

The Effect of Local Road Maintenance Tax Cuts on House Values

David Brasington and Saani Rawat

Discussion by

Chao Liu

The Chinese University of Hong Kong

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This Paper

Research question:

- How does failing to renew local road-maintenance tax levies affect house prices?

Setting:

- Local roads are primarily funded by local governments through property taxes in Ohio
- Over 3000 votes to renew local road tax levies

Empirical design:

- Sharp dynamic regression discontinuity at the 50% cutoff

Main findings: Tax cuts $\Rightarrow$

- -11% road-maintenance funds
- -15% road quality index
- -9% median house price over the 10-year period

My Take

Clean identification setup

- Maintenance of existing roads (Asher and Novosad, 2020)
- Renewal votes (Cellini et al., 2010)
- Cities just below and above the 50% cutoff

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- Use satellite images to fine-tune a Vision Transformer
- Predict road quality on a 0-2 scale

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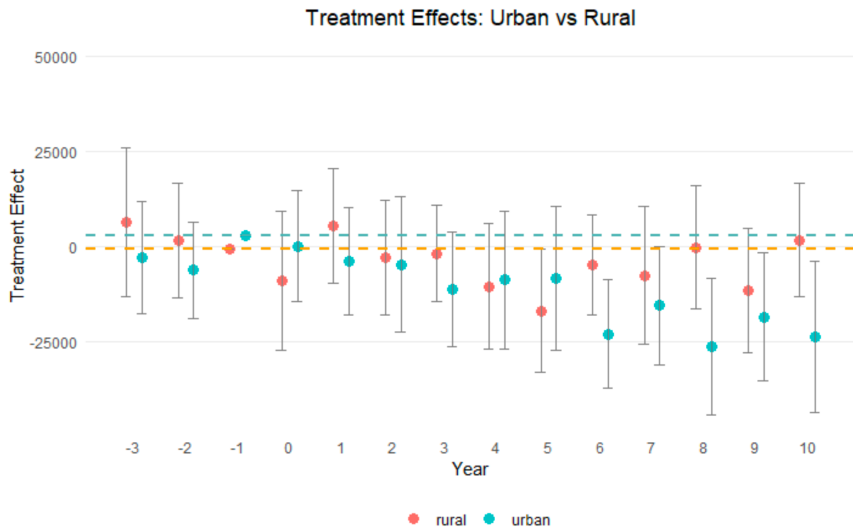
- Interpretation and Magnitude
- Mechanisms

Comment 1: Interpretation and Magnitude

Measure of price impact

- Heterogeneous effect: urban $>$ rural; high-priced $>$ low-priced houses

Treatment Effects: Urban vs. Rural



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Measure of price impact

- Heterogeneous effect: urban > rural; high-priced > low-priced houses
- Overall effect = $\frac{15,350}{166,000} = 9.2\%$; Effect in urban areas = $\frac{13,302}{175,217} = 7.6\%$
- Use $\log(\text{house price})$ as the outcome

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Interpretation of heterogeneous effects

- Housing supply elasticity
- Public transportation usage

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Short-term vs. long-term trade-off

- Annual tax saving \$79 vs. Sale price loss \$21,638 by year 4
- Pay \$1.50 more for \$1 in school capital spending (Cellini et al. 2010)
- Does such a large elasticity imply additional channels?

Comment 2: Mechanisms

Tax cuts $\Rightarrow$ Maintenance funds $\downarrow$

- Road Tax_{it} = Millage Rate_{it} $\times$ Assessed Value_{it} $\times$ #Households_{it}
- Discontinuity test on millage rate
- Use expenditure by the public works department as the outcome to do RDD

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Tax cuts $\Rightarrow$ Maintenance funds $\downarrow \Rightarrow$ Road quality $\downarrow$

- Report transformer performance metrics

Predicting Road Quality (Brewer et al., 2021)

Table 2. Architecture results.

Network Base Model	Overall (%)	Low Quality (%)	Mid-Quality (%)	High Quality (%)
InceptionResNetV2	78.0	79	58	89
Inceptionv3	77.5	72	60	90
VGG16	75.4	76	47	90
ResNet50V2	75.3	64	56	91
DenseNet201	73.4	59	44	97
ResNet50 (BigEarth)	72.8	63	55	88
ResNet152V2	72.5	63	52	88
Xception	70.0	68	21	97

- The overall most accurate ensemble (IncpetionResNet, Inception, and DenseNet) can achieve 80.0% classification accuracy

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- Show how road quality declines by time

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Tax cuts $\Rightarrow$ Maintenance funds $\downarrow \Rightarrow$ Road quality $\downarrow \Rightarrow$ House prices $\downarrow$

- Capitalization of road quality into house prices
- Other public goods: police, school, park

Conclusion

My take

- Clean empirical setting
- Innovative data
- Important policy implications

My suggestions

- Make ML methodology more transparent
- Use RDD for all main outcomes
- Interpret the price effect in percentage
- Provide more evidence on mechanisms