Institutions and Global Crop Yields

David Wuepper,[1,2] Wolfram Schlenker,[3,4] Meha Jain,[5] Haoyu Wang,[5] and Robert Finger[2]

February 2023

Abstract

We examine the effect of a country's economic and legal institutions on agricultural yields. We first estimate annual discontinuities in crop yields around all global land borders that have cropland within a 100km band on both sides of the border using fine-scale satellite readings resulting in 83million pixels for 2001-2019. We then link these annual discontinuities to a panel of institutional quality by the Fraser Institute. We find that changes in institutional quality translate into changes in the border discontinuity over the next five years: each point of the overall index, which is on a 0-10 scale, increases the discontinuity by 2.2%, highlighting that institutional reforms have the potential to close some of the crop yield gap. When we include the 24 subcategories of the index, three of them consistently come back significant: inflation, credit market regulation, and the top marginal tax rate. While changes in the index have a significant effect on mean yields, we find no effect on yield variability. When examining extensive margin responses, we find results of a similar magnitude, but with less significance and suggestive evidence that the increase in the number of cropland pixels causes deforestation.

Keywords: Institutions, Crop Yields, Yield Gap, Agricultural Development
JEL Codes: O13, Q1

Acknowledgments: We would like to thank Kai Gehring and seminar participants at the University of Bern and OARES for comments on an earlier draft of the paper. Schlenker acknowledges support for this work by USDA National Institute of Food and Agriculture, Grant No. 2022-67023-36400.

[1] Land Economics group, University of Bonn, Germany
[2] Agricultural Economics and Policy group, ETH Zürich
[3] School of International and Public Affairs, Columbia University
[4] National Bureau of Economic Research (NBER)
[5] School for Environment and Sustainability, University of Michigan

Workers and firms interact in human-designed institutional settings.[1] Establishing a well-functioning market economy has long been argued to give the right incentives to individuals (Smith 1776) and be a key ingredient for economic development (Acemoglu, Gallego and Robinson 2014a). Various papers have focused on different aspects, for example, enforceable contacts and well-functioning credit markets (Banerjee 2003) or secure property rights (Acemoglu and Johnson 2005, Behrer, Glaeser, Ponzetto and Shleifer 2021).

The agriculture sector is a major, often the largest, employer in developing countries. Attainable yields and comparative advantages are evolving with climate change (Costinot, Donaldson and Smith 2016), which, coupled with existing high trade barriers, can further aggravate the situation as countries are predicted to employ more labor in the agricultural sector despite having a comparative disadvantage to satisfy domestic food needs (Nath 2022). Still, even today, there is a gap in many countries between realized yields relative to what is attainable based on natural endowments (e.g., soils and weather). This "yield gap" is often attributed to institutional failures, e.g., farmers not adopting higher-yielding varieties with higher average returns[2] but also higher variability because a lack of insurance markets, or the inability to purchase required inputs or insurance due to liquidity constraints (Casaburi and Willis 2018).

Our paper provides novel estimates whether changes in institutions translate into changes in observed yields. We focus on discontinuities in yields around country borders where institutions change and link changes in discontinuities over time to an annual measure of institutional quality, the economic freedom index by the Fraser Institute. In doing so we make four major contributions:

First, our study complements previous studies that focus on one particular reform in a country by systematically accessing discontinuities across all land borders between countries in the world that have cropland within a 100km (62 mile) band on each side. This approach allows to construct a larger sample with varying conditions. We rely on a remote sensing product, the annual maximum of the Enhanced Vegetation Index (EVI) to derive fine-scaled yield proxies on a 1x1km grid using a common measure.[3] Having a common

[1] Lin and Nugent (1995) define an institution "as a set of humanly devised behavioral rules that govern and shape the interactions of human beings, in part by helping them to form expectations of what other people will do.[...] It is clear from this definition why institutions can consist of both formal entities like laws, constitutions, written contracts, market exchanges and organizational by-laws and informal ones like shared values, norms, customs, ethics, and ideology."

[2] Laajaj, Macours, Masso, Thuita and Vanlauwe (2020) caution that not all predicted yield gains from field trials are obtained under real-world growing conditions.

[3] We obtained the 1x1km grid from Google Earth Engine, see the data section below. The native resolution is even finer at 250meters.

outcome measure and set of assumptions is a key ingredient for a global analysis. For example, Ittersum, Cassman, Grassini, Wolf, Tittonell and Hochman (2013) argue that "there are serious limitations to current estimations of the exploitable gap between current average yields and yield potential. It is essential that yield gap studies provide clarity regarding their underpinning assumptions, models and parameters and include verification with measured data." Our data consists of 83million pixel readings over cropland areas within 100km of country borders for the years 2001-2019. Agriculture is a unique sector as outcomes are directly observable from space on a fine-scale geographic scale around borders. While other sectors beyond agriculture are also impacted by institutions, it is much harder to obtain global fine-scald estimates.[4] As such, our study offers a unique setting with implications for the broader literature on the role of institutions.

Second, we offer a defensible identification strategy, by first estimating spatial discontinuities in yields at borders and then linking them in a panel setup to changes in institutional quality. This two-step approach first derives how yields "jump" at country borders and then uses them in a panel setting with border fixed effects, effectively linking *changes* in yield discontinuities to *changes* in institutions.[5] The advantage of relying on changes is twofold: soil or other environmental factors might not be smooth at all border segments[6] and the measure of institutional quality we employ, the economic freedom index by the Fraser Institute, has sometimes been criticised for omitting important aspects. Importantly, it exclusively focuses on formal entities and does not model informal ones like shared values or norms. In both cases the fixed effects will be helpful: the possible changes in natural endowment across borders are time-invariant and hence absorbed by the border fixed effect. In case of the economic freedom index by the Fraser Institute, as long as informal norms do not concurrently change with the formal measures, they will also be absorbed in the border fixed effects.

Third, given the global scope of our analysis, our data also includes borders between developed countries. This allows to test empirically whether improvements at various baseline levels are different. A priori, both a concave and convex response functions are feasible.

[4] Pinkovskiy (2017) uses nightlight data as proxy for economic development at borders and shows that there are jumps at borders.

[5] Earlier studies have linked growth rates to measures of institutional quality in the cross-section (Scully 1988), but we show below that the cross-sectional association in our case is different from our panel estimate.

[6] For example, recent studies have derived natural tree cover, which has been modeled using the observed tree cover in protected areas around the world and a random forest algorithm using a long list of environmental characteristics to predict the natural tree cover outside of these protected areas (Bastin, Finegold, Garcia, Mollicone, Rezende, Routh, Zohner and Crowther 2019, Bastin, Finegold, Garcia, Mollicone, Rezende, Routh, Zohner and Crowther 2020). There are discontinuity in this natural tree cover at some border sections.

The concave response function would imply a leveling-off once a critical level is met, i.e., further improvements in institutions have smaller effects on yields once a certain level is reached. The convex response function would suggest that improvements have little effect at low baseline levels but increase as institutions improve, e.g., markets only start to develop when a critical level is reached, but are less responsive to changes in institutional changes for levels below the threshold. In the end we find that improvements in institutional quality have positive effects on yields at both low and high levels of the Fraser Index, i.e., being applicable to all areas around the globe including developed countries.

Fourth, our results have clear implications for policy advice. We provide empirical evidence that market reforms, i.e., the reforms the IMF or the World Bank often advocate, lead to measurable improvements in observed yields, with the potential to narrow the observed yield gap and the possibility to foster economic growth. For example, increasing crop yields has been shown to be a highly effective means to raise incomes in developing countries (Gollin, Hansen and Wingender 2021). We consistently find three sub-categories of the Fraser Index to have strong predictive power: inflation, credit market regulation, and the top marginal tax rate.

The effect of national institutions on agricultural production is especially important given the strong demand growth for agricultural production, the large share of the world's poor that depend on agriculture for their livelihoods and the environmental implications of loosing increasingly valuable natural ecosystems to cropland expansion instead of boosting yield on existing land (Foley, Ramankutty, Brauman, Cassidy, Gerber, Johnston, Mueller, O'Connell, Ray and West 2011). Predicted population and income growth imply that global crop production needs to grow by 25-70% from 2015 to 2050 to match demand (Hunter, Smith, Schipanski, Atwood and Mortensen 2017).

Our research also connects to the long standing question why there are such large and persistent differences in agricultural production between countries (Schultz 1953, Hayami and Ruttan 1970). For example, comparing the ten percent of countries with the highest yield per hectare to the 10 percent of countries with the lowest yield per hectare, there is a productivity gap of 790% (Adamopoulos and Restuccia 2022). Noteworthy, this is not explained by differences in natural endowments at all, as Adamopoulos and Restuccia (2022) show that the agricultural potential is possibly slightly higher in the currently less productive countries, which mostly have in common that they are poor.

The literature offers a list of technological and socioeconomic explanations for the global differences in agricultural productivity. For example, differences in the availability of modern agricultural inputs, such as high yielding varieties and how well they are adapted to countries' growing conditions (Gollin et al. 2021, Moscona and Sastry 2021). This is clearly connected to the vast global inequality in agricultural research and development (Alston, Pardey and Rao 2021). Another explanation are differences in input-costs. These are higher in lower-income countries, especially because of transportation costs (McArthur and McCord 2017). High transport costs that make inputs more expensive in developing countries also lower productivity because they tax the output side as well and they reduce trade (Adamopoulos 2011, Tombe 2011, Sotelo 2020). Moreover, farmers with lower incomes also tend to use fewer production inputs to mitigate their exposure to uninsured shocks, such as drought and floods (Donovan 2020, Emerick, Janvry, Sadoulet and Dar 2020). Finally, the quantity and quality of agricultural extension differs a lot around the world, such that low-income farmers often have far less information available than farmers in high-income countries (Deutschmann, Duru, Siegal and Tjernstrom 2019, Suri and Udry 2022).

While there are several cross-country studies examining the link between institutions and GDP (Acemoglu et al. 2014a, Pinkovskiy 2017) that document significant effects, comparable research is currently lacking for the agricultural sector. To the best of our knowledge, there are only case studies in single countries (Tseng, Robinson, Bellemare, BenYishay, Blackman, Boucher, Childress, Holland, Kroeger, Linkow et al. 2021). These case studies point towards a potentially important role for national institutions, especially when connected to property rights. For example, Chen, Restuccia and Santaeulàlia-Llopis (2022) document how improving tenure security in rural Ethiopia boosted agricultural productivity by 43 percent because land markets could function better. In China, Adamopoulos, Brandt, Chen, Restuccia and Wei (2022) find that improving tenure security improved agricultural productivity by more than ten percent, also here via the improvement of land markets. Other research has also shown how improved tenure security can incentivize agricultural investments, especially larger ones with longer term payoffs, e.g. soil conservation practices (Ali, Deininger and Goldstein 2014).

A priori, the importance of a country's institutions for agricultural production is unclear. In principle, it is possible that local institutions work well without control from a higher level (Ostrom 1998, Ostrom 2000). However, without strong national institutions, local elites might provide a setting that are more in their own than the general interest (Acemoglu, Reed and Robinson 2014b). There is a rich case study literature documenting that, e.g., formalizing tenure security is usually followed by economic, social, and economic improvements, especially for the least powerful (Tseng et al. 2021). However, it must also be noted that rural areas tend to be remote and especially in countries with low state capacity, it is not clear how much remote crop fields close to borders are actually impacted by national institutions (Herbst 2014, Besley 1995, Besley and Persson 2009). As such, the question here is both whether national institutions are generally important for agricultural production and whether they are able to provide it in rural areas.

1 Empirical Methodology

Our empirical framework can be motivated with areal images shown in Figure 1. At many international borders, environmental conditions are similar on both sides, such as in this example of the border between Lesotho and South Africa in the top panel, the border with the highest average discontinuity in our data. The bottom row displays the case of Turkey and Syria. While the natural vegetation would look the same across the border due to similar environmental conditions, we see that the agricultural areas look vastly different.[7] At these exemplary borders, South Africa and Turkey have considerably more productive crop fields, and the change is abrupt exactly at the political border where institutional regimes change.[8] Turkey has a higher value on the economic freedom index by the Fraser Index, a measure of institutional quality, leading to a positive association. On the other hand, there are also borders (e.g, China-Kazhakstan or Peru-Bolivia) where the country with the higher economic freedom index has lower average yields, suggesting a negative association between the index of institutional quality and yields in the cross-section. As discussed above, there are other differences in culture and norms, highlighting the advantages of our two-step setup: when we link *changes* in the border discontinuity and the Fraser Index, we find a significant positive relationship across borders.

1.1 Estimating Annual Discontinuities at Country Borders

While Figure 1 provides areal photos of border segments to highlight our approach, the top panels of Figure 2 show a more systematic picture along the entire border for four borders in various continents in our data that have among the largest discontinuity. We plot the raw values of the annual maximum EVI of all pixels within 100km of the border for the years

[7] Similar discontinuities at political borders have previously been found for economic growth (Pinkovskiy 2017), soil erosion (Wuepper, Borrelli and Finger 2020a), and nitrogen pollution (Wuepper, Le Clech, Zilberman, Mueller and Finger 2020b).

[8] While these pictures are taken in 2018, similar effects are seen even before the Syrian war going back to the 1990s.

2001-2019 in our data.[9] We normalize the border to be at distance 0, while negative distance are in the western country, and positive distance being in eastern countries. The "greener" side of the border in Figure 1 is shown in green, while the other side of the border is shown in brown. Circles give the average for the raw data for each 5km bin. The straight line is a linear fit in the distance measure while also allowing for a discontinuity at zero, which is clearly visible.

We formalizes this approach to all borders in the data. We derive annual discontinuities in crop yields at borders between country-pairs where institutional regimes abruptly change. We employ a regression discontinuity framework using our proxy for yields, the annual maximum of the enhanced vegetation index (EVI). This approach requires two key components (Cattaneo, Idrobo and Titiunik 2018, Wuepper and Finger 2022): a continuously distributed running variable with a sharp threshold value, and a discontinuous treatment assignment rule, that sorts observations above and below the threshold value into "treatment" and "control." Under well-established assumptions (Hahn, Todd and der Klaauwo 2001, Turner, Haughwout and Klaauw 2014, Calonico, Cattaneo, Farrell and Titiunik 2019), the abrupt change in treatment assignment allows for causal identification of the treatment effect. Assuming that other factors, e.g., soil quality, altitude, temperature, access to water are continuous across the border, the one factor that changes abruptly as one crosses the border is the institutional setup. The assigned treatment is the change in institutional regime. We would get an unbiased estimate of the effect by looking at the discontinuity:

$$\beta_{bt} = \mathbb{E}[y_i(1) - y_i(0)|X_i = 0] = \lim_{d\uparrow 0} \mathbb{E}[y_i|X_i = d] - \lim_{d\downarrow 0} \mathbb{E}[y_i|X_i = d] \tag{1}$$

where $y_i(1)$ and $y_i(0)$ are the outcomes if a country are treated to better or worse institutions, respectively. Our running variable X is the distance of each pixel to the border, which controls for spatially continuously distributed confounding environmental factors. We normalize the border to be at distance 0, where treatment assignment abruptly changes.

In practice, there three major challenges: first, not every pixel around a border is cropland, and we hence might not have observations for all distances at every point of the border, the assumption of a smooth running variable. Figure 3 illustrates this point: Panel A displays the pixel location around the Turkey-Syria border, which is evenly balanced, while Panel B shows pixels around the Cambodia-Vietnam border were there are many more pixels on the Vietnamese side and in different parts of the border, i.e., borders are in a two-dimensional

[9] While EVI ranges between -1 and 1, our measure is multiplied by a factor of 1000.

(longitude-latitude) rather than a one-dimensional space. Second, borders sometimes follows natural geography (e.g., rivers, mountain ranges) and other factors (soil, water access, climate) might change at the border as well. Third, not just environmental factors, but part of the institutional quality we trying to measure might change at the border that are not captured by the economic freedom index we use.

We address the last two challenges in the next Section 1.2 by liking the annual border discontinuities to institutional quality in a panel setting with border fixed effects to net out persistent other changes.

To address the first challenge, we construct narrow border segments and only compare points across each border segment to derive the average discontinuity for a country-pair. Specifically, each pixel is assigned to the closest border point. We then bin the border using a half-degree longitude and latitude grid (equivalent to 55km or 34 miles at the equator), shown as grey raster in Figure 3. Border segments entail all border points that fall into a particular grid.[10] Specifically, we estimate the following equation (in practice this equation is run for each border and year separately for all borders that have at least 100 observations (pixels) on each side of the border):

$$y_{ibt} = \alpha_{s[i,b]t} + \beta_{bt} I_{[i \in H]} + \boldsymbol{\gamma}_{s[i,b]t}\mathbf{X}_i + \boldsymbol{\delta}_{bt}\mathbf{Z}_{it} + \epsilon_{ibt} \tag{2}$$

where y_{ibt} are crop yields (the log of the annual maximum EVI) of pixel i in year t along border b of a country-pair. The coefficient $\alpha_{s[i,b]t}$ capture border-segment by year fixed effects, where $s[i,b]$ is the border segment in which pixel i along border b is located. Furthermore, $\boldsymbol{\gamma}_{s[i,b]t}$ are border-segment specific coefficients that are allowed to vary by year and include three time-invariant variables $\mathbf{X}_i$: a smooth function in longitude, latitude as well as the cross-term. Finally, $\mathbf{Z}_{it}$ includes common controls where the coefficient $\boldsymbol{\delta}_{bt}$ is forced to be the same across all border segments. In our baseline this includes a dummy for cells that have higher cropland fraction and hence higher reflectivity as measured by the satellite.[11] Finally, in some sensitivity checks we furthermore include the following controls in $\mathbf{Z}_{it}$, some of which are time-varying (a quadratic in average temperature, precipitation, solar radiation) while others are time-invariant (a quadratic in altitude as well as soil class fixed effects) to see whether accounting for drivers of crop-yield changes the results, which would be the case if these change discontinuously at the border. Since these parameters model

[10] Pixels do not have to fall into the grid, but rather the closest border point as we are interested in the discontinuity at the border and hence classify pixels by closest border point.

[11] We have two landcovers in our data, medium and high cropland intensity, see the data section below

the responsiveness of crops to environmental factors, the coefficients $\boldsymbol{\delta}_{bt}$ are assumed to be the same across all border segments. Finally, $I_{[i \in H]}$ is an indicator variable for the country that has the higher country code. This normalization is inconsequential as we link it in the next step to differences in institutional regimes across borders, taking the difference from the country with the higher code to the one with the lower code.[12]

The resulting residuals after removing the four border-segment specific controls – i.e., a border-segment fixed effect as well as smooth polynomials in latitude, longitude and the cross-term – as well as a dummy for pixels with a higher share of cropland are shown in the bottom panels of Figure 2. Note that there is no longer a gradient with respect to distance, and a discontinuity is visible at zero.

We vary the distance cutoff for the pixels that are included in the regression, setting it at 15km, 20km, 25km, 30km, 35km, 40km, 50km, 75km, 100km. On the one hand, we would like to choose a narrow bandwidth to ensure that pixels on both side of the border are comparable. On the other hand, a wider bandwidth ensures that we have enough pixels on both sides. Our default bandwidth is 25km, i.e., we include pixels on both side of the border that are within 25km of the closest border point. Recall that each pixel is 1x1km in size. We always exclude pixels that are less than 1km in distance from the border, as their average might include readings from across the border, which we want to avoid when measuring the border discontinuity.

1.2 Panel of Border Discontinuities and Measures of Institutions

We next link the estimated border-discontinuities in yields ($\widehat{\beta_{bt}}$) from equation (2) to measures of institutional quality in a panel setting including border fixed effects a_b, thereby linking *changes* in the border discontinuity in yields to *changes* in our institutional measures. This gives us the intensive margin results - we selected the 83 million pixels that are classified as cropland in all years 2001-2019. In case there are other discontinuous changes at the border due changes in the natural endowment, these natural factors are fixed and do not change year-to-year and will hence be absorbed by the border fixed effect. Errors are clustered by border to account for serial correlation across years.

$$\widehat{\beta_{bt}} = a_b + \frac{1}{L} \sum_{l=1}^{L} \left[f(q_{H[t-l]}) - f(q_{L[t-l]}) \right] + e_{bt} \tag{3}$$

[12]The important thing is that discontinuity in the first step and difference in institutional quality in the second step are aligned.

Our specification includes the average across lags $l = 1 \ldots L$ as it may take time for changes in institutional quality to be detected in the form of higher crop yields, e.g., because farmers are willing to invest more into fields or undergo over productivity-enhancing investments that take time to materialize, e.g., building new irrigation canals. We start with a semi-parametric specification that allows for a nonlinear response function $f()$, which is approximated using restricted cubic splines with three knots, which are set at the 10^{th}, 50^{th}, and 90^{th} percentile of observed values of institutional quality.[13] This setup would allow us detect whether there are critical levels below or above which there are no responses to changes in institutional quality. For examples, countries with very poor quality below a critical level might not be responsive to changes in institutional quality as the situation remains too dire to invest. Alternatively, once countries reach a high level, further improvements in institutional quality might not result in changes in what farmers do. The semi-parametric approach is also able to pick up other possible non-linarities at intermediate ranges.

We also consider possible effects on the extensive margin, i.e., that the cropland area expands. We revert to a difference-in-difference analysis where our dependent variable becomes the difference in the number of pixels Δn_{bt}^k at border b in year t that are classified as landcover type k (H and L are the two sides of border b)

$$\Delta n_{bt}^k = n_{Ht}^k - n_{Lt}^k = a_b + \frac{1}{L} \sum_{l=1}^{L} \left[(q_{H[t-l]} - q_{L[t-l]} \right] + e_{bt} \tag{4}$$

We now no longer focus our data on the 83 million pixels that continuously are cropland, but instead add all of the 351 million pixels that are within various bandwidths and classified as $k \in \{$cropland, forest, or grassland$\}$.[14] This allows to examine whether the amount of cropland expands after reforms, and whether it comes at the cost of forests or grasslands.

[13]This setup imposes a linear approximation below the lowest knot and above the highest knot (1 degree of freedom each) as well as a cubic approximation (third-order polynomials) between the lowest and the middle as well as the middle and the highest knot (3 degrees of freedom each) for a total of 8 degrees of freedom. At the same time, the function is forced to be continuous with a continuous derivative (slope) at each of the three knots, which equates to a loss of $3 \times 2 = 6$ degrees of freedom. As a result there are two spline variables with the second capturing possible non-linearities.

[14]Pixel classifieds as landcover class 12 or 14 in Friedl and Sulla-Menashe (2019) are counted as cropland, pixels classifieds as landcover class 1-5 as forest, and landcover type 10 as grassland.

2 Data

We combine remotely sensed data on crop yields with measures of institutional quality around the entire globe, described in further detailed below.

2.1 Globally Consistent Crop Yields Data

It is important that our measure of crop yields stems from a global, methodologically unified source, with repeated measurements over time that are independent of country-level variables to avoid systematic measurement error. For example, if countries with deteriorating institutional quality collect less reliable or infrequent data, an analysis using country-level data could be biased. For economic growth data, for example, it is well documented that autocracies systematically over-report their progress (Martinez 2022).

Here we use the annual maximum Enhanced Vegetation Index (EVI), which is tightly correlated with crop yields across the globe. High temporal-resolution MODIS satellite data has been shown to capture crop phenology well, and specifically can be used to identify crop heading date (Sakamoto, Yokozawa, Toritani, Shibayama, Ishitsuka and Ohno 2005, Son, Chen, Chen, Minh and Trung 2014). Furthermore, vegetation biomass measured using satellite data during the heading period has been shown to correlate highly with crop yield, with correlation values up to 0.84 across crop types, e.g., rice, wheat, and maize (corn), as well as regions, e.g., North America, Asia, and Australia (Johnson 2016, Liu, Huffman, Qian, Shang, Li, Dong, Davidson and Jing 2020, Son et al. 2014). We use EVI instead of other vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), because it has been shown to measure biomass more accurately at high values and is also not as influenced by background soil signatures (Huete, Didan, Miura, Rodriguez, Gao and Ferreira 2002).

It is important to note several potential limitations of our satellite estimate of yield. First, by using annual maximum EVI, we only capture the peak growing period of the main growing season that has the highest amount of vegetation biomass. We are unable to measure agricultural production across multiple seasons in regions where farmers may plant more than one crop per year.

Second, maximum EVI is influenced by multiple factors that may alter vegetation biomass, including crop yield, crop type, and crop area (Jain, Mondal, Galford, Fiske and DeFries 2017). If two sides of a border were to grow different crops with different biomasses, the discontinuity would not only be due to a difference in yields but also due to the planted crop.

However, as long as both crops have similar relative yield sensitivities to EVI and farmers grow the same crop over time, the difference due to crop types would be absorbed by the border fixed effect in the second step of our analysis. Moreover, we show in Table 1 below that three quarters of the growing area around a border grows the same dominant crop on both sides of each border segment, the level at which we conduct cross-border comparisons. If one country changes the crop type, it is part of the response that we want to measure.

Third, we conducted our analysis at a 1 km resolution, which may result in mixed pixels in regions where farm sizes are smaller than 1 km. However, we conduct a sensitivity analysis below in Table A12 and find no evidence the institutional quality influences the share of a 1x1km pixel that is cropland.

Finally, our satellite measurements of peak biomass can sometimes be impacted by cloud cover given that farms usually show the highest levels of biomass production during the growing season with the greatest amounts of precipitation. This, however, is unlikely to impact our results for several reasons: we filtered our data to remove pixels that were contaminated with cloud cover before calculating maximum EVI. Moreover, cloud cover is commonly not systematically different across borders and we are relying on border discontinuities. We further test this in a sensitivity check in Appendix Table A5 where we include environmental variables, such as rainfall, temperature, and solar radiation as a control variable, and our results remain robust.

2.2 Selection of Pixels Included in Analysis

Our study focuses on agriculture and we therefore select pixels that are predominately cropland. In our baseline specification on the effect on log yields, we are interested in the intensive margin effect and hence focus on pixels that consistently report throughout our sample period where the EVI data is available, i.e., 2001-2019. Annual information on land cover is taken from Friedl and Sulla-Menashe (2019), which has 17 land cover classes, of which two classify grid-cells as cropland. Class number 12 is labeled "cropland," which the requirement that at least 60% of the area is cultivated cropland. Class number 14 is labeled as "cropland/natural vegetation mosaic," which are mosaics of 40-60% small-scale agricultural cultivation and the rest is natural tree, shrub, and herbaceous vegetation between and around the fields. Pixels are included in our baseline regression if the landcover categorizing is class 12 or 14 in each of the years 2001-2019. All of our regression include landcover fixed effects to account for the fact that class 12 and 14 pixels might have different average greenness. This leaves us with 83 million pixels for 2001-2019.[15]

For analyses on the effect of countries' institutions on the expansion and abandonment of cropland, we use the larger data set of 351 million pixels that is not restricted to pixels that are cropland (classified as class 12 or 14) in each year, but rather count the amount of cropland, i.e., the number of pixels that are classified as either class 12 or 14 in a year.

2.3 Additional Controls for Yields

Our baseline analysis in equation (2) uses a regression discontinuity design at borders. The assumption of a RD is that all other variables are balanced around the border and we hence only include border-segment controls (i.e., fixed effects and smooth polynomials in longitude and latitude) to make sure we compare pixels across narrwoly defined sections of the border.

In a sensitivity check in the appendix we further control for variables that have been shown to influence yields. The following data set provide these variables at the same 1x1km pixel resolution. The sources are: annual rainfall (Schneider, Becker, Finger, Meyer-Christoffer, Rudolf and Ziese 2011), annual average temperature (Wan 2021), annual solar radiation (Tang, Yang, Qin, Li and Niu 2019), topography (Robinson, Regetz and Guralnick 2014), and soil characteristics (Batjes 2012).

2.4 Measure of Institutional Quality

Our analysis uses the economic freedom index by the Fraser Institute, specifically the Economic Freedom of the World database[16] Thy institute states that "This index is the most objective and accurate measure of economic freedom published by any organization. It was developed by a research team led by Nobel Laureate Milton Friedman and former Fraser Institute Executive Director Michael Walker." It has been used in a long list of academic studies. It derives a quantitative score on a 0-10 scale that is the weighted averages of five sub-areas, namely (i) size of government, (ii) legal system and property rights, (iii) sound money, (iv) freedom to trade internationally, and (v) regulation. Each of these areas is again derived using various sub-scores. The 24 sub-scores are listed in Table A11.

The overall economic freedom index is displayed by year in Figure A1 for the 2000s and Figure A2 for the 2010s. A few illustrative examples are clearly visible, e.g., the downward trend in Venezuela's scores, the country with one of the lowest overall scores, or Syria's down-

[15] Our panel is not perfectly balanced as some pixel have no readings in a year due to cloud cover.

[16] https://www.fraserinstitute.org

ward trend starting in 2012. Other countries have seen remarkable progress, e.g., Myanmar during its reform period 2011-2015. Notably, there is considerable variation over time that we utilize in our panel setting.

3 Empirical Results

Earlier studies have sometimes relied on cross-sectional correlation between growth rates and institutional quality. For comparison, we present the corresponding correlation in our data in Figure A5. We find a strong positive correlation between log yields and the economic freedom index, our measure of institutional quality in panel A. On the other hand, when we correlate border discontinuities in log yields to changes in the economic freedom index across the border, we find a negative association in panel B, likely because other things vary across borders beyond the economic freedom index, e.g., norms, government programs for agriculture, etc. This highlight the need for our identification strategy: the annual border discontinuity allows us to construct a credible control group,[17] while also differencing out other persistent differences by the relying on a panel setup with border fixed effects.

3.1 Annual Border Discontinuities in Yields

We start by estimating annual border discontinuities at each border while controlling for border-segment fixed effects and segment-specific smooth polynomials in space as outlined in equation (2) above. The borders and pixels that are used in the analysis are displayed in Figure 4. We consider all land borders that have cropland pixels within 100km of the border. Figure 4 displays in yellow an aggregated version of where the 83 million pixels are located, by aggregating them to a 0.1 degree grid (roughly 11x11km). The land borders in the data are highlighted. A blue color indicates that at least 100 pixels were available on each side of the border per year and that the economic freedom index by the Fraser institute was available. Red lines imply that either the index was missing or that the number of pixels did not met our minimum of 100 in the baseline regression using a 25km bandwidth. The results are 135 blue borders that are in our baseline data, which are from around the world. When we increase the bandwidth, additional borders might satisfy the minimum number of pixel cutoff. In the following we always include a line that lists the number of borders that

[17] A simple panel linking EVI to measures of institutional quality does not account for the possibility that institutions might change to world events, e.g., the 2008 financial crisis, that have themselves an effect on farm operations.

are included in the analysis.

We start by examining whether the two sides of a border segment grow comparable crops. Table 1 uses two data sources, one for 2000 and one for 2010. The 2000 data consist of 175 unique crop identifiers (Monfreda, Ramankutty and Foley 2008), which we aggregate to the same 1x1km grid by summing the area of each crop in hectares. The 2010 data has 42 unique crop codes (Yu, You, Wood-Sichra, Ru, Joglekar, Fritz, Xiong, Lu, Wu and Yang 2020), which is similarly aggregated. Since the different studies use different crop classifications, they are not directly comparable and we treat them separately. We derive the combined crop acreage for each crop type on each side of a border segment and pick the dominant crop, i.e., the crop with the largest growing area. If both sides of a border segment grow the same dominant crop, we label them as having similar cropping systems. Panel A1 and B1 give the fraction of the total growing area along a border for the border segments where both sides grow the same dominant crop (irrespective of what cop they plant). Different columns choose different bandwidths: generally, the narrower the bandwidth, the higher the percentage of the border segments that grow the same crop, although the fraction is consistently high and ranges between 63 and 76 percent. Panels A2 and B2 show the fraction of the overall area the dominant crops account for, i.e., by only summing the growing area of the dominant crop over all border segments where both sides grow the same dominant crop, relative to the total area, and the fraction reduces by a factor of two. Together these panels show that while a significant majority of border segments grow the same dominant crop, there is heterogeneity in the crops grown as the acreage of the dominant crop is roughly half of the overall area. This is likely due to crop rotation and crop diversification.

As describe in the data section, our intensive-margin analysis selects pixels that are predominately cropland, and selects pixels that remain cropland for all 19 years in our baseline regression. Differences in EVI that are due to differences in the what crops are grown are differenced out in two ways: by looking at border discontinuities we pick up shifts in demands for various crops across time as long as the change impacts both sides the same way. By examining changes in the discontinuity over time we difference out time-invariant differences in what crops are grown. Table A1 shows the variation in the data for both our border discontinuity (top row) as well as measures of institutional quality, separating the overall variation into between variation (differences in the average across borders) as well as within variation (year-to-year fluctuations at each border around the border average). It is noteworthy that there is significant within variation in both the border discontinuity and the measure of institutional quality, allowing us to link the two in a panel setting in the next step.

3.2 Border Discontinuities and Institutional Quality

Figure 5 display the spline results of equation (3) when we include between 1 and 9 lags of the dependent variable, color-coded from blue to red. The graphs display the difference in log yields (difference in y-values along the spline function) for various differences in institutional quality (difference in x-values). Since the function is allowed to be non-linear, moving from a score from 5 to 6 can result in a different improvement in log yields than moving from a score of 7 to 8. The top panel of Figure 5 focuses on the 10-90 percentile range of observed values of the measure of institutional quality, normalizing them to be at zero at the lower knot (10^{th} percentile).[18] The delayed response is clearly visible: as the number of lags increases from 1 to 5 lags, the estimated effect (difference in y-value) increases. The effect stabilizes once five lags are included and further lags do not result in additional cumulative effects.

While there is a significant non-linearity when using one lag (the p-value on the second spline variable is 0.07), the function flattens out and approaches a linear response as more lags are included (the p-values successively decrease). Such behavior is consistent with a quicker initial response by farmers that have higher baseline levels of institutional quality. However, farmers in location with lower initial institutional quality eventually catch up as the functional form approaches a linear straight line, suggesting that the cumulative effect eventually is the same irrespective of the baseline level and a linear functional form is appropriate.

Table 2 presents the baseline results assuming a homogeneous linear response. Each entry is from a separate regression, with the three lines giving the point estimate, standard error, and p-value, respectively. Panels A-C present results for the cumulative effects when including 1, 3 or 5 lags. Similarly to Figure 5, the cumulative effect increases when moving from 1 to 3 to 5 lags, i.e., by moving down a column. The coefficient gives the change in log yields ($\times$ 100), i.e., in percent terms for a one-point increase in the economic freedom index that is reported on a 0-10 scale. Our baseline specification, using a bandwidth of 25km and five lags has a coefficient of 2.2, i.e., each point of the economic freedom index increases the border discontinuity by 2.2%. Results when further lags are included are shown in Table A2, but the effects again stabilize after five lags are included. While we have used a

[18]The inclusion of border fixed effects implies that all result are in relative terms that measure *changes* in the y-value (log yields) in response to *changes* in the x-value (institutional quality), so a normalization does not alter the results.

log specification in our baseline assuming constant relative impacts, we obtain very similar results when using the level of the dependent variable, i.e., the maximum of the Enhanced Vegetation Index in Table A3 when assuming a constant absolute impact. Our results are not driven by functional form assumptions.

Columns differ by the chosen bandwidth, ranging from 15km to 100km. The bottom three rows of each panel give the number of borders, observations in our 19-year sample period 2001-2019, as well as pixels used in the first step when border discontinuities are derived. The coefficients are very robust across various bandwidths. All of them are statistically significant at least at the 10% level, with larger bandwidths giving more significant results. Moving to larger bandwidth increases the number of pixels used in the first step as a wider range of pixels around the border is included. Since we require at least 100 pixel on each side of the border to estimate annual border discontinuities, the number of borders also increases as the number of pixels on each side increases with larger bandwidths. To differentiate the robustness with respect to the bandwidth around the same borders versus what borders are included, Table A4 keeps the same set of borders across bandwidths for each row, i.e., fixes them to the set of borders that have at least 100 observations within 15km of each border, and again finds very robust results that vary even less than the ones in Table 2. Also note that the number of observations in the panel regression decreases when we include more lags. The economic freedom index is reported annually starting in 2000, so for any additional lag beyond the first one we loose one additional year of our 2001-2019 remote sensing data. This places a limit on how many lags we can include.

One might wonder whether particular countries are driving the results, e.g., because one neighbor is on a strong trend, e.g., the decline in the economic freedom index in Venezuela or Syria, or its improvement in Myanmar. We split our sample into two sub-samples in Table 3 depending on whether the same country always has the better (higher) index value (column 2) or whether the better side changes (column 1).[19] For comparison, column (3) again lists the baseline results when all observations are pooled, i.e., column 3 of Panel C in Table 2. The coefficient is the same for each sub-sample or the combined sample, ranging from a 2.17-2.24 percent increase in the border discontinuity in response to a widening of the economic freedom index across the border by one point. Our results are hence not driven by borders where one side is consistently better (e.g., Switzerland always has a higher index than France or Germany) or borders where the better side switches (e.g., the Nigeria-Chad

[19] We select borders into the "constant" sample if the explanatory variable, the average of the five lags of institutional quality, is always higher for one country relative to its neighbor

or Bulgaria-Greece border).

Table 4 furthermore conducts a sensitivity check where we include five leads rather than five lags. Using the combined sample (column 3), as well as borders where one side of the border always has a higher index of institutional quality (column 2) results in insignificant results verifying that the changes in crop yields are in response to changes in *past* changes in institutional quality. For the sub-sample of borders where the better side switches, the coefficients remains significant and of similar magnitude, the point estimate even increases to 2.79. The reason is that borders where the better side switches have significant trends in the differences of the economic freedom index as shown in Figure A4, usually because one country improves or deteriorates continuously. The 5 leads are therefore correlated with the 5 lags, implying that leads are also significant. For example, two borders with high trends over time are the Bulgaria-Greece border, where Bulgaria saw continued improvements (it joined the European Union in 2007) and eventually overtook Greece. Similarly, Nigeria continuously improved and overtook its neighbor Chad. Taken together, Table 3 and 4 imply that our results are found by countries with or without strong trends in the economic freedom index and stable for different subsets.

3.3 Examining Sub-scores of Economic Freedom Index

So far we have focused on the overall economic freedom index and found a robust significant response of crop yields to the changes in the index, accumulating over the next five years. One advantage of the construction of the index is that it is the weighted average of several clearly defined subcategories. We next decompose the index into various subcategories. Table 5 includes each of the five sub-areas, both individually and jointly as the scores could be correlated. Columns (1)-(5) include the the five individual scores individually while column (6a) includes them jointly in the estimation. Each of those columns requires that all five area scores are non-missing, even if an area score is not included. Some countries only have data for some of the areas and it is hence possible that area scores are missing. Column (6b) includes all observations where at least one of the area scores is non-missing and sets the missing values for the other area scores to the border-specific sample mean. Recall that we have border fixed effects in our regression and hence our identification rests on deviations from border-specific means.

Four of the five areas show consistent results. The two areas "area 3 - sound money" and "area 5 - regulation" always have low p-values whether we include them individually or jointly, with coefficients ranging from 0.6-0.8 for area 3 and coefficients ranging from 0.7-1.3

for area 5. The combined effect is close to our baseline estimate for the overall economic freedom index, which was 2.2 for the case of a bandwidth of 25km and 5 lags that we are using here. On the other hand, scores for the two areas "area 1 - size of government" and "area 2 - legal system and property rights" have consistently high p-values and point estimates that are of small magnitude. Finally, "area 4 - freedom to trade internationally" is significant when included individually but no longer so when all five sub-scores are included.

Table A6 through A10 replicate a comparable exercise by including the sub-components of each of the five areas. When doing so for area 1 (size of government) in Table A6, two subcategories are significant. Score "1D - top marginal tax rate" is always significant and positive with coefficients ranging from 0.36-0.57. On the other hand, score "1C - government investment," is negative and significant with a similar magnitude for the consistent set of borders where all scores are non-missing. This might not be surprising as agriculture is a sector that in many countries strongly benefits from government investments (irrigation canals, pumps, etc). If these projects are designed to help agriculture, an increase in the freedom score equates to a reduction in beneficial projects. The two countervailing effects also explains why the overall category "size of government" has no significant effect.

Table A7 reports the results for individual components of "area 2 - legal system and property rights" are included. Two components stand out when included individually "2B - impartial courts" and "2C - protection of property rights" are individually significant at the 5% and 10%, respectively with sizable coefficients of 1.22 and 0.61. However, whenever the results are jointly included with other subcategories, the significance level decreases and neither is significant at the 10%, although "2B - impartial courts" is close with a p-value of 0.11 in column (9a). When we include other sub-scores below, the significance decreases even further and some coefficient flip signs, suggesting that legal aspects are correlated with other factors that either are better at explaining crop yields in border areas that are often far removed from the capitol and governed by local institutions, or the other variable are easier to measure (e.g., inflation rate) and hence suffer from less attenuation bias and come in more strongly.

Other components that are both individually significant and remain so when all sub-scores of an area are included are "3C - inflation: most recent year" in Table A8 with a point estimate ranging from 0.53-0.72, "5A - credit market regulation" in Table A10 with a point estimate of 0.6-0.62, and "area 4D - controls of the movement of capital and people" in Table A9 with a point estimate ranging from 0.31-0.50

Table A11 includes all 24 sub-scores jointly in one estimation. Of the four that are significant, we previously highlighted three as being individually significant: "1D - top marginal tax rate," "3C - inflation: most recent year," and "5A - credit market regulation." These coefficients are remarkable robust, being significant when included individually, jointly with the other sub-scores of their particular area, or when all sub-scores are jointly included. The fourth sub-score that are significant in the joint regression is "1A - government consumption," although it is not when included individually.

Table 6 summarizes the effect of the dominant sub-cores by including only the four significant sub-scores of Table A11 in a separate regression, again finding very similar results to including all 24. All of these sub-scores are measured on a 0-10 scale. Moving each one of them up by one point, would result in an effect on crop yields that is the sum of the four coefficients, i.e., 2.08 in column (5a) and 2.04 in column (5b), which aligns with the overall effect of the economic freedom index (the average of the sub-scores) in column (3) of panel C in Table 2 that came in at 2.2.

In summary, conducting an analysis using various sub-scores is challenging as they are correlated and might pick up each others effects. However, we emphasize that at least three sub-scores are remarkable robust to inclusion and exclusion of other sub-scores. While there might of course still be other omitted variables that co-vary, they cannot be correlated with the other sub-scores we include and exclude, as doing so would pick up their effect. This gives us some reassurance that they are indeed important drivers.

3.4 Yield Variability and Institutional Quality

So far we have focused on the effect of changes in institutional quality on mean yields. As discussed above, one concern with the adoption of high-yielding varieties is that while they do improve mean yields, they also increase yield variability. Risk-averse farmers, especially those that are liquidity-constraint or not insured, might be reluctant to adopt such a crop variety. We therefore examine yield variability next.

While mean yields in a location can be estimates using annual data, estimates of yield variability require several years of data. We start by splitting our 20-year data into five 4-year intervals.[20] We derive the mean, standard deviation, and coefficient of variation for each pixel over each four-year period, ranging from 2004-2007 to 2016-2019 and the average institutional quality for the previous four years, i.e., 2000-2003 to 2012-2015. The regression

[20] We have satellite data on yields for 19 years from 2001-2019, and data on institutional quality from 2000-2019, or 20 years. Since we rely on lagged values on institutional quality, the first years of the satellite data 2001-2003, which is only three years, will effectively not be used.

in the first step is analogous to equation (2) except that we estimate the discontinuity at country borders using the mean, standard deviation and coefficient of variation over four-year periods.[21] The second step again links them to lagged values of the economic freedom index, which now includes one lag of the four-year average rather than the average of five-year periods we used before.

Panel A of Table 7 starts with the effect on mean yields to validate that we detect similar effects when using four-year averages rather than annual observations. The coefficients are again all highly statistically significant and comparable to what we obtained above in Table 2. Since we are using four-year periods, the regression should fall between the point estimates of panels B and C of Table 2 that use 3 and 5 lags, respectively, which it does.

On the other hand, we see no increase in the standard deviation in Panel B of Table 7. None of the coefficients is close to being statistically significant at conventional levels, and the point estimate is even negative for the five smallest bandwidths of 15km, 20km, 25km, 30km, and 40km. Similarly, there is no significant effect on the coefficient of variation, where we divided the standard deviation at each pixel by its mean over the same period. The point estimates are again negative for the five smallest bandwidths.

Table 7 shows that improvement in yields due to changes in institutional quality were achieved without an increase in variability, which is remarkable.

3.5 Extensive Margin Results

The previous sections have focused on a consistent set of pixels that are classified as cropland in every single year to detect intensive margin results, i.e., the effects on yields. At the same time, institutional reforms might also encourage additional land to be farmed, or discourage farmers from continuing to do so when conditions deteriorate. We examine such extensive margin results by estimating a difference-in-difference analysis according to equation (4). The dependent variable is no longer the border discontinuity in yields, but rather the difference in the number of pixels across the border that are classified as various landcover types. For example, reverting to our motivating example of the Turkish-Syrian border, we count the number of pixels that are classified as cropland within a given bandwidth in both Turkey and Syria and take the difference and link it to the difference in the economic freedom index across the border. We again use a panel setup with border fixed effects, i.e., in effect examining how the difference in pixel counts changes in response to changes in the economic

[21] To keep the sample selection consistent, we now require 400 observation on each side of the border over the four year period rather than 100 per period.

freedom index.

We focus on three landcover types: cropland, forests, and grasslands, which are displayed in the different panels of Table 8. The coefficient is consistently positive for the number of cropland pixels in panel A and of similar magnitude across various bandwidths. We normalize the score by the bandwidth to make them comparable and the coefficient hence gives the additional number of pixels per km of bandwidth.[22] A coefficient of 1.87 in column (3) of panel A implies that for every point increase in the economic freedom index, the number of pixels within 25km of the border that are classified as cropland increase by 45 pixels. The corresponding average number of pixels within 25km of the border (one side) is 3323, and the results equate to a roughly 1.4% point increase.[23] The effects are statistically significant for a bandwidth of 30km or greater at conventional levels.

The expansion of croplands has to come at the expense of some of the other landcover types. Panel B presents the results for forests, which are consistently negative, albeit not statistically significant at conventional levels except for the three smallest bandwidth up to 25km. The results on grasslands in Panel C are even smaller, switch sign, and never significant.[24]

4 Discussion

There are striking agricultural production differences between countries around the world (Adamopoulos and Restuccia 2022, Gollin, Lagakos and Waugh 2014). To ensure global food security, mitigate poverty, and to protect remaining natural and semi-natural ecosystems from agricultural area expansion, it is important to improve crop yields on fields that are currently performing below their potential.

This paper focuses on one potential policy lever to improve yields: Improving the institutional quality, specifically economic reforms and secure property rights. More specifically, we examine institutional quality as measured by the economic freedom index by the Fraser Institute that focuses on economic and legal aspects. As emphasized in the introduction, there are other important institutional details that might matter, like values and norms, which are not measured by the index. We find that a linear model is appropriate and that

[22] Since we also exclude pixels with a distance less than 1km, we normalize by (bandwidth-1)

[23] The corresponding percent changes are 1.1%, 1.2%, 1.4%, 1.9%, 1.9%, 1.8%, 2.2%, and 3.0% for the eight bandwidths in panel A.

[24] There are other landcover types, e.g., wetlands, savannas, shrublands, and urban areas that we do not show here.

each point increase on the 0-10 scale increases the border discontinuity in yields by 2.2% over the next five years. This finding is remarkably robust across various bandwidth around the border and what subsets we use in the estimation. We find results of similar magnitude on the extensive margin, although the results are less significant.

We employ a remote sensing product (annual maximum of the Enhanced Vegetation Index) to measure peak biomass during the main growing season. The sensed biomass is a product of the yield for each pixel and what fraction of a pixel is farmed. The detected increase in agricultural production could hence come from either the intensive margin (higher yields on fields) or by a larger faction of the pixel being cropped. We formally test the latter hypothesis in Table A12, where we use another, even finer, remote sensing product that classified whether each 30x30m pixels is cropland for the years 2003, 2007, 2011, 2015, 2019 (Potapov, Turubanova, Hansen, Tyukavina, Zalles, Khan, Song, Pickens, Shen and Cortez 2022). These are the same years we used in our analysis using four-year averages in Table 7. We hence aggregate the 30x30m pixels to our 1x1km grid and derive the fraction of a pixel that is cropland. We then run the equivalent analysis to panel A of Table 7, but with a different dependent variable, i.e., the faction of a pixel that is cropland rather than the log EVI. Panel A of Table A12 shows that none of the coefficients are significant and we get tightly estimated zeros, i.e., the standard error for a one-point increase in the economic freedom index is a 0.007 increase in the cropland fraction of the pixel (on a 0-1 scale). We therefore interpret our results as changes in log yields in the intensive margin regressions, i.e., within pixels. Recall that our extensive margin results focused on the *number* of pixels that are cropland.

One qualification of our results is that they miss impacts that take a longer time to materialize. Given the limited length of our satellite data, there is the possibility that long-term effects of improved institutions are larger than the short-term effect we identify. The reasoning is that short-term changes in institutions immediately change farmer behavior by changing the investment climate (i.e. farmers increase their agricultural investments if they become less risky) or improving the functioning land markets (e.g. land can be rented and sold if it is secure). In the longer term, however, more fundamental changes might occur too, including investments in larger irrigation infrastructure, machinery, roads, or a change of marketing channels. Moreover, some investments pay out slowly over time (e.g. improved soil fertility, returns to new skills), and also a potential expansion of research and development and its effect take longer to fully materialize than the effects we have studied here (Alston et al. 2021).

There are other important qualifications to our findings: we focus on a remotely sensed product that measures yields, but have no data on inputs. For example, additional use of fertilizer might boost yields but also lead to more nutrient and pesticide pollution. Similarly, our extensive margin analysis provides suggestive results that the increase in cropland comes at the expense of deforestation. A welfare analysis would have to balance the gains from higher yields and more cropped area against the additional cost: both private cost to farmers and external costs to society. Our analysis so far has quantified neither cost: while farmers balance private gains against cost, external cost are generally not priced correctly and hence not adequately accounted for by profit-maximizing farmers. On the other hand, our analysis might also omit some welfare private benefits by focusing exclusively on yields. For example, some welfare gains to farmers might come from using inputs more efficiently, e.g., Caunedo and Kala (2021) find that a significant part of the welfare improvement of mechanizing Indian agriculture is an increase in leisure.

Finally, when maximizing welfare, policies can have opposite effects on producers and consumers. One aspect of the economic freedom index is access to international markets. Trade greatly reduces price volatility as local production shocks can be counterbalanced by changes in imports and exports smoothing local prices (which used to be a natural hedge for local producers) and making prices more dependent to world fluctuations. This change in volatility can induce farmers to grow different crops (Allen and Atkin 2022).

5 Conclusion

We study whether change in institutional quality as measured by the economic freedom index by the Fraser Institute influences border discontinuities in crop yields as measured by satellites. The index gives annual scores to measure economic and legal institutional since 2000. We find that a one point increase on the 0-10 scale increases border discontinuities over the next 5 years by 2.2%. As such, improving institutions provides a policy lever to improve global food security, mitigate poverty.

Three sub-scores consistently come back significant and of sizable magnitude. They measure inflation, credits market regulation, and the top marginal tax rate. The first two both allude to the fact that farmers face an inter-temporal problem, where inputs have to be purchased at the beginning of the growing season and the payout happens only after the harvest. Measures of property rights are significant when included as sole explanatory variable, but loose significance when we jointly include all controls.

We also explore whether institutional changes have an effect on farmers' risk exposure and on cropland area changes. We estimate that institutional improvements do not increase yield variability. Regarding changes in cropland extent, we do find a statistically significant cropland expansion effect, with some suggestive evidence that it led to deforestation.

References

Acemoglu, Daron and Simon Johnson, "Unbundling Institutions," *Journal of Political Economy*, October 2005, *113* (5), 949–995.

___ , Francisco A Gallego, and James A Robinson, "Institutions, human capital, and development," *Annu. Rev. Econ.*, 2014, *6* (1), 875–912.

___ , Tristan Reed, and James A Robinson, "Chiefs: Economic development and elite control of civil society in Sierra Leone," *Journal of Political Economy*, 2014, *122* (2), 319–368.

Adamopoulos, Tasso, "Transportation Costs, Agricultural Productivity, and Cross-Country Income Differences," *International Economic Review*, May 2011, *52* (2), 489–521.

___ and Diego Restuccia, "Geography and Agricultural Productivity: Cross-Country Evidence from Micro Plot-Level Data," *Review of Economic Studies*, July 2022, *84* (4), 1629–1653.

___ , Loren Brandt, Chaoran Chen, Diego Restuccia, and Xiaoyun Wei, "Land Security and Mobility Frictions," *National Bureau of Economic Research*, 2022.

Ali, Daniel Ayalew, Klaus Deininger, and Markus Goldstein, "Environmental and gender impacts of land tenure regularization in Africa: Pilot evidence from Rwanda," *Journal of Development Economics*, 2014, *110*, 262–275.

Allen, Treb and David Atkin, "Volatility and the Gains From Trade," *Econometrica*, 2022, *90* (5), 2053–2092. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA14411.

Alston, Julian M., Philip G. Pardey, and Xudong Rao, "Payoffs to a Half Century of Cgiar Research," *American Journal of Agricultural Economics*, August 2021, pp. 1–28.

Banerjee, Abhijit V., *Contracting Constraints, Credit Markets, and Economic Development*, Vol. 3 of *Econometric Society Monographs*, Cambridge University Press,

Bastin, Jean-Francois, Yelena Finegold, Claude Garcia, Danilo Mollicone, Marcelo Rezende, Devin Routh, Constantin M Zohner, and Thomas W Crowther, "The Global Tree Restoration Potential," *Science*, July 2019, *365* (6448), 76–79.

___ , ___ , ___ , ___ , ___ , ___ , ___ , and ___ , "Erratum for the Report:"The Global Tree Restoration Potential" and the Technical Response "Response to Comments on the Global Tree Restoration Potential"," *Science*, May 2020, *368* (6494).

Batjes, Niels H, "Isric-Wise Derived Soil Properties on a 5 by 5 Arc-Minutes Global Grid (Ver. 1.2)," *ISRIC-World Soil Information*, 2012.

Behrer, A Patrick, Edward L Glaeser, Giacomo AM Ponzetto, and Andrei Shleifer, "Securing property rights," *Journal of Political Economy*, 2021, *129* (4), 1157–1192.

Besley, Timothy, "Property rights and investment incentives: Theory and evidence from Ghana," *Journal of political Economy*, 1995, *103* (5), 903–937.

___ **and Torsten Persson**, "The origins of state capacity: Property rights, taxation, and politics," *American economic review*, 2009, *99* (4), 1218–44.

Calonico, Sebastian, Matias D. Cattaneo, Max H. Farrell, and Rocio Titiunik, "Regression Discontinuity Designs Using Covariates," *The Review of Economics and Statistics*, July 2019, *101* (3), 442–51.

Casaburi, Lorenzo and Jack Willis, "Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya," *American Economic Review*, December 2018, *108* (12), 3778–3813.

Cattaneo, Matias D., Nicolá Idrobo, and Rocío Titiunik, *A Practical Introduction to Regression Discontinuity Designs*, Cambridge University Press, 2018.

Caunedo, Julieta and Namrata Kala, "Mechanizing Agriculture," *NBER Working Paper 29061*, July 2021.

Chen, Chaoran, Diego Restuccia, and Raül Santaeulàlia-Llopis, "The effects of land markets on resource allocation and agricultural productivity," *Review of Economic Dynamics*, 2022, *45*, 41–54.

Costinot, Arnaud, Dave Donaldson, and Cory Smith, "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World," *Journal of Political Economy*, 2016, *124* (1), 205–248. _eprint: https://doi.org/10.1086/684719.

Deutschmann, Joshua W, Maya Duru, Kim Siegal, and Emilia Tjernstrom, "Can Smallholder Extension Transform African Agriculture?," Working Paper 26054, National Bureau of Economic Research July 2019.

Donovan, Kevin, "The Equilibrium Impact of Agricultural Risk on Intermediate Inputs and Aggregate Productivity," *The Review of economic studies*, December 2020, *88* (5), 2275–307.

Emerick, Kyle, Alain De Janvry, Elisabeth Sadoulet, and Manzoor H Dar, "Technological Innovations, Downside Risk, and the Modernization of Agriculture," *American Economic Review*, June 2020, *106* (6), 1537–61.

Foley, Jonathan A, Navin Ramankutty, Kate A Brauman, Emily S Cassidy, James S Gerber, Matt Johnston, Nathaniel D Mueller, Christine O'Connell, Deepak K Ray, and Paul C West, "Solutions for a Cultivated Planet," *Nature*, October 2011, *478* (7369), 337–342.

Friedl, M and D Sulla-Menashe, "Mcd12q1 Modis/Terra+ Aqua Land Cover Type Yearly L3 Global 500m Sin Grid V006. 2019, Distributed by Nasa Eosdis Land Processes Daac," 2019.

Gollin, Douglas, Casper Worm Hansen, and Asger Mose Wingender, "Two Blades of Grass: The Impact of the Green Revolution," *Journal of political Economy*, August 2021, *129* (8), 2344–84.

____, David Lagakos, and Michael E Waugh, "Agricultural Productivity Differences across Countries," *American Economic Review*, May 2014, *104* (5), 165–70.

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauwo, "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, September 2001, *69* (1), 201–09.

Hayami, Yujiro and Vernon W Ruttan, "Agricultural Productivity Differences among Countries," *The American Economic Review*, December 1970, *60* (5), 895–911.

Herbst, Jeffrey, *States and power in Africa: Comparative lessons in authority and control*, Vol. 149, Princeton University Press, 2014.

Huete, A., K. Didan, T. Miura, E. P. Rodriguez, X. Gao, and L. G. Ferreira, "Overview of the radiometric and biophysical performance of the MODIS vegetation indices," *Remote Sensing of Environment*, 2002, *83* (1), 195–213.

Hunter, Mitchell C, Richard G Smith, Meagan E Schipanski, Lesley W Atwood, and David A Mortensen, "Agriculture in 2050: recalibrating targets for sustainable intensification," *Bioscience*, 2017, *67* (4), 386–391.

Jain, Meha, Pinki Mondal, Gillian L. Galford, Greg Fiske, and Ruth S. DeFries, "An Automated Approach to Map Winter Cropped Area of Smallholder Farms across Large Scales Using MODIS Imagery," *Remote Sensing*, 2017, *9* (6).

Johnson, David M., "A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products," *International Journal of Applied Earth Observation and Geoinformation*, 2016, *52*, 65–81.

Laajaj, Rachid, Karen Macours, Cargele Masso, Moses Thuita, and Bernard Vanlauwe, "Reconciling yield gains in agronomic trials with returns under African smallholder conditions," *Scientific Reports*, August 2020, *10* (1), 14286.

Lin, Justin Yifu and Jeffrey B. Nugent, "Chapter 38 Institutions and economic development," in "in," Vol. 3 of *Handbook of Development Economics*, Elsevier, 1995, pp. 2301–2370. ISSN: 1573-4471.

Liu, Jiangui, Ted Huffman, Budong Qian, Jiali Shang, Qingmou Li, Taifeng Dong, Andrew Davidson, and Qi Jing, "Crop Yield Estimation in the Canadian Prairies Using Terra/MODIS-Derived Crop Metrics," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2020, *13*, 2685–2697.

Martinez, Luis R, "How much should we trust the dictator's GDP growth estimates?," *Journal of Political Economy*, 2022, *130* (10), 2731–2769.

McArthur, John W. and Gordon C. McCord, "Fertilizing Growth: Agricultural Inputs and Their Effects in Economic Development," *Journal of Development Economics*, July 2017, *127*, 133–152.

Monfreda, Chad, Navin Ramankutty, and Jonathan A Foley, "Farming the Planet: 2. Geographic Distribution of Crop Areas, Yields, Physiological Types, and Net Primary Production in the Year 2000," *Global Biogeochemical Cycles*, March 2008, *22* (1).

Moscona, Jacob and Karthik A. Sastry, "Inappropriate Technology: Evidence from Global Agriculture," *Working Paper MIT*, November 2021.

Nath, Ishan, "Climate Change, The Food Problem, and the Challenge of Adaptation through Sectoral Reallocation," *Working Paper*, May 2022.

Ostrom, Elinor, "A Behavioral Approach to the Rational Choice Theory of Collective Action," *American Political Science Review*, 1998, *92* (1), 1–22.

——, "Collective Action and the Evolution of Social Norms," *Journal of Economic Perspectives*, 2000, *14* (3), 137–158.

Pinkovskiy, Maxim L., "Growth discontinuities at borders," *Journal of Economic Growth*, June 2017, *22* (2), 145–192.

Potapov, Peter, Svetlana Turubanova, Matthew C. Hansen, Alexandra Tyukavina, Viviana Zalles, Ahmad Khan, Xiao-Peng Song, Amy Pickens, Quan Shen, and Jocelyn Cortez, "Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century," *Nature Food*, January 2022, *3* (1), 19–28.

Robinson, Natalie, James Regetz, and Robert P Guralnick, "Earthenv-Dem90: A Nearly-Global, Void-Free, Multi-Scale Smoothed, 90m Digital Elevation Model from Fused Aster and Srtm Data," *ISPRS Journal of Photogrammetry and Remote Sensing*, July 2014, *87*, 57–67.

Sakamoto, Toshihiro, Masayuki Yokozawa, Hitoshi Toritani, Michio Shibayama, Naoki Ishitsuka, and Hiroyuki Ohno, "A crop phenology detection method using time-series MODIS data," *Remote Sensing of Environment*, 2005, *96* (3), 366–374.

Schneider, Udo, Andreas Becker, Peter Finger, Anja Meyer-Christoffer, Bruno Rudolf, and Markus Ziese, "GPCC Full Data Reanalysis Version 6.0 at 0.5: Monthly Land-Surface Precipitation from Rain-Gauges Built on Gts-Based and Historic Data," *GPCC Data Rep.*, 2011.

Schultz, Theodore W, *The economic organization of agriculture*, McGraw-Hill Book. Co, 1953.

Scully, Gerald W., "The Institutional Framework and Economic Development," *Journal of Political Economy*, 1988, *96* (3), 652–662. _eprint: https://doi.org/10.1086/261555.

Smith, Adam, *An Inquiry into the Nature and Causes of the Wealth of Nations*, Oxford University Press, 1776.

Son, N. T., C. F. Chen, C. R. Chen, V. Q. Minh, and N. H. Trung, "A comparative analysis of multitemporal MODIS EVI and NDVI data for large-scale rice yield estimation," *Agricultural and Forest Meteorology*, 2014, *197*, 52–64.

Sotelo, Sebastian, "Domestic Trade Frictions and Agriculture," *Journal of Political Economy*, 2020, *128* (7), 2690–2738.

Suri, Tavneet and Christopher Udry, "Agricultural technology in africa," *Journal of Economic Perspectives*, 2022, *36* (1), 33–56.

Tang, Wenjun, Kun Yang, Jun Qin, Xin Li, and Xiaolei Niu, "A 16-year dataset (2000–2015) of high-resolution¡? xmltex\break?¿(3 h, 10 km) global surface solar radiation," *Earth System Science Data*, 2019, *11* (4), 1905–1915.

Tombe, Trevor, "The Missing Food Problem: Trade, Agriculture, and International Productivity Differences," *American Economic Journal: Macroeconomics*, July 2011, *7* (3), 226–58.

Tseng, Tzu-Wei Joy, Brian E Robinson, Marc F Bellemare, Ariel BenYishay, Allen Blackman, Timothy Boucher, Malcolm Childress, Margaret B Holland, Timm Kroeger, Benjamin Linkow et al., "Influence of land tenure interventions on human well-being and environmental outcomes," *Nature Sustainability*, 2021, *4* (3), 242–251.

Turner, Matthew A, Andrew Haughwout, and Wilbert Van Der Klaauw, "Land Use Regulation and Welfare," *Econometrica*, July 2014, *82* (4), 1341–1403.

van Ittersum, Martin K., Kenneth G. Cassman, Patricio Grassini, Joost Wolf, Pablo Tittonell, and Zvi Hochman, "Yield gap analysis with local to global relevance—A review," *Field Crops Research*, 2013, *143*, 4–17.

Wan, Zhengmin, "Modis/Aqua Land Surface Temperature/Emissivity Daily L3 Global 1 Km Sin Grid," 2021.

Wuepper, David and Robert Finger, "Regression Discontinuity Designs in Agricultural and Environmental Economics," *European Review of Agricultural Economics*, 2022, *forthcoming*, 1–26.

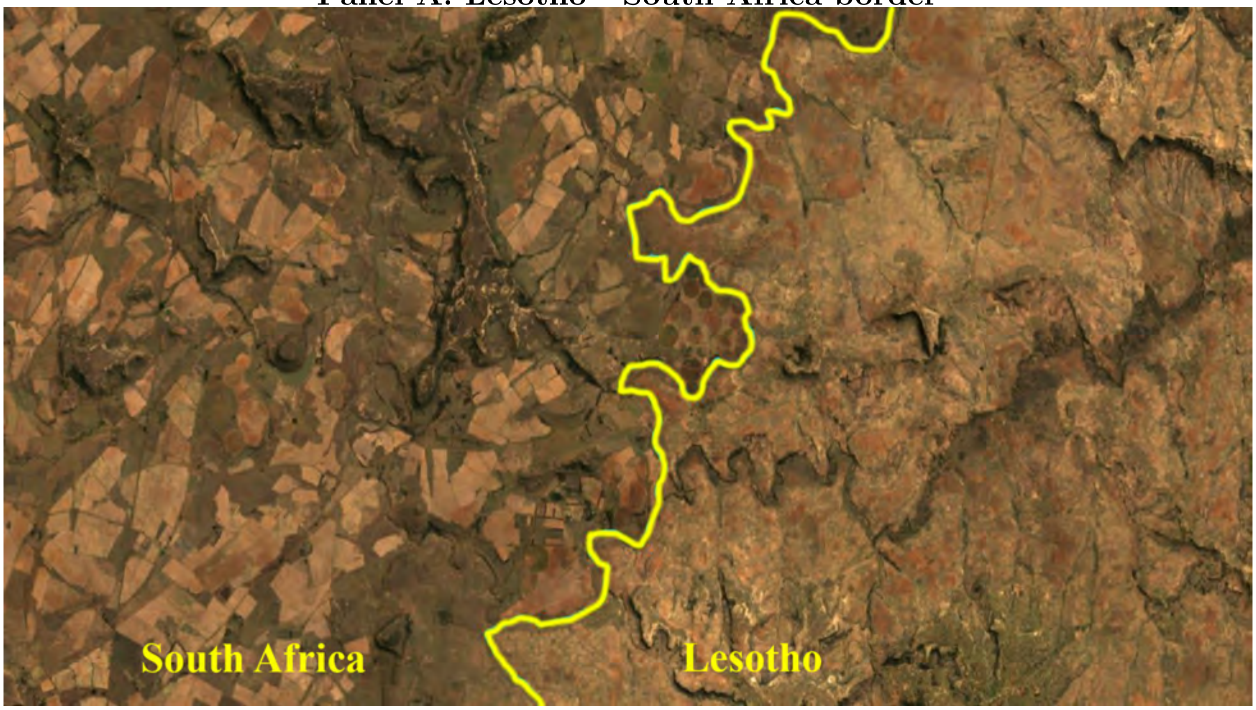
____ **, Pasquale Borrelli, and Robert Finger**, "Countries and the Global Rate of Soil Erosion," *Nature Sustainability*, January 2020, *3* (1), 51–55.

____ **, Solen Le Clech, David Zilberman, Nathaniel Mueller, and Robert Finger**, "Countries influence the trade-off between crop yields and nitrogen pollution," *Nature Food*, 2020, *1* (11), 713–719.

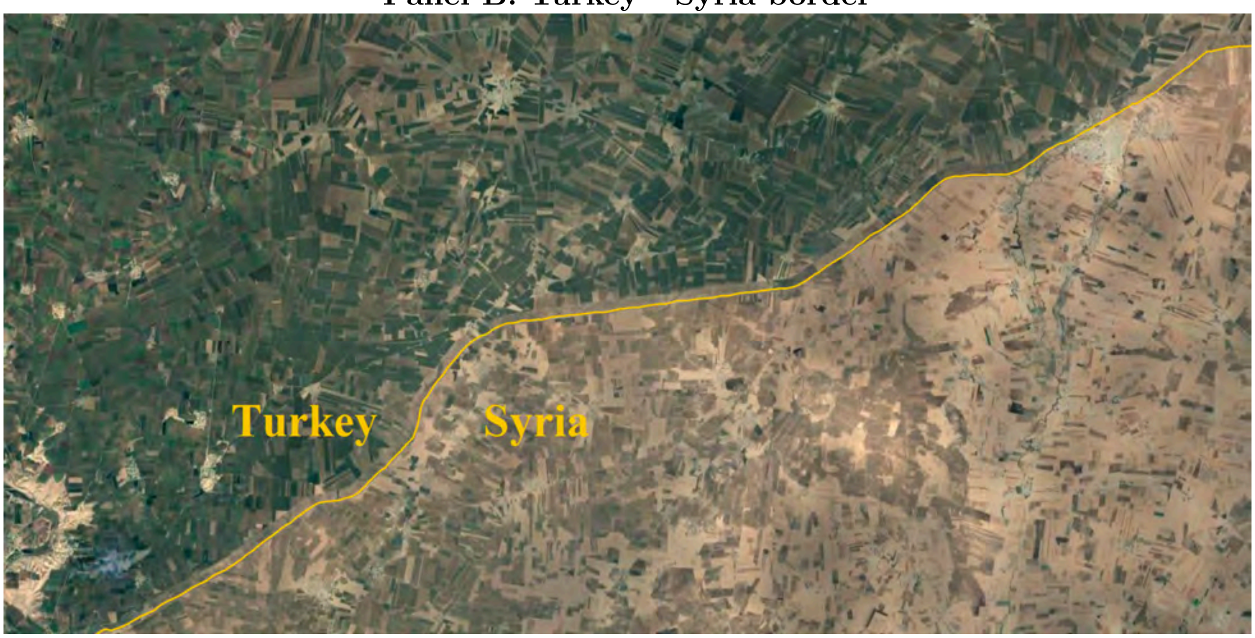
Yu, Qiangyi, Liangzhi You, Ulrike Wood-Sichra, Yating Ru, Alison K. B. Joglekar, Steffen Fritz, Wei Xiong, Miao Lu, Wenbin Wu, and Peng Yang, "A Cultivated Planet in 2010 – Part 2: The Global Gridded Agricultural-Production Maps," *Earth System Science Data*, December 2020, *12* (4), 3545–72.

Figure 1: Motivating Example: Images of -South Africa-Lesotho and Turkey-Syria Border

Panel A: Lesotho - South Africa border



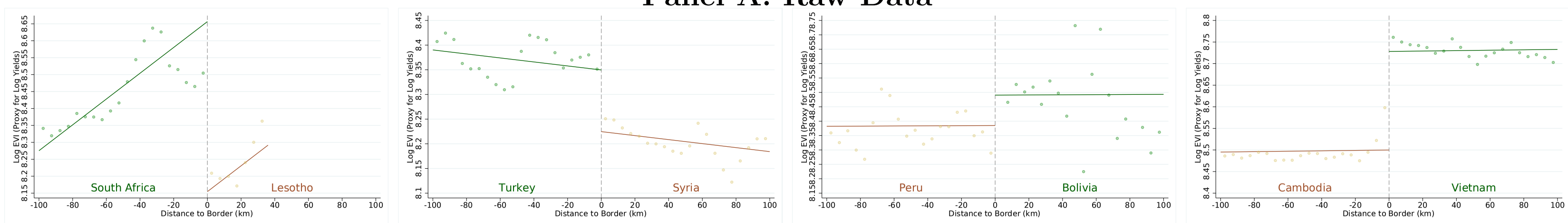
Panel B: Turkey - Syria border



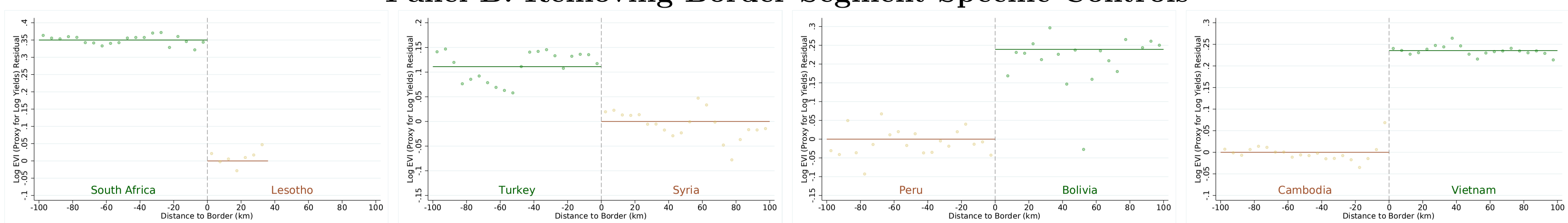
Notes: Figure shows an areal photograph of the borders between South Africa (western part of figure) and Lesotho (eastern part of figure) in the top row and Turkey (north-western part of the figure) and Syria (south-eastern part of the figure) in the bottom row. The border is shown in yellow. A clear discontinuity is visible, with the fields on the Turkish and Chinese side showing considerably more green (higher yields). The areal photographs are from 2018.

Figure 2: Motivating Examples: Border Discontinuity in Crop Yields

Panel A: Raw Data



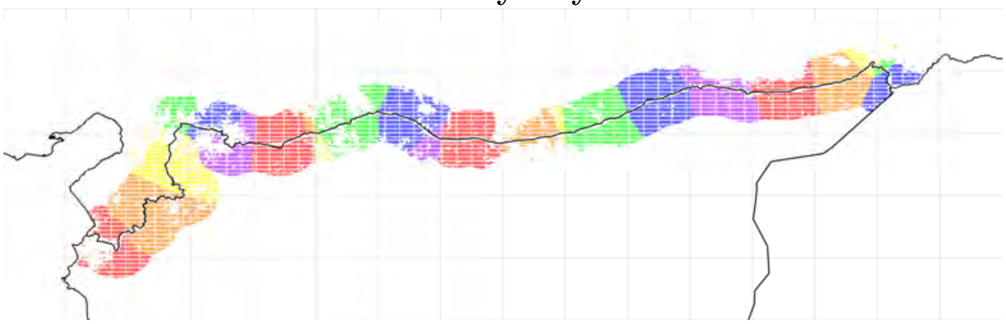
Panel B: Removing Border-Segment Specific Controls



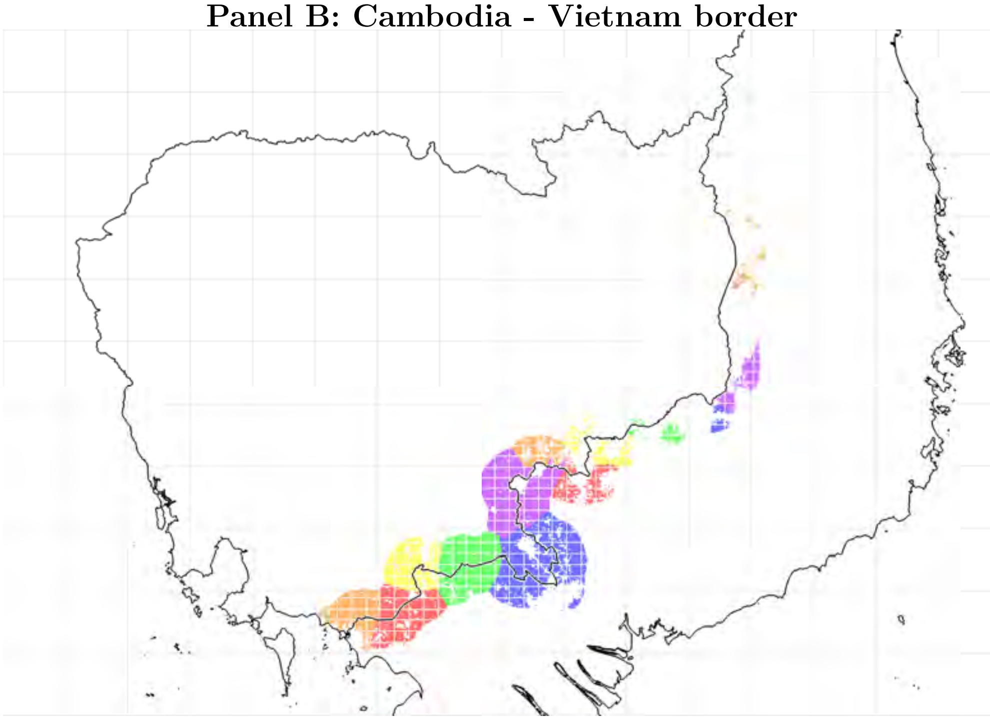
Notes: Figure shows the distribution of log crop yields (measured using the log of the annual maximum of the Enhanced Vegetation Index) around the South Africa-Lesotho, Turkey-Syria, Peru-Bolivia, and Cambodia-Vietnam borders, respectively. All graphs uses all EVI readings during the years 2001-2019 that are within 100km of each side of the border. Negative distances are for the western countries, while positive distances are for eastern countries. The top graphs uses the raw data, while the bottom graphs remove the controls in our baseline specification in equation (2): border-segment by year fixed effects, border-segment by year specific polynomials in longitude, latitude and the cross-term, as well as landcover by year fixed effects. Dots display averages for each 5km bin. Linear polynomials in the distance variable from the border on each side are added as solid line in the top graphs. A clear discontinuity is visible at the border (distance = 0).

Figure 3: Constructing Border Segments

Panel A: Turkey - Syria border



Panel B: Cambodia - Vietnam border



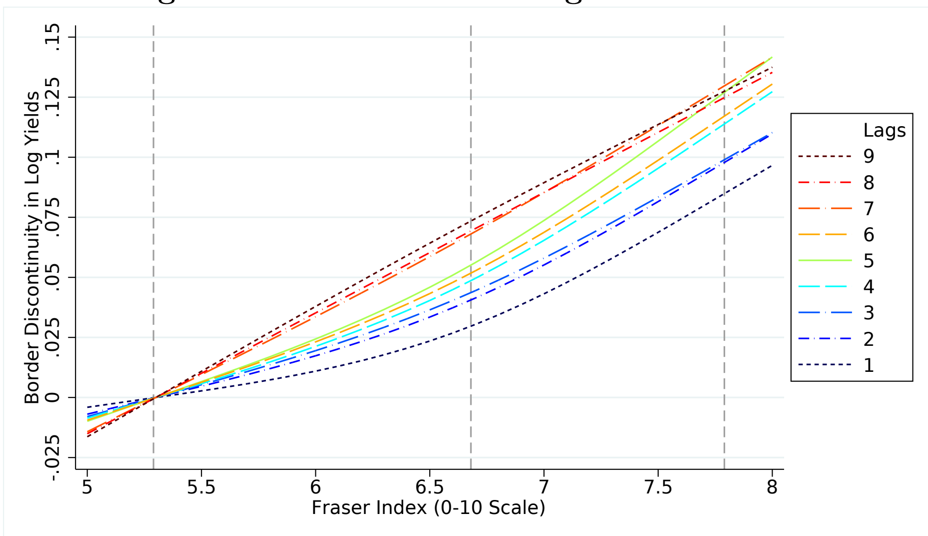
Notes: Figure shows the individual pixels within a 25km band of the Turkey-Syria border (top) and Cambodia-Vietnam border (bottom). We include half-degree border point fixed effects. Specifically, each pixel is assigned to the closest border point, which are binned by a 0.5 degree (roughly 55km) grid in both latitude and longitude, shown in grey. The pixels themselves might fall outside of the bins since we classify them by the closest border pixel given that we are interested in the discontinuity at the border. Pixels that are assigned to the same border-point bin are shown in the same color. In our baseline regression below where we estimate the discontinuity at borders between country-pairs for a given year, we include four terms for each 0.5x0.5 border-pixel bin: a fixed effect as well as smooth polynomials in longitude, latitude, and the cross-term of longitude and latitude to allow unobservables to vary smoothly in space.

Figure 4: Map of Borders and Pixels Used In Baseline Sample

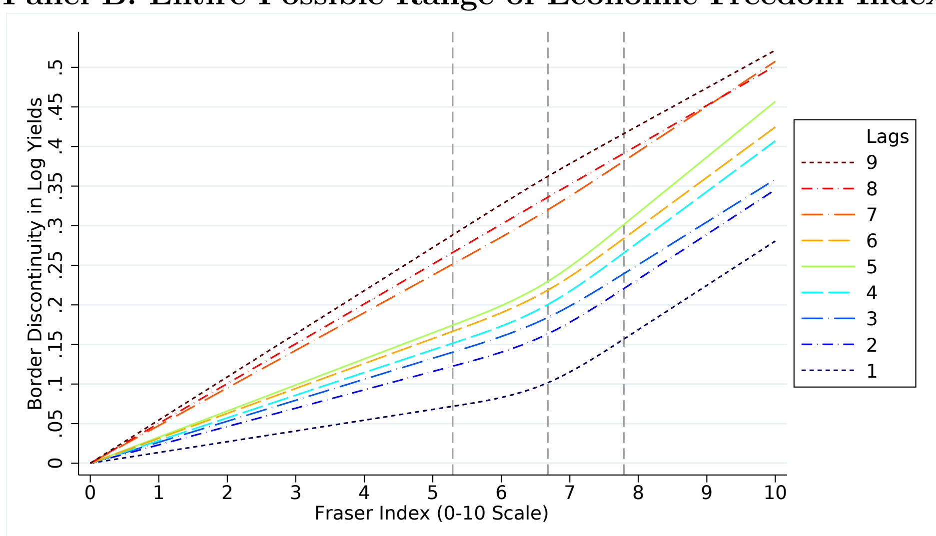
Notes: Figure shows the borders and cropland data in our analysis. Since we have 83 million individual 1kmx1km pixel readings for pixrels that are consistently classified as cropland, we cannot individually display them. The yellow squares are instead 0.1 degree aggregates (roughly 11x11km at equator), i.e., a grid is shown in yellow if it includes a pixel that is classified as cropland. All borders that have cropland within 100km of each side of a land border (islands are excluded) are shown in red or blue, where the latter color indicates that it is included in our baseline panel that requires that at least 100 pixels are present within 25km of each side of the border in a year and that the economic freedom index by the Fraser Institute is available for both neighboring countries.

Figure 5: Border Discontinuities and Changes In Institutional Quality

Panel A: Focusing on 10-90 Percentile Range of Economic Freedom Index



Panel B: Entire Possible Range of Economic Freedom Index



Notes: Figure shows the effect of the economic freedom index by the Fraser Institute on the border discontinuity in log yields. The effect is modeled using restricted cubic splines with 3 knots (shown as vertical dashed lines). The lowest knot is set at the 10th percentile, while the top knot is set at the 90th percentile of observed indices in the data. Different colors include different numbers of lags. The top panel focuses on the 10-90 percentile range, normalizing the effect relative to the 10th percentile. The bottom panel uses the entire [0,10] range of possible values. P-values for the second spline variable capturing nonlinearities are 0.07, 0.22, 0.36, 0.30, 0.30, 0.41, 0.83, 0.99, 0.89 when including lags 1 through 9, respectively.

Table 1: Border Segments That Grow Same Dominant Crop On Both Sides

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A1: Area with Same Dominant Crop (2000)							
Percent	76.2	74.6	73.2	72.2	71.3	69.9	68.1	66.9
	Panel A2: Area Growing Dominant Crop (2000)							
Percent	34.9	34.1	33.6	33.1	32.6	31.7	30.4	29.5
	Panel B1: Area with Same Dominant Crop (2010)							
Percent	65.7	64.3	63.7	62.7	62.6	63.1	63.5	63.6
	Panel B2: Area Growing Dominant Crop (2010)							
Percent	34.2	33.7	33.3	32.8	32.4	32.2	31.5	31.2
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table examines whether pixels on each side of the border grow the same crop. We merge each pixel with the area of various crops grown in its pixel. The 2000 data has the acreage for 175 crops (Monfreda et al. 2008), while the 2010 data has the acreage for 42 crops (Yu et al. 2020). In each case we first derive the combined acre for each crop in each border segment in hectares and then pick the crop with the largest acreage on each side of a border segment. Panels A1 and B1 sum the acreage of all crops for border segments that have the same dominant crop on each side relative to the total growing area (including border segments that do *not* grow the same crop). Panels A2 and B2 divide the combined acreage of the dominant crop for segments that grow the same crop by the total crop area.

Table 2: Border Disontinuities and Changes In Institutional Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Using One Lag $L = [1, 1]$							
Score (x100)	1.43	1.52	1.34	1.02	1.27	1.22	1.45	1.06
	(0.64)	(0.58)	(0.57)	(0.60)	(0.53)	(0.50)	(0.57)	(0.56)
	[0.028]	[0.010]	[0.020]	[0.090]	[0.017]	[0.015]	[0.013]	[0.060]
Borders	129	136	146	150	154	160	177	179
Observations	1949	2082	2195	2302	2387	2474	2742	2780
Pixels (10^6)	9.0	12.2	15.2	18.2	24.3	30.5	46.4	61.3
	Panel B: Using Three Lags $L = [1, 3]$							
Score (x100)	1.30	1.76	1.74	1.29	1.63	1.72	2.80	1.79
	(0.73)	(0.71)	(0.71)	(0.72)	(0.61)	(0.60)	(0.75)	(0.56)
	[0.077]	[0.014]	[0.015]	[0.077]	[0.009]	[0.005]	[<0.001]	[0.002]
Borders	118	126	136	139	144	150	167	167
Observations	1693	1814	1913	2003	2075	2152	2385	2414
Pixels (10^6)	7.9	10.6	13.3	15.9	21.3	26.6	40.6	53.6
	Panel C: Using Five Lags $L = [1, 5]$							
Score (x100)	1.52	2.21	2.20	1.67	1.88	1.97	2.83	1.86
	(0.85)	(0.83)	(0.84)	(0.82)	(0.74)	(0.72)	(0.73)	(0.69)
	[0.076]	[0.009]	[0.010]	[0.044]	[0.012]	[0.007]	[<0.001]	[0.008]
Borders	117	124	135	137	142	148	161	161
Observations	1469	1574	1660	1738	1795	1860	2057	2082
Pixels (10^6)	6.8	9.2	11.5	13.8	18.5	23.1	35.2	46.6
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table regresses border discontinuities (x100) in log crop yields (measured by EVI) between countries on the difference in the economic freedom index by the Fraser Institute between those countries. All regressions include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Different panels include different lags of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table 3: Border Disontinuities Where Side With Better Institutional Quality Flips

	(1)	(2)	(3)
Score (x100)	2.24	2.17	2.20
	(1.06)	(1.23)	(0.84)
	[0.042]	[0.080]	[0.010]
Borders	39	96	135
Observations	511	1149	1660
Pixels (10^6)	4.0	7.5	11.5
Sample	Switch	Constant	All
Bandwidth	25	25	25

Notes: Table regresses log border discontinuities (x100) on the economic freedom index by the Fraser Institute. Column (3) is the same as column (3) in Panel C of Table 2, i.e., uses 5 lags and a bandwidth of 25km to identify the border discontinuity. Columns (1) and (2) split the sample into the subset of borders where the country with the higher economic freedom index switches between years (column 1) and borders where one country constantly has a higher index across all years (column 2). Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table 4: Using 5 Leads Rather Than 5 Lags

	(1)	(2)	(3)
Score (x100)	2.79	-0.37	0.66
	(1.36)	(0.91)	(0.87)
	[0.048]	[0.689]	[0.445]
Borders	38	93	131
Observations	498	1089	1587
Pixels (10^6)	3.8	7.3	11.1
Sample	Switch	Constant	All
Bandwidth	25	25	25

Notes: Table replicates Table 3 except that it uses five leads of the economic freedom index by the Fraser Institute rather than 5 lags. It again regresses log border discontinuities (x100) on the economic freedom index by the Fraser institute using a bandwidth of 25km. Columns (1) and (2) split the sample into the subset of borders where the country with the higher economic freedom index switches between years (column 1) and borders where one country constantly has a higher index across all years (column 2). Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table 5: Separate Scores for the 5 Subareas of the Economic Freedom Index

	(1)	(2)	(3)	(4)	(5)	(6a)	(6b)
Score 1 (x100)	-0.02					-0.22	0.09
	(0.55)					(0.49)	(0.31)
	[0.972]					[0.649]	[0.774]
Score 2 (x100)		0.21				-0.15	-0.43
		(0.60)				(0.56)	(0.50)
		[0.730]				[0.789]	[0.391]
Score 3 (x100)			0.82			0.62	0.64
			(0.26)			(0.25)	(0.27)
			[0.002]			[0.015]	[0.017]
Score 4 (x100)				0.99		0.45	0.42
				(0.43)		(0.40)	(0.42)
				[0.022]		[0.270]	[0.324]
Score 5 (x100)					1.33	0.87	0.73
					(0.62)	(0.52)	(0.48)
					[0.035]	[0.097]	[0.129]
Borders	135	135	135	135	135	135	146
Observations	1657	1657	1657	1657	1657	1657	2073
Pixels (10^6)	11.5	11.5	11.5	11.5	11.5	11.5	13.9
Bandwidth	25	25	25	25	25	25	25

Notes: Table separately includes scores for the five areas of the economic freedom index. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(5) include each of the five areas individually, while columns (6a) and (6b) include all of them jointly. Column (6a) uses only observation where scores for all five areas are non-missing, while column (6b) uses observations where at least one of the scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. Errors are clustered at the border. The five subareas area:
Area 1 - size of government
Area 2 - legal system and property rights
Area 3 - sound money
Area 4 - freedom to trade internationally
Area 5 - regulation

Table 6: Including Four Significant Sub-scores of the Economic Freedom Index

	(1)	(2)	(3)	(4)	(5a)	(5b)
Score 1A (x100)	0.24				0.58	0.52
	(0.32)				(0.29)	(0.26)
	[0.465]				[0.046]	[0.045]
Score 1D (x100)		0.52			0.38	0.37
		(0.15)			(0.15)	(0.15)
		[<0.001]			[0.011]	[0.013]
Score 3C (x100)			0.69		0.59	0.63
			(0.26)		(0.25)	(0.25)
			[0.008]		[0.018]	[0.012]
Score 5A (x100)				0.66	0.53	0.52
				(0.29)	(0.24)	(0.22)
				[0.023]	[0.030]	[0.019]
Borders	134	134	134	134	134	146
Observations	1446	1446	1446	1446	1446	1730
Pixels (10^6)	9.9	9.9	9.9	9.9	9.9	11.9
Bandwidth	25	25	25	25	25	25

Notes: Table includes the four sub-scores that were significant at the 10% level in Table A11. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(4) include each of the four sub-scores individually, while columns (5a) and (5b) include all of them jointly. Column (5a) uses only observation where all sub-scores are non-missing, while column (5b) uses observations where at least one of the sub-indices is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The four sub-scores area:
Score 1A - government consumption
Score 1D - top marginal tax rate
Score 3C - inflation: Most recent year
Score 5A - credit market regulation

Table 7: Yield Variation and Institutional Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Average Yields				
Score (x100)	1.33	1.89	1.98	1.42	1.35	1.63	2.58	1.85
	(0.59)	(0.61)	(0.64)	(0.67)	(0.66)	(0.61)	(0.69)	(0.47)
	[0.026]	[0.002]	[0.002]	[0.037]	[0.044]	[0.009]	[<0.001]	[<0.001]
Borders	112	119	125	132	135	142	154	156
Observations	400	432	451	479	493	513	565	576
Pixels (10^6)	7.5	10.1	12.6	15.2	20.2	25.3	38.5	51.1
				Panel B: Standard Deviation of Yields				
Score (x100)	-0.07	-0.13	-0.11	-0.12	-0.04	0.22	0.53	0.14
	(0.22)	(0.20)	(0.19)	(0.21)	(0.33)	(0.24)	(0.38)	(0.24)
	[0.733]	[0.501]	[0.566]	[0.570]	[0.897]	[0.344]	[0.167]	[0.559]
Borders	111	119	125	129	134	138	153	155
Observations	398	432	451	472	491	504	561	571
Pixels (10^6)	7.4	10.0	12.6	15.0	20.1	25.1	38.2	50.5
				Panel C: Coefficient of Variation of Yields				
Score (x100)	-0.01	-0.02	-0.02	-0.02	-0.01	0.02	0.06	0.01
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)
	[0.638]	[0.409]	[0.461]	[0.480]	[0.823]	[0.443]	[0.196]	[0.660]
Borders	111	119	125	129	134	138	153	155
Observations	398	432	451	472	491	504	561	571
Pixels (10^6)	7.4	10.0	12.6	15.0	20.1	25.1	38.2	50.5
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table uses four-year averages in EVI and economic freedom index, ending in 2003, 2007, 2011, 2015, 2019. Panel A replicates an analysis using one lag of the four-year period, and finds similar results to the annual analysis in Panel C of Table 2 using five annual lags. Panel B and C conduct an analogous analysis where the discontinuity in the standard deviation over the four-year period and coefficient of variation, respectively, are regressed on the lagged index. All regressions include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Each entry is from a separate regression, with the point estimate in the first line (% change per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table 8: Extensive Margin: Difference in Number of Pixels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Cropland Pixels				
Normalized Score	1.81	1.79	1.87	2.53	2.75	2.78	3.76	3.44
	(1.46)	(1.34)	(1.25)	(1.33)	(1.27)	(1.23)	(1.42)	(1.39)
	[0.218]	[0.186]	[0.138]	[0.060]	[0.032]	[0.025]	[0.009]	[0.014]
Borders	117	124	135	137	142	148	161	161
Observations	1530	1612	1754	1784	1849	1929	2112	2112
Avg # of Pixels	2256	2879	3323	3914	5042	6057	8458	11258
				Panel B: Forest Pixels				
Normalized Score	-3.92	-3.61	-3.27	-2.76	-2.51	-2.30	-1.63	-1.22
	(2.35)	(2.06)	(1.95)	(1.76)	(1.74)	(1.76)	(1.60)	(1.45)
	[0.098]	[0.082]	[0.096]	[0.119]	[0.151]	[0.195]	[0.312]	[0.403]
Borders	117	124	135	137	142	148	161	161
Observations	1530	1612	1754	1784	1849	1929	2112	2112
Avg # of Pixels	470	630	781	972	1287	1555	2282	2969
				Panel C: Grassland Pixels				
Normalized Score	1.08	0.72	0.51	0.01	-0.47	-0.90	-1.47	-1.44
	(1.81)	(1.49)	(1.31)	(1.18)	(1.12)	(1.12)	(1.04)	(0.93)
	[0.552]	[0.630]	[0.698]	[0.990]	[0.677]	[0.422]	[0.157]	[0.124]
Borders	117	124	135	137	142	148	161	161
Observations	1530	1612	1754	1784	1849	1929	2112	2112
Avg # of Pixels	2001	2633	3106	3711	4904	5978	8518	11067
Bandwidth	15	20	25	30	40	50	75	100

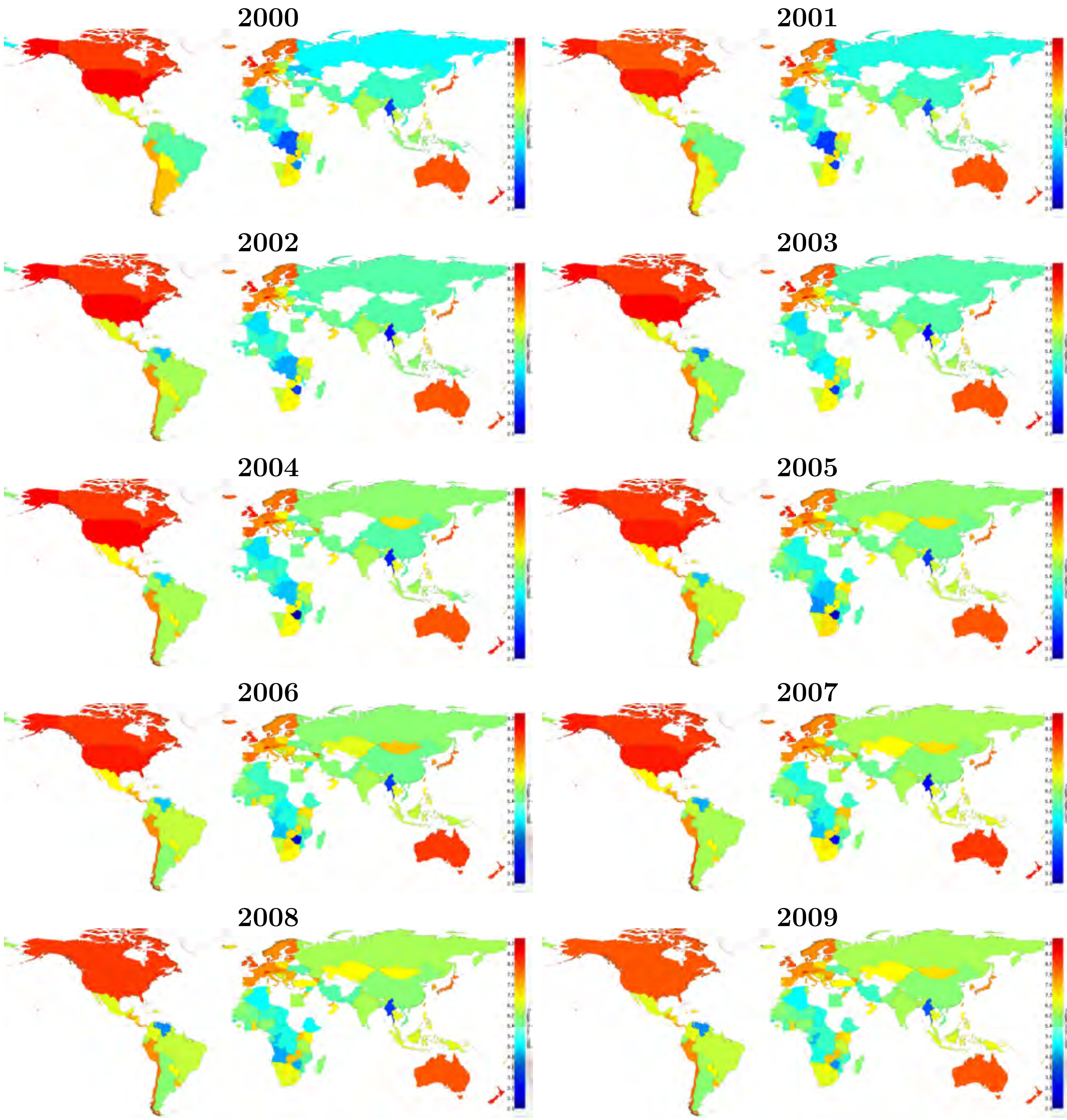
Notes: Table regresses the differences in the number of pixels across a border on the corresponding difference in the economic freedom index by the Fraser Institute. All regressions include border fixed effects and five lags. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Panel A adds all pixels that are classified as cropland (landcover class 12 or 14), panel B adds all pixels that are classified as forests (class 1, 2, 3, 4, or 5), while panel C uses grasslands (class 10). Each entry is from a separate regression, with the point estimate in the first line (% change in number of pixels per bandwidth per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The normalized score divides the score by the bandwidth in km minus one (the border pixel is always excluded) to account for the fact that a bandwidth that is twice as large roughly includes twice as many pixels. Each panel gives the average number of pixels on each side of the border for various landcover classes and bandwidths.

A Appendix

List of Figures

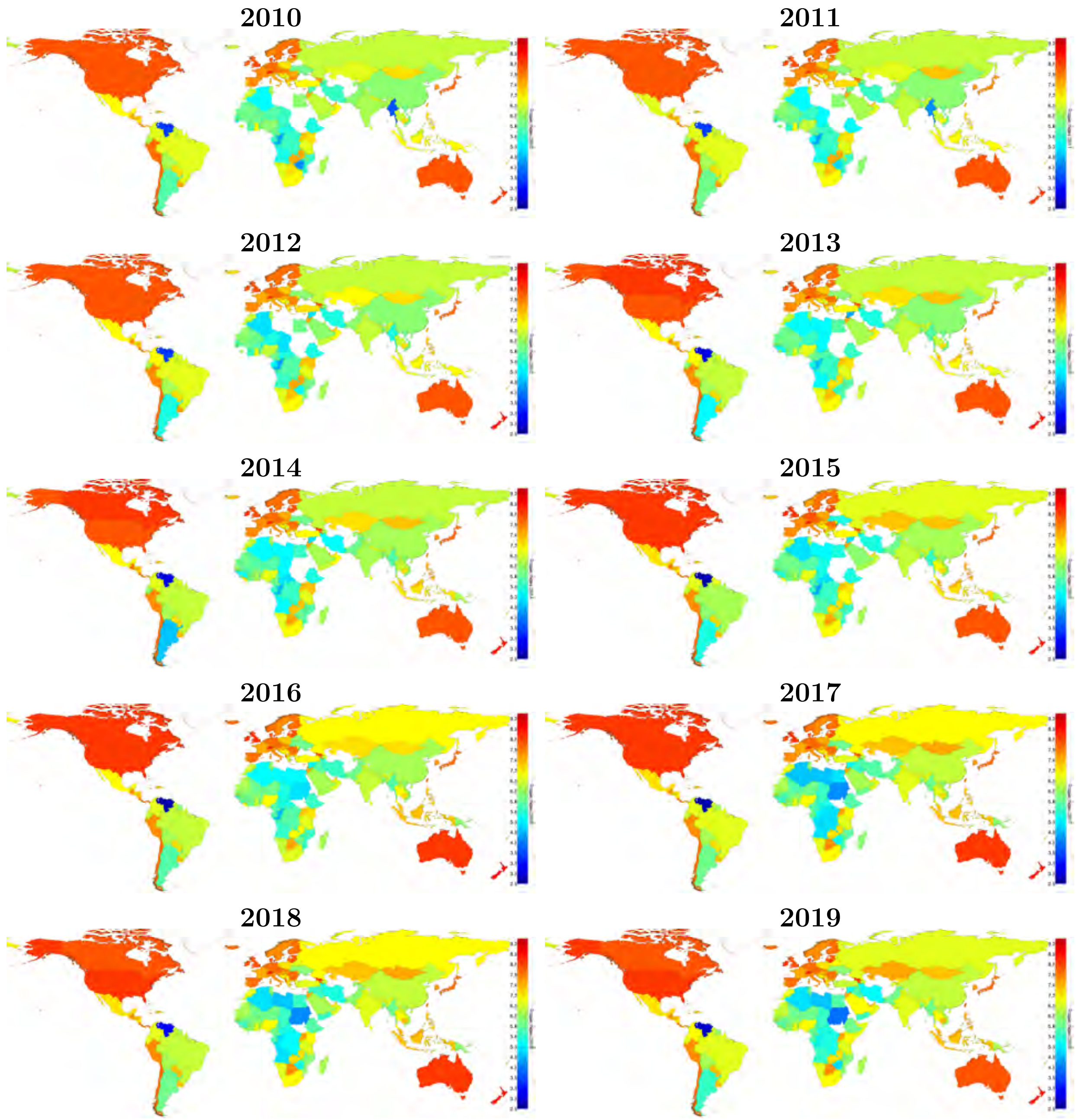
List of Tables

Figure A1: Economic Freedom Index Over Time (2000-2009)



Notes: Figure displays the economic freedom index by the Fraser Institute for 2000-2009. The color scale is the same throughout all panels of Figures A1 and A2.

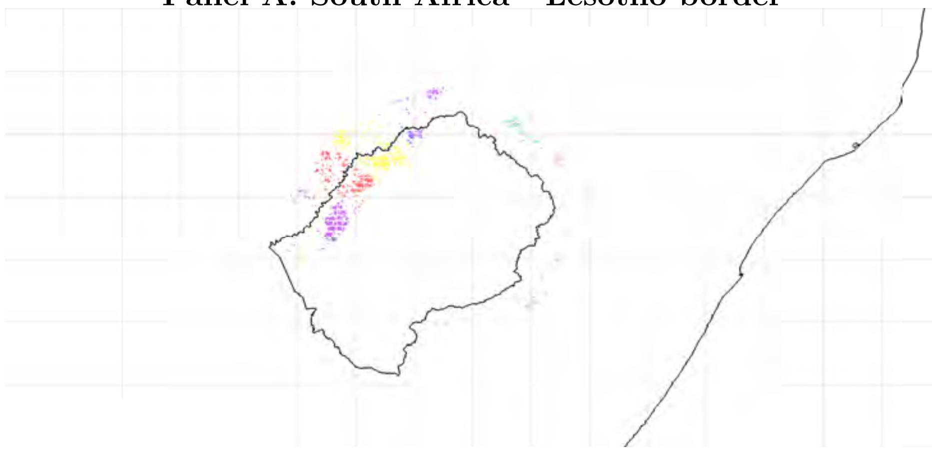
Figure A2: Economic Freedom Index Over Time (2010-2019)



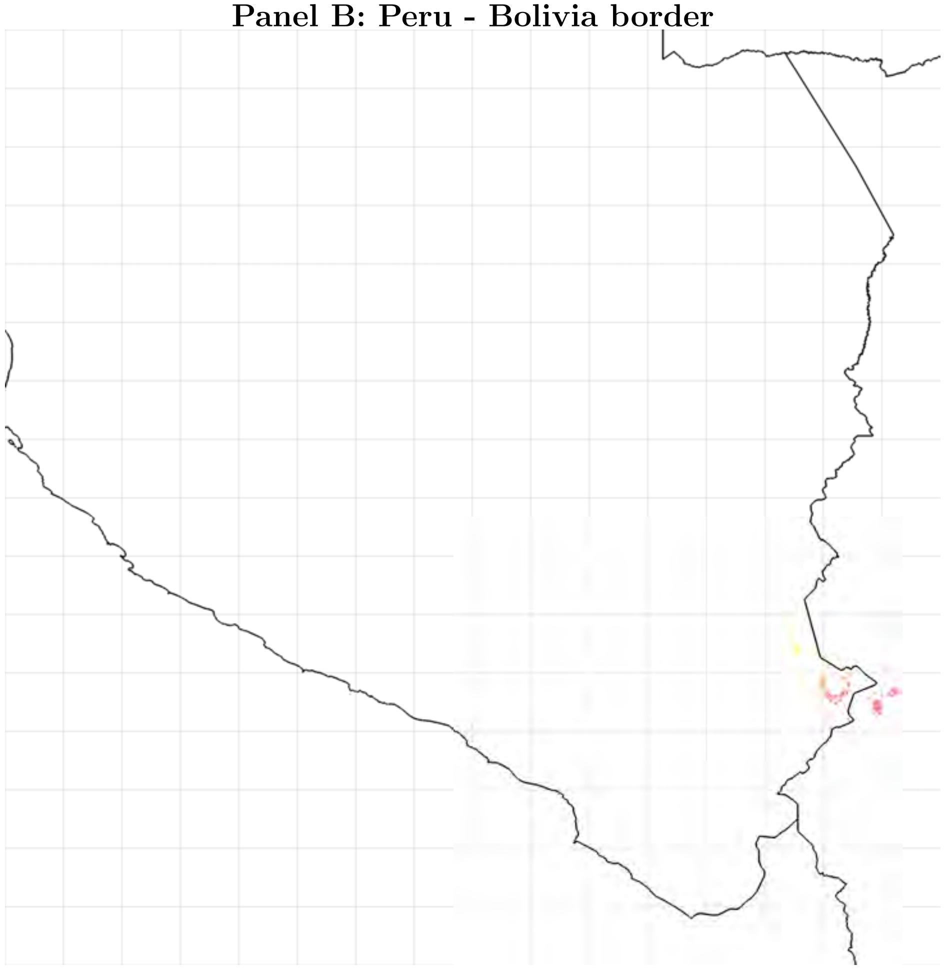
Notes: Figure displays the economic freedom index by the Fraser Institute for 2010-2019. The color scale is the same throughout all panels of Figures A1 and A2.

Figure A3: Constructing Border Segments: South Africa-Lesotho and Peru-Bolivia

Panel A: South Africa - Lesotho border

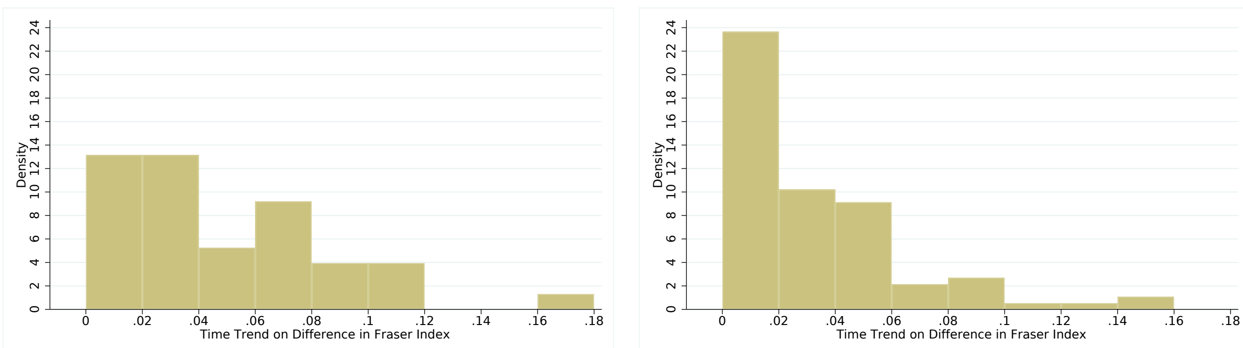


Panel B: Peru - Bolivia border



Notes: Figure replicates Figure 3 for the South Africa - Lesotho (top) and Peru-Bolivia (bottom) border. It again shows the individual pixels within a 25km band of the border with half-degree border segments.

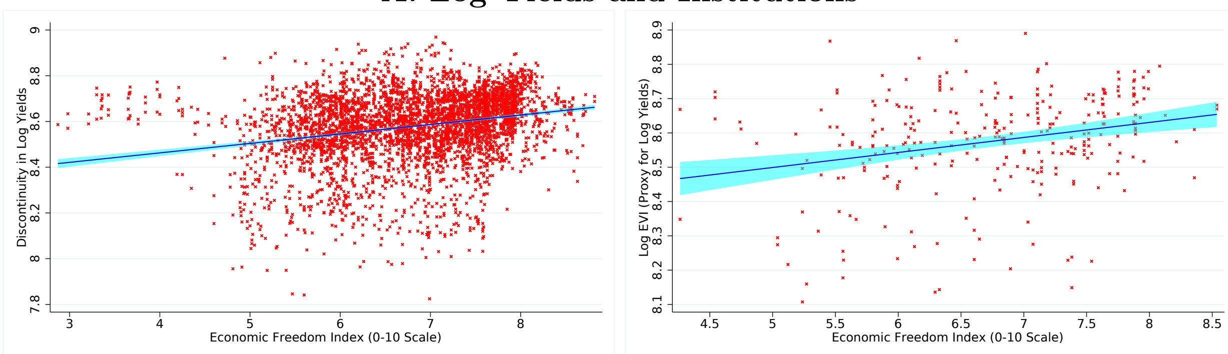
Figure A4: Time Trend in Difference of Economic Freedom Index Across Border



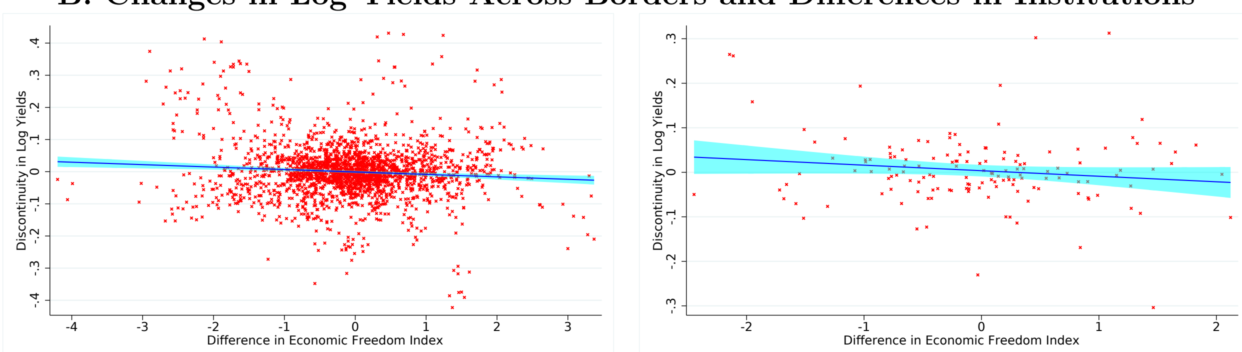
Notes: Figure shows the time trend in the difference of the economic freedom index by the Fraser Institute across a border. For easier disposition, all trends are normalized to be positive as the meaningful part is whether they are significantly different from zero. The left graph corresponds to column (1) of Table 4, i.e. the 38 borders where the country with the higher index changes between years. The right graph corresponds to column (2) of Table 4, i.e. the 93 borders where one side always has a higher index. Note that the trends in the left graph are larger in magnitude and more significant, 27 out of the 38 (71%) are statistically significant at the 1% level.

Figure A5: Cross-Sectional Relationship between Yields and Institutional Quality

A: Log Yields and Institutions



B: Changes in Log Yields Across Borders and Differences in Institutions



Notes: Figure displays the cross-sectional relationship between log EVI (a proxy for log yields) and the economic freedom index by the Fraser Institute. Panel A pairs the average of the log EVI (proxy for log yields) for the 25km band around a border, where each side of the border is included as a separate observation, with the economic freedom index. The bottom row pairs the discontinuity in log yields across a border with the corresponding difference in the economic freedom index. The left column stacks the 19 individual individual years, while the right column uses the average across all 19 years. The slope coefficient is positive in the top row (4.1 and 4.4, respectively) and negative the bottom row (-0.8 and -1.2, respectively).

Table A1: Variation in Border Discontinuities and Economic Freedom Index

Variable	Variation	Mean	SDev	Range
Discontinuity	Overall	0.05	(0.07)	[-0.27, 0.43]
	Between	0.05	(0.06)	[0.00, 0.31]
	Within		(0.04)	[-0.30, 0.27]
Fraser Index	Overall	0.00	(0.97)	[-3.37, 4.20]
	Between	-0.03	(0.90)	[-2.21, 2.58]
	Within		(0.36)	[-1.88, 1.65]
Score 1	Overall	-0.10	(1.35)	[-3.88, 5.11]
	Between	-0.06	(1.26)	[-2.79, 3.76]
	Within		(0.63)	[-2.46, 3.32]
Score 2	Overall	0.02	(1.23)	[-3.63, 3.93]
	Between	-0.01	(1.15)	[-2.74, 2.98]
	Within		(0.36)	[-1.57, 1.65]
Score 3	Overall	0.13	(1.74)	[-8.05, 8.57]
	Between	0.03	(1.47)	[-3.20, 4.78]
	Within		(1.02)	[-5.44, 5.01]
Score 4	Overall	0.05	(1.39)	[-6.63, 6.12]
	Between	0.03	(1.24)	[-3.73, 3.30]
	Within		(0.64)	[-3.10, 3.32]
Score 5	Overall	-0.08	(1.13)	[-4.17, 3.09]
	Between	-0.12	(1.02)	[-2.92, 1.88]
	Within		(0.47)	[-1.96, 1.71]

Notes: Table displays the variation underlying column (3) in panel A (1 lag) of Table 2. Overall variation is using all 2195 observations, while between variation focuses on the mean for the 146 borders. Finally, the within variation looks at fluctuations around the border-specific mean. The mean of the within variation is by construction zero and hence not listed. Discontinuities are for log yields, while the economic freedom index and the scores for the five areas that comprise it are on a [0,10] scale. The areas are:
Area 1 - size of government
Area 2 - legal system and property rights
Area 3 - sound money
Area 4 - freedom to trade internationally
Area 5 - regulation

Table A2: Discontinuities and Institutional Quality - Further Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Using Five Lags $L = [1, 5]$							
Score (x100)	1.52	2.21	2.20	1.67	1.88	1.97	2.83	1.86
	(0.85)	(0.83)	(0.84)	(0.82)	(0.74)	(0.72)	(0.73)	(0.69)
	[0.076]	[0.009]	[0.010]	[0.044]	[0.012]	[0.007]	[<0.001]	[0.008]
Borders	117	124	135	137	142	148	161	161
Observations	1469	1574	1660	1738	1795	1860	2057	2082
Pixels (10^6)	6.8	9.2	11.5	13.8	18.5	23.1	35.2	46.6
	Panel B: Using Seven Lags $L = [1, 7]$							
Score (x100)	1.79	2.43	2.51	1.96	2.19	2.23	2.29	1.91
	(0.96)	(0.90)	(0.92)	(0.88)	(0.84)	(0.80)	(0.77)	(0.81)
	[0.065]	[0.008]	[0.007]	[0.028]	[0.010]	[0.006]	[0.003]	[0.020]
Borders	114	121	131	133	137	143	157	157
Observations	1247	1333	1405	1473	1519	1573	1744	1764
Pixels (10^6)	5.8	7.9	9.8	11.8	15.7	19.7	30.1	39.8
	Panel C: Using Nine Lags $L = [1, 9]$							
Score (x100)	1.55	2.39	2.62	2.34	2.12	2.03	2.40	1.75
	(1.20)	(1.10)	(1.06)	(0.99)	(1.07)	(1.09)	(1.06)	(1.10)
	[0.198]	[0.032]	[0.015]	[0.019]	[0.050]	[0.063]	[0.025]	[0.114]
Borders	106	112	121	123	127	133	147	147
Observations	1020	1088	1147	1205	1243	1289	1428	1443
Pixels (10^6)	4.8	6.5	8.1	9.7	13.0	16.2	24.8	32.8
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table replicates Table 2 including further lags. Regressions again include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Different panels include different lags of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table A3: Discontinuities and Institutional Quality - Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Using One Lag $L = [1, 1]$							
Score (x100)	1.30	1.38	1.22	0.98	1.29	1.21	1.48	1.07
	(0.62)	(0.56)	(0.54)	(0.56)	(0.49)	(0.47)	(0.53)	(0.52)
	[0.038]	[0.015]	[0.027]	[0.083]	[0.010]	[0.010]	[0.005]	[0.041]
Borders	129	136	146	150	154	160	177	179
Observations	1949	2082	2195	2302	2387	2474	2742	2780
Pixels (10^6)	9.0	12.2	15.2	18.2	24.3	30.5	46.4	61.3
	Panel B: Using Three Lags $L = [1, 3]$							
Score (x100)	1.16	1.56	1.56	1.22	1.59	1.70	2.65	1.73
	(0.71)	(0.68)	(0.68)	(0.69)	(0.58)	(0.58)	(0.69)	(0.56)
	[0.107]	[0.023]	[0.024]	[0.080]	[0.007]	[0.004]	[<0.001]	[0.002]
Borders	118	126	136	139	144	150	167	167
Observations	1693	1814	1913	2003	2075	2152	2385	2414
Pixels (10^6)	7.9	10.6	13.3	15.9	21.3	26.6	40.6	53.6
	Panel C: Using Five Lags $L = [1, 5]$							
Score (x100)	1.36	1.98	1.98	1.56	1.80	1.96	2.58	1.82
	(0.83)	(0.79)	(0.81)	(0.77)	(0.69)	(0.70)	(0.66)	(0.68)
	[0.105]	[0.014]	[0.016]	[0.046]	[0.011]	[0.006]	[<0.001]	[0.009]
Borders	117	124	135	137	142	148	161	161
Observations	1469	1574	1660	1738	1795	1860	2057	2082
Pixels (10^6)	6.8	9.2	11.5	13.8	18.5	23.1	35.2	46.6
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table replicates Table 2 except that it regresses the discontinuity in the level of EVI rather than the log of EVI. The average EVI in each sample is re-scaled to equal 1 to make the coefficient comparable. Regressions again include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Different panels include different lags of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table A4: Discontinuities and Institutional Quality - Constant Set of Borders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Using One Lag $L = [1, 1]$							
Score (x100)	1.43	1.34	1.26	1.19	1.49	1.50	1.56	1.66
	(0.64)	(0.63)	(0.63)	(0.63)	(0.62)	(0.56)	(0.57)	(0.52)
	[0.028]	[0.035]	[0.047]	[0.059]	[0.018]	[0.009]	[0.007]	[0.002]
Borders	129	129	129	129	129	129	129	129
Observations	1949	1949	1949	1949	1949	1949	1949	1949
Pixels (10^6)	9.0	12.0	15.0	17.9	23.6	29.3	43.5	56.2
	Panel B: Using Three Lags $L = [1, 3]$							
Score (x100)	1.30	1.23	1.24	1.26	1.62	1.69	1.88	1.90
	(0.73)	(0.72)	(0.72)	(0.71)	(0.69)	(0.64)	(0.64)	(0.61)
	[0.077]	[0.091]	[0.087]	[0.079]	[0.021]	[0.009]	[0.004]	[0.003]
Borders	118	118	118	118	118	118	118	118
Observations	1693	1693	1693	1693	1693	1693	1693	1693
Pixels (10^6)	7.9	10.5	13.1	15.6	20.6	25.6	38.0	49.1
	Panel C: Using Five Lags $L = [1, 5]$							
Score (x100)	1.52	1.46	1.46	1.42	1.53	1.51	1.80	1.79
	(0.85)	(0.85)	(0.85)	(0.87)	(0.82)	(0.76)	(0.74)	(0.73)
	[0.076]	[0.087]	[0.090]	[0.102]	[0.065]	[0.050]	[0.017]	[0.016]
Borders	117	117	117	117	117	117	117	117
Observations	1469	1469	1469	1469	1469	1469	1469	1469
Pixels (10^6)	6.8	9.1	11.4	13.6	17.9	22.3	33.0	42.7
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table replicates Table 2 except that the set of borders are fixed to the one in column (1) for each panel, thereby comparing different bandwidth without changing the set of borders. Table regresses border discontinuities (x100) in log crop yields (measured by EVI) between countries on the difference in the economic freedom index by the Fraser Institute between those countries. All regressions include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Different panels include different lags of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table A5: Discontinuities and Institutional Quality - Controlling for Weather

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Using One Lag $L = [1, 1]$							
Score (x100)	1.31	1.49	1.46	0.96	1.89	1.25	0.58	0.11
	(0.60)	(0.55)	(0.54)	(0.76)	(0.81)	(0.55)	(1.06)	(1.10)
	[0.032]	[0.007]	[0.008]	[0.208]	[0.021]	[0.024]	[0.589]	[0.923]
Borders	128	136	145	149	154	160	176	177
Observations	1923	2053	2157	2280	2376	2455	2730	2771
Pixels (10^6)	8.9	12.1	15.1	18.1	24.1	30.2	46.0	60.8
	Panel B: Using Three Lags $L = [1, 3]$							
Score (x100)	1.18	1.58	1.80	1.23	2.80	2.11	2.04	1.22
	(0.72)	(0.64)	(0.67)	(0.89)	(1.03)	(0.68)	(0.71)	(0.93)
	[0.104]	[0.015]	[0.008]	[0.170]	[0.007]	[0.002]	[0.004]	[0.191]
Borders	118	126	135	139	144	150	165	166
Observations	1674	1787	1878	1987	2072	2141	2377	2409
Pixels (10^6)	7.8	10.6	13.2	15.8	21.1	26.4	40.3	53.2
	Panel C: Using Five Lags $L = [1, 5]$							
Score (x100)	1.43	1.86	2.12	1.70	3.47	2.65	2.66	1.49
	(0.80)	(0.72)	(0.77)	(0.89)	(1.37)	(0.89)	(0.75)	(0.80)
	[0.078]	[0.011]	[0.007]	[0.059]	[0.012]	[0.003]	[<0.001]	[0.065]
Borders	116	123	132	136	142	148	160	161
Observations	1454	1548	1628	1723	1795	1858	2054	2081
Pixels (10^6)	6.8	9.2	11.5	13.8	18.4	23.0	35.0	46.3
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table replicates Table 2 except that it includes a quadratic in temperature, precipitation, solar radiation, and altitude as well as soil class fixed effects in the first step when discontinuities are derived. Table regresses border discontinuities (x100) in log crop yields (measured by EVI) between countries on the difference in the economic freedom index by the Fraser Institute between those countries. All regressions include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Different panels include different lags of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.

Table A6: Separate Sub-scores for Area 1 - Size of Government

	(1)	(2)	(3)	(4)	(5)	(6a)	(6b)
Score 1A (x100)	0.33					0.25	0.22
	(0.28)					(0.25)	(0.24)
	[0.234]					[0.332]	[0.359]
Score 1B (x100)		-0.33				-0.49	-0.49
		(0.42)				(0.38)	(0.32)
		[0.427]				[0.202]	[0.131]
Score 1C (x100)			-0.27			-0.29	-0.06
			(0.16)			(0.16)	(0.09)
			[0.083]			[0.076]	[0.486]
Score 1D (x100)				0.36		0.37	0.57
				(0.15)		(0.17)	(0.16)
				[0.020]		[0.037]	[<0.001]
Score 1E (x100)					-0.21	0.07	0.37
					(0.33)	(0.39)	(0.39)
					[0.540]	[0.852]	[0.340]
Borders	125	125	125	125	125	125	146
Observations	1300	1300	1300	1300	1300	1300	2073
Pixels (10^6)	9.1	9.1	9.1	9.1	9.1	9.1	13.9
Bandwidth	25	25	25	25	25	25	25

Notes: Table separately includes the five sub-scores for area 1. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(5) include each of the five sub-scores individually, while columns (6a) and (6b) include all of them jointly. Column (6a) uses only observation where all sub-scores are non-missing, while column (6b) uses observations where at least one of the sub-scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The five sub-scores are:
Score 1A - government consumption
Score 1B - transfers and subsidies
Score 1C - government investment
Score 1D - top marginal tax rate
Score 1E - state ownership of assets

Table A7: Separate Sub-scores for Area 2 - Legal System and Property Rights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9a)	(9b)
Score 2A (x100)	0.47								-0.31	-0.62
	(0.51)								(0.69)	(0.62)
	[0.359]								[0.648]	[0.319]
Score 2B (x100)		1.22							1.12	0.82
		(0.60)							(0.70)	(0.59)
		[0.043]							[0.112]	[0.167]
Score 2C (x100)			0.61						0.43	0.51
			(0.34)						(0.39)	(0.36)
			[0.074]						[0.280]	[0.160]
Score 2D (x100)				-0.27					-0.25	-0.32
				(0.23)					(0.23)	(0.24)
				[0.241]					[0.280]	[0.193]
Score 2E (x100)					-0.36				-0.48	0.07
					(0.57)				(0.57)	(0.42)
					[0.530]				[0.404]	[0.871]
Score 2F (x100)						0.19			-0.31	-0.22
						(0.52)			(0.48)	(0.40)
						[0.710]			[0.530]	[0.591]
Score 2G (x100)							0.22		0.24	0.09
							(0.16)		(0.16)	(0.15)
							[0.172]		[0.147]	[0.552]
Score 2H (x100)								0.43	0.19	0.20
								(0.27)	(0.28)	(0.25)
								[0.120]	[0.498]	[0.421]
Borders	136	136	136	136	136	136	136	136	136	146
Observations	1821	1821	1821	1821	1821	1821	1821	1821	1821	2073
Pixels (10^6)	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	13.9
Bandwidth	25	25	25	25	25	25	25	25	25	25

Notes: Table separately includes the eight sub-scores for area 2. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(8) include each of the eight sub-scores individually, while columns (9a) and (9b) include all of them jointly. Column (9a) uses only observation where all sub-scores are non-missing, while column (9b) uses observations where at least one of the sub-scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The eight sub-scores are:
Score 2A - judicial independence
Score 2B - impartial courts
Score 2C - protection of property rights
Score 2D - military interference in rule of law and politics
Score 2E - integrity of the legal system
Score 2F - legal enforcement of contracts
Score 2G - regulatory restrictions on the sale of real property
Score 2H - reliability of police

Table A8: Separate Sub-scores for Area 3 - Sound Money

	(1)	(2)	(3)	(4)	(5a)	(5b)
Score 3A (x100)	0.48				0.25	0.21
	(0.16)				(0.17)	(0.16)
	[0.003]				[0.133]	[0.183]
Score 3B (x100)		0.47			0.10	0.10
		(0.18)			(0.16)	(0.15)
		[0.012]			[0.521]	[0.524]
Score 3C (x100)			0.72		0.53	0.57
			(0.27)		(0.23)	(0.22)
			[0.009]		[0.025]	[0.012]
Score 3D (x100)				0.03	0.01	0.02
				(0.15)	(0.11)	(0.12)
				[0.832]	[0.915]	[0.878]
Borders	135	135	135	135	135	146
Observations	1657	1657	1657	1657	1657	1831
Pixels (10^6)	11.5	11.5	11.5	11.5	11.5	12.4
Bandwidth	25	25	25	25	25	25

Notes: Table separately includes the four sub-scores for area 3. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(4) include each of the four sub-scores individually, while columns (5a) and (5b) include all of them jointly. Column (5a) uses only observation where all sub-scores are non-missing, while column (5b) uses observations where at least one of the sub-scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The four sub-scores are:
Score 3A - money growth
Score 3B - standard deviation of inflation
Score 3C - inflation: Most recent year
Score 3D - freedom to own foreign currency bank accounts

Table A9: Separate Sub-scores for Area 4 - Freedom to Trade Internationally

	(1)	(2)	(3)		(4)	(5a)
(5b)						
Score 4A (x100)	0.61				0.50	0.20
	(0.35)				(0.33)	(0.31)
	[0.085]				[0.128]	[0.517]
Score 4B (x100)		0.46			0.23	0.30
		(0.23)			(0.23)	(0.24)
		[0.053]			[0.316]	[0.201]
Score 4C (x100)			0.34		0.21	0.22
			(0.31)		(0.30)	(0.24)
			[0.268]		[0.495]	[0.369]
Score 4D (x100)				0.50	0.43	0.31
				(0.19)	(0.19)	(0.17)
				[0.011]	[0.023]	[0.074]
Borders	133	133	133	133	133	143
Observations	1555	1555	1555	1555	1555	1929
Pixels (10^6)	10.9	10.9	10.9	10.9	10.9	13.2
Bandwidth	25	25	25	25	25	25

Notes: Table separately includes the four sub-scores for area 4. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(4) include each of the four sub-scores individually, while columns (5a) and (5b) include all of them jointly. Column (5a) uses only observation where all sub-scores are non-missing, while column (5b) uses observations where at least one of the sub-scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The four sub-scores are:
Score 4A - tariffs
Score 4B - regulatory trade barriers
Score 4C - black market exchange rates
Score 4D - controls of the movement of capital and people

Table A10: Separate Sub-scores for Area 5 - Regulation

	(1)	(2)	(3)	(4a)	(4b)
Score 5A (x100)	0.61			0.60	0.62
	(0.28)			(0.28)	(0.27)
	[0.029]			[0.033]	[0.023]
Score 5B (x100)		0.42		0.29	0.21
		(0.27)		(0.27)	(0.27)
		[0.123]		[0.290]	[0.427]
Score 5C (x100)			0.41	0.40	0.46
			(0.49)	(0.48)	(0.47)
			[0.408]	[0.408]	[0.325]
Borders	135	135	135	135	135
Observations	1620	1620	1620	1620	1677
Pixels (10^6)	11.5	11.5	11.5	11.5	11.6
Bandwidth	25	25	25	25	25

Notes: Table separately includes the three sub-scores for area 5. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1)-(3) include each of the three sub-scores individually, while columns (4a) and (4b) include all of them jointly. Column (4a) uses only observation where all sub-scores are non-missing, while column (4b) uses observations where at least one of the sub-scores is non-missing and sets all missing observations to the border-specific mean. Each entry gives the point estimate in the first line (% change in crop yields per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line. The three sub-scores are:
Score 5A - credit market regulation
Score 5B - labor market regulation
Score 5C - business regulation

Table A11: Separate Sub-scores for Areas 1-5

	(1) est	(2) (se)	(3) [p-val]
1A - government consumption	0.43	(0.24)	[0.077]
1B - transfers and subsidies	-0.31	(0.35)	[0.380]
1C - government investment	-0.08	(0.09)	[0.377]
1D - top marginal tax rate	0.37	(0.15)	[0.013]
1E - state ownership of assets	0.30	(0.38)	[0.436]
2A - judicial independence	-0.78	(0.61)	[0.207]
2B - impartial courts	0.42	(0.61)	[0.493]
2C - protection of property rights	0.29	(0.27)	[0.287]
2D - military interference in rule of law and politics	-0.19	(0.26)	[0.462]
2E - integrity of the legal system	-0.01	(0.42)	[0.976]
2F - legal enforcement of contracts	0.18	(0.31)	[0.555]
2G - regulatory restrictions on the sale of real property	0.02	(0.15)	[0.890]
2H - reliability of police	0.27	(0.25)	[0.280]
3A - money growth	0.18	(0.16)	[0.272]
3B - standard deviation of inflation	-0.05	(0.15)	[0.739]
3C - inflation: Most recent year	0.66	(0.23)	[0.005]
3D - freedom to own foreign currency bank accounts	0.03	(0.10)	[0.751]
4A - tariffs	0.34	(0.25)	[0.181]
4B - regulatory trade barriers	0.14	(0.25)	[0.578]
4C - black market exchange rates	-0.10	(0.27)	[0.707]
4D - controls of the movement of capital and people	-0.01	(0.17)	[0.954]
5A - credit market regulation	0.50	(0.21)	[0.020]
5B - labor market regulation	0.24	(0.26)	[0.349]
5C - business regulation	-0.24	(0.40)	[0.544]
Borders	146		
Observations	2073		
Pixels (10^6)	13.9		
Bandwidth	25		

Notes: Table separately includes all sub-scores of the economic freedom index of the Fraser Institute. Results are from one joint regression that uses 5 lags and a bandwidth of 25km, i.e., the specification of column (3) in panel C of Table 2. Columns (1) gives the point estimate, column (2) the standard error, and column (3) the p-value.

Table A12: Fraction of Pixel that is Cropland

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Share of pixel that is cropland (0-1 range)							
Score (x100)	0.55	0.16	-0.06	0.04	-0.09	0.39	1.44	0.56
	(0.65)	(0.61)	(0.70)	(0.87)	(0.72)	(0.72)	(1.10)	(1.07)
	[0.395]	[0.789]	[0.934]	[0.962]	[0.906]	[0.591]	[0.194]	[0.601]
Borders	112	119	125	132	135	142	154	156
Observations	400	432	451	479	493	513	565	576
Pixels (10^6)	7.5	10.1	12.6	15.2	20.2	25.3	38.5	51.1
Bandwidth	15	20	25	30	40	50	75	100

Notes: Table uses four-year averages in the economic freedom index, ending in 2003, 2007, 2011, 2015, 2019 as in Table 7 and pairs them with detailed satellite scans that identify whether each 30x30m pixel is cropland in that year. We aggregate the 30x30m cropland indicator to the same 1x1km pixel resolution as in our baseline and restrict the data to the same pixels as in the baseline. Table examines whether changes in institutions impact how intensively a pixel is farmed (fraction that is cropland). Regression again include one lag of the four-year average of the economic freedom index. All regressions include border fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is always excluded. Each entry is from a separate regression, with the point estimate in the first line (change in percentage points of the fraction of a pixel that is cropland per unit of the economic freedom index that is on a [0,10] scale), the standard error in round brackets in the second line, and the p-value in square brackets in the third line.