A Cliometric Perspective on Cultural Spread: Roman and Christian Names in Ancient Greece

Laurent Gauthier

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Abstract

Explaining culture through contagion mechanics has appealed to some anthropologists, from a theoretical standpoint, and some quantitative sociologists have proposed formal models for this phenomenon. Studying the spread of culture through the lens of epidemiology has a kind of natural appeal, as it seems to intuitively make sense. The dynamics of epidemics, with their sometimes explosive behavior in a pandemic, combined with oscillations or endemic patterns, seem to capture the phase transitions of cultural spread. The particular links between economics and epidemiology were surveyed in Avery et al. (2020): economics can bring new perspectives in epidemiological modeling by endogenizing certain parameters, which can have a significant impact on how contagion dynamics are understood and projected. The research into the endogeneization of important parameters in epidemiological models, however, has been purely concentrated on medical or biological applications. We propose a utility-based model for cultural contagion, which extends the class of so-called SIR models in epidemiology, and apply it first to the spread of Romanity in the ancient Greek world, through the dynamics of Roman names acquisition, and then to the spread of Christianism through Christian names acquisition. The dynamics of the transition from a pure Greek world to a Romanized world, explosive at the outset, appear to have been fundamentally driven by an intense adoption of Romanity, but combined with an equally intense return to traditional Greek traits. The transition from pagan to Christian names, on the other hand, saw less of a reversal effect.

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The "spectre of the natural sciences of the social," as Sperber (1996) put it in his seminal work in anthropology on explaining culture through contagion mechanisms, can be seen as an intellectual goal, maybe stemming from Auguste Comte's positivist perspective on sociology (Ritzer [2004] 2014). Beyond these theoretical connections one may establish between natural sciences and social relations, studying the spread of culture through the lens of epidemiology has a kind of natural appeal: it seems to intuitively make sense. The dynamics of epidemics, with their sometimes explosive behavior in a pandemic, combined with oscillations or endemic patterns, seem to capture the phase transitions of cultural spread. The notion of contagion, as an analogy or a heuristic, can be applied to a very wide range of historical or social questions, as the fifty case-studies in Delaurenti and Le Roux (2021) illustrate. In the context of this link between biology and the social sciences, the analogy of contagion and cultural transfer further extends to the evolution, and improvement in fitness over time, of infections. For example, Sperber (1997) applied the mechanics of evolution, in particular through selection and improved fitness to the study of how culture disseminates. In trying to understand "how things change," in the most general way, this particular angle of enquiry appears promising.

While anthropological approaches tend not to rely on formal models, but rather on Weberian *Idealtypus*, the mathematical models of epidemiology have been directly applied to social contagion in many occasions. The most ubiquitous modeling approach in epidemiology relies on compartments, representing buckets of population, such as susceptible, infected and recovered individuals. Under the acronym SIR, this class of models is the workhorse of the field (Brauer and Castillo-Chavez 2012). These kinds of models belong to the realm of complex systems analysis, due to their typical non-linear nature (Boccara 2010). Such formal epidemiological models have been applied, some with adhoc adjustments, to the social sciences. Bettencourt et al. (2006), for example, applied SIR modeling to the spread of Feynman diagrams amongst physicists. Hill et al. (2010) adapted the SIR model to account for "spontaneous" social infection, and applied it to the obesity epidemic. Sooknanan and Comissiong (2017) offers a survey of recent research in the field. One particular application has been the analysis of church growth through contagion effects in religious following. Following Hayward (1999) and Hayward (2012), Jo, Kim, and Lee (2021) accounted for the evolution of certain South Korean church communities with an adjusted SIR model. This approach into the modeling of religious preferences is clearly distinct from economists' perspectives on the subject, such as the ones surveyed in Iannaccone (1998). In fact, the epistemological framework in which the application of epidemiology models to social contagion has been carried out does not seem to strongly recoup with economic research. These approaches

are closer to quantitative sociology, and, to some extent, to a mean-field approach to agent-based simulation (Conte, Hegselmann, and Terna 1997; Takadama, Cioffi-Revilla, and Deffuant 2010; Acerbi, Mesoudi, and Smolla 2022). If one considers historical phenomena, then these approaches are somewhat similar in philosophy to cliodynammics (Turchin [2003] 2018), because they do not address the optimality of the underlying individual choices. In the particular case of Roman history, Brughmans et al. (2019) have argued for a more generalized application of complex systems analysis and the associated formal models to historical material. The inconsiderate use of dynamic models to study history has been criticized, for example by the review of Turchin ([2003] 2018) in Bonneuil (2005).

The interaction of networks and epidemiological models has been widely studied, both from a pure epidemiological perspective and from the standpoint of social sciences applications. SIR models operate on an assumption that the population is well mixed; reflecting the granularity of the social networks that connect people can significantly affect the spread of epidemics (social or biological) in models (Keeling and Eames 2005; Bernardes, Latapy, and Tarissan 2013). Some approaches to the modeling of information spread rely only on network modeling, such as, for example, Ruan et al. (2015), Bikhchandani et al. (2021), Draief and Massoulié (2010) or Golub and Jackson (2010), but this type of modeling requires the detailed knowledge of the underlying network structure. SIR-type models remain more common, since they only make very general assumptions about the underlying network.

While the integration of epidemiology into anthropological or sociological questions relates to social sciences in general, the links to economics have indeed not been numerous. Only recently did Shiller (2019) examine the importance of information spread for economics in general. The way in which information travels on social networks, and the kind of information that travels in this way, have a significant impact on economic decisions at many levels. The particular links between economics and epidemiology were surveyed in Avery et al. (2020): economics can bring new perspectives in epidemiological modeling by endogenizing certain parameters, which can have a significant impact on how contagion dynamics are understood and projected. The research into the endogeneization of important parameters in epidemiological models, so far, has been purely concentrated on medical or biological applications, even if they may factor in economics-related concepts or metrics (Morin, Fenichel, and Castillo-Chavez 2013; Manfredi and D'Onofrio 2013; Arthur et al. 2021; Alutto, Como, and Fagnani 2021; Engle et al. 2021). Factoring in more complex spread mechanisms needs to rely on behavioral economics, and game theory in particular, such as in Reluga (2010).

The use of complexity sciences in economics has grown, and it is expected to provide a better understanding of the details of many social mechanisms (Foster 2005), and in the particular case of cliometrics, complexity sciences have expanded the range of methods that one could consider in empirical or theoretical modeling (Abry et al. 2022; Bastidon et al. 2020). Hence, developing an economic perspective into the endogeneization of parameters in an SIR-like model does not have to be related to epidemiology, but can also allow us to form a more precise understanding of social phenomena. We will concentrate here on two particular historical examples of diffusion of a cultural trait: the spread of Roman names, and then the spread of Christian names in ancient Greece. The uses of epidemiology in history or historical anthropology have typically been more concerned with past infections (Raoult and Drancourt 2008), and there has not been many applications of epidemiological models to past social dynamics. Nevertheless, many studies in historical research on Antiquity have relied on the notion of network, in particular among city-states, in order to appreciate the diffusion of numerous cultural features, such as Malkin (2011) or Müller (2019) for example. We have limited information about the structure of these social networks in ancient cities, but we do possess large amounts of data on certain particular aspects of the Ancients' social life. In particular, there is a large volume of data on the names that individuals carried, thanks to very numerous inscriptions. Without detailed network information, the use of a general approach based on epidemiological models appears to be sensible.

In the first section, we will first discuss the context of the Romans' effective conquest of the Greek world and its subsequent Christianization. We will examine the nature of the data available that may allow us to measure these cultural transitions quantitatively. Then, in the second section, we will focus on the formal modeling of the adoption of a cultural trait, starting with the basic SIR model. We will extend this model with an economic perspective by having individuals maximize a certain utility function, which result in particular SIR-like dynamics. Finally, we will discuss the available data on ancient Greek names, and fit the dynamic model to that data. We will also examine some potential econometric drivers of the intensity of Roman and Christian name spread; in particular, we find that the close proximity to a major battle site was a driver of Romanity. The dynamics of the transition from a pure Greek world to a somewhat Romanized world appear to have been fundamentally driven by an intense adoption of Romanity, but combined with an equally intense return to traditional Greek traits. The dynamics of Christianization shared some common dynamics but it appears that there were much more limited benefits to switching back to prior names in this case.

1 Romanization and Christianization

In this section, we will begin with an overview of the historical relationships between the Romans and the Greeks in Antiquity, and look into the available data on the use of Roman names by the ancient Greeks. We will then examine the history of chritianization and its spread through the ancient Greek world.

1.1 Greeks and Romans: Onomastics as Cultural Spread

> *Graecia capta ferum victorem cepit et artis*
> *intulit agresti Latio.* [. . .]
> Greece, the captive, made her savage victor captive, and brought the arts into rustic Latium[1].

The great 1st century BCE poet Horace expressed what was then considered rather obvious, the fact that a form of Greek culture had seized the Romans, affecting their aesthetics in significant ways. The Romans had an ambivalent relationship to Greek culture: on one hand they aspired to the refinement of Greek art, on the other, they resented how it pushed them away from their revered and idealized rusticity. In any case, they recognized the importance and influence the Greeks had on them (Henrichs 1995), and the *topos* of the Greek conquest of the Roman mind is one of the fixtures of ancient history. We may wonder, however, to what extent the Greek culture was affected by the Romans, which, one would expect, should be the first order effect.

The Romanization process started in areas of ancient Greece that were directly conquered by Rome, such as Macedonia and Achaia. Indeed, the drivers of the Roman expansion into the Greek world, a series of upheavals, retaliations and wars, spanned from the 3rd century to the 1st century BCE, spotted with frequent battles. Table 1, relying on the chronologies in Bugh (2006), shows the locations of the major conflicts in this process. The battles shown in the table did not necessarily involve Romans fighting against Greeks, but due to the various alliances, typically there were Greeks fighting on both sides. Apart from Pyrrhus's attack in Southern Italy at the beginning of the 3rd century, the combats were concentrated, using today's geopolitical definitions, in Continental and Northern Greece, and in Western and Northern Turkey.

Roman governors introduced Roman laws, institutions, and practices to these regions, and encouraged citizens to adopt Roman culture. Citizens of Greek *poleis* were enticed to become Roman citizens, which gave them additional privileges and responsibilities. The Latin language

[1] Horace, *Epistles*, 2, 156-157, Horace (1929).

Table 1: *Most Important Wars and Battles Involving Greeks and Romans*

War Name	War Period	Battle Location	Battle Year
Pyrrhic War	280–275	Battle of Heraclea	280
		Battle of Asculum	279
		Battle of Beneventum	275
First Macedonian War	214–205	No significant event	
Second Macedonian War	200–197	Battle of the Aous	198
		Battle of Cynoscephalae	197
Roman–Seleucid War	192–188	Battle of Thermopylae	191
		Battle of the Eurymedon	190
		Battle of Myonessus	190
		Battle of Magnesia	190
Aetolian War	191–189	No significant event	
Galatian War	189	Battle of Mount Olympus	189
		Battle of Ancyra	189
Third Macedonian War	171–168	Battle of Callicinus	171
		Battle of Pydna	168
Fourth Macedonian War	150–148	Second Battle of Pydna	148
Achaean War	146	Battle of Corinth	146
First Mithridatic War	90–85	Siege of Athens and Piraeus	87-86
		Battle of Chaeronea	86
		Battle of Orchomenus	85
Second Mithridatic War	83–82	Battle of Halys	82
Third Mithridatic War	73–63	Battle of Cyzicus	73
		Battle of Cabira	72
		Battle of Tigranocerta	69
		Battle of Artaxata	68
		Battle of the Lycus	66
War with Pontus	47	Battle of Zela	47

Note: All the dates are BCE.

became an important language in administration and communication, alongside with Greek, and Greek cities adopted new forms of architecture, sculpture or painting inspired by Roman art. Religious beliefs and practices were also somewhat influenced by Roman religions, for example, during the imperial period, through imperial cults. Over the following centuries, Romanization expanded in areas of Greece that were not directly conquered by Rome, such as Attica and Boeotia. Greek city-states continued to adopt Roman customs and institutions, and local elites sought Roman citizenship. Thus Romanization was a continuous and gradual process that had a profound impact on Greek societies and led them to become an integral part of the Roman Empire.

The Roman conquest of the Greek world had for a long time been considered as a part of Roman

history, but a change in this historiographical perspective, around the 1980s, led to the study of the Roman expansion from the perspective of the Greeks (Vial 1995; Chamoux 1985; Préaux 1978). There are many ways through which one could study the expansion of Roman cultural traits through the Greek world. For example, once may consider the use of certain facilities or the manner in which they are constructed: Kelly (2013) examined the spread of Roman bath houses in Crete. With a different and more quantitative perspective, Glomb et al. (2018) looked at the spread of certain Egyptian cults as a function of the distribution of Ptolemaic military facilities.

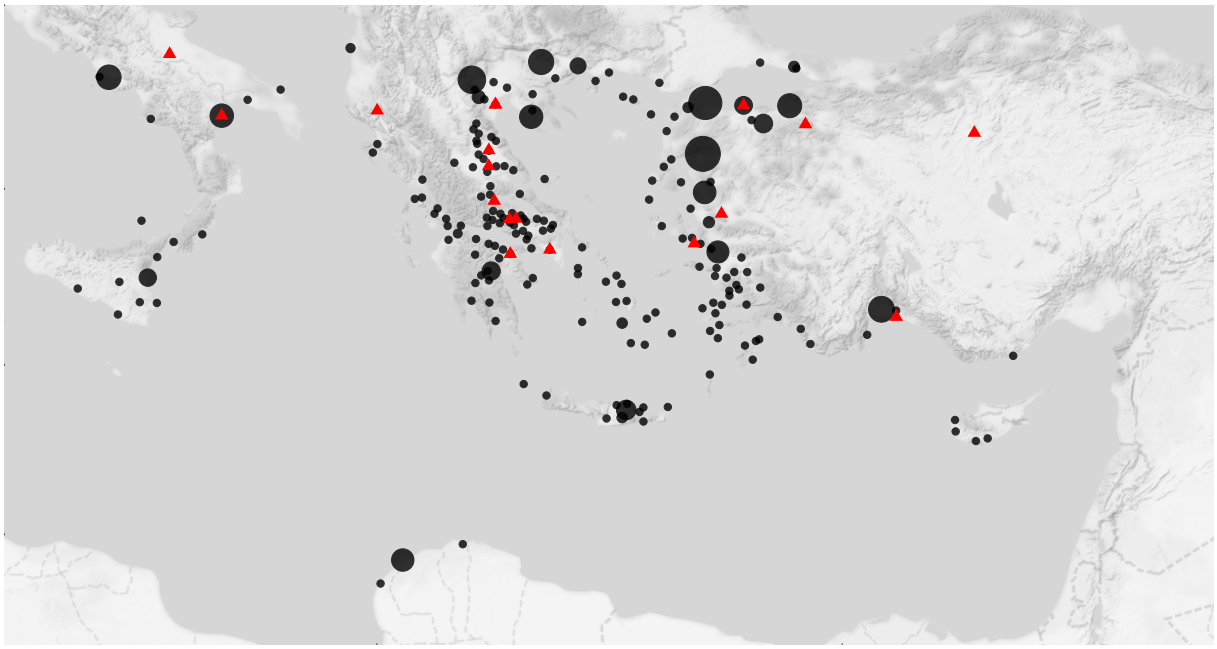
One particular approach benefits from a sizable volume of data supporting it: onomastics, the study of names. The study of the names of the ancient Greek or Romans typically relies on inscriptions, as the epigraphic sources are where one finds the most numerous mentions of personal names (Karila-Cohen 2016, 2018). The evolution of Greek names in general has been recently tackled in Parker (2019). The analysis of names, including their etymology or their distribution, can be an efficient way to drill into social relationships among the Ancients. For example, Parker (2000) examined theophoric names, names derived from that of a god, and related their occurrences to the expansion of particular cults. Oulhen (2009) looked into feminine theophores and stressed how much scarcer they were than for men, pointing out a form of isolation of women from cultual practice. Broux and Clarysse (2016) explored the use of Ptolemaic queens' names in the population in the Hellenistic and Roman periods, and showed that it expanded as a form of fashion. Vlassopoulos (2010) focused on Athenian slave names, and studied their etymology and distribution in order to better understand how these names were formed.

More specifically focusing on Roman influence, Lewis (2017) examined how slaves received Roman names, and Kantola (2017) specifically focused on the use of Roman names by people in prominent social positions, in the Imperial period. The survey of Roman onomastic practices by Salway (1994) shows that after Roman citizenship was granted to all residents by Caracalla in 212 CE, many in the Greek world used the first name (*praenomen*) Aurelius, which led some Roman elites to choose other names, such as Flavius, in order to signal a higher status. Dogaer and Depauw (2017) examined intercultural contacts and cultural spread in Graeco-Roman Egypt using onomastics by focusing on names that combined etymologies from Egyptian divinities with Greek suffixes, and showed these hybrid names increased over time. The mechanics through which different cultural influences could be combined into names in Galatia (corresponding to modern Northern Turkey) during the Hellenistic and Roman periods has been studied by Coşkun (2012).

In order to carry out a large-scale study of the evolution of Greek names, we rely on the Lexikon of Greek Personal Names (LGPN), an electronic database that systematically records Greek personal names (Parker, Yon, and Depauw 1996), and our method for extracting this data is detailed in the Appendix. The LGPN attempts to collect all attested occurrences of Greek names, along with categorization information, such as the date estimate, based on the epigraphic source, geographic location information, and parental or child information. In many instances, the names of individuals, anthroponyms, appear with the name of their father, the patronym: for example, ὁ Ἀγάθων τοῦ Ἀθάμβου in an inscription would refer to Agathon, son of Athambos. While we can extract about 380 thousand individual names, a little less than 120 thousand have information on a parent's name. We are interested in the Roman names that may appear in Greek inscriptions. These names were transliterated into Greek from Latin, with some phonetic adjustments, which were not systematically carried out in the same way: the Latin *Publius* (a first name, or *praenomen*), for example, being translated into Πόπλιος or Πόβλιος. In order to systemagically flag Roman names in Greek, we started from a list of Roman names (*praenomina* and *nomina*), as comprehensive as possible, based on the indications from McLean (2002) and from Kantola (2017). Then, for each Roman name in that list, we applied every possible combination of phonetic variations in the transliteration, also according to the main ones identified in the references. Finally, if any Greek name matched one of the Roman name phonetic combinations, we categorized it as Roman.

Figure 1 displays the LGPN onomastic data that could be linked to specific *poleis*, where the local share of Roman name occurrences is represented by the size of the dots. We can see that, as one could expect, Roman names occurred more frequently in *Magna Graecia* (Southern Italy and Sicily), as one would expect, and also in Northern Greece and Western Turkey. The Continental Greek world and the Aegean do not seem to show high occurrences of Roman names. It does appear as though the higher concentration of Roman names loosely matches the geographic distribution of major battles.

Figure 1: *Geographic Distribution of Roman Name Concentrations in the Greek World, and Location of Battles Involving Greeks and Romans*

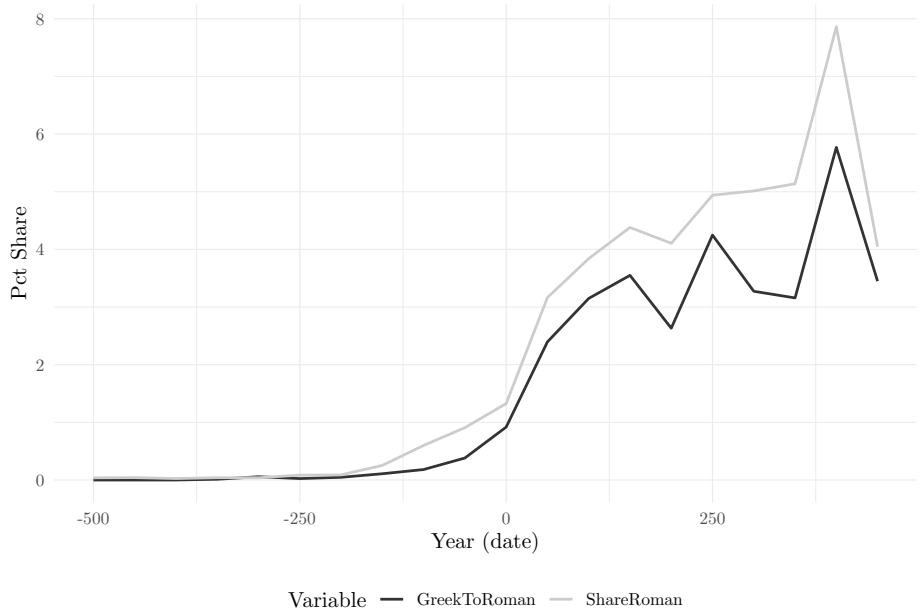


Note: The size of the dots is proportional to the average share of Roman names out of all attested names in each *polis*, between 500 BCE and 500 CE. The red triangles indicate the approximate location of the known major battles involving Greeks and Romans in the Hellenistic period. The political boundaries are contemporary.

We can also look at the occurrences of Roman names through time. Figure 2 displays the evolution in the share of Roman names, across all geographic locations, through time, using the base LGPN data. The Figure also displays the "Greek to Roman" transition: the percentage of parents with a Greek name who elect to give a Roman name to a child, relative to all entries in the data mentioning a Greek-named parent at the time. We can observe that the epigraphic material only starts showing a noticeable number of Roman names in Greek after the 1st century BCE, and these occurrences plateau roughly between the 2nd and 5th centuries CE. The spread of Roman names in the Greek world appear to have taken place only after the series of wars and battles that set the Romans in a dominant position relative to the Greek *poleis*.

The transition from Greek to Roman names follows a very similar pattern, both in shape and in absolute value. In fact, these transitions average around 80% of the occurrence of Roman names. Although we observed, earlier, a potential geographic link between battle sites and occurrences of Roman names, this evolution data tells us there is a significant time difference: the battles listed in Table 1 generally took place one or two centuries before the ramp up in Roman names took place, according to Figure 2.

Figure 2: *Evolution in the Aggregate Occurrences of Roman Names, and in the Transition of Greek to Roman Names*

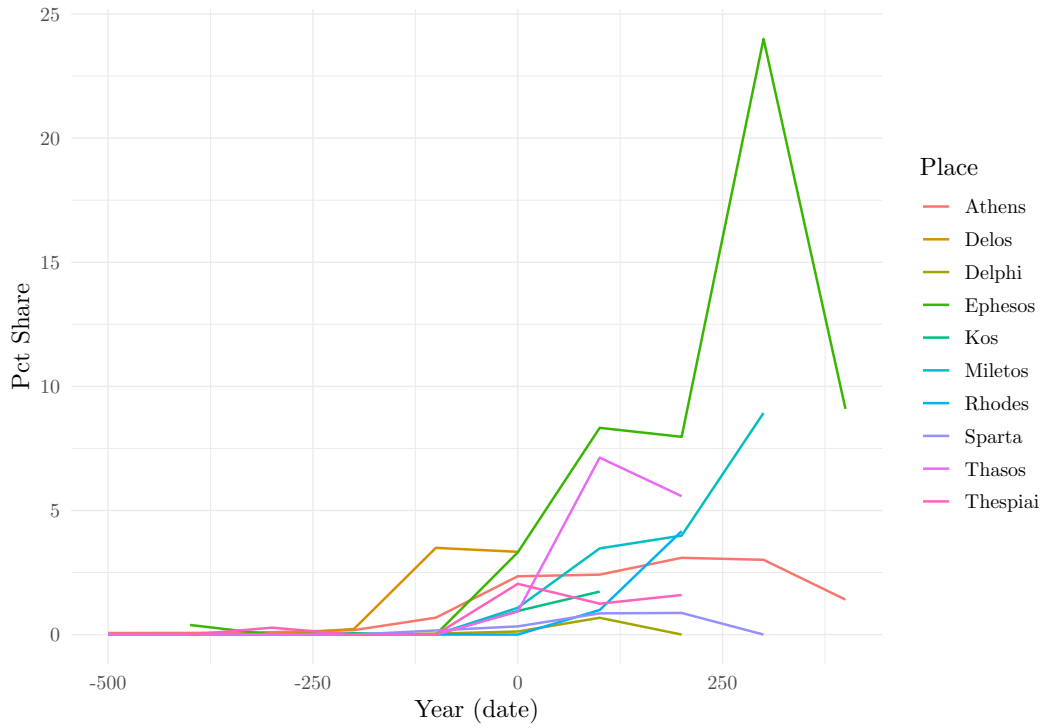


While a certain number of people bearing a Greek name decided to give their child a Roman name, the converse is also true. We can observe in Figure 3 the evolution of the transitions into Greek names. First, we see that a very large majority of the people who bore Greek names did give their children Greek names: this is the reflection of what we saw in Figure 2. Interestingly, we can also see that a substantial share of the people who had Roman names gave their children Greek names, and that share increased over time. If we consider families over time, it appears that they transitioned from being culturally Greek to Roman, from a name standpoint, and back to being Greek, at a non negligible rate.

Figure 3: *Evolution in the Transitions of Greek to Greek Names and Roman to greek Names*

Given the relatively low overall rate of occurrence of Roman names, the sparsity of the data prevents us from carrying out a detailed dynamic and geographic analysis. Nevertheless, if we examine a few specific *poleis* for which there are enough observations, we can see that for each one, the overall dynamics resemble the ones for the aggregate, as shown in Figure 4. The absolute level varies from one *polis* to the next, consistently with what we noted in Figure 1, but, with few exceptions, the initial increase and the plateauing are similar enough. The most apparent exception is Delos, which was an important commercial hub during the Hellenistic period.

Figure 4: *Evolution of the Rate of Occurrence of Roman Names in a Selection of Poleis*



1.2 Cultural Spread through the Use of Christian Names

The Christianization of ancient Greece at the beginning of the Common Era began with the arrival of the first Christian missionaries in the Greek city-states, such as the apostle Paul. The early Christians were primarily Jews who converted to Christianity. During the first centuries, Christianity began to gain popularity among the lower classes of Greek society, especially slaves and women. However, it encountered strong resistance from pagan religious and political authorities, for whom Christianity could not fir within the framework of *polis* religion. At the beginning of the 4th century CE, Emperor Constantine adopted Christianity as the official religion of the Roman Empire. This led to a period of persecution of other pagan religions, and a sharp acceleration in the Christianization of Greece. Christian churches were built on the sites of ancient pagan temples, and pagan priests and priestesses were replaced by Christian priests.

Over the following centuries, Christianity became the dominant religion of the Greek world, and the cultural heritage from the Ancients was significantly influenced by Christian teachings. There were still pagans in late Antiquity, in Greece and elsewhere, but the archaeological evidence shows that temples and sanctuaries were transformed into churches, destroyed, and sometimes kept for aesthetic reasons (Saradi 2011).

The Christianization of the Roman Empire has been extensively studied over more than two hundred years, and has been animated by a series of historiographical debates. Among them, MacMullen (1984) considered that paganism stayed strong until the 4th Century, and was able to also evolve, but was in opposition with the Christian principles and was effectively bankrupted by the Christian emperors. Brown (1995), on the contrary, saw an evolution from a religious system centered on places, the temples, to one centered on the persons, holy men. For Markus (1990), between then end of the 4th century and the end of the 6th century, it is not so much dogma or the Church's organization that changed, but rather the cult of martyrs, the sacralization of time and space, and the development of asceticism. There was a shift towards religious culture solely based on the Bible. Veyne (2007), to the contrary of the more systemic understanding of Christianization in these works, analyzed the transformation as a kind of accident, a bifurcation due to Constantine that was not necessary in a historical perspective.

One of the advantages of becoming a Christian was the sense of community and belonging that came with being part of the faith. Christianity also offered a sense of hope and salvation, particularly for individuals who were marginalized or oppressed in society, and the promise of eternal life in heaven could be an incentive incentive for many people to convert. The early Christian communities also provided support for the poor, the sick, and the elderly. In addition to the signs that people could wear showing their faith, such as the cross, their names could also constitute an important signal. The onomastic study of early Christianity is therefore an important angle into the understanding of this cultural spread.

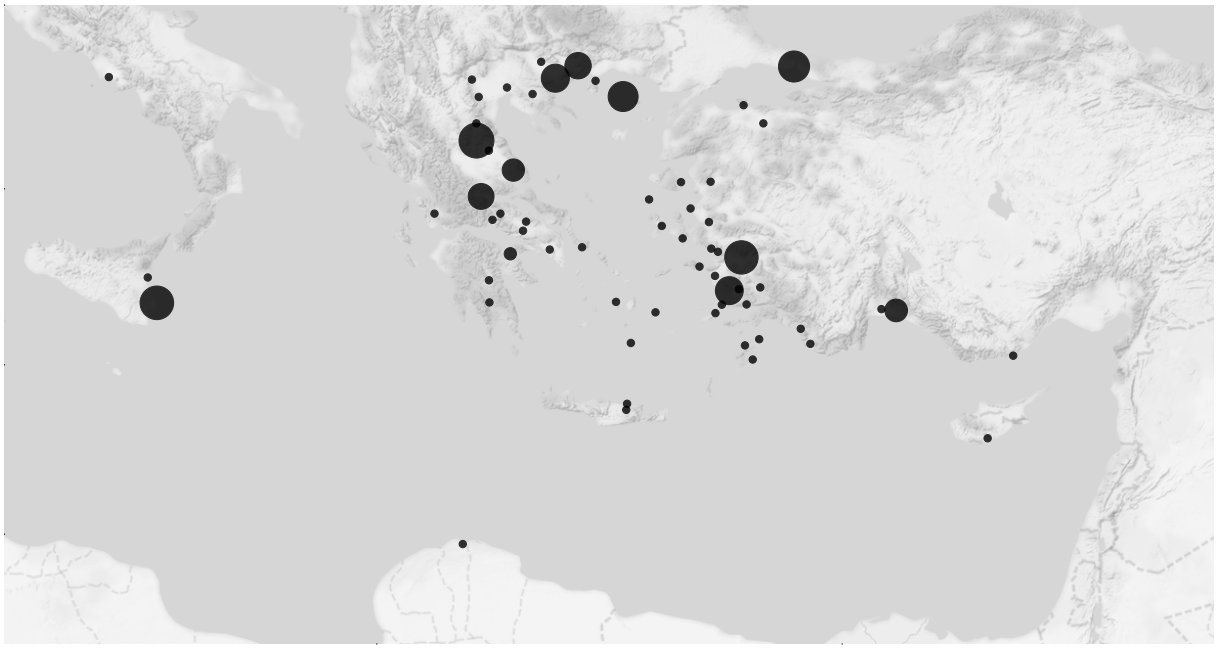
Bagnall (1982) was the first to use onomastics in order to assess the spread of Christianity, in the case of ancient Egypt. Also concentrating on Egypt in the Late Antiquity, Depauw and Clarysse (2013), using a dedicated dataset, defined various possible sets of Christian names, and analyzed their frequency from the 4th to the 8th century. Having built their data in a way that allowed them to identify Christian individuals, they showed that "the very high specificity of Christian names for Christians practically rules out 'false positives' " (p. 413). Revisiting some of results of Bagnall (1982), they show that there was a strong acceleration in the early 4th century in the share of Christians. Staying focused on Late Antiquity, Destephen (2019) analyzed Christian

names in Asia Minor through epigraphic evidence, and focused in particular on clerics and monks, including bishops, priests and deacons. He showed their names were strongly concentrated, with a few divine, biblical or pious names accounting for a large percentage of the total.

In order to study the occurrence of Christian names, we rely on the LGPN in the same manner as we did for Roman names. We created a list of less than 30 names categorized as Christian, based on the names used by Destephen (2019) and Depauw and Clarysse (2013), and on the Latin or ancient Greek names of Christian saints from late Antiquity. These names (in Latin form) include Petrus, Paulus, Ioannes, Domnus, or Simon, for example. Any Greek name corresponding to the transcription of one of these names or of one of its derivatives, such as a feminine, was flagged as Christian. Since, as was pointed out by Destephen (2019), naming practices evolved in the late Christian Antiquity towards a heavy concentration, and a few names became very common, this short list of names appears to be sufficiently representative. We restrict the time period for the analysis to the Common Era.

Figure 5 shows a synchronic geographic distribution of Christian names, where the size of the points is related to the share of Christian names in all the names observed. If the larger concentrations appear to be exclusively in the northern part of the map, it is a reflection of the fact that there are very few Greek inscriptions over the period in North Africa. There does not appear to be any clear pattern in the geographic distribution of Christian Greek names, *a priori*.

Figure 5: *Geographic Distribution of Christian Name Concentrations in the Greek World*



Note: The size of the dots is proportional to the average share of Christian names out of all attested names in each *polis*, between 1 and 600 CE. The political boundaries are contemporary.

We can also examine the prevalence of Christian names in a diachronic perspective. Figure 6 shows the total rate of occurrence of Christian names, along with the rate of transition of non-Christian to Christian names. We can see that there was a very clear acceleration at the end of the 4th century. Emperor Theodosius's Edict of Thessalonika in 380 CE declared the Christian religion as the state religion for the empire, excluding various alternative currents, and further promoted laws preventing paganism.

We can see in Figure 7 that, while there were always transitions from Christian names to non-Christian names, at an overall rate of about 75%, this dropped significantly in the late 4th and early 5th century, during the time when paganism began being outlawed. At the same time, the transition of non-Christian names to non-Christian names started progressively to decline in the 5th century.

Figure 6: *Evolution in the Aggregate Occurrences of Christian Names, and in the Transition of Non-Christian to Christian Names*

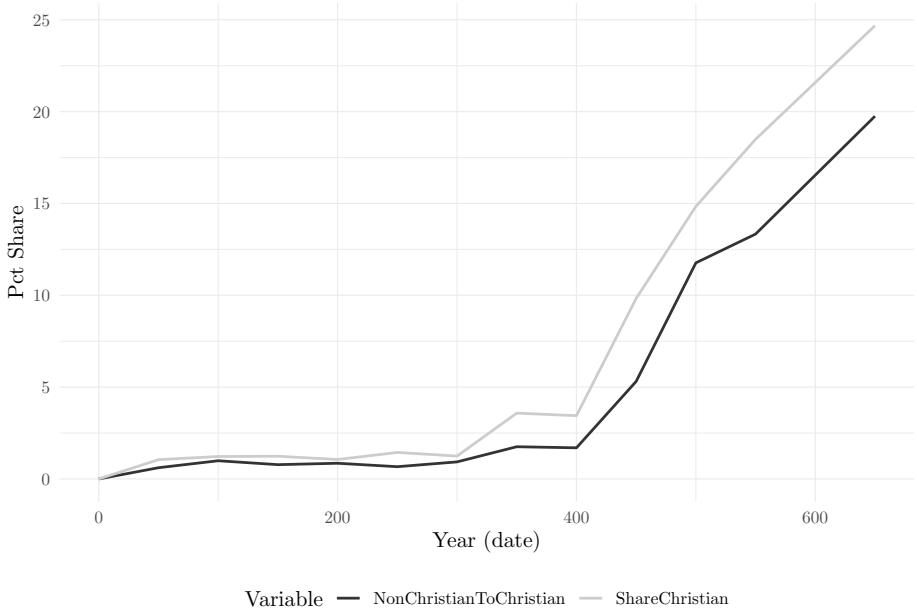
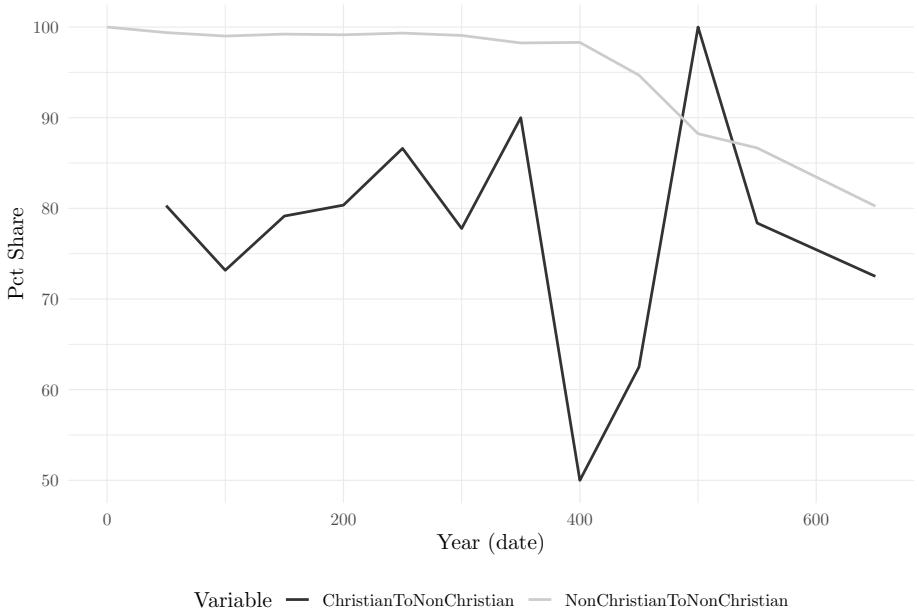
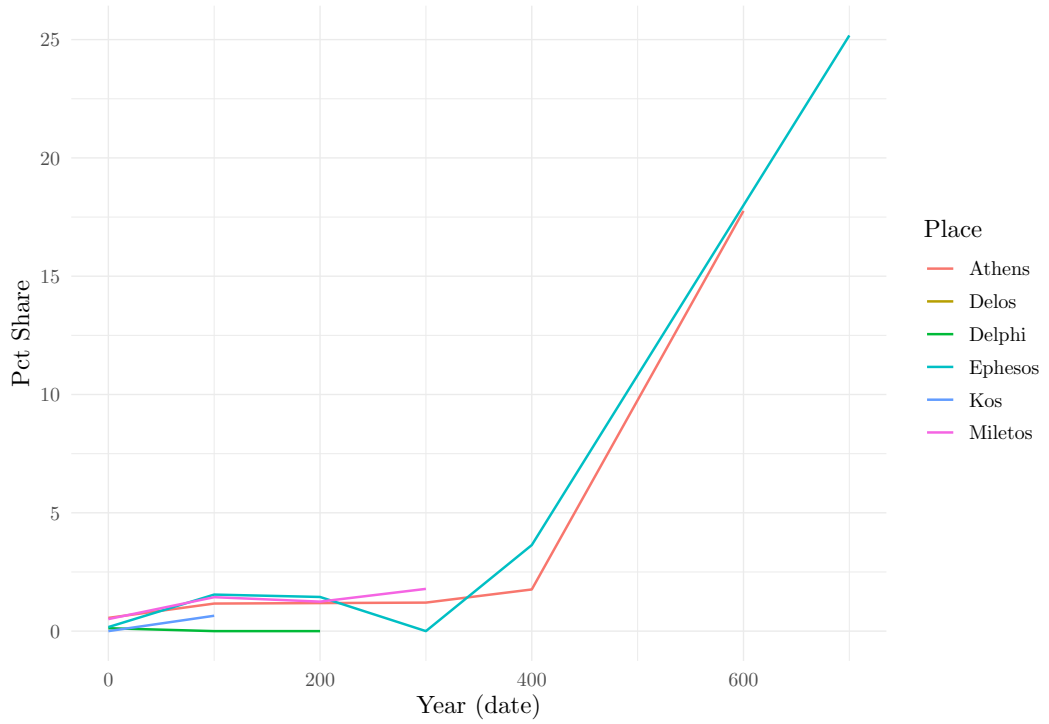


Figure 7: *Evolution in the Transitions of Non-Christian to Non-Christian Names and Christian to Non-Christian Names*



Since epigraphic sources dried up in the Late Antiquity, as the habit of inscribing religious or administrative information in stone disappeared, the data becomes in fact sparse after the 4th century. As a result, detailed geographic differences cannot truly be distinguished, as Figure 8 illustrates.

Figure 8: *Evolution of the Rate of Occurrence of Christian Names in a Selection of Poleis*



2 Modeling Cultural Spread

Cultural evolution has been extensively analyzed with the tools of economics or game theory: the seminal works in Boyd and Richerson (1988) and Boyd and Richerson (2005), in particular, established a general approach into the theoretical modeling of the existence of culture, as well as many of its specifically human features. In this stream of research, concentrating on human evolution, the core focus is on the conditions that make the emergence of culture, in parallel with genetics, optimal and evolutionarily stable. The study of how information or technique may spread, within groups where some may innovate and others immitate, also recoups with the mechanics of the evolution of culture (Chamley 2004). These approaches, however, do not focus on specific cultural traits, but rather on the general mechanism that favor, or hinder, the spread of general forms of culture. The analysis of how particular cultural traits, types of information, or technical knowledge percolate through a population typically requires that one reflects detailed and specific assumptions and constraints, and may not easily fall within a very general economic framework. In consequence, this type of research work appears to have been

mostly tackled through the use of agent-based simulations. For example, Conte, Hegselmann, and Terna (1997), and more recently, Takadama, Cioffi-Revilla, and Deffuant (2010) covered a wide variety of different social situations, many of them involving diffusion through interactions.

For the purpose of analyzing how a particular cultural aspect may spread, relying on relatively sparse data, we cannot specify a very complex model; on the other hand, it is important to understand how the dynamics may arise from simple assumptions concerning individual behavior. Combining the techniques used in epidemiological modeling with some simple economic setup, we will attempt to determine a reasonable framework applicable to the use of Roman names in the Greek world. In this section, we will first describe the most basic SIR epidemiological model and discuss some aspects of its dynamics. Stressing that, while it may account for a diffusion phenomenon in a population, it does not fundamentally account for how a cultural trait could spread, we then turn to a more economics-based approach to this model. We will explicitly model the choice by people to adopt a new cultural trait, and to later shed it, and examine the dynamics that can be derived from this set up.

2.1 The Basic SIR Model

The susceptible-infected-recovered (SIR) model consists in a system of non-linear ordinary differential equations, each one representing the population in these categories. Brauer and Castillo-Chavez (2012) offers an overview of the most basic model, along with some more complex models adapted for specific viral or bacterial behaviors observed in natural history. As can be seen in Frauenthal (1980), these models have existed for some time, although they were not designated by this particular acronym.

In our approach of this SIR model, we will express the susceptible S, infected I and recovered population R as fractions of the total population, and will not specifically model the total population size, for simplicity. At each time step, the susceptible population is reduced, and the infected population is increased, by an amount proportional to the product of the susceptible and infected populations. The parameter β represents the probability, over a short period of time, that a susceptible person gets infected through random interactions with the infected population. The parameter γ represents the probability that an infected person recovers: the expected time during which a person is infectious is $\frac{1}{\gamma}$.

$$\begin{cases} dS_t = -\beta I_t S_t dt \\ dI_t = \beta I_t S_t dt - \gamma I_t dt \\ dR_t = \gamma I_t dt \end{cases}$$

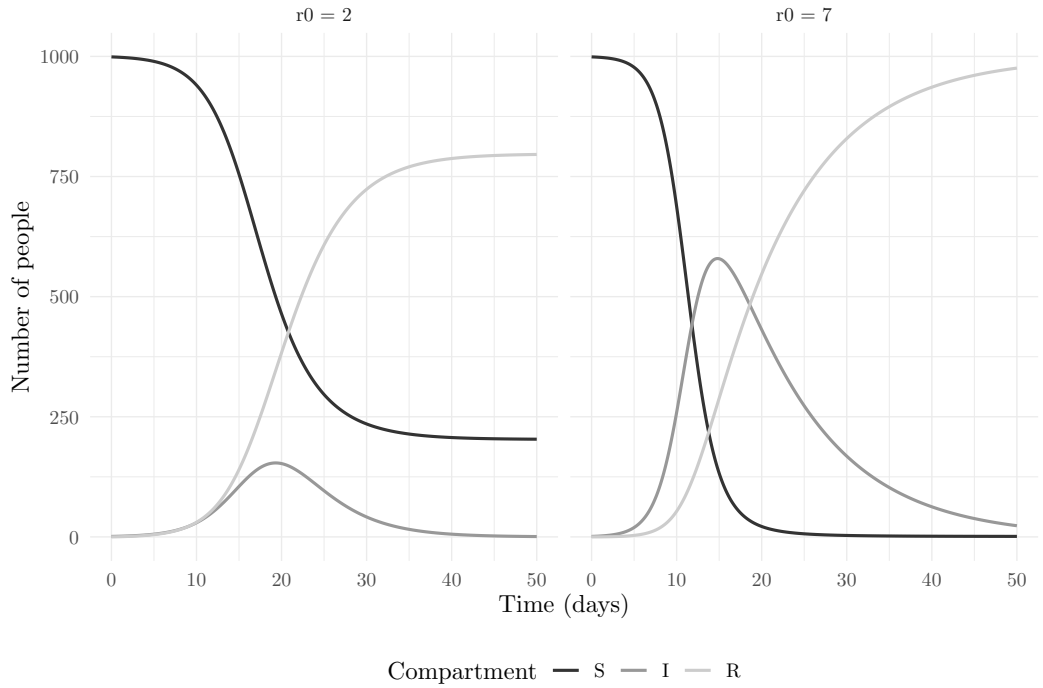
At the beginning of a potential epidemic, we consider that S_0 is very close to 1, and I_0 very close to zero. For an epidemic to occur, it is necessary that the numbers of infected people initially increases, so it is necessary that $dI_0 > 0$, or equivalently, approximating S_0 by 1, $\frac{\beta}{\gamma} > 1$. The ratio $r_0 = \frac{\beta}{\gamma}$ effectively expresses the number of people one infected person will infect, and conditions whether an epidemic will occur, and how fast it will spread.

Closed form expressions of SIR dynamics are difficult to determine, so one can only formally derive certain specific properties (Turkyilmazoglu 2021). In particular, by setting $\frac{dI_t}{dt} = 0$, we can see that the number of infected people peaks when the number of susceptibles reaches $\frac{1}{r_0}$. Also, we have $\frac{dS_t}{dR_t} = -r_0 S_t$, so that $\ln(S_t) - \ln(S_0) = -r_0(R_t - R_0)$. However, S_0 is very close to 1, and R_0 is very close to zero, so we can approximate as $S_0 = 1$ and $R_0 = 0$. Also, since the total population is scaled to 1, we have $R_t = 1 - I_t - S_t$. However, as t goes to infinity, the number of infected people vanishes, so that $R_\infty = 1 - S_\infty$. Hence, at the limit, the total number of susceptibles remaining as a fraction of the total population, S_∞ verifies the equation $\ln(S_\infty) = r_0(S_\infty - 1)$.

Such a model can be resolved numerically, Figure 9 displays two examples of SIR dynamics, one with $\beta = 0.7$ and $\gamma = 0.35$, so that $r_0 = 2$, and the other with $\beta = 0.7$ and $\gamma = 0.1$, so that $r_0 = 7$.

While the modeling approach used in epidemiology generates dynamics that resemble what we may observe in the cultural spread of Roman names or of Christian names, there is no fundamental reason why such cultural features should spread by contact in the same way as a disease.

Figure 9: *Typical SIR-Model Dynamics*



2.2 An Economic SIR Model

In order to better account for the adoption of a cultural trait, we will develop here a model where the "infected" compartment reflects an actual choice by the susceptible population, rather than a mechanistic diffusion of the trait by contact, as in the epidemiological SIR model we just reviewed. The attractiveness of a particular cultural trait may be driven by the prestige of those who exhibit it, for example (Jiménez and Mesoudi 2019), and while there is a notion of contact involved in the fact that potential adopters of the trait could randomly be exposed to it, there is also a notion of choice in adopting the trait.

We express the gain that an individual would obtain from a transition from the susceptible population S to the infected I as a function of the number of people who are currently infected as well as the number of people who will be transitioning at the same time. Given $b > 0$ and $c > 0$, we have, for an individual i who is transitioning from S to I:

$$G_i(p) = bI - cp,$$

where p is the number of new entrants into I, expressed as a proportion of the population. The parameter b expresses a measure of attractiveness of the new cultural trait, while c is a cost of adoption in the form of a sharing cost of the new trait. The term bI captures a network effect, whereby the more people there are in this I community, the more beneficial it is for new entrants. However, the more new entrants there are, the worse-off they are, individually, because the newly

acquired benefits need to be shared individually to some extent, which is captured by the term cp.

Once individuals are in the I compartment, infected with the new cultural trait, we consider that they will over time "forget" the benefits of being in that category. Indeed, as we model families transitioning into one compartment to another, it is actual individuals who make the decisions, from their own limited perspective. Given $g > 0$ and $e > 0$, an individual i in I, when going back to the initial cultural trait, is assumed to receive an additional gain of:

$$F_i(q) = g - eq,$$

where q is the proportion of people transitioning at the same time. The term g represents an absolute gain in reverting to the prior cultural trait, while e is the cost of doing so. The form of F_i expresses a baseline attractiveness, consistent with the notion of "forgetting" the benefits of the new cultural trait, combined with an effect that reduces this attractiveness if there are many people transitioning at the same time, a cost similarly expressed to that in G_i.

Proposition 2.1 (Cultural Dynamics)**.** *When individuals behave optimally at equilibrium, the dynamics of the population compartments S, I and R are as follows:*

$$\begin{cases} dS_t = -\beta I_t S_t^2 dt \\ dI_t = \beta I_t S_t^2 dt - \gamma I_t^2 dt \\ dR_t = \gamma I_t^2 dt \end{cases}$$

with $\beta = \frac{b}{2c}$ and $\gamma = \frac{g}{2e}$.

Proof. The gain is the same for all individuals in the same situation. Each potential new entrant from S chooses a probability p_i of transitioning, so that the expected gain for the individuals in S writes:

$$\mathbb{E}\left[G_i(p, p_i)\right] = p_i \left(bI - cp\right).$$

However, at the optimum, the mixed-strategy equilibrium calls for setting p_i to the same value p_0 that maximizes G_i for all. Besides, p, expressed relative to the entire population, is then simply equal to $\frac{p_0}{S}$. Hence, we have:

$$\mathbb{E}\left[G_i(p_0)\right] = p_0 \left(bI - c\frac{p_o}{S}\right).$$

Maximizing over p_0, we obtain $p_0^* = \frac{bIS}{2c}$. Expressed as a continuous evolution, the variation in

S_t can therefore be written as a function of the probability p_0^* taken as a proportion of S_t:

$$dS_t = -p_0^* S_t dt = -\frac{bI_t S_t}{2c} S_t dt = -\beta I_t S_t^2 dt,$$

with $\beta = \frac{b}{2c}$.

Now we express the gain from a transition from I to R. For an individual with a probability q_i of transitioning, the expected gain is:

$$\mathbb{E}\left[F_i(q, q_i)\right] = q_i \left(g - eq\right).$$

However, assuming at the equilibrium all select the same probability q_0, we have $q = \frac{q_0}{I}$. Then, the optimal probability is $q_0^* = \frac{gI}{2e}$. Expressed as a continuous rate of transition, we hence have:

$$dR_t = q_0^* I_t dt = \frac{gI_t}{2e} I_t dt = \gamma I_t^2 dt.$$

The dynamics for I can be derived from those for S and for R, and we obtain the result from the proposition. □

These dynamics are not exactly the same as those from a standard SIR model, because of the quadratic terms in I and in S. The share of infected I solves a non-linear differential equation:

Proposition 2.2 (Infected Dynamics)**.** *In the cultural spread SIR model, the share of infected verifies $I_t = F_t'$ where F is the solution of the following differential equation:*

$$F_t'' + \gamma F_t'^2 - \beta \frac{F_t'}{(1 + \beta F_t)^2} = 0.$$

Proof. From $dS_t = -\beta I_t S_t^2 dt$, and considering as an approximation that $S_0 = 1$, we get:

$$\begin{aligned}
\frac{dS_t}{S_t^2} &= -\beta I_t \\
\int_0^t \frac{S_s'}{S_s^2} ds &= -\beta \int_0^t I_s ds \\
1 - \frac{1}{S_t} &= -\beta \int_0^t I_s ds \\
S_t &= \frac{1}{1 + \beta \int_0^t I_s ds}.
\end{aligned}$$

Replacing this expression for S into the dynamics for I, we obtain:

$$dI_t = \beta I_t S_t^2 dt - \gamma I_t^2 dt$$
$$I_t' = \frac{\beta I_t}{\left(1 + \beta \int_0^t I_s ds\right)^2} - \gamma I_t^2.$$

We now define $F_t = \int_0^t I_s ds$, so that $F_t' = I_t$ and $F_t'' = I_t'$. The equation can hence be written:

$$F_t'' = \frac{\beta F_t'}{(1 + \beta F_t)^2} - \gamma F_t'^2$$
$$F_t'' + \gamma F_t'^2 - \beta \frac{F_t'}{(1 + \beta F_t)^2} = 0.$$

□

The condition for an epidemic to occur in this model writes $dI_0 > 0$, that is $\beta I_0 S_0^2 - \gamma I_0^2 > 0$. Approximating S_0 by 1 at the beginning of the epidemic, this is equivalent to $\frac{\beta}{\gamma} > I_0$. With these dynamics, and epidemic is sure to occur: r_0 only needs to be greater than some $\varepsilon > 0$. The share of the population who becomes infected cannot be written with a closed-form expression, but we have the following condition:

Proposition 2.3 (Condition for Maximum and Full Infection)**.** *In the cultural spread SIR model, the maximum infection rate at time t_m verifies: $I_{t_m} = \frac{r_0}{\left(1+\beta \int_0^{t_m} I_s ds\right)^2}$. Further, the susceptible population converges to zero, and equivalently, everyone becomes converted at some point in time, if and only if $\int_0^\infty I_s ds = \infty$.*

Proof. Setting $dI = 0$, we find that the maximum infection rate is reached when $S = \sqrt{\frac{I}{r_0}}$. Setting $t_m = \{t : I_t = \max_u I_u\}$, we can hence write:

$$S_{t_m}^2 = \frac{1}{\left(1 + \beta \int_0^{t_m} I_s ds\right)^2} = \frac{I_{t_m}}{r_0},$$

and hence at the maximum, I verifies the following:

$$I_{t_m} = \frac{r_0}{\left(1 + \beta \int_0^{t_m} I_s ds\right)^2}.$$

Based on the expression for S as a function of I, $S_t = \frac{1}{1+\beta \int_0^t I_s ds}$, we have:

$$S_\infty = \frac{1}{1 + \beta \int_0^\infty I_s ds}.$$

We can see that the entire population is never converted as far as $\int_0^\infty I_s ds < \infty$, and this also holds reciprocally. □

Numerical simulations with various parameters show that S_t comes near zero, but at a slow rate, so that in practice the entire population is not converted in a reasonable amount of time. The dynamics we have expressed above do not explicitly reflect the rates of transition from one population to another, but we can compute them explicitly. We write T^I the rate of transition of S to I, and T_t^R the rate of transition from I to R.

Proposition 2.4 (Population Transition Rates)**.** *The rates of transition T^I and T_t^R verify: $\frac{T_t^I}{T_t^R} = r_0 S_t$.*

Proof. We are interested in the actual rates of transitions, so we need to express the rate at which transitions appear within a family. Indeed, the decision to give a name only occurs when there is a birth, which we will assume takes place at some rate ρ. T^I is the rate of transition of S to I, relative to the population who are in a position to make such a transition, and we express it over a period of time dt:

$$T_t^I = \frac{-dS_t}{\rho S dt} = \frac{\beta I_t S_t^2}{\rho S_t} = \frac{\beta}{\rho} I_t S_t,$$

The transition from I to R, expressed equivalently, is:

$$T_t^R = \frac{dR_t}{\rho I_t dt} = \frac{\gamma I_t^2}{\rho I_t} = \frac{\gamma}{\rho} I_t.$$

Hence, we have:

$$\frac{T_t^I}{T_t^R} = \frac{\beta}{\gamma} S_t = r_0 S_t.$$

□

Therefore, within the context of the model, the ratio of transitions into the converted category relative to transitions out of the converted category is proportional to the susceptible population.

3 Applying the Cultural Spread Model to the Ancient Greek's Use of Roman and Christian Names

In this section, we fit the cultural SIR model we developed earlier, and see to what extent it can account for the empirical dynamics of the use of Roman names and christian names, in aggregate

or at the *polis* level, when enough data is available. Then, we will focus on the explanatory factors that may account for the absolute levels of Romanity and Christianity that can be observed through the use of names.

In order to parameterize the dynamic model to the data, we follow the usual method in epidemiology, and carry out ordinary least-squares (OLS) estimations (Brauer and Castillo-Chavez 2012). The minimization is non-linear, and the model's projected "infection" rate is computed as the numerical solution to the system of differential equations that describe the model. Given the scarcity of the data, and the need to aggregate observations across buckets of one or two generations (25 or 50 years), there are only a few observations over time on which we can apply the model. This situation is somewhat comparable to epidemiology studies considering the very early stages of a new infection wave, when very few observations are available because only a fraction of the infected may be tested for the new disease.

3.1 SIR Cultural Model Fit Application to Roman Names

We consider a time span ranging from 500 BCE to 500 CE, further filtered so that there are more than 50 observations of Roman names, and aggregated into buckets of 50 years. For the *polis*-level observations, we also required that there be at least 4000 observations. The OLS minimization is carried out without applying weights. Table 2 displays the parameters that were obtained for the fits, for a selection of *poleis* as well as for the entire dataset. Figure 10 shows the actual and projected data for the same *poleis*.

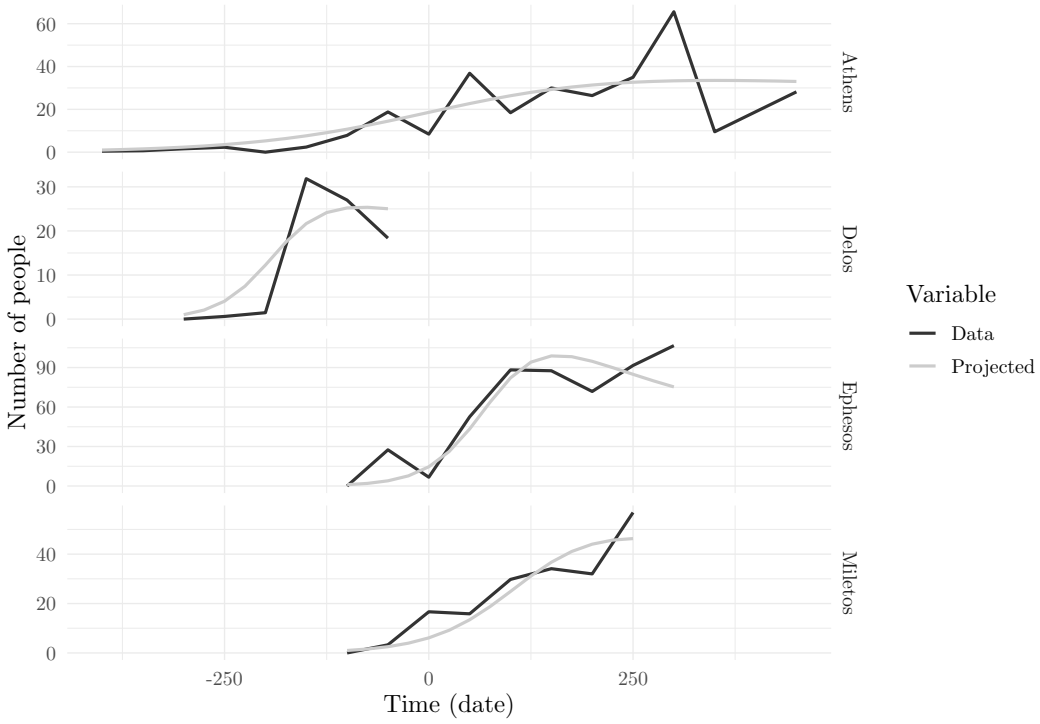
There are not many *poleis* for which we had substantial amounts of data, and the parameters are somewhat variable at the *polis* level. In fact, Delos appears to stand out, with a very high γ, while for the other *poleis*, its value only varied by a multiple of 1 to 2. The β seems particularly low in Athens, on the other hand. Delos, in the Hellenistic period, was a particular case, as it was a city mostly populated by transient people, and many merchants. It was considered as a market hub, in particular for the trade of slaves, and it suffered heavy destruction, by the Athenians in the 2nd Century BCE, and during the Mithridatic wars. In these conditions, it may seem logical that both the rate of adoption of the new rulers' culture, but also the rate of renewal and forgetting, would be high in Delos. Athens, on the other hand, as a Greek cultural center, may have been slower than other cities to adopt new cultural norms We can observe that the parameters can lead to a prolonged peak, or rather a plateau as in the case of Athens, for the "infected" dynamics, unlike the patterns we observed on the basic SIR model, in Figure 9.

Figure 11 displays the actual and projected data across the entire dataset. The parameters

Table 2: *Roman Names Spread: Fitted Parameters for Selected Poleis*

Place	Beta	Gamma
Athens	0.009	0.214
Delos	0.030	1.003
Ephesos	0.028	0.168
Miletos	0.019	0.310
All	0.011	0.160

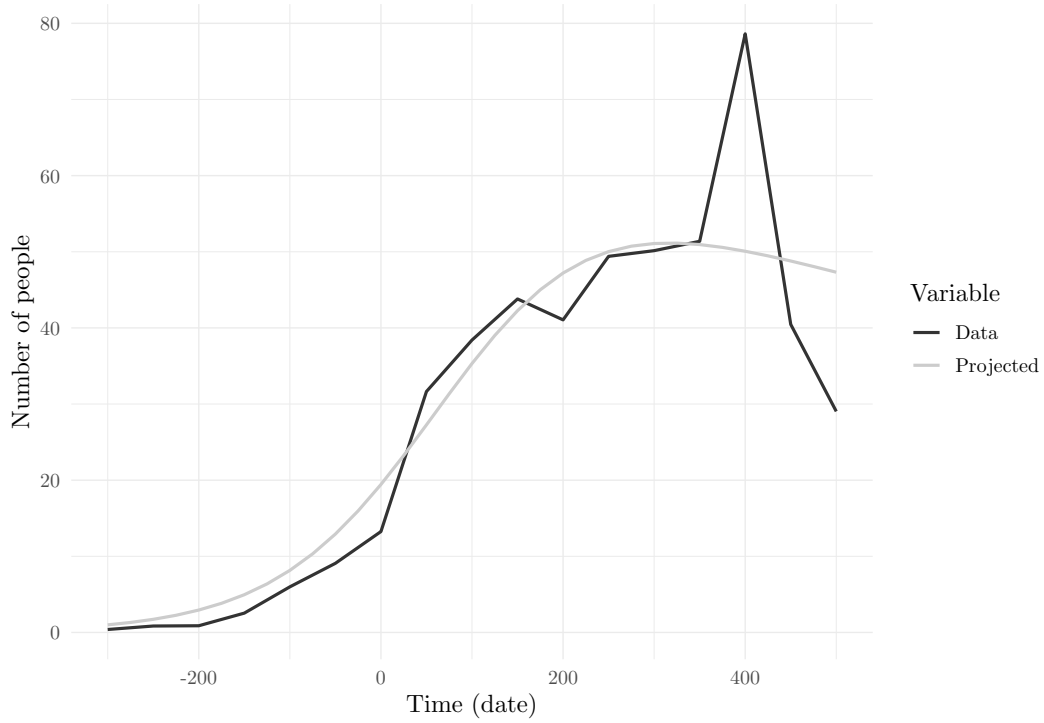
Figure 10: *Projected and Actual Rates of Occurrence of Roman Names for Selected Poleis*



Note: The number of people is scaled to a total population of 1000.

for the whole data, in Table 2, are somewhat lower than the specific parameters for each *polis*. The parameter γ, which drives the return to the original culture, is quite high relative to the parameter β, which is the rate of adoption of the new culture by traditional Greek people. If we run the model forward with the fitted parameters for an extra 500 years, until 1000, then the remaining susceptible population compartment is still about 67% of the entire population. Hence, according to Romanization dynamics as they were until the 3rd century CE, only a minority of the Greek families would have been affected by this trend.

Figure 11: *Projected and Actual Rates of Occurrence of Roman Names for All Data*



Note: The number of people is scaled to a total population of 1000.

The fit shown above were only carried out based on the size of the I compartment, from which the parameters were derived. However, we have seen earlier that determining the implicit ρ, or generation length, was not necessary if we looked at the ratio of transitions $\frac{T_t^I}{T_t^R} = r_0 S_t$. Hence one may also use the empirical rates of transitions in order to derive the value of $r_0 = \frac{\beta}{\gamma}$. Table 3 shows a regression of T_t^I over $T_t^R S_t$. The coefficients obtained in the regression are significant, and the R-squared is fairly high. In the empirical relationship, the ratio $\frac{T_t^I}{T_t^R} = r_o S_t$ comes out at approximately $0.042 S_t$, while the fitted dynamics gave us an r_0 of about 0.069. While these do not match exactly, they have a comparable order of magnitude. The observed transitions into Roman names are less than the transitions out of Roman names would imply, according to the model. The onomastic data for which transitions are available is quite smaller than the entire dataset, since in the case of many inscriptions, one cannot not determine the person's father name, and this data inconsistency may account for the divergence in the estimation of the r_0 parameter.

Table 3: *Scaled Empirical Relationship Between the Transition of Roman Names to Greek and the Transition of Greek Names to Roman*

	Dependent variable:	
	GreekToRoman	
	OLS	
	Base-case	Weighed by Number of Observations
	(1)	(2)
I(RomanToGreek ∗S)	0.042***	0.041***
	(0.006)	(0.006)
Observations	12	12
R^2	0.803	0.794
Adjusted R^2	0.785	0.775
Residual Std. Error (df = 11)	0.015	1.774
F Statistic (df = 1; 11)	44.759***	42.281***
Note:		*p<0.1; **p<0.05; ***p<0.01

3.2 SIR Cultural Model Fit Application to Chritianism

In order to apply the model to Christian names, we restrict the time period to the Current Era, up to 700 CE, but again apply the same filters for the number of observations. As we have pointed out earlier, the number of observations drops quickly after the end of the Antiquity, as the epigraphic habit disappeared. The data is unfortunately too sparse to carry out *polis*-level analyzes, and in any case the very notion of a city-state tended to disappear under the Roman Empire and, later, the Byzantine Empire.

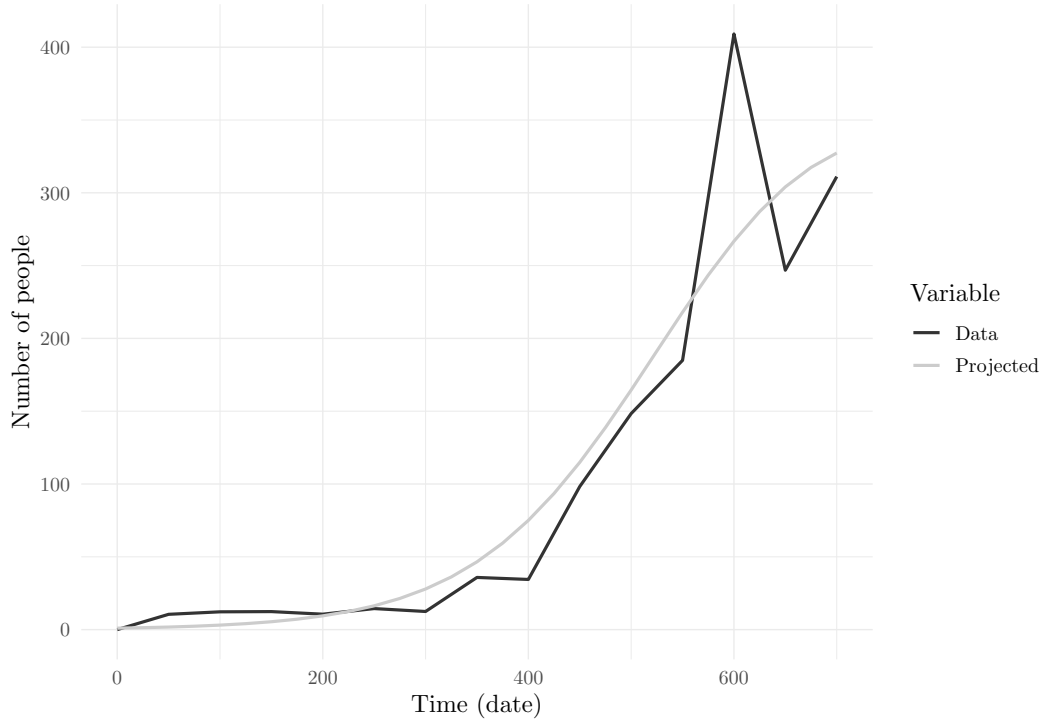
Parameters shown in Table 4 are hence only applicable to the entire dataset. Figure 12 also plots the actual and fitted evolution in the share of Christian names over time. The available data shows a steep acceleration, continuing into the early Middle Ages, and the model matches that pattern. The parameter β corresponding to this fit is very close to the one we observed for Romanization. This is interesting, as it could imply that the rate of adoption of Romanity and Christianity, as per our measures, were comparable. Nevertheless, the short list of names we categorized as Christian is arbitrary, and could be expanded, or reduced, which would likely change the fitted parameters. The parameter γ, which represents the rate of reversion to the priori cultural traits, however, is very low: about 50 times smaller than what we observed in Table 2. Hence, the rapid spread of Christianity does not appear to be due to a particularly high rate of adoption, but rather to a high rate of continuous adherence to the new cultural trait, compared to Romanization. This could reflect a particularly high cost e in reverting to a non-Christian name, or a very low attractiveness g in doing so, in the economic model.

Table 4: *Christian Names Spread: Fitted Parameters Across Poleis*

Place	Beta	Gamma
All	0.011	0.008

We can also run the model forward, as we did in the case of Roman names, for an extra 500 years, until 1200. The remaining susceptible population reaches about 28% of the total. Based on the spread of Christian names in late Antiquity, continuing along the same dynamics, a majority of the families would have been touched. Naturally, the actual evolution of this trend in the Greek world was affected by other significant dynamics, such the spread of Islam.

Figure 12: *Projected and Actual Rates of Occurrence of Christian Names for All Data*



Note: The number of people is scaled to a total population of 1000.

The transition data fit, shown in Table 5, tells us that one cannot find a good relationship between the rates, as would be expected according to the model. As we pointed out earlier, the transition data is much more reduced than the occurrence data, and this is all the more the case in the Late Antiquity.

Table 5: *Scaled Empirical Relationship Between the Transition of Christian Names to Non-Christian and the Transition of Non-Christian Names to Christian*

	Dependent variable:	
	NonChristianToChristian	
	OLS	
	Base-case	Weighed by Number of Observations
	(1)	(2)
I(ChristianToNonChristian ∗S)	0.057	0.014
	(0.043)	(0.011)
Observations	13	13
R^2	0.129	0.114
Adjusted R^2	0.057	0.040
Residual Std. Error (df = 12)	0.106	3.381
F Statistic (df = 1; 12)	1.780	1.548
Note:		*p<0.1; **p<0.05; ***p<0.01

3.3 Cross-Sectional Analysis

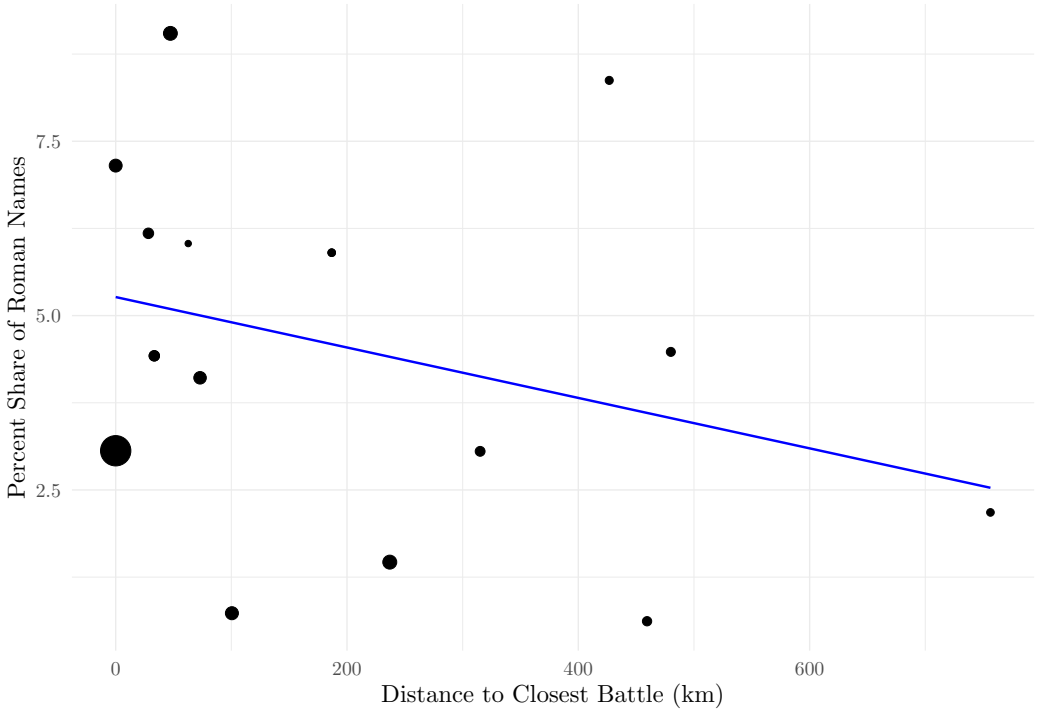
In this section, we explore some cross-sectional factors that may account for the level of Romanization. While we do have a sizable amount of data on Roman names after the initial ramp up in occurrences, this is not the case for Christian names. Indeed, their rate of occurrence was still steeply increasing in the early Middle Ages, while epigraphic evidence disappeared, so that it is not possible to isolate a stable rate; there is too little data.

The so-called POLIS data (Johnson and Ober 2014), derived from the encyclopedic work of Hansen and Nielsen (2004) on ancient Greek *poleis*, gathers aggregate information on over a thousand ancient Greek cities. This data includes mainly categorization information, such as, for example, whether there was a democratic regime at a point in time, how much the city was discussed in ancient texts, or an approximate measure of the city's geographic extent. We linked this POLIS data with the LGPN data, in order to be able to categorize each *polis* according to these metrics. Further, we also calculated, for each *polis* to which name observations could be attached, the distance to the closest battle recorded in Table 1. The data shown in the chart is filtered so that only the rates of occurrence corresponding to the plateau we observed in the dynamics are factored in, approximately, in order to avoid periods of significant variations of occurrence rates over time.

Figure 13 displays the relationship between the distance to the closest battle and the rate of occurrence of Greek names, filtering out locations where there was less than a total of 500 observations. We can see that there is a clear relationship, and the intuition we derived from Figure 1 can be confirmed. Even though the pick up in Roman names took place at the end of the Hellenistic period and during the early Empire, and the rates we are observing are measured after 100 CE, it seems its intensity may have been related with the Roman's show of force in the

region in earlier times.

Figure 13: *Relationship Between the Rate of Occurrence of Roman Names at the Polis Level and the Distance to the Closest Major Battle*



Note: The date is filtered between 100 CE and 400 CE. The regression line does not have a constraint on intercept.

Table 6 shows the results from three logistic regressions relating the occurrence of Roman names to several potential explanatory variables. The first regression uses all the variables that were available in the data, excluding those that are very sparsely populated and would significantly reduce the number of observations. We can see that, in that full regression, the coefficient for the distance to the closest battle is negative, and hence the more distant it is, the less likely are people to give their children Roman names. The second regression contains the full list of *polis*-level variables, but excludes the distance measure. We can observe that, while the remaining coefficients vary to some extent, their generally keep the same sign and same level of significance, which would suggest that this battle proximity metric is independent enough from the other effects. The size of a city has a positive impact on the spread of Romanity, and so does the fact that the city belonged to the League of Delos, that is a pact among many Ionian cities and islands, corresponding to the Athenian empire of the 5th century BCE. Democracy, in these regressions, appear to have implied a lesser interest in Romanity, but it is also strongly correlated with being in the League.

The third model shows the coefficients obtained if we only keep a limited number of explanatory variables. We can see that in this case, the distance to a battle site plays a stronger effect, and city size also still plays a role. Democracy, now has a strong positive coefficient, so that the fact that a *polis* was a democracy increased the use of Roman names. In a democratic city-state, as compared to an oligarchic one for example, citizens were more involved in the actual running of the city's affairs, and hence more likely to be in close proximity to the Roman rulers or delegates. As a result, it is likely that a greater share of the population, in a democracy, would be dealing with Romans in an official capacity, leading to more absorption of their culture, and names. The "Fame" metric, established by Johnson and Ober (2014), captures a city's importance through the amount of texts that were written about it. It reflects, in a way, the cultural importance of that city in ancient Greek. It may be that the *poleis* with the most established cultural aura, all else being equal, were less likely to adopt Roman names.

Table 6: *Logistic Regression of the Rate of Occurrence of Roman Names*

	Dependent variable:		
	IsRoman		
	logistic		
	Full Variables and Distance	Full Variables	Selected Variables
	(1)	(2)	(3)
Greek	0.426	0.527*	
	(0.300)	(0.294)	
DelianLeague	0.444***	0.492***	
	(0.095)	(0.088)	
HasWalls	1.722***	1.793***	
	(0.247)	(0.240)	
SizeProxy	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
GaveProxeny	0.078	0.031	
	(0.104)	(0.099)	
Fame	−0.005	0.004	−0.057***
	(0.017)	(0.016)	(0.004)
Democracy	−0.271*	−0.322**	0.511***
	(0.149)	(0.140)	(0.089)
HasVictories	0.017	0.049	
	(0.101)	(0.096)	
Colonies	−0.011*	−0.013**	
	(0.006)	(0.006)	
BattleDistance	−0.379		−1.169***
	(0.258)		(0.231)
Constant	−5.414***	−5.624***	−3.242***
	(0.423)	(0.395)	(0.099)
Observations	37,400	37,508	37,400
Log Likelihood	-5,973.272	-5,996.915	-6,013.342
Akaike Inf. Crit.	11,968.540	12,013.830	12,036.680
Note:			*p<0.1; **p<0.05; ***p<0.01

4 Conclusion

Although epidemiological models, with their full formal complexity, have been used in the social sciences to some extent, effectively developing some general ideas that were introduced by

anthropologists such as Dan Sperber, they did not truly percolate to economics. In economics, according to the survey by Avery et al. (2020), epidemiological modeling has been largely taken as face value, and economic tools were mostly used at the intersection between the economy and the spread of diseases.

It would seem that the epistemological framework of infectious disease tracking, understanding and modeling could be fructuous if applied to economics in a broader sense. For Lowe, Phillipson, and Wilkinson (2013), it is important that social scientists engage with natural scientists; this relationship, however, is not simply to be viewed as the transfer of formal or quantitative approaches from the hard sciences to the broader humanities. It should go in both directions, as the social sciences can raise epistemological questions of import to other fields. In the context of historical sciences, one can argue that it is a good objective to try and put more history in cliometrics (Gauthier 2022). By joining history, some economic modeling, and a cliometric perspective on ancient Greek epigraphic data, we have tried to do that precisely.

The simple economic model we proposed, combined with dynamics inspired from epidemiology gave us a reasonable way of accounting for historical onomastic data, and provided us with a narrative for the limited expansion of a particular aspect of Roman culture into the Greek world. The same model, applied to the expansion of Christianity in ancient Greece through the use of particular names, showed us that this particular cultural reaction followed fundamentally different dynamics.

5 Appendix

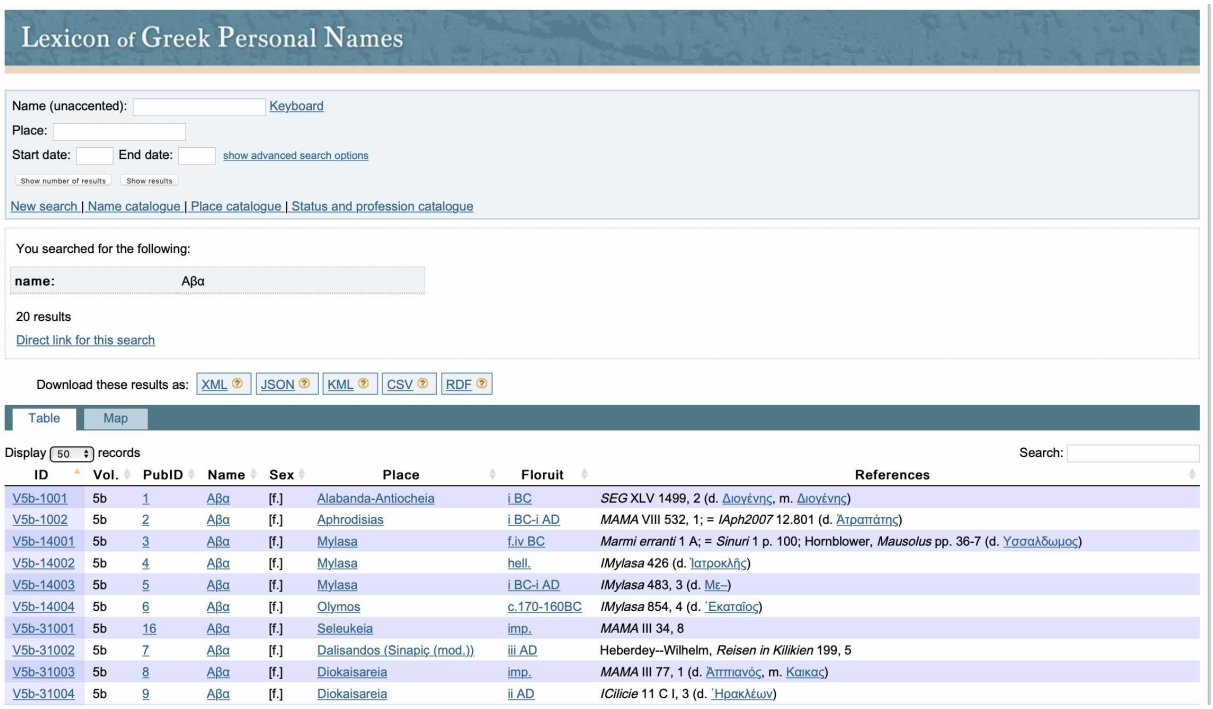
The electronic interface to the LGPN is not designed for its data to be processed and analyzed in bulk (Parker, Yon, and Depauw 1996). It is designed as a tool to query a name or a name root, and observe its occurrences. Figure 14 shows the results of query for a name. This feminine name, Αβα, appears 20 times and for each one of those there is a separate identification, the ID, because each entry may be considered a separate individual. Information is provided on the volume and publication from which this observation is pulled. Some chronological information is given (on the first line, for example, "i BC-i AD" means "within a century before or after CE"), itself typically derived from the epigraphic analysis of the inscription where the name was observed. The reference gives an inscription and a line number. On the first line, "*SEG XLV* 1499, 2" refers to the *Supplementum Epigraphicum Graecum* volume 45:1499. Finally, the reference field shows the name of the mother and the daughter of this person, based on prosopographic analysis.

One can also see from Figure 14 that although it is possible to obtain the data in various formats, this data only pertains to the multiple occurrences of a single name. It is hence impossible to simply download the entire data in a structured form in one batch; it has to be reconstructed from the data pertaining to each possible name. In addition, the various file formats that are illustrated in the figure do not all contain the same information. In particular, the file in CSV format contains the core individual and name data, while the XML file contains data on relationships, locations, and bibliographical references. Both data files hence need to be extracted each time.

In order to programmatically flow through the steps of a manual search, we use the package RSelenium (Harrison and Kim 2020). First, the function "extract_name_list" runs searches for the names starting with every possible letter, in order to generate an up-to-date and comprehensive list of names accessible in the database. Then the functions "extract_all_names_csv" and "extract_all_names_xml" loop through all these names and download the corresponding files (which takes about a day on a fast server).

The specialized function "extract_xml_spec," given a file name, parses and flattens the XML tree and extracts the information on family relationships, name aliases, bibliographical references, and geographical details. The CSV data is easier to process and does not require specialized treatment. The function "create_single_dt" treats all the files in parallel processing (this still takes another day on a fast server).

Figure 14: *Query for a Name in the LGPN*



Lexicon of Greek Personal Names

Name (unaccented): Keyboard
Place:
Start date: End date: show advanced search options
Show number of results Show results
New search | Name catalogue | Place catalogue | Status and profession catalogue

You searched for the following:

name: Αβα

20 results
Direct link for this search

Download these results as: XML JSON KML CSV RDF

Table Map

Display 50 records Search:

ID	Vol.	PubID	Name	Sex	Place	Floruit	References
V5b-1001	5b	1	Αβα	[f.]	Alabanda-Antiocheia	i BC	*SEG* XLV 1499, 2 (d. Διογένης, m. Διογένης)
V5b-1002	5b	2	Αβα	[f.]	Aphrodisias	i BC-i AD	*MAMA* VIII 532, 1; = *IAph2007* 12.801 (d. Ἀτραπάτης)
V5b-14001	5b	3	Αβα	[f.]	Mylasa	f.iv BC	*Marmi erranti* 1 A; = *Sinuri* 1 p. 100; Hornblower, *Mausolus* pp. 36-7 (d. Ὑσσαλδωμος)
V5b-14002	5b	4	Αβα	[f.]	Mylasa	hell.	*IMylasa* 426 (d. Ἰατροκλῆς)
V5b-14003	5b	5	Αβα	[f.]	Mylasa	i BC-i AD	*IMylasa* 483, 3 (d. Με--)
V5b-14004	5b	6	Αβα	[f.]	Olymos	c.170-160BC	*IMylasa* 854, 4 (d. Ἑκαταῖος)
V5b-31001	5b	16	Αβα	[f.]	Seleukeia	imp.	*MAMA* III 34, 8
V5b-31002	5b	7	Αβα	[f.]	Dalisandos (Sinapiç (mod.))	iii AD	Heberdey--Wilhelm, *Reisen in Kilikien* 199, 5
V5b-31003	5b	8	Αβα	[f.]	Diokaisareia	imp.	*MAMA* III 77, 1 (d. Ἀπφιανός, m. Καικας)
V5b-31004	5b	9	Αβα	[f.]	Diokaisareia	ii AD	*ICilicie* 11 C I, 3 (d. Ἡρακλέων)

```
## Extraction of data
library(dplyr)
library(RSelenium)
library(rvest)
library(wdman)
library(stringr)
# Store
csv_path <- "../../Data/ExtractLGPN/CSV_downloads/"
xml_path <- "../../Data/ExtractLGPN/XML_downloads/"
allst_path <- "../../Data/ExtractLGPN/allst_names.Rdata"
namesdata_path <- "../../Data/ExtractLGPN/namesdata.Rdata"
relvarsdata_path <- "../../Data/ExtractLGPN/relvarsdata.Rdata"
namevarsdata_path <- "../../Data/ExtractLGPN/namevarsdata.Rdata"
placevarsdata_path <- "../../Data/ExtractLGPN/placevarsdata.Rdata"
biblivarsdata_path <- "../../Data/ExtractLGPN/biblivarsdata.Rdata"
dwlink_csv <- ";style=csv"
dwlink_xml <- ";style=xml"
## General data on Greek names
extract_name_list <- function() {
  # Overall setup
  lgpn_start_link <- "http://clas-lgpn5.classics.ox.ac.uk:8080/exist/apps/lgpn1-search/index.ht
ml"
  partial_link <- "http://clas-lgpn2.classics.ox.ac.uk/cgi-bin/lgpn_search.cgi?name="
  # Start browser phantom
  pJS <- phantomjs()
  pJS$process
  remDr <- remoteDriver(browserName = 'phantomjs', port = 4567)
  remDr$open()
  remDr$navigate(lgpn_start_link)
  alllt <- paste0(letters, "*")
  allnms <- list()
  for (ix in 1:length(alllt)) {
    try({
      Sys.sleep(0.5)
      # Find entry for search
      myel <- remDr$findElement("id", "namequery")
      # Send letter wildcard
      myel$clearElement()
      myel$sendKeysToElement(list(alllt[ix], key = "enter"))
      # Get list of names
      srcnm <- remDr$getPageSource()
      linklist <- gsub("[?]$", "", gsub("<", "", gsub(">", "",
        gsub("\"", "", gsub("'", "",
          str_extract_all(srcnm, "\"http[:][/][/].*\"[>][<]")[[1]], fixed = T),
```

```
            fixed = T), fixed = T), fixed = T), fixed = F)
      linklist <- linklist[grepl(partial_link, linklist, fixed = T)]
      # Create storage
      dttmp <- data.frame(Filter = alllt[ix],
                          Name = gsub(partial_link, "", linklist, fixed = T),
                          Link = linklist,
                          stringsAsFactors = F)
      allnms[[alllt[ix]]] <- dttmp
    })
  }
  remDr$close()
  pJS$stop()
  allnames <- bind_rows(allnms)
  save(allnames, file = allst_path)
}
# Saving all CSVs
extract_all_names_csv <- function() {
  load(allst_path)
  cleanallnames <- as_tibble(allnames) %>% distinct(Filter, Name, Link) %>% data.frame()
  llks <- cleanallnames$Link
  dirnm <- substr(cleanallnames$Filter, 1, 1)
  for (flnm in unique(dirnm)) {
    dir.create(file.path(csv_path, flnm), showWarnings = FALSE)
  }
  for (nmi in 1:length(llks)) {
    lkdwl <- paste0(llks[nmi], dwlink_csv)
    try(download.file(lkdwl, destfile = paste0(csv_path, dirnm[nmi], "/", nmi, ".csv"), method
= "wget"))
    if (nmi %% 100 == 0) {
      Sys.sleep(2)
    }
  }
}
# Saving all XMLs
extract_all_names_xml <- function() {
  load(allst_path)
  cleanallnames <- as_tibble(allnames) %>% distinct(Filter, Name, Link) %>% data.frame()
  llks <- cleanallnames$Link
  dirnm <- substr(cleanallnames$Filter, 1, 1)
  for (flnm in unique(dirnm)) {
    dir.create(file.path(xml_path, flnm), showWarnings = FALSE)
  }
  for (nmi in 1:length(llks)) {
    lkdwl <- paste0(llks[nmi], dwlink_xml)
    try(download.file(lkdwl, destfile = paste0(xml_path, dirnm[nmi], "/", nmi, ".xml"), method
= "wget"))
    if (nmi %% 100 == 0) {
      Sys.sleep(2)
    }
  }
}
# XML extraction adhoc function
extract_xml_spec <- function(flenm, tbtype = NULL) {
    dta <- data.table(fxml_importXMLFlat(flenm))
    ix_nms <- dta[elem. == 'person' & attr. == 'id' & level4 == 'listPerson', which = T]
    if (length(ix_nms) > 0) {
      ix_nms <- c(ix_nms, dim(dta)[1])
      for (cnti in 1:(length(ix_nms) - 1)) {
        dta[ix_nms[cnti]:(ix_nms[cnti + 1] - 1), PersonId := dta[ix_nms[cnti], value.]]
      }
      if (ix_nms[length(ix_nms) - 1] < dim(dta)[1]) {
        dta[dim(dta)[1], PersonId := dta[dim(dta)[1] - 1, PersonId]]
      }
      if (tbtype == 'namevars') {
        # Extract names and variants
        dta[, PersonName := ifelse(elem. == 'persName' & is.na(attr.) &
                                   level6 == 'persName' & is.na(level7), value., NA)]
        dta[, PersonNameType := ifelse(elem. == 'persName' & is.na(attr.) &
                                   level6 == 'persName' & is.na(level7), shift(value., type =
 'lead'), NA)]
        namevars <- dta[!is.na(PersonName), list(PersonId, PersonName, PersonNameType)]
        return(namevars)
      }
      if (tbtype == 'biblivars') {
        # Extract Bib references
        dta[, Title := ifelse(elem. == 'title' & level6 == 'bibl' & level7 == 'title', value.,
```

```
NA)]
        dta[, Biblio := ifelse(elem. == 'title' & level6 == 'bibl' &
                                 level7 == 'title', shift(value., type = 'lag'), NA)]
        biblivars <- dta[!is.na(Title), list(PersonId, Title, Biblio)]
        return(biblivars)
      }
      if (tbtype == 'placevars') {
        # Extract place references
        dta[, PlaceName := ifelse(elem. == 'placeName' & is.na(attr.) & level6 == 'birth', valu
e., NA)]
        dta[, PlaceCode := ifelse(elem. == 'placeName' & is.na(attr.) &
            level6 == 'birth', ifelse(shift(attr., n = 1, type = 'lead') == 'key',
              shift(value., n = 1, type = 'lead'),
                ifelse(shift(attr., n = 2, type = 'lead') == 'key',
                   shift(value., n = 2, type = 'lead'), NA)), NA)]
        placevars <- dta[!is.na(PlaceName), list(PersonId, PlaceName, PlaceCode)]
        return(placevars)
      }
      if (tbtype == 'relvars') {
        # Extract relationship data
        dta[, Relationship := ifelse(elem. == 'persName' &
            attr. == 'type' & value.=='relationship' & level7 == 'label',
              shift(value., n = 2, type = 'lag'), NA)]
        dta[, RelName := ifelse(elem. == 'persName' &
            attr. == 'type' & value.=='relationship' & level7 == 'label',
              shift(value., type = 'lag'), NA)]
        relvars <- dta[!is.na(Relationship), list(PersonId, Relationship, RelName)]
        return(relvars)
      }
    }
    return(NULL)
}
## Loading all files into a single one
create_single_dt <- function() {
  library(readr)
  library(purrr)
  library(flatxml)
  library(furrr)
  library(data.table)
  future::plan(multisession)
  flas <- list.files(csv_path)
  alldt <- list()
  for (fla in flas) {
    print(paste("Doing directory", fla))
    dirpath <- paste0(csv_path, "/", fla, "/")
    csv_nms <- list.files(dirpath)
    alldt[[fla]] <- paste0(dirpath, csv_nms) %>%
      future_map_dfr(read_csv, col_types = cols("volume" = col_character()))
  }
  namesdata <- bind_rows(alldt)
  save(namesdata, file = namesdata_path)
  flbs <- list.files(xml_path)
  alldt_relvars <- list()
  alldt_namevars <- list()
  alldt_placevars <- list()
  alldt_biblivars <- list()
  for (flb in flbs) {
    print(paste("Doing directory", flb))
    dirpath <- paste0(xml_path, "/", flb, "/")
    xml_nms <- list.files(dirpath)
    alldt_relvars[[flb]] <- paste0(dirpath, xml_nms) %>%
      future_map_dfr(extract_xml_spec, tbtype = 'relvars')
    print("done relvars")
    alldt_namevars[[flb]] <- paste0(dirpath, xml_nms) %>%
      future_map_dfr(extract_xml_spec, tbtype = 'namevars')
    print("done namevars")
    alldt_placevars[[flb]] <- paste0(dirpath, xml_nms) %>%
      future_map_dfr(extract_xml_spec, tbtype = 'placevars')
    print("done placevars")
    alldt_biblivars[[flb]] <- paste0(dirpath, xml_nms) %>%
      future_map_dfr(extract_xml_spec, tbtype = 'biblivars')
    print("done biblivars")
  }
  relvarsdata <- bind_rows(alldt_relvars)
  namevarsdata <- bind_rows(alldt_namevars)
  biblivarsdata <- bind_rows(alldt_biblivars)
```

```
  placevarsdata <- bind_rows(alldt_placevars)
  save(relvarsdata, file = relvarsdata_path)
  save(namevarsdata, file = namevarsdata_path)
  save(biblivarsdata, file = biblivarsdata_path)
  save(placevarsdata, file = placevarsdata_path)
}
```

The resulting data is structured, in the sense that, for example, the entirety of the names in the LGPN is in the "namesdata" dataframe, and the entirety of all family relationships are in the "relvarsdata" dataframe. However, it still requires further processing in order to be more precisely categorized, and also in order to be made compatible with other data.

In particular, the geographic information obtained from the LGPN comes both in the form of coordinates and as place names. We had to address some issues raised with geographic location with the PHI, about inscriptions, but in the case of the LGPN it is more complex, as there are several layers of interpretation. First, there is a distinction between where an inscription is found and where the people that it refers to used to live, a piece of information that may not be explicit in the source. Further, when ancient locations are referred to in a source, it is not necessarily clear where exactly that location is.

Geographic coordinates provided in an electronic source may hence give an artificial sense of precision, although their semantics are imprecise: on one extreme they could point to the exact location where an inscription was found (and the meaning of that location actually remains to be understood), on the other they could point to the center of a modern city according to Google Maps, because that city is presumably the same as the location referenced in a source. Given these considerations, our pre-processing maps the location information from the LGPN to that of the POLIS catalogue, first based on names and then based on coordinates (using a distance threshold in terms of degrees of latitude and longitude). The names are manually identified, as the code below illustrates.

```
## Process / analysis of LGPN data
library(data.table)
library(dplyr)
library(readxl)
library(stringdist)
library(fields)
source("../../Data/ExtractPOLIS/clean_polis.R")
namesdata_path <- "../../Data/ExtractLGPN/namesdata.Rdata"
nameaugdata_path <- "../../Data/ExtractLGPN/nameaugdata.Rdata"
# Load names data "namesdata"
load(namesdata_path)
namesdata <- namesdata %>%
  mutate(CleanSettlement = gsub("-", " ", gsub("[ ][(].*", "", settlement), fixed = T))
# Exclude poleis that do not have Hanssen/ data
all_polis <- all_polis[!is.na(all_polis$Polisity), ]
# Settlement / Polis clean name mapping
# CleanSettlementLGPN / PolisNameMap
manual_map <- list(
  c("Thessalonike", "Thessalonica"),
```

```
  c("Athens", "Athenai"),
  c("Delphi", "Delphoi"),
  c("Taras Tarentum", "Tarentum"),
  c("Chytroi", "Chyton"),
  c("Gorgippia", "Gorgippeia"),
  c("Poseidonia Paestum", "Poseidonia"),
  c("Makyneia", "Makynea"),
  c("Rhithymna", "Rhithymnos"),
  c("Syracuse", "Syrakousai"),
  c("Chersonesos", "Chersonasos"),
  c("Metropolis", "Matropolis"),
  c("Polurrhenia", "Polyrhen"),
  c("Aigai", "Aigeai"),
  c("Korinth", "Korinthos"),
  c("Thisbe", "Thisbai"),
  c("Alalkomenia", "Alalkomenai"),
  c("Mantineia Antigoneia", "Mantinea"),
  c("Hermione", "Hermion"),
  c("Sybaris Thourioi Copiae", "Thourioi"),
  c("Myrmekion", "Myrmekeion"),
  c("Bouthrotos", "Bouthroton"),
  c("Nysa", "Nyssa"),
  c("Tralles Seleukeia", "Tralleis"),
  c("Stratonikeia", "Stratonicea"),
  c("Knossos", "Knosos"),
  c("Hierapytna", "Hierpytna"),
  c("Hyele Velia", "Hyele Elea"),
  c("Besbykos", "Bysbikos"),
  c("Hierapolis Kastabala", "Hierapolis"),
  c("Telmessos", "Telemessos"),
  c("Hipponion Vibo Valentia", "Hipponion"),
  c("Gonnoi", "Gonnos"),
  c("Salymbria", "Selymbria"),
  c("Pargasa Bargasa", "Bargasa"),
  c("Taucheira Arsinoe", "Taucheira"),
  c("Angeiai", "Angeia"),
  c("Bisanthe Panion", "Bisanthe"),
  c("Myrleia Apameia", "Myrleia"),
  c("Phanagoreia", "Phanagoria"),
  c("Brentesion Brundisium", "Brentesion"),
  c("Nikaia", "Nicaea"),
  c("Halaisa", "Alaisa"),
  c("Koliorgeis", "Koliyrgeis"),
  c("Kasthanaia", "Kasthanaie"),
  c("Methana Arsinoe", "Methana"),
  c("Kytenion", "Kytinion"),
  c("Megalopolis", "Megale polis"),
  c("Pythion", "Pythoion"),
  c("Olympe", "Olympa"),
  c("Kassope", "Kassopa"),
  c("Trichonion", "Trichoneion"),
  c("Euesperides Berenike", "Euhesperides"),
  c("Thebai", "Thebe"),
  c("Pyrgoi", "Pyrgos"),
  c("Phellos", "Phelloe"),
  c("Pithekoussai Aenaria", "Pithekoussai"),
  c("Alyzia", "Alyzeia"),
  c("Bylliones", "Byllis"),
  c("Isioi", "Issioi"),
  c("Laodikeia", "Laodicea"),
  c("Charadros", "Charadrous"),
  c("Adramyteion", "Adramyttion")
  )
manual_map_df <- as.data.frame(do.call(rbind, manual_map), stringsAsFactors = F)
names(manual_map_df) <- c("CleanSettlementLGPN", "PolisNameMap")
lgpn_locs <- unique(namesdata$CleanSettlement)
lgpn_locs <- lgpn_locs[!is.na(lgpn_locs)]
polis_locs <- all_polis[, c("polis_id", "PolisName")]
multi_names <- polis_locs %>%
          group_by(PolisName) %>%
          summarise(Nb = n()) %>%
          filter(Nb > 1) %>% as.data.frame()
polis_locs <- polis_locs[!(polis_locs$PolisName %in% multi_names$PolisName), ]
names(polis_locs) <- c("polis_id_map", "PolisNameMap")
lgpn_locs <- lgpn_locs[gsub(" ", "", lgpn_locs) != ""]
polis_locs <- polis_locs[gsub(" ", "", polis_locs$PolisNameMap) != "", ]
```

```r
# Compute name string distance
matdist <- adist(lgpn_locs, polis_locs$PolisNameMap)
min_dist <- apply(matdist, 1, min)
pot_maps_nm <- list()
for (bdi in 1:length(lgpn_locs)) {
  pots <- polis_locs[(1:dim(polis_locs)[1])[matdist[bdi, ] == min_dist[bdi]], ]
  pottmp <- data.frame(CleanSettlementLGPN = lgpn_locs[bdi], MinDistMap = min_dist[bdi], pots)
  pot_maps_nm[[bdi]] <- pottmp
}
name_map <- bind_rows(pot_maps_nm)
zero_match <- name_map %>% filter(MinDistMap == 0) %>%
          select(polis_id_map, PolisNameMap, CleanSettlementLGPN)
manual_match <- manual_map_df %>% left_join(polis_locs)
lay1_match <- bind_rows(zero_match, manual_match)
names(lay1_match) <- c("name_polis_id_map", "name_PolisNameMap", "CleanSettlement")
namesdata <- namesdata %>% left_join(lay1_match)
# Mapping by geo coordinates and verification
## Map by geo coordinates
polis_coord <- all_polis[, c("polis_id", "PolisName", "xcoord", "ycoord")]
polis_coord <- polis_coord[!is.na(polis_coord$xcoord), ]
names(polis_coord) <- c("geo_polis_id_map", "geo_PolisNameMap", "LongPolis", "LatPolis")
matdist <- rdist(namesdata[, c("lat", "long")], polis_coord[, c("LatPolis", "LongPolis")])
min_dist <- apply(matdist, 1, min)
min_dix <- apply(matdist, 1, which.min)
geo_thres <- 0.05
namesdata <- namesdata %>%
  mutate(
    geo_polis_id_map = ifelse(min_dist < geo_thres, polis_coord$geo_polis_id_map[min_dix], NA),
    geo_PolisNameMap = ifelse(min_dist < geo_thres, polis_coord$geo_PolisNameMap[min_dix], NA),
    geo_MinDist = ifelse(min_dist < geo_thres, min_dist, NA))
# Synthesizes mapping
nameaugdata <- namesdata %>%
  rename(
    PersonId = id,
    PersonName = name) %>%
  mutate(
    polis_map_id = ifelse(!is.na(name_polis_id_map), name_polis_id_map, geo_polis_id_map))
save(nameaugdata, file = nameaugdata_path)
```

6 References

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