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Abstract

Do wildfires have a causal effect on economic development? Using satellite data, I analyze every country's exposure to wildfire exposure from 1982-2018. I use synthetic controls to model the impact of wildfire exposure on GDP per capita having controlled for population density, trade, agriculture, Foreign Direct Investment (FDI), and polity score. I find that the impacts of wildfires are fairly localized, impacting parts of Africa that both experience high numbers of wildfires and are developing.

Keywords

economic development, wildfires, economic modelling, natural disasters

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Working Paper

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Abstract: Do wildfires have a causal effect on economic development? Using satellite data, I analyze every country's exposure to wildfire exposure from 1982-2018. I use synthetic controls to model the impact of wildfire exposure on GDP per capita having controlled for population density, trade, agriculture, Foreign Direct Investment (FDI), and polity score. I find that the impacts of wildfires are fairly localized, impacting parts of Africa that both experience high numbers of wildfires and are developing.

1. Introduction

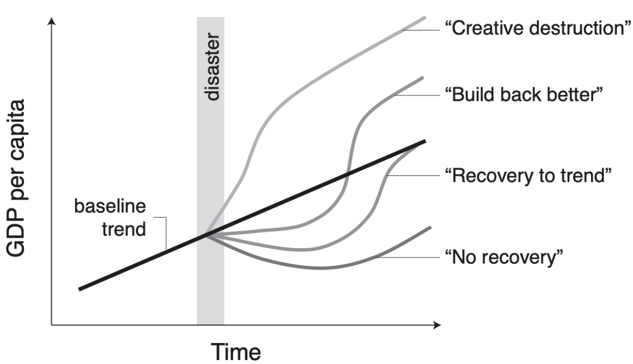
The influence of natural disasters and environmental phenomena on economic growth is an ongoing question, in part due to the challenge of identifying causal effects. While the structure of short-run disasters has been studied (e.g. Barro (2006); Jones and Olken (2010); Gabaix (2012)), and papers over the past two decades have identified the impacts of specific shocks such as currency crises, banking crises, political crises and civil wars (Cerra and Saxena (2008)), financial crises (Reinhart and Rogoff (2009)), tax increases (Romer and Romer (2010)), there appears to be little research on the long-run impacts of natural disasters. I examine how wildfires, a specific type of natural disaster, impact countries' economic growth in the long run. Based on prior literature (Paudel, 2021; Hsiang and Jina, 2014; Dell, Jones, and Olken, 2012, I will modify the methodology presented by Dell, Jones, and Olken (2012), Hsiang and Jina (2014), and Donadelli et al. (2021) who analyzed the impact of changes in temperature and cyclones on economic growth, respectively. I aggregate the spatial data to the country level similarly to Hsiang and Jina (2014) and use synthetic controls to model the causal impacts of wildfires on economic growth.

My results will inform two different, but important, bodies of literature. The first, the role of geography in economic growth, has been widely debated. Some authors suggest that geography matters because it determines the "initial conditions" of an economy by impacting its institutions ((Acemoglu, Johnson, and Robinson (2002), Rodrik, Subramanian, and Trebbi (2004)) whereas others suggest that geography determines the "boundary conditions" of an economy throughout its development through the health of a population (Gallup, Sachs, and Mellinger (1999); Miguel and Kremer (2004)) or the costs of trade (Frankel and Romer (1999)).

Secondly, there exists a large body of work analyzing the economic impacts and management of climate change from a theoretical perspective (Nordhaus, W., Yang, Z. (1996); Stern (2008); Weitzman (2009); Tol (2009); Heal (2009)) but less with an empirical grounding. Prior empirical studies have analyzed temperature's effect on agriculture (e.g. Schlenker and Roberts (2009)), health (e.g. Deschenes, Greenstone, and Guryan (2009)), labor (e.g. Graff Zivin and Neidell (2014)), energy (e.g. Deschenes and Greenstone (2011)), social conflict (e.g. Hsiang, Burke, and Miguel (2013)), cyclones (Hsiang and Jina, 2014) and growth generally (e.g. Dell, Jones and Olken (2012)). The impact of wildfires on climate change has not been considered either theoretically or empirically and, with the threat of wildfires increasing with climate change (Westerling, A.L., 2016; Reidmiller et al., 2018), there may have ramifications for growing economies.

2. Natural disasters and Economic Growth

It is frequently argued that natural disasters elicit different macroeconomic responses when compared to man-made shocks such as financial shocks. Prior theoretical literature has argued that one of four hypotheses is likely, but no study has empirically falsified any of them (Field et al., 2012). Figure 1 illustrates these four hypotheses below.



1. The **“creative destruction” hypothesis** argues that disasters temporarily stimulate economic growth as populations need to replace lost capital, because inflows of international aid may promote growth or because natural disasters bring about innovation (Skidmore & Toya, 2002). The construction industry often experiences short-lived, 1–2-year booms in growth following disasters (Belasen and Polachek (2008); Hsiang (2010); Deryugina (2011)). It is unknown if these increases have a broader impact on the economy as a whole. I formally analyze this hypothesis below, primarily as it relates to an increase in agricultural production following wildfires.
2. The **“build back better” hypothesis** argues that growth suffers initially, as infrastructure and capital are destroyed, they are replaced with newer and upgraded assets (Cuaresma, Hlouskova and Obersteiner (2008); Hallegatte and Dumas (2009). If countries do not update their capital efficiently in the absence of wildfires, this hypothesis may make sense if the productivity benefits of post-disaster capital spending outweigh the productivity losses imposed by the fires in the long run.
3. The **“recovery to trend” hypothesis** argues that, though growth suffers in the short term, it will rebound to abnormally high levels causing income to converge to pre-disaster trend. This hypothesis has mixed empirical support: disasters transfer an inflow of wealth into the impacted region (Strömberg (2007); Yang (2008); Deryugina (2011)); however population inflows are roughly equivalent to outflows and no migration is just as likely (Smith et al. (2006); Vigdor (2008); Belasen and Polachek (2009); Hornbeck (2012); Strobl (2011); Boustan, Kahn and Rhode (2012); Bohra-Mishra, Oppenheimer, and Hsiang (2014)). I formally analyze this hypothesis below.
4. Finally, the **“no recovery” hypothesis** argues that disasters slow growth and that funds used to rebuild displace funds that would otherwise be used for productive investments. No rebound occurs because the various recovery methods do not make

up for the losses caused by the disaster. This is particularly important if consumption falls so much that the marginal utility of consumption rises enough to make post-wildfire consumption preferable compared to investment (Antilla-Hughes and Jina, 2011). Post-wildfire output may grow in the long run but it remains permanently lower than its pre-wildfire trajectory. Additionally, wildfires may also generate economic impacts by permanently altering consumer preferences (e.g. Cameron and Shah (2013)), motivating populations to irreversibly disinvest in durable human or physical capital (e.g. Maccini and Yang (2009)) or by triggering political actions that have lasting economic consequences (e.g. Healy and Malhotra (2009)). Empirical evidence suggests that tropical cyclones exhibit the "no recovery" hypothesis.

3. Theory of Wildfire Effects on Long-Run Growth

3.1 Recovery to Trend Hypothesis Formalized

In the long run, wildfire risk can shape a country's economy through factors of production. The Solow-Swan Growth model is often used to explain how a country or society may experience output growth (Solow, 1956; Swan, 1956). A change in production eventually has ramifications for future output and the standard of living. In this section, I propose a model that explains how wildfire risk can change the amount of investment in factors of production using the Solow model.

Consider an economy with no technological progress, which will be relaxed later. The constant returns to scale production function is as follows:

$$Y = F(K, L) \quad (1)$$

where Y denotes total output, K is the level of capital accumulation, and L is the amount of labor input. With constant returns to scale, the production function can be converted to a per-capita form:

$$y = f(k) \quad (2)$$

Where y is per-capita output, $y = Y/L$, and k is per-capita capital stock, $k = K/L$. Let s denote the savings rate, δ the depreciation rate, and n the population rate. The steady-state level of capital shock k^* satisfies the following:

$$\Delta k = s * f(k) - (n+ς)*k = 0 \quad (3)$$

Rearranging terms,

$$s * f(ḳ) = (n + ς)*ḳ \quad (4)$$

Suppose a wildfire occurs and damages physical capital but leaves the human population unharmed. The amount of per capita capital stock decreases from ḳ to k_d where k_d < ḳ and the economy's output per-capita decreases from the steady state Ỵ to y_d.

Following the disaster, the economy initially suffers but then undergoes a recovery period due to the damages and decreased level of per capita capital stock. The distance between points B and C in Figure 1 represents space for per capita capital accumulation during the recovery process. The economy accelerates to increase per capita capital from k_d to ḳ as the recovery process takes effect. Simultaneously, additional resources are allocated towards the reconstruction process than under an alternative scenario in which the wildfire never occurred. Therefore, the savings rate may become higher for capital accumulation than it was previously. The recovery savings rate s_r, where $s_r > s$, may accelerate recovery efforts and capital accumulation. As the economy recovers, the gap between the recovery savings rate and the savings rate should gradually diminish. Furthermore, as the level of capital accumulation becomes close to the steady state level, ḳ, the speed of recovery goes toward zero.

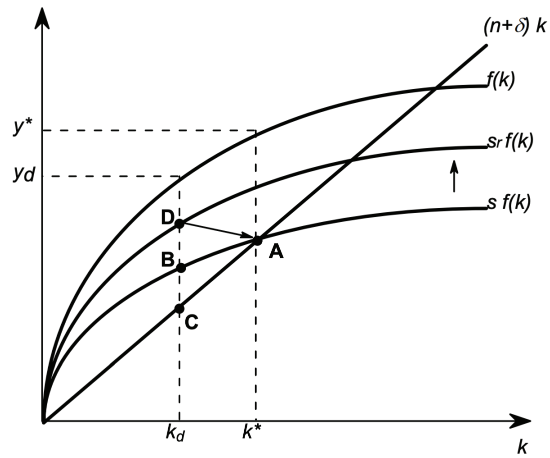


Figure 1: Solow-Swan model and wildfires

Figure 3 depicts the dynamics around the steady state of the Solow-Swan model. At the steady state, $\underset{\cdot}{k}$, the growth rate is zero because of the intersection of $s * f(\underset{\cdot}{k})/k = (n + \varsigma)$. When a catastrophic wildfire occurs, the per capita level of capital becomes k_d and, as a result of the shift away from the steady state, the growth rate of *k* becomes positive (distance between B and C on Figure 2). As above, reconstruction increases the savings rate to s_r. The result is that the growth rate of *k* becomes higher, represented by the distance between D and C. While reconstruction efforts continue, the savings rate gradually returns to *s* and the growth rate returns to *k* (from D to A in Figure 2). The more resources allocated towards recovery and reconstruction, the faster the rate of capital accumulation and therefore recovery which may change due to technological progress.

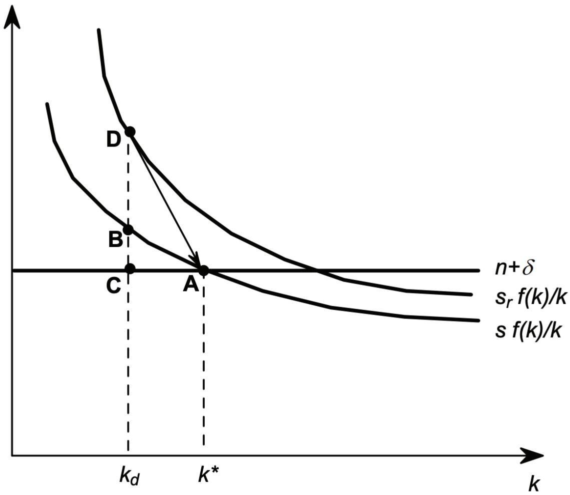


Figure 2: Recovery Dynamics

I now relax the assumption of no technological progress. Wildfires, while indiscriminate, often damage older and outdated facilities more than the new and updated ones as a result of weaker structures and outdated building codes. During the recovery process, damaged and outdated facilities are upgraded and replaced with new technologies that better production. The level of technology in an economy is an aggregate of old and new technology, with the recovery process increasing the rate of technological progress through the retirement of old units with newer ones (Figure 3). This increase in technological progress is temporary, as recovery efforts may not be able to increase the level of technology. Barro and Sala-i-Martin (1995; pp. 34-36) expanded on the Solow-Swan model with labor-augmenting progress and assume that the level of technology $A(t)$ grows at a constant rate under normal circumstances but a faster rate x_r $(x_r > x)$ during the recovery process due to the replacement of old capital (Figure 4).

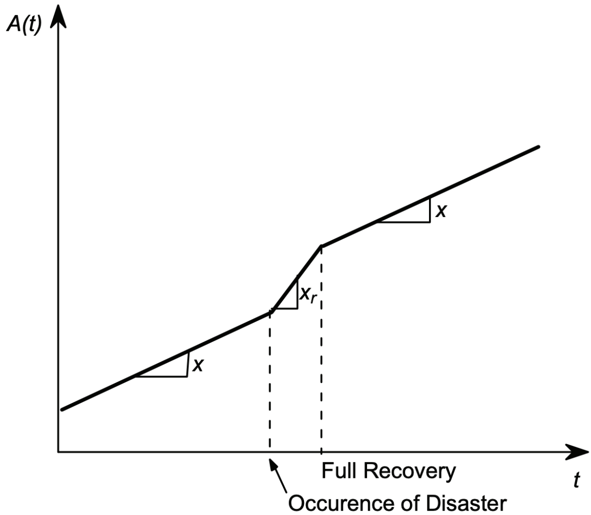


Figure 3: Wildfires and technological progress

When accounting for this technical progress, the previous model becomes:

$$Y = F(K, L * A(t)) \ (5)$$

$$\dot{k} = s * f(k, A(t)) - (n + \varsigma) * k \ (6)$$

To analyze the dynamics of this model with technological progress, it is effective to write the model using the effective amount of labor Ļ = *L*A(t)* which represents the labor force multiplied by its efficiency. Thus, the quantity of per capita labor can be written as

$$\check{k} = K/Ļ = K/(L * A(t)) = K/A(t) \ (7)$$

With the quantity of output per effective unit of labor, ŷ = Y/Ļ, the model becomes

$$\hat{y} = f(\check{k}) \ (8),$$

Equation 6 then becomes

$$\check{k} = s * f(\check{k}) - (x + n + \varsigma) * \check{k}$$

and the growth rate becomes

$$\gamma k = s * f(\check{k})/\check{k} - (x + n + \varsigma)$$

At the steady state, $\check{k}$ becomes $\check{k}^*$ as its growth rate becomes zero:

$$s * f(\check{k}^*)/\check{k}^* = (x + n + \varsigma)$$

As before, the economy suffers from a catastrophic wildfire and capital stock is destroyed. Therefore, the quantity of effective labor shifts from the steady state $\check{k}^{*}$ to the damaged level $\check{k}^{*d}$. Now, the growth rate is between B and C if there are no recovery efforts. If recovery efforts are made, the savings rate can be increased like above and the growth of $\check{k}$ is the distance between D and C. This is similar to the previous model except now technological replacement can increase the rate of technological progress during the recovery process. The increase is reflected in the shift from $(x + n + \varsigma)$ to $(xr + n + \varsigma)$. As a result of this technological replacement, the growth rate of $\check{k}$ is the distance between D and E as opposed to between D and C. Faster technological progress leads to faster growth of effective labor and a slightly quicker recovery process.

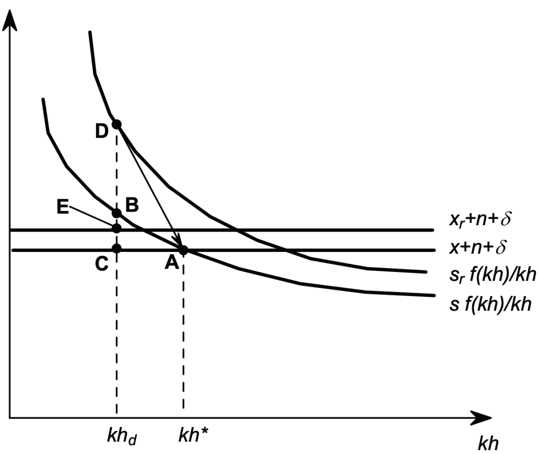


Figure 4: Solow-Swan model

3.2 Growth Drag in the Solow Model

Wildfires may also impact land use and increase agriculture or agricultural productivity (Brandt, 1966). Building off of Romer (2006), assume that the production function is given by:

$$Y(t) \;=\; K(t)^{a}(A(t)(L(t))^{1-a} \qquad (1)$$

where long-run economic growth is explained through capital accumulation (K), labor (L), population growth (n), and technological progress (A). These variables can then be rewritten as fluctuating with time:

$$\underset{\cdot}{K}(t) \;=\; sY(t) \;-\; \text{ç}K(t) \qquad (2)$$

$$\underset{\cdot}{L}(t) \;=\; nL(\mathrm{t}) \qquad (3)$$

$$A(t) = g_A\,(t) \qquad (4)$$

A dot under a variable indicates a derivative with respect to time; *n* and *g* are exogenous. In my analysis, I include natural capital and land as wildfires can increase natural capital through increasing land productivity. I extend the Cobb-Douglas production function (1) to include a number of new variables: *R*, resources used in production; *B,* the effectiveness of a given resource's use; *W*, wildfires; and *T*, the amount of land:

$$Y(t) \;=\; K(t)^{a}[B(t)R(t)C(t)]^{\beta}T(t)^{\gamma}W(t)^{\rho}[A(t)L(t)]^{1-\alpha-\beta-\gamma} \qquad (5)$$

$$\alpha > 0,\ \beta > 0,\ \gamma > 0, \rho > 0,\ \alpha + \beta + \gamma + \rho < 1$$

Resource use in production, R, grows at a negative rate because they decrease in the amount used in the production process.

$$R(t) =- bR(t),\ b > 0 \qquad (6)$$

The effectiveness of resource use, B, increases with the rate of technological progress and the use of controlled burns as resource extraction depends on technology and proper land management.

$$B'(t) \;=\; g_B B(t) \,+\, g_C C(t) \qquad (7)$$

The amount of land, T, on earth and in a given country is fixed, therefore the amount used in production does not change.

$$\underset{\cdot}{T}(t) \;=\; 0 \qquad (8)$$

The amount of fire, W, fluctuates with the available vegetation and time.

$$W(t) = g_W(t) * g_V(t)$$

If I exclude R, T, W, and B in my analysis, K/AL would converge to some value that enables me to analyze the behavior of the economy. When I include the new variables, I assume that A, B, L, R, W, and T grow at constant rates. To achieve a balanced growth path, K and Y must grow at a constant rate

$$\frac{\dot{K}(t)}{K(t)} = s\frac{Y(t)}{K(t)} - \varsigma$$

To find the balanced growth path of Y that equals the growth rate of K, I use the production function and take the log of both sides

$$lnY(t) = \alpha lnK(t) + \beta[lnB(t) + lnC(t) + lnR(t)] + \gamma lnT(t) + \rho lnW(t) + (1 - \alpha - \beta - \gamma - \rho)[lnA(t) + ln(L(t)] \quad (10)$$

I then differentiate with respect to time,

$$g_Y(t) = \alpha g_k(t) + \beta[g_B(t) + g_C(t) + g_R(t)] + \gamma g_T(t) + \rho g_W(t) + (1 - \alpha - \beta - \gamma - \rho)[gA(t) + gL(t)] \quad (11)$$

For simplification, I use the growth rates of L, A, R, W, and T as outlined above in (3), (4), and (6), and (8).

$$g_y(t) = ag_k(t) - \square(b - g_B) ++ (1 - a - \beta - \gamma)(n + g_A) \quad (12)$$

If the economy is on a balanced growth path, I impose $g_k = g_Y$ on (9)

$$g_Y^{bgp} = \frac{(1-\alpha-\beta-\gamma)(n+g_A)-\beta(b-g_B)}{1-\alpha},\ 1 - \alpha > 0 \quad (13)$$

where g_Y^{bgp} represents the growth rate of Y on the balanced growth path. We can see that technological advancement plays an important role in economic growth as it influences both L and R, in addition to the drag itself. b-g_B can either be larger or smaller than zero. If the rate of natural resource use in production is greater than technological advancement, then the growth rate of Y on the balanced growth path is smaller. If b is bigger than g_B, the g_Y^{bgp} is larger.

If the growth rate of K exceeds its balanced growth path, the growth rate of Y does as well but not by as much as K. The growth rate of K is determined by α, and therefore is negatively correlated with Y. Y grows slower than K because it is determined by more factors ($n, -b, g$). Following intuition, Y/K is falling. Because the growth rate is $s(Y/K) - \varsigma$, if Y/K is falling then so is the growth rate of K. Therefore, the growth rate of K converges to its balanced growth path and the economy as a whole also converges.

The limited amount of natural resources should be a drag to economic growth whereas technological progress should be a boon to growth. If the spur created by technological progress is greater than the drag of resources, there is sustained output. To count the amount of drag, we need to replace the assumptions of T and R on growth:

$$\dot{T}(t) = n_T(t) \qquad (14)$$

$$\dot{R}(t) = n_R(t) \qquad (15)$$

Now, land and resources grow as the population grows and therefore do not create a drag on growth. The economy on a balanced growth path without limitations looks as follows:

$$\check{g}_y^{bpg} = \frac{(1-\alpha-\beta-\gamma)(n_L+g_A)+\beta(n_R+\gamma n_T)}{1-\alpha} \qquad (16)$$

To calculate the amount of drag caused by resource limitations, we need to subtract the growth rate of income per capita (Y/L) on the balanced growth path from the growth rate in the hypothetical case where there are no limitations.

$$Drag = \check{g}_{Y/L}^{bpg} - g_{Y/L}^{bpg} = \frac{(1-\alpha-\beta-\gamma)(n+g_A)+\beta(n+g_B)+\gamma n-[(1-\alpha-\beta-\gamma)(n+g_A)-\beta(n-g_B)]}{1-\alpha} = \frac{\beta(b-g_B)+\beta}{1-\alpha}$$

(17)

If $n_R = n_T = n_A = n$

then,

$$\check{g}_Y^{bpg} - g_Y^{bpg} = \frac{(\beta+\gamma)n+\beta(b-g_B)}{1-\alpha} \qquad (18)$$

The growth drag gets larger as resources share β, land share γ, the rate the resource use b, the rate of population growth n, technological progress g, and capital share α represent a larger share. If more technological progress or controlled burning takes place to increase agricultural yield, more substitution takes place and lowers the drag. If $b < g_B$ the drag is smaller because, by increasing g_B, the effectiveness of resource use, the drag is reduced. Looking at wildfires, increasing the effectiveness of land use through controlled burns may play a part in a country's economic growth but, on the other hand, may make a country more dependent on agriculture raising the share of resource use in the economy, and therefore dragging GDP growth.

3.3 Agriculture and Controlled Burns in the Solow Model

I then extend the Green Solow model from Brock and Taylor (2010) and Guilló and Magalhaes by introducing a natural resource dimension representing land capital. Looking more specifically at fires, land capital is framed as agriculturally productive land. As the land is planted, it becomes less fertile as nutrients are used in the growing process. Controlled burns are one strategy for increasing the productivity of agricultural land. More broadly, land erosion and degradation are a byproduct of economic activity that can be balanced through maintenance, management, and improvement of natural resources:

$$F(K,\ Z,\ BL) = K^{\alpha}Z^{\beta}(BL)^{1-\alpha-\beta} \qquad \alpha,\ \beta \in (0, 1) \qquad (19)$$

$$K = s_K Y - \delta_K K \qquad (20)$$

$$\dot{Z} = S_Z Y - \mu Z, \qquad Z = \underline{N}Q \qquad (21)$$

$$\mu = \psi \frac{F(K, Z, BL)}{Z} + \delta_Z \qquad (22)$$

$$\dot{L} = g_L L, \qquad \dot{B} = g_B B \qquad (23)$$

$$s_i,\ \delta_i,\ \psi \in (0,\ 1).$$

In this set of equations, *F* represents the aggregate production function of economic goods and services, *K* is the stock of manufactured capital, *Z* is the stock of land-capital, $\underline{N}$ is the fixed land area, *Q* is a land productivity factor, *B* represents labor augmenting technical progress, *L* is labor, and *Y* is available output for consumption or investment (Output net of abatement effort). The parameter s_i is the exogenous fraction of available output devoted to investment in factor *i*, which in the case of land capital includes conservation, prevention, and improvement of environmental services. The parameter δ_i is the depreciation rate upon use in the production of factor *i*, which in the case of land represents production depletion net of natural regeneration, assumed to be positive. The overall rate of land depletion μ in equation 22 also includes a specific term related to the human-induced damage of the natural input or production externality that is assumed proportional to the land intensity of economic activity, $\psi\frac{F}{Z}$, where Ψ is an exogenous positive parameter. Land that is perpetually used for growing agricultural products will be less fertile than land allowed to fallow. Equation 21 states that without investment in land capital, the natural input will become unproductive.

Equation 21 implies that the productivity factor of land, *Q*, depends on an economy's efforts to maintain, manage, and improve the natural input. In the context of fire, investment in land capital includes controlled or wild burns that make depleted land productive. The resources needed to obtain one unit of land-capital are inversely related to the vegetation index, $Q = qAgriculture$. In other words, land-capital is the product of a physical measure (agricultural land) and an endogenous productivity measure *q*. The more agricultural land in a given country, the more resources needed to obtain one unit of land-capital.

Transforming the measures of output, manufactured capital, and land capital into intensive units, the augmented Green Solow model taking into account land degradation can be written as:

$$\dot{k} = s_K(1 - \theta)f(k, z) - (\delta_K + g_B + g_L)k, \qquad (24)$$

$$\dot{z} = s_Z(1 - \theta) - \psi]f(k, z) - (\delta_Z + g_B + g_L)z \quad (25)$$

given k(0), z(0) > 0

where $f(k, z) = k^{\alpha}z^{B}$. Equations 24 and 25 from this system follow from Equations 20 and 21 taking into account Equations 22 and 23.

3.2.1 Sustainable Balanced Growth

Equations 24 and 25 describe a dynamic system similar to the augmented Solow model of Mankiw et al. (1992). Along a balanced growth path or stationary solution to this system, these equations imply that the land-capital ratio, z/f, and manufactured-capital ratio, k/f, must satisfy the following conditions:

$$s_K(1 - \theta) = (\delta_K + g_B + g_L)\frac{k}{f(k,z)} \qquad (26)$$

$$s_Z(1 - \theta) - \psi = (\delta_Z + g_B + g_L)\frac{z}{f(k,z)} \qquad (27)$$

$$s_Z(1 - \theta) = (\mu + g_B + g_L)\frac{z}{f(k,z)} \qquad (28)$$

where equations 27 and 28 represent the same thing but are written two different ways taking the depreciation of μ defined in equation 22 into account. It is easy to show that my dynamic system has a unique, non-trivial steady state or balanced growth path (k^*, z^*) at which the economy converges for any given $k(0) > 0$ and $z(0) > 0$ provided that the left hand side of equation 27 is positive. Effectively, the system has a unique, non-trivial solution provided that each period the amount of degraded land per unit of output is less than the fraction of output invested to recover it. In the event this condition does not hold, the land becomes infertile and cannot sustain life in the long run. This steady state takes the form:

$$k^* = \left(\frac{s_K(1-\theta)}{\delta_K+g_B+g_L}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{(s_Z(1-\theta)-\psi)}{\delta_Z+g_B+g_L}\right)^{\frac{\beta}{1-\alpha-\beta}} \qquad (29)$$

$$z^* = \left(\frac{s_K(1-\theta)}{\delta_K+g_B+g_L}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{(s_Z(1-\theta)-\psi)}{\delta_Z+g_B+g_L}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \quad (30)$$

Along the balanced growth path presented in equations 29 and 30, output per efficiency unit of labor, $f(k, z)$, and consumption per efficiency unit of labor $c = (1 - \theta)(1 - s_K - s_Z)f(k, z)$ are constant magnitudes. Total output *F*, land capital *Z*, manufactured-capital *K*, and total consumption *C* will grow at a rate of $g_B + g_L$ with their corresponding per capita magnitudes growing at g_B. Because land is fixed, the land productivity factor *Q* must be also growing at a rate of $g_B + g_L$. A higher rate of investment in land capital through controlled burning or other management leads to a higher land-capital output ratio in the long run and increased economic growth.

Similar to technological progress, the use of controlled burns and fire as a regenerative force in agriculture helps mitigate the depletion of land capital which can help overcome the drag on growth implied by the use of exhaustible resources and in Section 3.2. As the land capital regenerates following a fire, it has a positive impact on other factors and contributes to economic growth.

Section 3.4 Prior Literature and Data Concerns

Looking more broadly, recent literature argues that this question about the impacts of natural disasters on economic growth is still open, in part because of data quality. Prior estimates are impacted by the endogenous nature of their independent variable, the type of natural disaster. Much of the literature uses data from the Emergency Events Database (EM-DAT), which is self-reported on a country-year basis and the data is known to depend heavily on economic and political conditions in a given country (Kahn (2005), Strömberg (2007), Kellenberg and Mobarak (2008), Noy (2009), Hsiang and Narita (2012)). These economic and political conditions also impact growth and therefore may confound my results.

Following the methodology of Hsiang and Jina (2014), I construct a novel database describing year-to-year variation in each country's exposure to wildfires. Using satellite data from the European Space Agency, I reconstruct each country's yearly exposure to wildfires.

Unlike the EM-DAT data, my objective data on area burned is constructed using satellite data and is unlikely to be influenced by economic or political issues within each country.[1]

4. Wildfires

Globally, wildfires are becoming a widespread issue. Fires are now burning nearly twice as much tree cover as they did 20 years ago and wildfires impacted 6.2 million people between 1998-2017 (World Health Organization). Furthermore, the size, intensity, and frequency of wildfires is increasing as the climate changes. Hotter and drier ecosystems are creating new fire-prone areas.

Wildfires are large, often violent, and fast-moving blazes that form in hot, dry conditions and cause physical damage and loss of life. I focus on wildfires because they are common, yet unpredictable in their timing, location, and intensity (Petersen, 2014; Egorova and Pagnini, 2022). To estimate the impacts of wildfires, particularly in the natural sciences, previous studies have either used differences in pre- and post-wildfire destruction to determine post-disturbance regrowth of vegetation (Kennedy et al., 2012) or used control regions as counterfactual vegetation to compare results (Steiner et al., 2020). Following the work of Serra-Burriel et al. (2021) and Hsiang and Jina (2014), I use synthetic controls to estimate the impacts of wildfires on economic growth.

[1] My approach is similar to that identified, but not implemented, by Noy (2009) who used EM-DAT data but noted that it was not determined endogenously:

> "Without the exogeneity assumption, the only way to infer causality from our specifications would entail finding an appropriate instrument for the initial disaster impact (i.e., an index of disaster magnitude that is completely uncorrelated with any economic indicator). Regrettably, we did not find such an instrument.... The exogeneity issue can potentially be fully overcome by producing an index of disaster intensity that depends only on the physical characteristics of the disaster (e.g., area affected, wave height, or storm circumference). The collection of such data from primary sources and the construction of a comprehensive index for the all the different disaster types are beyond the scope of this paper but may be worth pursing in future research." - p. 224

I also adjust the work of Hsiang and Jina (2014) by tailoring their approach to analyzing tropical cyclones to fit my analysis of wildfire risk.

5. Data and Summary Statistics

I use data drawn from the European Space Agency between 1982-2018 to recreate wildfire exposure across 123 countries. Summary statistics for both geophysical and economic characteristics are in Table 2, aggregated to the country level. My data covers 123 countries and includes 4,428 country-year observations. To better create counterfactuals, I used macroeconomic data starting from 1970. Countries with no wildfire exposure were excluded from the study, as were countries that lack economic or population data at any point during the study period. This means that I am excluding countries such as those that make up the former Soviet Union among others as I don't have a reliable way to estimate macroeconomic, population, or wildfire exposure prior to their creation.

As Table 1 shows, GDP per capita growth was roughly 3.58% across countries between 1982 and 2018. GDP growth is logged because it trends over time and the log helps remove the skewness of the data. Population averages 45,200,000 and, on average, 4% of countries have a poverty level greater than 50%. The average log of the land area is 5.32 and is logged to present a more normal distribution.

Figure 1 shows the tremendous variation in wildfire exposure across countries. The country with the most wildfire exposure is the Central African Republic, with 282837 km^2 of the country, on average, being burned each year. Figure 1 also depicts the relationship between wildfire exposure, as defined as the log of burned area, and GDP growth in 2001, with those countries that experience more fires having lower GDP values compared to those that have fewer fires. The exception to this appears to be Australia.

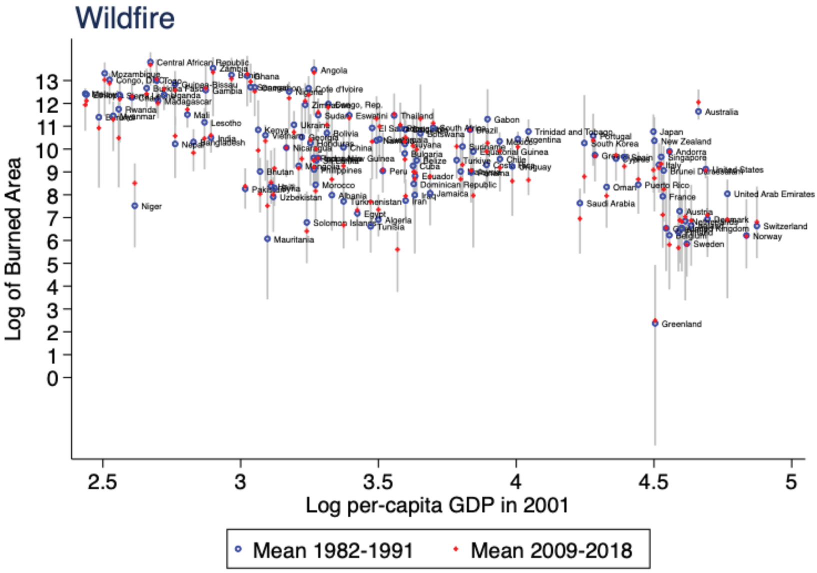


Figure 5: This graph presents data on each country's logged burned area, plotted against

per capita GDP from the World Development Indicators (WDI) in the year 2001. For each country, the circle symbols represent the mean level of burned area in the first decade of my sample (1982–1991), the plus symbols represent the mean level of burned area in the last decade of my sample (2009-2018), and the gray lines indicate the range of annual burned area I observe for that country during the sample period.

Table 1

Variable	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Economic Characteristics					
GDP per capita in PPP	6733.568	12697.7	22.85037	102913.5	5,117
Population Density	144.2313	543.1886	1.04502	7908.721	5,117
Polity Score	2.081441	7.143692	-10	10	5,108
Trade	-6.68e+08	3.90e+10	-7.64e+11	3.58e+11	5,117
Agriculture	344193.9	810845.1	6.6	5290386	5,117
FDI	-3.90e+08	1.69e+10	-3.45e+11	1.77e+11	5,117

Physical Characteristics					
Land Area	5.320436	.7975236	2.672098	6.974268	4,428
Burn Area	102588.8	195953.6	0	1527320	4,428

Data on economic characteristics and land area are from the World Bank. Data on burned area is from the European Space Agency.

5.1 Wildfire Data

My central innovation is the creation of a novel dataset describing the exposure of all countries to all known wildfires from 1982-2018. Because my macroeconomic data was at the country-year level, but wildfire exposure was initially calculated at $0.05^\circ \times 0.05^\circ$ resolution across the globe (approximately 5.6km x 5.6km at the equator), a secondary contribution is generating a general framework for aggregating granular spatial data to country-year units that can then be analyzed alongside macroeconomic data.

I expand on the work of Hsiang (2010), Hsiang and Narita (2012), and Hsiang and Jina (2014) to measure each country's level of exposure to wildfires over history. I combine a dataset of ground, aerial, and satellite-based observations with estimates for burned area at monthly intervals. I then use the findings of Antila-Hughes and Hsiang (2011) and Hsiang and Jina (2014) to gain insight into how to collapse this spatial data over countries that differ in magnitude to create a scale-invariant measure that is compatible with economic growth, another scale-invariant measure.

5.2 Reconstructing wildfire exposure data

I then generate a measure of the burn area for every wildfire in the European Space Agency's (ESA) database, which is the most complete dataset of global wildfires.[2] For this

[2] These data are publicly available through the European Space Agency's Climate Data Dashboard https://climate.esa.int/en/odp/#/project/fire where they are described in greater detail.

analysis, I use data from 123 countries between 1982 and 2018. The expansion of homes and communities into the Wildland Urban Interface (WUI) over the past couple of decades has increased, which increases the likelihood of a fire being reported. However, I do not think this change has overly biased the portions of the records I analyze as I am interested in the intersection of wildfires and economic activity and these fires would have been reported. The smoke from any given fire travels further than the actual fire and would be noticed further away from the burn site.

To provide a neat point-wise summary of wildfire data, I average pixel level exposure to wildfire as categorized through the number of burned pixels across all 36 years of data. This gives the average burn area across each country. Wildfires are not uniformly distributed around the globe, however, due to three factors: vegetative resources to burn, environmental conditions that promote combustion, and ignitions. While wildfire-prone areas span ecosystems from boreal forests to tropical savannahs, the likelihood of fire increased with vegetation productivity in conjunction with seasonality, episodic wind events, low moisture levels, or ignitions.

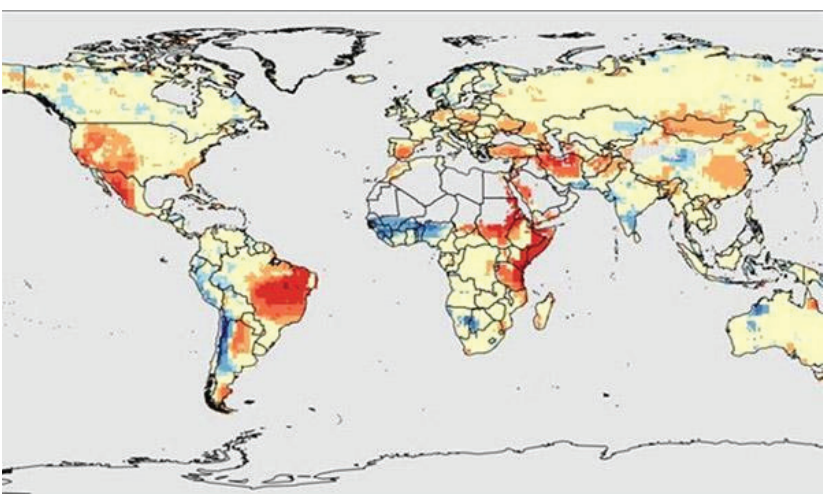


Figure 6: Global exposure to wildfires displayed as burned area per pixel for each year from 1982-2018

5.3 Matching wildfire data to macroeconomic data

The dataset of wildfire exposure can be resolved with high spatial and temporal resolution because each 0.05 ∘ × 0.05 ∘ pixel of the earth's surface takes a different monthly value. Yet macroeconomic data that I want to match with the exposure data is country-by-year. Economic growth does not depend on the size of an economy. Ideally, I construct a measure of wildfire exposure at the country-year level that is scale-free and does not depend on the physical or economic size of a country to create a scale-invariant relationship between wildfire exposure and economic growth. This type of relationship describes the average pixel-level interaction between wildfire exposure and economic growth.

To do so, I follow the work of Hisang and Jina (2014), collapsing the data to the country-by-year unit using a spatially weighted average over all pixels in a given country[3]. For pixels indexed by p each of area a_p exposed to burned area W_p, contained in country i which has n pixels in total, this is simply:

$$\hat{W}_i = \frac{\sum_{p \varepsilon i} W_p a_p}{\sum_{p \varepsilon i} a_p}$$

This measure can be thought of intuitively in two ways: the value is the expected exposure of a unit of land that is randomly selected from a country. Alternatively, the value could represent the exposure all units would have if the burned area could be spread equally throughout a country. Seeing as many pixels in a given country have no wildfire exposure, they are averaged out with highly exposed pixels.

Constructing this scale-free measure of GDP requires that the weighted sum of each exposed pixel is divided by the area of a country. This approach follows that of Nordhaus (2006) and Hsiang and Jina (2014) and aims to identify the average impact of wildfire exposure on an

[3] Scale-free variables linking geophysical and disaster data has been replicated at the national level in regional (Hsiang, 2010) and global (Hsiang and Narita, 2012) levels as well as at the provincial or adminstrative regional level (Antilla-Hughes and Hsiang (2011).

average pixel, regardless of how the pixel is used. A larger denominator will lead to a smaller measure of $\hat{W}_i$ if the numerator is held fixed. Thus, a physically identifiable wildfire that impacts exactly one pixel will result in a larger value for $\hat{W}_i$ in a smaller country than in a larger one. This yields the desired impact of a scale-free metric as *ceteris paribus* the single pixel impacted by the wildfire is more economically important in percentage terms in the smaller country because it is a larger percentage of land area. It aims to recover the average impact of wildfire exposure across the average pixel, agnostic about a given pixel's use.

Two important questions arise when collapsing wildfire data in such a manner. Does area-weighting bias response functions in terms of small countries because their denominator is small? My approach, following Hsiang and Jina (2014), scales exposure to the pixel level but it is possible that pixels in a small country will have fundamental differences in their response compared to a large country. This issue is best addressed by stratifying countries by country size, and I find that countries exhibit similar characteristics outside of the largest and smallest countries. Second, will my estimates be biased because some wildfires impact heavily populated or economically important regions while others impact empty regions? This is not a concern as long as there is no correlation between the overall intensity of a pixel's burned area and the likelihood that the most intense wildfires impact the most vulnerable pixels. The conditions for an unbiased estimation restrict spatial correlation of exposure and economic activity within a wildfire to be unrelated to the intensity across wildfires.[4] As long as relatively more intense

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[4] Suppose pixels have heterogenous pre-fire capital K_p (capital could be physical, human, social, political, etc.) which has a long run production $f(K_p)$. Damage to this capital from a fire suffered at p is $D(W_p, K_p)$, a function of wildfire intensity W_p experienced at pixel p. Anttila-Hughes and Hsiang (2011) find $D(W_p, K_p)= \alpha W_p K_p)$, where α is a constant describing the marginal fraction of capital that is destroyed by each additional unit of W_p. Thus, $\alpha W_p \in [0, 1]$ for observed values of W_p. I assume a similar linear form holds generally. Long-run output lost to a wildfire is the difference between output with baseline capital when no wildfire occurs (my simple counterfactual here, but a trend could be accounted for) and output with fire-damaged capital, both summed over all pixels in country i:

$$Lost\_income_i = \Sigma f(K_p)-\Sigma f(K_p-\alpha K_P W_p).$$

If changes to the total capital stock from a single storm are modest relative to the curvature of f(.), by Taylor's theorem we can linearize $f(K_p - \alpha K_p W_p) \approx f(K_p) - f((K_p)\alpha K_p W_p$ at each pixel.

′

Letting $g(K_p) = f((K_p)\alpha K_p$, we write

$$Lost\_income_i = \Sigma f(K_p)-\Sigma(f(K_p)-f'(K_p)\alpha K_P W_p) = \Sigma(g(K_p)W_p$$

Thus losses are roughly the inner product of wildfire intensity in each pixel and the marginal effect of fire intensity on production in each pixel, where the latter depends on both the capital density at p and the shape of the production function.

wildfires do not differently impact centers of economic activity within a country, it is unnecessary to account for the spatial distribution of economic activity in my measure of wildfire exposure in order to obtain an unbiased estimate of the effect of fires on growth.

5.4 Economic data

I obtain gross domestic product (GDP) data for 1970-2018 from the World Bank's World Development Indicators. To create better counterfactuals, GDP is inflation adjusted and measured in per capita units. I also use data on Polity score, agriculture, trade, population density, FDI, and land area.

6. Empirical Methodology

Once wildfire and macroeconomic data are constructed, measuring the impacts of wildfires on economic growth requires that we compare what actually occurred to a synthetic counterfactual had there been no wildfires. In an ideal experiment, we would compare two identical populations and expose one to wildfires while exposing the other to no wildfires. The control population serves as the counterfactual population for reality. While this is unfeasible, as no single country represents a perfect counterfactual for another due to a variety of factors, we need to find a group of countries that have the same secular GDP per capita growth rate.

To estimate the impact of wildfires on economic growth I adopt a synthetic controls approach, modeling GDP per capita as an impulse-response function that is linear in contemporaneous and historical area-averaged wildfire exposure W out to a maximum lag length k. I account for unobservable differences in growth rates between countries using a country fixed effect γ, which may arise due to a country's particular geography (Gallup, Sachs and Mellinger, 1999;), culture (Sala-i-Martin, 1997) or institutions (Acemoglu, Johnson and Robinson, 2002). In an extension of my main model, I also control for various time-specific trends such as trade, (Sachs, Warner, Aslund and Fischer (1995)) or rainfall (Miguel, Satyanath, and Sergenti (2004)). This leads to the model

$$GDP_{pc} = \delta Wildfire_{ct} + \beta Agriculture + \varsigma Trade + \rho Population + \lambda Polity + a_c + \gamma_{rt} + \epsilon_{ct''} \quad (1)$$

Previous studies have measured variations of Equation 1 with fewer lags, focusing on the years immediately following the disaster, or did not try and measure long-run economic growth.

7. Results

To evaluate the impacts of wildfires on long-run economic growth, the synthetic control method analyzes how long-run economic growth would have evolved in a given country in the absence of wildfires by constructing an appropriate treatment group and comparing it to the actual growth of a country, holding all else constant. My estimator does not differentiate between direct and indirect causal effects of wildfires on economic growth.

As illustrated in Figure 6 above, there are strong cross-sectional differences in average wildfire exposure: some countries are regularly hit, and in large swaths, while others are rarely hit, or hit only over small areas. How do these long-run growth impacts that I estimate above interact with cross-sectional patterns in a given country's geographic endowment?

If a country is repeatedly hit by wildfires, it will repeatedly incur growth penalties that can substantially alter said country's economic growth trajectory. Each wildfire has a short-term impact and any additional wildfires further lower economic growth for the next couple of years. The impact of sequential fires is smaller, or may vanish entirely, compared to earlier fires because they replace or offset the impact of previous ones.

Across the majority of countries analyzed, there was no significant impact of wildfires on economic growth after controlling for political institutions, agriculture, population, and trade. Actual and counterfactual GDP mirror each other closely both before and after an increase in wildfires. Any differences between the two were not statistically significant at conventional levels. Countries that experience both a large amount of their total land area burned and are developing tend to experience a statistically significant shock from wildfires whereas countries that do not experience a large amount of area burned and or are not developing are not significantly impacted by wildfires (see Appendix for a list of countries and exact results).

Generally, somewhere between 0.4-1% of GDP per capita is lost every year for the first year or two after a wildfire based on the synthetic control approach for countries that are both developing and experience a large number of wildfires. Figures 7 and 10 below display the simulated “actual” GDP trajectory using the full model (baseline at y=0) and the “wildfire-free” model (solid black for bias-controlled results) overlaid with the largest year of wildfire on record for two example countries. In countries with very weak wildfire climates, such as Greenland or Jordan, removing wildfires has no impact on the model’s prediction for long-run economic growth. However, as wildfires become more intense and a country becomes less developed, the long-term trajectories for GDP per capita begin to diverge in the short term following an increase in wildfires.

As an example, consider Morocco. Synthetic Morocco is a weighted combination of the countries found in Table 3. Figure 7 depicts the impact of wildfires on Moroccan GDP following an increase in fires in 1982 compared to the surrounding years. As shown, the pre-treatment period synthetic and counterfactual are largely similar. In the first six years after the increase in wildfires in 1982, GDP in Morocco is less than it would be if Morocco never suffered from wildfires.

Country Name	Weight
Botswana	.46
Democratic Republic of the Congo	.355
Egypt	.127
Gabon	.023
Kenya	.021
South Africa	.008
Algeria	.007

Morocco Synthetic Control Weights

In the first year after the fires, GDP per capita fell by $220.88. GDP per capita then fell by $142.88 two years after the increase in wildfires. It then continued to fall by 564.06 three years after, $497.16 four years after, and by an additional $253.03 five years later compared to the synthetic Morocco that had no wildfires.

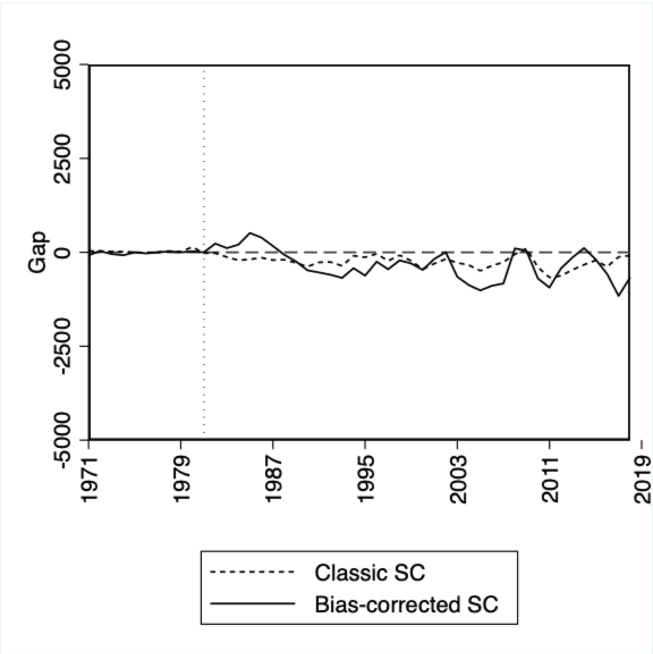

Figure 7: Graph of synthetic Moroccan GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Morocco

These results are statistically significant at the 10% level after running a number of placebo tests as seen in Figure 5. The idea is that synthetic Moroccan GDP is measured against a number of other countries that did not experience an increase in wildfires in the same year. I then compute each placebo run's estimated effects, giving a distribution of values to create confidence intervals. The black line in Figure 5 represents the estimated gap between the treated and synthetic Moroccos. The grey lines denote the estimated gap between placebo runs and treated Morocco.

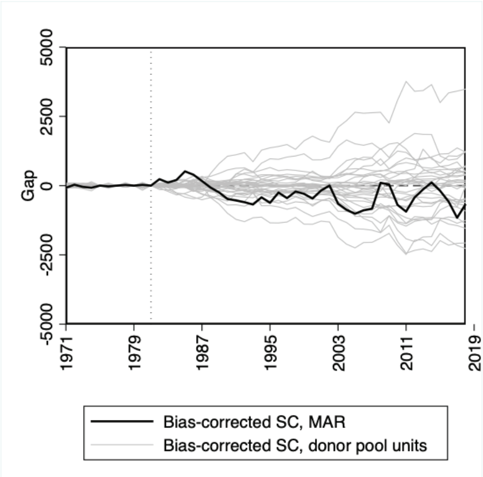

Figure 8: Placebo tests for Moroccan GDP per capita. The graphs report the difference, in terms of GDP per capita, between the treated country (Morocco) and the same differences for all other countries in the region (placebo in gray lines).

An important consideration when measuring the impacts of wildfires on economic growth is controlled burns to increase agricultural yield. In Morocco, as seen in Figure 6, agriculture did not significantly increase compared to synthetic Morocco nor the placebo runs. While the impact may look statistically significant, the confidence intervals rule out an increase in agriculture following wildfires in 1982. As such, we can rule out that an increase in agriculture led to an upwards nudge of the impacts of wildfires on economic growth in Morocco. Prior literature has raised the idea of controlled burns increasing GDP as one confounding factor in measuring the impact of wildfire yet after both controlling for agriculture in the initial model and rerunning the model looking at the impact of wildfires on agriculture yielded no significant difference from the counterfactual.

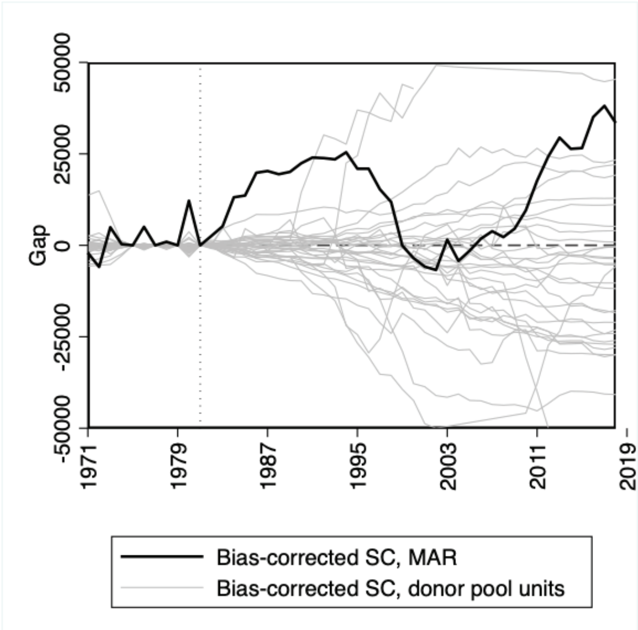

Figure 9: Moroccan agriculture following an increase in wildfires in 1985. Placebo tests for Moroccan agriculture. The graphs report the difference, in terms of agriculture as a percent of GDP, between the treated country (Morocco) and the same differences for all other countries in the region (placebo in gray lines).

Synthetic Central African Republic displays a similar story. It's counterfactual is created by weighting the countries found in Table 4. Following an abnormal increase in wildfire exposure in 1984, GDP per capita decreased from 1985-1992, before increasing back to pre-1984 levels in 1993. My central result, that GDP decreased in the Central African Republic following an increase in wildfires is statistically significant but only for the four years immediately following an increase in wildfires. While the synthetic and actual Central African Republic diverged again in 1997, the divergence is not statistically significant.

Country Name	Weight
Burkina Faso	.269
Democratic Republic of the Congo	.067
Republic of the Congo	.067
Mali	.463
Sierra Leone	.071
Chad	.05
Zimbabwe	.013

Table 3: Central African Republic Synthetic Control Weights

Following an increase in wildfires in 1984, GDP per capita in Central African Republic is $87.31 less than synthetic CAR in which no wildfires took place in 1985. In 1986, the GDP per capita in synthetic CAR is $159.41 higher than actual CAR. In 1987, synthetic CAR is $144.90 higher than actual CAR. Synthetic CAR is $147.96 higher than actual CAR in 1988 and $128.765 in 1989 before the two countries converge.

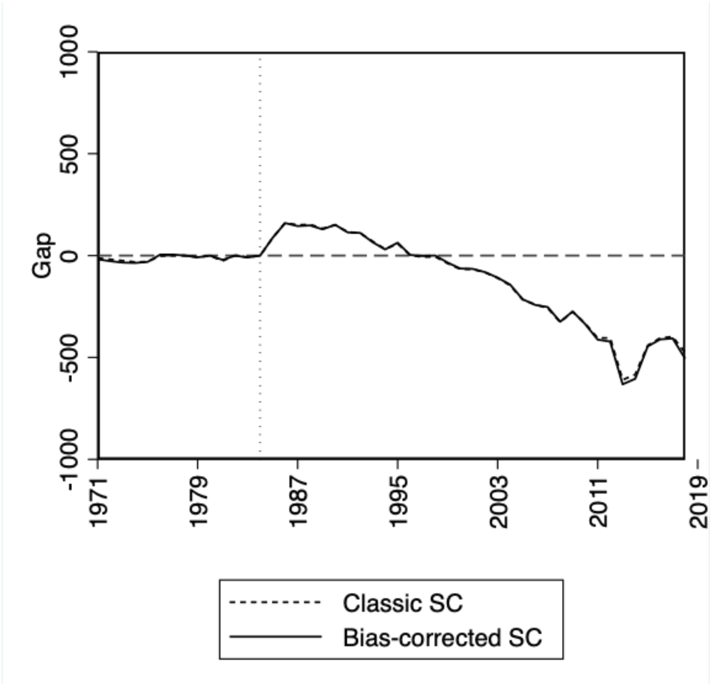

Figure 10: Graph of synthetic Central African Republic GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Central African Republic

The decrease in GDP from 1985-1992 seems to follow the same trend as Morocco after controlling for institutional changes through the Polity2 score. As seen in Figure 3, neither the amount of agricultural land nor agriculture as a percent of GDP significantly increased in the Central African Republic following the increase in wildfire exposure in 1984.

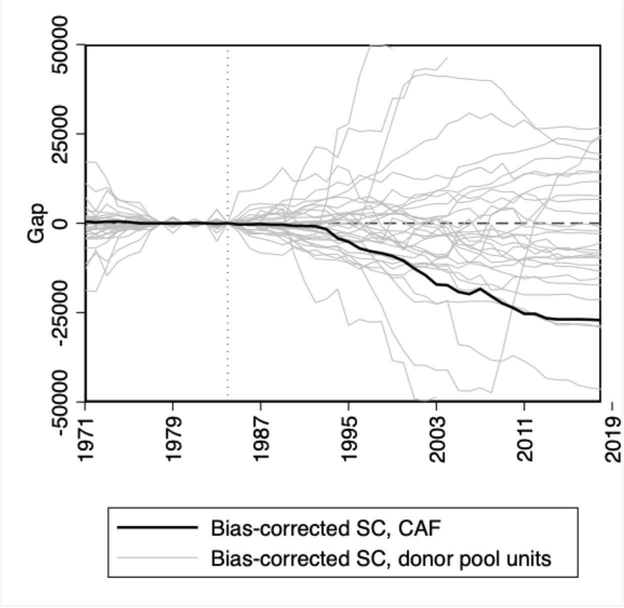

Figure 11: Placebo tests for CAR agriculture. The graphs report the difference, in terms of agriculture as a percent of GDP, between the treated country (Central African Republic) and the same differences for all other countries in the region (placebo in gray lines).

In contrast, wildfires in Algeria temporarily increase GDP. The synthetic Algeria weights can be found in table 4. Following an increase in wildfires in 1994, Algeria's GDP per capita was $326.12 lower in synthetic Algeria compared to the actual by 1995. Following a one-year increase, the difference between actual and synthetic Algeria collapses back to being indistinguishable from zero in the following years.

Country Name	Weight
Cameroon	.681
Gabon	.313
South Africa	.006

Table 4: Algeria Synthetic Control Weights

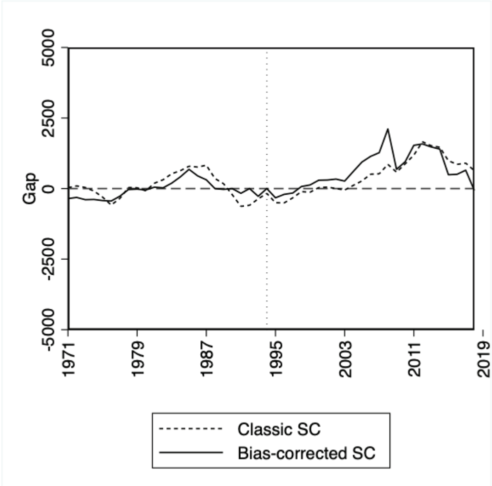

Figure 12: Graph of synthetic Algerian GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Algeria

These results are confirmed through both the placebo test, seen in figure 13, and the IRF plot. Based on the impulse response function, GDP increases by about 0.4% following an increase in wildfires. Figure 14 indicates that agriculture increases by about .0016% following an increase in wildfires which confirms the synthetic control results.

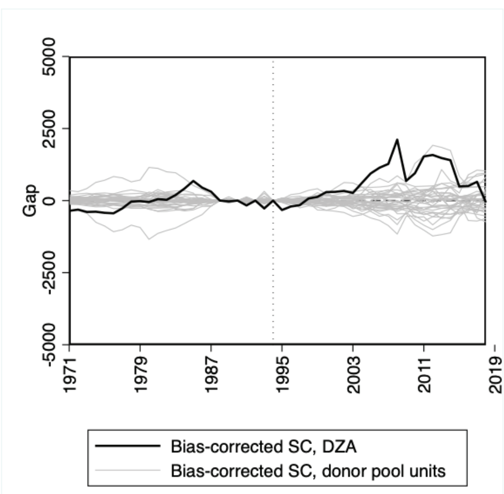

Figure 13: Placebo tests for Algerian agriculture. The graphs report the difference, in terms of agriculture, between the treated country (Algeria) and the same differences for all other countries in the region (placebo in gray lines).

Across countries that are significantly impacted by wildfires, the magnitude of the impact is small but impactful. Within impacted countries that see a decrease, GDP per capita losses range from a loss of 0.2-0.4% of GDP or anywhere between $111-514 per year for 3-5 years. Countries, like Algeria, that see a 0.4-1% increase in GDP per capita for the 1-2 years following a wildfire before GDP per capita converges back to the pre-wildfire trend.

My results allow me to decisively reject the hypotheses that per capita GDP never recovers following wildfire incidence or that it "builds back better". Following a wildfire, GDP per capita tends to suffer in the short term before stabilizing near the pre-wildfire growth rate 3-5 years after the event year. The "recovery to trend" hypothesis (Figure 1) describes the true behavior of GDP per capita for a large majority of impacted countries following a wildfire for developing countries that experience many fires. Some countries, such as Algeria, see a temporary boost of GDP per capita following wildfires that corresponds with an increase in agriculture. These countries follow the "creative destruction" hypothesis as they are able to more effectively use the land for agricultural purposes, which in turn increases GDP per capita.

8. Robustness Checks

There are outsized differences in the wildfire exposure countries are endowed with and my results suggest that wildfires can have a significant impact on developing countries that are repeatedly exposed to them. How much variation in average GDP per capita is explained by cross-country variation in wildfire climate?

To explore this question, I above ran a synthetic control model in which the difference between the "actual" and "synthetic" country represented the missing GDP per capita from cyclones. Below, I utilize impulse-response graphs to measure the impact of an additional percentage point of land burned in a given country to ensure my results above are robust. If wildfires explain the cross-country differences in growth rates between the actual and synthetic models, rough calculations should find the IRF giving similar results. I do not observe this, as the

IRF plots indicate a decrease in economic growth for a year or two following an increase in area burned at roughly 0.2-1% of GDP per capita per year, indicating that wildfires are only one of the multitude of factors that influence growth. For countries that experience an increase in economic growth, likely as a result of increased agricultural production, GDP per capita increases by roughly 0.4-1% per kilometer burned in the year following an increase in wildfires.

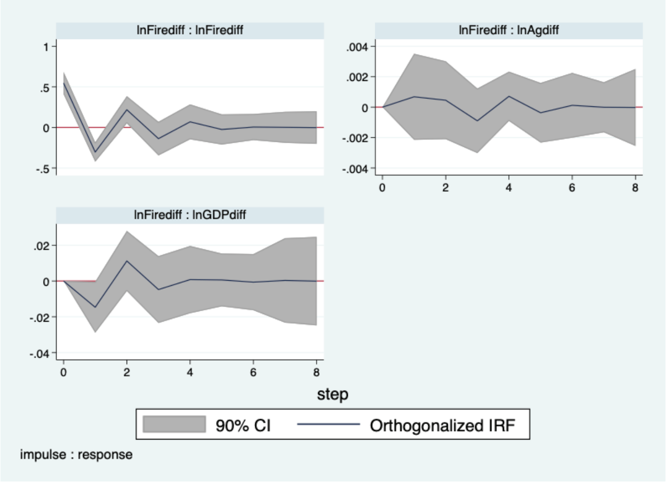

Figure 14: Morocco IRF Graph

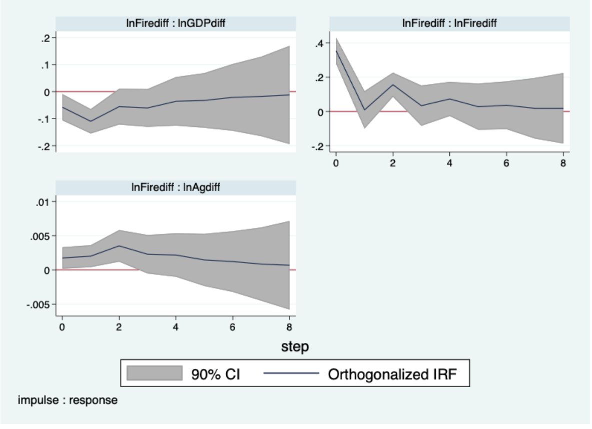

Figure 15: CAR IRF graph

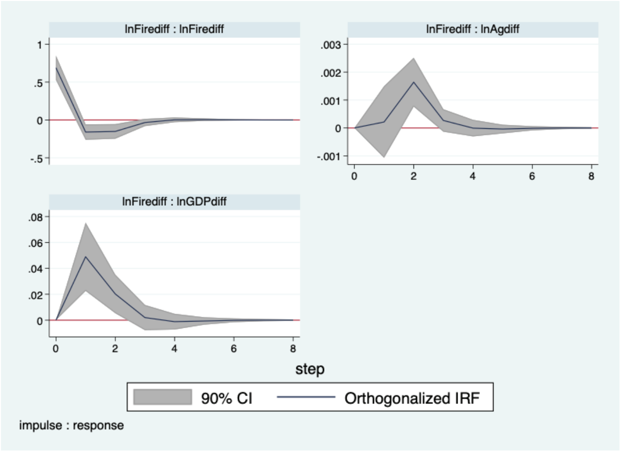

Figure 16: Algeria IRF graph

While these IRF graphs help us understand the impact an increase in wildfire exposure has on per capita GDP in countries with different wildfire climates, they should be interpreted cautiously. I cannot account for the plethora of interacting general equilibrium adjustments that may accompany a change in the distribution of wildfires. If all wildfires were to disappear, for example, Africa and South America would need to adjust for the growing season. Additionally, there may also be unobservable factors that limit growth in a given country and therefore it may be impossible to achieve the per capita GDP that my synthetic control model suggests. There may also be secondary impacts, such as civil war or political turmoil, that may not have occurred had it not been for wildfire-induced contraction of economic growth. As such, the exact values of these "wildfire-free" simulations should not be interpreted too literally. I do think, however, that the general distribution and magnitude of these impacts indicate that wildfires do play a role in economic development.

9. Comparison with previous studies

While several studies have analyzed the impacts of disasters on growth, few can be directly compared to mine. However, a previous study combines spatial wildfire data and economic growth metrics in Southern Europe so I use these to benchmark my results. Meier et al.

(2023) analyzes the impact of wildfires on the growth rate of gross domestic product (GDP) and employment of regional economies in Southern Europe from 2011 to 2018. panel fixed effects instrumental variable estimation results suggest an average contemporary decrease in a region's annual GDP growth rate of 0.11–0.18% conditional on having experienced at least one wildfire in the short run. Across an average wildfire season, this leads to total losses of 13–21 billion euros for Southern Europe. Without a comprehensive theory connecting long and short-run losses, I refrain from speculating whether my results represent the same losses found in my study. I found that no European country was significantly impacted by wildfires indicating that there may be a difference at the national versus regional levels.

10. Summary

A growing body of literature has examined the impacts of natural disasters on economic growth however the long-run implications and the impacts of wildfires specifically have not been previously studied. I constructed a novel dataset of wildfires and analyzed a global panel of countries to demonstrate the impacts of fire on economic growth. Both the synthetic control approach and the IRF plots indicate that wildfires decrease economic growth in the short term across developing countries in Africa that experience a large number of wildfires. My results are supported by theoretical predictions, although regional European findings (Meier et al., 2023) differ from mine as I found no impact of wildfires on a country level in Europe.

The estimated impact of wildfires on economic growth is short-lived, only lasting for a year or two after each wildfire rendering them undetectable. Considering that a large number of developing countries, particularly those in Africa, these start to depress growth more significantly.

10.1 Implications for disaster risk management

In general, disaster policies have two prongs: pre-disaster risk reduction and post-disaster recovery or income smoothing. While the latter is often the focus of policy, the former is sometimes highly cost-effective (Healy and Malhotra, 2009); Deryugina, 2011;

UNISDR, 2011). Previous literature finds that these two instruments are not the substitutes that they are commonly thought to be. Post-disaster smoothing is often achieved through borrowing, transfers, and insurance mechanisms. They generate no net income but are effective at reducing welfare losses in the short run. In contrast, pre-disaster investments such as controlled burns, fire-hardening of infrastructure, etc. are likely to not only influence long-run disaster outcomes but are also likely to reduce the impacts of future wildfires. Many risk reduction efforts mirror adaptive investments and my results seem to indicate that adaptive behaviors are probably effective at lowering the marginal impact of wildfires. Policymakers, therefore, should optimally allocate resources to both post-disaster income smoothing and recovery efforts. While wildfire impacts seemingly only impact the short run, future risk reduction is important as it can mitigate the impacts of future fires.

My estimates provide new evidence on the short and long-term impacts of wildfire on wildfires. Contrary to previous work, I find that wildfires only have a significant impact on African countries that experience a large percentage of total land area burned and that are still developing.

Works Cited:

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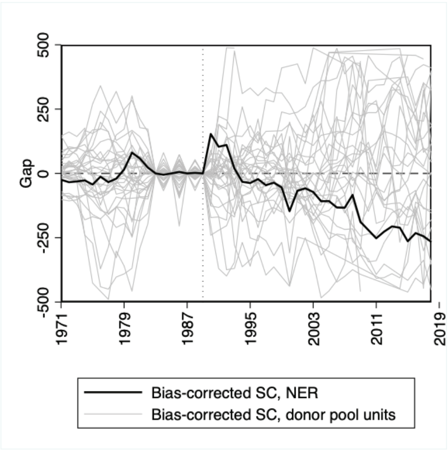
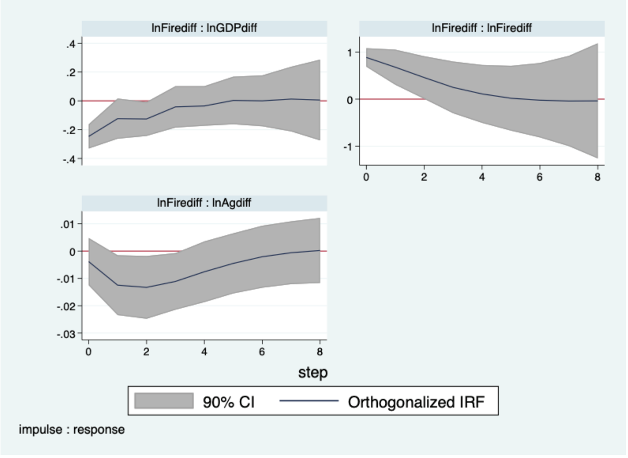
Appendix

Niger

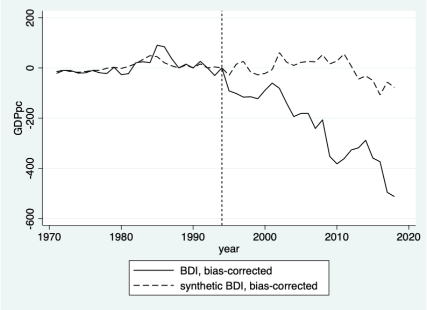


Niger Synthetic Controls

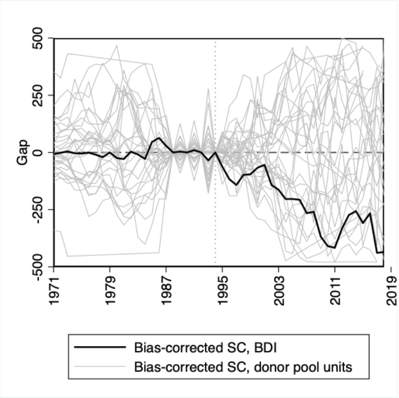


Niger IRF

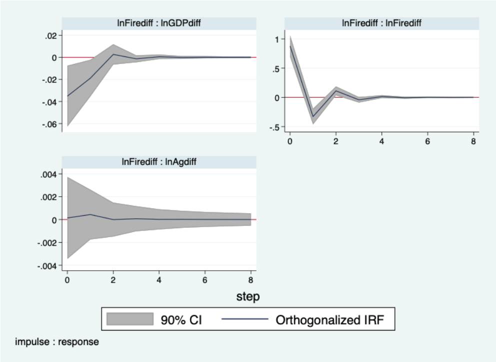
Burundi



GDPpc
200
0
-200
-400
-600
1970
1980
1990
2000
2010
2020
year
BDI, bias-corrected
synthetic BDI, bias-corrected

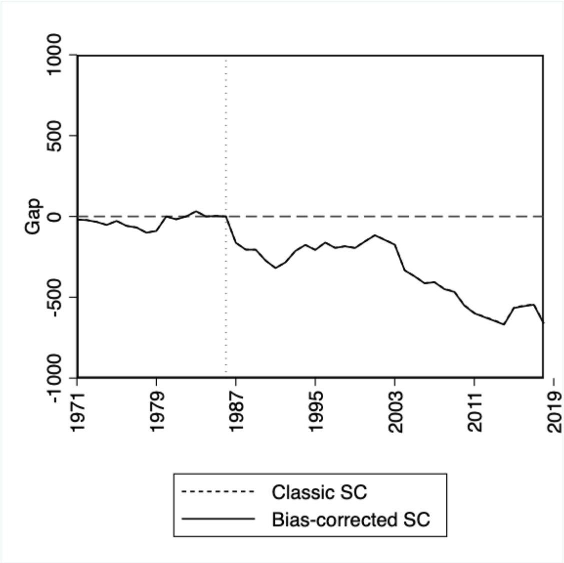


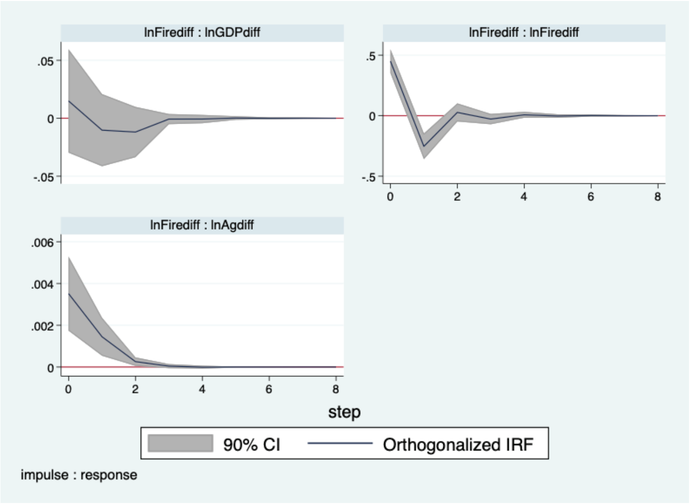
Gap
500
250
0
-250
-500
1971
1979
1987
1995
2003
2011
2019
Bias-corrected SC, BDI
Bias-corrected SC, donor pool units



lnFirediff : lnGDPdiff
lnFirediff : lnFirediff
lnFirediff : lnAgdiff
step
90% CI
Orthogonalized IRF
impulse : response

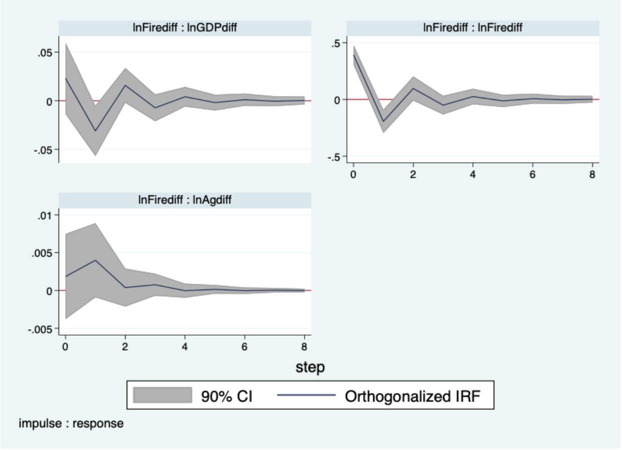
Madagascar


Gap
1000
500
0
-500
-1000
1971
1979
1987
1995
2003
2011
2019
Classic SC
Bias-corrected SC


lnFirediff : lnGDPdiff
lnFirediff : lnFirediff
lnFirediff : lnAgdiff
step
90% CI
Orthogonalized IRF
impulse : response

Benin


Gap
1000
500
0
-500
-1000
1971
1979
1987
1995
2003
2011
2019
Bias-corrected SC, BEN
Bias-corrected SC, donor pool units


lnFirediff : lnGDPdiff
lnFirediff : lnFirediff
lnFirediff : lnAgdiff
step
90% CI
Orthogonalized IRF
impulse : response

South Africa, Tanzania, Egypt, the Democratic Republic of the Congo, Kenya, Ghana, Tunisia, Namibia, Gambia, Botswana, Togo, Namibia, and Cameroon found no significant impact of wildfires on economic growth.

There were data collection issues with Angola, Ethiopia, Mozambique, Namibia, Equatorial Guinnea, Cote d'Ivoire, and Guinea-Bissau and they were therefore excluded from the study.

Panel Vector Autoregression and Assumptions

To estimate the causal impacts of wildfires on economic growth for robustness checks, I adopt a panel vector autoregression (PVAR) approach following Noy. Panel data techniques have been widely applied to the study of economic growth and using panel fixed effects when analyzing natural disasters allow for controlling the unobserved time-invariant heterogeneity and time-variant shocks that are common for all cross-sectional units (Cunado and Ferreira; Fomby, Ikeda, and Loayza, 2013). The aim is to measure the magnitude and duration of the response to an increase in wildfires. My model specification follows that of Noy (2009) and Loayza et al. (2012).

To estimate these effects, I run a panel vector autoregression of the form

Where Y_{it} represents a five-variable vector, with every variable being logged: {Population density, GDP, FDI, and Trade}, are country fixed effects, are time fixed effects, and is an error term clustered simultaneously by country and region-year (following Cameron, Gelbach, and Miller 2011). For the logged count of burned area, trade, GDP, FDI, and population density, all tests indicate that at least one of the panels are stationary.

GMM estimation requires that I select both the order and number of lags to be used for the moment conditions. Bello (2017), Drabo (2021), Melecky and Raddatz (2015) find that 1-3 lags work best. Using techniques developed by Abrigo and Love (2016), I estimate the PVAR using allowing a maximum lag length $p = 6$. As seen in Table two, the optimal lag is 1.

Table 2: Optimal Lag Selection

lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	.5567791	237.3068	7.19e-06	-926.3791	-62.69322	-377.307
2	.0080828	152.4465	.0480143	-817.2918	-97.55348	-359.7316
3	-4.356849	55.96173	.9998897	-719.8289	-144.0383	-353.7808
4	-40.2796	35.37738	.9999725	-546.4656	-114.6226	-271.9295
5	-90.54686	10.89448	1	-377.0008	-89.10552	-193.9768
6	-385.2625	2.209622	1	-191.738	-47.79038	-100.226

I test for stationarity using a variety of panel root tests. I find that the assumption of stationarity is warranted after taking the first difference of GDP, trade, FDI, and population density as seen in table. The model is estimated using a generalized method of moments (GMM) estimation, with the logs of GDP, trade, FDI, and population acting as instruments. The PVAR satisfies the stability condition after first differencing. I then perform Monte-Carlo estimations to estimate the 10^{th} and 90^{th} percent of the distribution, which are used as the confidence intervals for the impulse-response. The Monte-Carlo simulation is run 500 times.

Table 3: Unit Root Tests

	Trade	Population	GDP	FDI	Burn Area
Hadri, Bartlett kernel	$P < 0.0001$	$p<0.0001$	$P< 0.9917$	$P< 0.1198$	$P < 0.0529$
Im–Pesaran–Shin	$p < 0.0001$	$p< 1.000$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Fisher-type Phillips-Perron	$p < 0.0001$	$p< 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Levin-Lin-Chu	$p < 0.0001$	$P < 0.0001$	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$

In a PVAR model the estimated coefficients are not structural form, but rather are in their reduced form and are contemporaneous. As such, they cannot be used to identify the long-run impacts of a shock without imposing additional restrictions. I impose the order from least to most exogenous: wildfires, agriculture, GDP.