Uneven Wage Growth and Public Goods

The Case of US Public Education

Ebba Mark

Abstract

Explores the effect of uneven industrial growth on public education expenditure through its effect on local property values in the US. The work aims to illuminate the elasticity of public education expenditure to changes in local livelihoods and economic conditions with implications for the delivery of public services in a political economy defined by an uneven industrial landscape and greater income and wealth inequality. Employing various methods to account for observed and unobserved heterogeneity in state-level tax regimes, income, and economic growth rates we find that this heterogeneity almost entirely determines the elasticity of public education expenditure to uneven wage growth….[These results provide insight into region- and state-specific adjustments that can be made to ensure that uneven economic development and structural transformation does not exacerbate existing inequalities in public service delivery in the United States…]

Table of contents

1 Working Notes

The following are notes to keep in mind while the project is still underway.

The following document summarises the progress made thus far on Chapter 1: Local Fiscal Risks of Decarbonisation of my DPhil. The work aims to pursue a better understanding of how industrial transformation impacts local well-being. From an original interest in looking at all aspects of local public finance, the project has narrowed to focus on expenditure on public education and its connection to industrial prosperity and transformation.

Current strategy/research plan:
1. Outcome: Educational Expenditure
2. Treatment (endogenous): Wages, Economic Growth, Property Values, Property Taxes
3. Instrument: Industry Shares of Employment in high vs. low wage growth industries/sectors

Items to be adjusted:

- AR(1) bias correction to account for fixed effect interaction.
- Include additional control variables (migration, poverty, race, rurality, home ownership rates, private school enrollment)
- Local CPI. Do I need to correct for local price levels?
- Spatial autocorrelation term
- Run gets on central model with CFESIS (preliminary testing indicates coefficient breaks in 2006 and 2013 which neatly bookends the financial crisis/housing market collapse - interesting?)
- Separate shift-share on more granular industrial categories (ie. high and low-wage areas correcting for local CPI)

Note: Any warnings about "missing observations" or "NA being removed" relates to the lags incorporated, except in the Bartik estimations.

2 Introduction

Though considerable debate has recently been stoked in the United States regarding the inherent value of public goods provision, majority of developed economies around the world agree on the importance of securing a reasonable standard of living for all as well as the reiteration of education as a human right.

2.1 Uneven Wage Growth

2.2 Uneven Public Goods Expenditure

One channel through which such challenges will present themselves is the potential hollowing out of local public revenues. In many parts of the United States, local well-being is heavily cointegrated with industrial prosperity and stability, not least through the channel of public expenditure. US revenues from fossil fuels generated about $138 billion annually for US localities, states, tribes, and the federal government Raimi et al. (2022) . This amount is forecast to decline by 2050 even in a business-as-usual scenario (assuming no changes in climate policy stringency). Wyoming, North Dakota, Alaska, and New Mexico are the states most dependent on fossil fuel revenues with at least 14% of state and local revenues generated from the fossil fuel industry (Wyoming's dependence is above 50%). The work makes a demonstrative statement about the link between this revenue stream and essential services like schools, public health, and infrastructure, but stops short of an empirical analysis into the impact of fossil fuel decline on revenues and associated expenditure, even at the state level.

Furthermore, (adding insult to injury) community well-being and public expenditure in the US is already characterised by a high degree of spatial heterogeneity. Not only does the US consistently rank among the top five most unequal OECD countries [1], but evidence of how income and wealth inequality perpetuate other forms of inequality (opportunity, health, infrastructure quality, and broader well-being) is steadily compounding.

Economic history and trajectories of industrial development have heterogeneously impacted the development trajectories of US regions.

2.3 Public Education Expenditure

Boustan et al. (2013) find that greater income inequality leads to higher public expenditure across all public goods indicating that a presence of higher-earnes in a local area contributes to higher levels of expenditure. Though this does not support an unambiguous denunciation of inequality as such, it provides additional evidence for the fact that local incomes affect public expenditure raising the potential for "superstar" and "left behind" regions to emerge absent significant and even income growth.

One public service that has particularly important ties to ensuring generational resilience to economic decline is education. Public schools around the US are responsible for educating over 80% of school-age children. In 2019, governments around the US (including the federal government) spent a total of $870 billion on public education, roughly $17,013 per pupil National Center for Education Statistics (2023) . However, the quality of services delivered varies widely across the country. [2]

The quality of public education, especially at an early age, can have long-lasting consequences for personal and economic well-being over an individual's lifetime as well as generations following them Alfonso and DuPaul (2020) . Therefore, ensuring that local or regional economic decline does not disrupt or worsen the

[1] The US consistently ranks among the top 5 most unequal countries in the OECD alongside Turkey, Mexico, Chile, and Costa Rica across all relevant indicators reported by the OECD: Gini coefficient, three interdecile income ratios (P50/P10; P90/P10; P90/P50), Palma ratio, S80/S20 quintile share.}, this inequality is further reflected in uneven and unequal quality of infrastructure, education, healthcare leading to real consequences for particular people and places Chetty et al. (2016), Logan, Minca, and Adar (2012), Semuels (2016), Avanceña et al. (2021), Flavin et al. (2009) .

[2] In 2016, for example, the Connecticut State Department of Education reported that the town of Greenwich, one of the highest-income towns in the country, spent \$8,000 more per pupil than Bridgeport (\$21.9k versus \$13.7k per pupil), despite both towns being part of the same county, located less than 40 kilometers apart Semuels (2016) .

quality of education delivered is of paramount importance to ensure greater equality in the long-run. [3] [4]

Altogether, this evidence points to the value of identifying the extent to which expenditure on public education is reliant on local economic health across the country. In other words, this work aims to answer the following research questions:

RQ1: How has uneven industrial wage growth affected public education expenditure?

RQ2: Do intergovernmental transfers alleviate wealth-driven inequalities in public education expenditure?

RQ3: Can accounting for non-constant relationships between explanatory variables improve our understanding of the relationship between public goods and uneven economic growth?

In the sections that follow, I outline in Section 3 the data to be used in the analysis; Section 4 the proposed methods;

3 Data

This work employs Willamette University's Annual Government Finance Database at the commuting zone (CZ) level. This resource is a harmonised repository of the data collected annually as part of the US Census Bureau's Annual Survey of State & Local Government Finances, the 'only comprehensive source of information on the finances of local governments in the United States' Pierson, Hand, and Thompson (n.d.) . I aggregate school district measures up to the commuting zone-level to ensure the availability of adequate control and treatment variables. [5]

[3]Perhaps the most prominent and often-cited relationship between education and extractive industries is through the lens of the 'resource curse.' The validity and empirical existence of a 'resource curse' has been tested since its conception with disparate results Wiens, Poast, and Clark (2014). The literature is divided into two strands focusing on either political (the relationship between resource wealth and governance) Deacon (2011) or economic (the relationship between resource wealth and economic growth or human capital) resource curses. Empirical investigation of the economic resource curse has explored the effect of resource dependence on economic growth, public health and education expenditure and outcomes, mainly at a national level Sincovich et al. (2018). In the case of education, the distinct outcome measured is level of educational attainment, in other words, whether the presence of a booming resource extraction economy provides disincentives to education for young people. It is worth noting that this literature has been repeatedly questioned on theoretical and conceptual grounds as institutional context often dictates whether a resource curse exists and empirical analyses seem to be very sensitive to methodological choices Dialga and Ouoba (2022). Although awareness of this strand of literature is of relevance to this work, the unresolved nature of the 'debate' surrounding its existence requires caution if eventually utilised as a theoretical framework for answering the research question.

[4]Ahlerup, Baskaran, and Bigsten (2020) find that for 30 countries in Africa, the presence of gold mines during adolescence have a significant effect on educational attainment. Badeeb, Lean, and Clark (2017) investigates whether resource dependence slows economic growth with no explicit mention of education. Blanco and Grier (2012) find that in Latin America, petroleum export has a significant long-run negative relationships with human capital. Borge, Parmer, and Torvik (2015) find support for the paradox of plenty hypothesis in Norway - that higher local public revenue negatively affects the efficiency of local public good provision. Brunnschweiler and Bulte (2008) critically evaluate 'the empirical basis for the so-called resource curse and find that, despite the topic's popularity in economics and political science research, this apparent paradox may be a red herring. The most commonly used measure of "resource abundance" can be more usefully interpreted as a proxy for "resource dependence"—endogenous to underlying structural factors. In multiple estimations that combine resource abundance and dependence, institutional, and constitutional variables, we find that (i) resource abundance, constitutions, and institutions determine resource dependence, (ii) resource dependence does not affect growth, and (iii) resource abundance positively affects growth and institutional quality.' Cockx and Francken (2014) use a panel on 140 countries from 1995-2009 and find an inverse relationship between resource dependence and and public health spending over time. Cockx and Francken (2016) investigate a panel of 140 countries from 1995-2009 to find an adverse effect of resource depdence on public education expenditures relative to GDP. Dialga and Ouoba (2022) find disparate results for health and education controlling for institutional quality. Douglas and Walker (2017) "measure the effect of resource-sector dependence on long-run income growth using the natural experiment of coal mining in 409 Appalachian counties selected for homogeneity. Using a panel data set (1970–2010), we find a one standard deviation increase in resource dependence is associated with 0.5–1 percentage point long-run and a 0.2 percentage point short-run decline in the annual growth rate of per capita personal income. We also measure the extent to which the resource curse operates through disincentives to education, and find significant effects, but this "education channel" explains less than 15 percent of the apparent curse.' Haber (n.d.) focus on authoriarian regimes. Menaldo (2016) argues again that this is an institutions curse and not a resource curse issure. Sincovich et al. (2018) provide a literature review of resource curse investigations in the Australian context.

[5]The database is provided for six different levels of government: state, county, municipal, township, special district, and school district. Reporting is only mandated in Census years (every five years), and even then missing data remains a challenge. This means that data provided at any other level of government suffers from significant levels of missing data, with a high level of selection bias correlated with administrative capacity. However, strengthened by a partnership with the National Center for

Thus, this dataset provides estimates in current $USD on total public school revenue disaggregated by source (federal, state, local intergovernmental versus own local sources) and expenditure disaggregated by item (level of schooling, teacher salaries, debt, etc.). Finally, I gather GDP control variables from the Bureau of Economic Analysis (BEA). This BEA data is only available after 2001, therefore the panel reported and used below is restricted to 2001-2021. This results in a complete and balanced panel of 636 US commuting zones between 2001-2021. [6] [7]

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[1] "Running analysis on CZs (cz_id)."
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All data used is reported annually at the commuting zone level. [8]

Therefore, no time-invariant variables are included (apart from the state in which a commuting zone is in). Finally, our data represents 636 commuting zones in 40 states between 2001-2021.

Expenditure and Revenue: The dependent variables of interest come from Willamette University's Government Finance Database. The data includes commuting-zone level revenue and expenditure on public education including disaggregated values by revenue source (federal, state, or other intergovernmental revenue) and expenditure item (lunches, wages, debt). All values are reported in real US dollars. The data for property taxes collected used in regressions below also come from this dataset. Expenditure on vocational training and from Educational Service Agencies (ESAs) are also sourced from this dataset.

GDP Controls: US Bureau of Economic Analysis. Values are also reported in current US dollars (real GDP values exist). The controls used in the below are commuting zone-level rivate industry GDP. We decide to use private industry GDP as a control variable given the remaining portion of GDP is government expenditure which includes education expenditure.

Population controls: US Census Bureau.

Property Prices: The US Federal Housing Financy Agency provides a geographically linked data on single-family house prices called the Housing Price Index. HPI is a broad measure of the movement of single-family house prices. The FHFA HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975 Source. It is reported at the county level at an annual frequency. We aggregate to the commuting zone level via a mean. should do a population weighted average!

3.1 Summary statistics

All dollar values are reported in real 2017-chained thousands.

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Statistic N Mean St. Dev. Min Max

———————————————————— Enrollment 13,356 62 170 0 3,170 Population 13,356 405 1,078 1 18,733 Elem. Expenditure per pupil 13,356 11 3 6 58

Property Tax per pupil 13,356 4 2 0 33

Education Statistics, observations for US school districts exhibit near-complete coverage between 1997-2021 Pierson, Hand, and Thompson (n.d.) . I choose to conduct the analysis on the commuting zone level because (1) it is a more accurate picture of a local labor market area (Carpenter, Lotspeich-Yadao, and Tolbert (2022)) and (2) a lack of availability of control variables at a school district level.

[6] The reason 13% of CZs are missing from the dataset is because of (1) the exclusion criteria already outlined; (2) Hawaii and Alaska have been excluded due to the methodological challenge of incorporating their school districts into spatial econometric work; and (3) Connecticut, Maryland, North Carolina, and Virginia have been excluded due to unconventional or incomplete public school district reporting. I aim to resolve this, especially in the case of Virginia given its relatively high rates of employment in the coal sector.

[7] Given the work's intent to rely on data on property taxes collected, any CZ that reports more than five 0 values for property taxes collected is excluded.

[8] In line with similar work on US economic geography, commuting zones were chosen as the unit of analysis as they are a far less arbitrary and more accurate representation of local labour market areas/economies \href{https://www.ddorn.net/data.htm\#Local\%20Labor\%20Market\%20Geography}{David Dorn's Resource Page}, \href{https://www.nature.com/articles/s41597-024-03829-5}{Fowler et al. 2024}.}

IG Revenue per pupil 13,356 7 2 1 28
State IG Revenue per pupil 13,356 7 2 1 26
GDP per capita 13,356 45 25 15 389
GDP pc - Private Industry 13,356 38 25 6 383
House Price Index 12,717 255 156 86 1,948

4 Analysis

Given the high degree of both structural (state-specific tax, regulatory, and legislative regimes) and evolved heterogeneity (industrial activity, income, inequality, economic diversity) the following analysis only briefly explores the potential to arrive at national-level average treatment effects using various pooled estimation strategies. These serve to establish foundational relationships between local economic conditions that seem to reasonably generalise across the country.

However, considerable investigation uncovered the need for a regional or state–by-state estimation strategy to truly account for the heterogeneity across the units of observation. Therefore, the body of the analysis is dedicated to state-by-state and industry-by-industry estimation of the relevant econometric specifications. We dedicate majority of this manuscript to discussion of this latter exploration of heterogeneity. Wherever possible, we include information about the uncertainty surrounding our results.

4.1 Descriptive Regressions

4.1.1 Baseline

First, I employ a two-way fixed effects ordinary least-squares panel model with standard errors clustered by commuting zone. I outline the model specification immediately below:

$$Y_{it} = \beta_0 + \beta_x X_{it} + \delta_1 Enrollment_{it} + \delta_2 IGR_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

$$Y_{it} = \beta_0 + \beta_x X_{it} + \delta_1 Enrollment_{it} + \delta_2 IGR_{it} + \lambda Y_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2}$$

Y_{it} is the natural logarithm of elementary (serving ages 6-12) education expenditure per pupil for CZ i in year t. α_i and γ_t represent CZ- and year-fixed effects, respectively, and ε_{it} represents the error term. We control for enrollment to account for scaling factors in education expendture and intergovernmental transfers to account for the significant role of such transfers in funding education expenditure. Additionally, we optionally include a lagged dependent variable to account for the persistence of education expenditure. X_{it} takes three forms represented by Equation 3, Equation 4, Equation 5 where $h = [0, 2]$ represents h-year time lags. We estimate all equations in levels and growth rates.

$$X_{it}^{GDP} = \sum_{h=0}^{2} \beta_k^{\text{GDP}} \log(\text{GDP}_{i,t-h}) \tag{3}$$

$$X_{it}^{Wage} = \sum_{h=0}^{2} \beta_k^{\text{Wage}} \log(\text{Wage}_{i,t-h}) \tag{4}$$

$$X_{it}^{HPI} = \sum_{h=0}^{2} \beta_k^{\text{HPI}} \log(\text{HPI}_{i,t-h}) \tag{5}$$

As demonstrated in Table X, education expenditure has a highly relevant time dependence. The effect of increases in GDP two years prior has the greatest effect on current education expenditure, implying a delayed effect of commuting zone-level economic growth on public education expenditure. Across all specifications, the results underscore two important facts: the central role of intergovernmental transfers and broader local economic fundamentals in shaping patterns of education spending.

Intergovernmental revenue per pupil emerges as the strongest and most consistent predictor of education expenditure. A 1% increase in intergovernmental transfers is associated with approximately a 0.2–0.35% increase in per-pupil education spending, controlling for unit and year fixed effects. This finding highlights the importance of state and federal aid in sustaining local education budgets. Lagged economic indicators, particularly private industry GDP and average weekly wages, are also positively and significantly associated with education spending. The magnitude of the coefficients increases with the number of lags, suggesting a gradual adjustment process by which local economic growth translates into higher public investment in education over time. For example, a 1% increase in lagged (t–2) real private GDP per capita is associated with a 0.14% increase in per-pupil spending.

The house price index also enters positively and significantly in contemporaneous and short-lag specifications (up to t–3) underscoring the fundamental relationship between community asset wealth and public education expenditure.

The growth rate regressions, while explaining less variance overall (as expected), largely confirm the patterns observed in the level specifications. Intergovernmental revenue growth remains a strong and highly significant determinant of education expenditure growth, with coefficients >0.3%. Lagged wage and GDP growth also emerge as important predictors, particularly at longer lags. Notably, wage growth two years prior is associated with a 0.31% increase in education spending growth, suggesting that labor market improvements take at least a year to materialize in local education budgets. Growth in house prices is also associated with increases in education spending which hints at the relevance of our primary identifying relationship.

Taken together, these results offer three key insights. First, public education investment is strongly mediated by external fiscal flows, reaffirming the role of intergovernmental transfers in equalizing local education finance. Second, local labor market conditions—captured through wages and GDP—exert lagged, cumulative effects on education spending consistent with lagged effects of local economic conditions to industrial change. Third, local housing markets play a significant role shaping education budgets, reflecting the link between property values and tax revenues.

We also estimate these regressions using state rather than commuting-zone level fixed effects to account for the relevance of state-level tax regimes and policies that govern education.

Dependent Variable:	(log) Elem.Ed.Exp.pp					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(log) Real GDP Priv. Industry pc	0.0130	0.0132				
	(0.0187)	(0.0152)				
(log,l1) Real GDP Priv. Industry pc	0.0691***	0.0520***				
	(0.0135)	(0.0155)				
(log,l2) Real GDP Priv. Industry pc	0.1457***	0.0583***				
	(0.0231)	(0.0138)				
(log) IG Revenue pp	0.3512***	0.2361***	0.3220***	0.2103***	0.3287***	0.2135***
	(0.0295)	(0.0205)	(0.0328)	(0.0230)	(0.0318)	(0.0221)
(log) Enrollment	-0.2936***	-0.1796***	-0.3022***	-0.1925***	-0.3297***	-0.2066***
	(0.0241)	(0.0142)	(0.0247)	(0.0142)	(0.0270)	(0.0155)
(l1, log) Elem.Ed.Exp.pp		0.5071***		0.5282***		0.5301***
		(0.0142)		(0.0177)		(0.0181)
(log) Annual Avg. Wkly. Wage			0.1706***	0.0624		
			(0.0600)	(0.0493)		
(log, l1) Annual Avg. Wkly. Wage			0.1767***	0.1936***		
			(0.0459)	(0.0548)		
(log, l2) Annual Avg. Wkly. Wage			0.3169***	0.0544		
			(0.0796)	(0.0480)		
(log) House Price Index					0.1450***	0.1113***
					(0.0256)	(0.0211)
(log, l1) House Price Index					0.0557**	0.0315
					(0.0263)	(0.0340)
(log, l2) House Price Index					0.0481**	0.0049
					(0.0208)	(0.0277)
(log, l3) House Price Index					0.0447**	-0.0155
					(0.0210)	(0.0236)
(log, l4) House Price Index					0.0024	0.0111
					(0.0215)	(0.0199)
Fixed-effects						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,084	12,084	13,356	12,720	12,588	12,029
R^2	0.86608	0.90687	0.86135	0.90573	0.86500	0.90945
Within R^2	0.31070	0.52065	0.30255	0.52306	0.29461	0.52418

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	(GR) Elem.Ed.Exp.pp					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(GR) Real GDP Priv. Industry pc	0.0048	0.0030				
	(0.0138)	(0.0135)				
(GR,l1) Real GDP Priv. Industry pc	0.0509***	0.0510***				
	(0.0148)	(0.0148)				
(GR,l2) Real GDP Priv. Industry pc	0.0191***	0.0199***				
	(0.0070)	(0.0070)				
(GR) IG Revenue pp	0.3061***	0.3044***	0.3266***	0.3033***	0.3286***	0.3058***
	(0.0321)	(0.0325)	(0.0224)	(0.0317)	(0.0228)	(0.0309)
(GR) Enrollment	-0.5990***	-0.5897***	-0.0144**	-0.5899***	-0.0060	-0.5995***
	(0.0420)	(0.0432)	(0.0064)	(0.0430)	(0.0069)	(0.0461)
(GR, l1) Elem.Ed.Exp.pp		-0.0604***		-0.0394***		-0.0460***
		(0.0149)		(0.0098)		(0.0094)
(GR) Annual Avg. Wkly. Wage			-0.0269	0.0233		
			(0.0547)	(0.0459)		
(GR, l1) Annual Avg. Wkly. Wage			0.2065***	0.1815***		
			(0.0500)	(0.0441)		
(GR, l2) Annual Avg. Wkly. Wage			0.3108***	0.3066***		
			(0.0600)	(0.0557)		
(GR) House Price Index					0.0631***	0.1044***
					(0.0240)	(0.0197)
(GR, l1) House Price Index					0.1074***	0.0772***
					(0.0289)	(0.0245)
(GR, l2) House Price Index					0.0586***	0.0590***
					(0.0205)	(0.0186)
(GR, l3) House Price Index					0.0207	0.0276
					(0.0256)	(0.0199)
(GR, l4) House Price Index					0.0325	0.0209
					(0.0211)	(0.0172)
Fixed-effects						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,083	12,083	13,355	12,719	12,535	11,978
R^2	0.26799	0.27126	0.35113	0.27420	0.36048	0.28754
Within R^2	0.22090	0.22438	0.15363	0.22691	0.14768	0.23367

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Furthermore, given the heterogeneity in reliance on intergovernmental transfers (largely coming from the state), we interact all economic predictors above with a variable that represents the share of total elementary education expenditure coming from state-level funding.

I need help interpreting the below...?

Dependent Variable:	(log) Elem.Ed.Exp.pp				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) Real GDP Priv. Industry pc	-0.2313***				
	(0.0743)				
(log,l1) Real GDP Priv. Industry pc	0.1026*				
	(0.0590)				
(log,l2) Real GDP Priv. Industry pc	0.3435***				
	(0.0794)				
Funding Share_state × (log) Real GDP Priv. Industry pc	0.4094***				
	(0.1201)				
Funding Share_state × (log,l1) Real GDP Priv. Industry pc	-0.1083				
	(0.0948)				
Funding Share_state × (log,l2) Real GDP Priv. Industry pc	-0.4455***				
	(0.1203)				
(log) Annual Avg. Wkly. Wage		-0.0203		-0.1835	
		(0.2249)		(0.1563)	
(log, l1) Annual Avg. Wkly. Wage		0.2182		0.4342**	
		(0.1495)		(0.1848)	
(log, l2) Annual Avg. Wkly. Wage		0.5056**		0.0446	
		(0.2281)		(0.1329)	
Funding Share_state × (log) Annual Avg. Wkly. Wage		0.4976		0.5489**	
		(0.3530)		(0.2429)	
Funding Share_state × (log, l1) Annual Avg. Wkly. Wage		-0.0604		-0.4605	
		(0.2369)		(0.2906)	
Funding Share_state × (log, l2) Annual Avg. Wkly. Wage		-0.6441*		-0.1731	
		(0.3567)		(0.2149)	
(log) House Price Index			-0.0917		0.0145
			(0.1127)		(0.0852)
(log, l1) House Price Index			0.1650		0.0693
			(0.1372)		(0.1772)
(log, l2) House Price Index			0.3735***		0.3195**
			(0.0988)		(0.1547)
(log, l3) House Price Index			0.0167		-0.1905
			(0.1131)		(0.1214)
(log, l4) House Price Index			-0.1410		-0.1228
			(0.0908)		(0.0993)
(log, l5) House Price Index			-0.0015		0.0638
			(0.0833)		(0.0649)
Funding Share_state × (log) House Price Index			0.4886***		0.2440*
			(0.1765)		(0.1308)
Funding Share_state × (log, l1) House Price Index			-0.1802		-0.0872
			(0.2087)		(0.2627)
Funding Share_state × (log, l2) House Price Index			-0.5013***		-0.4871**
			(0.1499)		(0.2282)
Funding Share_state × (log, l3) House Price Index			0.0058		0.2786
			(0.1765)		(0.1863)
Funding Share_state × (log, l4) House Price Index			0.2056		0.1613
			(0.1415)		(0.1463)
Funding Share_state × (log, l5) House Price Index			-0.0651		-0.1146
			(0.1299)		(0.0983)
Funding Share_state	0.8906	0.7015	-0.4236	0.0852	-0.4418**
	(0.5640)	(0.4808)	(0.3661)	(0.2881)	(0.2212)
(log) Fed IG Rev. pp	-0.0030	-0.0014	-0.0020	-0.0006	-0.0014
	(0.0024)	(0.0020)	(0.0020)	(0.0014)	(0.0013)
(log) Enrollment	-0.3461***	-0.3498***	-0.3711***	-0.2169***	-0.2334***
	(0.0263)	(0.0257)	(0.0265)	(0.0168)	(0.0171)
(l1, log) Elem.Ed.Exp.pp				0.5339***	0.5185***
				(0.0163)	(0.0144)
Fixed-effects					
unit	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,084	13,356	12,536	12,720	11,979
R^2	0.86083	0.85889	0.86869	0.90725	0.91299
Within R^2	0.28372	0.29018	0.31243	0.53074	0.54183

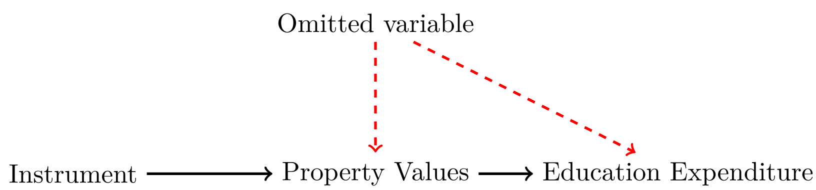
Clustered (unit) standard-errors in parentheses

4.2 Approaching Causal Identification

Though the descriptive relationship between various economic variables and public education expenditure provides convincing evidence of the reliance of local education expenditure on economic conditions, this relationship has no causal interpretation.

Indeed, there is a significant endogeneity concern in using wages or property prices as a treatment variable given the likely attracting factor of high levels of education expenditure for higher-income families. However, the structure of public financing (described in further detail in Section A of the Supplementary Materials Will add appropriate reference.) provides an avenue for a causal identification strategy. In brief, revenue for public education comes from a combination of intergovernmental and local sources. Revenue generated from local sources comes almost entirely from property taxes. Given this, we can isolate the channel through which our treatment (industry-specific wage growth) will affect our outcome variable using an instrumental variable approach. We outline the underlying path diagram of this econometric specification in \ref{fig:iv-approach.

Figure 1: Instrumental Variable Path Diagram



As seen in Figure 1, we hypothesize that property values have an effect on education expenditure. However, there is significant concern of a reverse causal effect as higher income families likely gravitate towards school districts with higher levels of expenditure per pupil, driving up property values.

Shift-share or *Bartik* instruments have gained popularity in empirical work as a method of handling endogeneity issues in panel data Bartik (1991). Effectively, they combine time-variant yet unit-invariant changes in aggregate economic variables (ie., national changes in industry wage levels) with time-invariant yet unit-variant shares in exposure to these macro-level changes (ie., local shares of employment in particular industries). This decomposition of local-level changes via a delocalisation over space and time allows for a defensible 'de-endogenising' of the treatment. Notably, the method can also be considered to serve a further purpose, allowing for, by construction, the examination of a macro phenomenon's effect on more local units.

[9] [10]

Therefore, we adopt an identification strategy via a shift-share or Bartik instrument. A shift-share instrument interacts local industry shares with national industry-level growth rates to attain a plausibly exogenous local shock. In the context of this work, we construct the instrument by interacting a constant industrial employment share variable with a national industry-level wage.

The literature on Bartik instruments derives plausible exogeneity from two sources. First, authors argue that local industry shares are exogenous by imposing that shares be fixed to a particular base year and are

[9] Autor et al use a shift-share instrument to assess the effect of Chinese import competition on manufacturing employment in US commuting zones @autor2013 . As an extension, @feler2017 use a similar shift-share instrument to assess the effect of the same shock on the size of local government. @baccini2021 employ a shift-share instrument for manufacturing layoffs to tease out the effect of a decline in manufacturing on both economically motivated and racial identity voting patterns in the US.

[10] An additional popular indicator for modelling industrial shocks is *oil price* as values are often assumed to be exogenous to local and even national conditions @scheer2022 . Third, separate from specifically green transformation shocks, various indicators for measuring *deindustrialisation* have been proposed including the manufacturing share of employment, value added, and GDP [@tregenna2009, @tregenna2020]. These deindustrialisation metrics could be used in combination with a shift-share instrument. Finally, in rare instances, exogeneity can be secured due to *geographical, climatological, or geological factors*. For example, @borge2015 obtain an exogenous measure of local revenue by "instrumenting the variation in hydropower revenue, and thus total revenue, by topology, average precipitation and meters of river in steep terrain." Certain authors have argued that the fact that the location of hydrocarbon deposits is dictated by geomorphological processes provides a plausible argument for exogeneity [@esposito2021, @chen2022].

therefore unable to adapt to changes in national-level growth rates. Such a shift-share instrument would look as follows:

$$Z_{it} = \sum_{j=1}^{k} S_{ij\tau} G_{njt} \tag{6}$$

where $S_{ij\tau}$ is the local share of unit i's economy (potentially measured by metrics like employment, wages, revenue) in industry j at a fixed base year τ and G_{njt} is the growth rate of industry j at a national level n at time t.

Alternatively, authors may argue that the claim of exogeneity in the national-level growth rates is unlikely to be violated even when allowing the local shares to vary over time. This approach is likely to come at significant expense to instrument exogeneity. It is constructed as follows:

$$Z_{it} = \sum_{j=1}^{k} S_{ijt} G_{njt}$$

Finally, authors might be concerned about the implausible exogeneity of both shares and national-level growth rates in which case they could construct the instrument as follows where the local shares are fixed at a common base year and industry-specific growth rates G are derived from data on other similar regions o rather than national-level changes that are inherently comprised of local-level shifts. This approach likely comes at significant expense to instrument relevance.

$$Z_{it} = \sum_{j=1}^{k} S_{0jt} G_{ojt}$$

Finally, the authors can make an additional design choice about whether the effect of these instruments should be assumed common to an aggregate local-level wage growth indicator or allowed to vary by industry. In other words, whether to construct the first-stage relationship of the 2SLS as:

$$X_{it} = \alpha_i + \beta \sum_{j=1}^{k} S_{ijt} G_{njt} + \epsilon_{it}$$

$$X_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j S_j G_{jt} + \epsilon_{it}$$

We choose to employ the first of these options, assuming that industry shares are only exogenous at a given base year/period and that national level growth rates are exogenous and therefore allowed to vary with time.

Using data from the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW) and Bureau of Economic Analysis, we construct two types of shift-share Bartik instruments at the commuting zone level using local employment shares by industry and national changes in industry-specific wages and real value added. Equation Equation 7 demonstrates the Bartik instrument as outlined in Ferri (2022) and Goldsmith-Pinkham, Sorkin, and Swift (2020) and defined in Bartik (1991) . G_{njt} represents national-level changes in wages or value added in industry j in time t and $\frac{N_{ij\tau}}{N_{i\tau}}$ represents the "sensitivity'' of a CZ to these national shocks proxied by an initial share of local employment in industry j in a baseline time period τ. The product of these two values defines the shift-share indicator $\tilde{Z}_{i,t,s}$. In order to construct the share portion, we compute the total local share of employment in a particular industry j. Due to challenges with missing data, we compute an average share across 2001-2005 as our 'base year'. [11]

$$\tilde{Z}_{ijt} = G_{njt} * \frac{N_{ij\tau}}{N_{i\tau}} \tag{7}$$

The below table displays the 2-digit NAICS industrial categories we use to construct our shift-share instrument. The plot immediately following displays the remaining issues with data coverage indicating what proportion of total commuting zone level employment is represented by the industry-specific data points (industry-level disaggregation requires the suppression of certain data). Given the high degree of missingness in the 3-digit categorisation we proceed with the 2-digit NAICS codes in the rest of the work.

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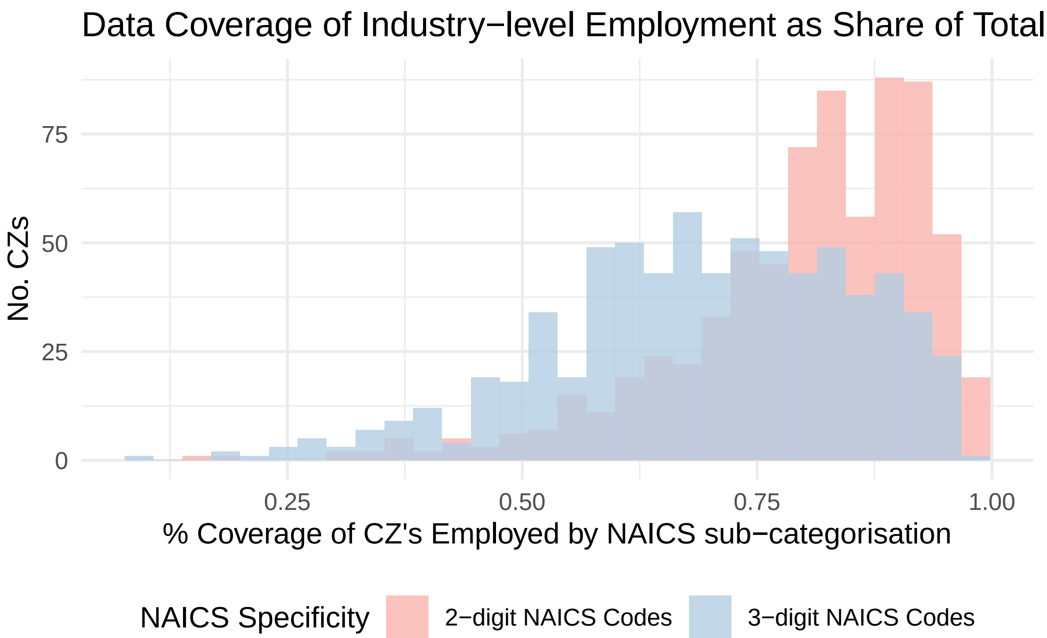
NAICS.Code	Industry
11	Agriculture, Forestry, Fishing, and Hunting
21	Mining
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
22	Utilities
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and waste management services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services, except government
92	Public Administration

[11] We explore the sensitivity of results to the choice of base period τ by constructing the instrument for various base periods as well as a rolling window. I have done this unsystematically so far (testing 2001, 2004, and 2005) but arrived at the decision to compute an average to deal with missing data. Will include a more systematic testing of this in the appendix.



Before displaying the regression results using our shift-share instrument we discuss the plausibility of our identification strategy by exploring the relationships between wage and GDP on housing prices. We provide evidence of this relationship below.

4.2.0.1 Industry-level Wages

The two regression models show that wage levels and wage growth both play important roles in influencing house prices, but in different ways. The log-level model indicates that increases in average wages have a strong and persistent effect on the level of house prices, with significant positive effects extending up to four years. In contrast, the growth rate model suggests that house price growth responds primarily to contemporaneous wage growth, with little evidence of lagged effects. Together, these findings imply that while higher wages steadily raise housing values over time, short-term changes in wage growth do not affect the growth rate of house prices over time. Together, they suggest that housing markets are more responsive to trends than to transitory shocks in wages.

Dependent Variables:	(log) House Price Index		(GR) House Price Index	
Model:	(1)	(2)	(3)	(4)
Variables				
(log) Annual Avg. Wkly. Wage	0.9365***	0.7937***		
	(0.0643)	(0.0162)		
(log, l1) Annual Avg. Wkly. Wage	0.0544***	-0.0415***		
	(0.0137)	(0.0039)		
(log, l2) Annual Avg. Wkly. Wage	0.0861***	-0.0936***		
	(0.0146)	(0.0045)		
(log, l3) Annual Avg. Wkly. Wage	0.0303*	0.0374***		
	(0.0148)	(0.0063)		
(log, l4) Annual Avg. Wkly. Wage	0.0863***	-0.0269***		
	(0.0205)	(0.0057)		
(log, l5) Annual Avg. Wkly. Wage	0.0261	0.0410***		
	(0.0153)	(0.0025)		
(log, l6) Annual Avg. Wkly. Wage	0.0388	0.0060		
	(0.0296)	(0.0052)		
(log, l7) Annual Avg. Wkly. Wage	0.0222	0.0369***		
	(0.0224)	(0.0047)		
(log) Real GDP Priv. Industry pc	0.0710***	-0.0188***		
	(0.0112)	(0.0046)		
(log) Population	0.4165***	0.1001***		
	(0.0594)	(0.0020)		
(GR) Annual Avg. Wkly. Wage			0.3164***	0.3236***
			(0.0635)	(0.0610)
(GR, l1) Annual Avg. Wkly. Wage			0.0040	0.0056
			(0.0168)	(0.0154)
(GR, l2) Annual Avg. Wkly. Wage			0.0242	0.0252
			(0.0157)	(0.0149)
(GR, l3) Annual Avg. Wkly. Wage			0.0035	0.0073
			(0.0205)	(0.0194)
(GR, l4) Annual Avg. Wkly. Wage			0.0263	0.0292
			(0.0232)	(0.0229)
(GR, l5) Annual Avg. Wkly. Wage			6.34×10^{-5}	0.0002
			(0.0199)	(0.0183)
(GR, l6) Annual Avg. Wkly. Wage			-0.0118	-0.0073
			(0.0216)	(0.0196)
(GR, l7) Annual Avg. Wkly. Wage			-0.0093	-0.0091
			(0.0234)	(0.0226)
(GR) Real GDP Priv. Industry pc			0.0078	0.0080
			(0.0107)	(0.0106)
(GR) Population			0.0063***	0.0066***
			(0.0010)	(0.0008)
Fixed-effects				
unit	Yes		Yes	
year	Yes	Yes	Yes	Yes
state		Yes		Yes
Fit statistics				
Observations	12,570	12,570	12,543	12,543
R^2	0.96815	0.76680	0.39690	0.38516
Within R^2	0.32132	0.49909	0.02349	0.02496

Clustered (year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Finally, we display the results for a 2SLS estimation using our wage-based shift-share instrument.

The instrumental variable estimates provide evidence of a robust causal relationship between national wage and GDP fluctuations and public education expenditure. Utilising our wage-based shift-share instrument we see highly significant and relevant first-stage relationships when the shift-share instrument is imposed both in levels and growth rates. Though the growth rate specification is only relevant with at least a 1-year lag. In each case, the first-stage regression yields a statistically significant and economically large coefficient. Varying the time-lag and inclusion of state or commuting zone fixed effects, we see that a 1% increase in the shift-share measure (which can be interpreted as a logarithm) is associated with a 0.05-0.5% increase in the local House Price Index ($p < 0.01$), with an F-statistic between 47-140 - all well above conventional weak instrument thresholds—confirming instrument relevance. However, the second-stage results are only significant in the case in which we include state-fixed effects rather than commuting zone level fixed effects.

In specifications that include year and state fixed effects (Columns 3, 4, 7, and 8), we find a statistically significant and positive effect of wage shocks on education spending. However, once we include commuting zone fixed effects in place of state fixed effects (Columns 1, 2, 5, 6), the second-stage coefficients become statistically insignificant, even though the first-stage remains strong.

This suggests that the estimated effect is driven primarily by cross-sectional variation across commuting zones within states, rather than by within-CZ variation over time. In other words, places with persistently higher wage shocks also tend to have higher education spending, but temporal changes in wage shocks within a given CZ are not reliably associated with changes in spending. These results emphasize that the cross-sectional component of the variation (e.g., differences between CZs in long-run exposure to wage shocks) may be driving the overall effect. If policy relevance hinges on place-based differences, then the specification with state fixed effects may better reflect the real-world variation of interest.

Dependent Variables:	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Wage SS (lvl)	0.5390***		0.0525***					
	(0.1005)		(0.0201)					
(log) IG Revenue pp	0.1625***	0.2852***	-0.1687***	0.4166***	0.1687***	0.2285***	-0.1711***	0.4177***
	(0.0191)	(0.0386)	(0.0442)	(0.0895)	(0.0192)	(0.0683)	(0.0449)	(0.0906)
(log) Real GDP Priv. Industry pc	0.2563***	0.0594	0.1007***	0.0631	0.2554***	-0.0118	0.1014***	0.0633
	(0.0265)	(0.0446)	(0.0276)	(0.0528)	(0.0273)	(0.0911)	(0.0277)	(0.0529)
(log) Enrollment	0.2498***	-0.3893***	0.1329***	-0.1635***	0.2726***	-0.4983***	0.1327***	-0.1642***
	(0.0307)	(0.0531)	(0.0091)	(0.0552)	(0.0316)	(0.1106)	(0.0091)	(0.0547)
(log) House Price Index		0.4890***		0.9686**		0.7861**		0.9707**
		(0.1554)		(0.3817)		(0.3576)		(0.3789)
Wage SS (lvl,l1)					0.2925***		0.0534***	
					(0.1045)		(0.0202)	
Fixed-effects								
unit	Yes	Yes			Yes	Yes		
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state			Yes	Yes			Yes	Yes
Fit statistics								
Observations	12,717	12,717	12,717	12,717	12,122	12,122	12,122	12,122
R^2	0.96262	0.85437	0.74285	-0.06411	0.96437	0.81823	0.74242	-0.06726
Within R^2	0.20416	0.24258	0.44925	-1.6609	0.20606	0.04756	0.45088	-1.6418
F-test (1st stage)	175.64		142.56		47.378		140.07	
F-test (1st stage), (log) House Price Index		175.64		142.56		47.378		140.07
F-test (1st stage), p-value	8×10^{-40}		1.1×10^{-32}		6.14×10^{-12}		3.87×10^{-32}	
F-test (1st stage), p-value, (log) House Price Index		8×10^{-40}		1.1×10^{-32}		6.14×10^{-12}		3.87×10^{-32}
F-test (2nd stage)		45.679		472.97		30.389		461.61
F-test (2nd stage), p-value		1.45×10^{-11}		5.49×10^{-103}		3.61×10^{-8}		1.62×10^{-100}
Wu-Hausman		17.914		395.73		17.515		385.52
Wu-Hausman, p-value		2.33×10^{-5}		9.85×10^{-87}		2.87×10^{-5}		1.62×10^{-84}
Wald (IV only)	28.757	9.8995	6.8250	6.4402	7.8357	4.8314	6.9654	6.5624
Wald (IV only), p-value	8.35×10^{-8}	0.00166	0.00900	0.01117	0.00513	0.02797	0.00832	0.01043

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Wage SS (GR)	0.0907		0.8346***					
	(0.0587)		(0.2664)					
(log) IG Revenue pp	0.1694***	0.5244***	-0.1815***	0.3618***	0.1725***	0.3459***	-0.1841***	0.3897***
	(0.0191)	(0.1916)	(0.0447)	(0.0586)	(0.0192)	(0.1192)	(0.0454)	(0.0715)
(log) Real GDP Priv. Industry pc	0.2480***	0.4096	0.1120***	0.0969***	0.2509***	0.1589	0.1129***	0.0804*
	(0.0260)	(0.2751)	(0.0269)	(0.0370)	(0.0269)	(0.1632)	(0.0270)	(0.0428)
(log) Enrollment	0.2819***	0.0088	0.1432***	-0.1203***	0.2888***	-0.3017	0.1432***	-0.1425***
	(0.0305)	(0.3184)	(0.0079)	(0.0340)	(0.0310)	(0.1905)	(0.0079)	(0.0425)
(log) House Price Index		-0.9224		0.6692***		0.1056		0.8201***
		(1.098)		(0.2359)		(0.6440)		(0.2923)
Wage SS (GR,l1)					0.1165*		0.7554***	
					(0.0615)		(0.2549)	
Fixed-effects								
unit	Yes	Yes			Yes	Yes		
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state			Yes	Yes			Yes	Yes
Fit statistics								
Observations	12,717	12,717	12,717	12,717	12,122	12,122	12,122	12,122
R^2	0.96210	0.68520	0.74024	0.37874	0.96424	0.86820	0.73967	0.17843
Within R^2	0.19321	-0.63723	0.44366	-0.55352	0.20307	0.30941	0.44502	-1.0336
F-test (1st stage)	1.0676		14.002		1.8710		11.410	
F-test (1st stage), (log) House Price Index		1.0676		14.002		1.8710		11.410
F-test (1st stage), p-value	0.30151		0.00018		0.17139		0.00073	
F-test (1st stage), p-value, (log) House Price Index		0.30151		0.00018		0.17139		0.00073
F-test (2nd stage)		0.99781		21.631		0.02168		26.184
F-test (2nd stage), p-value		0.31786		3.34×10^{-6}		0.88295		3.15×10^{-7}
Wu-Hausman		1.4158		16.199		0.01227		20.835
Wu-Hausman, p-value		0.23412		5.74×10^{-5}		0.91179		5.05×10^{-6}
Wald (IV only)	2.3893	0.70632	9.8169	8.0483	3.5876	0.02688	8.7808	7.8734
Wald (IV only), p-value	0.12219	0.40069	0.00173	0.00456	0.05824	0.86978	0.00305	0.00502

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.2.0.2 Industry-level GDP

The first regression tables investigate the relationship between real GDP per capita in the private industry and house prices. In the log-level specification, real GDP (including current and lagged values up to 7 periods) is positively and significantly associated with house prices. The contemporaneous coefficient is large and highly significant, and several lags (especially lags 1, 2, 3, and 5) are also positive and statistically significant, indicating a cumulative and persistent effect of GDP on housing values.

In contrast, the growth-rate specification shows a much weaker relationship. Most coefficients are small and not statistically significant, with the exception of lag 5, which shows a modest but significant positive association (0.0073) though this could likely be a spurious association.

Dependent Variables:	(log) House Price Index		(GR) House Price Index	
Model:	(1)	(2)	(3)	(4)
Variables				
(log) Real GDP Priv. Industry pc	0.2411***	0.1438***		
	(0.0209)	(0.0048)		
(l1,log) Real GDP Priv. Industry pc	0.0276***	-0.0136***		
	(0.0057)	(0.0010)		
(l2,log) Real GDP Priv. Industry pc	0.0204***	-0.0256***		
	(0.0034)	(0.0041)		
(l3,log) Real GDP Priv. Industry pc	0.0199***	0.0373***		
	(0.0041)	(0.0011)		
(l4,log) Real GDP Priv. Industry pc	0.0045	-0.0078**		
	(0.0031)	(0.0036)		
(l5,log) Real GDP Priv. Industry pc	0.0371***	-0.0061***		
	(0.0052)	(0.0022)		
(l6,log) Real GDP Priv. Industry pc	0.0112*	0.0212***		
	(0.0057)	(0.0025)		
(l7,log) Real GDP Priv. Industry pc	0.0060	0.0146***		
	(0.0063)	(0.0023)		
(log) Population	0.5459***	0.1524***		
	(0.0499)	(0.0024)		
(GR) Real GDP Priv. Industry pc			0.0161	0.0169
			(0.0162)	(0.0165)
(GR,l1) Real GDP Priv. Industry pc			0.0093	0.0101
			(0.0057)	(0.0061)
(GR,l2) Real GDP Priv. Industry pc			0.0062	0.0063
			(0.0043)	(0.0045)
(GR,l3) Real GDP Priv. Industry pc			-0.0009	-0.0010
			(0.0034)	(0.0033)
(GR,l4) Real GDP Priv. Industry pc			-0.0025	-0.0027
			(0.0024)	(0.0024)
(GR,l5) Real GDP Priv. Industry pc			0.0070***	0.0062***
			(0.0020)	(0.0019)
(GR,l6) Real GDP Priv. Industry pc			8.67×10^{-5}	0.0010
			(0.0043)	(0.0041)
(GR,l7) Real GDP Priv. Industry pc			-0.0002	-3.7×10^{-5}
			(0.0026)	(0.0025)
(GR) Population			0.0060***	0.0064***
			(0.0011)	(0.0008)
Fixed-effects				
unit	Yes		Yes	
year	Yes	Yes	Yes	Yes
state		Yes		Yes
Fit statistics				
Observations	12,570	12,570	12,542	12,542
R^2	0.96261	0.74492	0.38588	0.37331
Within R^2	0.20336	0.45210	0.00564	0.00618

Clustered (year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Moving on to investigate the GDP-based shift-share instrument, we find a similar effect as with wages when estimating level shift-share shocks. The first-stage relationship between GDP shocks and house prices ranges from 0.1-0.7% increase in response to a 1% increase in the shift-share instrument (interpreted as wage levels) with an F-statistic between 110-400. However, we see an even weaker relationship when imposing the shift-share instrument as a growth rate shock where the first-stage relationship are spurious and statistically insignificant.

Together, these findings suggest that levels (rather than short-run changes) in GDP are more systematically and substantially associated with house price dynamics. The stronger fit and significant lag effects in the level regression underscore the longer-term influence of economic fundamentals on housing markets. It also indicates that wage growth is more important for house prices than the more general presence of industry-level GDP growth. This makes intuitive sense in that the link from industrial success (labour) to personal and community wealth creation is mediated via wage and not necessarily the total industrial output which might not be reflected in wages (especially given recent evidence of decoupling of wages from productivity) Source here - OECD and FRED Data.

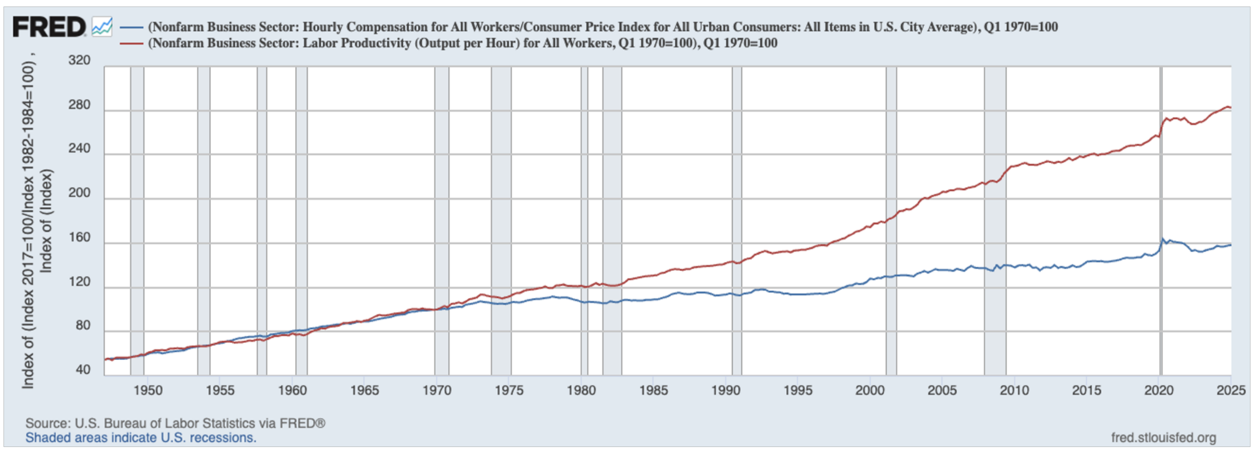


Figure 2: Wages and Productivity

Dependent Variables:	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
GDP SS (Lvl)	0.6954***		0.0997***					
	(0.1548)		(0.0216)					
(log) IG Revenue pp	0.1629***	0.2987***	-0.1390***	0.3209***	0.1659***	0.2618***	-0.1412***	0.3217***
	(0.0190)	(0.0410)	(0.0435)	(0.0384)	(0.0190)	(0.0488)	(0.0442)	(0.0392)
(log) Real GDP Priv. Industry pc	0.2520***	0.0792	0.0906***	0.1222***	0.2542***	0.0366	0.0915***	0.1221***
	(0.0260)	(0.0523)	(0.0277)	(0.0253)	(0.0272)	(0.0633)	(0.0278)	(0.0258)
(log) Enrollment	0.2482***	-0.3668***	0.1185***	-0.0881***	0.2620***	-0.4426***	0.1183***	-0.0897***
	(0.0309)	(0.0581)	(0.0101)	(0.0179)	(0.0314)	(0.0724)	(0.0101)	(0.0180)
(log) House Price Index		0.4094**		0.4456***		0.5933***		0.4537***
		(0.1821)		(0.1216)		(0.2263)		(0.1225)
GDP SS (lvl,l1)					0.6109***		0.1007***	
					(0.1551)		(0.0218)	
Fixed-effects								
unit	Yes	Yes			Yes	Yes		
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state			Yes	Yes			Yes	Yes
Fit statistics								
Observations	12,717	12,717	12,717	12,717	12,122	12,122	12,122	12,122
R^2	0.96255	0.86074	0.74809	0.58914	0.96456	0.84566	0.74773	0.58162
Within R^2	0.20278	0.27571	0.46046	-0.02740	0.21012	0.19129	0.46221	-0.03561
F-test (1st stage)	153.43		408.46		109.88		397.06	
F-test (1st stage), (log) House Price Index		153.43		408.46		109.88		397.06
F-test (1st stage), p-value	4.92×10^{-35}		2.03×10^{-89}		1.34×10^{-25}		5.99×10^{-87}	
F-test (1st stage), p-value, (log) House Price Index		4.92×10^{-35}		2.03×10^{-89}		1.34×10^{-25}		5.99×10^{-87}
F-test (2nd stage)		27.969		276.75		39.965		275.80
F-test (2nd stage), p-value		1.25×10^{-7}		1.73×10^{-61}		2.68×10^{-10}		2.95×10^{-61}
Wu-Hausman		8.5597		176.20		18.721		176.29
Wu-Hausman, p-value		0.00344		6.06×10^{-40}		1.53×10^{-5}		5.98×10^{-40}
Wald (IV only)	20.172	5.0522	21.233	13.423	15.518	6.8699	21.404	13.718
Wald (IV only), p-value	7.14×10^{-6}	0.02461	4.11×10^{-6}	0.00025	8.22×10^{-5}	0.00878	3.76×10^{-6}	0.00021

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variables:	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
GDP SS (GR)	-0.0032		1.239***					
	(0.1038)		(0.3979)					
(log) IG Revenue pp	0.1695***	-35.39	-0.1819***	0.1682***	0.1724***	-1.014	-0.1856***	-0.0077
	(0.0191)	(1,166.8)	(0.0448)	(0.0539)	(0.0192)	(5.109)	(0.0455)	(0.3921)
(log) Real GDP Priv. Industry pc	0.2481***	-52.16	0.1118***	0.2167***	0.2509***	-1.820	0.1134***	0.3241
	(0.0260)	(1,706.8)	(0.0269)	(0.0295)	(0.0269)	(7.412)	(0.0270)	(0.2340)
(log) Enrollment	0.2821***	-59.76	0.1427***	0.0321	0.2889***	-2.580	0.1436***	0.1657
	(0.0305)	(1,941.2)	(0.0079)	(0.0322)	(0.0310)	(8.533)	(0.0079)	(0.2990)
(log) House Price Index		211.0		-0.3891*		7.993		-1.320
		(6,884.5)		(0.2199)		(29.52)		(2.075)
GDP SS (GR,l1)					-0.0435		0.3658	
					(0.1618)		(0.4994)	
Fixed-effects								
unit	Yes	Yes			Yes	Yes		
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state			Yes	Yes			Yes	Yes
Fit statistics								
Observations	12,717	12,717	12,717	12,717	12,122	12,122	12,122	12,122
R^2	0.96210	-6,665.5	0.74020	0.46512	0.96423	-7.7331	0.73944	-1.3699
Within R^2	0.19315	-34,670.9	0.44356	-0.33752	0.20295	-44.759	0.44454	-4.8662
F-test (1st stage)	0.00050		11.711		0.07855		0.81846	
F-test (1st stage), (log) House Price Index		0.00050		11.711		0.07855		0.81846
F-test (1st stage), p-value	0.98217		0.00062		0.77927		0.36565	
F-test (1st stage), p-value, (log) House Price Index		0.98217		0.00062		0.77927		0.36565
F-test (2nd stage)		24.478		6.1087		5.2191		4.8641
F-test (2nd stage), p-value		7.61×10^{-7}		0.01346		0.02236		0.02744
Wu-Hausman		24.151		10.029		4.9045		5.8489
Wu-Hausman, p-value		9.03×10^{-7}		0.00154		0.02681		0.01560
Wald (IV only)	0.00094	0.00094	9.6888	3.1307	0.07225	0.07331	0.53645	0.40502
Wald (IV only), p-value	0.97555	0.97555	0.00186	0.07685	0.78809	0.78658	0.46392	0.52452

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.3 Accounting for Heterogeneity

We suspect that the inability to detect a meaningful relationship between local economic conditions (wages and GDP) and local public services at the national level, barring design and data issues with our shift-share instrument, likely comes from masked heterogeneity across states and commuting zones. Therefore, this next section is dedicated to unpacking this heterogeneity. Below, we explore various metrics of local economic growth and decline to (1) partition our sample according to metrics of economic health, employ (2) state-by-state and (2) industry-by-industry estimations using our baseline descriptive models, wage- and GDP-based shift-share instruments.

4.3.1 Declining vs. Growing Regions

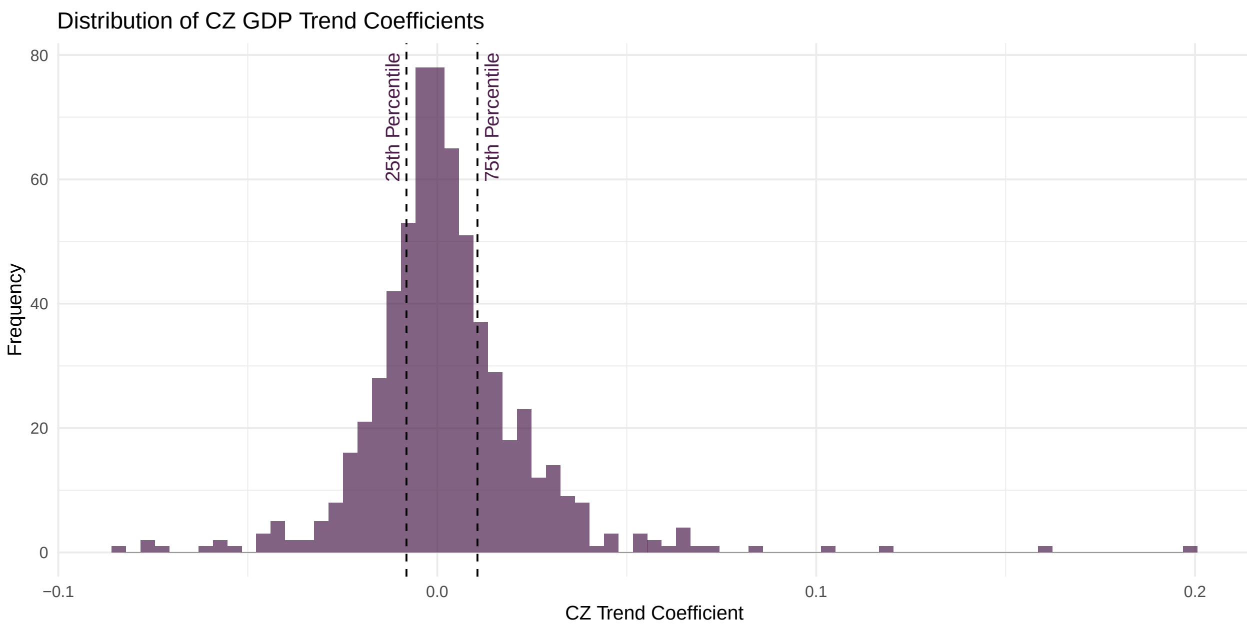
First, we identify declining and growing regions by estimating commuting-zone growth rates conditional on state and national level growth rates and partition our sample after this distribution.

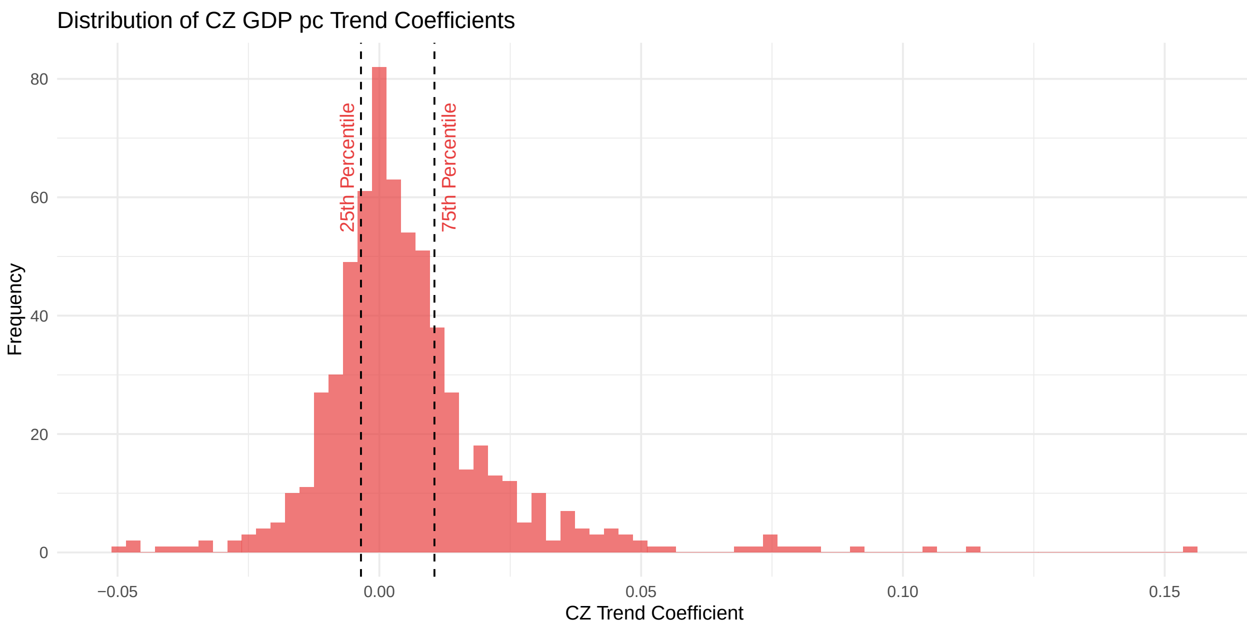
In order to identify declining and growing commuting zones, we estimate time series regressions by commuting zone in which:

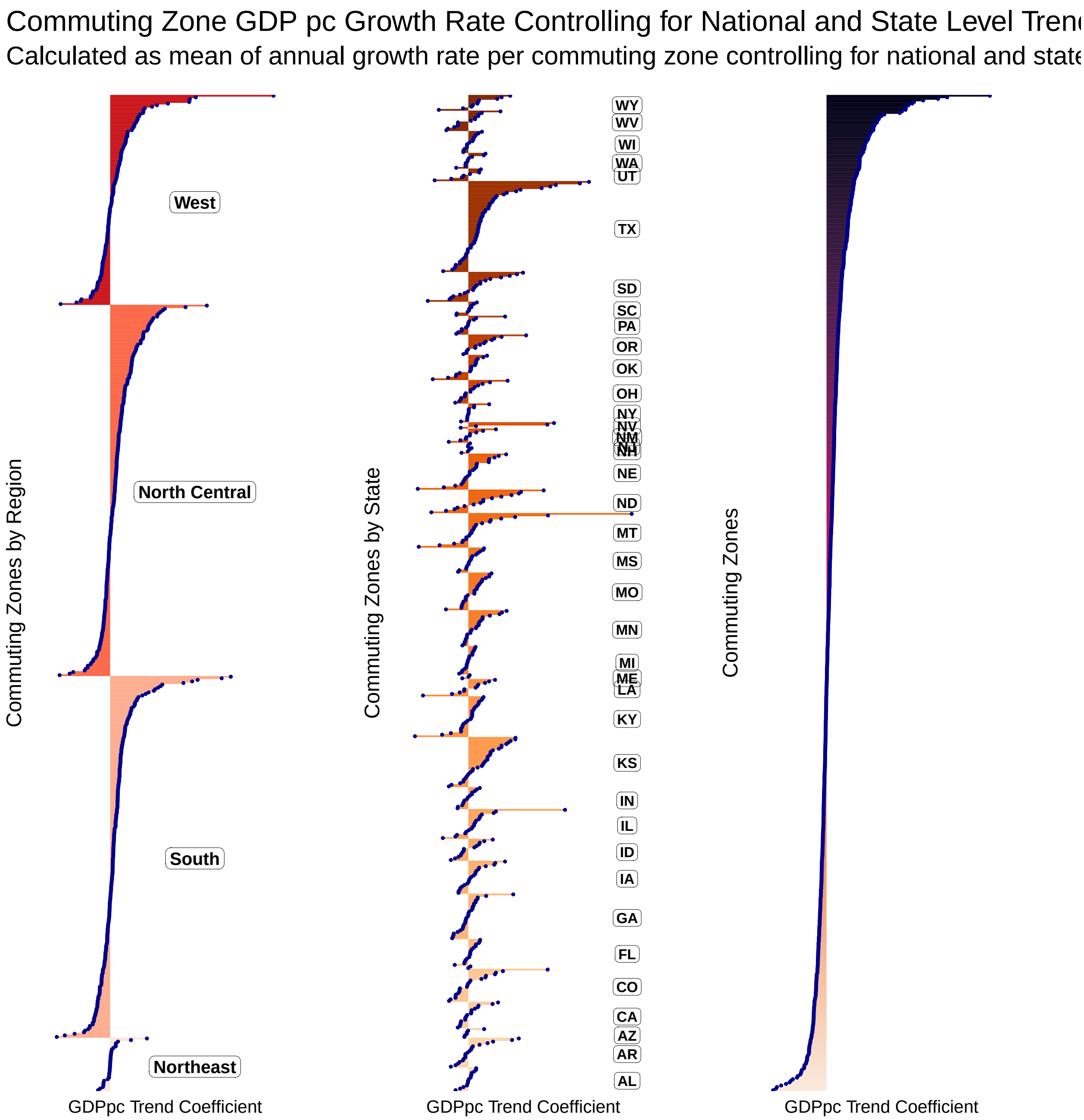
$$\Delta(log)IndustryGDP_t^{CZ} = \alpha + \Delta(log)IndustryGDP_t^{state} + \Delta(log)IndustryGDP_t^{national} + \epsilon_t$$

Where each GDP term represents the private industry GDP at the CZ, state, or national level. Effectively, we estimate the commuting zone level growth rate controlling for state and national trends. We then classify commuting zones by the value of α which represents their deviation from state- and national-level GDP growth rates. We estimate this trend deviation in both gross and per capita values of private industry GDP. Figure X demonstrates the considerable variability in GDP-level growth rates across commuting zones in the US between 2001-2021. Visualising the per capita growth rate deviations by state and region demonstrates heterogeneity in this variability across states and regions. For example, Texas, Montana, Illinois, and Colorado have outstanding positive outliers in the distribution (check which CZ these are: likely Dallas, Chicago, Denver. Montana's outlier is potentially an oil-rich area (indeed the map confirms this)). Whereas, South Dakota, Nebraska, Montana, Louisiana, and Kentucky contain some of the outstanding declining areas (SD, Louisiana, and Kentucky make intuitive sense which is great! Just confirm which these commuting zones are. Might be useful to highlight some examples in the graph itself.)

Include a correlation plot between GDP and Wage trends.


Distribution of CZ GDP Trend Coefficients
Frequency
CZ Trend Coefficient
25th Percentile
75th Percentile
0
20
40
60
80
−0.1
0.0
0.1
0.2


Distribution of CZ GDP pc Trend Coefficients
Frequency
CZ Trend Coefficient
25th Percentile
75th Percentile
0
20
40
60
80
−0.05
0.00
0.05
0.10
0.15

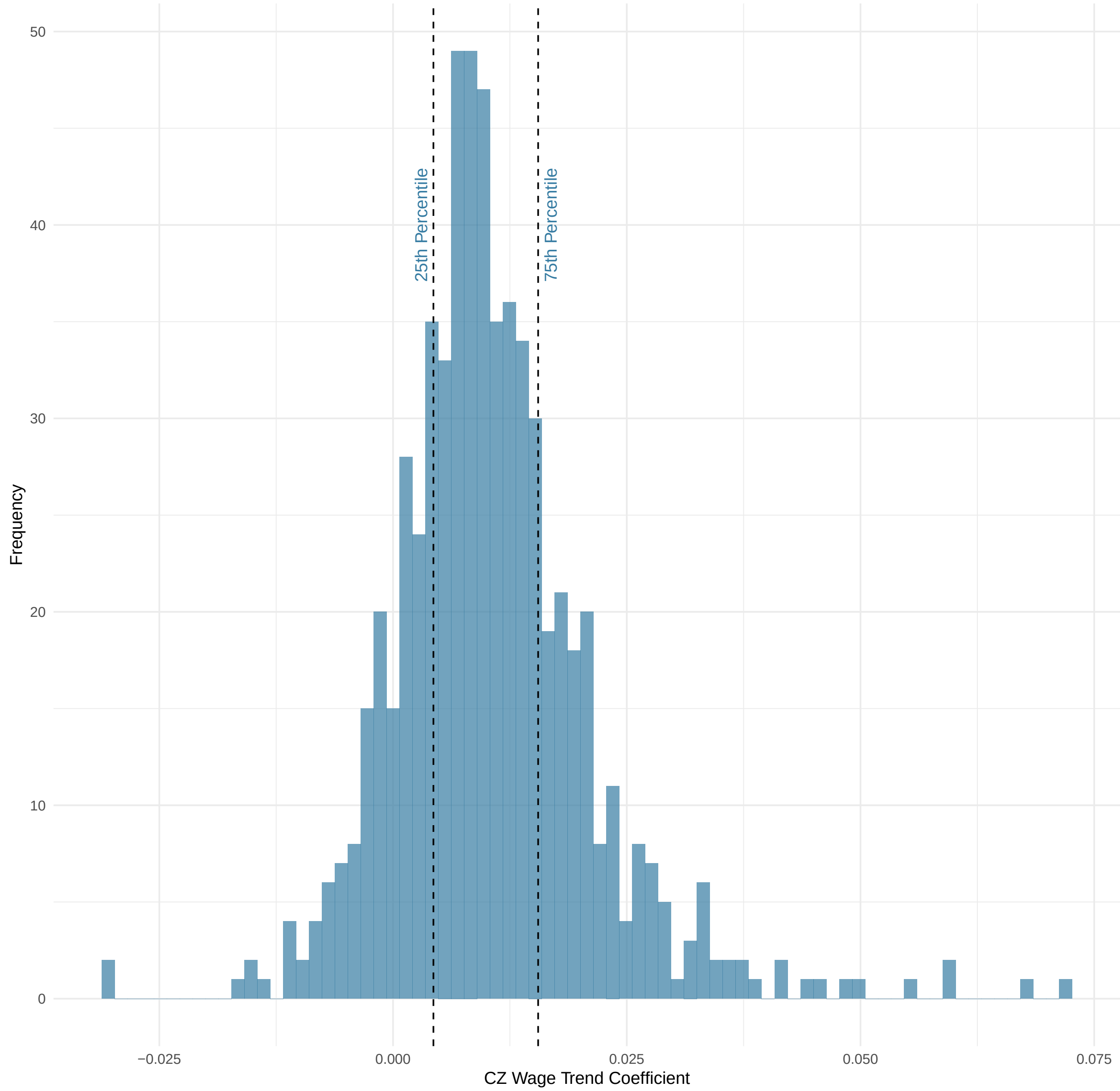


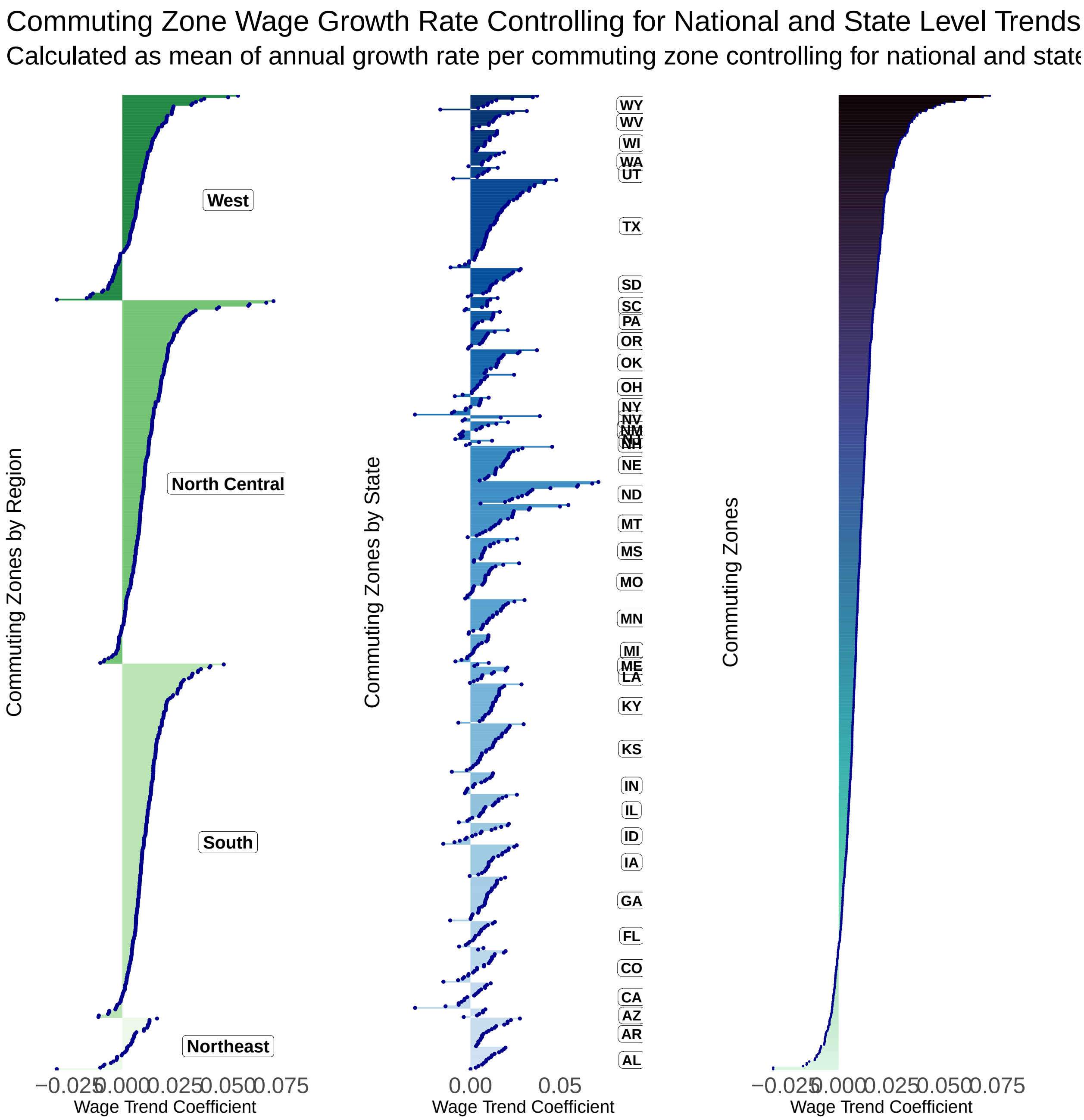
We perform the same trend deviation calculation for wages where each Wage variable represents the commuting zone, state, and national level growth rate in the weekly average wage as reported in QCEW.

$$\Delta(log)Wage_t^{CZ} = \alpha + \Delta(log)Wage_t^{state} + \Delta(log)Wage_t^{national} + \epsilon_t$$

In Figure X, we see that there is similar variability though the patterns do not consistently indicate the same high- and low-performing outliers across states indicating that GDP and wage growth are not consistently correlated across regions. We demonstrate this fact in Figure X (scatterplot with pink regression linear fit) where, although there is a positive correlation between commuting zone GDP and wage trend deviations, the wage trend deviation represents a nearly inelastic relationship to GDP growth.

Distribution of CZ Wage Trend Coefficients

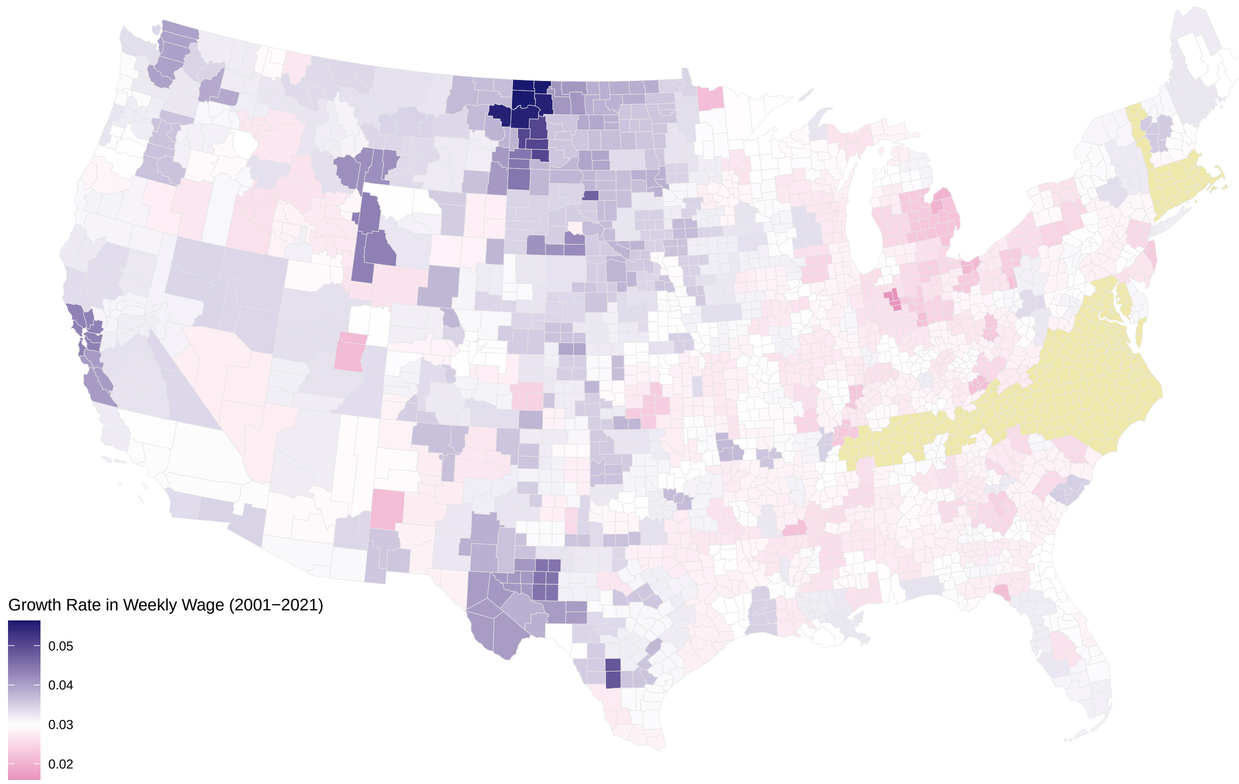




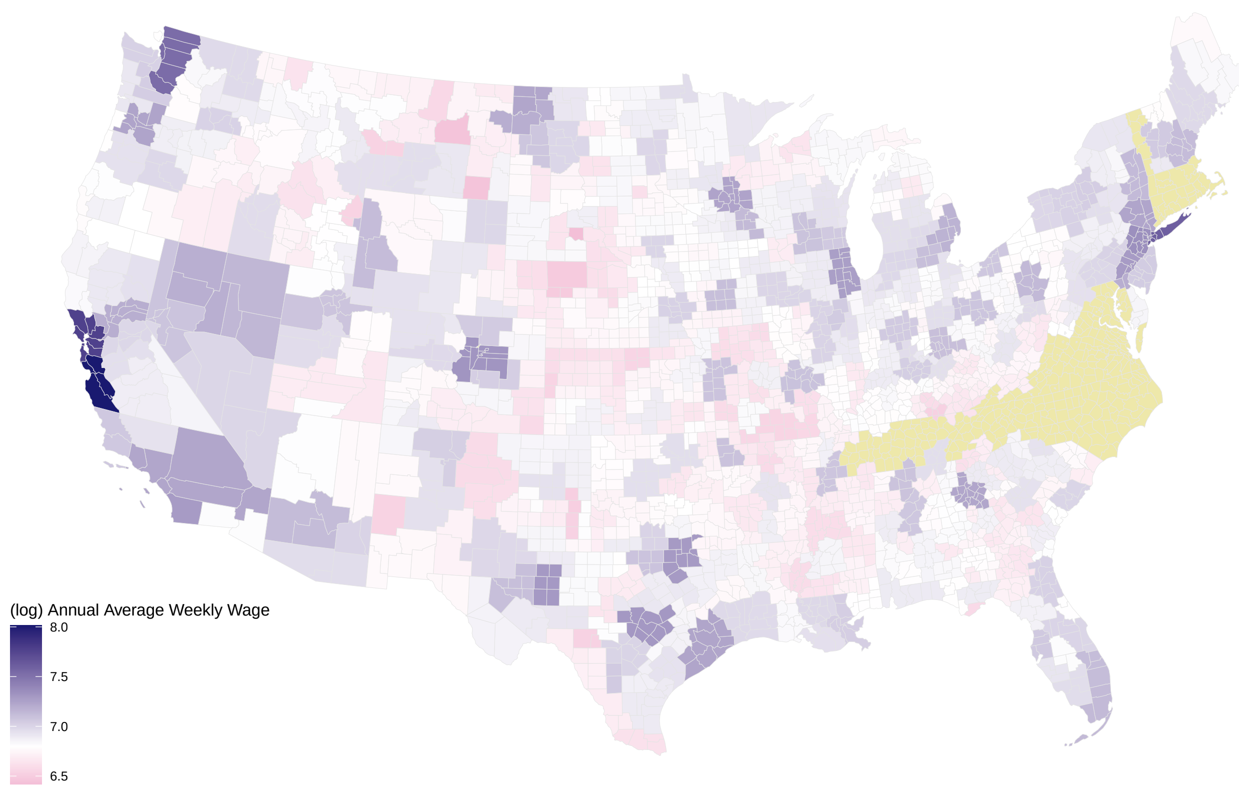
Commuting Zone Wage Growth Rate Controlling for National and State Level Trends
Calculated as mean of annual growth rate per commuting zone controlling for national and state
Commuting Zones by Region
West
North Central
South
Northeast
−0.025
0.000
0.025
0.050
0.075
Wage Trend Coefficient
Commuting Zones by State
WY
WV
WI
WA
UT
TX
SD
SC
PA
OR
OK
OH
NY
NV
NM
NH
NE
ND
MT
MS
MO
MN
MI
ME
LA
KY
KS
IN
IL
ID
IA
GA
FL
CO
CA
AZ
AR
AL
0.00
0.05
Wage Trend Coefficient
Commuting Zones
−0.025
0.000
0.025
0.050
0.075
Wage Trend Coefficient


Relationship Between GDPpc and Wage Trends (per CZ)
Wage Trend
Real GDP pc Trend
0.075
0.050
0.025
0.000
−0.025
−0.05
0.00
0.05
0.10
0.15

Growth Rate of Weekly Wage in Relation to Median (CZ)



Weekly Wage Level (2021) in Relation to Median (CZ)



4.3.2 Baseline Models

Table 1: Baseline Regression Applied to Declining GDP vs. Growing GDP Regions

Dependent Variable:	(log) Elem.Ed.Exp.pp											
		Declining			Hyper-Declining			Growing			Hyper-Growing	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
(log) Real GDP Priv. Industry pc	0.0054			-0.0125			0.0206			0.0105		
	(0.0351)			(0.0444)			(0.0243)			(0.0299)		
(log,l1) Real GDP Priv. Industry pc	0.0738***			0.0756**			0.0622***			0.0569***		
	(0.0242)			(0.0295)			(0.0171)			(0.0208)		
(log,l2) Real GDP Priv. Industry pc	0.1024***			0.1095***			0.1549***			0.1697***		
	(0.0231)			(0.0249)			(0.0323)			(0.0393)		
(log) IG Revenue pp	0.3722***	0.3729***	0.3541***	0.3183***	0.3276***	0.2935***	0.3928***	0.3532***	0.3864***	0.3806***	0.3171***	0.3181***
	(0.0548)	(0.0520)	(0.0545)	(0.0681)	(0.0660)	(0.0682)	(0.0359)	(0.0422)	(0.0406)	(0.0567)	(0.0662)	(0.0681)
(log) Annual Avg. Wkly. Wage		0.0871			0.0659			0.2066***			0.1748	
		(0.0969)			(0.1231)			(0.0776)			(0.1115)	
(log, l1) Annual Avg. Wkly. Wage		0.1642**			0.1997*			0.1869***			0.2536***	
		(0.0820)			(0.1013)			(0.0582)			(0.0955)	
(log, l2) Annual Avg. Wkly. Wage		0.2610***			0.2262**			0.2359**			0.2795	
		(0.0826)			(0.0911)			(0.1161)			(0.1696)	
(log) House Price Index			0.0386			0.0985*			0.1003***			0.1090**
			(0.0431)			(0.0510)			(0.0309)			(0.0473)
(log, l1) House Price Index			0.0745**			0.0896**			0.0578			0.0844
			(0.0319)			(0.0408)			(0.0364)			(0.0525)
(log, l2) House Price Index			0.0239			-0.0264			0.0553**			0.0560
			(0.0318)			(0.0382)			(0.0260)			(0.0407)
(log, l3) House Price Index			0.1171***			0.1484***			0.0145			-0.0058
			(0.0350)			(0.0430)			(0.0255)			(0.0337)
(log, l4) House Price Index			-0.0833**			-0.1263***			0.0072			-0.0416
			(0.0347)			(0.0452)			(0.0274)			(0.0437)
Fixed-effects												
unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	4,883	5,397	5,223	3,021	3,339	3,173	7,201	7,959	7,365	3,021	3,339	2,904
R^2	0.85785	0.85948	0.86073	0.83249	0.83401	0.83486	0.85734	0.84617	0.85014	0.79061	0.77279	0.77875
Within R^2	0.22345	0.25049	0.22873	0.18513	0.21740	0.19832	0.28656	0.24697	0.23978	0.28823	0.22654	0.16829

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.3.3 IV Models

The following implements an employment based Bartik instrument for various industries available from the Quarterly Census of Employment and Wages. I have not figured out how to suppress the R2 and within R2 of the second-stage regressions. One should only pay attention to the IV diagnostic tests in the second-stage regression.

4.3.4 High-income Outliers

As you can see in the scatterplot below, there is a somewhat non-linear relationship between property taxes and elementary expenditure as property taxes collected rise. This happens largely as a result of very high-income commuting zones. Therefore, I exclude any commuting zone that spends more than 28k per pupil to avoid any distorting effects. This removes 12 CZs (~2% of the sample). This could benefit from more robust outlier detection.

Table 2: Wage-based Shift-Share Instrument (l1) Applied to Declining GDP vs. Growing GDP Regions

Dependent Variable:	(log) Elem.Ed.Exp.pp				
	All	Declining (GDP)	Hyper-Declining (GDP)	Growing (GDP)	Hyper-Growing (GDP)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) House Price Index	0.9707**	0.9063***	1.555	1.698	-5.040
	(0.3789)	(0.2830)	(1.174)	(1.867)	(36.37)
(log) IG Revenue pp	0.4177***	0.3785***	0.3983**	0.5845	-0.5816
	(0.0906)	(0.0843)	(0.1770)	(0.3725)	(5.982)
(log) Real GDP Priv. Industry pc	0.0633	0.0931	0.0182	-0.0198	0.4651
	(0.0529)	(0.0699)	(0.1951)	(0.2056)	(2.354)
(log) Enrollment	-0.1642***	-0.1490***	-0.2690	-0.2773	0.7879
	(0.0547)	(0.0385)	(0.1783)	(0.2762)	(5.880)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,122	4,992	3,033	7,130	2,845
R^2	-0.06726	0.19395	-1.2580	-1.7150	-24.908
Within R^2	-1.6418	-1.1592	-4.5252	-5.8114	-50.939
F-test (1st stage), (log) House Price Index	140.07	145.93	29.567	16.654	0.35818
F-test (1st stage), p-value, (log) House Price Index	3.87×10^{-32}	3.94×10^{-33}	5.84×10^{-8}	4.54×10^{-5}	0.54957
F-test (2nd stage)	461.61	430.47	245.45	152.30	22.379
F-test (2nd stage), p-value	1.62×10^{-100}	9.67×10^{-92}	3.24×10^{-53}	1.24×10^{-34}	2.35×10^{-6}
Wu-Hausman	385.52	332.30	226.78	140.73	23.483
Wu-Hausman, p-value	1.62×10^{-84}	6.68×10^{-72}	1.92×10^{-49}	3.71×10^{-32}	1.33×10^{-6}
Wald (IV only)	6.5624	10.259	1.7553	0.82725	0.01920
Wald (IV only), p-value	0.01043	0.00137	0.18532	0.36310	0.88979

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: Wage-based Shift-Share Instrument (l1) Applied to Declining Wage vs. Growing Wage Regions

Dependent Variable:	(log) Elem.Ed.Exp.pp				
	All	Declining (GDP)	Hyper-Declining (GDP)	Growing (GDP)	Hyper-Growing (GDP)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) House Price Index	0.9707**	0.7404	1.169*	0.8769**	0.4162
	(0.3789)	(0.4451)	(0.6305)	(0.3641)	(0.4671)
(log) IG Revenue pp	0.4177***	0.3630***	0.4551***	0.4119***	0.2829***
	(0.0906)	(0.1343)	(0.1654)	(0.0884)	(0.0621)
(log) Real GDP Priv. Industry pc	0.0633	-0.0124	-0.0335	0.0861**	0.1094**
	(0.0529)	(0.1669)	(0.1910)	(0.0436)	(0.0544)
(log) Enrollment	-0.1642***	-0.1246**	-0.1747**	-0.1502***	-0.1184
	(0.0547)	(0.0603)	(0.0778)	(0.0509)	(0.0747)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,122	1,520	3,060	10,602	2,822
R^2	-0.06726	0.60726	-0.16496	0.03176	0.59866
Within R^2	-1.6418	-0.48644	-2.4209	-1.3083	-0.02148
F-test (1st stage), (log) House Price Index	140.07	47.453	55.276	140.02	41.427
F-test (1st stage), p-value, (log) House Price Index	3.87×10^{-32}	8.33×10^{-12}	1.36×10^{-13}	4.21×10^{-32}	1.44×10^{-10}
F-test (2nd stage)	461.61	70.621	256.33	383.32	21.828
F-test (2nd stage), p-value	1.62×10^{-100}	1.01×10^{-16}	2×10^{-55}	7.19×10^{-84}	3.12×10^{-6}
Wu-Hausman	385.52	47.014	210.21	324.43	23.718
Wu-Hausman, p-value	1.62×10^{-84}	1.04×10^{-11}	4.31×10^{-46}	1.84×10^{-71}	1.18×10^{-6}
Wald (IV only)	6.5624	2.7674	3.4365	5.8010	0.79401
Wald (IV only), p-value	0.01043	0.09642	0.06387	0.01603	0.37297

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: GDP-based Shift-Share Instrument (l1) Applied to Declining Wage vs. Growing Wage Regions

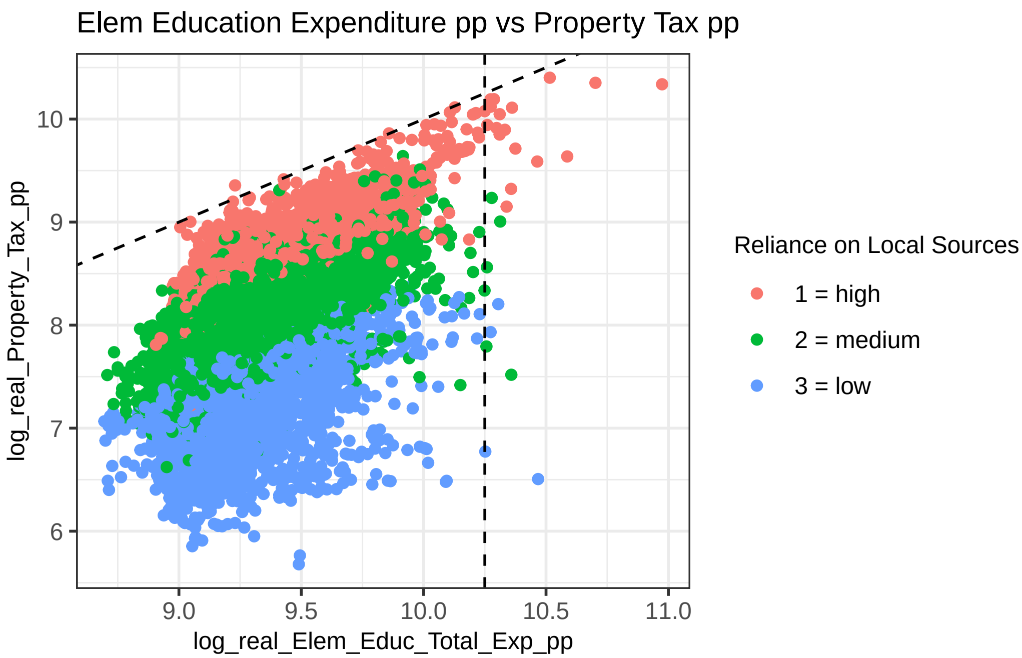
Dependent Variable:	(log) Elem.Ed.Exp.pp				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) House Price Index	0.4537***	0.4421**	0.6652***	0.3869***	-0.0710
	(0.1225)	(0.1987)	(0.2376)	(0.1208)	(0.1747)
(log) IG Revenue pp	0.3217***	0.2843***	0.3311***	0.3261***	0.2659***
	(0.0392)	(0.0832)	(0.0794)	(0.0402)	(0.0401)
(log) Real GDP Priv. Industry pc	0.1221***	0.0806	0.0835	0.1297***	0.1622***
	(0.0258)	(0.0891)	(0.0973)	(0.0239)	(0.0331)
(log) Enrollment	-0.0897***	-0.0838***	-0.1109***	-0.0822***	-0.0427
	(0.0180)	(0.0298)	(0.0286)	(0.0171)	(0.0317)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,122	1,520	3,060	10,602	2,822
R^2	0.58162	0.75465	0.51254	0.60370	0.74149
Within R^2	-0.03561	0.07142	-0.43143	0.05522	0.34205
F-test (1st stage), (log) House Price Index	397.06	102.81	143.50	379.26	93.045
F-test (1st stage), p-value, (log) House Price Index	5.99×10^{-87}	2.13×10^{-23}	2.47×10^{-32}	5.14×10^{-83}	1.12×10^{-21}
F-test (2nd stage)	275.80	51.996	206.30	194.26	1.3917
F-test (2nd stage), p-value	2.95×10^{-61}	8.87×10^{-13}	2.7×10^{-45}	9.11×10^{-44}	0.23822
Wu-Hausman	176.29	23.467	135.86	126.44	0.91974
Wu-Hausman, p-value	5.98×10^{-40}	1.41×10^{-6}	9.74×10^{-31}	3.61×10^{-29}	0.33763
Wald (IV only)	13.718	4.9519	7.8373	10.253	0.16524
Wald (IV only), p-value	0.00021	0.02621	0.00515	0.00137	0.68441

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: GDP-based Shift-Share Instrument (l1) Applied to Declining GDP vs. Growing GDP Regions

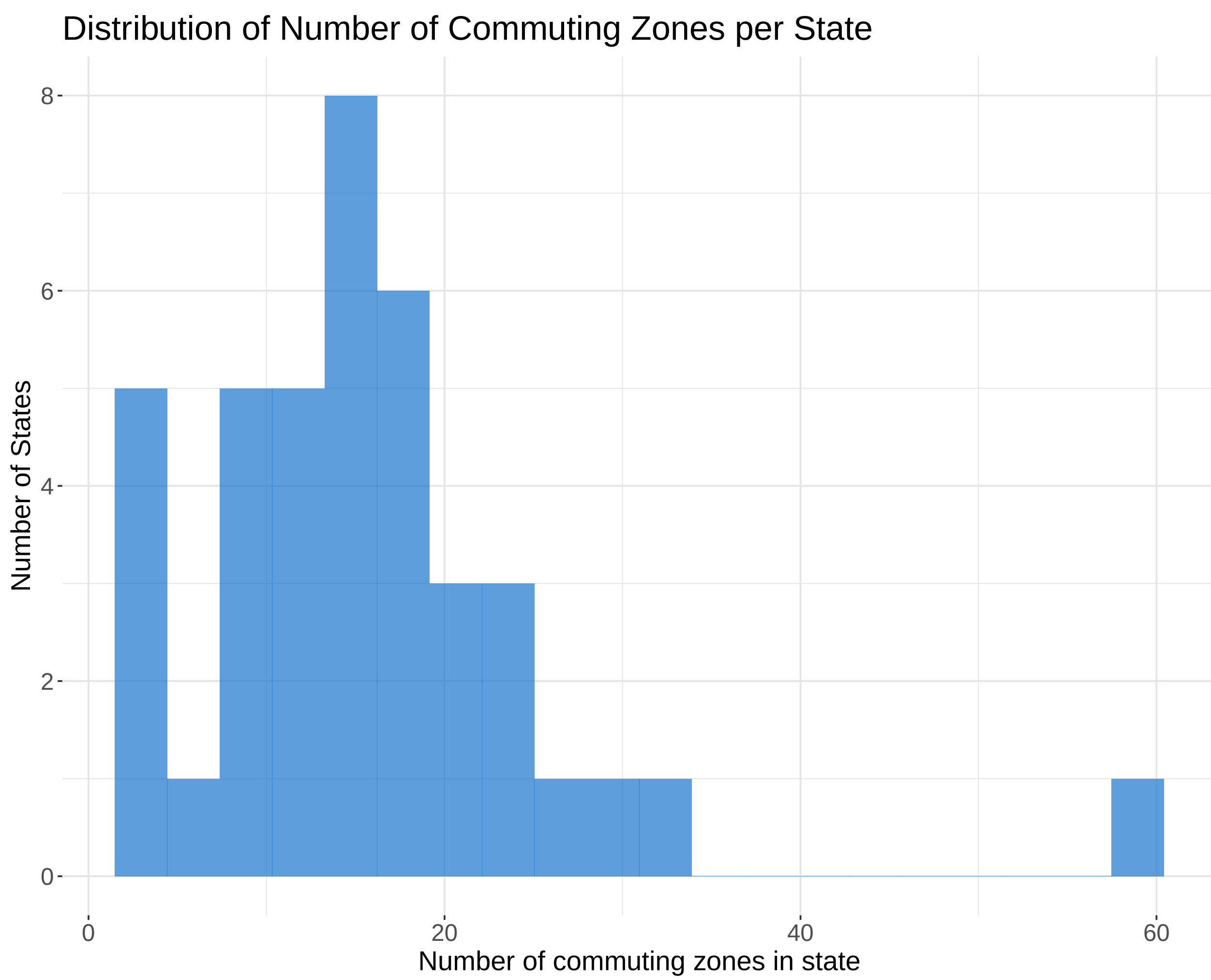
Dependent Variable:	(log) Elem.Ed.Exp.pp				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) House Price Index	0.4537***	0.6786***	0.8673**	0.3476*	0.3098
	(0.1225)	(0.1891)	(0.3571)	(0.1771)	(0.4352)
(log) IG Revenue pp	0.3217***	0.3415***	0.3257***	0.3207***	0.2884***
	(0.0392)	(0.0606)	(0.0822)	(0.0522)	(0.0947)
(log) Real GDP Priv. Industry pc	0.1221***	0.1213**	0.1008	0.1252***	0.1151**
	(0.0258)	(0.0550)	(0.0915)	(0.0323)	(0.0560)
(log) Enrollment	-0.0897***	-0.1185***	-0.1650***	-0.0780***	-0.0777
	(0.0180)	(0.0256)	(0.0543)	(0.0266)	(0.0703)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,122	4,992	3,033	7,130	2,845
R^2	0.58162	0.47219	0.15677	0.64325	0.55673
Within R^2	-0.03561	-0.41385	-1.0634	0.10500	0.11134
F-test (1st stage), (log) House Price Index	397.06	189.16	89.405	163.41	21.279
F-test (1st stage), p-value, (log) House Price Index	5.99×10^{-87}	2.9×10^{-42}	6.31×10^{-21}	5.23×10^{-37}	4.15×10^{-6}
F-test (2nd stage)	275.80	302.79	224.80	60.538	4.9555
F-test (2nd stage), p-value	2.95×10^{-61}	7.3×10^{-66}	4.81×10^{-49}	8.24×10^{-15}	0.02609
Wu-Hausman	176.29	207.33	193.79	36.171	2.7658
Wu-Hausman, p-value	5.98×10^{-40}	4.48×10^{-46}	1.01×10^{-42}	1.9×10^{-9}	0.09641
Wald (IV only)	13.718	12.877	5.8985	3.8531	0.50675
Wald (IV only), p-value	0.00021	0.00034	0.01521	0.04969	0.47661

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

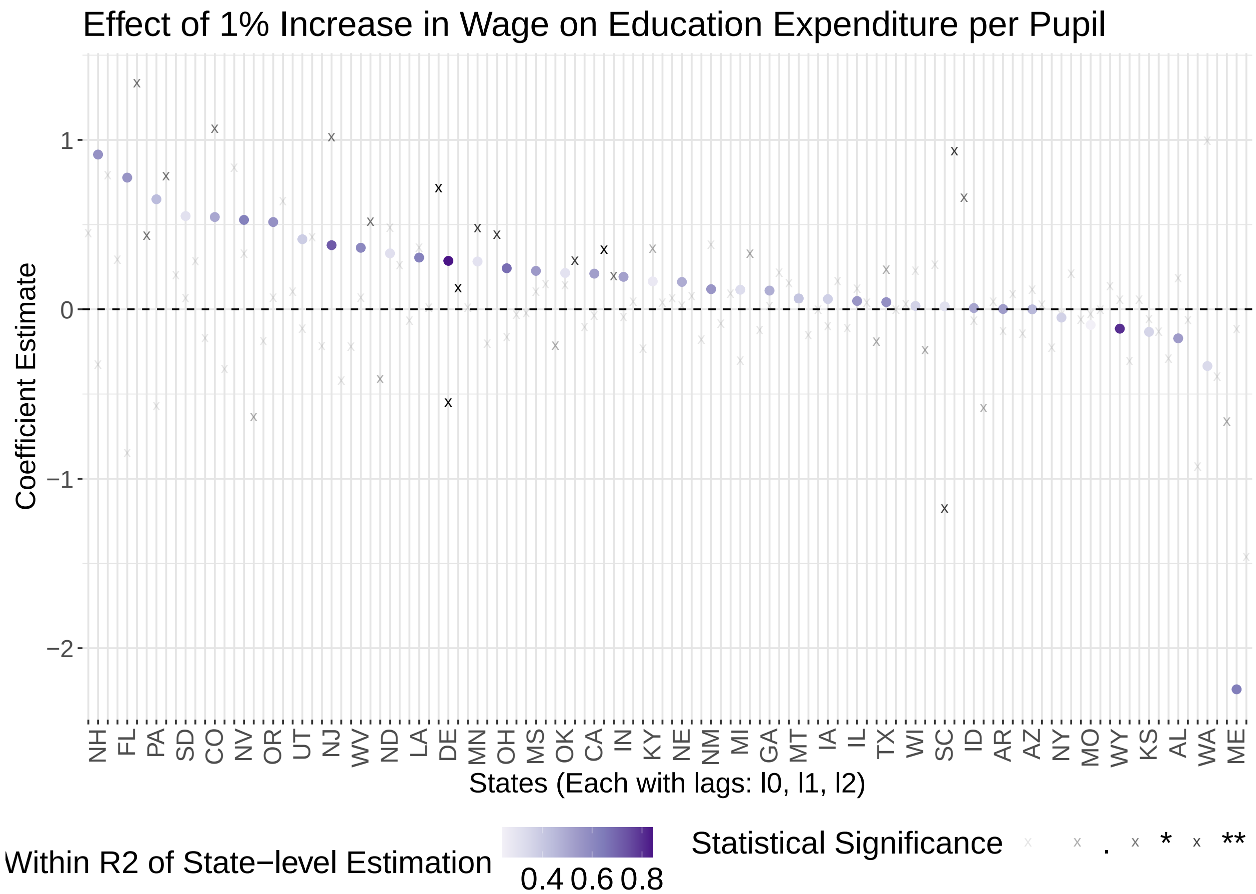


4.3.5 State-by-state estimation

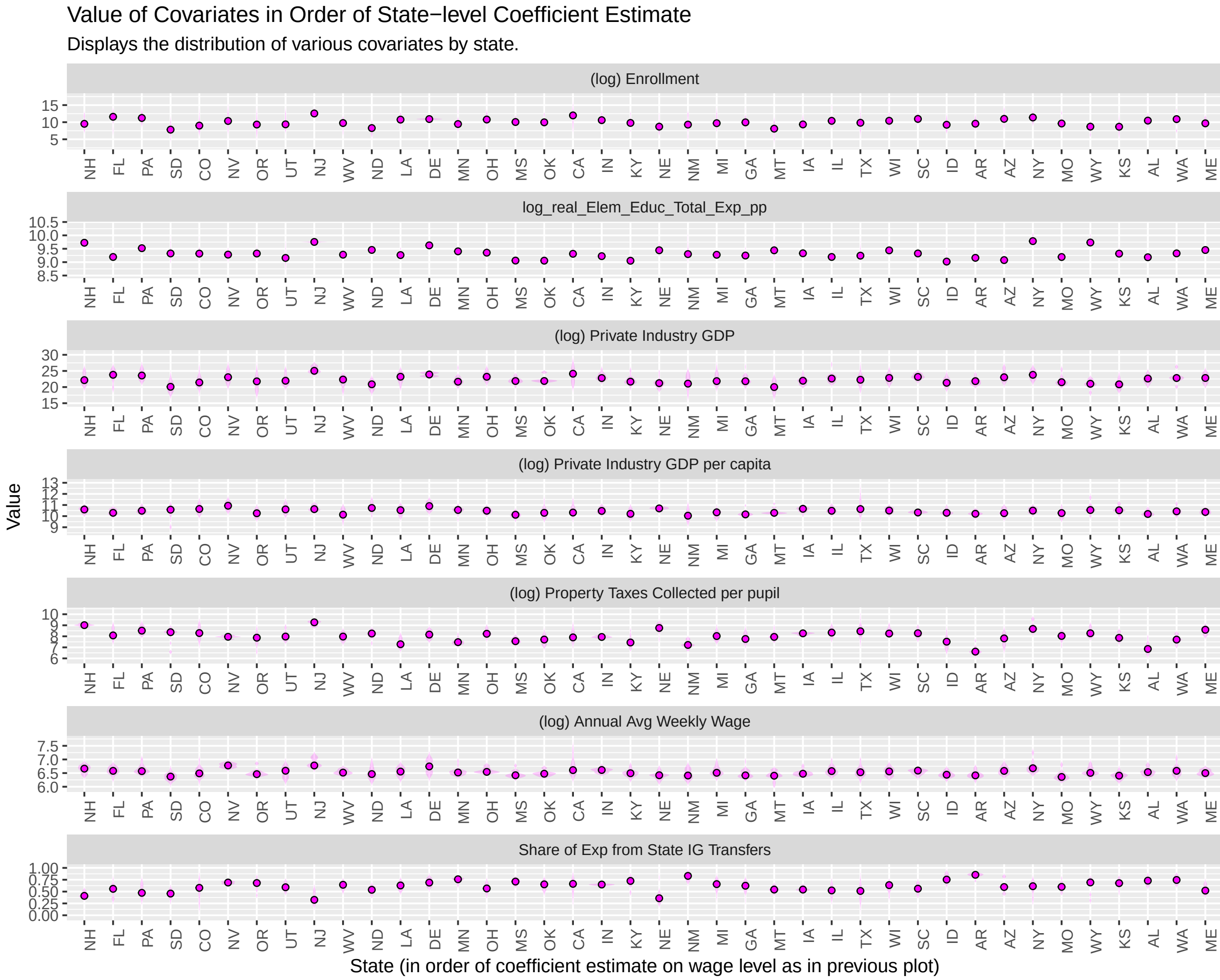
4.3.5.1 Baseline



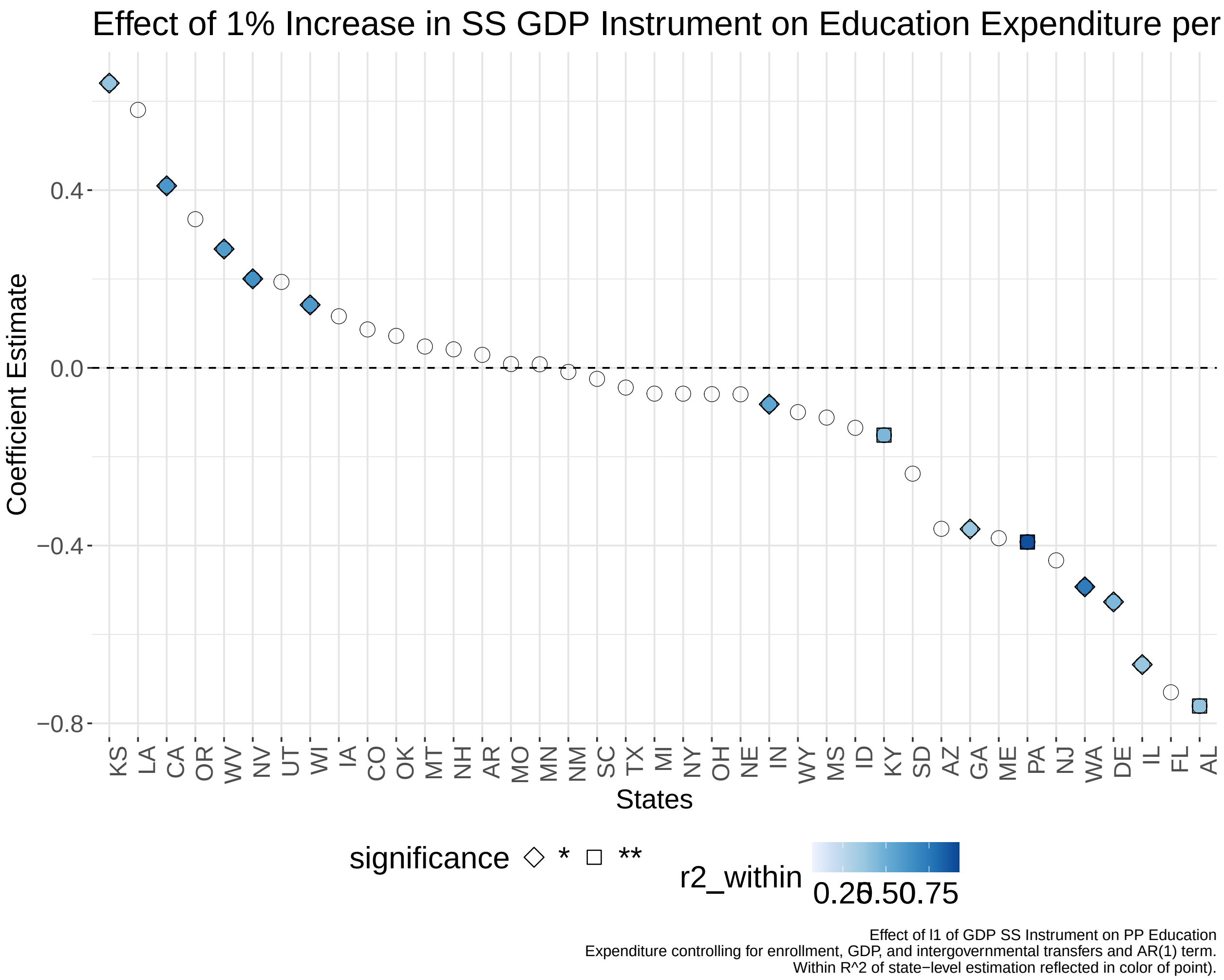
Distribution of Number of Commuting Zones per State
Number of States
Number of commuting zones in state
0
2
4
6
8
0
20
40
60

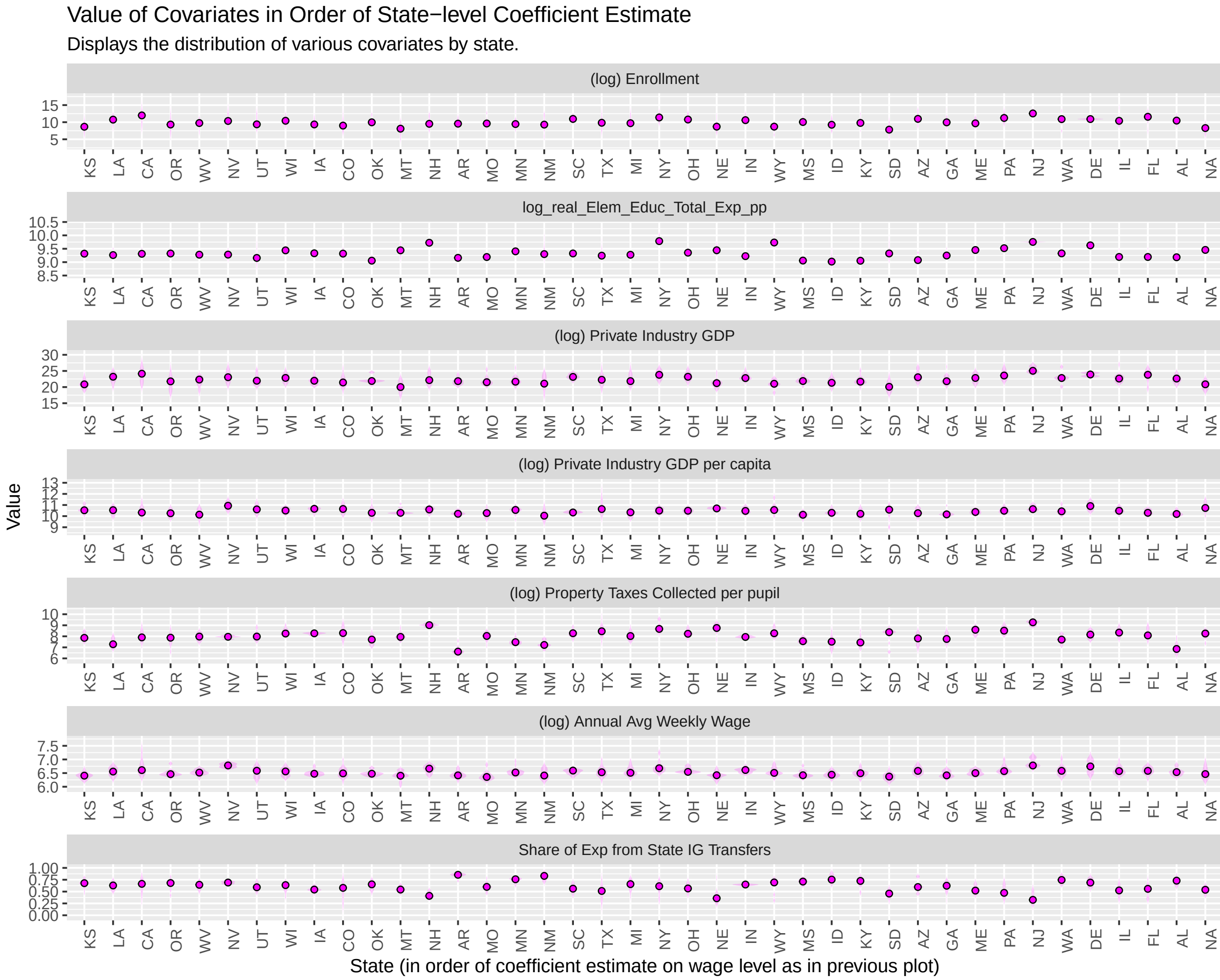


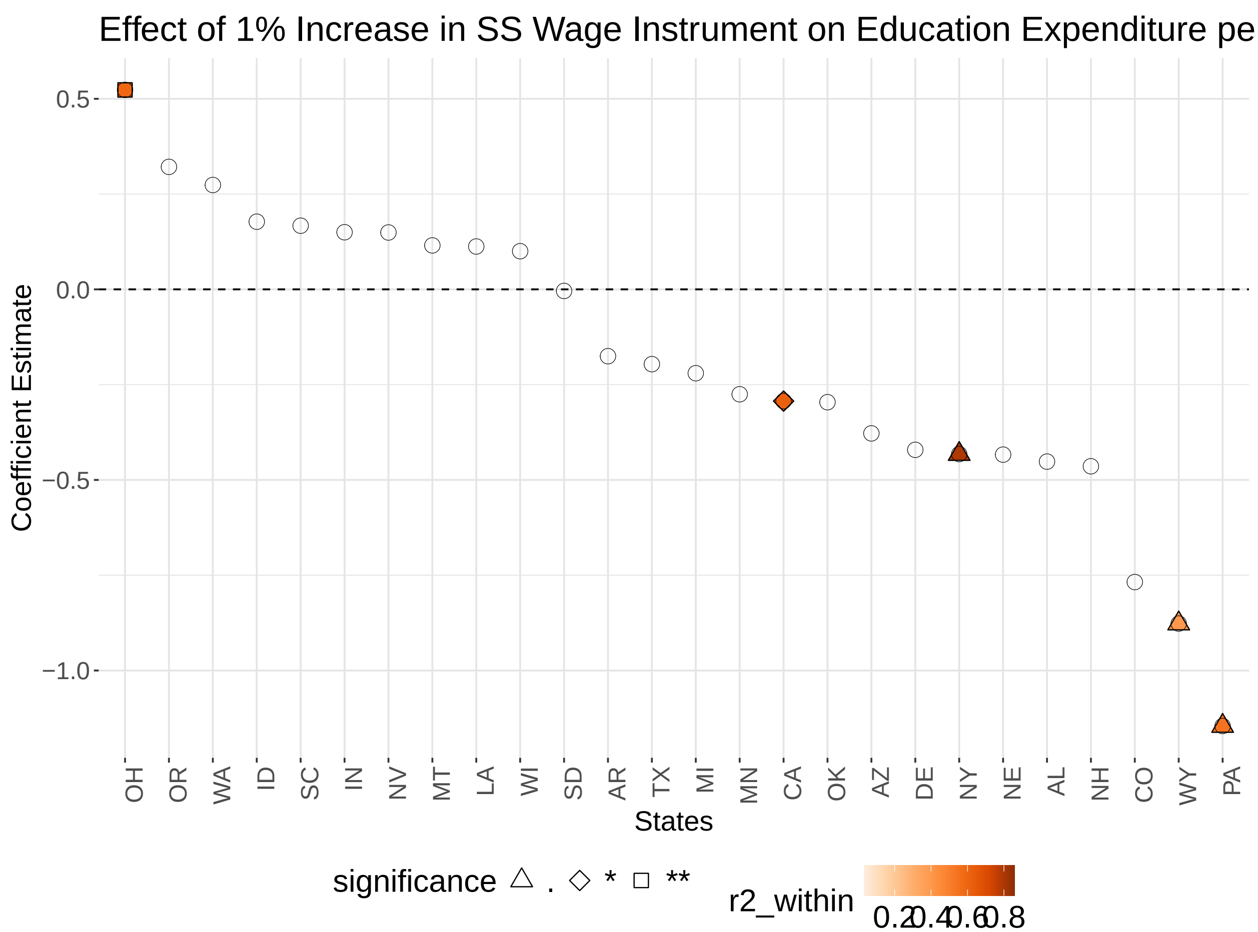
Effect of contemporaneous, l1, l2 lag of avg weekly wage on PP Education Expenditure controlling for enrollment, GDP, and intergovernmental transfers.
Each state has 3 lagged wage coefficients (l0, l1, l2).
Blue dots show total effect across lags, plotted at the l1 position.
Within R^2 of state−level estimation reflected in color of point).



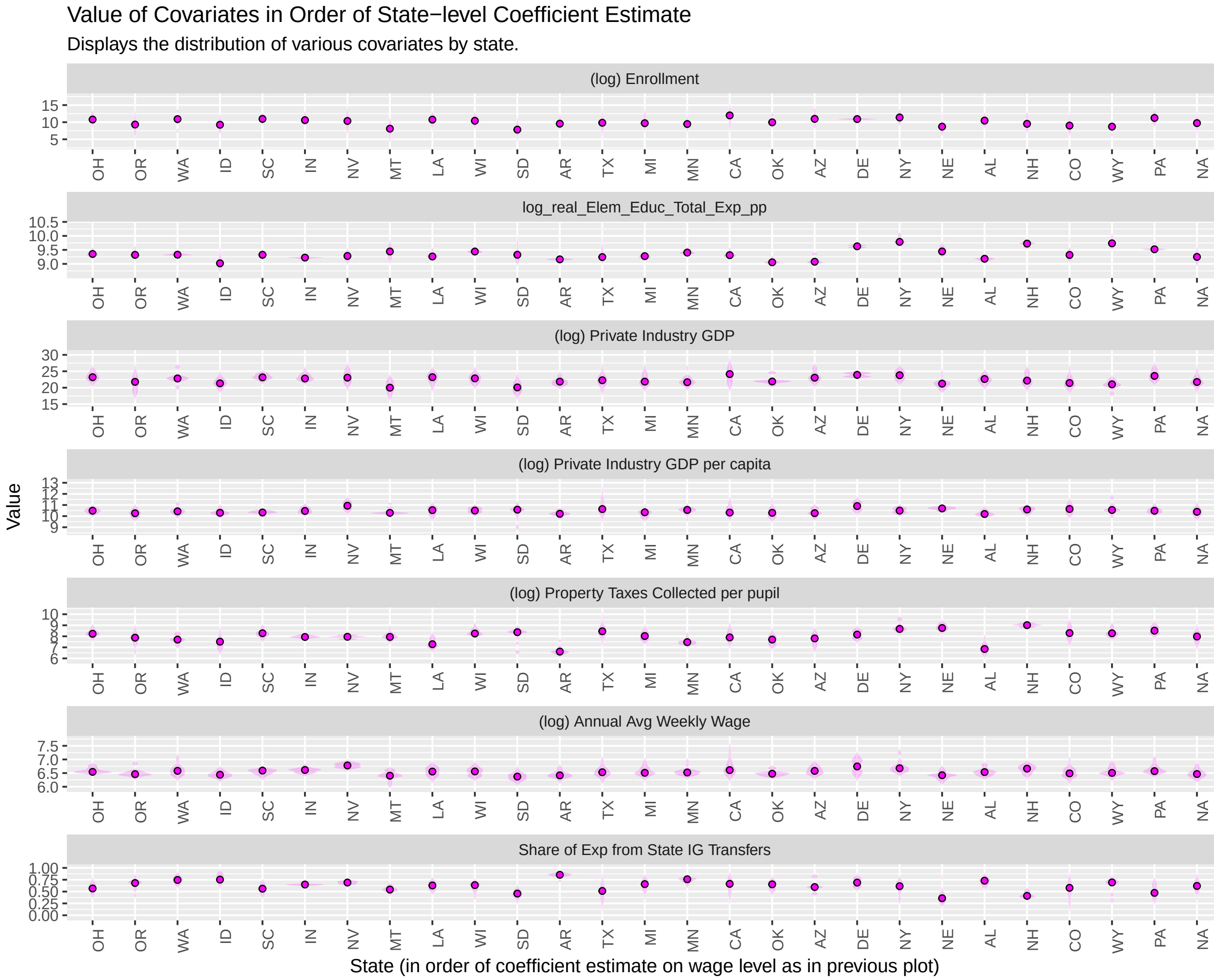
4.3.5.2 Shift-share


Effect of 1% Increase in SS GDP Instrument on Education Expenditure per
Coefficient Estimate
0.4
0.0
−0.4
−0.8
KS LA CA OR WV NV UT WI IA CO OK MT NH AR MO MN NM SC TX MI NY OH NE IN WY MS ID KY SD AZ GA ME PA NJ WA DE IL FL AL
States
significance * **
r2_within
0.25 0.50 0.75
Effect of l1 of GDP SS Instrument on PP Education
Expenditure controlling for enrollment, GDP, and intergovernmental transfers and AR(1) term.
Within R^2 of state−level estimation reflected in color of point).

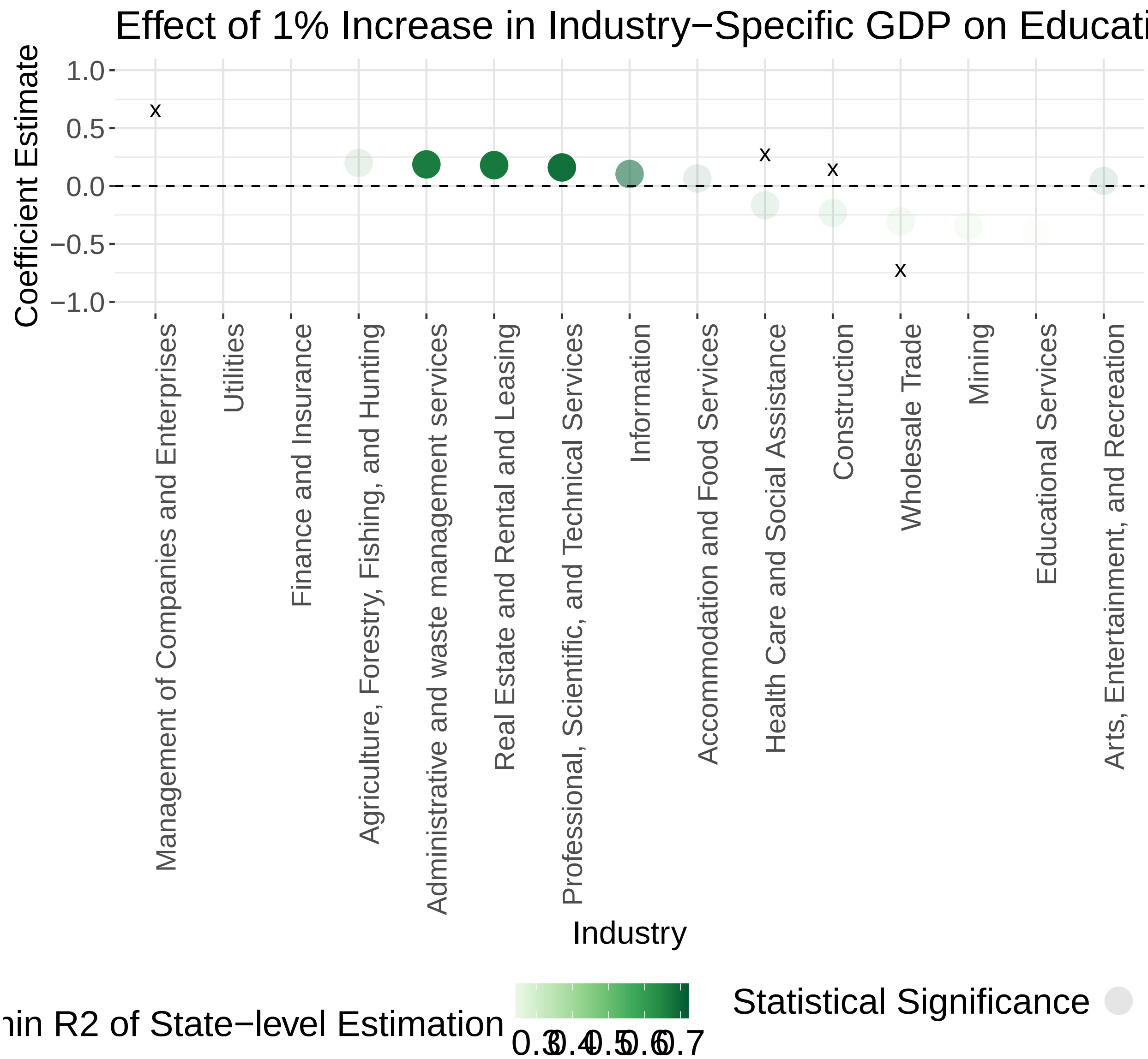

Value of Covariates in Order of State−level Coefficient Estimate
Displays the distribution of various covariates by state.
(log) Enrollment
log_real_Elem_Educ_Total_Exp_pp
(log) Private Industry GDP
(log) Private Industry GDP per capita
(log) Property Taxes Collected per pupil
(log) Annual Avg Weekly Wage
Share of Exp from State IG Transfers
Value
KS LA CA OR WV NV UT WI IA CO OK MT NH AR MO MN NM SC TX MI NY OH NE IN WY MS ID KY SD AZ GA ME PA NJ WA DE IL FL AL NA
State (in order of coefficient estimate on wage level as in previous plot)



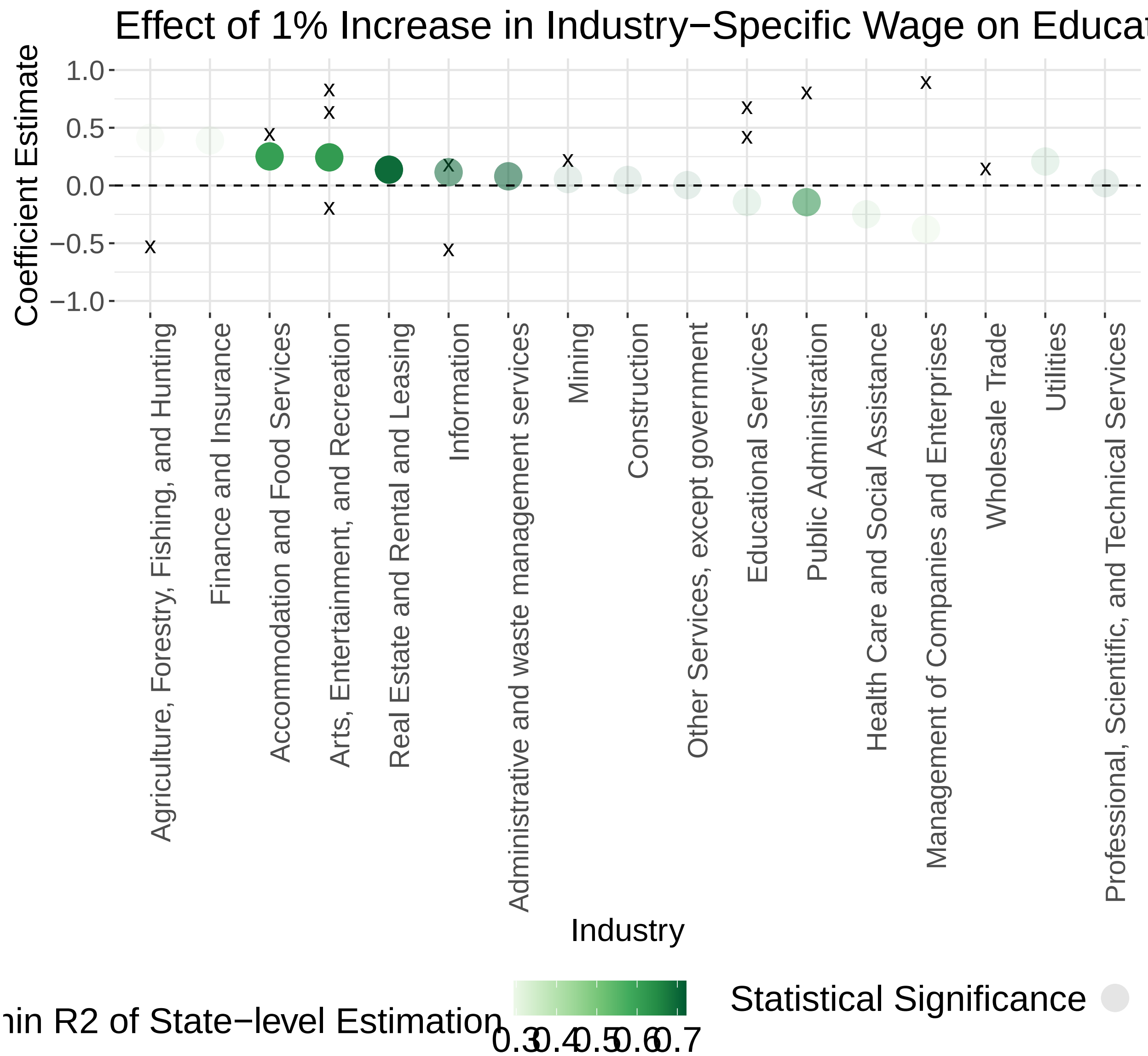
Effect of l1 of Wage SS Instrument on PP Education
Expenditure controlling for enrollment, GDP, and intergovernmental transfers and AR(1) term.
Within R^2 of state−level estimation reflected in color of point).



4.3.5.2.1 Industry by Industry: GDP

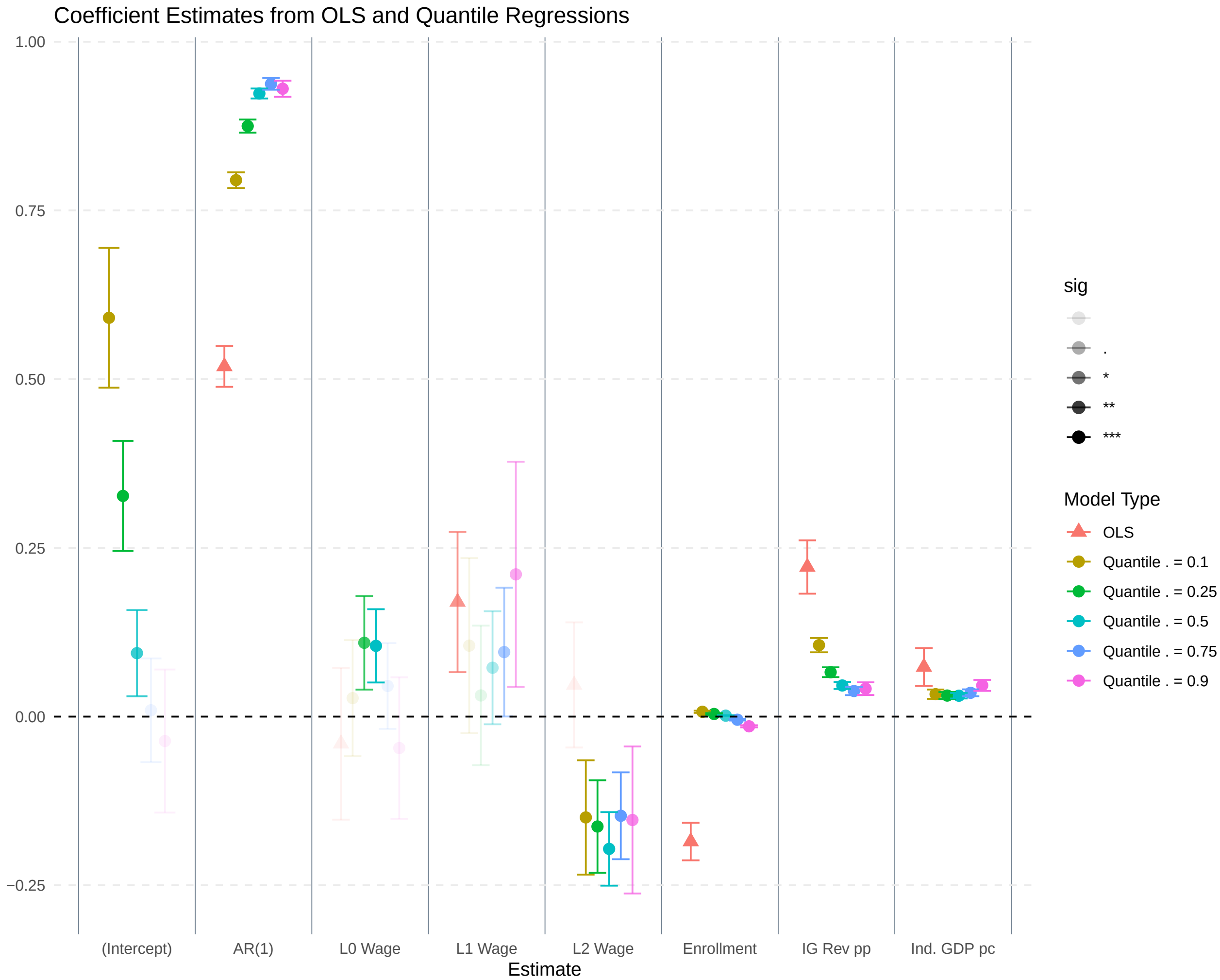


Effect of 1% increase in Industry−Specific GDP (measured as shift−share instrument) on Education Expenditure controlling for enrollment, GDP, and intergovernmental transfers, AR(1) term, year and state−level fixed effects. Within R^2 of estimation reflected in color of point).



Effect of 1% increase in Industry−Specific Wage (measured as shift−share instrument) on Education Expenditure controlling for enrollment, GDP, and intergovernmental transfers, AR(1) term, year and state−level fixed effects. Within R^2 of estimation reflected in color of point).

4.3.6 Quantile Regression



5 Property Prices

Dependent Variables:	(log) House Price Index	(GR) House Price Index	log_real_Elem_Educ_Total_Exp	diff_log_real_Elem_Educ_Total_Exp	(log) Elem.Ed.Exp.pp	(GR) Elem.Ed.Exp.pp
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(log) Annual Avg. Wkly. Wage	0.5112***		0.1377*		0.2436***	
	(0.0648)		(0.0746)		(0.0646)	
(log, l1) Annual Avg. Wkly. Wage	0.2073***		0.1899***		0.1661***	
	(0.0377)		(0.0549)		(0.0579)	
(log, l2) Annual Avg. Wkly. Wage	0.2874***		0.1542**		-0.0011	
	(0.0892)		(0.0773)		(0.0590)	
(log) Real GDP Priv. Industry	0.1224***		0.0257			
	(0.0265)		(0.0214)			
(GR) Annual Avg. Wkly. Wage		0.3141***		0.0609		0.0369
		(0.0332)		(0.0506)		(0.0552)
(GR, l1) Annual Avg. Wkly. Wage		0.3308***		0.1867***		0.1652***
		(0.0319)		(0.0481)		(0.0498)
(GR, l2) Annual Avg. Wkly. Wage		0.2514***		0.2743***		0.2146***
		(0.0253)		(0.0492)		(0.0495)
l1_log_real_gdp_priv_ind			0.0481***			
			(0.0138)			
l2_log_real_gdp_priv_ind			0.1291***			
			(0.0238)			
diff_log_real_gdp_priv_ind				0.0064		
				(0.0139)		
l1_diff_log_real_gdp_priv_ind				0.0343***		
				(0.0132)		
l2_diff_log_real_gdp_priv_ind				0.0031***		
				(0.0011)		
(log) Real GDP Priv. Industry pc					-0.0112	
					(0.0203)	
(log,l1) Real GDP Priv. Industry pc					0.0306**	
					(0.0145)	
(log,l2) Real GDP Priv. Industry pc					0.0873***	
					(0.0214)	
(GR) Real GDP Priv. Industry pc						0.0029
						(0.0160)
(GR,l1) Real GDP Priv. Industry pc						0.0185
						(0.0141)
(GR,l2) Real GDP Priv. Industry pc						0.0165***
						(0.0049)
Fixed-effects						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,612	12,585	11,856	11,855	11,856	11,855
R^2	0.96752	0.41767	0.99640	0.09403	0.82812	0.07072
Within R^2	0.30439	0.05311	0.16011	0.01143	0.07834	0.00665

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	(log) Elem.Ed.Exp.pp
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	0.1770***
	(0.0597)
(log,l2) Real GDP Priv. Industry pc	0.0622**
	(0.0259)
(log) Prop Taxpp	0.1940***
	(0.0157)
(log) House Price Index	0.1643***
	(0.0197)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	11,521
R^2	0.84815
Within R^2	0.18964

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	(log) Elem.Ed.Exp.pp
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage × share_own_discrete = 1=high	0.1663^{**}
	(0.0650)
(log) Annual Avg. Wkly. Wage × share_own_discrete = 2=medium	0.1866^{***}
	(0.0602)
(log) Annual Avg. Wkly. Wage × share_own_discrete = 3=low	0.1425^{**}
	(0.0652)
(log,l2) Real GDP Priv. Industry pc	0.0609^{**}
	(0.0262)
(log) Prop Taxpp	0.1960^{***}
	(0.0160)
(log) House Price Index	0.1645^{***}
	(0.0200)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	11,521
R^2	0.84830
Within R^2	0.19044

Clustered (unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

6 Results

7 Discussion

8 Conclusion

The determinants of inequality in public education delivery in the US are multiple and complex. Significant evidence exists of the role of historically discriminatory policies related to congressional districting, under-investment in low-income areas of color. Though this work does not directly inform this debate, further work could explore the extent to which wage growth interacts with such structural policies.

Appendices

A Potential Methodological Challenges

Below, I provide a brief discussion of anticipated methodological challenges and constraints.

A.1 Structure of Financing for Local Public Education

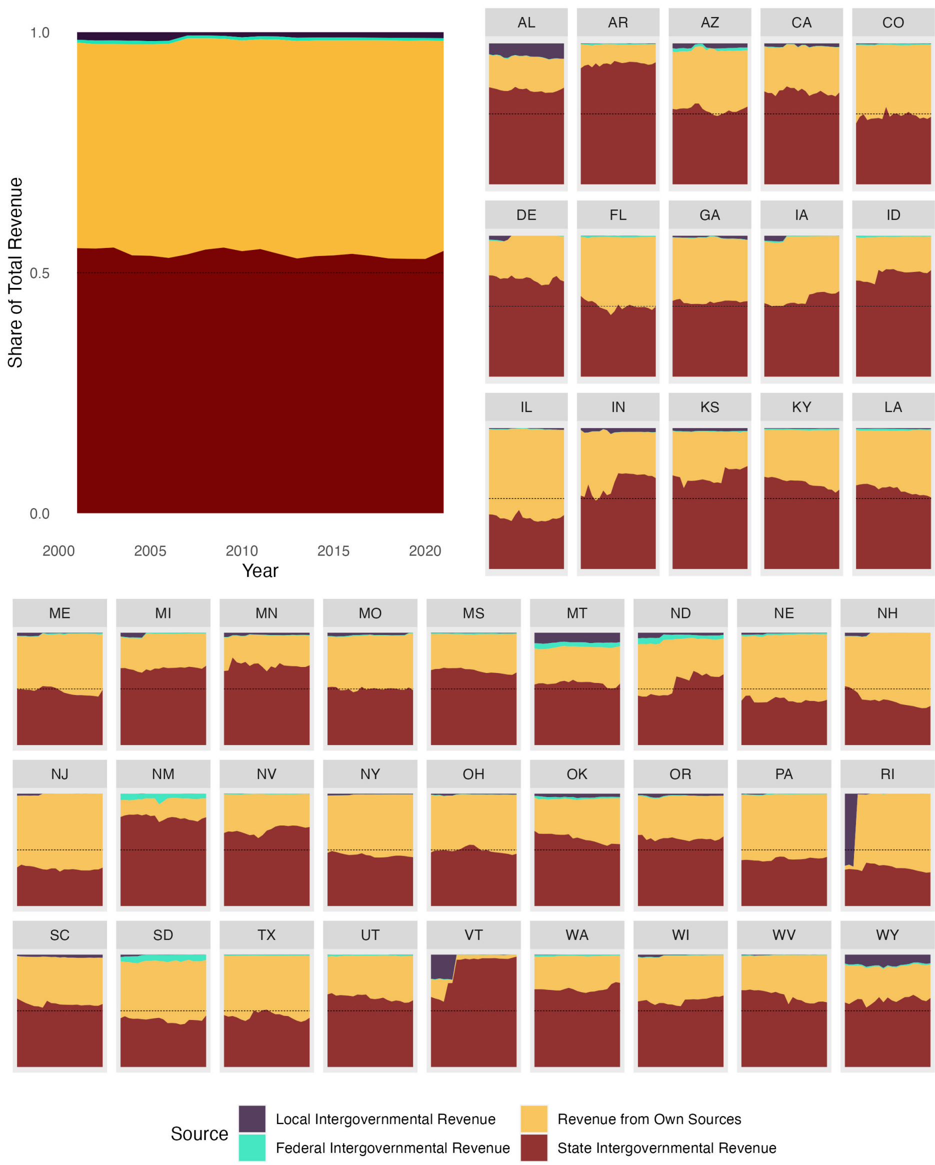
In order to appropriately make use of the outlined data as well as robustly define the econometric methods to be utilised in this work, an understanding of the funding structure of

public school districts in the US is critical. Public school districts in the United States are funded by a combination of federal (8.3% in 2019), state (47% in 2019), and local (44.8% in 2019) revenues **?**, with shares varying by county. This variation in public funding structure will need to be incorporated into the modelling efforts, likely through a weighted regression approach based on shares of intergovernmental versus own-source revenues **?**. Using the data outlined, Figure 3 displays the share of public education revenue coming from three sources of intergovernmental revenue (federal, state, and local) as well as revenue from own county-level sources by state. The figure demonstrates the clear near-even split between state intergovernmental and own source revenue and the overall small share of revenue coming from federal or other local governments. The larger panel on the top left provides the summarising share at the national level. All plots share the axes as labeled in the top left panel.

A.2 Trends over time

According to the most recent data available from the US Congressional Research Service, the revenue share has shifted from local to state sources whereas federal funding has remained the same albeit with fluctuations over time **?**.

Figure 3: Share of Revenue from Federal, State, Local Sources



A.3 Historical efforts to “equalise” US public education

Another factor that greatly impacts the data generating process in this study is that increasing recognition of the level of inequality of public education provision in the US has led to the implementation of several efforts to “equalise” public education by aiming for ”per pupil” expenditure targets ?. The most significant change in this respect has been the creation of Educational Service Agencies (ESAs). These ESAs are apportioned state funding to serve multiple school districts in sub-regions of each state. Most of these ESAs were established around 2007 and persist to this day. ESAs are listed by state in Table 6. Currently, there are 553 agencies nationwide in 45 states. According to the Association of Educational Service Agencies (AESA), ESAs reach over 80% of the public school districts and well over 80% of public and private school students. Annual budgets for ESAs total approximately $15 billion ?. Because ESA revenue and expenditure is inconsistently reported across years in our dataset, as well as attributed to individual counties despite often serving multiple, there is a significant risk that ESA expenditure is misattributed to counties in our dataset. Therefore, I exclude ESA revenue and expenditure totals from the measures of county-level expenditure and revenue at all levels of aggregation, and retain these values as possible control variables.

Preliminary investigation, both descriptive and using regression models, indicate that public expenditure from ESAs have not acted as a substitute for other revenue sources. In other words, they have not displaced intergovernmental or local school revenue. Although this fact ensures that changes in public spending on education detected in our models are not overestimated due to substitution effects from unmodelled ESA expenditure, it does risk underestimating values of actual expenditure per pupil. This remains to be resolved.

A.4 Availability of varying local-level outcomes

Approaching a more ”local” analysis of such challenges is often inhibited by data availability. First, data limitations including infrequent periodicity and missingness due to strained local reporting capacity or low stringency impose a limit on the statistical power in a panel analysis. Furthermore, infrequent periodicity poses the additional challenge to interpretation when assessing the impact of industrial changes that are often subject to within-year cyclicality.

A.5 Structural and policy heterogeneity

County-level analysis of the US poses an inherent trade-off between greater local insight and requisite model complexity. First, county-level variables are subject to unit- and time-dependent variation, which can be partly, although likely not adequately, dealt with through the incorporation of appropriate control variables and two-way fixed effects. This work will aim to incorporate consideration of spatial autocorrelation between counties to further deal with these estimation challenges. Second, and perhaps most challenging, counties are subject to state-wide regulatory, economic, and social conditions that can vary greatly across states. I aim to control for state-level variation using either an additional state-fixed effect in our regression models or state-level time trends. However, I remain wary of the residual effect of state-level heterogeneity in policy regimes and culture on our estimation results. I remain open to the idea of restricting our analysis to a smaller set of states or even a state-by-state analysis.

A.6 Cross-Sectional Dependence

This latter point on state-level heterogeneity points to an additional challenge when modelling more local- or county-level variation: cross-sectional dependence. Neighboring counties, particularly counties in the same state, will inevitably exhibit high levels of spatial dependence and auto-correlation. Adding further complication, state boundaries implicate any assumption of linearity in spatial dependence at the county level (ie. neighboring counties on either side of a state border will likely be less similar than neighboring counties within the same border).

Table 6: Educational Service Agencies by State

State	**ESA Name**	**#**
Alabama		
Alaska	Educational Resource Center (SERRC)	1
Arizona	Office County of School Superintendent	15
Arkansas	Education Service Cooperative	15
California	County Office of Education	58
Colorado	Board of Cooperative Educational Services	21
Connecticut	Regional Education Service Center	6
Delaware		
Florida	Regional Consortium Service Organization	3
Georgia	Regional Education Service Agency	16
Hawaii		
Idaho		
Illinois	Regional Office of Education; Intermediate Service Center	35; 3
Indiana	Educational Service Center	9
Iowa	Area Education Agency	9
Kansas	Interlocal Cooperative - Service Center	7
Kentucky	Education Cooperative	8
Louisiana	Special School District	0
Maine		
Maryland		
Massachusetts	Educational Collaborative	25
Michigan	Intermediate School District	56
Minnesota	Regional Service Cooperative; Intermediate School District	9; 4
Mississippi	Regional Educational Service Agency	6
Missouri	Educational Service Agency	4
Montana	Educational Cooperative	2
Nebraska	Educational Service Unit	17
Nevada		
New Hampshire	Educational Service Center	4
New Jersey	Educational Services Commission	11
New Mexico	Regional Education Cooperative	10
New York	Board of Cooperative Educational Services	37
North Carolina	Regional Educational Service Agency	8
North Dakota	Regional Education Association	7
Ohio	Educational Service Center	51
Oklahoma		
Oregon	Educational Service District	19
Pennsylvania	Intermediate Unit	29
Rhode Island	Educational Collaborative	3
South Carolina	Regional Consortium	6
South Dakota	Educational Service Unit	14
Tennessee	Educational Cooperative	Unknown
Texas	Regional Education Service Center	20
Utah	Regional Education Service Agency	4
Vermont		
Virginia		
Washington	Educational Service District	9
West Virginia	Educational Service Cooperative	3
Wisconsin	Cooperative Educational Service Agency	12
Wyoming	Board of Cooperative Educational Services	3

[a] Source: Association of Educational Service Agencies, State by State ESA Report 2021

B Descriptive Regression Results

In the following set of results, I report descriptive regressions to establish relationships between property taxes, education expenditure, GDP (total, private industry, O&G&mining), etc. All regression models that follow include TWFE (CZ- and year- fixed effects) and standard errors clustered by commuting zone. All functional forms in the feols() functions below are of the form Y ~ X In the cases in which multiple estimations are included via sw(Xa, Xb, Xc + Xd), the function will return results for Y~Xa, Y~Xb, Y ~ Xc + Xd.

```
## Property Tax ~ GDP

GDP has a highly relevant relationship to property taxes. A 1% increase in GDP (per capita) leads to a
```

B.1 Education Expenditure ~ Revenue Sources

The below regressions are included to establish the relationship between education expenditure and its component parts. These regressions simply corroborate what is displayed in the section on Key Relationships in LINK (ie. that the largest form of IG revenue is state funding and Own Source revenue is largely sourced from Property Taxes).

```
## Education Expenditure ~ GDP

A 1% increase in GDP pc is associated with a 0.19% increase in education expenditure per pupil, dominat
```

C Key Relationships between Economic Variables

Below we display key relationships between several of the economic variables in our study.

```
## Baseline Regressions with State Fixed Effects

Regressions establishing baseline relationships between local economic variables and elementary educati
```

C.1 SS Construction

Plots of the data inputs to the shift-share instrument.

“‘

C.2 Panel VAR Specification

$$Y_{it} = \alpha_i + \sum_{k=1}^{4} \gamma_k A_{i,t-k} + \beta X_{it} + \varepsilon_{it}$$

Where we approach a level and per capita value expression of the relationship between total education expenditure, intergovernmental revenue, house prices conditioned on GDP and wage levels.

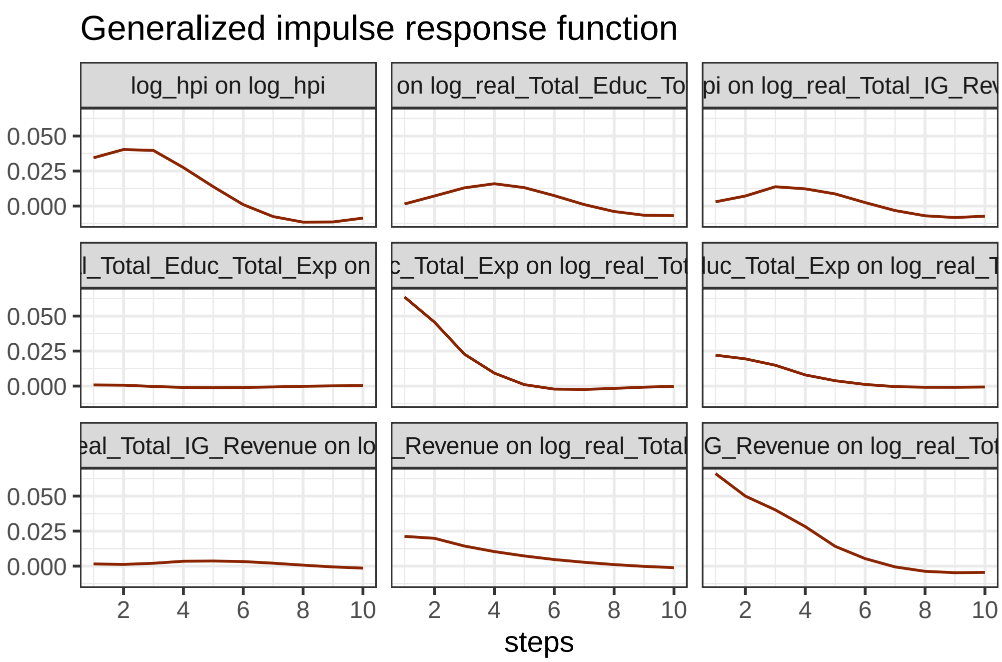
$$Y_{it} = \begin{bmatrix} \log(\text{real Total Educ. Exp.})_{it} \\ \log(\text{real Total IG Revenue})_{it} \\ \log(\text{HPI})_{it} \end{bmatrix}, \quad X_{it} = \begin{bmatrix} \log(\text{real GDP})_{it} \\ \log(\text{wage})_{it} \end{bmatrix}$$

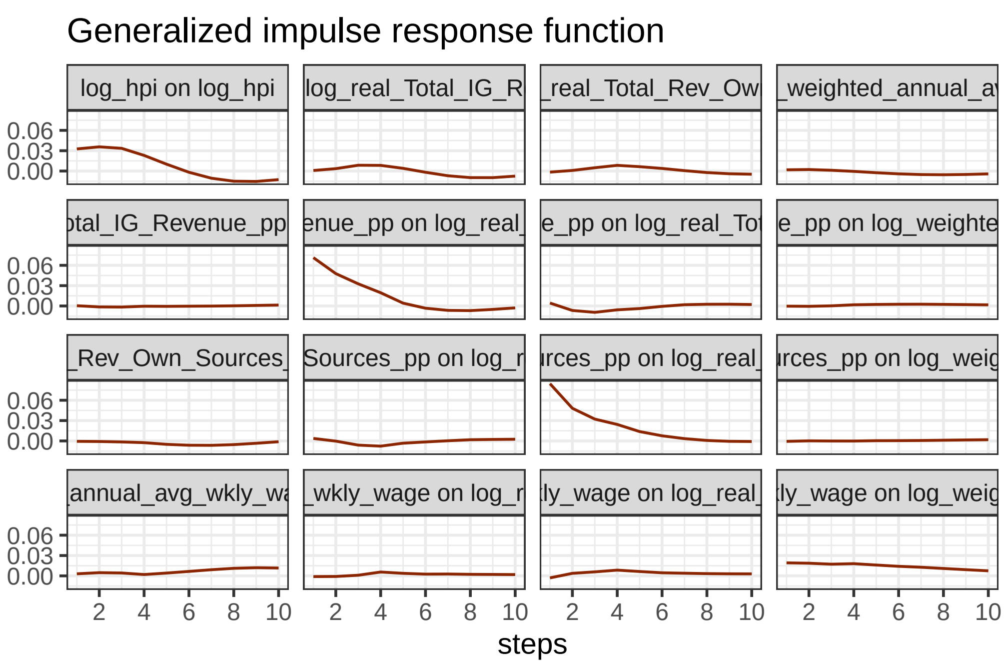
- A_1, A_2, A_3, A_4 are 3×3 coefficient matrices
- β is a 3×2 matrix of coefficients on the exogenous variables
- α_i is a vector of unit fixed effects
- ε_{it} is the error term

Where

$$
Y_{it} = \begin{bmatrix} \log(\text{real Own Source Rev. per person})_{it} \\ \log(\text{real IG Revenue per person})_{it} \\ \log(\text{wage})_{it} \\ \log(\text{HPI})_{it} \end{bmatrix}, \quad X_{it} = [\log(\text{real GDP per capita})_{it}]
$$

- A_1, A_2, A_3, A_4 are 4×4 coefficient matrices
- B is a 4×1 coefficient matrix
- α_i unit fixed effects
- ε_{it} error term





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