

Effect of Road Maintenance on Housing Values, Employment and Wages

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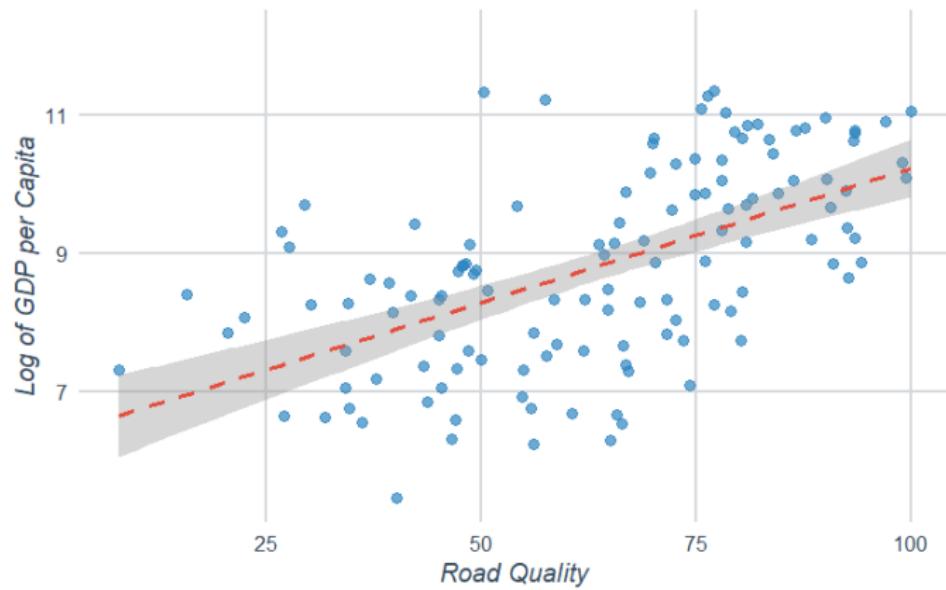
8 Oct 2024



Background

Roads are important for economic well-being.

GDP per Capita vs Road Quality: 2018



Source: World Bank Global Competitive Index 4.0



Background

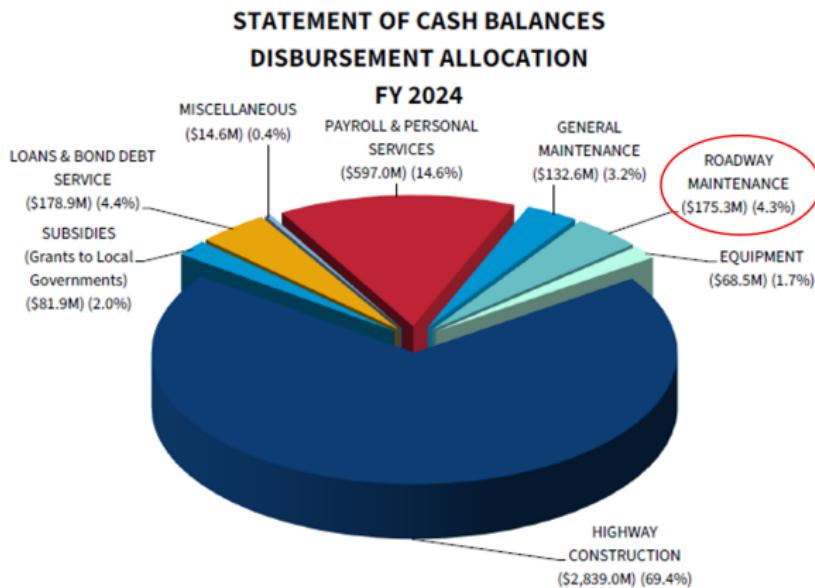
How are roads maintained in the US?

- Gas taxes: Federal (\$0.18 per gallon) and State (\$0.38 per gallon for Ohio)
- Federal Grants and State funds for new projects and highways
- Vehicle registration fees, License plate fees, tolls and "user" taxes
- Local governments can use local tax revenue collected from property and income taxes to fund road maintenance
-



Background

How are roads maintained in Ohio?



Source: Ohio Department of Transportation (ODOT) Annual Report 2024



Background

How are roads maintained in Ohio?

- Only 4% of ODOT budget is spent on road maintenance
- ODOT manages state highways and interstates
- Local roads maintained by townships and cities using local tax revenue (income and property taxes)
- Townships and municipalities can propose local road levies, which are property tax assessments specifically earmarked for road maintenance and improvements. These levies must be approved by voters



Motivation

Natural experiment: Local road maintenance tax levies that just pass or fail a road levy vote

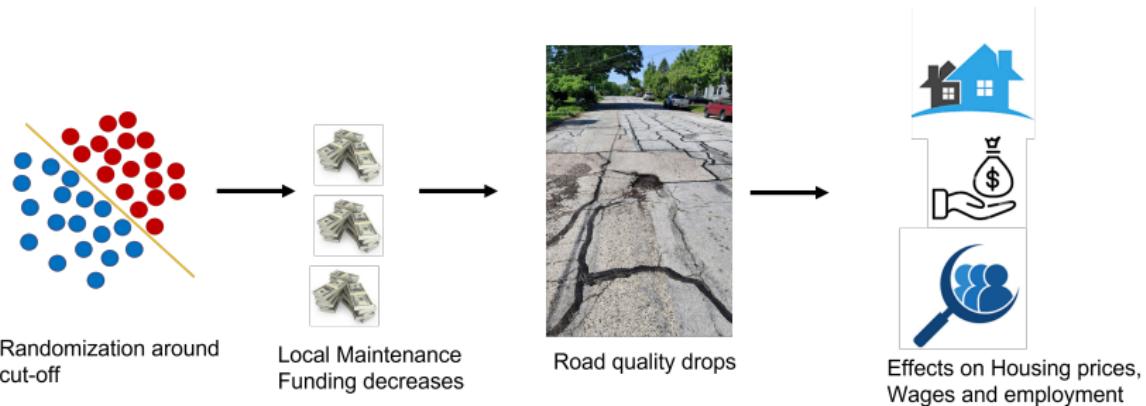


Research Question

Do poorly maintained roads lead to a reduction in property values,
employment and wages?



Diagram of Thought Process



Preview of Results

- Cities that cut road maintenance spending see a decline in property values of \$20,729 relative to similar cities that renewed funding, starting at four years after the vote.
- Houses in urban areas declined more than houses in rural areas.
- More expensive houses saw a larger decline in property values than cheaper houses.
- High-poverty cities that cut road spending have 11% lower employment compared to similar cities that renewed funding and %17.8 lower wages.



Contribution

- While most of the research has focused on effects of new infrastructure (new highways, trains etc.), we show long-term effects of road maintenance on different economic outcomes in a developed economy.
- We aim to develop a novel road quality index using a Machine Learning model - Convolutional Neural Networks (CNN) to measure road quality.



Literature Review: Roads and Economic Outcomes

- New road projects -
Asher and Novosad (2020): India
Shamdasani (2021): India
Mu and Van De Walle (2010): Vietnam
- Road quality measurement -
Currier, Glaeser & Kreindler (2023): using vertical acceleration data from smartphones
Brewer et al (2021): use satellite images to measure road quality

For more details, see the slides on [more literature](#).



Taxation and Housing Data

Sources:

1. Ohio Secretary of State's Office
2. CoreLogic
3. U.S. Census Bureau

Period:

1991-2021

Variables:

Dependent variable: Sale amount of a property in county subdivision (or village) i and period t

Running variable: % Votes in favor for renewal of a road tax levy.

Cutoff = 50%

Covariates: Village-specific characteristics Specific Variables



Spending & Road quality Data

Spending:

Sunshine Law, OH: Ohio Auditor's report by Ohio Auditor of State

- After a tax cut, average drop in cash disbursements for road maintenance is 34%
- We are working on other measures of road maintenance spending deduction

Road Quality:

- Google Earth and Google Street Maps
- Ethan Brewer's road quality data buffet



Andover vs Morgan: A Tale of Two Townships in Ashtabula County, OH

County Subdi- vision	Subdivision Type	County	Renewals	Cuts	Percent Cut
Andover	Township	Ashtabula	16	0	0%
Morgan	Township	Ashtabula	7	9	56%



Andover vs Morgan: A Tale of Two Townships in Ashtabula County, OH



(a) Grand Army of the Republic Hwy:
2007



(b) Grand Army of the Republic Hwy:
2022



Andover vs Morgan: A Tale of Two Townships in Ashtabula County, OH



(a) OH-45: 2009



(b) OH-45: 2018



Road Quality Index using CNN

Currently, we are pursuing development of a measure for road quality using images from Google Earth and Google Street Maps.

- Using 53,000 satellite images from roads in U.S, we leverage work from Ethan Brewer et al (2021) and use Google's InceptionV3 ML model. This model has been shown to have an out-of-sample prediction accuracy of 94%.
- We plan to fine tune the model on Ohio specific images, and then use it to predict road quality in Ohio.



Road Quality Index using CNN

Sample images from Google Earth, with poor (0), decent (1) and high (2) quality.

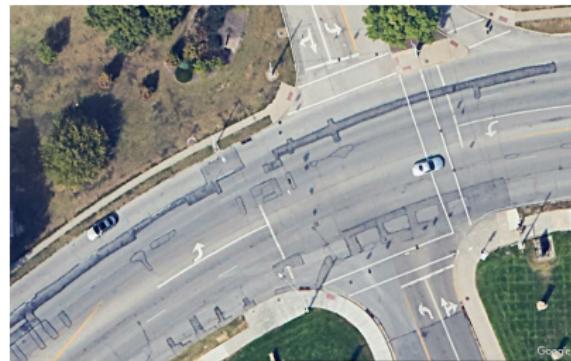


Figure: a "poor quality" road



Figure: a "high quality" road

RD plots

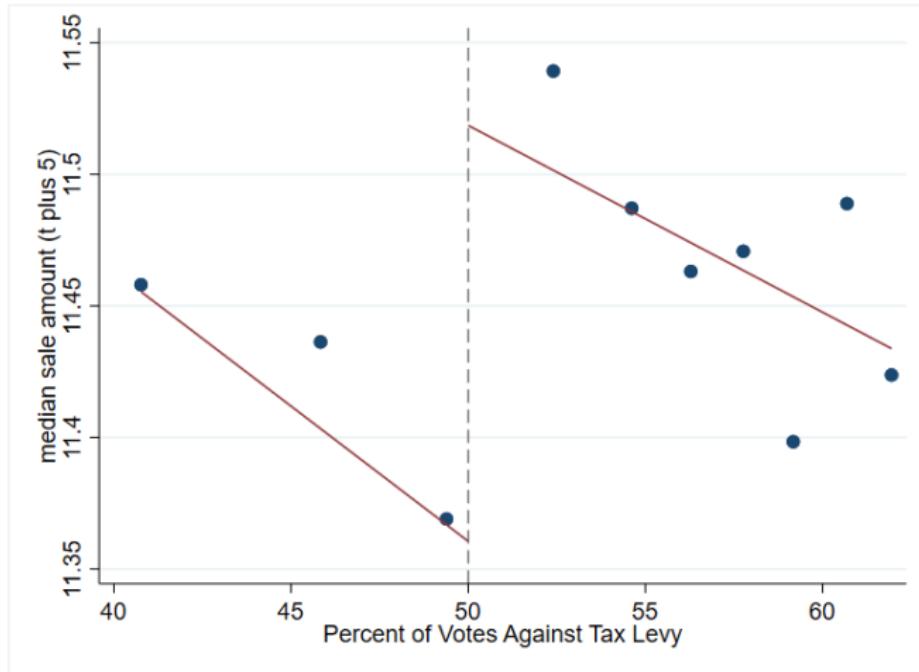


Figure: Log of Median Sale Amount: 5 years after the vote



Quasi-Experiment Design: Regression Discontinuity

Model equation

$Y_{it} = \alpha + \tau D_{it} + \beta_1 X_{it} + \beta_2 D_{it}X_{it} + \delta_1 W_{1it} + \dots + \delta_k W_{kit} + \epsilon_{it}$,
where

$i \in \{1, \dots, N\}$, $T \in \{1, \dots, T\}$, for $N, T \in \mathbb{Z}_+$

Y_{it} : economic outcome such as median sale amount of property,
wages per worker, employment, for village i at time t

X_{it} : % votes against for renewing a road tax levy for village i at
time t

$$D_{it} = \begin{cases} 1 & , \text{if \% votes against } > 50, \\ 0 & , \text{if \% vote against } \leq 50 \end{cases}$$



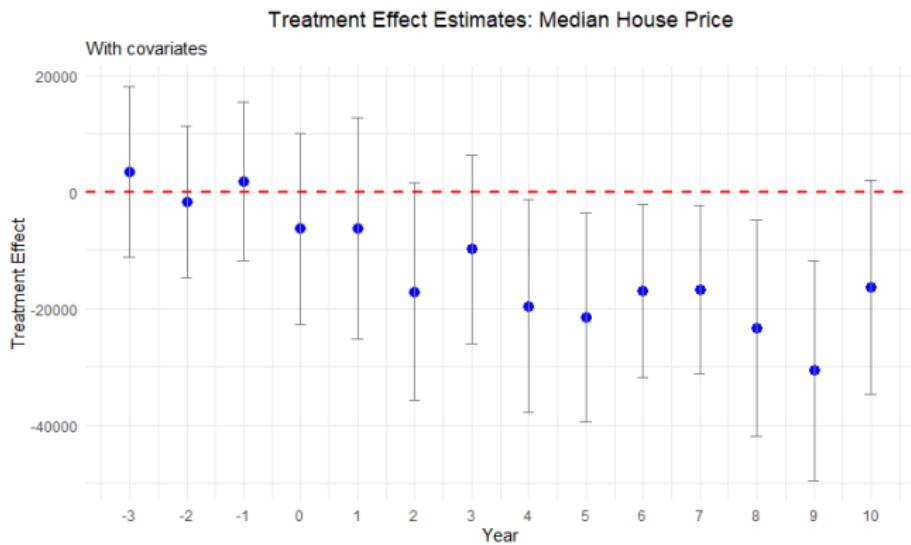
Quasi-Experiment Design: Regression Discontinuity

Specifications:

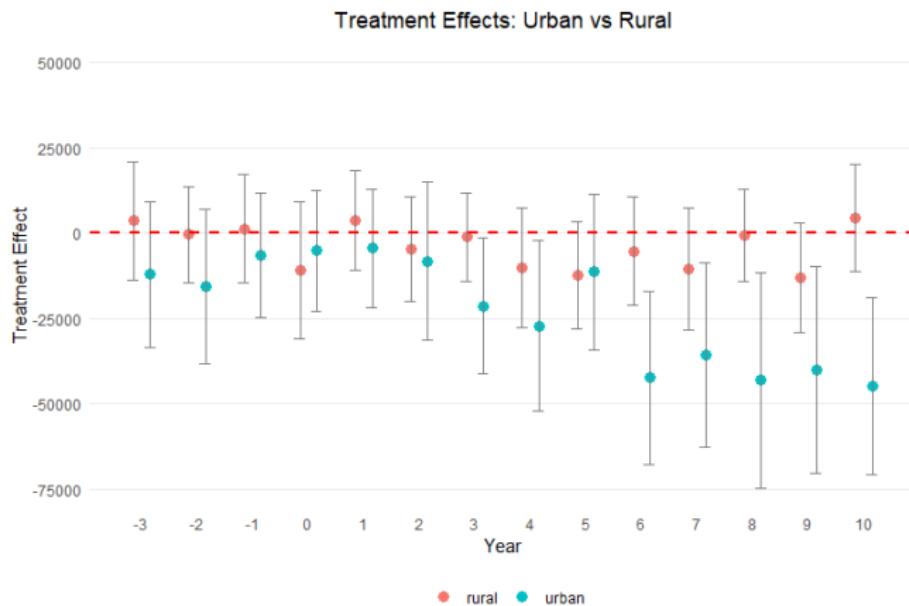
- bandwidth selection: mserd
- kernel: triangular
- p: order of local polynomial for point estimator
- q: order of local polynomial for bias correction



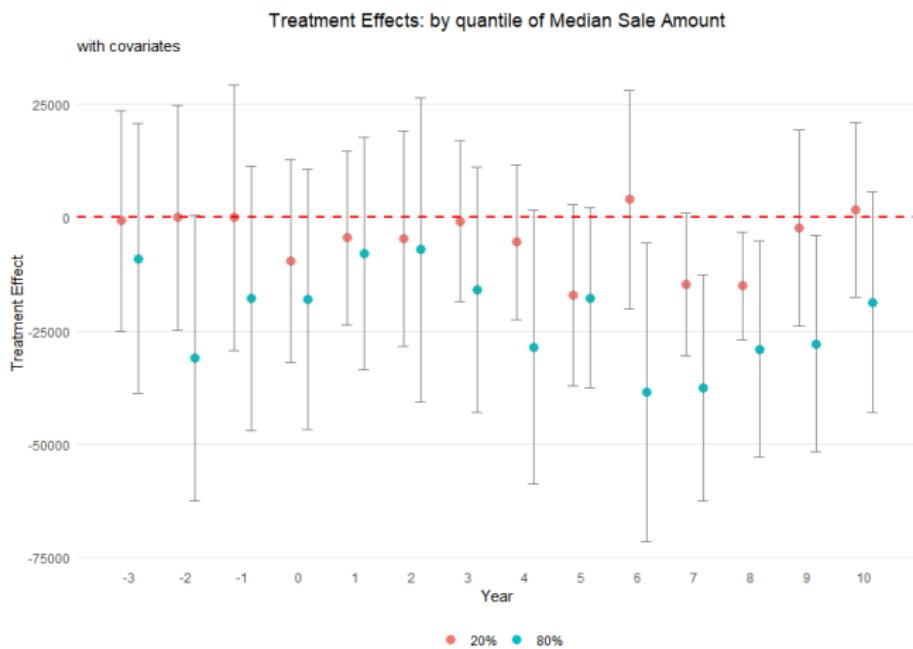
Results: Median Housing Prices



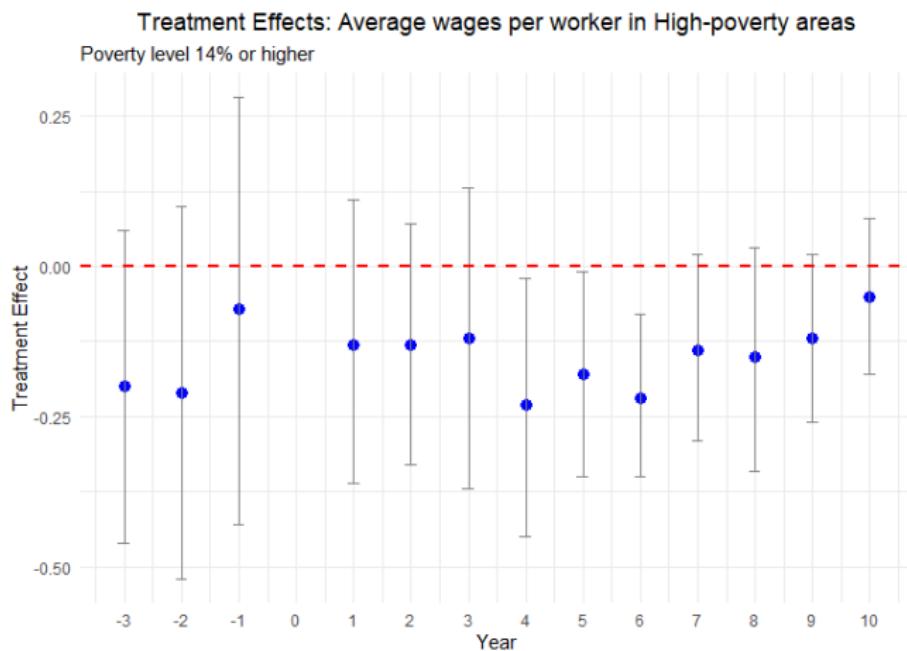
Results: Urban vs Rural



Results: Quantile Effect



Results: Wages per worker



Appendix



Housing: RD plots

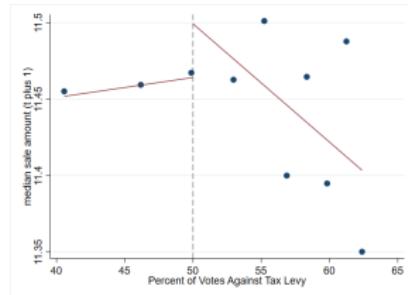


Figure: Year 1 after vote

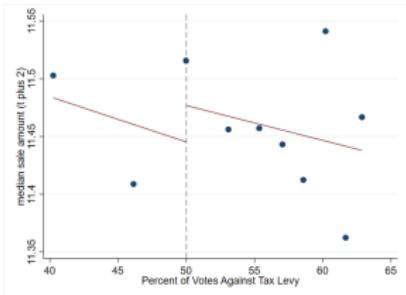


Figure: Year 2 after vote

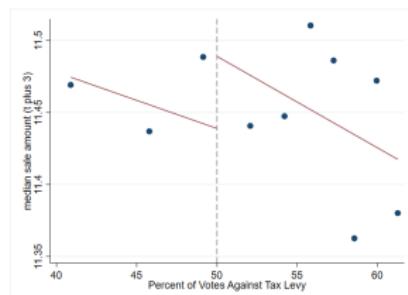


Figure: Year 3 after vote

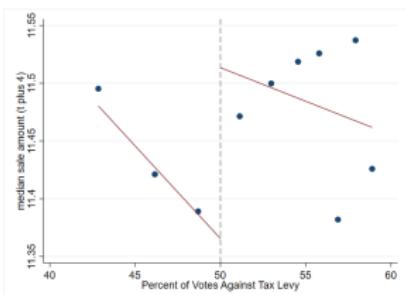


Figure: Year 4 after vote



Housing: RD plots

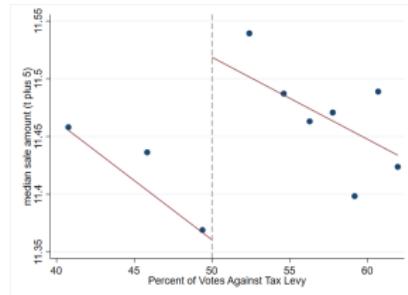


Figure: Year 5 after vote

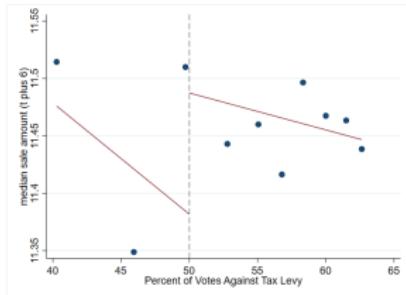


Figure: Year 6 after vote

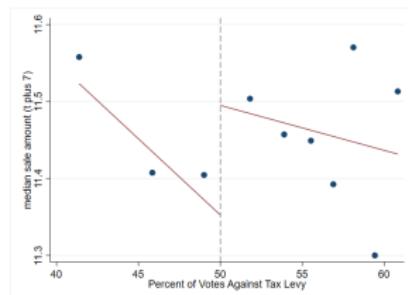


Figure: Year 7 after vote



Literature Review: People study roads

Prior Econ Literature

JEL code **R42**: Government and Private Investment Analysis •
Road Maintenance • Transportation Planning

1. Asher and Novosad (2020) -

Setting: India

Policy: Pradhan Mantri Gram Sadak Yojana (PMGSY) in 2000

Design: Regression Discontinuity Design (RDD)

Conclusion: Limited causal effect on changes to employment in the village firms after 4 years, but large reallocation of labor out of agriculture.

main literature



Literature Review: People study roads

Prior Econ Literature

2. Yogita Shamdasani (2021) -

Policy: Pradhan Mantri Gram Sadak Yojana (PMGSY) in 2000

Design: Difference-in-Differences (DID)

Conclusion: New roads induce movement of workers out of agriculture for villages with access to non-agricultural sector. However, large gains in agricultural output for villages with little access to non-agricultural sector

3. Ren Mu and Van De Walle (2010) -

Policy: Rural Transport Project I (RTPI) in Vietnam

Design: Difference-in-Differences (DID)

Conclusion: It takes atleast 27 months to see any effect on economic development. Large increase in frequency of markets, primary school completion rates and households switch from agriculture to non-agriculture sector.



Tables

Table: Effect on median house prices of failing to renew a road tax levy

Year relative to vote	$t + 4$	$t + 5$	$t + 6$	$t + 7$	$t + 8$	$t + 9$	$t + 10$
Treatment effect	-19,535	-21,531	-16,994	-16,691	-23,323	-30,620	-16,411
Standard error	(9,289)	(9,147)	(7,558)	(7,357)	(9,449)	(9,586)	(9,342)
Effective bandwidth (h)	8.9	12.1	14.1	14.0	8.2	8.2	8.3
Bias bandwidth (b)	15.4	20.0	24.1	24.2	15.5	16.3	17.5
Effective Observations	714	1,020	1,182	1,127	593	584	557
Total Observations	2,618	2,535	2,442	2,328	2,204	2,119	2,022



Table: Quantile-level Treatment Effects of Cutting Road Spending on Median House Prices

Percentile	$t + 4$	$t + 5$	$t + 6$	$t + 7$	$t + 8$	$t + 9$	$t + 10$
10%	-6,433 (9,364)	-22,570 (9,065)	-9,602 (9,205)	-12,984 (8,420)	-11,217 (9,136)	-6,569 (10,809)	-1,326 (8,793)
20%	-5,400 (9,983)	-15,070 (9,886)	4,014 (7,443)	-14,682 (8,502)	-15,040 (8,160)	-3,228 (10,435)	624 (8,509)
70%	-21,760 (12,333)	-11,171 (11,806)	-38,082 (12,835)	-36,685 (12,163)	-21,356 (12,218)	-25,605 (13,984)	-18,600 (9,872)
80%	-28,478 (13,343)	-16,379 (11,404)	-38,460 (18,623)	-37,470 (12,169)	-28,950 (12,507)	-27,800 (12,421)	-18,658 (11,808)
90%	-51,470 (18,409)	-34,604 (15,837)	-38,510 (22,194)	-27,039 (16,308)	-29,010 (16,640)	-49,093 (14,498)	-36,662 (19,110)

