0.02	0.02	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
$YEAR = 1300$	0.02**	0.26***	0.01	0.01	0.01	0.01	0.01	0.02	0.02
	(0.01)	(0.06)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$YEAR = 1400$	0.02***	0.01	0.30***	0.01	0.01	0.02	0.00	0.00	0.00
	(0.00)	(0.01)	(0.08)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
$YEAR = 1500$	0.02**	0.01	0.01	0.21***	0.02	0.03**	0.02	0.03*	0.03
	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
$YEAR = 1600$	0.02**	0.01	0.02	0.03**	0.20***	0.03**	0.02**	0.04**	0.04**
	(0.01)	(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)
$YEAR = 1700$	0.02**	0.01	0.01	0.02*	0.03*	0.19***	0.03**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.02)
$YEAR = 1750$	0.02**	0.01	0.01	0.02**	0.02*	0.04**	0.18***	0.03**	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.02)
$YEAR = 1800$	0.02**	0.01	0.01	0.03*	0.02	0.04**	0.02	0.19***	0.04**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
$YEAR = 1850$	0.02**	0.01	0.01	0.03*	0.02	0.04**	0.02	0.04**	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Sanderson-Windmeijer									
multivariate F-test	27.94	33.84	29.94	70.19	27.85	39.20	48.48	95.16	90.61

First stage regression coefficients of $Eclipse \cdot Year$ of the specification reported in column (1) of Table B9 in the Appendix. City and year fixed effects included in all regressions. Standard errors are robust and clustered by grids of 1,000$\times$ 1,000 km^2 in parentheses. All of the control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively.

Table B11: Clockmakers, clocks, and population

Dependent variable:	*ln CLOCK Makers*	*asinh CLOCK Makers*	$\ln POP$	$\ln POP$
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
$CLOCK\cdot$				
$YEAR = 1200$			0.15	2.25*
			(0.31)	(1.36)
			[0.58]	
$YEAR = 1300$			0.66**	1.60
			(0.27)	(0.29)
			[0.02]	
$YEAR = 1400$			0.59**	1.31
			(0.26)	(0.99)
			[0.02]	
$YEAR = 1500$	0.15**	0.20**	0.36	2.94**
	(0.07)	(0.09)	(0.28)	(1.25)
	[0.01]	[0.01]	[0.16]	
$YEAR = 1600$	0.35**	0.43***	0.28	3.43
	(0.13)	(0.15)	(0.25)	(2.19)
	[0.01]	[0.01]	[0.18]	
$YEAR = 1700$	0.51***	0.61***	0.30	3.94**
	(0.18)	(0.21)	(0.29)	(1.89)
	[0.00]	[0.00]	[0.23]	
$YEAR = 1800$	0.41**	0.48**	0.08	1.16
	(0.19)	(0.21)	(0.29)	(0.62)
	[0.01]	[0.01]	[0.76]	
$CLOCK\ Makers\cdot$				
$YEAR = 1500$			0.12	-0.36
			(0.10)	(0.24)
			[0.23]	
$YEAR = 1600$			0.29***	-0.35
			(0.08)	(0.76)
			[0.00]	
$YEAR = 1700$			0.50***	-0.14
			(0.12)	(0.38)
			[0.00]	
$YEAR = 1800$			0.46***	0.56**
			(0.09)	(0.13)
			[0.00]	
Adjusted R^2	0.57	0.58	0.69	
N. of clusters	27	27	27	16
N. of observations	2,916	2,916	4,443	4,845

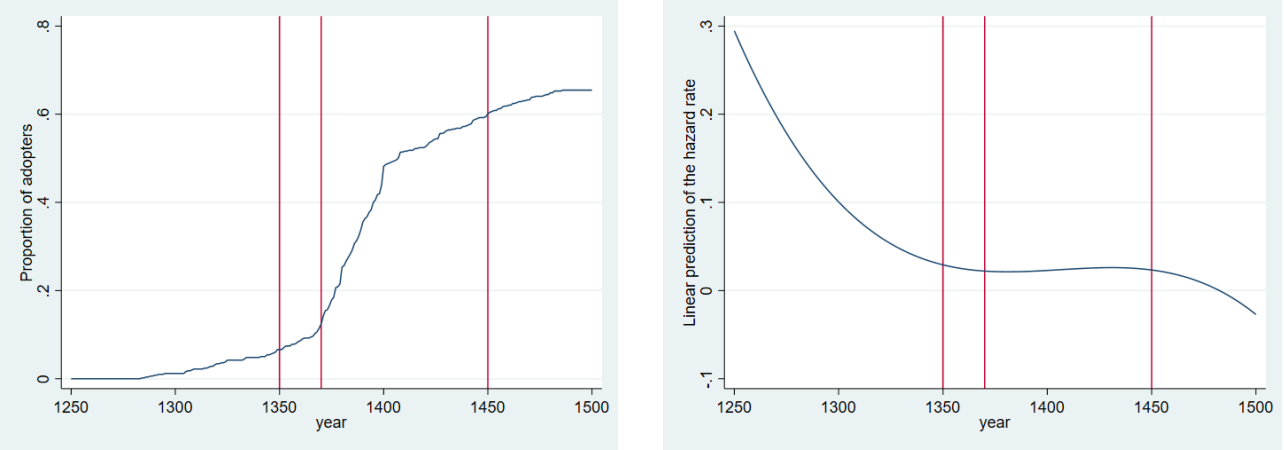
Dependent variables in the first two columns: $lnCLOCK\ Makers$ is equal to $\ln(1 + number\ of\ makers)$; $aisnh$ is equal to $asinh(number\ of\ makers)$. Variable $CLOCK\ Makers$ defined in Section 7 in the main text. City and year fixed effects included in all regressions. Standard errors are robust and clustered by country. p-values for t-test of parameter significance using wild bootstrapped standard errors presented in brackets (Cameron and Miller (2015)). Year considered: 1400, 1500, 1600, 1700, and 1800. Control variables are the ones considered in Table 2 in the main text, column (4), plus the 100-year lag of population. Instruments considered in column (4): $Eclipse \cdot T_t$. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively.

Table B12: Seemingly unrelated regressions

	CLOCK MAKERS				*lnPOP*			
	1500	1600	1700	1800	1500	1600	1700	1800
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CLOCK	0.14***	0.21***	0.22***	0.12***	0.71***	0.76***	0.82***	0.53***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.08)	(0.07)	(0.07)	(0.05)
CLOCK MAKERS					0.77***	0.96***	1.05***	0.70***
					(0.14)	(0.10)	(0.08)	(0.05)
Adjusted R^2	0.30	0.33	0.34	0.32	0.11	0.27	0.16	0.20
N. of observations	572	844	1,100	1,868	572	844	1,100	1,868

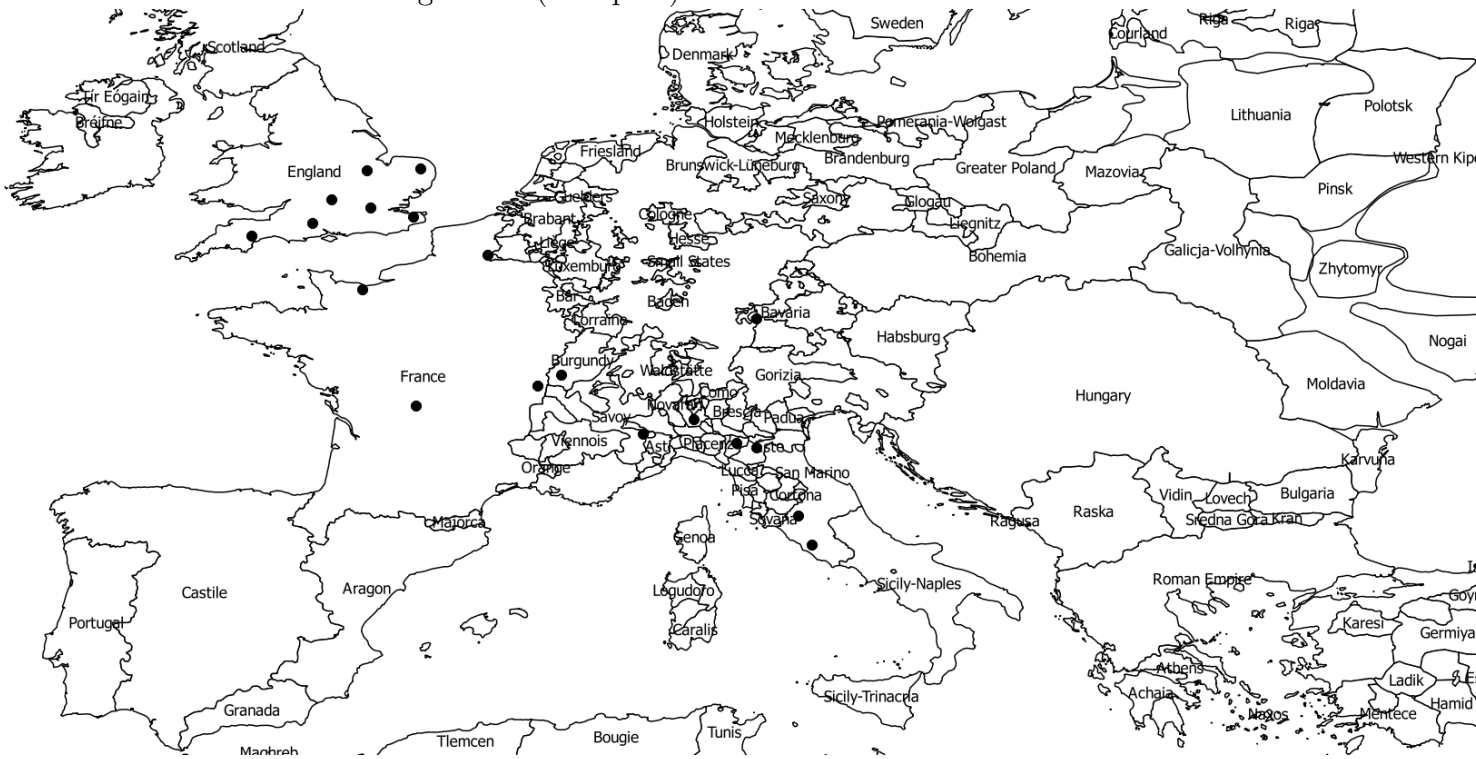
The seemingly unrelated regressions including controls (without time interactions) considered in column (4) of Table 2 included in all regressions. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively.

Figure B1: Cumulative distribution and hazard rate of mechanical clock.



The left-hand side of Figure B1 shows the cumulative distribution of the proportion of technological adopters using our dataset described in Section II of the main text for the period of 1283-1500. In the figure we have a proportion of adopters that is lower than 70% in 1500. This can be explained by our definition of the early adoption of mechanical clocks reported in the main text. It is estimated that the public clocks arrived in almost all the cities by the end of the 18th century. In this graph, we observe an S-shaped curve with a slow start in adopting the new technology and two structural breaks during the second half of the 14th and 15th centuries and beyond. This forms the typical diffusion curve of new technologies, as described in Rogers (2003)'s analysis of diffusion processes. Moreover, a more specific analysis based on the hazard rate (Young (2009)), which is shown in the right part of Figure B1. More precisely, we consider the strategy applied by Young (2009) on Griliches (1957)'s dataset on the adoption of hybrid corn in the US. We define p_t the proportion of adopters at year t, and we define the hazard rate of adoption H_t, i.e., the conditional probability of adopting a mechanical clock as $H_t = \frac{p_{t+1}-p_t}{p_t(1-p_t)}$. The right-hand side of Figure B1 shows the OLS prediction of a cubic polynomial, $H_t = a + b_1 t + b_2 t^2 + b_3 t^3 + u_t$. The correspondent hazard rate is almost equal to zero after 1450, confirming the use of 1450 as an endpoint and defines the number of early adopters in our sample.

Figure B2 (first part): Diffusion until 1300

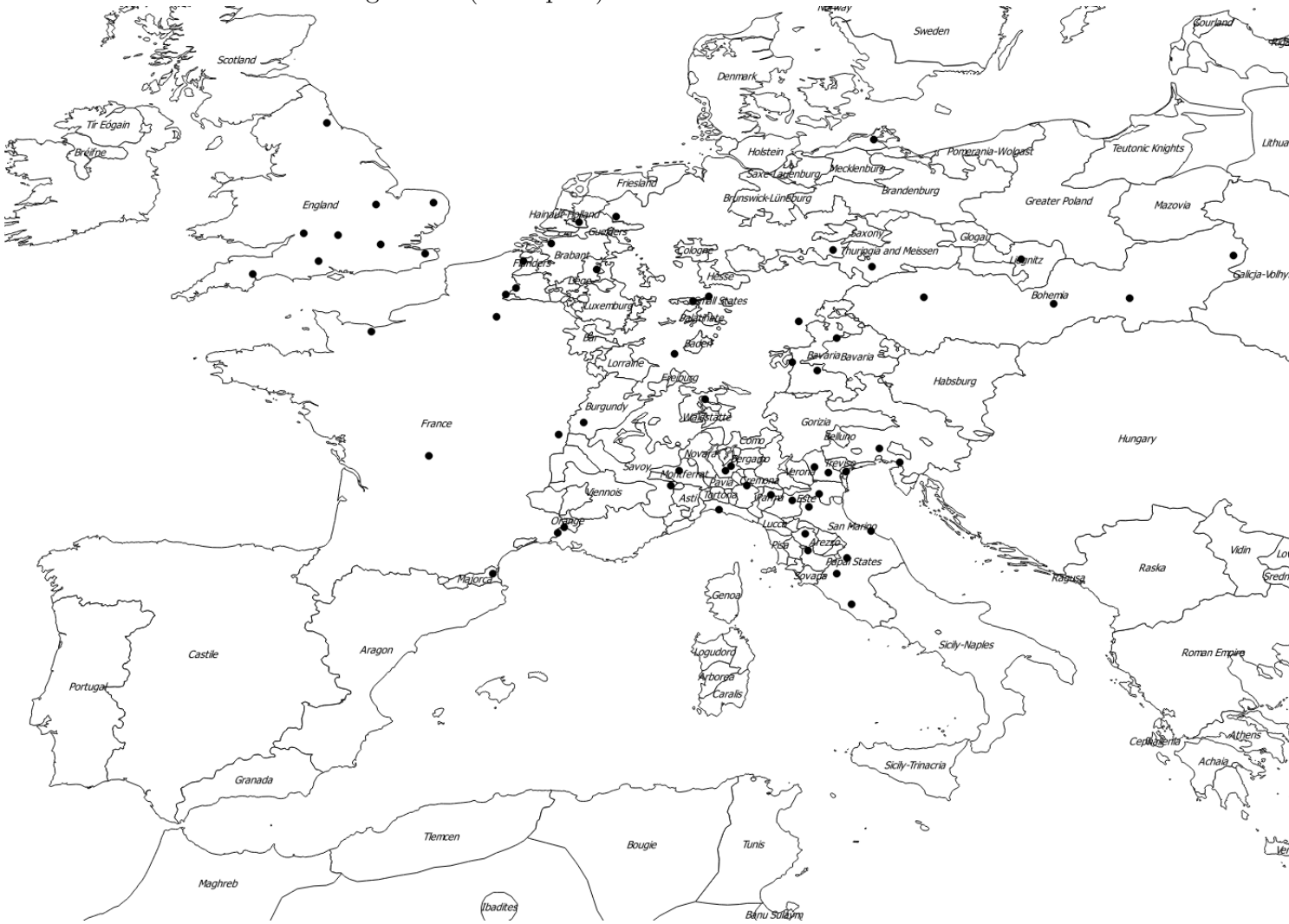


Note: Only public mechanical clocks adopters displayed. Political borders in the year 1200, according to Nuessli (2011).

Figure B2 (second part): Diffusion until 1350

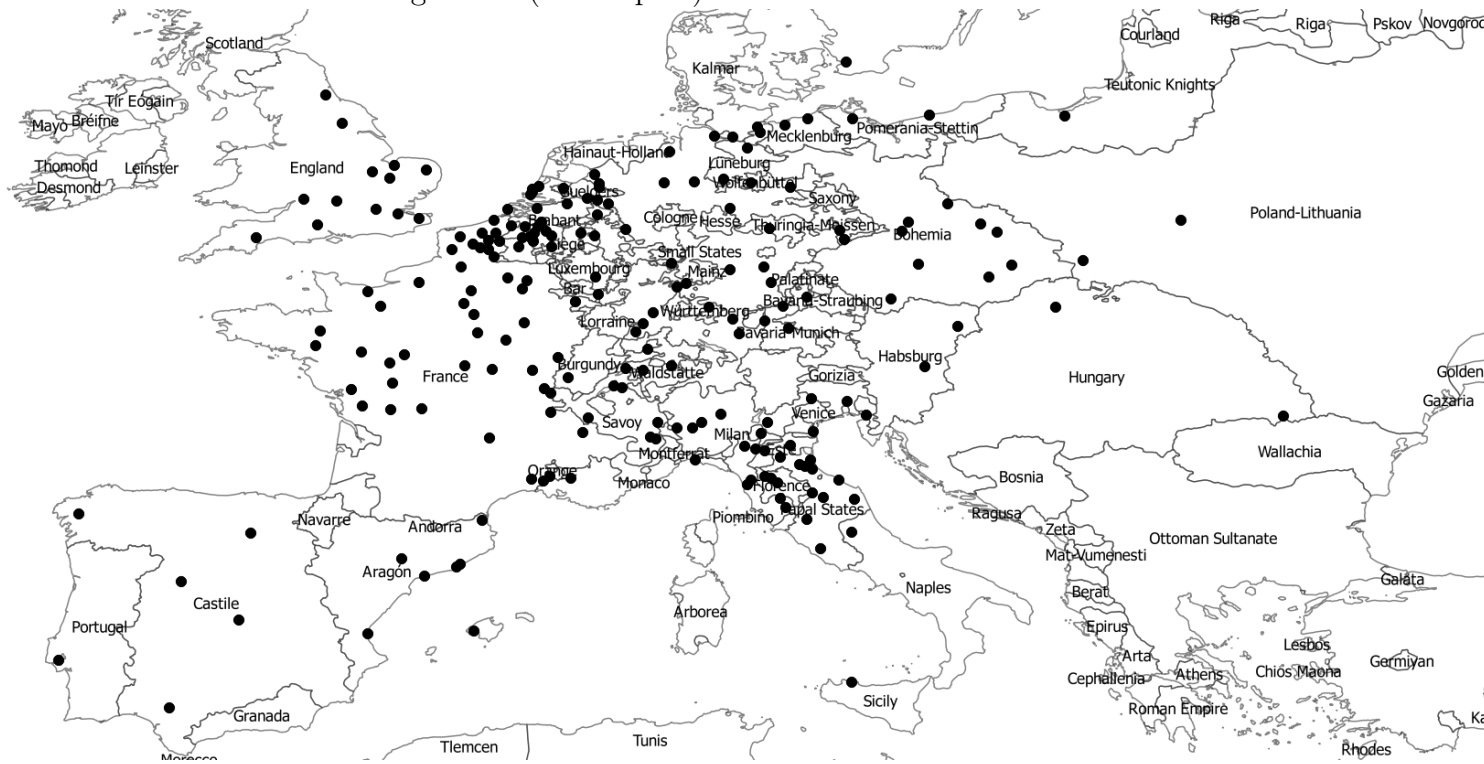
Note: Only public mechanical clocks adopters displayed. Political borders in the year 1300, according to Nuessli (2011).

Figure B2 (third part): Diffusion until 1370



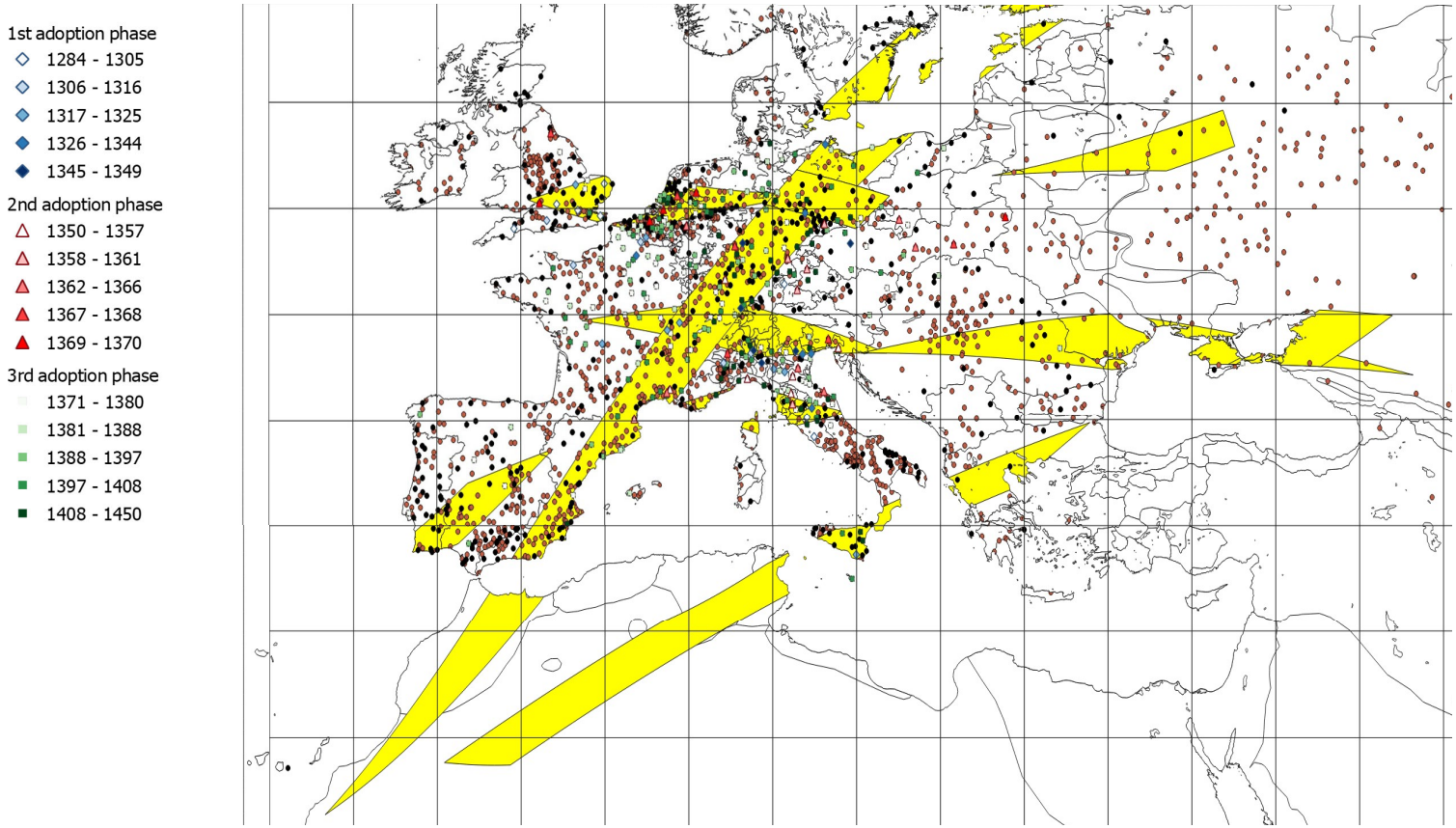
Note: Only public mechanical clocks adopters displayed. Political borders in the year 1300, according to Nuessli (2011).

Figure B2 (fourth part): Diffusion until 1400



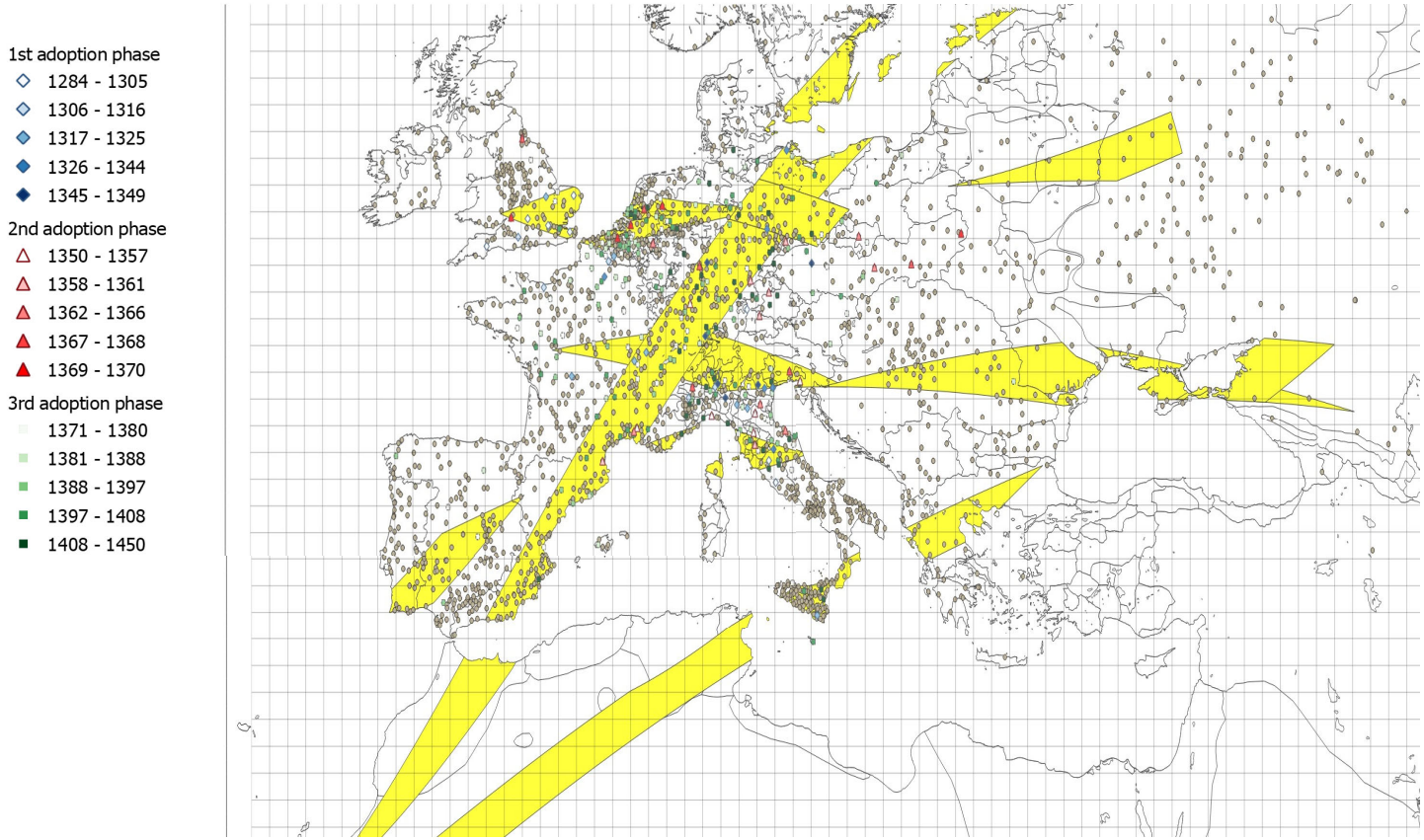
Note: Only public mechanical clocks adopters displayed. Political borders in the year 1400, according to Nuessli (2011).

Figure B2 (fifth part): The diffusion of the mechanical clock in Europe: entire period with 1,000×1,000 km grid



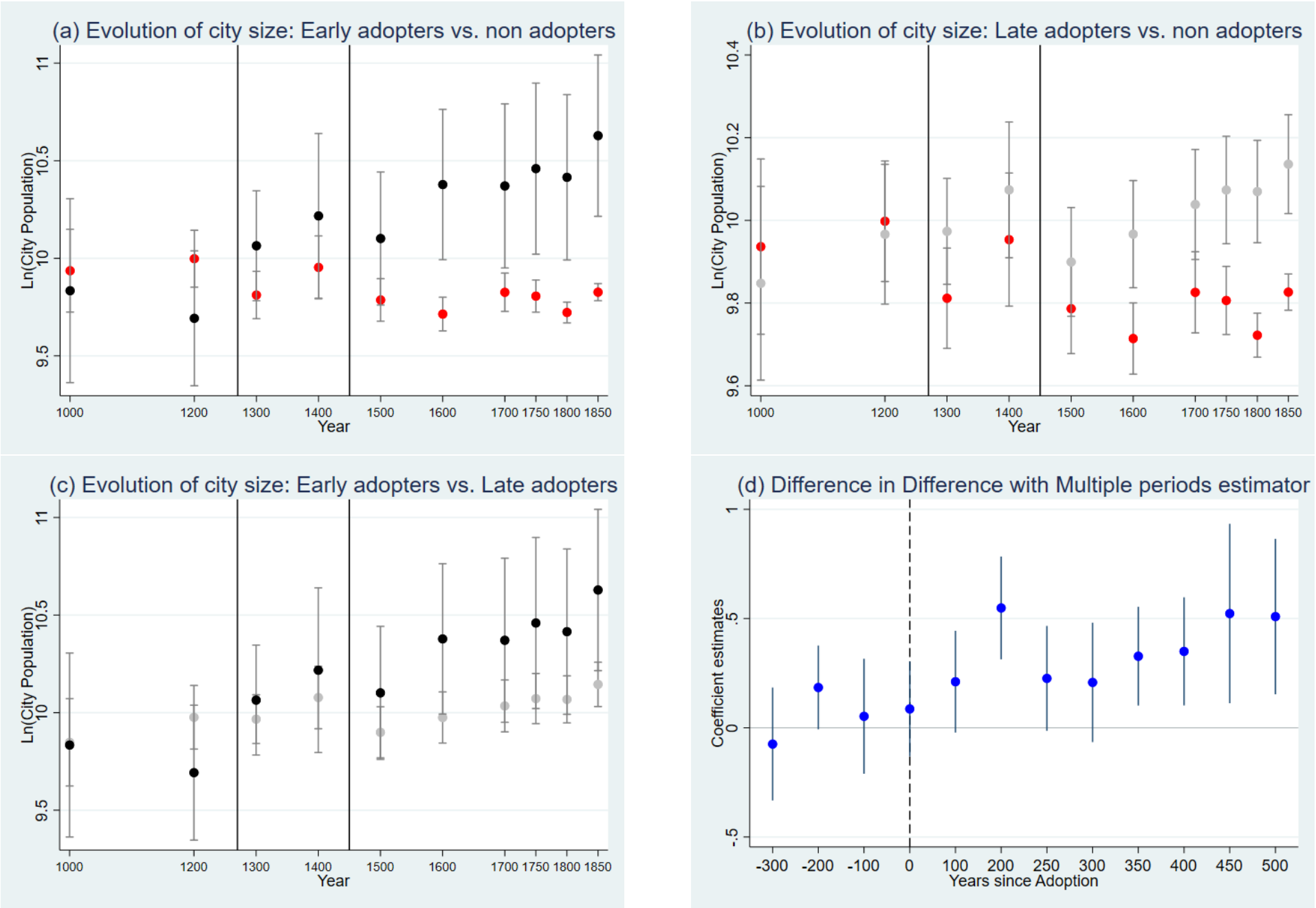
The diffusion of the mechanical clock in Europe and Areas in Europe with more than one total or annular solar eclipse. Clocks adopters and city available in Bairoch dataset displayed. Source: Authors' calculation described in Section II of the main text.

Figure B2 (sixth part): The diffusion of the mechanical clock in Europe: entire period with 100×100 km grid



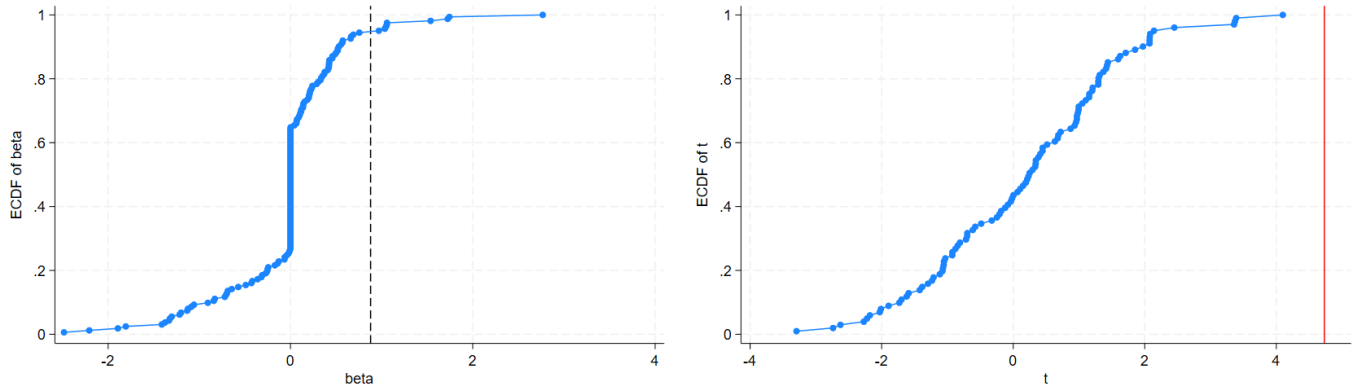
The diffusion of the mechanical clock in Europe and Areas in Europe with more than one total or annular solar eclipse. Clocks adopters and city available in Bairoch dataset displayed. Source: Authors' calculation described in Section II of the main text.

Figure B3: City size and the adoption of the public mechanical clock.



A comparison of the unweighted average city population is presented in the first three panels: (a) between early adopters and non-adopters, (b) between late adopters and non-adopters, and (c) between early adopters and late adopters. First adopters are represented in black, late adopters in grey, and non-adopters in

Figure B4: Placebo test based on 168 historical and future total solar eclipses

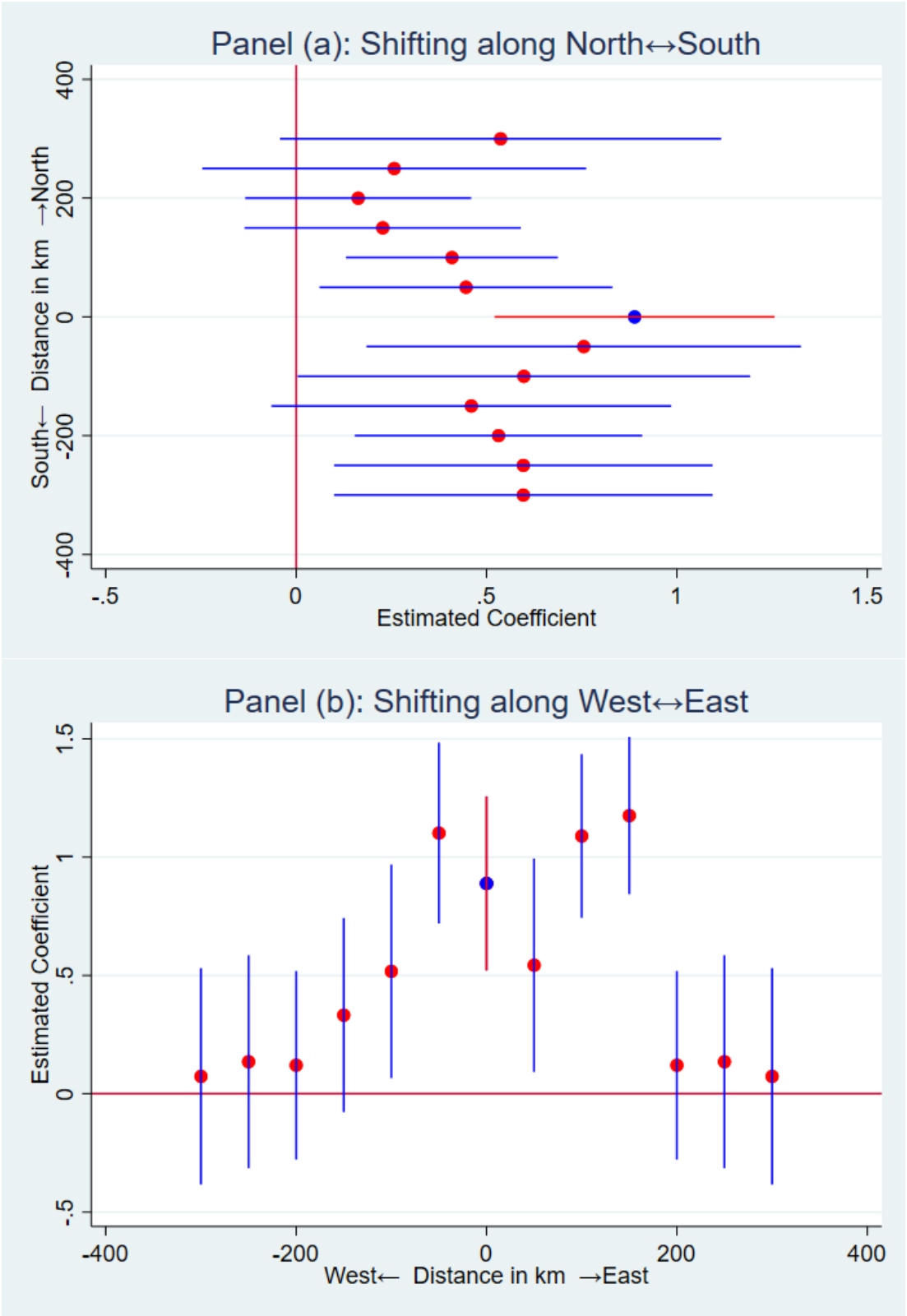


On the left we compare the effective estimates of the logit regression reported in Table 4 (red line) with the empirical cumulative distribution function (ECDF) obtained by 168 placebos. On the right the figure displays the effective $z-$statistics with the ECDF of the placebos.

Figure B4 shows a set of placebo tests that exploit both the past and the future trajectories of total and annular eclipses. The data provided by Espenak (2015) allow us to track these astronomical events for a period before the contribution of our instrument (i.e., from 2000 B.C. to 800 A.D.). In addition, we collect information over the period 1450 to 3000 A.D. We construct the instruments while summing up the number of overlapping eclipses for cities in intervals of 100 years.[3] We move the sum each year, which allows us to construct 168 different placebos. We rerun the regressions by substituting one of the placebos each time. Similar to the graphical representation of placebos in Madestam et al. (2013), the left-hand side of Figure B4 shows the empirical cumulative distribution function of the different coefficients of *Eclipse* from the 168 different placebos of the logit regression reported in column (1) of Table 4 of the main text compared to the actual estimates. On the right-hand side we report the comparison of the respective $z-$statistics. The figure suggests that not only are the actual estimates (represented by the vertical line) outliers with respect to the entire distribution (only 7.00% of the coefficients are higher) but also that only 4.95% of the coefficients are significantly different (99%). This provides additional support for the positive causal relationship between the frequencies of the actual eclipses and the adoption of the public mechanical clock. The verage is about 252 km, the one chosen 273.

[3]To be restrictive in our exercise, we consider all of the cities that are available in the dataset, independently of their appearance in particular years in the Bairoch et al. (1988) dataset.

Figure B5: Placebo tests spatially shifting the eclipse's umbral patterns



In both graphs, coefficients of the variable Eclipse (reported with the blue dot) obtained from regression of column (1) of Table 4 together with the placebo a 95% confidence interval is reported. The sample is based on cities with 10,000 inhabitants or more.

Appendix C: Additional robustness checks

In this appendix we consider the long-run growth regressions reminiscent of the classical formula derived by Mankiw et al. (1992), whose original equation relates economic growth to input of production and human capital, and an initial economic condition as in Barro (1991). Similar to Dittmar (2011), we consider the following equation:

$$\Delta \ln Pop_{it-x} = \alpha_0 + \alpha_1 CLOCK_i + \alpha_2 X_i + \alpha_3 \ln POP_{i0} + \epsilon_{it} \tag{1}$$

where for city i ΔPOP_{it-x} is the growth rate of population measured as $\ln\left(\frac{POP_{it}}{POP_{ix}}\right)$ and $\ln POP_{i0}$ is an initial value of population. The OLS estimates and the variables considered are reported in Table C1. To study the long-run effects, we consider seven different time-intervals: 1000-1200, 1200-1300, 1200-1400, 1400-1500, 1500-1600, 1500-1700, and 1500-1800, with an initial population level of 1000 for columns (1), (2), and 1400 in column (3). The other columns have a starting population level of 1500. The first three columns, which consider century growth rates for which the clocks have no impact, display the placebo exercise, rejecting the hypothesis that cities that had adopted the new technology were already following an independent growth pattern. On the one hand, in the first five columns we observe no effects. On the other hand, the coefficients based on the introduction of the mechanical clock display both positive and significant results for the periods of 1500-1700 and 1500-1800.

Table C1: OLS growth regressions.

	Dependent variable: $\Delta \ln POP$						
	1200-1000	1300-1200	1400-1200	1500-1400	1600-1500	1700-1500	1800-1500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CLOCK	0.21	0.09	0.30	0.03	0.10*	0.22***	0.18**
	(0.20)	(0.19)	(0.22)	(0.07)	(0.06)	(0.08)	(0.07)
*Cistercian*10	0.51*	-0.72***	-0.04	-0.10	0.20**	0.28**	0.29**
	(0.27)	(0.26)	(0.55)	(0.15)	(0.10)	(0.13)	(0.12)
*Cistercian*10·	-0.17	0.73*	0.14	0.21	-0.15	0.04	-0.04
CLOCK	(0.46)	(0.38)	(0.70)	(0.21)	(0.14)	(0.19)	(0.22)
Calories	0.36	-0.89	-0.27	0.05	0.06	-0.32**	-0.26*
	(0.51)	(0.93)	(0.61)	(0.21)	(0.10)	(0.14)	(0.15)
Potato	-0.07	0.03	-0.10	0.07*	-0.02	0.03	0.02
	(0.07)	(0.08)	(0.08)	(0.04)	(0.02)	(0.03)	(0.02)
Land suitability	-0.08	-0.09	0.06	-0.08	-0.00	-0.04	-0.02
	(0.24)	(0.44)	(0.10)	(0.06)	(0.03)	(0.05)	(0.04)
Ruggedness	0.08	0.37	0.15	-0.10	-0.13	0.02	-0.08
	(0.24)	(0.33)	(0.42)	(0.13)	(0.08)	(0.13)	(0.14)
Elevation	-0.17	0.00	-0.12	-0.09	0.01	-0.12	0.09
	(0.22)	(0.23)	(0.29)	(0.10)	(0.07)	(0.10)	(0.11)
Longitude	0.02**	-0.01	0.00	0.00	0.01**	0.01**	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Latitude	-0.03	0.03	0.04	-0.03***	-0.02***	-0.02*	0.00
	(0.02)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
University			0.41**	0.10	0.24***	0.40***	0.45***
			(0.19)	(0.11)	(0.08)	(0.10)	(0.11)
Atlantic					0.43***	0.64***	0.84***
					(0.11)	(0.21)	(0.21)
$LnPop_0$	-0.68***	-0.23***	-0.30***	-0.21***	-0.23***	-0.31***	-0.50***
	(0.08)	(0.08)	(0.11)	(0.03)	(0.04)	(0.05)	(0.05)
	(6.11)	(8.61)	(7.77)	(2.24)	(1.21)	(1.67)	(1.80)
Adjusted R^2	0.67	0.13	0.13	0.18	0.16	0.18	0.29
N. of clusters	-	-	90	189	274	271	315
N. of observations	66	64	102	291	496	519	626

Standard errors are robust in columns (1) and (2). Standard error clustered by the 1,000×1,000-kilometer grid in parentheses. Initial population level at year 1000 in column (1) and (2), at year 1400 in column (3), at year 1500 in all the others. All regressions include a constant. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively.

Dynamic linear models

The estimations of flexible DiD and the different long-run regressions presented may present several limitations. First, the adoption of the public mechanical clock might have been correlated with other technological or institutional changes of a city that cannot be observed. Second, in the DiD framework the assumption of parallel trends might be violated because the adoption of the mechanical clock might have been determined by previous trends at the city level, which are good predictors of future trends of performance. In Appendix C we analyzed the dynamics associated with the nature of the treatment effects by first looking at an event-study exercise and then following the approaches suggested by Acemoglu et al. (2019) to study the relationship between democracy and growth.

In the third approach, given the different limitations of the DiD that were previously reported, we can follow the three different econometric strategies suggested by Acemoglu et al. (2019) based on the following full dynamic linear model:

$$\ln POP_{it} = \beta CLOCK_{it} + \sum_{j=100}^{p} \gamma_{j=100}^{p} \ln POP_{it-j} + C_i + T_t + \epsilon_{it} \tag{2}$$

where for city i and year t, C_i and T_t are city and year fixed effects, respectively, POP_{it} represents city size in terms of population, $CLOCK$ is a dummy that takes a value equal to 1 if the city has adopted at time t the mechanical clock, and is 0 otherwise and ϵ_{it} is the error term. In addition, population dynamics are controlled by a set of p lags. The coefficient β is computed considering as counterfactual the growth of a parametric regression of year fixed effects and 4 lags of population.[4] Given the notation that $\ln POP_{it}^{S}(CLOCK)$ is the potential logarithm of the population in period $t+s$ and that at time t a city does not have a clock ($CLOCK = 0$) or has a clock ($CLOCK = 1$). This means that the potential causal effect of the clock (i.e., the average treatment effect for the treated (ATET)) can be measured as

$$\beta^S = E\left(\delta \ln POP_{it}^{s} - \delta \ln POP_{it-100}^{s} | CLOCK_{it} = 1, CLOCK_{it-100}\right) \tag{3}$$

Following Jordá (2005) and Kline (2011), the β^S can be estimated from a linear regression adjustment,

[4] In our case, given that our panel is unbalanced and the year 1100 is missing, we need to make two extra assumptions to perform this econometric exercise: we assign for the year 1100 the population of 1000 and-following Cantoni (2015)- when population is missing we attribute a level of 500 inhabitants.

that is

$$\hat{\beta}^s = \hat{E}\left[\Delta^s \ln POP_{it}\left(d\right)|CLOCK_{it}=1, CLOCK_{it-100}=0\right]$$

$$-\left[\hat{E}\left[x_{IT}^{S}|CLOCK_{it}=1, CLOCK_{it-100}=0\right]\hat{\pi}^s\right] \quad (4)$$

where $\left[\hat{E}\left[x|s\right]\right]\hat{\pi}$ denotes the sample average of the regressors in (2), while the second term of the equation is the counterfactual cumulative growth for cities adopting the clock at period.[5] Table C2 provides the average effect of the adoption of the public mechanical clock on the natural logarithm of population over centuries for three different periods: before the adoption of the technologies, one century after the adoption and after one and two centuries. Additionally, from these results, there is no evidence that the adoption of the technology has been driven by a dip in population dynamics, with a more pronounced significant result during the first three centuries after the adoption of the technology.

Table C2: The effect of the mechanical clock on population: Linear regression with semiparametric estimation

Before 0	0-100	100-200	200-300
(1)	(2)	(3)	(4)
-0.01	0.06	0.49***	0.12***
(0.15)	(0.13)	(0.12)	(0.06)

All of the reported estimates display the average effect of the adoption of the public mechanical clock on the natural logarithm of population over centuries, according to the linear regression adjustments method (Jordá (2005) and Kline (2011)). Robust standard errors clustered at country level via 100 bootstrapped replications.

Geographical balance

An additional and legitimate concern is that, by chance, total and solar eclipses might have overlapped in very active economic area (e.g., the southern part of England, the Netherlands, and the northern part of Italy), thus creating potential problems related to the geographical balance of the dataset. Table C3 shows the OLS estimates excluding Germany, Italy, the Netherlands, Switzerland, and the Atlantic ports, respectively. Even if regressions that leave out parts of the dataset seem to exclude this, we investigate even further this potential bias by adopting the estimation technique of the Entropy

[5]Given the unbalanced structure of our dataset, we cannot estimate an inverse-propensity-score reweighting.

balancing algorithm proposed by Hainmueller and Xu (2013) and recently used by Angelucci et al. (2017). In contrast to a propensity score approach, this methodology computes the regression weights using an algorithm based on entropy such that our control group data (i.e., the early adopters of mechanical clocks) can match the treatment group in terms of the mean and variance. The results are reported in Table C4, which is divided into two parts: in the upper part, we observe the comparison between the treated and control groups before and after the weighting, respectively, while the lower part reports the results of the weighted regression, which are consistent with the previous results.

Table C3: OLS regressions excluding some geographical areas.

Dependent variable: $\ln POP$					
	(1)	(2)	(3)	(4)	(5)
Sample without:	*Germany*	*the Netherlands*	*Italy*	*Switzerland*	*Atlantic ports*
$CLOCK*$					
$YEAR = 1200$	0.30*	0.11	0.15	0.09	0.09
	(0.16)	(0.16)	(0.14)	(0.15)	(0.16)
$YEAR = 1300$	0.89***	0.76***	0.79***	0.73***	0.73***
	(0.17)	(0.10)	(0.10)	(0.11)	(0.11)
$YEAR = 1400$	0.88***	0.66***	0.71***	0.63***	0.64***
	(0.19)	(0.13)	(0.10)	(0.13)	(0.14)
$YEAR = 1500$	0.66***	0.53***	0.59***	0.48***	0.53***
	(0.18)	(0.13)	(0.10)	(0.10)	(0.13)
$YEAR = 1600$	0.68***	0.54***	0.65***	0.50***	0.53***
	(0.17)	(0.16)	(0.14)	(0.14)	(0.16)
$YEAR = 1700$	0.89***	0.68***	0.79***	0.65***	0.64***
	(0.20)	(0.18)	(0.17)	(0.17)	(0.19)
$YEAR = 1750$	0.66***	0.47***	0.58***	0.43***	0.46**
	(0.15)	(0.17)	(0.17)	(0.15)	(0.17)
$YEAR = 1800$	0.56***	0.37**	0.45***	0.31**	0.35*
	(0.13)	(0.17)	(0.17)	(0.16)	(0.18)
$YEAR = 1850$	0.51***	0.34*	0.42**	0.25	0.31
	(0.14)	(0.19)	(0.19)	(0.17)	(0.19)
p-value for joint significance $CLOCK$	0.00	0.00	0.00	0.00	
Adjusted R^2	0.12	0.11	0.10	0.10	0.08
Number of observations	8,088	9,000	7,525	9,058	9,148

Controls considered in column (2) of Table 1 included in all regressions. City and year fixed effects included in all regressions. Standard errors corrected by spatial autocorrelation within 1,000 km. All of the control variables are interacted by year dummies. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively.

Table C4: Weighting regressions using the entropy algorithm technique

Variable	Before the weighting		After the weighting	
	Treated	*Control*	*Treated*	*Control*
Atlantic	0.01	0.03	0.01	0.01
Potato	9.40	9.62	9.40	9.40
$\Delta Calories$	0.35	0.02	0.35	0.35
Land suitability	10.00	9.62	10.00	10.00
Ruggedness	2.46	2.56	2.46	2.46
Elevation	6.11	6.20	6.11	6.11
	Weighted Regression			
	Years included:	1000 & 1600	1000 & 1700	1000 & 1800
CLOCK		1.09**	0.99**	0.82**
		(0.42)	(0.40)	(0.35)
*Cistercian*10		0.00	0.22	0.30
		(0.51)	(0.47)	(0.37)
Constant		-0.31	-0.18	0.33
		(0.30)	(0.29)	(0.22)
Adjusted R^2		0.06	0.05	0.04
N. of observations		82	82	82

On the upper part of the table comparison treated vs control before and after the weighting applying the entropy algorithm technique (Hainmueller and Xu (2013)). On the lower part OLS regression using the entropy weights. Standard errors are corrected by clustering at the grid level. Due to convergence, all controls considered in column (2) of Table 1 except calories included in all regressions.

Propensity score analysis

To test whether our regression are affected by , we consider a propensity score analysis suggested by Wooldridge (2010), with the estimation of the average treatment effect following the equation

$$\Delta \ln POP_{it-x} = \gamma_0 + \gamma_1 CLOCK_i + \gamma_1 Prob\,(CLOCK) + \gamma_2 Prob\,(CLOCK) + \tag{5}$$

$$\gamma_3 Prob\,((CLOCK) - MEAN\,(Prob\,(CLOCK)))$$

where, among the other variables, $Prob\,(CLOCK)$ is the propensity score obtained from the logit regression in column (6), Table B5 and $MEAN\,(Prob\,(CLOCK)))$ is the average of the above-mentioned variables. The results are reported in Table C5 and they show that the dummy $CLOCK$ is both the entire sample and in the trimmed sample (i.e., considering only the probabilities between 0.1 and 0.9), while the coefficients related to γ_3 do not suggest a positive self-selection of the cities.

Table C5: Propensity score analysis.

	Dependent variable: $\Delta \ln POP$					
	All sample			*Trimmed sample*		
Years included:	1000 & 1600	1000 & 1700	1000 & 1800	1000 & 1600	1000 & 1700	1000 & 1800
	(1)	(2)	(3)	(4)	(5)	(6)
	1800-1000	1700-1000	1500-1000	1800-1000	1700-1000	1500-1000
	(1)	(2)	(3)	(4)	(5)	(6)
$CLOCK$	1.57***	1.39**	1.14**	1.84***	1.60***	1.39***
	(0.57)	(0.53)	(0.48)	(0.52)	(0.51)	(0.46)
$Prob\,(CLOCK)$	-0.79	-0.76	-0.74	-1.54	-1.52	-1.49
	(0.91)	(0.78)	(0.73)	(1.00)	(1.01)	(0.92)
$Prob\,(CLOCK) -$	0.19	0.13	0.44	1.34	2.14	1.39
$MEAN\,(Prob\,(CLOCK))$	(1.11)	(1.16)	(0.97)	(1.06)	(1.31)	(1.27)
Adjusted R^2	0.07	0.06	0.04	0.16	0.09	0.09
N. of observations	82	82	82	57	57	57

Robust Standard errors. Constant is not reported. Significance at the 90%, 95%, and 99% confidence levels is indicated by *, **, and ***, respectively. The trimmed sample considers only probabilities between 0.1 and 0.9.

Table C6: OLS and IV Regressions: Bayesian inference

	(I) Regression results		(II) Bayesian inference	
	Worst Case Boundary			
$\Delta Clock$	OLS	IV	$\rho_{u\zeta}$	β
Years included:				
1000 & 1600 ($n = 82$)	1.50***	3.05***	$[-0.10, 0.70]$	$[-12.09, 4.93]$
$(\kappa, \rho_{u\xi^*}) \in (0.5, 1] \times [0, 0.9]$	(0.54)	(1.28)		
1000 & 1700 ($n = 82$)	1.03**	2.51***	$[-0.09, 0.72]$	$[-14.01, 3.37]$
$(\kappa, \rho_{u\xi^*}) \in (0.5, 1] \times [0, 0.9]$	(0.52)	(1.23)		
1000 & 1700 ($n = 82$)	0.79**	1.28***	$[-0.17, 0.68]$	$[-11.04, 5.71]$
$(\kappa, \rho_{u\xi^*}) \in (0.5, 1] \times [0, 0.9]$	(0.34)	(1.47)		

The table compares the results of the OLS and IV in the main text with the fully estimates Bayesian procedure introduced by DiTraglia and García-Jimeno (2021). More precisely, the first two columns reports the coefficients of the "'worst case boundary" of Table 3 (columns (4), (5) and (6)), which are controlled for the variables $Cisternian10$, $\Delta Atlantic$, $\Delta Calories$, $\Delta Land\ suitability$, $\Delta Potato$, $\Delta Ruggnedness$, $\Delta Elevation$ and a constant. The value κ is the signal-to-noise ratio (i.e., the amount of variation of the signal contained in the reduced form error) and it is set into the interval $(0.5, 1]$, while the the correlation coefficient between the endogenous regressor and the error term of the second stage equation $(\kappa, \rho_{u\xi^*})$ is is set to the interval $[0, 0.9]$ Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respectively..

Appendix D: Famous People and Professions

In this section, we investigate whether part of the long history of public mechanical clocks also has an impact on upper-tail-human capital and we study whether cities with higher concentrations of particular types of economic activities, such as those connected to engineering and precision, benefited from the early adoption of the public mechanical clock. We use the datasets of "famous" people from the *Index Bio-Bibliographicus Notorum Hominum*[6] and we also scrap the information collected and elaborated by the Historical Commission of the Bavarian Academy of Science.[7] We first take

[6]We use the version constructed by de la Croix and Licandro (2015), which contains information such as profession and vital places approximately 300,000 personalities between 1790 B.C. and 1955 A.D..

[7]The dataset and a description of the information contained can be found at the following link of the *Neue Deutsche Biographie* (NDB, *New German Biography*). For additional information, see Reinert et al. (2015). This dataset covers approximately 730,000 famous personalities and families in German-speaking areas from the medieval period to today and can be considered a proxy for upper-tail-human capital (Dittmar and Meisenzahl (2020)), containing, among other types of information, name and family name, date and place of birth and death, and a classification of the profession of the individuals. Table E2 in this Appendix provides the detailed classification of the profession and their aggregation for both personalities' datasets. If available, we match the location of the individual using the nearest city from the geographical coordinates provided by the website; otherwise, we match the name of the location with our cities using

the subsample of European cities from the data provided by de la Croix and Licandro (2015)[8] and compute the median of the share of "famous people" in a particular sector over the total number of personalities.[9] Then, computing the same share from the data of the German cities, we construct an index I^{Famous} which is equal to one if the city share is higher than the median, and is 0 otherwise. This should capture the likelihood that a city has more specialized famous people in the precision sector that involves the following professions: engineer, engraver goldsmith, industrialist, inventor, manufacturer, pewterer, and printer; while in the German dataset precision makers are active in the following sectors: crafts, printing and publishing industry, the mining and energy industry, metalworking, mechanized engineering, precision mechanism, optical engineering, electronic engineering, glass working, ceramic engineering, and papermaking. [10]

Table D1: OLS regression: Famous people and mechanical clocks

FAMOUS	*Precision*	*Science*	*Humanities*	*Arts*	*Government*	*Business*
	(1)	(2)	(3)	(4)	(5)	(6)
CLOCK	0.04***	0.01	0.22***	0.01	-0.12***	0.03
	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Press	0.03***	0.23***	0.00	0.07***	-0.01	0.04***
	(0.01)	(0.03)	(0.06)	(0.00)	(0.04)	(0.00)
Adjusted R^2	0.06	0.07	0.08	0.08	0.11	0.05
N. of observations	155	155	155	155	155	155

The same controls that we considered in Table 3 of the main text are included in all regressions. Dependent variables constructed according the methodology reported above. Significance at the 90%, 95%, and 99% confidence levels are indicated by *, **, and ***, respect. Controls not reported: $\Delta Atlantic$, $\Delta Cistercian10$, $\Delta Calories$, $\Delta Land\ suitability$, $\Delta Potato$, $\Delta Ruggedness$, $\Delta Elevation$, geographical coordinates, and constant.

fuzzy merge of the data using the Stata command *reclink*.

[8]For our index we consider the following non-German speaking European cities from the list provided by de la Croix and Licandro (2015): Amsterdam, Antwerp, Barcelona, Bologna, Bordeaux, Brussels, Budapest, Copenhagen (aggregated with Frederiksberg), Dublin, Edinburgh, Florence, Genoa, Ghent, The Hague, Helsinki, Krakow, Leiden, Liege, Lisbon London, Lviv, Lyon, Madrid, Marseille, Metz, Milan, Moscow, Naples, Oslo, Paris, Prag, Riga, Roma, Rotterdam, Rouen, Saint Petersbourg, Stockholm, Strasbourg, Toulouse, Turin, Utrecht, Versailles, and Warsaw.

[9]Because the personalities are measured in a different way, we prefer to consider this ratio instead with respect to population.

[10]We match the following categories from the dictionary to the ones constructed by de la Croix and Licandro (2015) in the following way: "Humanities, social science, religion" with "Humanities" and "Religion", "Arts, literature and music" with "Arts and metiérs"; "'Science, medicine and mathematics" with "Science"; "States and church" with "Law and government"; "Business industry and technology" with "Business".

Table D2: Classification of the profession (first part): De la Croix and Licandro (2015)

Arts and métiers	**Business**	**Education**	**Humanities**
Actor	Antiquary	Author	Archaeologist
Artist	Bookseller	Academician	Classicist
Cantor	Banker	Dean	Economist
Collector	Printer	Lecturer	Historian
Composer	Publicist	Professor	Journalist
Designer	Businessman	Rector	Orientalist
Dramatist	Director	Scholar	Pedagogue
Engraver	Editor	Student	Philologe
Goldsmith	Farmer	Teacher	Philosopher
Illustrator	Librarian	Writer	Translator
Kapellmeister	Industrialist		
Lithograph	Merchant		
Musician	Trader		
Organist	Manufacturer		
Painter	Wholesaler		
Pewterer			
Pianist			
Poet			
Regisseur			
Sculptor			
Singer			
Violinmaker			
Violinist			

The source of this table can be found at in the Appendix of De la Croix and Licandro (2015).

Table D2: Classification of the profession (second part): De la Croix and Licandro (2015)

Law and government	**Military**	**Nobility**	**Religious**	**Sciences**
Administrator	Admiral	Baron	Abbot	Agronomist
Adviser	Brigadier-general	Chamberlain	Archbishop	Architect
Ambassador	Captain	Duke	Archdeacon	Astronomer
Bailiff	Colonel	Earl	Capuchin	Botanist
Beamter	Commander	King	Cardinal	Builder
Congressman	Fighter Knight	Clergyman	Cartographer	
Consul	General	Lord	Deacon	Chemist
Councillor	Lieutenant	Noble	Franciscan	Doctor
Deputy	Lieutenant-colonel	Prince	Jesuit	Engineer
Diplomat	Major	Queen	Martyr	Geographer
Governor	Major-general		Missionary	Geologist
Inspector	Marshal		Pastor	Inventor
Judge	Military		Piarist	Mathematician
Jurist	Office		Preacher	Naturalist
Lawyer	Soldier		Priest	Pharmacist
Magistrato			Rabbi	Physician
Mayor			Theologian	Physicist
Minister			Vicar	Surgeon
Notary				Zoologist
Politician				
Prefect				
President				
Procureur				
Secretary				
Senator				
Sheriff				

The source of this table can be found at in the Appendix of De la Croix and Licandro (2015).

Table D2: Classification of the profession in *Neue Deutsche Biographie* (third part)

Humanities, social science and religion	**Arts, literature, music**	**Sciences, medicine, mathematics**
Catholic church, religion and theology	Visual arts	Mathematics
Evangelic church, religion and theology	Architecture	Physics
Other churches, religion and theology	Applied arts	Chemistry
Philosophy	Literature	Geology, paleontology
Psychology	Theater, film, photography and dance	Geodesy
Pedagogy, education	Music	Mineralogy
Historical science and archive studies	Other arts	Meteorology
Book science and library science		Astrology
Archaeology		Geography
Ethnology, cultural anthropology		Biology
Linguistics, literary science		Medicine
Jurisprudence		Veterinary medicine
Political science		Pharmacology
Social science		Botany
Economics		Other sciences
Musicology		
Science of Art, fine arts, art collection		

The source of this information can be found at `https://www.deutsche-biographie.de/?language=en`.

Table D2: Classification of the profession in *Neue Deutsche Biographie* (foturth part)

States and churches	**Business, industry and technology**	**Miscellaneous**
Dynasts and princes of the church	Crafts	No information
Politics	Printing and publishing industry	Social Acquaintances
Diplomacy	Mining and energy industry	Occupation Unknown
Public administration	Metalworking	Other
Military	Mechanical engineering	Sports
Other areas of state and church administration	Automotive, marine and aviation engineering	Women's right movement
	Precision mechanics, optical engineering	Families
	Electronic engineering	
	Chemical engineering	
	Glass working, ceramic engineering, paper makers	
	Textile and clothing industry	
	Food, beverages and tobacco	
	Building industry	
	Finance and insurance industry	
	Commerce	
	Transportation, tourism, catering	
	Agriculture, forestry, fishing industry	
	Political, industrial, social association	
	Trade unions	
	Media and communication	
	Other branches of business, industry and technology	

The source of this information can be found at `https://www.deutsche-biographie.de/?language=en`.

References

Abadie, A. (2005). Semiparametric Difference-in-Differences Estimators. *Review of Economic Studies*, 72(1):1–19.

Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2019). Democracy Does Cause Growth. *Journal of Political Economy*, 127(1):47–100.

Addomine, M. (2018). Italian astronomical clocks as public astrological machines. In Richard Dunn, S. A. and Strano, G., editors, *Heaven and Earth United. Instruments in Astrological Contexts.*, pages 104–132. Brill, Leiden.

al Jazari (1206). *The Book of Knowledge of Ingenious Mechanical Devices: Kitáb fí ma'rifat al-hiyal al-handasiyya, translated by Donald R. Hill.* Springer Science+Business Media, Berlin.

Angelucci, C., Meraglia, S., and Voigtlaender, N. (2017). The Medieval Roots of Inclusive Institutions: From the Norman Conquest of England to the Great Reform Act. NBER Working Papers 23606, National Bureau of Economic Research, Inc.

Bairoch, P., Batou, J., and Chevre, P. (1988). *The Population of European Cities from 800 to 1850.* Librairie Droz, Geneva.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2):407–43.

Beard, D. (2004). Eclipse predictions in the Kalendarium of Nicholas of Lynn. *Journal of the British Astronomical Association*, 114(6):343–348.

Beeson, C. F. C. (1971). English Church Clocks 1280-1850. . *London: The Antiquarian Horological Society.*, page 15.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2):200–230.

Cameron, A. C. and Miller, D. L. (2015). A Practitioner's Guide to Cluster-robust Inference. *Journal of Human Resources*, 50(2):317–372.

Canova, G. M. (2011). Padua and the stars: Medieval painting and illuminated manuscripts. In Corsini, E. M., editor, *VI. Proceedings of a conference held October 18-23, 2009 in Venezia, Italy.*, volume 441. ASP Conference Series, San Francisco.

Cantoni, D. (2015). The Economic Effects Of The Protestant Reformation: Testing The Weber Hypothesis In The German Lands. *Journal of the European Economic Association*, 13(4):561–598.

Carley, H. M. (1992). *Courting Disaster: Astrology At The English Court And University In The Later Middle Ages.* Palgrave McMillan, London.

Cipolla, C. M. (1967). *Clocks and Culture, 1300-1700.* Norton, New York.

de la Croix, D. and Licandro, O. (2015). The longevity of famous people from Hammurabi to Einstein. *Journal of Economic Growth*, 20(3):263–303.

DiTraglia, F. J. and García-Jimeno, C. (2021). A framework for eliciting, incorporating, and disciplining identification beliefs in linear models. *Journal of Business & Economic Statistics*, 39(4):1038–1053.

Dittmar, J. E. (2011). Information Technology and Economic Change: The Impact of The Printing Press. *The Quarterly Journal of Economics*, 126(3):1133–1172.

Dittmar, J. E. and Meisenzahl, R. R. (2020). Public Goods Institutions,Human Capital, and Growth:Evidence from German History. *Review of Economic Studies.*

Dohrn-van Rossum, G. (1996). *History of the Hour: Clocks and Modern Temporal Orders.* The University of Chicago Press, Oxford.

Espenak, F. (2015). Eclipse predictions. *NASA/GSFC,* ***http://eclipse.gsfc.nasa.gov/eclipse.html***.

Falk, S. (2018). What's on the back of an astrolabe. astrolabes as supports for planetary calculators. In Richard Dunn, S. A. and Strano, G., editors, *Heaven and Earth United. Instruments in Astrological Contexts.*, pages 24–41. Brill, Leiden.

Griliches, Z. (1957). Hybrid Corn: An Exploration of the Economics of Technological Change. *Econometrica*, 25(5):501–522.

Hainmueller, J. and Xu, Y. (2013). ebalance: A Stata Package for Entropy Balancing. *Journal of Statistical Software*, 54(i07).

Hawkings, G. S. (1988). *Stonehenge decoded*. Hippocrene Books, New York.

Jordá, O. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1):161–182.

Kline, P. (2011). Oaxaca-Blinder as a Reweighting Estimator. *American Economic Review*, 101(3):532–537.

Landes, D. (1983). *Revolution in Time*. Harvard University Press, Cambridge.

Lawrence-Mathers, A. (2012). *The True History of Merlin the Magician.* Yale University Press, New Haven. CT.

Madestam, A., Shoag, D., Veuger, S., and Yanagizawa-Drott, D. (2013). Do Political Protests Matter? Evidence from the Tea Party Movement. *The Quarterly Journal of Economics*, 128(4):1633–1685.

Mancha, J. L. (2006). *Studies in Medieval Astronomy and Optics.* Ashgate, Aldershot.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2):407–37.

McCluskey, S. C. (2000). *Astronomies and Cultures in Early Medieval Europe*. Cambridge University Press, Cambridge, 2nd edition.

Michele, R. and De Derleke, J. (1909). ELes Premieres horloges du palais pontifical d'Avignon. *Melanges d'Archeologie et d'histoire.*, 29:213–224.

Millas y Vallicrosa, J. M. (1962). *Las Tablas Astronomicas del rey Don Pedro el Ceremonioso Edicion critica de los textos hebraico, catalan y latino, con estudio y nota.* Escuela de la Casa Provincial de Caridad, Madrid.

Murphy, D. (2015). *The Bitter Age: A Banned Book by Cecco d'Ascoli, a Medieval Heretic.* Capponi Ediotri, Ascoli Piceno.

Nakayama, S. (1966). Characteristics of Chinese Astrology. *Isis*, 57(4):442–454.

Nelson, L. H. e. (1991). *The Chronicle of San Juan de la Pena. A Fourteenth-Century Official History of the Crown of Aragon.* University of Pennsylvania Press, Philadelphia.

Neugebauer, O. and Parker, R. A. (1988). *Egyptian Astronomical Texts: volume 1.* Brown University Press, London.

North, J. D. (1975). Monasticsm and the first mechanical clocks. In Fraser, J. and Lawrence, N., editors, *The Study of Time II, Proceedings of the second Conference of the International Society for the Study of Time Lake Yamanaka-Japan.*, pages 399–416. Springer, New York.

North, J. D. (2005). *God's Clockmaker: Richard of Wallingford and the Invention of Time.* Bloomsbury Academic, London.

Nothaft, C. P. E. (2016). Walter Odington's De Etate mundi and the Pursuit of a Scientific Chronology in Medieval England. *Journal of the History of Ideas*, 77(2):183–201.

Nuessli, C. (2011). Geographical maps, `http://www.euratlas.com/about.html`.

Oestmann, G. (2014). *Geschichte, Konstruktion und Anwendung des Astrolabiums bei Zifferblaettern astronomischer Uhren.* Musee international d'horologerie, La Chaux-de-Fonds.

Perez-Alvarez, V. (2013). Mechanical clocks in the medieval castilian royal cour. *Antiquarian Horology*, 34(4):498–502.

Price, D. J. d. S. (1956). The Prehistory of Clocks. *Discovery*, pages 153–157.

Price, D. J. d. S. (1959). An Ancient Greek Computer. *Scientific American*, 200(6):60–67.

Reinert, M., Maximillian, S., and Ebneth, B. (2015). Frombiographies to datacuration - the making of www.deutsche-biographie.de. In *CEUR Workshop Proceedings, edited by Serge Braake*, volume 1399, pages 13–19. de Gruyter.

Rogers, E. M. (2003). *Diffusion of Innovations.* Free Press, New York, 5th edition.

Ryan, M. A. (2011). *A Kingdom of Stargazers: Astrology and Authority in the Late Medieval Crown of Aragon.* Cornell University Press, Ithaca, NY.

Sadowski, R. M., Ziolkowski, M., and Piasecki, K. (1993). Stone rings of northern poland. In *Archaeoastronomy in the Old World, edited by Douglas C. Heggie*. Cambridge University Press.

Schmidl, P. G. (2018). Astrolabes for astrological purposes: The earliest evidence revisted. In Richard Dunn, S. A. and Strano, G., editors, *Heaven and Earth United. Instruments in Astrological Contexts.*, pages 8–23. Brill, Leiden.

Sloley, R. (1931). Primitive Methods of Measuring Time: With Special Reference to Egypt. *The Journal of Egyptian Archaeology*, 17(3-4):166–178.

Steele, J. (2000). *Observations and Predictions of Eclipse Times by Early Astronomers.* Kluwer Academic Publishers, Dordrecht, Boston and London.

Stephenson, F. R. (1997). *Historical Eclipses and Earth's Rotation.* Cambridge University Press, Cambridge.

Thomann, J. (2019). Astrolabes as eclipse computers: Four early arabic texts on construction and use of the safiha kusufiyya. In Rodriguez-Arribas, J., editor, *Astrolabes in Medieval Culture.*, pages 8–45. Brill, Leiden.

Thorndyke, L. (1941). Invention of the mechanical clock about 1271 a.d. *Speculum*, 16(2):242–3.

Williamson, R. A. (1984). *Living the Sky: The Cosmos of the American Indian.* Houghton Mifflin Co., Boston.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data.* MIT press, Cambridge, MA.

Young, H. P. (2009). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *American Economic Review*, 99(5):1899–1924.