ECON 8000/9000 Empirical Energy Econ

Topic 04: Review of IV Regressions

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January 28, 2026

Outline

- PS1-2
- Review: IV Regressions
- Example 1 Fabra et al. (2021) AEA P&P
- Example 2 Davis and Hausman (2020) Energy Journal
- Potential Data Sources for Research Project

PS1. Q1.B Part 2 Explanation

Explain pattern changes

Some of you made very good observations:

- Comment 1. "The models that control for the trend act as a Regression Discontinuity Design"
- Comment 2. "The naive version is misleading because it mixes up the oil crisis effect with the fact that younger people naturally have different habits than older people. Controlling for the trend removes these normal age-related differences, forcing the model to identify only the sudden change caused specifically by the 1979 crisis."

Regarding comment 1: It is a sharp RD using age as a running variable (or age relative to 15 cutoff)

- `gen D = inrange(birthyr, 1965, .)` // aka ppl 15 in 1980
  `gen T = 1964 - birthyr`
- Then this is like a sharp RD

```
reg t_drive D birthyr if inrange(birthyr, 1964, 1966) [aw=perwt], robust
reg t_drive D T       if inrange(birthyr, 1964, 1966) [aw=perwt], robust
```

PS1. Q1.B Part 2 Explanation

Explain pattern changes

	(1) 1964-66	(2) 1964-67	(3) 1964-68	(4) 1964-69	(5) 1964-70	(6) 1964-71	(7) 1964-1972	(8) 1964-1973
A. Naive Spec								
D	-0.00341***	-0.00383***	-0.00409***	-0.00440***	-0.00497***	-0.00531***	-0.00539***	-0.00576***
	(0.00111)	(0.00104)	(0.00101)	(0.00099)	(0.00097)	(0.00096)	(0.00095)	(0.00095)
B. Control for birth year								
D	-0.00499**	-0.00307*	-0.00293**	-0.00277**	-0.00224*	-0.00238**	-0.00292**	-0.00268**
	(0.00224)	(0.00167)	(0.00145)	(0.00132)	(0.00124)	(0.00119)	(0.00115)	(0.00113)
birthyr	0.00107	-0.00039	-0.00047	-0.00056*	-0.00079***	-0.00074***	-0.00055***	-0.00063***
	(0.00132)	(0.00067)	(0.00043)	(0.00030)	(0.00023)	(0.00018)	(0.00015)	(0.00013)
C. Control for T								
D	-0.00499**	-0.00307*	-0.00293**	-0.00277**	-0.00224*	-0.00238**	-0.00292**	-0.00268**
	(0.00224)	(0.00167)	(0.00145)	(0.00132)	(0.00124)	(0.00119)	(0.00115)	(0.00113)
T	-0.00107	0.00039	0.00047	0.00056*	0.00079***	0.00074***	0.00055***	0.00063***
	(0.00132)	(0.00067)	(0.00043)	(0.00030)	(0.00023)	(0.00018)	(0.00015)	(0.00013)

Pattern: coefficients increase (in terms of size) from (1) to (8) in Panel A, but drop from (1) to (8) in Panels B-C. What does that imply?

- As we add more individual with later birth years, we are adding the "treated" group in 2000
- Instead of studying 34-36 yr-old in 2000, we expand to study 27-36 yr-old in 2000
- How does age correlate with outcome `t_drive`? Do you find evidence in Panels B-C?
- Why else is happening? Hint: heterogeneous effect

PS1. Q1.D

Student answers

- "A design of a similar style would look at cohort exposure due to an exogenous shock, with the benefit of not needing panel data, so a cross-sectional dataset (like the ACS) would be helpful. Trying to relate this to energy, an example of this idea could be to look at the effect of exposure to an **environmental shock**, like a **weather natural disaster**, on long-run energy demand. For example, it could be that cohorts who were raised in an area where they faced many hurricanes, might stay as adults and choose to have alternate energy methods as an adult, like solar power or a generator...."
- "An idea would be to study the effect of experiencing a **natural disaster** during teenage years on the likelihood of moving away from one's home state later in life."
- "One potential research question relates lived experiences to transportation behavior, with the **September 11** attacks serving as a salient example. A key distinction could be whether an individual was old enough to meaningfully comprehend the events of 9/11. Using this cutoff, we could survey individuals on their age at the time of the attacks and their current frequency of air travel. The hypothesis is that individuals who did not directly experience or remember 9/11 are more likely to travel by air than those who did. However, this analysis would need to account for confounding factors such as the long-run growth of air travel and the evolution of airport security procedures over time.
  Alternatively, ... we could study what alternative modes of transportation individuals may have adopted. "

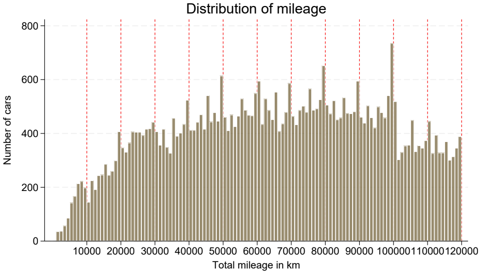
PS1. Q1.D

Student answers

- "A research design here could involve whether or not experiencing the **COVID pandemic** during one's formative years affects social behavior (such as hugging and handshaking), employment-seeking behavior (in person vs remote work) or even the effect on public health behavior (like hand-washing or cleaning gym equipment after use)."
- "Electricity Prices and Heating Choices: This study would investigate whether the **price of electricity when a person buys their first home (typically around age 30)** permanently influences how they heat their house. The goal is to see if those initial high or low prices "lock" homeowners into using specific electric heating systems, like heat pumps, for decades, even if electricity prices change later on."
- "Gas Prices and Carpooling: While the original paper focused on public transit, this idea looks at whether **high gas prices during a person's teenage years (age 16)** create a lifelong habit of carpooling instead of driving alone. This would show if early exposure to expensive gas creates a permanent preference for sharing travel costs rather than driving solo."
- "How being exposed to the news of the **Three Mile Island incident** during formative years changes one's perception of nuclear energy? My hypothesis would be that since this event was a negative shock to peoples' perception of the safety of nuclear energy, people in their formative years at this time would be more apprehensive to using nuclear power as well as living nearby nuclear power plants."

PS2 Q1.C Part 5

Is this really RDD?



Some of you made very good observations:

- Comment 1. "Strictly speaking, this is not a valid RDD. A core assumption of RDD is that the running variable (mileage) cannot be precisely manipulated. However, the histogram plotted in Q1.A (and Figure 3 of the paper) reveals significant "bunching" of observations just to the left of the 10,000 km thresholds."
- Comment 2. "The fact that dealers appear to bunch sales before the 10,000 mile thresholds, implies manipulative sorting, which violates the no sorting assumption of RDD"

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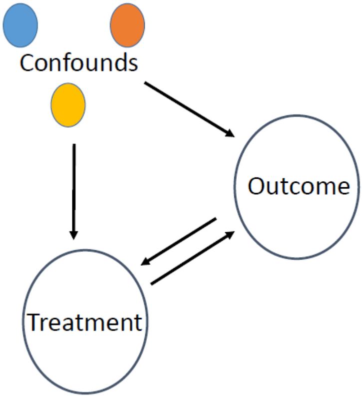
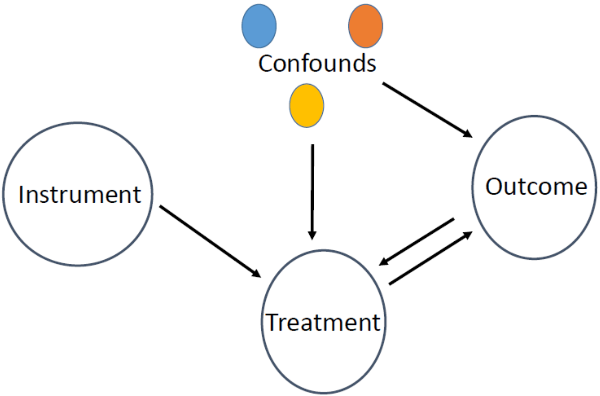
1. Review: Purpose of IV Regressions

Consider $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, usually we don't have $E[\varepsilon|x] = 0$



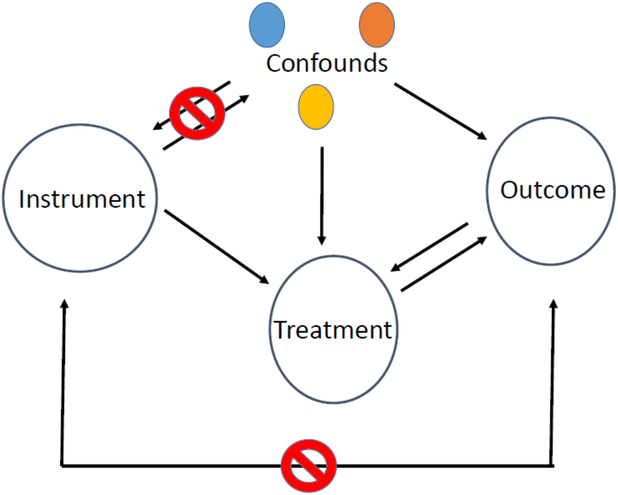
1. Review: Purpose of IV Regressions

Consider $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, consider an IV z_i, regress $x_i = \pi_0 + \pi_1 z_i + \nu_i$



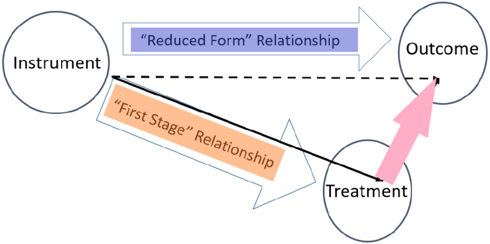
2. Requirement of IV: z_i Need to be

(i) $cov(x, z) \neq 0$ **(relevant) (ii)** $E[u|z] = 0$ **(exogenous) (iii) meet exclusive restriction**



3. IV Chain Reaction

IV Estimator $\hat{\beta}_{iv}$ in the bivariate Case with one IV



"Reduced Form" = "First Stage" $*$ "Causal Effect", so

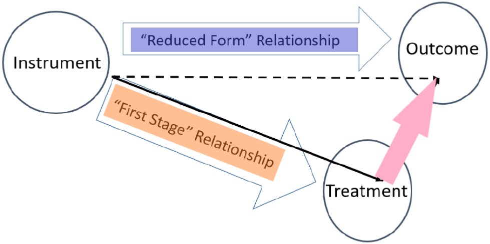
$$\boxed{\text{"Causal Effect"}} = \frac{\text{"Reduced Form"}}{\text{"First Stage"}}$$

- Denote
- Second stage $y = \beta_0 + \beta_1 x + \varepsilon$
- First stage $x = \pi_0 + \pi_1 z + \nu$
- Reduced-form $y = \delta_0 + \delta_1 z + \eta$
- Then the IV estimator: $\hat{\beta}_1 = \frac{\hat{\delta}_1}{\hat{\pi}_1}$
- Or simply

$$\hat{\beta}_{iv} = \frac{\hat{\delta}_{redudcedform}}{\hat{\pi}_{firststage}}$$

Back to 2. The Exogeneity Requirement Again

Consider $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, consider an IV z_i, regress $x_i = \pi_0 + \pi_1 z_i + \nu_i$



"Reduced Form" = "First Stage" $*$ "Causal Effect", so

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- Denote
- Second stage $\quad y = \beta_0 + \beta_1 x + \varepsilon$
- First stage $\quad x = \pi_0 + \pi_1 z + \nu$
- Reduced-form $\quad y = \delta_0 + \delta_1 z + \eta$
- Then the IV estimator: $\hat{\beta}_1 = \frac{\hat{\delta}_1}{\hat{\pi}_1}$
- We need $E[\varepsilon|z] = 0$
- We do not need $E[\nu|z] = 0$
- Aka the first stage does not need to be causal! Remember IV(s) serve as predictors in the first stage

4. Easy to Implement IV Estimator in Panel Data

E.g., (i) TWFE, (ii) DID, (iii) Event Study, (iv) LPDID, (v) FD, etc

- Stata:

```
ivreghdfe yvar x1 x2 x3 (t1 t2 = iv1 iv2 iv3) if xxxx [aweight = pop2005],
abs(i.firm_id i.year i.state i.state_id#c.year) cluster(state_id)
```

- Stata:

```
global x_ctrl     = "x1 x2 x3 x4"
global treat      = "t1 t2"
global iv         = "iv1 iv2 iv3"
global ifcond     = "year <= 2014"
global fe_list    = "i.firm_id i.year i.state i.state_id#c.year"
global cluster_id = "state_id"
ivreghdfe yvar $x_ctrl ($treat = $iv) if $ifcond [aweight = pop2005],
abs($fe_list) cluster($cluster_id)
```

- R:

```
x_ctrl  <- c("x1", "x2", "x3")
treat   <- c("t1", "t2")
iv      <- c("iv1", "iv2", "iv3")
df_if   <- subset(df, year <= 2014)
fe_list <- c("firm_id", "year_id", "state_id", "state_id[year]")
x_ctrl  <- c("x1", "x2", "x3")
ivstore <- feols(yvar ~.[x_ctrl] | .[fe_list] | .[treat] ~.[iv], weight =
df_if$pop_2005, data=df_if, vcov =~state_id)
etable(ivstore)
```

4. Typical Checks for IV Regression

4.1 Exogeneity of IVs

- Can we prove exogeneity?
  - It is a claim that cannot be realistically proved... and can only be argued
  - Q1: Do you know why we cannot prove exogeneity, i.e. $E[u|Z] = 0$?
  - The same goes for the exclusive restriction requirement
  - What about sanity checks to support an exogeneity claim?

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  - What about sanity checks to support an exogeneity claim?
- Special case: RCT or RCT-esque
  - If your IV is a random/quasi-random assignment $\Rightarrow$ Balance tests
  - In fact many RCT use random assignment as IV
    `ivreg yvar xctrlvars (enroll = lottery)`
  - Then you can use a balance test to check lottery status is exogenous to (i) characteristics related to yvar and/or (ii) pre-period yvar if you can observe them

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- A placebo demonstration
  - Idea: If we randomly draw IVs, those fake IVs should generate a null effect on average.
  - Suppose you find $\hat{\beta}_{iv} = 10$, then we expect $\hat{\beta}^{placebo}_{2ndstage}$ to be centered around 0
  - See Scott (2022) Figure 3. In his case, he is doing an OLS not an IV. But the same principle applies
  - The first exercise is always to randomly draw z_{it} across all is and ts
  - But if you particularly worry about exogeneity across is, then you can draw random z_{it} across is for each t
  - Q2. What does it means if you find that your placebo exercise fails?

4. Typical Checks for IV Regression

4.2 Strength of first stage, weak IV concerns, etc.

- Can we use first-stage t-stat or p-value?
  - It is helpful when there is only 1 endogenous xvar and 1 IV
  - But when you have more than 1 IV, then given IVs can be correlated with one another, no need to expect all t-stat to be sizable
- Run first stage Wald F-test as typical sanity test
  - Stata:
    Suppose you run `ivreg yvar x1 x2 (t1 t2 = z1 z2)`
    You can run first stage `reg t1 x1 z1 z2` and run a F-test `test z1 z2`

4. Typical Checks for IV Regression

4.2 Strength of first stage, weak IV concerns, etc.

- Some Wald F tests for weak IVs
- Stata:

```
ivreghdfe yvar $x_ctrl ($treat = $iv) if $ifcond [aweight = pop2005],
abs($fe_list) cluster($cluster_id)
```

  `di e(cdf)` for a Cragg-Donald Wald F of both stages

  `di e(kpf)` for a Kleibergen-Paap Wald F test for both stages

- R:

```
myfitstat <- as.formula(~n + r2 + + ivf1.stat + ivf1.p + ivfall.stat +
ivfall.p + ivwald1.stat + ivwald1.p + ivwaldall.stat + ivwaldall.p")
```

  Here `ivf1` `ivfall` are CD Wald F for 1st stage and both stages, and `ivwald1` `ivwaldall` are KP Wald F for 1st and both stages

```
ivstore <- feols(yvar ~.[x_ctrl] | .[fe_list] | .[treat] ~.[iv], weight =
df_if$pop_2005, data=df_if, vcov =~state_id)
etable(summary(ivstore, stage(1:2)), fitstat = myfitstat)
```

- We expect for CD-F and KP-F to be sizable
- Drawbacks:
  CD-F relies some some specific assumption on error terms
  KP-F doesn't have consensus in critical values

4. Typical Checks for IV Regression

4.2 Strength of first stage, weak IV concerns, etc.

- Some better tests for weak IV: Anderson-Rubin (AR) and Conditional Likelihood Ratio (CLR) Test
- Suppose you regression is `ivreghdfe yvar $x_ctrl ($treat = $iv) if $ifcond [aweight = pop2005], abs($fe_list) cluster($cluster_id)`
- Your weak iv test can be
  `estat weakrobust, ar` for an AR test
  `estat weakrobust, ci` for an AR CI
  `estat weakrobust, clr` for an CLR test
- CLR is the most flexible, proposed by Finlay and Magnusson (2009)
- Drawback of AR:
  AR test needs just-identification, i.e., No. of endo var = No. of IVs
  AR CI can only handle 1 endo var

4. Typical Checks for IV Regression

4.2 Strength of first stage, weak IV concerns, etc.

- Placebo tests can also be helpful here!
- Recall to provide some support for exogeneity, we can randomly draw IVs, and check if the distribution of 2nd stage coefficients $\hat{\beta}^{placebo}_{2ndstage}$ amongst these draws is centered around 0
- Here you can redraw IVs and run first stage
  - Suppose you have 1 endo var and 1 IV
  - Then for each draw you will obtain coefficient and t-stat for your IV
  - Check if the distribution of the t-stat of individual IVs $t^{placebo}_{stat,1ststage}$ amongst these draws is centered around 0
- If you have 1 endo var and 2 IVs
  - Then you will obtain two t-stats each draw
  - Then check the distribution of $t^{placebo}_{stat,1ststage,iv1}$ and $t^{placebo}_{stat,1ststage,iv2}$

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Fabra, Rapson, Reguarnt, Wang (2021) AEA P&P

"Estimating the Elasticity to Reat-Time Pricing (RTP): Spain"

Research Question: What is the demand elasticity for electricity?

Why is it important parameter to estimate?

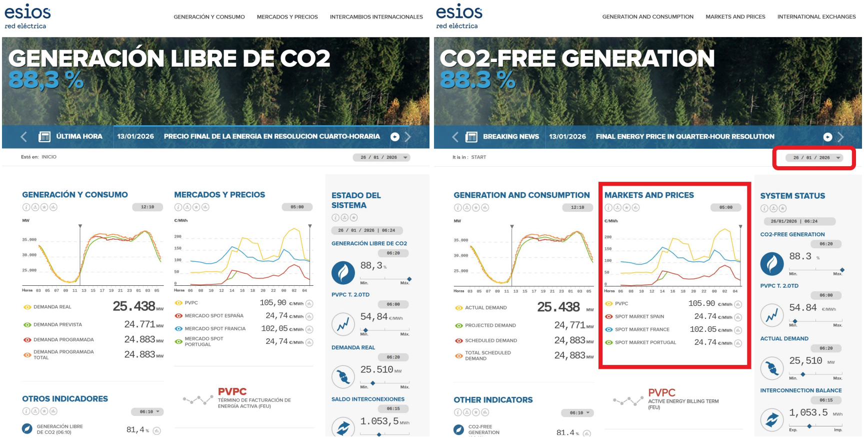
- Crucial for policymakers when any regulation reform or policies that may alter price
- Crucial for regulators in electricity markets in any types of market reform
- Crucial to draw implications regarding efficiency gains from implementing efficient price from the typical pricing structure

Why is it so difficult to estimate?

- Often, we don't observe price variation that much in market...
  Q1: Why is that problematic?
- Even when we observe price variation, we cannot guarantee exogeneity
  Exception: Some critical-peak pricing (CPP) cases as we studied in Topic 2
- Also RCT is not feasible
  No utility companies will randomize electricity price throughout the day
- **Novelty**: RTP will generate quasi-randomly price variation throughout the day

Fabra et al. (2021) AEA P&P

Main xvar: Mext day’s hourly price schedule published everyday at 8:30pm



Source: Operator’s website www.esios.ree.es

Fabra et al. (2021) AEA P&P

Key yvar & xvar and key equation

TABLE 1—SUMMARY STATISTICS

	Mean	SD	P25	P50	P75
Price (cents euro/KWh)	10.82	1.73	9.84	10.78	11.73
Ratio max/min price within a day	1.23	0.12	1.14	1.20	1.26
Average HH hourly KWh consumption	0.24	0.08	0.17	0.25	0.30
Temperature (F)	57.67	11.27	49.41	56.46	65.26
Iberian system hourly demand (GWh)	34.13	8.69	30.87	35.14	39.53
Wind hourly forecast (GWh)	5.49	3.21	3.00	4.84	7.34
Solar hourly output (GWh)	1.47	1.71	0.08	0.64	2.61

Note: Sample contains 13,772 hours.

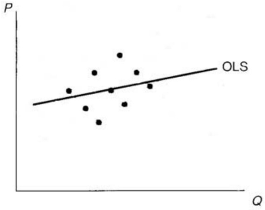
$$y_{it} = \beta_{i0} + \beta_{i1} p_t + \Omega_i \mathbf{X}_t + \lambda_i \mathbf{W}_{it} + \varepsilon_{it}$$

- y_{it}: Kwh electricity consumption at time (day and hour) t
- p_t: Hourly price
- $\Omega_i \mathbf{X}_t$: Time-varying FEs, hour-of-day FE, month-of-year FE
- $\mathbf{W}_{it}$: Household-specific temperature bins (linked by geocode)
- β_{i1}: Use interactiosn to allow dq/dp to vary by 2 hh groups (RTP vs non-RTP)
- Note: Converted to inverse hyperbolic sine (archsin) as better approxy than log-log
- Good news: We have good variation in xvar + yvar
- Key challenge: Endogeneity

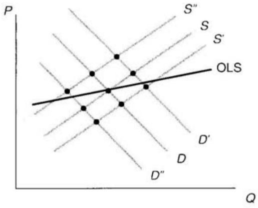
  $\Rightarrow$ Quantity demanded is high when price is high ...

Estimating Demand Elasticity

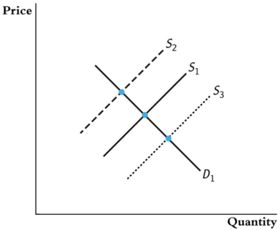
The classic challenge...



Panel b: OLS regression



Panel c: Demand and supply interaction



Solution: Using a cost shifter

- With naive OLS regression, one may get a much more smaller negative demand elasticity
- Or worse, a positive demand elasticity (as in the picture)
- This is a problem... We know electricity is not a Giffen good
- What do we want to compare instead?
- One of the solutions: Using a cost shifter as an IV

Cost shifter as an IV

Hourly wind generation

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$$y_{it} = \beta_{i0} + \beta_{i1} p_t + \Omega_i \mathbf{X}_t + \lambda_i \mathbf{W}_{it} + \varepsilon_{it}$$

- y_{it}: Kwh electricity consumption at time (day and hour) t
- p_t: Hourly price
- IV: day-ahead hourly wind generation (GWh) forecast
- Q2: How does this IV work? Does this IV satisfy the typical IV requirement?

Main Results

Very low demand elasticity for electricity consumption

Panel B. Mean estimates with alternative specifications

	(1)	(2)	(3)	(4)
RTP	−0.054	−0.0072	−0.014	−0.017
	(0.0025)	(0.0019)	(0.0016)	(0.0027)
No RTP	−0.058	−0.0031	−0.011	−0.013
	(0.0028)	(0.0022)	(0.0016)	(0.0030)

Notes: Table shows mean elasticities by type of tariff (RTP versus non-RTP). Standard errors clustered at the postal code level. $N = 17{,}928$. Individual elasticity estimates using (1) block and temperature bin fixed effects and interactions, plus block times solar output; (2) all variables in (1) plus aggregate demand as a control; (3) all in (1) and (2) but with temperature and temperature squared instead of temp bins; and (4) post-lasso with Fourier transforms at daily, weekly, and annual frequency interacted with aggregate demand, solar production, temperature, and temperature square.

- Q3: Does this surprise your?
- Q4: What does this imply for future implementation of RTP?

Some Institution Background for Day-ahead Market

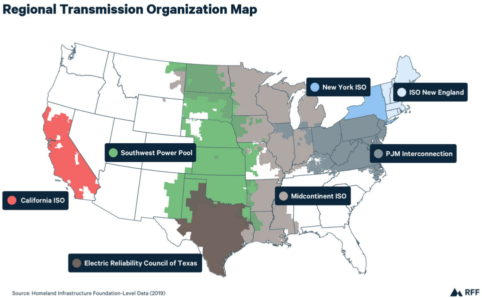
Day-ahead market and real-time market

- Day-ahead market
  - Most of kwh transactions are cleared here
  - Firms submit bids
  - Bids are at the granularity for each hour
  - Balancing authority (or the spot market) clears the market by equating the day-ahead demand forecast
- Real-time market
  - Balancing authority or dispatcher will match real-time demand (as frequent as every 5-15 min) with supply
  - Purchase: cater real-time demand shocks
- Other market: Ancillary services market (as a backup of the backup)
  - Usually the so-called "peak plants" are turned on to deal with extreme unanticipated demand shock, either in real-time market or ancillary service market
- An US electricity market 101 here: Link
- High-frequent data here: Link
  EIA links to the data for each of 7 competitive wholesale markets

Some Institution Background for Electricity Market

Markets in Continental US

Left: All markets



Right: 7 Deregulated wholesale markets

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Davis & Hausman (2020) Energy Journal

"Are Energy Executives Rewarded for Luck"

Research Question: Are Energy CEOs Get Paid for Luck?

- Authors' own blogpost: Link

Why important?

- If energy CEOs are paid for luck... then we get some inefficiency problems...
- 1. Misallocation of labor in the labor market of CEOs
- 2. Misallocation of products in various energy markets these CEOs handle...

Related work on pay-for-luck

- Strand #1 Are CEOs paid for luck?
  $\Rightarrow$ focus: can we identify/detect this?
- Strand #2 Why are CEOs pay-for-luck?
  $\Rightarrow$ mostly theories (e.g., Feriozzi 2011 RAND, Campbell & Thompson 2015 J Corp Fin)

DH (2020) Energy CEO's Pay

Estimation Equation

For firm i, CEO p, in year t

$$\ln C_{ipt} = \alpha + \beta_1 \ln V_{it} + \Theta \mathbf{X}_{itp} + \varepsilon_{it} \qquad \text{(Eq(1) in DH 2020)}$$

- C_{ipt}: CEO compensation
- V_{it}: firm's market value
- $\mathbf{X}$: Controls, e.g., GDP growth, unemployment, linear trend, firm FE
- β_1: The effect of market value changes (driven by oil price shocks) on compensation
- Key challenge: endogeneity
  - Q1: What are potential confounders?

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- β_1: The effect of market value changes (driven by oil price shocks) on compensation
- Key challenge: endogeneity
  - Q1: What are potential confounders?
- Solution: Use crude oil price $\ln Q_t$ as IV
  - Note: This IV only varies by t
  - Q2: Why authors choose not to include year FE in Eq(1)?
  - Q3: Is β_1 identified by comparing firm A's CEO vs firm B's CEO over time?
  - Q4: If not, how is β_1 identified?
    Hint: (i) They have firm FE and linear trend and (ii) IV only varies by t

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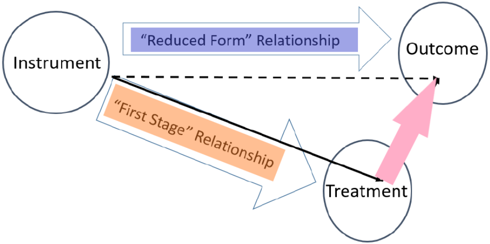
Data

- Main xvar and yvar: Compustats 1992-2016
  - Publicly traded companies
  - Exclude vertically-integrated copanies (e.g., Exxon)
  - Include 78 energy companies (e.g., Marathon)
  - Include 934 CEOs
- Key IV: Crude oil price from West Texas Intermediate (WTI)
  - One can also use Brent crude oil price
  - Technically these can be very high-frequent data
  - But for authors' startegy, yearly price is sufficient

Review: The IV Chain Reaction

Consider $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, consider an IV z_i, regress $x_i = \pi_0 + \pi_1 z_i + \nu_i$



"Reduced Form" = "First Stage" $*$ "Causal Effect", so

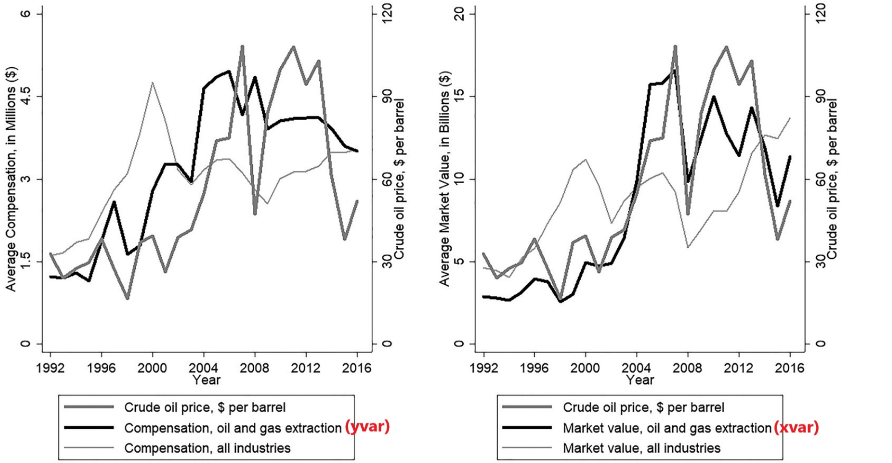
$$\boxed{\text{“Causal Effect”}} = \frac{\text{“Reduced Form”}}{\text{“First Stage”}}$$

- Consider the 1 endo var 1 IV case
- Second stage $y = \beta_0 + \beta_1 x + \varepsilon$
- First stage $x = \pi_0 + \pi_1 z + \nu$
- Reduced-form $y = \delta_0 + \delta_1 z + \eta$
- Then the IV estimator: $\hat{\beta}_1 = \frac{\hat{\delta}_1}{\hat{\pi}_1}$
- Run the first-stage
- Run the reduced-form
- If both have some actions, we can have some confidence in the 2SLS design
- Sometimes, ppl also run the naive OLS

Visual Evidence

Equiv to a naive OLS of yvar $\ln C_{ipt}$ on xvar $\ln V_{it}$

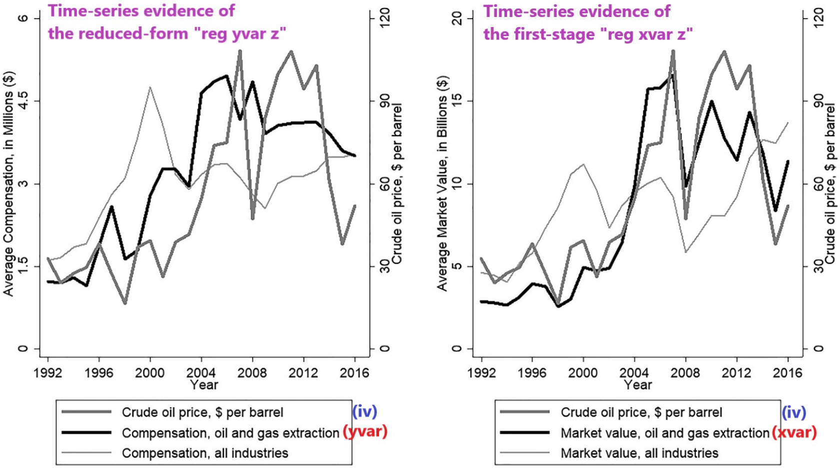
Figure 1: Executive Compensation, Market Value, and Oil Prices



Visual Evidence

Equiv. to reduced-form (yvar on IV) and first-stage (xvar on IV)

Figure 1: Executive Compensation, Market Value, and Oil Prices



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Main results

Table 1: Does Executive Compensation Increase with Oil Prices?

	(1) OLS	(2) IV	(3) OLS
Log market value	0.29***	0.19***	
	(0.04)	(0.05)	
Log crude oil price			0.19***
			(0.06)
First-stage F-statistic		90.59	
Observations	4,673	4,673	4,673
Within R^2	0.52	0.51	0.46

- Col (2) IV result: 10% market value increase leads to 1.9% increase in pay
- Col (3) reduced-form: 10% crude oil price rise leads to 1.9% increase in pay
- Given the "chain-reaction formula", 0.19/0.19=1, i.e.. the 1st stage effect is 1
- On average, energy CEOs' value-added for the market value on top of the effect from crude oil price shocks is not detectable...

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First-stage results

Table A5: First Stage: The Effect of Oil Prices on Market Value

	(1) Log market value
Log crude oil price	0.99***
	(0.10)
Observations	4,673
Within R^2	0.52

- Run first-stage directly
- On average, energy CEOs' value-added in the market value on top of the effect from crude oil price shocks is not detectable...

DH (2020) Energy CEO's Pay

Additional fun results documented

Table 3: For Which Components of Pay Is There an Oil Price Effect?

	(1) IV Salary	(2) IV Stocks and options	(3) IV Bonuses	(4) IV Other incentives	(5) IV Other pay
Log market value	–0.05*	0.08	0.59***	0.56***	0.21**
	(0.02)	(0.09)	(0.17)	(0.15)	(0.10)
First-stage F-statistic	84.37	101.75	56.65	175.26	84.31
Observations	4,546	3,934	3,083	1,729	4,443
Within R^2	0.34	0.48	0.27	0.38	0.14

Note: This table reports results from five separate IV regressions. The regressions are identical to Column 4 of Table 2, but with alternative dependent variables: each of five components of executive pay (logged). Standard errors are two-way clustered by firm and by year. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

- The effect of market value (driven by oil price variation on CEOs' compensation Do not show up for (i) salary and (ii) stocks and options

DH (2020) Energy CEO's Pay

Additional fun results documented

Table 5: Is the Oil Price Effect Asymmetric?

	(1) OLS	(2) OLS	(3) 2SLS
Log market value, if rising	0.28***		
	(0.04)		
Log market value, if falling	0.21***		
	(0.04)		
Log oil price, if rising		0.20***	
		(0.07)	
Log oil price, if falling		0.06	
		(0.06)	
Log market value, if oil price rising			0.29***
			(0.10)
Log market value, if oil price falling			0.18*
			(0.10)
p-value, rising versus falling	0.004	0.006	0.067
First-stage F-statistic			17.92
Observations	4,357	4,357	4,357
Within R^2	0.53	0.51	0.52

- CEOs' reward received from market value rises driven by oil price, is greater than
- CEOs' blame received from market value drops driven by oil price

Outline

- PS1-2 ✓
- Review: IV Regressions ✓
- Example 1 Fabra et al. (2021) AEA P&P ✓
- Example 2 Davis and Hausman (2020) Energy Journal ✓
- Potential Data Sources for Research Project

Typical Data

- Power plants data
  - US EIA: energy generation (Kwh), capacity (MW), siting, entry, shutdown, retirement, vintage, including coal-fired power plants, natural-gas-fired power plants, renewables, oil etc.
  - US EPA CEMS: end-of-pipe emissions (CO2, SO2, NOx, etc)
  - US EPA ECHO: all federal complaint and lawsuit milestones
  - US NREL: Renewable potential and other renewable energy data
- Energy-use in travel/transportation
  - NHTSA's NHTS surveys
  - ACS's commute vars for workers
  - Census LODES data: Origin-destination (OD)
- Electricity consumption or energy-efficiency investment
  - US EIA's Residential Energy Consumption Survey (RECS) and Commercial Building Energy Comption Survey (CBECS)
  - US DOE's Low-income Energy Affordability Data (LEAD)
  - US EPA Fuel economy website: Vehicle attributes
  - US LBL: Tracking-the-sun
  - CEX has vehicle ownership surveyed at model level
  - Google project sunroof
- Energy price
  - EIA: Gas and diesel price at state and zip level
  - 7 RTOS: ISOs and PJM: High-frequent electricity price

Typical Data

- Socioeconomic, demographics, employment
  - All IPUMS data (CPS, ACS, CBP, etc.), American Time Use Survey (ATUS)
  - US Energy & Employment Report (USEER)
- Meteorological data
  - NOAA
- Other data
  - EIA has electricity-reliability data
  - EIA has coal production data
  - STB of DOT has PUMS of Waybill data for railroad transportation
  - Scrape online car trade data for attributes and prices
  - NASA has nightlight data
- Some states and cities have good open data
  - State: TX, CA, WA, NY, etc.
  - City: Austin, NYC, etc.
  - Some states need you to contact them for administrative data, e.g., DMV