

Natural Resource Management with Institutional Shifts

Case Studies from Agriculture and Bitcoin

Alexander Gebben

PhD Candidate, Mineral and Energy Economics

October 24th, 2024



COLORADO SCHOOL OF
MINES

- 1 Chapter I: Collective Action to Manage Agricultural Groundwater, Drivers and Outcomes
- 2 Chapter II: Policy Interactions of Water Conservation Programs. Is Efficiency Always Efficient?
- 3 Chapter III: Bitcoin Mining, the Next Shale Boom?

Collective Action to Manage Agricultural Groundwater.

Was collective action in the San Luis Valley (SLV) undertaken primarily to improve farm profits or to avoid institutional risk?

Hedonic difference-in-difference of the formation of the water conservation Subdistrict 1 (Sbd1). Farm census DiD of revenue and operating costs. .

- Collective action was a response to risk of well curtailment by Colorado.
- Farm values declined by 43% when Sbd1 formed.
- Yearly farm profits fall by 20%.

Was collective action in the San Luis Valley (SLV) undertaken primarily to improve farm profits or to avoid institutional risk?

Hedonic difference-in-difference of the formation of the water conservation Subdistrict 1 (Sbd1). Farm census DiD of revenue and operating costs. .

- Collective action was a response to risk of well curtailment by Colorado.
- Farm values declined by 43% when Sbd1 formed.
- Yearly farm profits fall by 20%.

Was collective action in the San Luis Valley (SLV) undertaken primarily to improve farm profits or to avoid institutional risk?

Hedonic difference-in-difference of the formation of the water conservation Subdistrict 1 (Sbd1). Farm census DiD of revenue and operating costs. .

- Collective action was a response to risk of well curtailment by Colorado.
- Farm values declined by 43% when Sbd1 formed.
- Yearly farm profits fall by 20%.

Was collective action in the San Luis Valley (SLV) undertaken primarily to improve farm profits or to avoid institutional risk?

Hedonic difference-in-difference of the formation of the water conservation Subdistrict 1 (Sbd1). Farm census DiD of revenue and operating costs. .

- Collective action was a response to risk of well curtailment by Colorado.
- Farm values declined by 43% when Sbd1 formed.
- Yearly farm profits fall by 20%.

Was collective action in the San Luis Valley (SLV) undertaken primarily to improve farm profits or to avoid institutional risk?

Hedonic difference-in-difference of the formation of the water conservation Subdistrict 1 (Sbd1). Farm census DiD of revenue and operating costs. .

- Collective action was a response to risk of well curtailment by Colorado.
- Farm values declined by 43% when Sbd1 formed.
- Yearly farm profits fall by 20%.

How have pumping fees and other self imposed groundwater policies changed farmer welfare?

Event study of farm land prices.

- Sbd1 land values increase as the policies are adopted.
- Rebound of 85% by 2020.

How have pumping fees and other self imposed groundwater policies changed farmer welfare?

Event study of farm land prices.

- Sbd1 land values increase as the policies are adopted.
- Rebound of 85% by 2020.

How have pumping fees and other self imposed groundwater policies changed farmer welfare?

Event study of farm land prices.

- Sbd1 land values increase as the policies are adopted.
- Rebound of 85% by 2020.

How have pumping fees and other self imposed groundwater policies changed farmer welfare?

Event study of farm land prices.

- Sbd1 land values increase as the policies are adopted.
- Rebound of 85% by 2020.

Subdistrict 1 background: formation and policy

Subdistrict 1 is granted authority through the larger Rio Grande Water Conservation District (RGWCD) and was formed in 2006.

- Majority vote by farms required for formation
- Pumping fee in 2011
- The fee lowered water use by 33% (Smith et al., 2017)
- Fees fund administration, conservation, and augmentation

Subdistrict 1 background: formation and policy

Subdistrict 1 is granted authority through the larger Rio Grande Water Conservation District (RGWCD) and was formed in 2006.

- Majority vote by farms required for formation
- Pumping fee in 2011
- The fee lowered water use by 33% (Smith et al., 2017)
- Fees fund administration, conservation, and augmentation

Subdistrict 1 background: formation and policy

Subdistrict 1 is granted authority through the larger Rio Grande Water Conservation District (RGWCD) and was formed in 2006.

- Majority vote by farms required for formation
- Pumping fee in 2011
- The fee lowered water use by 33% (Smith et al., 2017)
- Fees fund administration, conservation, and augmentation

Subdistrict 1 background: formation and policy

Subdistrict 1 is granted authority through the larger Rio Grande Water Conservation District (RGWCD) and was formed in 2006.

- Majority vote by farms required for formation
- Pumping fee in 2011
- The fee lowered water use by 33% (Smith et al., 2017)
- Fees fund administration, conservation, and augmentation

Subdistrict 1 background: formation and policy

Subdistrict 1 is granted authority through the larger Rio Grande Water Conservation District (RGWCD) and was formed in 2006.

- Majority vote by farms required for formation
- Pumping fee in 2011
- The fee lowered water use by 33% (Smith et al., 2017)
- Fees fund administration, conservation, and augmentation

Why initiate collective action?

Externalities

- Tragedy of the commons
- Cones of depression
- Salinity and subsidence

Institutional threat

- Prior appropriations
- Seniority of wells
- State compacts

Reasons to self organize

- 1 Piguivian tax (Pigou, 1924)
- 2 Crowding in norms (Smith, 2018)
- 3 Avoid State intervention
- 4 Risk aversion and institutional shifts (Bredehoeft & Young, 1983; Menapace et al., 2013)

Why initiate collective action?

Externalities

- Tragedy of the commons
- Cones of depression
- Salinity and subsidence

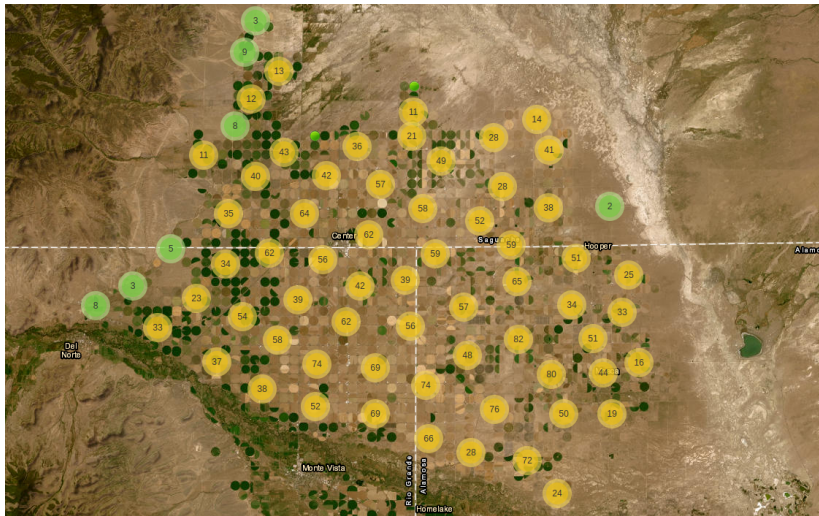
Institutional threat

- Prior appropriations
- Seniority of wells
- State compacts

Reasons to self organize

- 1 Piguivian tax (Pigou, 1924)
- 2 Crowding in norms (Smith, 2018)
- 3 Avoid State intervention
- 4 Risk aversion and institutional shifts (Bredehoeft & Young, 1983; Menapace et al., 2013)

Location of Subdistrict 1 wells



Map creation tool from (Colorado Division of Water Resources, 2024)

San Luis Valley Agriculture

- 350,000 irrigated acres by 1890 (Carlson, 1973)
- Groundwater rights over appropriated in 1900 (Kuenhold, 2006)
- 2,704 wells by 1940 (Cody et al., 2015)
- 26% of employment still comes from agricultural (San Luis Valley Development Resources Group, 2024)



San Luis Valley potato harvest (Rothstein, 1939)



San Luis Valley potato field (Krakel, 2024)

San Luis Valley Agriculture

- 350,000 irrigated acres by 1890 (Carlson, 1973)
- Groundwater rights over appropriated in 1900 (Kuenhold, 2006)
- 2,704 wells by 1940 (Cody et al., 2015)
- 26% of employment still comes from agricultural (San Luis Valley Development Resources Group, 2024)



San Luis Valley potato harvest (Rothstein, 1939)



San Luis Valley potato field (Krakel, 2024)

San Luis Valley Agriculture

- 350,000 irrigated acres by 1890 (Carlson, 1973)
- Groundwater rights over appropriated in 1900 (Kuenhold, 2006)
- 2,704 wells by 1940 (Cody et al., 2015)
- 26% of employment still comes from agricultural (San Luis Valley Development Resources Group, 2024)



San Luis Valley potato harvest (Rothstein, 1939)



San Luis Valley potato field (Krakel, 2024)

San Luis Valley Agriculture

- 350,000 irrigated acres by 1890 (Carlson, 1973)
- Groundwater rights over appropriated in 1900 (Kuenhold, 2006)
- 2,704 wells by 1940 (Cody et al., 2015)
- 26% of employment still comes from agricultural (San Luis Valley Development Resources Group, 2024)



San Luis Valley potato harvest (Rothstein, 1939)



San Luis Valley potato field (Krakel, 2024)

San Luis Valley Agriculture

- 350,000 irrigated acres by 1890 (Carlson, 1973)
- Groundwater rights over appropriated in 1900 (Kuenhold, 2006)
- 2,704 wells by 1940 (Cody et al., 2015)
- 26% of employment still comes from agricultural (San Luis Valley Development Resources Group, 2024)



San Luis Valley potato harvest (Rothstein, 1939)



San Luis Valley potato field (Krakel, 2024)

Shortages and Legal Obstacles

- Rio Grande Water Conservation District (RGWDCD) formed in 1976
- 1984 lawsuit prevented new wells protected the status quo (Cody et al., 2015)
- Court ruling changed well operation rules (Coats, 2003)
- 3,000 wells in the South Platte were curtailed in 2004. (Cech, 2008; Loos et al., 2022)



Shortages and Legal Obstacles

- Rio Grande Water Conservation District (RGWDCD) formed in 1976
- 1984 lawsuit prevented new wells protected the status quo (Cody et al., 2015)
- Court ruling changed well operation rules (Coats, 2003)
- 3,000 wells in the South Platte were curtailed in 2004.(Cech, 2008; Loos et al., 2022)



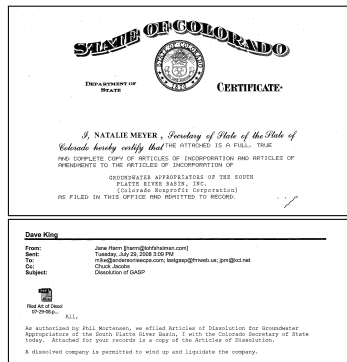
Shortages and Legal Obstacles

- Rio Grande Water Conservation District (RGWDCD) formed in 1976
- 1984 lawsuit prevented new wells protected the status quo (Cody et al., 2015)
- Court ruling changed well operation rules (Coats, 2003)
- 3,000 wells in the South Platte were curtailed in 2004.(Cech, 2008; Loos et al., 2022)



Shortages and Legal Obstacles

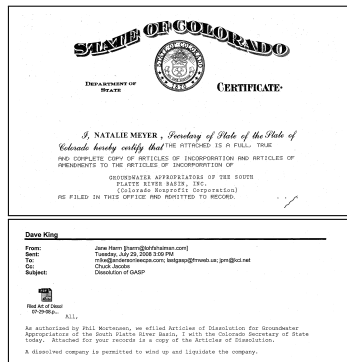
- Rio Grande Water Conservation District (RGWDCD) formed in 1976
- 1984 lawsuit prevented new wells protected the status quo (Cody et al., 2015)
- Court ruling changed well operation rules (Coats, 2003)
- 3,000 wells in the South Platte were curtailed in 2004.(Cech, 2008; Loos et al., 2022)



(Kryloff et al., 2009)

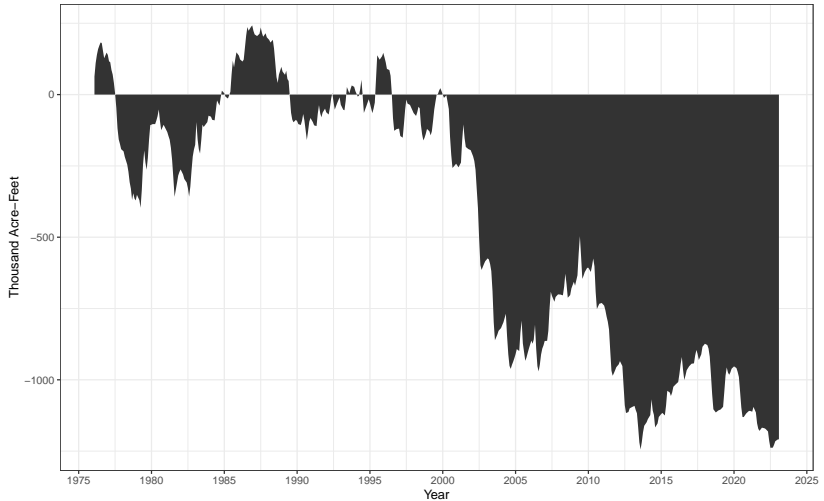
Shortages and Legal Obstacles

- Rio Grande Water Conservation District (RGWDCD) formed in 1976
- 1984 lawsuit prevented new wells protected the status quo (Cody et al., 2015)
- Court ruling changed well operation rules (Coats, 2003)
- 3,000 wells in the South Platte were curtailed in 2004.(Cech, 2008; Loos et al., 2022)



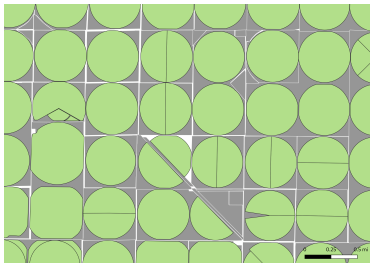
(Kryloff et al., 2009)

Water level of the San Luis Valley confined aquifer



County assessors office

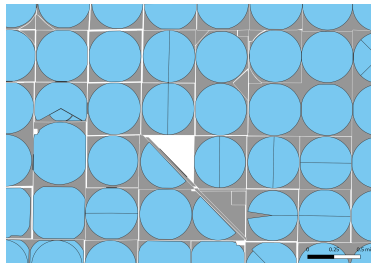
- Sales records
- Names
- Dates
- Valuation



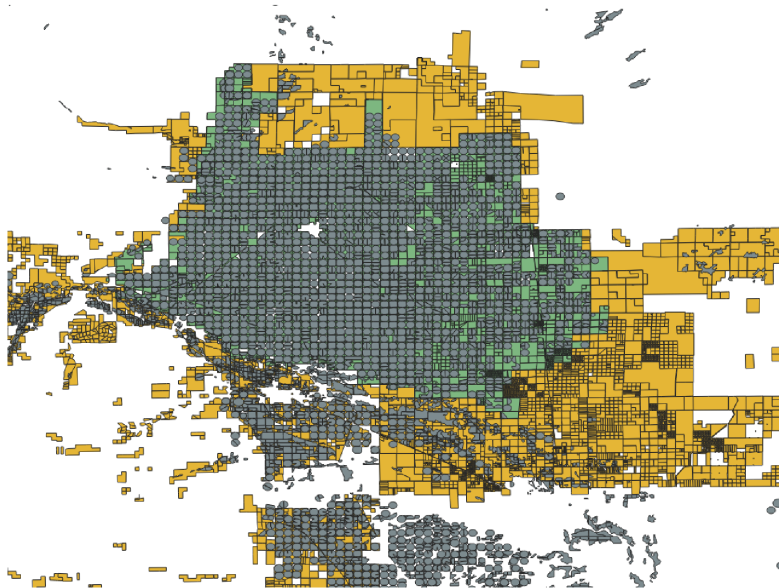
(a) Crop Parcels and Legal Parcels

Colorado Hydrobase

- Crop area
- Crop types
- Water sources
- Well data



(b) Intersection of Parcels



Data: weighting and matching

Generalized boosted machine learning model for propensity score.
Used to match and weight records (McCaffrey et al., 2016).

Variable	Sbd. 1	Weighted Sbd. 1	Control	Weighted Control	Difference (Units)	Difference (S.D.)	Improvement
Area (Acres)	170	167	126	128	44	0.74	8.89%
Area of Crops (Acres)	130	126	97	98	33	0.69	16.22%
Potatoes (%)	0.4	0.36	0.01	0.02	0.39	1.25	10.51%
Alfalfa (%)	0.21	0.24	0.4	0.41	0.2	0.61	14.70%
Small Grains (%)	0.31	0.28	0.13	0.13	0.18	0.73	14.62%
Pasture (%)	0.02	0.05	0.38	0.37	0.35	2.95	8.86%
Fallow (%)	0.08	0.11	0.19	0.18	0.1	1.26	27.73%
Uses a Ditch (yes/no)	0.92	0.92	0.99	0.99	0.07	0.26	-5.35%
Uses a Well (yes/no)	0.99	0.97	0.58	0.58	0.41	4.15	6.15%
Ditch Distance (meters)	5,041	4,858	1,736	1,754	3,305	1.27	6.07%
Water Rights (Af./Year)	6.59	6.2	1.38	1.43	5.21	0.93	8.57%
Building Value (USD)	2,341	2,334	4,474	4,478	2,133	0.34	-0.51%

$$Y_{i,t} = Sbd_i \cdot \left(1 + \sum_{s=1}^S (\theta_{s(i,t)})\right) + Ditch_i + County_i + \tau_t + \beta \cdot X_{i,t} + \epsilon_{i,t}$$

$Y_{i,t}$ is the natural log of the sale price. Sbd_i is an indicator that a parcel is within a specific subdistrict boundary. $Ditch_i$ is a series of indicators if a parcel is using specific ditches in the SLV. $S(i, t)$ identifies a shock for the subdistrict of parcel i at time t . $\theta_{S(t)}$ is an indicator variable for being post-shock. τ is the year fixed effect. $X_{i,t}$ is an array of attributes that have coefficients β .

$$Y_{i,t} = \gamma_i + Sbd_i \cdot \theta_{S(i,t)} + \tau_t + \epsilon_{i,t}$$

The parcel fixed effect γ_i captures unobserved time invariant attributes of the parcel. τ_t captures the remaining variation for attributes.

Table: Hedonic models of Subdistrict One outcomes

Dependent Variable:	Price (ln)				
			Parcel Fixed Effect		
Model:	IPTW (1)	Matched (2)	No Adj. (3)	IPTW (4)	No Adj. (5)
<i>Variables</i>					
Sbd.1:Post 2006	-0.5677** (0.2263)	-0.5239** (0.2092)	-0.5317** (0.2362)	-0.5211* (0.2946)	-0.5033* (0.2798)
Sbd.1:Post 2011	0.5013** (0.2436)	0.4032* (0.2331)	0.4343 (0.2608)	0.3687 (0.2572)	0.4560* (0.2478)
Crop Area (ln)	0.9052*** (0.0567)	0.9269*** (0.0671)	0.9239*** (0.0490)		
Distance from Ditch (ln)	-0.0377 (0.0430)	-0.0498 (0.0477)	-0.0604* (0.0348)		
Water Rights (ln)	0.0066 (0.0085)	0.0094 (0.0081)	0.0066 (0.0076)		
Sbd1:Water Rights (ln)	0.0382* (0.0204)	0.0325 (0.0219)	0.0350* (0.0203)		
% Potatoes	0.4657*** (0.2032)	0.6323*** (0.1704)	0.6712*** (0.1708)		
% Small Grains	0.3340** (0.1559)	0.4105*** (0.1447)	0.4364*** (0.1330)		
% Alfalfa	0.1412 (0.1200)	0.1418 (0.1194)	0.1881 (0.1148)		
Value of Buildings (ln)	-0.0003 (0.0029)	0.0007 (0.0023)	0.0014 (0.0024)		
<i>Fixed-effects</i>					
Ditch	✓	✓	✓		
Subdistricts 1-6	✓	✓	✓		
Year	✓	✓	✓	✓	✓
County	✓	✓	✓		
No Reported Acreage	✓	✓	✓		
Parcel				✓	✓
<i>Fit statistics</i>					
Observations	463	420	463	718	718
R ²	0.75359	0.75107	0.75014	0.95687	0.95285
Within R ²	0.55605	0.51782	0.55027	0.04475	0.03939
- Clustered (Arbitrary Spatial Region & Year) standard errors in parentheses - Signif. Codes: ***: 0.01, **: 0.05, *: 0.1					

Table: Hedonic models of Subdistrict One outcomes

Model:	Parcel Fixed Effect				
	IPTW (1)	Matched (2)	No Adj. (3)	IPTW (4)	No Adj. (5)
Sbd.1:Post 2006	-0.5677** (0.2263)	-0.5239** (0.2092)	-0.5317** (0.2362)	-0.5211* (0.2946)	-0.5033* (0.2798)
Sbd.1:Post 2011	0.5013** (0.2436)	0.4032* (0.2331)	0.4343 (0.2608)	0.3687 (0.2572)	0.4560* (0.2478)
Crop Area (ln)	0.9052*** (0.0567)	0.9269*** (0.0671)	0.9239*** (0.0490)		
% Potatoes	0.4657** (0.2032)	0.6323*** (0.1704)	0.6712*** (0.1708)		
% Small Grains	0.3340** (0.1559)	0.4105*** (0.1447)	0.4364*** (0.1330)		
% Alfalfa	0.1412 (0.1200)	0.1418 (0.1194)	0.1881 (0.1148)		
<i>Fixed-effects</i>					
Parcel				✓	✓
Other	✓	✓	✓		
<i>Fit statistics</i>					
Observations	463	420	463	718	718
R ²	0.75359	0.75107	0.75014	0.95687	0.95285
Within R ²	0.55605	0.51782	0.55027	0.04475	0.03939
- Signif. Codes: ***: 0.01, **: 0.05, *: 0.1					

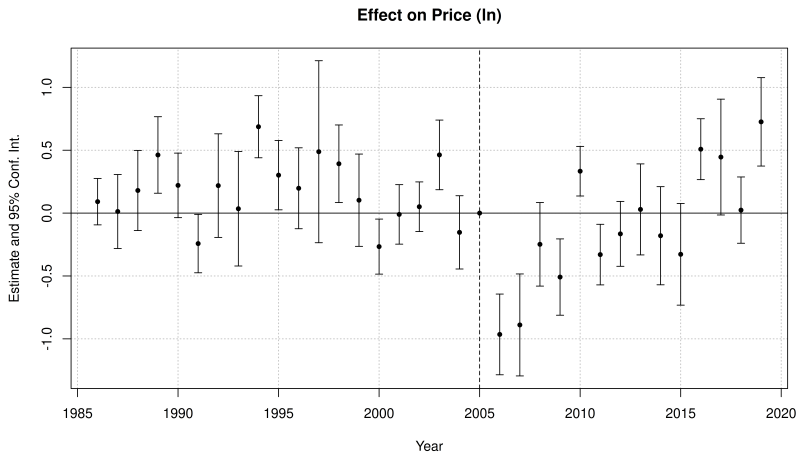


Figure: Event study of Subdistrict One formation

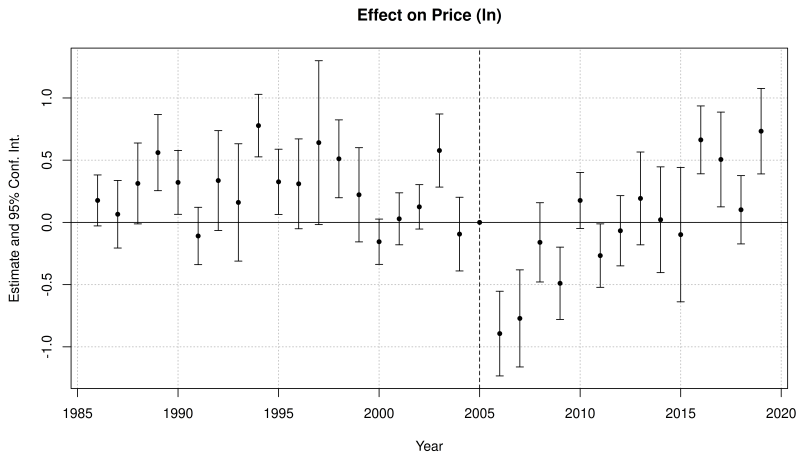
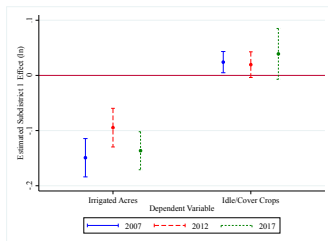
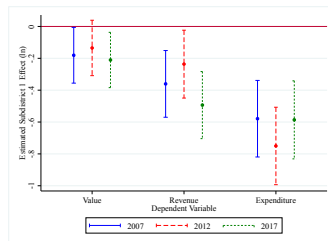


Figure: Event study of Subdistrict One formation with parcel weighting

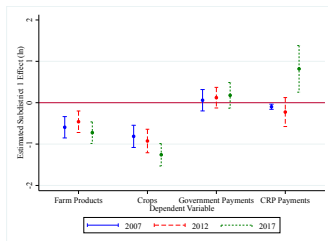
Difference-in-differences estimates, microdata



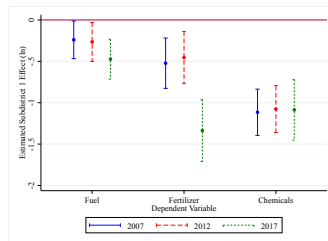
(a) Land use



(b) Total effects



(c) Revenue effects



(d) Expense effects

Ralph Curtis, former manager of RGWCD

"They've pumped the bottom out of the barrel. And we are trying to get a groundwater management subdistrict up there, and it is like pulling teeth...A lot of people will say, 'Oh, they will never come in here and regulate wells.' And Hal Simpson [the State Engineer] has told them several times, 'If you don't do something, I'm going to be here'." (The Colorado Foundation for Water Education, 2005)

Ray Wright, President of RGWCD

"I think it is inevitable that ground in the SLV is going to be fallowed whether by subdistricts or CREP or well regulation or simply running out of adequate supplies of water....I am in a position to understand what we are facing whether it feels like 'Chicken Little' or not. [We have] to try to come to some resolution without a wreck." (Heide, 2005)

Conclusion

Policy Interactions of Water Conservation Programs.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

How does Subdistrict 1 water management change the efficacy of federal payment for environmental services (PES) water conservation efforts?

Staggered DiD study of the Conservation Reserve Enhancement Program (CREP) for Subdistrict 1 farms initiated in 2014.

- Effect from enrolled wells, neighboring wells, and selection in the program
- The federal PES conserves 32% less ground water.
- Program costs rise by 29.5%.
- Pays the farmers most harmed by the pumping fee.

Provides payments to fallow irrigated land in environmentally sensitive regions. The first contracts started in 2014.

Goals

- 1 Enroll 40,000 acres of cropland
- 2 Reduce water use by 60,060 acre-feet per year.
- 3 Reduce erosion
- 4 Increase native cover crops

Current Status

- 1 10,868 acres enrolled (27.1% of goal)
- 2 Estimate of 14,755 acre-feet saved a year (24.6% of goal)

Provides payments to fallow irrigated land in environmentally sensitive regions. The first contracts started in 2014.

Goals

- 1 Enroll 40,000 acres of cropland
- 2 Reduce water use by 60,060 acre-feet per year.
- 3 Reduce erosion
- 4 Increase native cover crops

Current Status

- 1 10,868 acres enrolled (27.1% of goal)
- 2 Estimate of 14,755 acre-feet saved a year (24.6% of goal)

Provides payments to fallow irrigated land in environmentally sensitive regions. The first contracts started in 2014.

Goals

- 1 Enroll 40,000 acres of cropland
- 2 Reduce water use by 60,060 acre-feet per year.
- 3 Reduce erosion
- 4 Increase native cover crops

Current Status

- 1 10,868 acres enrolled (27.1% of goal)
- 2 Estimate of 14,755 acre-feet saved a year (24.6% of goal)

Different payments depending on contract length. Additional support from RGWCD and Sbd1.

Farm Service Agency (FSA) payments

- ① 15 year contract
- ② \$288 per acre per year
- ③ \$300 per acre sign up bonus

Subdistrict 1 payments

- ① Permanent retirement
- ② \$22 per acre per year
- ③ \$100 per acre sign up bonus

Requirement

- ① $\frac{1}{2}$ acre-feet per acre applied
- ② Four years of irrigation between 2008 and 2013
- ③ $\frac{1}{2}$ acre-feet per acre two years before application

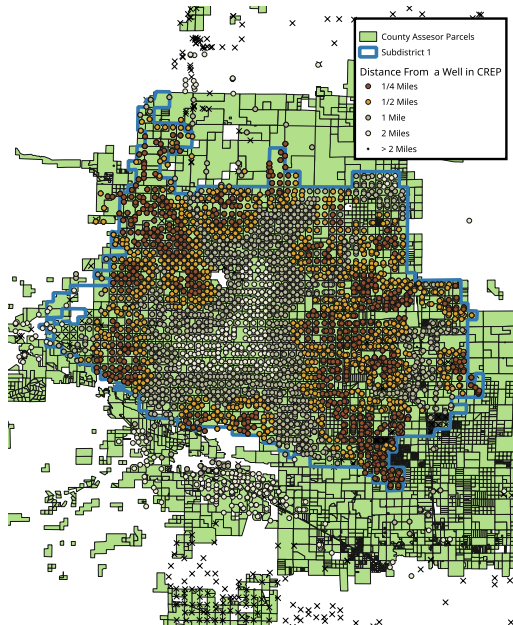
Sbd1 pumping fee was \$45 per acre-foot in 2011, raised to \$75 in 2012. *Only one year with a high pumping fee in eligibility period*

Requirement

- 1 $\frac{1}{2}$ acre-feet per acre applied
- 2 Four years of irrigation between 2008 and 2013
- 3 $\frac{1}{2}$ acre-feet per acre two years before application

Sbd1 pumping fee was \$45 per acre-foot in 2011, raised to \$75 in 2012. *Only one year with a high pumping fee in eligibility period*

CREP: Location



How can existing Sbd1 conservation affect a PES?

CREP can induce water savings directly through enrolled wells, or indirectly through the response of neighboring wells (Rouhi Rad et al., 2021).

Possible Effects

- More wells enrolled (+)
- Less water saved by enrolled wells (-)
- Neighbouring wells change pumping (+)
- Different wells enroll (+/-)

How can existing Sbd1 conservation affect a PES?

CREP can induce water savings directly through enrolled wells, or indirectly through the response of neighboring wells (Rouhi Rad et al., 2021).

Possible Effects

- More wells enrolled (+)
- Less water saved by enrolled wells (-)
- Neighbouring wells change pumping (+)
- Different wells enroll (+/-)

How can existing Sbd1 conservation affect a PES?

CREP can induce water savings directly through enrolled wells, or indirectly through the response of neighboring wells (Rouhi Rad et al., 2021).

Possible Effects

- More wells enrolled (+)
- Less water saved by enrolled wells (-)
- Neighbouring wells change pumping (+)
- Different wells enroll (+/-)

How can existing Sbd1 conservation affect a PES?

CREP can induce water savings directly through enrolled wells, or indirectly through the response of neighboring wells (Rouhi Rad et al., 2021).

Possible Effects

- More wells enrolled (+)
- Less water saved by enrolled wells (-)
- Neighbouring wells change pumping (+)
- Different wells enroll (+/-)

How can existing Sbd1 conservation affect a PES?

CREP can induce water savings directly through enrolled wells, or indirectly through the response of neighboring wells (Rouhi Rad et al., 2021).

Possible Effects

- More wells enrolled (+)
- Less water saved by enrolled wells (-)
- Neighbouring wells change pumping (+)
- Different wells enroll (+/-)

Colorado Hydrobase

- Well
- Ditch
- Crop

Subdistrict 1 Annual Plan

- CREP enrollment
- Linked to legal parcels
- First fallow year
- Contract type

Calculated distance matrix between wells and ditches. Generated two by two mile grid for spatial clusters (Bester et al., 2011).

Econometrics: Subdistrict 1 effect on CREP well pumping

$$Y_{i,t} = (Sbd_i + CREP_i) \cdot (1 + \sum_{s=1}^S (\theta_{s(i,t)})) + Ditch_i + County_i + \tau_t + \beta \cdot X_{i,t} + \epsilon_{i,t}$$

This is the same DiD model previously used but with a second term for a well that eventually enters CREP.

Two steps are used to estimate the change in CREP efficacy due to changes in well enrolment. The number of wells enrolled changes the direct effect of CREP. The location of the enrolled wells changes which wells are neighbors that reduce groundwater.

- 1 Probit model predicting if a well enrolees in CREP based on attributes and response to the pumping fee
- 2 Monte Carlo simulation of well enrolment location

$$\widehat{CREP\ ATT}_g = \frac{1}{|g|} \sum_{\ell \in g} \sum_e \hat{\phi}_{e,\ell} \cdot \hat{\delta}_{\ell,e}$$

Where g is the set of all lags ℓ . The final equation estimates the ATT, by the sum of cohort treatment effects weighted by the cohort sample share in and scaled by the number of periods in the set $|g|$ (Sun & Abraham, 2021).

Results: Subdistrict 1 effect on CREP well pumping

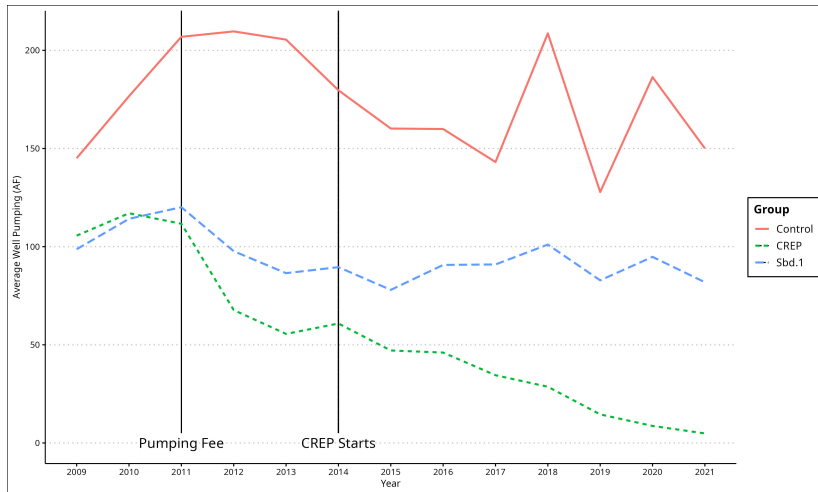
Table: Response to 2011 pumping fee

Dependent Variable:	AF
Model:	(1)
<i>Variables</i>	
Sbd.1-Post 2011	-30.87*** (8.477)
In CREP-Post 2011	-31.17*** (7.072)
Near to CREP-Post 2011	-5.407** (2.218)
<i>Fixed Effects</i>	
Subdistrict-Year	✓
Ditch-Year	✓
Near CREP-Post CREP	✓
In Fallow Program	✓
Well	✓
Year	✓
<i>Fit statistics</i>	
Observations	48,563
R ²	0.74535
Within R ²	0.00271

a) Clustered (Well & Year) standard errors in parentheses

b) Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Adjustments in average pumping by well group



Results: direct effect on CREP and nearby well pumping

Table: CREP and neighbor pumping response

Dependent Variable:	AF	
	CREP Wells	Neighbor Wells
Model:	(1)	(2)
<i>Variables</i>		
ATT	-38.70*** (2.905)	-2.788** (1.021)
<i>Fixed Effects</i>		
Subdistrict-Year	✓	✓
Ditch-Year	✓	✓
In Fallow Program	✓	✓
Well	✓	✓
In CREP After Treatment		✓
In CREP-Year		✓
<i>Fit statistics</i>		
Observations	49,439	49,439
R ²	0.74748	0.74705
Within R ²	0.01114	0.00174

a) Clustered (Well & Year) standard errors in parentheses

b) Signif. Codes: ***, 0.01, **, 0.05, *, 0.1

Results: direct effect on CREP and nearby well pumping

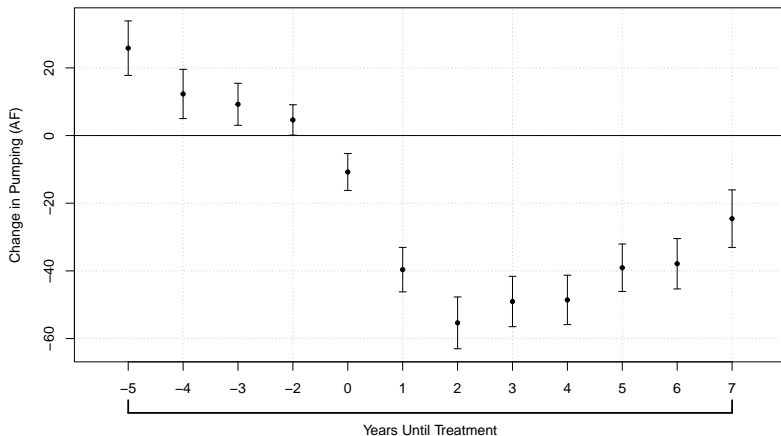


Figure: CREP event study

Results: direct effect on CREP and nearby well pumping

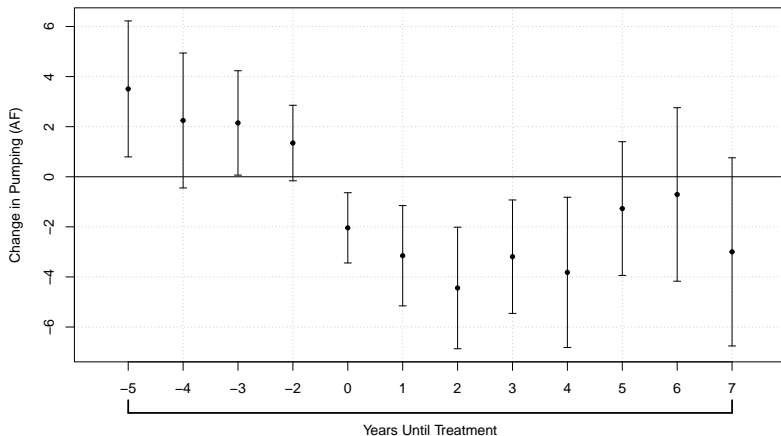


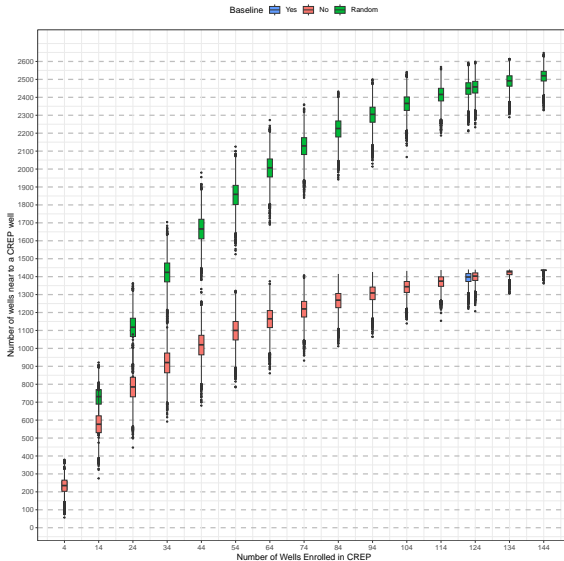
Figure: Nearby well event study

Results: Subdistrict 1 effect on CREP enrollment

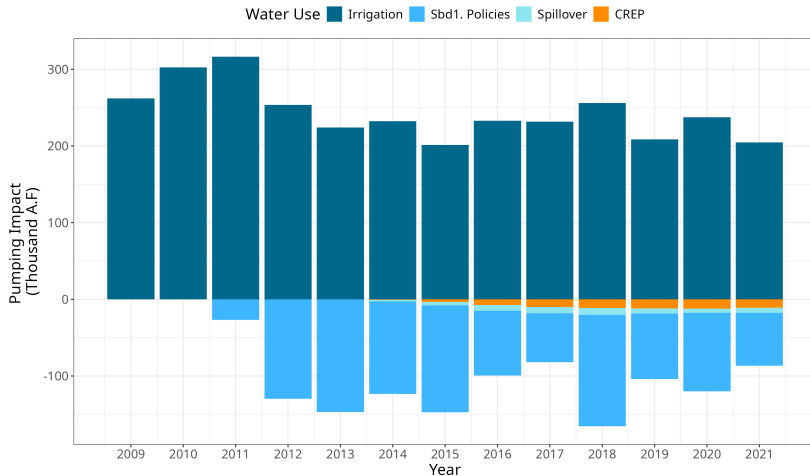
Table: Probit model of selection into CREP

Dependent Variable:	Well Enters CREP	
Model:	(1)	(2)
<i>Variables</i>		
Change in Avg. Water Use (AF)	-0.0050*** (0.0013)	
Pre-Fee pumping (AF/year)		0.0049*** (0.0012)
Post-Fee Pumping (AF/year)		-0.0055*** (0.0018)
Water Rights (AF)	-0.1928*** (0.0552)	-0.1871*** (0.0536)
Well Depth (log feet)	0.1875* (0.1030)	0.2213** (0.1068)
Potatoes (%)	-1.267*** (0.2452)	-1.257*** (0.2445)
Alfalfa (%)	-0.1998 (0.1667)	-0.1781 (0.1680)
Other Crops (%)	0.3271 (0.2455)	0.3073 (0.2481)
<i>Fixed effects</i>		
Ditch	✓	✓
<i>Fit statistics</i>		
Observations	2,149	2,149
Squared Correlation	0.14192	0.14612
Pseudo R ²	0.20896	0.20959
BIC	821.08	828.17
<i>Heteroscedasticity-robust standard errors in parentheses</i>		
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>		

Results: Subdistrict 1 effect on number of neighbor wells



Overall Change



Total effect of Subdistrict 1 on CREP

- ① CREP conserves 32% less ground water.
- ② 29.5% increase in enrollment and cost
- ③ Nearby wells reduce water use

Conclusion

Bitcoin Mining, the Next Shale Boom?

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

How will bitcoin mining change oil production decisions in the United States?

Basin and state fixed effect model of flared gas value.
Structural vector autoregression (SVAR) model of oil production elasticity. Time series model of bitcoin mining energy use.

- Effect depends on location
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price
- Up to a 0.55% increase in oil production
- Oil revenues could increase by 0.63%
- Global oil price would decline by 0.2%

Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Background: Bitcoin mining

- Adds transactions to the block chain
- Limited size in a block
- Miner reward
- User fees
- Hash function
- Difficulty adjustment
- Application-specific integrated circuit (ASIC)



Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



North Dakota flared gas
(Dalrymple, 2018)

Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



North Dakota flared gas
(Dalrymple, 2018)

Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



North Dakota flared gas
(Dalrymple, 2018)

Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



North Dakota flared gas
(Dalrymple, 2018)

Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



North Dakota flared gas
(Dalrymple, 2018)

Why is natural gas flared?

- Natural gas is always produced with oil
- Gas oil ratio (GOR)
- Expensive pipelines required to move the gas
- Flaring is cheaper in new or remote fields

Bitcoin miners have a mobile demand for low cost energy sources.



Crusoe Energy Bitcoin miner
(Robertson, 2021)

Enverus

- Well location
- Well attributes
- Oil and gas production

Bitcoin Data

- Block difficulty
- Blocks added
- Bitcoin price

Other Data

- Oil price
- Natural gas price
- Industrial index
- Temperature

Volume of oil and gas produced by a well is discounted to the date it was drilled (Anderson et al., 2018).

Three econometric results.

- 1 Structural vector autoregression: Elasticity of oil production
- 2 Fixed effect model of flared gas: Total subsidy from selling flared gas
- 3 Nonlinear Cointegrating Autoregressive Distributed Lag Mode (NARDL): Effect of bitcoin price shocks

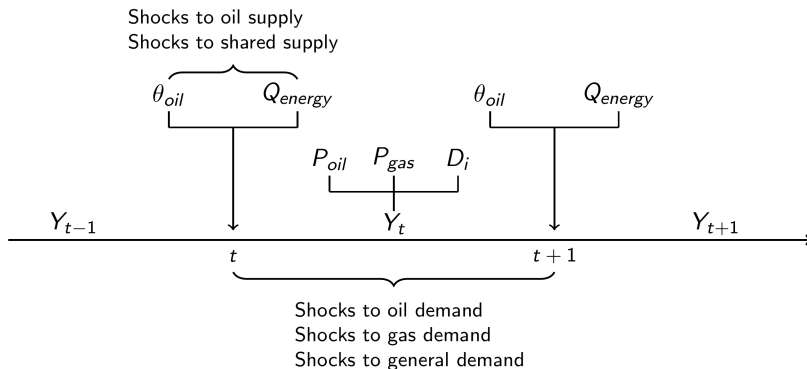
Three econometric results.

- 1 Structural vector autoregression: Elasticity of oil production
- 2 Fixed effect model of flared gas: Total subsidy from selling flared gas
- 3 Nonlinear Cointegrating Autoregressive Distributed Lag Mode (NARDL): Effect of bitcoin price shocks

Three econometric results.

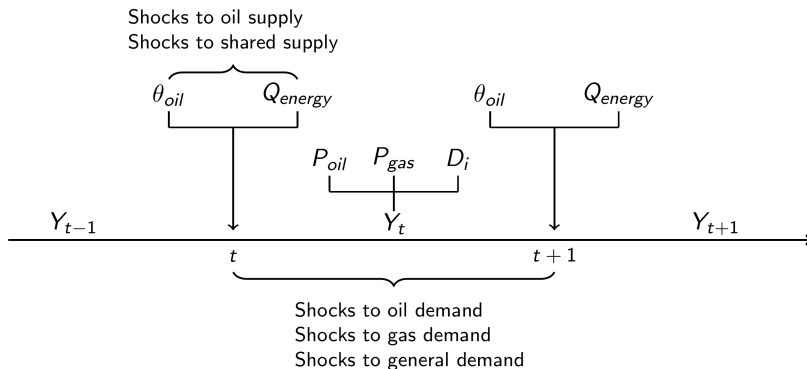
- 1 Structural vector autoregression: Elasticity of oil production
- 2 Fixed effect model of flared gas: Total subsidy from selling flared gas
- 3 Nonlinear Cointegrating Autoregressive Distributed Lag Mode (NARDL): Effect of bitcoin price shocks

Information flow in oil markets



Restriction that drilling rates do not respond to price shocks within the same month (Kilian & Murphy, 2009). It takes time to acquire drilling rig contracts, licenses, and create engineering plans

Information flow in oil markets

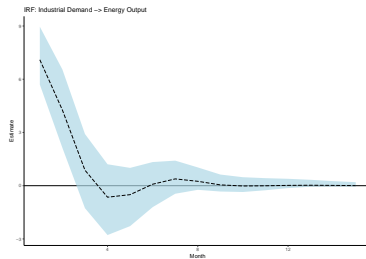
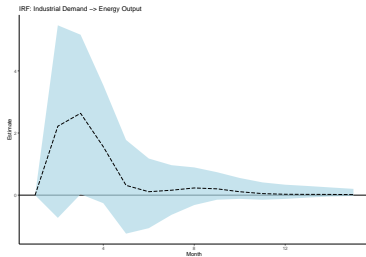


Restriction that drilling rates do not respond to price shocks within the same month (Kilian & Murphy, 2009). It takes time to acquire drilling rig contracts, licenses, and create engineering plans

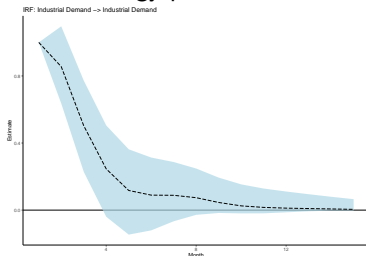
A matrix restrictions of the SVAR model

$$\begin{pmatrix} e_t^{\Delta BTU} \\ e_t^{\Delta \theta} \\ e_t^{\Delta D_i} \\ e_t^{\Delta P_g} \\ e_t^{\Delta P_o} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ a_{3,1} & a_{3,2} & 1 & 0 & 0 \\ a_{4,1} & a_{4,2} & a_{4,3} & 1 & 0 \\ a_{5,1} & a_{5,2} & a_{5,1} & a_{5,1} & 1 \end{bmatrix} \begin{pmatrix} \epsilon_q \\ \epsilon_\theta \\ \epsilon_{D_i} \\ \epsilon_g \\ \epsilon_o \end{pmatrix} \begin{matrix} \text{Joint Supply Shock} \\ \text{Composition Shock} \\ \text{Industrial Demand Shock} \\ \text{Gas Specific Demand Shock} \\ \text{Oil Specific Demand Shock} \end{matrix}$$

Key impulse response from industrial shock

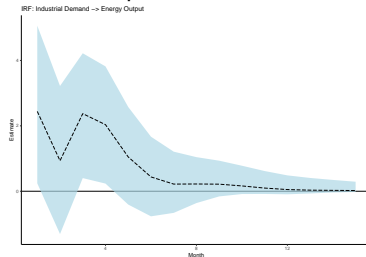


IRF on energy production



IRF on industrial demand

IRF on oil price



IRF on natural gas price

Elasticity estimate

$$Elasticity_S = \sum_{t=0}^t \left(\frac{\Delta\theta_t \cdot \Delta q_t}{\Delta P_{oil,t}} \right)$$

$$0.55 = \sum_{t=0}^{120} \left(\frac{\Delta\theta_t \cdot \Delta q_t}{\Delta P_{oil,t}} \right)$$

Elasticity estimate

$$Elasticity_S = \sum_{t=0}^t \left(\frac{\Delta\theta_t \cdot \Delta q_t}{\Delta P_{oil,t}} \right)$$

$$0.55 = \sum_{t=0}^{120} \left(\frac{\Delta\theta_t \cdot \Delta q_t}{\Delta P_{oil,t}} \right)$$

Average U.S. subsidy estimated to be $0.11 \frac{MCF}{BBL}$

$$\text{Oil subsidy equivalent} = \frac{\$0.0605 \cdot P_{gas}}{BBL}$$

How sensitive are payments to oil companies depending on the price of bitcoin?

Bitcoin mining model

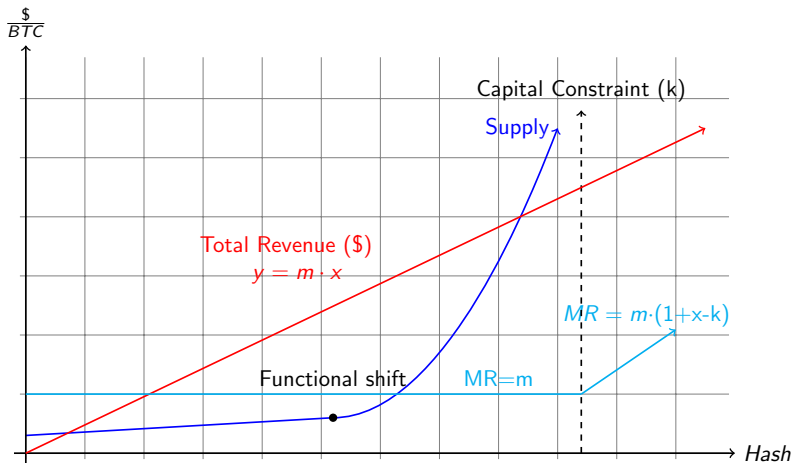


Figure: Short-run simplified hash supply

The proposed model uses the estimations of (Shin et al., 2014) and can be written in a simple form as:

$$h_t = \sum_{j=1}^p \phi_j h_{t-j} + \sum_{j=0}^q \left(\theta_{t-j}^+ x_{t-j}^+ + \theta_{t-j}^- x_{t-j}^- \right) + \epsilon_t$$

With h_t being the hash rate of all miners on day t and x_t as the total miner reward. A $(+/-)$ indicating a positive or negative change in reward. P is the autoregressive lags on hash, and q is the lags on miner reward. The coefficients of the regression are ϕ for lags on hash and θ for lags on reward.

Bitcoin NARDL model

	hash	
	Short Run	Long Run
$hash_{t-1}$	-0.015** (0.01)	
Rev^+	0.286*** (0.006)	18.89** (8.42)
Rev_{t-1}^+	-0.348*** (0.058)	-22.95** (10.48)
Rev_{t-1}^+	0.0847** (0.038)	5.59** (3.27)
Rev^-	0.331*** (0.038)	21.88* (9.62)
Rev_{t-1}^-	-0.321*** (0.037)	-21.21** (9.30)
$trend$	-0.001 (0.001)	-0.040** (0.04)
$Const$	0.454** (0.185)	
Asymmetry		
W-stat	0.5021178	2187.54 ***
Observations	323	
R ²	0.4104	
Adjusted R ²	0.3977	
Residual Std. Error (df = 323)	0.0504	
F Statistic (df = 7; 323)	32.18***	

Note: *p<0.1; **p<0.05; ***p<0.01

A shock of less than 18% is approximately the same whether the price increase is negative or positive

- Average U.S. oil output increase of $\frac{\$0.0605 \cdot P_{gas}}{BBL}$
- Response is *not sensitive* to bitcoin price
- Response is sensitive to natural gas price

Conclusion

Conclusion

Bibliography I



Anderson, S. T., Kellogg, R., & Salant, S. W. (2018). Hotelling under Pressure. *Journal of Political Economy*, 126(3), 984–1026. <https://doi.org/10.1086/697203>



Bester, C. A., Conley, T. G., & Hansen, C. B. (2011). Inference with dependent data using cluster covariance estimators. *Journal of Econometrics*, 165(2), 137–151. <https://doi.org/10.1016/j.jeconom.2011.01.007>



Bredenhoeft, J. D., & Young, R. A. (1983). Conjunctive use of groundwater and surface water for irrigated agriculture: Risk aversion. *Water Resources Research*, 19(5), 1111–1121. <https://doi.org/10.1029/WR019i005p01111>



Carlson, A. W. (1973). Seasonal Farm Labor in the San Luis Valley. *Annals of the Association of American Geographers*, 63(1), 97–108. <https://doi.org/10.1111/j.1467-8306.1973.tb00908.x>



Cech, T. (2008, January 9). *The Well Shutdown Situation in Colorado 2003-Present*. Bainbridge, Georgia.



MOYER v. EMPIRE LODGE HOMEOWNERS ASSOCIATION. Retrieved March 18, 2024, from <https://caselaw.findlaw.com/court/co-supreme-court/1262144.html>



Cody, K., Smith, S., Cox, M., & Andersson, K. (2015). Emergence of Collective Action in a Groundwater Commons: Irrigators in the San Luis Valley of Colorado. *Society and Natural Resources*. <https://doi.org/10.1080/08941920.2014.970736>



Colorado Division of Water Resources. (2024). *Structures*. Retrieved October 19, 2024, from <https://dwr.state.co.us/Tools/Structures>

Bibliography II



Dalrymple, A. (2018). North Dakota natural gas flaring hits records, improvement expected in 2019 [newspaper]. *The Bismarck Tribune*. Retrieved October 23, 2024, from https://bismarcktribune.com/bakken/north-dakota-natural-gas-flaring-hits-records-improvement-expected-in-2019/article_201e38f4-54db-5b96-a03a-31af0fd077e0.html



Heide, R. (2005). Declining Aquifers: San Luis Valley water users struggle to pump groundwater sustainably [magazine]. *Headwaters, Fall 2005*. Retrieved May 11, 2024, from <https://issuu.com/cfwe/docs/headwaters9>



Kilian, L., & Murphy, D. P. (2009). Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market VAR Models. *IDEAS Working Paper Series from RePEc*. Retrieved February 11, 2023, from <https://search.proquest.com/publiccontent/docview/1698253301?pq-origsite=primo>



Krakel, D. (2024, February 7). A potato field is watered by an irrigation system near Center, Colorado on July 19, 2022. The irrigation system uses water from the Rio Grande delivered by a system of canals and headgates that form the largest water delivery system in the San Luis Valley. Retrieved October 19, 2024, from <https://i0.wp.com/newspack-coloradosun.s3.amazonaws.com/wp-content/uploads/2022/09/P7190524-1-scaled.jpeg?resize=1200%2C824&quality=85&ssl=1>



Kryloff, N., Leighton, J., & Colorado State University Special Collections. (2009). *CSU - GASP Records*. Retrieved October 20, 2024, from <https://archives.mountainscholar.org/digital/collection/p17393coll161/id/1090>



CONCERNING THE MATTER OF THE RULES GOVERNING NEW WITHDRAWALS OF GROUND WATER IN WATER DIVISION NO. 3 AFFECTING THE RATE OR DIRECTION OF MOVEMENT OF WATER IN THE CONFINED AQUIFER SYSTEM Aka "CONFINED AQUIFER NEW USE RULES FOR DIVISION 3". Retrieved March 17, 2024, from <https://www.courts.state.co.us/Courts/Water/Rulings/Div3/04CW24%20Part%20I-IV.pdf>

Bibliography III



Loos, J. R., Andersson, K., Bulger, S., Cody, K. C., Cox, M., Gebben, A., & Smith, S. M. (2022). Individual to collective adaptation through incremental change in Colorado groundwater governance. *Frontiers in Environmental Science*, 10. Retrieved November 1, 2022, from <https://www.frontiersin.org/articles/10.3389/fenvs.2022.958597>



McCaffrey, D., Burgette, L., Griffin, B. A., & Martin, C. (2016, June 16). Propensity Scores for Multiple Treatments: A Tutorial for the MNPS Macro in the TWANG SAS Macros. *RAND Corporation*.



Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk Aversion, Subjective Beliefs, and Farmer Risk Management Strategies. *American Journal of Agricultural Economics*, 95(2), 384–389. Retrieved April 17, 2024, from <https://www.jstor.org/stable/23358407>



Pigou, A. C. (1924). *The Economics of Welfare* (1st ed.). Macmillan.



Robertson, H. (2021). Meet the company mining bitcoin using the flare gas from oil drilling - and drawing investment from Coinbase and the Winklevii — Business Insider India [newspaper]. *Business Insider*. Retrieved October 23, 2024, from <https://www.businessinsider.in/cryptocurrency/news/meet-the-company-mining-bitcoin-using-the-flare-gas-from-oil-drilling-and-drawing-investment-from-coinbase-and-the-winklevii/articleshow/83685982.cms>



Rothstein, A. (1939). [Untitled photo, possibly related to: Picking potatoes in San Luis Valley, Rio Grande County, Colorado]. Retrieved October 19, 2024, from <https://www.loc.gov/pictures/resource/fsa.8a12431>



Rouhi Rad, M., Manning, D. T., Suter, J. F., & Goemans, C. (2021). Policy Leakage or Policy Benefit? Spatial Spillovers from Conservation Policies in Common Property Resources. *Journal of the Association of Environmental and Resource Economists*, 8(5), 923–953. <https://doi.org/10.1086/714148>

Bibliography IV



San Luis Valley Development Resources Group. (2024). *San Luis Valley Statistical Profile*. Retrieved September 7, 2024, from <https://www.slvdr.org/wp-content/uploads/2021/03/2021-SLV-Statistical-Profile.pdf>



Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In R. C. Sickles & W. C. Horrace (Eds.), *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications* (pp. 281–314). Springer. https://doi.org/10.1007/978-1-4899-8008-3_9



Smith, S. M. (2018). Economic incentives and conservation: Crowding-in social norms in a groundwater commons. *Journal of Environmental Economics and Management*, 90, 147–174. <https://doi.org/10.1016/j.jeem.2018.04.007>



Smith, S. M., Andersson, K., Cody, K. C., Cox, M., & Ficklin, D. (2017). Responding to a Groundwater Crisis: The Effects of Self-Imposed Economic Incentives. *Journal of the Association of Environmental and Resource Economists*, 4(4), 985–1023. <https://doi.org/10.1086/692610>



Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199. <https://doi.org/10.1016/j.jeconom.2020.09.006>



The Colorado Foundation for Water Education. (2005, September). An Interview with Ralph Curtis. Retrieved May 11, 2024, from <https://issuu.com/cfwe/docs/headwaters9>