C The model

C.1 Illustrations

Figure C.1 provides an illustration of how Y^* varies with $N = 1/s$ for the same numerical example as in Figure 2 in the paper.

Figure C.2 shows how location specific productivity varies across space and how it changes as territories shift. The numerical example is the same as in Figure 2 in the paper, except that $N = 4$ and $\varepsilon = 0.2$. This means that 20% of the locations belong to different states when territories shift between the left and right position. When territories are in the left position, the state territories are as follows: for state 1: $(0, 0.2) \cup (0.95, 1)$; for state 2: $(0.2, 0.45)$; for state 3: $(0.45, 0.7)$; for state 4: $(0.7, 0.95)$. The associated border locations are located at 0.2, 0.45. 0.7, and 0.95. The capitals are located at 0.125, 0.375, 0.625, and 0.875, for states 1 to 4, respectively.

To illustrate how Proposition 4 works, consider the border at 0.2 when territories are in the left position. The productivity levels are 0.65 and 0.85 on the different sides of the border; the higher productivity is in state 1, i.e., on the side of the border that is closest to the capital. When territories shift to the right position the productivity level is 0.85, since the location is now in the interior of state 1, the state whose capital the location is closest to.

C.2 Other ways to model spatial resource allocation

This section considers a version of the model where the elite allocate resources non-uniformly across the state's territory. To economize on notation, we here set $\varepsilon = 0$, meaning borders are assumed to be stable. However, nothing changes qualitatively if we assume $\varepsilon > 0$, only that γ is replaced by $\gamma(1 + \varepsilon^2)$.

The major change compared to the setup in the paper is that resources are dependent on location, and now denoted by $\widetilde{R}_{i,t}(d)$, where d denotes distance to the center, and i and t index country and period. Output at distance d from the center is denoted $\widetilde{Y}_{i,t}(d)$, and now given by

$$\widetilde{Y}_{i,t}(d) = \left[\widetilde{Z}(d)A_{i,t}\right]^{\alpha}\left[\widetilde{R}_{i,t}(d)\right]^{1-\alpha}, \tag{C.1}$$

where $A_{i,t}$ is country i's provision of a public good, located at the center of a country, which here benefits locations at distance d from the center by a factor $\widetilde{Z}(d)$, given by (2) in the paper. As in the paper, $A_{i,t}$ could represent country i's level of technology.

In each period, the elite first allocate the resources under their control to maximize total output. Denoting their total amount of resources by $R_{i,t}^{tot}$, the elite thus maximize

$2\int_0^{s/2}\widetilde{Y}_{i,t}(x)dx$, subject to $2\int_0^{s/2}\widetilde{R}_{i,t}(x)dx = R_{i,t}^{tot}$, taking $R_{i,t}^{tot}$ as given. Somewhat informally, ignoring that the control variable is continuous, the Lagrangian associated with this maximization problem can be written as $\mathcal{L} = 2\int_0^{s/2}\widetilde{Y}_{i,t}(x)dx + \Omega\left[R_{i,t}^{tot} - 2\int_0^{s/2}\widetilde{R}_{i,t}(x)dx\right]$, where Ω is the Lagrangian multiplier. The first-order condition can be written as

$$\frac{\partial \widetilde{Y}_{i,t}(d)}{\partial \widetilde{R}_{i,t}(d)} = (1-\alpha)\left[\widetilde{Z}(d)A_{i,t}\right]^{\alpha}\left[\widetilde{R}_{i,t}(d)\right]^{-\alpha} = \Omega, \tag{C.2}$$

for all $d \in [0, s/2]$, which states that the marginal productivity of resources is equalized across locations.

Using (C.2), we can write resources at each location as $\widetilde{R}_{i,t}(d) = ([1-\alpha]/\Omega)^{\frac{1}{\alpha}}\widetilde{Z}(d)A_{i,t}$. Using the budget constraint for resources gives

$$2\int_0^{s/2}\widetilde{R}_{i,t}(x)dx = 2\left(\frac{1-\alpha}{\Omega}\right)^{\frac{1}{\alpha}}A_{i,t}\left[\int_0^{s/2}\widetilde{Z}(x)dx\right] = R_{i,t}^{tot}. \tag{C.3}$$

Recall from (2) in the paper that $\widetilde{Z}(d) = 1-4\gamma d$, which implies that $\int_0^{s/2}\widetilde{Z}(x)dx = (s/2)(1-\gamma s)$. Inserted into (C.3), this gives

$$\left(\frac{1-\alpha}{\Omega}\right)^{\frac{1}{\alpha}} = \frac{R_{i,t}^{tot}}{A_{i,t}s(1-\gamma s)}, \tag{C.4}$$

which can be inserted into (C.2) to give resources per location as

$$\widetilde{R}_{i,t}(d) = \left(\frac{1-\alpha}{\Omega}\right)^{\frac{1}{\alpha}}\widetilde{Z}(d)A_{i,t} = \frac{R_{i,t}^{tot}}{s}\frac{\widetilde{Z}(d)}{1-\gamma s}. \tag{C.5}$$

Intuitively, resources allocated to locations at distance d from the center, relative to the average resources across the country, are proportional to each location's productivity, relative to the average productivity of the country. Substituting (C.5) into the production function in (C.1) shows that

$$\widetilde{Y}_{i,t}(d) = \widetilde{Z}(d)\left(\frac{1}{1-\gamma s}\right)^{1-\alpha}A_{i,t}^{\alpha}\left(\frac{R_{i,t}^{tot}}{s}\right)^{1-\alpha}. \tag{C.6}$$

Again using $\int_0^{s/2}\widetilde{Z}(x)dx = (s/2)(1-\gamma s)$, and recalling that average output per location equals $(2/s)\int_0^{s/2}\widetilde{Y}_{i,t}(d)dx = Y_{i,t}$, we get

$$Y_{i,t} = (1-\gamma s)\left(\frac{1}{1-\gamma s}\right)^{1-\alpha}A_{i,t}^{\alpha}\left(\frac{R_{i,t}^{tot}}{s}\right)^{1-\alpha} = (1-\gamma s)^{\alpha}A_{i,t}^{\alpha}\left(\frac{R_{i,t}^{tot}}{s}\right)^{1-\alpha}. \tag{C.7}$$

Finally, we can set total resources to $R_{i,t}^{tot} = sR_{i,t}$, where $R_{i,t}$ denotes resources per location, as given by (4) in the paper. This produces the same expression for $Y_{i,t}$ as in (3) in the paper, with $\varepsilon = 0$, except that the factor $1-\gamma s$ is now replaced by $(1-\gamma s)^{\alpha}$.

C.3 When do fragmented regions having higher output than unified?

Proposition 1 in the paper states that the model is ambiguous as to whether more fragmented regions have higher or lower output per area than less fragmented ones. Here we try to say something about when each case prevails. We do this by comparing a fully unified region to one with two states, and pin down parametric conditions under which the former or latter has higher output. We restrict attention to the case when $\varepsilon = 0$, since the concept of unstable borders ($\varepsilon > 0$) has no meaning in a fully unified region.

For ease of exposition, first let

$$Q = \left(\frac{1}{2}\right)^{\frac{1+\alpha}{\alpha}} \left(\frac{2-\gamma}{1-\gamma}\right)^{\frac{1}{\alpha}}, \tag{C.8}$$

which is increasing in γ. Intuitively, a high Q is associated with a high cost of distance (a high γ). It can be seen that $Q \geq 1/2$, since $\gamma \geq 0$. We can now state the following:

Proposition C.1 *Suppose $\varepsilon = 0$, and consider two regions, one fully unified ($s = 1$) and one with two states ($s = 1/2$).*
(a) If $Q \geq 1$, then steady-state output per location (Y^*) is always (weakly) higher in the fragmented region.
(b) If $Q \leq \left(\frac{\alpha}{1+\alpha}\right)\left(\frac{2-\beta+\alpha\beta}{1-\beta+\alpha\beta}\right)$, then steady-state output per location (Y^*) is always (weakly) higher in the unified region.
(c) If $\left(\frac{\alpha}{1+\alpha}\right)\left(\frac{2-\beta+\alpha\beta}{1-\beta+\alpha\beta}\right) < Q < 1$, then steady-state output per location (Y^*) is (weakly) higher in the fragmented region if, and only if,

$$\lambda \geq \frac{2\alpha}{1-\alpha}\left[\frac{(1-Q)(1-\beta+\alpha\beta)}{Q(1-\beta+\alpha\beta)-\alpha\beta}\right]. \tag{C.9}$$

Proof: First rewrite (11) in the paper, with $\varepsilon = 0$, as

$$Y^* = \left[s^\alpha\left(1-\gamma s\right)\right]^{\frac{1}{1-\alpha}} \left[\frac{\tau\beta F(s,\lambda)}{1-\beta+\beta F(s,\lambda)}\right]^{\frac{\alpha}{1-\alpha}} \overline{R} \equiv \widehat{Y}(s). \tag{C.10}$$

The task is to find conditions under which $\widehat{Y}(\frac{1}{2}) \gtreqless \widehat{Y}(1)$. Using (C.10), and the expression for $F(s,\lambda)$ in (9) in the paper, gives

$$\begin{aligned}
\frac{\widehat{Y}(\frac{1}{2})}{\widehat{Y}(1)} &= \left\{\left[\frac{\left(\frac{1}{2}\right)^{1+\alpha}(2-\gamma)}{1-\gamma}\right]\left[\left(\frac{1-\beta+\beta F(1,\lambda)}{\beta F(1,\lambda)}\right)\left(\frac{\beta F(1/2,\lambda)}{1-\beta+\beta F(1/2,\lambda)}\right)\right]^{\alpha}\right\}^{\frac{1}{1-\alpha}} \\
&= \left\{\left[\left(\frac{1}{2}\right)^{1+\alpha}\left(\frac{2-\gamma}{1-\gamma}\right)\right]^{\frac{1}{\alpha}}\left(\frac{1-\beta+\beta\alpha}{\beta\alpha}\right)\left(\frac{\beta[\alpha+(1-\alpha)\lambda/2]}{1-\beta+\beta[\alpha+(1-\alpha)\lambda/2]}\right)\right\}^{\frac{\alpha}{1-\alpha}} \\
&= \left\{Q\left(\frac{1-\beta+\beta\alpha}{\beta\alpha}\right)H(\lambda)\right\}^{\frac{\alpha}{1-\alpha}},
\end{aligned} \tag{C.11}$$

where we have used the definition of Q in (C.8), and where we let

$$H(\lambda) = \frac{\beta\left[\alpha + (1-\alpha)\lambda/2\right]}{1-\beta+\beta\left[\alpha+(1-\alpha)\lambda/2\right]}. \tag{C.12}$$

Note that $H'(\lambda) > 0$, and recall that $\lambda \in [0,1]$. Then some algebra demonstrates that

$$\begin{aligned} H(0) &= \frac{\alpha\beta}{1-\beta+\beta\alpha}, \\ H(1) &= \frac{\beta\left(\frac{1+\alpha}{2}\right)}{1-\beta+\beta\left(\frac{1+\alpha}{2}\right)} = \frac{\beta(1+\alpha)}{2-\beta+\alpha\beta}. \end{aligned} \tag{C.13}$$

We can now show the following:

If $Q \geq 1$, then $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1) \geq 1$ always holds. To see this, use (C.11) and (C.13) to note that it holds even when $\lambda = 0$, and since $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1)$ is increasing in λ, this proves part (a) of the proposition.

If $Q \leq \left(\frac{\alpha}{1+\alpha}\right)\left(\frac{2-\beta+\alpha\beta}{1-\beta+\alpha\beta}\right)$, then $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1) \leq 1$ always holds. To see this, use (C.13), and some algebra, to note that the given condition on Q is equivalent to $Q\left(\frac{1-\beta+\beta\alpha}{\alpha\beta}\right)H(1) \leq 1$, which implies that $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1) \leq 1$ holds even when $\lambda = 1$; then recall again that $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1)$ is increasing in λ, so it must hold also for $\lambda < 1$. This proves part (b) of the proposition.

Finally, if $Q \in \left(\left(\frac{\alpha}{1+\alpha}\right)\left(\frac{2-\beta+\alpha\beta}{1-\beta+\alpha\beta}\right), 1\right)$, then $\widehat{Y}(\frac{1}{2})/\widehat{Y}(1) \geq 1$ holds if, and only if,

$$Q\left(\frac{1-\beta+\beta\alpha}{\alpha\beta}\right)H(\lambda) \geq 1. \tag{C.14}$$

Using (C.12), some algebra shows that this inequality can be written as in (C.9). This proves part (c) of the proposition. Q.E.D.

Proposition C.1 is illustrated in Figure C.3. Part (a) describes the case when the cost of distance is so high that fragmented regions are always richer, even without technology-inducing resource competition ($\lambda = 0$). Part (b) describes the case when the cost of distance is so low that fragmented regions are always poorer, even with maximum resource competition ($\lambda = 1$). Part (c) describes the case with intermediate costs of distance. Then the fragmented region is richer if λ is large enough.

D Descriptive statistics

D.1 State coverage

Section 3 in the paper provided some motivation of the choice of period over which we measure borders, i.e., 1500-2000. We noted, among other things, that the spatial coverage shrinks as we go back in time. The reason is that we restrict attention to cells with at least one state present throughout the period over which we measure border presence. For example, the 5202 cells in our benchmark sample are covered by statehood at each turn of the century from 1500 to 2000.

Figure D.1 shows the change over time in the fraction cells covered by states among all land cells in our data (i.e., cells that could potentially be covered by statehood) starting at different turns of centuries from 800 to 2000. By 2000, almost all land cells (99.5%) are covered by states, according to the Euratlas maps. The fraction cells covered by a state from 1500 and on is about 61%, and the corresponding fraction starting in 800 is 38%.

In the paper we consider border frequency 1300-1800 as an alternative to our benchmark border frequency measure. One reason for this choice of alternative starting point can be understood from Figure D.1. There it can be seen that the fraction cells with statehood makes a relatively large drop from 60% to 53% when starting in 1200 instead of 1300.

D.2 Cross-correlations between different border variables

Table D.1 presents cross-correlations between each of the six Euratlas border dummies ($b_{i,t}$) and border frequency 1500-2000 (B_i).

We also construct two other border dummies based on other sources than Euratlas. The first of these we call the current border dummy, which is based on maps from the Global Administrative Areas (www.gadm.org). These are supposed to show contemporary state borders. We do not know to which specific point in time that these refer, but the GADM Version 2 data that we use were posted in January 2012.[1] The other dummy variable is one for language borders constructed from the World Language Mapping System (www.worldgeodatasets.com/language).

All border dummies in Table D.1 show highly significant and large positive correlations with border frequency. The border dummy for 2000 has the lowest correlation with border frequency, but even that coefficient is as high as 0.599. The border dummies also show positive correlation with each other, typically larger between closer years, suggesting that borders are not stationary but change gradually over time. Despite the rise and fall of several states and empires over these centuries, the locations of the borders between them are thus quite persistent. This is consistent with a theory where some underlying constant factor, such as geography, ultimately determines border locations.

Table D.1 also shows a very high correlation coefficient (0.934) between the Euratlas border dummy for 2000 and the current border dummy, which also speaks to the reliability of the Euratlas data.

The language border dummy shows the highest correlation with the Euratlas dummy for 2000 (a correlation coefficient of 0.510) and the current border dummy (0.531). It thus seems

[1] We also adjust the GADM data to let the Channel Islands belong to Great Britain and Åland belong to Finland. While these have some degree of autonomy it is hard to categorize them as sovereign states.

that state formation today follows ethnic lines more closely than in preindustrial times. This may reflect the spread of democracy, making it easier for ethnic minorities living in a well defined territory to secede and form their own states (see, e.g., Alesina and Spolaore 2003). It could also be due to genocide, ethnic cleansing, and policies by state governments that make ethnic and linguistic minorities comply with the state's majority identity, as well as more voluntary forms of migration.

D.3 Cross-correlations between different measures of historical population densities

Table D.2 shows the pairwise correlation coefficients between different measures of historical and current population densities. The benchmark measure used in the paper is here denoted LPD-GPW. This is the log of one plus the population density in a cell, where the population measure comes form the Gridded Population of the World (averaged over the period 2000-2015), and land area from Natural Earth (see Section B of the appendix to the paper for more details).

The other measures of population density refer to different historical years, and are calculated following the same principles using data on historical populations from HYDE, a source that we discuss more in Section I below. The measures from HYDE are here denoted LPD-HYDE and refer to the years 1500, 1800, and 2000, respectively. The number of cells with data from both the GPW and HYDE is 5150, i.e., most of the cells in our benchmark sample of 5201 cells with data from GPW.

The main insight from Table D.2 is that population levels today and in preindustrial times show high positive correlation. Log population densities in 2000 and 1800 from HYDE have a correlation coefficient of 0.835, and the correlation between the HYDE measure for 1800 and our modern benchmark measure from GPW is 0.731. This illustrates that modern and historic population densities measure roughly the same thing. That is, spatial variation in modern population densities across this area was in large part determined several centuries ago. This is hardly surprising, since cities are located in roughly the same places today as they were several centuries ago.

Since the modern-day measure from the GPW presumably comes with less measurement error than those from HYDE, is also used in many other studies, and has slightly larger spatial coverage, we utilize this in our benchmark regressions in the paper.

D.4 Cross-correlations between different measures of modern outcomes

Table D.3 shows the unconditional correlation coefficients between border frequency (B_i) and various measures of modern outcomes. Log night lights and log population density are the main variables used in the paper; recall that log night lights is measured per unit of land area. For further details on sources and definitions of these, see Section B of the appendix to the paper.

Log night lights per capita is constructed from the same sources by first dividing total night lights by total population in each cell, to get night lights per capita. What we here call log night lights per capita equals the log of one plus night lights per capita.

GDP data are from Kummu et al. (2018) and provide GDP estimates at the level of 30 arc-second resolution. From these we construct two variables. The first we call log of GDP per area. This is constructed by first computing the mean GDP across pixels in a cell for the years 2000 and 2015, and then taking the log of one plus the average GDP across the two years.

The other variable is log GDP per capita. This is constructed by dividing total GDP with population by cell and by relevant years (2000 and 2015), where the population data come from the Gridded Population of the World (the same used to calculate population density). Log GDP per capita is then defined as the log of one plus average GDP per capita across the two years.

The Kummu et al. (2018) data rely on interpolations from regional National Accounts data, and are not commonly used in the literature (perhaps because they are relatively recent). Therefore, we have chosen not to include these in the benchmark analysis in the paper. The purpose of this section is mainly to assess what our benchmark measures might capture. We first note from Table D.3 that both log night lights and log population density show positive and significant correlations with log GDP per capita, with coefficients of 0.464 and 0.148, respectively. As argued in the paper, this seems to reflect that per-capita incomes are higher in cities.

More importantly, log GDP per capita shows higher correlation with log night lights per land area (our chosen benchmark measure) than with log night lights per capita, with correlation coefficients of 0.464 and 0.092, respectively. This speaks against using night lights per capita as a measure of living standards.

E Geography variables

E.1 Motivation and interpretation of geography variables

Table E.1 tries to provide an overview of the different geography variables we have chosen for our benchmark specification, and what motivates these choices. The categories are the same as in the paper, although not all geography factors are mutually exclusive.

E.2 Elevation and ruggedness

We have considered various measures of how mountainous a territory is. Our benchmark measures have been log ruggedness (i.e., the log of the standard deviation in elevation), and two so-called mountain dummies, indicating if the average elevation of a cell exceeds 1000 and 2000 meters, respectively.

An alternative measure is the log mean elevation of a cell, which we explore in this section. When constructing this variable, in order not to drop cells with negative elevation (73 cells in total among the 5202 in our benchmark sample), we use elevation exceeding 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 close to the Caspian Sea), then log elevation is constructed as $\ln(1 + x_i - \widehat{x})$, which equals zero for the cell with the lowest elevation.

Table E.2 shows that both log elevation and log ruggedness show positive and significant pairwise correlations with border frequency, and also high correlation with each other. The two thus seem to capture similar channels through which a mountainous terrain might cause state fragmentation. This makes sense, since areas at high elevation also have cliffs and steep slopes and thus high variation in elevation.

We also computed an alternative measure of ruggedness, following the formula used by Nunn and Puga (2012). This is essentially designed to measure the ability for human and other prey to hide. A very rough description of how it is constructed runs as follows. Starting with a grid of raster points at which elevation is measured, let $e_{r,c}$ be elevation at a raster point located in column c and row r of that grid. The Nunn-Puga measure of ruggedness at that raster point is then defined as

$$\sqrt{\sum_{i=r-1}^{r+1} \sum_{j=c-1}^{c+1} (e_{i,j} - e_{r,c})^2},$$

which can then be averaged across all raster points in a cell (in our case), or a country (as in Nunn and Puga 2012).

As shown in Table E.2, the log of one plus the Nunn-Puga ruggedness measure has a correlation of 0.928 with our benchmark measure. They thus essentially capture the same thing.

Columns (1)-(3) of Table E.3 consider some regression specifications where we use different combinations of these variables. Column (1) of Table E.3 replicates column (10) in Table 2 in the paper. Column (2) enters log elevation in lieu of the 2000 meter mountain dummy, and column (3) drops log ruggedness. Log elevation has a relatively high positive unconditional correlation with border frequency in Table E.2, and in column (3) of Table E.3, where it is the only variable capturing mountainousness. However, the coefficient on log elevation comes out with a negative and significant sign when entered together with log ruggedness in column (2).

As discussed, the reason is that log elevation is highly correlated with log ruggedness, which gives rise to multicollinearity, and likely explains the negative sign on the log elevation coefficient. This is why we choose not to enter both. By contrast, the 2000-meter mountain dummy and log ruggedness both come out as positive and significant in many (if not all) specifications, e.g., in column (1) of Table E.3.

Columns (4)-(5) of Table E.3 are identical to columns (1)-(2), but replace our benchmark measures of ruggedness with the one based on the Nunn-Puga method. The results are virtually identical, which is not surprising given the high correlation between the two measures.

Columns (6)-(10) of Table E.3 repeat the regressions in columns (1)-(5), but control for latitude; column (6) is identical to column (1) of Table 3 in the paper. As in the paper, we find that log ruggedness now loses significance, which holds also for the Nunn-Puga measure.

E.3 Coal, temperature, and lakes

Table E.4 considers three other geography variables. The coal dummy indicates presence of coal in the cell, as defined by the presence of rock of specific ages in maps provided by the Bundesanstalt für Geowissenschaften und Rohstoffe (BGR) in Hannover, Germany.[2]

Temperature refers to mean annual temperature measured in degrees Celsius averaged over the period 1961-90. The source is GAEZ, which we used also for agricultural suitability and rainfall.

The last variable measures the fraction of the cell's area covered by lakes, based on Natural Earth data, which is the source used also for, e.g., coasts and rivers.

[2] We use the map IGME 5000 from BGR, and the file "age (chronostratigraphic).lyr" in a folder labelled "layer." The coal dummy indicates presence of rocks from the following geological periods: Carboniferous (C), Carboniferous-Permian (C-P), Carboniferous-Middle Permian (C-P2), Early Carboniferous (C1), Late Carboniferous (C2), Late Carboniferous-Permian (C2-P), and Late Carboniferous-Middle Permian (C2-P2).

Consider first columns (1)-(3). Coal and temperature show positive and negative correlations with borders, respectively, both highly significant, while the lake variable comes out as positive and slightly less significant. The same pattern holds when all three are entered together in column (4). However, none of them comes out as significant when controlling for our benchmark set of controls in column (5)-(8).

All specifications in Table E.4 control for latitude, but the results referring to these three variables do not change qualitatively without this control.

E.4 Alternative agricultural suitability variables

Recall that our two benchmark measures of agricultural suitability are based on the four most common grains (wheat, barley, oats, and rye), and refer to potential yields when using rainfed and irrigated agriculture, respectively. Table E.5 examines two alternative measures of agricultural suitability.

Suitability for potato agriculture is constructed from GAEZ, the source used for our benchmark measures, and has been used by Nunn and Qian (2011). The Caloric Suitability Index (CSI) comes from Galor and Özak (2016) and is also partly based on GAEZ, but is a calorie weighted measure of the yield a cell can generate if growing the crop with the highest caloric content. Here we use the definition that considers all crops available after 1500, i.e., in the wake of the Columbian exchange. Both are constructed under the assumption that rainfed agriculture is used.

Columns (1)-(3) of Table E.5 enter the potato measure and CSI, both separately and together, in lieu of the two benchmark agricultural suitability measures, keeping all other benchmark controls unchanged. There is a positive significant effect from CSI on borders, and the potato measure comes out as negative, but significant only when entered together with CSI in column (3).

This pattern holds broadly when including our benchmark measure for suitability for rainfed agriculture as control in columns (4)-(6), and when entering both of our benchmark suitability measures, rainfed and irrigated suitability, in columns (7)-(9).

The two alternative measures are highly correlated with our benchmark measure of suitability for rainfed agriculture: the correlation coefficients are 0.81 and 0.75 for the potato measure and CSI, respectively. They are somewhat less correlated with the irrigated suitability measure, for which the corresponding correlation coefficients are 0.45 and 0.41. Since both the potato measure and CSI are constructed under the assumption that rainfed agriculture is used, this is not too surprising.

Because we want to be able to capture the possibly different effects of suitability for rainfed and irrigated agriculture, and because the potato and CSI measures do not have any irrigation based equivalents, we choose the measures based on the four common grains as our benchmark controls.

One other argument against using the potato measure could be that the four common grains may have been an overall more important source of nutrition than the potato for the region and period that we consider. According to Leff et al. (2004, Table 5), wheat is currently the most commonly grown crop by land area in the region that we consider (Asiatic Russia, Central Asia, Europe, the Middle East, and Northern Africa). The land most suitable for potato cultivation is concentrated in Europe (Nunn and Qian 2011, pp. 611-612).

E.5 Alternatives to river and coast dummies

Table E.6 shows the results when regressing border frequency on the benchmark set of geography controls, but using non-dummy measures of river and coast presence. We consider two alternative measures: river and coastline density, defined as the length of a river or coast line, divided by the cell's land area; and the log of one plus the length of the river or coastline, respectively. (These lengths are measured in kilometers.) Because we control for the log size of the cell's land area, the latter measures correspond approximately to the log of the former.

The dummies used in the paper are indicators of the presence of a river or coast in the cell, so they take the value one when the corresponding density or log length variables are strictly positive, and zero otherwise.

Column (1) is identical to column (10) in Table 2 in the paper. Column (2) uses the density measures, and column (3) the log length measures. Columns (4)-(6) are identical to columns (1)-(3) but control for latitude; column (4) is thus identical column (1) of Table 3 in the paper.

Not too surprisingly, most results are qualitatively similar. The major difference is that coastline density here comes out as positive. This is driven by a strong negative correlation between log land area and coastline density; their pairwise correlation coefficient is -0.75. When not controlling for log land area, the estimated coefficient is negative. In other words, the positive correlation seems to be driven by variation in the denominator in the coastline density measure.

E.6 Alternative transformations of geography variables

There are no clear rules when choosing whether to log a variable, or not, and/or whether to transform it in other ways. One informal rule of thumb might be to log a variable that appears to have a log-normal distribution, since the distribution of its logged cousin is normally distributed. The same argument might apply for any variable that skews to the right. This is roughly the approach taken in our paper. Figure E.1 shows the distribution of ruggedness and rainfall, before and after log transformation. As seen, the distribution of ruggedness is skewed, which is why we choose to log it. The distribution of rainfall is much less skewed, and indeed becomes more skewed when logging it.

Table E.7 explores how our results change using logged instead of non-logged variables, and vice versa. Column (1) reproduces column (1) of Table 3 in the paper; column (2) uses non-logged distances to coast and steppe; column (3) uses non-logged distances and non-logged ruggedness; and column (4) reverts to the benchmark setting, but with logged rainfall. (When logging rainfall we follow the same approach as when logging other variables: we use the log of one plus the deviation of rainfall from the sample minimum.)

The estimated coefficients on all variables carry the same signs as those on their logged or non-logged equivalents, and come out as equally significant, or more significant (in the case of ruggedness). The coefficients on the other variables are largely unchanged, except that the steppe dummy now comes out as less significant.

F Beta coefficients

Table F.1 reports the standardized (or beta) coefficients, for a number of specifications where border frequency is regressed on geography. To simplify the coding, we also report robust but non-Conley adjusted standard errors, but that alteration has no effect on the estimated beta coefficients. Column (1) applies the same specification as in column (10) of Table 2 in the paper, and reproduce the beta coefficient estimates reported in the text in Section 4.1 of the paper. Column (2) is identical to column (1), but uses the 1000 meter (instead of 2000 meter) mountain dummy. Columns (3)-(4) and (5)-(6) use the same specifications as columns (1)-(2), but add controls for latitude, and latitude fixed effects, respectively.

Table F.1 shows that the beta coefficients change size depending on specification, but mostly not by large amounts. The sum of the absolute values of the eleven beta coefficients (except log land area and latitude) is close to one in all specifications. Recall that this sum measures the effect on border frequency when changing all variables together in the direction which raises border frequency.

We also note that the standard errors are much smaller when not applying the Conley (1999) adjustment, as we did in the paper (i.e., when not adjusting for spatial correlation). This is why many coefficients, such as log ruggedness and mountain dummies over 1000 meters, come out as more significant here than in the corresponding specifications in Tables 2 and 3 in the paper.

Table F.2 reports results for various specifications when regressing modern outcomes on border frequency, with beta coefficients (and robust standard errors). All coefficient estimates come out as significant, which they did also in the corresponding specifications with Conley adjusted standard errors. The magnitude of the beta coefficients shrinks when adding more controls. The estimated beta coefficients reported in the text in Section 5.1 of the paper (0.13 and 0.14 for log night lights and log population density, respectively) are confirmed in columns (3) and (7).

G Fixed effects for artificial countries

Tables 4 and 6 in the paper reported results in terms local deviations in dependent and independent variables. This absorbs factors that are relatively constant among neighboring cells. Another approach that achieves roughly the same thing is to enter fixed effects for clusters of cells that are close to each other. Here we use square clusters of (at most) nine cells: one cell in the middle, plus neighboring cells to the south, north, west, east, and in four diagonal directions. (Where neighboring cells are missing there will be fewer than nine cells.) We can think of these clusters as artificial countries.

Obviously, no unobserved characteristic would be distributed exactly in square clusters, and how they are centered will always be somewhat arbitrary. However, they should arguably do a good job absorbing any factor that is *approximately* constant between closely neighboring cells.

Tables G.1 and G.2 present results from regressions identical to those in Tables 3 and 5 in the paper (including controls for latitude or latitude fixed effects as indicated), but with fixed effects for artificial countries of nine neighboring cells. The estimated coefficients are similar to those in Tables 4 and 6 in the paper, where we have used the same specifications but in terms of local deviations. For example, the more spatially clustered geography variables, measuring distances to coast and steppe, come out as less significant both in Table G.1 and Table 4 compared to Table 3.

Notably, the coefficients on border frequency in Table G.2 carry the opposite signs compared to Table 5 in the paper. This is consistent with Proposition 2 in the paper, and also what we would expect to find given the results in Table 6. As discussed, both methods absorb unobserved characteristics among cells that are close to each other.

G.1 What do artificial country fixed effects absorb?

As argued, entering these artificial country fixed effects amounts to the same thing as running regressions in terms of local deviations. The model in the paper explains why we may see different results at the global and local levels when we study effects of borders on modern outcomes.

Here we want to better understand what these fixed effects absorb when we study the effects of geography on borders. To that end, consider a world where cells can be located in one of several artificial countries, or regions, indexed by a. Let $B_{i,a}$ be border frequency in cell i, located in region a, and suppose the true data generating process is

$$B_{i,a} = \alpha + \beta G^1_{i,a} + \eta G^2_a + \chi I_a + \varepsilon_{i,a}, \tag{*}$$

where I_a is some non-geography variable (e.g., institutions or culture) that varies only between regions, and $G^1_{i,a}$ and G^2_a are two geography variables: $G^1_{i,a}$ varies both between and within regions, while G^2_a is a geography variable that varies only between regions. For example, rivers and mountains can be found to some extent in all regions, and might thus be captured by $G^1_{i,a}$. By contrast, G^2_a could represent suitability for rainfed or irrigated agriculture, or distances to steppe or coast, which are very spatially clustered and thus (almost) completely constant within (small) regions.

Suppose we do not have data on I_a. Omitting I_a when estimating (*) could be problematic if I_a is correlated with G^2_a. The OLS estimate of η may then be biased. One way to address this is to enter region fixed effects, i.e., a full set of dummies, one for each region. However, if we estimate (*) with region fixed effects, then we cannot get an estimate of η, since (by assumption) it does not vary within regions. The fixed effects would absorb the variation we are after. We might get a more precise estimate of β, but it would still be wrong to conclude that $\eta = 0$ (i.e., that G^2_a has no effect on $B_{i,a}$).

In other words, entering fixed effects for small regions (such as nine-cell artificial countries) can give the false impression that some geography variables have no effect on borders. These fixed effects may be good at removing any bias when estimating η that is caused by omitting I_a, but they also absorb the effects of G^2_a. This is why we want to be careful when interpreting the estimated coefficients on some geography variables in Table G.1, and in Table 4 in the paper, in particular those that are spatially clustered.

Moreover, we are not necessarily trying to estimate η, since this parameter probably does not capture all the ways in which borders depend on geography. That is, I_a itself should depend on G^2_a, since geography is a primitive, while culture or institutions are endogenous, and presumably depend on geography, directly or indirectly. To make this point, suppose that

$$I_a = \varphi + \pi G^2_a + \xi_a, \tag{**}$$

where φ and π are coefficients and ξ_a is an error term. Using (**), we can write (*) as

$$B_{i,a} = \widetilde{\alpha} + \beta G^1_{i,a} + \widetilde{\eta} G^2_a + \widetilde{\varepsilon}_{i,a}, \tag{***}$$

where $\widetilde{\alpha} = \alpha + \chi\varphi$, $\widetilde{\eta} = \eta + \chi\pi$, and $\widetilde{\varepsilon}_{i,a} = \varepsilon_{i,a} + \chi\xi_a$. Estimating (***) with OLS without region fixed effects would give us an unbiased estimate of $\widetilde{\eta}$, which is what we are really interested in, since this captures *all* the ways in which geography affects borders, including those that work through I_a.

H Fixed effects for modern countries

Tables H.1 and H.2 show the results when we enter fixed effects for existing countries, as defined by modern borders from GADM (see Section D.2 for details). The specifications are otherwise identical to those in Tables 3 and 5 in the paper.

The results when regressing borders on geography in Table H.1 have some similarities with those where we entered artificial country fixed effects in Table G.1, and the local regressions in Table 4 in the paper. Note, e.g., that mountains over 1000 meters come out as more significant than those above 2000 meters. This may not be too surprising, since many countries are relatively small. Within modern countries current and historical borders tend to be located, e.g., by rivers, in rugged terrain, and where it rains.

Table H.2 reports results from regressing modern outcomes on borders. Here we find no significant results. One interpretation is that many of the positive effects through which borders affect development work through institutions and other factors that are relatively constant within modern countries. For example, institutions may depend on the size and shape of modern countries, which is in itself ultimately the outcome of geography. In other words, these modern country fixed effects may be endogenous, and thus not very good controls.

Moreover, as just mentioned, because many modern countries are relatively small, these regressions may partly capture the (negative) local correlations, not only the (positive) global ones. Recall from the model that within countries, the poorest regions tend to be around the borders, while more fragmented regions (i.e., with more countries) can still have better outcomes on average.

I Alternative measures of urbanization

Table 8 in the paper reported results from a series of panel regressions using data from Bosker et al. (2013) on historical urban populations. These data cover eleven turns of centuries from 800 to 1800. In the paper, we consider the period from 1500, since this is when our benchmark border data start. (Section 3 in the paper discusses the choice of benchmark period.)

Tables I.1 and I.2 show the results for the periods 1300-1800 and 800-1800, respectively, in specifications otherwise identical to those in Table 8 in the paper. (Note, however, that the number of cells shrinks to 598 in Table I.2, due to a smaller sample when imposing the restriction of continual statehood present from 800.)

The result are very similar results to Table 8. In particular, the coefficient on the same-century border dummy comes out as negative and significant. That is, cells that lose a border from one century to the next experience a simultaneous rise in urbanization, consistent with Proposition 4 in the paper.

Recall that Bosker et al. (2013) report urban population numbers only for some well documented cities, making us lose much of the sample. Table I.3 instead utilizes data from the History Database of the Global Environment (HYDE), which provides data on historical urban and rural populations with greater spatial coverage (Klein Goldewijk et al., 2010, 2011). We calculate the urbanization rate as urban population over total population, referred to below as the fraction urban for short. While HYDE has greater spatial coverage than Bosker et al. (2013), our understanding is that it interpolates across space to generate more spatial disaggregation. This is why we choose not to use these data in our benchmark regressions in the paper, but they help showing how robust our results are.

The regressions in Table I.3 are based on a panel of 5025 cells from 1500 to 2000; these are the cells with HYDE data available that overlap with our benchmark sample of 5202 cells. (To get a balanced sample, we drop all cells with HYDE data missing for any century, but this has very little impact on the results.) The results in Table I.3 are also close to those in Table 8 in the paper.

J Dropping subsamples of cells

Table J.1 reports results when regressing border frequency on geography and dropping different subsamples. Column (1) replicates column (10) of Table 2 in the paper. Columns (2)-(5) drop coast cells, fully unified cells ($B_i = 0$), fully fragmented cells ($B_i = 1$), and cells in Northern Europe, respectively.[3] Some correlations change compared to the benchmark specification in column (1). For example, when we drop coastal cells in column (2), ruggedness and distance from the coast come out as insignificant, and the steppe dummy as more significant.

Dropping unified cells in column (3) shrinks the sample from 5202 to 1807 cells, rendering most coefficients insignificant, but log ruggedness, the river dummy, and rainfall are still significant, and of the same sign as in the benchmark specification. By contrast, dropping the 70 cells that are fully fragmented in column (4) changes the results very little compared to the benchmark in column (1).

In column (5) we drop cells in Northern Europe, which includes, e.g., Britain and Scan-

[3]Cells in Northern Europe include all cells intersected by the GADM territories of the following contemporary countries: Denmark, Estonia, the Faeroe Islands, Finland (including the Åland Islands), Iceland, Latvia, Lithuania, Norway, Sweden, and Great Britain (including the Channel Islands, Isle of Man, and Northern Ireland). This is based on the UN classification codes for detailed regions, using the STATA command `kountry`. See https://unstats.un.org/unsd/methodology/m49/

dinavia. The major change here is that suitability for rainfed agriculture loses significance. Part of the reason is that this region has below average suitability for any type of agriculture, also rainfed, even though it rains more there; it is also slightly less fragmented than other cells, with fewer city states of the type seen on the continent. However, the change is also due to a positive correlation between borders and suitability for rainfed agriculture *within* Northern Europe, which is lost when dropping this region.

Columns (6)-(10) report the results from the same regressions as in columns (1)-(5), but control for latitude; column (6) thus replicates column (1) of Table 3 in the paper. The differences between column (6) and columns (7)-(10) are qualitatively similar to those between column (1) and columns (2)-(5).

Notably, almost all estimated coefficients that come out as significant when dropping these subsamples carry the same sign as in the corresponding benchmark regression; log distance to coast is a borderline exception in column (7). In other words, the benchmark correlations between geography and borders do not differ qualitatively when dropping any of these particular subsamples.

Table J.2 reports the results when regressing modern outcomes on border frequency. We enter our benchmark set of geography controls in columns (1)-(5), and add latitude controls in columns (6)-(10). Border frequency comes out as positive and significant throughout. When dropping unified cells in columns (3) and (8), the estimated coefficients on border frequency even become larger.

The correlation stays positive and significant also when we drop Northern Europe. This contrasts with the results in Table 5 in the paper, where we saw that the correlation between modern outcomes and border frequency weakened considerably when we dropped Western Europe or the Holy Roman Empire. In other words, these results are not driven by Britain and Scandinavia, but rather continental Europe.

K The Abramson data

Our border variables were computed from the maps compiled by Euratlas (Nüssli 2010). In this section we apply the same procedure to another set of maps used by Abramson (2017). These use as starting point the Centennia Historical Atlas, the original creator of which is Reed (2008). We refer to these as the Abramson data for short.

These data obviously measure something very similar to Euratlas. They also measure borders at a higher temporal frequency than the Euratlas data. On the other hand, they cover a smaller area, and only up to 1790.

Because these data are proprietary we do not use them in our benchmark regressions. Rather, the exercise undertaken here is to compare the results when using the Abramson data for the same, or adjacent, years as those for which we have Euratlas data.

To that end, and because the Abramson data end in 1790, we first compute border frequency across the years 1500, 1600, 1700, and 1790 from the Abramson data. This gives us a border frequency variable defined over a total of 3861 cells overlapping with our benchmark Euratlas data, which we can compare to the corresponding Euratlas border frequency index based on the years 1500, 1600, 1700, and 1800. The two border frequency measures have a correlation coefficient of 0.80 across these 3861 cells.

Table K.1 shows the results when regressing the Abramson and Euratlas border frequency measures on our benchmark set of geography controls. Columns (1)-(3) include latitude controls and columns (4)-(6) latitude fixed effects.

Consider first column (1), which shows the results for the Euratlas 1500-1800 border frequency measure based on all 5202 cells. These are similar to those based on the same source for the years 1500-2000 in column (1) in Table 3 in the paper. Column (2) again uses the Euratlas 1500-1800 measure as the dependent variable, but on a restricted sample of 3861 cells on which the Abramson measure is defined. Distance to coast and the steppe dummy lose significance; the estimated coefficient on log ruggedness comes out as negative but not significant. Column (3) uses the Abramson measure as the dependent variable. The main surprise here is that the negative coefficient on log ruggedness comes out as significant at the 5% level. However, the other coefficients do not change much between columns (2) and (3).

Columns (4)-(6) use identical specifications as columns (1)-(3), but enter a full set of latitude fixed effects instead of latitude controls. Now the coefficient on log ruggedness comes out as positive again, although less significant with the Abramson sample in column (5) compared to the Euratlas sample in column (4). Notably, all estimated coefficients are very similar between columns (5) and (6), i.e., when we keep the sample region constant and only change the border data.

Table K.2 presents the results when regressing modern outcomes on the Abramson and Euratlas border frequency measures, with our benchmark set of geography controls and latitude controls. Both measures of border frequency show positive and significant correlation with both night lights and population density.

The Abramson data are useful for one more exercise. As discussed in the paper, the areas once covered by the Holy Roman Empire exhibit very high levels of border frequency. In short, we can think of the HRE not as an empire, but rather a type of multi-state agreement that in effect prevented actual unification. Table K.3 provides one way to illustrate this. First, we note that border frequency 1500-1800 among cells in the HRE in the Euratlas equals 0.65, while border frequency for cells outside the HRE is just 0.08. To see that this is not an artefact of the Euratlas data, we note that the corresponding numbers using border frequency 1500-1790 from Abramson are 0.69 and 0.09, respectively. That is, these two sources report just about equally large variation in state fragmentation within and outside the HRE.

L Using other measures of modern outcomes

Table L.1 explores regressions using alternative outcome variables. Panels A and B regress log night lights and log population density on border frequency in five different specifications, repeating the first five columns of Table 5 in the paper. Recall that our benchmark log night lights variable refers to night lights per area (i.e., the average across pixels in a cell).

Panels C and D report results using contemporary data on GDP per area and GDP per capita, respectively, using GDP data from Kummu et al. (2018) and population data from GPW. Panel E makes use of population density measured in 1800 based on HYDE. These data sources are discussed in further detail in Sections D.4 and I above, and in Section B of the appendix to the paper.

Columns (1)-(3) confirm that the correlation between border frequency and modern outcomes broadly holds for these alternative outcome variables, although the results for log GDP per capita are somewhat weaker when using latitude fixed effects in column (3). The results are not too sensitive to the choice of outcome variable, but the effects seem larger on population density than livings standards.

Columns (4) and (5) show that the correlation weakens or is reversed when dropping Western Europe, or the HRE. In the case of GDP per capita, the correlation turns negative and highly significant. According to this measure of modern outcomes, state fragmentation has been harmful to development outside Western Europe or the HRE.

Table L.2 runs the same regressions as in Table L.1 but using border frequency 1300-1800 instead of the benchmark 1500-2000 measure, and also redefines the HRE to be based on the period 1300-1800. The results do not change much. However, the effect of borders 1300-1800 on population density in 1800 in Panel E is still positive and significant at the 5% level when we drop Western Europe. In other words, some positive effects of state fragmentation on population seem to be present even outside the Western core when we focus on preindustrial (or Malthusian) times.

M Controlling for preindustrial urbanization and population density

One concern is that the correlation between modern outcomes and border frequency is caused by some third factor that affected both. For example, Western Europe may be more developed and have higher population density today because it was already more urbanized and densely populated in preindustrial times—for reasons not related to factors that we already control for in our regressions—and this might have caused it to have a more fragmented state structure.

A similar concern can be raised about the correlation between border frequency and geography. Rather than geography determining border locations directly, the correlations between geography and border frequency could be due to geography affecting population density and urbanization, which in turn could affect state fragmentation, and thus borders. That is, urbanization and population density could be a channel through which (some of) our geography variables affect borders. While potentially interesting, this would not necessarily contradict our model, where cities (capitals) are located at the center of states, i.e., away from border areas.

We first explore the latter of these two possibilities. Table M.1 presents results from regressing border frequency on our benchmark set of geography variables and latitude, with column (1) replicating column (1) of Table 3 in the paper. The remaining seven columns enter controls for five different measures of preindustrial urbanization (two from Bosker et al. 2013, and three form HYDE), and two preindustrial population density measures (from HYDE).[4] For details about the data sources, see Section I above.

Some correlations do change when we control for log city population from Bosker et al. (2013) in columns (2) and (3). The coefficient on the 2000-meter mountain dummy turns negative, and that on log distance to the coast turns positive, i.e., the opposite of the result in column (1). The reason seems to be a sample composition effect: among the 644 cells with Bosker data available, border frequency shows negative partial correlation with the 2000-meter mountain dummy, and positive partial correlation with log distance to coast; the coefficients are approximately -0.04 and 0.2, respectively. The coefficients on the other geography variables are relatively unchanged when comparing column (1) to columns (2) and (3).

In columns (4)-(8) of Table M.1, where we use the HYDE variables as controls, the results are almost identical to those in column (1). Using these controls is arguable more

[4]Although we use the fraction urban 1500-2000 from HYDE as a control in some regressions, we refer to all these controls as preindustrial for short. The periods are somewhat arbitrarily chosen, but the results are not very sensitive to these choices.

informative, given that the samples are larger and closer to the benchmark. The overall conclusion should thus be that the effect of geography on borders does not work primarily through population density or urbanization.

The other concern discussed above was that the correlation between modern outcomes and border frequency could be driven by variation in preindustrial urbanization or population density. Tables M.2-M.4 regress night lights and population density on border frequency 1500-2000, controlling for the same measures of preindustrial population density and urbanization as those used in Table M.1. All specifications include our benchmark set of geography controls and latitude. As expected, all measures of preindustrial population density and urbanization correlate with both night lights and population density, but border frequency still comes out as positive and significant in all specifications. In other words, borders do seem to have a positive effect on modern development, even when we control for a number of preindustrial measures of development.

N Measuring borders over other time periods

In the paper we used border frequency from 1500 to 2000 as our benchmark measure. This section considers border frequency measured over other time periods: 1300-1800 (as sometimes reported already in the paper), 1300-1900, 1300-2000, and 800-2000. We apply the associated state samples, meaning we only consider cells that had a state present throughout the period over which we measure borders frequency, i.e., at all turns of the centuries starting in 1300 (5095 cells), or 800 (3269 cells), respectively.

Table N.1 shows the results when regressing different measures of border frequency on latitude and the benchmark set of geography controls, alternating between the 1000- and 2000-meter mountain dummies. Columns (1) and (2) of Table N.1 replicate columns (6) and (7) of Table 3 in the paper.

The other estimated coefficients in Table N.1 are similar to those in Table 3 in the paper, but not identical. Log ruggedness comes out as more significant, and log distance to the coast and the steppe dummy as less significant, when measuring borders from 800 to 2000 in columns (7) and (8). This is to large extent a sample composition effect, driven by cells which are dropped (i.e., cells gaining statehood between 800 and 1500). The dropped cells tend to be located in more eastern and inland areas, which have become relatively unified when states formed there after 800.

For example, we already saw that the benchmark border frequency measure based on the period 1500-2000 shows negative pairwise correlation with log distance to the coast if we use the benchmark 1500-2000 state sample (see Table 1 in the paper), which holds also when controlling for other geography variables (Tables 2-3). However, the pairwise correlation between the same two variables turns negative in the 800-2000 state sample.

Table N.2 reports results from the same regressions as in Table N.1, but with all border and geography variables expressed in local deviations from neighboring cells. Columns (1) and (2) replicate columns (6) and (7) of Table 4 in the paper. The estimates in the other columns are very similar. In other words, the local correlations between borders and geography do not seem sensitive to the period considered.

Finally, Tables N.3 and N.4 show the global and local correlations between borders and modern outcomes, using the same alternative periods for measuring border frequency. Columns (1) and (5) of Table N.3 replicate the two panels for column (6) of Table 5 in the paper, while columns (1) and (5) of Table N.4 replicate the two panels in column (6) of Table 6. The remaining results in Tables N.3 and N.4 closely resemble those in the paper. The global correlations in Table N.3 are positive and the local correlations in Table N.4 are negative, just as in Tables 5 and 6, respectively.

Table D.1: Cross-correlation table

Variables	Border freq.	Border 1500	Border 1600	Border 1700	Border 1800	Border 1900	Border 2000	Current bdr.	Lang. bdr.
Border freq.	1.000								
Border 1500	0.719	1.000							
	(0.000)								
Border 1600	0.722	0.499	1.000						
	(0.000)	(0.000)							
Border 1700	0.815	0.538	0.630	1.000					
	(0.000)	(0.000)	(0.000)						
Border 1800	0.721	0.419	0.395	0.581	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)					
Border 1900	0.600	0.230	0.224	0.342	0.385	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Border 2000	0.599	0.228	0.217	0.291	0.305	0.458	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Current bdr.	0.571	0.226	0.209	0.281	0.290	0.444	0.934	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Lang. bdr.	0.274	0.080	0.107	0.120	0.099	0.227	0.510	0.531	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: Unconditional pairwise correlation coefficients between border frequency 1500-2000 and different border dummies, with p-values in parentheses.

Table D.2: Cross-correlation table

Variables	LPD-HYDE 1500	LPD-HYDE 1800	LPD-HYDE 2000	LPD GPW
LPD-HYDE 1500	1.000			
LPD-HYDE 1800	0.928	1.000		
	(0.000)			
LPD-HYDE 2000	0.751	0.835	1.000	
	(0.000)	(0.000)		
LPD GPW	0.702	0.731	0.868	1.000
	(0.000)	(0.000)	(0.000)	

Notes: Unconditional pairwise correlation coefficients between different measures of modern and preindustrial population densities, from HYDE and the Gridded Population of the World, with p-values in parentheses. LPD-GPW is the benchmark measure used in the paper, i.e., Log Population Density from the Gridded Population of the World, and refer to the period 2000-2015. LPD-HYDE is Log Population Density from HYDE for 1500, 1800, and 2000. The number of cells is 5150.

Table D.3: Cross-correlation table

Variables	Border freq.	Log night lights	Log night lights p.c.	Log pop. dens.	Log GDP per area	Log GDP per capita
Border freq.	1.000					
Log night lights	0.172	1.000				
	(0.000)					
Log night lights p.c.	−0.016	−0.022	1.000			
	(0.247)	(0.121)				
Log pop. dens.	0.185	0.818	−0.081	1.000		
	(0.000)	(0.000)	(0.000)			
Log GDP per area	0.092	0.581	−0.069	0.590	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)		
Log GDP per capita	0.104	0.464	0.092	0.148	0.441	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: Unconditional pairwise correlation coefficients between border frequency 1500-2000 and different measures of modern outcomes, with p-values in parentheses. The number of cells varies between 4949 and 5202, depending on the pair of variables.

Table E.1: Motivation of the choice of geography variables.

Variable(s)	**Examples, comments**	**Related literature**
Mountains>2000,1000m; Log ruggedness	The Pyrenees between France, Spain, and Andorra, the Alps between, e.g., Italy and Austria, the Himalayas (McMahon Line) between China/Tibet and India. The Jinshanling segment of the Great Wall of China is located in mountainous terrain	Holdich (1916), Brigham (1919), Diamond (1997, pp. 414-415), Pounds (1972, pp. 86-89)
River dummy	The Rhine between France and Germany, the Shatt al-Arab river between Iran and Iraq, the Amur and Ussuri rivers between Russia and China	Pounds (1972, pp. 88-92), Lord Curzon of Keddleston (1907)
Agricultural suitability: rainfed and irrigated	Farming can affect population density, state development. First states preceded by Neolithic Revolution. Irrigation crucial for state development in the Middle East (and democracy in modern times); likely to affect territorial expansion of states	Wittfogel (1957), Hibbs and Olsson (2004), Bentzen et al. (2017)
Rainfall	Found to be highly correlated with linguistic diversity. Proxy for deserts, arid regions, cattle farming. Helps pick up variation not fully absorbed by related variables: e.g., rainfed/irrig. agriculture, mountains, coasts (higher rainfall in mountains, along Atlantic coast)	Nettle (1996, 1998, 1999), Umesao (2003), Michalopoulos (2012)
Log dist. to coast; Coast dummy	Europe's indented coastline relative to China's; some states are islands (England, Ireland, Japan)	Cosandey (1997, Ch. 6), Diamond (1997, pp. 414-415), Hoffman (2015, Ch. 4)
Log dist. to steppe; Steppe dummy	State development in China linked to Mongol invasions from the steppe; larger states in Asia and Eastern Europe than in Western Europe (e.g., Russia, Ukraine)	Barfield (1989), Turchin (2009), Ko et al. (2018)

Table E.2: Cross-correlation table

Variables	Border freq.	Log elevation	Log rugg. (KL)	Log rugg. (NP)
Border freq.	1.000			
Log elevation	0.119	1.000		
	(0.000)			
Log rugg. (KL)	0.147	0.812	1.000	
	(0.000)	(0.000)		
Log rugg. (NP)	0.140	0.752	0.928	1.000
	(0.000)	(0.000)	(0.000)	

Notes: Unconditional pairwise correlation coefficients between border frequency 1500-2000 and different measures of elevation and ruggedness, with p-values in parentheses. Measures of log ruggedness based on the standard deviation of elevation, and used in the paper, are indicated by KL. Those based on the method used by Nunn and Puga (2012) are indicated by NP.

Table E.3: Geography and border frequency: comparing elevation and ruggedness.

	Dependent variable: Border frequency 1500-2000									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mountain >2000m	0.129***			0.129***		0.146***			0.146***	
	(0.042)			(0.042)		(0.043)			(0.043)	
Log elevation		−0.015*	0.014**		−0.008		−0.022**	0.003		−0.020**
		(0.009)	(0.006)		(0.008)		(0.009)	(0.007)		(0.009)
Log rugg. (KL)	0.017***	0.030***				0.007	0.026***			
	(0.005)	(0.008)				(0.006)	(0.008)			
Log rugg. (NP)				0.015***	0.023***				0.007	0.023***
				(0.006)	(0.008)				(0.006)	(0.008)
River dummy	0.078***	0.077***	0.079***	0.078***	0.077***	0.075***	0.073***	0.074***	0.075***	0.073***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. rainfed	0.074***	0.066**	0.064**	0.068**	0.058**	0.124***	0.113***	0.116***	0.124***	0.110***
	(0.027)	(0.028)	(0.028)	(0.027)	(0.028)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)
Ag. suit. irrig.	−0.102***	−0.104***	−0.104***	−0.101***	−0.101***	−0.100***	−0.103***	−0.102***	−0.099***	−0.100***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
Rainfall	0.049***	0.050***	0.056***	0.050***	0.050***	0.064***	0.065***	0.071***	0.064***	0.065***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)
Log dist. to coast	−0.108***	−0.084**	−0.136***	−0.113***	−0.100***	−0.104***	−0.071**	−0.114***	−0.105***	−0.078**
	(0.037)	(0.037)	(0.034)	(0.037)	(0.038)	(0.036)	(0.036)	(0.033)	(0.036)	(0.037)
Coast dummy	−0.059***	−0.072***	−0.057***	−0.059***	−0.067***	−0.064***	−0.081***	−0.069***	−0.065***	−0.080***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)	(0.014)	(0.015)
Log dist. to steppe	0.103***	0.093***	0.081***	0.102***	0.095***	0.168***	0.155***	0.150***	0.171***	0.164***
	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Steppe dummy	0.027*	0.020	0.021	0.028*	0.024	0.045***	0.035**	0.038**	0.047***	0.041**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Log land area	0.014***	0.014***	0.017***	0.019***	0.021***	0.012***	0.011**	0.014***	0.013***	0.018***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.14	0.14	0.13	0.14	0.14	0.15	0.15	0.14	0.15	0.15
Number of obs.	5202	5202	5202	5201	5201	5202	5202	5202	5201	5201
Latitude control	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The table considers two different measures of ruggedness: the one used in the paper (KL), and the main one used by Nunn and Puga (2012) (NP). * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table E.4: Geography and border frequency: coal, temperature, and fraction lake.

	Dependent variable: Border frequency 1500-2000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coal dummy	0.053***			0.050***	0.009			0.009
	(0.018)			(0.018)	(0.017)			(0.017)
Temperature		−0.009***		−0.009***		−0.002		−0.002
		(0.003)		(0.003)		(0.003)		(0.003)
Fraction lake			−0.148*	−0.115			−0.024	−0.022
			(0.087)	(0.088)			(0.083)	(0.083)
Mountain >2000m					0.146***	0.137***	0.146***	0.136***
					(0.043)	(0.045)	(0.043)	(0.045)
Log ruggedness					0.007	0.005	0.007	0.005
					(0.006)	(0.006)	(0.006)	(0.006)
River dummy					0.075***	0.075***	0.075***	0.075***
					(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. rainfed					0.124***	0.121***	0.124***	0.121***
					(0.031)	(0.032)	(0.031)	(0.032)
Ag. suit. irrig.					−0.100***	−0.098***	−0.100***	−0.098***
					(0.021)	(0.020)	(0.021)	(0.021)
Rainfall					0.063***	0.064***	0.064***	0.063***
					(0.013)	(0.012)	(0.012)	(0.013)
Log dist. to coast					−0.104***	−0.106***	−0.104***	−0.106***
					(0.036)	(0.035)	(0.036)	(0.035)
Coast dummy					−0.064***	−0.062***	−0.064***	−0.062***
					(0.014)	(0.015)	(0.014)	(0.014)
Log dist. to steppe					0.166***	0.173***	0.168***	0.171***
					(0.032)	(0.033)	(0.032)	(0.033)
Steppe dummy					0.045***	0.047***	0.045***	0.046***
					(0.017)	(0.017)	(0.017)	(0.017)
Log land area	0.027***	0.021***	0.028***	0.020***	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.03	0.03	0.02	0.04	0.15	0.15	0.15	0.15
Number of obs.	5202	5202	5202	5202	5202	5202	5202	5202

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include latitude controls (not reported). * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table E.5: Geography and border frequency: alternative measures of agricultural suitability.

	Dependent variable: Border frequency 1500-2000								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mountain >2000m	0.133***	0.169***	0.162***	0.142***	0.168***	0.161***	0.140***	0.166***	0.160***
	(0.042)	(0.045)	(0.045)	(0.043)	(0.045)	(0.045)	(0.043)	(0.045)	(0.045)
Log ruggedness	0.010	0.007	0.004	0.004	0.008	0.003	0.003	0.006	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
River dummy	0.073***	0.063***	0.063***	0.067***	0.063***	0.062***	0.074***	0.070***	0.068***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. potato	−0.018		−0.140***	−0.190***		−0.191***	−0.189***		−0.189***
	(0.034)		(0.035)	(0.043)		(0.042)	(0.042)		(0.041)
Caloric Suit. Index		0.158***	0.226***		0.195***	0.195***		0.199***	0.199***
		(0.036)	(0.040)		(0.044)	(0.044)		(0.044)	(0.044)
Ag. suit. rainfed				0.191***	−0.049	0.075*	0.246***	0.007	0.129***
				(0.038)	(0.033)	(0.040)	(0.041)	(0.035)	(0.042)
Ag. suit. irrig.							−0.099***	−0.102***	−0.101***
							(0.020)	(0.020)	(0.020)
Rainfall	0.066***	0.059***	0.053***	0.060***	0.058***	0.053***	0.059***	0.056***	0.051***
	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
Log dist. to coast	−0.080**	−0.084**	−0.027	−0.051	−0.073**	−0.023	−0.054	−0.075**	−0.025
	(0.040)	(0.034)	(0.039)	(0.040)	(0.036)	(0.040)	(0.039)	(0.035)	(0.039)
Coast dummy	−0.074***	−0.069***	−0.061***	−0.058***	−0.070***	−0.057***	−0.051***	−0.063***	−0.050***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log dist. to steppe	0.147***	0.197***	0.185***	0.181***	0.189***	0.193***	0.171***	0.180***	0.183***
	(0.031)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)
Steppe dummy	0.033**	0.063***	0.059***	0.051***	0.060***	0.062***	0.048***	0.057***	0.059***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Log land area	0.013***	0.014***	0.016***	0.005	0.017***	0.012***	0.007	0.019***	0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
R^2	0.14	0.15	0.16	0.15	0.15	0.16	0.16	0.16	0.17
Number of obs.	5202	5202	5202	5202	5202	5202	5202	5202	5202

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include latitude controls (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table E.6: Geography and border frequency: alternative measures of rivers and coasts.

	Dependent variable: Border frequency 1500-2000					
	(1)	(2)	(3)	(4)	(5)	(6)
Mountain >2000m	0.129***	0.137***	0.129***	0.146***	0.153***	0.145***
	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.043)
Log ruggedness	0.017***	0.019***	0.017***	0.007	0.010*	0.007
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
River dummy	0.078***			0.075***		
	(0.011)			(0.011)		
River density		1.933***			1.840***	
		(0.670)			(0.660)	
Log river length			0.021***			0.020***
			(0.003)			(0.003)
Ag. suit. rainfed	0.074***	0.094***	0.073***	0.124***	0.140***	0.122***
	(0.027)	(0.028)	(0.027)	(0.031)	(0.032)	(0.031)
Ag. suit. irrig.	−0.102***	−0.101***	−0.103***	−0.100***	−0.099***	−0.101***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Rainfall	0.049***	0.048***	0.051***	0.064***	0.061***	0.065***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Log dist. to coast	−0.108***	−0.046	−0.104***	−0.104***	−0.037	−0.099***
	(0.037)	(0.035)	(0.037)	(0.036)	(0.034)	(0.036)
Coast dummy	−0.059***			−0.064***		
	(0.014)			(0.014)		
Coastline density		0.035***			0.023*	
		(0.013)			(0.013)	
Log coastline length			−0.014***			−0.015***
			(0.003)			(0.003)
Log dist. to steppe	0.103***	0.110***	0.104***	0.168***	0.168***	0.167***
	(0.028)	(0.029)	(0.028)	(0.032)	(0.032)	(0.032)
Steppe dummy	0.027*	0.032**	0.027*	0.045***	0.048***	0.044**
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
Log land area	0.014***	0.036***	0.017***	0.012***	0.032***	0.015***
	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)
R^2	0.14	0.13	0.14	0.15	0.13	0.15
Number of obs.	5202	5202	5202	5202	5202	5202
Latitude control	No	No	No	Yes	Yes	Yes

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. * indicates $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Table E.7: Geography and border frequency: logged and non-logged variables.

	Dependent variable: Border frequency 1500-2000			
	(1)	(2)	(3)	(4)
Mountain >2000m	0.146***	0.140***	0.113***	0.133***
	(0.043)	(0.043)	(0.041)	(0.045)
Log ruggedness	0.007	0.006		0.012*
	(0.006)	(0.006)		(0.006)
Ruggedness			0.000***	
			(0.000)	
River dummy	0.075***	0.075***	0.076***	0.078***
	(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. rainfed	0.124***	0.130***	0.132***	0.088***
	(0.031)	(0.032)	(0.031)	(0.031)
Ag. suit. irrig.	−0.100***	−0.097***	−0.092***	−0.108***
	(0.021)	(0.021)	(0.020)	(0.021)
Rainfall	0.064***	0.065***	0.056***	
	(0.012)	(0.013)	(0.012)	
Log rainfall				0.054***
				(0.007)
Log dist. to coast	−0.104***			−0.113***
	(0.036)			(0.035)
Distance to coast		−0.077***	−0.068***	
		(0.023)	(0.022)	
Coast dummy	−0.064***	−0.064***	−0.061***	−0.064***
	(0.014)	(0.014)	(0.014)	(0.014)
Log dist. to steppe	0.168***			0.219***
	(0.032)			(0.033)
Distance to steppe		0.197***	0.210***	
		(0.041)	(0.040)	
Steppe dummy	0.045***	0.031*	0.033**	0.024
	(0.017)	(0.016)	(0.016)	(0.017)
Log land area	0.012***	0.011***	0.009**	0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.15	0.15	0.15	0.15
Number of obs.	5202	5202	5202	5202
Logged or non-logged alteration	Benchmark	Non-logged distances	Non-logged distances & ruggedness	Benchmark with logged rainfall

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include latitude controls (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table F.1: Geography and border frequency: standardized coefficients and robust standard errors.

	Dependent variable: Border frequency 1500-2000					
	(1)	(2)	(3)	(4)	(5)	(6)
Mountain >2000m	0.074***		0.084***		0.092***	
	(0.030)		(0.030)		(0.029)	
Mountain >1000m		0.030*		0.038**		0.080***
		(0.013)		(0.013)		(0.013)
Log ruggedness	0.090***	0.090***	0.039**	0.040**	0.089***	0.078***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
River dummy	0.148***	0.148***	0.142***	0.142***	0.125***	0.124***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ag. suit. rainfed	0.085***	0.079***	0.142***	0.132***	0.023	0.016
	(0.015)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)
Ag. suit. irrig.	−0.124***	−0.123***	−0.122***	−0.120***	−0.123***	−0.116***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Rainfall	0.176***	0.179***	0.228***	0.227***	0.080***	0.078***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Log dist. to coast	−0.084***	−0.080***	−0.081***	−0.077***	−0.044**	−0.040**
	(0.019)	(0.019)	(0.018)	(0.018)	(0.022)	(0.022)
Coast dummy	−0.108***	−0.108***	−0.118***	−0.116***	−0.091***	−0.079***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Log dist. to steppe	0.134***	0.129***	0.219***	0.208***	0.394***	0.388***
	(0.015)	(0.015)	(0.017)	(0.017)	(0.022)	(0.021)
Steppe dummy	0.034***	0.031***	0.057***	0.052***	0.060***	0.056***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Log land area	0.058***	0.058***	0.049***	0.049***	0.050***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.14	0.14	0.15	0.15	0.24	0.24
Number of obs.	5202	5202	5202	5202	5202	5202
Latitude (Control/FE)	None	None	Control	Control	Fixed effects	Fixed effects
Summed absolute values of coefficients	1.057	0.997	1.232	1.152	1.121	1.055

Notes: Ordinary least squares regressions with standardized (beta) coefficients and robust standard errors. * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table F.2: Borders and modern outcomes: standardized coefficients and robust standard errors.

	Dependent variable:							
	Log night lights				Log population density			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Border frequency 1500-2000	0.172***	0.139***	0.130***	0.053***	0.185***	0.148***	0.137***	0.052***
	(0.050)	(0.051)	(0.050)	(0.047)	(0.073)	(0.077)	(0.076)	(0.068)
R^2	0.03	0.31	0.32	0.40	0.03	0.30	0.31	0.43
Number of obs.	5202	5202	5202	5202	5201	5201	5201	5201
Geography controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Latitude (Control/FE)	None	None	Control	Fixed effects	None	None	Control	Fixed effects

Notes: Ordinary least squares regressions with standardized (beta) coefficients and robust standard errors. * indicates $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Table G.1: Geography and border frequency: nine-cell artificial country fixed effects.

	Dependent variable:						
	Border frequency 1500-2000					Border freq. 1300-1800	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mountain >2000m	0.043		0.046	0.017	0.016	0.037	
	(0.032)		(0.031)	(0.027)	(0.026)	(0.023)	
Mountain >1000m		0.047***					0.044**
		(0.018)					(0.019)
Log ruggedness	0.024***	0.022***	0.026***	0.022***	0.020***	0.018***	0.016***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
River dummy	0.027***	0.027***	0.030***	0.026***	0.027***	0.024***	0.025***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ag. suit. rainfed	−0.062*	−0.057*	−0.082**	−0.087**	−0.084**	−0.080**	−0.075**
	(0.036)	(0.034)	(0.035)	(0.034)	(0.036)	(0.036)	(0.034)
Ag. suit. irrig.	−0.006	−0.002	−0.006	0.001	0.011	−0.013	−0.009
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.019)	(0.019)
Rainfall	0.060***	0.063***	0.060***	0.023	0.046**	0.064***	0.067***
	(0.018)	(0.018)	(0.018)	(0.015)	(0.019)	(0.019)	(0.019)
Log dist. to coast	0.033	0.019	0.017	−0.124	−0.046	−0.007	−0.021
	(0.114)	(0.114)	(0.113)	(0.111)	(0.109)	(0.126)	(0.125)
Coast dummy	0.001	0.005	0.002	−0.010	−0.005	−0.011	−0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Log dist. to steppe	−0.074	−0.090	−0.055	−0.089	−0.084	−0.027	−0.044
	(0.128)	(0.128)	(0.166)	(0.125)	(0.126)	(0.132)	(0.131)
Steppe dummy	−0.044**	−0.041**	−0.053***	−0.038**	−0.052***	−0.047***	−0.043***
	(0.017)	(0.017)	(0.017)	(0.015)	(0.017)	(0.017)	(0.016)
Log land area	0.009**	0.009**	0.010**	0.012***	0.007*	0.025***	0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
R^2	0.61	0.61	0.61	0.50	0.47	0.65	0.66
Number of obs.	5202	5202	5202	4566	4664	5095	5095
Artificial country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude (Control/FE)	Control	Control	FE	Control	Control	Control	Control
Drop Western Europe	No	No	No	Yes	No	No	No
Drop HRE	No	No	No	No	Yes	No	No

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications are the same as in Table 3 in the paper, except that they all include fixed effects for artificial regions of nine cells. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table G.2: Borders and modern outcomes: nine-cell artificial country fixed effects.

Panel A	Dependent variable: Log night lights						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Border frequency 1500-2000	−0.158***	−0.134***	−0.136***	−0.255***	−0.188***		
	(0.055)	(0.051)	(0.049)	(0.061)	(0.061)		
Border frequency 1300-1800						−0.112**	−0.114**
						(0.048)	(0.047)
R^2	0.70	0.74	0.75	0.73	0.72	0.74	0.75
Number of obs.	5202	5202	5202	4566	4664	5095	5095
Panel B	**Dependent variable: Log population density**						
Border frequency 1500-2000	−0.255***	−0.228***	−0.238***	−0.356***	−0.307***		
	(0.083)	(0.076)	(0.074)	(0.088)	(0.091)		
Border frequency 1300-1800						−0.192***	−0.208***
						(0.070)	(0.068)
R^2	0.71	0.74	0.75	0.75	0.74	0.73	0.74
Number of obs.	5201	5201	5201	4565	4663	5094	5094
Artificial country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Latitude (Control/FE)	None	Control	FE	Control	Control	Control	FE
Drop Western Europe	No	No	No	Yes	No	No	No
Drop HRE	No	No	No	No	Yes	No	No

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications are the same as in Table 5 in the paper, except that they all include fixed effects for artificial regions of nine cells. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table H.1: Geography and border frequency: modern country fixed effects.

	Dependent variable:						
	Border frequency 1500-2000					Border freq. 1300-1800	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mountain >2000m	0.016		0.019	0.020	0.016	0.018	
	(0.018)		(0.019)	(0.017)	(0.016)	(0.020)	
Mountain >1000m		0.035***					0.048***
		(0.011)					(0.015)
Log ruggedness	0.012***	0.010**	0.017***	0.007*	0.008**	0.017***	0.014**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
River dummy	0.019***	0.020***	0.019***	0.021***	0.016***	0.026***	0.026***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.007)
Ag. suit. rainfed	0.023	0.029	0.016	0.016	0.014	0.022	0.031
	(0.019)	(0.018)	(0.019)	(0.020)	(0.019)	(0.025)	(0.024)
Ag. suit. irrig.	−0.019	−0.017	−0.029***	−0.018	−0.022**	−0.003	0.001
	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)	(0.015)	(0.015)
Rainfall	0.019***	0.021***	0.001	0.012	0.001	0.036***	0.039***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.011)	(0.011)
Log dist. to coast	−0.035	−0.038	−0.030	−0.066**	−0.051**	−0.078*	−0.083**
	(0.028)	(0.028)	(0.034)	(0.027)	(0.025)	(0.040)	(0.040)
Coast dummy	−0.019**	−0.014*	−0.014*	−0.014	−0.002	−0.035***	−0.029**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.012)	(0.012)
Log dist. to steppe	0.055**	0.061***	0.158***	0.033	0.007	0.135***	0.145***
	(0.023)	(0.023)	(0.040)	(0.022)	(0.020)	(0.032)	(0.032)
Steppe dummy	0.008	0.011	0.007	0.000	−0.012	0.030***	0.034***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.011)	(0.011)
Log land area	0.005*	0.005*	0.002	0.008***	0.004*	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
R^2	0.73	0.73	0.74	0.61	0.67	0.63	0.64
Number of obs.	5199	5199	5199	4563	4661	5092	5092
Modern country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude (Control/FE)	Control	Control	FE	Control	Control	Control	Control
Drop Western Europe	No	No	No	Yes	No	No	No
Drop HRE	No	No	No	No	Yes	No	No

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications are the same as in Table 3 in the paper, except that they all include fixed effects for modern countries from GADM. * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table H.2: Borders and modern outcomes: modern country fixed effects.

Panel A	Dependent variable: Log night lights						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Border frequency 1500-2000	0.024	0.074	−0.047	0.009	0.034		
	(0.086)	(0.084)	(0.083)	(0.096)	(0.099)		
Border frequency 1300-1800						−0.021	−0.092
						(0.066)	(0.065)
R^2	0.44	0.54	0.58	0.51	0.50	0.54	0.57
Number of obs.	5199	5199	5199	4563	4661	5092	5092
Panel B	**Dependent variable: Log population density**						
Border frequency 1500-2000	−0.013	0.130	−0.078	0.101	0.130		
	(0.128)	(0.122)	(0.118)	(0.138)	(0.144)		
Border frequency 1300-1800						0.033	−0.103
						(0.095)	(0.092)
R^2	0.40	0.51	0.55	0.50	0.49	0.50	0.54
Number of obs.	5198	5198	5198	4562	4660	5091	5091
Modern country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Latitude (Control/FE)	None	Control	FE	Control	Control	Control	FE
Drop Western Europe	No	No	No	Yes	No	No	No
Drop HRE	No	No	No	No	Yes	No	No

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications are the same as in Table 5 in the paper, except that they all include fixed effects for modern countries from GADM. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table I.1: Borders and urbanization: the period 1300-1800.

	Dependent variable: Log urban population$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Log urban pop.$_{t-1}$	0.714***	0.712***	0.713***	0.231***	0.234***	0.231***
	(0.012)	(0.012)	(0.012)	(0.027)	(0.027)	(0.027)
Border dummy$_t$	-0.105^{**}		-0.225^{***}	-0.326^{***}		-0.325^{***}
	(0.046)		(0.059)	(0.070)		(0.070)
Border dummy$_{t-1}$		0.063	0.192***		-0.027	-0.019
		(0.044)	(0.056)		(0.068)	(0.067)
R^2	0.61	0.61	0.61	0.73	0.73	0.73
Number of obs.	3220	3220	3220	3220	3220	3220
Cell FE	No	No	No	Yes	Yes	Yes

Notes: Ordinary least squares regressions with robust standard errors in parentheses, based on a panel with 644 cells and six centuries (1300-1800); the first century is dropped due to the lagged variables. Log urban population is from Bosker et al. (2013), and measures the log population of all cities in a cell that exceed 10,000 people. Columns (1)-(3) include century fixed effects and geography controls, and columns (4)-(6) include cell and century fixed effects. * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table I.2: Borders and urbanization: the period 800-1800.

	Dependent variable: Log urban population$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Log urban pop.$_{t-1}$	0.795***	0.795***	0.795***	0.516***	0.515***	0.516***
	(0.008)	(0.009)	(0.008)	(0.018)	(0.018)	(0.018)
Border dummy$_t$	-0.062^{**}		-0.102^{***}	-0.091^{***}		-0.109^{***}
	(0.030)		(0.034)	(0.034)		(0.036)
Border dummy$_{t-1}$		0.024	0.077**		0.023	0.057
		(0.030)	(0.035)		(0.034)	(0.036)
R^2	0.68	0.68	0.68	0.73	0.73	0.73
Number of obs.	5980	5980	5980	5980	5980	5980
Cell FE	No	No	No	Yes	Yes	Yes

Notes: Ordinary least squares regressions with robust standard errors in parentheses, based on a panel with 598 cells and eleven centuries (800-1800); the first century is dropped due to the lagged variables. Log urban population is from Bosker et al. (2013), and measures the log population of all cities in a cell that exceed 10,000 people. Columns (1)-(3) include century fixed effects and geography controls, and columns (4)-(6) include cell and century fixed effects. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table I.3: Borders and urbanization: fraction urban from HYDE.

	Dependent variable: Fraction $urban_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction $urban_{t-1}$	1.025***	1.025***	1.024***	0.802***	0.804***	0.802***
	(0.007)	(0.007)	(0.007)	(0.012)	(0.012)	(0.012)
Border $dummy_t$	−0.003		−0.006**	−0.011***		−0.011***
	(0.002)		(0.003)	(0.003)		(0.003)
Border $dummy_{t-1}$		0.003*	0.006***		0.002	0.002
		(0.002)	(0.002)		(0.003)	(0.003)
R^2	0.81	0.81	0.81	0.85	0.85	0.85
Number of obs.	25125	25125	25125	25125	25125	25125
Cell FE	No	No	No	Yes	Yes	Yes

Notes: Ordinary least squares regressions with robust standard errors in parentheses, based on a panel with 5025 cells and six centuries (1500-2000); the first century is dropped due to the lagged variables. The fraction urban is based data from HYDE, and defined as urban population as a fraction of total population in a cell. Columns (1)-(3) include century fixed effects and geography controls, and columns (4)-(6) include cell and century fixed effects. * indicates $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Table J.1: Geography and border frequency: dropping different subsamples.

	Dependent variable: Border frequency 1500-2000									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mountain >2000m	0.129***	0.145***	0.041	0.118***	0.135***	0.146***	0.137***	0.044	0.135***	0.139***
	(0.042)	(0.041)	(0.044)	(0.039)	(0.040)	(0.043)	(0.040)	(0.045)	(0.040)	(0.040)
Log ruggedness	0.017***	−0.002	0.020**	0.011**	0.013**	0.007	−0.001	0.018*	0.002	0.011*
	(0.005)	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)	(0.008)	(0.010)	(0.006)	(0.006)
River dummy	0.078***	0.065***	0.081***	0.067***	0.060***	0.075***	0.053***	0.081***	0.064***	0.060***
	(0.011)	(0.011)	(0.015)	(0.010)	(0.011)	(0.011)	(0.011)	(0.015)	(0.010)	(0.011)
Ag. suit. rainfed	0.074***	0.068*	−0.060	0.098***	−0.030	0.124***	−0.042	−0.055	0.149***	−0.014
	(0.027)	(0.037)	(0.041)	(0.025)	(0.028)	(0.031)	(0.035)	(0.046)	(0.028)	(0.032)
Ag. suit. irrig.	−0.102***	−0.119***	−0.043	−0.092***	−0.101***	−0.100***	−0.125***	−0.044	−0.090***	−0.100***
	(0.021)	(0.022)	(0.036)	(0.019)	(0.021)	(0.021)	(0.022)	(0.036)	(0.019)	(0.021)
Rainfall	0.049***	0.119***	0.103***	0.032***	0.088***	0.064***	0.070***	0.104***	0.046***	0.092***
	(0.012)	(0.017)	(0.018)	(0.010)	(0.013)	(0.012)	(0.018)	(0.019)	(0.010)	(0.014)
Log dist. to coast	−0.108***	−0.026	0.012	−0.135***	−0.138***	−0.104***	0.065*	0.012	−0.130***	−0.134***
	(0.037)	(0.038)	(0.069)	(0.035)	(0.038)	(0.036)	(0.039)	(0.069)	(0.034)	(0.038)
Coast dummy	−0.059***		−0.024	−0.054***	−0.047***	−0.064***		−0.025	−0.059***	−0.049***
	(0.014)		(0.026)	(0.013)	(0.015)	(0.014)		(0.026)	(0.013)	(0.015)
Log dist. to steppe	0.103***	0.221***	0.120**	0.105***	0.224***	0.168***	0.334***	0.130**	0.171***	0.237***
	(0.028)	(0.043)	(0.050)	(0.025)	(0.037)	(0.032)	(0.051)	(0.062)	(0.029)	(0.037)
Steppe dummy	0.027*	0.071***	0.048	0.027*	0.067***	0.045***	0.055***	0.049	0.045***	0.071***
	(0.016)	(0.021)	(0.031)	(0.015)	(0.017)	(0.017)	(0.021)	(0.031)	(0.016)	(0.018)
Log land area	0.014***	0.407***	0.010	0.014***	0.022***	0.012***	2.858***	0.009	0.011***	0.021***
	(0.004)	(0.081)	(0.011)	(0.004)	(0.005)	(0.004)	(0.357)	(0.011)	(0.004)	(0.005)
R^2	0.14	0.20	0.20	0.12	0.22	0.15	0.24	0.20	0.13	0.22
Number of obs.	5202	3869	1807	5132	4537	5202	3869	1807	5132	4537
Latitude control	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Group of cells dropped	None	Coast cells	Fully unified cells	Fully fragm. cells	Northern Europe	None	Coast cells	Fully unified cells	Fully fragm. cells	Northern Europe

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. Fully unified cells, and fully fragmented cells, are those where border frequency equals zero and one, respectively. * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table J.2: Borders and modern outcomes: dropping different subsamples.

	Dependent variable:									
	Log night lights					Log population density				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Border frequency 1500-2000	0.551***	0.451***	1.100***	0.552***	0.504***	0.853***	0.473***	1.072***	0.853***	0.795***
	(0.095)	(0.098)	(0.148)	(0.095)	(0.089)	(0.137)	(0.133)	(0.204)	(0.137)	(0.135)
R^2	0.31	0.35	0.31	0.31	0.34	0.31	0.38	0.28	0.31	0.34
Number of obs.	5202	3869	706	5202	4537	5201	3869	715	5201	4536
Latitude control	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Group of cells dropped	None	Coast cells	Fully unified cells	Fully fragm. cells	Northern Europe	None	Coast cells	Fully unified cells	Fully fragm. cells	Northern Europe

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. Fully unified cells, and fully fragmented cells, are those where border frequency equals zero and one, respectively. All specifications include controls for the benchmark set of geography controls. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.1: Borders and geography: using Abramson data.

	Dependent variable: Border frequency 1500-1790/1800					
	(1)	(2)	(3)	(4)	(5)	(6)
Mountain >2000m	0.146***	0.424***	0.256**	0.160***	0.362***	0.161*
	(0.040)	(0.089)	(0.119)	(0.038)	(0.097)	(0.096)
Log ruggedness	0.005	−0.018	−0.023**	0.019***	0.020*	0.020*
	(0.007)	(0.011)	(0.011)	(0.007)	(0.010)	(0.011)
River dummy	0.077***	0.076***	0.096***	0.069***	0.068***	0.082***
	(0.012)	(0.014)	(0.016)	(0.011)	(0.014)	(0.014)
Ag. suit. rainfed	0.151***	0.085*	0.115**	0.027	−0.042	−0.037
	(0.036)	(0.045)	(0.048)	(0.034)	(0.045)	(0.048)
Ag. suit. irrig.	−0.120***	−0.154***	−0.142***	−0.122***	−0.121***	−0.099***
	(0.025)	(0.029)	(0.031)	(0.026)	(0.029)	(0.032)
Rainfall	0.071***	0.073***	0.083***	0.026*	0.025	0.028
	(0.014)	(0.018)	(0.019)	(0.014)	(0.017)	(0.017)
Log dist. to coast	−0.135***	−0.014	−0.050	−0.100**	−0.076	−0.099
	(0.043)	(0.065)	(0.065)	(0.048)	(0.064)	(0.073)
Coast dummy	−0.068***	−0.086***	−0.101***	−0.052***	−0.070***	−0.082***
	(0.017)	(0.021)	(0.023)	(0.016)	(0.020)	(0.021)
Log dist. to steppe	0.228***	0.368***	0.342***	0.362***	0.403***	0.382***
	(0.041)	(0.067)	(0.060)	(0.055)	(0.065)	(0.067)
Steppe dummy	0.049***	0.034	0.043	0.053***	0.017	0.018
	(0.017)	(0.027)	(0.031)	(0.018)	(0.028)	(0.033)
Log land area	0.013**	0.032***	0.033***	0.013**	0.020**	0.021**
	(0.005)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)
R^2	0.15	0.16	0.15	0.24	0.26	0.25
Number of obs.	5202	3861	3861	5202	3861	3861
Border variable	Euratlas	Euratlas	Abramson	Euratlas	Euratlas	Abramson
Sample	Euratlas	Abramson	Abramson	Euratlas	Abramson	Abramson
Latitude (Control/FE)	Control	Control	Control	FE	FE	FE

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial auto-correlation among observations within 1.45 degrees of each other. The dependent variable is border frequency 1500-1800, or 1500-1790, for the Euratlas and Abramson data, respectively. Columns (2) and (5) use border frequency based on Euratlas, but restricts the sample to cells where Abramson data are not missing. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.2: Borders and modern outcomes: using Abramson data.

	Dependent variable:					
	Log night lights			Log population density		
	(1)	(2)	(3)	(4)	(5)	(6)
Border frequency 1500-1790/1800	0.557***	0.552***	0.607***	0.846***	0.746***	0.800***
	(0.079)	(0.082)	(0.074)	(0.117)	(0.115)	(0.106)
R^2	0.33	0.28	0.29	0.32	0.31	0.32
Number of obs.	5202	3861	3861	5201	3860	3860
Border variable	Euratlas	Euratlas	Abramson	Euratlas	Euratlas	Abramson
Sample	Euratlas	Abramson	Abramson	Euratlas	Abramson	Abramson

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include the benchmark set of geography controls and latitude (not reported). The independent variable of interest is border frequency 1500-1800, or 1500-1790, for the Euratlas and Abramson data, respectively. Columns (2) and (5) use border frequency based on Euratlas, but restricts the sample to cells where Abramson data are not missing. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table K.3: Border frequency inside and outside the HRE in the Euratlas and Abramson data.

	Inside the HRE		Outside the HRE		Ratio border frequency inside the HRE to outside the HRE	
	Euratlas	Abramson	Euratlas	Abramson	Euratlas	Abramson
Number of cells	538	535	4664	3326		
Border frequency	0.65	0.69	0.08	0.09	8.12	7.67

Notes: Average border frequency among cells located inside and outside the Holy Roman Empire, according to the Euratlas and Abramson data. Border frequency is measured over the period 1500-1800 for the Euratlas data and 1500-1790 for the Abramson data. Cells inside the HRE are those that were ever covered by the HRE in any century 1500-1800 according to the Euratlas data.

Table L.1: Borders and modern outcomes: other outcome variables.

Panel A	Dependent variable: log night lights (per area)				
	(1)	(2)	(3)	(4)	(5)
Border frequency 1500-2000	0.680***	0.513***	0.210***	−0.045	−0.184**
	(0.097)	(0.093)	(0.075)	(0.101)	(0.088)
R^2	0.03	0.32	0.40	0.30	0.33
Number of obs.	5202	5202	5202	4566	4664
Panel B	**Dependent variable: log population density**				
Border frequency 1500-2000	1.157***	0.853***	0.323***	0.261*	0.080
	(0.134)	(0.137)	(0.107)	(0.147)	(0.140)
R^2	0.03	0.31	0.43	0.33	0.32
Number of obs.	5201	5201	5201	4565	4663
Panel C	**Dependent variable: log GDP per capita**				
Border frequency 1500-2000	0.509***	0.257***	0.129*	−0.264***	−0.351***
	(0.104)	(0.078)	(0.072)	(0.090)	(0.098)
R^2	0.01	0.26	0.30	0.24	0.25
Number of obs.	4949	4949	4949	4314	4411
Panel D	**Dependent variable: log GDP per area**				
Border frequency 1500-2000	0.524***	0.518***	0.348***	−0.131	−0.253*
	(0.119)	(0.129)	(0.113)	(0.142)	(0.138)
R^2	0.01	0.14	0.23	0.15	0.15
Number of obs.	4993	4993	4993	4358	4455
Panel E	**Dependent variable: log population density in 1800**				
Border frequency 1500-2000	1.275***	0.655***	0.173**	0.143	−0.078
	(0.117)	(0.108)	(0.073)	(0.112)	(0.104)
R^2	0.07	0.48	0.59	0.45	0.48
Number of obs.	5150	5150	5150	4517	4612
Geography controls	No	Yes	Yes	Yes	Yes
Latitude (Control/FE)	None	Control	FE	Control	Control
Drop Western Europe	No	No	No	Yes	No
Drop HRE	No	No	No	No	Yes

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications in Panels A and B are identical to the first five columns of Table 5 in the paper. * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table L.2: Borders and modern outcomes: other outcome variables and using borders 1300-1800.

Panel A	Dependent variable: log night lights (per area)				
	(1)	(2)	(3)	(4)	(5)
Border frequency 1300-1800	0.683***	0.483***	0.252***	−0.053	−0.254***
	(0.085)	(0.085)	(0.070)	(0.100)	(0.091)
R^2	0.04	0.31	0.39	0.29	0.31
Number of obs.	5095	5095	5095	4459	4522
Panel B	**Dependent variable: log population density**				
Border frequency 1300-1800	1.021***	0.770***	0.311***	0.152	−0.071
	(0.119)	(0.126)	(0.098)	(0.137)	(0.138)
R^2	0.04	0.30	0.42	0.31	0.31
Number of obs.	5094	5094	5094	4458	4521
Panel C	**Dependent variable: log GDP per capita**				
Border frequency 1300-1800	0.664***	0.324***	0.251***	−0.141*	−0.283***
	(0.082)	(0.068)	(0.065)	(0.082)	(0.093)
R^2	0.03	0.28	0.31	0.25	0.26
Number of obs.	4872	4872	4872	4237	4299
Panel D	**Dependent variable: log GDP per area**				
Border frequency 1300-1800	0.472***	0.488***	0.350***	−0.151	−0.344**
	(0.106)	(0.123)	(0.113)	(0.142)	(0.144)
R^2	0.01	0.14	0.23	0.16	0.16
Number of obs.	4908	4908	4908	4273	4335
Panel E	**Dependent variable: log population density in 1800**				
Border frequency 1300-1800	1.306***	0.688***	0.270***	0.217**	−0.039
	(0.097)	(0.098)	(0.069)	(0.107)	(0.108)
R^2	0.10	0.48	0.58	0.44	0.47
Number of obs.	5046	5046	5046	4413	4473
Geography controls	No	Yes	Yes	Yes	Yes
Latitude (Control/FE)	None	Control	FE	Control	Control
Drop Western Europe	No	No	No	Yes	No
Drop HRE	No	No	No	No	Yes

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. The specifications in Panels A and B of columns (2) and (3) are identical to columns (6) and (7) of Table 5 in the paper. * indicates $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Table M.1: Borders and geography: controlling for preindustrial population density and urbanization.

	Dependent variable: border frequency 1500-2000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mountain >2000m	0.146***	−0.101	−0.092	0.148***	0.147***	0.149***	0.147***	0.157***
	(0.043)	(0.071)	(0.073)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)
Log ruggedness	0.007	0.002	0.003	0.006	0.006	0.006	0.003	0.006
	(0.006)	(0.013)	(0.013)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
River dummy	0.075***	0.089***	0.085***	0.071***	0.073***	0.069***	0.060***	0.053***
	(0.011)	(0.024)	(0.025)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. rainfed	0.124***	0.193**	0.199**	0.121***	0.123***	0.125***	0.080***	0.074**
	(0.031)	(0.080)	(0.079)	(0.032)	(0.032)	(0.032)	(0.030)	(0.030)
Ag. suit. irrig.	−0.100***	−0.117**	−0.120**	−0.105***	−0.103***	−0.107***	−0.125***	−0.138***
	(0.021)	(0.055)	(0.055)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Rainfall	0.064***	0.111***	0.113***	0.065***	0.066***	0.065***	0.054***	0.046***
	(0.012)	(0.032)	(0.032)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Log dist. to coast	−0.104***	0.004	0.017	−0.093**	−0.096***	−0.092**	−0.059*	−0.039
	(0.036)	(0.166)	(0.164)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)
Coast dummy	−0.064***	−0.064*	−0.061*	−0.066***	−0.064***	−0.065***	−0.075***	−0.076***
	(0.014)	(0.035)	(0.034)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Log dist. to steppe	0.168***	0.462***	0.456***	0.176***	0.177***	0.177***	0.159***	0.132***
	(0.032)	(0.100)	(0.100)	(0.033)	(0.034)	(0.034)	(0.031)	(0.029)
Steppe dummy	0.045***	0.111***	0.112***	0.044**	0.045***	0.045**	0.043**	0.046***
	(0.017)	(0.040)	(0.039)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
Log land area	0.012***	−0.024	−0.027	0.015**	0.015**	0.016***	−0.006	0.011**
	(0.004)	(0.025)	(0.025)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Log city pop. 1500-1800		−0.011						
		(0.009)						
Log city pop. in 1500			0.006					
			(0.007)					
Fraction urban 1500-2000				0.039				
				(0.031)				
Fraction urban 1500-1800					0.024			
					(0.037)			
Fraction urban 1500						0.090**		
						(0.040)		
Log pop. dens. 1500-1800							0.021***	
							(0.004)	
Log pop. dens. in 1500								0.049***
								(0.008)
R^2	0.15	0.23	0.23	0.15	0.15	0.15	0.16	0.18
Number of obs.	5202	644	644	5025	5035	5036	5150	5150

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include latitude controls (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table M.2: Borders and modern outcomes: controlling for preindustrial urbanization from Bosker et al. (2013).

	Dependent variable:					
	Log night lights			Log population density		
	(1)	(2)	(3)	(4)	(5)	(6)
Border frequency 1500-2000	0.513***	0.535***	0.469***	0.853***	0.587***	0.463**
	(0.093)	(0.151)	(0.151)	(0.137)	(0.223)	(0.224)
Log city pop. 1500-1800		0.196***			0.371***	
		(0.030)			(0.054)	
Log city pop. in 1500			0.129***			0.228***
			(0.021)			(0.036)
R^2	0.32	0.47	0.40	0.31	0.44	0.34
Number of obs.	5202	644	644	5201	644	644

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include controls for the benchmark set of geography controls and latitude (not reported). * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table M.3: Borders and modern outcomes: controlling for preindustrial urbanization from HYDE.

Panel A	Dependent variable: log night lights			
	(1)	(2)	(3)	(4)
Border frequency 1500-2000	0.513***	0.448***	0.479***	0.450***
	(0.093)	(0.072)	(0.083)	(0.086)
Fraction urban 1500-2000		3.074***		
		(0.101)		
Fraction urban 1500-1800			2.749***	
			(0.145)	
Fraction urban 1500				2.313***
				(0.153)
R^2	0.32	0.53	0.42	0.38
Number of obs.	5202	5025	5035	5036
Panel B	**Dependent variable: log population density**			
Border frequency 1500-2000	0.853***	0.747***	0.793***	0.764***
	(0.137)	(0.114)	(0.127)	(0.130)
Fraction urban 1500-2000		3.977***		
		(0.159)		
Fraction urban 1500-1800			3.114***	
			(0.211)	
Fraction urban 1500				2.420***
				(0.218)
R^2	0.31	0.44	0.35	0.32
Number of obs.	5201	5025	5035	5036

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include controls for the benchmark set of geography controls and latitude (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table M.4: Borders and modern outcomes: controlling for preindustrial population density from HYDE.

	Dependent variable:					
	Log night lights			Log population density		
	(1)	(2)	(3)	(4)	(5)	(6)
Border frequency 1500-2000	0.513***	0.100*	0.119**	0.853***	0.236***	0.265***
	(0.093)	(0.056)	(0.058)	(0.137)	(0.089)	(0.093)
Log pop. density 1500-1800		0.653***			0.975***	
		(0.017)			(0.032)	
Log population density in 1500			0.639***			0.952***
			(0.018)			(0.033)
R^2	0.32	0.64	0.60	0.31	0.59	0.56
Number of obs.	5202	5150	5150	5201	5150	5150

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include controls for the benchmark set of geography controls and latitude (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table N.1: Geography and border frequency: using alternative time periods.

	Dependent variable:							
	Border frequency 1300-1800		Border frequency 1300-1900		Border frequency 1300-2000		Border frequency 800-2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mountain >2000m	0.126***		0.117***		0.133***		0.095***	
	(0.038)		(0.037)		(0.040)		(0.033)	
Mountain >1000m		0.033		0.034*		0.035*		0.019
		(0.021)		(0.020)		(0.020)		(0.015)
Log ruggedness	0.010	0.010	0.011*	0.010	0.011*	0.010	0.016***	0.016***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
River dummy	0.072***	0.071***	0.071***	0.071***	0.072***	0.072***	0.062***	0.061***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ag. suit. rainfed	0.137***	0.130***	0.121***	0.115***	0.122***	0.115***	0.114***	0.106***
	(0.037)	(0.037)	(0.034)	(0.034)	(0.033)	(0.033)	(0.032)	(0.032)
Ag. suit. irrig.	−0.089***	−0.087***	−0.079***	−0.076***	−0.081***	−0.078***	−0.095***	−0.092***
	(0.025)	(0.025)	(0.023)	(0.023)	(0.021)	(0.021)	(0.024)	(0.024)
Rainfall	0.079***	0.079***	0.074***	0.074***	0.073***	0.073***	0.060***	0.059***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
Log dist. to coast	−0.171***	−0.165***	−0.151***	−0.145***	−0.137***	−0.131***	0.024	0.035
	(0.044)	(0.044)	(0.040)	(0.040)	(0.038)	(0.038)	(0.062)	(0.063)
Coast dummy	−0.080***	−0.078***	−0.076***	−0.073***	−0.073***	−0.071***	−0.044***	−0.042***
	(0.018)	(0.018)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Log dist. to steppe	0.250***	0.244***	0.224***	0.220***	0.201***	0.195***	0.100***	0.092***
	(0.040)	(0.039)	(0.036)	(0.035)	(0.033)	(0.033)	(0.034)	(0.035)
Steppe dummy	0.041**	0.038**	0.039**	0.036**	0.042***	0.039**	0.028*	0.025
	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)
Log land area	0.016***	0.017***	0.014***	0.015***	0.014***	0.015***	0.011***	0.011***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
R^2	0.18	0.18	0.18	0.18	0.18	0.18	0.22	0.22
Number of obs.	5095	5095	5095	5095	5095	5095	3269	3269

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications control for latitude (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table N.2: Geography and border frequency: local deviations using alternative time periods.

	Dependent variable:							
	Δ Border freq. 1300-1800		Δ Border freq. 1300-1900		Δ Border freq. 1300-2000		Δ Border freq. 800-2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Mountain >2000m	0.051*		0.041		0.054*		0.063**	
	(0.029)		(0.029)		(0.031)		(0.028)	
Δ Mountain >1000m		0.061***		0.071***		0.075***		0.050***
		(0.018)		(0.018)		(0.017)		(0.015)
Δ Log ruggedness	0.016***	0.015**	0.018***	0.017***	0.020***	0.019***	0.015***	0.015***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Δ River dummy	0.036***	0.037***	0.036***	0.037***	0.037***	0.038***	0.037***	0.038***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Δ Ag. suit. rainfed	−0.102***	−0.098***	−0.107***	−0.099***	−0.104***	−0.097***	−0.072**	−0.076**
	(0.037)	(0.035)	(0.036)	(0.034)	(0.035)	(0.033)	(0.031)	(0.032)
Δ Ag. suit. irrig.	−0.007	−0.001	−0.004	0.003	0.002	0.010	−0.009	0.000
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)	(0.019)
Δ Rainfall	0.077**	0.077**	0.076**	0.077**	0.074**	0.075**	0.048*	0.050*
	(0.032)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.027)	(0.027)
Δ Log dist. to coast	−0.224	−0.251	−0.168	−0.204	−0.169	−0.204	−0.058	−0.077
	(0.260)	(0.257)	(0.244)	(0.240)	(0.239)	(0.233)	(0.239)	(0.236)
Δ Coast dummy	−0.012	−0.009	−0.010	−0.006	−0.012	−0.007	−0.015	−0.012
	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Δ Log dist. to steppe	0.124	0.145	0.112	0.132	0.027	0.051	−0.085	−0.087
	(0.229)	(0.231)	(0.217)	(0.216)	(0.210)	(0.209)	(0.212)	(0.213)
Δ Steppe dummy	−0.006	−0.002	−0.006	−0.002	−0.010	−0.006	−0.015	−0.011
	(0.015)	(0.015)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
Δ Log land area	0.022***	0.022***	0.019***	0.018***	0.016***	0.016***	0.016***	0.016***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04
Number of obs.	5095	5095	5095	5095	5095	5095	3268	3268

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications control for latitude (not reported and not in local deviations). * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table N.3: Borders and modern outcomes: using alternative time periods.

	Dependent variable:							
	Log night lights				Log population density			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Border frequency 1300-1800	0.483***				0.770***			
	(0.085)				(0.126)			
Border frequency 1300-1900		0.513***				0.817***		
		(0.091)				(0.137)		
Border frequency 1300-2000			0.473***				0.810***	
			(0.096)				(0.143)	
Border frequency 800-2000				0.451***				0.592***
				(0.112)				(0.170)
R^2	0.31	0.31	0.31	0.32	0.30	0.29	0.29	0.20
Number of obs.	5095	5095	5095	3269	5094	5094	5094	3269

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include for the benchmark set of geography controls and latitude (not reported). * indicates p <0.10, ** p <0.05, and *** p <0.01.

Table N.4: Borders and modern outcomes: local deviations using alternative time periods.

	Dependent variable:							
	Δ Log night lights				Δ Log population density			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Border freq. 1300-1800	−0.172***				−0.265***			
	(0.049)				(0.070)			
Δ Border freq. 1300-1900		−0.195***				−0.307***		
		(0.052)				(0.074)		
Δ Border freq. 1300-2000			−0.224***				−0.343***	
			(0.052)				(0.075)	
Δ Border freq. 800-2000				−0.211***				−0.350***
				(0.073)				(0.106)
R^2	0.12	0.12	0.13	0.15	0.08	0.08	0.08	0.10
Number of obs.	5095	5095	5095	3268	5094	5094	5094	3268

Notes: Ordinary least squares regressions with Conley standard errors in parentheses assuming spatial autocorrelation among observations within 1.45 degrees of each other. All specifications include local deviations in the benchmark set of geography controls, and latitude (not reported and not in local deviations). * indicates $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Figure C.1: How average output per location, Y^*, depends on the number of countries, N, for the same numerical example as in Figure 2 in the paper.

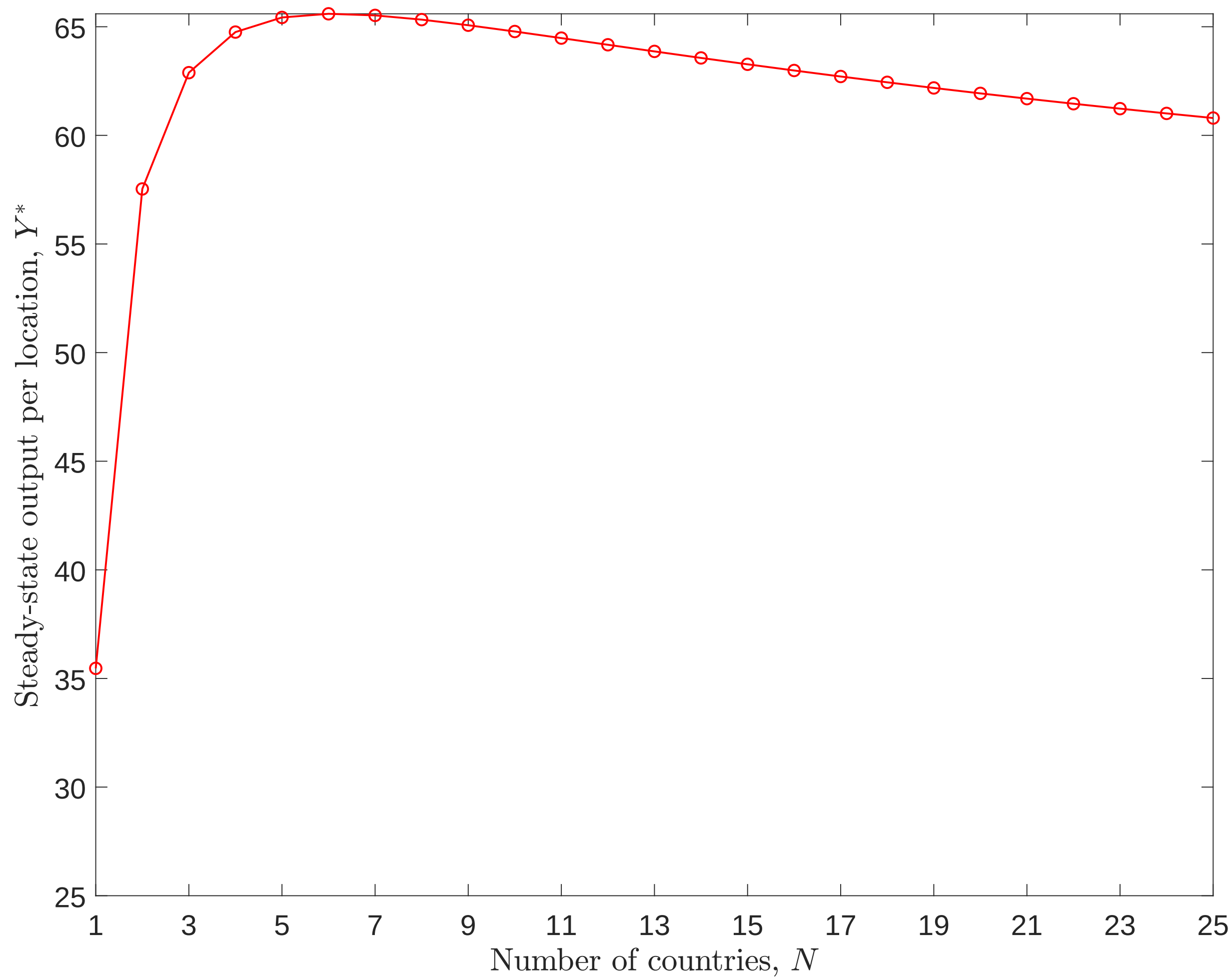


Figure C.2: How location specific productivity, $\widetilde{Z}(d)$, shifts across locations in a region with four countries ($N = 4$), and where $\varepsilon = 0.2$ and $\lambda = 0.5$.

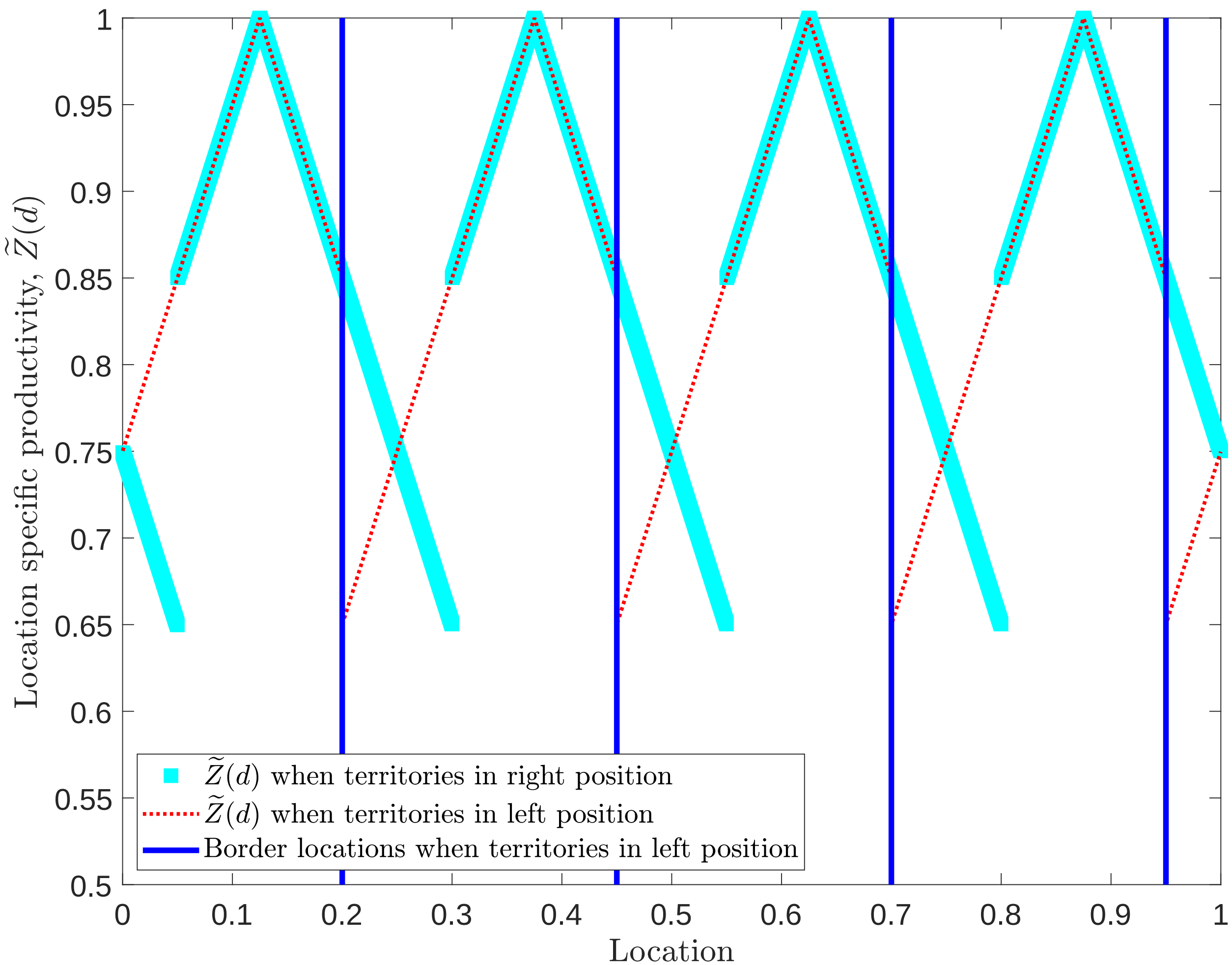


Figure C.3: Illustration of Proposition C.1.

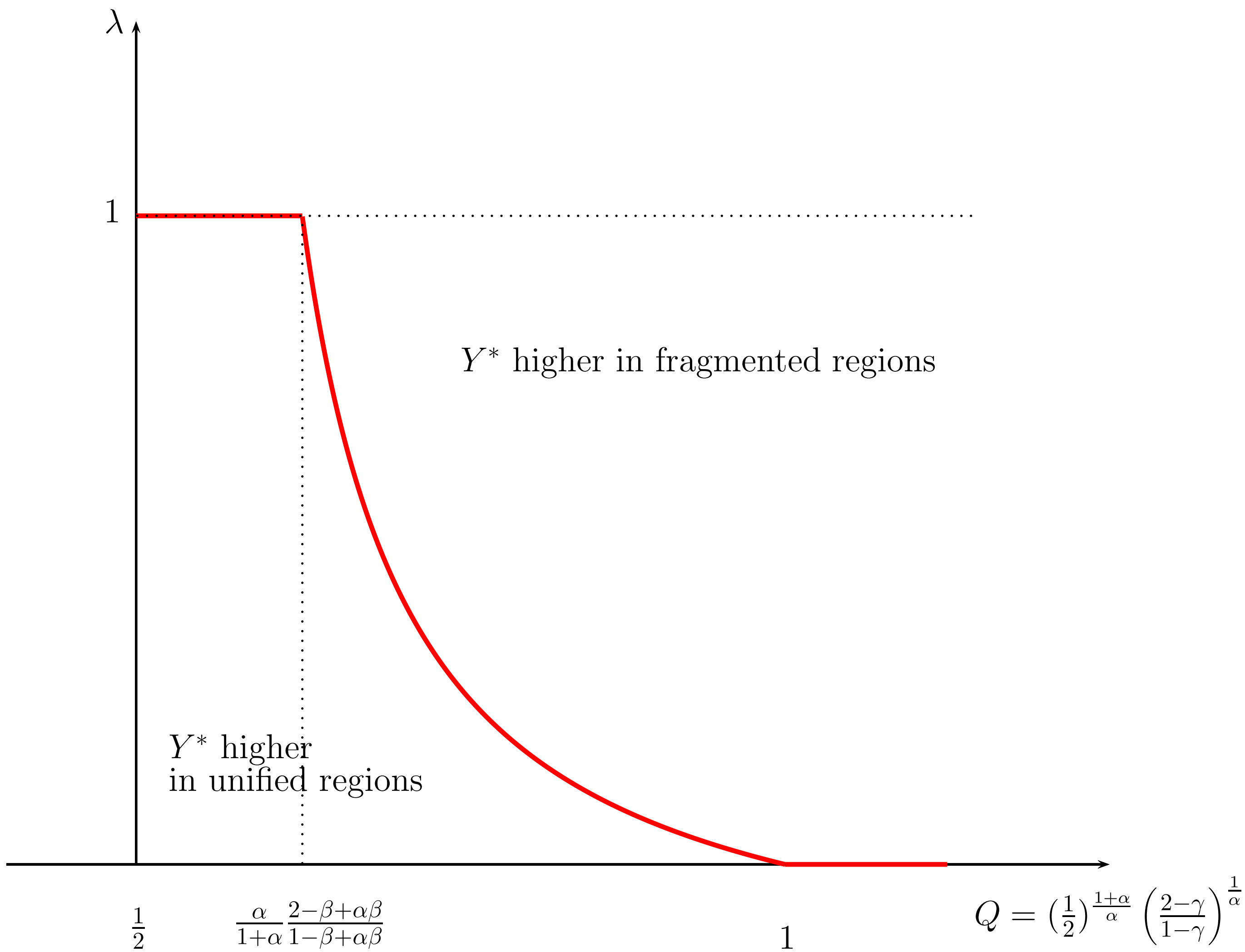


Figure D.1: Time path of state presence in the Euratlas data 800-2000 CE.

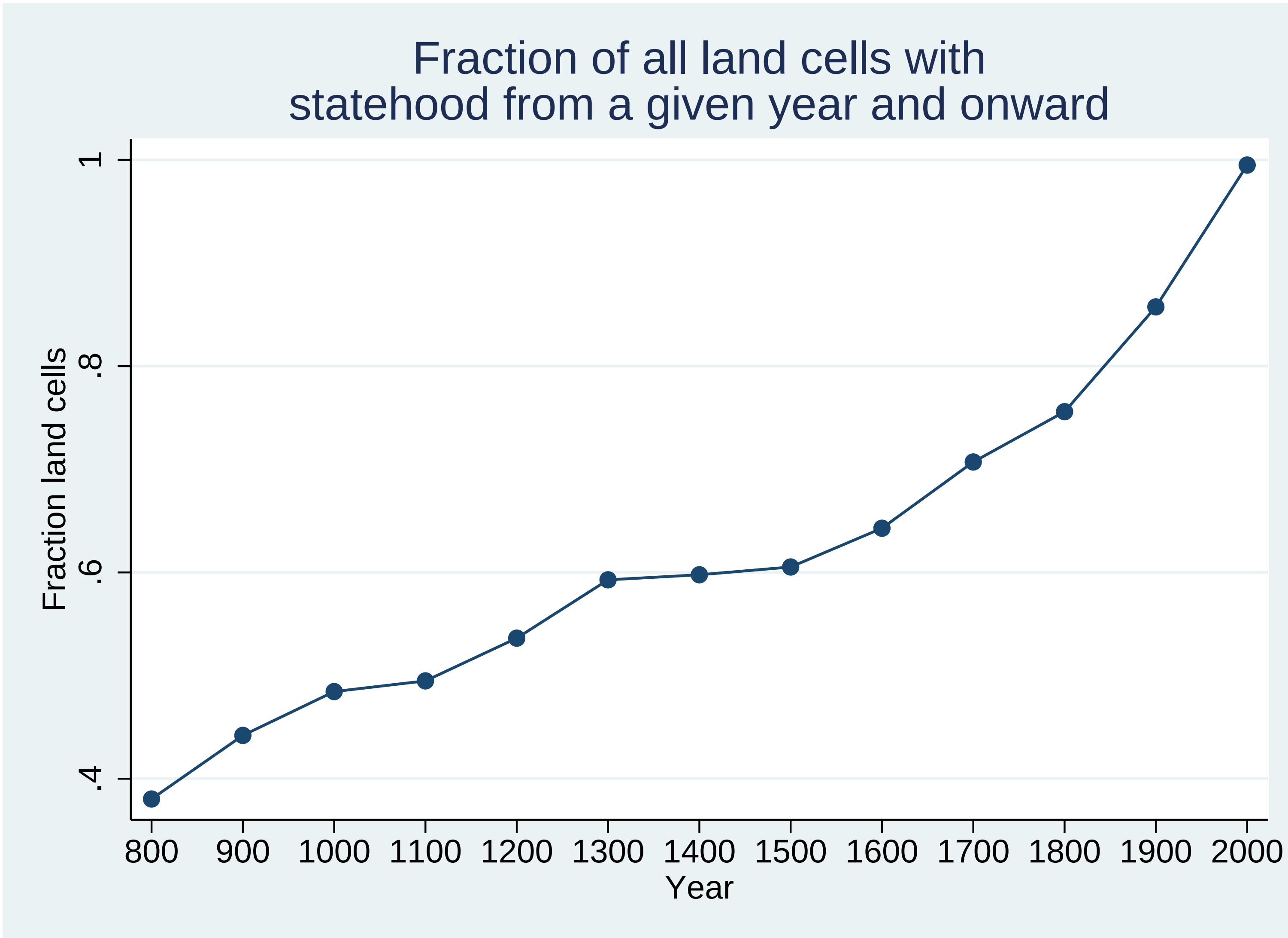
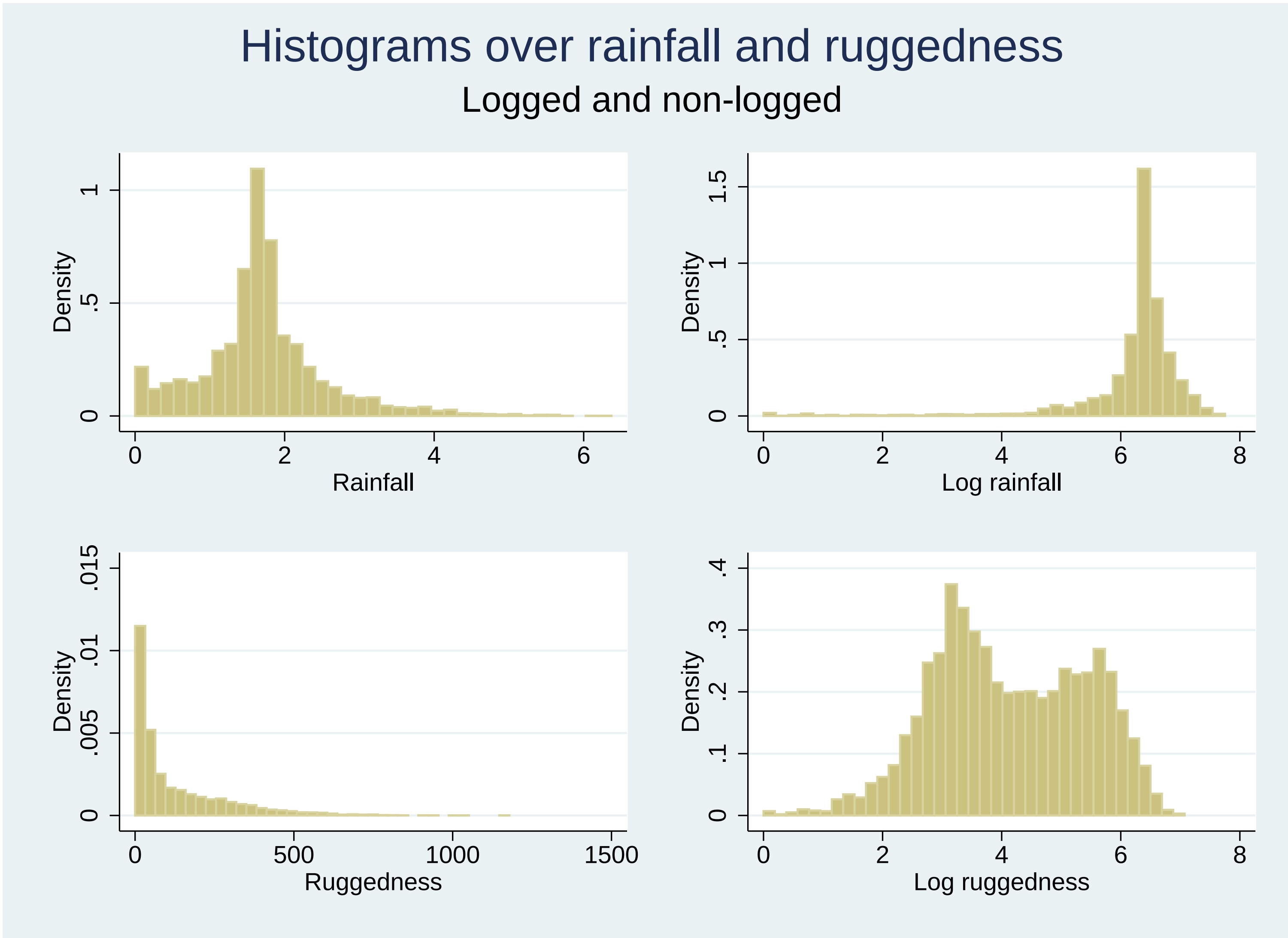


Figure E.1: Histograms over two geography variables, logged and non-logged.



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