Using Big Data to Solve Economic and Social Problems

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Estimating the Social Cost of Carbon

- Three general steps in estimating the social cost of carbon:

  1. Predict impact of 1 extra ton of CO_2 on climate using a climate forecasting model

  2. Measure impacts of changes in climate on economic productivity, health, property damage, etc.

  3. Calculate current social cost by converting future costs to current dollars (discounting)

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Discounting Future Costs

- Studies discussed thus far examine costs of environmental damage in a single year
  - Ex: loss of GDP of 23% in 2100 due to climate change or $6.5 billion cost of greater air pollution for kids born each year
- Final step in calculating social costs of environmental damage: add up this sequence of costs to generate a single current value
- Critical question in this step: how much is money tomorrow worth today?
  - If we don’t care about future generations, then costs are not large
  - If we care equally about all generations, costs can be infinite

Estimating Long-Run Discount Rates

- Challenge: how can we estimate how people value cash flows over a period of hundreds of years using real-world data?
- Giglio, Maggiori, and Stroebel (2015) develop an innovative approach
- Use data on all residential properly sales in the U.K. and Singapore in 2000s
- Compare how much people pay for two different types of housing contracts
  - Freeholds: perpetual ownership (like in the U.S.)
  - Leasehold: ownership for a fixed period (e.g., 100 years or 1000 years)


Price Discount by Remaining Lease Length
Average Discount to Freehold
0
-.05
-.1
-.15
-.2
80-99
100-124
125-149
150-300
700+
Lease Length Remaining
People pay 12% less for a house that they will own for 100 years relative to a house they will own forever

Estimating Long-Run Discount Rates

- Price discount even for 100 yr+ leaseholds shows that they place substantial value on money then will have more than 100 years from now

- Implied annual discount rate is 2.6%, i.e. $1,000 a year from now is worth $974 today

Summary: Social Cost of Carbon

- Putting together all of these estimates, what is the social cost of carbon?

- Obama Interagency Working Group on Social Cost of Carbon was tasked with answering this question

- Compiled data on estimated impacts of carbon emissions

- Applied a discount rate of 3% to future costs

→ Social cost of carbon set at $40 per ton of CO_2 emitted

  - This number is now used in numerous policy decisions, ranging from fuel-economy rules for cars to regulations on power plants

Summary: Social Cost of Carbon

- But this social cost estimate is not set in stone and is highly debated

- Trump administration suggests using a 7% discount rate instead

  - Yields a social cost of carbon of $5 per ton [Greenstone *NYT* 2016]

- Would dramatically change the set of policies that the government will pursue

Policies to Mitigate Climate Change

How Can We Mitigate Climate Change and Reduce Pollution?

- Given estimates of the costs of climate change, we can agree on targets in terms of reducing carbon emissions or air pollution
- What policies can we use to change human behavior to achieve these social goals?
- Most common policy tool: corrective (“Pigouvian”) taxes that increase private costs of consumption

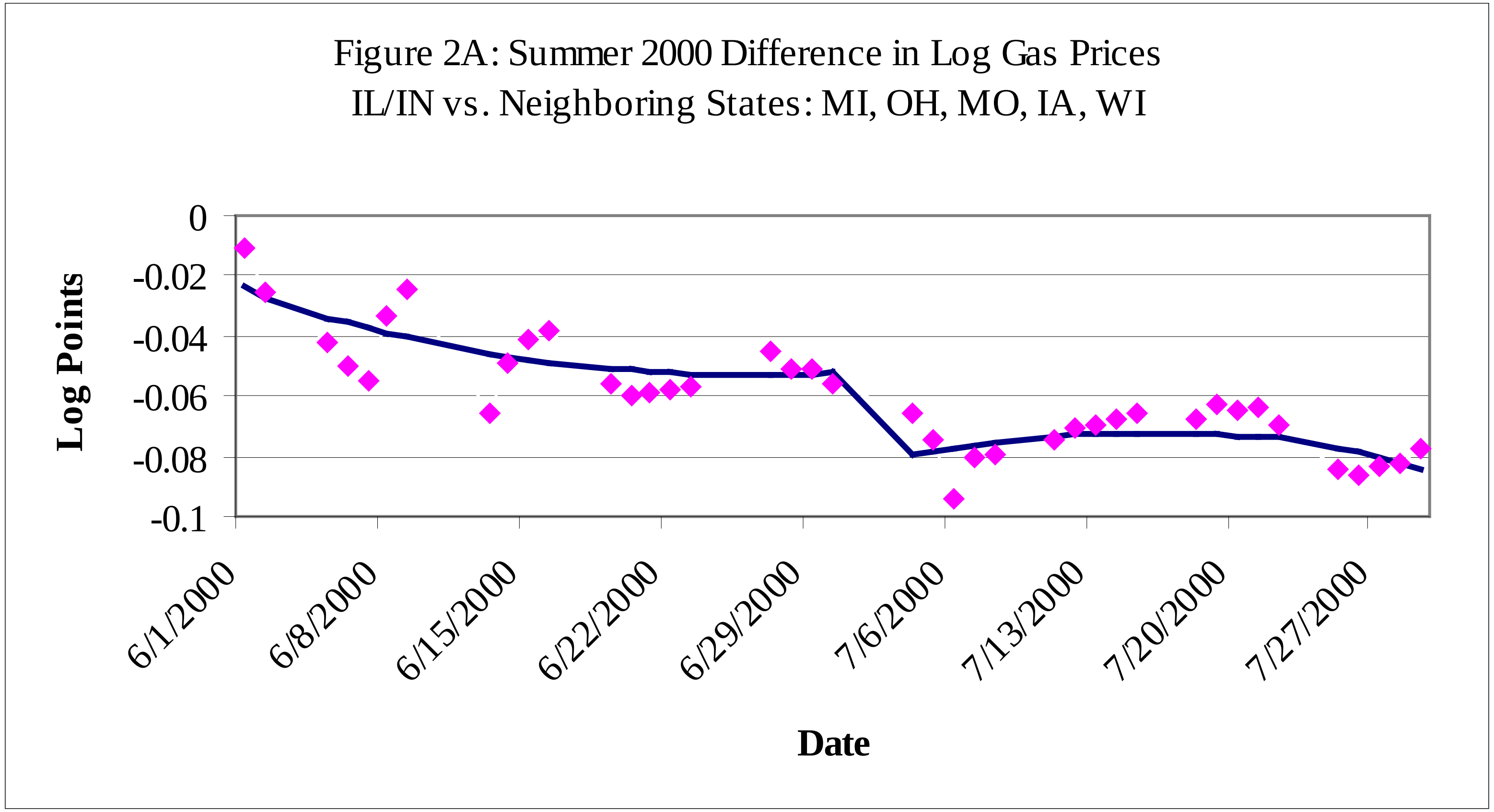
Effects of Gasoline Taxes

- Taxes on gasoline are one potential way to reduce gas consumption and CO_2 emissions

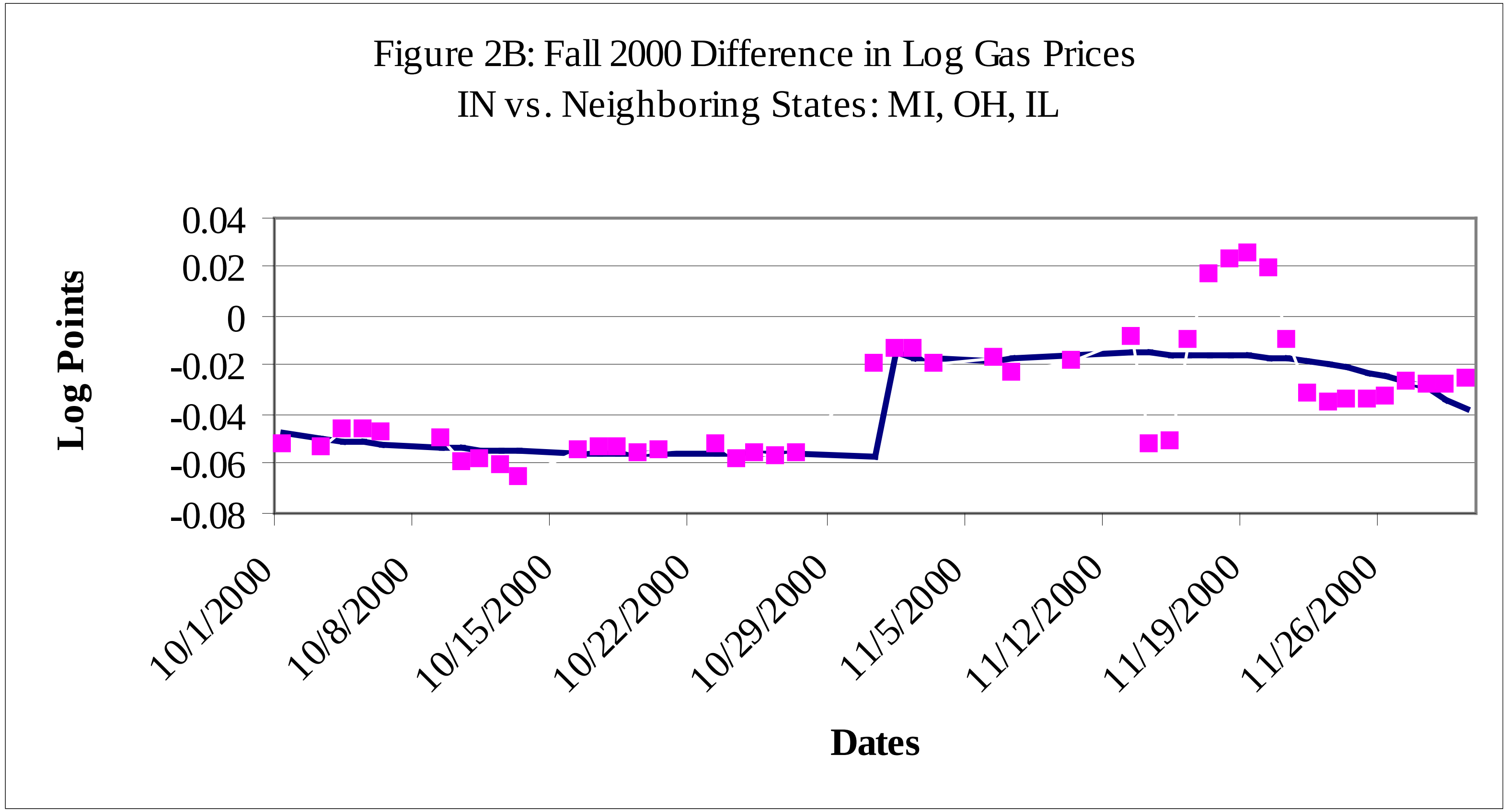
- First question: are gas tax changes passed through to consumers or do just they affect the profits of oil companies?

- Doyle and Sampatharank (2008) study this question using state-level gas tax reforms and a difference-in-differences design
  - Gas prices spiked above $2.00 in 2000
  - IN suspended its gas tax on July 1 and reinstated it on Oct 30
  - IL suspended its gas tax on July 1 and reinstated it on Dec 31

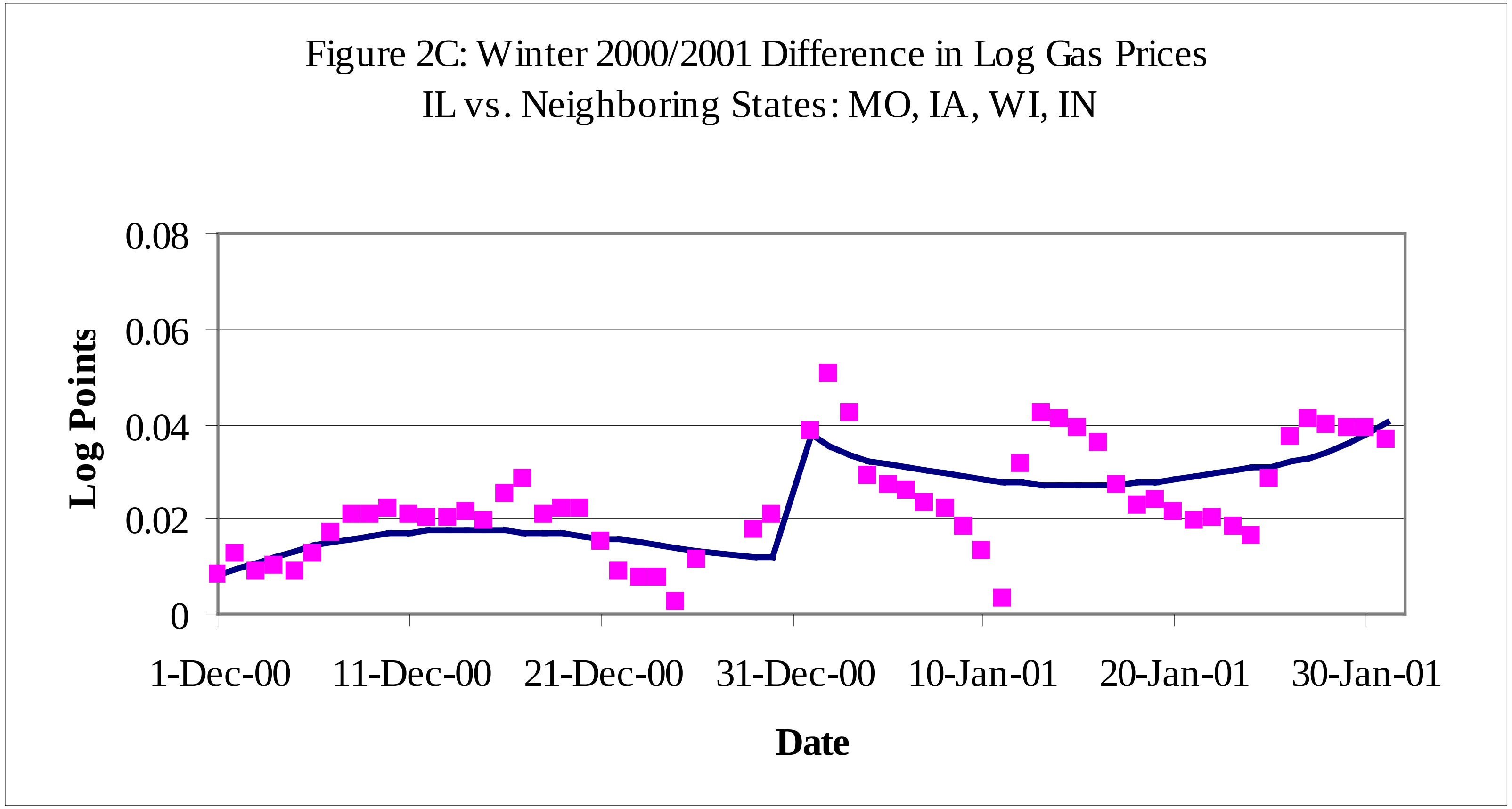
Summer 2000 Difference in Log Gas Prices
IL/IN vs. Neighboring States: MI, OH, MO, IA, WI



Fall 2000 Difference in Log Gas Prices
IL/IN vs. Neighboring States: MI, OH, IL



Winter 2000/2001 Difference in Log Gas Prices
IL vs. Neighboring States: MI, IA, WI, IN



Effects of Gasoline Taxes on Gasoline Prices

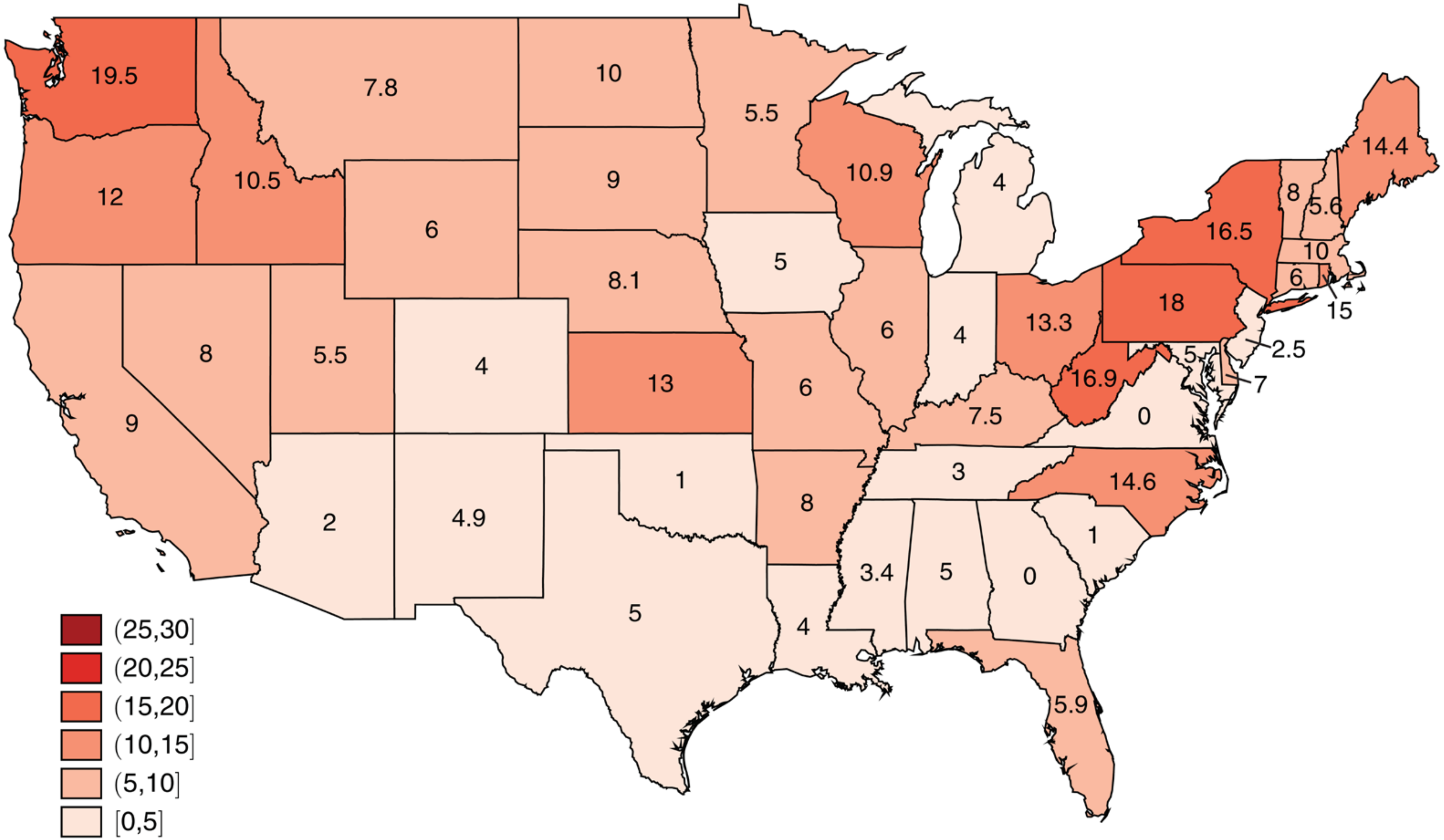
- Finding: 10 cent increase in gas tax → 7 cent increase in price paid by consumers
- Implies that gas taxes could potentially reduce consumption of gas
- Next question: how much less gas do people use when prices go up?

Effects of Gasoline Taxes on Gasoline Demand

- Li et al. (2014) generalize this approach to estimate effects of state tax changes on demand for gas

- Use data covering all 50 states and exploit changes in tax rates in *all* states from 1966-2008

Changes in State Gas Taxes from 1987-2008 (cents per gallon)



Effects of Gasoline Taxes on Gasoline Demand

- To generalize diff-in-diff approach to 50 states and 44 years (more than 500 “experiments”), use a method called fixed effects regression

- Relate differential changes in a state’s gas consumption (relative to avg. national change in a given year) to differential change in its tax rate

    - Regress $\Delta g_{sy} - \Delta g_{y}$ on $\Delta tax_{sy} - \Delta tax_{y}$

- Resulting coefficient represents causal effect of tax change assuming that trends would be parallel across states absent tax changes

TABLE 5—GASOLINE TAXES, TAX-EXCLUSIVE PRICES, AND CONSUMPTION, MONTHLY

	Levels		First-differenced		First-differenced seasonal data	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
log (gas price)	−0.196***		−0.248***		−0.109*	
	(0.030)		(0.030)		(0.057)	
log (tax-excl. gas price)		−0.217***		−0.365***		−0.172***
		(0.028)		(0.047)		(0.061)
log (1 + tax ratio)		−0.414***		−0.769***		−0.394***
		(0.046)		(0.157)		(0.140)
p-value: $\alpha = \beta$		< 0.001		< 0.001		0.038
Observations	14,898	14,898	14,763	14,763	4,893	4,893
R^2	0.987	0.987	0.446	0.446	0.466	0.467

Notes: The dependent variable is the log of gasoline consumption per adult. All specifications include time fixed effects. Levels regressions also include state fixed effects. Robust standard errors are clustered by state.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Effects of Gasoline Taxes on Gasoline Demand

- $1 increase in gas tax → 17% reduction in gasoline consumption

- Transportation sector accounts for about 1/3 of carbon emissions → $1 increase in gas tax reduces carbon emissions by about 5%
  [Davis et al. 2011]

- For comparison, scientists predict that we need to cut CO_2 emissions by about 50% to stop increase in global temperatures

- Lesson: gas taxes make a difference, but need very large taxes to have a meaningful impact on climate change

Effect of Electricity Prices on Electricity Usage

- Next, consider effects of prices on electricity consumption

- Electricity is priced using **tiered rates**: price of an additional kilowatt is higher when you are already using a lot of electricity

- Intended to discourage heavy usage without making electricity very expensive for the poor

- Does tiered pricing work?

Analyzing Impacts of Tiered Price Schedules

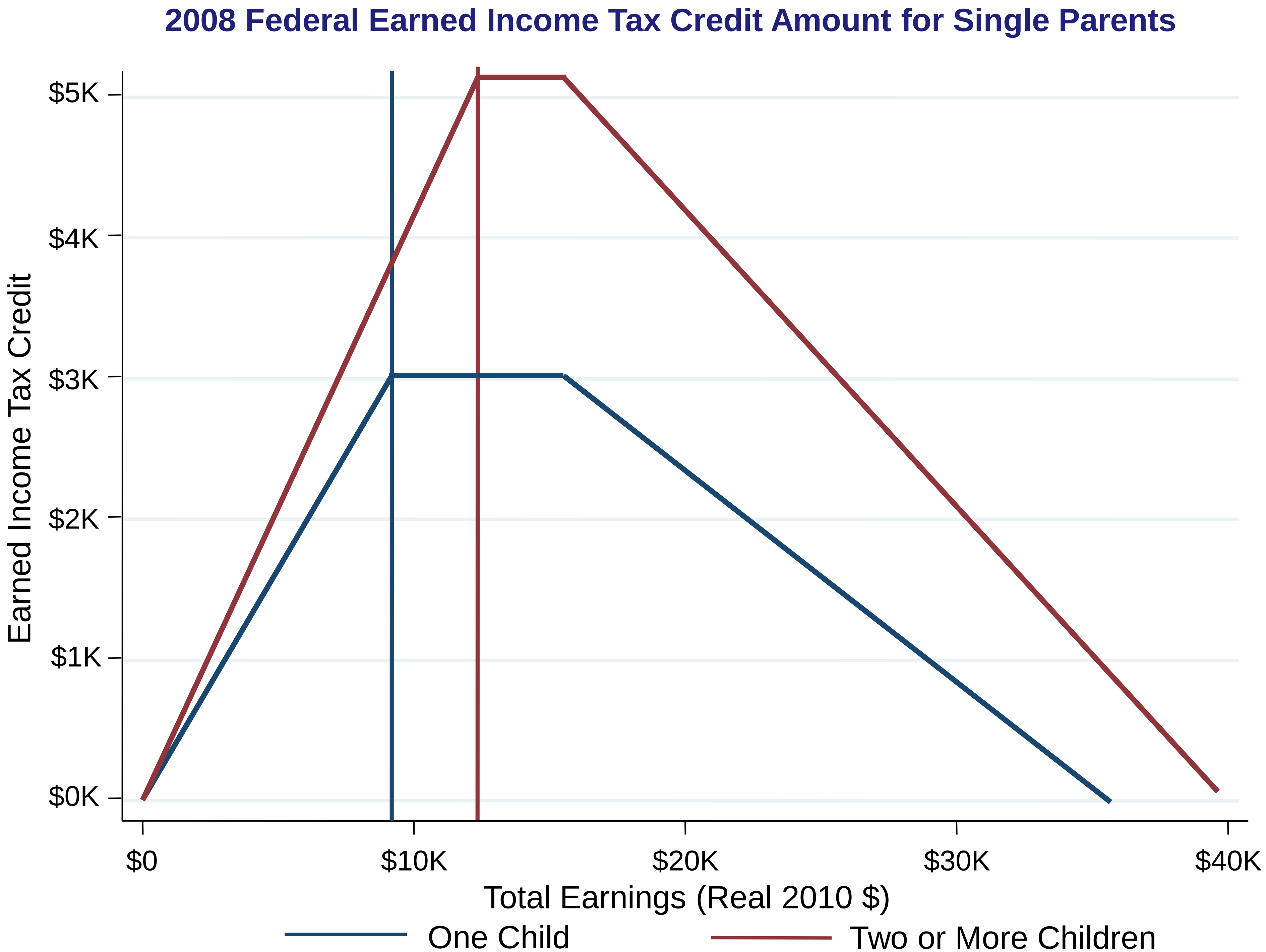
- Impacts of tiered price schedules can be analyzed by examining distribution of outcome variable

- At points where prices change, we expect “bunching” in the distribution if people are responding [Saez 2010]

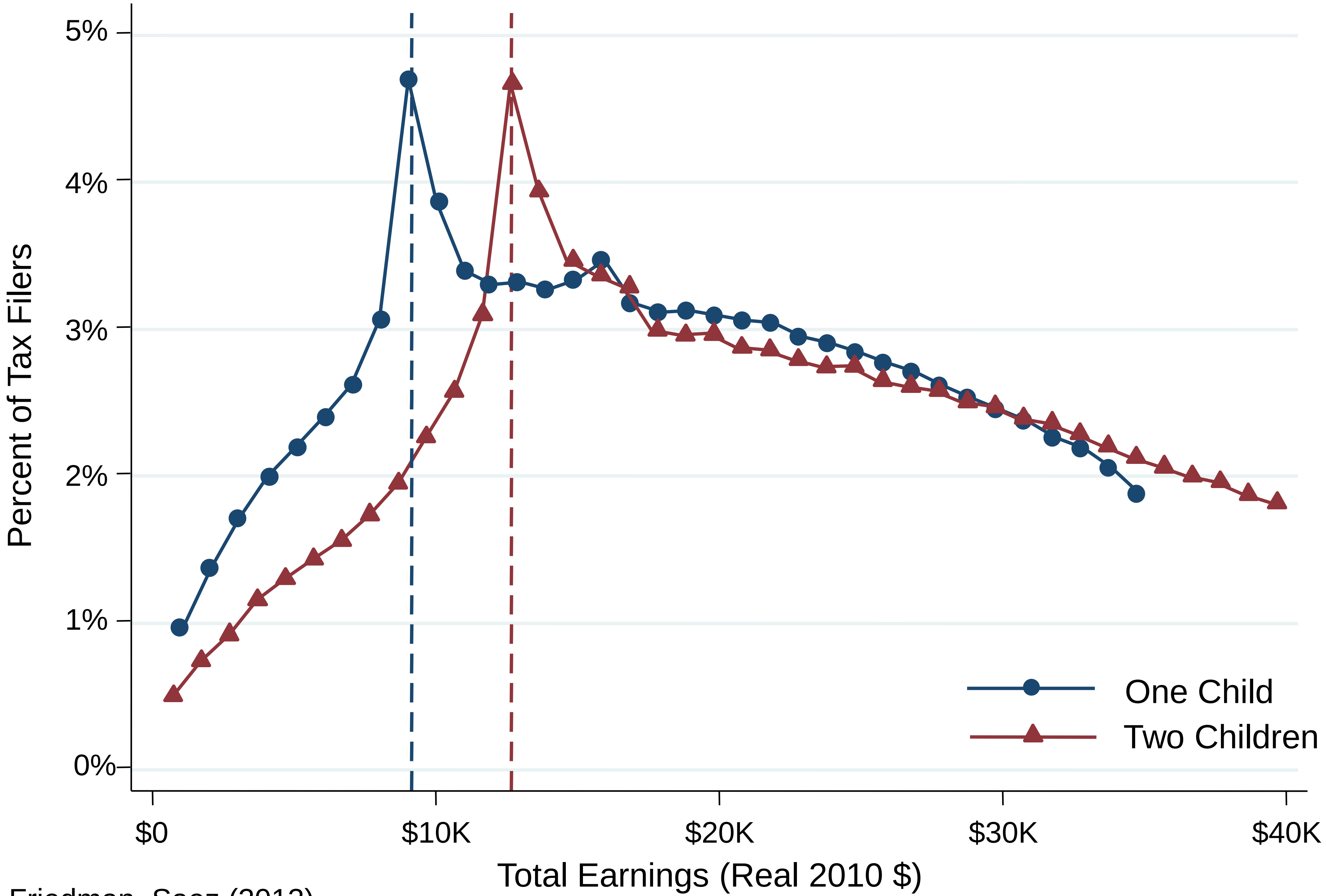
- Simplest example: progressive income tax schedule

  - Tax rate changes discontinuously at certain thresholds, analogous to a tiered pricing plan

- Ex: low-income households receive Earned Income Tax Credit, which provides subsidies for earning more up to certain cutoffs


2008 Federal Earned Income Tax Credit Amount for Single Parents
$5K
$4K
$3K
$2K
$1K
$0K
Earned Income Tax Credit
$0
$10K
$20K
$30K
$40K
Total Earnings (Real 2010 $)
One Child
Two or More Children

Income Distributions for Individuals with Children in 2008 Based on U.S. Tax Data



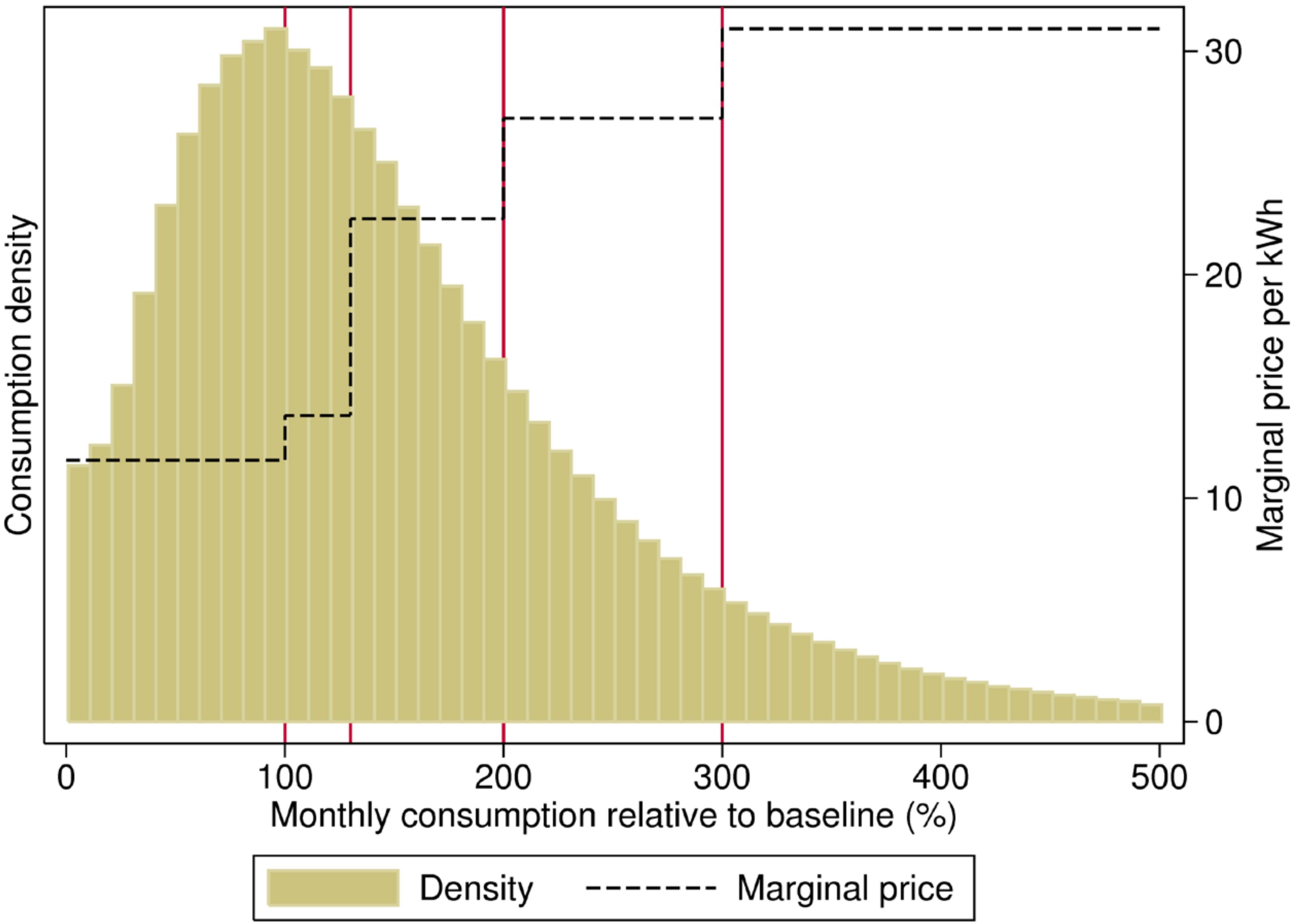
Source: Chetty, Friedman, Saez (2013)

Effects of Tiered Prices on Electricity Usage

- Ito (2014) studies impact of prices on electricity usage using household-level billing data from utility companies in Orange County, CA

- Begin by examining effect of tiered pricing on distribution of electricity consumption for customers of Southern California Edison (SCE)

Prices and Distribution of Electricity Consumption for SCE Customers in 2007



Effects of Tiered Prices on Electricity Usage

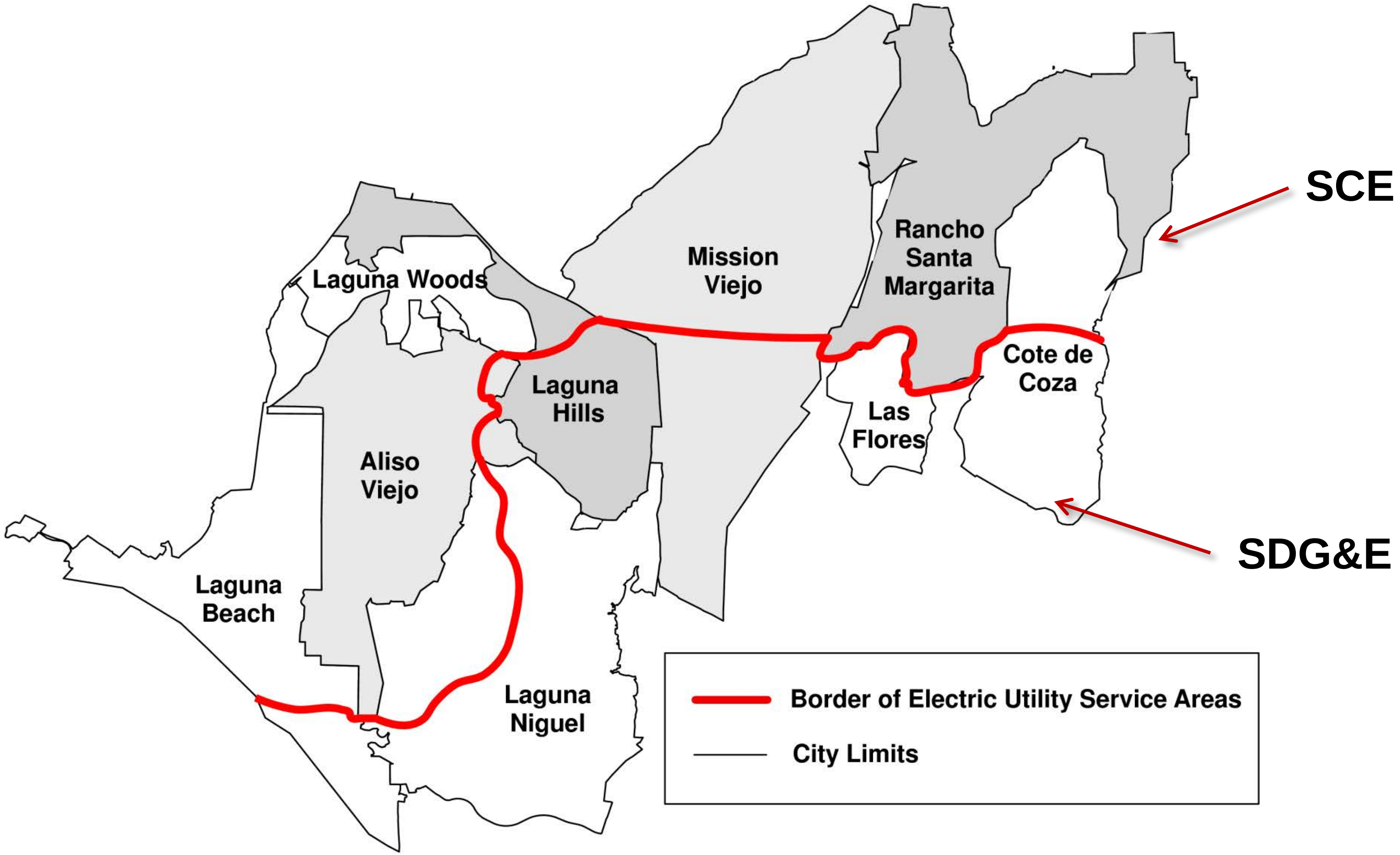
- No evidence of bunching at points where electricity prices jump → suggests that consumers are not responding to changes in tiered pricing
- Two interpretations:
  1. Consumer demand for electricity is insensitive to price
  2. Lack of salience: consumers are unaware of electricity price schedule

Effects of Tiered Prices on Electricity Usage

- To distinguish between these explanations, Ito uses a second strategy

- Utility company that provides service depends upon where families live: Southern California Edison (SCE) vs. San Diego Gas and Electric (SDG&E)

A Spatial Discontinuity in Electric Utility Service Areas in Orange County, California



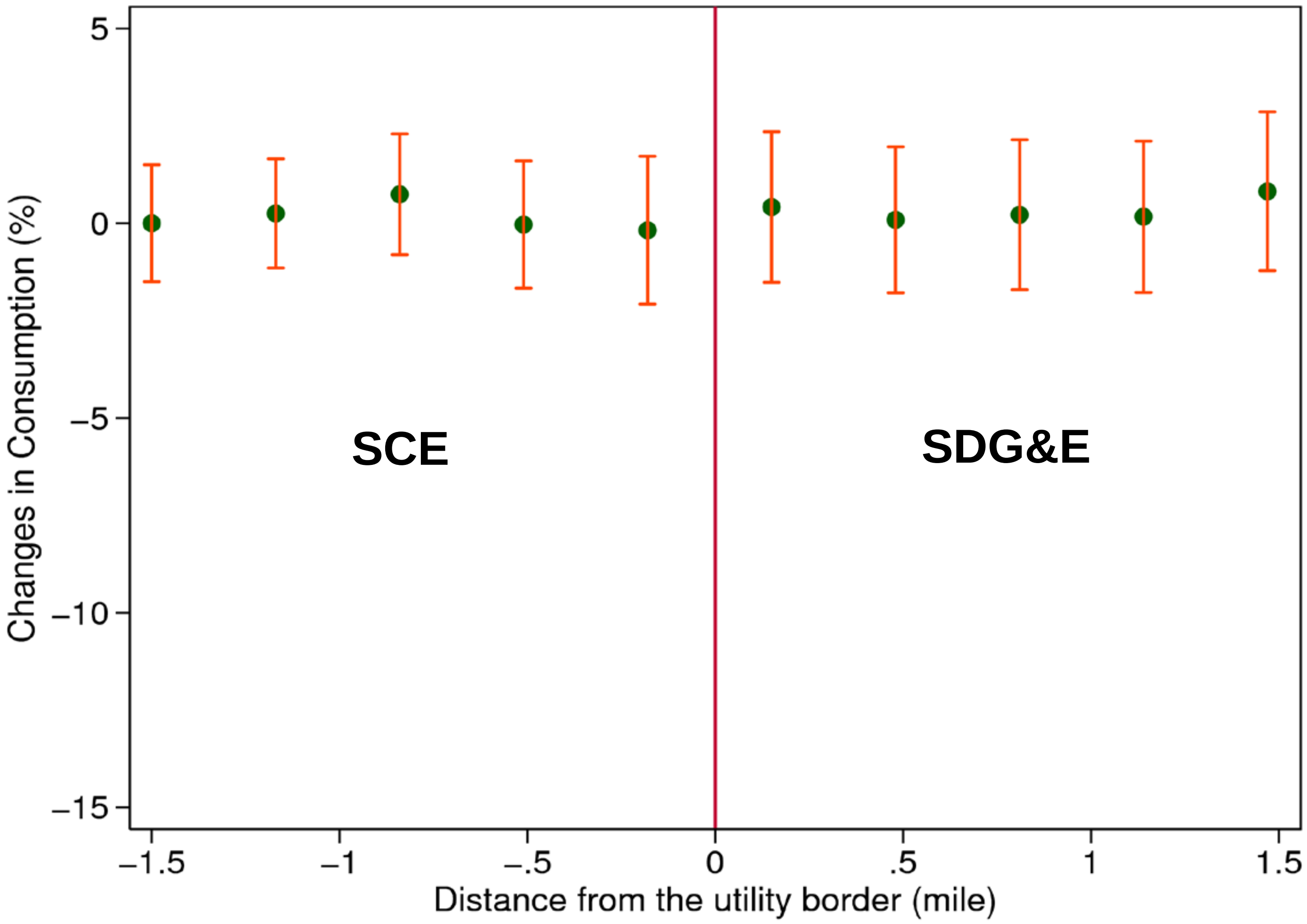
Effects of Tiered Prices on Electricity Usage

- To distinguish between these explanations, Ito uses a second strategy

- Utility company that provides service depends upon where families live: Southern California Edison (SCE) vs. San Diego Gas and Electric (SDG&E)

- In August 2000, SDG&E raised average electricity prices, while SCE did not
  - Uses a spatial regression-discontinuity design to estimate effect of this change

Changes in Consumption from July 1999 to July 2000, by Distance from the Utility Border



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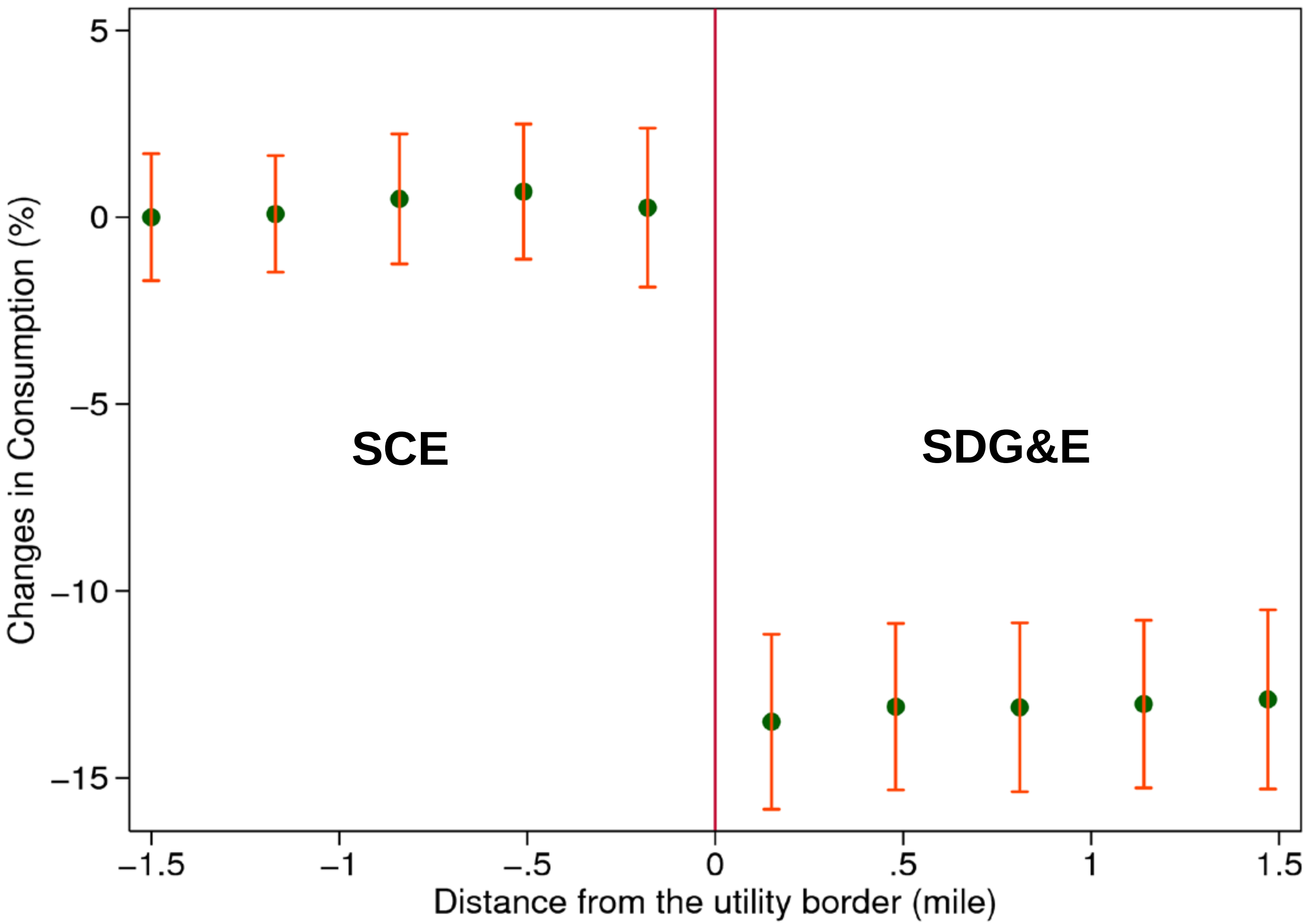


Effects of Tiered Prices on Electricity Usage

- Result: consumers are very sensitive to electricity prices when change is clearly visible, but do not respond to tiered pricing schedule

- Implies that most consumers are not aware of the price they are paying for using additional electricity

- Reinforces message that when designing corrective taxes, salience and structure of incentives matters as much as the dollars involved

  - Traditional economics assumption that consumers are fully rational and perfectly informed about prices does not hold

How Can We Reduce Electricity Consumption More Effectively?

- Two potential remedies to lack of effectiveness of tiered prices:

1. Make prices more salient to consumers using smart meters
   - Pioneering technological work in this area done by O-Power

2. Use non-price tools motivated by results in social psychology
   - Cialdini and collaborators (2007) demonstrate that social comparisons and injunctive social norms have significant effects on electricity use

Last Month Neighbor Comparison | You used **42% more** natural gas than your efficient neighbors.

* Therms: Standard unit of measuring heat energy

How you're doing:

Great

▶ **GOOD**

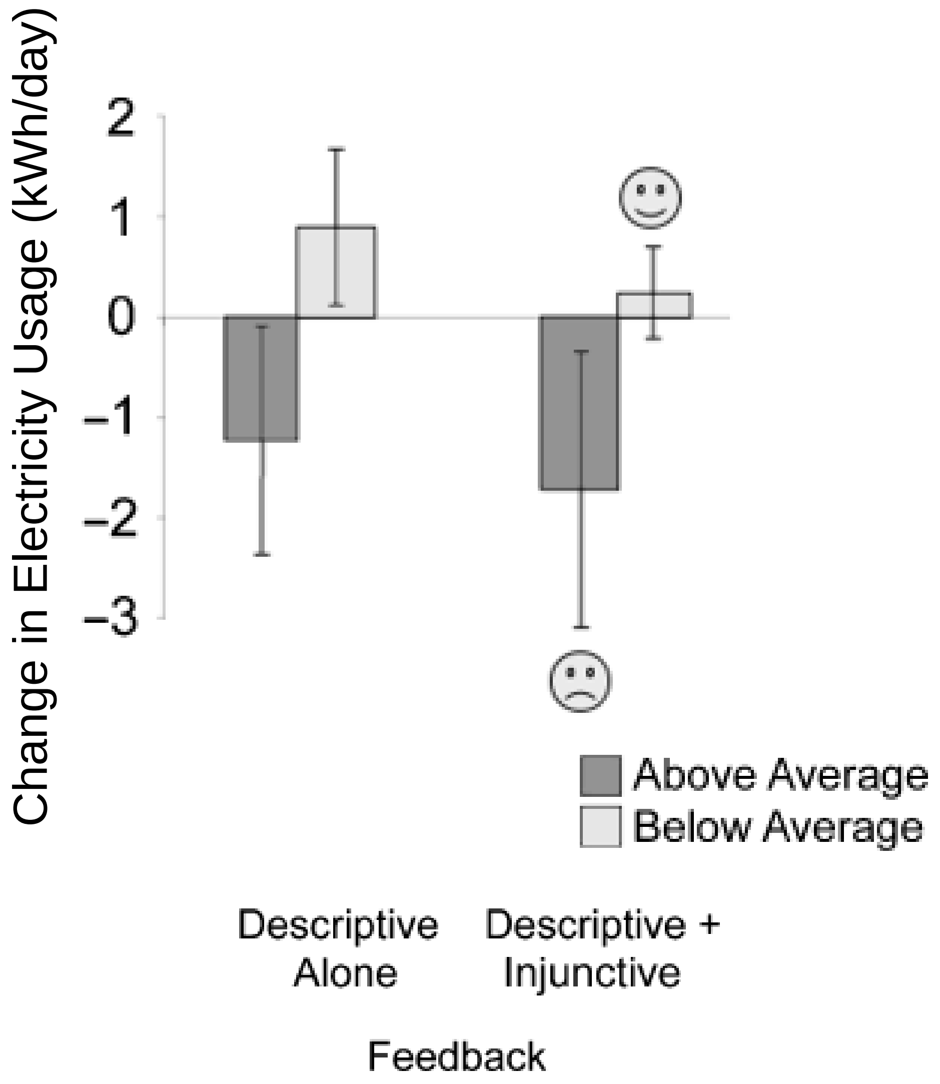
More than average

Who are your Neighbors?

All Neighbors: Approximately 100 occupied, nearby homes that are similar in size to yours (avg 1,517 sq ft)

Efficient Neighbors: The most efficient 20 percent from the "All Neighbors" group

Effects of Social Norm Treatments on Daily Electricity Consumption



Source: Schultz et al. (2007)

Magnitude of Social Norm Treatment

- Social norms treatment reduces electricity usage by about 1 kilowatt-hour per day
    - Equivalent to about a 2.5% reduction in electricity usage
    - Analogous to turning off 10 hundred-watt lightbulbs for an hour a day
    - Modest effect, but does not require charging consumers higher prices

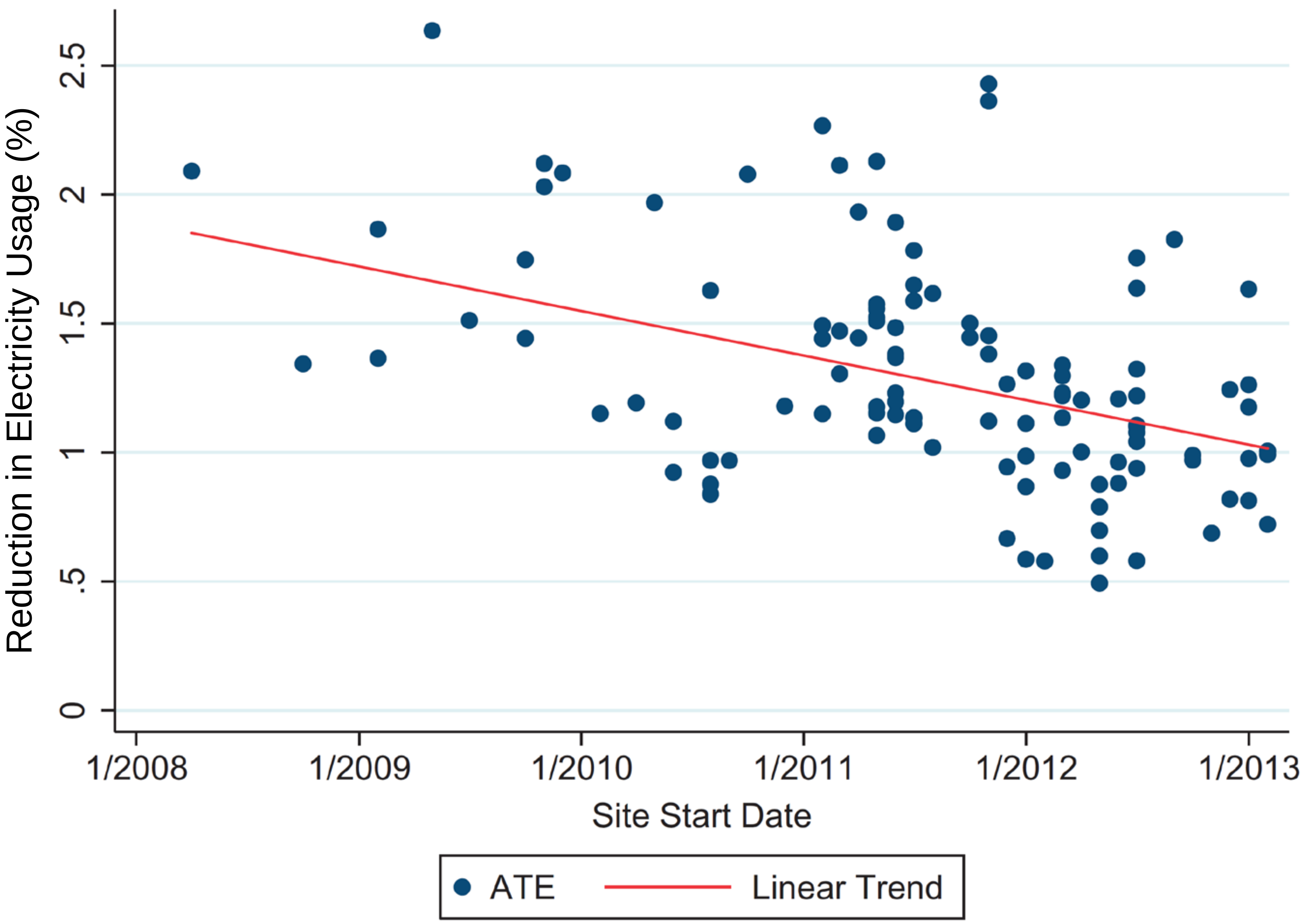
Differential Effects of Social Norms Across Markets

- OPower began mailing Home Energy Reports to millions of electricity customers in markets across the U.S.

- In some markets, mailings were randomly assigned, permitting experimental estimates of causal effects

- Allcott (2015) estimates impact of home energy reports for 111 markets separately to analyze whether impacts vary across areas

Effects of OPower Home Energy Reports Across Utilities, by Program Start Date



Site Selection Bias in Experimental Estimates

- Illustrates an broader methodological lesson: experimental/quasi-experimental estimates in social science are not necessarily stable across settings

- Important to continue to conduct studies across areas and time periods to understand policy impacts, rather than assuming effects will generalize

Perceptions of Climate Change

- Why might public concern about climate change (and hence political support) be limited?

- Moore et al. (2019) hypothesis: gradual change in climate → remarkability/salience of changes in climate lower

  - “Boiling frog” phenomenon: gradual increases in temperature go unnoticed, even though total absolute change relative to past is large

- Present evidence for such adjustment of perceptions using data from Twitter to measure how much people discuss weather

Measuring Perceptions of Climate Change: Methods

- Data: 2.2 billion geocoded Tweets from 2014-16 and local area temperature measurements from 1981-2016

- Goal: estimate a model that relates frequency of weather related tweets to temperature anomalies

- “Bag of words” classification algorithm: define a tweet as weather-related if it contains any word in a list of pre-defined weather related terms

Words Related to Climate Change

arid, aridity, autumnal, balmy, barometric, blizzard, blizzards, blustering, blustery, blustery, breeze, breezes, breezy, celsius, chill, chilled, chillier, chilliest, chilly, cloud, cloudburst, cloudbursts, cloudier, cloudiest, clouds, cloudy, cold, colder, coldest, cooled, cooling, cools, cumulonimbus, cumulus, cyclone, cyclones, damp, damp, damper, damper, dampest, dampest, deluge, dew, dews, dewy, downdraft, downdrafts, downpour, downpours, drier, driest, drizzle, drizzled, drizzles, drizzly, drought, droughts, dry, dryline, fahrenheit, flood, flooded, flooding, floods, flurries, flurry, fog, fogbow, fogbows, fogged, fogging, foggy, fogs, forecast, forecasted, forecasting, forecasts, freeze, freezes, freezing, frigid, frost, frostier, frostiest, frosts, frosty, froze, frozen, gale, gales, galoshes, gust, gusting, gusts, gusty, haboob, haboobs, hail, hailed, hailing, hails, haze, hazes, hazy, heat, heated, heating, heats, hoarfrost, hot, hotter, hottest, humid, humidity, hurricane, hurricanes, icy, inclement, landspout, landspouts, lightning, lightnings, macroburst, macrobursts, meteorologic, meteorologist, meteorologists, meteorology, microburst, microbursts, microclimate, microclimates, millibar, millibars, mist, misted, mists, misty, moist, moisture, monsoon, monsoons, mugginess, muggy, nor'easter, nor'easters, noreaster, noreasters, overcast, parched, parching, precipitation, rain, rainboots, rainbow, rainbows, raincoat, raincoats, rained, rainfall, rainier, rainiest, raining, rains, rainy, sandstorm, sandstorms, scorcher, scorching, shower, showering, showers, sleet, slicker, slickers, slush, smog, smoggier, smoggiest, smoggy, snow, snowed, snowier, snowiest, snowing, snowmageddon, snowpocalypse, snows, snowy, sprinkle, sprinkling, squall, squalls, squally, storm, stormed, stormier, stormiest, storming, storms, stormy, stratocumulus, stratus, subtropical, summery, sun, sunnier, sunniest, sunny, temperate, temperature, tempest, thaw, thawed, thawing, thaws, thermometer, thunder, thundering, thunderstorm, thunderstorms, tornadic, tornado, tornadoes, tropical, troposphere, tsunami, turbulent, twister, twisters, typhoon, typhoons, umbrella, umbrellas, vane, warm, warmed, warms, weather, wet, wetter, wettest, wind, windchill, windchills, windier, windiest, windspeed, windy, wintery, wintry

Measuring Perceptions of Climate Change: Methods

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- Goal: estimate a model that relates frequency of weather related tweets to temperature anomalies

- “Bag of words” classification algorithm: define a tweet as weather-related if it contains any word in a list of pre-defined weather related terms

- Validation: sample 6,000 tweets and manually define them as weather-related or not to evaluate accuracy of classification of algorithm

Examples of Correctly Classified Tweets (“True Positives”)

- it's too hot to be dressin cute
- I swear when it comes to driving in the rain, people in Southern California are idiots on the road
- Thinking of another day full of rain makes me cringe
- It's pretty warm
- Its so hot dawg
- I want want to go swimming! Its too hot out here!!
- I cold af
- Hot as f**k
- Something about a rainy day so cozy
- I am so mad about this snow outside omg..
- the weather is nuts!

Examples of Misclassified Tweets ("False Positives")

- I need an ice cold Bud Light. @budlight
- In so tired of never being able to go out to dinner because everything is jam packed due to the Heat game. every year. Same bs.
- "The cold never bothered me anyway." This movie never gets old
- me- he looks familiar. ash- he is familiar he's hot
- I live for all of the intense parts of songs by Arctic Monkeys.
- 1st degree burns from making hot coco. Hurts like hell
- dad never failed to buy the ocean breeze
- I wish I could freeze moments to be able to appreciate them more. Things are so fleeting

Measuring Perceptions of Climate Change: Methods

- Data: 2.2 billion geocoded Tweets from 2014-16 and local area temperature measurements from 1981-2016

- Goal: estimate a model that relates frequency of weather related tweets to temperature anomalies

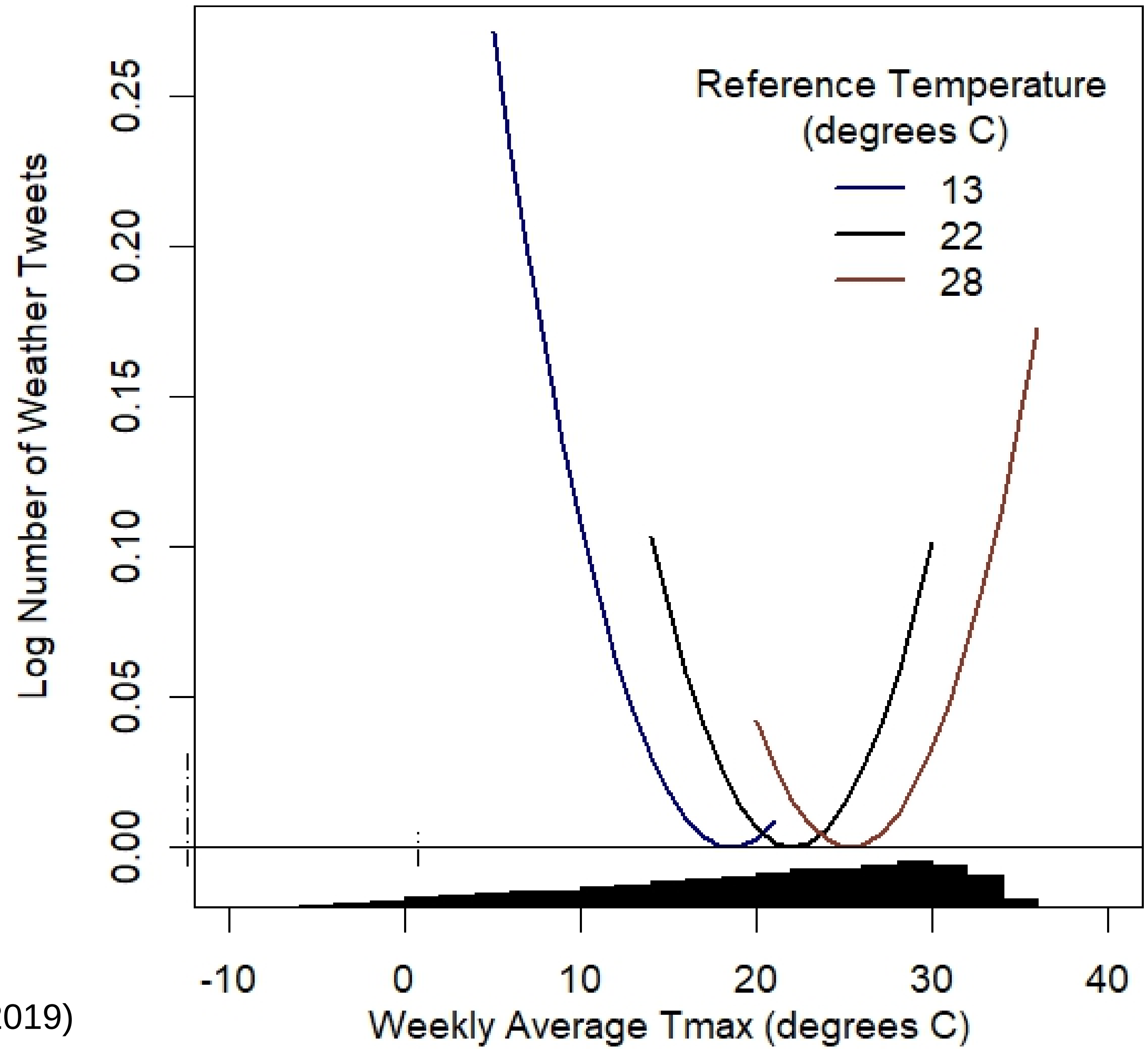
- “Bag of words” classification algorithm: define a tweet as weather-related if it contains any word in a list of pre-defined weather related terms

- Validation: sample 6,000 tweets and manually define them as weather-related or not to evaluate accuracy of classification of algorithm

  - 46% of tweets classified as “weather-related” are false positives

  - But frequency of errors is **uncorrelated** with temperature fluctuations → unbiased estimates of link between weather and climate perceptions despite errors

Weather-Related Tweets vs. Temperature, by Historical Avg. Temperature



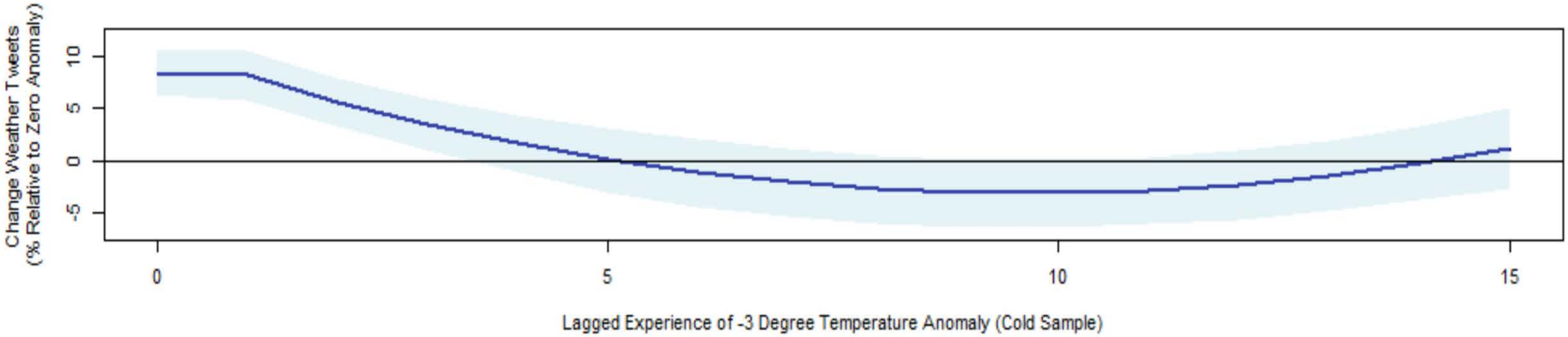
Source: Moore et al. (2019)

Dynamic Adjustment Model

- Next, relate tweets in a given week to rate of temperature anomalies both in that week and to frequency of similar anomalies in **previous years**

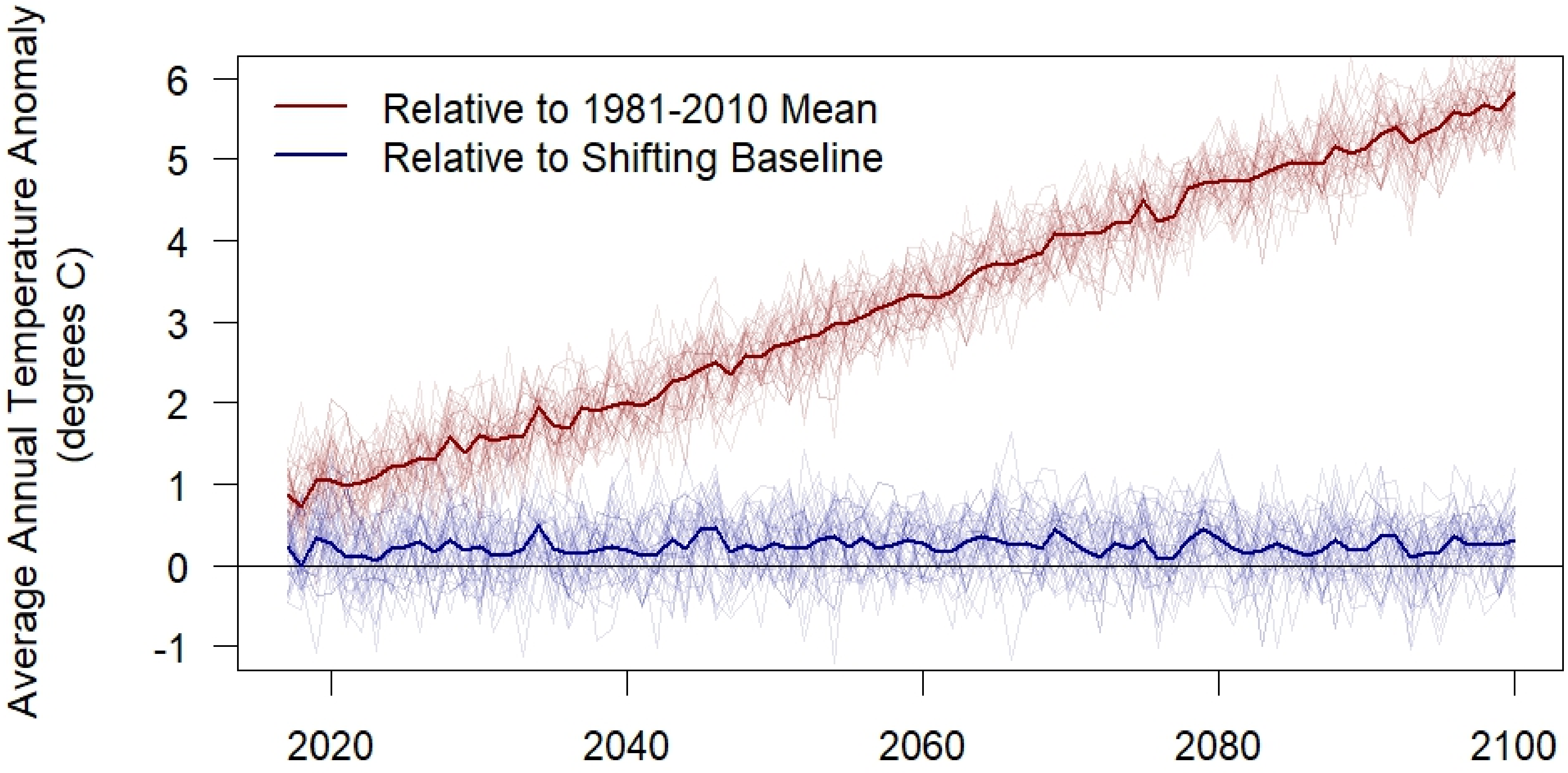
- Dynamic adjustment model: captures how a sequence of anomalies (i.e., hotter temperatures over time) affect perceptions

Short Run vs. Long Run Impacts of Temperature Anomalies



Source: Moore et al. (2019)

Perceived vs. Actual Changes in Temperature



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