Natural Borders*

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Abstract: This paper examines how geography affects the location of borders between sovereign states in Europe and surrounding areas from 1500 to today. We find that borders tend to be located on mountains, by rivers, closer to coasts, and in areas suitable for rainfed, but not irrigated, agriculture. Borders are also highly spatially clustered and persistent across centuries. Over time, mountains have become more important determinants of borders, while most other measures of geography have become less important. We also find that rivers are more likely to delineate state borders than language borders. We propose a simple model which can account for some of these observations.

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1 Introduction

When comparing political and geographic layers on a map it is hard not to become curious. Does geography determine the size and shape of countries? Are some borders more "natural" than others, i.e., determined more by geography than social or political factors? If so, which borders? What precise geographic characteristics make a border more or less natural? Are some regions more culturally homogenous and politically unified today due to their geography? Is Europe's relative diversity a by-product of its physical landscape? How has the role of geography in shaping borders changed over time? Does geography affect political borders – or "political diversity" – differently than ethnic diversity?

In this paper we attempt to address these questions using data on geography and border locations, mostly between sovereign states, but also between language areas. We look at the grid-cell level over a region encompassing Europe, Western Asia, and North Africa, from 1500 to modern days.

We find that borders between states are more often found in mountainous terrain and along rivers than elsewhere. Language borders are also more common in mountainous areas, but not as much along (in particular small) rivers, consistent with anecdotal evidence.

Locations closer to the coast also tend to have more borders.

How suitable the land is for agriculture matters too, but differently depending on the type of agriculture: locations more suitable for rainfed agriculture tend to have more borders; those more suitable for irrigated agriculture have fewer. One possible explanation, inspired by Wittfogel (1957), is that empires emerged where rulers could control water supply.

When regressing our baseline outcome variable – border frequency from 1500 to 2000 – on our preferred set of geography variables, the R-squared reaches about 10%. While not negligible, this leaves plenty to be explained. By comparison, when entering border frequency in neighboring cells as a control the R-squared rises to about 60%. In other words, borders are highly clustered. At the same time, the effects of most geography variables remain significant also with such neighbor controls.

We also try to assess if Europe's fragmentation can be explained by its geography. This is an important question, because many have suggested that interstate competition was instrumental to Europe's unique historical path. If geography caused Europe's fragmentation, then it might have indirectly caused the rise of Europe, and all that followed with it.

To explore this, we enter a Europe dummy into the regressions, somewhat arbitrarily defined as cells north of Gibraltar and west of Odessa, although alternative definitions generate the same results. Due to Europe's high political fragmentation, this dummy on its own has a positive and significant correlation with borders. Moreover, it stays positive and significant when entering any combination of our geography controls. This suggests that geography, as we measure it, cannot account for Europe's fragmentation.

Interestingly, the Europe dummy does turn insignificant when entering neighbor controls. One interpretation is that Europe became fragmented not due to geography, but by luck – borders just happened to cluster there – but we discuss other interpretations too.

We also find that borders change very gradually over time: borders today are located similarly to where they were centuries ago. When running panel regressions with cell and time fixed effects, and interacting time with geography, we find that most geography variables have become less important determinants of borders over time. One exception is mountains, which have become more important. In a sense, borders have "moved up mountains."

Finally, to interpret what we find, we propose a model of endogenous borders, where states trade off greater tax revenue from a larger territory against the costs of administering that territory and defending its borders. Both tax revenues and the cost of border defence are lower at higher elevations, so a country expanding its territory does not stop in a valley, but at an easy-to-defend location, from where further territorial gains bring little marginal tax revenue. In our setting, this is a local mountain peak, but more generally it could be a river, a coast, or any other type of natural border.

This paper is inspired by a sizable body of literature, discussed further in Section 2.1 below, on the positive effects of political fragmentation on long-run economic development. However, our interest is in the determinants of political fragmentation, not its effects.

In that regard, our paper contributes to a debate on whether geography caused Europe's fragmentation compared to the more unified China (e.g., Diamond 1997, Ko et al. 2014; see also Section 2.3 below). Our data do not cover China, so we cannot speak to that directly; we do not compare regions, but rather grid cells within a region. However, our approach may complement existing Europe-China comparisons, since if geography does determine fragmentation, then we should presumably expect political borders to follow some distinguishable features of the landscape.

This paper also relates to recent work on the determinants of ethno-linguistic fractionalization (e.g., Ahlerup and Olsson 2012, Michalopoulos 2012, Ashraf and Galor 2013). For example, our data allow us to compare the effects that geography has on political and language borders, with some interesting results.

Finally, our paper shares a lot topics-wise with several studies on the size, shape, and composition of countries (e.g., Bolton and Roland 1997, Alesina and Spolaore 2003, Gancia et al. 2014). Alesina et al. (2011) measure how artificial, or non-natural, modern borders are and correlate this measure with economic outcomes. We rather examine what geographical features constitute natural borders in the first place. Given the focus on Europe and its surroundings, and going back to 1500, the borders we observe should be natural almost by definition, or at least not drawn up by colonial powers.

The rest of this paper is organized as follows. Next Section 2 discusses why political fragmentation is interesting, and summarizes some of the existing discussion on the geography of borders. In Section 3 we discuss our data. Section 4 presents our empirical results with different border measures as the dependent variable, using ordinary least-squares, logistic, and panel regressions, and entering a variety of different controls. Section 5 sets up a simple model to interpret some of our results. Section 6 ends with a concluding discussion.

2 Background

2.1 Political fragmentation and development

As argued above, the roots of political fragmentation are interesting because of the many possible links from fragmentation to preindustrial economic and institutional development. For example, it has been proposed and/or documented that interstate competition created incentives for ruling elites to build state and fiscal capacity (Tilly 1992, Besley and Persson 2011, Dincecco and Prado 2012), invest in education (Aghion et al. 2014), and be less hostile to technological change than they would otherwise have been (Jones 1981, McNeill 1982, Lagerlöf 2014a). Interstate conflict also promoted the emergence of credit markets as rulers sought to finance wars through borrowing (Ferguson 2009, Gennaioli and Voth 2013).

Other mechanisms relate to migration. For example, political fragmentation allowed talented individuals to flee somewhere when authorities went after them (Mokyr 2006, 2007). Evidence suggests that events that increased repression spurred emigration by writers in Europe 1660-1961 (Potrafke and Vaubel 2014). Despots who cared about the size of their populations also had incentives to reform to curb emigration (Karayalçin 2008).

Finally, political fragmentation might serve as a mechanism for spreading risks. When there are several small states it is less likely that widespread destructive consequences will follow if one single ruler makes one bad decision, as could happen in more unified regions. The perhaps most commonly cited example is that of China's large 15th-century overseas explorations, which ended in the wake of infighting within the Chinese court, while Christopher Columbus could solicit funding for his voyages from different European monarchs (e.g., Diamond 1997, pp. 412-413; Landes 1998, pp. 93-98).

2.2 Geography and borders

The role of mountains and rivers in determining political borders has been well recognized, probably since the emergence of the first states, and at least since the early 20th century (e.g., Lord Curzon of Keddleston 1907, Holdich 1916, Brigham 1919; for a nice and more recent overview, see Pounds 1972).

One reason that mountains might constitute natural borders is that they tend to be sparsely populated and easy to defend militarily (Pounds 1972, pp. 86-88). Many famous defensive fortifications were located in mountainous and rugged areas, like the Great Wall of China, Hadrian's Wall in Britain, and the Walls of Ston in modern-day Croatia.

Rivers are different, in that they often had a unifying character; people have always lived, traveled, and traded along rivers (Pounds 1972, Ch. 11). The fragmenting role of rivers seems to be a by-product of states growing militarily stronger. In the words of Lord Curzon of Keddleston (1907, p. 8): "As States developed and considerable armies were required for their defence, the military value of rivers, in delaying the enemy, and in concentrating defensive action at certain bridges, or fords, or posts, became apparent." Consistent with this interpretation, we find that the positive effect of rivers is stronger on political borders (i.e., between states) than on language borders, the latter possibly predating the emergence of states. We also find that big rivers over time became more important determinants of borders up until 1900.

How suitability for rainfed and irrigated agriculture could impact borders may relate to work by Wittfogel (1957), who argued that large-scale irrigation projects tended to make societies more despotic; see also Bentzen el al. (2012) for a test of this hypothesis. Strong and despotic states and rulers may in turn have been prone to, and capable of, spatial expansion. The Middle Eastern regions where states and irrigated agriculture first evolved were also centres of several of the world largest empires (Taagepera 1978, Lagerlöf 2014b). The rise of the first central states in the region has been linked to centralized control of the water supply (see, e.g., Nissen and Heine 2009, Ch. 5). By contrast, where it rains a lot no single group or state can monopolize water supply for a larger region, making it harder to dominate smaller states.

2.3 Diamond's explanation of Europe's fragmentation

Diamond (1997, pp. 414-415) may be the first to explicitly suggest geography as the fundamental cause of political (and linguistic) fragmentation. He uses the examples of Europe and China, the latter being outside the region we study, but his main points could apply also when comparing Western Europe to Russia or the Middle East.[1]

Diamond explains Europe's fragmentation partly by its indented coastline, i.e., its many peninsulas and islands, like Iberia, Italy, Scandinavia, Britain, and Ireland. This is hard to test because not all coasts constitute borders between countries. For example, Denmark and Greece are made up partly by archipelagos.[2] In our data, coasts are not counted as

[1] See also, e.g., Van Evera (1998, p. 19) and Ko et al. (2014).

[2] Scania (Skåne), today located in southern Sweden, was part of Denmark up until 1658. Before that the coast of Denmark were less of a border than it is today.

borders, unless they contain more than one state. However, we do find that cells closer to a coast have more borders, suggesting a fragmenting effect of an indented coastline, as Diamond suggested, since many land borders are located around the mainland connections of peninsulas, e.g., between Spain and France.

Diamond also proposes that Europe is particularly disconnected by mountain chains, like the Alps and Pyrenees. While we do find that mountains are more likely to have borders, as we shall see this does not account for Europe's fragmentation relative to its surrounding areas, which are just as mountainous.

Diamond also suggests that rivers in Europe (compared to China, in his argument) are particularly likely to separate states and peoples because they run north-to-south, thus connecting regions which are climatically different. Our data cannot speak to this directly. We do find that cells with rivers are more likely to have political borders than other cells, but we cannot tell if this depends on the directions in which rivers flow.

3 Data

Here we provide a brief description of our data. (See Section A of the appendix for more details.) The unit of observation is a cell with sides 0.5 degrees. (One degree is approximately 111 km at the equator.)

Our basic source for borders is Euratlas (Nüssli 2010), which supplies data on sovereign state territories at the turn of the centuries 1500-2000 (i.e., for six different years), over a large region centered on Europe; cf. Figure 1. Sovereign statehood seems like the relevant criterion, given the discussion in Section 2.1 about, e.g., state competition and opportunities to flee despots. Our border dummies take the value one if more than one sovereign state was present in a cell in a given year, and zero otherwise.

After dropping sea cells, and cells lacking a state in any of the six years, we end up with a baseline sample of 5202 land (including coastal) cells.[3] We sometimes use a dummy for an area which might represent Europe: cells located north of Gibraltar and west of Odessa; see Figure 1 again.

We also use data on language borders, defined as cells with more than one language, according to the World Language Mapping System. Similarly, we compute a dummy for what we here label current borders from the Global Administrative Areas, a common source for contemporary country borders. This is highly correlated with the Euratlas border dummy for 2000.

We use a couple of different measures of how mountainous a territory is. Log elevation

[3] Sea cells are those completely covered by sea. All other cells we call land cells, some of which are coastal cells, meaning they are partly covered by sea. See Section A of the appendix for details.

is the natural logarithm of the mean elevation across a cell and log ruggedness is the logged standard deviation in elevation.[4] Most of our regressions use what we call mountain dummies, indicating whether the mean elevation of the cell exceeds 1000 or 2000 meters, respectively.

Big and small rivers are those defined by Euratlas. Examples of big rivers are the Rhine, the Danube, and the Nile. The big and small river dummies indicate whether, or not, such a river is present in the cell.

Data on agricultural suitability come from the Global Agro-Ecological Zones project. These measure agricultural output when using intermediate levels of input, relative to the maximum attainable with the same inputs, under perfect environmental conditions. These data are available separately for rainfed and irrigated agriculture, and for various crops. We use the average of the most common crops – wheat, barley, oats and rye – and normalize them to fall between zero and one.

Among the 5202 cells in the baseline sample, suitability for rainfed agriculture is missing for 346 cells, many around the Nile and the Red Sea. Data on suitability for irrigated agriculture is missing for the same 346 cells plus 581 more, including most of Scotland and Ireland. (See Figure 6 for a map.) It seems plausible that these data points, had they not been missing, would have taken extreme values on these two variables, in ways that would have amplified the patterns we document, so it is reassuring that our results hold without them.

Log distance from the coast is the (log) distance in radians to the nearest coastal cell, defined as a cell covered by both land and sea. This is calculated through a Haversine formula, using the Stata command `nearstat`.

4 Empirical results

4.1 Descriptive statistics

From the summary statistics in Table 1 we note that the fraction border cells declines monotonically from about 18% in 1500 to about 9% 1900, and then increases to almost 16% in 2000. This mirrors the trends in the number of sovereign states overall (e.g., Alesina and Spolaore 2003, Gancia et al. 2014).

Figure 2 shows a map of the border locations in 1500 and 1900. The decline in the number of border cells is clearly visible; note e.g. the unifications of Germany and Italy.

Table 2 shows partial correlations between border dummies for different years. All correlation coefficients are positive and significant, but typically larger between closer years.

[4] While related, ours is not exactly the same definition of ruggedness as in Nunn and Puga (2012), but rather similar to what Michalopoulos (2012) calls variation in elevation.

That is, borders are not stationary but change gradually over time; today's borders were often borders centuries ago. Such strong historical dependence is perhaps surprising, given the rise and fall of several states and empires over these centuries, and that borders and the states they delineate have meant so different things in different eras. This might suggest some underlying constant factor determining border locations.

To analyze the cross-sectional correlation between borders and geography we construct a general border index, which is simply the fraction of the six years (1500 to 2000) in which a cell had a border. Averaging across centuries this way should alleviate concerns about the changing roles of state borders, e.g. due to growing geographical reach of state capacity. Letting $b_{i,t}$ be the border dummy, indicating if a border was present in cell i and year t, this index can be written

$$B_i = \frac{1}{6} \sum\nolimits_{t=1500}^{2000} b_{i,t}. \tag{1}$$

Figure 3 shows the means of some geography variables for different levels of the border index. Among cells with a border present in all six years ($B_i = 1$) almost 10% had mountains above 2000 meters and about 50% had a big river present; the corresponding numbers for cells with no borders in any year ($B_i = 0$) were about 2% and 20%, respectively. Similarly, ruggedness and distance from coast change more or less monotonically, but in different directions, when moving from low to high border frequency.

In Table 3 we see that the border index shows a highly significant partial correlation with several geography variables, in particular dummies for mountains over 1000 and 2000 meters, and log elevation and log ruggedness; borders tend to be located by high mountains and in rugged terrain. See also Figure 4. As we would expect, in particular log elevation and log ruggedness are highly positively correlated, since more mountainous areas also have steep slopes and thus more variation in elevation; the correlation coefficient is over 0.8.

Big and small river dummies also show a strong positive correlation with the border index, and much less correlation with the mountain variables. Rivers thus capture a dimension quite separate from mountains, through which geography correlates with borders.

The variables measuring agricultural suitability (rainfed and irrigated) do not show as strong correlations with the border index as the other variables, but an interesting observation is that they carry different signs, a pattern which we return to below.

Log distance from the coast shows a negative correlation with the border index, which we also interpret below.

4.2 Regressing borders on geography

We next present the results from a number of cross-cell regressions when using the border index in (1) as the dependent variable. Our baseline regression specification is:

$$B_i = \alpha + \mathbf{G}_i\boldsymbol{\beta} + \varepsilon_i, \tag{2}$$

where i indicates the cell, B_i is the border index, $\mathbf{G}_i$ a vector containing different geography variables, $\boldsymbol{\beta}$ a vector with the coefficients of interest, α a constant, and ε_i an error term.

Table 4 shows the results when estimating (2) with ordinary least squares. (This estimation technique seems most intuitive, but the results below are very similar when using ordered logistic regressions.) Columns (1)-(3) confirm that borders are more common in cells with high mountains and rugged terrain, consistent with the partial correlations in Table 3. As discussed, the mountain dummies and log ruggedness to some extent measure the same variation, but mountains over 2000 meters and log ruggedness both come out as positive and significant when entered together in column (4).

Column (5) confirms that cells with small and big rivers have more borders, also with other geography controls.

Columns (6)-(8) show that areas suitable for rainfed agriculture have more borders, while those more suitable for irrigated agriculture have fewer. This holds when these are entered both separately and together.

To interpret this, Figure 5 shows a cross-cell plot of the two suitability variables. These are highly correlated (cf. Table 3), but many cells unsuitable for rainfed agriculture are quite suitable for irrigated agriculture. Cells with maximum border frequency ($B_i = 1$), and European cells, are underrepresented among these. For example, cells with rainfed suitability below 0.3 and irrigated above 0.6 are located in Spain, North Africa, the Middle East, and along the Volga River close to the Caspian sea in today's Russia. These are areas that have been comparatively politically unified, and lie mostly outside Europe.

As discussed in Section 2.2, this pattern is reminiscent of the theories of Wittfogel (1957) about the role of irrigation in the rise to despotic states. In our context, the correlations suggest that smaller states may have found it easier to survive in regions where external powers could not control water supply.

Column (9) shows that locations farther from the coast have fewer borders. This partly captures the fact that (western) Europe, which is more fragmented than other regions, also has a relatively indented coastline, thus placing its land cells on average closer to the coast (many being coastal cells themselves, thus having zero distance).

Recall also that we measure only land borders. For example, most cells along the British Isles are non-border cells, since they contain only one sovereign state. (Exceptions are cells containing both France and England, located by the most narrow segments of the English

Channel.) In that sense, Europe's indented coastline could have a more fragmenting effect than we measure here.

Finally, Table 4 shows that, except for agricultural suitability, the effects of most geography variables are relatively stable in size across specifications. They thus seem to capture quite different features of the landscape that constitute natural borders.

4.3 Adding borders in neighboring cells

One possible concern is that our results might be driven by spatially correlated errors. For example, a small state surrounded by several other small states might be more likely to survive than one located next to a big empire. Then border presence would depend directly on the (possibly random) border presence in neighboring cells. Some regions could end up having many borders by sheer luck, or coincidence.

To address this we add the average border index among the eight closest neighboring cells as a control. More precisely, if $\mathcal{N}_i$ is the set of (indices of) the eight closest neighboring cells of cell i, and B_j is the border index in cell j, defined by (1), then

$$\overline{B}_{-i} = \frac{1}{8} \sum\nolimits_{j \in \mathcal{N}_i} B_j \tag{3}$$

is the average border frequency among cells surrounding cell i. The regression equation can now be written

$$B_i = \alpha + \mathbf{G}_i \boldsymbol{\beta} + \gamma \overline{B}_{-i} + \varepsilon_i. \tag{4}$$

We want to know if the estimates of the coefficients in the vector $\boldsymbol{\beta}$ remain significant when adding the third term on the right-hand side of (4). Columns (1) and (3) of Table 5 are identical to columns (5) and (9) in Table 4, respectively, showing the results when regressing the border index on two different sets of geography variables without any neighbor control (imposing $\gamma = 0$); columns (2) and (4) add the third term.

An immediate insight from Table 5 is that borders in neighboring cells come out as highly significant, and raise the R-squared to about 60%, compared to less than 10% with only geography controls. This clearly illustrates how highly clustered borders are. In Section 4.4 below, we discuss how such clustering could arise through coordination.

Entering a neighbor control also renders mountains and small rivers insignificant. This may not be too surprising, since they are themselves clustered around the same regions as borders. For example, many borders follow mountain chains. Small rivers are present in most places (about 68% of the cells; cf. Table 1), but less so in today's Russia, a relatively unified region.

However, the other geography variables – big rivers, log distance from coast, the agricultural suitability variables, and log ruggedness – still show significant correlation with borders, although the estimated coefficients are smaller in size and sometimes significant at somewhat lower confidence levels. Because some geography variables are clustered by nature it is difficult to isolate the effects of geography, but it is reassuring that some of geography variables remain significant when controlling for clustering.

4.3.1 Predicting border locations

We can examine how geography performs compared to the neighbor control by examining where each of these (sets of) variables under- or overpredicts borders. This may also provide some clues about which factors our geography variables fail to capture.[5]

Out of 4275 cells with data for all geography variables, 54 had borders in all six years 1500-2000 ($B_i = 1$). Panel (a) of Figure 6 shows a map of the locations of these cells, as well as the 54 cells predicted to have the highest border frequency, based on two different regressions: one using only geography as explanatory variables [the specification in column (9) of Table 4], and one with only neighbor effects ($B_i = \alpha + \gamma\overline{B}_{-i} + \varepsilon_i$). Panel (b) does the same for 388 cells with borders in at least four of the six years ($B_i \geq 2/3$). Note that cells missing agricultural suitability data are disregarded, since we use these variables in our predictions.

Both geography and neighbor effects predict high border frequency around the Alps. While the neighbor control does better overall, in particular around today's Germany, geography better predicts the border separating Spain and France in the Pyrenees.

Geography overpredicts border frequency in the Caucasus area, meaning this region has been more unified than geography would suggest. One reason could be its relative vicinity to large empires, such as the Ottoman Empire and Russia.

4.4 Europe effects

Next we examine if geography can explain Europe's fragmentation compared to its surrounding regions. To that end, we construct a Europe dummy, indicating if a cell is located north of Gibraltar and west of Odessa (cf. Figure 1). This definition of Europe is arbitrary but the results below are robust to using, e.g., log distance from Paris as a measure of "Europeness."

The regression equation can now be written

$$B_i = \alpha + \mathbf{G}_i\boldsymbol{\beta} + \gamma\overline{B}_{-i} + \delta E_i + \varepsilon_i, \tag{5}$$

where E_i is the Europe dummy, and the notation is otherwise the same as in (4). If our estimate of δ is significantly different from zero, then the interpretation is that something makes Europe more fragmented, in ways that the other variables cannot account for.

[5] We are grateful to Kris Inwood for this suggestion.

In Table 6, the Europe dummy does come out as positive and significant, both on its own in column (1), and when controlling for various sets of geography variables in columns (2)-(4). That is, geography seems unable to explain Europe's political fragmentation. The reason is that Europe's geography is not very different from its surrounding regions. For example, while there are many borders around the European Alps, many non-European and relatively unified regions were equally mountainous; see Figure 4.

At the same time, the estimated coefficients of most geography variables are largely unchanged when including a Europe dummy, suggesting that the effect of geography on borders is a general phenomenon, not specific to Europe.[6]

In columns (5)-(8) we enter neighbor controls, here computed as the border index for both the eight and 24 closest neighbors. Either of these is enough to make the Europe dummy insignificant, with or without geography controls. As we saw in Section 4.3, borders are highly clustered, and the Europe dummy comes out as significant because these clusters are mostly located in Europe. Conditional on being close to a border cluster, cells in Europe do not have more borders. As in Section 4.3, neighbor controls also render some geography variables insignificant, but others stay significant at conventional levels, although smaller in size.

Why are most border clusters located in Europe then? One possibility is that borders are fundamentally determined by geography, but that geography itself is more clustered in Europe than elsewhere. However, then geography should probably pick up more of the variation in border frequency, and render the neighbor effect and the Europe dummy less significant.

Another possibility is that there are multiple equilibria. If one cell has a border, neighboring cells could be more likely to have them too, making a whole region fragmented. For example, small states may be more likely to survive when surrounded by other small states, and located far from empires. Once a state becomes stronger than its neighbors it can conquer more land and resources, allowing its population to grow, making it stronger still, eventually leading to complete unification.[7] Then borders can be clustered even if geography has no direct effect on borders. That is, Europe's fragmentation could be coincidental, and unrelated to geography.[8]

[6]The exception is the coefficient on log distance to the coast in column (4), which turns positive when entering the Europe dummy. As discussed earlier, this variable partly captures Europe's indented coastline, and here the Europe dummy absorbs that effect. The estimate shifts back to negative when entering neighbor controls in columns (6) and (8).

[7]This type of mechanics is modelled by Lagerlöf (2014b) in a multi-country setting with Malthusian population dynamics.

[8]This explanation is similar to Hui (2004), who compares China and Europe, arguing that differences in fragmentation are due more to seemingly random historical events than geography.

A third possibility is that geography determines which equilibrium a region coordinates on, the unified or the fragmented one. For example, Europe's mountains may be distributed such that it was harder for any single state to get that initial empire-building momentum. If the Pyrenees had been flat land, for instance, then France and Spain might have evolved into a single political and cultural entity, much larger than its neighbors, and thus harder for other European powers to resist militarily. Similarly, if some other region is initially more unified because its land is more suitable for irrigated agriculture, or because it has a less inundated coastline, that may have tilted the outcome toward the unified equilibrium.

This would allow geography to exert a multiplicative effect on fragmentation, working through the neighbor effect: natural borders can fragment a region directly, by dividing it into two or more separate political entities, and indirectly, by making it less likely that any of them absorbs the others.

Indicative of the direct effect being present is that some geography variables do remain significant also with neighbor controls.

4.5 Logistic regressions

Our analysis so far has been based on the average border frequency 1500-2000 defined in (1). Next we look at border dummies in each of the six centuries separately, as well as current and language borders from the GAA and WLMS, respectively (see Section 3). Let $b_{i,j} \in \{0,1\}$ be the same border dummy as before, equal to one if cell i had a border in year j, or in this case a language or current border. That is, $j \in \{1500, ..., 2000, \text{LB}, \text{CB}\}$, with LB and CB indicating language and current borders, respectively.

The logistic regression equations (one for each outcome variable j) can now be written:

$$\Pr(b_{i,j} = 1) = F(\eta_j + \mathbf{G}_i \boldsymbol{\lambda}_j + \epsilon_{i,j}), \tag{6}$$

where $F(x) = e^x/(1+e^x)$ is the logistic function, $\mathbf{G}_i$ the same vector of geography variables as before, η_j a constant, $\boldsymbol{\lambda}_j$ a vector of coefficients, and $\epsilon_{i,j}$ an error term. Note that η_j and $\boldsymbol{\lambda}_j$ are allowed to differ across outcome variables. We want to learn how the estimated elements of $\boldsymbol{\lambda}_j$ differ across j.

Columns (1)-(6) of Tables 7 and 8 show the results for border dummies in the six different centuries, and columns (7) and (8) the corresponding results with current and language border dummies as dependent variables. We report the coefficient estimates, rather than the odds ratios, since we are primarily interested in the signs of the effects.

Table 7 uses a smaller set of geography variables – mountains above 2000 meters, log ruggedness, and small and big rivers. The coefficient estimates in columns (1)-(6), when significant, carry mostly the same signs as in the ordinary least squares regressions in column (5) of Table 4, and they are mostly significant. In other words, the results when using the average border index in (1) as dependent variable do not seem to be driven by any particular year.

The outcomes when using current and language borders in columns (7) and (8) are also qualitatively similar, even though these borders come from different sources and, in the case of language borders, arguably measure something quite different. This suggests that the patterns documented earlier are not a reflection of any peculiarities in the Euratlas data.

The same patterns hold with a broader set of explanatory variables in Table 8, adding the two agricultural suitability variables and log distance to coast. Most coefficients carry the same signs as in the ordinary least squares regressions in column (9) of Table 4. One exception is log distance to the coast which carries a significantly positive sign for language borders: more inland locations tend to be more linguistically fragmented, but more politically unified.

We also note the smaller and less significant effect of (in particular small) rivers on language borders in Tables 7 and 8, compared to political borders. This fits with the idea that rivers are unifying at the micro level, while also constituting natural borders between states, as discussed in Section 2.2. That is, rivers may have become political borders for reasons related to the military expansion of states, while people living by the same river have continued to share language.[9]

4.6 Panel regressions

Recall that our Euratlas border dummies, $b_{i,t}$, vary both over time (i.e., across the six centuries 1500-2000) and across space (i.e., across the cells), allowing us to control for both time (i.e., century) and cell fixed effects. Because geography (as we measure it) is constant over time, we cannot enter geography variables when controlling for cell fixed effects, so these regressions cannot speak directly to how geography has affected fragmentation. However, we can learn which geographical characteristics have become more or less important over time. We do this by entering interaction terms between the different geography variables and a variable we label Century, which increases (linearly) from 1 to 6 between 1500 and 2000.

The regression equation can be now written:

$$\Pr(b_{i,t} = 1) = F(\rho_i + \pi_t + C_t \mathbf{G}_i \boldsymbol{\theta} + \upsilon_{i,t}), \tag{7}$$

where $F(\cdot)$ is the logistic function, ρ_i and π_t are cell and century fixed effects, C_t the variable Century (i.e., $C_t = [t - 1400]/100$), $\boldsymbol{\theta}$ a vector of coefficients to be estimated, and $\upsilon_{i,t}$ an error term.

[9] The result is also similar to Michalopoulos (2012, p. 1525 and Footnote 10), who finds that the effect of rivers and lakes on lingustic diversity is either positive and insignificant, or negative and signficant, implying that these are, if anything, unifying.

Table 9 shows the results. Columns (1)-(6) let the interaction effects enter separately (although the two agricultural suitability variables enter together), and column (7) shows a "horse race" regression, where all enter together. Recall from Table 1 that border frequency reaches a minimum in 1900, so Column (8) drops the year 2000, allowing changes in the effects of geography to reverse around then.

To interpret the results, note that if a geographical factor has become more (less) important over time, then the geography-century interaction should carry the same (opposite) sign as in the cross-sectional regressions in Tables 4 to 8.

The positive and significant estimates of the interactions between Century and the two mountain dummies in columns (1) and (2) indicate that mountains, which already have a positive effect on borders, have become more important determinants of borders. The probability of a cell having a border, while decreasing overall since 1500, has decreased less in cells with mountains. This holds whether we define mountains as elevation exceeding 1000 or 2000 meters. It also holds when the 2000-meter dummy is entered together with other interaction terms in column (7), and when dropping the year 2000 in column (8). In short, borders have "moved up mountains."

To get an understanding of what drives this result, Figure 7 shows what we can think of as the profile of a mountain, namely mean elevation levels for cells with a midpoint of 49 degrees latitude, i.e., the 49th parallel, passing through today's France (close to Paris), into Germany (close to Stuttgart), Austria (north of Vienna), and then the Czech Republic, ending in current Slovakia close to the mountain peak Kriváň at 20 degrees east longitude.[10] Figure 7 also indicates which cells were border cells in 1500 and in 1900, respectively, the peak and trough years for border frequency in our data. As seen, the borders that are still there in 1900 tend to be at higher elevations. The disappearing borders illustrate the expansion of France from the west, and the Habsburg Empire from the east.

Columns (3) and (7) in Table 9 show that land suitability for rainfed and irrigated agriculture, respectively, have become less important determinants of border locations. That is, rainfed agriculture tends to make cells more likely to have a border, but less so over time, and vice versa for irrigated agriculture. One interpretation could be that the importance of local food production declined with increased trade, which could have made local rainfall a less important determinant of the survival of small states, while also making borders more costly. (As argued by Gancia et al. 2014, growing trade may have directly reduced the usefulness of borders.) By contrast, areas with irrigated agriculture were already relatively unified.

Distance from the coast has a direct negative effect on borders. Columns (4) and (7)

[10] The 49th parallel is chosen arbitrarily but is known for constituting part of the border between the US and Canada.

indicate that this negative effect weakened over time. Put differently, the unifying effect of being far from the coast weakened. One explanation could be that the state-building effects of sea travel increased over time in this era, exerting a unifying effect in coastal regions, not felt as strongly inland. Another could be the break-up of empires located in more inland regions.

Small and big rivers have a direct positive effect on borders. How these effects changed over time depends on the time period considered. When considering the whole period 1500-2000, small rivers seem to have become less important [columns (5) and (7)], while there is no significant effects for big rivers [columns (6) and (7)]. For the period 1500-1900 [column (8)], the results instead suggest that big rivers have become *more* important, while the corresponding effect for small rivers is no longer significant.

The result for big rivers up to 1900 seems consistent with Lord Curzon's argument in Section 2.2: rivers became borders because they were easy to defend militarily, and thus a by-product of the emergence of military states. That this effect goes away after 1900 may suggest that new technologies, e.g. improved fire power, eventually diminished the military obstacle of even big rivers.[11]

5 Model

In the preceding sections we learned several interesting facts about borders. Here we propose a model to help interpret some of these, in particular the following: that borders show persistence over time; that they are geographically clustered; that they are more likely to be located in mountainous terrain; and that mountains over time have become more important determinants of borders.

We thus model only one geographical variable, elevation, but our results may carry over to a framework where geography varies in multiple dimensions across the landscape.

The model itself rests on a few plausible assumptions. First, countries (or their respective elites) set their territories to maximize tax revenues net of spending on border defence and control of the territory. Second, higher elevations generate less tax revenue. Third, borders are less costly to defend at more elevated points.

There is a continuum of locations, $l \in [0, 1]$, with elevations $h(l) > 0$. Location $l = 0$ is the coast. We assume that $h(1) > h(0)$, but $h(l)$ need not be monotonically increasing. Going from low to high l is thought of as moving up the mountain.

There are $N > 1$ countries, indexed $i \in \{1, ..., N\}$, with adjacent territories ordered such that lower-i countries are closer to the coast. Country i's territory is $(\tau_{i-1}, \tau_i]$, where τ_{i-1}

[11] The weaker interaction effects for small rivers could be due to other factors, as they might have always been less of a military obstacle. Recall also that small rivers are present in 68% of the cells.

and τ_i are referred to as its downhill and uphill borders, respectively. Country 1's downhill border is the coast, $\tau_1 = 0$.

Lower-i countries (closer to the coast) are militarily stronger, in the sense that they can take as much uphill territory as they want (although at a cost, as detailed below). Each country takes the border to its downhill neighbor (if any) as given, and chooses the location of the border to its uphill neighbor. The exception is country N, which has territory $(\tau_{N-1}, 1]$ and survives only as long as country $N-1$ sets $\tau_{N-1} < 1$.

There are many possible interpretations of this geographical power structure. For example, France grew by annexing the land of smaller and weaker states, often in mountainous regions, like Lorraine and Savoy. The expansion of the Roman Empire could be another example.[12]

Let tax revenue at location l be $Z\,[h(l)]^{-\alpha}$, where $Z > 0$ and $\alpha > 0$. This negative relationship between tax revenue and elevation may be interpreted as population density, or other determinants of the tax base, being lower at higher elevations. Z is an elevation-neutral measure of population density, which we will later vary to study how the border structure changes. Tax revenue of country i, which controls territory $(\tau_{i-1}, \tau_i]$, now becomes:

$$R_i = \int_{\tau_{i-1}}^{\tau_i} Z\,[h(l)]^{-\alpha}\,dl, \tag{8}$$

where (recall) country 1's downhill border is the coast, $\tau_1 = 0$.

While country i's uphill border is chosen freely, it needs to be defended, and the territory needs to be administered, which carries the cost

$$C_i = a(\tau_i - \tau_{i-1})^{\gamma} + b\,[r(\tau_i, d)]^{-\beta}, \tag{9}$$

where $a > 0$, $b > 0$, $\gamma > 1$, $\beta > 1$, and $r(\tau_i, d)$ is the relative height of the border post over a distance $d > 0$ from τ_i:

$$r(\tau_i, d) = \frac{h(\tau_i)}{h(\tau_i + d)}. \tag{10}$$

Costs of border defense are thus falling with the local elevation at the border location: it is less expensive to defend mountain peaks.[13] Letting the cost of holding the territory (the first term in C_i) be increasing and convex in size of the territory ensures that country 1 does not take all land.

[12] The assumption can also be motivated by lower-i countries having higher territorial profits, which will soon be seen to be an equilibrium outcome.

[13] More formally, we could assume that the probability of an uphill neighbor overtaking its downhill neighbor equals one if spending on border fortifications by the downhill power falls below $b\,[r(\tau_i, d)]^{-\beta}$. Note also that the downhill border does not need defending, since it abuts a stronger power; if it wanted the territory it would just expand its border uphill.

At any given level of Z, and other exogenous parameters, an equilibrium is a set of border locations, $\{\tau_i\}_{i=1}^{N-1}$, such that $\tau_i \in [\tau_{i-1}, 1]$ maximizes $\pi_i = R_i - C_i$.[14]

5.1 Simulation

We want to examine how the equilibrium border structure changes when increasing Z, capturing a long-run rise in population density. To this end, we simulate the model for a simple numerical example with six countries ($N = 6$) and five borders, approximating the continuous set of locations by a grid of about 2000 points. Since this serves only as illustration other parameters are set arbitrarily (see Section B of the appendix). However, we enter some realism by letting $h(l)$ match elevation data along the same 49th parallel illustrated in Figure 7, although here at a finer grid level. To match scales, the peak at 20 degrees east longitude (here $l = 1$) is normalized so that $h(1) = 50$.

Figure 8 shows this mountain profile, and the five uphill border locations, for $Z = 0.3$ and $Z = 1$; country 1's border is most downhill and country 5's most uphill (facing the residual country 6). For any given Z, borders tend to be located on local mountain peaks. As Z increases from 0.3 to 1 the territories and borders move up the mountain, each country being pushed by its respective downhill neighbor.

Figure 8 also shows border frequency. This is measured as the number of times a location has a border when Z varies in 50 steps from 0.3 to 1; a border frequency of 50 means that a location has a border continuously for all levels of Z. As seen, some locations have higher border frequency than others, in particular around mountain peaks. Some segments of the $[0, 1]$ line have many border dense locations, e.g., around 0.5-0.75. Others are almost completely border free, e.g., around 0.75-0.9, even though this segment belongs to different countries for different levels of Z.

Such variation in border density resembles the border clustering observed in the data and discussed in Section 4.3. It is here driven by the spatial profile of the single geography variable, elevation, and its assumed effects on tax revenues and defense costs. Intuitively, when countries expand their territories uphill, they do not stop in rich and populous valleys, but expand until they reach a location that is easy to defend and from where further conquests bring little marginal tax revenue. Here that location is a mountain peak. In a richer model it could be a river, a coast, or any other type of natural border.

Figure 9 lets Z vary in 50 discrete steps from 0.3 to 1. The top left panel shows the locations on the $[0, 1]$ scale of the most uphill and downhill borders, and the average location of all five. These are constant over long intervals, making discrete jumps when Z passes

[14] Country i can set its uphill border at the same location as its downhill border, $\tau_i = \tau_{i-1}$, in which case it ceases to exist spatially. In the numerical example considered below, however, all countries have positive territory in equilibrium.

certain thresholds. Intuitively, when borders do change they leap from one mountain top to another. Borders are in that sense rigid, as in the data discussed in Section 4.1.

The top right panel shows elevation at the border locations, and the average elevation across both the five border locations and all locations on $[0, 1]$. Border locations have above-average elevation, consistent with elevation and mountain dummies showing a positive correlation with borders in the cross section. Moreover, elevation at border locations increases with Z. Thus, long-run increases in population density can explain why borders have moved up mountains since 1500, as found in the panel regressions in Section 4.6. Similarly, the top left panel shows that borders move away from the coast (i.e., location zero) as Z increases, also consistent with the panel regressions.[15]

The bottom left panel shows the profits gained by each country in equilibrium, $\pi_i = R_i - C_i$. Profits of downhill countries are higher, and increase more with Z. Intuitively, these hold territories where increases in Z have the greatest impact (namely at low elevations), and can also expand their territories more. A richer (perhaps dynamic) model could thus link these higher revenues to greater military strength, as is here imposed by assumption.

There are many more possible extensions of this model. We could interpret the negative relationship between tax revenue and elevation as land being less productive at higher elevations. To be consistent with our data, this should refer to productivity in irrigated agriculture, because more elevated locations have more borders and, recall, suitability for irrigated – but not rainfed – agriculture shows a negative correlation with border frequency.

A model with multiple geography variables could distinguish explicitly between productivity of rainfed and irrigated agriculture, along the lines discussed in Section 2.2. For example, the cost of controlling a territory in (9), and/or the tax revenue it provides in (8), could vary with the type of agriculture for which it is suitable, and the type of agriculture could itself be a choice variable. We leave such extensions for future work.

6 Conclusions

Does geography determine where borders between sovereign states are located? To answer this, we have examined grid-cell level data across Europe and surrounding areas from 1500 to 2000. We find that several measures of geography indeed correlate with borders: mountains, rivers, distance to the coast, and suitability for rainfed and irrigated agriculture.

These measures do not by any means explain all of the variation in border frequency. Taken together their explanatory power reaches about 10% by a standard R-squared measure.

[15] Note, however, that log distance to the coast is negatively correlated with average border density (B_i) in the data, while in this simulation the corresponding variable – border frequency as shown in Figure 8 – does not increase monotonically when moving away from the coast.

Neither can geography account for Europe's fragmentation relative to its neighboring regions: a dummy for Europe stays significant also when controlling for geography.

At the same time, borders are highly clustered: adding borders in neighboring cells as a control pushes the R-squared to 60%, and renders the Europe dummy insignificant. We discussed how a multiple-equilibrium story might drive this pattern, but we readily admit that this conjecture calls for further research.

We also examined how the importance of geography has changed over time since 1500. Somewhat surprisingly, some dimensions of geography, in particular elevation, have become more important border determinants over time.

To interpret many of these results, we also proposed a model of endogenous borders. In short, countries set borders where they are easy to defend, and from where further territorial gains bring little marginal tax revenue. In our model, this means borders are located on mountain peaks, because both costs of border defence, and tax revenues, depend negatively on elevation.

APPENDIX

A Data

A.1 Border variables

A.1.1 Cell size

The cells are of size 0.5×0.5 degrees, and span from -19.25 to 60.25 degrees longitude, and from 19.25 to 60.25 degrees latitude. One degree is about 111 km at the equator; the exact length depends on where on earth it is measured.

A.1.2 Euratlas data (1500-2000)

The border data were purchased from Euratlas (www.euratlas.com), © 2010 Christos Nüssli. For each turn of the century from 1 to 2000 CE, the Euratlas data contain shapefiles for different political formations in Europe and its surroundings (as well as data on rivers, as discussed below). We define a cell as having a border if it contains more than one *sovereign* state, which is defined by Euratlas as a state with an authority, ruling over a territory and a population, and where "this authority is sovereign, i.e. not subject to any other power or state" (Nüssli 2010).

For the first several centuries after 1 CE, it is unclear if (sovereign) statehood meant the same as today, as central government capacities were often limited. Many of the mechanisms through which political fragmentation might have impacted economic and institutional development may not have been at play either. Here we measure borders from 1500 (i.e., in 1500, 1600, 1700, 1800, 1900, and 2000).

Over this time span more regions have come to be covered by states. Since our ambition is to analyze how geography correlates with state fragmentation, rather than the presence of states in the first place (an interesting question in itself), we restrict attention to cells where some state was present in all years 1500-2000.

Because we define border cells as those with more than one sovereign state, we in effect consider only (or mostly) land borders. Coasts, which make up the contours of many sovereign states, e.g. England, are typically not counted as borders. The exception is when two sovereign states enter the same cell from opposite sides of a narrow coast. For example, France and England/UK share a border in a few cells by the English Channel.

This also means that an indented coastline does not automatically translate to higher border frequency, but we compute distance from the nearest coastal cell, which may capture some of the effect on an indented coast line (see below).

Our Europe dummy is defined as cells within the Euratlas map, and with midpoints located at 36 degrees latitude north (the approximate latitude of Gibraltar), or north of that; and at 31 degrees longitude (the approximate longitude of Odessa), or west of that (see Figure 1).

A.1.3 Language and current borders

Data on borders between language areas are from the World Language Mapping System (www.worldgeodatasets.com/language).

Current border data are from Global Administrative Areas Version 2 (www.gadm.org). We do not know which specific point in time that these current borders refer to, but the GADM Version 2 data that we use were posted in January 2012. As discussed, current borders are highly correlated with the Euratlas border dummy for 2000.

A.2 Geography variables

Data on elevation (topography) is from the National Geophysical Data Centre (NGDC) at the National Oceanic and Atmospheric Administration (NOAA), available to download here:

www.ngdc.noaa.gov/mgg/topo/globe.html

These data refer to land areas only and are provided at the 30-arc-second (about 1 km) grid-cell level. For each cell that we use as unit of observation (of size 0.5×0.5 degrees), there are thus at most about 100 elevation points, depending on how much of it is covered by land.

We define *sea cells* as those cells for which either the NGDC data are completely missing, or which have zero variation in elevation. The latter category are flat-surface cells according to the NGDC elevation data, consisting of the Caspian and Aral seas. These are so-called endorheic basins, i.e., disconnected from other oceans and with run-off through evaporation.

Cells that are not sea cells are *land cells* (i.e., they do not miss NGDC data and have non-zero variation in elevation).

Some land cells are covered only partly by the NGDC data. These we define as *coastal cells*. Land cells surrounding the Caspian and Aral seas are fully covered by NGDC data (although some of it with zero variation in elevation), and are thus not classified as coastal cells; see Figure 1. This makes sense since these basins are endorheic, making boat travel to other seas impossible.

In our baseline sample of 5202 land cells with state presence in all years, about 73 cells have negative elevation. In order not to drop these cells when constructing our variable log elevation, we take logs of elevation exceeding (one plus) the lowest level in the sample. That is, if x_i denotes mean elevation of cell i (in meters) and $\widehat{x}$ is the minimum x_i across the 5202 cells (which in our baseline sample is -28 meters, located around the Caspian Sea), then log elevation is constructed as

$$\ln(1 + x_i - \widehat{x}),$$

which starts at zero. For consistency we do the same when generating log ruggedness; in that case x_i is the standard deviation in elevation across the cell, and $\widehat{x}$ is the minimum standard deviation across all 5202 cells, which equals around .37.

We also construct two indicator variables for whether or not a large or small river was present in the cell, which is from the Euratlas data (see above). There are some minor changes in the location of these rivers over time, but those changes are extremely small, so we use the river data in 1500 for all years. (The only new river in the Euratlas data is essentially the Suez canal, which we do not count as a river.)

A.3 Agricultural variables

The source for the agricultural suitability data is the Global Agro-Ecological Zones (GAEZ) website (www.fao.org/nr/gaez), sponsored by the Food and Agriculture Organization of the United Nations (FAO).

This suitability index measures agricultural output of some given crop and level of input, relative to the output level for the same crop and the same level of inputs, but under perfect environmental conditions, and based on the climatic conditions 1960-91.

The data sources also distinguish between two types of water supply, rain and irrigation. The variables we construct refer to the average of wheat, barley, oats and rye, under intermediate inputs, and for each of the two water-supply categories. We normalize these variables to run from 0 to 1 (the original scale runs from 0 to 10,000).

B Simulation

To create the mountain profile, we first let ArcGIS generate mean elevation across 3000 cells of size 0.01×0.01 degrees, with centroids from -2.995 to 26.995 degrees longitude, and with the common latitude of 49.000 north. Among these we select cells which are completely on land (and for which we can thus measure elevation), and which are located at, or to the west of, the cell with centroid 19.565 degrees longitude, which has the highest elevation of all 3000 cells (1423 meters). This leaves us with 2113 cells from -1.555 to 19.565 degrees longitude, which can be interpreted as the western slope of a mountain. Letting $z \in \{1, ..., 2113)$ be an index ordering the cells from west to east, $h(l)$ is then approximated by the mean elevation in cell z, where $l = z/2113$, but here normalized so that $h(1) = 50$.

For each z (and approximated l), we approximate $r(l,d)$ at $l = z/2113$ by $h(z/2113)/h([z+30]/2113)$; cf. (10). This implies a value of d of $30/2113 \approx 0.014$.

Other parameter values are set as follows: $a = .0001$, $\alpha = 1$, $\gamma = \beta = b = 2$, and $N = 6$.

We then choose a sequence of 50 values for Z on $[0.3, 1]$. For each Z, we compute location of the $N-1$ borders, using the following algorithm:

1. For the first (lowest) value for Z find τ_i (i.e., the uphill boundary of country i) as follows:

   (a) Given τ_{i-1}, and the value chosen value for Z (and the values for other parameters), let Matlab find optimal τ_i by searching across the 2113 cells and select the $\tau_i = z/2113$ that maximizes $\pi_i = R_i - C_i$. (Note that $\tau_1 = 0$ is given.)

   (b) Given τ_i determined under (a), find τ_{i+1}. Then iterate on Step (a) until $i = N-1$.

2. Choose the next value for Z and iterate on Step 1.

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Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Observations**
Border dummy 1500	0.179	0.384	0	1	5202
Border dummy 1600	0.145	0.352	0	1	5202
Border dummy 1700	0.146	0.353	0	1	5202
Border dummy 1800	0.101	0.301	0	1	5202
Border dummy 1900	0.087	0.283	0	1	5202
Border dummy 2000	0.156	0.363	0	1	5202
Current border dummy	0.166	0.372	0	1	5202
Language border dummy	0.374	0.484	0	1	5202
Mountain dummy ($>$ 2000m)	0.019	0.136	0	1	5202
Mountain dummy ($>$ 1000m)	0.116	0.32	0	1	5202
Log elevation	5.484	1.084	0	7.906	5202
Log ruggedness	4.113	1.287	0	7.073	5202
Big river dummy	0.246	0.431	0	1	5202
Small river dummy	0.681	0.466	0	1	5202
Agric. suitability (irrigated)	0.708	0.203	0	1	4275
Agric. suitability (rainfed)	0.550	0.230	0	1	4856
Log distance to coast	0.037	0.040	0	0.225	5202
Europe dummy	0.564	0.496	0	1	5202

Table 1: Summary statistics.

Variables	Border 1500	Border 1600	Border 1700	Border 1800	Border 1900	Border 2000	Current border
Border dummy 1600	0.500	1.000					
	(0.000)						
Border dummy 1700	0.539	0.631	1.000				
	(0.000)	(0.000)					
Border dummy 1800	0.420	0.397	0.581	1.000			
	(0.000)	(0.000)	(0.000)				
Border dummy 1900	0.230	0.224	0.342	0.385	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)			
Border dummy 2000	0.228	0.216	0.290	0.303	0.459	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Current border dummy	0.214	0.201	0.270	0.287	0.432	0.915	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Language border dummy	0.080	0.107	0.120	0.099	0.227	0.509	0.526
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2: Correlation coefficients across 5202 cells for the different border dummies, with p-values in parentheses.

Variables	Border 1500-2000	Mountain ($>$ 2000m)	Mountain ($>$ 1000m)	Log elevation	Log ruggedness	Big river	Small river	Agric. suit. (rainfed)	Agric. suit. (irrigated)
Mountain ($>$ 2000m)	0.085	1.000							
	(0.000)								
Mountain ($>$ 1000m)	0.086	0.382	1.000						
	(0.000)	(0.000)							
Log elevation	0.119	0.284	0.613	1.000					
	(0.000)	(0.000)	(0.000)						
Log ruggedness	0.145	0.204	0.474	0.812	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)					
Big river	0.162	-0.020	-0.010	-0.001	-0.019	1.000			
	(0.000)	(0.146)	(0.491)	(0.923)	(0.181)				
Small river	0.245	0.074	0.156	0.277	0.303	0.106	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Agric. suit. (rainfed)	0.045	-0.095	-0.154	-0.057	-0.185	0.088	0.100	1.000	
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Agric. suit. (irrig.)	-0.036	-0.034	-0.009	0.072	-0.019	0.047	0.073	0.688	1.000
	(0.018)	(0.026)	(0.555)	(0.000)	(0.204)	(0.002)	(0.000)	(0.000)	
Log dist. to coast	-0.074	0.031	0.008	0.053	-0.251	0.072	-0.106	0.290	0.178
	(0.000)	(0.027)	(0.557)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3: Pairwise correlation coefficients across cells for the border index 1500-2000 (B_i) and some of the more important geography variables, with p-values in parentheses.

	Dependent variable: Fraction borders 1500-2000								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mountain dummy (> 2000m)	0.148***			0.100***	0.100***	0.101***	0.073**	0.081**	0.100***
	(4.516)			(3.061)	(3.114)	(3.145)	(2.065)	(2.344)	(2.857)
Mountain dummy (> 1000m)		0.064***							
		(5.292)							
Log ruggedness			0.027***	0.025***	0.014***	0.016***	0.011***	0.017***	0.015***
			(9.848)	(9.021)	(5.038)	(5.440)	(3.692)	(5.202)	(4.287)
Big river dummy					0.079***	0.078***	0.074***	0.072***	0.075***
					(9.493)	(9.143)	(8.593)	(8.431)	(8.834)
Small river dummy					0.103***	0.096***	0.102***	0.095***	0.090***
					(18.828)	(15.584)	(15.868)	(14.443)	(13.806)
Agric. suitability (rainfed)						0.038***		0.152***	0.184***
						(2.859)		(7.800)	(8.939)
Agric. suitability (irrigated)							−0.064***	−0.179***	−0.185***
							(−3.364)	(−7.106)	(−7.264)
Log distance to coast									−0.571***
									(−6.950)
R^2	0.01	0.01	0.02	0.02	0.09	0.08	0.07	0.08	0.09
Observations	5202	5202	5202	5202	5202	4856	4275	4275	4275

Table 4: Ordinary least squares regressions with robust standard errors. The dependent variable is the fraction years 1500-2000 that the cell had a border (B_i). t statistics in parentheses; * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Dep. var.: Fraction borders 1500-2000			
	(1)	(2)	(3)	(4)
Fraction borders in eight neighb. cells		1.004***		1.000***
		(57.525)		(52.421)
Mountain dummy (> 2000m)	0.100***	0.033	0.100***	0.015
	(3.114)	(1.614)	(2.857)	(0.705)
Log ruggedness	0.014***	0.004**	0.015***	0.004*
	(5.038)	(2.263)	(4.287)	(1.669)
Big river dummy	0.079***	0.018***	0.075***	0.019***
	(9.493)	(3.438)	(8.834)	(3.391)
Small river dummy	0.103***	0.000	0.090***	−0.000
	(18.828)	(0.126)	(13.806)	(−0.064)
Agric. suitability (rainfed)			0.184***	0.030**
			(8.939)	(2.041)
Agric. suitability (irrigated)			−0.185***	−0.035**
			(−7.264)	(−2.164)
Log distance to coast			−0.571***	−0.141**
			(−6.950)	(−2.439)
R^2	0.09	0.60	0.09	0.58
Observations	5202	5202	4275	4275

Table 5: Ordinary least squares regressions with robust standard errors. The dependent variable is the fraction years 1500-2000 that the cell had a border (B_i). The fraction borders in neighboring cells is the variable $\overline{B}_{-i}$ in the text. t statistics in parentheses; * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Dependent variable: Fraction borders 1500-2000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Europe dummy	0.129***	0.110***	0.110***	0.120***	0.001	−0.000	0.001	−0.003
	(21.854)	(18.689)	(17.086)	(14.998)	(0.341)	(−0.106)	(0.095)	(−0.579)
Mountain dummy (> 2000m)		0.157***	0.136***	0.133***			0.015	0.021
		(5.158)	(4.130)	(4.037)			(0.709)	(0.808)
Log ruggedness		0.015***	0.018***	0.019***			0.004*	0.006**
		(5.584)	(5.580)	(5.685)			(1.664)	(2.270)
Big river dummy		0.077***	0.072***	0.070***			0.019***	0.014**
		(9.614)	(8.664)	(8.493)			(3.382)	(2.361)
Small river dummy		0.063***	0.057***	0.056***			−0.000	0.001
		(11.610)	(8.816)	(8.594)			(−0.083)	(0.134)
Agric. suitability (rainfed)			0.130***	0.114***			0.029**	0.043***
			(6.761)	(5.469)			(1.973)	(2.630)
Agric. suitability (irrigated)			−0.149***	−0.145***			−0.035**	−0.049***
			(−6.053)	(−5.858)			(−2.164)	(−2.798)
Log distance to coast				0.246**			−0.138*	−0.214***
				(2.440)			(−1.959)	(−2.787)
Fra. borders in 8 nb cells					1.017***		1.000***	
					(57.645)		(52.043)	
Fra. borders in 24 nb cells						1.048***		1.028***
						(50.245)		(46.295)
R^2	0.07	0.13	0.12	0.12	0.59	0.52	0.58	0.50
Observations	5202	5202	4275	4275	5202	5202	4275	4275

Table 6: Ordinary least squares regressions with robust standard errors. The dependent variable is the fraction years 1500-2000 that the cell had a border (B_i). The fraction borders in neighboring cells is the variable $\overline{B}_{-i}$ in the text. The Europe dummy (E_i) is an indicator variable for the region north of Gibraltar and west of Odessa. t statistics in parentheses; * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Dependent variable: Border dummies for different years (or current/language)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1500	1600	1700	1800	1900	2000	Current	Language
Mountain dummy ($>$ 2000m)	0.174	0.494**	0.287	0.990***	0.249	1.097***	1.035***	1.265***
	(0.753)	(2.042)	(1.124)	(4.155)	(0.920)	(5.120)	(4.803)	(5.442)
Log ruggedness	0.149***	0.040	0.050	0.123***	0.318***	0.137***	0.099***	0.123***
	(4.679)	(1.182)	(1.430)	(2.932)	(6.835)	(3.908)	(2.850)	(5.011)
Big river dummy	0.566***	0.506***	0.679***	0.700***	0.753***	0.602***	0.520***	0.207***
	(7.060)	(5.903)	(8.019)	(7.082)	(7.300)	(7.174)	(6.343)	(3.111)
Small river dummy	1.276***	1.510***	1.229***	1.581***	0.928***	0.836***	0.785***	0.116*
	(11.468)	(11.910)	(10.530)	(9.707)	(6.423)	(8.068)	(7.957)	(1.769)
Pseudo R^2	0.06	0.06	0.06	0.08	0.07	0.05	0.04	0.01
Observations	5202	5202	5202	5202	5202	5202	5202	5202

Table 7: Logistic regressions with robust standard errors. The dependent variable is an indicator variable for the presence of a border in the cell in the given year, or whether the cell had a current or language border ($b_{i,t}$). t statistics in parentheses; * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Dependent variable: Border dummies for different years (or current/language)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1500	1600	1700	1800	1900	2000	Current	Language
Mountain dummy (> 2000m)	−0.070	0.877***	0.707**	1.122***	0.585*	0.894***	0.795***	1.112***
	(−0.227)	(3.015)	(2.216)	(3.897)	(1.916)	(3.546)	(3.179)	(4.349)
Log ruggedness	0.130***	0.042	0.017	0.094*	0.307***	0.186***	0.153***	0.192***
	(3.592)	(1.058)	(0.430)	(1.916)	(5.551)	(4.431)	(3.709)	(6.430)
Big river dummy	0.527***	0.486***	0.690***	0.682***	0.735***	0.539***	0.473***	0.219***
	(6.150)	(5.237)	(7.509)	(6.422)	(6.719)	(6.117)	(5.464)	(3.076)
Small river dummy	0.929***	1.373***	0.985***	1.403***	0.920***	0.768***	0.770***	0.124
	(7.655)	(9.174)	(7.498)	(7.529)	(5.389)	(6.313)	(6.449)	(1.568)
Agric. suitability (rainfed)	2.015***	2.409***	2.350***	1.213***	1.144***	1.561***	1.175***	0.504**
	(7.275)	(7.757)	(7.347)	(3.200)	(2.671)	(4.717)	(3.666)	(2.306)
Agric. suitability (irrigated)	−1.809***	−2.411***	−2.333***	−1.386***	−1.102***	−1.158***	−1.022***	−0.816***
	(−6.380)	(−7.562)	(−7.104)	(−3.698)	(−2.822)	(−3.736)	(−3.396)	(−3.659)
Log distance to coast	−7.664***	−6.539***	−11.104***	−3.812***	−4.009**	0.004	1.500	4.725***
	(−6.183)	(−4.867)	(−8.327)	(−2.576)	(−2.350)	(0.004)	(1.277)	(4.981)
Pseudo R^2	0.06	0.07	0.07	0.06	0.06	0.04	0.04	0.02
Observations	4275	4275	4275	4275	4275	4275	4275	4275

Table 8: The same logistic regressions as in Table 7, but with more controls.

	Dependent variable: Border dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Century × mountain> 1000 m	0.132***							
	(2.973)							
Century × mountain> 2000 m		0.262***					0.267**	0.368**
		(3.061)					(2.190)	(2.476)
Century × agric. suitability (rainfed)			−0.285**				−0.350***	−0.620***
			(−2.394)				(−2.837)	(−3.203)
Century × agric. suitability (irrigated)			0.488***				0.481***	0.684***
			(3.494)				(3.495)	(3.416)
Century × log distance to coast				3.081***			2.797***	1.645**
				(6.045)			(4.921)	(2.002)
Century × small river					−0.137***		−0.089**	−0.064
					(−3.537)		(−2.025)	(−0.986)
Century × big river						0.017	0.049	0.132***
						(0.516)	(1.363)	(2.673)
Pseudo R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.09
Observations	10416	10416	9084	10416	10416	10416	9084	6495

Table 9: Logistic regression with year (century) and cell fixed effects (coefficient estimates not reported here). The variable Century increases from 1 to 6 between 1500 and 2000 and is interacted with different geography variables to examine which ones of these become more important determinants of borders over time. Column (8) drops the year 2000. t statistics in parentheses; * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.