Volume 12 Article 1

2023

The Gettysburg Economic Review, Volume 12, Spring 2023

The

GETTYSBURG ECONOMIC REVIEW

Volume 12

Spring 2023

Department of Economics
Gettysburg College
Gettysburg, Pennsylvania 17325

The Economics Department and Omicron Delta Epsilon congratulate **Megan McCook** and **Nicholas Silvis**, winners of the *2023 Dwight D. Eisenhower Society / R.M. Hoffman Family Memorial Prize in Economics*. The Eisenhower/Hoffman Prize is awarded to the economics students writing the best quantitative paper or project with public policy implications.

The Economics Department and Omicron Delta Epsilon congratulates **Nicholas Silvis,** winner of the *2023 Best Thesis Award*.

The Economics Department and Omicron Delta Epsilon congratulates **Ben Durham**, winner of the *2023 James Boyd Hartzell Memorial Award*, awarded to one student with junior standing possessing excellent scholarship in the social sciences.

The Economics Department and Omicron Delta Epsilon congratulates **Jasper Givens** for being selected as a *2023 Kolbe Fellow*.

The Economics Department and Omicron Delta Epsilon congratulate **Aayusha Lamicchane** and **Megha Shakya**, winners of the 2023 *Dr. and Mrs. William F. Railing Fellowship for Faculty-Student Research in Economics*.

The Economics Department and Omicron Delta Epsilon congratulates **Mikayla Holmbeck**, winner of the *2023 John Edgar Baublitz Pi Lambda Sigma Award*.

The Economics Department and Omicron Delta Epsilon congratulate **Lauren Cosgrave, Katherine Fullowan** and **Mikayla Holmbeck** for their induction into Phi Beta Kappa. Phi Beta Kappa celebrates and advocates excellence in the liberal arts and sciences. Its campus chapters invite for induction the most outstanding arts and sciences students at America's leading colleges and universities.

The Economics Department and Omicron Delta Epsilon congratulate the following students for their achievements in the 2022-2023 academic year:

Economics Graduation Banner Carriers:

BA: Lauren Cosgrave
BS: Allyson Schnell

2023 Economics Honors Graduate:

Megan McCook
Shubh Parekh
Nicholas Silvis

CONTENTS

Up in Smoke: Wildfires and Economic Growth

Nicholas Silvis

Working Paper

I thank Solomon Hsiang, Jesse Anttila-Hughes, Amir Jina, Gernot Wagner, Linus Nyiwul, Gokcer Ozgur, Margaret Blume-Kohout, the Honors Thesis Seminar, and Gettysburg College for the wonderful discussions and suggestions. The views expressed herein are those of the author and do not reflect the views of Gettysburg College.

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

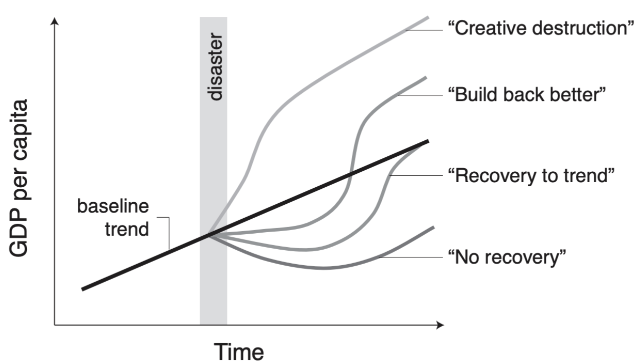
The influence of natural disasters and environmental phenomena on economic growth is an ongoing question, in part due to the challenge of identifying causal effects. While the structure of short-run disasters has been studied (e.g. Barro (2006); Jones and Olken (2010); Gabaix (2012)), and papers over 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:

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

Rearranging terms,

$$s * f(ḳ) = (n + ς)*ḳ \ (4)$$

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.

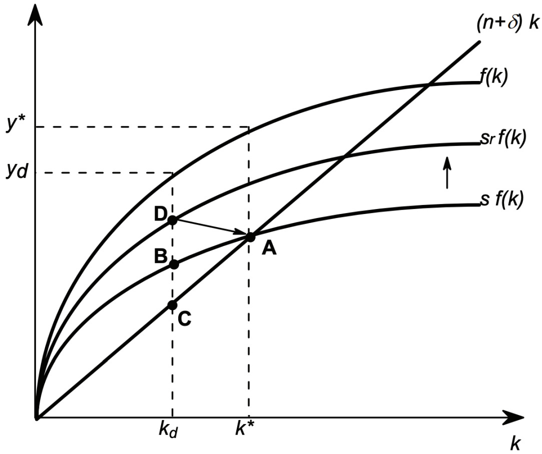


Figure 1: Solow-Swan model and wildfires

Figure 3 depicts the dynamics around the steady state of the Solow-Swan model. At the steady state, ḳ, the growth rate is zero because of the intersection of $s * f(\text{ḳ})/k = (n + ς)$. 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.

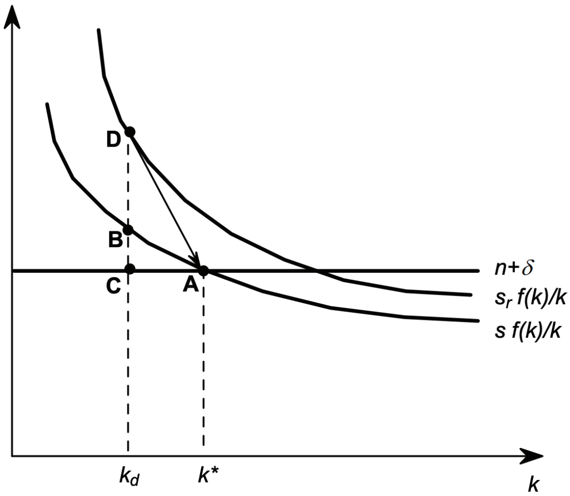


Figure 2: Recovery Dynamics

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).

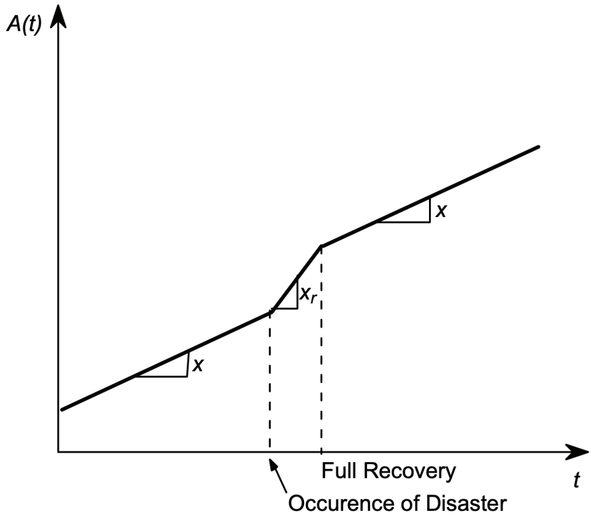


Figure 3: Wildfires and technological progress

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

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

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

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

$$ǩ = K/Ļ = K/(L * A(t)) = K/A(t) \ (7)$$

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

$$ŷ = f(ǩ) \ (8),$$

Equation 6 then becomes

$$ǩ = s * f(ǩ) - (x + n + ς) * ǩ$$

and the growth rate becomes

$$ɣk = s * f(ǩ)/ǩ - (x + n + ς)$$

At the steady state, ǩ becomes $ǩ^*$ as its growth rate becomes zero:

$$s * f(ǩ^*)/ǩ^* = (x + n + ς)$$

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.

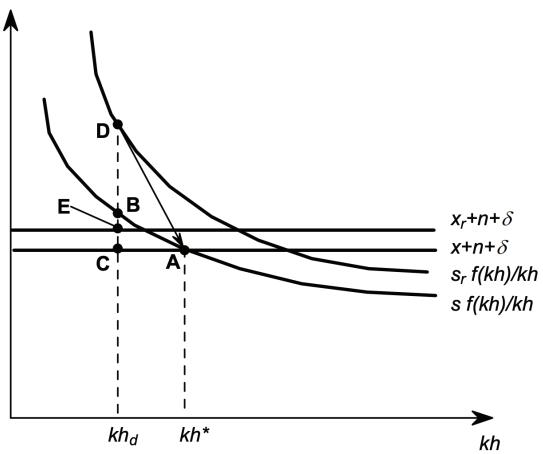


Figure 4: Solow-Swan model

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:

$$\underset{.}{K}(t) \;=\; sY(t) \;-\; \varsigma K(t) \qquad (2)$$

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

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

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.

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

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

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

I then differentiate with respect to time,

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

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

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

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

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

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:

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

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

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.

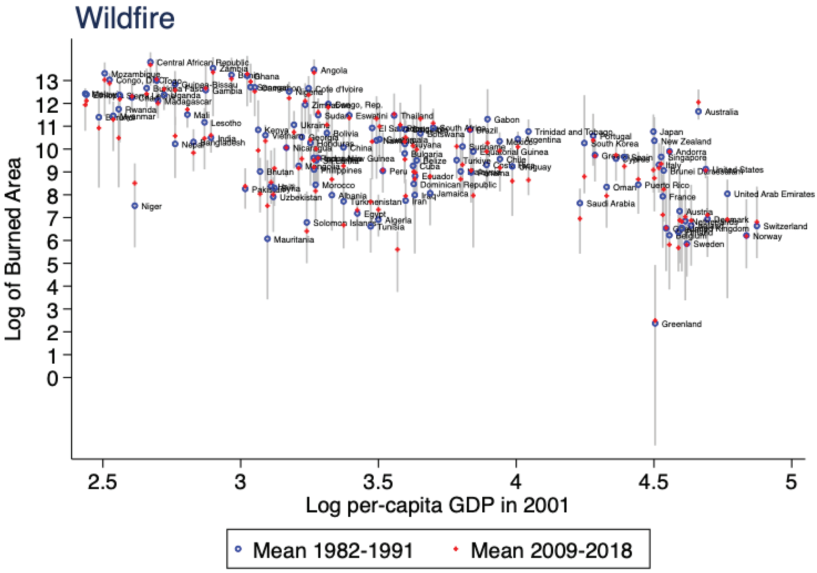


Figure 5: This graph presents data on each country's logged burned area, plotted against per capita GDP from the World Development Indicators (WDI) in the year 2001. For each country, the circle symbols represent the mean level of burned area in the first decade of my sample (1982–1991), the plus symbols 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.

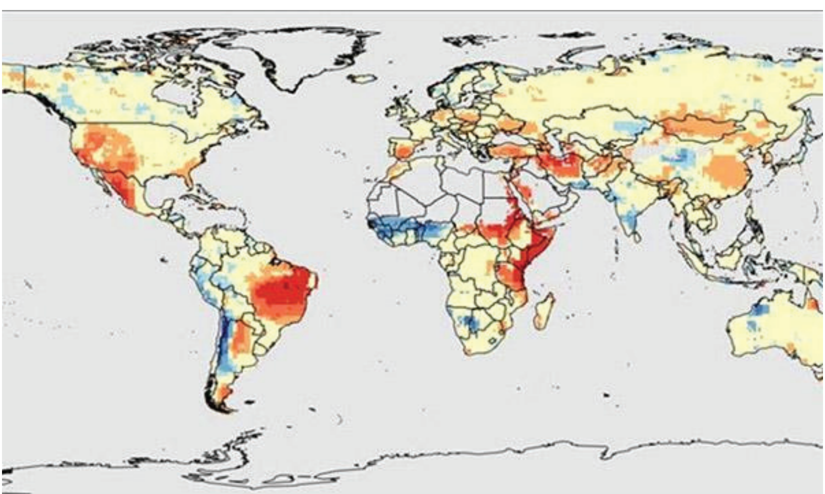


Figure 6: Global exposure to wildfires displayed as burned area per pixel for each year from 1982-2018

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

[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:

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

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

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

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.

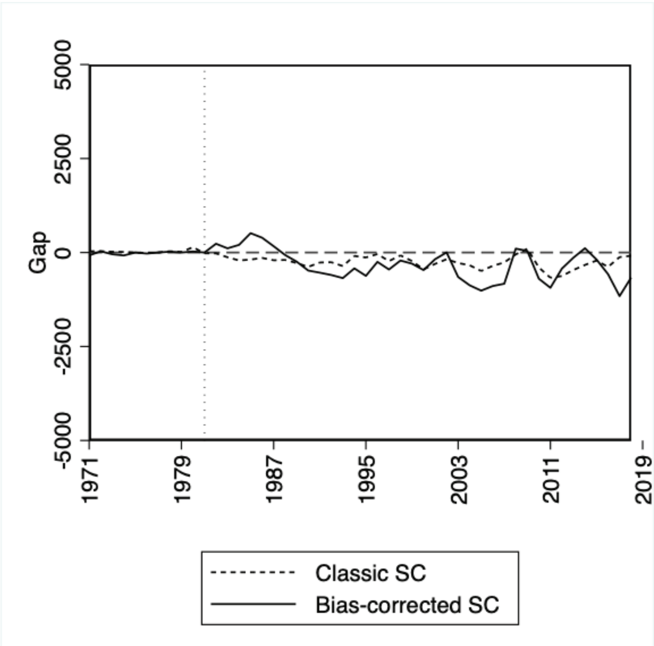


Figure 7: Graph of synthetic Moroccan GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Morocco

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.

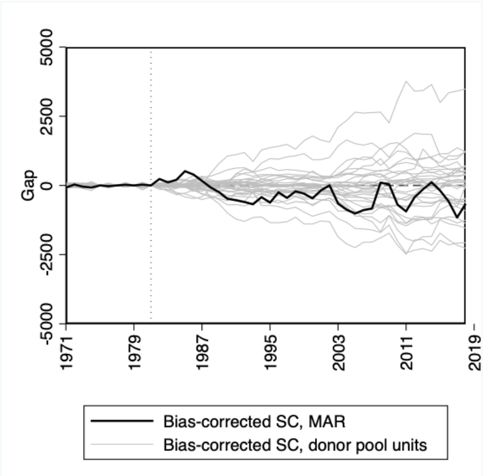


Figure 8: Placebo tests for Moroccan GDP per capita. The graphs report the difference, in terms of GDP per capita, between the treated country (Morocco) and the same differences for all other countries in the region (placebo in gray lines).

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.

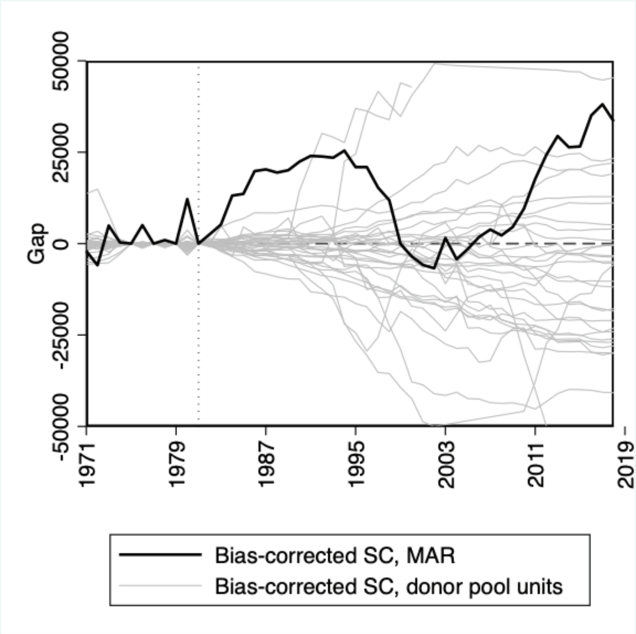


Figure 9: Moroccan agriculture following an increase in wildfires in 1985. Placebo tests for Moroccan agriculture. The graphs report the difference, in terms of agriculture as a percent of GDP, between the treated country (Morocco) and the same differences for all other countries in the region (placebo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

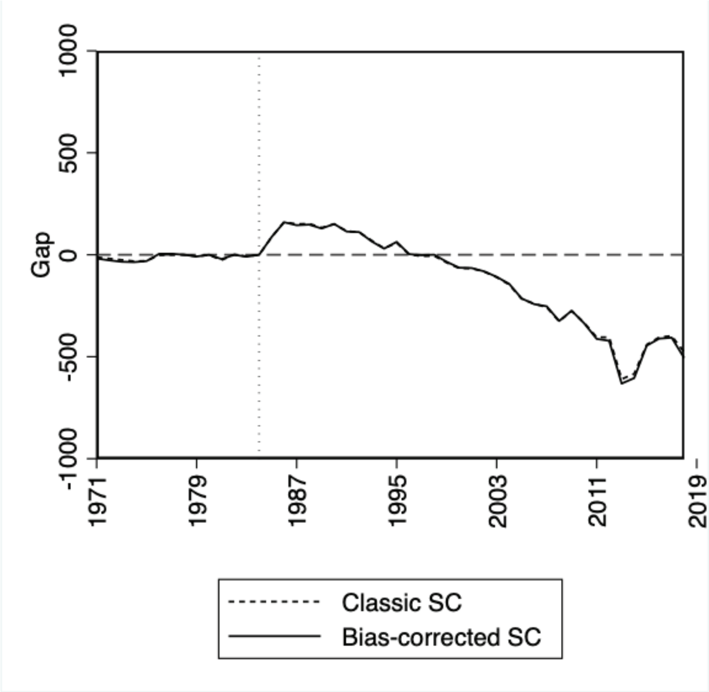


Figure 10: Graph of synthetic Central African Republic GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Central African Republic

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.

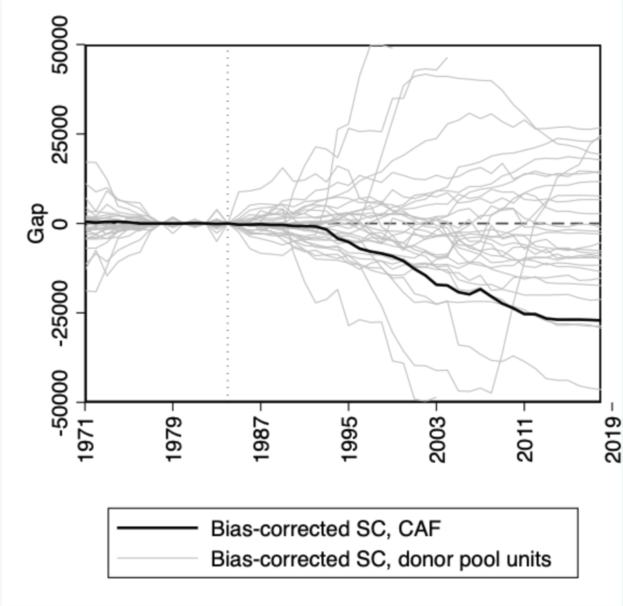


Figure 11: Placebo tests for CAR agriculture. The graphs report the difference, in terms of agriculture as a percent of GDP, between the treated country (Central African Republic) and the same differences for all other countries in the region (placebo in gray lines).

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

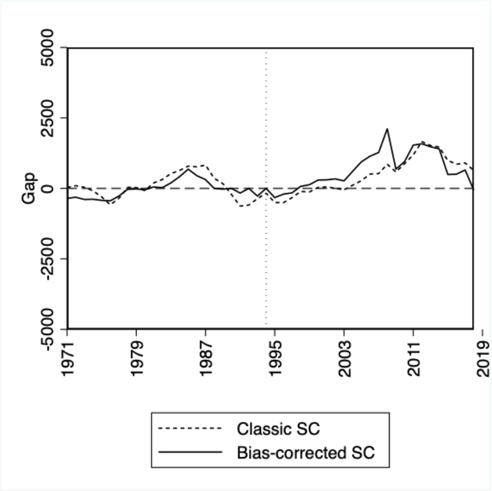


Figure 12: Graph of synthetic Algerian GDP (in black) with no wildfires compared to a baseline of 0, the GDP of actual Algeria

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.

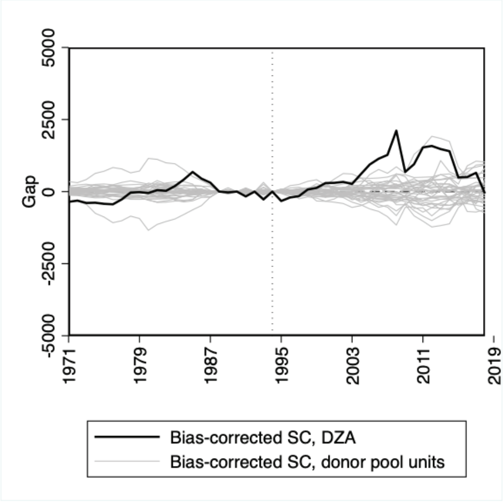


Figure 13: Placebo tests for Algerian agriculture. The graphs report the difference, in terms of agriculture, between the treated country (Algeria) and the same differences for all other countries in the region (placebo in gray lines).

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.

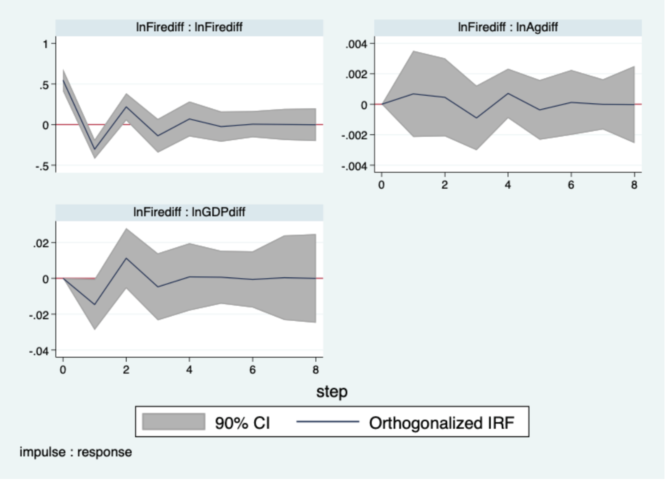


Figure 14: Morocco IRF Graph

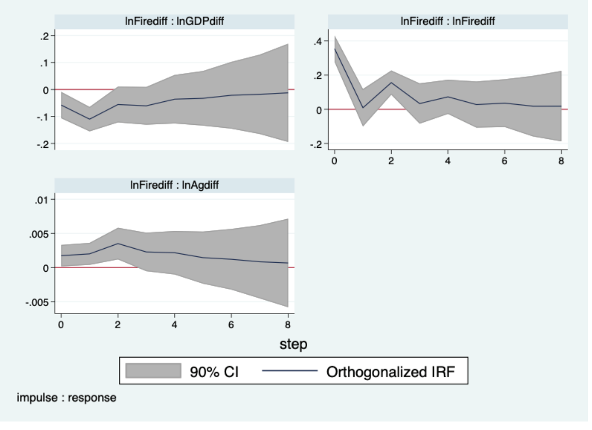


Figure 15: CAR IRF graph

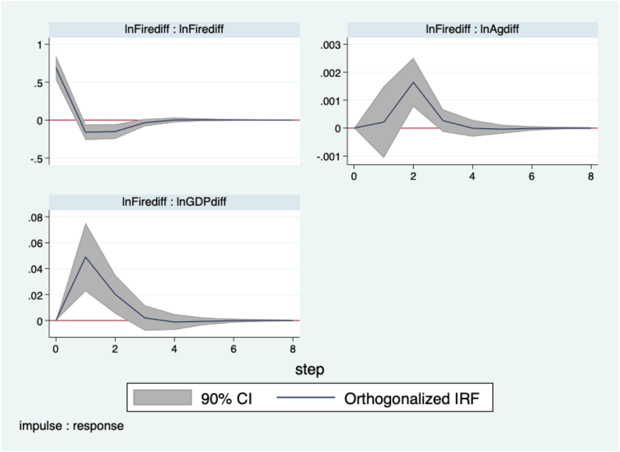


Figure 16: Algeria IRF graph

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:

Acemoglu, Daron, Simon Johnson, and James A Robinson. 2002. “Reversal of fortune: Geography and institutions in the making of the modern world income distribution.” The Quarterly Journal of Economics 117 (4):1231–1294.

Anttila-Hughes, Jesse K. and Solomon M. Hsiang. 2011. “Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster.” Working paper URL http://conference.nber.org/confer//2012/EEEHC12/Hsiang_Antilla-Hughes.pdf.

Barro, Robert J. 2006. “Rare disasters and asset markets in the twentieth century.” The Quarterly Journal of Economics 121 (3):823–866.

Barro, Robert J. and Xavier Sala-i-Martin. 2003. Economic Growth, 2nd edition. The MIT Press.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang. 2014. “Nonlinear permanent migration responses to climatic variations but minimal response to disasters.” Proceedings of the National Academy of Sciences 111 (27):9780–9785.

Cameron, L and M Shah. 2013. “Risk-taking behavior in the wake of natural disasters.” NBER Working Paper No. 19534 .

Cerra, V., Saxena, S. C. 2008. “Growth dynamics: the myth of economic recovery.” The American Economic Review 98 (1):439–457.

Conley, Timothy. 1999. “GMM Estimation with Cross Sectional Dependence.” Journal of Econometrics 92 (1):1–45.

Cressie, Noel and Christopher K Wikle. 2011. Statistics for spatio-temporal data. John Wiley & Sons.

Cuaresma, J Crespo, J Hlouskova, and M Obersteiner. 2008. “Natural disasters as creative destruction? Evidence from developing countries.” Economic Inquiry 46 (2):214–226.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. “Temperature Shocks and Economic Growth: Evidence from the Last Half Century.” American Economic Journal: Macroeconomics 4 (3):66–95.
Deschˆenes, Olivier and Michael Greenstone. 2007. “The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather.” The American Economic Review 97 (1):354–385.

Donadelli, M., Jüppner, M. and Vergalli, S., 2021. Temperature variability and the macroeconomy: A world tour. Environmental and Resource Economics, pp.1-39.

Egorova, V., & Pagnini, G. (2022). Predicting the Arrival of the Unpredictable: An Approach for Foreseeing the Transition to Chaos in Wildfire Propagation. *Environmental Sciences Proceedings*, *17*(1), 69.

Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley. 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press

Frankel, Jeffrey A and David Romer. 1999. “Does trade cause growth?” American economic review 89:379–399.

Gabaix, Xavier. 2012. “Variable rare disasters: An exactly solved framework for ten puzzles in macrofinance.” The Quarterly Journal of Economics 127 (2):645–700.

Gallup, John Luke, Jeffrey D Sachs, and Andrew D Mellinger. 1999. “Geography and economic development.” International regional science review 22 (2):179–232.

Gollier, Christian. 2012. Pricing the planet’s future: the economics of discounting in an uncertain world. Princeton University Press. Graff Zivin, Joshua and Matthew Neidell. 2014. “Temperature and the allocation of time: Implications for climate change.” Journal of Labor Economics 32:1–26.

Greene, William H. 2003. Econometric Analysis, Fifth Edition. Prentice Hall.

Hallegatte, S and P Dumas. 2009. “Can natural disasters have positive consequences? Investigating the role of embodied technical change.” Ecological Economics 68 (3):777–786.

Heal, Geoffrey. 2009. “Climate economics: a meta-review and some suggestions for future research.” Review of Environmental Economics and Policy 3 (1):4–21.

Heal, Geoffrey. 2009. “Climate economics: a meta-review and some suggestions for future research.” Review of Environmental Economics and Policy 3 (1):4–21.

Hornbeck, Richard. 2012. “The Enduring Impact of the American Dust Bowl: Short-and Long-Run Adjustments to Environmental Catastrophe.” The American Economic Review 102 (4):1477–1507.

Houser, Trevor, Robert Kopp, Solomon M. Hsiang, Michael Delgado, Amir Jina, Kate Larsen, Michael Mastrandrea, Shashank Mohan, Robert Muir-Wood, DJ Rasmussen, James Rising, and Paul Wilson. 2014. “American Climate Prospectus: Economic Risks in the United States.” Rhodium Group .

Hsiang, Solomon M, Marshall Burke, and Edward Miguel. 2013. “Quantifying the influence of climate on human conflict.” Science 341 (6151):1235367.

Hsiang, Solomon M and Kyle C Meng. 2014. "Reconciling disagreement over climate–conflict results in Africa." Proceedings of the National Academy of Sciences :201316006.

Hsiang, Solomon M., Kyle C. Meng, and Mark A. Cane. 2011. "Civil conflicts are associated with the global climate." Nature 476 (7361):438–441.

Hsiang, S. M., & Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones (No. w20352). National Bureau of Economic Research.

Jones, Benjamin and Benjamin Olken. 2010. "Climate shocks and exports." American Economic Review: Papers and Proceedings 100:454–459.

Kahn, Matthew E. 2005. "The Death Toll from Natural Disasters: the role of Income, Geography, and Institutions." The Review of Economics and Statistics 87:271–284.

Kellenberg, Derek K. and Ahmed Mushfiq Mobarak. 2008. "Does rising income increase or decrease damage risk from natural disasters?" Journal of Urban Economics .

———. 2011. "The Economics of Natural Disasters." The Annual Review of Resource Economics 3:297–312.

Kunreuther, Howard C., Erwann O. Michel-Kerjan, Neil A. Doherty, Martin F. Grace, Robert W. Clein, and Mark V. Pauly. 2009. At War With the Weather. MIT Press.

Legates, David R. and Cort J. Willmott. 1990a. "Mean seasonal and spatial variability in gaugecorrected, global precipitation." International Journal of Climatology 10 (2):111–127.

———. 1990b. "Mean seasonal and spatial variability in global surface air temperature." Theoretical and Applied Climatology 41:11–21. 10.1007/BF00866198.

Mendelsohn, Robert, Kerry Emanuel, Shun Chonobayashi, and Laura Bakkensen. 2012. "The impact of climate change on global tropical cyclone damage." Nature Climate Change 2 (3):205–209.

Miguel, E., S. Satyanath, and E. Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." J. Political Economy 112 (4):725–753.

Miguel, Edward and Michael Kremer. 2004. "Worms: identifying impacts on education and health in the presence of treatment externalities." Econometrica 72 (1):159–217.

Newey, Whitney K. and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." Econometrica 55 (3):703–708.

Nordhaus, W. D. 2006. "Geography and macroeconomics: New Data and new findings." Proceedings of the National Academy of Sciences 103 (10).

Nordhaus, William D and Zili Yang. 1996. “A regional dynamic general-equilibrium model of alternative climate-change strategies.” American Economic Review 86 (4):741–765.

Nordhaus, William D and Zili Yang. 1996. “A regional dynamic general-equilibrium model of alternative climate-change strategies.” American Economic Review 86 (4):741–765.

Noy, Ilan. 2009. “The macroeconomic consequences of disasters.” Journal of Development Economics 88:221–231.

Pindyck, Robert S. 2013. “Climate Change Policy: What Do the Models Tell Us?” Journal of Economic Literature 51 (3):860–872. Reinhart, Carmen M and Kenneth S Rogoff. 2009. “The Aftermath of Financial Crises.” American Economic Review 99 (2):466–72.

Rodrik, Dani, Arvind Subramanian, and Francesco Trebbi. 2004. “Institutions rule: the primacy of institutions over geography and integration in economic development.” Journal of economic growth 9 (2):131–165

Petersen, K. G. (2014). *Mapping a Wildfire: Mapping Practices, Authoritative Knowledge, and the Unpredictable Nature of Disaster*. University of California, San Diego.

Reinhart, Carmen M and Kenneth S Rogoff. 2009. “The Aftermath of Financial Crises.” American Economic Review 99 (2):466–72.

Rodrik, Dani, Arvind Subramanian, and Francesco Trebbi. 2004. “Institutions rule: the primacy of institutions over geography and integration in economic development.” Journal of economic growth 9 (2):131–165.

Romer, Christina D and David H Romer. 2010. “The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks.” The American Economic Review :763–801.

Skidmore, Mark and Hideki Toya. 2002. “Do Natural Disasters Promote Long-Run Growth?” Economic Inquiry 40 (4):664–687.

Smith, V. Kerry, Jared C. Carbon, Jaren C. Pope, Daniel G. Hallstrom, and Michael E. Darden. 2006. “Adjusting to natural disasters.” Journal of Risk and Uncertainty 33:37–54.

Stern, Nicholas. 2006. Stern Review: The Economics of Climate Change. Cambridge University Press. ———. 2008. “The economics of climate change.” The American Economic Review 98 (2):1–37.

Str¨omberg, D. 2007. “Natural disasters, economic development, and humanitarian aid.” The Journal of Economic Perspectives 21 (3):199–222.

Struzik, E. (2018, December). Firestorm: How Wildfire Will Shape Our Future: Wildfires are burning bigger, hotter, and in increasingly unpredictable ways. Policy-makers and the public have been slow to respond to this new paradigm. The need to invest in wildfire science is needed to give firefighters and forested communities the tools required to deal with future fires. In *AGU Fall Meeting Abstracts* (Vol. 2018, pp. A23E-06).

Udry, Christopher. 1994. “Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria.” Review of Economic Studies 61 (3):495–526.

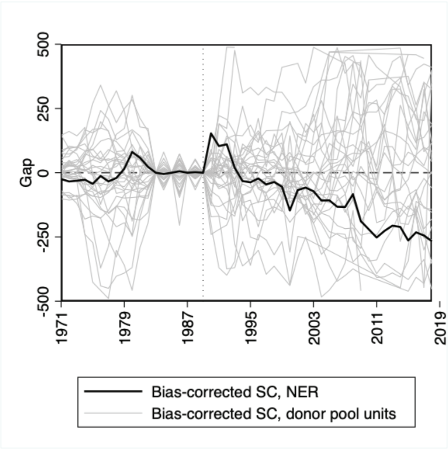
UNISDR. 2011. Global Assessment Report on Disaster Risk Reduction. United Nations Publication.

Tol, Richard SJ. 2009. “The economic effects of climate change.” The Journal of Economic Perspectives 23 (2):29–51.

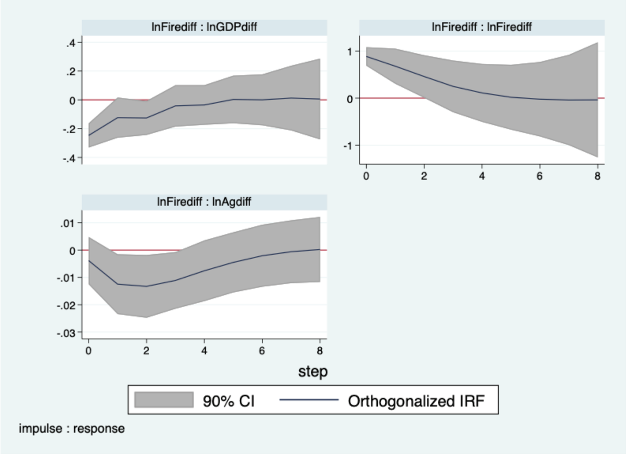
Weitzman, Martin L. 2009. “On modeling and interpreting the economics of catastrophic climate change.” The Review of Economics and Statistics 91 (1):1–19.

Appendix

Niger

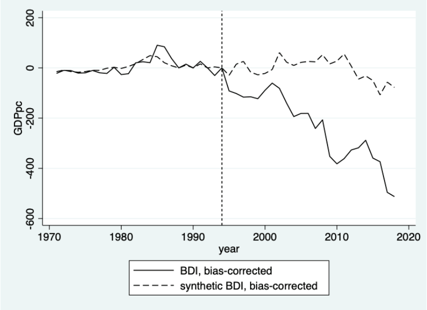


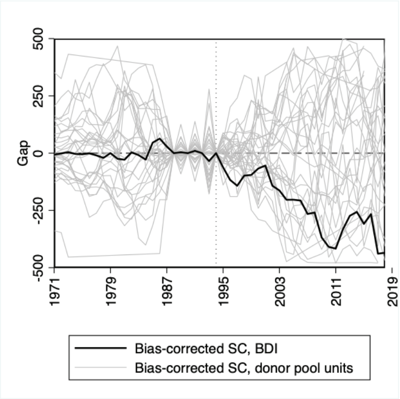
Niger Synthetic Controls

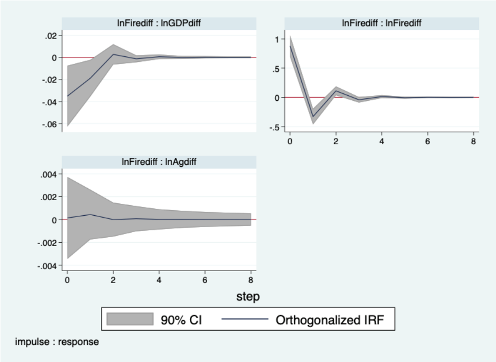


Niger IRF

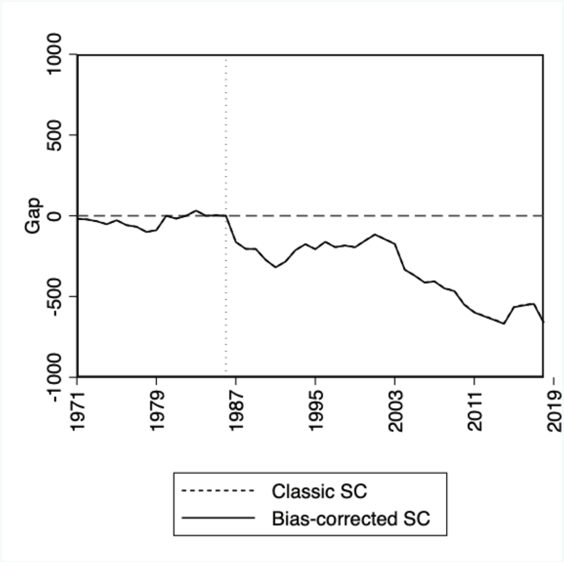
Burundi


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

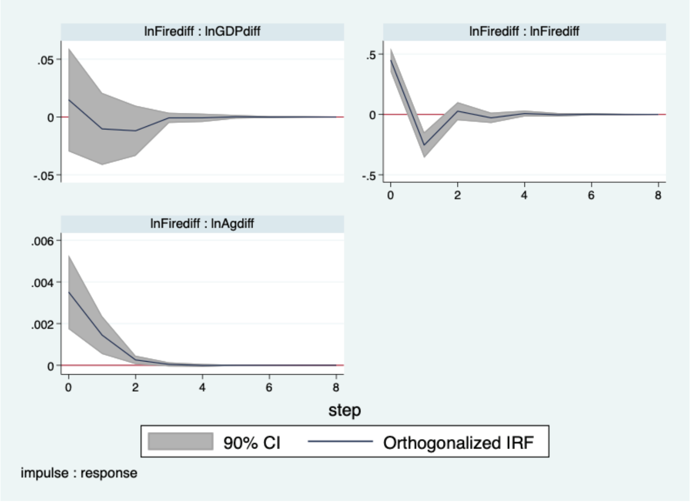

Gap
500
250
0
-250
-500
1971
1979
1987
1995
2003
2011
2019
Bias-corrected SC, BDI
Bias-corrected SC, donor pool units


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

Madagascar

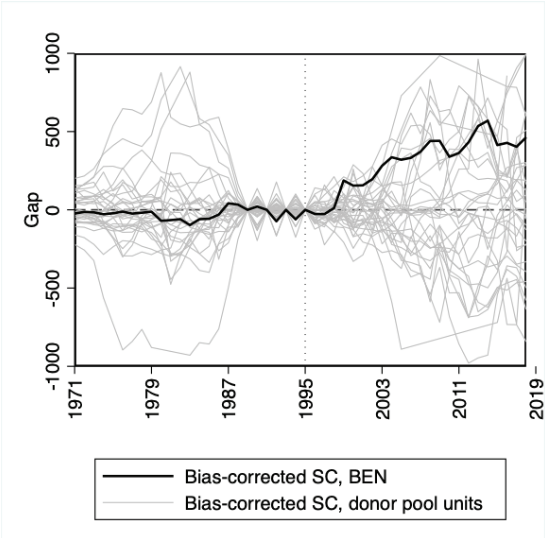


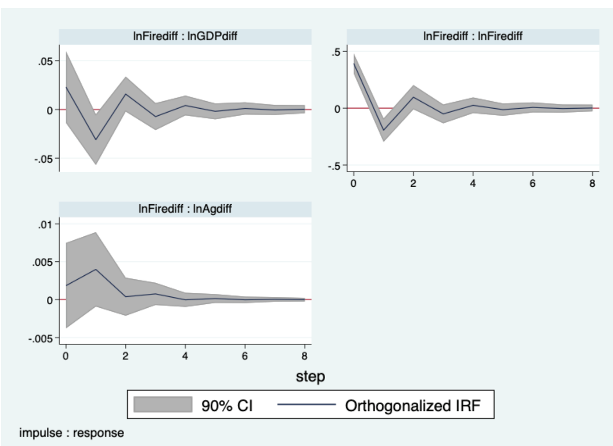
Gap
1000
500
0
-500
-1000
1971
1979
1987
1995
2003
2011
2019
Classic SC
Bias-corrected SC



lnFirediff : lnGDPdiff
lnFirediff : lnFirediff
lnFirediff : lnAgdiff
.05
0
-.05
.5
0
-.5
.006
.004
.002
0
0
2
4
6
8
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 10th and 90th 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.

The Effect of Remote Work on Firm Level Productivity

Katie Fullowan

May 1, 2023

Abstract

This paper investigates the impact of remote work on firm-level productivity. To observe this trend, we develop a theoretical model to understand how an economy performs. We consider the economy as a collection of firms in an attempt to maximize profit. By observing a firms profit function, we are able to derive their productivity by maximizing a representative firm's profit function. For simplicity purposes, this study treats labor as the only factor of production to focus solely on how changes in the number of remote workers impact productivity. We ultimately find that productivity increases when the number of remote workers increases relative to non-remote workers. This holds true under the stipulation that remote workers are paid higher wages than non-remote workers.

Keywords Work from Home · Productivity · Theoretical Analysis · Efficiency Wage Theory

Acknowledgements: I would like to thank Professor Hu for her feedback and assistance with this research paper.

I affirm that I will uphold the highest principles of honesty and integrity in all my endeavors at Gettysburg College and foster an atmosphere of mutual respect within and beyond the classroom.

1. Introduction

A recent shift towards remote work has made it increasingly more important for researchers to understand how the economy is being affected. This paper observes the impact of remote work on productivity with theoretical analysis. Furthermore, we look at how wages paid to remote and non-remote workers influence a firm's productivity. The growing presence of remote work around the world was accelerated in March of 2020 when the Coronavirus disease 19 (Covid-19) struck the United States with force.

The U.S. reported its first confirmed case of Covid-19 on January 20, 2020, with the first reported death occurring about a month later. The positive case count exceeded to a total of 60 cases across 12 different states by March 3rd. Between March 11th to March 19th, the World Health Organization declared Covid-19 a worldwide pandemic, the U.S. declared a nationwide emergency, public school systems began shutting down, and states began issuing mandatory stay-at-home orders. By April 10th, 2020, over 500,000 cases were reported in the U.S. alone, with the death count exceeding 18,600 (Center for Disease Control and Prevention, 2022).

Not only did the Covid-19 pandemic have significant immediate health effects, but it also seriously impacted employment. From mid-March to the end of April, over 26.5 million people in the U.S. became unemployed. By May 9th, unemployment rates reached their highest levels since the Great Depression at

14.7% and roughly 20.5 million workers from the Arts, Entertainment, and Recreation industry were out of work (Center for Disease Control and Prevention, 2022). Between issued stay-at-home orders and a spike in unemployment rates, not only were many people looking to minimize spending, but there was also little to spend money on. Travel was heavily restricted, many non-essential businesses were temporarily shut down, and people overall were scared to go out in public and risk exposure.

This major demand shock was brought on by the combination of stay-at-home orders and Covid cases. Stay-at-home orders forced many individuals to make a shift to remote work where possible. In 2021, about 17.9% of Americans were primarily working from home. This number tripled since 2019 when roughly only 5.7% of Americans primarily worked from home. The percentage of individuals working from home varied greatly by region with upwards of 48.3% of workers in the District of Columbia working remotely (US Census Bureau, 2022). Thus, remote work not only has grown in response to the Covid-19 pandemic, but it is still heavily prevalent across the United States. It is essential to understand if this recent movement towards remote work has an impact on productivity.

This paper is unique from most other in the way it develops a theoretical model to study how an economy performs. More specifically, it attempts to understand the impact of remote work on productivity. To do so, we consider the economy as a collection of firms with an attempt to maximize its profit function, shown in Equation 3. Maximizing profit allows us to find out the optimal number of remote and non-remote workers. This value can then be substituted into the model for output, shown in Equations 5 and 6. By dividing this output model by workers in the labor force, I generate a model for productivity which is further analyzed to answer the research question. In doing so, this study ultimately finds that when the ratio of remote to non-remote workers increases, firm productivity is positively impacted. Conversely, if this ratio decreases, meaning the number of remote workers is declining with respect to non-remote workers, then productivity is negatively impacted.

Section 2 of this paper dives into relevant literature, followed by the development of the theoretical model in Section 3. Results and a discussion of results from the modeling section are covered in Section 4, with concluding remarks included in Section 5.

2. Literature Review

The urgent need to adjust to working throughout a pandemic ultimately shifted how people worked, whether it be at limited capacity in the grocery store or at home with a house full of children. Workers adapted and found ways to work under the new circumstances. In some studies, work from home (WFH) has been found to improve work performance, in addition to increasing job satisfaction (Bloom et al., 2022). In this study by Bloom et al. researchers use data on employee's six-month performance review in conjunction with promotion rates for engineers and finance and marketing employees at a technology firm. Bloom et al. found that when employees worked from home a couple days per week, they reported 33% less attrition and higher levels of job satisfaction. Researchers subsequently found that non-managers were not only more likely to volunteer for remote work, but also to report experiencing positive productivity impacts. Managers on the other hand, were found to be less likely to volunteer for remote work and to be more likely to quit their job when asked to work remotely. Since managers are responsible for the oversight of their employees, it appears reasonable to conclude that they would prefer working in closer proximity to their workers.

A study by Morikawa (2020) found contradictory evidence that average productivity from home was lower than that in the office. In this study, Morikawa used data from a survey in June of 2020 on prevalence, frequency, and productivity of work from home. Morikawa ultimately finds that the average productivity when working from home was roughly 60-70% of normal, in-office productivity levels. Furthermore, he finds that productivity was even lower for workers that only started working remotely after the pandemic had begun.

Another by Felstead and Rueschke (2020) found that there was little impact at all of WFH on productivity. When conducting their research, Felstead and

Rueschke look at data from a report that observes at-home work before and during the lockdown in the UK. Results from a survey described in the data set includes individuals reported levels of productivity in comparison to before they made the shift to remote work. This survey found conflicting evidence with 40.9% reporting getting as much work done at home, 28.9% reporting getting more done, and 30.2% reporting getting less done. These conflicting findings are likely explained by the wide range of occupations included.

A study performed by Kitagawa et al. (2021) uses empirical analysis to observe whether productivity changed for workers that had to WFH because of the Pandemic. They observe changes in productivity levels, similar to what is done in this study. Some key differences between this paper and mine are its empirical nature and the unit of study being individual vs. firm. The study used self-reported data from a manufacturing company in Japan which may largely contribute to the results. Kitagawa et al. find that workers working from home reported declines in productivity, largely due to poor office set up and internet connection. This data was collected in April and June of 2020, likely before workers had chances to upgrade their office set up at home.

Many papers, such as those by Bloom et al. (2020), Morikawa (2020), Felstead and Rueschke (2020), and Kitagawa (2021), that look at working from home and productivity levels take an empirical approach. A study by Zhang et al. (2021) takes both an empirical and theoretical approach to understanding when firm choose to WFH, setting it apart from many other studies. In their empirical analysis, researchers use a data set that follows small businesses and their performance. In this analysis, Zhang et al. find that WFH rates increased even after stay-at-home orders were no longer in place. Therefore, even after workers were permitted to return to the office, working preferences shifted. This further emphasizes the importance of understanding any changes in productivity that may result. More relevant to this study, they also find that rational employers would select to WFH as opposed to work in the office. Furthermore, in states with higher WFH rates, small businesses performed better overall (after controlling for various factors).

While this paper also takes a theoretical approach, the two are done very differently and reach different conclusions. In Zhang et al.'s theoretical analysis, they predict that firms would choose to allow WFH if the ratio of variable revenue to cost is greater in WFH setting than in a standard office setting. Thus, their model uses a firm-revenue expense accounting framework, considering four key factors of production (labor, capital, land, and entrepreneurship). In this paper I simplify my analysis by looking at just one factor of production, labor. My major finding is consistent with the wage efficiency theory which indicates that in hiring more remote workers, firms tend to improve their productivity. This largely occurs because remote workers become more productive when paid better wages than non-remote workers.

3. Modeling

To study how remote working affects productivity, I consider an economy that consists of a collection of firms. Each firm is assumed to be homogenous with an attempt to maximize its profit. For simplicity, a representative firm is assumed to produce by only relying on one production factor – labor. Labor is further divided up into two types, including labor provided by remote workers and non-remote workers, as noted in Equations 1 and 7. The firm then adopts technology to combine these two types of labor to produce.

As stated by basic economic theory, a firm's profit is defined as the difference between total revenue and total cost. Thus, to formulate a profit function, I look at how much total revenue and total cost the representative firm earns and incurs, respectively.

Total revenue is defined in economics as the product of price and quantity. Equation 1 below represents total revenue as a function of average price level (P_t) and quantity produced, or output (Y_t). Output in this model is measured by a Cobb-Douglass production function with inputs (L_{1t} and L_{2t}) and technology (A_t), defined in Equation 5 below. β and δ are elasticities of output while L_{1t} and L_{2t} are the number of remote and non-remote workers, respectively. For simplicity purposes, the model used in this paper does not consider capital as a factor of production. Rather, the model focuses solely on the impact of changes in number of remote and non-remote workers on profit and, ultimately, on productivity. The exponents of β and δ represent elasticity of output with respect to each group of workers.

$$TR = P_t A_t L_{1t}^{\beta} L_{2t}^{\delta} \quad (1)$$

where $L_{1t} = number\ of\ remote\ workers$

$L_{2t} = number\ of\ non-remote\ workers$

$P_t = average\ price\ of\ all\ goods\ and\ services\ produced$

$A_t = total\ factor\ productivty$

As previously indicated, the models observed in this paper only consider labor as a factor of production. Thus, total costs is a function of workers' wages and number of workers. The products of W and T below show the product of number of remote and non-remote workers and their respective wages. The sum of these products gives us our total cost equation below.

$$TC = W_1 L_{1t} + W_2 L_{2t} \quad (2)$$

where $W_1 = wages\ paid\ to\ remote\ workers$

$W_2 = wages\ paid\ to\ non-remote\ workers$

Putting together the equations for total revenue and total cost, we reach Equation 3 below, which models the nation's profit. The constraint on equation 3 denotes α as the ratio between the number of remote and non-remote workers. Ultimately this constraint indicates that as the workforce transitions between remote and non-remote work, profits vary as well.

$$max\Pi_t = P_t A_t L_{1t}^{\beta} L_{2t}^{\delta} - W_1 L_{1t} - W_2 L_{2t} \quad (3)$$

$$\text{s.t. } \frac{L_{1t}}{L_{2t}} = \alpha \rightarrow L_{1t} = \alpha L_{2t}$$

After substituting L_{1t} into the above profit function, using first order conditions with respect to L_{2t}, and solving for L_{2t}, we reach the following. See appendix for more detailed steps.

$$L_{2t}^{*} = \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}} \quad (4)$$

As previously noted, output (Y_t) is modeled in a Cobb-Douglass production function. Keeping in mind that $L_{1t} = \alpha L_{2t}$, L_{2t}^{*} can be substituted into the equation for output. Upon doing so, we derive the following equations.

$$Y_t^{*} = A_t L_{1t}^{\beta} L_{2t}^{\delta} \rightarrow Y_t^{*} = A_t \alpha^{\beta} L_{2t}^{\beta+\delta} \quad (5)$$

$$Y_t^{*} = A_t \alpha^{\beta} \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}\beta+\delta} \quad (6)$$

The Bureau of Labor Statistics defines productivity as output divided by input. Therefore, we can calculate productivity as demonstrated in Equation 7 below. This is further simplified in equation 8. As previously mentioned, this paper does not consider capital as a factor of production for both the sake of the research question and simplicity. Thus, L_t represents total input or total number of workers in the economy and thus is the sum L_{1t} and L_{2t}.

$$y_t^{*} = \frac{Y_t}{L_t}, where\ L_t = L_{1t} + L_{2t} \ (7)$$

After dividing Y_t by L_t and simplifying, Equation 8 is reached. See appendix for more detailed steps.

$$y_t^* = \frac{\left(\frac{\alpha W_1 + W_2}{(\beta+\delta)P_t}\right)}{(\alpha+1)} \rightarrow y_t^* = \frac{\alpha W_1 + W_2}{(\beta+\delta)(\alpha+1)P_t} \quad (8)$$

Since this productivity, y_t^*, equation is a function of α, we can take the partial derivative with respect to α to determine how productivity varies with changes in the ratio of the number of remote to non-remote workers. We use comparative statistical analysis, holding exogenous variables constant and allowing α to vary. In doing so, we can understand how a changing α changes with productivity, y_t^*. After performing the derivation, Equation 9 is reached. See appendix for further steps.

$$\frac{dy_t^*}{d\alpha} = \frac{1}{(\beta+\delta)P_t(\alpha+1)^2}(W_1 - W_2) \quad (9)$$

This equation demonstrates the relationship between α and productivity, y_t^*. By observing this relationship between productivity and the ratio between remote and non-remote workers, we are able to understand how a changing ratio impacts productivity. This model will be further interpreted in section 1.4 below.

4. Results and Discussion

As can be seen in Equation 9, $\frac{dy_t^*}{d\alpha}$ takes on positive values for all $W_1 > W_2$. This is determined by analyzing the values of each component of the function. The values of β and δ represent output elasticities and thus, are assumed to be positive. These values are summed and multiplied by P_t, which represents price level which must be positive. These values are further multiplied by the sum of α and 1 squared. Since α is the ratio between two populations of workers, it too must be positive. While this product is in the denominator, the value does not change. Therefore, since $\frac{1}{(\beta+\delta)P_t(\alpha+1)^2} > 0$, the value of $\frac{dy_t^*}{d\alpha}$ depends solely on W_1 and W_2.

So, if the wages paid to remote workers is higher than the wages paid to non-remote workers, then changes in productivity will be positive. This positive value indicates that as the number of remote workers increases, relative to non-remote workers, productivity will also increase. Conversely, if the number of remote workers decrease, relative to non-remote workers, productivity will also decrease. This positive relation between productivity and remote work falls in line with the findings from Bloom et al.'s empirical analysis (2022).

These results are consistent with the efficiency wage theory. Essentially, this theory states that firms are willing to pay individuals higher wages to retain workers and will make them less likely not to work (Shapiro and Stiglitz, 1984). If workers are paid more, then they are motivated to work harder to maintain their jobs. Thus, as proven in this paper, higher wages paid to workers are positively associated with productivity. The theory further acknowledges that with higher wages paid to workers, there is less of a need to closely monitor workers (Shapiro and Stiglitz, 1984). When employees work remotely, there is inherently less supervision. By paying remote workers higher wages, firms can ensure that their employees are worker harder than they would if they were paid less.

These findings only hold true if W_1 is in fact greater than W_2. Since the onset of the pandemic, highly educated and high-income workers were more likely to maintain their job and to work remotely (Bick et al., 2020 & Dingel and Neiman, 2020). Thus, it is likely those remote workers categorized by L_{1t} earn wages higher than non-remote workers categorized by L_{2t}. In other words, it is likely that $W_1 > W_2$.

If $W_1 < W_2$ then the value of $\frac{dy_t^*}{d\alpha}$ takes on negative values. This means that if non-remote workers are paid higher wages than remote workers, productivity would decrease. If remote workers are typically more highly educated than non-remote workers, then they may become discouraged from working their lower paying jobs. Rather, they would be incentivized to leave their current role in remote work and take an in-person job to be paid higher wages, all else equal. In doing so, the productivity of the firm would be negatively impacted.

5. Conclusion

In this study I find that hiring more remote workers will lead to higher firm productivity. Conversely, the study also finds that hiring more remote workers will lead productivity to decline instead. However, a study by Bick et al.

(2020) found that higher paid workers are more likely to work remotely. Thus, it is plausible to conclude that it is likely for remote wages to be higher than non-remote wages.

This paper contributes to prior literature in its theoretical nature. Previous studies, such as those by Felstead and Rueschke (2020), Kitagawa et al. (2021), Morikawa (2020), and Hipp and Bünning (2020), all take an empirical approach to observing productivity levels during the pandemic. A study by Zhang et al. (2020) used both a theoretical and empirical approach to observe when firms select to WFH. While they used theory, the results focused on whether employers choose WFH or work in an office setting as opposed to how differing wages influence productivity.

The findings of this study have important implications for firms. We prove that if firms pay wages to remote workers that are higher than those paid to non-remote workers, then productivity will increase. Thus, if firms are aware of these results, they can offer higher wages to employees to work from home. In doing so, they incentivize workers to work harder while unsupervised to maintain their job. This is consistent with the efficiency wage theory that paying higher wages increases the opportunity cost of to not working (Bowles, 1981 and Eaton and White, 1982).

6. References

Bick, A., Blandin, A., & Mertens, K. (2020). Work from Home After the COVID-19 Outbreak. *Federal Reserve Bank of Dallas, Working Papers*, *2020*(2017). https://doi.org/10.24149/wp2017r1

Bloom, N., Han, R., & Liang, J. (2022, July). How hybrid working from Home Works Out. *NBER Working Paper Series,* (30292). doi:10.3386/w30292

Bowles, S (1981). Technical change and the profit rate: A simple proof of the Okishio theorem. Cambridge Journal of Economics, 5(2), 183–186.

Bullard, J. (2021, December 09). Long-run GDP growth requires higher productivity growth: St. Louis Fed. Retrieved December 7, 2022, from https://www.stlouisfed.org/publications/regional-economist/october-2016/higher-gdp-growth-in-the-long-run-requires-higher-productivity-growth

Center for Disease Control and Prevention. (2022, August 16). CDC Museum Covid-19 Timeline. Retrieved December 8, 2022, from https://www.cdc.gov/museum/timeline/covid19.html

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home?. Journal of Public Economics, 189, 104235.

Eaton, CB and W White (1982). Agent compensation and the limits of bonding. Economic Inquiry, 20(3), 330–343.

Felstead Alan & Reuschke Darja. (2020, August). Homeworking in the UK: before and during the 2020 lockdown. WISERD Report, Cardiff: Wales Institute of Social and Economic Research, https://wiserd.ac.uk/ publications/homeworking-uk-and-during-2020-lockdown.

Hipp, Lena, and Mareike Bünning. “Parenthood as a Driver of Increased Gender Inequality during Covid-19? Exploratory Evidence from Germany.” European Societies 23, no. sup1 (2020). https://doi.org/10.1080/14616696.2020.1833229.

Kitagawa, Ritsu, et al. “Working from Home and Productivity under the COVID-19 Pandemic: Using Survey Data of Four Manufacturing Firms.” PLOS ONE, vol. 16, no. 12, 2021, https://doi.org/10.1371/journal.pone.0261761.

Mongey, Simon, et al. (2021). Which Workers Bear the Burden of Social Distancing? The Journal of Economic Inequality, vol. 19, no. 3, pp. 509–526., https://doi.org/10.1007/s10888-021-09487-6.

Morikawa, M. (2020). Productivity of Working from Home during the COVID-19 Pandemic: Evidence from an Employee Survey. *RIETI Discussion Paper,* 20(E).

Shapiro C and JE Stiglitz (1984) Equilibrium unemployment as a worker discipline device. The American Economic Review, 74(3), 433–444.

U.S. Census Bureau. (2022, September 15). The Number of People Primarily Working From Home Tripled Between 2019 and 2021. Retrieved April 16, 2023, from Census.gov website: https://www.census.gov/newsroom/press-releases/2022/people-working-from-home.html.

U.S. Bureau of Labor Statistics. (2020, June 24). What is Productivity? : U.S. Bureau of Labor Statistics. Retrieved from Bls.gov website: https://www.bls.gov/k12/productivity-101/content/what-is-productivity/home.htm#:~:text=Productivity%20is%20a%20measure%20of

Zhang, T., Gerlowski, D., & Acs, Z. (2021). Working from home: small business performance and the COVID-19 pandemic. *Small Business Economics*, *58*(2). https://doi.org/10.1007/s11187-021-00493-6

7. Appendix

The below equation is reached after substituting L_{2t} into Equation 3 in section 1.3.

$$max\Pi_t = P_t A_t \alpha^{\beta} L_{2t}^{\beta+\delta} - L_{2t}(\alpha W_1 + W_2)$$

From here, the first order condition is derived with respect to L_{2t} below. This equation is then used in section 1.3 to solve for L_{2t}^{*}.

$$\frac{d\Pi_t}{dL_{2t}} = (\beta+\delta) P_t A_t \alpha^{\beta} L_{2t}^{\beta+\delta-1} - (\alpha W_1 + W_2) = 0$$

Below shows the steps to get from Equation 7 to 8. Here, Y_t is divided by L_t which is rewritten as a function of L_{2t} and α.

$$L_t = \alpha L_{2t} + L_{2t}$$

$$L_t = L_{2t}(\alpha + 1)$$

$$L_t = \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}} (\alpha + 1)$$

$$y_t^{*} = \frac{A_t \alpha^{\beta} \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}\beta+\delta}}{\left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}} (\alpha+1)}$$

$$y_t^{*} = \frac{A_t \alpha^{\beta} \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)^{\frac{1}{\beta+\delta-1}\beta+\delta-1}}{(\alpha+1)}$$

$$y_t^{*} = \frac{A_t \alpha^{\beta} \left(\frac{\alpha W_1 + W_2}{(\beta+\delta) P_t A_t \alpha^{\beta}}\right)}{(\alpha+1)}$$

Below we walk through the steps to reach Equation 9. To do so, the derivative of the productivity equation (8) is taken with respect to α to show how a changing ratio of remote to non-remote workers will impact productivity.

$$\frac{dy_t^*}{d\alpha} = \frac{1}{\alpha+1}\left(\frac{W_1}{(\beta+\delta)P_t}\right) + \frac{\alpha W_1 + W_2}{(\beta+\delta)P_t}\left(\frac{-1}{(\alpha+1)^2}\right)$$

$$\frac{dy_t^*}{d\alpha} = \frac{W_1}{(\beta+\delta)P_t}\left(\frac{-\alpha}{(\alpha+1)^2} + \frac{1}{\alpha+1}\right) - \frac{W_2}{(\beta+\delta)P_t(\alpha+1)^2}$$

$$\frac{dy_t^*}{d\alpha} = \frac{W_1}{(\beta+\delta)P_t}\left(\frac{1}{(\alpha+1)^2}\right) - \frac{W_2}{(\beta+\delta)P_t(\alpha+1)^2}$$

Educational Attainment: An Analysis of Teenage Parenthood and Dropout Prevention Programs

Megan McCook ‘23
Senior Honors Thesis

This paper explores how teenage parenthood affects students’ high school education attainment, and evaluates the effectiveness of dropout prevention programs that offer on-site childcare. I use data from the High School Longitudinal Study (2009), collected by the National Center for Educational Statistics through the US Department of Education. These data combine survey responses from students, their parents, and school staff. Using school fixed effects and instrumental variable estimation I evaluate the impact of teenage parenthood on the probability of dropout. Female students with a child have, on average, 13.8 percentage points higher likelihood of dropping out of high school. The increased probability is offset by the existence of a dropout prevention that provides childcare. Among female students with children, attending a school with a dropout prevention program that provides childcare is associated with a 28.0 percentage point lower probability of dropping out of high school.

JEL Classification: 121, I24, J13

Introduction

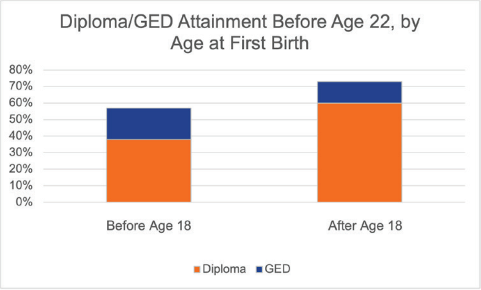
In 2015, the US The Centers for Disease Control and Prevention reports 232,000 teenage births to teenage mothers. Roughly half of teenage mothers continue their education and go on to earn their high school diploma. In comparison, around ninety percent of non-teenage mothers will receive their high school diploma. Dropout prevention programs that offer childcare may be valuable to teenage parents because these students may not have family members or friends available to watch their child during the school day. The programs complement the decision for students to remain in the classroom to complete their high school education which, in turn, makes the opportunity to continue into higher education more accessible.

In this paper, I investigate the effectiveness of dropout prevention programs for high school students, a potential mediating factor that could decrease the likelihood a student drops out of high school and one that is not highly focused on with the empirical literature. I use the High School Longitudinal Study (2009) from the National Center for Education Statistics to empirically analyze the effects being a teenage parent has on the likelihood of dropping out of high school. I implement school fixed effects to account for unobserved differences across schools that may be correlated with both students, dropout risk and presence of dropout prevention programs, with a specific focus on dropout prevention programs that provide childcare services to students. I hypothesize that having a child while in high school increases the probability of the student dropping out. Furthermore, I hypothesize that the effect may be minimized if there is a dropout prevention program that offers childcare to students who are teenage parents.

Arguably the most impactful policy to change the educational experiences for women is Title IX. As part of the 1972 amendment to the Civil Rights Act, Title IX first prevented schools that receive federal funding from excluding pregnant teenagers from the classroom(Guldi, 2016). This policy led to further program and policy improvements because the presence and experiences of pregnant students in the classroom highlighted educational policies that made continuing education inaccessible to teenage parents. For example, pregnancy is often associated with hyperemesis gravidarum, more commonly known as morning sickness. Hyperemesis gravidarum or other medical experiences that go along with pregnancy may make it difficult for students to be present to school on time or may require them to leave the classroom at various points, making their attendance different from peers (SmithBattle, 2007). Schools also realized the need to adjust their attendance policy for teenage parents who needed to attend prenatal medical appointments during school hours. To further understand the effects of Title IX, Guldi (2016) compares the trends of female high school dropout rates from 1970 to 1980 which captures a period of time before the policy and then a few years after for the effects of its implementation to be observed. Guldi notes the lack of data that exists and is accessible regarding the topic of teenage mothers prior to the time around Title IX. By signing the Title IX legislation, education became more accessible as a quasi-public good (Macchia et al., 2021). The opportunity cost of education therefore decreased, resulting in higher investment in education. These changes were present for all women, but most notably for black teenage others (Guldi, 2016).

A successful transition into parenthood is dependent on both support and maturity (Assini-Meytin, Garza & Green, 2022). Pregnancies may be planned or unplanned, and different attitudes towards the pregnancies based on if they were wanted, unwanted or mistimed (National

Center for Health Statistics). "American Sexual Behavior" reports that older teens, ages 17 to 19, would be more upset if they were to get pregnant. This is possibly due to how older teenage girls may have more viable education or career goal paths than younger girls, ages 15 to 16. Therefore the pregnancy could put more of a barrier on the plans of the older girls because they are closer to either completing high school or beginning college careers. Graph A: Diploma/GED Attainment Before Age 22, by Age at First Birth illustrates the differences in high school and GED completion for young parents. The National Longitudinal Study of Youth - 1997 Cohort reports the trends of diploma or GED compilation. Before age 18 is the time-frame in which a student would still be in high school but having a child before 18 is associated with less high school diplomas and GEDs in comparison to older than age 18. Only 57% of female students who had a child before the age of 18 received a high school diploma or GED. 73% of the students who had their first child between ages 18 and 19 received their GED or high school diploma. 60.2 percent of teenage girls, ages 15 to 17, from the National Center for Health Statistics, said that they would feel 'very upset' if they were to get pregnant in 2002. The majority of the surveyed students would be upset if they were to get pregnant, but there are around five-percent who said that they would be pleased about a pregnancy.



Graph A: Adapted from Child Trend' analyses of data from the National Longitudinal Study of Youth - 1997 Cohort

In their longitudinal study, Assini-Meytin, Garza and Green find that the socioeconomic future of a teenage mother is partially dependent on the degree of their adult identity. Ages 18 and 19 are near the end of the students' high school years and may possibly make it more accessible to receive a diploma or GED, and these students may have more associations with their adult identity (Assini-Meytin, Garza & Green, 2022). Assini-Meytin, Garza and Green (2022) also contribute to the literature on teenage parenthood by finding that a teenage mother's ability to continue their education relates to if they have personal support from their family, but this is not statistically significant to their socioeconomic future. However, it may be theorized that there are in fact signals from a teenage mother's education level to her socioeconomic status' future, which has been a strong focus of the prior literature on teenage parenthood (Fletcher and Wolfe, 2009).

Hendrick and Maslowsky (2019) use a multiple-group path model approach and create conceptual models for which a mother's education level indicates her child's risk for teenage childbearing. It is hypothesized that the lower the education level, the higher the risk for the child to experience teenage childbearing. It is then the case that if a child's parent was a teenager during the pregnancy, then the risk for their teenage childbearing is increased. This cycle is often continuous due to different resources and attitudes that are passed between the generations. As found in epidemiology studies, childbirth during teenage years is associated with higher risk of poor health for the mother and child (Paranjothy, Broughton & Adappa). Therefore, it may not be possible for the mother to return to continue her high school education during the time of the pregnancy or to return after the birth. Poor health results in costly medical bills, making pursuing a secondary education less likely as well due to the socioeconomic stress.

The Personal Responsibility and Work Opportunity Reconciliation Act did not reduce the risk or the rate of school dropout rates (Hao & Cherlin, 2004). Understanding why the welfare reform did not decrease school dropout rates is challenging to study because there are many social connotations and perspectives associated with teenage pregnancy that cannot fully be isolated from the policy change. As included in Levine and Painter's (2003) research, President Bill Clinton argued, "Our most serious social problem is the epidemic of teen pregnancies and births where there is no marriage," and this created a national, social standard that teenage pregnancies were some sort of disease that were ruining society. The Personal Responsibility and Work Opportunity Reconciliation Act itself uses language that alludes to negative consequences. By the establishment of the policy, there is the implication that non-marital, teenage pregnancies are going to the futures for the teenage parents in the hope that there will be changes in the attitudes and perspectives around sexual activity and contraceptive usage (Hao & Cherlin, 2004).

In order to measure the differences between mothers and teenage mothers, whether or not a woman experiences a miscarriage has been used as an instrumental variable. However, it is argued that miscarriages are not random among pregnant women, but rather there are environmental factors that are associated with varying rates of miscarriages (Fletcher & Wolfe, 2009). Another incomplete part of the prior literature is that the focus of social, educational and economic changes are on the mother of the child and incoherently addresses the father's position. As mentioned, it is assumed that the mother's priorities will change after their pregnancy and birth, and they will be the dominant provider for the child, but the engagement of their partner is not often included in the conclusions on the subject.

The time frame in which studies are conducted and the privacy of students are two further reasons why prior literature has struggled with researching teenage pregnancy. In an attempt to address the qualitative elements that play a role in the experience of teenage pregnancy, SmithBattle (2007) utilizes interviews over six different points during the pregnancy to create profiles of the families and take field notes during the longitudinal study. However participants in the study were dependent on whether there was a parent or guardian that would agree to the teenager's participation, as it is the case that consent is necessary due to the age of the sample. This signals that the subject pool for research regarding teenage pregnancies is restricted. Following teenage mothers ten months after their pregnancy to learn about their thoughts and feelings also only provides the researcher with ten months of postpartum information (SmithBattle, 2007). It may be the case that the prior literature that does a snapshot analysis of socioeconomic status or educational degree is incomplete in a short time frame after the pregnancy because life outcomes may change later on. This paper plans to contribute to these shortcomings by using longitudinal data to capture these changes.

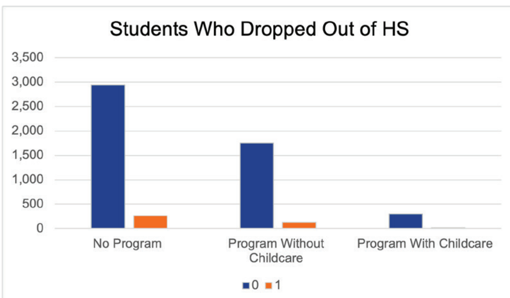
Empirical Approach

Data and Data Sources

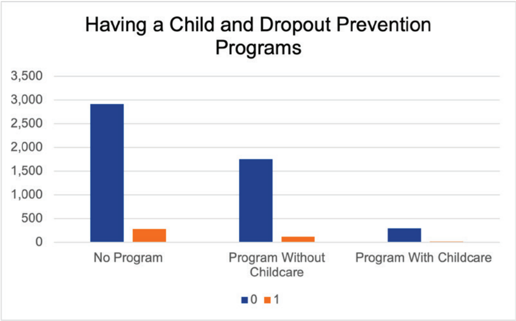
This paper uses the panel dataset from the High School Longitudinal Study of 2009. The study was conducted through the National Center for Education Statistics in the U.S. Department of Education's Institute for Education Sciences with over 23,000 respondents. The sample population of respondents were Freshman students in both private and public schools in the United States in the Fall of 2009. Their information was collected through computerized web-questionnaire surveys. The students' parents, school counselors, mathematics and science teachers and administrators also completed surveys. For the student, the 2009 base year questionnaire included questions to collect information such as demographics, school attitudes, plans for high school, future educational expectations and potential career goals. Parents, teachers, and administrators completed sections as well, discussing household composites, highest degree of education completed, income, and school climate and policies. A first follow-up was done in 2012, a second in 2016, and then high school transcripts collected from 2013-2014 and any postsecondary transcripts collected in 2017-2018. Follow-up years of the study includes similar identifying characteristic questions, as well as expansions such as extracurriculars, employment, and updated plans for future college choices.

Appendix A illustrates the portions of the survey questionnaires with the selected and participation rates for each section. In the base year, there were 944 selected school respondents and 21,444 completed student questionnaires. Participants were able to skip questions or sections of the survey. Science and mathematics assessments were also taken during the survey to evaluate the students' performances within the curriculum they are taught. Teachers, counselors and administrators reported school characteristics for knowledge of the curriculum. Appendix B provides a portion of the discousled information about the schools that were of interest in the study, as well as those that took part. To account for variation within the sample selection survey, schools of different private and public statuses, locales, and regions were included in the study. The majority school type that responded to the survey were public schools. The majority of schools were in a Suburban locale. The region with the highest participation was the South. Specific state responses are not accessible through the public use-data.

The paper looks to explore the effects of teenage parenthood on dropout status for high school students. I first generate a dummy variable indicating the dropout status of each student based on the status of the student in the fourth wave, collected in February 2016. The *Dropout* variable is coded with a 1 if the student did not receive a High School credential, in comparison to students who did receive a high school diploma, Generalized Development Test (GED), or some other certificate completion. This paper chooses to focus mostly on the effects of teenage parenthood of female students. The *Female* variable indicates if a student is female or non-female. I generate *HasChildHS* to determine if a student was or was not a parent in their high school years. The variable indicates if the date of birth for their child was earlier than the date of their fourth wave high school completion date. Prior to any sample restriction, there are



Graph 1: Students Who Dropped Out of High School. Data taken from the National Center for Education Statistics. The left bars (0) indicate that a student did not dropout of high school. The right bars (1) indicate that a student did dropout of high school. There are 13 students who dropped out of high school in a school with a dropout prevention program that provided childcare services.



Graph 2: Having a Child and Dropout Prevention Programs. Data taken from the National Center for Education Statistics. The left bars (0) indicate that a student did not have a child during their high school years. The right bars (1) indicate that a student did have a child during their high school years. There are 19 students who had a child in high school and attended a school with a dropout prevention program that provided childcare services.

497 students whose first child was born before they completed high school or dated their dropout status. I first distinguish between schools that have some existent dropout program and those who do not have a dropout prevention program in order to evaluate the programs' effects on dropout rates. I then generate the variable *DOPP* for schools that do have an existent dropout prevention program. I use *DOPP* to specify the difference between schools that have a dropout prevention with childcare and schools that have a childcare program without childcare.

Table 1: Summary Statistics:

Has Child HS	425
Underrepresented Minority	2,256
Math Scores	Mean: 48.03 Min: 24.40 Max: 82.19
Behavior	334
Expects to Dropout	30
Sibling in College	1,924

Sibling Dropped Out	221
Young Mom	443
No Dad	1,100
Religion	2,406
Act Out	124
DOPP No Childcare	3,262
DOPP Has Childcare	2,129
Family Income Min: >$15,000 and <= $35,000 Max: >$235,000	 1,311 11

Source: National Center for Education Statistics, 2009 High School Longitudinal Study. DOPP No Childcare, DOPP Childcare, Has Child HS, Family Income, Behavior, Young Mom and URM are out recorded from 5,391 observations. Others are recorded through the parent responses. Parent responses contain less observations. Expects to Dropout, Siblings in College, Siblings Dropout, Actout, Religion, No Dad are recorded from 5,313 observations.

Graph 1: Students Who Dropped Out of High School depicts the relationship between the types of dropout prevention programs that existed for students who dropped out of high school. The most common program in the surveyed schools is actually the existence of no program at all. There are almost 300 students from the survey who dropped out of high school where there is no existent program. Around 125 students dropped out of high school where there is an existent program, but it was one that did not provide childcare. There are 13 students who dropped out of a school where there are childcare services with the dropout prevention program.

Graph 2: Having a Child and Dropout Prevention Programs then depicts the relationship between students who do or do not have a child and the school's status with a dropout prevention program. 281 students who have a child attend a school where there is no existing dropout prevention program. Around 1,750 students who do not have a child attend a school where there is a dropout program, but does not provide childcare services. Finally, only 19 students who have a child attend a school where there is a dropout program that provides childcare services. These summary statistics allude to the limited number of schools that have childcare services in their dropout prevention programs, despite teenage parenthood being acknowledged as a significant reason why students dropout of high school and do not complete their diploma or GED (CDC).

The other covariates in the model are *Under Represented Minority*, which indicates a student from a historically underrepresented group, *ExpectDropout*, indicating if a student does not believe they will complete high school, as well as *SiblingCollege* and *SiblingDropout* to indicate and trends that may be an influence within a family. I also include *Income* as a representation of socioeconomic status in 2008. The variable is based on ranges through $20,000 integers and ranges between less than or equal to $15,000 and greater than $235,000. The *ActOut* variable is a report from the parent regarding the students' behavioral issues. One issue with the variable is that it is limited in observations. There are 124 parents who reported that their child has a lot of difficulty with their behavioral issues, but there were 1,250 missing responses with parents who did not respond. Parents not responding to the survey are a limitation to a full understanding of the data due to the limited observations. To account for the limited observations, we generate a variable indicating if the parent did not respond to the questions asked. We then use this variable in the process of generating the binary variables such as *ActOut*, so that 0 includes parents who do not have a lot of difficulty with their child's behavior, and parents who did not respond. Therefore we are able to correct a potential issue of limited observations.

I use the following candidate instrumental variables for instrumental variable estimation: the age of the student's mother, the presence of a father figure in the student's household, religious activity, and the parent's evaluation of their student's behavior. I generate *YoungMom* from the dataset's variables indicating the students' parents' birth years, and restrict it to biological mother. I compare the students' date of birth with the mothers' date of birth and define a young mother up until the age of twenty-two. I use twenty-two as the definition of young mom in order to account for variation between young mom and teenage parent, and because of precedents done in generational risk research (Hendrick and Maslowsky, 2019). I use the binary variable, *NoDad*, that is an indicator of whether there was some sort of father figure in the household during the student's youth years. *Religion* indicates if the student takes part in any religious organization. Finally, I record any behavioral issues through reports done by the parents in which they indicate if they have been contacted by the school three or more times regarding the student's behavior.

Econometric Model

In this paper, I utilize a linear regression model, fixed effects model, and instrumental variable estimation model (IV) to model the effects of teenage parenthood on the probability of dropping out of high school. I begin by running probit regression to ensure there is no strong presence of reverse causality between having a child and childcare services as part of a dropout prevention program. In this model I use *childcare*, the existence or non-existence of a childcare program, as the dependent variable, and *HasChildHS* as the independent variable, along with the model's covariates. I find that having childcare services as part of a school's dropout prevention program does not predict teenage parenthood.

I then first run a linear regression with a variance-covariance matrix of the estimators standard errors. I estimate the model:

$$\begin{gathered} DroppedOut_i = \beta_0 + \beta_1\text{Female} + \beta_2\text{UnderrepresentedMinority} + \beta_3\text{Female x UnderrepresentedMinority} + \\ \beta_4\text{Female x HadChildHS} + \beta_5\text{Female x HadChildHS x DropoutPreventionProgram} + \beta_6\text{MathTest} + \\ \beta_7\text{Behavior} + \beta_8\text{ExpectedDropout} + \beta_9\text{Income} + \beta_{10}\text{SiblingInCollege} + \beta_{11}\text{SiblingDroppedOut} + \varepsilon_i \end{gathered}$$

where epsilon serves as the error term for any unobservable characteristics. I interact *Female* and *Underrepresented Minority* to measure any additional impacts that may exist for the historically underrepresented groups. The interaction between *Female* and *HasChildHS* is included to measure the effects that having a child has on female students in comparison to female students who do not have children. It is also a way to measure the dropout comparisons between female and non-female students who both have children. The last interaction term between *Female*, *HasChildHS*, and *DropoutPreventionProgram* is a measurement of the mediating effects of dropout prevention programs. Through this interaction term, we are able to see the different dropout outcomes for female and non-female students, students who do and do not have a child during high school, and for those students who attend a school with a dropout prevention program with child and students who attend a school with a dropout prevention program without childcare.

I then implement fixed effects by using a School Identification variable. The inclusion of fixed effects eliminate bias for any of the differences that may exist across the schools themselves that are unobservable in the data. Due to data restrictions, these unobservables may include school population, unemployment rates in the community, or other support programs that may already exist but are not noted in the data. There are more schools than the 1,151 schools that took part in the survey but also many differing characteristics between the 1,151 schools. Fixed effects therefore eliminates bias in analysis for any of the unobservable characteristics for the schools. The model is restricted to schools in which there was at least one teenage parent at the school during the time of the longitudinal survey. The fixed effects model therefore includes 307 clusters in the school identifications in the sample.

I next use instrumental variable estimation with four candidate instrumental variables: the age of the student's mother, the presence of a father figure in the student's household, religious activity, and the parent's evaluation of their student's behavior. For the instrumental variable estimation, I use a limited information maximum likelihood model. Limited information maximum likelihood (LIML) is a justified approach because it has a median that is closer to its beta estimator than the mean or median of a two-stage least squares regression analysis, and is better suited to reduce bias when using potentially weaker instruments (Stock, Wright, Yogo, 2002).

Results

The regression results are presented in Table 2. Consistent between the Control, Fixed Effects and LIML IV estimation, being female decreases the likelihood that a student drops out of high school. For the fixed effects model with limited information maximum likelihood estimation, being female is associated with a 6.9683 percentage point decrease for the likelihood of dropping out of high school. For the fixed effects model without LIML, being female is associated with a 3.33 percentage point decrease in the likelihood of dropping out of high school. In the same model, being female and having a child in high school is associated with a 13.206 percentage point increase of dropping out of high school. Dropping out of high school is more likely for female students with children than female students who do not have children. Similarly, a non-female student also experiences an increase in the likelihood of dropping out of high school by 13.765 percentage points.

The results in Table 3 evaluates the dropout likelihood for effects being female and non-female students, students who do and do not have a child during high school, and for those students who attend a school with a dropout prevention program with child and students who attend a school with a dropout prevention program without childcare. There is no significant relationship on the likelihood of dropout in the fixed effects model for a female student who has a child but does not attend a school with a dropout prevention program that provides childcare services. In contrast, a female student who has a child and attends a school that provides childcare services within its dropout prevention program experiences a decrease in the likelihood that they dropout of high school by 28.028 percentage points. For the LIML model, there are statistically significant impacts of dropout prevention programs when interacted with the student characteristics. The existence of the dropout prevention programs with childcare or without childcare are not statistically significant on their own. There was no significant impact experienced by non-female students who had a child and attended a school with childcare services within its dropout prevention program for the prior models. In LIML, being non-female, having a child and having childcare services at the school is associated with a 92.066 percentage point decrease in the likelihood that the student drops out of high school. A female student who also has a child and attends a school with a dropout prevention program with

Table 2: Results	(1) Pooled	(2) School Fixed Effects	(3) IV Estimation - LIML
Female	-0.0327835** (.015244)	-0.0333031** (0.0155395)	-.0696833** (.0270837)
URM	.0463561** (.0199142)	.0225435 (.0191796)	-.0083463 (.0142919)
Female x URM	-.044421* (.0253012)	-.0381352 (.0265475)	-.0577059*** (.0272403)
Female x Has Child HS			
Non-female, Has Child	.1360834* (.0743247)	.1375608* (.0774943)	
Female, Has Child	.1414372*** (.0499351)	.1320552*** (.0502512)	
Math Scores	-.0442253*** (.0006929)	-.0039958*** (.0007618)	-.0010102 (.0012218)
No Behavior Issues Reported	.0467605 (.0319638)	.0317198 (.0319637)	-.0030723 (.0363688)
Behavior Issues Reported	.0495467*** (.0168773)	.0375694** (.0187102)	.012521 (.0191893)
Expects to Dropout	-.0191414 (.0565824)	-.0699583 (.0765859)	.0437649 (.080504)
Income	-.00144 (.0017405)	-.0006335 (.0019763)	.0034669 (.0026893)
Sibling in College	-.0401082*** (.0122387)	-.0333483*** .(0127651)	-.0078107 (.0113212)
Sibling Dropped Out	.0646678** (.0282266)	.0597406** (.0294153)	-.0101837 (.0994689)
DOPP No Childcare			.013721 (.0432379)
DOPP Has Childcare			.0090093 (.0914196)
Has Child HS			1.073789** (.4342421)
School Fixed Effects	No	Yes	Yes

* p<.1 , **p<.05 , ***p<.01

Results from model predicting the probability of dropping out of high school. Standard errors robust to arbitrary heteroskedasticity and clustering on school presented in parenthesis below each coefficient estimate.

childcare services experiences a 93.752 percentage point decrease in the likelihood of dropping out of high school. This result offsets the impacts experienced for females in the pooled model, where being female and having a child is associated with a 14.144 percentage point increase of dropping out of high school. It is therefore possible that the presence of the dropout prevention program with childcare services is a mediating factor for the students with children in their opportunities to continue their high school education.

Table 3: Regression Results of Female or Non-Female, Has Child or No Child, and DOPP with Child or DOPP no Childcare

nale x Has Child x Dropout Prevention Program	Control Models	F.E. Model	F.E. with LIML
Non-Female, No Child, DOPP no Childcare	-.0373359*	-.0607343*	
	.(021547)**	(.0327876)	
Non-Female, No Child, DOPP Has Childcare	-.0630563	-.1917872**	
	(.0283725)	(.0803347)	
Non-Female, Has Child, DOPP no Childcare	.1793412	.1476083	
	(.1441964)	(.1451938)	
Non-Female, Has Child, DOPP Has Childcare	.0306746	-.038588	-.9206597**
	(.20124)	(.236259)	(.4690968)
Female, No Child, DOPP no Childcare	.0052563	-.0199211	
	(.0166273)	(.0339844)	
Female, No Child, DOPP Has Childcare	-.0387667***	-.1556686**	
	(.0143898)	(.0740052)	
Female, Has Child, DOPP no Childcare	.0083763	-.0101029	
	(.0813857)	(.0791141)	
Female, Has Child, DOPP Has Childcare	-.1500923**	-.280283***	-.9375241**
	(.0699445)	(.0978951)	(.4310733)

* p<.1 , **p<.05 , ***p<.01

Academic success of students may also play a role in their decision to complete or not to complete high school. Education is an investment that some may or may not be interested in pursuing, also relating to why some students may choose to drop out of high school. Fairly consistent and statistically significant from the results in Table 2, an increase in the average Math Score is associated with a decrease in the likelihood that a student drops out of high school. In the school fixed effects model, improvements in the mean Math Score is associated with a 3.996 percentage point decrease in their likelihood of dropping out. For the control and fixed effects models, there is a statistically significant relationship between their sibling's high school and college status and the student's high school completion. A student who has a sibling in college experiences a 3.335 percentage point decrease in the likelihood they drop out of high school in the fixed effects model. However a student who has a sibling who also dropped out and did not receive some sort of high school credential experiences a 5.974 percentage point increase in the likelihood that they do drop out of high school.

Discussion

In this paper I utilized econometric analysis to evaluate the effects that dropout prevention programs with childcare could have on receiving a high school diploma for teenage parents. The results are consistent with the paper's hypothesis and research question, finding that the presence of a dropout prevention program with childcare services decreases the likelihood that a female student with a child drops out of high school. In this analysis, there were also positive effects on students not dropping out of high school when in the presence of a school with a dropout prevention program with childcare services, despite themselves not being parents, such as non-female students who do not have a child but attend a school with childcare services. Restricted data regarding the school's identification may be able to compare the different dropout prevention programs that exist in the schools. It may be the case that a school has another dropout prevention program in addition to one that provides childcare services. The presence of another program may have spillover effects that are observed in this analysis for non-female students without children. More focused case-studies may be helpful in understanding the specific effects that different dropout prevention programs are evoking.

This paper finds that female students with children are more likely to drop out of high school when having a child than non-female students with children. This alludes to issues in the educational system that prohibit the success of female students who are having a child during their high school years because their needs are different than non-female students. Female students may need to leave classes due to morning sickness, appointments with doctors, or for similar maternity leave protocols, increasing their time away from the classroom. For many, this may seem like the end to their education if the school is not able to accommodate their specific needs. Therefore policies that address issues such as different attendance policies for pregnant students are necessary to best accommodate these students in their continued education. These policies fall within a well-rounded family planning approach. Access to family planning in its different forms shape expectations about individual's futures, such as planning into the future with academic or career plans (Jones & Pineda-Torres, 2021).

Academic investment and perception are also valuable for teenage parents. Higher Math Scores are associated with decreases in the probability that a student will drop out of high school. The coefficient was statistically significant until the limited information maximum likelihood model, but maintained its negative value. Students who invest themselves academically are more likely to complete an education, especially a high school diploma. In the case of teenage parents, a female student who becomes pregnant and does not see themselves as a high academic achiever, may choose to not continue their education because they do not see much value or meaning from a diploma or GED (Guidli, 2016). This decision may be different for a female student who becomes pregnant but is a high academic achiever; they may feel more confident in the abilities to continue their education. This type of student may already have academic or career goals and may find themselves more motivated to work towards their diploma or GED while being pregnant, in comparison to students who do not see education as a valuable investment. Therefore implementation of policies such as female STEM programs or other academic motivations may be able to assist pregnant teenage females as an aid to understanding the value of education.

None of the models indicate statistical significance for the family's income. The prior literature has paid most attention to the socioeconomic outcome of the teenage parent later in their lives and has found that being or not being a teenage parent based on education level is a good predictor for future socioeconomic outcomes (Fletcher and Wolfe, 2009). This paper finds that income is not a statistical predictor of having a child in high school for female students, but still leaves the possibility that it is a predictor of future income through the means of educational attainment. Individuals with lower family incomes are historically less likely to go to college than those of higher income (U.S. Department of Commerce). Therefore there may be a multiplier effect present for children of teenage parents because they are predicted to be of lower socioeconomic status, and they themselves are more likely to be teenage parents, limiting the access and likelihood of a college education.

The relationship a student's sibling has with their academics may also play a role in their individual experiences. Both sibling relationships with either high school or college are statistically significant before instrumental variable implementation. Students who have siblings in college experience a decrease in their likelihood that they will drop out of high school. Students who have siblings who dropped out of high school experience an increase in their likelihood of also dropping out of high school. The data does not specify if the student surveyed was an older or young sibling. Therefore it cannot be concluded that a student will follow the steps of their sibling since we do not know who would either dropout or graduate first, but there is a strong relationship between students, their sibling, and their high school degree completion.

High school education is a public good that may begin to seem unattainable for female students who have children during their high school years. The cost of childcare would be more for what most high school students would be making from income in their early years of work. If students do not have support from family, friends, or their school, they could not have the means to pay for childcare services while also attending school. The cost of education therefore rises, leading to female students with children to increase their likelihood of dropping out. If schools provided resources such as childcare services in their school as part of their dropout prevention program, the cost of the parent's education would not be as high as it was when they had to pay for these services on their own. Therefore to keep the cost of education low and high school diplomas or GED accessible, schools can implement programs with these childcare services.

The results find that female students have a negative relationship with the likelihood of dropping out, unless they have a child during high school. Their likelihood of dropping out of high school then increases. Non-female students who have children also experience similar increases in the likelihood of dropping out but the relationship is less statistically significant in comparison to female students. However, female students who have a child and attend a school with a dropout prevention program with childcare services experience a decrease in their likelihood of dropping out of high school. This alludes to the medicating effects dropout prevention programs with childcare services have on female students who have a child during their high school years. The dropout prevention program with childcare services assists in offsetting the negative effects having a child has on female students' academic attainment. This paper therefore contributes to the literature in its analysis of the positive educational attainment effects teenage parents receive from childcare services in a dropout prevention program. Further studies that can expand the literature in educational attainment may focus on evaluating the effectiveness of the variety of dropout prevention programs that exist in the United States, and how further policy may be implemented to make those that report positive results more accessible.

Thank you Professor Blume-Kohout and Professor Nyiwul for their guidance and support in the completion of this paper.

Works Referenced:

American Sexual Behavior : Demographics of Sexual Activity, Fertility, and Childbearing. Ithaca, N.Y: New Strategist Publications, 2006.

Assini-Meytin, Garza, M. A., & Green, K. M. (2022). Teen Mothers' Family Support and Adult Identity in the Emerging Adulthood: Implications for Socioeconomic Attainment Later in Life. *Emerging Adulthood (Thousand Oaks, CA)*, *10*(1), 161–172. https://doi.org/10.1177/2167696819879251

Fletcher, & Wolfe, B. L. (2009). Education and labor market consequences of teenage childbearing: Evidence using the timing of pregnancy outcomes and community fixed effects. *The Journal of Human Resources*, *44*(2), 303–325. https://doi.org/10.1353/jhr.2009.0026

Guldi. (2016). Title IX and the education of teen mothers. *Economics of Education Review*, *55*, 103–116. https://doi.org/10.1016/j.econedurev.2016.09.005

Hao, & Cherlin, A. J. (2004). Welfare Reform and Teenage Pregnancy, Childbirth, and School Dropout. *Journal of Marriage and Family*, *66*(1), 179–194. https://doi.org/10.1111/j.0022-2445.2004.00012.x-i1

Hendrick, & Maslowsky, J. (2019). Teen Mothers' Educational Attainment and Their Children's Risk for Teenage Childbearing. *Developmental Psychology*, *55*(6), 1259–1273. https://doi.org/10.1037/dev0000705

Jones, Kelly M.; Pineda-Torres, Mayra (2021) : TRAP'd Teens: Impacts of Abortion Provider Regulations on Fertility & Education, IZA Discussion Papers, No. 14837, Institute of Labor Economics (IZA), Bonn

Levine, & Painter, G. (2003). The Schooling Costs of Teenage Out-of-Wedlock Childbearing: Analysis with a within-School Propensity-Score-Matching Estimator. *The Review of Economics and Statistics*, *85*(4), 884–900. https://doi.org/10.1162/003465303772815790

Lipka, Sara. The Truth About Student Success : Myths, Realities, and 30 Practices That Are Working. Washington, D.C: The Chronicle of Higher Education, 2019.

Loughran, & Zissimopoulos, J. M. (Julie M. (2009). Why Wait? The Effect of Marriage and Childbearing on the Wages of Men and Women. *The Journal of Human Resources*, *44*(2), 326–349. https://doi.org/10.1353/jhr.2009.0032

Marcotte. (2013). High school dropout and teen childbearing. *Economics of Education Review*, *34*, 258–268. https://doi.org/10.1016/j.econedurev.2013.01.002

Martin JA, Hamilton BE, Osterman MJK, Driscoll AK. Births: final data for 2018. *Natl Vital Stat Rep*. 2019;68(13):1–47.

Paranjothy, Broughton, H., Adappa, R., & Fone, D. (2009). Teenage pregnancy: who suffers? *Archives of Disease in Childhood*, *94*(3), 239–245. https://doi.org/10.1136/adc.2007.115915

Penman-Aguilar A, Carter M, Snead M, Kourtis A. Socioeconomic disadvantage as a social determinant of teen childbearing in the *US Public Health Rep*. 2013;128(suppl 1):5–22.

Perper K, Peterson K, Manlove J. *Diploma Attainment Among Teen Mothers. Child Trends, Fact Sheet* Publication #2010-01: Washington, DC: Child Trends; 2010.

SmithBattle. (2007). “I Wanna Have a Good Future”: Teen Mothers’ Rise in Educational Aspirations, Competing Demands, and Limited School Support. *Youth & Society*, *38*(3), 348–371. https://doi.org/10.1177/0044118X06287962

Stock, James H, Jonathan H Wright, and Motohiro Yogo. “A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments.” Journal of Business & Economic Statistics 20, no. 4 (2002): 518–29. https://doi.org/10.1198/073500102288618658.

Appendix A: Summary of HSLS:09 base-year response rates: 2009.

Ingles, S.J., Pratt, D.J., Herbert, D.R., Burns, L.J., Dever, J.A., Ottem, R., Rogers, J.E., Jin, Y., and Leinwand, S. (2011). *High School Longitudinal Study of 2009 (HSLS:09). Base-Year Data File Documentation* (NCES 2011-328). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved March 9, 2023 from nttp://nces.ed.gov/pubsearch.

Table ES-1. Summary of HSLS:09 base-year response rates: 2009

Instrument	Selected	Participated	Weighted percent	Unweighted percent
School	1,889	944	55.5	50.0
School administrator[1]	944	888	94.9	94.1
School counselor[1]	944	852	91.3	90.3
Student questionnaire[2, 3]	25,206	21,444	85.7	85.1
Student assessment[2, 3]	25,206	20,781	83.0	82.4
Parent questionnaire[2]	25,206	16,995	67.5	67.4
School administrator[2]	25,206	23,800	94.5	94.4
School counselor[2]	25,206	22,790	90.0	90.4
Teacher questionnaire				
Mathematics teacher[4]	23,621	17,882	71.9	75.7
Science teacher[5]	22,597	16,269	70.2	72.0

[1] Uses the school base weight.
[2] Uses the student base weight.
[3] Among questionnaire-capable students (n = 24,658), some 21,444 completed the student questionnaire, and 20,781 completed the mathematics assessment. Thus, 87.0 percent (unweighted) completed the student interview or 87.4 percent weighted. Likewise, 84.3 percent (unweighted) completed a mathematics assessment or 84.7 percent weighted.
[4] Uses the student base weight. Results reflect students who were enrolled in a mathematics course.
[5] Uses the student base weight. Results reflect students who were enrolled in a science course.
NOTE: All percentages are based on the row under consideration.
SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Appendix B: HSLS:09 School Sample Size and Participation Yield by Type and Locale

Ingles, S.J., Pratt, D.J., Herbert, D.R., Burns, L.J., Dever, J.A., Ottem, R., Rogers, J.E., Jin, Y., and Leinwand, S. (2011). *High School Longitudinal Study of 2009 (HSLS:09). Base-Year Data File Documentation* (NCES 2011-328). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved March 9, 2023 from nttp://nces.ed.gov/pubsearch.

Table 32. HSLS:09 school sample size and participation yield by type and locale

	Eligible	Target	Participating schools
Total	1,889	944	944
School type			
Public	1,495	744	767
Total private	394	200	177
Catholic	194	100	102
Other private	200	100	75
Locale			
City	626	308	272
Suburban	693	344	335
Town	198	103	117
Rural	372	189	220
Region			
Northeast	340	161	149
Midwest	474	235	251
South	702	364	380
West	373	184	164
Total for state representation	888	409	454

NOTE: Information concerning the states that have state-representative data is provided in documentation for the restricted-use files.
SOURCE: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Intrinsic Unrealism: The Ineffectiveness of Neoclassical Economic Models

Robert N. Meyer

Received: 25 April 2022 / Accepted: 2 May 2022 / Published online: 6 May 2022

Abstract The idea of equilibrium and the usefulness of the neoclassical models that employ it are questionable due to the unrealistic built-in assumptions that they utilize, which have androcentric biases and fail to consider the open-endedness of human choice. This essay will replace the idea that neoclassical economic models are effective and that realism does not matter in the field of economics. It will rely on historical and contemporary sources in the areas of Philosophy, Sociology, Politics, and of course, Economics to explain why these unrealistic and androcentric assumptions nullify the usefulness of the neoclassical models that employ them. The essay will also present and reject counterarguments made against my claims by renowned neoclassical economist Milton Friedman. Research on this topic matters because neoclassical models are seen as the mainstream when it comes to the entire field of economics when a lot of their theory and their overarching reliance on mathematics are questionable.

Keywords Neoclassical · Realism · Assumptions · Equilibrium · Models · Androcentrism

R.N. Meyer
Department of Economics, Gettysburg College, 300 N Washington St, Gettysburg, 17325, United States of America
E-mail: meyero01@gettysburg.edu

1 Introduction

Realism is integral to the study of economics. After all, economists are tasked with studying the behavior of humans and their actions in the real-world economy. To suggest that economists should utilize models and theories that employ unrealistic built-in assumptions that fail to take into account the open-endedness of human choice, including androcentric biases, is preposterous. These built-in assumptions are put in place in order to try to improve the lack of realism of these models and make them more applicable to the study of the real-world market. However, these assumptions fail in this endeavor, as the models that employ them render the open-endedness of human choice down to these impractical assumptions that are held constant regardless of varying factors. Moreover, the androcentric biases ingrained in these assumptions distort the results of the neoclassical models that utilize them, as they disproportionately weigh the presence and influence of females in the economy as well. Since the conclusions of these models are implicit in their assumptions, this essay will go on to argue against the erroneous assertions made by neoclassical economists on how individuals are expected to work toward the idea of equilibrium and utilize the results of these models if the assumptions that exist within the models are not necessarily correct all of the time (Hayek, 1948, 361).

The main counterargument to these claims is that realism is not important for economics and that the assumptions of neoclassical models are not integral to ensuring its accuracy since the validity of these assumptions can be judged by their empirical results (Friedman, 1953, 14). This counterargument is not substantial enough to debunk the logical thought process against the practical application of these models due to their unrealistic assumptions. This paper will respond by delving further into how it is absurd to deem realism as unimportant because economists are applying the study to real-world activities and how its empirical results depend on its assumptions' accuracy. When it is proven that the thesis is correct, there is a potential for widespread change in terms of the way the world looks at the study of economics from an empirical standpoint, as well as the models that economists utilize to explain the actions of individuals, what influences these actions, and the economy as a whole.

In Section 2 of this paper, I will discuss the relevant literature on this topic, including criticisms on the realism and androcentrism of neoclassical assumptions, as well as the counter-arguments of these criticisms. In Section 3, I will discuss the damaging effects that the lack of realism of neoclassical assumptions has on the effectiveness of their models. This section will include an in-depth look at general equilibrium theory and typical neoclassical assumptions, as well as proposed solutions for their adverse effects. In Section 4, I will talk about the impact that androcentrism has had on the field of economics as a whole. I will also focus on the effects of androcentric biases on the applicability of neoclassical assumptions while also proposing solutions for how to move forward and improve. In Section 5, I will go over Milton Friedman's view on realism in economic analysis as well as rebuttals to his claims. Lastly, in Section 6, I will summarize my paper by presenting my findings throughout my research while also providing potential avenues for future research and the implications this study will have on economics as a whole.

2 Literature Review

2.1 Criticisms on the Realism of Neoclassical Assumptions in Literature

Studies regarding the ineffectiveness of neoclassical economic models have been clearly expressed in a wide variety of economic journals. This criticism largely stems from the models' assumptions, which makes sense as Hamminga and Balzer (1975) describe that an economic model is given by a set of assumptions. Throughout the research, the main criticism of neoclassical models, which can be seen with Becker (1962), McCormick (1989), and Farrell (1993), is their unrealistic built-in assumptions, precisely the assumption that traditional economic behavior is rational. Becker (1962) points to the fact that the term, rational, is outdated and how it assumes unrealistic behavior in the market. Becker (1962) explains that this impractical assumption implies that the market will experience consistent maximization, which is impossible and misconstrues economic and behavior-explaining theories. McCormick (1989) argues against using these models as while they do consider the fact that all humans are self-interested, this does not necessarily equal rationality. Farrell (1993) takes it further and questions if rationality is even quantifiable. Farrel (1993) ultimately suggests that if actors cannot be rational in a sense, the neoclassical models employing the assumption of rationality in the market are impractical.

Bromiley and Papenhausen (2003) go on to suggest an alternative to rational-choice theory, stating that behavioral theory is more advantageous when analyzing economic markets as it does not have unrealistic assumptions that limit the correctness of its results. Solow (1956) also discusses the effect of incorrect assumptions on economic growth models, and he argues against using these models due to this. In addition to this main criticism revolving around the lack of realism in rational-choice theory, Bagchi (2017) points out that these models and the idea of equilibrium do not include money, negating their practicalness. The fact that money is absent in economic theory is illogical. Kirzner (1997) places it as the main reason why these neoclassical models wrongly nullify the open-endedness of human choice and are, therefore, ineffective. The logicalness of these models is also a widely-held criticism. Mises (1949), in which is considered his magnum opus, “Human Action”, also talks about how humans have a logical structure with the aim to select the best means of satisfying ends, despite all having different information about the market. These neoclassical models assume that individuals in the market will act with perfect information and that the tastes of individuals are unchanging and exogenous. Mises’ (1949) work proves that this is not true, rejecting the notion of positivism that the market shapes an individual's actions and that, in fact, the individual acts within their own consciousness.

2.2 Criticisms on the Androcentrism of Neoclassical Assumptions in Literature

Another criticism of these neoclassical models is the presence of androcentrism in their assumptions. This issue is minimally discussed within the field and makes this paper more unique. Rothschild (2014) gives a background on what gender bias is, describing it as favoritism of one gender over another, and Wooley (1993) highlights the challenges regarding gender equality for females in economics. England (2002) points out that gender bias makes neoclassical economics imbalanced, as economists tend to favor the male experience over the female experience when crafting the assumptions of their model and theories. In addition to the fact that these assumptions distort the results garnered from neoclassical economic models, England (2002) also mentions that these assumptions also point to the fact that these biases lead to the furthering of male interests as they take attention away from the female experience in markets. England (1989), in her previous work, also talks about how rational-choice theory also has androcentric biases that plague its assumptions.

2.3 Counter-Arguments to Criticisms of Neoclassical Assumptions in Literature

While the fact that the built-in assumptions of these neoclassical models are undeniable, famous neoclassical economist Milton Friedman (1953), argues that realism is unimportant for economics. Friedman (1953) explicitly argued that the realism of the assumptions of neoclassical models is not integral to ensuring its accuracy because their empirical results can judge the validity of these assumptions. This paper will utilize evidence from Mises (1949) to argue against the positivism littered throughout Friedman's (1953) claims, as well as Nagel's (1963) work to argue against

Friedman's lack of firm support in his writing. Hayek's (1948) work, "The Meaning of Competition", will also be used to disprove Friedman's counterargument to the thesis. In his work, Hayek (1948) pointed out how a model's conclusions are implicit in its assumptions, which led to this paper, and the further exploration into research about questioning the effectiveness of neoclassical models, such as perfect competition.

3 The Effects of Unrealistic Built-in Assumptions on Neoclassical Economic Models

3.1 The Inefficient Role of Neoclassical Assumptions in General Equilibrium Theory

The role of neoclassical models is aimed at explaining the actions of the market, such as production, consumption, and pricing, through the focus on the law of supply and demand. The models are concerned with figuring out the efficient allocation of resources. To figure this out, the models possess an intrinsic overreliance on mathematics and impractical assumptions. A prime example of the misuse of mathematics in neoclassical models is with general equilibrium theory. This model assumes that "All markets exist in all time commodities for all time to come" (Bagchi 2017, 4). Therefore at any point of equilibrium, goods and prices are set forever, meaning that if there is any change to the market, you move into an entirely different world (Bagchi 2017, 4). This nullifies the potential for comparing two different economic outcomes, diminishing the model's usefulness. The model has also experienced many failed attempts to introduce money into its theory (Bagchi 2017, 4). It is bewildering that money can not be involved in this economic model, and it shows its lack of applicability to the real world.

3.2 The Unquantifiable and Unrealistic Nature of Rational-Choice Theory

The assumption that all individuals are rational in the economy is another example of the unrealistic nature of neoclassical models. The idea of rationality is questionable in and of itself, and it is seemingly unquantifiable. Critics have described this long-held mainstream assumption as an outdated term that presumes unrealistic behavior (Becker 1962, 1). In his paper, “Utility-maximizing Intentions and the Theory of Rational Choice”, Farrell discusses a scenario that exhibits this. The scenario goes as follows: a billionaire guarantees you a million dollars if you intend to consume a drink with toxins that will make you sick for a couple of days at noon tomorrow (Farell 1993, 53). The billionaire specifies that the deal is off if you ensure that your intention is not to consume the drink with toxins between the time he proposes and the time you are supposed to drink it (Farell 1993, 53). Farrell then argues that consuming the drink with toxins is irrational if you can merely get the million dollars by intending to do so (Farell 1993, 53). However, he also notes that it is impossible for an individual to intend to drink the toxins if they believe it is irrational (Farell 1993, 53). The situation could also be looked at from a lens that it is questionable whether it is rational to take the million dollars and be sick for a couple of days or reject the potential of sickness and a million dollars. This scenario shows that the idea of rationality is complex with not clearly defined parameters, making it pointless to use a universal assumption in economics as the possibilities of human choice are endless.

3.3 The Impracticality of the Assumption of Individual Utility-Maximization

Another mainstream economic assumption is that individuals are strictly utility-maximizing actors. These assumptions render the open-endedness of human choice into forgone and useless conclusions. This means that if an individual is assumed to be a utility-maximizing actor, then that individual does everything to maximize their own utility, regardless of how irrational they may seem to someone else (McCormick 1989, 314). The assumption that individuals are strictly utility-maximizing actors only points to the fact that individuals are confined to a set of given prices as well as their income and are to make decisions based on their preference scale (McCormick 1989, 314). The idea of a utility-maximizing preference scale is particularly questionable. It is impossible to quantify the utility rankings and preferences needed on an individual basis for an entire economy. Quantifying this is doing a disservice to the field of economics as portraying individual decision-making as a mechanical exercise in constrained maximization accomplishes rendering the uniqueness of human choice into statistical probabilities and presumptions (Kirzner 1997, 64). This makes it invalid in terms of explaining and predicting economic behavior. It is also important to note that this assumption does not require rationality or self-consciousness when making economic decisions. This leads both the assumptions of utility-maximization and rationality to contradict each other. These are wide-held assumptions that are seen as the mainstream, which ultimately nullify their model's effectiveness in predicting economic behavior.

3.4 Other Notable Unrealistic Assumptions

Other notable assumptions typically held by many neoclassical models are that the tastes of individuals are unchanging and exogenous, that individuals act on perfect information of the market, and that interpersonal utility comparisons are impossible. Similar to the issues with utility-maximization, suggesting that individuals are not the ones making conscious choices in the markets and that their preferences are scaled by a given set of goods and prices is an unreasonable assumption to hold when predicting economic behavior. This is far from the case, as "It is impossible for the human mind to conceive logical relations at variance with the logical structure of our mind", particularly for an entire economy (Mises 1949, 25). The assumption that individuals act on perfect market information is a notion of positivism, which is a philosophical theory widely held by neoclassical economists that maintain that all genuine knowledge is true by definition. Mises describes positivism as a theory devoid of a scientific foundation, making it useless for research and economic analysis (Mises 1949, 17-18). It is absurd to assume that every individual has perfect knowledge of the market, and this assumption invalidates the results of the models that suppose it. Presuming that interpersonal utility comparisons are impossible is unrealistic as it deems that individuals are not emotionally connected and are strictly influenced by the market, not by themselves. This leads to the notion of a separative self in neoclassical economics, which is problematic when performing economic analysis, as individuals are not autonomous, but rather are governed by their own consciousness (England 2002, 158).

3.5 Proposed Solutions: A Behavioral Approach

It is undeniable that "... all theory depends on assumptions which are not quite true" as this makes theory what it is (Solow 1956, 65). This paper is not expressing the idea that all theories with unrealistic assumptions are false and pointless. However, when crucial assumptions heavily affect the results of the models, this is when the results of these models should be questioned (Solow 1956, 65). The assumptions previously mentioned are chief examples of this, as the empirical evidence rejects them. A possible solution to these limiting assumptions would be for these neoclassical models to shift from rational-choice theory and equilibrium to a behavioral approach (Bromiley & Papenhausen 2003, 413). This strategy is based on a behavioral view that "... accepts psychological and sociological findings about organizations" (Bromiley & Papenhausen 2003, 419). Instead of relying on assumptions that deem the actions of individuals to foregone conclusions strictly focused on utility-maximization and the unquantifiable idea of rationality, economists should make the reasonable assumption that "... people could change their behavior in ways that may improve their performance" (Bromiley & Papenhausen 2003, 419). If the field of economics goes down this route and makes this behavioral approach the mainstream, the practicalness and accuracy of these models can be guaranteed.

4 Androcentrism in Neoclassical Economics

4.1 Background of Androcentrism in Economics

In addition to the unrealistic built-in assumptions that misconstrue the results of neoclassical economic models, there is an underlying bias of androcentrism rooted in the basic structure of neoclassical economics. This bias influences the assumptions of these models as well. Androcentrism is a form of gender bias, which is "... favoritism of one gender over another" and is usually attributed to the favoritism of men over women (Rothchild 2014). Androcentrism in economics is when these assumptions are "... biased in favor of men's interests" (England 2002, 154). Because of this, the interests of men have been furthered regarding economic analysis, with the female perspective put to the wayside. Pointing out these androcentric biases also takes into account that these assumptions presume that humans are autonomous beings that are not affected by empathy or social influences (England 2002, 154). These biased assumptions are highly damaging to the accuracy of economic analysis and the usefulness of these economic models and theories. The four specific assumptions that this section will be focusing on are: (1) that interpersonal utility comparisons are impossible; (2) the tastes of individuals are unchanging and exogenous; (3) individuals are strictly utility-maximizing actors, and (4) individuals are rational. While this paper previously discussed the unrealistic nature of these behavioral assumptions, this section will speak specifically to the implications related to their androcentric biases.

4.2 Issues with Androcentric Biases in Neoclassical Assumptions

The assumption that interpersonal utility comparisons are impossible has an androcentric bias in the way that it negates the possibility for individuals in the market to possess empathy (England 2002, 158). Females tend to be more empathetic than males, so the absence of the possibility of empathy from these models highlights the androcentric bias. This neoclassical principle is also applicable to groups in the economy. Presuming that utility comparisons are impossible on a group level leads to a lack of research into generalizations such as that women are more disadvantaged than men in the market, which further exacerbates the apparent male-centered bias (England 2002, 158). While it is evident that the second assumption that the tastes of individuals are unchanging and exogenous is unreasonable, its intrinsic androcentric biases also have a significant effect on its lack of realism. Dismissing the endogeneity of preferences obscures "...some of the processes through which gender inequality is perpetuated" (England 2002, 159). Making this assumption eliminates potential scenarios where male-centered field employers discriminate against women, and women want to alter their preferences to different field employers (England 2002, 159). This has the potential to affect the tastes of the next generations as this discrimination and lack of ability to change preferences for individuals in the field of economics creates gender-related tastes, which could further perpetuate women's lower earnings for generations to come (England 2002, 159).

The third assumption is that individuals are strictly utility-maximizing actors, which also presumes that individuals are selfish. It is important to note that self-interest does not necessarily mean selfishness. While it is agreeable that individuals are self-interested, it does not mean that they do not care for others. This altruistic assumption invalidates the possibility for an individual to care for the needs of a child or to mentor a student, which are female-dominated roles in society (England 2002, 160). This assumption also does not support the possibility for employers to prefer a worker over their gender, which is not valid. Neoclassical economists should assume selective altruism instead of altruism in totality in order to be able to take into account that discrimination is present in competitive markets, as individuals have conscious biases (England 2002, 161). Finally, it is imperative that this paper speaks to the androcentric biases that come with rational-choice theory. The feminist critique of the assumption that individuals are rational comes with the fact that rationality is seen as radically separate from emotion (England 1989, 21). This distorts the neoclassical conceptualization of rationality as individuals are emotional beings, and their preferences are affected by this. Women are typically more emotional than men, which shows the inherent male-centered bias in these neoclassical models.

4.3 Proposed Solutions: An Equitable Approach

These assumptions further the interests of men and direct our attention away from “the ways in which typical arrangements between men and women perpetuate women’s disadvantage both in their families and in labor markets” (England 2002, 161). These are the significant effects of these androcentric biases that affirm that mainstream economists can learn more from feminist economists in order to “...be more attentive to gender biases in economic work and in the world” (Woolley 1993, 485). Neoclassical economists must neutralize the effects of these biases by recognizing the variability of selfishness, the possibility of interpersonal utility comparisons, individuals’ tastes as changeable and endogenous, and the emotional aspect of rationality (England 1989, 22-23). This will allow for a more equitable approach to economic analysis as there will be a heightened focus on the economic well-being of women, leading to more policies that promote equality (Woolley 1993, 486-497).

5 Counter-Argument: A Neoclassical Economist's View on 'Unrealistic' Assumptions and A Response to Milton Friedman

Despite the critics, neoclassical economists remain firm in their beliefs on the validity of their models, despite the intrinsic unrealism. This firmness helps the neoclassical school of thought stay as the mainstream. Milton Friedman is among the former intellectual leaders of the neoclassical school of economic thought, which is associated with the University of Chicago. Friedman, a Nobel Memorial Prize recipient, was a very influential economist, specifically in the fields of consumption analysis and monetary theory. One of his notable books, "The Methodology of Positive Economics", embodies these firm beliefs. The key rebuttal in the book to the notion that the unrealistic nature of the assumptions of neoclassical models distorts their results is that realism is not important for economics (Friedman, 1953, 14). Friedman maintains that the assumptions of neoclassical models are not integral to ensuring their accuracy since the validity of these assumptions can be judged by their empirical results (Friedman, 1953, 14).

Regarding Friedman's counterargument, the notion that realistic assumptions are not integral to ensuring the accuracy of these models due to empirical research is a flawed assertion. As Friedrich Hayek, a renowned Austrian economist, states concerning economic modeling, "Its conclusions are implicit in its assumptions" (Hayek, 1948, 361). The assumptions of a model shape the results, regardless if it is being studied empirically or not. The assumptions of these neoclassical models are at the center of the explanations garnered from them. Ernest Nagel's critique of Friedman's defense of the unrealistic assumptions commonly found in neoclassical economics, "Assumptions in Economic Theory", also speaks to this by stating "... if by an assumption of a theory we understand one of the theory's fundamental statements, a theory with an unrealistic assumption is patently unsatisfactory; for such a theory entails consequences that are incompatible with observed fact, so that on pain of rejecting elementary logical canons the theory must also be rejected" (Nagel 1963, 215). Nagel also points out the ambiguity of Friedman's claims, and this assertion is a quality example of Friedman's lack of firm support for his arguments (Nagel 1963, 218). An example of a model where the assumptions are fundamental to its meaning would be the perfect competition model, which has numerous unrealistic and idealized assumptions that are impossible. These unrealistic assumptions, such as individuals having perfect market information, firms being strictly profit-maximizers, and that all products are homogenous, are central tenets of the theory. Since these assumptions can tell the tale of the fundamental idea of this theory, its results are invalid. This debunks Friedman's claims that realism does not matter for economics, as it is a crucial component to ensure the accuracy of economic analysis.

6 Conclusion and Findings

Challenging the mainstream is paramount to progressing the quality and accuracy of economic analysis. The unrealistic nature of neoclassical assumptions and the underlying androcentric bias that influences these assumptions need to be confronted. If realism continues to be disregarded in relation to economic analysis, the applicability and precision of the results will continue to remain invalid. In order to combat this, the field of economics needs to start by explaining the faults of these mainstream economic models, theories, and their assumptions through education. Too often, these neoclassical models are held as the norm, leaving little room for students and professors to challenge them. The field should also start incorporating different schools of thought more heavily, such as the Keynesian and Austrian schools of thought. This will balance the field and ensure that the status quo will be challenged appropriately.

Regarding the neoclassical models themselves, neoclassical economists can improve the accuracy of these models by utilizing the strategy of a behavioral approach. Neoclassical models need to assume that individuals are unique and have the ability to change their behavior in ways to improve their performance. The notion of rationality also needs to be questioned and abandoned when making assumptions regarding economic theory, as the nature of rationality makes it unquantifiable. The androcentric bias also needs to be eliminated as these models disregard the female perspective in the economy, choosing only to focus on the male perspective. Specifically, neoclassical economists need to assume the ability of individuals in the economy to feel empathy and emotion when making decisions, as this is the reality, especially for females. By going down this route, there will be widespread change in the way economic analysis is approached from an empirical standpoint as the models will more efficiently explain the actions of individuals, what influences these actions, and the economy as a whole.

With that said, and given the novel contribution of this paper, the question of how to effectively improve on these unrealistic assumptions and the overarching discussion on whether realism is essential in economic analysis is worth continued exploration. The direction offered by this paper could apply to the development of new approaches to economic analysis, as well as a new approach to mainstream economic theory overall. If investigated further, the lack of real-world application of neoclassical models and the lack of balance between considering both the female and male experience in the economy could be solved. If successfully investigated, it could lead to more accurate economic analysis and could also solve the issue of the female population experiencing inherent disadvantages in the economic realm. With more accurate assumptions in terms of gender, it could lead to more economic policies that promote equality, which could lead to a decreased gender pay gap. Overall, if the findings of this paper are further investigated, it will improve the field of economics in terms of education, analysis, and equality.

Acknowledgments I thank Professor Robert Cavender for helpful suggestions and conversation as well as for providing valuable research assistance. I also thank Gettysburg College where I conducted this research, for providing me with the online tools to do so.

References

Bagchi, A. K. (2017). Problems with Neoclassical Economics. *Social Scientist*, *45*(9/10), 3–11. https://www.jstor.org/stable/26380447

Becker, G. S. (1962). Irrational Behavior and Economic Theory. *Journal of Political Economy*, *70*(1), 1–13. https://www.jstor.org/stable/1827018

Bromiley, P., & Papenhausen, C. (2003). Assumptions of Rationality and Equilibrium in Strategy Research: The Limits of Traditional Economic Analysis. *Strategic Organization*, *1*(4), 413–437. https://doi.org/10.1177/14761270030014003

England, P. (1989). A Feminist Critique of Rational-Choice Theories: Implications for Sociology. *The American Sociologist*, *20*(1), 14–28. https://www.jstor.org/stable/27698446

England, P. (2002). The Separative Self: Androcentric Bias in Neoclassical Assumptions. *Readings in Economic Sociology*, 154–167. https://doi.org/10.1002/9780470755679.ch9

Farrell, D. M. (1993). Utility-maximizing Intentions and the Theory of Rational Choice. *Philosophical Topics*, *21*(1), 53–78. https://www.jstor.org/stable/43154141

Friedman, M. (1953). The Methodology of Positive Economics. *The Methodology of Positive Economics*, 3–44. https://doi.org/10.1017/cbo9780511581427.002

Hamminga, B., & Balzer, W. (1986). The Basic Structure of Neoclassical General Equilibrium Theory. *Erkenntnis*, *25*(1). https://www.jstor.org/stable/20012029

Hayek, F. A. (1948). The Meaning of Competition. *Individualism and Economic Order*, *13*(2), 360-371. https://competitionandappropriation.econ.ucla.edu/wp-content/uploads/sites/95/2018/06/HayekMeaningOfCompetition.pdf

Kirzner, I. M. (1997). Entrepreneurial Discovery and the Competitive Market Process: An Austrian Approach. *Journal of Economic Literature*, *35*(1), 60–85. http://www.jstor.org/stable/2729693

McCormick, K. (1989). An Essay on the Assumption of Rational Behavior in Economics. *Review of Social Economy*, *47*(3). https://www.jstor.org/stable/29769466

Mises, L. V. (1949). Human Action: A Treatise on Economics. *Human Action*, 1–69. https://mises.org/library/human-action-0/html

Nagel, E. (1963). Assumptions in Economic Theory. *The American Economic Review*, 53(2), 211–219. https://www.jstor.org/stable/1823864

Rothchild, J. (2014). Gender Bias. *The Blackwell Encyclopedia of Sociology*. https://doi.org/10.1002/9781405165518.wbeosg011.pub2

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, *70*(1), 65–94. https://www.jstor.org/stable/1884513

Woolley, F. R. (1993). The Feminist Challenge to Neoclassical Economics. *Cambridge Journal of Economics*, *17*(4), 485–500. https://www.jstor.org/stable/23599798

Impact of Charging Infrastructure on Electric Vehicle Sales:

An analysis from Counties in 13 US States

Shubh Nimesh Parekh

Economics Department, Gettysburg College

Honors Thesis

Abstract

Adoption of battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs), has become a priority for the government because of the constant threat of climate change. Over the years, government monetary incentives like tax credits, tax rebates, and other monetary subsidies are the leading way to increase electric vehicle sales in the United States. While these incentives are necessary to combat the high costs of electric vehicles (EVs), there hasn't been too much attention given to combat range anxiety. Since EVs are run on lithium-ion batteries, there is a limited range for different EVs, with the maximum being around 400 miles on a full charge. Charging Infrastructure is a way to reduce range anxiety and further incentivize EVs in the United States. Many states have different incentives for private gas station owners to build charging stations to increase EVs in a state. I use an Ordinary Least Squares (OLS) model to see the impact of charging infrastructure on EV registration from the year 2018- 2022 on a county level in 13 states. In order to see the true effect of charging infrastructure, I control for monetary incentives using state * year interaction fixed effects, total vehicle registration in each of the counties, income, and population. I find that Charging Infrastructure has a positive significant relationship with EV registrations.

Keywords: Battery EV (BEVs), Plug in Hybrid EV (PHEVs), EV (EVs), Charging Infrastructure, Charging Station, Incentives.

Introduction

Electric Vehicles (EVs) have grown in popularity after the need to decrease carbon emissions. In 2016, Tesla produced approximately 75,000 cars and in 2021, the same company produced approximately 700,000 cars: a nearly 800% increase in 7 years (Carlier, 2023). This is a similar trend with other EV manufacturers showing that EVs are growing in popularity. EVs are run on lithium-ion batteries that need to be charged via a public charging station or charging ports installed in the house. In return, there is fewer greenhouse gas emission by EVs as it is operated via a battery in contrast to internal combustion vehicles that emit CO2 in the atmosphere. The EPA predicts that a typical gas-powered vehicle passenger emits 4.6 metric tons of carbon dioxide per year (2022). According to the IEA, energy security is a “lifeblood” of the modern economy, and with the growing security issues, reliance on imports of fossil fuels hinders a nation's energy efficiency. Therefore, adoption of EVs are a crucial way to have energy security while also limiting effects of climate change.

There are two main roadblocks to adopting EVs: the increased cost and range anxiety. While EV owners spend less money on fuel prices, due to lack of technology, the prices for EVs are still significantly higher than gas-powered vehicles, about $10,000 price difference (Lindwall, 2022). To promote EVs, the federal government provides a $7500 tax credit for purchase of a new EV (IRS 2023). Nevertheless, according to J.D. Powers, a private research company, consumers are hesitant to buy EVs due to range anxiety (Wardlaw, 2020). Range anxiety is the worry consumers have that the EV they drive will run out of battery before reaching a suitable battery station or their destination. This is a critical concern for most buyers as many states in the US don’t have good infrastructure for EV charging stations (Kampshoff, Kumar, Peloquin, Sahdev, 2022). The FAST act authorizes the installation, operation, and maintenance of electric vehicle supply equipment (EVSE) for the purpose of recharging privately owned vehicles under the custody or control of the General Services Administration or the Federal agency (2015). This act extends to having workplaces provide charging stations for their employees and it contains a roadmap for agency workplace charging programs and defines roles and responsibilities.

On February 15, 2023, the Biden- Harris administration extended their efforts to build a national network of electric vehicle chargers by building 500,000 chargers along the national highways (The White House: Fact Sheet, 2023). Since this infrastructure law is fairly new, there hasn't been too much research about the impacts of charging infrastructure on EV sales in the US. Prior research shows that charging infrastructure has a positive relationship with EV sales when looking at state level data. Since this is a fairly new topic, EV market data for plug-in hybrid vehicles is used along with EVs for the year 2011- 2015 on a state level.

In my research, I analyze the effect of charging infrastructure on EV sales on a county level in 13 states in the United States. I use county level data because county-level associations can better account for regional trends not captured by state data. I use an Ordinary Least Squared (OLS) model with fixed effects to control for the changes within a county, within a year and within a state and year the county is based in. I find that charging stations have a significant positive relationship with EV sales when controlling for federal incentives, state-level incentives, income, total population, education, unemployment, and total vehicle share. I use Gas Stations as my instrumental variable to solve the reverse causality while also exploring other instrumental variables like Alternative Fuel Stations and Business Establishments. My second stage results show that an increase in one charging station per person would increase EVs by 52.

Background (Literature Review)

The significance of EVs have been identified by multiple authors to combat the ongoing issues with climate change while also creating energy security within a country. Countries in Europe and China are increasing their efforts to promote EV and lower their carbon footprint in the world (IEA, *fast publicly available chargers*, 2021). The most decisive way to make this change is by promoting technological advancements and increasing incentives that promote electric vehicle sales. EVs are also linked with population density, education, GDP per capita, and income per capita (Vergis et Chen, 2015). Prior literature mentioned below summarizes the research that has been conducted by economists in different parts of the world. These articles provide a blueprint for my research as I intend to build upon the knowledge that is already published by using different control variables and conducting my research through a smaller unit of observation.

Federally, the most popular incentive provided by the government is the $7,500 tax credits for electric vehicle purchase (IRS, 2023). While this is a substantial amount, tax credits aren't promised to every household and at the same time, the amount varies from household to household. Some other incentives provided by the government are in the form of rebates, toll credits, access to HOV lanes and other monetary incentives (Department of Energy: Alternative Fuels Data Center (AFDC), 2023). I am going to focus my research on charging infrastructure while also considering the effects of other incentives provided by the state and federal governments.

Hardman et al. (2017) evaluate the effectiveness of financial purchase incentives for battery EV in the United States. This article is a thorough review of prior research in a similar area. Their findings show that incentives that are provided before the purchase of an electric vehicle are significantly more beneficial than incentives that are provided after. They also conclude that incentives show significant results when they are applied to BEVs rather than PHEVS. One of the key components of this paper was the effectiveness of tax exemptions on electric vehicle purchase rather than subsidies for private sectors.

While incentives are slowly going out of favor, prior research shows that incentives have a significant impact on electric vehicle sales in the United States. In an article by Jenn et al. (2018), they measure the effect of monetary and non-monetary incentives on the adoption of EV. Their results show that every $1000 offered as a rebate or tax credit increases average sales of EV by 2.6%. This includes monetary incentives provided by both the state and the federal government. Similarly, they find that HOV lane access is a significant contributor to EV, with an effect of a 4.7% increase corresponding to density of HOV lanes (every 100 vehicles per hour). These results match the results found in a paper published by the Massachusetts Institute of Technology Energy Initiative, where two researchers study the impact of financial incentives on battery electric vehicle adoption (Clinton & Steinberg, 2019). They use national level data and account for state level incentives in their regression analysis and accounting for variation in years from 2011- 2015. Their results show that incentives offered as direct purchase rebates generate increased levels of new BEV registrations at a rate of approximately 8 percent per thousand dollars of incentive offered. Vehicle rebate incentives are associated with an increase in overall BEV registrations of approximately 11 percent.

In a more global view, many countries in Europe have begun the pursuit of cleaner vehicles earlier than the United States. Similar to the US, European countries have also implemented EV purchase incentives in monetary and non-monetary form. Münzel et al. (2019)

look at the impact of incentives in 32 European countries from 2010 to 2017. In their regression analysis they control income, fuel prices and other economic factors that might increase EV adoption. They use year fixed effects and account for the change in incentives for different countries in that time period. Results showed that incentives have a positive relationship with EV adoption in European countries with an effect of 5-7% increase in EV sales for an additional €1000 in incentive subsidies. He et al. (2018) also looks at how incentives provided by the government affect EV sales. They find that the termination of HOV lanes leads to a decrease in EV sales. This negative effect is also greater in counties where the work commutes are longer and household income is higher. This shows that incentives have an effect on EVs and thus should be used to promote EVs. In another article, Gu et al. (2017) discuss the effects of government subsidies and battery recycling programs on EV manufacturers' production strategy. They hypothesize that an increase in both these sectors would lead to an increase in production. The main issue they tackle in this paper is the battery recycling rate; since many households are changing to EVs, the near future looks to have an abundance of used batteries. In order to efficiently use EVs and have the least impact on the environment, manufacturers and government subsidies should incentivize the battery recycling rate. The authors use a profit function and utility maximization function to back their theories.

Hardman et al. (2017) discuss the incentives people have to buy an EV compared to an internal combustion engine vehicle. They suggest that the incentives provided by the government (around \$2500- \$20000) are not enough for consumers to purchase an expensive commodity like an EV. This article looks at past literature on purchase incentives and how that has motivated consumers to buy EVs. Simultaneously, it also looks at how sales have not increased even with the implementation of policies that should have produced more sales. One of the key findings from their data suggests that consumers held high importance on incentives and played a big role in their willingness to buy an EV. Thus, it was important to look at other types of incentives or policies that may increase EV sales. Nadine, et al. (2015) write about range anxiety among people considering purchasing EVs. In this paper, they compare experienced BEV drivers and inexperienced BEV drivers to look at the difference between range anxiety for these two groups. They find that more experienced drivers tend to have less range anxiety and thus conclude that it is important to have experience driving BEVs. Additionally, it is important to educate consumers on how to use BEVs to reduce the wrong notion about range anxiety. While this paper talks about the issues with EV promotion and Range anxiety, it doesn't give a statistical analysis of incentives or policies as a way to improve EV sales.

Insights from prior research suggest that incentives have the ability to influence EV sales in the United States of America however growing interest in charging station incentives and concerns regarding range anxiety show that charging stations are a vital aspect of EV sales. My research could help policy makers make informed decisions about how to incentivize customers to buy EVs without having a financial burden. Policymakers can then make thorough decisions about the allocation of funds towards incentives. My research also pertains to county level observations in 15 states that range from large population states like California, New York, and Texas to small population states like Montana and Vermont. This provides a comprehensive population for my analysis as different states promote EVs via different incentives.

Theoretical Framework

Charging infrastructure is vital for long range commutes as EVs have a limit on how far they can travel on one charge. The maximum miles traveled on EVs is about 400 miles on a full charge, although many existing automobile companies are trying to increase the mileage (Dungs, 2022). A new startup, Lightyear, is trying to create a solar EV that would have a mileage of 500 miles; this is still a work in progress and thus doesn't solve the issue of range anxiety (Doll, 2023).

EVs are very new to the market compared to regular gas-powered vehicles since they were only widely introduced in the late 2000's when Tesla came out with their first EV model. Although there were EVs and hybrid vehicles before Tesla's first model, they were not widely popular because they were mainly designed to be used locally for short distances. Since the 2016 Paris COP summit, there was an agreement, which was agreed upon by the United States, to keep the global temperature below 2 degrees Celsius and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius (Paris Agreement, 2016). There has been a more advanced effort to create net-zero economies on a state and country level. One of the main contributors to greenhouse gases is gas powered vehicles, so the government is incentivizing automobile companies to make electric vehicles.

One of the ways to incentivize the public to change their behavior towards EV purchases is to incentivize using monetary and other benefits. In the past, EV purchases came with benefits such as tax credits and rebates from the federal government up to $7500 (IRS, 2023). Different states have used other mechanisms like HOV lane access, toll discounts, additional credits, and tax benefits. Some states like California and New York, have been successful in implementing incentives that benefit the public and thus promote EVs. In recent years, EV incentives have become unpopular and households that have range anxiety are hesitant to purchase EVs. In this case charging infrastructure will prove to incentivize households that worry about range anxiety.

I argue that Charging infrastructure will increase EV sales as consumers will not worry about the running out of battery before they reach a suitable charging station or their destination.

To see the relationship between electrical vehicle incentives, particularly charging infrastructure, and electrical vehicle registration, I use a function that predicts that an increase in electric vehicle incentives will lead to an increase in electric vehicle registration:

Electrical Vehicle Registration = f (Charging Infrastructure)

Where my independent variable and dependent variable have a linear relationship due to the measure of impact incentives can have on electric vehicle sales.

My model shows that electric vehicle incentives, particularly Charging Station count per capita in each county will increase electric vehicle registration per capita in that county. Using this theoretical model, I theorize that there will be an upward-sloping, positive relationship, linear model for the relationship between charging stations and electric vehicle registration.

Model

I estimate the relationship between charging infrastructure and electric vehicles using a linear reduced- form model. The main challenge to estimate the relationship between my dependent and independent variable are extraneous variables that factor into the regression. Many of these variables can be accounted for with information in data collected by the American Community Survey, the Census Bureau and the Department of Transportation such as population, net income, education, commuting patterns and unemployment. Unobserved factors such as monetary incentives, HOV lane access, percent population that works in another county or state are more problematic to control for as data is not available for these variables on a county level. For example, individuals who spend more time traveling will benefit from charging infrastructure than individuals who do not travel. Similarly, counties that have more people owning EVs will have a higher demand for charging stations.

To address the question regarding the relationship between charging infrastructure and electric vehicles, we model using two different equations.

$$(1)\quad Y_i = \beta_0 + \beta_i X_i + \beta_h X_h + \varepsilon_i$$

Where Y_i electric vehicle share and X_i is charging infrastructure in the form of charging station count. X_h are control variables for charging infrastructure and electric vehicles.

When running my regressions with other variables such as population, total vehicle in counties, and income distribution; I model this equation as a control on charging infrastructure.

$$(2)\quad Y_i = \beta_0 + \beta_i X_i + X_h \beta_h + \varepsilon_i$$

Where β_h shows the coefficient of , which are all my control variables including all the nonlinearities, the natural log of adjusted net income. In doing so, I can analyze the relationship between charging infrastructure and electric vehicles controlling income distribution in different counties. Similarly, I do the same thing with total vehicle share to improve my variance of the regression. I also include interaction variables that tell me the effect of a variable given my independent variable.

I use a fixed effects model to eliminate variables that are constant over time such as region, climate change, federal and state incentives, etc. In my research I use year fixed effect and county fixed effect to eliminate these biases. In doing so, I create a model that predicts changes for one particular county and changes in one particular year.

$$(3)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + X_{it}\,\beta_h + \alpha_i + \lambda_t + \varepsilon_i$$

Here, α_i is my fixed effects for the county and λ_t is the fixed effect for time, measured by county. This particularly allows me to get rid of effects such as pandemics, recessions and other variables that have occurred throughout the world.

To control changes at a state level, I use a State * Time fixed effects that will capture the changes made at a state level for the counties residing in those states. This will allow me to control the change in state incentives as they apply to all the counties in that particular state.

$$(4)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + X_{it}\,\beta_h + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

Here, delta (δ_{st}) is the state * time interaction fixed effect to control for the changes made in a state on a yearly basis. In doing so, I control state laws like monetary incentives, infrastructure laws, education standards, etc.

I also use a model with an instrumental variable in order to control for instrumental variables.

$$(5)\ \ X_{it} = \pi 0 + \pi\ 1\ Z_{it} + \pi\ h\ X_{it} + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

$$(6)\ \ Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_h X_{it} + \alpha_i + \lambda_t + \delta_{st} + \varepsilon_i$$

Z_{it} represents a gas station count variable that charging infrastructure without directly affecting Electric Vehicles. This is my first stage OLS model regressing charging infrastructure, dependent variable, on gas station count, instrumental and independent variable (5). In my second stage model, I use Y_{it} to represent electric vehicle share and X_{it} to represent the change in charging infrastructure (6). Similarly, I use Alternative Fuels Stations as another instrumental variable that allows me to use all 13 states from my vehicle registration data. As mentioned above, I use the equation (4) for my first stage regression and equation (5) for my second stage regression.

The results for my regressions will be presented by showing a unit change in my dependent variables, based on the change in my independent variable. These results change when I add more control variables to my regression, making my analysis more sound and compelling. The instrument variable affects my independent variable without any relationship to my dependent variable. This will estimate the true causal effect that my independent variable has on my dependent variable.

Data

I will be using data from the Department of Energy for Charging stations in each state and zipcode, this is measured using other charging station data sources like Blink, ChargePoint, Electrify America, EVgo, FLO, Greenlots, SemaConnect, OpConnect, and Webasto, via each network's application programming interface. The data provides information from 2007 to 2022. The raw data comes on a zip code level that needs to be aggregated to county level data. Some of the other variables included in the dataset are EVSEs, City, State, address, charging station type, Private/Public, and open date. I use Geocodio, a geocoding website, to match the zip code, City, State and Address to correspond to the county that it belongs in. After further exploration of the data, one of the issues with cleaning the data for an OLS regression model was the duplicates in county names. For example, since there are many counties across different states with the same name, I instead use county GEOID as a unit of measurement. GEOIDs are numeric codes that uniquely identify all administrative/legal and statistical geographic areas for which the Census Bureau tabulates data (United States Census Bureau). This is a 5-digit unique number that identifies the state and county, the first two digits uniquely identify the state, and the last three digits identify the county.

I use EV registration data from EV Hub that collects their data through affiliation with state governments that are willing to participate in this initiative. The source provides data for 13 states in the United States with the unit of observation being zip code. The States included in the data are California, Colorado, Connecticut, New Jersey, New York, Oregon, Minnesota, Montana, Texas, Washington, Wisconsin, Virginia, and Vermont. I have EV registration data for the years 2018- 2021 because that is the time frame I had data for all the 13 states mentioned above. Other variables for each observation include registration date, VIN model, VIN number, state, vehicle type, vehicle model, and vehicle make. I intend to use vehicle models and vehicle make in my regression to analyze the relationship of just tesla vehicles and tesla charging stations. The vehicle registration data was a little more tedious to work with as the dataset came only on a zip code level. I could not use Geocodio to convert the zip code to county GEOID as the address and city name was not available.

I use a master file that has a list of all GEOID codes corresponding to zip code, county name, county code, state code. I could not use the merge tool through Stata to correspond the zip codes in my vehicle registration file and charging station file to the county names associated with it because there are multiple zip codes in the United States that correspond to two or more counting. There are more than 9000 zip codes in the United States that associate with two or more counties. In this case, I had to manually assign zip codes with equal weights to different counties. To do so, I use the 2021 population data for each county GEOID using the American Consumer Survey. I correspond the population of each county GEOID to my master file of all GEOID to zip code using the merge code in Stata. I then merge my master GEOID and population file with the vehicle registration file. This gives me vehicle registration data that corresponds to county statistics depending on the population of the county.

For my control variables, I use county transportation profiles from the US Department of Transportation that provide variables like population that commutes. I also use the American Community Survey to extract county demographics data like total population, education attainment (population over the age of 25 that have a high school degree), population of white/Caucasian, population that is unemployed and income. The American Consumer Survey reports estimates based on consumer survey data that is recorded each year. They report a one-year estimate and a five-year estimate for each year. The one-year estimate is recorded using survey data from just one year, whereas the five-year estimate data uses the surveys from the previous 5 years to report the data. The five-year estimate is more accurate, however, the American Consumer Survey does not have a five-year estimate for 2020 due to the pandemic and thus I use the one-year estimates for all the years to keep my data consistent. The data also differs in the total counties that are measured; for example, some datasets only record data for half the total number of counties. Therefore, it's tricky to find data that corresponds to the counties that have an EV registration and Charging Station data.

Based on prior research, I estimate that income per capita will have positive relationship with EV registration because EV's cost significantly more than Gas-powered vehicles (NRDC). Therefore, including income in my analysis will account for the changes in EV registration based on county demographics and wealth. Similarly, I use white population per capita as a control for the income distribution in the United States. Predominantly, white Americans have more wealth than other races in the US, hence I hypothesize that counties with more white population per capita will have higher number of EVs per capita because of the wealth distribution. Population that is unemployed also makes an impact on EV share because higher share of unemployed people in a county will lead to a fewer people purchasing a more expensive vehicle. Therefore, I hypothesize that the increase in unemployed people per capita will decrease the EV share per capita in a county.

I also include the population that commutes to work as a control variable; this is the population either commutes to different counties or the same county for work. The data also comprises of population that either commutes to work with another person or alone. Thus, based on the HOV incentive, I hypothesize that increase in population that commutes would increase the EV share per capita in that county.

I also include the population that has high school degree over the age of 25 as a control variable. As EVs were widely introduced in 2010, there may not be enough education regarding the benefits of EVs to people who don't have a high school degree. Simultaneously, the US made a pledge to have net-zero carbon emissions by 2050 which may not be widely known to people who are not educated about climate change. One of the ways to increase EV registration is education and thus I theorize the Education attainment has a positive relationship with EV registration.

I also include total population and total vehicle registration as a control variable because I hypothesize that an increase in both these factors increase EV registration in a county. I use a weighted method to find the total vehicle registration for each county for the states I include. I collect the total vehicle registration data from the U.S. Department of Transportation, Federal Highway Administration for the 13 states. I then use the estimate of total population for each year and county to find the percentage of population in that county for that particular year. I then multiply the percentages of county population with the total vehicle registration in the state to find a weighted vehicle registration based on total population. I understand that population as vehicle registration may not have a positive correlation with vehicle registration. However, since there are more manufacturers promoting EVs, there might be a correlation between total vehicle registration and EV registration in a county. Therefore, it is important to include this as a control variable and thus account for the change in total vehicle registrations.

The descriptive statistics for my independent variables, my dependent variables, and my control variables (including the instrumental variable) are presented in Table 1 of the appendix. It is worth reiterating that my total vehicle registration data is generated through a weighted method using vehicle registration data for the state. California is the only state that reports total vehicle registration data at a county level that is publicly accessible and thus does not use the weighted method in the analysis. For my model with instrumental variables, I only have data for California and thus may not be able to explain the endogeneity issues for all the 13 states. The gas station data comes from the California Energy Commission with zip code and county location. I also use Alternative Fuels Station as another instrumental variable that affects charging stations but not EV registration. I find my data for Alternative Fuels Station from the AFDC for all the counties in the United States. Similar to the charging station data, I use GEOCODIO to decode my zip code and street address data to county level specifics.

Results

I run two preliminary regressions, with my dependent variable being EV registration and my independent variable being, first, Charging Stations and, second, Electric Vehicle Supply Equipment (EVSE) port using equation (1). The regression results for charging station as independent variable show that an increase in 1 charging station would increase EV registration by 376 vehicles in a county for the 15 states, significant at 95% confidence. Similarly, my regression results for EVSE port count as an independent variable shows that an increase in 1 EVSE port would increase EV registration by 158 vehicles, significant at the 99% confidence. There is a small variability in both regressions, therefore in order to increase my *R-squared* and the variability in my regression, I add control variables and other OLS tools to strengthen my results. I also end up not using EVSE ports because I wanted to look at the charging stations per person.

I then compare my regression results for individual states to see how charging infrastructure affects different states. Here I find that observations for three states are significantly lower than the rest of the ten states. This could be due to no EV registration in those counties, the lack of American Consumer Survey data or no charging stations in those counties. Nevertheless, I include all the 13 states in my regression analysis to have a larger set of observations and increase the variability. For my regression with fixed effects, equation (4), like I mentioned earlier, I use a county fixed effect, time fixed effects and an interaction of State * Time fixed effects. I use EV count per capita by dividing the EV counts and population of the county to capture how EV per person increases with changes in Charging Infrastructure per capita. Here, I find that an increase in one Charging Infrastructure per capita at a county level results in an increase in EV count per capita by 83 vehicles per person (Table 2). Other control variables like mean income per capita, white population per capita, total population, education attainment per capita and population that commutes per capita are controlled for. Mean income per capita shows a significant positive relationship with EV count per capita which can be justified due to the higher cost for purchasing EV according to NRDC (2021). Increase in income by $100,000 results in an increase in EV registration by 0.03 per person. Similarly white population per capita also shows significant positive relationships. An increase in white population per capita will increase EV registrations per capita by 0.04 vehicles. Commuter population per capita and unemployment per capita have a negative relationship with EV registration per capita, showing that when unemployment per capita increases there is a decrease in EV registration per capita, and when commuters per capita increase , there is a decrease in EV registration per capita, however these are not statically significant (Table 2). While I hypothesize that unemployment per capita has a negative relationship with EV registration, the results for population that commutes per capita does go against my hypothesis. I suspect that since this dataset consists of people who carpool and commute to work as well, if there is an increase in people who carpool, there will be a decrease in EV registrations as people may not be motivated to purchase a vehicle that is costlier than internal combustion gas vehicles.

Furthermore, I include an instrumental variable to strengthen the validity of my argument. Instrumental variables are variables that are exogenous in nature, meaning that it does not affect my dependent variable, EV registration, unless it is through my independent variable, Charging Stations. I choose gas stations as my instrumental variable because the number of gas stations in a county does not have a direct effect on EV registrations. This variable, therefore, allows me to account for unexpected behavior between my dependent variable, independent variable, and other control variables. Since gas-station count per capita has an f-test score of less than 10, I cannot use this variable as my instrumental variable. However, theoretically, this variable should work as an instrument and may not have a high F-test score due to low number of observations for the state of California. When I add Gas Stations per capita as my instrumental variable, I run a first stage OLS regression for Charging Stations per capita as my dependent variable and Gas Stations as my independent variable along with other control variables from before. Results show an increase in Gas Stations per capita leads to an increase in Charging Stations per capita, statistically significant at 95% level. Population that is white has a negative significant relationship with charging station; showing that increase in 1 white person per capita, there is a decrease in charging station by 0.0004. Total vehicle share per capita also has a negative significant relationship with charging stations per capita showing that increase in vehicles per person, there is a decrease in charging stations. I suspect that this is because if there is an increase in gas powered vehicles there will lesser use of charging stations. However, after running an F-test for my instrumental variable, I find that the score is less than 10 showing that it may not be the best instrument to use. I also argue that due to the limited observations for California, I may not receive a significant F-test score (Table 3).

I then use the change in charging stations as an independent variable in my second stage regression where the dependent variable is EV registrations per capita. I find that an increase in 1 charging station per capita leads to an increase in 52 EV registration per capita. However, this is not statistically significant and therefore may not be used to make sound arguments for policy implications. The result with my instrumental variable drops the significance for all my variables other than income. Income per capita has a positive relationship with EV registration per capita; increase in $100000 leads to an increase in 0.01 EV per capita. The results of my first stage OLS regression are presented in Column 1 of Table 3 and the second stage is presented in Column 2 of Table 3. Although the f-test score for gas stations per capita as my instrument does not show explanatory power, it may show some insight to future research with data for each state in the United States.

To test another instrumental variable to solve for the reverse causality issue, I use alternative fuel stations (other than charging stations). I theorize that an increase in alternative fuel stations will lead to an increase in charging stations. In doing so, I gain the advantage of having data for all the 13 states in the US while also being able to see the effect of alternative fuel stations per capita on charging infrastructure. In my first stage regression, using charging stations per capita as my dependent variable and alternative fuel stations as my independent variable, I find that Alternative Fuel stations per capita have a positive relationship with Charging stations per capita, however not statistically significant. My f-test score for alternative fuel stations is 1.33 thus being lower than the threshold of 10. Simultaneously, my second stage regression shows that an increase in charging stations per capita leads to a 42 EV registration per capita not statistically significant. Income is the only variable that remains statistically significant showing that an increase in $100000 would lead to an increase in 0.3 EVs per capita. Although I have data for all the counties, I cannot use this variable as there are low number of Alternative Fuel Stations (n = 256).

Similarly, I use a third instrumental variable where I look at the real estate establishments; more specifically, number of establishments that are parking lots, convenient stores, retail stores, etc. I hypothesize that an increase in real estate establishments will increase charging stations because charging stations are being implemented in more parking lots, malls, etc. I find that there is a positive significant relationship with Charging Stations and real estate establishments in my first stage results, aligning with my hypothesis. Similarly, in my second stage results, I also find a positive significant relationship with charging stations and EV registration. However, it is important to note that my standard error is 129 which is statistically very high. The result for this regression is in Table 5 of the appendix.

I also use general business establishments as an instrument and hypothesize the same relationship with charging station as above. In my first stage regression analysis, total establishments have a positive significant relationship with charging stations 100000 establishments would lead to an increase in 0.2 charging stations per person. Here too my f-test score is lower than the 10 threshold and thus cannot be used to make conclusions. However I do also find a positive relationship between EV registration and charging stations. The p-value is not less than 95% hence it is not significant and the standard errors are very high (92). The results are listed in Table 6 of the appendix.

Conclusion

Electric Vehicles are a great way to combat climate change while also keeping the same lifestyle as humans already do. With more technological advancements, the cost of EVs have lowered in the last 5 years and thus the monetary incentives provided by the government may not be the right way to promote EVs in the United States. Similarly, the concern of range anxiety brings up a different challenge to EV promotion and the single way to combat this is improving Charging Infrastructure in the US. Compared to China and the EU, the US has done a poor job at implementing charging stations for public use. Therefore, I argue that Charging Infrastructure will increase EV sales in the US.

My results for 13 states in the US show that charging infrastructure has a positive relationship with EV sales when holding vehicle registration, income and other variables constant. However, there is an endogeneity issue where one may argue that EV sales may affect the number of charging stations in the US. To solve this reverse causality, I use gas stations as my instrumental variable because gas stations have an effect on EV sales only if it is through charging stations. Here gas stations have a positive relationship with charging stations, however it does not show statistical power due to the low number of observations. I also try using alternative fuel stations as an instrumental variable; although I have data for all the states in the US, I only have 250 observations that merge with my county level registration data. This is due to the low amount of Alternative Fuel Stations in the US. Thus, the F- test for this instrument is low as well.

Despite the limitations with my data, I do believe that gas stations are a good instrumental variable that will allow future researchers to solve the endogeneity issue. COVID-19 also affected the data that was reported by the ACS as they did not have the 5-year estimates for the year 2020. Hence, that might affect the data a little bit. Along with that the ACS also does not report statistics for counties with population less than 5000, thus limiting the true population size and effect of the variables. Researchers can focus on refining the data to get more precise statistics on the variables found from the ACS and the vehicle registration data on a county level.

In the future I would also like to see the effects of household preferences on EV sales as consumers may be motivated to purchase EVs due to their concern of climate change. This brings up a different issue that goes beyond the variable I find from ACS and thus may require experimental or survey level data to see the change in preferences based on worry of Climate Change. I also think including electricity prices and gas prices on a county level may help increase validity and limit causal biases. Vehicle prices for different EVs may also help determine the quantity demanded by the consumers based on the price of the vehicle.

References

Alternative Fuel Vehicle Rebates for Consumers. (2023). https://www.dep.pa.gov/Citizens/GrantsLoansRebates/Alternative-Fuels-Incentive-Grant/pages/alternative-fuel-vehicles.aspx

Alternative Fuel Vehicles and High Occupancy Vehicle Lanes. (2023). https://afdc.energy.gov/laws/HOV

Alternative Fuels Data Center . (2023). https://afdc.energy.gov/laws/all?state=CA

Beare, M. (2018, November). The importance of energy security. *Oxford Policy Management* https://www.opml.co.uk/blog/importance-energy-security

Bentley Clinton and Daniel Steinberg.Providing the Spark: Impact of
Financial Incentives on Battery
Electric Vehicle Adoption. https://ceepr.mit.edu/wp-content/uploads/2021/09/2019-015.pdf

Carlier, M. (2023). *Number of Tesla vehicles delivered worldwide from 1st quarter 2016 to 4th quarter 2022*. https://www.statista.com/statistics/502208/tesla-quarterly-vehicle-deliveries/

Chris Harto. (2020). *Electric Vehicle Ownership Costs: Today's Electric Vehicles Offer Big Savings for Consumers*. (). https://advocacy.consumerreports.org/wp-content/uploads/2020/10/EV-Ownership-Cost-Final-Report-1.pdf

Christian Wardlaw. (2020, November 03,). What is Range Anxiety with Electric Vehicles? https://www.jdpower.com/cars/shopping-guides/what-is-range-anxiety-with-electric-vehicles

Christiane Münzel, Patrick Plötz, Frances Sprei and Till Gnann.How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis.

https://econpapers.repec.org/article/eeeeneeco/v_3a84_3ay_3a2019_3ai_3ac_3as0140988319302749.htm

Copley, M. (2022, December 5,). The U.S. wants to slash carbon emissions from power plants. Natural gas is in the way. *Npr* https://www.npr.org/2022/12/05/1139401121/the-u-s-wants-to-slash-carbon-emissions-from-power-plants-natural-gas-is-in-the-#:~:text=Under%20President%20Joe%20Biden%2C%20the,to%20rein%20in%20climate%20change.

Credits for New Clean Vehicles Purchased in 2023 or After. https://www.irs.gov/credits-deductions/credits-for-new-clean-vehicles-purchased-in-2023-or-after

Doll, S. (2023, February 20,). Lightyear tries to claw back from bankruptcy as new company using Solar EV tech as collateral. *Electrek* https://electrek.co/2023/02/20/lightyear-back-bankruptcy-new-company-solar-ev-tech-collateral/

Electric Vehicles. https://www.iea.org/reports/electric-vehicles

FACT SHEET: Biden-Harris Administration Announces New Standards and Major Progress for a Made-in-America National Network of Electric Vehicle Chargers. (2023, February 15,). https://www.whitehouse.gov/briefing-room/statements-releases/2023/02/15/fact-sheet-biden-harris-administration-announces-new-standards-and-major-progress-for-a-made-in-america-national-network-of-electric-vehicle-chargers/#:~:text=These%20steps%20will%20help%20the,all%20while%20advancing%20an%20industrial

FACT SHEET: President Biden Announces New Initiatives at COP27 to Strengthen U.S. Leadership in Tackling Climate Change. (2022). https://www.whitehouse.gov/briefing-room/statements-releases/2022/11/11/fact-sheet-president-biden-announces-new-initiatives-at-cop27-to-strengthen-u-s-leadership-in-tackling-climate-change/

Fast Publicly Available Chargers, 2015- 2021. (2022). https://www.iea.org/data-and-statistics/charts/fast-publicly-available-chargers-2015-2021

Gaffen, D. (2022, December 15,). How the Russia-Ukraine war accelerated a global energy crisis. *Reuters* https://www.reuters.com/business/energy/year-russia-turbocharged-global-energy-crisis-2022-12-13/

Global electric car sales by key markets, 2010-2020. https://www.iea.org/data-and-statistics/charts/global-electric-car-sales-by-key-markets-2015-2020

Global EV Outlook 2020. https://www.iea.org/reports/global-ev-outlook-2020

Greenhouse Gas Emissions from a Typical Passenger Vehicle. (2023). https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle

Holman, J. O., & Hacherl, A. (2022). Consumer Ecoregions and the Geography of Automotive Brand Preference: An Analysis of Vehicle Registration Data. *The Journal of Applied Business and Economics, 24*(3), 1-9. https://10.33423/jabe.v24i3.5188

Notes: ID: cdi_proquest_journals_2679345175.

Jennifer Jacobs Dungs. (2022, Aug 18,). 1000 Miles Per Charge – What's 'Under The Hood' Of The Longest Range Electric Cars? *Forbes* https://www.forbes.com/sites/jenniferdungs/2022/08/18/1000-miles-per-charge--whats-under-the-hood-of-the-longest-range-electric-cars/?sh=54f4c8bc481e

Lindwall, C. (2022, May 25,). Electric vs. Gas Cars: Is It Cheaper to Drive an EV? *Nrdc* https://www.nrdc.org/stories/electric-vs-gas-cars-it-cheaper-drive-ev?gclid=Cj0KCQjw2cWgBhDYARIsALggUhoUXc24hei9dKCAeyBiog2gNqAFjbDCWi1BeB8YyXlD-T7LLVRakGQaAmcCEALw_wcB

THE LONG-TERM STRATEGY

OF THE UNITED STATES. (2021). (). Washington DC: United States Department of State and the United States Executive Office of the President. https://www.whitehouse.gov/wp-content/uploads/2021/10/US-Long-Term-Strategy.pdf

PARIS AGREEMENT (mm UNITED NATIONS 2015

The Paris Agreement, What is the Paris Agreement? https://unfccc.int/process-and-meetings/the-paris-agreement

Penney, V. (2021, January 15,). Electric Cars Are Better for the Planet – and Often Your Budget, Too. *New York Times* https://www.nytimes.com/interactive/2021/01/15/climate/electric-car-cost.html

Phillipp Kampshoff , Adi Kumar , Shannon Peloquin , and Shivika Sahdev. (2022, April 18,). The United States needs many more EV-charging stations—and federal funds for them are coming. Seven principles could help US states and companies accelerate this buildout effectively. https://www.mckinsey.com/industries/public-and-social-sector/our-insights/building-the-electric-vehicle-charging-infrastructure-america-needs

Holman, & Hacherl, A. (2022). Consumer Ecoregions and the Geography of Automotive Brand Preference: An Analysis of Vehicle Registration Data. The Journal of Applied Business and Economics, 24(3), 1–9. https://doi.org/10.33423/jabe.v24i3.5188

Münzel, Plötz, P., Sprei, F., & Gnann, T. (2019). How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis. Energy Economics, 84, 104493–. https://doi.org/10.1016/j.eneco.2019.104493

Vergis, & Chen, B. (2015). Comparison of plug-in electric vehicle adoption in the United States: A state by state approach. Research in Transportation Economics, 52, 56–64. https://doi.org/10.1016/j.retrec.2015.10.003

Ledna, Muratori, M., Brooker, A., Wood, E., & Greene, D. (2022). How to support EV adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in California. Energy Policy, 165, 112931–. https://doi.org/10.1016/j.enpol.2022.112931

White, Carrel, A. L., Shi, W., & Sintov, N. D. (2022). Why are charging stations associated with electric vehicle adoption? Untangling effects in three United States metropolitan areas. Energy Research & Social Science, 89, 102663–. https://doi.org/10.1016/j.erss.2022.102663

Esmaeili, Anvari-Moghaddam, A., Muyeen, S. M., & Peric, V. S. (2022). On the Role of Renewable Energy Policies and Electric Vehicle Deployment Incentives for a Greener Sector Coupling. IEEE Access, 10, 53873–53893. https://doi.org/10.1109/ACCESS.2022.3176012

Wee, Coffman, M., & La Croix, S. (2018). Do electric vehicle incentives matter? Evidence from the 50 U.S. states. Research Policy, 47(9), 1601–1610. https://doi.org/10.1016/j.respol.2018.05.003

Liu, Kim, D., Li, H., Rodgers, M. O., & Guensler, R. (2022). Synthetic control methods for estimating the effect of purchase incentives on plug-in electric vehicles sales in the United States. Transportation (Dordrecht). https://doi.org/10.1007/s11116-022-10350-4

Jenn, Springel, K., & Gopal, A. R. (2018). Effectiveness of electric vehicle incentives in the United States. Energy Policy, 119(C), 349–356. https://doi.org/10.1016/j.enpol.2018.04.065

Hardman, Chandan, A., Tal, G., & Turrentine, T. (2017). The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. Renewable & Sustainable Energy Reviews, 80, 1100–1111. https://doi.org/10.1016/j.rser.2017.05.255

Wang, Wang, X., & Yang, W. (2020). Optimal design of electric vehicle battery recycling network – From the perspective of electric vehicle manufacturers. Applied Energy, 275, 115328–. https://doi.org/10.1016/j.apenergy.2020.115328

Tie, & Tan, C. W. (2013). A review of energy sources and energy management system in electric vehicles. Renewable & Sustainable Energy Reviews, 20, 82–102. https://doi.org/10.1016/j.rser.2012.11.077

Hawkins, Gausen, O. M., & Strømman, A. H. (2012). Environmental impacts of hybrid and electric vehicles—a review. The International Journal of Life Cycle Assessment, 17(8), 997–1014. https://doi.org/10.1007/s11367-012-0440-9

IEA (2019), Multiple Benefits of Energy Efficiency, IEA, Paris https://www.iea.org/reports/multiple-benefits-of-energy-efficiency License: CC BY 4.0

Appendix

Table 1. Descriptive Statistics for Independent Variable, Dependent Variable, Control Variables and Instrumental Variables.

Variables	*N*	Mean	St. Dev.
Electric Vehicle Registration	2555	4041	17726
Charging Station Count	2555	6	22
Charging Ports (EVSE)	2555	17	56
Income	1287	176361	301385
Total Population	1287	490366	892625
White/Caucasian Population	1061	292612	446557
Education Attainment	1287	73842	128640
Unemployment	1059	12707	25849
Commuter Population	1059	223868	404720
Total Vehicle Registration	1287	144971	301993
Gas Station (California Only)	314	185.27	305.89
Alternative Fuel Stations	954	1.55	5.04

Table 2. Results with aggregated control variables and county, year and state * year interaction fixed effects.

Variables Dependent: Electric Vehicle per capita	Preliminary Results	Control Variables
Independent: Charging Station per capita	101.44***	83.75**
	(43.153)	(38.321)
Total Population * 100000		-0.004
		(0.018)
Income per capita * 100000		0.03**
		(0.001)
Education Attainment per capita		-0.014
		(0.043)
Unemployment per capita		0.1
		(0.109)
Commuter Population per capita		-0.019
		(0.036)
White/ Caucasian Population per capita		0.042**
		(0.019)
Vehicle Registration		0.004
		(0.007)
Constant	0.03	-0.08
	(0.003)	(0.045)
Observations	1287	1,058
R-squared	0.842	0.317
Number of GEOID	433	430
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 3. Results for first and second stage regressions with instrumental variable of Gas Station.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		52.957
		(33.538)
Instrument: Gas Stations per capita	0.492**	
	(0.192)	
Income per capita * 100000	0.0000115	0.002**
	(9.22e-10)	(8.93e-06)
Total Population *100000	-0.0000017	-0.0003
	(2.79e-10)	(2.44e-6)
White/Caucasian Population per capita	-0.00042***	-0.021
	(0.00015)	(0.019)
Education Attainment per capita	-0.0006	0.001
	(0.00046)	(0.045)
Unemployment per capita	0.002*	-0.064
	(0.001)	(0.097)
Commuter Population per capita	0.0006	0.047
	(0.0005)	(0.040)
Total Vehicle Share	-5.42e-10***	1.70e-8
	(1.62e-10)	(2.26e-8)
Constant	-0.00003	-0.044
	(0.0005)	(0.043)
Observations	151	151
R-squared	0.0133	0.063
Number of GEOID	50	50
Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$		

Table 4. Results for first and second stage regressions with instrumental variable of Alternative Fuel Station.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		43.038
		(509.001)
Instrument: Alternative Fuel Stations	0.261	
	(0.227)	
Income per capita	3.58e-10**	3.47e-07*
	(1.70e-10)	(2.11e-07)
Total Population	1.73e-11	7.56e-08
	(4.17e-10)	(2.44e-07)
White/Caucasian Population per capita	-0.00003	-0.047
	(0.00004)	(0.031)
Education Attainment per capita	-0.00002	-0.106
	(0.0002)	(0.145)
Unemployment per capita	0.001**	0.663
	(0.0005)	(0.736)
Commuter Population per capita	0.0001	0.123
	(0.0002)	(0.152)
Total Vehicle Share	-8.10e-10	1.39e-07
	(1.36e-09)	(8.96e-07)
Constant	-0.00006	-0.044
	(0.0002)	(0.043)
Observations	256	256
R-squared	0.0003	0.040
Number of GEOID	153	153
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 5. Results for first and second stage regressions with instrumental variable of real estate establishments.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		114.583
		(129.741)
Instrument: Real Estate	0.008	
	(0.005)	
Income per capita	8.15e-10	3.74e-07
	(1.25e-09)	(2.77e-07)
Total Population	1.67e-09	-2.56e-07
	(3.14e-10)	(6.76e-07)
White/Caucasian Population per capita	-0.0003	-0.052
	(0.0003)	(0.050)
Education Attainment per capita	-0.00007	-0.167*
	(0.0004)	(0.080)
Unemployment per capita	0.0004	0.051
	(0.0009)	(0.204)
Commuter Population per capita	-0.0003	0.034
	(0.0004)	(0.091)
Total Vehicle Share	-3.89e-09	8.76e-07
	(8.96e-09)	(1.89e-06)
Constant	-0.008	-0.043
	(0.005)	(0.116)
Observations	153	153
R-squared	0.6773	0.040
Number of GEOID	60	60
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Table 6. Results for first and second stage regressions with instrumental variable of total establishments.

Variables	Column 1	Column 2
Dependent: Electric Vehicle per capita	First Stage	Second Stage
Independent: Charging Station per capita		123.448
		(92.219)
Instrument: Total Establishments	2.14e-08**	
	(9.55e-09)	
Income per capita	7.62e-10	3.66e-07
	(1.123e-09)	(2.66e-07)
Total Population	-3.00e-09	-2.40e-07
	(3.15e-09)	(6.60e-07)
White/Caucasian Population per capita	-0.00009	-0.050
	(0.0004)	(0.046)
Education Attainment per capita	-0.0001	-0.165**
	(0.0004)	(0.076)
Unemployment per capita	0.0006	0.046
	(0.0009)	(0.197)
Commuter Population per capita	-0.0003	0.037
	(0.0004)	(0.086)
Total Vehicle Share	-8.18e-08	8.39e-07
	(9.01e-09)	(1.86e-06)
Constant	-0.0001	-0.047
	(0.0005)	(0.109)
Observations	153	153
R-squared	0.0020	0.015
Number of GEOID	60	60
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		