Uneven Wage Growth and Public Goods

The Case of US Public Education

Ebba Mark

Abstract

Wage growth is a key driver of local wealth accumulation, enabling greater household and community investment in public goods. Unfortunately, wage growth has diverged markedly from productivity growth in the United States in recent decades. As such, regions whose wages track productivity gains tend to benefit from broader economic growth, while lagging regions risk weaker savings capacity and declining support for public services. This work estimates the effect of local wage shocks on education spending using a shift-share instrumental variable design, exploiting variation in commuting zone industrial composition interacted with national industry growth shocks. We estimate that a 10% increase in local wages generates a 2.3% short-run increase in per-pupil education expenditure, with a long-run effect of approximately 4.6%. This result is only driven by a handful of states, whereas others exhibit little wage responsiveness. These results expedite the need to enable education equalisation programmes to account for future potential wage disparities.

Table of contents

1 Introduction

Since the 1970s, a persistent divergence between productivity growth and wage growth has emerged in the United States ?], ?], ?], ?]. While labour productivity has continued to rise, the earnings of typical workers have increased far more slowly, leading to a substantial decoupling between the two trends. Economists cite various contributors to this phenomenon from human capital ?], ?], ?], ?] to competition ?], ?], ?], ?], ?] to institutional and policy forces ?], ?], ?], ?], ?], ?], ?], ?] .[1] Though its causes are hotly debated, the fact itself is well-documented, especially for lower- and middle-income workers, contributing to what is often termed the "hollowing of the middle class" ?]. [2]

The direct consequences of this decoupling are clear. Though households and individuals often have stakes in firm productivity by means other than wages, wages remain the most direct link between aggregate productivity growth and local economic health. Therefore, aggregate productivity growth is not sufficient to secure broad-based improvements in living standards if the most direct link between productivity and livelihoods is weak ?]. Furthermore, in a context in which the benefits of economic growth have already accrued unevenly across communities in the United States by virtue of economic history and industrial concentration, allowing this pattern to continue could have adverse consequences for households and communities ?], ?], ?], ?] ?] ?].

A link that has been far less explored in this context is the spillover effect of local wages to local wealth-building and its effect on public goods. Wage growth is an important contributor to local wealth-building, allowing households and communities to invest more in local public goods ?]. Communities whose wages rise in line with productivity growth will likely reap the benefits of economic growth whereas those who do not, risk falling behind. This link is particularly important in the US given the structure of local public financing. Majority of local public services are funded via property taxes. This funding structure entrenches a mechanism for generating inequality of opportunity between diversely affluent regions of the country ?] ?] ?] ?] .[3] Put plainly, given the structure of US public services, wherein they are tied to asset values, inequality in wealth-building can have significant effects for the quality of local public services. Furthermore, a sometimes lacking, or at best under-performing, federal equalisation systems perpetuates this structural force ?] ?] ?] ?] ?] .

Community well-being and public expenditure in the US is already characterised by a high degree of spatial heterogeneity ?], ?], ?] . Evidence of how income inequality perpetuates other forms of inequality (opportunity, health, infrastructure quality, and broader well-being) is steadily increasing ?], ?], ?], ?], ?]. ?] find that greater income inequality leads to higher public expenditure across all public goods indicating that a presence of higher-earners in a local area contributes to higher levels of expenditure. Though this does not support an unambiguous denunciation of inequality in itself, it provides additional

[1] Summers & Stansbury 2018 argue that productivity growth still exerts a positive influence on wages overall, but that institutional and structural changes have weakened the link for large segments of the workforce (?] ?]). They point to declining union density, erosion of the minimum wage, globalization, and increased market concentration as key factors that have shifted bargaining power away from workers and reduced labour's share of national income ?]. Furthermore, additional evidence finds that this decoupling is far from a universal phenomenon. Rather, decoupling applies almost strictly to lower- and medium-wage earners, while already higher wages manage to keep up (relatively) with productivity growth rates.

[2] Though authors find that wage inequality growth has stagnated in the last decade this is not a result of a "catch-up" effect of lower- or middle-income earners with top income earners, but rather wage growth at the bottom of the wage distribution ?]. Additionally, further evidence indicates that metric choice can influence the ambiguity of earnings and wage inequality conclusions ?].

[3] A burgeoning literature points to the role of racial segregation and its enduring legacy in perpetuating inequality in local economic health, wealth, and public service expenditure ?] ?] ?] .

evidence for the fact that local incomes affect public expenditure raising the potential for "superstar" and "left behind" regions to emerge absent even income growth.

One public service that has particularly important ties to ensuring generational resilience to economic decline is education. Public schools around the US are responsible for educating over 80% of school-age children. In 2019, governments around the US (including the federal government) spent a total of $870 billion on public education, roughly $17,013 per pupil **?**]. However, the quality of services delivered varies widely across the country **?**]. Take Connecticut for example. In 2016, according to the Connecticut State Department of Education, the town of Greenwich town, one of the highest-income towns in the country, spent $22,000 per pupil while Bridgeport, although only located 40Km away, spent $14,000 **?**].

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 ?], ?]?] . Although only a small piece of the puzzle that determines quality public education, expenditure levels ensure adequate funding for facilities, teachers, administrators, and other services **?**] **?**] **?**] . Furthermore, evidence suggests that progressive spending delivers efficiency gains in school performance **?**] . Therefore, ensuring that local or regional economic decline does not disrupt or worsen the quality of education delivered is of paramount importance to ensure greater equality in the long-run. Altogether, this evidence points to the value of identifying the extent to which expenditure on public education is reliant on local wage growth across the country.

This study therefore determines whether elasticities of public elementary education expenditure to local wage growth are non-zero. If productivity gains translate unevenly into wages across regions, then the fiscal capacity of local governments may be shaped as much by institutional and structural conditions as by the distribution of aggregate economic growth. We investigate the following questions:

RQ1: Do local wage gains affect public education expenditure in levels?

RQ2: If so, is this relationship constant across commuting zones? What sources of heterogeneity mediate this relationship?

RQ3: In light of recent reforms to intergovernmental education funding aimed at reducing disparities in educational expenditure, do intergovernmental transfers mitigate wealth-driven inequalities in public education spending?

1.1 Theoretical Motivation and Empirical Approach

Any study of the linkage between two or more local socio-economic outcomes presents considerable endogeneity challenges. In the context of this study, wages and public education expenditure are undoubtedly endogenous. Higher-income families may self-select into districts with greater education spending, confounding causal inference. Lower-income families likely struggle financially to make similar mobility decisions. Local education contributes to the quality of local human capital impacting wages and potentially preferences for education.

Therefore, we approach causal identification by instrumenting local wages using a shift-share instrumental variable design. More precisely, to interrogate the elasticity of public education expenditure to wages across US commuting zones, we construct a shift-share instrument that combines fixed local industry employment shares with national industry-level changes real value added using data from the US Bureau of Labor Statistics and Bureau of Economic Analysis. This instrument generates plausibly exogenous local variation by exploiting how different regions are differentially exposed to common national trends, while abstracting from endogenous local dynamics. It is particularly well suited in this setting, since the local tax base, and thus education spending, likely depends on industries that are unevenly distributed across regions but subject to similar industry-specific wage shocks. Finally, we use this instrument to identify the effect of wage shocks on local public education expenditure as reported by the US Census Bureau's Annual Survey of State and Local Government Finances.

Given the substantial heterogeneity across U.S. states arising both from structural sources (such as differences in tax systems, regulatory environments, and legislative institutions) and from evolved characteristics (including industrial composition, income levels, inequality, and broader measures of economic diversity) the scope for identifying a policy-relevant single national average treatment effect is inherently limited. Therefore, we proceed in two steps. First, we provide an initial benchmark using a pooled estimation to establish a baseline relationship between wages and education expenditure that generalizes reasonably across the national economy. Second, we investigate the regional and industrial heterogeneity that these pooled estimates mask via a state-by-state estimation, industry-by-industry estimation, and grouping commuting zones by their historic wage and GDP growth trajectories to improve comparability of treatment and control groups in our instrumental variable design. In the latter heterogeneity analysis, we construct commuting zone growth rates as idiosyncratic variables absent state and national-level growth rates, understanding that *relative* growth rates are of particular importance in a landscape where local economies determine the actual *value* of wage levels.

1.2 Detailed results

1. Public education expenditure is not agnostic to local economic conditions. We establish a strong positive causal link between public education expenditure and local wages, wherein a 10% increase in local wages drives a 2.2% increase in public elementary education expenditure, with a long-run increase of 4.6%.
2. Estimating the instrumental variable model separately for each state reveals substantial heterogeneity in the relationship between wages and education expenditure. Only a third of the 40 states analysed in this study show persistent causal relationships between wages and education expenditure, indicating that these carry the weight of national-level identification. Majority of the states in which we identify a statistically significant effect rely on an above-average share of education funding coming from local sources rather than intergovernmental transfers. Across these states the wage elasticity varies between 2-10% increases in response to a 10% increase in local wages, with Colorado, Florida, and South Dakota exhibiting highest wage elasticities.
3. Furthermore, we find that this elasticity is strongest (weakest) in magnitude and statsitical significance for commuting zones whose wage growth rates are low (high) relative to those of other regions, indicating the potential risk for depressed education expenditure in regions where wages are stagnating or potentially declining.

In the sections that follow, we outline the various data sources used in Section 2; provide a detailed overview of our shift-share construction and methodological approach Section 3 with accompanying results; and conclude with a discussion of policy implications in **?@sec-discussion**.

2 Data

We compile a panel dataset of the following indicators across 636 commuting zones (CZ) in 40 US states annually between 2001-2021.

Expenditure and Revenue: This work relies on a harmonised repository from Willamette University of the data collected annually as part of the US Census Bureau's Annual Survey of State & Local Government Finances (SLGF). The SLGF is the 'only comprehensive source of information on the finances of local governments in the United States' **?**]. The data includes county-level revenue, property taxes, 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. We aggregate school district measures up to the commuting zone-level to ensure the availability of adequate control and treatment variables. We choose to conduct the analysis on the commuting zone level because it is a more accurate picture of a local labor market area **?**]. [4] Our main outcome variable is per pupil spending on elementary education.

[4]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 (**?**]).

Population controls: We source commuting-zone level population statistics by aggregating data from county-level populations statistics from the US Census Bureau

Local GDP: We gather local GDP control variables by aggregating county-level GDP data from the Bureau of Economic Analysis (BEA). This BEA data is only available after 2001, defining the lower limit of our panel's time dimension. We primarily rely on private industry GDP as a control variable given a large remaining portion of GDP is government expenditure which includes public education expenditure.

Property Prices: The US Federal Housing Finance Agency maintains an annual county-level Housing Price Index (HPI) metric, a geographically linked measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index, measuring average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac (two US government-sponsored enterprises that guarantee most US mortgages) **?**]. We aggregate to the commuting zone level via a population-weighted mean.

Race Controls: The National Institute of Health National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) Program provides annual estimates of total White, Black, American Indian/Alaska Native, Asian/Pacific Islander populations at the county level, optionally by Hispanic or non-Hispanic origin **?**] . Though the US Census Bureau provides county-level estimates of racial make-up of local areas in the American Community Survey, this data is unavailable prior to 2009 and is considered less accurate than those provided by the National Cancer Institute's SEER Database.

Adequate Education Spending: The University of Wisconsin's School Finance Indicators Database provides provides detailed data on School Funding Adequacy, measured as the dollar estimate needed per pupil to achieve U.S. average test scores **?**].

This data aggregation results in a complete and balanced panel of 636 US commuting zones across 40 states between 2001-2021. [5] All data used is reported annually at the commuting zone level. [6] Therefore, apart from an indicator of a commuting zone's state, all variables are time-variant.

Table 1 reports summary statistics across relevant variables. All (dollar) values are reported in (real 2017-chained) thousands except for the House Price Index. Table 2 represents the order of integration of relevant variables calculated using a unit root test designed for heterogeneous panels **?**]. All variables are integrated I(0) indicating minimal concern for non-stationarity except in the case of enrollment and population numbers.

Table 1

Statistic	N	Mean	St. Dev.	Min	Max
Enrollment	13,356	62.39	169.90	0.13	3,169.73
Population	13,356	405.18	1,077.99	0.88	18,732.54
Elementary Expenditure per pupil	13,356	11.39	2.99	5.97	58.35
Property Tax per pupil	13,356	3.60	2.43	0.29	32.91
Intergovernmental (IG) Revenue per pupil	13,356	7.12	2.28	1.04	27.50
State IG Revenue per pupil	13,356	6.73	2.03	0.79	26.23
GDP per capita	13,356	44.52	25.27	15.32	388.73
GDP pc - Private Industry	13,356	38.42	25.18	5.85	383.06
House Price Index	12,717	255.18	155.71	85.53	1,947.97

[5] 20% of US states are missing from the dataset because (1) we impose an exclusion restriction wherein any commuting zone reporting more than five $0 values for property taxes collected is excluded due to likely measurement error and (2) Connecticut, Maryland, North Carolina, and Virginia have been excluded due to unconventional or incomplete public school district reporting.

[6] In line with similar work on US economic geography, commuting zones were chosen as the unit of analysis as they are a far less arbitrary and more accurate representation of local labour market areas/economies (David Dorn's Resource Page) (Fowler et al. 2024).

Table 2: Order of Integration

Variable	Order of Integration	I(0) test p-value	I(1) test p-value
Enrollment	I(1)	0.608	<0.0001
Population	I(1)	0.286	<0.0001
Elementary Expenditure per pupil	I(0)	<0.0001	
Property Tax per pupil	I(0)	<0.0001	
Intergovernmental (IG) Revenue per pupil	I(0)	<0.0001	
State IG Revenue per pupil	I(0)	<0.0001	
GDP per capita	I(0)	<0.0001	
GDP pc - Private Industry	I(0)	<0.0001	

Note:
Order of integration determined using the Im-Pesaran-Shin (IPS) panel unit root test with intercept. Lag length selected via AIC with maximum of 4 lags. The null hypothesis is non-stationarity; rejection at the 5% level indicates stationarity. I(0) denotes stationarity in levels and I(1) denotes stationarity in first differences. All variables are log-transformed prior to testing to account for heteroskedasticity.

Figure 1 demonstrates the spread of elementary education expenditure per pupil by commuting zone, grouped by state. Each state's population-weighted mean expenditure per pupil is represented in black. There is considerable within-state variation in per-pupil expenditure levels. Notably, Texas, Montana, and Idaho have commuting zones that spend nearly twice as much as other zones in the same state. Furthermore, the mean level of expenditure is nearly four times as high in the highest-spending state (New York) as in the lowest-spending state, Idaho. We additionally display these values in relation to the estimated "adequate" level of expenditure required for students to achieve U.S. average test scores, represented by the green and red arrows. Majority of states fall short of the deemed adequate expenditure value. Mississippi boasts the greatest shortfall in spending while Wyoming boasts the greatest overshoot in spending. Figure 1 demonstrates the considerable within state variability in spending rates as well as between state variation in levels and student needs.

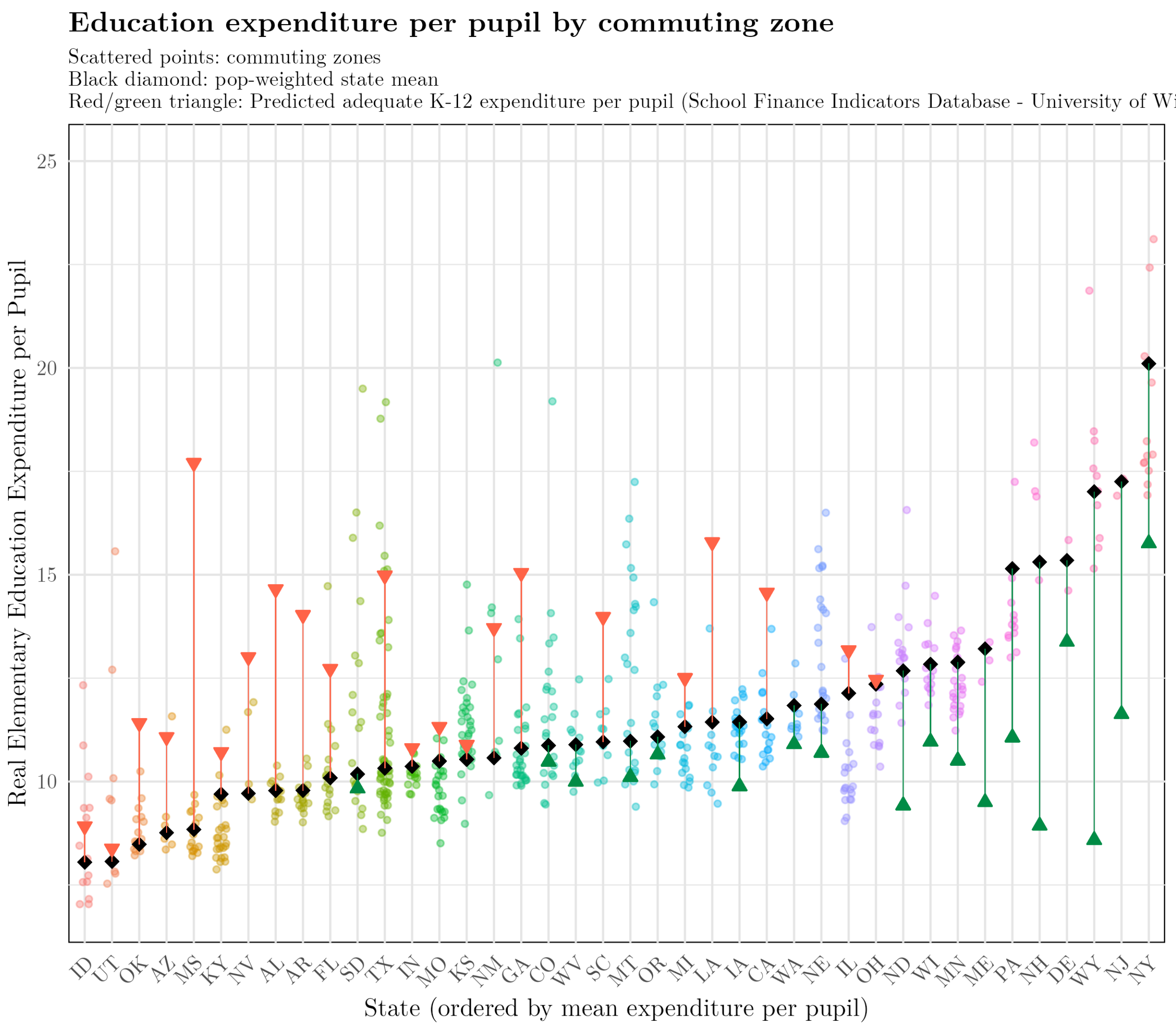


Figure 1: Per Pupil Education Expenditure

Figure 2 demonstrates the trajectories of local wages from an initial level in 2001, demonstrating, the diverging wage growth trajectories of commuting zones in our sample. Blue commuting zones represents those exhibiting relatively high wage growth trajectories as deemed by the calculation in Section 3.2.1. The black dashed line represents the annual national wage growth rate.

3 Methods

3.1 Identification Strategy

We are centrally interested in the effect of changes in local wages on public education expenditure where there is an evident endogeneity concern between public education expenditure and wage. First, there is a likely attracting factor of high levels of education expenditure for higher-income families. Second, absent migration, education systems provision local labour markets with individuals with diverse human capital.

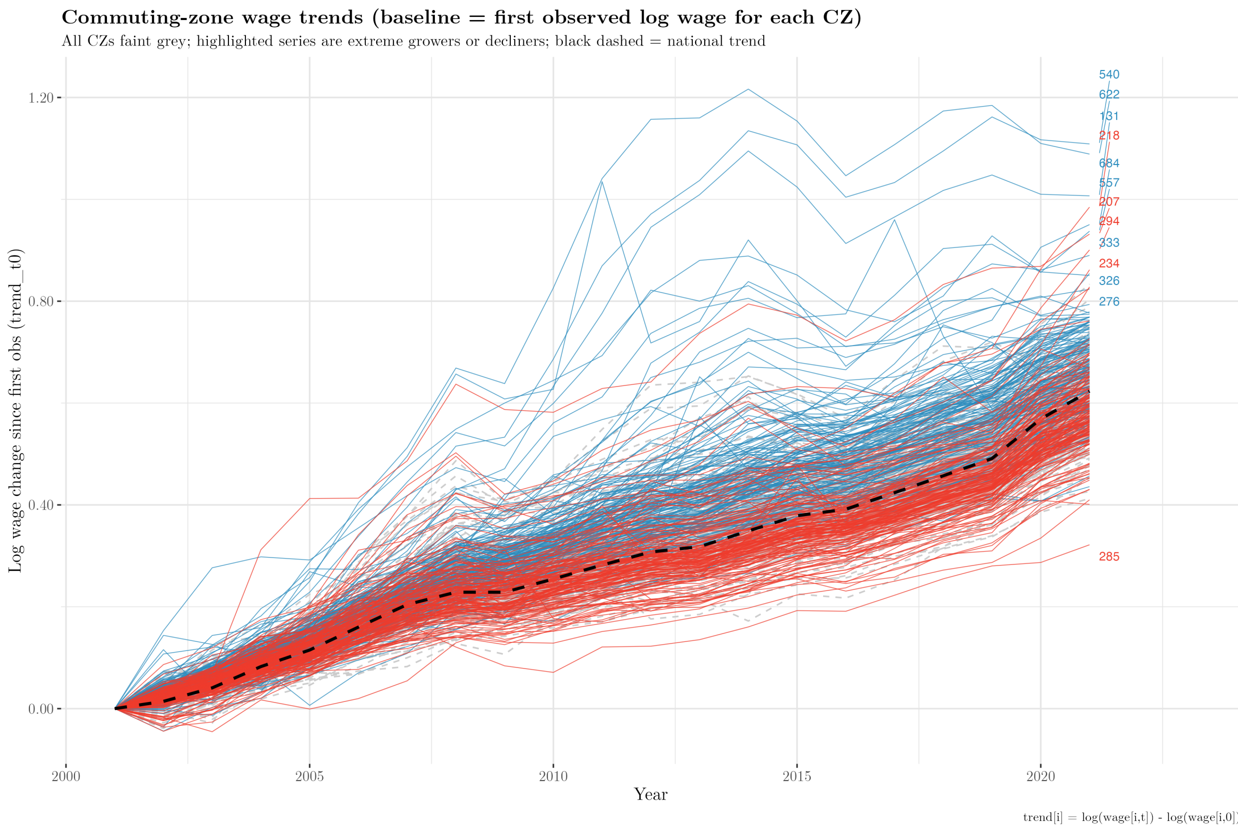
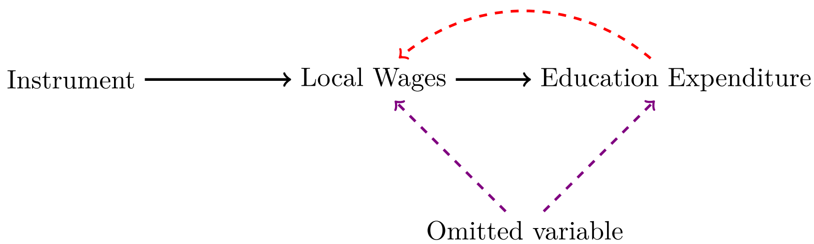


Figure 2: Wages and Productivity

Figure 3: Instrumental Variable Path Diagram



3.1.1 Shift-share Instrument

Therefore, we adopt a causal identification strategy via a shift-share instrument. Shift-share or *Bartik* instruments have gained popularity in empirical work as a method of handling endogeneity issues in panel data (**?**], **?**], **?**]).[7] Such instruments combine time-variant, unit-invariant changes in aggregate economic variables (i.e., national changes in industry value added levels) with time-invariant, unit-variant shares in exposure to these macro-level changes (i.e., local shares of employment in particular industries). This decomposition of local-level changes delocalises variation over space and time. In doing so, it provides a defensible strategy for 'de-endogenising' the treatment, as local exposure is predetermined with respect to contemporaneous shocks. Moreover, by construction, the approach enables the examination of how macro-level phenomena propagate to and affect local units, as it generates local shocks that are driven by national industry trends weighted but the community exposure to this industries.[8]

In the context of this work, we construct the instrument by interacting commuting-zone level industrial employment shares held constant at a base period with national real value added growth by industry. The literature on Bartik instruments allows for an argument of plausible exogeneity via various channels. 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 is designed as in Equation 1.

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

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

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

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

[7] Autor et al. use a shift-share instrument to assess the effect of Chinese import competition on manufacturing employment in US commuting zones (**?**]). As an extension, **?**] use a similar shift-share instrument to assess the effect of the same shock on the size of local government. **?**] 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.

[8] 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 (**?**]). Third, various indicators for measuring *deindustrialisation* have been proposed including the manufacturing share of employment, value added, and GDP **?**], **?**]. Finally, in rare instances, exogeneity can be secured due to *geographical, climatological, or geological factors*. For example, **?**] 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 **?**], **?**].

Finally, authors might be concerned about the implausible exogeneity of both shares and national-level growth rates in which case they construct the instrument as in Equation 2 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.

$$Z_{it} = \sum_{j=1}^{k} S_{0jt} G_{ojt} \tag{2}$$

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

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

...or...:

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

We employ the formulation in Equation 1, assuming that base-period local industry shares and time-varying national rates are exogenous to local outcomes and construct the former of the first-stage relationship assuming a common β to the sum of these shares.

Using data from the Bureau of Economic Analysis, we construct a shift-share Bartik instrument at the commuting zone level using local employment shares by industry and national changes in industry-specific real value added represented in Equation 3. G_{njt} represents national-level changes in value added in industry j in time t and $\frac{N_{ij\tau}}{N_{i\tau}}$ represents the 'sensitivity' of a CZ to these national shocks proxied by an initial share of local employment in industry j in a baseline time period τ. The product of these two values defines the shift-share indicator $\tilde{Z}_{i,t,s}$. In order to construct the share portion, we compute the total local share of employment in a particular industry j. Due to challenges with missing data, we compute an average share across 2001-2005 as our 'base year'.

We compute the relevant shift-share instrument across 19 two-digit NAICS industrial categories listed in Table 3. Given industry-level disaggregation of local employment data requires data suppression for anonymity reasons, Figure 2 displays the data coverage of our commuting zone level shift-share instruments. Given the high degree of missingness in the 3-digit categorisation we proceed with the 2-digit NAICS codes.

In the Appendices, we provide an additional estimation using a wage-based shift-share instrument constructed using data from the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). This shift-share instrument is constructed as described above using industry-level changes in real wages. Concerns about endogeneity between the instrument and outcome variable are greater using this shift-share instrument and is therefore excluded from the main text. [9]

$$\tilde{Z}_{it} = \sum_{j=1}^{k} G_{njt} * \frac{N_{ij\tau}}{N_{i\tau}} \tag{3}$$

[9] 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.

3.1.2 Empirical Estimation

This yields a 2SLS AR(1) model defined by the first- and second-stage regressions represented in Equation 4 and Equation 5. Due to the likely presence of time-dynamic effects, we include contemporaneous, 1-year, 2-year time lags as instruments.

$$\textbf{(First stage)} \qquad X_{it} \;=\; \rho\, X_{i,t-1} \;+\; \phi\, Y_{i,t-1} \;+\; \sum_{\ell=0}^{2} \pi_\ell\, \tilde{Z}_{i,t-\ell} \;+\; \theta \mathbf{W}'_{it} \;+\; \alpha_i \;+\; \lambda_t \;+\; u_{it}, \tag{4}$$

$$\textbf{(Second stage)} \qquad Y_{it} \;=\; \phi^{*}\, Y_{i,t-1} \;+\; \beta\, \widehat{X}_{it} \;+\; \delta \mathbf{W}'_{it} \;+\; \alpha_i \;+\; \lambda_t \;+\; \varepsilon_{it} \tag{5}$$

where W_{it} is a vector of control variables. We control for enrollment levels to account for scaling factors in education expenditure, intergovernmental transfers to account for the significant role of such transfers in funding education expenditure, percentage of the population that is Black, percentage of the population that is Hispanic, and private industry GDP per capita levels to account for local price levels.

Y_{it} is the natural logarithm of elementary (serving ages 6-12) education expenditure per pupil for CZ i in year t. We focus on elementary education for two reasons. First, this restriction partly shields against a justifiable concern about the endogeneity between wages and quality of local public education. Whereas funding for high school could likely affect local wages given such students are of working age, funding for elementary education is unlikely to impact wage rates via a human capital or skills channel. Second, in terms of public impact, elementary education is of foundational importance in the lives of children. Slips in public education provision at a young age could have scarring effects.

α_i represents a CZ fixed effect and λ_t represents year-fixed effects, with stage-relevant superscripts. ε_{it} and u_{it} represents the error term of the second and first stage, respectively.

We additionally adopt a dynamic specification by including lagged dependent variables in both stages of the IV estimation to avoid spurious correlation identification arising from persistence in expenditure and wage levels, as well as better accounting for heterogeneity across units. Education spending likely exhibits inertia due to slowly evolving budgetary and relevant policy cycles (i.e., property tax rate setting). Similarly, local wage levels are well-predicted by a previous year's wage levels. Failing to account for these dynamics, our estimates would conflate the causal effect of wage innovations with mechanical persistence in levels. This yields a more conservative and interpretable elasticity, though we demonstrate that the exclusion of the AR(1) term in the second-stage yields a contemporaneous effect estimate nearly identical to the long-run wage effect as derived from the dynamic specification in Table 4.

3.1.3 Interpretation

The elasticity of public education expenditure to local wages has an ambiguous interpretation. A positive elasticity would suggest that higher wages increase household savings rates and willingness to invest in local public goods, consistent with standard wealth effects. However, this relationship raises concerns about possible divergence wherein wage growth in high-earning regions could amplify educational investment, potentially widening spatial inequality in public education quality aligning with patterns of income inequality.

Conversely, a negative elasticity could emerge through several channels. Any response in needs-based intergovernmental revenue mechanisms may partially offset local fiscal capacity, creating an inverse relationship between wages and education spending. Alternatively, in more affluent communities, rising wages may enable households to substitute towards private education, crowding out or reducing demand for public expenditure. Furthermore, such a relationship could provide additional empirical support for a "resource curse" dynamic[10] wherein local communities reprioritise fiscal windfalls toward government expenditure other than public education.

[10] 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 [**?** , **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**], **?**]]. The literature is divided into two strands focusing on either political (the relationship between resource wealth and governance) [**?** , **?**], **?**], **?**]] or economic (the relationship between resource wealth and economic growth or human capital) resource curses. Empirical investigation of

In either case, the consequence of a non-zero elasticity, whether positive or negative, has potential adverse consequences for spatial inequality of public education delivery by either boosting public education in affluent areas or dampening investment in less affluent areas.

Finally, a near-zero elasticity either has a modelling or policy-relevant implication. On the modelling side, a near-zero elasticity could indicate either that the wage-public goods relationship operates on a longer time scale than that examined in this work. This would indicate the need for an alternative identification strategy. Alternatively, a near-zero elasticity could indicate that local public education systems are effectively insulated from local wage changes partly because intergovernmental transfers successfully equalise funding across regions.

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

Table 3: Industry Categories

3.1.4 Results

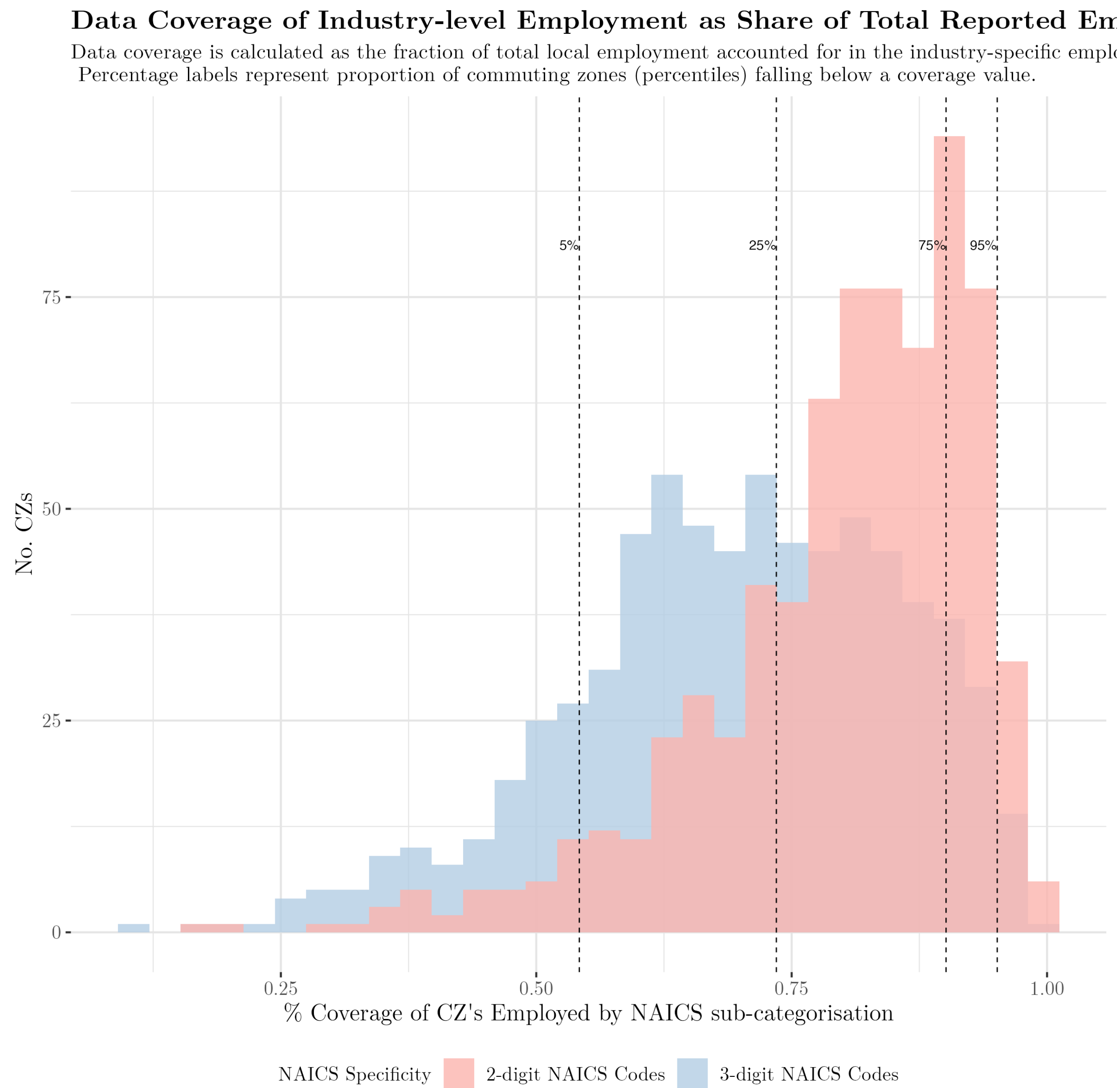


Figure 4: Data Coverage of Industry-level Employment as Share of Total Reported Employed

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 [? , ?], ?], ?]]. 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 [? , ?], ?]]. 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. **?**] find that for 30 countries in Africa, the presence of gold mines during adolescence have a significant effect on educational attainment. **?**] investigates whether resource dependence slows economic growth with no explicit mention of education. **?**] find that in Latin America, petroleum export has a significant long-run negative relationships with human capital. **?**] find support for the paradox of plenty hypothesis in Norway - that higher local public revenue negatively affects the efficiency of local public good provision. **?**] 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.' **?**] use a panel on 140 countries from 1995-2009 and find an inverse relationship between resource dependence and and public health spending over time. **?**] investigate a panel of 140 countries from 1995-2009 to find an adverse effect of resource depdence on public education expenditures relative to GDP. **?**] find disparate results for health and education controlling for institutional quality. **?**] "measure the effect of resource-sector dependence on long-run

In Table 4, we demonstrate a strong and highly significant first-stage relationship wherein our shift-share instrument indicates a strong positive contemporaneous relationship with local wages. Our main specification in Columns 1-2 indicates that a 10% nicrease in local wages leads to a 2.23% increase in per-pupil education expenditure in the short run. The first-stage F-statistic substantially exceeds conventional weak instrument thresholds. The Wu-Hausman test definitevely rejects the exogeneity of wages, validating our instrumental variable approach. However, the Wald over-identification test suggests potential instrument invalidity, though this is likely an artifact of the inclusion of AR(1) terms in the first-stage and not an indictment of the exclusion restriction itself. The implied long-run elasticity is near 0.46, indicating that the cumulative effect of a 10% wage increase is a 4.6% increase in education spending.

In Columns 3-4, we corroborate this long-run effect by removing the AR(1) term in the second-stage regression. The statistically significant causal effect of the treatment approaches this long-run effect of 4.6% (5.6%), capturing the total association between wages and expenditures, including both the immediate and long-run effects. This near-equivalence in the estimated effect reflects the fact that the underlying data-generating process is defined by dynamics, validating our use of a fully dynamic system.

Understanding that wage shocks are likely transmitted to education expenditure through property taxes, we test this potential mechanism in columns 5-6 (adjusting the set of control variables to better suit the first-stage relationship in theory). We find a highly significant house price elasticity, wherein a 10% increase in wages generate an 8.4% increase in local house prices. Note that the sample size decreases because of missing data in the housing price index for several of our commuting zones.

Our findings indicate that, in a decentralised education system, local labour market strength affects public education expenditure. Regions experiencing wage growth see spillovers into public education expenditure, whereas communities facing wage stagnation or decline might see their educational spending erode as a result.

Table 4: IV Estimation Using VA-based Shift-share instrument (l0, l1, l2) in Levels with CZ and year fixed effects and lags.

Dependent Variables:	(log) Annual Avg. Wkly. Wage	(log) Elem.Ed.Exp.pp	(log) Annual Avg. Wkly. Wage	(log) Elem.Ed.Exp.pp	(log) Annual Avg. Wkly. Wage	(log) House Price Index
IV stages	First	Second	First	Second	First	Second
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(log, l1) Annual Avg. Wkly. Wage	0.7828***		0.7848***		0.7787***	
	(0.0120)		(0.0113)		(0.0120)	
VA SS (Lvl)	-0.0179		-0.0203		0.0257	
	(0.0484)		(0.0485)		(0.0454)	
VA SS (Lvl, l1)	-0.1808***		-0.1831***		-0.1759***	
	(0.0592)		(0.0600)		(0.0509)	
VA SS (Lvl, l2)	0.1614***		0.1668***		0.1318***	
	(0.0497)		(0.0516)		(0.0444)	
(l1, log) Elem.Ed.Exp.pp	0.0039	0.5086***				
	(0.0041)	(0.0156)				
(log) IG Revenue pp	0.0135***	0.2230***	0.0143***	0.3213***		
	(0.0030)	(0.0211)	(0.0028)	(0.0316)		
(log) Real GDP Priv. Industry pc	0.0390***	0.0662***	0.0394***	0.0946***	0.0403***	0.0381***
	(0.0044)	(0.0144)	(0.0044)	(0.0243)	(0.0060)	(0.0083)
(log) Enrollment	0.0109**	-0.1957***	0.0099**	-0.3306***		
	(0.0044)	(0.0157)	(0.0042)	(0.0282)		
% Black	-0.1685**	0.3333*	-0.1668**	0.6541*	-0.0916	-0.4356***
	(0.0724)	(0.1924)	(0.0720)	(0.3622)	(0.0745)	(0.1586)
% Hispanic	-0.0526	0.0483	-0.0529	0.0381	-0.0433	-0.0217
	(0.0327)	(0.1509)	(0.0326)	(0.2516)	(0.0345)	(0.0594)
(log) Annual Avg. Wkly. Wage		0.2269***		0.5618***		0.0873**
		(0.0477)		(0.0765)		(0.0404)
(log, l1) House Price Index					0.0142***	0.8378***
					(0.0049)	(0.0098)
Fixed-effects						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	12,084	12,084	12,084	12,084	11,509	11,509
R^2	0.99247	0.90636	0.99247	0.86539	0.99337	0.99074
Within R^2	0.77623	0.51804	0.77617	0.30715	0.78832	0.78569
Wu-Hausman		44.905		138.75		115.32
Wu-Hausman, p-value		2.17×10^{-11}		7.64×10^{-32}		9.12×10^{-27}
Wald (IV only)	1,345.2	22.645	1,517.9	53.948	1,103.7	4.6738
Wald (IV only), p-value	0×10^{-16}	1.97×10^{-6}	0×10^{-16}	2.19×10^{-13}	0×10^{-16}	0.03065
F-test (1st stage)	5,972.4		6,261.7		5,008.7	
F-test (1st stage), (log) Annual Avg. Wkly. Wage		5,972.4		6,261.7		5,008.7
F-test (1st stage), p-value	0×10^{-16}		0×10^{-16}		0×10^{-16}	
F-test (1st stage), p-value, (log) Annual Avg. Wkly. Wage		0×10^{-16}		0×10^{-16}		0×10^{-16}

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

3.2 Accounting for Heterogeneity

In order to make meaningful policy-related insights, we need to unmask the substantial heterogeneity obscured by national-level average treatment effects. These national-level estimates are unlikely to apply uniformly across states and commuting zones, especially given heterogeneity in local tax regimes.

Therefore, we (1) use data on local wages and GDP to create indicators for whether regions are exhibiting relative decline or growth compared to other commuting zones to partition our sample in a data-driven manner, employ (2) industry-by-industry and (2) state-by-state estimations in our IV specifications using our VA-based shift-share instrument.

For completeness, we provide results of average treatment effects for all implemented estimations in the Appendices.

3.2.1 Declining vs. Growing Regions

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

In order to identify declining and growing commuting zones, we estimate separate time series models by commuting zone as follows. These models allow for the identification of commuting-zone level growth rates while controlling for state and national trends in a two-step framework. First, we orthogonalize the state-level growth rate with respect to the national trend, isolating state-specific fluctuations unrelated to the national business cycle:

$$\Delta \log \widetilde{GDPpc}_t^{state} = \Delta \log GDPpc_t^{state} - \hat{\gamma}\, \Delta \log GDPpc_t^{nat}$$

Second, we regress commuting zone growth on both the national growth rate and the orthogonalized state residuals, thereby decomposing local growth into national, state, and idiosyncratic components. This approach identifies commuting zones whose trajectories systematically diverge from higher-level aggregate patterns, providing a clean measure of relative local economic performance.

$$\Delta \log GDPpc_t^{CZ} = \alpha_g + \beta_n\, \Delta \log GDPpc_t^{nat} + \beta_s\, \Delta \log \widetilde{GDPpc}_t^{state} + \varepsilon_t$$

In these equations, each GDP term represents the private industry GDP per capita at the CZ, state, or national level, denoted by superscript.

Intuitively, this specification measures how much of each CZ's growth can be explained by broader aggregate trends versus localized factors. By controlling for orthogonalized state and national variation, the estimated intercept (α_g) and residual terms capture persistent, region-specific trends that are not driven by common macroeconomic forces. This allows us to identify which commuting zones are systematically growing or declining relative to their state and national baselines, thereby providing a purer measure of local economic dynamics that is robust to shared higher-level shocks.[11]

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

$$\Delta \log \widetilde{Wage}_t^{state} = \Delta \log Wage_t^{state} - \hat{\gamma}\, \Delta \log Wage_t^{nat}$$

$$\Delta \log Wage_t^{CZ} = \alpha_w + \beta_n\, \Delta \log Wage_t^{nat} + \beta_s\, \Delta \log \widetilde{Wage}_t^{state} + \varepsilon_t$$

Figure 5 plots the distribution of values of α_g, α_w, and the distribution of commuting-zone level loadings on national and state-level growth rates. The figure demonstrates that commuting zones load more variably

[11] We provide similar analysis of gross GDP in the Appendix.

onto state-level growth rates and more consistently onto national-level growth rates. These distributions are expected by design as the state-level growth rates provide variation that the national level rates do not.

Next, Figure 6 demonstrates the considerable variability in GDP-level growth rates across commuting zones in the US between 2001-2021. Visualising the per capita growth rate deviations by state and region demonstrates heterogeneity in this variability across states and regions. For example, Texas, Montana, North Dakota, and Colorado have outstanding positive outliers in the distribution whereas Kentucky, Louisiana, South Dakota have outstanding negative outliers. The grey lines represent the commuting zones value of α_w, indicating that in a large share of cases, wage growth rates are defined by a different sign than the GDP growth rates, indicating even potential local divergence in growth rates. Though the calculations above could lead to insignificant such relationships because the growth rates are calculated in reference to different data, the volume of states exhibiting diverging wage and GDP per capita growth rates indicate that such a divergence is likely a fact of life in many commuting zones.

To account for this inherent incomparability of the growth rates α_w and α_g, we display a standard Pearson correlation coefficient between teh commuting zone time series of GDP per capita and wages, indicating that several states house commuting zones whose wages do not track GDP growth. Many states see nearly exclusively positive correlation coefficients, whereas others see a mix of commuting zones where the relationship is positive or negative.

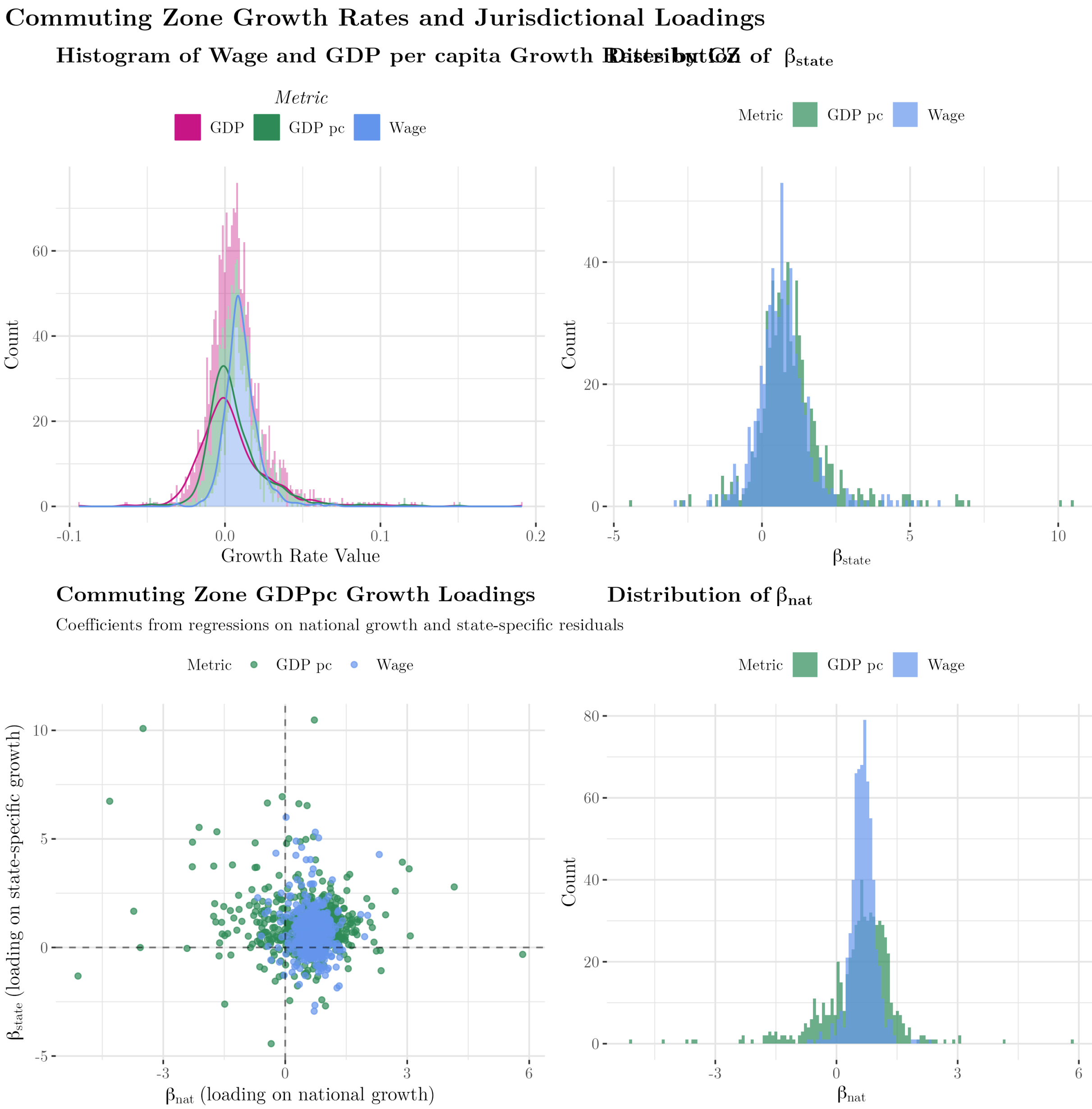


Figure 5: GDPpc and Wage Growth Rates and Loadings

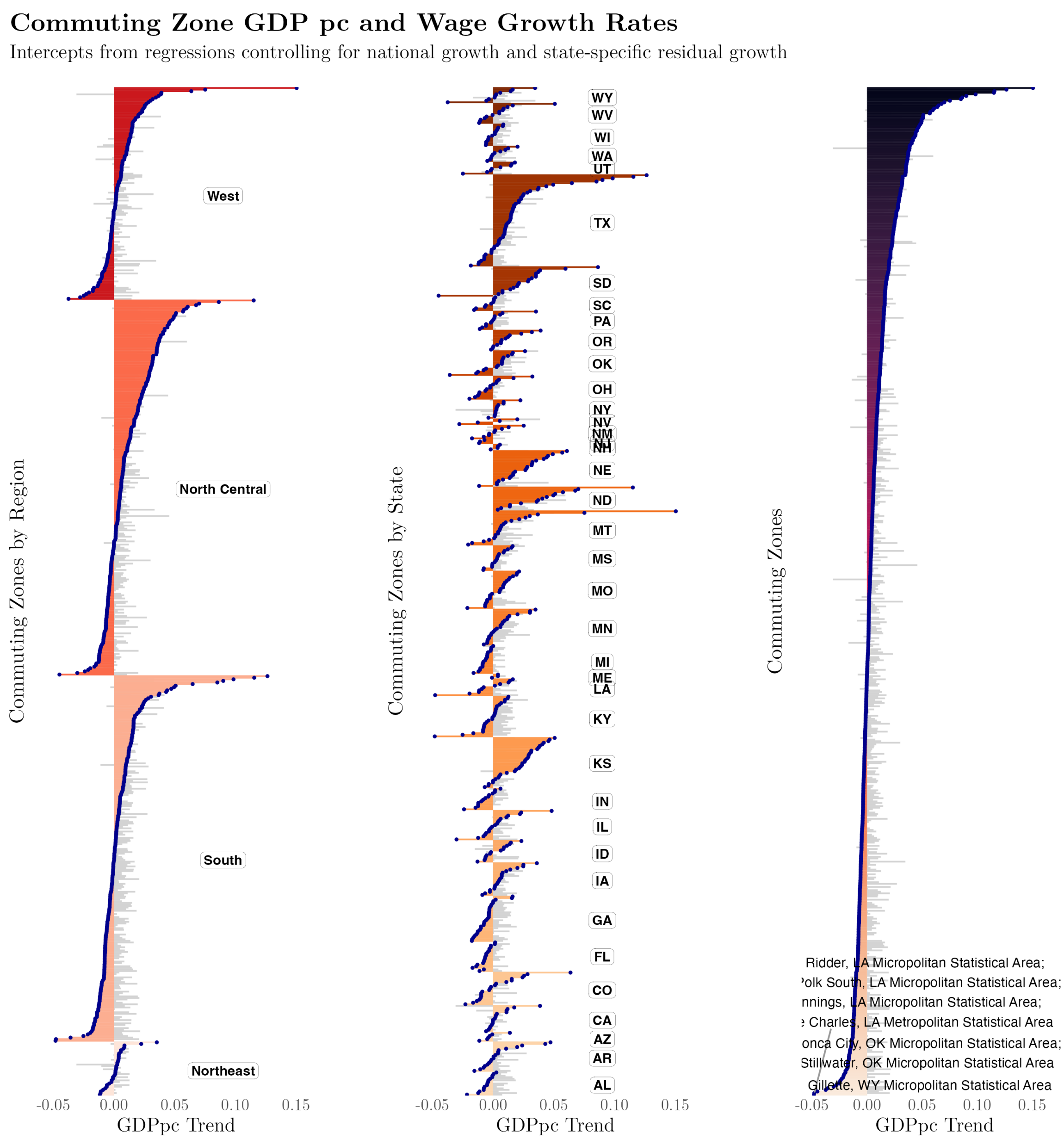


Figure 6: Lollipop Plot of Wage and GDPpc Growth Rates

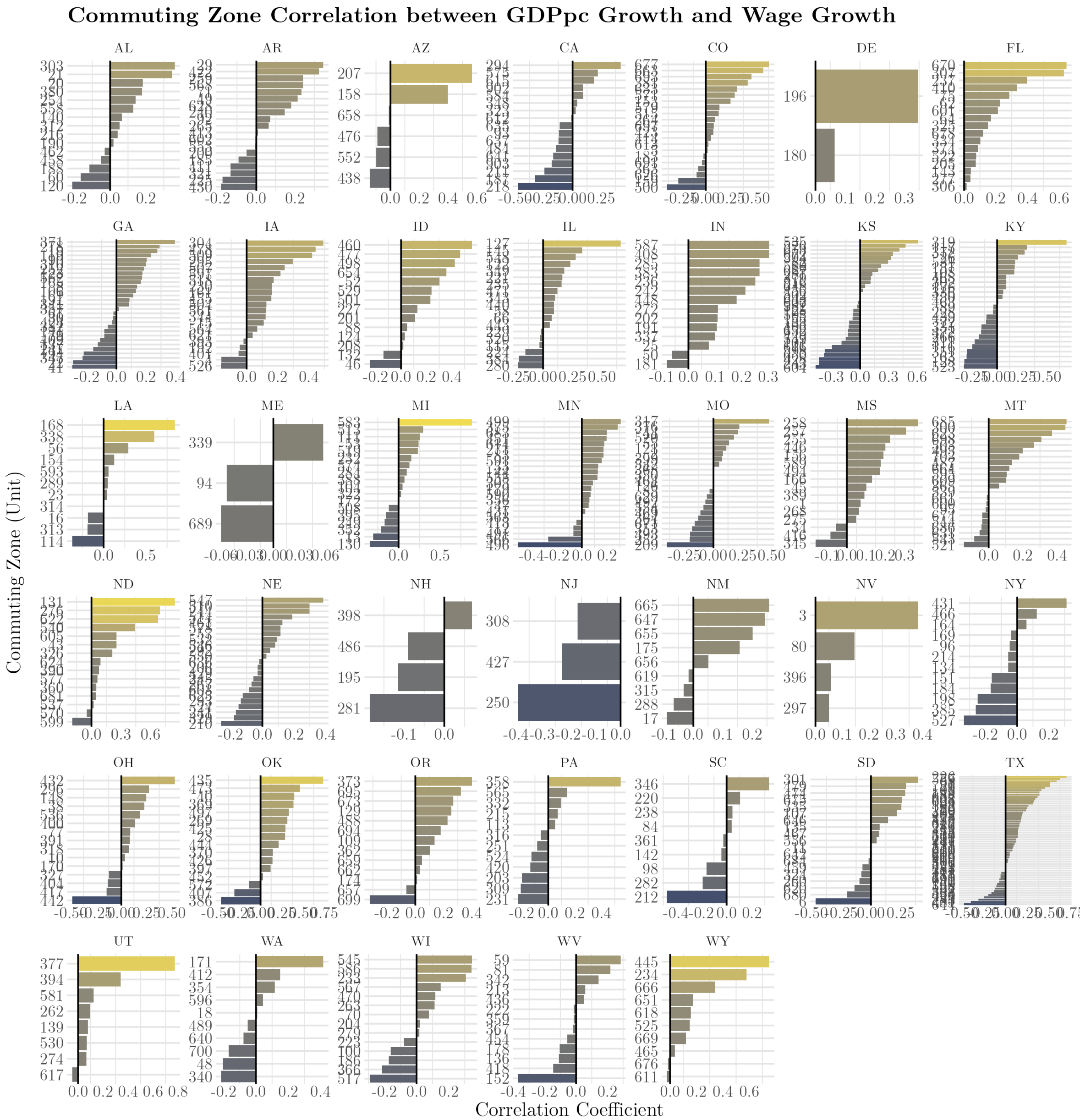


Figure 7: Correlation Between GDP Growth Rates and Wage Growth Rates by State

3.2.1.1 Sample Partitioning by Growth Rates

Using these growth rates, we partition the sample according to the percentiles described above. Table 6 and Table 7 examine how the relationship between local economic conditions and elementary education expenditure per pupil varies across structurally growing and declining regions as defined in the previous section. We partition our sample into four sub-samples by their values of α_w and α_g as shown in Table 5.

Table 5: Category Definitions

Category	Definition (α_w, α_g)
Declining	$\alpha < 0$

Category	Definition (α_w, α_g)
Hyper-Declining	$\alpha < P_{25}$
Growing	$\alpha > 0$
Hyper-Growing	$\alpha > P_{75}$

Zones with negative (positive) values of α_w or α_g are designated as declining (growing), while those in the bottom (P25) and top (P75) quartiles are labelled hyper-declining and hyper-growing, respectively. This stratification enables comparison of fiscal responsiveness across local economies with different long-run growth trajectories.

Table 6 partitions CZs by α_w. Interestingly, we observe positive statistically significant relationships between wages and public education expenditure though the magnitude and statistical significance of this relationship declines almost uniformly as α_w discretely increases. We see a similar declining size and significance in the explanatory variable accounting for inter-governmental revenue, indicating that these revenues play a smaller role in regions exhibiting above-average wage growth.

In Table 7 partitions CZs by long-run GDP per capita trends. The statistical significance and magnitude variations in the wage response tell a less monotonic story here, likely mirroring the lack of systematic correlation between α_w and α_g When partitioning the sample by GDP growth rates, the interpretation is more straight-forward.

Regardless, all models remain well-identified, with high first stage F statistics, convincing performance on the Wu-Hausman endogeneity tests and Wald tests. Combined, these results indicate that partitioning by background wage growth rates provides greater insight into the sample's heterogeneity than diversity in GDP per capita growth rates. More precisely, given communities feel wage growth more directly than GDP per capita improvements, it is likely that the relationship between public education and wage changes is better captured by sub-sampling by wage growth rates.

Table 6: Second-Stage: VA-based Shift-Share Instrument (l1) Applied to Declining Wage vs. Growing Wage Regions

Dependent Variable:	(log) Elem.Ed.Exp.pp				
	All	Hyper-Declining (Wage)	Declining (Wage)	Growing (Wage)	Hyper-Growing (Wage)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) Annual Avg. Wkly. Wage	0.2269***	0.3277***	0.3394***	0.2128***	0.1551*
	(0.0477)	(0.0683)	(0.0861)	(0.0527)	(0.0830)
(l1, log) Elem.Ed.Exp.pp	0.5086***	0.5148***	0.5543***	0.5019***	0.5311***
	(0.0156)	(0.0267)	(0.0332)	(0.0173)	(0.0290)
(log) IG Revenue pp	0.2230***	0.2800***	0.2101***	0.2245***	0.1553***
	(0.0211)	(0.0341)	(0.0317)	(0.0239)	(0.0391)
(log) Real GDP Priv. Industry pc	0.0662***	0.0156	0.0220	0.0703***	0.0685***
	(0.0144)	(0.0238)	(0.0313)	(0.0150)	(0.0160)
(log) Enrollment	-0.1957***	-0.2269***	-0.1995***	-0.1941***	-0.2001***
	(0.0157)	(0.0254)	(0.0351)	(0.0175)	(0.0332)
% Black	0.3333*	0.2172	0.2137	0.3892*	1.193**
	(0.1924)	(0.2664)	(0.3680)	(0.2294)	(0.5557)
% Hispanic	0.0483	0.2597	0.2509	0.0110	0.1335
	(0.1509)	(0.2566)	(0.1897)	(0.1781)	(0.3037)
Fixed-effects					
unit	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,084	3,021	1,520	10,564	3,021
R^2	0.90636	0.92102	0.94210	0.89805	0.90098
Within R^2	0.51804	0.57170	0.58942	0.50752	0.50064
Wu-Hausman	44.905	12.495	8.9646	36.833	18.989
Wu-Hausman, p-value	2.17×10^{-11}	0.00041	0.00280	1.33×10^{-9}	1.36×10^{-5}
Wald (IV only)	22.645	23.023	15.549	16.276	3.4973
Wald (IV only), p-value	1.97×10^{-6}	1.68×10^{-6}	8.41×10^{-5}	5.52×10^{-5}	0.06157
F-test (1st stage), (log) Annual Avg. Wkly. Wage	5,972.4	1,354.5	813.43	5,156.1	1,214.4
F-test (1st stage), p-value, (log) Annual Avg. Wkly. Wage	0×10^{-16}	0×10^{-16}	0×10^{-16}	0×10^{-16}	0×10^{-16}

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

Table 7: Second-Stage: VA-based Shift-Share Instrument (l1) Applied to Declining GDP vs. Growing GDP Regions

Dependent Variable:	(log) Elem.Ed.Exp.pp				
	All	Hyper-Declining (GDP)	Declining (GDP)	Growing (GDP)	Hyper-Growing (GDP)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(log) Annual Avg. Wkly. Wage	0.2269***	0.2785***	0.2912***	0.1874***	0.2532***
	(0.0477)	(0.0737)	(0.0648)	(0.0595)	(0.0822)
(l1, log) Elem.Ed.Exp.pp	0.5086***	0.5430***	0.5286***	0.4937***	0.4893***
	(0.0156)	(0.0212)	(0.0193)	(0.0218)	(0.0282)
(log) IG Revenue pp	0.2230***	0.2290***	0.2575***	0.2086***	0.1911***
	(0.0211)	(0.0405)	(0.0345)	(0.0275)	(0.0397)
(log) Real GDP Priv. Industry pc	0.0662***	0.0378	0.0398	0.0714***	0.0759***
	(0.0144)	(0.0358)	(0.0320)	(0.0160)	(0.0172)
(log) Enrollment	-0.1957***	-0.2011***	-0.1911***	-0.2017***	-0.2353***
	(0.0157)	(0.0332)	(0.0238)	(0.0209)	(0.0295)
% Black	0.3333*	0.1517	0.1511	0.6266*	0.7367
	(0.1924)	(0.2226)	(0.1964)	(0.3421)	(0.7621)
% Hispanic	0.0483	-0.1417	-0.0061	0.0687	-0.0070
	(0.1509)	(0.2286)	(0.1702)	(0.1938)	(0.2165)
Fixed-effects					
unit	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	12,084	3,021	5,016	7,068	3,021
R^2	0.90636	0.90369	0.90765	0.90377	0.85786
Within R^2	0.51804	0.54248	0.55592	0.47980	0.48120
Wu-Hausman	44.905	10.070	18.286	20.577	22.401
Wu-Hausman, p-value	2.17×10^{-11}	0.00152	1.94×10^{-5}	5.83×10^{-6}	2.32×10^{-6}
Wald (IV only)	22.645	14.299	20.216	9.9366	9.5022
Wald (IV only), p-value	1.97×10^{-6}	0.00016	7.07×10^{-6}	0.00163	0.00207
F-test (1st stage), (log) Annual Avg. Wkly. Wage	5,972.4	1,846.6	2,651.0	3,287.8	1,501.4
F-test (1st stage), p-value, (log) Annual Avg. Wkly. Wage	0×10^{-16}	0×10^{-16}	0×10^{-16}	0×10^{-16}	0×10^{-16}

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

3.2.2 State-by-state estimation

Next, given the substantial heterogeneity in state-level economic makeup and public finance regimes, we investigate state-specific relationships between our variables of interest.

First, states vary in the number of commuting zones they contain. Figure 12 demonstrates that states have anywhere between 2 (Delaware) and 58 (Texas) commuting zones. This allows us to estimate panel-style regressions within each state to net out between-state variation that might be confounding our current treatment estimates.

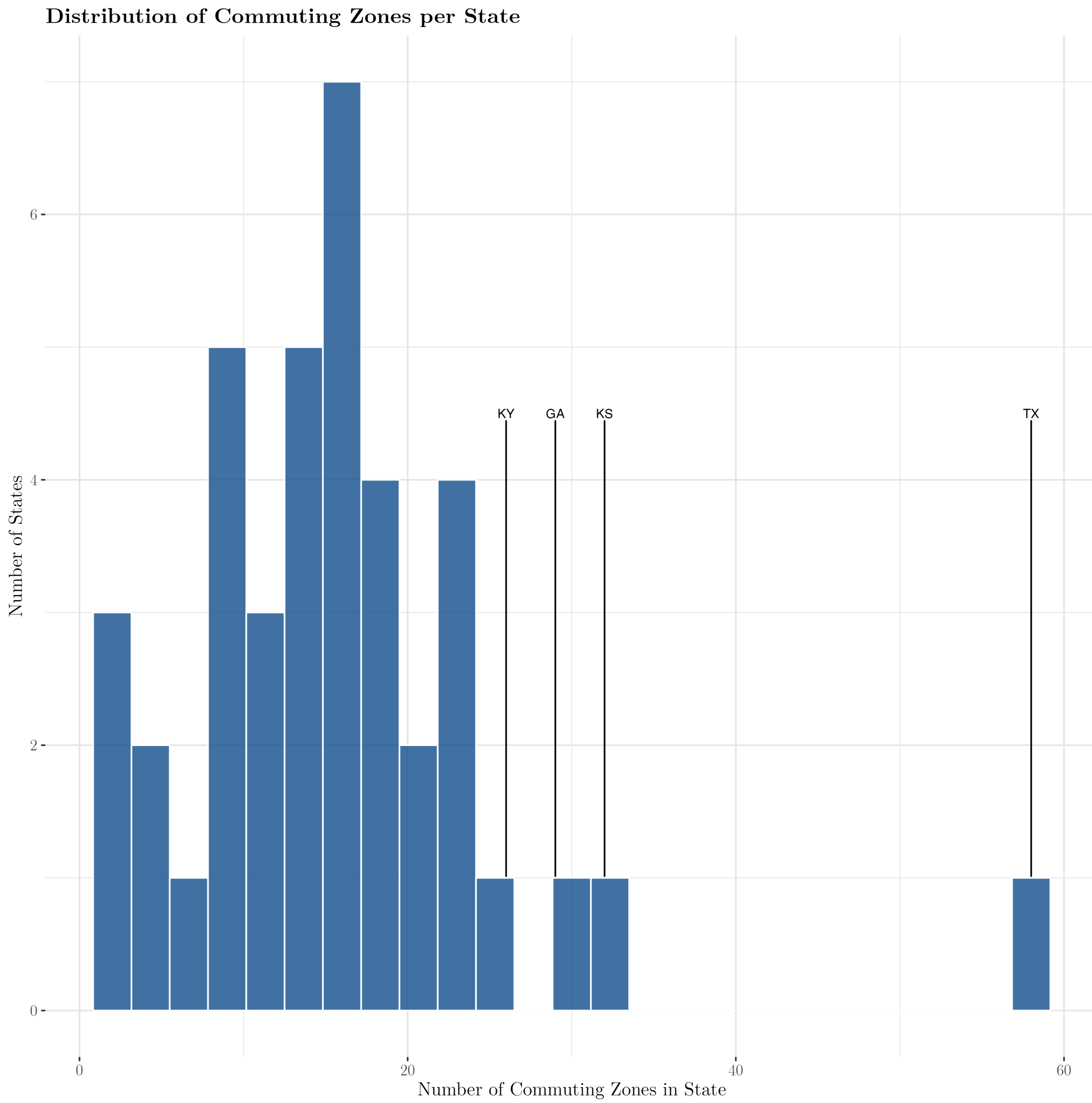


Figure 8: Histogram: Commuting Zones by State

Using our instrumental variable approach with a value-added based shift-share instrument, we corroborate the directionality and magnitude of the effect for 12 states: New Hampshire, Colorado, Florida, South Dakota, Kentucky, Louisiana, Pennsylvania, North Dakota, Oregon, Oklahoma, Arizona, and Indiana. In estimating the state-by-state regressions, we exclude any states where our F-statistic is below conventional weak instrument thresholds (F statistics $<= 12$ and p-value < 0.05) and the p-value of the second stage coefficient of interest is < 0.1.

Examining various characteristics of these states, we find that they vary widely in demographic composition, enrollment levels, and wage levels indicating that the detected effects are not attributable to any extremes in these values. Notably, majority of them reuly on a significant share of educational expenditure from local sources rather than intergovernmental sources.

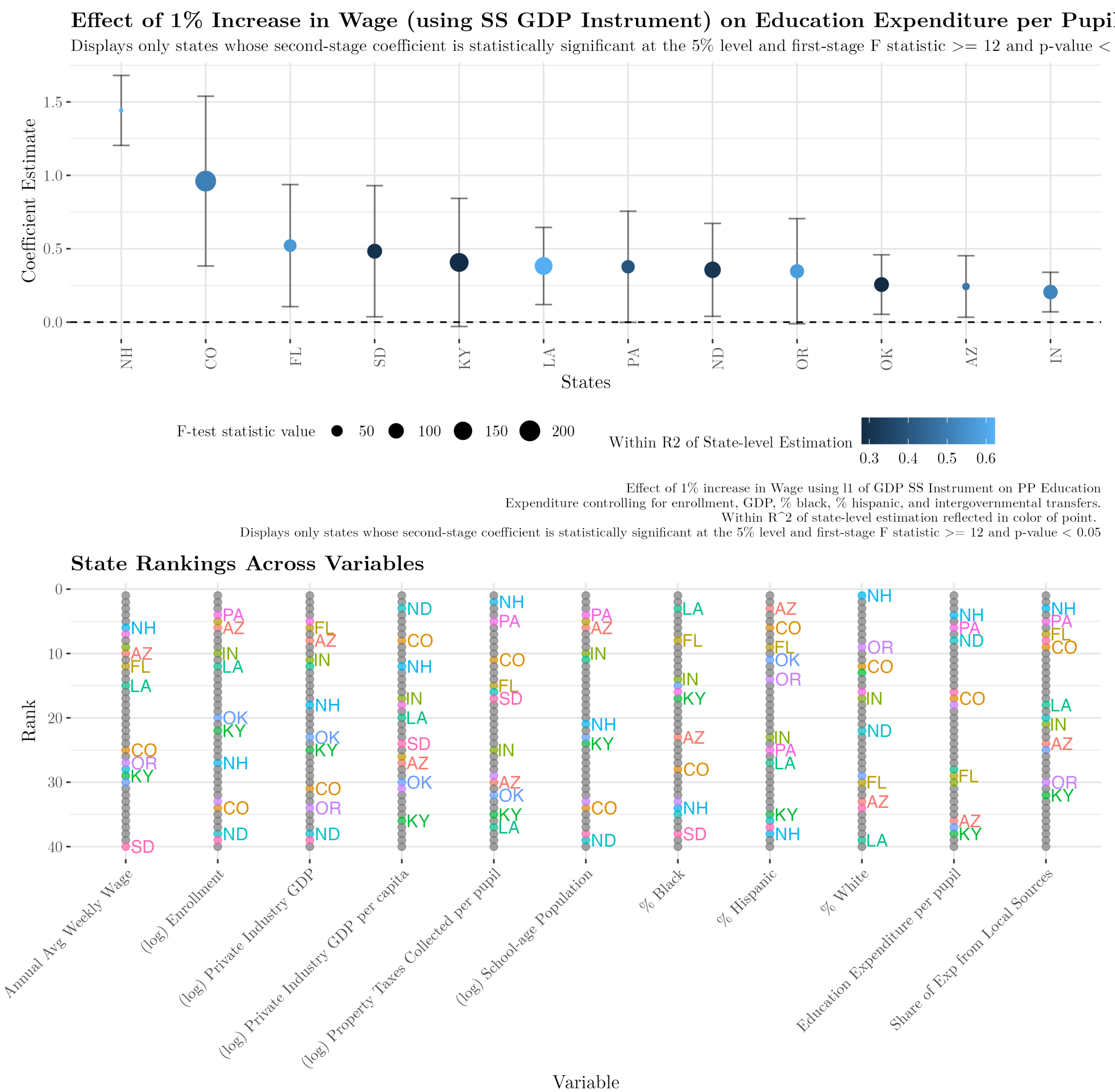


Figure 9: State-by-State Wage Effect Using SS GDP Shock

3.2.3 Industry by Industry

Finally, given our shift-share instruments are the composite effect of shifts in industry-level real value added (VA), we can decompose this instrument into industry-specific real value added shocks. This decomposition allows us to examine the effect of industry-specific changes across states in a more explicit manner. In other words, we re-design our instrument as...

$$\tilde{Z}_{ijt} = G_{njt} * \frac{N_{ij\tau}}{N_{i\tau}} \tag{6}$$

...rather than the sum of all industry-level shocks.

We estimate separate panel regressions using the full commuting zone sample and then grouping commuting zones by state instrumenting local level wages by these decomposed shift-share shocks by industry.

Using our value added-based shift share instrument, Figure 10 demonstrates the overall treatment effect of local wage changes instrumented via an industry-specific GDP shock. We find that regardless of the instrument design, the coefficient estimate is consistent with the baseline results, where the estimated effect of a 10% change to local wages on public education expenditure is a 2.2% increase, with the effect's magnitude varying meaningfully for several states. We plot the relevant state-level effects for those states whose estimations pass the same restriction criteria as above (F statistics <= 12 and p-value < 0.05 and the p-value of the second stage coefficient of interest is < 0.1).

Again, I want to improve this.

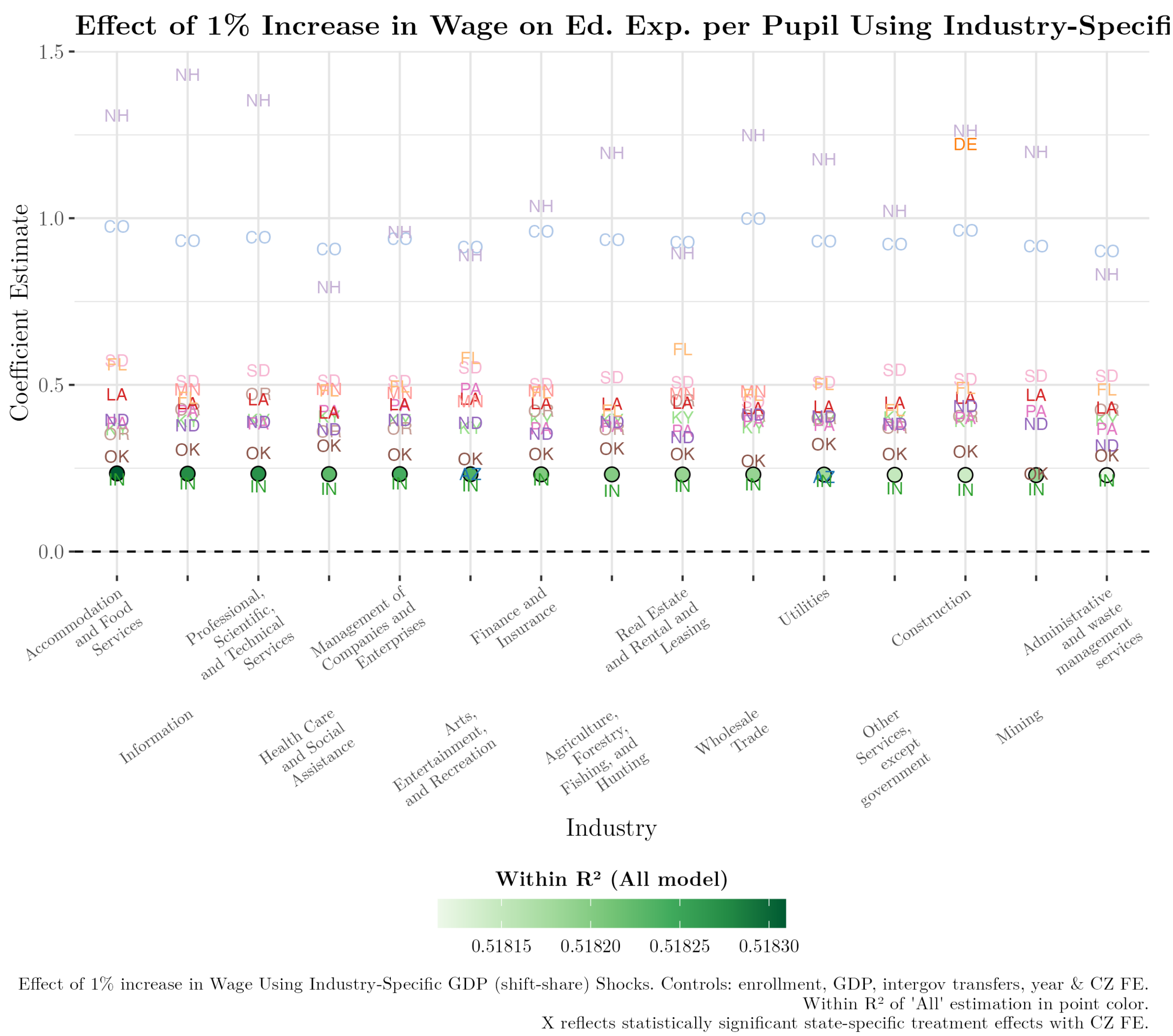


Figure 10: Wage Effect via Industry VA SS Shock

3.3 Additional Analysis Inventory

In the Appendices we include:

- Panel VAR Estimation
- Quantile regression estimation
- Exclusion of high-income CZ outliers
- Implementation of a wage-based (rather than VA-based) shift-share instrument
- National average treatment effects for all econometric estimation strategies outlined in the main text
- Information about the construction of the shift-share instrument

4 Conclusion

4.1 Discussion

This work establishes a causal link between local wage growth and public education expenditure. Our baseline estimates reveal a short-run wage elasticity of 0.23, with a long-run cumulative effect of approximately 0.46. The dynamic components of the econometric specification indicate significant persistence in local public education budgets, indicating both institutional inertia but also the likely rare revision of local tax rates allowing local wage growth to boost education spending. This persistence indicates potential for asymmetric adjustment likely correlated with local growth trajectories, wherein communities experiencing wage growth are likely to see gradual spending increases, while declining communities could experience the opposite effect.

This positive elasticity is concentrated in a third of the states in the sample (New Hampshire, Colorado, Florida, South Dakota, Kentucky, Louisiana, Pennsylvania, North Dakota, Oregon, Oklahoma, Arizona, and India), whereas other states exhibit minimal or insignificant responsiveness.

Though outcomes measured in this study are not direct inequality metrics, our findings reveal that the decentralised school financing system in the US has the potential to exacerbate inequalities in local public well-being by failing to equalise across regions experiencing diverging growth trajectories. As a result, in the states in which local spending is responsive to changes in local wages, the quality of early childhood education might be compromised by macroeconomic trends and industry-specific shocks beyond local control. Thus, equalisation formulas at the state and federal level that fail to account for wage trends and fiscal multipliers may contribute to disparities in public goods delivery. Theories of effective equalisation, and indeed preferences for redistribution, differ especially across regions of the the United States. However, equalisation efforts should at least aim to insulate communities from potential downward pressures on public education expenditure.

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.

Addressing structural inequality requires rethinking education finance, taking the decentralised American context as given. Ensuring educational equity for all children requires not just strengthening existing mechanisms for redistribution, but also, in light of our results, insulating communities from macroeconomic trends that impact communities heterogeneously.

4.2 Limitations

- Excludability assumptions about local industry composition
- Data limits true consideration of non-stationarity issues. Estimating this model in first differences or growth rates would be preferable to address non-stationarity concerns as well as allow for asymmetric

treatmetn estimation to distinguish between negative and positive wage pressures. However, this would require improvements in data collection of the required variables.

- Commuting zones mask substantial within-commuting zone heterogeneity

5 Data and Code Availability

Code and data to reproduce the analysis will be made available on Github or Zenodo.

6 Use of AI

- Used ChatGPT to help improve readability of plots (formatting, margins, labeling, font size).
- Used ChatGPT to debug errors in R during data cleaning and plotting.
- Used ChatGPT to provide suggestions for reducing run time of repetitive tasks (ex. downloading and processing multiple data files).

7 Acknowledgements

Appendices

A Modelling Challenges

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

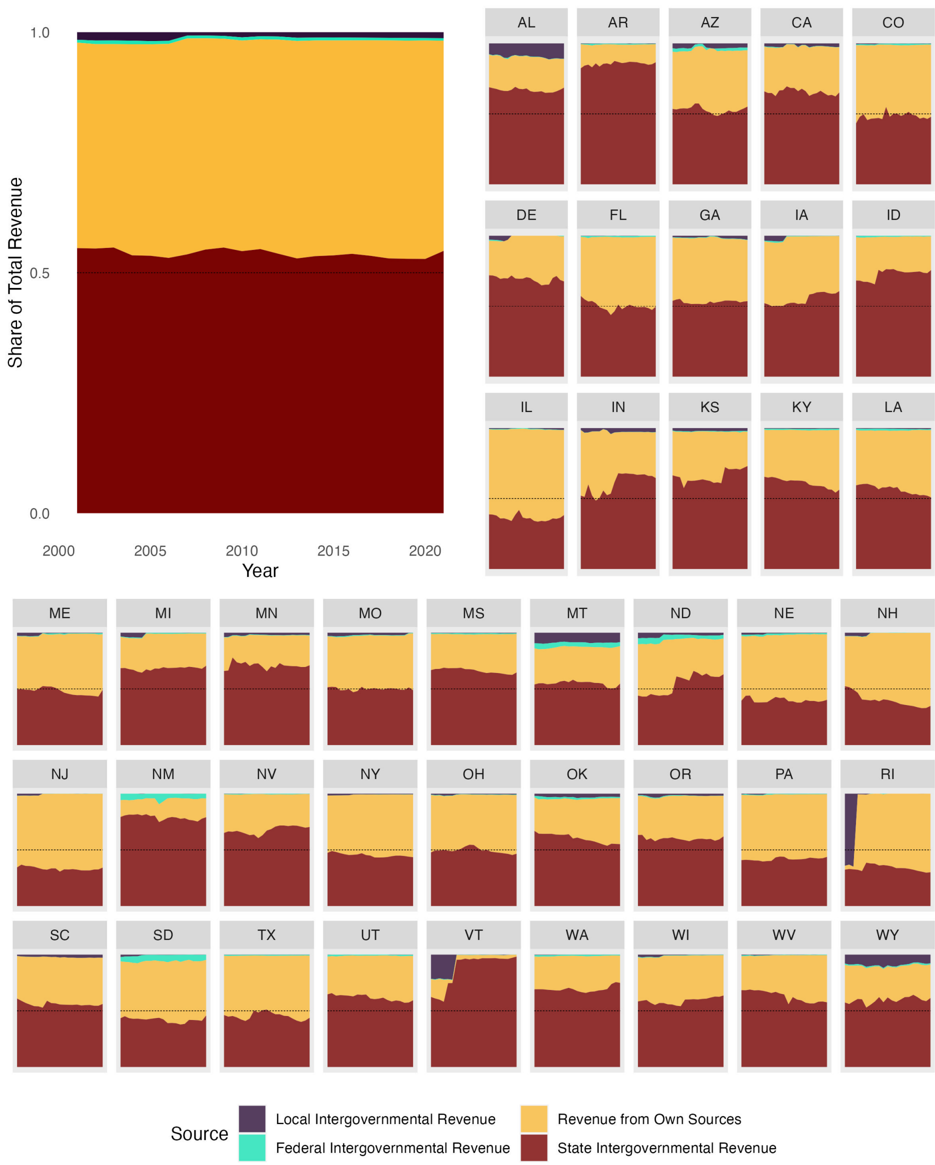
A.1 Structure of Financing for Local Public Education

In order to appropriately make use of the outlined data as well as robustly define the econometric methods to be utilised in this work, an understanding of the funding structure of public school districts in the US is critical. Public school districts in the United States are funded by a combination of federal (8.3% in 2019), state (47% in 2019), and local (44.8% in 2019) revenues [**?**], with shares varying by county. This variation in public funding structure will need to be incorporated into the modelling efforts, likely through a weighted regression approach based on shares of intergovernmental versus own-source revenues [**?**]. Using the data outlined, Figure 11 displays the share of public education revenue coming from three sources of intergovernmental revenue (federal, state, and local) as well as revenue from own county-level sources by state. The figure demonstrates the clear near-even split between state intergovernmental and own source revenue and the overall small share of revenue coming from federal or other local governments. The larger panel on the top left provides the summarising share at the national level. All plots share the axes as labeled in the top left panel.

A.2 Trends over time

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

Figure 11: Share of Revenue from Federal, State, Local Sources



A.3 Historical efforts to "equalise" US public education

Another factor that greatly impacts the data generating process in this study is that increasing recognition of the level of inequality of public education provision in the US has led to the implementation of several efforts to "equalise" public education by aiming for "per pupil" expenditure targets [?]. The most significant change in this respect has been the creation of Educational Service Agencies (ESAs). These ESAs are apportioned state funding to serve multiple school districts in sub-regions of each state. Most of these ESAs were established around 2007 and persist to this day. ESAs are listed by state in Table 8. Currently, there are 553 agencies nationwide in 45 states. According to the Association of Educational Service Agencies (AESA), ESAs reach over 80% of the public school districts and well over 80% of public and private school students. Annual budgets for ESAs total approximately $15 billion [?]. Because ESA revenue and expenditure is inconsistently reported across years in our dataset, as well as attributed to individual counties despite often serving multiple, there is a significant risk that ESA expenditure is misattributed to counties in our dataset. Therefore, I exclude ESA revenue and expenditure totals from the measures of county-level expenditure and revenue at all levels of aggregation, and retain these values as possible control variables.

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

A.4 Availability of varying local-level outcomes

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

A.5 Structural and policy heterogeneity

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

A.6 Cross-Sectional Dependence

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

References

Table 8: Educational Service Agencies by State

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

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