Uneven Wage Growth and Public Goods

The Case of US Public Education

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Abstract

Explores the effect of uneven industrial wage 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 greater income and wealth inequality.

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1 Procedural Notes

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 - plausible exogeneity comes from industrial shares. Need to justify the choice of base-year for the shift-share instrument such that industries were "present" but still nascent (this is important because there are likely to be certain industries that "cropped up" post-baseline completely unrelated to the industrial composition before right?)

Recall the work from the previous meeting:

1. After reading more work on US economic geography, it became clear that aggregating counties up to commuting zones was the better choice for analysis at sub-state level as these areas more accurately represent local labour markets/economies/commuting zones David Dorn's Resource Page Fowler et al. 2024.
2. Below, I provide some baseline regressions to demonstrate the relationships between key variables in the dataset.
3. Next, I turn to an instrumental variable application in which I use coal mine counts and production volumes as an instrument for property taxes. Coal mine counts do not serve as good instruments but coal production passes relevance and exogeneity restrictions. I believe a strong argument can be made for the exclusion restriction to be satisfied. I provide supporting statistical tests for all that demonstrate the unfitness of coal mine counts but fitness of coal production. Along this line, we can hopefully discuss other sources of variation in industrial/economic productivity that might lead to property value spirals (positive or negative) to test the property tax channel.
4. I identify declining vs. growing regions by estimating commuting-zone growth rates conditional on state and national level growth rates. Using this distinction (on both a per capita and total gdp bases and a lenient vs. stringent magnitude threshold), I rerun the key regressions identified in steps 2 and 3 on the subgroups (declining and growing regions).

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

2 Introduction

Although emissions-intensive energy demand is (somewhat) uniformly distributed across the country, extraction of inputs to energy supply is highly geographically concentrated Tomer, Kane, and George (2021), Lim, Aklin, and Frank (2023), Hendrickson, Muro, and Galston (2018) .[1]

[1] Currently, about 1.7 million people (1% of US employment) work in the fossil fuel sector. The fossil fuel sector is defined here as all oil, gas, and coal operations including extraction, support activities, and utilities Tomer, Kane, and George (2021).

Concentrated industries often play a significant role in community-building and, in certain instances, create entire communities that were not there before Bell and York (2010), Lochery (2022), Rhodes, Price, and Walker (2020), Hendrickson, Muro, and Galston (2018), Walker (2021) . If not handled with care, disentangling fossil fuel production from communities dependent on the industry can, and already has, resulted in some of the well-documented ills that often accompany poorly managed deindustrialisation Rhodes, Price, and Walker (2020). For example, declines in manufacturing jobs (including coal extraction) in pockets of the US have led to documented underemployment, a rise in deaths of despair, and a rising discontent with existing political structures Autor, Dorn, and Hanson (2013), Broz, Frieden, and Weymouth (2021), Farré, Fasani, and Mueller (2018), Metcalf and Wang (2019), Young et al. (2023), Rodríguez-Pose, Lee, and Lipp (2021), Mathews and Botero (2010), McLean (2016), Carley, Evans, and Konisky (2018) .

Finally, the US labor market is historically, socially, and politically embedded in the fossil fuel industry in a spatially heterogeneous way Lim, Aklin, and Frank (2023) . [2]

Furthermore, the dismantling of an embedded industry risks clashing with community economic identities formed around it. Evidence from political economy, ethnographical, and economic history investigations indicate the presence and strong persistence of community economic identities, particularly as they interact with questions of class Bell and York (2012), Bell and York (2010) . For example, long-term exposure to oil and gas production in counties across the US have been found to influence current climate change denial, even when such production ceased decades earlier Dewitte (n.d.) .

Stoking such community economic identities have been found to contribute to polarization if they are under particular economic duress or pressure. For example, Stewart et al. find, through a two-group agent-based model of social interactions under different economic conditions, that under conditions of economic decline or increasing inequality, some members of the population benefit from adopting a risk-averse, in-group favoring strategy Stewart, McCarty, and Bryson (2020) . Look at sources cited in Stewart et al. good lit review on the effect of economic decline on polarisation.

Abolishing the fossil fuel industry would also eliminate one of the most dangerous legal professions on offer in the United States. Decarbonisation, although it stands to set off the cascading local effects of deindustrialisation, could importantly eliminate some of the more dangerous and grueling professions legally available in the US. According to the US Occupational Safety and Health Administration, mining is consistently reported as one of the top ten most dangerous occupations in the US from the perspective of workplace injury and death. [Could include statistic here about black lung disease as an affliction only affecting miners - 16% of miners with 25 years of work experience - incurable with life expectancy reduced by 8-12 years.]

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.

- Proof of cointegrating relationship
- Economic diversity and public well-being

A recent study by Resources for the Future found that 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. The study also finds that Wyoming, North Dakota, Alaska, and New Mexico are the states

Although this number is small in relation to overall US employment, these workers are highly geographically concentrated with entire communities often dependent on these industries for their livelihoods Lim, Aklin, and Frank (2023), Hendrickson, Muro, and Galston (2018), Tomer, Kane, and George (2021), Aklin and Urpelainen (n.d.). Additionally, the workers set to be displaced by a green transition are not located in the areas that will see the greatest job growth and have historically exhibited low geographic mobility Lim, Aklin, and Frank (2023).

[2] Somewhat fortunately, the proportion of US workers embedded in the fossil fuel industry is relatively small, implying a lower than feared cost of ensuring a just transition for these workers. In 2022, in terms of extraction, oil represents the largest source of employment with around 500,000 workers, natural gas with 200,000, and coal with 50,000 employees. This smaller number should not be interpreted as a reason not to invest in stabilising community and worker well-being given the consequences of poorly managed and localised industrial decline have been well documented in both US and global history.

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.

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. This part of my DPhil project aims to fill this critical evidence gap.

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 5 most unequal OECD countries [3].

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. [4]

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 quality of education delivered to resource-dependent communities will be of paramount importance in a net-zero transition. [5]

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

[3] 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) .

[4] 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) .

[5] 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.

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

Altogether, this evidence points to the value of identifying the extent to which expenditure on public education is reliant on fossil fuel revenues in particular geographies. In other words, this work aims to answer the following research questions:

RQ1: To what extent are local public education systems in the United States dependent on industrial prosperity?

RQ2: How can we safeguard the delivery of education as a public good given the ineffable scale and speed of required US decarbonisation?

In the sections that follow, I outline Section Section 2.1 the data to be used in the analysis; Section 2.3 the proposed methods;

2.1 Data

This work will make use of Willamette University's Annual Government Finance Database. 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 county-level to ensure the availability of adequate control and treatment variables. [6]

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 2,710 of 3,143 US

[6] 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 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 of a lack of availability of control variables at a school district level.

counties between 2001-2021. [7] [8]

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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. Therefore, no time-invariant variables are included (apart from the State in which a commuting zone is in, which is made time-variant through the inclusion of a state-level trend in various models). 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 total, private industry, and oil, gas, mining and quarrying commuting zone-level GDP.

Population controls: US Census Bureau.

Coal mine activity and production levels: Mine Safety and Health Administration

2.2 Summary statistics

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

Table 1

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
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

First, 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., changes in national fossil fuel employment levels) with time-invariant yet unit-variant shares in exposure to these macro-level changes (ie., local shares of employment in fossil fuels). 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.

[7] The reason 13% of counties 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.

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

\footnote{Autor et al use a shift-share instrument to assess the effect of Chinese import competition on manufacturing employment in US counties Autor, Dorn, and Hanson (2013) . As an extension, Feler and Senses (2017) use a similar shift-share instrument to assess the effect of the same shock on the size of local government. Baccini and Weymouth (2021) 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.}

Second, 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 Scheer et al. (2022) . 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 Tregenna and Andreoni (2020). 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, Borge, Parmer, and Torvik (2015) 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 Chen et al. (2022).

In order to arrive at a final estimation strategy, I plan to explore various treatment variables to proxy industrial transformation from the outlined alternatives. Thus far, I have employed data on coal mining activity in a two-way fixed effects ordinary least squares framework and an instrumental variable approach as well as constructed, although not yet estimated, shift-share instruments using employment and wage shares in the coal, oil and gas, and extraction sectors. I present preliminary results from these estimation efforts below. I do not yet claim that these results provide a causal interpretation nor that they are robustly specified. However, I provide these results as evidence of preliminary attempts to answer the outlined research questions as well as important building blocks toward eventually arriving at a credible estimation strategy.

2.2.1 Coal Mining Activity

First, the Mining Safety and Health Administration (MSHA) provides data at the mine level on activity and production. I have thus far aggregated this data for a panel of annual county-level estimates of the number of active coal mines and production volumes (reported in thousand short tons) between 1996-2021. I restrict the sample to 2001-2021 to align with the county finance data.[9]

2.3 Baseline TWFE Model

2.3.1 Using Standard OLS

First, I employ a two-way fixed effects ordinary least-squares panel model with standard errors clustered by county and with and without state-specific time trends. I outline the model specification immediately below:

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

$$Y_{it} = \beta_0 + \beta_x X_{it} + (t - 2000) * state_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2}$$

Y_{it} takes two values: the natural logarithm of (1) total and (2) elementary (serving ages 6-12) education expenditure per pupil for county i in year t. α_i and γ_t represent county- and year-fixed effects, respectively, and ε_{it} represents the error term. In Equation 2, $(t - 2000) * state_i$ represents a state-level trend. X_{it} takes six forms with a combination of a contemporaneous and lagged control variable (natural logarithm of private industry GDP) and contemporaneous and lagged treatment variables (change in the volume of coal produced by active coal mines and the number of active coal mines), where $h = [0, 2]$ in the specifications that incorporate time lagged variables.

[9] I do not yet make a distinction between different types of mining or coal product (ie. surface and undeground mines; (sub)bituminous, lignite, versus anthracite coal), although such distinctions are possible using the data collected.

2.3.2 Incorporating time lags

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.

Table X reports a series of fixed effects regressions estimating the association between local economic conditions and elementary education expenditure per pupil, expressed in both levels (left panel) and growth rates (right panel). Across all specifications, the results underscore the central role of intergovernmental transfers and broader local economic fundamentals in shaping patterns of education spending.

In the levels regressions, 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 0.35–0.38% 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, while lagged wage growth shows similar cumulative effects.

The house price index also enters positively and significantly in contemporaneous and short-lag specifications (up to t–3), but its influence diminishes and turns negative at longer lags. This pattern is consistent with the hypothesis that local housing markets influence education budgets through changes in property tax bases and local fiscal capacity, but that these effects are most salient in the short run and may attenuate over time due to institutional lags in budgeting and allocation.

The growth rate regressions, while explaining less variance overall (as expected), largely confirm the patterns observed in the levels specifications. Intergovernmental revenue growth remains a strong and highly significant determinant of education expenditure growth, with coefficients ranging from 0.33 to 0.40. 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 time to materialize in local education budgets. Growth in house prices also predicts increases in education spending, but these effects are concentrated in the contemporaneous and first-lag specifications.

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 fiscal inertia and political delays in budgetary response. Third, local housing markets play a more modest and short-term role in shaping education budgets, reflecting the link between property values and tax revenues, but also potential constraints in translating asset wealth into public service provision.

From a policy perspective, the findings highlight the importance of designing school finance systems that are responsive to both the timing and structure of economic change. Given the lagged transmission from labor market improvements to education investment, reliance on local economic conditions alone may exacerbate disparities in educational funding across space and time. Mechanisms that smooth fiscal shocks or front-load investment in response to projected economic growth could help ensure that educational resources more closely track the evolving needs of communities.

Dependent Variable:	(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(log) Real GDP Priv. Industry pc	0.0178		
	(0.0190)		
(log,l1) Real GDP Priv. Industry pc	0.0666^{***}		
	(0.0140)		
(log,l2) Real GDP Priv. Industry pc	0.1390^{***}		
	(0.0239)		
(log) IG Revenue pp	0.3832^{***}	0.3574^{***}	0.3699^{***}
	(0.0299)	(0.0332)	(0.0333)
(log) Annual Avg. Wkly. Wage		0.1728^{***}	
		(0.0595)	
(log, l1) Annual Avg. Wkly. Wage		0.1793^{***}	
		(0.0470)	
(log, l2) Annual Avg. Wkly. Wage		0.2481^{***}	
		(0.0794)	
(log) House Price Index			0.0791^{***}
			(0.0260)
(log, l1) House Price Index			0.0622^{**}
			(0.0273)
(log, l2) House Price Index			0.0518^{**}
			(0.0211)
(log, l3) House Price Index			0.0470^{**}
			(0.0214)
(log, l4) House Price Index			-0.0252
			(0.0220)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	12,084	13,356	12,588
R^2	0.85719	0.85074	0.85341
Within R^2	0.26497	0.24919	0.23404

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)
Variables			
(GR) Real GDP Priv. Industry pc	0.0080		
	(0.0143)		
(GR,l1) Real GDP Priv. Industry pc	0.0439***		
	(0.0152)		
(GR,l2) Real GDP Priv. Industry pc	0.0190**		
	(0.0074)		
(GR) IG Revenue pp	0.4008***	0.3304***	0.3298***
	(0.0289)	(0.0224)	(0.0227)
(GR) Annual Avg. Wkly. Wage		-0.0223	
		(0.0547)	
(GR, l1) Annual Avg. Wkly. Wage		0.1972***	
		(0.0499)	
(GR, l2) Annual Avg. Wkly. Wage		0.3088***	
		(0.0601)	
(GR) House Price Index			0.0604**
			(0.0240)
(GR, l1) House Price Index			0.1070***
			(0.0290)
(GR, l2) House Price Index			0.0599***
			(0.0206)
(GR, l3) House Price Index			0.0193
			(0.0258)
(GR, l4) House Price Index			0.0330
			(0.0213)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	12,083	13,355	12,535
R^2	0.21456	0.34883	0.36009
Within R^2	0.16403	0.15062	0.14716

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

Dependent Variable:	(log) House Price Index
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	1.140***
	(0.0564)
l(log_weighted_annual_avg_wkly_wage,1)	0.0592***
	(0.0129)
l(log_weighted_annual_avg_wkly_wage,2)	0.0616***
	(0.0166)
l(log_weighted_annual_avg_wkly_wage,3)	0.0274*
	(0.0157)
l(log_weighted_annual_avg_wkly_wage,4)	0.0804***
	(0.0207)
l(log_weighted_annual_avg_wkly_wage,5)	0.0283*
	(0.0158)
l(log_weighted_annual_avg_wkly_wage,6)	0.0346
	(0.0286)
l(log_weighted_annual_avg_wkly_wage,7)	0.0073
	(0.0193)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	12,570
R^2	0.96590
Within R^2	0.27349

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

Dependent Variable:	(GR) House Price Index
Model:	(1)
Variables	
(GR) Annual Avg. Wkly. Wage	0.3200***
	(0.0682)
l(gr_weighted_annual_avg_wkly_wage,1)	0.0059
	(0.0164)
l(gr_weighted_annual_avg_wkly_wage,2)	0.0250
	(0.0158)
l(gr_weighted_annual_avg_wkly_wage,3)	0.0021
	(0.0209)
l(gr_weighted_annual_avg_wkly_wage,4)	0.0265
	(0.0235)
l(gr_weighted_annual_avg_wkly_wage,5)	-0.0014
	(0.0201)
l(gr_weighted_annual_avg_wkly_wage,6)	-0.0104
	(0.0219)
l(gr_weighted_annual_avg_wkly_wage,7)	-0.0090
	(0.0239)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	12,543
R^2	0.39476
Within R^2	0.02003

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

Dependent Variable:					(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
(log) Real GDP Priv. Industry pc	0.0094	-0.0144	-0.0095	0.0171	0.0061	0.0041	
	(0.0203)	(0.0204)	(0.0199)	(0.0198)	(0.0195)	(0.0197)	
(log,l1) Real GDP Priv. Industry pc	0.0612***	0.0400***	0.0241	0.0344**	0.0316**	0.0348**	
	(0.0145)	(0.0153)	(0.0178)	(0.0169)	(0.0160)	(0.0164)	
(log,l2) Real GDP Priv. Industry pc	0.1325***	0.1073***	0.0944***	0.1092***	0.0989***	0.0984***	
	(0.0225)	(0.0232)	(0.0234)	(0.0197)	(0.0200)	(0.0198)	
(log) Annual Avg. Wkly. Wage		0.1998***	0.1319*	0.0483	0.0493	0.0567	0.2645***
		(0.0668)	(0.0699)	(0.0732)	(0.0754)	(0.0734)	(0.0632)
(log, l1) Annual Avg. Wkly. Wage		0.1779***	0.1339**	0.1417**	0.1537***	0.1593***	0.2201***
		(0.0525)	(0.0578)	(0.0571)	(0.0547)	(0.0551)	(0.0484)
(log, l2) Annual Avg. Wkly. Wage		0.0215	0.0090	0.0079	0.0819	0.0722	0.1945***
		(0.0637)	(0.0647)	(0.0637)	(0.0593)	(0.0604)	(0.0678)
(log) House Price Index			0.0186	-0.0310	0.0504**	0.0563**	
			(0.0299)	(0.0271)	(0.0251)	(0.0249)	
(log, l1) House Price Index			0.0726**	0.0573*	0.0501*	0.0482	
			(0.0327)	(0.0315)	(0.0301)	(0.0299)	
(log, l2) House Price Index			0.0776***	0.0498**	0.0518**	0.0496**	
			(0.0259)	(0.0245)	(0.0237)	(0.0235)	
(log, l3) House Price Index			0.0158	0.0235	0.0104	0.0097	
			(0.0237)	(0.0231)	(0.0217)	(0.0214)	
(log, l4) House Price Index			-0.0118	0.0109	0.0047	0.0029	
			(0.0260)	(0.0230)	(0.0211)	(0.0212)	
(log, l5) House Price Index			-0.0799***	-0.0588***	-0.0180	-0.0166	
			(0.0243)	(0.0207)	(0.0179)	(0.0178)	
(log) State IG Rev pp				0.3600***	0.3135***	0.3140***	
				(0.0334)	(0.0311)	(0.0310)	
(log) Fed IG Rev. pp				0.0056**	0.0030	0.0029	
				(0.0025)	(0.0023)	(0.0022)	
(log) Enrollment					-0.3678***	-0.3693***	
					(0.0272)	(0.0273)	
diff_log_pop_total						-0.1641	
						(0.1819)	
Fixed-effects							
unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	12,084	12,084	11,420	11,420	11,420	11,420	13,356
R^2	0.82088	0.82430	0.83203	0.86309	0.87531	0.87535	0.81776
Within R^2	0.07806	0.09567	0.10150	0.26763	0.33300	0.33323	0.08329

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

Dependent Variable:				(log) Elem.Ed.E	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Funding Share_state	0.3807	0.4409	-0.4090	0.6326	0.6202
	(0.6027)	(0.6279)	(0.6709)	(0.6696)	(0.6686)
(log) Real GDP Priv. Industry pc	-0.2444***	-0.2447***	-0.1677**	-0.1613**	-0.1649**
	(0.0775)	(0.0814)	(0.0778)	(0.0690)	(0.0691)
(log,l1) Real GDP Priv. Industry pc	0.1036*	0.0778	-0.0283	-0.0269	-0.0224
	(0.0614)	(0.0630)	(0.0684)	(0.0647)	(0.0649)
(log,l2) Real GDP Priv. Industry pc	0.3252***	0.2954***	0.2816***	0.2727***	0.2719***
	(0.0801)	(0.0785)	(0.0724)	(0.0672)	(0.0673)
Funding Share_state × (log) Real GDP Priv. Industry pc	0.4415***	0.3919***	0.2482**	0.2255**	0.2345**
	(0.1274)	(0.1335)	(0.1258)	(0.1118)	(0.1115)
Funding Share_state × (log,l1) Real GDP Priv. Industry pc	-0.1160	-0.1056	0.0551	0.0488	0.0367
	(0.0996)	(0.1014)	(0.1082)	(0.1025)	(0.1025)
Funding Share_state × (log,l2) Real GDP Priv. Industry pc	-0.4256***	-0.4044***	-0.3903***	-0.3933***	-0.3916***
	(0.1235)	(0.1222)	(0.1031)	(0.0964)	(0.0966)
(log) Annual Avg. Wkly. Wage		-0.0579	-0.0523	-0.0988	-0.0988
		(0.1949)	(0.1995)	(0.1986)	(0.1980)
(log, l1) Annual Avg. Wkly. Wage		0.2640*	0.1269	0.1865	0.1827
		(0.1551)	(0.2255)	(0.2181)	(0.2233)
(log, l2) Annual Avg. Wkly. Wage		0.1513	0.0969	0.2571	0.2552
		(0.1657)	(0.1791)	(0.1742)	(0.1815)
Funding Share_state × (log) Annual Avg. Wkly. Wage		0.5684*	0.4082	0.4778	0.4713
		(0.3118)	(0.3189)	(0.3138)	(0.3129)
Funding Share_state × (log, l1) Annual Avg. Wkly. Wage		-0.1879	-0.0520	-0.1324	-0.1313
		(0.2504)	(0.3474)	(0.3357)	(0.3419)
Funding Share_state × (log, l2) Annual Avg. Wkly. Wage		-0.3645	-0.2613	-0.3905	-0.3785
		(0.2823)	(0.2785)	(0.2632)	(0.2738)
(log) House Price Index			-0.1954	-0.1312	-0.1288
			(0.1300)	(0.1150)	(0.1128)
(log, l1) House Price Index			0.1465	0.1258	0.1257
			(0.1673)	(0.1577)	(0.1586)
(log, l2) House Price Index			0.4083***	0.3826***	0.3825***
			(0.1190)	(0.1101)	(0.1089)
(log, l3) House Price Index			-0.0575	-0.0651	-0.0640
			(0.0980)	(0.0943)	(0.0942)
(log, l4) House Price Index			-0.1427	-0.1313	-0.1285
			(0.1095)	(0.0995)	(0.0992)
(log, l5) House Price Index			-0.0397	0.0050	0.0002
			(0.0831)	(0.0783)	(0.0780)
Funding Share_state × (log) House Price Index			0.4394**	0.4631***	0.4510***
			(0.1983)	(0.1784)	(0.1745)
Funding Share_state × (log, l1) House Price Index			-0.1329	-0.1151	-0.1119
			(0.2474)	(0.2343)	(0.2354)
Funding Share_state × (log, l2) House Price Index			-0.5463***	-0.5047***	-0.5029***
			(0.1807)	(0.1686)	(0.1668)
Funding Share_state × (log, l3) House Price Index			0.0967	0.0887	0.0878
			(0.1542)	(0.1501)	(0.1498)
Funding Share_state × (log, l4) House Price Index			0.1836	0.1619	0.1595
			(0.1668)	(0.1532)	(0.1525)
Funding Share_state × (log, l5) House Price Index			-0.0457	-0.0442	-0.0370
			(0.1276)	(0.1210)	(0.1207)
(log) Enrollment				-0.4193***	-0.4180***
				(0.0299)	(0.0298)
Funding Share_state × (log) Enrollment				-0.0039	-0.0039
				(0.0216)	(0.0218)
diff_log_pop_total					-0.1321

2.3.3 Incorporating state-level trends

The below take the Education Expenditure ~ GDP models and incorporate deterministic state time trends.

Dependent Variable:	(log) Elem.Ed.Exp.pp						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
(log) Real GDP Priv. Industry pc	0.0152	0.0021	0.0054	0.0253			
	(0.0192)	(0.0195)	(0.0203)	(0.0200)			
(log,l1) Real GDP Priv. Industry pc	0.0550***	0.0405***	0.0256	0.0355**			
	(0.0150)	(0.0154)	(0.0179)	(0.0170)			
(log,l2) Real GDP Priv. Industry pc	0.1044***	0.0917***	0.0815***	0.1110***			
	(0.0249)	(0.0245)	(0.0243)	(0.0213)			
(log) Annual Avg. Wkly. Wage		0.0902	-0.0291	-0.0329	0.2033***	0.0758	0.1010
		(0.0652)	(0.0678)	(0.0708)	(0.0595)	(0.0626)	(0.0655)
(log, l1) Annual Avg. Wkly. Wage		0.1676***	0.1200**	0.1276**	0.1840***	0.1355**	0.1370**
		(0.0518)	(0.0560)	(0.0567)	(0.0481)	(0.0543)	(0.0547)
(log, l2) Annual Avg. Wkly. Wage		0.0289	0.0803	0.0650	0.1607**	0.2098***	0.2432***
		(0.0629)	(0.0638)	(0.0593)	(0.0758)	(0.0571)	(0.0544)
(log) House Price Index			0.0628**	0.0272		0.0676***	0.0466*
			(0.0280)	(0.0261)		(0.0248)	(0.0238)
(log, l1) House Price Index			0.0522	0.0407		0.0466*	0.0385
			(0.0321)	(0.0309)		(0.0272)	(0.0260)
(log, l2) House Price Index			0.0712***	0.0409*		0.0550**	0.0276
			(0.0254)	(0.0248)		(0.0223)	(0.0211)
(log, l3) House Price Index			0.0262	0.0244		0.0281	0.0273
			(0.0237)	(0.0228)		(0.0216)	(0.0210)
(log, l4) House Price Index			-0.0032	0.0160		-0.0037	0.0180
			(0.0260)	(0.0227)		(0.0220)	(0.0190)
(log, l5) House Price Index			-0.1303***	-0.0601***		-0.1301***	-0.0627***
			(0.0239)	(0.0212)		(0.0217)	(0.0196)
(log) State IG Rev pp				0.3695***			0.3498***
				(0.0388)			(0.0380)
(log) Fed IG Rev. pp				0.0049**			0.0033
				(0.0023)			(0.0021)
Fixed-effects							
unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	12,084	12,084	11,420	11,420	13,356	12,536	12,536
R^2	0.83997	0.84139	0.85220	0.87704	0.83621	0.84900	0.87219
Within R^2	0.17635	0.18364	0.20940	0.34226	0.17607	0.20933	0.33076

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

2.4 Instrumental Variable Approach

There is a significant endogeneity concern in using wage growth as the treatment variable. Therefore, I have tried two instrumental variable approaches below and aim to add results using production- and employment-based Bartik instruments.

A critical break-through in this work came from understanding the structure of public financing (described in further detail in Section **??** of the Supplementary Materials). In brief, revenue for public education comes from a combination of intergovernmental and local sources and revenue generated from local sources comes almost entirely from property taxes. Given this, I can isolate the channel through which I assume our treatment (industrial production) will affect our outcome variable using an instrumental variable approach. I provide the results of an initial attempt at this theory below including the functional form and underlying theoretical path diagram of the econometric specification.

We consider using XX as an instrument affecting education expenditure through property taxes or GDP. We know that property taxes have an endogenous relationship with education expenditure, however, in theory, XX is unlikely to affect education expenditure, except via property taxes. We test this hypothesis below.

As a reminder, the intuition behind the idea is

Figure 1: Instrumental Variable Path Diagram

$$
\begin{tikzcd}
 & \text{Omitted variable} \arrow[d, dashed, red] \arrow[dr, dashed, red] & \\
\text{Instrument} \arrow[r] & \text{Property Values} \arrow[r] & \text{Education Expenditure}
\end{tikzcd}
$$

As seen in Figure 1, I hypothesize that property taxes 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. However, we assume that coal mining activity has no other effect on education expenditure except through the channel of property taxes.

A more commonly used identification strategy is 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 intend to create a unit-specific time-varying treatment variable by interacting a unit-specific, time-invariant industrial employment share variable with a national-level time-varying wage growth rate.

Y_{it} takes the same two values as above. $Z_{i,t}$ takes the value of either active coal production or the number of active coal mines in county i in year t. I further test for a time lagged effect and run alternate specifications where a one- and two-year lag $Z_{i,t}$ replaces the contemporaneous value. $X_{i,t}$ is the amount of property taxes collected per pupil in county i in year t.

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

$$Z_{it} = \sum_{j=1}^{k} S_{ij\tau} G_{njt} \tag{3}$$

where S_{ij0} 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 national-level growth rates are exogenous allowing the shares to vary over time, constructing the shift-share instrument as follows:

$$Z_{it} = \sum_{j=1}^{k} S_{ijt} G_{njt} \tag{4}$$

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.

$$Z_{it} = \sum_{j=1}^{k} S_{0jt} G_{ojt} \tag{5}$$

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:

$$X_{it} = \alpha_i + \beta \sum_{j=1}^{k} S_j G_j + \epsilon_{it} \tag{6}$$

$$X_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j S_{\star j \star} G_{\star jt} + \epsilon_{it} \tag{7}$$

2.4.1 Shift-share Instrument

Finally, using data from the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), I have constructed a total of six shift-share Bartik instruments across two metrics (employment and wage) for three sectoral aggregations (oil and gas, coal, and all extractive industries) at the county-level. Figure Figure 2 above shows the shift-share instrument by county from 2001-2021. Equation 8 demonstrates the Bartik instrument as outlined in Ferri (2022) and Goldsmith-Pinkham, Sorkin, and Swift (2020) and defined in Bartik (1991) . $\Delta X_{t,s}$ represents national-level changes in either employment or wages in industry s in time t and $\frac{N_{i,\tau,s}}{N_{i,\tau}}$ represents the "sensitivity'' of a county to these national shocks proxied by an initial share of local employment or wage in industry s in a baseline time period τ. The product of these two values defines the shift-share indicator $\tilde{X}_{i,t,s}$. In Figure Figure 2, I demonstrate the wage- and employment-based shift-share instruments (each line represents a separate county) using a base period $\tau = 2001$. [10]

$$\tilde{X}_{i,t,s} = \Delta X_{t,s} * \frac{N_{i,\tau,s}}{N_{i,\tau}} \tag{8}$$

[10] 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.

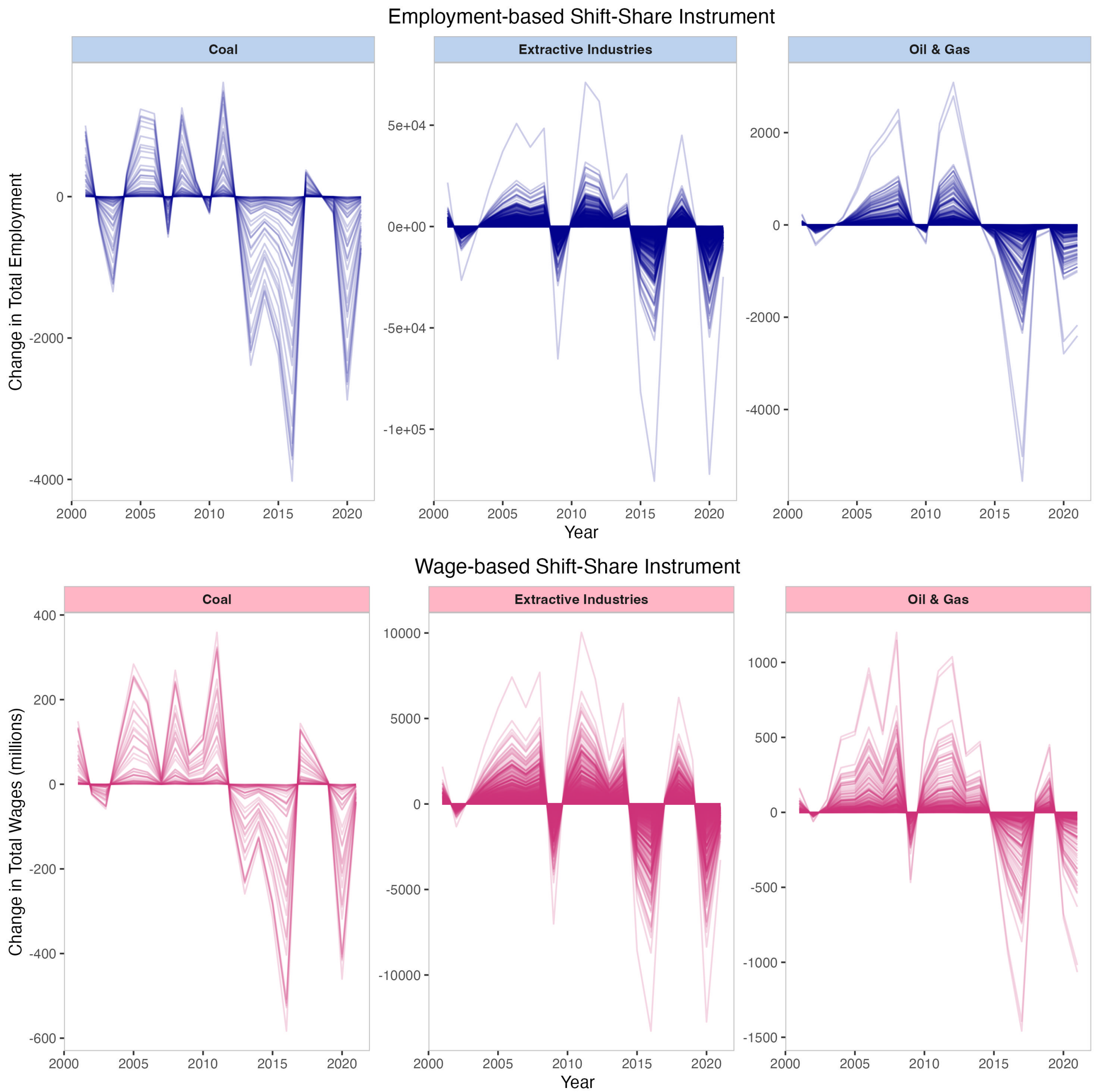
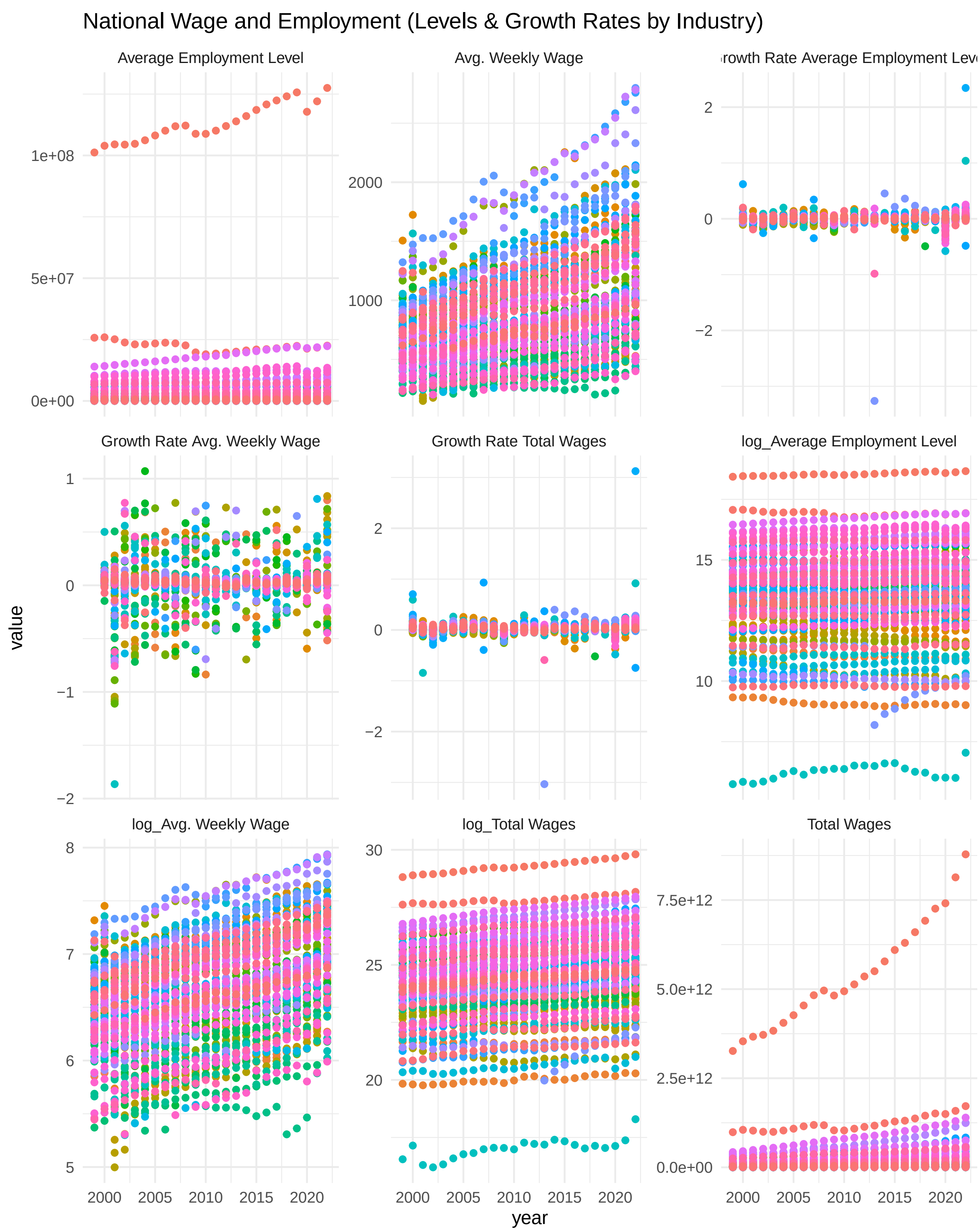
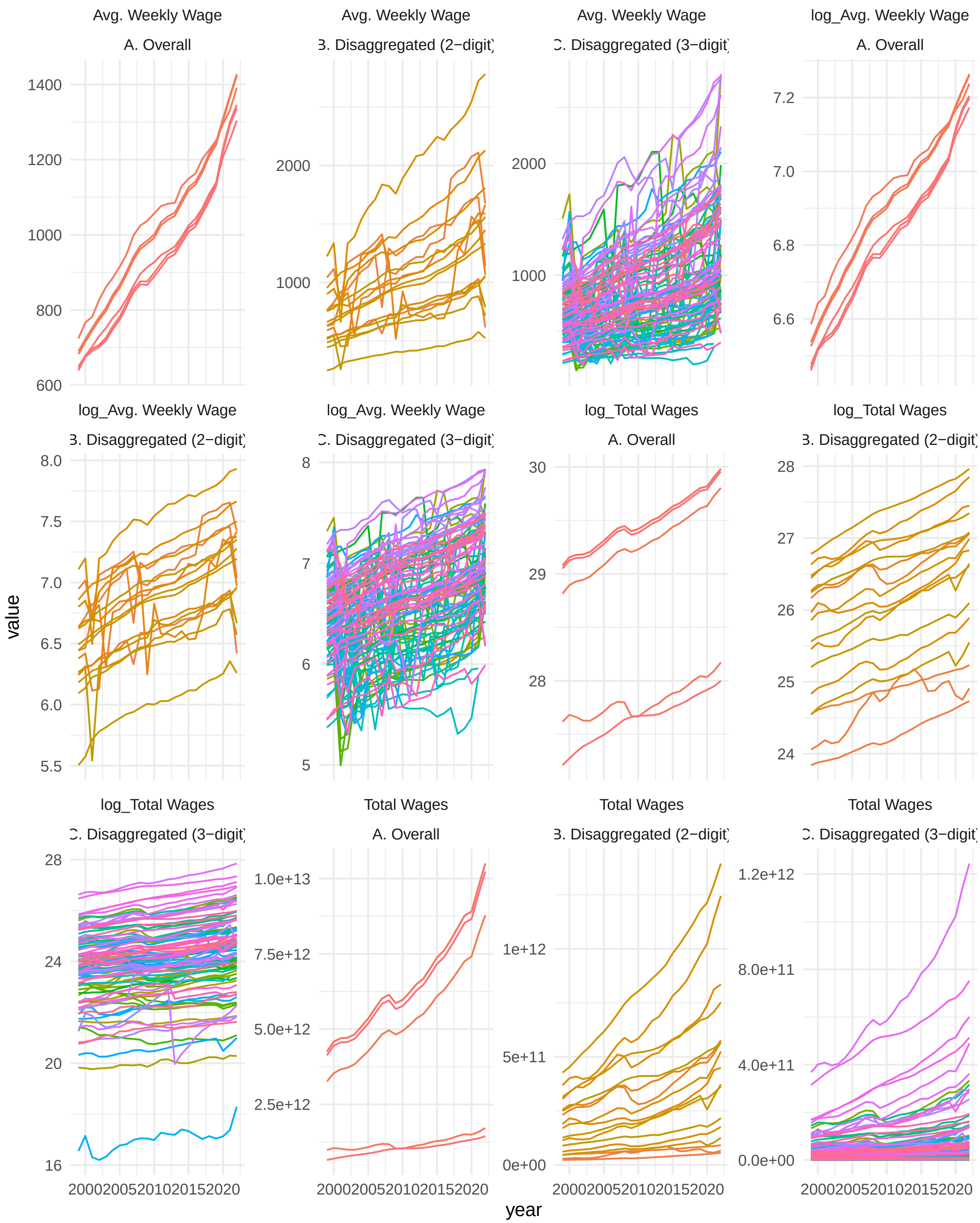
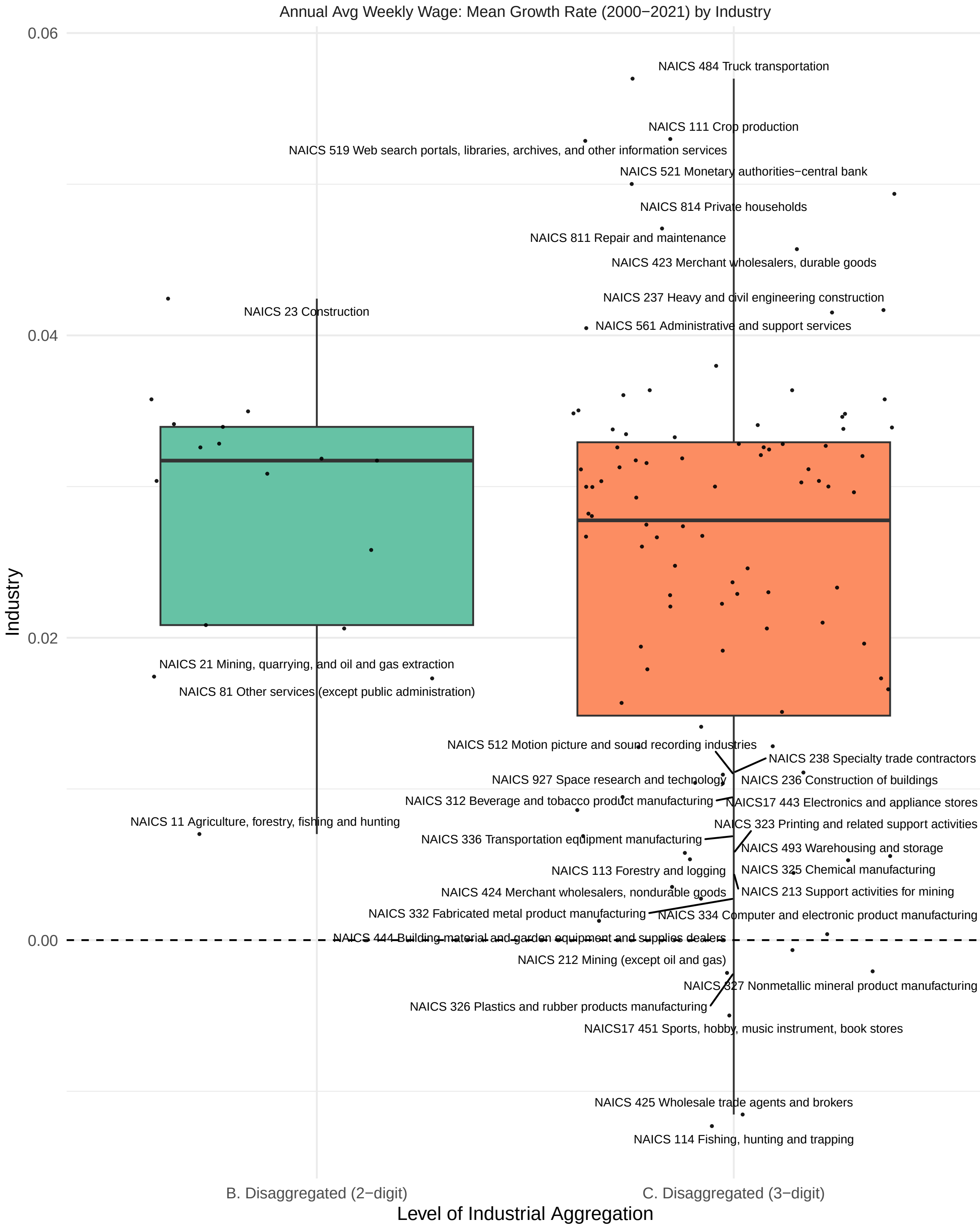


Figure 2: Coal Shift-share Instruments



National Wage and Employment (Levels & Growth Rates by Industry)
Average Employment Level
Avg. Weekly Wage
rowth Rate Average Employment Leve
Growth Rate Avg. Weekly Wage
Growth Rate Total Wages
log_Average Employment Level
log_Avg. Weekly Wage
log_Total Wages
Total Wages
value
year
0e+00
5e+07
1e+08
1000
2000
−2
0
2
−2
−1
0
1
10
15
5
6
7
8
20
25
30
0.0e+00
2.5e+12
5.0e+12
7.5e+12
2000
2005
2010
2015
2020

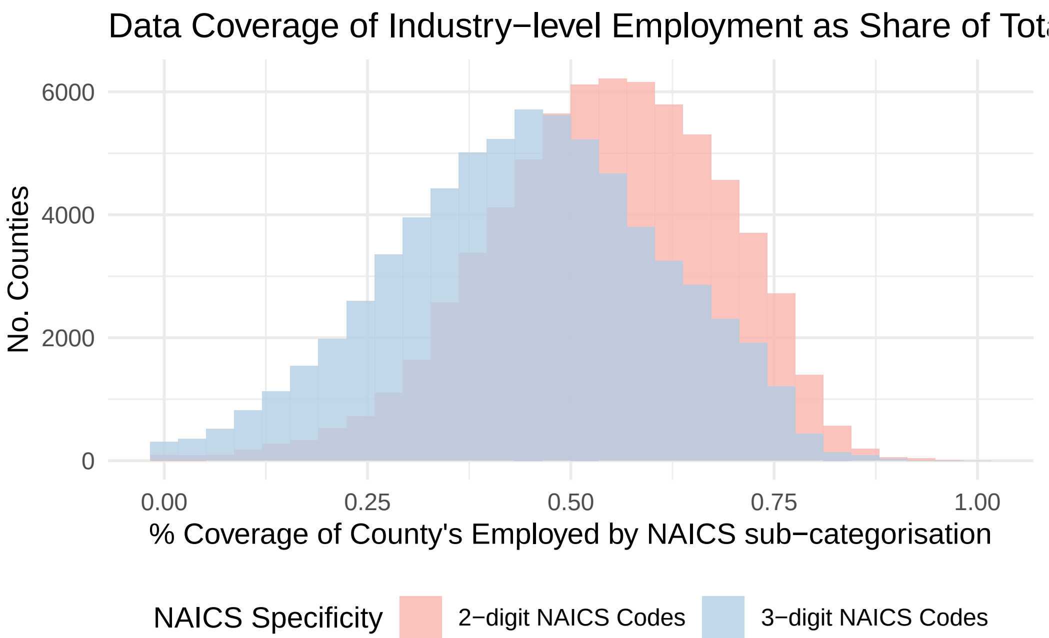

Avg. Weekly Wage
A. Overall
Avg. Weekly Wage
3. Disaggregated (2−digit)
Avg. Weekly Wage
C. Disaggregated (3−digit)
log_Avg. Weekly Wage
A. Overall
log_Avg. Weekly Wage
3. Disaggregated (2−digit)
log_Avg. Weekly Wage
C. Disaggregated (3−digit)
log_Total Wages
A. Overall
log_Total Wages
3. Disaggregated (2−digit)
log_Total Wages
C. Disaggregated (3−digit)
Total Wages
A. Overall
Total Wages
3. Disaggregated (2−digit)
Total Wages
C. Disaggregated (3−digit)
value
year




```
[1] "Downloaded QCEW data for 2004."

[1] "Cleaned temp file."
[1] "Created employment share values."
```

```
[1] "Appended national shock variables."
```

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[1] TRUE
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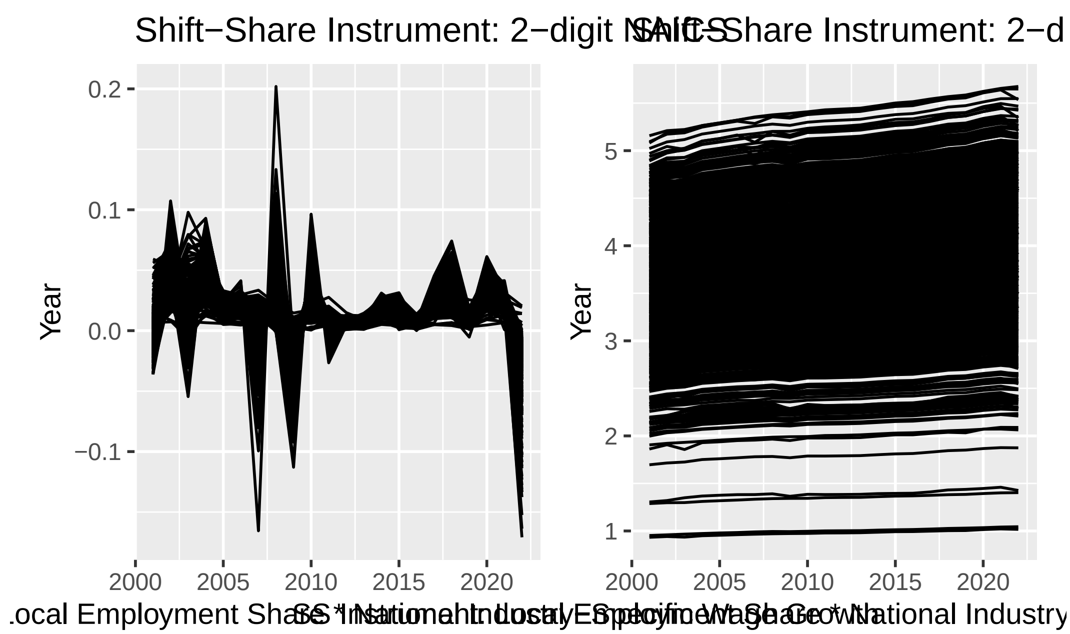


Dependent Variables:	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(log) Elem.Ed.Exp.pp	(log) House Price Index	(GR) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
SS (Lvl, 2d)	0.7711***					
	(0.1033)					
(log) IG Revenue pp	0.1335***	0.3911***	0.1387***	0.5330***	0.1387***	0.6903**
	(0.0194)	(0.0323)	(0.0196)	(0.1321)	(0.0196)	(0.3426)
(log) Real GDP pc	0.2893***	0.1971***	0.2768***	0.4807*	0.2767***	1.161*
	(0.0318)	(0.0388)	(0.0310)	(0.2537)	(0.0310)	(0.6754)
(log) House Price Index		0.0212		-1.003		-4.115*
		(0.1078)		(0.9046)		(2.375)
SS (GR,2d)			0.1124*		0.1136*	
			(0.0580)		(0.0581)	
Fixed-effects						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,717	12,717	12,717	12,717	12,716	12,716
R^2	0.96091	0.85748	0.95979	0.65943	0.95979	-9.8721
Within R^2	0.16773	0.25877	0.14395	-0.77129	0.14392	-13.522
F-test (1st stage)	364.23		1.5458		1.5797	
F-test (1st stage), (log) House Price Index		364.23		1.5458		1.5797
F-test (1st stage), p-value	4.45×10^{-80}		0.21378		0.20883	
F-test (1st stage), p-value, (log) House Price Index		4.45×10^{-80}		0.21378		0.20883
F-test (2nd stage)		0.17673		1.7270		21.893
F-test (2nd stage), p-value		0.67421		0.18882		2.91×10^{-6}
Wu-Hausman		3.5844		2.0817		20.779
Wu-Hausman, p-value		0.05835		0.14910		5.2×10^{-6}
Wald (IV only)	55.758	0.03864	3.7508	1.2283	3.8285	3.0008
Wald (IV only), p-value	8.73×10^{-14}	0.84417	0.05280	0.26776	0.05041	0.08325

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	(GR) Elem.Ed.Exp.pp
IV stages	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
SS (Lvl, 2d)	0.1947***					
	(0.0204)					
(log) IG Revenue pp	-0.2308***	0.2696***	-0.3129***	0.2643***	-0.3128***	-0.0012
	(0.0538)	(0.0293)	(0.0585)	(0.0288)	(0.0585)	(0.0163)
(log) Real GDP pc	0.1536***	0.1726***	0.2423***	0.1768***	0.2422***	0.0453***
	(0.0425)	(0.0220)	(0.0439)	(0.0233)	(0.0439)	(0.0122)
(log) House Price Index		0.0473		0.0308		-0.1233***
		(0.0369)		(0.0425)		(0.0417)
SS (GR,2d)			3.118***		3.121***	
			(0.4117)		(0.4119)	
Fixed-effects						
year	Yes	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,717	12,717	12,717	12,717	12,716	12,716
R^2	0.64755	0.68598	0.60057	0.68792	0.60060	0.13785
Within R^2	0.24512	0.21475	0.14451	0.21962	0.14450	-0.13273
F-test (1st stage)	1,832.8		129.04		129.26	
F-test (1st stage), (log) House Price Index		1,832.8		129.04		129.26
F-test (1st stage), p-value	0×10^{-16}		9.26×10^{-30}		8.3×10^{-30}	
F-test (1st stage), p-value, (log) House Price Index		0×10^{-16}		9.26×10^{-30}		8.3×10^{-30}
F-test (2nd stage)		18.452		0.62215		15.527
F-test (2nd stage), p-value		1.76×10^{-5}		0.43026		8.18×10^{-5}
Wu-Hausman		19.230		0.54290		18.298
Wu-Hausman, p-value		1.17×10^{-5}		0.46125		1.9×10^{-5}
Wald (IV only)	91.090	1.6472	57.354	0.52591	57.397	8.7357
Wald (IV only), p-value	1.62×10^{-21}	0.19937	3.89×10^{-14}	0.46834	3.81×10^{-14}	0.00313

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

The instrumental variable estimates provide evidence of a robust causal relationship between national labor demand shocks and local housing prices. Utilizing a shift-share instrument that interacts national industry-specific wage growth rates with local industrial exposure (proxied through property values), the first-stage regression yields a statistically significant and economically large coefficient. A one-unit increase in the shift-share measure is associated with a 50.4% increase in the local House Price Index ($p < 0.01$), with an F-statistic of 217.9—well above conventional weak instrument thresholds—confirming instrument relevance. However, the second-stage results indicate no statistically significant effect of instrumented housing wealth on local education expenditure per pupil. Conditional on intergovernmental revenues and local GDP per capita, the coefficient on log HPI is small in magnitude and not statistically distinguishable from zero. These findings suggest that while labor demand shocks substantially affect local housing markets through capitalized expectations and asset price adjustments, they do not necessarily translate into commensurate changes in public investment in elementary education, at least in the short-to-medium term.

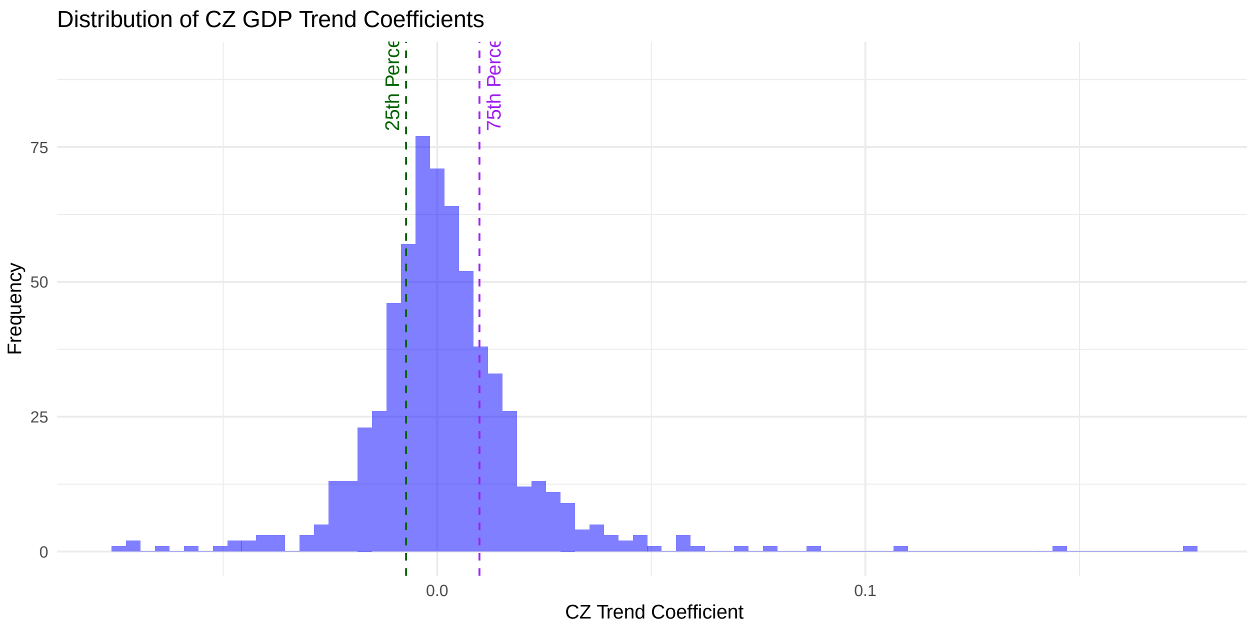
The lack of a causal link between housing wealth and public education spending highlights potential institutional rigidities in the fiscal transmission mechanism linking local economic conditions to public goods provision. In many U.S. localities, school finance systems remain only partially responsive to contemporaneous changes in the property tax base due to funding caps, state-level equalization formulas, or lags in budget-setting processes. As a result, the benefits of local labor market booms—reflected in rising property values—may be disproportionately captured by homeowners and landlords without being redistributed through improved public services. This creates a disconnect between private wealth accumulation and collective investment, with implications for the spatial distribution of educational opportunity. In areas where property values increase due to industry-specific wage growth, the absence of corresponding increases in education spending may exacerbate existing inequalities, especially in regions with historically lower fiscal capacity or institutional autonomy.

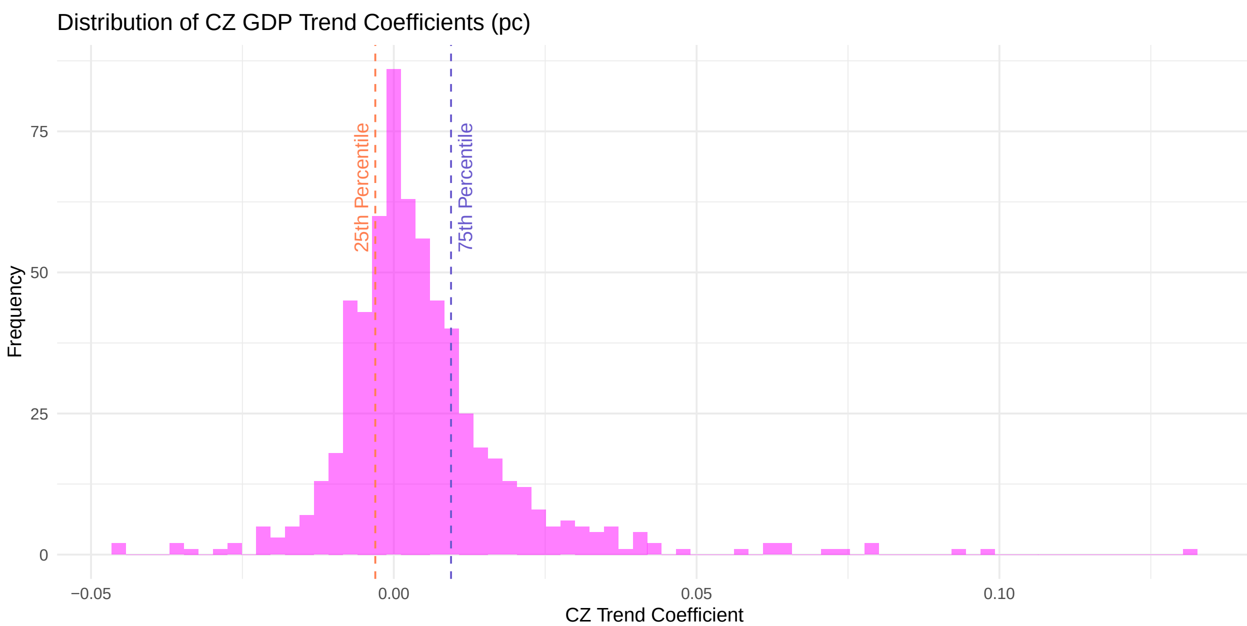
From a policy perspective, these results underscore the limitations of relying on localized property tax bases to fund essential public services in the context of an increasingly uneven and geographically concentrated labor market. The structure of shift-share instruments inherently leverages exogenous national variation in labor demand, but the outcomes indicate that even sizable positive economic shocks at the local level are insufficient to trigger automatic increases in education expenditure. This finding reinforces concerns about the decoupling of local economic gains from public service provision, particularly in jurisdictions that lack flexible or progressive fiscal institutions. Without deliberate policy mechanisms to translate housing market windfalls into educational investments—such as automatic stabilizers, revised state aid formulas, or property tax reform—the gains from macroeconomic growth may fail to improve educational equity or intergenerational mobility in affected regions.

2.4.2 Declining vs. Growing Regions

What would be great is to be able to econometrically test when a commuting zone is "declining." In the first step, it would be good to identify when a commuting zone is declining overall (GDP, poverty, etc) but ideally eventually apply this to the education outcome. My hope is that being able to identify counties that are "declining" we can either use this variable as a covariate or as a central point of analysis. The below analysis looks at state-level variables as a first step (mainly to aid in visual comparison and plotting). Ideally, once a method is decided on this would be applied to commuting zone-level data which would need to be summarise/collated in some way for plotting.

2.4.3 CZ GDP growth conditional on state and national level



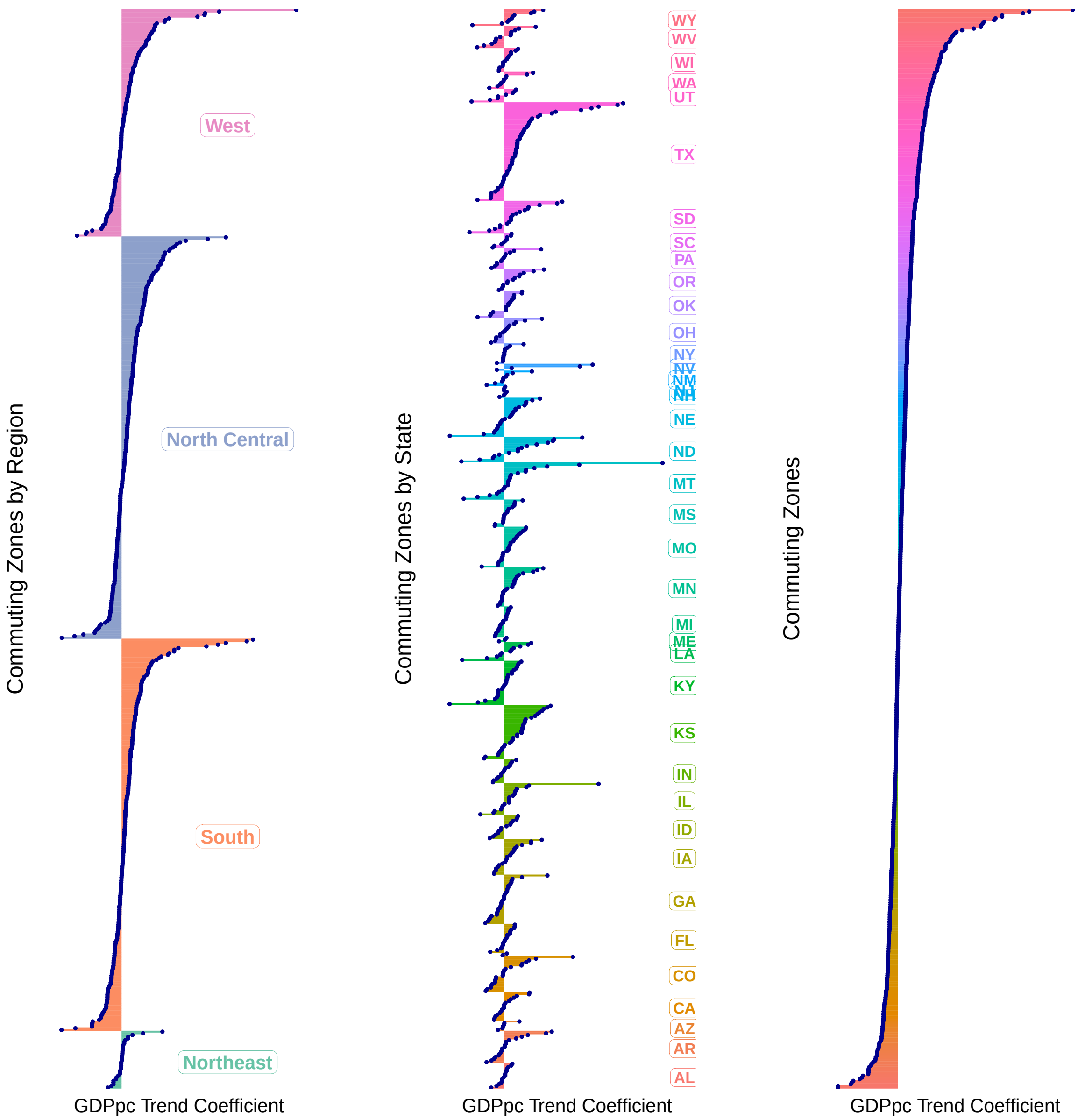



```
[1] 0.2154088
```

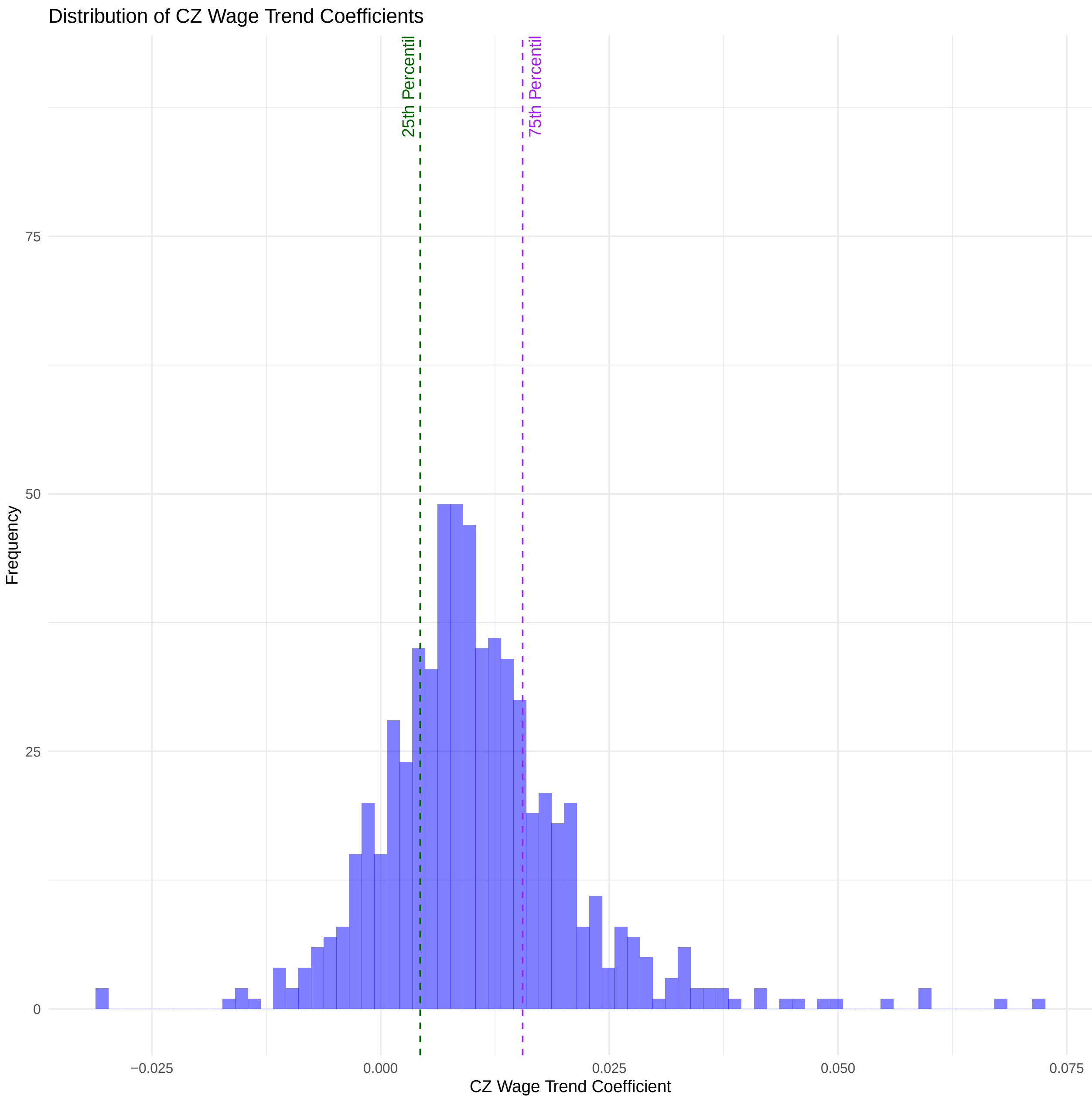
```
[1] 0.1540881
```

```
[1] 0.1194969
```

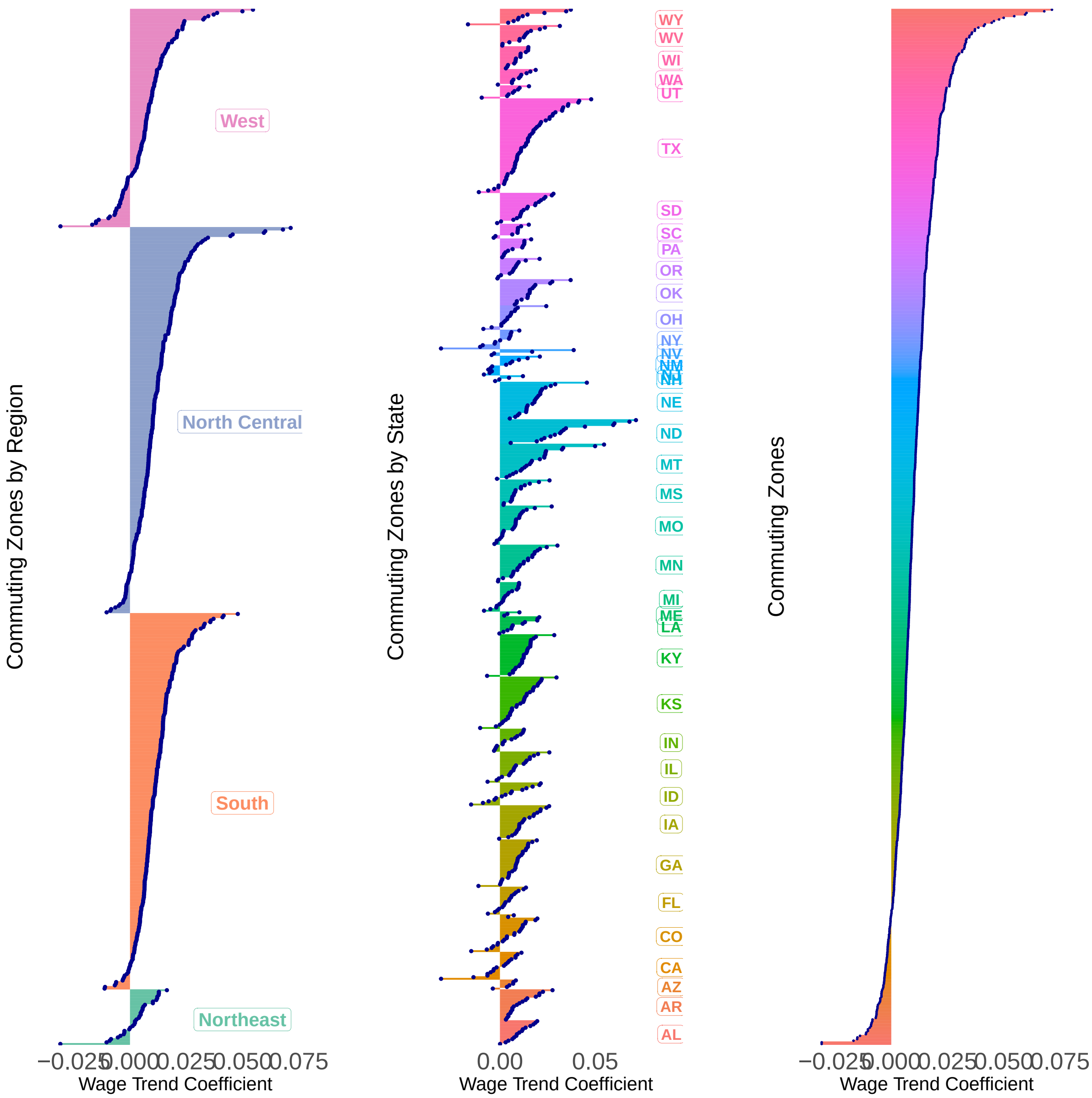
Commuting Zone GDP pc Growth Rate Controlling for National and State Level Tren
Calculated as mean of annual growth rate per commuting zone controlling for national and state

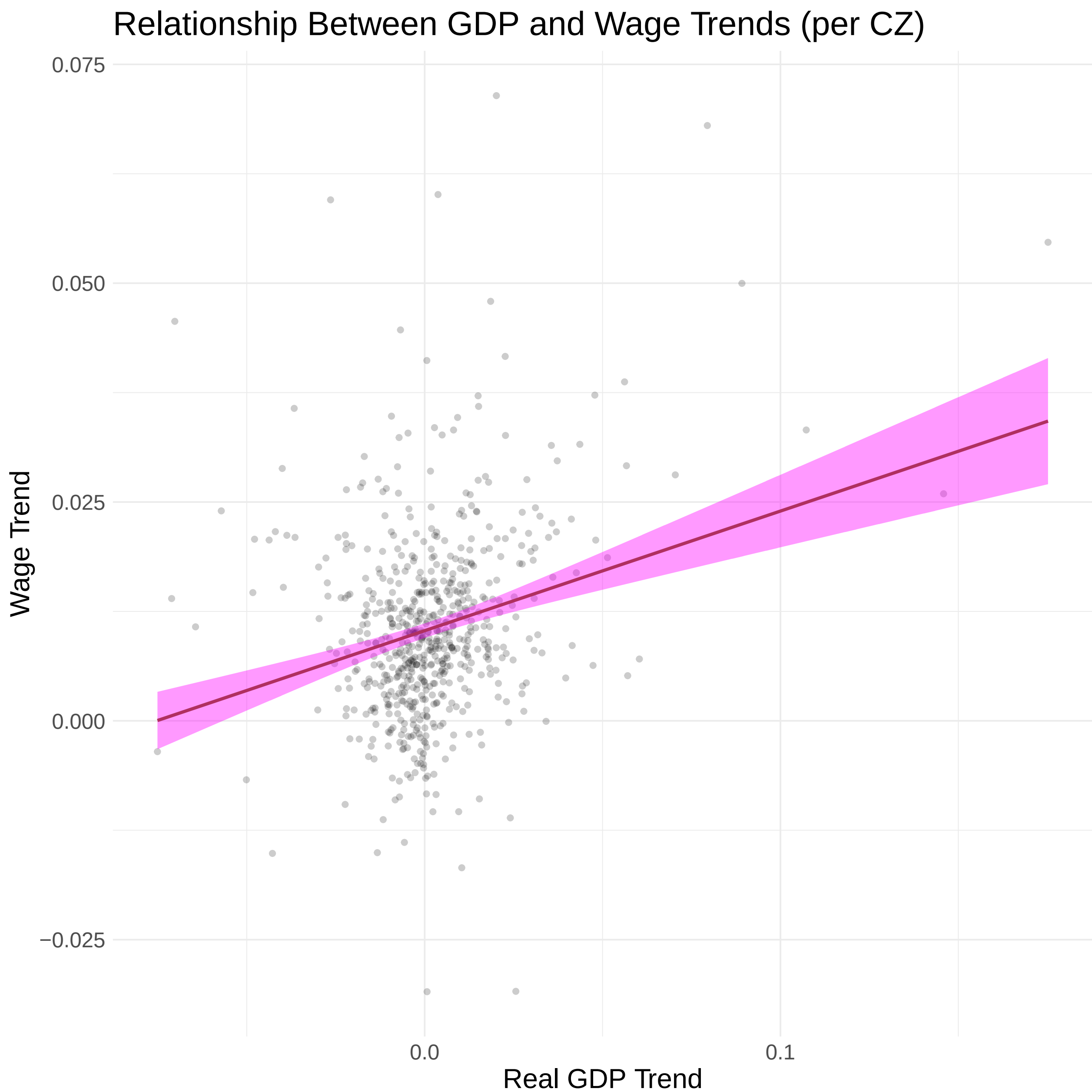


2.4.4 CZ Wage Growth

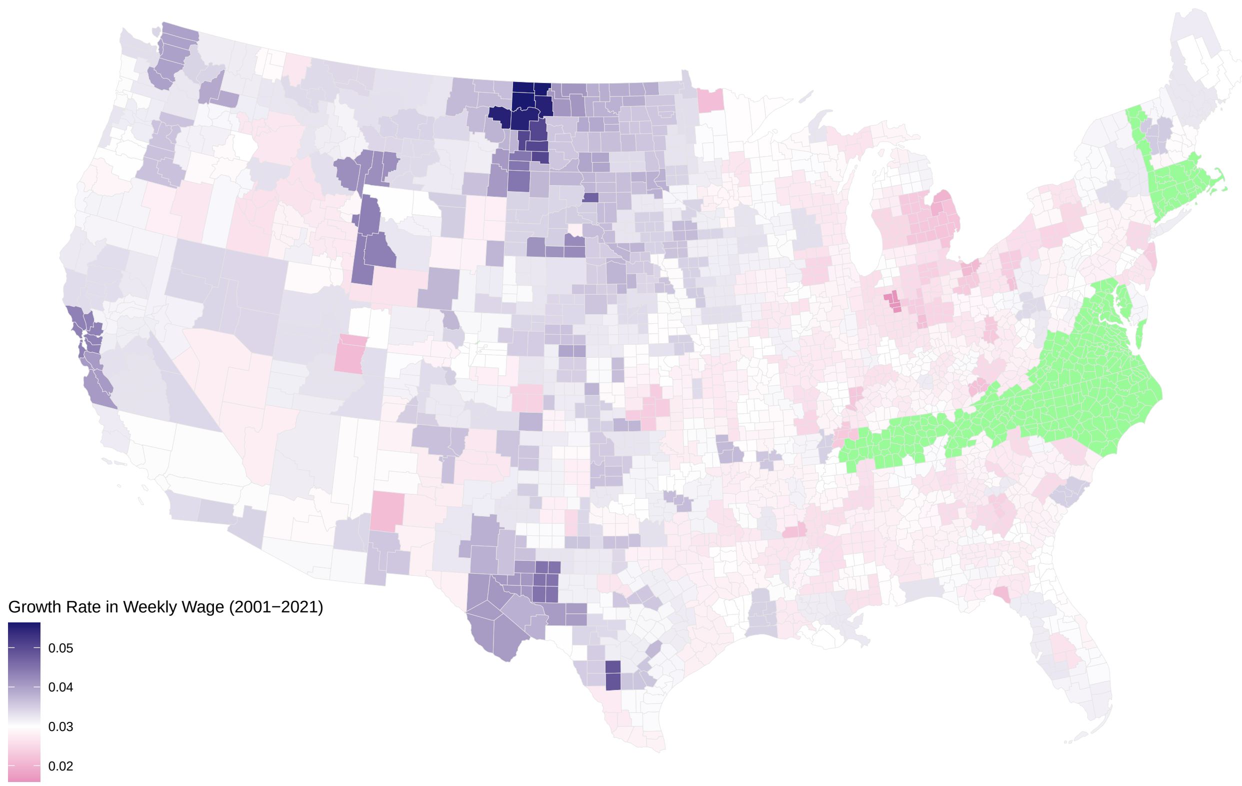


Commuting Zone Wage Growth Rate Controlling for National and State Level Trends
Calculated as mean of annual growth rate per commuting zone controlling for national and state

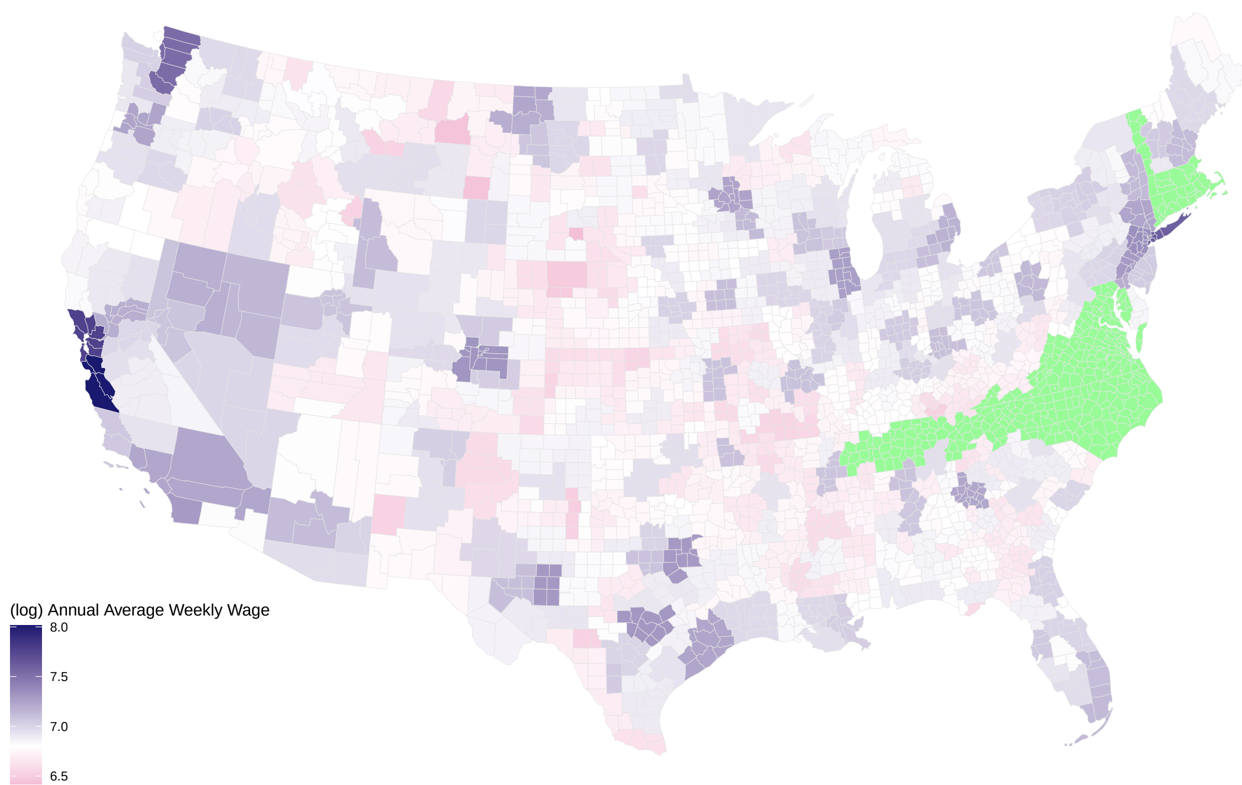



Relationship Between GDP and Wage Trends (per CZ)
0.075
0.050
0.025
0.000
−0.025
Wage Trend
0.0
0.1
Real GDP Trend

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



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



2.4.5 Running base models on declining vs. growing sub-groups

Table 2: Declining

Dependent Variable:	(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(log) Real GDP Priv. Industry pc	0.0155		
	(0.0389)		
(log,l1) Real GDP Priv. Industry pc	0.0812^{***}		
	(0.0260)		
(log,l2) Real GDP Priv. Industry pc	0.1225^{***}		
	(0.0236)		
(log) IG Revenue pp	0.3831^{***}	0.3841^{***}	0.3711^{***}
	(0.0521)	(0.0522)	(0.0553)
(log) Annual Avg. Wkly. Wage		0.1074	
		(0.1019)	
(log, l1) Annual Avg. Wkly. Wage		0.1678^{**}	
		(0.0828)	
(log, l2) Annual Avg. Wkly. Wage		0.2325^{***}	
		(0.0855)	
(log) House Price Index			0.0451
			(0.0416)
(log, l1) House Price Index			0.0576^{*}
			(0.0323)
(log, l2) House Price Index			0.0406
			(0.0316)
(log, l3) House Price Index			0.1067^{***}
			(0.0348)
(log, l4) House Price Index			-0.0870^{**}
			(0.0345)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	4,902	5,418	5,224
R^2	0.85999	0.85921	0.85979
Within R^2	0.23821	0.25227	0.24013

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

2.4.6 Running IV models on declining vs. growing sub-groups

The following implements an employment based Bartik instrument for various industries available from the Quarterly Census of Employment and Wages.

Table 3: Growing

Dependent Variable:	(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(log) Real GDP Priv. Industry pc	0.0200		
	(0.0232)		
(log,l1) Real GDP Priv. Industry pc	0.0605^{***}		
	(0.0166)		
(log,l2) Real GDP Priv. Industry pc	0.1484^{***}		
	(0.0318)		
(log) IG Revenue pp	0.3835^{***}	0.3450^{***}	0.3746^{***}
	(0.0365)	(0.0425)	(0.0404)
(log) Annual Avg. Wkly. Wage		0.2074^{***}	
		(0.0758)	
(log, l1) Annual Avg. Wkly. Wage		0.1842^{***}	
		(0.0578)	
(log, l2) Annual Avg. Wkly. Wage		0.2504^{**}	
		(0.1140)	
(log) House Price Index			0.0989^{***}
			(0.0314)
(log, l1) House Price Index			0.0631^{*}
			(0.0370)
(log, l2) House Price Index			0.0514^{*}
			(0.0267)
(log, l3) House Price Index			0.0173
			(0.0260)
(log, l4) House Price Index			0.0096
			(0.0273)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	7,182	7,938	7,364
R^2	0.85582	0.84607	0.85045
Within R^2	0.27832	0.24629	0.23145

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

Table 4: Hyper-Declining

Dependent Variable:	(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(log) Real GDP Priv. Industry pc	-0.0055		
	(0.0433)		
(log,l1) Real GDP Priv. Industry pc	0.0857***		
	(0.0291)		
(log,l2) Real GDP Priv. Industry pc	0.1265***		
	(0.0237)		
(log) IG Revenue pp	0.3262***	0.3289***	0.3081***
	(0.0610)	(0.0625)	(0.0664)
(log) Annual Avg. Wkly. Wage		0.0947	
		(0.1274)	
(log, l1) Annual Avg. Wkly. Wage		0.1970*	
		(0.1064)	
(log, l2) Annual Avg. Wkly. Wage		0.1806*	
		(0.0940)	
(log) House Price Index			0.1197**
			(0.0519)
(log, l1) House Price Index			0.0503
			(0.0457)
(log, l2) House Price Index			0.0136
			(0.0378)
(log, l3) House Price Index			0.1169**
			(0.0453)
(log, l4) House Price Index			-0.1268***
			(0.0443)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	3,021	3,339	3,172
R^2	0.82305	0.82068	0.82719
Within R^2	0.20900	0.21653	0.21560

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

Table 5: Hyper-Growing

Dependent Variable:	(log) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(log) Real GDP Priv. Industry pc	0.0027		
	(0.0294)		
(log,l1) Real GDP Priv. Industry pc	0.0615***		
	(0.0204)		
(log,l2) Real GDP Priv. Industry pc	0.1566***		
	(0.0405)		
(log) IG Revenue pp	0.3647***	0.3069***	0.3077***
	(0.0579)	(0.0652)	(0.0683)
(log) Annual Avg. Wkly. Wage		0.1472	
		(0.1068)	
(log, l1) Annual Avg. Wkly. Wage		0.2584***	
		(0.0935)	
(log, l2) Annual Avg. Wkly. Wage		0.2825*	
		(0.1656)	
(log) House Price Index			0.1375***
			(0.0474)
(log, l1) House Price Index			0.0828
			(0.0555)
(log, l2) House Price Index			0.0573
			(0.0417)
(log, l3) House Price Index			-0.0246
			(0.0340)
(log, l4) House Price Index			-0.0548
			(0.0445)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	3,021	3,339	2,845
R^2	0.79215	0.77898	0.78768
Within R^2	0.27183	0.21663	0.16657

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

Table 6: Declining

Dependent Variable:	(GR) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(GR) Real GDP Priv. Industry pc	0.0283		
	(0.0316)		
(GR,l1) Real GDP Priv. Industry pc	0.0420		
	(0.0261)		
(GR,l2) Real GDP Priv. Industry pc	0.0053		
	(0.0075)		
(GR) IG Revenue pp	0.3700***	0.3090***	0.3076***
	(0.0445)	(0.0349)	(0.0374)
(GR) Annual Avg. Wkly. Wage		0.0555	
		(0.1013)	
(GR, l1) Annual Avg. Wkly. Wage		0.1706**	
		(0.0856)	
(GR, l2) Annual Avg. Wkly. Wage		0.2728***	
		(0.0695)	
(GR) House Price Index			0.0639
			(0.0421)
(GR, l1) House Price Index			0.1356***
			(0.0451)
(GR, l2) House Price Index			0.0409
			(0.0343)
(GR, l3) House Price Index			0.0848**
			(0.0421)
(GR, l4) House Price Index			-0.0443
			(0.0278)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	4,901	5,417	5,213
R^2	0.19689	0.34989	0.36813
Within R^2	0.13448	0.13227	0.14121

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

Table 7: Growing

Dependent Variable:	(GR) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(GR) Real GDP Priv. Industry pc	-0.0022		
	(0.0154)		
(GR,l1) Real GDP Priv. Industry pc	0.0446**		
	(0.0188)		
(GR,l2) Real GDP Priv. Industry pc	0.0260**		
	(0.0103)		
(GR) IG Revenue pp	0.4166***	0.3434***	0.3477***
	(0.0361)	(0.0289)	(0.0276)
(GR) Annual Avg. Wkly. Wage		-0.0642	
		(0.0638)	
(GR, l1) Annual Avg. Wkly. Wage		0.2008***	
		(0.0614)	
(GR, l2) Annual Avg. Wkly. Wage		0.3215***	
		(0.0842)	
(GR) House Price Index			0.0545*
			(0.0290)
(GR, l1) House Price Index			0.0864**
			(0.0366)
(GR, l2) House Price Index			0.0621**
			(0.0252)
(GR, l3) House Price Index			-0.0127
			(0.0325)
(GR, l4) House Price Index			0.0761***
			(0.0288)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	7,182	7,938	7,322
R^2	0.22783	0.35064	0.35900
Within R^2	0.18083	0.16175	0.15396

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

Table 8: Hyper-Declining

Dependent Variable:	(GR) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(GR) Real GDP Priv. Industry pc	0.0043		
	(0.0353)		
(GR,l1) Real GDP Priv. Industry pc	0.0410		
	(0.0290)		
(GR,l2) Real GDP Priv. Industry pc	0.0100		
	(0.0092)		
(GR) IG Revenue pp	0.4196^{***}	0.3351^{***}	0.3447^{***}
	(0.0474)	(0.0447)	(0.0489)
(GR) Annual Avg. Wkly. Wage		0.0317	
		(0.1308)	
(GR, l1) Annual Avg. Wkly. Wage		0.1536	
		(0.1117)	
(GR, l2) Annual Avg. Wkly. Wage		0.1425^{**}	
		(0.0714)	
(GR) House Price Index			0.0328
			(0.0616)
(GR, l1) House Price Index			0.1557^{**}
			(0.0648)
(GR, l2) House Price Index			0.0036
			(0.0386)
(GR, l3) House Price Index			0.1140^{**}
			(0.0447)
(GR, l4) House Price Index			-0.0306
			(0.0380)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	3,020	3,338	3,163
R^2	0.21525	0.34943	0.37943
Within R^2	0.16022	0.14348	0.16113

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

Table 9: Hyper-Growing

Dependent Variable:	(GR) Elem.Ed.Exp.pp		
Model:	(1)	(2)	(3)
Variables			
(GR) Real GDP Priv. Industry pc	-0.0109		
	(0.0190)		
(GR,l1) Real GDP Priv. Industry pc	0.0508**		
	(0.0232)		
(GR,l2) Real GDP Priv. Industry pc	0.0308*		
	(0.0186)		
(GR) IG Revenue pp	0.4385***	0.3676***	0.3441***
	(0.0564)	(0.0441)	(0.0433)
(GR) Annual Avg. Wkly. Wage		-0.0838	
		(0.0937)	
(GR, l1) Annual Avg. Wkly. Wage		0.2423**	
		(0.0947)	
(GR, l2) Annual Avg. Wkly. Wage		0.3147**	
		(0.1351)	
(GR) House Price Index			0.0091
			(0.0504)
(GR, l1) House Price Index			0.0945
			(0.0576)
(GR, l2) House Price Index			0.0444
			(0.0371)
(GR, l3) House Price Index			-0.0429
			(0.0476)
(GR, l4) House Price Index			0.0182
			(0.0444)
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	3,021	3,339	2,812
R^2	0.22364	0.34920	0.34838
Within R^2	0.18685	0.17235	0.13744

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

Table 10: Declining

Dependent Variable:	(log) House Price Index
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	0.6411***
	(0.0787)
l(log_weighted_annual_avg_wkly_wage,1)	0.2595***
	(0.0711)
l(log_weighted_annual_avg_wkly_wage,2)	0.2374***
	(0.0475)
l(log_weighted_annual_avg_wkly_wage,3)	0.0871**
	(0.0386)
l(log_weighted_annual_avg_wkly_wage,4)	0.0536
	(0.0493)
l(log_weighted_annual_avg_wkly_wage,5)	-0.1042*
	(0.0551)
l(log_weighted_annual_avg_wkly_wage,6)	-0.0712
	(0.0442)
l(log_weighted_annual_avg_wkly_wage,7)	0.0646
	(0.0641)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	3,511
R^2	0.98005
Within R^2	0.23106

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

Table 11: Growing

Dependent Variable:	(log) House Price Index
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	0.5537***
	(0.0603)
l(log_weighted_annual_avg_wkly_wage,1)	0.2029***
	(0.0423)
l(log_weighted_annual_avg_wkly_wage,2)	0.2002***
	(0.0595)
l(log_weighted_annual_avg_wkly_wage,3)	0.0605
	(0.0468)
l(log_weighted_annual_avg_wkly_wage,4)	0.0113
	(0.0487)
l(log_weighted_annual_avg_wkly_wage,5)	-0.0458
	(0.0582)
l(log_weighted_annual_avg_wkly_wage,6)	-0.0370
	(0.0586)
l(log_weighted_annual_avg_wkly_wage,7)	-0.0962
	(0.0876)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	4,991
R^2	0.97418
Within R^2	0.15615

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

Table 12: Hyper-Declining

Dependent Variable:	(log) House Price Index
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	0.5553***
	(0.0859)
l(log__weighted__annual__avg__wkly__wage,1)	0.2732***
	(0.0903)
l(log__weighted__annual__avg__wkly__wage,2)	0.2182***
	(0.0553)
l(log__weighted__annual__avg__wkly__wage,3)	0.0796*
	(0.0434)
l(log__weighted__annual__avg__wkly__wage,4)	0.0451
	(0.0526)
l(log__weighted__annual__avg__wkly__wage,5)	-0.0566
	(0.0672)
l(log__weighted__annual__avg__wkly__wage,6)	-0.0976*
	(0.0515)
l(log__weighted__annual__avg__wkly__wage,7)	0.1138
	(0.0714)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	2,139
R^2	0.97774
Within R^2	0.27247

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

Table 13: Hyper-Growing

Dependent Variable:	(log) House Price Index
Model:	(1)
Variables	
(log) Annual Avg. Wkly. Wage	0.4685^{***}
	(0.0736)
l(log__weighted__annual__avg__wkly__wage,1)	0.2016^{***}
	(0.0547)
l(log__weighted__annual__avg__wkly__wage,2)	0.1803^{**}
	(0.0822)
l(log__weighted__annual__avg__wkly__wage,3)	0.0040
	(0.0635)
l(log__weighted__annual__avg__wkly__wage,4)	0.0458
	(0.0743)
l(log__weighted__annual__avg__wkly__wage,5)	-0.0568
	(0.0928)
l(log__weighted__annual__avg__wkly__wage,6)	0.0233
	(0.0854)
l(log__weighted__annual__avg__wkly__wage,7)	-0.1915
	(0.1217)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	1,967
R^2	0.97204
Within R^2	0.15797

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

Table 14: Declining

Dependent Variable:	(GR) House Price Index
Model:	(1)
Variables	
(GR) Annual Avg. Wkly. Wage	0.3196***
	(0.0473)
l(gr_weighted_annual_avg_wkly_wage,1)	0.3315***
	(0.0671)
l(gr_weighted_annual_avg_wkly_wage,2)	0.2279***
	(0.0344)
l(gr_weighted_annual_avg_wkly_wage,3)	0.0555
	(0.0353)
l(gr_weighted_annual_avg_wkly_wage,4)	-0.0261
	(0.0482)
l(gr_weighted_annual_avg_wkly_wage,5)	-0.1049**
	(0.0440)
l(gr_weighted_annual_avg_wkly_wage,6)	-0.1265***
	(0.0391)
l(gr_weighted_annual_avg_wkly_wage,7)	-0.0797*
	(0.0409)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	3,508
R^2	0.57995
Within R^2	0.08255

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

Table 15: Growing

Dependent Variable:	(GR) House Price Index
Model:	(1)
Variables	
(GR) Annual Avg. Wkly. Wage	0.3383***
	(0.0529)
l(gr_weighted_annual_avg_wkly_wage,1)	0.3069***
	(0.0380)
l(gr_weighted_annual_avg_wkly_wage,2)	0.2158***
	(0.0509)
l(gr_weighted_annual_avg_wkly_wage,3)	0.0747*
	(0.0429)
l(gr_weighted_annual_avg_wkly_wage,4)	0.0141
	(0.0565)
l(gr_weighted_annual_avg_wkly_wage,5)	-0.0676
	(0.0585)
l(gr_weighted_annual_avg_wkly_wage,6)	-0.0385
	(0.0457)
l(gr_weighted_annual_avg_wkly_wage,7)	-0.1493***
	(0.0575)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	4,987
R^2	0.42311
Within R^2	0.06547

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

Table 16: Hyper-Declining

Dependent Variable:	(GR) House Price Index
Model:	(1)
Variables	
(GR) Annual Avg. Wkly. Wage	0.2946***
	(0.0584)
l(gr_weighted_annual_avg_wkly_wage,1)	0.3064***
	(0.0860)
l(gr_weighted_annual_avg_wkly_wage,2)	0.2086***
	(0.0374)
l(gr_weighted_annual_avg_wkly_wage,3)	0.0443
	(0.0368)
l(gr_weighted_annual_avg_wkly_wage,4)	-0.0417
	(0.0535)
l(gr_weighted_annual_avg_wkly_wage,5)	-0.0766
	(0.0515)
l(gr_weighted_annual_avg_wkly_wage,6)	-0.1063**
	(0.0413)
l(gr_weighted_annual_avg_wkly_wage,7)	-0.1371***
	(0.0510)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	2,136
R^2	0.57799
Within R^2	0.09954

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

Table 17: Hyper-Growing

Dependent Variable:	(GR) House Price Index
Model:	(1)
Variables	
(GR) Annual Avg. Wkly. Wage	0.2935***
	(0.0791)
l(gr_weighted_annual_avg_wkly_wage,1)	0.2389***
	(0.0522)
l(gr_weighted_annual_avg_wkly_wage,2)	0.2074**
	(0.0824)
l(gr_weighted_annual_avg_wkly_wage,3)	0.0536
	(0.0652)
l(gr_weighted_annual_avg_wkly_wage,4)	0.0781
	(0.0867)
l(gr_weighted_annual_avg_wkly_wage,5)	-0.0254
	(0.0925)
l(gr_weighted_annual_avg_wkly_wage,6)	0.0760
	(0.0696)
l(gr_weighted_annual_avg_wkly_wage,7)	-0.0794
	(0.0870)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	1,963
R^2	0.30412
Within R^2	0.05323

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

Table 18: lev_ss_2d

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
	Declining		Hyper-Declining		Growing		Hyper-Growing	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
SS (Lvl, 2d)	0.7831***		0.5910***		0.7847***		0.5568**	
	(0.1503)		(0.1806)		(0.1414)		(0.2702)	
(log) IG Revenue pp	0.1522***	0.3900***	0.1601***	0.3533***	0.1145***	0.3948***	0.1017**	0.3843***
	(0.0250)	(0.0569)	(0.0296)	(0.0804)	(0.0260)	(0.0375)	(0.0423)	(0.0733)
(log) Real GDP pc	0.3843***	0.1937**	0.3631***	0.2130*	0.2481***	0.1973***	0.1490***	0.2355***
	(0.0559)	(0.0807)	(0.0636)	(0.1156)	(0.0326)	(0.0473)	(0.0280)	(0.0684)
(log) House Price Index		-0.0300		-0.1216		0.0562		-0.2448
		(0.1628)		(0.2960)		(0.1449)		(0.3742)
Fixed-effects								
unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	5,256	5,256	3,199	3,199	7,461	7,461	2,927	2,927
R^2	0.96549	0.85833	0.95866	0.81876	0.95616	0.85721	0.94976	0.77837
Within R^2	0.19363	0.22726	0.21838	0.16532	0.14655	0.27441	0.08780	0.13964
F-test (1st stage)	175.10		58.952		199.90		34.788	
F-test (1st stage), (log) House Price Index		175.10		58.952		199.90		34.788
F-test (1st stage), p-value	2.43×10^{-39}		2.14×10^{-14}		8.31×10^{-45}		4.1×10^{-9}	
F-test (1st stage), p-value, (log) House Price Index		2.43×10^{-39}		2.14×10^{-14}		8.31×10^{-45}		4.1×10^{-9}
F-test (2nd stage)		0.16471		0.82555		0.68177		1.8825
F-test (2nd stage), p-value		0.68487		0.36363		0.40900		0.17015
Wu-Hausman		3.7593		3.9502		0.94713		4.2833
Wu-Hausman, p-value		0.05257		0.04695		0.33048		0.03858
Wald (IV only)	27.144	0.03385	10.711	0.16883	30.795	0.15051	4.2482	0.42791
Wald (IV only), p-value	1.96×10^{-7}	0.85404	0.00108	0.68118	2.97×10^{-8}	0.69806	0.03938	0.51307

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

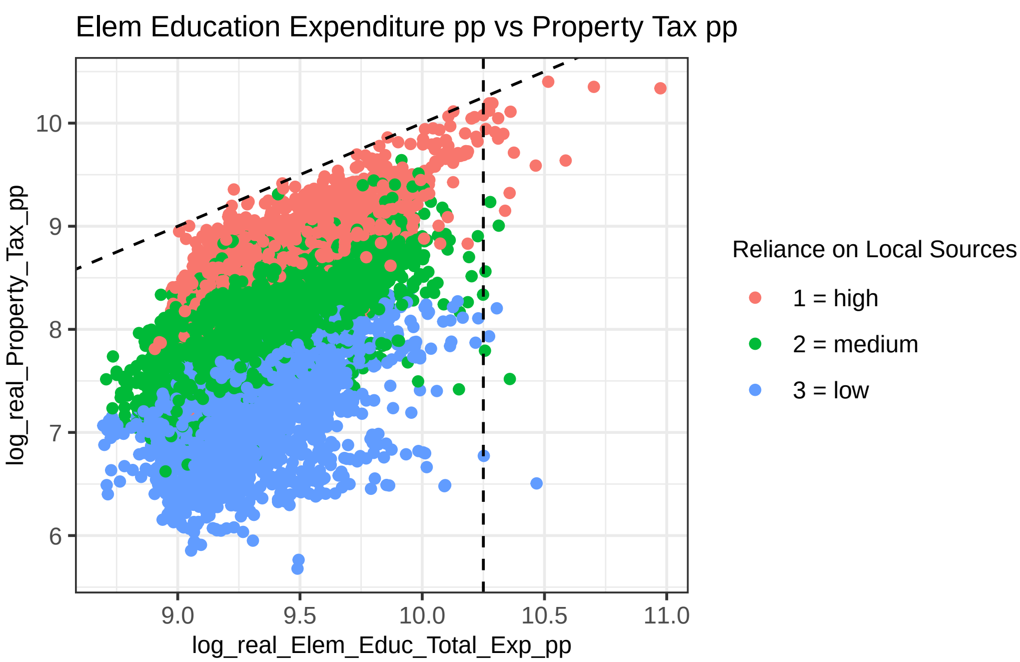
Table 19: lev_ss_2d

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
	Declining		Hyper-Declining		Growing		Hyper-Growing	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
SS (Lvl, 2d)	1.053***		0.9599***		0.7543***		0.8887***	
	(0.2507)		(0.1820)		(0.1155)		(0.2531)	
(log) IG Revenue pp	0.0947***	0.3523***	0.1026***	0.4284***	0.1363***	0.3933***	0.1771***	0.3312***
	(0.0351)	(0.0745)	(0.0267)	(0.0558)	(0.0217)	(0.0355)	(0.0443)	(0.0554)
(log) Real GDP pc	0.3298***	0.1772**	0.3481***	0.1153	0.2792***	0.1910***	0.2029***	0.1891***
	(0.0816)	(0.0879)	(0.0597)	(0.0700)	(0.0328)	(0.0411)	(0.0390)	(0.0582)
(log) House Price Index		0.0885		0.1326		0.0369		-0.0795
		(0.2426)		(0.1809)		(0.1153)		(0.2209)
Fixed-effects								
unit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,596	1,596	3,212	3,212	11,121	11,121	2,955	2,955
R^2	0.96951	0.88277	0.96646	0.85960	0.95483	0.85123	0.93063	0.85841
Within R^2	0.12788	0.23306	0.12600	0.26845	0.17464	0.26419	0.19888	0.20811
F-test (1st stage)	79.716		141.71		303.63		91.815	
F-test (1st stage), (log) House Price Index		79.716		141.71		303.63		91.815
F-test (1st stage), p-value	1.18×10^{-18}		5.31×10^{-32}		4.16×10^{-67}		1.95×10^{-21}	
F-test (1st stage), p-value, (log) House Price Index		1.18×10^{-18}		5.31×10^{-32}		4.16×10^{-67}		1.95×10^{-21}
F-test (2nd stage)		0.75859		2.8723		0.42434		0.59443
F-test (2nd stage), p-value		0.38390		0.09022		0.51479		0.44077
Wu-Hausman		0.04835		0.12760		1.9162		1.8965
Wu-Hausman, p-value		0.82600		0.72096		0.16630		0.16858
Wald (IV only)	17.638	0.13292	27.806	0.53739	42.632	0.10248	12.330	0.12935
Wald (IV only), p-value	2.82×10^{-5}	0.71547	1.43×10^{-7}	0.46357	6.9×10^{-11}	0.74888	0.00045	0.71914

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

2.4.7 Removing outliers - really high-income commuting zones!

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 counties (~2% of the sample) This could benefit from more robust outlier detection. This outlier exclusion weakens our results (and the validity of our instrument choice) in the production-based IV regression. Worth noting and thinking about!!



2.5 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 educaiton expenditure, intergovernmental revenue, house prices conditioned on GDP and wage levels.

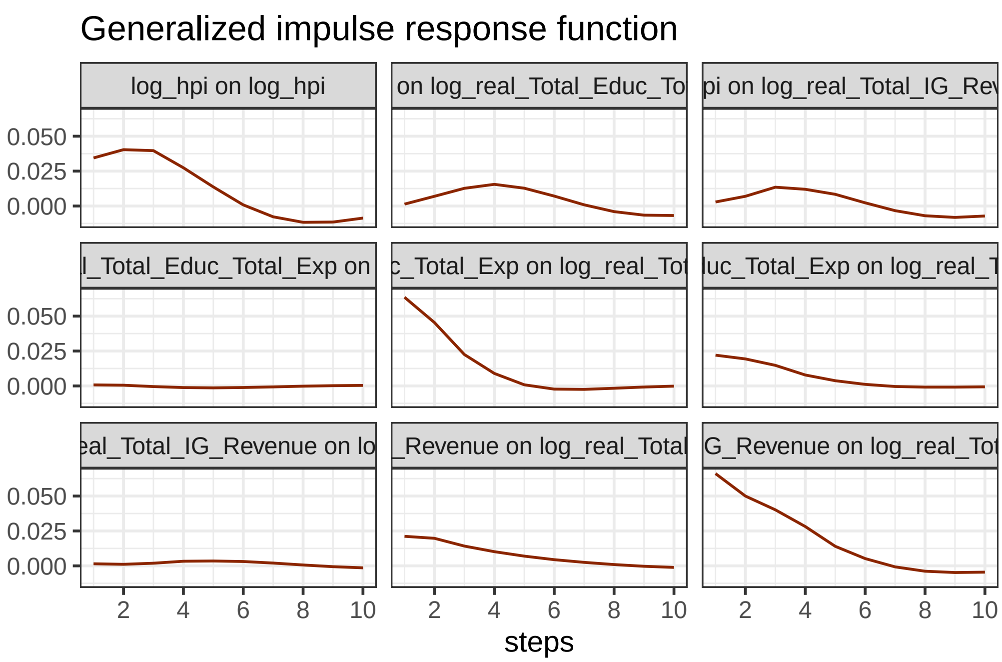
$$Y_{it} = \begin{bmatrix} \log(\text{real Total Educ. Exp.})_{it} \\ \log(\text{real Total IG Revenue})_{it} \\ \log(\text{HPI})_{it} \end{bmatrix}, \quad X_{it} = \begin{bmatrix} \log(\text{real GDP})_{it} \\ \log(\text{wage})_{it} \end{bmatrix}$$

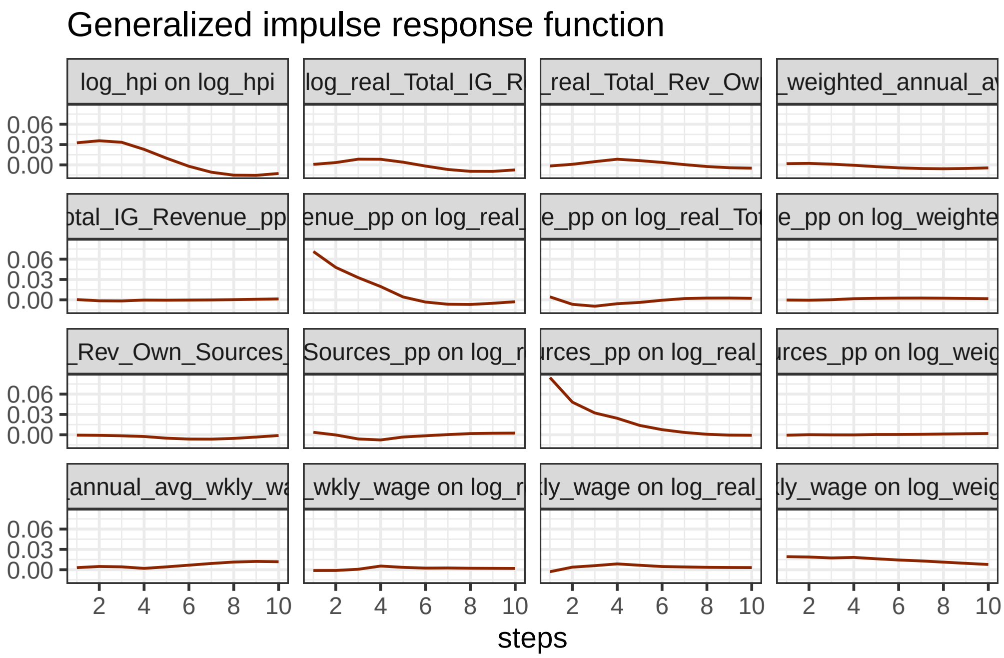
- A_1, A_2, A_3, A_4 are 3×3 coefficient matrices
- β is a 3×2 matrix of coefficients on the exogenous variables
- α_i is a vector of unit fixed effects
- ε_{it} is the error term

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




Generalized impulse response function
log_hpi on log_hpi
log_real_Total_IG_R
_real_Total_Rev_Ow
_weighted_annual_a
otal_IG_Revenue_pp
enue_pp on log_real_
e_pp on log_real_Tot
e_pp on log_weighte
_Rev_Own_Sources_
Sources_pp on log_r
urces_pp on log_real_
urces_pp on log_weig
_annual_avg_wkly_wa
_wkly_wage on log_r
kly_wage on log_real_
kly_wage on log_weig
0.06
0.03
0.00
2
4
6
8
10
steps

3 Property Prices

Dependent Variables:	(log) House Price Index	(GR) House Price Index	log__real__Elem__Educ__Total__E
Model:	(1)	(2)	(3)
Variables			
(log) Annual Avg. Wkly. Wage	0.5110***		0.1302*
	(0.0662)		(0.0727)
(log, l1) Annual Avg. Wkly. Wage	0.2052***		0.1796***
	(0.0376)		(0.0550)
(log, l2) Annual Avg. Wkly. Wage	0.2789***		0.1149
	(0.0885)		(0.0759)
(log) Real GDP	0.1368***		0.0305
	(0.0308)		(0.0251)
(GR) Annual Avg. Wkly. Wage		0.3141***	
		(0.0332)	
(GR, l1) Annual Avg. Wkly. Wage		0.3308***	
		(0.0319)	
(GR, l2) Annual Avg. Wkly. Wage		0.2514***	
		(0.0253)	
(log,l1) Real GDP			0.0612***
			(0.0171)
(log,l2) Real GDP			0.1589***
			(0.0297)
(GR) GDP			
(GR,l1) GDP			
(GR,l2) GDP			
(log) Real GDP pc			
(log,l1) Real GDP pc			
(log,l2) Real GDP pc			
(GR) GDP pc			
(GR,l1) GDP pc			
(GR,l2) GDP pc			
Fixed-effects			
unit	Yes	Yes	Yes
year	Yes	Yes	Yes
Fit statistics			
Observations	12,612	12,585	11,856
R^2	0.96755	0.41767	0.99644
Within R^2	0.30497	0.05311	0.17113

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	0.1704***
	(0.0610)
(log,l2) Real GDP pc	0.0729**
	(0.0301)
(log) Prop Taxpp	0.1932***
	(0.0156)
(log) House Price Index	0.1642***
	(0.0198)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	11,521
R^2	0.84827
Within R^2	0.19025

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	0.1589**
	(0.0666)
(log) Annual Avg. Wkly. Wage × share_own_discrete = 2=medium	0.1803***
	(0.0615)
(log) Annual Avg. Wkly. Wage × share_own_discrete = 3=low	0.1376**
	(0.0663)
(log,l2) Real GDP pc	0.0713**
	(0.0304)
(log) Prop Taxpp	0.1952***
	(0.0159)
(log) House Price Index	0.1645***
	(0.0200)
Fixed-effects	
unit	Yes
year	Yes
Fit statistics	
Observations	11,521
R^2	0.84841
Within R^2	0.19101

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

4 Results

5 Discussion

6 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.

7 Appendix

Ahlerup, Pelle, Thushyanthan Baskaran, and Arne Bigsten. 2020. "Gold Mining and Education: A Long-Run Resource Curse in Africa?" *The Journal of Development Studies* 56 (9): 1745–62. https://doi.org/10.1080/00220388.2019.1696959.

Aklin, Michael, and Johannes Urpelainen. n.d. "Enable a Just Transition for American Fossil Fuel Workers Through Federal Action." https://www.brookings.edu/articles/enable-a-just-transition-for-american-fossil-fuel-workers-through-federal-action/.

Alfonso, Vincent C., and George J. DuPaul. 2020. "Introduction: The Importance of Early Childhood Development, Education, and Intervention." In, 3–10. Washington, DC, US: American Psychological Association. https://doi.org/10.1037/0000197-001.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–68. https://doi.org/10.1257/AER.103.6.2121.

Avanceña, Anton L. V., Ellen Kim DeLuca, Bradley Iott, Amanda Mauri, Nicholas Miller, Daniel Eisenberg, and David W. Hutton. 2021. "Income and Income Inequality Are a Matter of Life and Death. What Can Policymakers Do about It?" *American Journal of Public Health* 111 (8): 1404–8. https://doi.org/10.2105/AJPH.2021.306301.

Baccini, Leonardo, and Stephen Weymouth. 2021. "Gone For Good: Deindustrialization, White Voter Backlash, and US Presidential Voting." *American Political Science Review* 115 (2): 550–67. https://ideas.repec.org//a/cup/apsrev/v115y2021i2p550-567_14.html.

Badeeb, Ramez Abubakr, Hooi Hooi Lean, and Jeremy Clark. 2017. "The Evolution of the Natural Resource Curse Thesis: A Critical Literature Survey." *Resources Policy* 51 (March): 123–34. https://doi.org/10.1016/j.resourpol.2016.10.015.

Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute. https://www.jstor.org/stable/j.ctvh4zh1q.

Bell, Shannon Elizabeth, and Richard York. 2010. "Community Economic Identity: The Coal Industry and Ideology Construction in West Virginia." *Rural Sociology* 75 (1): 111–43. https://doi.org/10.1111/J.1549-0831.2009.00004.X.

———. 2012. "Coal, Injustice, and Environmental Destruction: Introduction to the Special Issue on Coal and the Environment." *Http://Dx.doi.org/10.1177/1086026612468138* 25 (4): 359–67. https://doi.org/10.1177/1086026612468138.

Blanco, Luisa, and Robin Grier. 2012. "Natural Resource Dependence and the Accumulation of Physical and Human Capital in Latin America." *Resources Policy* 37 (3): 281–95. https://doi.org/10.1016/j.resourpol.2012.01.005.

Borge, Lars-Erik, Pernille Parmer, and Ragnar Torvik. 2015. "Local Natural Resource Curse?" *Journal of Public Economics* 131 (November): 101–14. https://doi.org/10.1016/j.jpubeco.2015.09.002.

Broz, J. Lawrence, Jeffry Frieden, and Stephen Weymouth. 2021. "Populism in Place: The Economic Geography of the Globalization Backlash." *International Organization* 75 (2): 464–94. https://doi.org/10.1017/S0020818320000314.

Brunnschweiler, Christa N., and Erwin H. Bulte. 2008. "The Resource Curse Revisited and Revised: A Tale of Paradoxes and Red Herrings." *Journal of Environmental Economics and Management* 55 (3): 248–64. https://doi.org/10.1016/j.jeem.2007.08.004.

Carley, Sanya, Tom P. Evans, and David M. Konisky. 2018. "Adaptation, Culture, and the Energy Transition in American Coal Country." *Energy Research & Social Science* 37 (March): 133–39. https://doi.org/10.1016/J.ERSS.2017.10.007.

Chen, Hanyi, Kui Liu, Tie Shi, and Linfeng Wang. 2022. "Coal Consumption and Economic Growth: A Chinese City-Level Study." *Energy Economics* 109 (May): 105940. https://doi.org/10.1016/j.eneco.2022.105940.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. "The Association Between Income and Life Expectancy in the United States, 2001–2014: Association Between Income and Life Expectancy in the United States." *JAMA* 315 (16): 1750. https://doi.org/10.1001/JAMA.2016.4226.

Cockx, Lara, and Nathalie Francken. 2014. "Extending the Concept of the Resource Curse: Natural Resources and Public Spending on Health." *Ecological Economics* 108 (December): 136–49. https://doi.org/10.1016/j.ecolecon.2014.10.013.

———. 2016. "Natural Resources: A Curse on Education Spending?" *Energy Policy* 92 (May): 394–408. https://doi.org/10.1016/J.ENPOL.2016.02.027.

Deacon, Robert T. 2011. "The Political Economy of the Natural Resource Curse: A Survey of Theory and Evidence." *Foundations and Trends(R) in Microeconomics* 7 (2): 111–208. https://ideas.repec.org//a/now/fntmic/0700000042.html.

Dewitte, Edgard. n.d. "Economic Identities and The Historical Roots of Climate Change Denial."

Dialga, Issaka, and Youmanli Ouoba. 2022. "How Do Extractive Resources Affect Human Development? Evidence from a Panel Data Analysis." *Resources, Environment and Sustainability* 7 (March): 100046. https://doi.org/10.1016/j.resenv.2022.100046.

Douglas, Stratford, and Anne Walker. 2017. "COAL MINING AND THE RESOURCE CURSE IN THE EASTERN UNITED STATES." *Journal of Regional Science* 57 (4): 568–90. https://doi.org/10.1111/jors.12310.

Esposito, Elena, and Scott F. Abramson. 2021. "The European Coal Curse." *Journal of Economic Growth* 26 (1): 77–112. https://doi.org/10.1007/s10887-021-09187-w.

Farré, Lídia, Francesco Fasani, and Hannes Mueller. 2018. "Feeling Useless: The Effect of Unemployment on Mental Health in the Great Recession." *IZA Journal of Labor Economics* 7 (1): 1–34. https://doi.org/10.1186/S40172-018-0068-5/FIGURES/6.

Feler, Leo, and Mine Z. Senses. 2017. "Trade Shocks and the Provision of Local Public Goods." *American Economic Journal: Economic Policy* 9 (4): 101–43. https://doi.org/10.1257/pol.20150578.

Ferri, Benjamin. 2022. "Novel Shift-Share Instruments and Their Applications." *Boston College Working Papers in Economics*, Boston College Working Papers in Economics, September. https://ideas.repec.org//p/boc/bocoec/1053.html.

Flavin, Patrick, Benjamin Radcliff, P Flavin, Á B Radcliff, and B Radcliff. 2009. "Public Policies and Suicide Rates in the American States." *Social Indicator Research* 90: 195–209. https://doi.org/10.1007/s11205-008-9252-5.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review* 110 (8): 2586–2624. https://doi.org/10.1257/aer.20181047.

Haber, Stephen. n.d. "The Rise and Fall of the Resource Curse." https://doi.org/10.2139/ssrn.4558080.

Hendrickson, Clara, Mark Muro, and William Galston. 2018. "Countering the Geography of Discontent: Strategies for Left-Behind Places." https://www.brookings.edu/research/countering-the-geography-of-discontent-strategies-for-left-behind-places/.

Lim, Junghyun, Michaël Aklin, and Morgan R. Frank. 2023. "Location Is a Major Barrier for Transferring US Fossil Fuel Employment to Green Jobs." *Nature Communications* 14 (1): 5711. https://doi.org/10.1038/s41467-023-41133-9.

Lochery, Emma. 2022. "Situating Extraction in Capitalism: Blueprints, Frontier Projects, and Life-Making." *The Extractive Industries and Society* 11 (September): 101137. https://doi.org/10.1016/j.exis.2022.101137.

Logan, John R., Elisabeta Minca, and Sinem Adar. 2012. "The Geography of Inequality: Why Separate

Means Unequal in American Public Schools." *Sociology of Education* 85 (3): 287–301. https://doi.org/10.1177/0038040711431588.

Mathews, Roderick, and Juan Carlos Botero. 2010. "Access to Justice in the United States Findings from the Newly Released Rule of Law Index of the World Justice Project."

McLean, Katherine. 2016. ""There's Nothing Here": Deindustrialization as Risk Environment for Overdose." *International Journal of Drug Policy* 29 (March): 19–26. https://doi.org/10.1016/J.DRUGPO.2016.01.009.

Menaldo, Victor. 2016. *The Institutions Curse: Natural Resources, Politics, and Development*. Business and Public Policy. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781316481530.

Metcalf, Gilbert E, and Qitong Wang. 2019. "Abandoned by Coal, Swallowed by Opioids?" Cambridge. http://www.nber.org/papers/w26551.

National Center for Education Statistics. 2023. "Public School Expenditures." https://nces.ed.gov/programs/coe/indicator/cmb.

Pierson, Kawika, Michael Hand, and Fred Thompson. n.d. "The Government Finance Database: A Common Resource for Quantitative Research in Public Financial Analysis | PLOS ONE." *PLoS ONE*. https://doi.org/10.1371/journal.pone.0130119.

Raimi, Daniel, Emily Grubert, Jake Higdon, Gilbert Metcalf, Sophie Pesek, and Devyani Singh. 2022. "The Fiscal Implications of the US Transition Away from Fossil Fuels." https://www.rff.org/publications/working-papers/the-fiscal-implications-of-the-us-transition-away-from-fossil-fuels/.

Rhodes, Mark Alan, William Price, and Amy Walker. 2020. *Geographies of Post-Industrial Place, Memory, and Heritage*. London: Routledge. https://doi.org/10.4324/9781003007494.

Rodríguez-Pose, Andrés, Neil Lee, and Cornelius Lipp. 2021. "Golfing with Trump. Social Capital, Decline, Inequality, and the Rise of Populism in the US." *Cambridge Journal of Regions, Economy and Society* 14 (3): 457–81. https://doi.org/10.1093/cjres/rsab026.

Ross, Michael L. 2015. "What Have We Learned about the Resource Curse?" *Annual Review of Political Science* 18 (1): 239–59. https://doi.org/10.1146/annurev-polisci-052213-040359.

———. 2018. "The Politics of the Resource Curse: A Review." In, edited by Carol Lancaster and Nicolas van de Walle. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199845156.013.42.

Scheer, Antonina, Moritz Schwarz, Debbie Hopkins, and Ben Caldecott. 2022. "Whose Jobs Face Transition Risk in Alberta? Understanding Sectoral Employment Precarity in an Oil-Rich Canadian Province." *Https://Doi.org/10.1080/14693062.2022.2086843*, July, 1–17. https://doi.org/10.1080/14693062.2022.2086843.

Semuels, Alana. 2016. "Why America's Public Schools Are so Unequal." https://www.theatlantic.com/business/archive/2016/08/property-taxes-and-unequal-schools/497333/.

Sincovich, Alanna, Tess Gregory, Ashleigh Wilson, and Sally Brinkman. 2018. "The Social Impacts of Mining on Local Communities in Australia." *Rural Society* 27 (1): 18–34. https://doi.org/10.1080/10371656.2018.1443725.

Stewart, Alexander J., Nolan McCarty, and Joanna J. Bryson. 2020. "Polarization Under Rising Inequality and Economic Decline." *Science Advances* 6 (50): eabd4201. https://doi.org/10.1126/sciadv.abd4201.

Tomer, Adie, Joseph W. Kane, and Caroline George. 2021. "How Renewable Energy Jobs Can Uplift Fossil Fuel Communities and Remake Climate Politics." https://www.brookings.edu/research/how-renewable-energy-jobs-can-uplift-fossil-fuel-communities-and-remake-climate-politics/.

Tregenna, Fiona. 2009. "Characterising Deindustrialisation: An Analysis of Changes in Manufacturing Employment and Output Internationally." *Cambridge Journal of Economics* 33 (3): 433–66. https://doi.org/10.1093/cje/ben032.

Tregenna, Fiona, and Antonio Andreoni. 2020. "Deindustrialisation Reconsidered: Structural Shifts and Sectoral Heterogeneity." In. Working Paper Series (IIPP WP 2020-06). https://www.ucl.ac.uk/bartlett/public-purpose/publications/2020/jul/deindustrialisation-reconsidered-structural-shifts-and-sectoral-heterogeneity.

Walker, Derek. 2021. "Biden's American Jobs Plan Is Smart Climate Policy. Here's Why. | Environmental Defense Fund." https://www.edf.org/blog/2021/05/06/bidens-american-jobs-plan-plan-smart-climate-policy-heres-why.

Wiens, David, Paul Poast, and William Roberts Clark. 2014. "The Political Resource Curse: An Empirical Re-Evaluation." *Political Research Quarterly* 67 (4): 783–94. https://doi.org/10.1177/

1065912914543836.

Young, Travis, Jennifer Baka, Zhongyang He, Sekhar Bhattacharyya, and Zhen Lei. 2023. “Mining, Loss, and Despair: Exploring Energy Transitions and Opioid Use in an Appalachian Coal Community.” *Energy Research & Social Science* 99 (May): 103046. https://doi.org/10.1016/j.erss.2023.103046.