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INSTITUTIONS AND GLOBAL CROP YIELDS

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Institutions and Global Crop Yields

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ABSTRACT

We estimate annual discontinuities in remotely-sensed crop yields at all international land borders and link them to changes in the economic freedom index by the Fraser Institute, a country-level measure of institutional quality. Each point of the ten-point index increases the discontinuity by 2.2% over the next five years, highlighting that institutional reforms have the potential to close some of the observed crop yield gap. Three subcategories are consistently significant: credit market regulation, inflation, and the top marginal tax rate. We present suggestive evidence that higher average yields are achieved through increased use of irrigation and mechanization. Yield variability remains unchanged, and reforms lead to cropland expansion through deforestation.

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The economy operates within the scope of human-designed institutional settings.¹ Establishing a well-functioning market economy with economic freedom has long been argued to be a main function of government (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 contracts and well-functioning credit markets (Banerjee 2003) or secure property rights (Acemoglu and Johnson 2005, Behrer, Glaeser, Ponzetto and Shleifer 2021). We examine the impact of a broad set of country-level institutional settings on agricultural outcomes with the help of novel remotely-sensed datasets that measure crop yields, date of maturity, and water use uniformly around the world from 2001-2019.

The agriculture sector is a major, usually the largest, employer in developing countries. Countries with the lowest yields often have the largest share of the population working in agriculture (Adamopoulos and Restuccia 2022). In most developing countries, crop yields are below what would be attainable given natural endowments (e.g., soils and weather).² Proximate causes for low crop yields are multi-fold and include, e.g., farmers not adopting higher-yielding varieties and not using the optimal amount of complementary inputs such as machinery, water, and fertilizers, for a lack of insurance markets, the inability to purchase required inputs or insurance due to liquidity constraints, and a lack of overall profitability (Casaburi and Willis 2018, Suri and Udry 2022). However, Laajaj, Macours, Masso, Thuita and Vanlauwe (2020) caution that not all predicted yield gains from field trials are obtained under real-world growing conditions, and the extent to which various factors account for observed yield gaps are still actively debated.

Our paper provides novel estimates whether changes in institutions, specifically economic and legal differences, translate into changes in observed yields and agricultural practices. We focus on discontinuities in yields around country borders where institutions change and link the temporal evolution of these discontinuities in a panel setting to an annual measure of institutional quality, the economic freedom index by the Fraser Institute. In doing so we

¹Lin 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.” Acemoglu, Johnson and Robinson (2005) distinguish between political and economic institutions. Political institutions determine the distribution of political power in society. Economic institutions determine the incentives of and the constraints on economic actors. Important indicators for countries’ economic institutions are the protection of private property and the enforcement of contracts.

²Attainable 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 developing country agriculture is especially adversely impacted by climate change yet predicted to attract more labor to satisfy domestic food needs (Nath 2022).

make five major contributions:

First, our study complements previous studies that focus on one particular reform in a country by systematically assessing 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 outcome measure and set of assumptions is a key ingredient for our global analysis. For example, Ittersum, Cassman, Grassini, Wolf, Titttonell 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 baseline 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 resolution around borders. While other sectors beyond agriculture are also impacted by institutions, it is much harder to obtain global fine-scaled 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 various institutional changes. 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 and other environmental factors are not smoothly distributed at all border segments⁶ 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 (“culture”). 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

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

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

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

⁶For example, topography has often been a natural factor associated with delineating political boundaries.

fixed effect. In case of the economic freedom index by the Fraser Institute, as long as culture does not concurrently change with the institutional changes without being caused it, it will also be absorbed in the border fixed effects. What helps our identification is that cultural practices evolve on a slower time-scale than the regulatory and legal systems we measure annually.

Third, given the global scope of our analysis, our data also includes borders between developed countries. This allows to test empirically whether changes at various baseline levels have a different effect. A priori, both a concave and convex response functions are possible. 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 crop 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 institutions have positive effects on crop yields at all 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 gaps and the possibility to foster rural 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. These determine the costs and financial feasibility of agricultural investments and the financial incentive to take on the risk of agricultural production. Agricultural production has an important inter-temporal aspects, where inputs have to be purchased at the beginning of the growing season, yet revenue streams generally occur after harvest, several months after planting. Inflation and credit market constraints aggravate this inter-temporal aspect.

Fifth, we provide suggestive evidence on the mechanism behind the observed yield increases due to market reforms. Using a different remote-sensing product in the same statistical setup, we find an increase in the discontinuity in evapotranspiration in the five years following the reforms, likely through an increase in the use of irrigation. Evapotranspiration is the sum water taken up by roots and transported through plant tissues before it is released

by leafs as water vapor (known as transpiration) as well as the water that evaporates directly into the atmosphere from soil in the vicinity of the plant. Similarly, mechanization (e.g., the use of tractors), allows farmers to plant faster when conditions are optimal and we find a decrease in the discontinuity of the day when maximum EVI is observed following reforms, although the significance of these results depend on the chosen bandwidth and is not as robust as our baseline finding. Together, they point towards likely avenues how economic liberalization can boost yields. We also find an extensive margin result with an expansion of the growing area at the cost of deforestation.

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 have in common that they are relatively 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 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 farmers in low-income countries usually have 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 on single institutional characteristics, such as, e.g., property rights (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, if one can extrapolate their findings across countries. For example, Chen, Restuccia and Santaella-Llopis (2022) document how improving tenure security in rural Ethiopia boosted agricultural productivity by 43 percent because land markets improved. 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). There is indirect evidence on sizeable effects of price fluctuations and the availability of financial instruments to deal with them (Burke, Bergquist and Miguel 2019). We provide novel empirical evidence available on the effect of credit market regulations, inflation control, agricultural taxation, and similar institutional characteristics.

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 influence from a higher level (Ostrom 1998, Ostrom 2000). However, without strong national institutions, local elites might provide a setting that is more in their own than the general interest (Acemoglu, Reed and Robinson 2014b). 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, there is even the question of whether national institutions even reach remote rural areas all around the world.

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 for the border between Lesotho and South Africa in the top panel, the border with the highest average discontinuity in crop yields 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-Kazakhstan 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 consistently find a significant positive relationship across various 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 discontinuities. We plot the raw values of the annual maximum EVI of all pixels within 100km of the border for the years 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.

⁷Similar 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).

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

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

To derive annual discontinuities in crop yields at countries’ borders, we employ a regression discontinuity framework, using as a 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 Klaauw 2001, Turner, Haughwout and Klaauw 2014, Calonico, Cattaneo, Farrell and Titiunik 2019), the abrupt change in treatment assignment at country borders allows for causal identification of their effect. The assigned treatment here is thus the change in country. In this first step, we estimate:

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

where $y_i(1)$ and $y_i(0)$ are the outcomes if a country are treated to be in one country or the other, respectively. Our running variable X is the distance of each pixel to the border, which controls for spatially continuously distributed confounding factors, such as rainfall, temperature, and many other environmental variables. We normalize the border to be at distance 0, where treatment assignment abruptly changes.

In practice, there are 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 where there are many more pixels on the Vietnamese side and in different parts of the border, i.e., borders are in a two-dimensional (longitude-latitude) rather than a one-dimensional space. Second, borders sometimes follow natural geography (e.g., rivers, mountain ranges) and other factors (soil, water access, climate) might sometimes change at the border as well. Third, not just environmental factors, but part of the institutions we are 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 linking the annual border discontinuities to the economic freedom index in a panel setting with border fixed effects to net out persistent and slow changing other differences.

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):

$$y_{ibt} = \alpha_{s[i,b]t} + \beta_{bt}I_{[i \in H]} + \gamma_{s[i,b]t}\mathbf{X}_i + \delta_{bt}\mathbf{Z}_{it} + \epsilon_{ibt} \quad (2)$$

where y_{ibt} are log 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, $\gamma_{s[i,b]t}$ 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 δ_{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 vegetation biomass 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 environmental drivers of crop-yield changes the results, which would be the case if these changed discontinuously at the border. Since these parameters model the responsiveness of crops to environmental factors, the coefficients δ_{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.

¹⁰Pixels 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.

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

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

We vary the distance cutoff for the pixels that are included in the regression, setting it at 5km, 10km, 15km, 20km, 25km, 30km, 35km, 40km, and 50km, and also present results for bandwidths of 75km and 100km (62 miles) in the appendix. We focus our baseline results on the intermediate bandwidth of 25km to counter two opposing forces: 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. Using a bandwidth of 25km, 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.

When examining mechanism, we run the same specification with a different dependent variable: y_{ibt} is either the log evapotranspiration of pixel i around border b in year t , or the day (linear specification) of the year when the pixel has the highest EVI value.

1.2 Panel of Border Discontinuities and Measures of Institutions

We next link the estimated border-discontinuities in crop yields ($\widehat{\beta}_{bt}$) from equation (2) to measures of institutional economic freedom 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 using a difference-in-discontinuities approach. In a first step we focus on 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.

$$\widehat{\beta}_{bt} = a_b + \frac{1}{L} \sum_{l=1}^L [f(q_{H[t-l]}) - f(q_{L[t-l]})] + e_{bt} \quad (3)$$

Our specification includes the average across lags $l = 1 \dots L$ as it may take time for changes in the institutional set up to be detected in the form of higher crop yields, e.g., because farmers become more willing to invest into their fields or make other productivity-enhancing investments which effect take time to materialize. 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 10th, 50th, and 90th percentile of

observed values of institutional economic freedom.¹³ This setup allows us to detect whether there are critical levels below or above which there is no more response to institutional changes. For examples, the farmers in countries with very little economic freedom might not be responsive to increases in economic freedom as the institutional set up might still mostly discourage agricultural investments. Alternatively, once countries reach a high level, further improvements in economic freedom might not anymore affect farmer behavior as this was already not a limiting factor before. The semi-parametric approach is also able to pick up other possible non-linearities at intermediate ranges.

In a second step we also consider possible effects at 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)

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

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 $k \in \{\text{cropland, forest, or grassland}\}$.¹⁴ This allows to examine whether the amount of cropland expands after reforms, and whether it comes at the cost of forests or grasslands.

2 Data

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

¹³This 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.

¹⁴Pixel 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.

2.1 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 report 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 spatial- and 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 yields for rice, wheat, and maize (corn), as well as in different 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 measure of yields. 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 A15 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 A6 where we include environmental variables, such as rainfall, temperature, and solar radiation as a control variable, and our results remain robust.

2.2 Data on Day of Maturity and Evapotranspiration

In a subsequent analysis on possible mechanism, we also examine both the day when maximum EVI is recorded and a measure of evapotranspiration. The day maximum EVI is reached comes from the same data source as for our yield proxy, which is the maximum enhanced vegetation index: it simply is the day of the year (between 1 and 365) when the maximum is observed, which we call day of maturity for simplicity. Earlier planting or the planting of short-duration varieties (under the same weather) will result in an earlier crop heading (maturity) date.

Our data on evapotranspiration is from a separate analysis of the same MODIS satellite. While maximum EVI captured the amount of vegetation biomass at one point in time, measures of evapotranspiration (Running, Mu and Zhao 2017) are either the mean over the entire year or the main growing season. The data on the start and the end of the growing season is averaged over the years 2014 to 2019, for which satellite data is available and uniformly applied across all years in our sample that spans from 2001 to 2019 (Zhang, Friedl and Henebry 2020).

2.3 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,” with 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 the largest 100km band for 2001-2019.¹⁵ The number of pixels in the regression is generally lower as not all borders have data on institutional quality, and because we use smaller bandwidths ranging from 5km to 100km and hence a subset of pixels.

For analyses on the effect of countries’ institutions on the expansion and abandonment of cropland, we use the larger data set of up to 351 million pixels within 100km of borders, which are not restricted to be cropland pixels (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.

2.4 Additional Controls for Yields

The start of our analysis, as described by equation (2), is a regression discontinuity analysis conducted at international borders. The baseline specification only includes border-segment controls (i.e., fixed effects and smooth polynomials in longitude and latitude) to make sure we compare pixels across narrowly defined sections of the border. In a sensitivity check in the appendix, we further control for additional variables that have been shown to influence crop yields. These additional controls all come in the same 1x1km pixel resolution and 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).

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

2.5 Measure of Countries' Economic Institutions

Our analysis uses the economic freedom index by the Fraser Institute, specifically the Economic Freedom of the World database.¹⁶ The 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 A13.

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 downward 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 correlations between growth rates and economic institutions of a country. 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 the difference 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., culture, government programs for agriculture, etc. The contradictory findings 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.

¹⁶<https://www.fraserinstitute.org>

¹⁷A simple panel linking EVI to measures of countries’ economic institutions 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.

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 under the intermediate 25km band 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 meet 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 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 we similarly aggregate. Since the 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 crop 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 81 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 roughly 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 described 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 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 economic freedom, 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 economic freedom, allowing us to link the two in a panel setting in the next step.

3.2 Yield Discontinuities and Economic Freedom

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 economic freedom (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 economic freedom, normalizing them to be at zero at the lower knot (10th 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 economic freedom. However,

¹⁸The 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 (economic freedom), so a normalization does not alter the results.

farmers in location with lower initial economic freedom 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 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 A4 when assuming a constant absolute impact. Our results are not driven by functional form assumptions.

Columns differ by the chosen bandwidth, ranging from 5km to 50km, with additional bandwidths up to 100km in Table A3. 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 18 point estimates for bandwidths of 15km or larger are statistically significant at least at the 10% level, while results for 5km and 10km are of similar magnitude but sometimes not statistically significant as we focus on a very narrow range around the border. 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. The statistical optimum and thus our preferred bandwidth is 25 km. To differentiate the robustness with respect to the bandwidth around the same borders versus what borders are included, Table A5 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 5km of each border, and again finds very robust results that vary even less than the ones in Table 2 and are also consistently significant for a bandwidth of 10km. 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 lose 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 consistently scores higher throughout (e.g., Switzerland always has a higher index than France or Germany) or borders where the better side switches (e.g., the Nigeria-Chad 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 economic freedom (column 2) results in insignificant results verifying that the changes in crop yields are in response to changes in *past* economic freedom. For the sub-sample of borders where the side with the higher freedom index switches, the coefficients remain significant and of similar magnitude, the point estimate increases slightly to 2.79. The reason is that borders where the freer 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 in the regression 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.

Finally, Table A7 conducts a falsification check by replicating the baseline specification

¹⁹We select borders into the “constant” sample if the explanatory variable, the average of the five lags of economic freedom, is always higher for one country relative to its neighbor

for different sets of pixels (landcover) around each border. The three panels look at pixels that are consistently classified as savanna, forests, or shrublands, respectively.²⁰ Out of the 28 point estimates for various bandwidths for savanna, forest, and shrubland pixels, only one is statistically significant at the 10% level (5km bandwidth for savanna, but it has a negative coefficient). This is reassuring as we only observe our response for pixels that are classified as cropland and not other pixels, ruling out that we are observing reverse causality where a change in environmental conditions leads to a change in the institutional settings²¹ If this was the case, we would expect the environmental change to be detected in various landcover classes, not just cropland.

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

²⁰We focus on pixels that are classified as landcover class 8 or 9 for savanna, landcover class 1-5 for forests, and landcover classes 6-7 for shrubland for all years 2001-2019 and have the remotely-sensed maximum EVI data available in all 19 years. In our baseline we used pixels that are classified as cropland (class 12 or 14) in all 19 years and included them even if maximum EVI was not available in all years. If we restrict the cropland sample to pixels that are perfectly balanced, the point estimates change slightly but are qualitatively similar.

²¹Recall that we are also using a lag structure, but given that we have trending variables the lag structure does not entirely ensure that we do not have reverse causality.

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 A8 through A12 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 A8, 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 A9 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 capital 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 A10 with a point estimate ranging from 0.53-0.72, “5A - credit market regulation” in Table A12 with a point estimate of 0.6-0.62, and “area 4D - controls of the movement of capital and people” in Table A11 with a point estimate ranging from 0.31-0.50

Table A13 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 remarkably robust, being significant when included individually, jointly with the other sub-scores of their particular area, and when all sub-scores are jointly included. The fourth sub-score that is 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-scores by including only the four significant sub-scores of Table A13 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 remarkably 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 countries’ economic institutions on mean yields. As discussed above, one concern with the adoption of high-yielding varieties is that while they do improve mean yields, they might also increase yield variability. Risk-averse farmers, especially those that are liquidity-constrained 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 estimated 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.²² 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 economic freedom for the previous four years, i.e., 2000-2003 to 2012-2015. The regression 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

²²We 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 of countries’ economic freedom index, the first years of the satellite data 2001-2003, which is only three years, will effectively not be used.

periods.²³ 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 point estimates are comparable to what we obtained above in Table 2, and the coefficients are again highly statistically significant for bandwidth of 15km and up, while the p-values for the two smallest bandwidths of 5km and 10km are 0.11 and 0.09, respectively. 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 smaller bandwidths ranging from 15km to 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 seven smallest bandwidths.

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

Another aspect of variability is how resilient a system is to shocks. We do examine this in Figure A6, where we link pixel-level changes around the 2007-2008 financial crisis to the 2006 scores of the Fraser index. This is a difference-in-difference analysis, and we find a highly nonlinear hill-shaped relationship for cropland pixels with respect to the tariff measure. Countries with intermediate values saw an increase in crop yields as is common through technological progress over time. However, both countries that were fully integrated with the world economy (high economic freedom score for tariffs, i.e., low tariffs) or not at all (low economic freedom score for tariffs) saw no change in crop yields. In case of the former, full exposure to the world market led shocks to spread more easily and to local disruptions. In case of the latter, countries that are insulated from the world market have generally lower growth rates over time. We only observe this significant relationship for cropland pixels, but not savanna or forest pixels, our placebos.

²³To 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.

3.5 Mechanism Behind Yield Increases

We have documented a statistically significant increase in the border discontinuity in crop yields following a widening in the gap of the economic freedom index between neighboring countries. This section provides further suggestive evidence on the possible mechanism behind the observed change in crop yields. As described in the introduction, there are a myriad of possible explanation for observed yield gaps, among them mechanization and better use of inputs. Since our analysis is global, we do not have detailed data on various inputs around country boundaries in a consistent way, however, there are two factors we can measure in a uniform way remotely around the globe and that reveal information: evapotranspiration and the date of peak EVI.

Table 8 replicates the same two step analysis outlined in equations (2) and (3) with a different dependent variable: instead of measuring peak EVI as in our baseline, i.e., “maximum greenness” that has been shown to be a proxy for crop yields, we rely on a remotely-sensed measure of evapotranspiration (ET), which is the total amount of water that plants transpire or that directly evaporates from the soil surrounding the plant. The adoption of irrigation will increase ET because both the plant transpires more of the water it takes up through its roots and, unless drip irrigation is used, there is a loss through evaporation from the soil directly into the atmosphere. The ET measure is constructed using the same MODIS satellite as our baseline data and available for the same years (see Data Section 2.2). Note that while our baseline data used an observation at one period throughout the year (the maximum EVI), we are now constructing the ET measure throughout either the main growing season or the entire year and find that a widening of the gap in the economic freedom index leads to a statistically significant increase in the discontinuity in ET. This is true even for the lower bandwidths of 5km and 10km that were not significant in the baseline Table 2 for yields. While ET is influenced by local weather, recall that we are relying on changes in the discontinuity across country-borders over time, and it appears unlikely that the weather is *changing* year-to-year in a different discontinuous way across a border. Table 8 provides strong evidence for an increase ET, which likely represent a combination of increased evapotranspiration due to increased irrigation use (Djaman, Irmak, R. Rathje, L. Martin and E. Eisenhauer 2013), as well as increased transpiration from higher yielding fields (Bennett and Harms 2011), as evidenced by the significant relationship in Table A14, where we conduct a pixel-level panel regression between $\log(\text{ET})$ and $\log(\text{EVI})$. However, the coefficients of Table A14 combined with the fact that the point estimates in Table 8 are larger than those in Table 2 suggest that about half of the observed increase in ET is due to higher

yields itself, and the rest is attributable to more irrigation.

We perform another test whether reforms lead to an earlier planting date through mechanization. Earlier research has shown that a benefit of mechanization or advanced technologies is that farmers can prepare the land faster and seed quickly as soon as conditions are optimal. Moreover, it sometimes allows farmers to plant seeds earlier when fields are still water-logged or muddy that complicate traditional seeding methods.²⁴ Table 9 therefore replicates our two step analysis outlined in equations (2) and (3) with another dependent variable: instead of measuring peak EVI, we look at the date when the peak EVI is reached. In case farmers plant earlier, we would expect an earlier heading date, and consequently to observe peak EVI at an earlier time. We otherwise follow the same procedure, i.e., by first estimating annual border discontinuities in the date peak EVI is reached over cropland pixels around borders, and then linking them to the panel of the economic freedom index. We estimate the model in levels (see Table A4) as a log model is less appropriate for the date of the year. The results are shown in Table 9. The top panel shows the results for the overall Fraser Index, while the bottom panel focuses on the sub-component measuring credit market regulation. While the results are now dependent on the chosen bandwidth, we observe a negative and significant effect for higher bandwidths, which we believe to be preferable for the following reason: The MODIS satellite does not provide daily measurements but rather periodically orbits the earth to provide readings. The data set consists of 16-day windows to derive EVI measurements that are averaged out.²⁵ We hence require larger datasets (bigger bandwidths) to detect a shift: for each point on the 10-point scale index measuring economic freedom, the discontinuity in planting date decreases by 1-2 days, i.e., advances the planting and harvest date forward. This finding is consistent with what we would expect from additional mechanization. There is also the possibility that farmers are switching to planting shorter duration varieties that would also head faster.

3.6 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

²⁴We would like to thank Peter Huybers for this suggestion.

²⁵The description states that “The algorithm for this product chooses the best available pixel value from all the acquisitions from the 16-day period. The criteria used are low clouds, low view angle, and the highest NDVI/EVI value.” While the dataset provides the exact date when peak EVI occurred, it is constructed from the 16-day window. This is less of a concern when looking at yields, as the EVI value flattens out around its maximum and taking an average over a several days has very little effect on the value, but the day the maximum occurred has more uncertainty and measurement error.

time, institutional reforms might also encourage additional land to be farmed, or discourage farmers from continuing to do so. 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 freedom index.

We focus on three landcover types: cropland, forests, and grasslands, which are displayed in the different panels of Table 10. 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.²⁶ A coefficient of 1.87 in column (5) 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.²⁷ 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 only statistically significant for four of the eight bandwidths. The results on grasslands in Panel C are even smaller, switch sign, and are never significant.²⁸

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 rural poverty, and to be in a position where we can globally afford

²⁶Since we also exclude pixels with a distance less than 1km, we normalize by (bandwidth-1)

²⁷The corresponding percent changes are 0.9%, 1.8%, 1.1%, 1.2%, 1.4%, 1.9%, 2.1%, and 2.2% for the eight bandwidths in panel A.

²⁸There are other landcover types, e.g., wetlands, savannas, shrublands, and urban areas that we do not show here.

to protect remaining natural and semi-natural ecosystems from agricultural area expansion, it is important to improve crop yields on fields that are already used for agriculture and currently performing below their potential.

This paper focuses on one potential policy lever to improve yields: increasing economic freedom via institutional reforms. More specifically, we examine economic institutions of countries as measured by the economic freedom index by the Fraser Institute that focuses on a very wide range of aspects, from legislation to policy outcomes. As emphasized in the introduction, there are other important institutional details that might matter, including cultural values and norms, which are not measured by the index. We find that a linear model is appropriate and that 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.

There is a trade-off to using a remotely-sensed product. On the upside, we have a globally consistent measure that is key for a global analysis of crop yields. On the other hand, we have less detailed information on the exact mechanism that causes the changes in average yields as we only have remotely-sensed data. There are, however, two indirect test that we can conduct on a possible channel: we find an analogous increase in evapotranspiration at the country boundary, consistent with an increased application of irrigation. We also find a statistically significant effect for earlier planting dates, although this effect is only observable for larger bandwidths.

There are possible drawbacks to using the remotely-sensed EVI product 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 fraction of the pixel being cropped. We formally test the latter hypothesis in Table A15, where we use another, even finer, remote sensing product that classified whether each 30x30m pixel 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 fraction of a pixel that is cropland rather than the log EVI. Panel A of Table A15 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 effects 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 more profitable) or improving the functioning of land markets (e.g. land can be rented and sold if credit markets function well and inflation is not too high). In the longer term, however, more fundamental changes might occur too, including public and private investments in larger irrigation infrastructure, extension systems, or crop breeding. 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 possibly take longer to fully materialize than the effects we have quantified 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 might also lead to more nutrient and pesticide pollution. Similarly, our extensive margin analysis suggests that the increase in crop yields can come with an increase in deforestation. This suggests the need for complementary regulation that controls such negative side effects and this again comes with its own costs and benefits. In a welfare analysis one would have to balance all the gains from higher yields and more cropped area against the all additional costs: 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 (Allen and Atkin 2022).

5 Conclusion

We study whether changes in country-level institutions 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 institutions 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, and to produce enough food on existing crop land so as to be able to spare natural ecosystems from conversion to cropland.

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.

In terms of mechanisms, we document an analogous increase in evapotranspiration that cannot be explained by higher yields themselves, implying a discontinuous expansion of irrigation around borders in response to the policy reforms. We find suggestive evidence in line with a discontinuous change towards earlier planting dates in response to the reforms, although this finding is only observed for larger bandwidths.

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 evidence that it leads to increased deforestation. This suggests that while improving yields has the potential to allow sparing natural land from cropland conversion, this requires appropriate policies to be implemented, so as to counteract the economic incentive to expand cropland that comes from increased yields.

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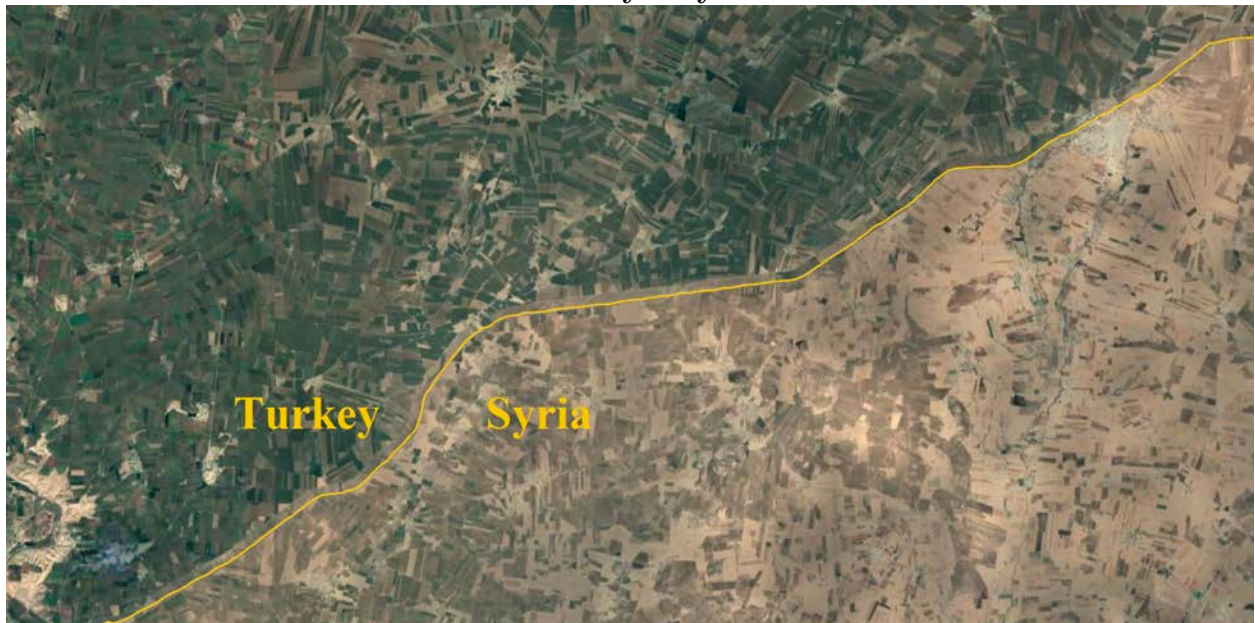
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Figure 1: Motivating Example: Images of -South Africa-Lesotho and Turkey-Syria Border

Panel A: Lesotho - South Africa border

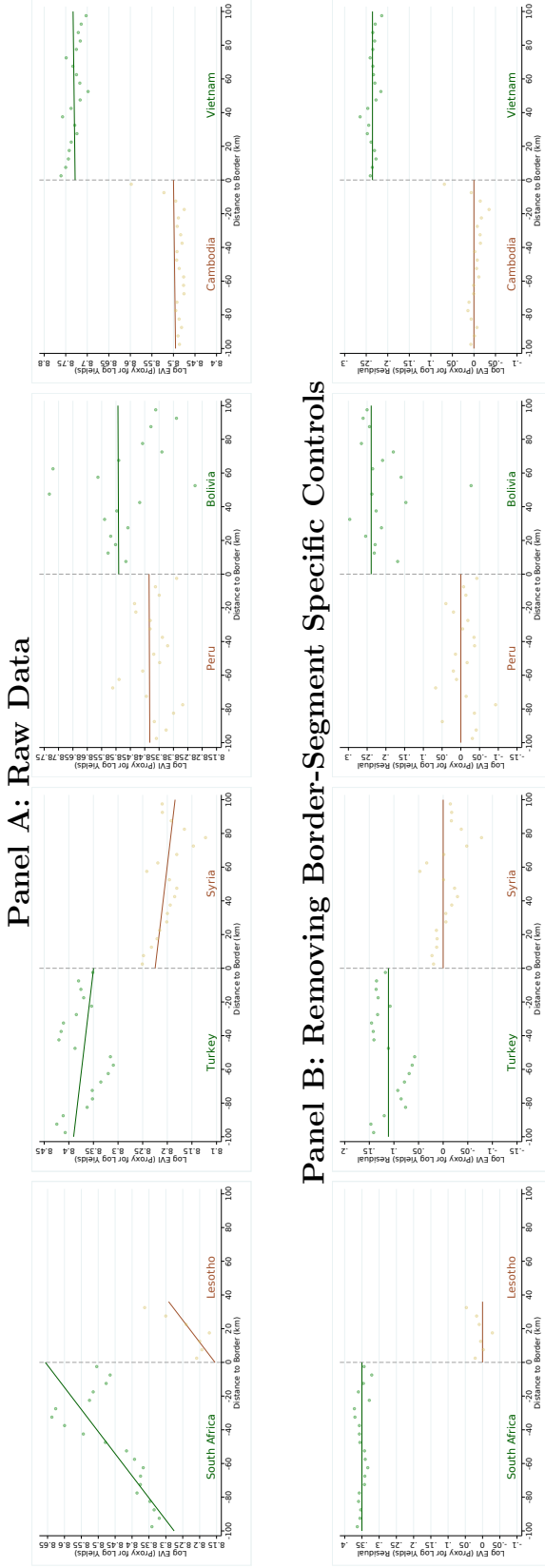


Panel B: Turkey - Syria border



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.

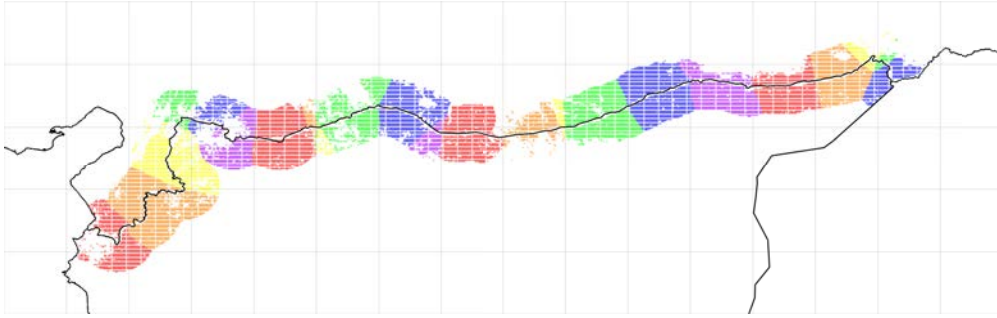
Figure 2: Motivating Examples: Border Discontinuity in Crop Yields



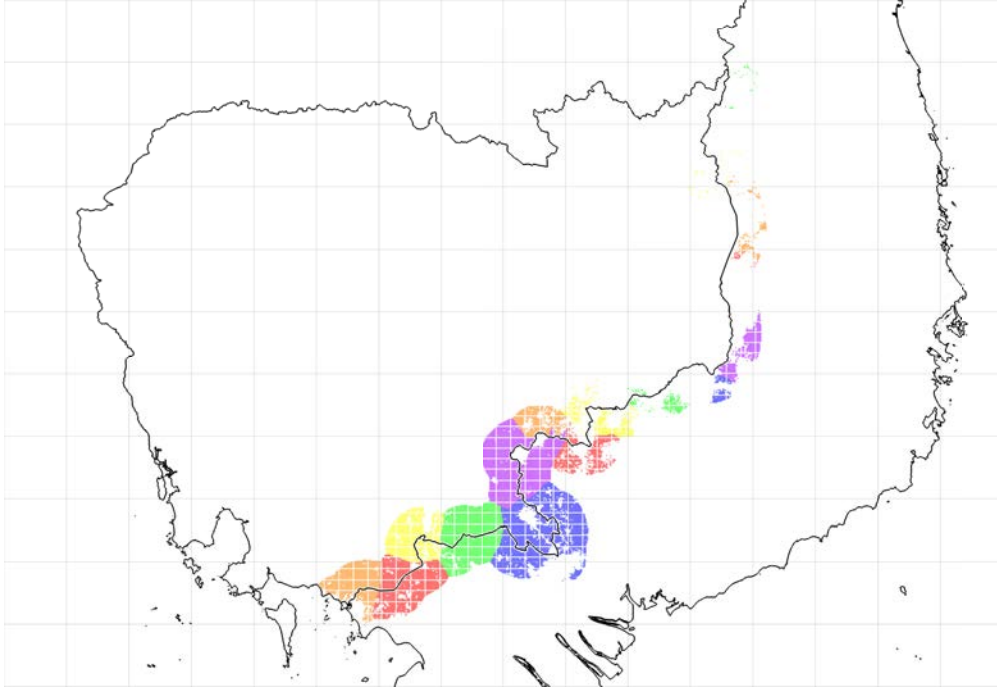
Notes: Figure shows the distribution of log crop yields (measured using the log of the annual maximum of the Enhanced Vegetation Index) around the South Africa-Lesotho, Turkey-Syria, Peru-Bolivia, and Cambodia-Vietnam borders, respectively. All graphs uses all EVI readings during the years 2001-2019 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

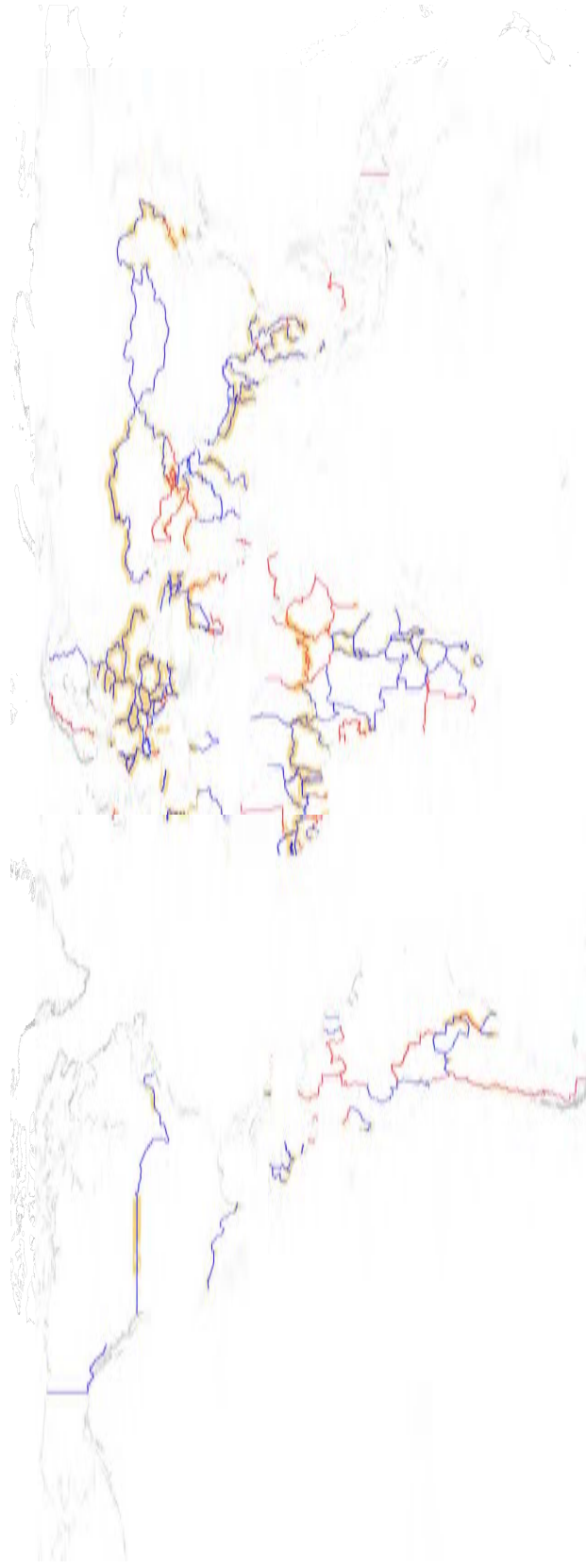


Panel B: Cambodia - Vietnam border



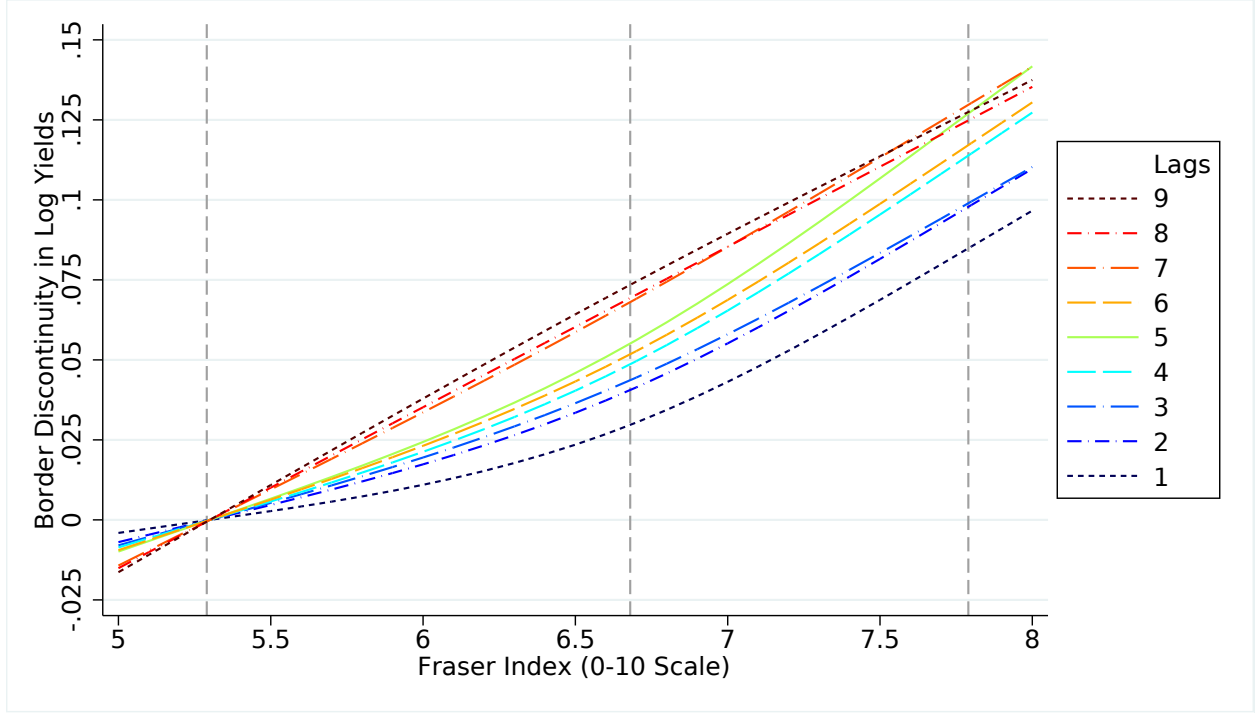
Notes: Figure shows the individual pixels within a 25km band of the Turkey-Syria border (top) and Cambodia-Vietnam border (bottom). We include half-degree border point fixed effects. Specifically, each pixel is assigned to the closest border point, which are binned by a 0.5 degree (roughly 55km) grid 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 pixels 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 Economic Freedom



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. The shown responses are normalized to equal zero at the lower knot. Different colors include different numbers of lags. 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: Fraction That Has Same Dominant Crop (2000)								
Percent	81.3	78.0	76.2	74.6	73.2	72.2	71.3	69.9
Panel A2: Fraction That Grows Dominant Crop (2000)								
Percent	36.6	35.6	34.9	34.1	33.6	33.1	32.6	31.7
Panel B1: Fraction That Has Same Dominant Crop (2010)								
Percent	69.8	67.2	65.7	64.3	63.7	62.7	62.6	63.1
Panel B2: Fraction That Grows Dominant Crop (2010)								
Percent	36.5	35.0	34.2	33.7	33.3	32.8	32.4	32.2
Bandwidth	5	10	15	20	25	30	40	50

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 pixels in a border segments with the same dominant crop 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 Discontinuities and Changes In Economic Freedom

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using One Lag $L = [1, 1]$								
Score (x100)	1.13 (0.93) [0.226]	0.93 (0.82) [0.257]	1.43 (0.64) [0.028]	1.52 (0.58) [0.010]	1.34 (0.57) [0.020]	1.02 (0.60) [0.090]	1.27 (0.53) [0.017]	1.22 (0.50) [0.015]
Borders	101	119	129	136	146	150	154	160
Observations	1511	1798	1949	2082	2195	2302	2387	2474
Pixels (10^6)	2.6	5.9	9.0	12.2	15.2	18.2	24.3	30.5
Panel B: Using Three Lags $L = [1, 3]$								
Score (x100)	1.01 (1.17) [0.388]	0.97 (1.00) [0.334]	1.30 (0.73) [0.077]	1.76 (0.71) [0.014]	1.74 (0.71) [0.015]	1.29 (0.72) [0.077]	1.63 (0.61) [0.009]	1.72 (0.60) [0.005]
Borders	93	109	118	126	136	139	144	150
Observations	1318	1564	1693	1814	1913	2003	2075	2152
Pixels (10^6)	2.3	5.1	7.9	10.6	13.3	15.9	21.3	26.6
Panel C: Using Five Lags $L = [1, 5]$								
Score (x100)	1.20 (0.65) [0.068]	1.31 (1.04) [0.209]	1.52 (0.85) [0.076]	2.21 (0.83) [0.009]	2.20 (0.84) [0.010]	1.67 (0.82) [0.044]	1.88 (0.74) [0.012]	1.97 (0.72) [0.007]
Borders	92	108	117	124	135	137	142	148
Observations	1149	1361	1469	1574	1660	1738	1795	1860
Pixels (10^6)	2.0	4.5	6.8	9.2	11.5	13.8	18.5	23.1
Bandwidth	5	10	15	20	25	30	40	50

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. Panels vary how many lags are included. 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 Disontinuties Where Side With Higher Economic Freedom Index Flips

	(1)	(2)	(3)
Score (x100)	2.24 (1.06) [0.042]	2.17 (1.23) [0.080]	2.20 (0.84) [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 (5) 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 (1.36) [0.048]	-0.37 (0.91) [0.689]	0.66 (0.87) [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 (0.55) [0.972]					-0.22 (0.49) [0.649]	0.09 (0.31) [0.774]
Score 2 (x100)		0.21 (0.60) [0.730]				-0.15 (0.56) [0.789]	-0.43 (0.50) [0.391]
Score 3 (x100)			0.82 (0.26) [0.002]			0.62 (0.25) [0.015]	0.64 (0.27) [0.017]
Score 4 (x100)				0.99 (0.43) [0.022]		0.45 (0.40) [0.270]	0.42 (0.42) [0.324]
Score 5 (x100)					1.33 (0.62) [0.035]	0.87 (0.52) [0.097]	0.73 (0.48) [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 (5) 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. The five area-scores are:

Score 1 - size of government

Score 2 - legal system and property rights

Score 3 - sound money

Score 4 - freedom to trade internationally

Score 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 (0.32) [0.465]				0.58 (0.29) [0.046]	0.52 (0.26) [0.045]
Score 1D (x100)		0.52 (0.15) [<0.001]			0.38 (0.15) [0.011]	0.37 (0.15) [0.013]
Score 3C (x100)			0.69 (0.26) [0.008]		0.59 (0.25) [0.018]	0.63 (0.25) [0.012]
Score 5A (x100)				0.66 (0.29) [0.023]	0.53 (0.24) [0.030]	0.52 (0.22) [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 A13. It uses 5 lags and a bandwidth of 25km, i.e., the specification of column (5) 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 are:

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 Economic Freedom

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Average Yields								
Score (x100)	1.01 (0.62) [0.106]	1.21 (0.71) [0.091]	1.33 (0.59) [0.026]	1.89 (0.61) [0.002]	1.98 (0.64) [0.002]	1.42 (0.67) [0.037]	1.35 (0.66) [0.044]	1.63 (0.61) [0.009]
Borders	87	101	112	119	125	132	135	142
Observations	313	369	400	432	451	479	493	513
Pixels (10^6)	2.2	4.9	7.5	10.1	12.6	15.2	20.2	25.3
Panel B: Standard Deviation of Yields								
Score (x100)	-0.47 (0.36) [0.197]	-0.05 (0.29) [0.852]	-0.07 (0.22) [0.733]	-0.13 (0.20) [0.501]	-0.11 (0.19) [0.566]	-0.12 (0.21) [0.570]	-0.04 (0.33) [0.897]	0.22 (0.24) [0.344]
Borders	84	101	111	119	125	129	134	138
Observations	307	369	398	432	451	472	491	504
Pixels (10^6)	2.2	4.8	7.4	10.0	12.6	15.0	20.1	25.1
Panel C: Coefficient of Variation of Yields								
Score (x100)	-0.06 (0.04) [0.172]	-0.01 (0.04) [0.761]	-0.01 (0.03) [0.638]	-0.02 (0.02) [0.409]	-0.02 (0.02) [0.461]	-0.02 (0.03) [0.480]	-0.01 (0.04) [0.823]	0.02 (0.03) [0.443]
Borders	84	101	111	119	125	129	134	138
Observations	307	369	398	432	451	472	491	504
Pixels (10^6)	2.2	4.8	7.4	10.0	12.6	15.0	20.1	25.1
Bandwidth	5	10	15	20	25	30	40	50

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: Discontinuity in Log Evapotranspiration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: ET over Growing Season								
Score (x100)	4.20 (1.69) [0.015]	2.97 (1.09) [0.008]	3.08 (1.30) [0.019]	3.02 (1.16) [0.010]	2.75 (1.30) [0.036]	2.26 (1.32) [0.089]	1.58 (1.21) [0.193]	1.83 (1.16) [0.116]
Borders	80	100	107	111	117	122	125	132
Observations	984	1214	1322	1397	1458	1531	1569	1632
Pixels (10^6)	1.7	3.8	5.8	7.7	9.6	11.5	15.3	19.1
Panel B: ET over Entire Year								
Score (x100)	3.11 (1.00) [0.003]	1.76 (0.91) [0.055]	1.99 (0.95) [0.038]	2.51 (0.85) [0.004]	2.63 (0.81) [0.002]	2.10 (0.74) [0.005]	1.82 (0.76) [0.018]	1.39 (0.75) [0.066]
Borders	92	108	117	124	135	138	142	148
Observations	1149	1365	1473	1575	1661	1741	1797	1866
Pixels (10^6)	2.0	4.5	6.9	9.2	11.5	13.9	18.5	23.1
Bandwidth	5	10	15	20	25	30	40	50

Notes: Table replicates Panel C Table 2 with a different dependent variable: it uses the border discontinuity in evapotranspiration and regresses it 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 scores of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (% change in ET 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 9: Discontinuity in Date of Year when Peak EVI is Reached

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overall Index Using Five Lags $L = [1, 5]$								
Date	0.15 (1.81) [0.935]	0.09 (1.53) [0.952]	-1.12 (1.70) [0.512]	-1.58 (1.38) [0.254]	-1.76 (1.27) [0.167]	-2.70 (1.45) [0.065]	-2.40 (1.52) [0.117]	-2.21 (1.63) [0.178]
Borders	92	108	117	124	135	138	142	148
Observations	1149	1365	1473	1575	1661	1741	1797	1866
Pixels (10^6)	2.0	4.5	6.9	9.2	11.5	13.9	18.5	23.1
Panel B: Credit Market Regulation - Five Lags $L = [1, 5]$								
Date	-0.18 (0.56) [0.753]	0.12 (0.44) [0.776]	0.07 (0.46) [0.877]	-0.47 (0.44) [0.289]	-0.78 (0.48) [0.110]	-1.21 (0.55) [0.028]	-1.54 (0.61) [0.012]	-1.51 (0.64) [0.019]
Borders	92	108	117	124	135	138	142	148
Observations	1149	1365	1473	1575	1661	1741	1797	1866
Pixels (10^6)	2.0	4.5	6.9	9.2	11.5	13.9	18.5	23.1
Bandwidth	5	10	15	20	25	30	40	50

Notes: Table replicates Panel C Table 2 with a different dependent variable: it uses the border discontinuity in the day of the year when maximum EVI occurred as dependent variable and regresses it 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 scores of the economic freedom index. Each entry is from a separate regression, with the point estimate in the first line (change in date of year 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 10: Extensive Margin: Difference in Number of Pixels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cropland Pixels								
Normalized Score	2.01 (1.57) [0.205]	3.14 (1.79) [0.083]	1.81 (1.46) [0.218]	1.79 (1.34) [0.186]	1.87 (1.25) [0.138]	2.53 (1.33) [0.060]	2.75 (1.27) [0.032]	2.78 (1.23) [0.025]
Borders	92	108	117	124	135	137	142	148
Observations	1231	1432	1530	1612	1754	1784	1849	1929
Avg # of Pixels	819	1577	2256	2879	3323	3914	5042	6057
Panel B: Forest Pixels								
Normalized Score	-5.61 (3.57) [0.120]	-4.75 (2.78) [0.091]	-3.92 (2.35) [0.098]	-3.61 (2.06) [0.082]	-3.27 (1.95) [0.096]	-2.76 (1.76) [0.119]	-2.51 (1.74) [0.151]	-2.30 (1.76) [0.195]
Borders	92	108	117	124	135	137	142	148
Observations	1231	1432	1530	1612	1754	1784	1849	1929
Avg # of Pixels	149	310	470	630	781	972	1287	1555
Panel C: Grassland Pixels								
Normalized Score	-0.20 (2.39) [0.932]	-0.80 (2.16) [0.711]	1.08 (1.81) [0.552]	0.72 (1.49) [0.630]	0.51 (1.31) [0.698]	0.01 (1.18) [0.990]	-0.47 (1.12) [0.677]	-0.90 (1.12) [0.422]
Borders	92	108	117	124	135	137	142	148
Observations	1231	1432	1530	1612	1754	1784	1849	1929
Avg # of Pixels	577	1327	2001	2633	3106	3711	4904	5978
Bandwidth	5	10	15	20	25	30	40	50

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

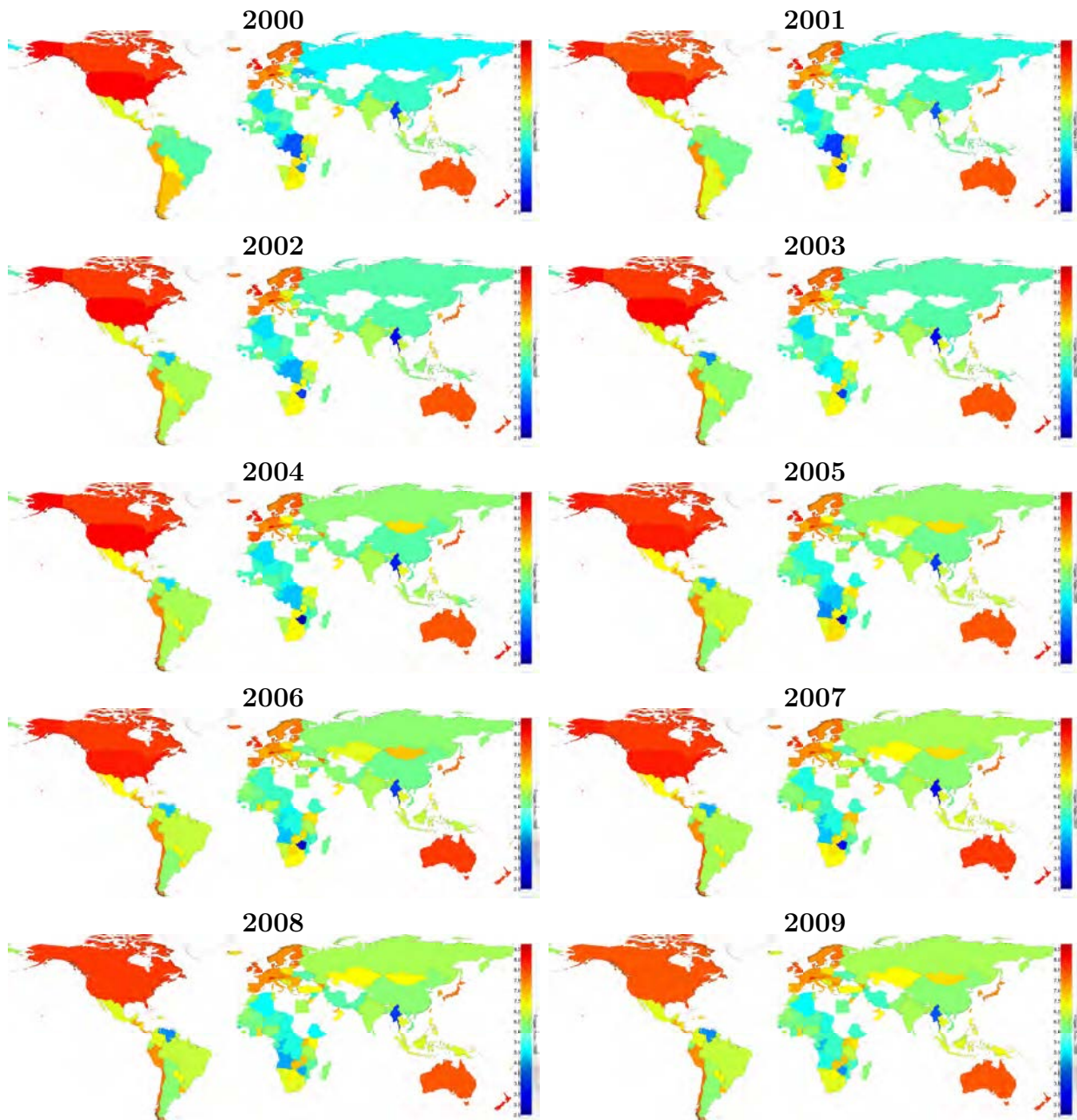
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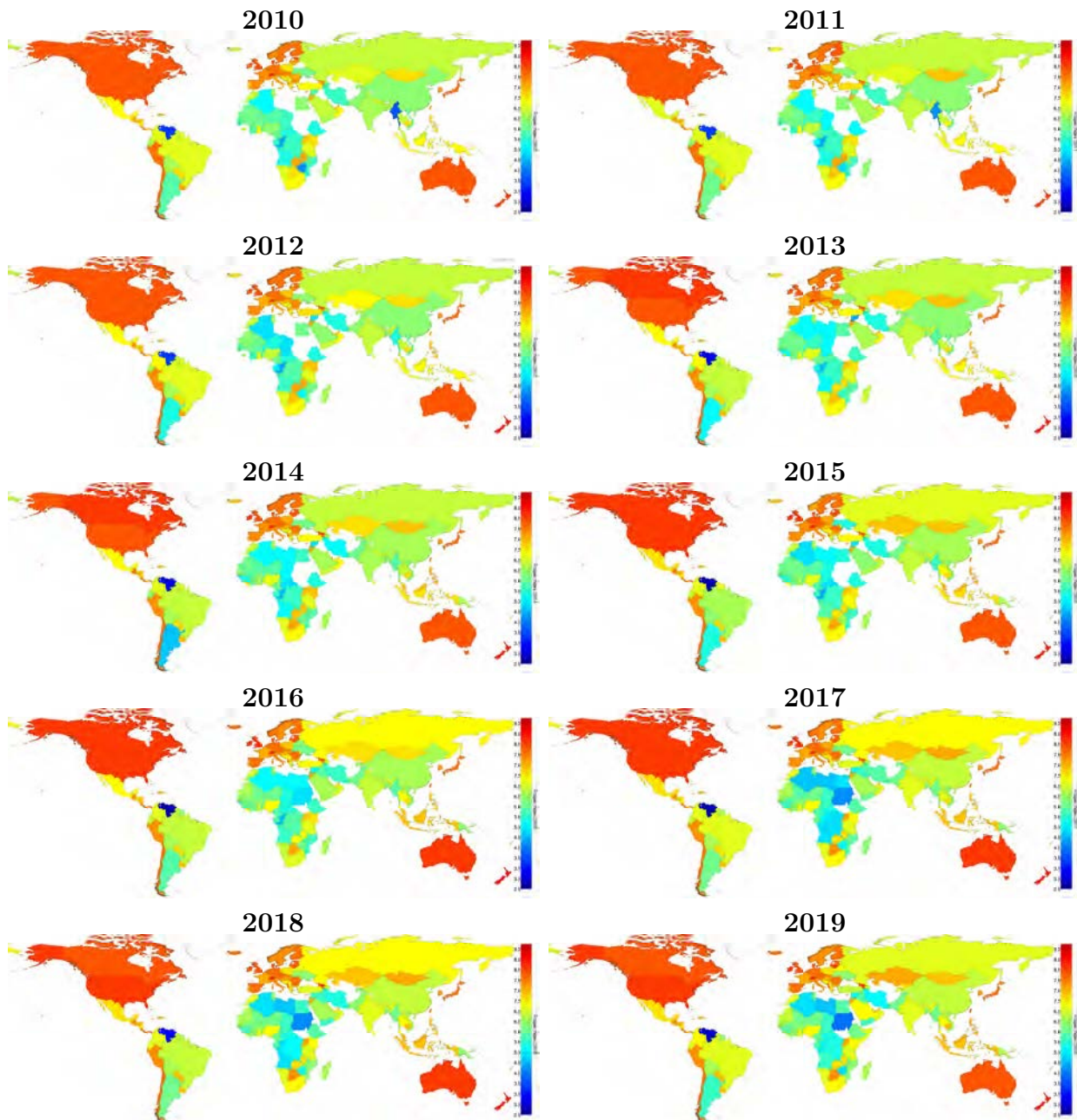
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Figure A1: Economic Freedom Index Over Time (2000-2009)



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.

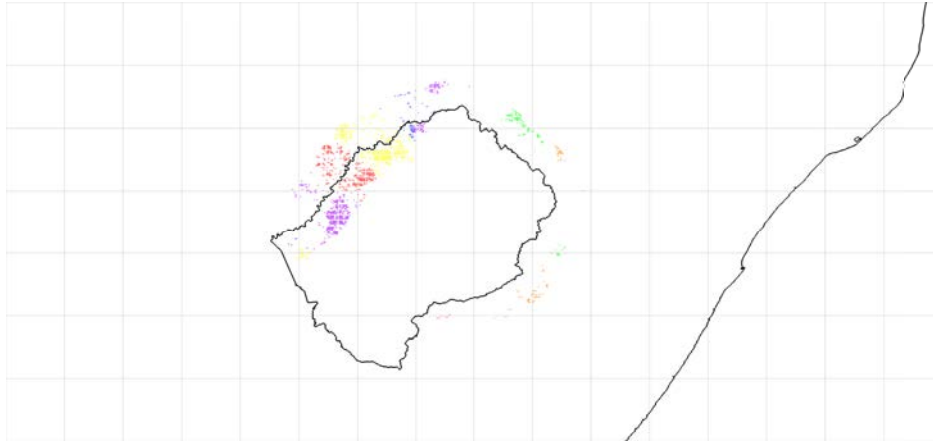
Figure A2: Economic Freedom Index Over Time (2010-2019)



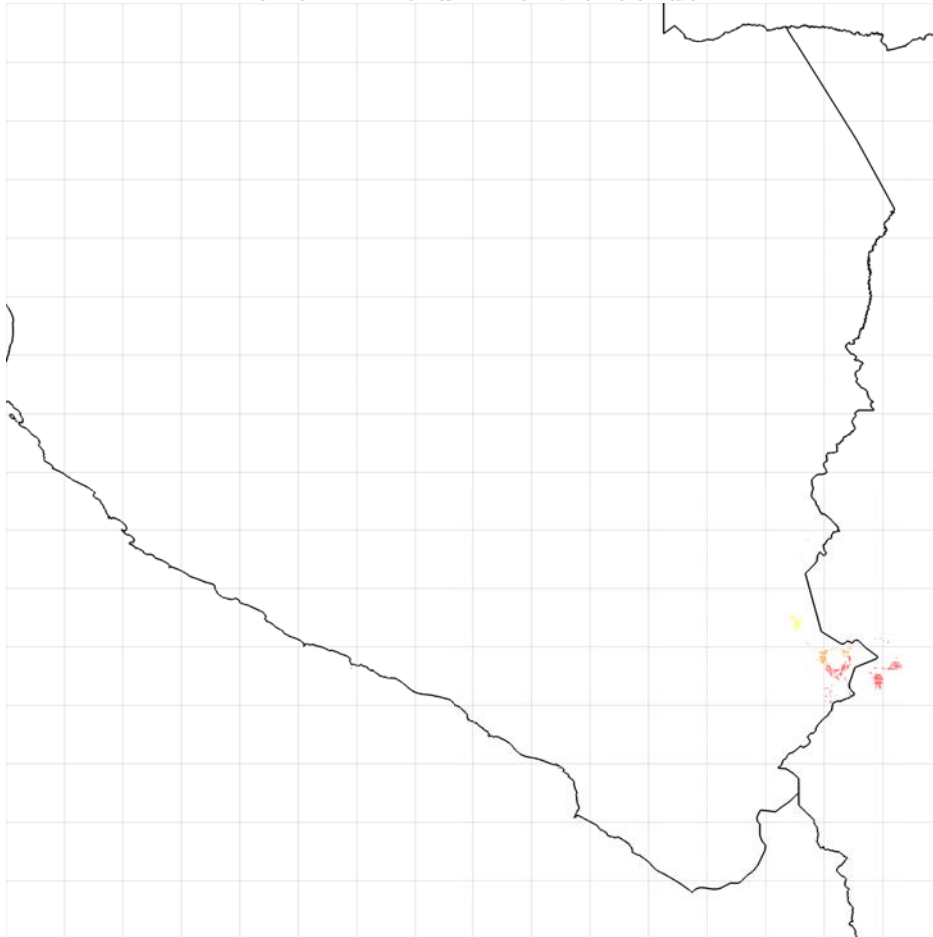
Notes: Figure displays the economic freedom index by the Fraser Institute for 2010-2019. The color scale is the same throughout all panels of Figures A1 and A2.

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

Panel A: South Africa - Lesotho border

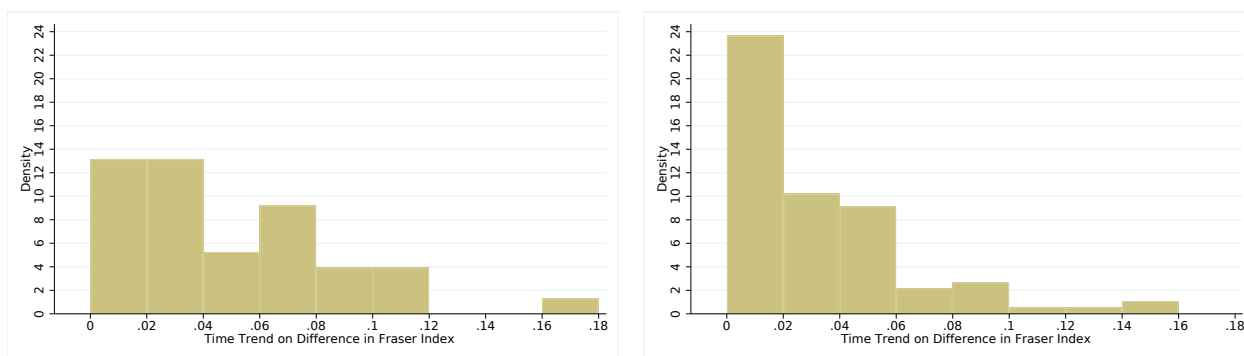


Panel B: Peru - Bolivia border



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.

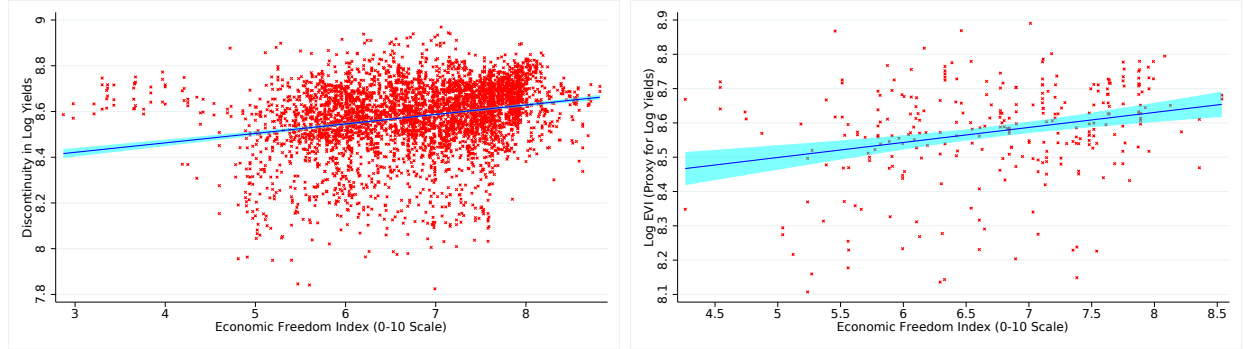
Figure A4: Time Trend in the Economic Freedom Index Difference Across Border



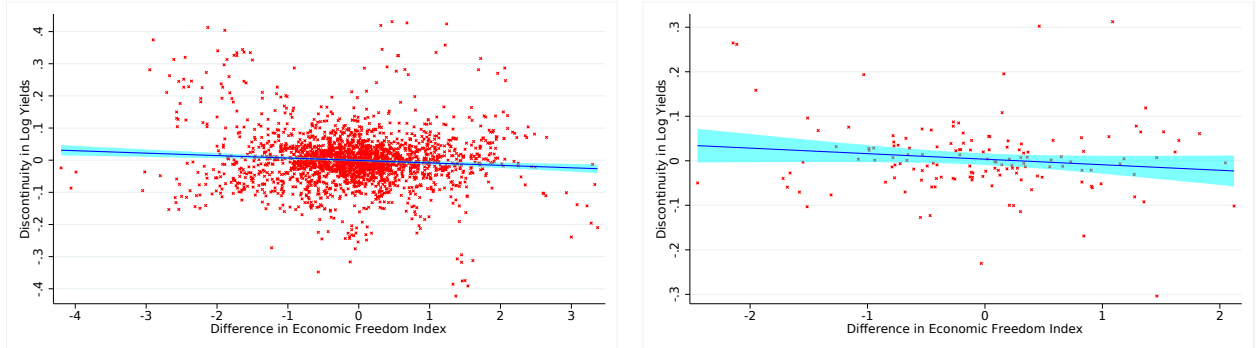
Notes: Figure shows the time trend in the difference of the economic freedom index by the Fraser Institute across a border. For easier disposition, all trends are normalized to be positive as the meaningful part is whether they are significantly different from zero. The left graph corresponds to column (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 Economic Freedom

A: Log Yields and Institutions

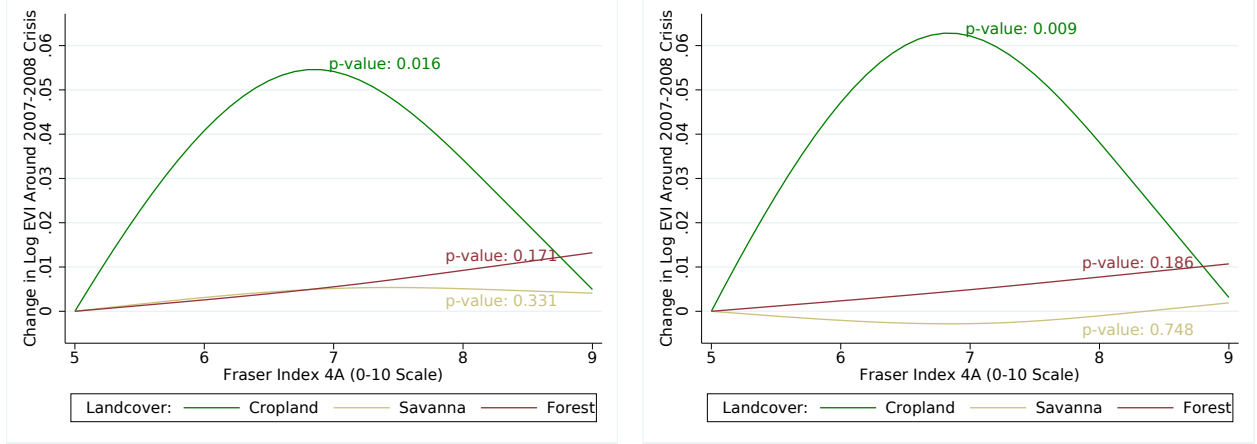


B: Changes in Log Yields Across Borders and Differences in Institutions



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).

Figure A6: Change in Yields around 2007-2008 Financial Crisis



Notes: Figure displays how log yields (log EVI) in countries at various levels of the economic freedom index in 2006 evolved around the financial crisis of 2007-2008. This regression no longer looks at border discontinuities but instead derives the change in average log EVI at each pixel around the financial crisis. The left graph uses 3-year averages of log EVI y_{it} , i.e., the post average in 2009-2011 ($\sum_{t=2009}^{2011} y_{it}$) minus the pre-average in 2004-2006 ($\sum_{t=2004}^{2006} y_{it}$), while the right graph uses 4-year averages (2009-2012 minus 2003-2006). Errors are clustered at the country level. Different colors focus on pixels that are consistently classified as cropland, savanna, and forest throughout 2001-2019. The p-value for joint significance of the two spline polynomials is added. We again examine the 24 subcategories, and the one that is consistently significant was score 4A - tariffs. The x-range reflects the 10-90th percentile on observed values in 2006. While there is no significant change in log EVI for savanna and forest pixels, log yields of cropland pixels are highly statistically significant. Countries with low and high tariffs had little change, while intermediate values showed a significant 6% increase, or roughly 1.2% per year for the left panel, in line with average yield growth through time.

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 (5) 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 area scores are:

Score 1 - size of government

Score 2 - legal system and property rights

Score 3 - sound money

Score 4 - freedom to trade internationally

Score 5 - regulation

Table A2: Discontinuities and Economic Freedom - Further Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using Five Lags $L = [1, 5]$								
Score (x100)	1.20 (0.65) [0.068]	1.31 (1.04) [0.209]	1.52 (0.85) [0.076]	2.21 (0.83) [0.009]	2.20 (0.84) [0.010]	1.67 (0.82) [0.044]	1.88 (0.74) [0.012]	1.97 (0.72) [0.007]
Borders	92	108	117	124	135	137	142	148
Observations	1149	1361	1469	1574	1660	1738	1795	1860
Pixels (10^6)	2.0	4.5	6.8	9.2	11.5	13.8	18.5	23.1
Panel B: Using Seven Lags $L = [1, 7]$								
Score (x100)	1.14 (0.80) [0.157]	1.34 (1.19) [0.265]	1.79 (0.96) [0.065]	2.43 (0.90) [0.008]	2.51 (0.92) [0.007]	1.96 (0.88) [0.028]	2.19 (0.84) [0.010]	2.23 (0.80) [0.006]
Borders	90	105	114	121	131	133	137	143
Observations	979	1156	1247	1333	1405	1473	1519	1573
Pixels (10^6)	1.7	3.8	5.8	7.9	9.8	11.8	15.7	19.7
Panel C: Using Nine Lags $L = [1, 9]$								
Score (x100)	-0.26 (2.04) [0.900]	0.92 (1.44) [0.525]	1.55 (1.20) [0.198]	2.39 (1.10) [0.032]	2.62 (1.06) [0.015]	2.34 (0.99) [0.019]	2.12 (1.07) [0.050]	2.03 (1.09) [0.063]
Borders	86	100	106	112	121	123	127	133
Observations	807	951	1020	1088	1147	1205	1243	1289
Pixels (10^6)	1.4	3.1	4.8	6.5	8.1	9.7	13.0	16.2
Bandwidth	5	10	15	20	25	30	40	50

Notes: Table replicates Table 2 including further lags in panels B and C. 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 Economic Freedom - Further Bandwidths

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Using One Lag $L = [1, 1]$							
Score (x100)	1.13 (0.93) [0.226]	0.93 (0.82) [0.257]	1.43 (0.64) [0.028]	1.34 (0.57) [0.020]	1.22 (0.50) [0.015]	1.45 (0.57) [0.013]	1.06 (0.56) [0.060]
Borders	101	119	129	146	160	177	179
Observations	1511	1798	1949	2195	2474	2742	2780
Pixels (10^6)	2.6	5.9	9.0	15.2	30.5	46.4	61.3
Panel B: Using Three Lags $L = [1, 3]$							
Score (x100)	1.01 (1.17) [0.388]	0.97 (1.00) [0.334]	1.30 (0.73) [0.077]	1.74 (0.71) [0.015]	1.72 (0.60) [0.005]	2.80 (0.75) [<0.001]	1.79 (0.56) [0.002]
Borders	93	109	118	136	150	167	167
Observations	1318	1564	1693	1913	2152	2385	2414
Pixels (10^6)	2.3	5.1	7.9	13.3	26.6	40.6	53.6
Panel C: Using Five Lags $L = [1, 5]$							
Score (x100)	1.20 (0.65) [0.068]	1.31 (1.04) [0.209]	1.52 (0.85) [0.076]	2.20 (0.84) [0.010]	1.97 (0.72) [0.007]	2.83 (0.73) [<0.001]	1.86 (0.69) [0.008]
Borders	92	108	117	135	148	161	161
Observations	1149	1361	1469	1660	1860	2057	2082
Pixels (10^6)	2.0	4.5	6.8	11.5	23.1	35.2	46.6
Bandwidth	5	10	15	25	50	75	100

Notes: Table replicates Table 2 but changes the bandwidths (cutoffs) around the border to estimate the border discontinuity – the pixel at the border is still always excluded. It further includes bandwidths of 75km and 100km in columns (6) and (7), respectively. Regressions again include border fixed effects. Errors are clustered at the border. 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 Economic Freedom - Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using One Lag $L = [1, 1]$								
Score (x100)	1.10 (0.89) [0.220]	0.87 (0.80) [0.276]	1.30 (0.62) [0.038]	1.38 (0.56) [0.015]	1.22 (0.54) [0.027]	0.98 (0.56) [0.083]	1.29 (0.49) [0.010]	1.21 (0.47) [0.010]
Borders	101	119	129	136	146	150	154	160
Observations	1511	1798	1949	2082	2195	2302	2387	2474
Pixels (10^6)	2.6	5.9	9.0	12.2	15.2	18.2	24.3	30.5
Panel B: Using Three Lags $L = [1, 3]$								
Score (x100)	0.95 (1.11) [0.396]	0.91 (0.97) [0.347]	1.16 (0.71) [0.107]	1.56 (0.68) [0.023]	1.56 (0.68) [0.024]	1.22 (0.69) [0.080]	1.59 (0.58) [0.007]	1.70 (0.58) [0.004]
Borders	93	109	118	126	136	139	144	150
Observations	1318	1564	1693	1814	1913	2003	2075	2152
Pixels (10^6)	2.3	5.1	7.9	10.6	13.3	15.9	21.3	26.6
Panel C: Using Five Lags $L = [1, 5]$								
Score (x100)	1.13 (0.62) [0.072]	1.18 (1.04) [0.256]	1.36 (0.83) [0.105]	1.98 (0.79) [0.014]	1.98 (0.81) [0.016]	1.56 (0.77) [0.046]	1.80 (0.69) [0.011]	1.96 (0.70) [0.006]
Borders	92	108	117	124	135	137	142	148
Observations	1149	1361	1469	1574	1660	1738	1795	1860
Pixels (10^6)	2.0	4.5	6.8	9.2	11.5	13.8	18.5	23.1
Bandwidth	5	10	15	20	25	30	40	50

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 A5: Discontinuities and Economic Freedom - Constant Set of Borders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using One Lag $L = [1, 1]$								
Score (x100)	1.13 (0.93) [0.226]	1.44 (0.72) [0.048]	1.71 (0.59) [0.004]	1.72 (0.56) [0.003]	1.70 (0.58) [0.004]	1.65 (0.60) [0.007]	1.98 (0.65) [0.003]	2.00 (0.63) [0.002]
Borders	101	101	101	101	101	101	101	101
Observations	1511	1511	1511	1511	1511	1511	1511	1511
Pixels (10^6)	2.6	5.7	8.6	11.5	14.3	17.0	22.3	27.6
Panel B: Using Three Lags $L = [1, 3]$								
Score (x100)	1.01 (1.17) [0.388]	1.64 (0.85) [0.057]	1.97 (0.66) [0.004]	1.96 (0.65) [0.003]	1.97 (0.68) [0.005]	1.99 (0.69) [0.005]	2.49 (0.74) [0.001]	2.55 (0.69) [<0.001]
Borders	93	93	93	93	93	93	93	93
Observations	1318	1318	1318	1318	1318	1318	1318	1318
Pixels (10^6)	2.3	5.0	7.6	10.1	12.5	14.9	19.5	24.2
Panel C: Using Five Lags $L = [1, 5]$								
Score (x100)	1.20 (0.65) [0.068]	2.10 (0.74) [0.006]	2.27 (0.83) [0.007]	2.33 (0.85) [0.007]	2.32 (0.91) [0.013]	2.29 (0.93) [0.015]	2.50 (0.94) [0.009]	2.51 (0.87) [0.005]
Borders	92	92	92	92	92	92	92	92
Observations	1149	1149	1149	1149	1149	1149	1149	1149
Pixels (10^6)	2.0	4.3	6.6	8.7	10.9	12.9	17.0	21.0
Bandwidth	5	10	15	20	25	30	40	50

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. 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: Discontinuities and Economic Freedom - Controlling for Weather

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using One Lag $L = [1, 1]$								
Score (x100)	1.33 (0.92) [0.151]	1.01 (0.87) [0.246]	1.31 (0.60) [0.032]	1.49 (0.55) [0.007]	1.46 (0.54) [0.008]	0.96 (0.76) [0.208]	1.89 (0.81) [0.021]	1.25 (0.55) [0.024]
Borders	100	119	128	136	145	149	154	160
Observations	1497	1789	1923	2053	2157	2280	2376	2455
Pixels (10^6)	2.6	5.8	8.9	12.1	15.1	18.1	24.1	30.2
Panel B: Using Three Lags $L = [1, 3]$								
Score (x100)	1.04 (1.20) [0.386]	0.95 (1.05) [0.366]	1.18 (0.72) [0.104]	1.58 (0.64) [0.015]	1.80 (0.67) [0.008]	1.23 (0.89) [0.170]	2.80 (1.03) [0.007]	2.11 (0.68) [0.002]
Borders	92	109	118	126	135	139	144	150
Observations	1304	1559	1674	1787	1878	1987	2072	2141
Pixels (10^6)	2.3	5.1	7.8	10.6	13.2	15.8	21.1	26.4
Panel C: Using Five Lags $L = [1, 5]$								
Score (x100)	1.14 (0.64) [0.078]	1.32 (1.07) [0.221]	1.43 (0.80) [0.078]	1.86 (0.72) [0.011]	2.12 (0.77) [0.007]	1.70 (0.89) [0.059]	3.47 (1.37) [0.012]	2.65 (0.89) [0.003]
Borders	90	108	116	123	132	136	142	148
Observations	1134	1360	1454	1548	1628	1723	1795	1858
Pixels (10^6)	2.0	4.4	6.8	9.2	11.5	13.8	18.4	23.0
Bandwidth	5	10	15	20	25	30	40	50

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 A7: Discontinuities and Economic Freedom - Falsification for Other Landcovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Savanna Pixels Using Five Lags $L = [1, 5]$								
Score (x100)	-0.60 (0.35) [0.088]	0.03 (0.21) [0.884]	0.22 (0.20) [0.279]	0.16 (0.17) [0.342]	0.07 (0.17) [0.683]	0.01 (0.16) [0.952]	0.04 (0.15) [0.820]	-0.03 (0.20) [0.878]
Borders	108	135	145	152	157	161	164	169
Observations	1430	1814	1951	2048	2118	2163	2203	2263
Pixels (10^6)	1.5	3.6	5.5	7.4	9.3	11.2	14.9	18.7
Panel B: Forest Pixels Using Five Lags $L = [1, 5]$								
Score (x100)	0.20 (0.19) [0.312]	-0.61 (0.61) [0.322]	0.14 (0.26) [0.585]	0.32 (0.34) [0.346]	0.26 (0.31) [0.395]	0.18 (0.24) [0.466]	0.05 (0.26) [0.850]	0.04 (0.25) [0.860]
Borders	57	86	107	116	125	129	138	141
Observations	796	1200	1477	1582	1692	1752	1874	1919
Pixels (10^6)	0.5	1.3	2.0	2.8	3.5	4.3	5.7	7.1
Panel C: Shrubland Pixels Using Five Lags $L = [1, 5]$								
Score (x100)	0.28 (0.58) [0.637]	0.77 (0.54) [0.179]	0.69 (0.49) [0.184]	0.49 (0.82) [0.563]	-0.35 (1.00) [0.735]	-2.95 (2.72) [0.295]	-0.40 (1.78) [0.825]	0.01 (2.04) [0.995]
Borders	9	13	13	13	14	17	21	21
Observations	120	170	170	170	180	211	268	268
Pixels (10^6)	0.1	0.2	0.4	0.5	0.6	0.8	1.0	1.2
Bandwidth	5	10	15	20	25	30	40	50

Notes: Table replicates Panel C of Table 2 except that it uses the EVI over other landcover categories. Rather than cropland pixels, panel A focus on savanna pixels, panel B on forest pixels, and panel C on shrubland pixels. It again 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 A8: Separate Sub-scores for Area 1 - Size of Government

	(1)	(2)	(3)	(4)	(5)	(6a)	(6b)
Score 1A (x100)	0.33 (0.28) [0.234]					0.25 (0.25) [0.332]	0.22 (0.24) [0.359]
Score 1B (x100)		-0.33 (0.42) [0.427]				-0.49 (0.38) [0.202]	-0.49 (0.32) [0.131]
Score 1C (x100)			-0.27 (0.16) [0.083]			-0.29 (0.16) [0.076]	-0.06 (0.09) [0.486]
Score 1D (x100)				0.36 (0.15) [0.020]		0.37 (0.17) [0.037]	0.57 (0.16) [<0.001]
Score 1E (x100)					-0.21 (0.33) [0.540]	0.07 (0.39) [0.852]	0.37 (0.39) [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 (5) 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 A9: 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 (0.51) [0.359]								-0.31 (0.69) [0.648]	-0.62 (0.62) [0.319]
Score 2B (x100)		1.22 (0.60) [0.043]							1.12 (0.70) [0.112]	0.82 (0.59) [0.167]
Score 2C (x100)			0.61 (0.34) [0.074]						0.43 (0.39) [0.280]	0.51 (0.36) [0.160]
Score 2D (x100)				-0.27 (0.23) [0.241]					-0.25 (0.23) [0.280]	-0.32 (0.24) [0.193]
Score 2E (x100)					-0.36 (0.57) [0.530]				-0.48 (0.57) [0.404]	0.07 (0.42) [0.871]
Score 2F (x100)						0.19 (0.52) [0.710]			-0.31 (0.48) [0.530]	-0.22 (0.40) [0.591]
Score 2G (x100)							0.22 (0.16) [0.172]		0.24 (0.16) [0.147]	0.09 (0.15) [0.552]
Score 2H (x100)								0.43 (0.27) [0.120]	0.19 (0.28) [0.498]	0.20 (0.25) [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 (5) 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 A10: Separate Sub-scores for Area 3 - Sound Money

	(1)	(2)	(3)	(4)	(5a)	(5b)
Score 3A (x100)	0.48 (0.16) [0.003]				0.25 (0.17) [0.133]	0.21 (0.16) [0.183]
Score 3B (x100)		0.47 (0.18) [0.012]			0.10 (0.16) [0.521]	0.10 (0.15) [0.524]
Score 3C (x100)			0.72 (0.27) [0.009]		0.53 (0.23) [0.025]	0.57 (0.22) [0.012]
Score 3D (x100)				0.03 (0.15) [0.832]	0.01 (0.11) [0.915]	0.02 (0.12) [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 (5) 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 A11: Separate Sub-scores for Area 4 - Freedom to Trade Internationally

	(1)	(2)	(3)	(4)	(5a)	(5b)
Score 4A (x100)	0.61 (0.35) [0.085]				0.50 (0.33) [0.128]	0.20 (0.31) [0.517]
Score 4B (x100)		0.46 (0.23) [0.053]			0.23 (0.23) [0.316]	0.30 (0.24) [0.201]
Score 4C (x100)			0.34 (0.31) [0.268]		0.21 (0.30) [0.495]	0.22 (0.24) [0.369]
Score 4D (x100)				0.50 (0.19) [0.011]	0.43 (0.19) [0.023]	0.31 (0.17) [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 (5) 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 A12: Separate Sub-scores for Area 5 - Regulation

	(1)	(2)	(3)	(4a)	(4b)
Score 5A (x100)	0.61 (0.28) [0.029]			0.60 (0.28) [0.033]	0.62 (0.27) [0.023]
Score 5B (x100)		0.42 (0.27) [0.123]		0.29 (0.27) [0.290]	0.21 (0.27) [0.427]
Score 5C (x100)			0.41 (0.49) [0.408]	0.40 (0.48) [0.408]	0.46 (0.47) [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 (5) 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 A13: Separate Sub-scores for Areas 1-5

	(1)	(2)	(3)
	est	(se)	[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 (5) in panel C of Table 2. Columns (1) gives the point estimate, column (2) the standard error, and column (3) the p-value.

Table A14: Regressing ET on EVI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: ET Over Entire Year								
Log EVI	0.48*** (0.07)	0.47*** (0.07)	0.46*** (0.06)	0.46*** (0.06)	0.45*** (0.06)	0.45*** (0.06)	0.45*** (0.06)	0.44*** (0.06)
Borders	92	108	117	124	135	138	142	148
Obs (Million)	2.0	4.5	6.9	9.3	11.6	13.9	18.6	23.2
Panel B: ET Over Growing Season								
Log EVI	0.65*** (0.08)	0.64*** (0.08)	0.63*** (0.08)	0.63*** (0.08)	0.62*** (0.07)	0.62*** (0.07)	0.62*** (0.07)	0.62*** (0.07)
Borders	80	100	107	111	117	122	125	132
Obs (Million)	1.7	3.8	5.8	7.8	9.7	11.6	15.3	19.2
Bandwidth	5	10	15	20	25	30	40	50

Notes: Table regress the log evapotranspiration on log EVI (measure for yields). All regressions include pixel fixed effects. Errors are clustered at the border. Different columns use different bandwidths (cutoffs) around the border for what pixels are included – the pixel at the border is always excluded. We include all borders from Panel C of Table 2 for which ET (and growing season data in Panel B) are available. Each entry is from a separate regression, with the point estimate in the first line (change in log ET per log EVI) and the standard error in round brackets in the second line. Stars indicate statistical significance.

Table A15: 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)	0.84 (0.89) [0.352]	0.86 (0.78) [0.270]	0.55 (0.65) [0.395]	0.16 (0.61) [0.789]	-0.06 (0.70) [0.934]	0.04 (0.87) [0.962]	-0.09 (0.72) [0.906]	0.39 (0.72) [0.591]
Borders	86	100	112	119	125	132	135	142
Observations	309	365	400	432	451	479	493	513
Pixels (10^6)	2.2	4.9	7.5	10.1	12.6	15.2	20.2	25.3
Bandwidth	5	10	15	20	25	30	40	50

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.