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Causal inference for ex-post evaluation of transport interventions

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Focus on **statistical modelling** approaches for **causal inference**

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Research challenge: use *observed* data linking interventions with outcomes to quantify cause-effect relationships

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In practice the **observed data** typically do to fulfil these criteria: we have **incomplete data** and **confounding**

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1. *Impacts of urban road network capacity expansions in the US*

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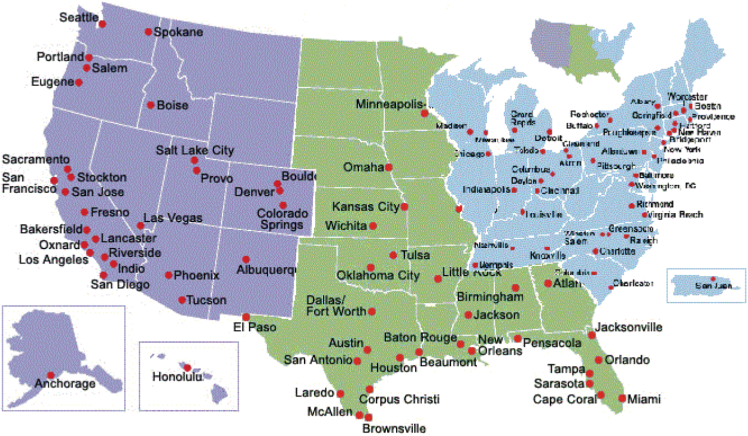
1. *Impacts of urban road network capacity expansions in the US*
2. *Regional economic impacts of High Speed Rail investments in Spain*

Case study 1: impacts of urban road capacity expansions



TTI urban mobility data on road traffic conditions for 101 US cities (1982-2007)

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Results: quantify changes in *'responses'* (i.e demand, performance, productivity) *caused* by treatments (i.e amount of capacity expansion) *net of confounding effects*

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for all doses $d^* \in \mathcal{D} \subseteq \mathbb{R}$ of interest.

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This is done by calculating **generalised propensity scores**

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iii. Use $\widehat{\beta}$ to calculate expected response at dose d^*

$$\widehat{\mu}(d^*) = \mathbb{E}[Y(d^*)] = \mathbb{E}_X\left[\mathbb{E}(Y|d^*,\widehat{\pi}(d^*|X;\widehat{\alpha}));\widehat{\beta}\right],$$

and repeat for all doses of interest.

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iv. Calculate **ATEs**: $\widehat{\tau}(d^*) = \widehat{\mu}(d^*) - \widehat{\mu}(0)$, using (block) bootstrap for variance estimation

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- ⋆ GPS can be used to form a number of ATE estimators via weighting, matching, or regression (combine for doubly robust)
- ⋆ A **longitudinal mixed model extension** of the GPS can address *unobserved effects* and *bi-directional causality* between response and treatment by subsuming these effects within the GPS

Methodological contribution of the paper

ATE estimates are unbiased **if the estimated GPS consistently estimates the true GPS**

A **necessary condition** is that X is sufficient to represent confounding

We show that with longitudinal data the GPS can be estimated via a **mixed model** approach to address

- ⋆ **Unmeasured confounding:** condition on unit level random effects, or correlated random effects, to adjust for unobserved time-invariant confounding: $\widehat{\pi}(d^*|x_{it}, u_i; \widehat{\alpha})$
- ⋆ **Reverse causality:** condition on lagged values of the response $y_{i,t-p}$, or the response history $\mathcal{H}^y_{i,t-1}$, to allow for endogeneity from reverse causation: $\widehat{\pi}(d^*|x_{it}, u_i, \mathcal{H}^y_{i,t-1}; \widehat{\alpha})$
- ⋆ **Dynamic assignment:** include lagged values of the treatment $d_{i,t-p}$, or treatment history $\mathcal{H}^d_{i,t-1}$, to represent the dynamic nature of assignment: $\widehat{\pi}(d^*|x_{it}, u_i, \mathcal{H}^y_{i,t-1}, \mathcal{H}^d_{i,t-1}; \widehat{\alpha})$

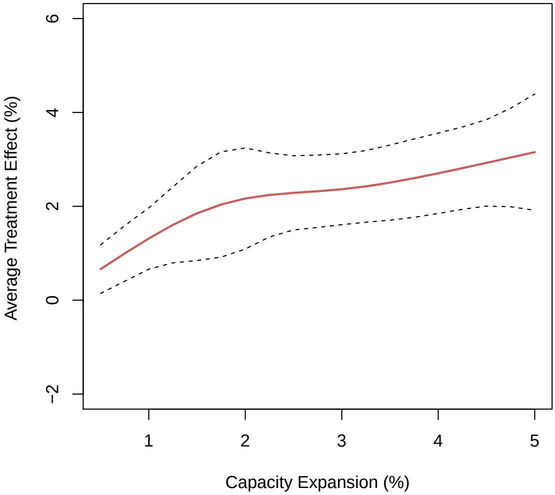
Algorithm for ATE estimation via mixed GPS model

1. Use a flexible mixed model (i.e. GAMM) to estimate $f_{D|X}(d|x, u; \alpha)$
2. Use $\widehat{\alpha}$, with the appropriate density function, to calculate the GPSs: $\widehat{\pi}(d^*|x, u; \widehat{\alpha})$, for all d^* of interest
3. Ensure common support by selecting only units which have a reasonable probability of being treated across the range of dose
4. Estimate $\mathbb{E}(Y|D, \widehat{\pi}(d|x, u; \widehat{\alpha}))$ using a penalised spline model
5. Average over predicted values from 4., evaluated at at dose d^*, to obtain a point estimate of the expected response at d^*: $\widehat{\mu}(d^*)$
6. Repeat for all dose of interest, form the dose-response curve, and estimate ATEs:
$$\widehat{\tau}(d^*) = \widehat{\mu}(d^*) - \widehat{\mu}(0)$$
7. Use a single (block) bootstrap re-sampling scheme over 1. to 6. to obtain standard errors

Urban longitudinal data (TTI and MSA)

- **Responses:** annual proportional change in traffic volume (vmt), network performance (delay per vmt), and productivity (average wage)
- **Treatment:** annual proportional change in network lane miles (freeway and arterial)
- **Pre-treatment covariates (confounders):**
  - ⋆ *Lagged responses:* to capture reverse causality
  - ⋆ *Congestion & traffic volume:* measured by delay and vmt
  - ⋆ *Network scale & mix:* network length, mix of freeway / arterial
  - ⋆ *Traffic mix:* volume on freeway / arterial
  - ⋆ *Mode characteristics:* public transport patronage, state fuel price
  - ⋆ *Economy:* productivity, income and economic structure
  - ⋆ *Employment and population distribution and growth*
- **Unobserved confounders:** physical characteristics, geographical features, aspects of road network design, activity/travel behaviour patterns
  - ⋆ Random city-level effects specified in longitudinal mixed models
- **Models:** Normal GAMMs for all sub models

Results: traffic volumes (vmt)



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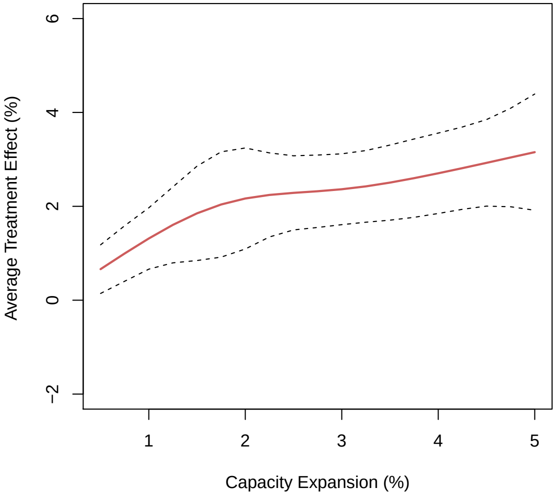

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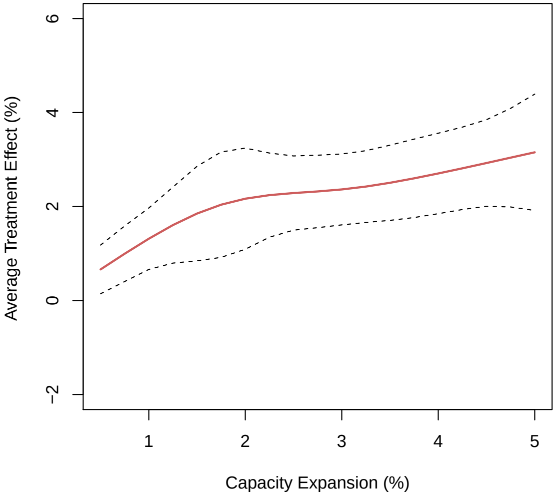

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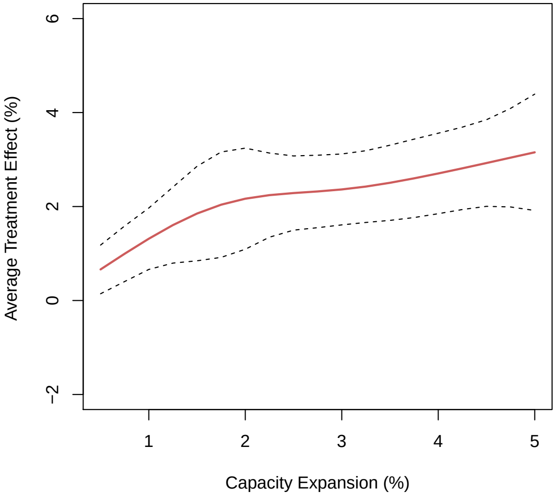

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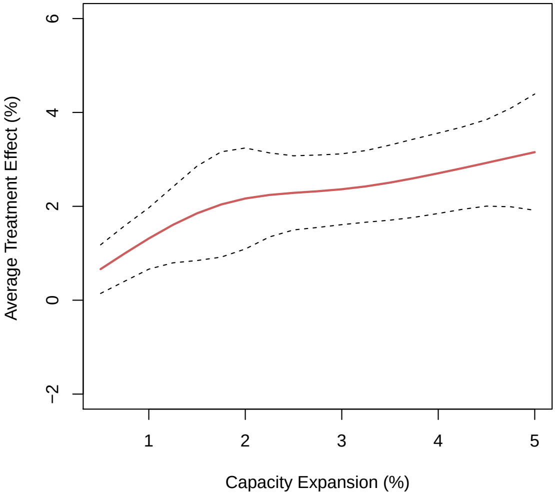

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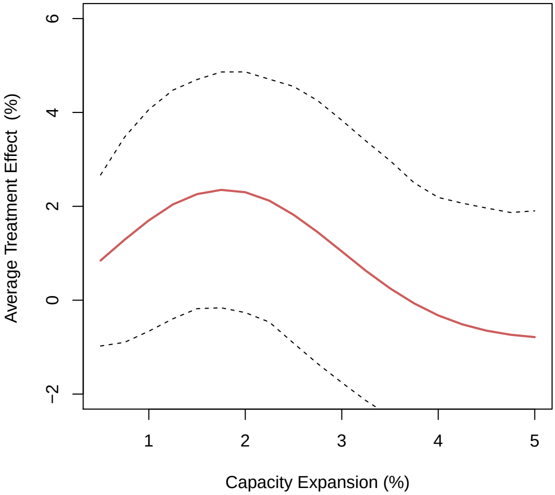
- ⋆ on average 10% increase in lane miles $\rightarrow$ 9% increase in vmt net of 'natural growth' (estimated 1.4% p.a.)
- ⋆ capacity expansions in the range considered have not in general reduced traffic density (vol. / cap.)

Results: network performance (delay per vmt)



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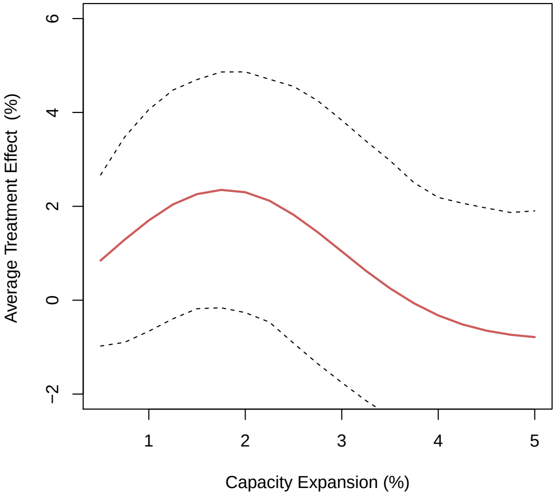

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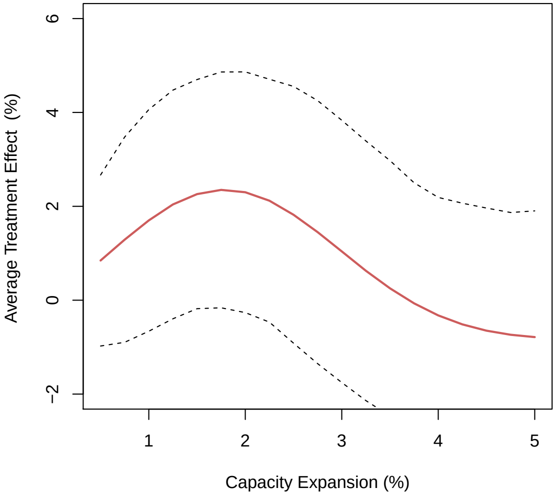

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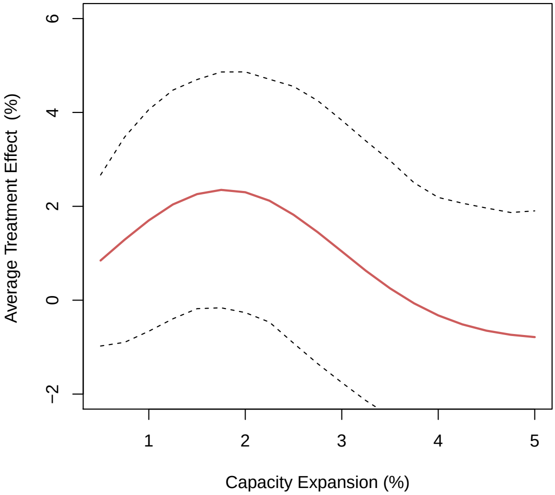

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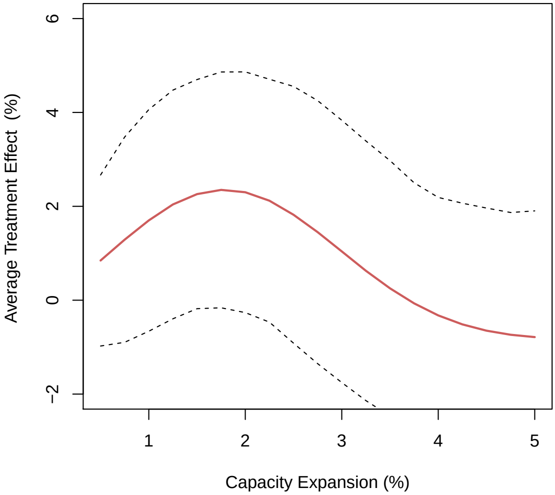

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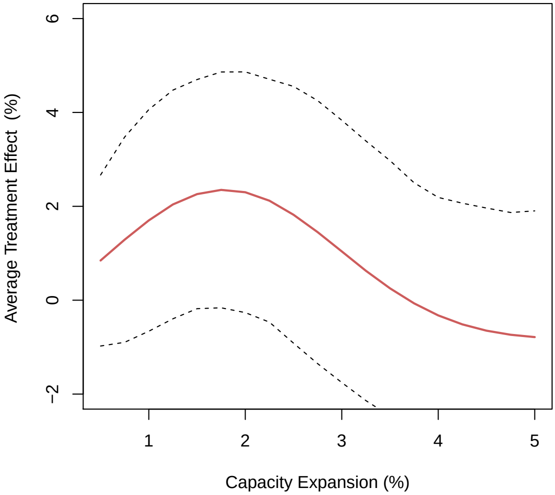

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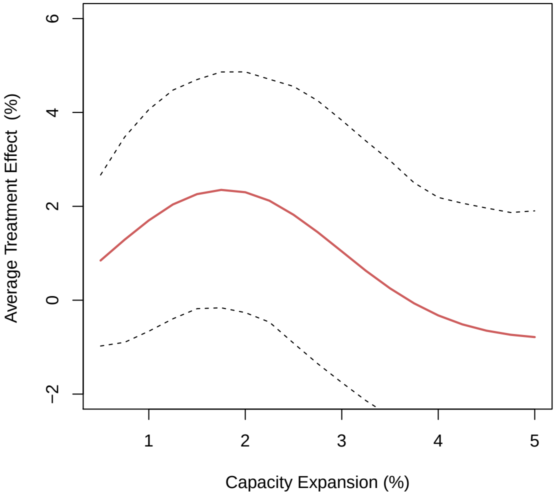

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- ⋆ due to natural growth congestion worsens further (approx. 3% p.a.)

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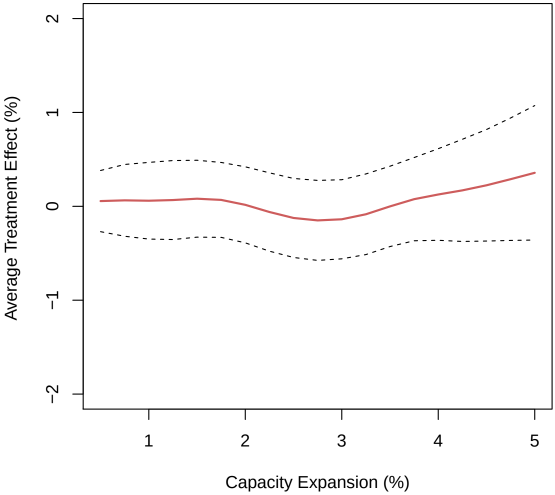

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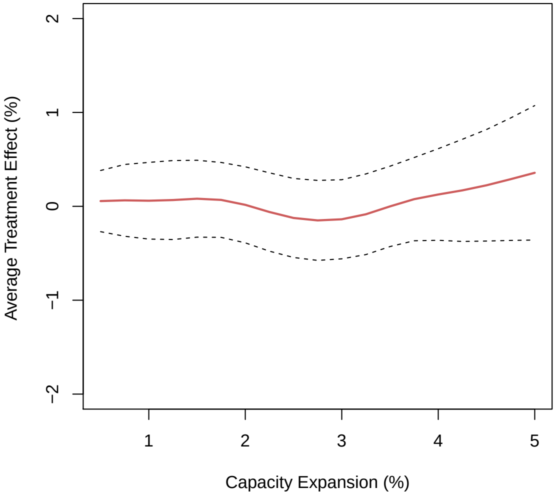

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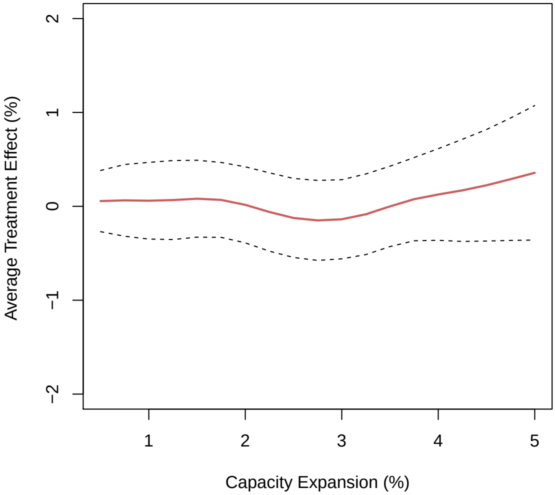

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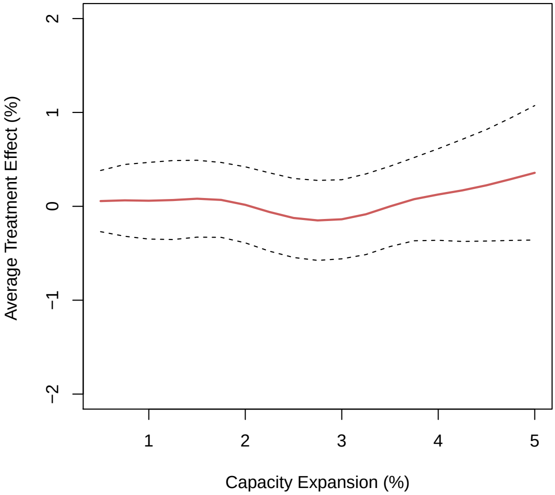

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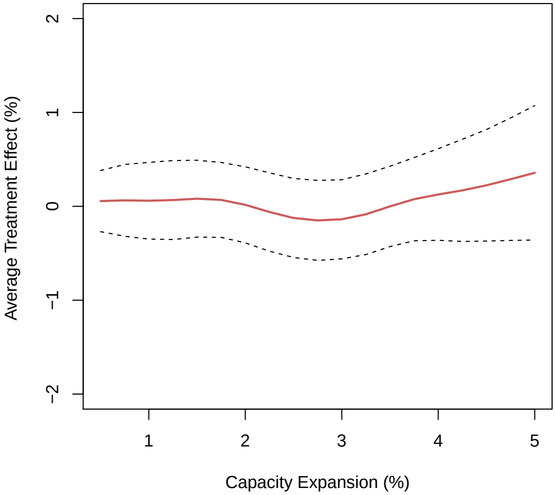

- ⋆ urban road network expansions have not induced higher productivity
- ⋆ 'naive' regressions of productivity on treatment do indicate a +ve association
- ⋆ but no significant ATEs having isolated a viable sample and adjusted for confounding
- ⋆ no fall in interaction costs and apparently no scale effects

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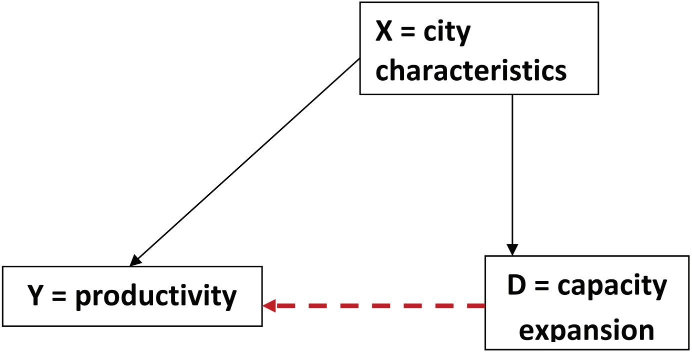
To improve urban road network performance and raise productivity a combination of efficient pricing with investment in both roads and mass transit may be more effective

The problem of confounding



The relationship between capacity and productivity is **confounded** by a set of city characteristics which

- ⋆ Are important for productivity
- ⋆ Influence the level of capacity expansion received

return