Why do travel surveys matter in the Age of Big Data?

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About the speaker…

Father: peripatetic Army helicopter pilot

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Mother: marriage and family therapist

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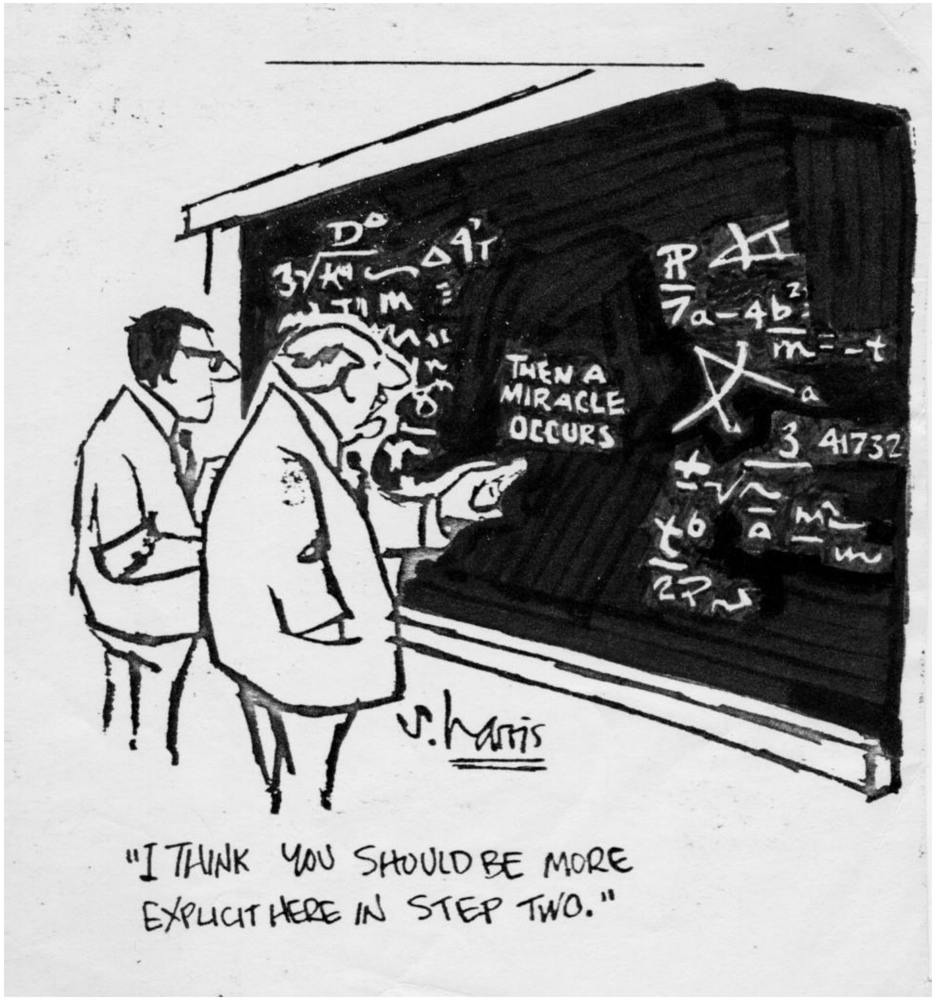
Daughter: specialist in travel behavior analysis

About the speaker… (2)

- Math major



About the speaker… (2)

- Math major
- Entire career (since 1970s) devoted to the design, adminis-tration, and analy-sis of surveys measuring travel-related attitudes and behavior

About the speaker… (2)

- Math major
- Entire career (since 1970s) devoted to the design, administration, and analysis of surveys measuring travel-related attitudes and behavior
- Have been teaching a course on survey-based research methods for most of my 28-year faculty career
- Compulsive about survey design details

About the speaker… (3)

- Have I peaked???

https://www.google.com/url?sa=i&rct=j&q=&esrc=s&source=imgres&cd=&cad=rja&uact=8&ved=2ahUKEwj2gLmCpdncAhXKnuAKHY8FAi4QjRx6BAgBEAU&url=https%3A%2F%2Fnsmb.com%2Farticles%2F2017-kona-hei-hei%2F&psig=AOvVaw2nyHd5c62UmA2qwhQT5Da8&ust=1533674539304990

About the speaker… (3)

- Have I peaked???
- Even now, it's rare to find a course on survey methods in graduate *transportation* programs
  - Common in *psychology or sociology*
  - In *transportation*, you may find a course on *"data acquisition methods"*
- Will survey design have disappeared entirely from such courses within 5 years?
  - Replaced by "*Using Machine Learning Methods to Analyze Big Data*"?

Get with the times!

- In an era of
  - GPS traces
  - Transit smart cards
  - Clickstreams
  - RFID chips and scanner data
  - Twitter feeds and other social media posts
  - Remote sensing
  - Targeted marketing and credit reporting data
  - and more
- … who needs old-fashioned surveys???

Why do we still need surveys?

Three reasons:

- There's not always a Big Data source for what we need to know
- The Big Datasets we do have are incomplete
- Big Data is *even more valuable* when used in conjunction with survey data!

1. There's not always a Big Data source for what we need to know

a. Qualitative research

- ***Interviews*** about
  - Procurement
  - Priority-setting
  - Intra-household decision-making
  - Activity rescheduling
  - Other decision processes
- ***Focus groups*** on
  - Unmet needs, latent demand
  - Prospective policy impacts
  - Product/service design
- ***Charrettes*** on
  - Land use/transportation system changes

1. There's not a Big Data source for … (2)

b. Reliably identifying and measuring small/specialized populations

- Infrastructure performance managers at State DOTs
- Municipal traffic engineers
- Recent immigrants
- Single parents

1. There's not a Big Data source for… (3)

c. Hypothetical choices

- Impacts of *currently unavailable technologies* on travel, residential/job location
- Behavioral impacts of *proposed new policies*
- Removal of *constraints*
- Behavioral *intentions*

2. Even when we have Big Data sources…

- The data are far from perfect
  - Take GPS traces (please!*):
    - Broken trips
    - Urban canyons:
      - Signal blockage
      - Multi-path interference
    - Poor within-building performance
    - Dead batteries
    - Forgotten phones
    - etc…

*With a nod to Henny Youngman

2. Even when we have Big Data sources… (2)

- The data are far from perfect
- Vital context is missing:
  - Often even standard demographics are unknown
  - Want to apply aggregate statistics for the associated geographical unit?
  - Beware the ***ecological fallacy****!

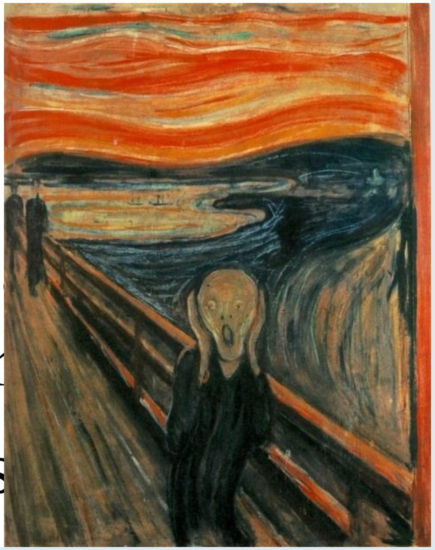
* Relationships at the ***aggregate*** level can be very different than – even the reverse of – those at the ***disaggregate*** level.

2. Even when we have Big Data sources… (3)

- The data are far from perfect
- Vital context is missing:
  - Often even standard demographics are unknown
  - Understanding the "why" of human behavior generally requires ***measuring the unobservable***, including
    - Constraints
    - Motivations (values)
    - Intentions
    - Personality
    - Lifestyle
    - Attitudes

2. Even when we have Big Data sources… (4)

- The data are far from perfect
- Vital context is missing
- Representativeness is (more) dubious
  - ~~“Since our sample is so large, representativeness is not a concern”~~
  - 1936 *Literary Digest* poll predicted over Roosevelt landslide: N = 2.3 m
  - Some exclusions are obvious, others



2. Even when we have Big Data sources… (5)

- The data are far from perfect
- Vital context is missing
- Representativeness is (more) dubious
- Correlation doesn’t equal causality

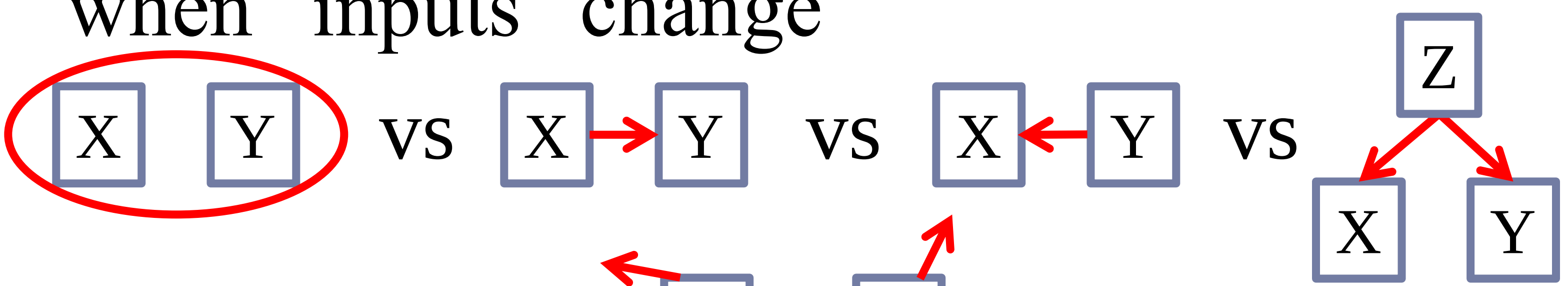
Wait – isn’t causality passé?

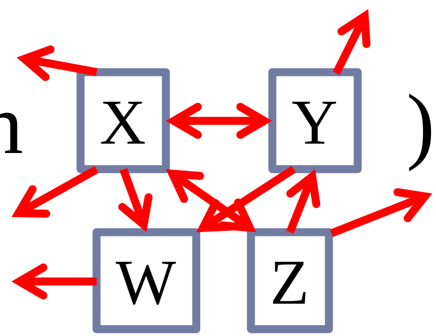
- “But today, data is so readily available and computers are so fast and powerful that **experts … have stopped trying to figure out why something – say, crime – happens**. Instead they look at crimes and notice what events or behaviors seem to precede them… [T]he tricky work of turning information into knowledge has **shifted from causation to correlation**.”

– Fareed Zakaria, *Time*, 7/8/2013

So why *does* causality matter?

- We're hardwired to ask, "Why?"
- It's our best hope of predicting "outcomes" when "inputs" change



(not to mention 

)

- because knowing the "why?" improves our understanding of the "what will happen if?"

A tale of two causal models

- "Whenever the dog tries to attack you, you give him a treat to get him to stop?" "Yes, and it works every time!"
- Human's model:
  - give treat → attack stops
- Poodle's model:
  - attack human → receive treat

"A client came in with her poodle and warned us that the dog would bite. She said that it would often corner her in a room at home, too, and snarl and sometimes bite. I asked how she handled it, and she said, 'Well, I started throwing food to get him away from me, and it worked. So now I keep snacks in every room just in case.' 'So ...,' I asked incredulously, 'whenever he tries to attack you, you give him a treat?' 'Yes,' she answered, 'and it works every time!'"

Dennis Leon, DVM

Reader's Digest, May 2012, p. 188

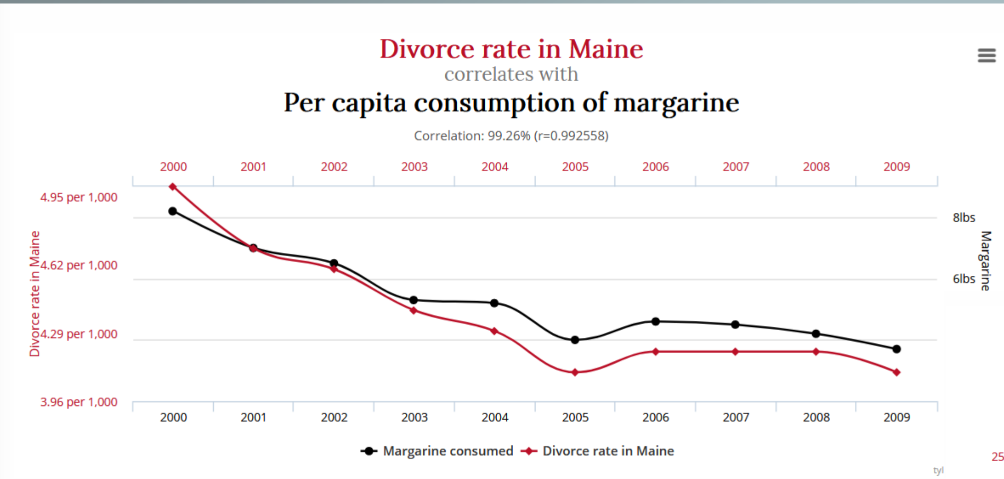
A tale of two causal models (2)

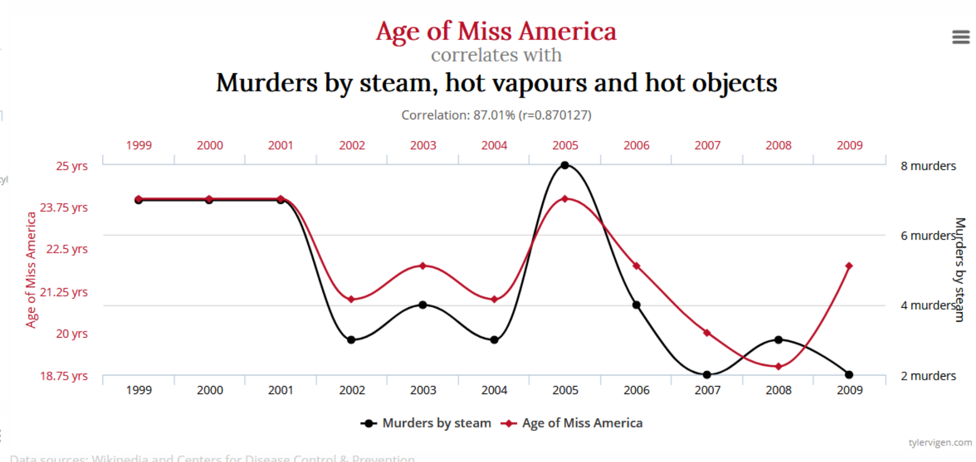
- Human
  - ***Model:*** give treat → attack stops
  - ***Policy implication:*** keep giving treats

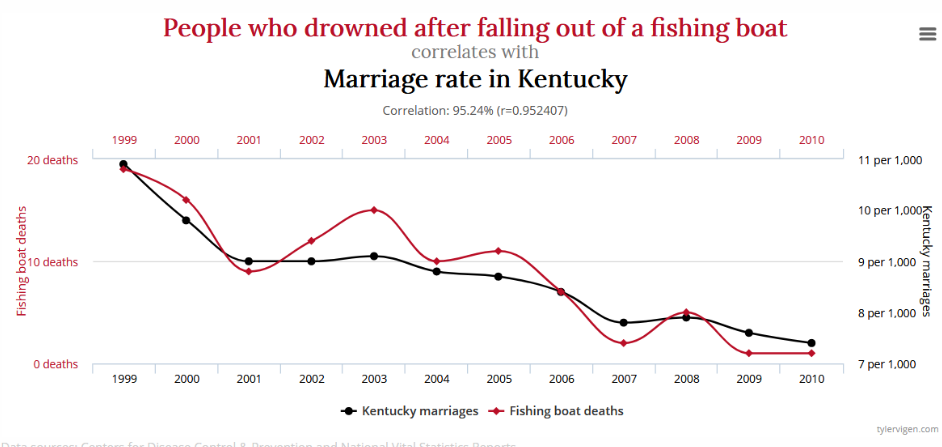
- Poodle
  - ***Model:*** attack human → receive treat
  - ***Policy implication:*** keep attacking

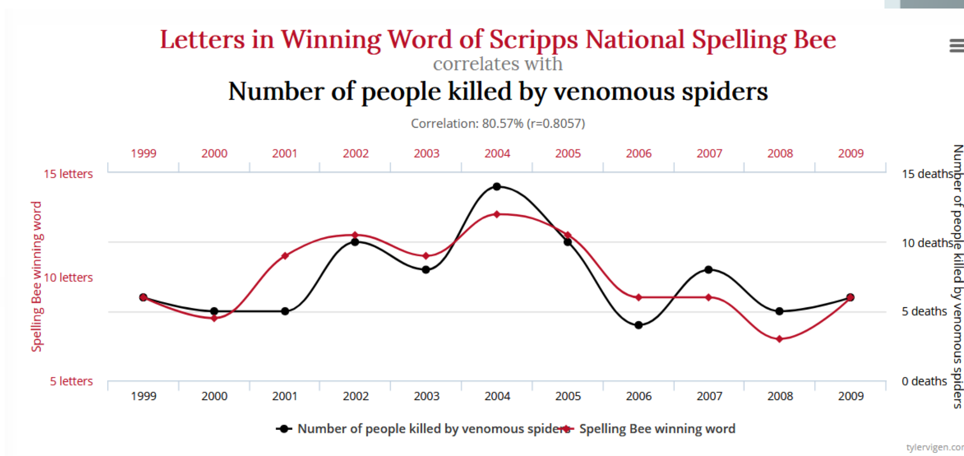
- Neither view of reality achieves the socially-optimal outcome…
- There's no substitute for domain knowledge…

If correlation is all you look at…









http://tylervigen.com/spurious-correlations

3. Big Data can enrich survey data

- We've previously considered some advantages afforded by ***survey data***
  - Measurement of specialized populations
  - Measurement of important, but unobserved, variables (constraints, motivations, etc.)
  - Greater representativeness
  - Greater illumination of "why?"
- Let's now consider some advantages offered by ***Big Data***

Also see Varian (2014)

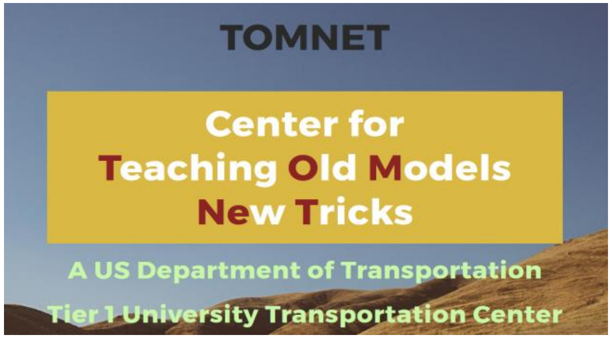
3. Big Data can enrich survey data (2)

- Some Big Data advantages *for causal models*
  - Improved matching
  - More cases around a regression discontinuity
  - Ability to analyze population segments
    - Assuming you can identify those segments, you're likely to have a lot of cases in them
  - Ability to "experiment" on a large scale, in "ecologically valid settings"
  - Ability to track dynamics

Grimmer 2015; also see Varian 2014

TOMNET (a Tier 1 UTC): Teaching Old Models (and Modelers) New Tricks

Arizona State University



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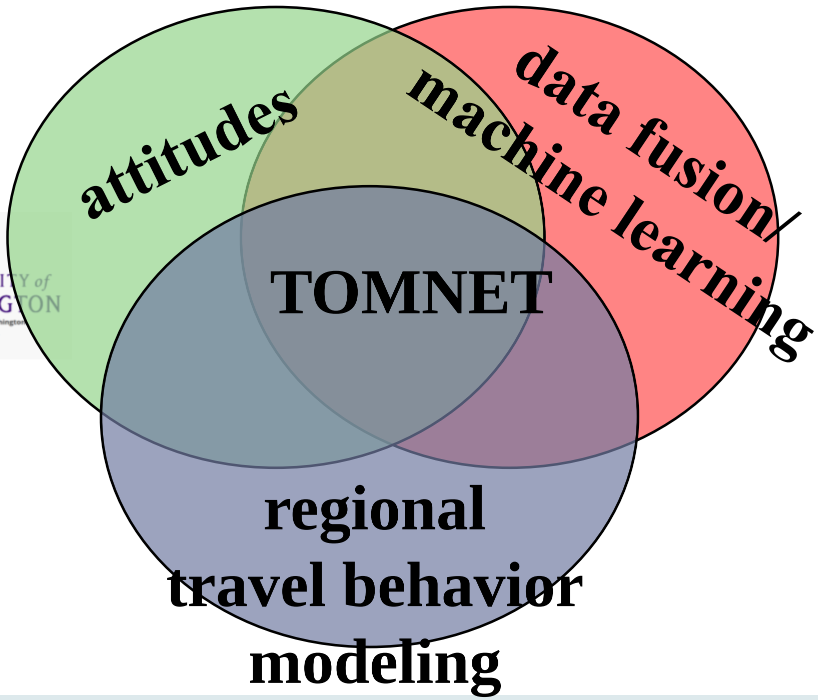
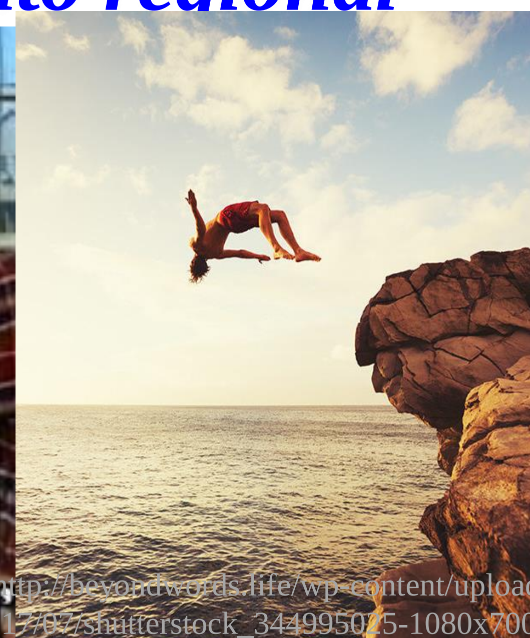


TOMNET (2)

- If you'd told me a few years ago that I'd be embracing ***machine learning***, and using it to pursue a decades-long dream of ***bringing attitudinal information into regional models***…

I'd have said …

But just look at me no



http://beyondwords.life/wp-content/uploads/2017/07/shutterstock_344995025-1080x700.jpg

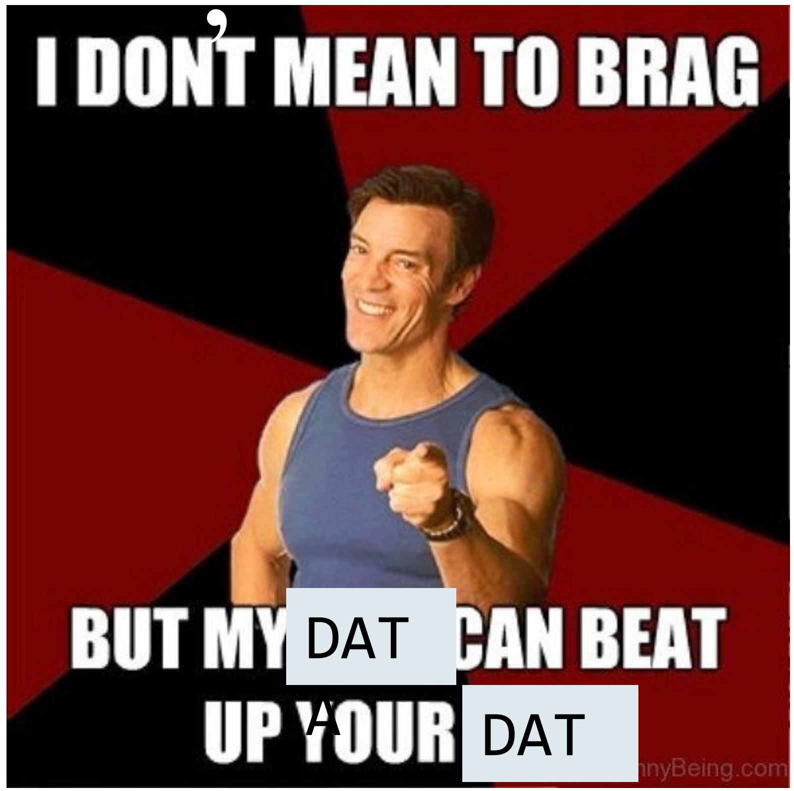
Here's what we're working on

GDOT survey data	NHTS (GA subsample)	Virtual survey
Donor (source)	*Recipient (target)*	*Fused data*
N = 3,000	N = 8,000	N = 8,000

Adapted from Fig. 1 (p. 2) of van der Putten et al. (2002). See Malokin et al. (2018).

In conclusion,
may I suggest …

Enough with the data strut and swagger, already!



http://www.funnybeing.com/wp-content/uploads/2017/03/I-Dont-Mean-To-Brag-600x600.jpg

Enough already! (2)

- We’ve seen that each of these approaches can
  - do things the other one can’t; and
  - make the other one better
- Discarding either one deprives planning/ policymaking of the insights made possible by the “other” kind of data, and by *both* kinds of data working in harmony

Enough already! (3)

- So instead of arguing about why we don't need this kind, or how the other kind can't be trusted, let's
  - have them *both* in our arsenal, using each singly – and both together – as appropriate
  - consider both perspectives, and how each can improve the other, e.g.,
    - Consider causality, representativeness when using Big Data
    - Integrate "Big Data methods" into survey data analysis
    - Combine survey data and passive data collection – like NextGen NHTS…

“Looking at things in multiple ways creates a richer and more true understanding of the world”

– Susan Handy (2013)

(speaking on the power of combining qualitative and quantitative methods)

Enough already! (4)

- Yes, that means I advise transportation students nowadays to take courses in machine learning…
- … while not forsaking the classics of survey design and causal modeling
- IT'S NOT AN EITHER-OR PROPOSITION…

Enough already! (4)

- Yes, that r… on students nowadays… e learning…
- … while r… f survey design and…
- IT'S NOT… OSITION…

- Let's make this the start of a beautiful friendship!

Selected references

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Thank you!

Questions?

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http://ce.gatech.edu/people/faculty/6251/overview