

Uneven Wage Growth and Public Goods

The Case of US Public Education

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Abstract

Over recent decades, the United States has experienced increasingly divergent patterns of economic and wage growth. Wage growth is a key driver of local wealth accumulation, enabling greater household and community investment in public goods. Regions whose wages track productivity gains likely benefit from broader economic growth, accumulating wealth that sustains local public services, while lagging regions risk weaker savings rates and eroding fiscal capacities. We estimate how divergent wage growth across U.S. regions affects public education expenditure using a shift-share instrumental variable design. Accounting for state-level heterogeneity in tax regimes, income, and economic growth, we find substantial variation in the elasticity of education spending to wages: the magnitude and statistical significance differ markedly across states. This heterogeneity explains the majority of spending responses and reflects both uneven economic fundamentals and diverse fiscal institutions that generate inequality in public goods provision. Our results demonstrate that average treatment effects in panel studies can obscure critical policy-relevant variation. The findings suggest that federal and local policies assuming uniform wage-spending relationships may fail to address or even exacerbate pervasive spatial inequality in educational investment.

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1 Introduction

Since the 1970s, a persistent divergence between productivity growth and wage growth has emerged in the United States (Hoffmann, Lee, and Lemieux (2020), Stansbury and Summers (n.d.), Economic Policy Institute (n.d.)). 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 (Autor (2014), Katz and Murphy (1992)) to competition (Stansbury and Summers (n.d.), Deb et al. (2022), Yeh, Macaluso, and Hershbein (2022), Azar, Marinescu, and Steinbaum (2022), (autor2013a?) , Wilmers (2018)) to institutional and policy forces (Egger, Nigai, and Strecker (2019), Lee (1999), Mishel and Bivens (2021), Barkai (2020), Autor, Manning, and Smith (2016), Card (2001)).¹ Though its causes are hotly debated, the fact itself is well-documented, especially for lower- and middle-income workers.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 national 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 (wages) is weak. The benefits of economic growth have already accrued unevenly across communities in the United States. Economic history and industrial activity have heterogeneously impacted the development trajectories of US regions (Fee (2025), Storper and Scott (2009)).

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. Put plainly, given the structure of US public services, wherein they are funded largely through property taxes and thus tied to asset values, inequality in wealth-building can have significant effects for the quality of local public services.

Community well-being and public expenditure in the US is already characterised by a high degree of spatial heterogeneity. Evidence of how income and wealth inequality perpetuate other forms of inequality (opportunity, health, infrastructure quality, and broader well-being) is steadily increasing (Chetty et al. (2016), Logan, Minca, and Adar (2012), Semuels (2016), Avanceña et al. (2021), Flavin et al. (2009)). Boustan et al. (2013) 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

¹Summers and 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 Autor (2014). 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.

²Though 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 Aeppli and Wilmers (2022).

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.

(Manduca 2025, Feler & Senses 2017)

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. 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)), and competing in academic and extra-curricular activities.

(Zheng & Graham, Biolsi 2022)

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 is of paramount importance to ensure greater equality in the long-run.³ ⁴ [^6] 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.

Expenditure numbers matter for education quality/outcomes. (Baker 2016, Jackson 2016),

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

³Perhaps 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.

⁴Ahlerup, Baskaran, and Bigsten (2020) find that for 30 countries in Africa, the presence of gold mines during adolescence have a significant effect on educational attainment. Badeeb, Lean, and Clark (2017) investigates whether resource dependence slows economic growth with no explicit mention of education. Blanco and Grier (2012) find that in Latin America, petroleum export has a significant long-run negative relationships with human capital. Borge, Parmer, and Torvik (2015) find support for the paradox of plenty hypothesis in Norway - that higher local public revenue negatively affects the efficiency of local public good provision. Brunschweiler 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 dependence 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 authoritarian regimes. Menaldo (2016) argues again that this is an institutions curse and not a resource curse issue. Sincovich et al. (2018) provide a literature review of resource curse investigations in the Australian context.

industries and regions, then the fiscal capacity of local governments may be shaped as much by institutional and structural conditions as by aggregate economic growth. We answer the following questions:

RQ1: Do local wage gains affect public education expenditure?

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

RQ3: In light of reforms to intergovernmental education funding to alleviate uneven educational expenditure, do intergovernmental transfers alleviate wealth-driven inequalities in public education expenditure?

The elasticity of public education expenditure to local wages has ambiguous interpretation that depend on various possible fiscal priorities (wording?) and possible substitution effects. 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.

Conversely, a negative elasticity could emerge through several channels. Any response in needs-based inter-governmental 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 wherein local communities reprioritise fiscal windfalls toward government expenditure other than in public education. (Cite Texas Shale Boom Paper).

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 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.

1.1 Theoretical Motivation and Empirical Approach

This work interrogates the elasticity of public education expenditure to uneven economic and wage growth across US commuting zones.

We construct a shift-share (Bartik) instrument that combines fixed local industry employment shares with national industry-level changes in wages and real value added. Following the established literature (Bartik 1991; Goldsmith-Pinkham, Sorkin, and Swift 2020; Ferri 2022), we fix local employment shares to a baseline period and interact them with national growth rates in industry real value added. Using data from the U.S. Bureau of Labor Statistics and Bureau of Economic Analysis, we construct commuting-zone-level Bartik instruments based on both outcomes. This provides a credible and transparent identification strategy that links macroeconomic shocks to local education funding.

This strategy 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, depends heavily on industries that are unevenly distributed across regions but likely 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 in a panel dataset from the Annual Survey of State and Local Government Finances.

The outlined instrumental variable strategy tackles the central endogeneity challenge present in any study of the linkage between two or more local socio-economic outcomes. In the context of this study, wages

and public education expenditure are undoubtedly endogenous, since higher-income families may self-select into districts with greater education spending, confounding causal inference. Therefore, we instrument local wages with the constructed shift-share instruments to circumvent this challenge allowing for plausibly causal inference.

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 single, well-defined national average treatment effect is inherently limited. We provide an initial benchmark using a pooled estimation to establish baseline relationships between wages, GDP, and asset values that appear to generalize reasonably across the national economy, before investigating the heterogeneity that these pooled estimates mask in our main analysis. We further advance this analysis via state-by-state and industry-by-industry estimations and group commuting zones by their historic growth trajectories to improve comparability of treatment and control groups in our instrumental variable design.

1.2 Detailed results

1. Public education expenditure is not agnostic to local economic conditions. We establish a strong causal link between public education expenditure and local wages using a shift-share instrumental variable estimation, and subsequently for specific industries and states and growth cohorts. The estimated treatment effect of local wages on public education expenditure varies in magnitude, and statistical significance across states.
2. Estimating the instrumental variable model separately for each state reveals substantial heterogeneity in the relationship between wages and education expenditure. Less than 10 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.
3. *Industry-level estimation result.* TBA

1.3 Roadmap

In the sections that follow, we outline in Section 2 the data to be used in the analysis; Section 3 the methodological approach with accompanying results; Section 4 and Section 5 provide a discussion and concluding remarks.

2 Data

We compile a panel dataset of the following indicators across 636 commuting zones (CZ) in 41 US states between 2001-2021.

Expenditure and Revenue: This work employs Willamette University's Annual Government Finance Database at the commuting zone (CZ) level. This resource is a harmonised repository of the data collected annually as part of the US Census Bureau's Annual Survey of State & Local Government Finances, the 'only comprehensive source of information on the finances of local governments in the United States' (Pierson, Hand, and Thompson (n.d.)). 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 the regressions below also come from this dataset. Expenditure on vocational training and from Educational Service Agencies (ESAs) are also sourced from this dataset. We aggregate school district measures up to the commuting zone-level to ensure the availability of adequate control and treatment variables.⁵

⁵The 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,

Thus, this dataset provides estimates in \$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.).

Population controls: US Census Bureau.

GDP Controls: We 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 from 2001-2021. The controls used in the below are commuting zone-level private industry GDP. We decide to use 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 provides geographically linked data on single-family house prices called the Housing Price Index. HPI is a broad measure of the movement of single-family house prices. The FHFA HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac (two US government-sponsored enterprises that guarantee most US mortgages) since January 1975 ([Source](#)). It is reported at the county level at an annual frequency. We aggregate to the commuting zone level via a mean.

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.

This data aggregation results in a complete and balanced panel of 636 US commuting zones across 40 states between 2001-2021.⁶ ⁷ All data used is reported annually at the commuting zone level.⁸ Therefore, no time-invariant variables are included (apart from an indicator of the state a CZ is in).

?? desc reports summary statistics across relevant variables. All (dollar) values are reported in (real 2017-chained) thousands except for the House Price Index.

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 %	Black	13,356	0.08	0.12	0.0005	0.72	
% White	13,356	0.87	0.14	0.09	1.00							

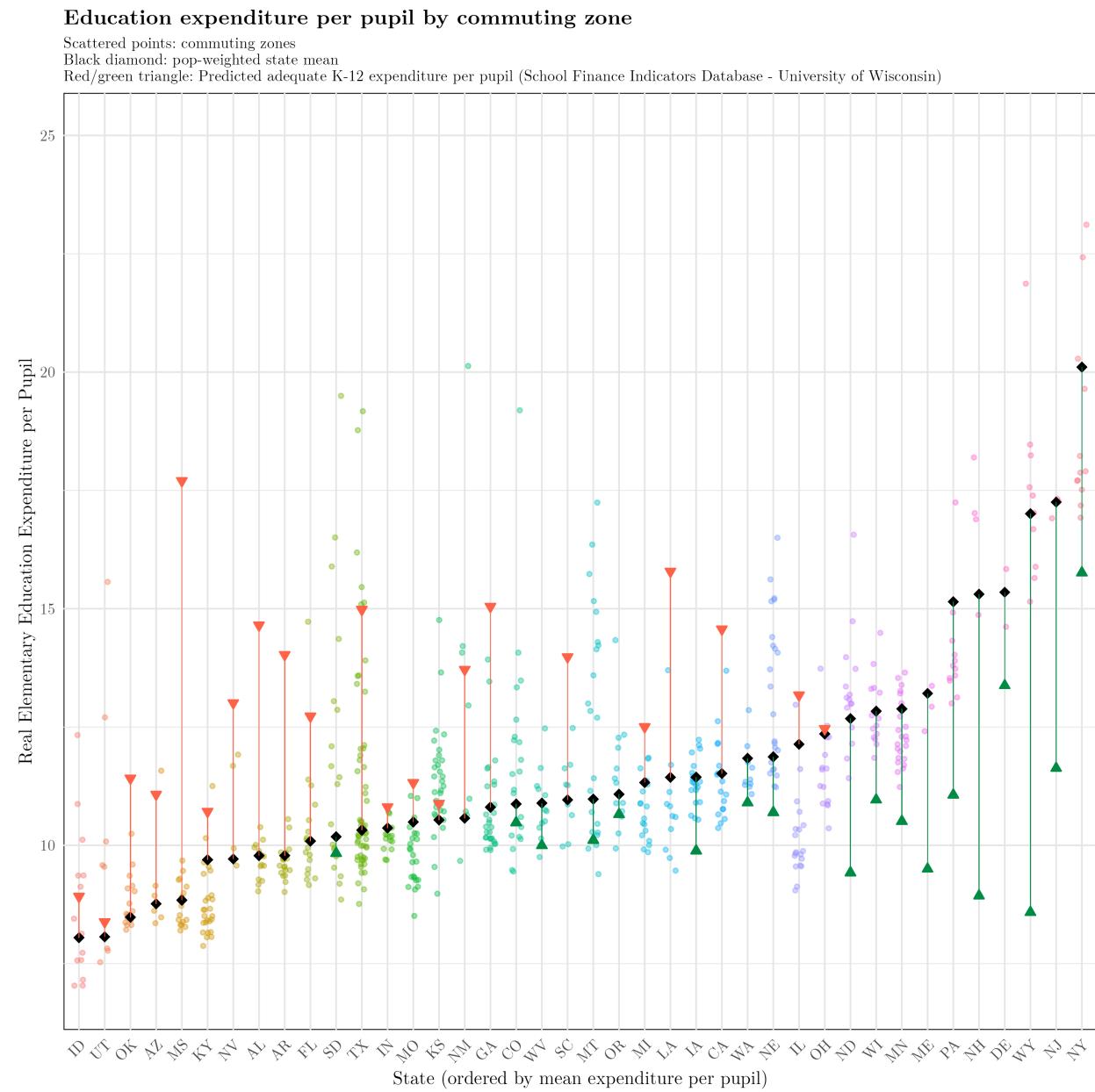
and Thompson (n.d.)). We choose to conduct the analysis on the commuting zone level because (1) it is a more accurate picture of a local labor market area (Carpenter, Lotspeich-Yadao, and Tolbert (2022)) and (2) a lack of availability of control variables at a school district level.

⁶The reason 13% of all US CZs are missing from the dataset is because of (1) the exclusion criteria already outlined; (2) Hawaii and Alaska have been excluded due to the methodological challenge of incorporating their school districts into spatial econometric work; and (3) Connecticut, Maryland, North Carolina, and Virginia have been excluded due to unconventional or incomplete public school district reporting.

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

⁸In 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](#)).

% Hispanic 13,356 0.10 0.15 0.002 0.96



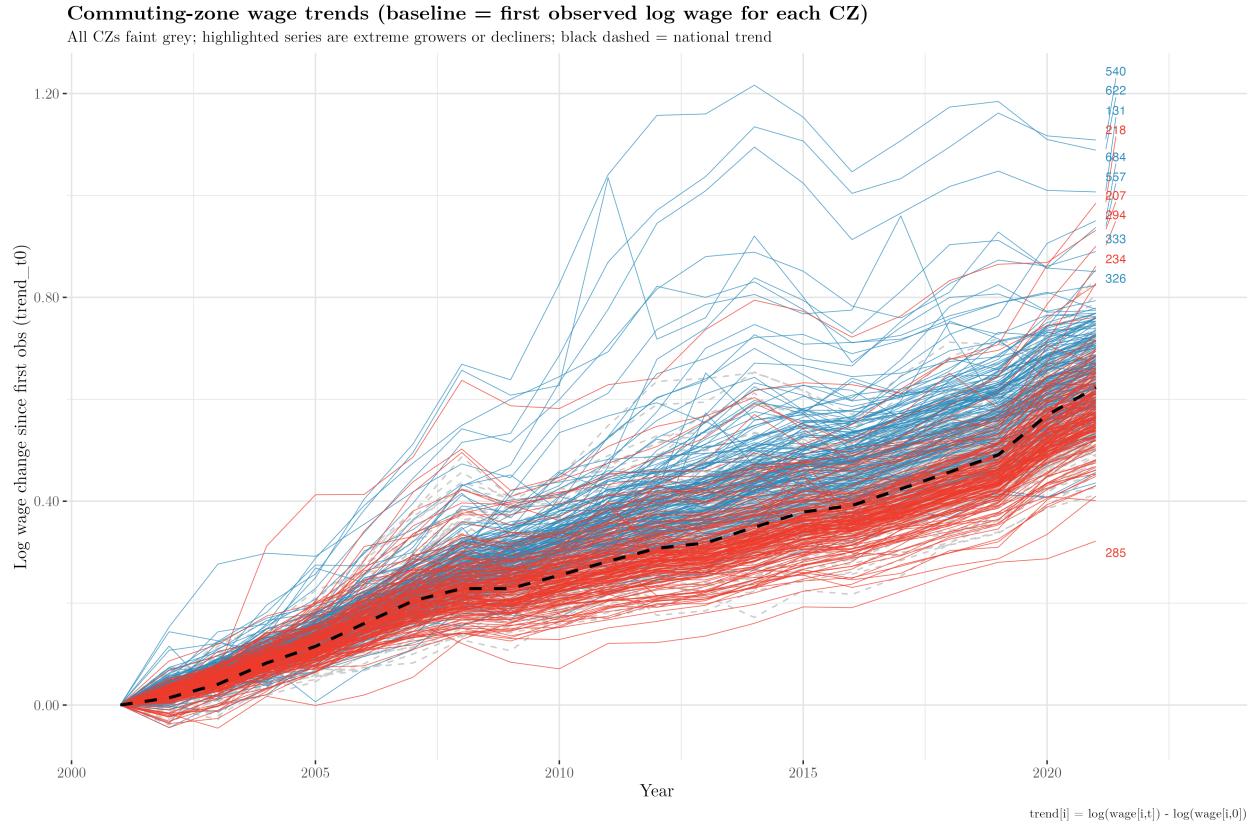


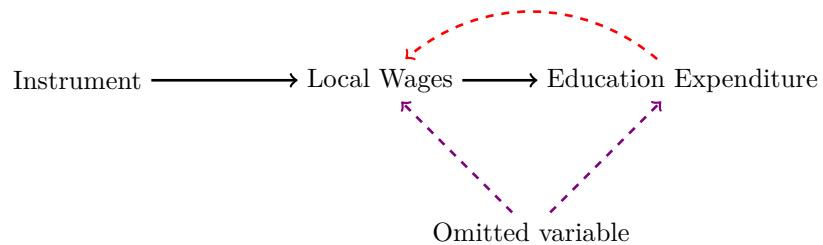
Figure 1: Wages and Productivity

3 Methods

3.1 Identification Strategy

We are centrally interested in the effect of changes in local wages on public education expenditure. There is a significant endogeneity concern in using local wages as a treatment variable for two reasons: (1) the likely attracting factor of high levels of education expenditure for higher-income families and, (2) absent migration, education systems provision local labour markets with individuals with diverse human capital. Therefore, we instrument local wages using a shift-share based instrument of real value added across 19 industrial categories.

Figure 2: Instrumental Variable Path Diagram



Shift-share or *Bartik* instruments have gained popularity in empirical work as a method of handling endogeneity issues in panel data (Ferri (2022), Goldsmith-Pinkham, Sorkin, and Swift (2020), Bartik (1991)).

Such instruments combine time-variant, unit-invariant changes in aggregate economic variables (ie., national changes in industry wage levels) with time-invariant, unit-variant shares in exposure to these macro-level changes (ie., local shares of employment in particular industries). This decomposition of local-level changes via a delocalisation over space and time allows for a defensible ‘de-endogenising’ of the treatment. Notably, the method can also be considered to serve a further purpose as, by construction, it allows for the examination of a macro phenomenon’s effect on more local units.

[9](#) [10](#)

Therefore, we adopt an identification strategy via a shift-share instrument. A shift-share instrument interacts local industry shares with national industry-level growth rates to obtain a plausibly exogenous local shock. In the context of this work, we construct the instrument by interacting a commuting-zone level constant industrial employment share variable with national industry-level real value added data.

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 would look as follows:

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

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:

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

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

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

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

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

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

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

...or...:

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

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

Using data from the Bureau of Economic Analysis, we construct a shift-share Bartik instruments at the commuting zone level using local employment shares by industry and national changes in industry-specific real value added represented in Equation 2. 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’.

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 are greater using this shift-share instrument and is therefore excluded from the main text.

[11](#)

$$\tilde{Z}_{it} = \sum_{j=1}^k G_{njt} * \frac{N_{ij\tau}}{N_{i\tau}} \quad (2)$$

This yields a 2SLS AR(1) model defined by the first- and second-stage regressions represented in Equation 3 and Equation 4. Due to the likely presence of time-dynamic effects, we include contemporaneous, 1-year, 2-year time lags as instruments.

$$(\text{First stage}) \quad X_{it} = \phi X_{i,t-1} + \sum_{\ell=0}^2 \pi_\ell \tilde{Z}_{i,t-\ell} + \theta \mathbf{W}'_{it} + \alpha_i + \lambda_t + u_{it}, \quad (3)$$

$$(\text{Second stage}) \quad Y_{it} = \phi^* Y_{i,t-1} + \beta \widehat{X}_{it} + \delta \mathbf{W}'_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

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 and economic performance.

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

¹¹We 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.

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 compute the relevant shift-share instrument across 19 two-digit NAICS industrial categories listed in [Table 1](#). 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 rest of the work.

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 1: Industry Categories

Data Coverage of Industry-level Employment as Share of Total Reported Employment

Data coverage is calculated as the fraction of total local employment accounted for in the industry-specific employment zones.

Percentage labels represent proportion of commuting zones (percentiles) falling below a coverage value.

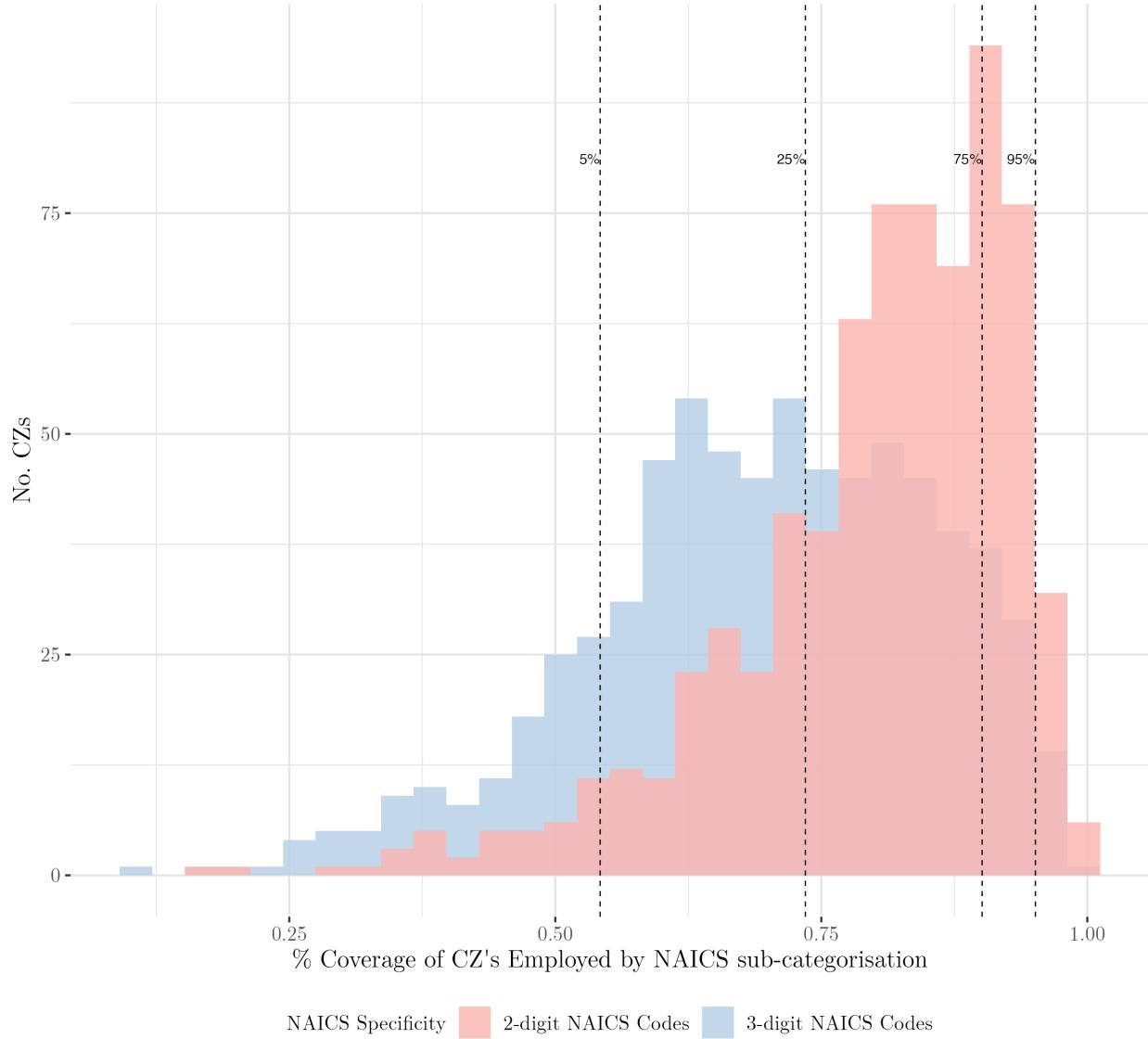


Figure 3: Data Coverage of Industry-level Employment as Share of Total Reported Employed

In Table 4, we demonstrate a strong and highly significant first-stage relationship wherein our VA-based shift-share instrument indicates a strong positive contemporaneous relationship with local wages. We find that a 1% increase in our shift-share instrument raises local wages by 0.25% in the same year though these wages rebound as evidenced by the statistically significant negative coefficient of a similar magnitude on the 11 regressor. Essentially, the time dynamics indicate that local wages respond quickly to national sectoral shocks, though not permanently. This can likely be interpreted as a temporary local demand boom following industry-level value added shocks. This provides additional evidence that the shift-share instrument captures short-term exogenous variation rather than slow-moving trends in local wages, boosting credibility in our instrumental variable relevance. The growth rate specification in columns 3-4 provide further evidence of the transitory nature of these demand shocks as only the contemporaneous growth rate effect is significant.

The first-stage F-statistic using the level SS instrument is well above conventional weak instrument thresholds

confirming instrument relevance. Furthermore, the Wu-Hausman tests reject the null of exogeneity, confirming that OLS estimates are biased and IV estimation is appropriate. Wald tests of joint significance further support the strength of the instruments and the importance of incorporating time-lagged instruments.

Using wage shocks in levels yields strong instruments, defensible first-stage F-statistics, and stable second-stage estimates: positive (negative) local wage shocks robustly decrease (increase) education spending.

Taken together, these two specifications yield consistent and meaningful results wherein the shift-share instrument allows for the causal identification of negative relationship between local wage shocks and education expenditure. The similarity in magnitude of the two designs implies that the estimated effect is robust to the timing and persistence of the underlying economic shocks. Most importantly, this indicates that the mechanism identified is driven by temporary demand shocks rather than permanent income effects. Interpretation of these results requires a further exploration of local heterogeneity, outlined in the following sections.

One could interpret this result as either a confirmation of resource course dynamics in communities dependent on industries employing lower-skill workers. If these effects are concentrated in less economically prosperous areas, local wage booms in particular sectors might be distracting public and administrative attention away from local public education investments. On the other hand, if these effects are driven by wage booms in communities reliant on higher-skill labour, one could see this as a potential feedback between decreases in intergovernmental revenues which are intended to be needs-based, even though the specification controls for this effect, or potentially a crowding out of public education by private education. The results below do not provide a meaningful ability to distinguish the relative accuracy of either of these hypotheses.

Computing bootstrap standard errors (399 replications)... Using 8 cores for parallel bootstrap... Bootstrap completed in 5.1 seconds

```
==== Standard Error Comparison ====
Variable Naive_SE Bootstrap_SE Ratio
l1_log_real_Elem_Educ_Total_Exp_pp
l1_log_real_Elem_Educ_Total_Exp_pp 0.0157 0.0152 0.9669
fitted_endog log_weighted_annual_avg_wkly_wage
0.0485 0.0502 1.0364
log_real_Total_IG_Revenue_pp log_real_Total_IG_Revenue_pp 0.0210 0.0207
0.9889
log_real_gdp_priv_ind_pc log_real_gdp_priv_ind_pc 0.0144 0.0151 1.0519
log_Enrollment
log_Enrollment 0.0158 0.0165 1.0440
pct_black pct_black 0.1886 0.1976 1.0477
pct_hispanic pct_hispanic
0.1509 0.1472 0.9756
```

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)... Using 8 cores for parallel bootstrap... Bootstrap completed in 4.5 seconds

```
==== Standard Error Comparison ====
Variable Naive_SE Bootstrap_SE Ratio
fitted_endog
gr_weighted_annual_avg_wkly_wage 0.7887 1.0888 1.3806
diff_log_real_Total_IG_Revenue_pp
diff_log_real_Total_IG_Revenue_pp 0.0317 0.0329 1.0358
diff_log_real_gdp_priv_ind_pc diff_log_real_gdp_priv_ind_pc
0.0473 0.0651 1.3761
diff_log_Enrollment diff_log_Enrollment 0.0425 0.0455 1.0712
fd_pct_black
fd_pct_black 1.4189 1.3520 0.9528
fd_pct_hispanic fd_pct_hispanic 0.8236 0.9837 1.1944
```

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)... Using 8 cores for parallel bootstrap... Bootstrap completed in 4.6 seconds

```
==== Standard Error Comparison ====
Variable Naive_SE Bootstrap_SE Ratio
fitted_endog
gr_weighted_annual_avg_wkly_wage 0.6608 0.8774 1.3277
diff_log_real_Total_IG_Revenue_pp
diff_log_real_Total_IG_Revenue_pp 0.0317 0.0310 0.9788
diff_log_real_gdp_priv_ind_pc diff_log_real_gdp_priv_ind_pc
0.0405 0.0545 1.3464
diff_log_Enrollment diff_log_Enrollment 0.0419 0.0439 1.0482
fd_pct_black
fd_pct_black 1.3713 1.3753 1.0029
fd_pct_hispanic fd_pct_hispanic 0.8161 0.8908 1.0915
```

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)... Using 8 cores for parallel bootstrap... Bootstrap completed in 4.8 seconds

==== Standard Error Comparison === Variable Naive_SE Bootstrap_SE Ratio l1_log_real_Elem_Educ_Total_Exp_pp
l1_log_real_Elem_Educ_Total_Exp_pp 0.0155 0.0158 1.0187 fitted_endog gr_weighted_annual_avg_wkly_wage
0.8583 1.6462 1.9180 log_real_Total_IG_Revenue_pp log_real_Total_IG_Revenue_pp 0.0219 0.0245
1.1172 log_real_gdp_priv_ind_pc log_real_gdp_priv_ind_pc 0.0142 0.0187 1.3164 log_Enrollment
log_Enrollment 0.0145 0.0190 1.3066 pct_black pct_black 0.2426 0.3722 1.5343 pct_hispanic pct_hispanic
0.1814 0.2676 1.4750

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)... Using 8 cores for parallel bootstrap... Bootstrap completed in 4.9 seconds

==== Standard Error Comparison === Variable Naive_SE Bootstrap_SE Ratio l1_log_real_Elem_Educ_Total_Exp_pp
l1_log_real_Elem_Educ_Total_Exp_pp 0.0157 0.0160 1.0202 fitted_endog log_weighted_annual_avg_wkly_wage
0.0485 0.0472 0.9745 log_real_Total_IG_Revenue_pp log_real_Total_IG_Revenue_pp 0.0210 0.0215
1.0256 log_real_gdp_priv_ind_pc log_real_gdp_priv_ind_pc 0.0144 0.0151 1.0485 log_Enrollment
log_Enrollment 0.0158 0.0158 1.0004 pct_black pct_black 0.1886 0.1868 0.9906 pct_hispanic pct_hispanic
0.1509 0.1514 1.0036

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Table 2: 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 (1)	(log) Elem.Ed.Exp.pp (2)	(GR) Annual Avg. Wkly. Wage (3)	(GR) Elem.Ed.Exp.pp (4)
<i>Variables</i>				
VA SS (Lvl)	-0.0203 (0.0353)			
VA SS (Lvl, l1)	-0.1831*** (0.0448)			
VA SS (Lvl, l2)	0.1668*** (0.0391)			
(log) IG Revenue pp	0.0143*** (0.0017)	0.2229*** (0.0210)		
(log) Real GDP Priv. Industry pc	0.0394*** (0.0015)	0.0662*** (0.0144)		
(log) Enrollment	0.0099*** (0.0028)	-0.1955*** (0.0158)		
% Black	-0.1668*** (0.0450)	0.3328* (0.1886)		
% Hispanic	-0.0529** (0.0218)	0.0484 (0.1509)		
(log, l1) Annual Avg. Wkly. Wage	0.7848*** (0.0051)			
(l1, log) Elem.Ed.Exp.pp		0.5095*** (0.0157)		
(log) Annual Avg. Wkly. Wage		0.2263*** (0.0485)		
VA SS (GR)			-0.1675*** (0.0369)	
VA SS (GR,l1)			-0.2374** (0.0411)	
VA SS (GR,l2)			0.0064 (0.0497)	
(GR) IG Revenue pp			0.0041 (0.0025)	0.3100*** (0.0317)
(GR) Real GDP Priv. Industry pc			0.0593*** (0.0026)	0.0749 (0.0473)
(GR) Enrollment			0.0153*** (0.0059)	-0.5813*** (0.0425)
fd_pct_black			-0.7505*** (0.1707)	-1.298 (1.419)
fd_pct_hispanic			0.3005** (0.1350)	1.817** (0.8236)
(GR) Annual Avg. Wkly. Wage				-1.313* (0.7887)
<i>Fixed-effects</i>				
unit	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	12,084	12,084	12,084	12,084
R ²	0.99247	0.90636	0.29876	0.26621
Within R ²	0.77617	0.51804	0.04945	0.21901
First-stage F		9.2412		14.495
F p-value		4.22 × 10 ⁻⁶		2.02 × 10 ⁻⁹
First-stage F (marginal)		15.675		14.495
F (marg) p-value		3.59 × 10 ⁻¹⁰		2.02 × 10 ⁻⁹
Wu-Hausman		0.46756		0.09282
WH p-value		0.49411		0.76062
Sargan		66.871		28.172
Sargan p-value		3.01 × 10 ⁻¹⁵		7.63 × 10 ⁻⁷

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3: 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 (FS) Manual IV - Full AR (1)	(log) Elem.Ed.Exp.pp (SS) Manual IV - Full AR (2)	(log) Annual Avg. Wkly. Wage (FS) Full AR (3)	(log) Elem.Ed.Exp.pp (SS) Full AR (4)	(log) Annual Avg. Wkly. Wage (FS) No AR (5)	(log) Elem.Ed.Exp.pp (SS) No AR (6)
<i>Variables</i>						
VA SS (Lvl)	-0.0203 (0.0353)		-0.0179 (0.0484)		0.2092** (0.1026)	
VA SS (Lvl, l1)	-0.1831*** (0.0448)		-0.1808*** (0.0592)		-0.3220*** (0.0629)	
VA SS (Lvl, l2)	0.1668*** (0.0391)		0.1614*** (0.0497)		-0.0190 (0.1069)	
(log) IG Revenue pp	0.0143*** (0.0017)	0.2229*** (0.0210)	0.0135*** (0.0030)	0.2230*** (0.0211)	0.0453*** (0.0101)	0.4550*** (0.0617)
(log) Real GDP Priv. Industry pc	0.0394*** (0.0015)	0.0662*** (0.0144)	0.0390*** (0.0044)	0.0662*** (0.0144)	0.1568*** (0.0156)	0.5716*** (0.1975)
(log) Enrollment	0.0099*** (0.0028)	-0.1955*** (0.0158)	0.0109*** (0.0044)	-0.1957*** (0.0157)	0.0629*** (0.0159)	-0.1502** (0.0825)
% Black	-0.1665*** (0.0450)	0.3328* (0.1886)	-0.1685** (0.0724)	0.3333* (0.1924)	-0.1519 (0.2154)	0.0962 (0.7547)
% Hispanic	-0.0529** (0.0218)	0.0484 (0.1509)	-0.0526 (0.0327)	0.0483 (0.1509)	0.2279** (0.1020)	0.6591 (0.4309)
(log, l1) Annual Avg. Wkly. Wage	0.7848*** (0.0051)		0.7828*** (0.0120)			
(I, log) Elem.Ed.Exp.pp		0.5095*** (0.0157)	0.0039 (0.0041)	0.5086*** (0.0156)		
(log) Annual Avg. Wkly. Wage		0.2263*** (0.0485)		0.2269*** (0.0477)		-2.463** (1.173)
<i>Fixed-effects</i>						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	12,084	12,084	12,084	12,084	12,084	12,084
R ²	0.99247	0.90636	0.99247	0.90636	0.97691	0.86098
Within R ²	0.77617	0.51804	0.77623	0.51804	0.31396	0.28448
First-stage F		9.2412				
F p-value		4.22 × 10 ⁻⁶				
Wu-Hausman			44.905			65.587
Wu-Hausman, p-value			2.17 × 10 ⁻¹¹			6.12 × 10 ⁻¹⁶
Wald (IV only)			1,345.2		9.4020	4.4097
Wald (IV only), p-value			0 × 10 ⁻¹⁶		3.34 × 10 ⁻⁶	0.03576
F-test (1st stage)			5,972.4			16.548
F-test (1st stage), (log) Annual Avg. Wkly. Wage			0 × 10 ⁻¹⁶			16.548
F-test (1st stage), p-value			0 × 10 ⁻¹⁶		9.99 × 10 ⁻¹¹	9.99 × 10 ⁻¹¹
F-test (1st stage), p-value, (log) Annual Avg. Wkly. Wage						
First-stage F (marginal)		15.675				
F (marg) p-value		3.59 × 10 ⁻¹⁰				
Wu-Hausman		0.46756				
WH p-value		0.49411				
Sargan		66.871				
Sargan p-value		3.01 × 10 ⁻¹⁵				

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

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 (FS) SS AR (1)	(log) Elem.Ed.Exp.pp (SS) SS AR (2)	(log) Annual Avg. Wkly. Wage (FS) FS AR (3)	(log) Elem.Ed.Exp.pp (SS) FS AR (4)	(log) Annual Avg. Wkly. Wage (FS) Full AR (5)	(log) Elem.Ed.Exp.pp (SS) Full AR (6)
<i>Variables</i>						
VA SS (Lvl)	0.2417** (0.1006)		-0.0203 (0.0485)		-0.0179 (0.0484)	
VA SS (Lvl, l1)	-0.2749*** (0.0625)		-0.1831*** (0.0600)		-0.1808*** (0.0592)	
VA SS (Lvl, l2)	-0.1061 (0.1058)		0.1668*** (0.0516)		0.1614*** (0.0497)	
(I, log) Elem.Ed.Exp.pp	0.0676*** (0.0086)	0.6475*** (0.0590)			0.0039 (0.0041)	0.5086*** (0.0156)
(log) IG Revenue pp	0.0304*** (0.0098)	0.2840*** (0.0331)	0.0143*** (0.0028)	0.3213*** (0.0316)	0.0135*** (0.0030)	0.2230*** (0.0211)
(log) Real GDP Priv. Industry pc	0.1459*** (0.0155)	0.3718*** (0.1230)	0.0394*** (0.0044)	0.0946*** (0.0243)	0.0390*** (0.0044)	0.0662*** (0.0144)
(log) Enrollment	0.0781*** (0.0155)	-0.0404 (0.0684)	0.0099** (0.0042)	-0.3306*** (0.0282)	0.0109** (0.0044)	-0.1957*** (0.0157)
% Black	-0.1828 (0.2105)	-0.1207 (0.4893)	-0.1668** (0.0720)	0.6541* (0.3622)	-0.1685** (0.0724)	0.3333* (0.1924)
% Hispanic	0.2216** (0.1029)	0.4591* (0.2667)	-0.0529 (0.0326)	0.0381 (0.2516)	-0.0526 (0.0327)	0.0483 (0.1509)
(log) Annual Avg. Wkly. Wage		-1.851** (0.7749)		0.5618*** (0.0765)		0.2269*** (0.0477)
(log, l1) Annual Avg. Wkly. Wage			0.7848*** (0.0113)		0.7828*** (0.0120)	
<i>Fixed-effects</i>						
unit	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	12,084	12,084	12,084	12,084	12,084	12,084
R ²	0.97765	0.90596	0.99247	0.86539	0.99247	0.90636
Within R ²	0.33602	0.51597	0.77617	0.30715	0.77623	0.51804
Wu-Hausman		53.013		138.75		44.905
Wu-Hausman, p-value		3.53 × 10 ⁻¹³		7.64 × 10 ⁻³²		2.17 × 10 ⁻¹¹
Wald (IV only)		7.9497	5.7063	1,517.9	1,345.2	22.645
Wald (IV only), p-value		2.72 × 10 ⁻⁵	0.01692	0 × 10 ⁻¹⁶	0 × 10 ⁻¹⁶	1.97 × 10 ⁻⁶
F-test (1st stage)		19.489		6,261.7		5,972.4
F-test (1st stage), (log) Annual Avg. Wkly. Wage			19.489		6,261.7	5,972.4
F-test (1st stage), p-value		1.34 × 10 ⁻¹²		0 × 10 ⁻¹⁶		0 × 10 ⁻¹⁶
F-test (1st stage), p-value, (log) Annual Avg. Wkly. Wage			1.34 × 10 ⁻¹²		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 the national-level average treatment effects described above. These national-level estimates are unlikely to apply uniformly across states and commuting zones. Therefore, this next section is dedicated to unpacking this heterogeneity. Below, we (1) explore various metrics of local economic growth and decline 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.

However, given the high degree of both structural (state-specific tax, regulatory, and legislative regimes) and evolved heterogeneity (industrial activity, income, inequality, economic diversity) the proposed analysis necessitates a disaggregated estimation strategy to truly account for the heterogeneity across the units of observation. Therefore, subsequent treatment estimation is dedicated to state-by-state, industry-by-industry, and a growth cohort sub-sampling procedure taking into account legacy income and wage growth rates.

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.

I think this can be supported by interesting literature from the "left behind" and "geographies of discontent" literature in which 'relative' economic performance is what matters most for individuals' happiness. Might be a conceptual leap but an interesting connection?

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.

We then classify commuting zones by the value of α_g which represents their deviation from state- and national-level GDP growth rates. We estimate this trend deviation in per capita values of private industry GDP.

Figure 3 plots the distribution of values of α_g where the vertical dashed lines represent the 25th and 75th percentiles.

Next, Figure 4 below 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, and Colorado have outstanding positive outliers in the distribution whereas Kentucky, Louisiana, South Dakota have outstanding negative outliers.

Finally, Figure 5 represents the distribution of the loadings on the residualised state factors and the national growth rates at the commuting zone level.

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.

$$\begin{aligned}\Delta \widetilde{\log Wage}_t^{state} &= \Delta \log Wage_t^{state} - \hat{\gamma} \Delta \log Wage_t^{nat} \\ \Delta \log Wage_t^{CZ} &= \alpha_w + \beta_n \Delta \log Wage_t^{nat} + \beta_s \Delta \widetilde{\log Wage}_t^{state} + \varepsilon_t\end{aligned}$$

In Figure 7, we see that there is similar variability though the patterns do not consistently indicate the same high- and low-performing outliers across states indicating that GDP and wage growth are not consistently correlated across regions. We demonstrate this fact in Figure 8 where, although there is a positive correlation between commuting zone GDPpc and wage trend deviations, the decile-decile plot demonstrates a noisy relationship largely driven by certain outliers.

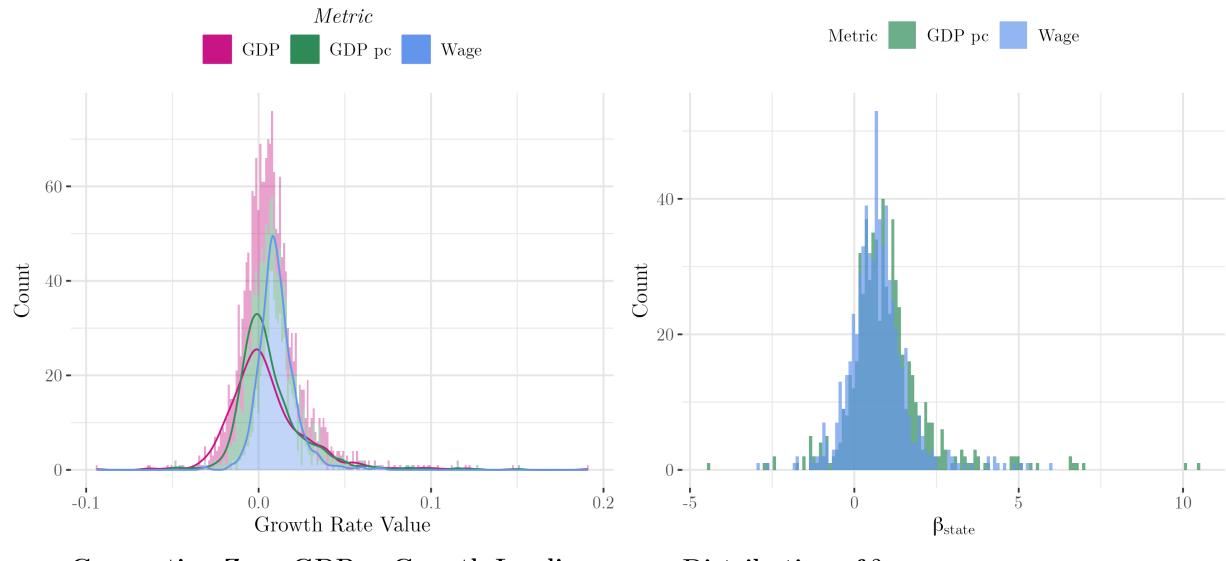
Figure 11 presents a correlation coefficient by commuting zone between the two rates, providing greater detail on this relationship.

?? ?? ?? ?? ?? ?? ?? ??

¹²We provide similar analysis of gross GDP in the Appendix.

Commuting Zone Growth Rates and Jurisdictional Loadings

Histogram of Wage and GDP per capita Growth ~~Distribution~~ of β_{state}



Commuting Zone GDPpc Growth Loadings

Coefficients from regressions on national growth and state-specific residuals

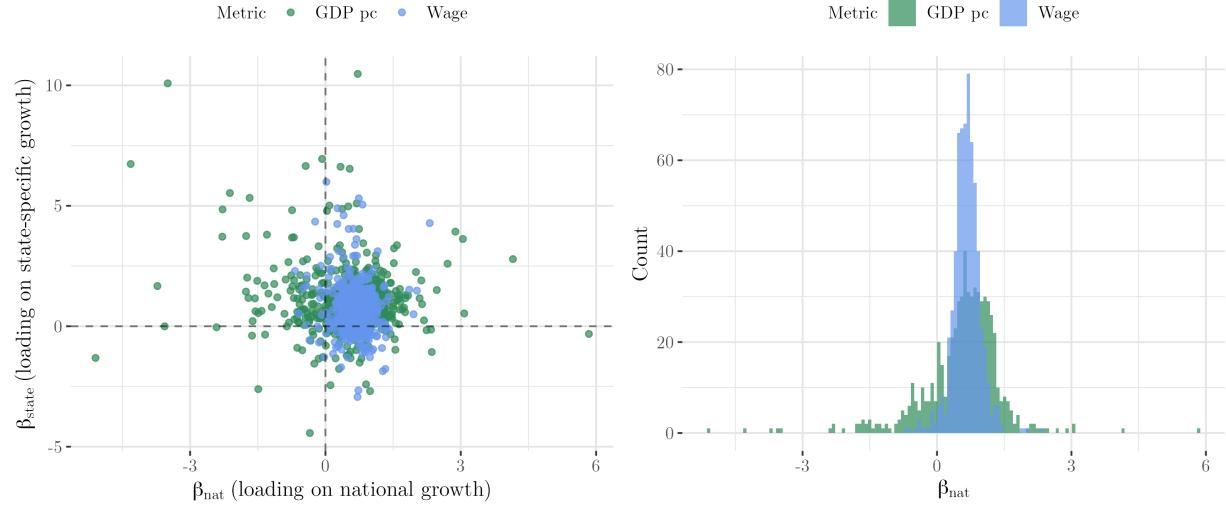


Figure 4: GDPpc and Wage Growth Rates and Loadings

Commuting Zone GDP pc and Wage Growth Rates

Intercepts from regressions controlling for national growth and state-specific residual growth

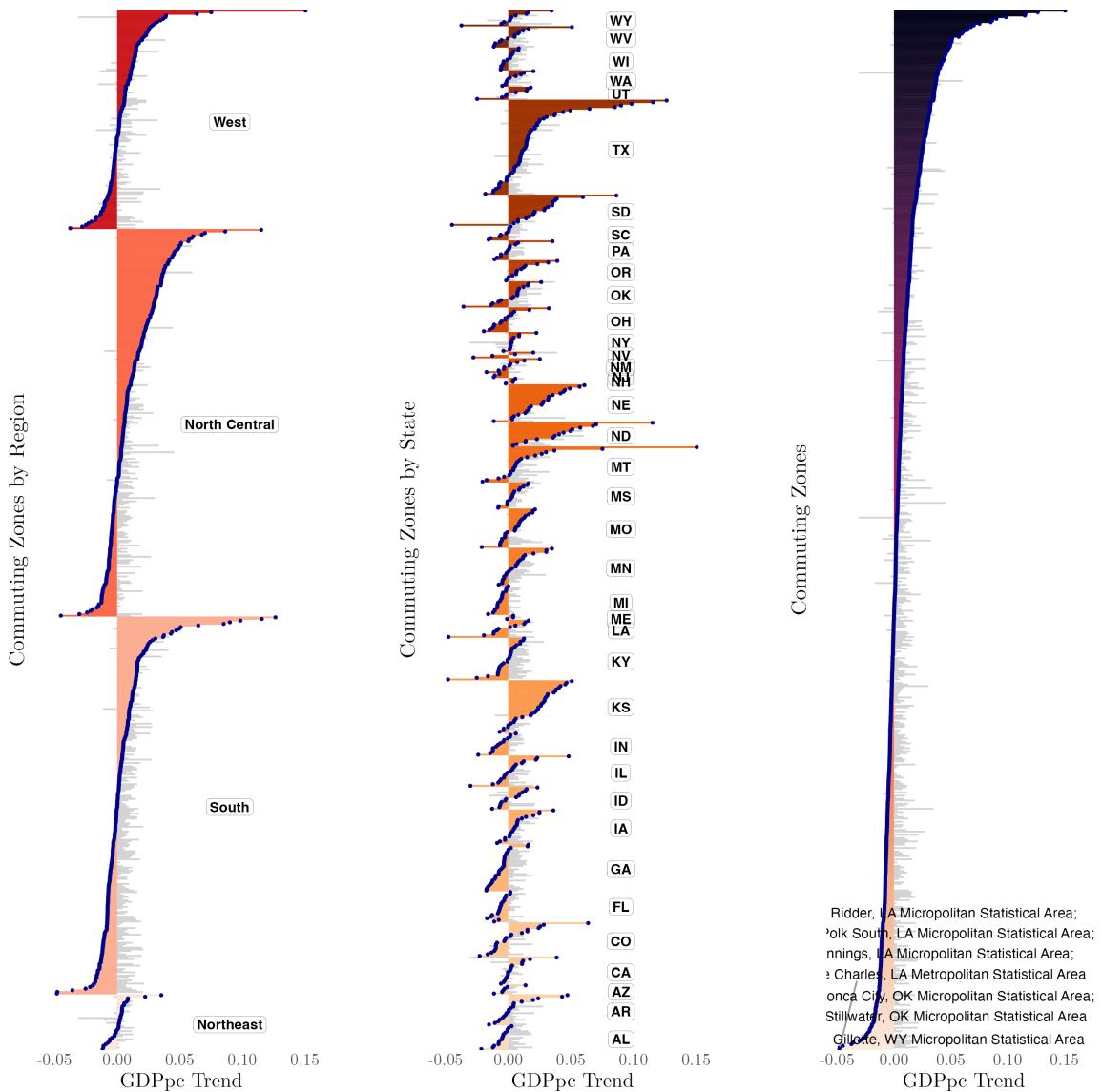


Figure 5: Lollipop Plot of Wage and GDPpc Growth Rates

Below, we display, by state, the Pearson correlation coefficient between CZ level GDP growth rates and wage growth rates. Interestingly, many states see nearly exclusively positive correlation coefficients, whereas others see a mix of commuting zones where the relationship is positive or negative.

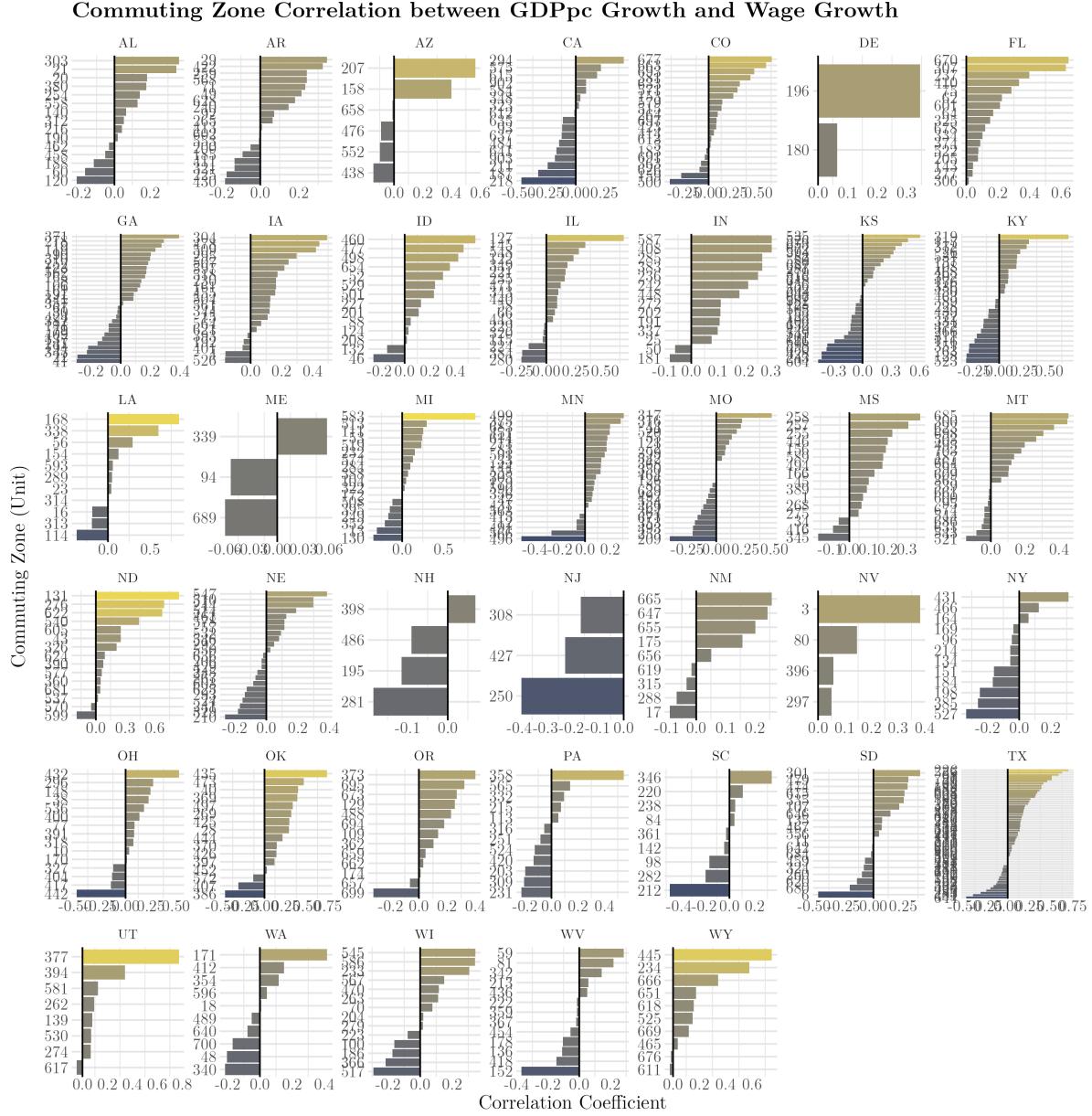


Figure 6: Correlation Between GDP Growth Rates and Wage Growth Rates by State

3.2.1.1 Sample Partitioning by Growth Rates

Using these growth rates, we partition the sample according to the percentiles described above. ?? and ?? 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.

?? partitions CZs by α_w . Interestingly, we see that the effect of intergovernmental revenue is nearly half the size in hyper-growing areas than the hyper-declining areas indicating the importance of intergovernmental transfers in areas where wages are declining. Additionally, the scaling effects of enrollment are only significant in regions where wages exhibit high growth or are moderately declining. Furthermore, the role of private industry GDP in local elementary education expenditure explains variation in education expenditure in those regions in which scaling laws do not seem to apply. Most importantly though, the negative relationship between annual wages and elementary education expenditure is only present in areas that exhibit historically hyper-declining or moderately growing wage trends. Additionally, the first-stage F statistics only support causal identification in these columns.

In regions where wages are already declining, positive wage shocks decrease spending on local public education providing potential support for a story in which regions with declining wages de-prioritise education when positive wage shocks “come to town.” In the case of moderately growing regions,

?? partitions CZs by long-run GDP per capita trends. When partitioning the sample by GDP growth rates, the interpretation is more straight-forward. Areas in which GDP is exhibiting relative decline, the causal relationship between wages and education expenditure is consistent with high first stage F statistics, convincing performance on the Wu-Hausman endogeneity test, and defensible, albeit weak, performance on the Wald test. These results suggest an asymmetric fiscal response where wage shocks in areas whose GDP is declining, have a negative effect on local public education spending, in contrast to growing regions.

```
Computing bootstrap standard errors ( 399  replications)...
```

```
Using 8 cores for parallel bootstrap...
Bootstrap completed in 6.5 seconds
```

```
==== Standard Error Comparison ===
```

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0158	1.0069	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0485	0.0477	0.9845	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0220	1.0472	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0143	0.9930	
log_Enrollment	log_Enrollment	0.0158	0.0159	1.0082	
pct_black	pct_black	0.1886	0.1990	1.0555	
pct_hispanic	pct_hispanic	0.1509	0.1535	1.0175	

```
Note: Ratio > 1 indicates naive SEs underestimate uncertainty
```

```
Computing bootstrap standard errors ( 399  replications)...
```

```
Using 8 cores for parallel bootstrap...
Bootstrap completed in 1.8 seconds
```

```
==== Standard Error Comparison ===
```

Variable	Naive_SE	Bootstrap_SE	Ratio
----------	----------	--------------	-------

11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0207	0.0207	1.0022
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0732	0.0741	1.0122
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0398	0.0392	0.9847
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0346	0.0376	1.0885
log_Enrollment	log_Enrollment	0.0324	0.0332	1.0243
pct_black	pct_black	0.2205	0.2711	1.2297
pct_hispanic	pct_hispanic	0.2248	0.2329	1.0357

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 2.4 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0190	0.0204	1.0696	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0639	0.0687	1.0740	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0340	0.0331	0.9718	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0309	0.0317	1.0246	
log_Enrollment	log_Enrollment	0.0234	0.0245	1.0475	
pct_black	pct_black	0.1957	0.2056	1.0506	
pct_hispanic	pct_hispanic	0.1690	0.1701	1.0064	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 3.1 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0219	0.0215	0.9812	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0602	0.0624	1.0368	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0273	0.0269	0.9859	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0162	0.0162	1.0028	
log_Enrollment	log_Enrollment	0.0211	0.0224	1.0585	
pct_black	pct_black	0.3369	0.3472	1.0307	
pct_hispanic	pct_hispanic	0.1945	0.1893	0.9733	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0282	0.0276	0.9799	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0804	0.0826	1.0282	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0394	0.0389	0.9863	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0173	0.0189	1.0931	
log_Enrollment	log_Enrollment	0.0296	0.0315	1.0660	
pct_black	pct_black	0.7404	0.7926	1.0705	

```
pct_hispanic          pct_hispanic  0.2183    0.2299  1.0531
```

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 5.4 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0152	0.9677
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0485	0.0487	1.0037
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0205	0.9772
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0152	1.0598
log_Enrollment	log_Enrollment	0.0158	0.0154	0.9768
pct_black	pct_black	0.1886	0.1966	1.0424
pct_hispanic	pct_hispanic	0.1509	0.1495	0.9909

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1.8 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0266	0.0260	0.9759
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0683	0.0732	1.0717
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0336	0.0320	0.9531
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0234	0.0245	1.0472
log_Enrollment	log_Enrollment	0.0250	0.0274	1.0966
pct_black	pct_black	0.2594	0.3185	1.2279
pct_hispanic	pct_hispanic	0.2536	0.2545	1.0036

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1.4 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0332	0.0343	1.0335
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0851	0.0910	1.0700
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0313	0.0335	1.0712
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0304	0.0330	1.0843
log_Enrollment	log_Enrollment	0.0343	0.0386	1.1258
pct_black	pct_black	0.3559	0.4815	1.3529
pct_hispanic	pct_hispanic	0.1887	0.2108	1.1170

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...
 Bootstrap completed in 4.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0173	0.0166	0.9589
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0535	0.0478	0.8929
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0238	0.0247	1.0397
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0151	0.0152	1.0080
log_Enrollment	log_Enrollment		0.0176	0.0172	0.9782
pct_black	pct_black		0.2254	0.2534	1.1243
pct_hispanic	pct_hispanic		0.1782	0.1823	1.0229

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 1.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0293	0.0298	1.0180
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0834	0.0886	1.0615
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0388	0.0403	1.0381
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0162	0.0160	0.9828
log_Enrollment	log_Enrollment		0.0335	0.0349	1.0444
pct_black	pct_black		0.5381	0.5339	0.9921
pct_hispanic	pct_hispanic		0.3026	0.3125	1.0327

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 4.9 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0164	1.0447
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0485	0.0505	1.0407
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0217	1.0364
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0147	1.0201
log_Enrollment	log_Enrollment		0.0158	0.0164	1.0370
pct_black	pct_black		0.1886	0.2085	1.1059
pct_hispanic	pct_hispanic		0.1509	0.1433	0.9495

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 1.4 seconds

==== Standard Error Comparison ===

Variable	Naive_SE	Bootstrap_SE	Ratio

11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0207	0.0213	1.0291
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0732	0.0796	1.0873
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0398	0.0421	1.0584
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0346	0.0365	1.0549
log_Enrollment	log_Enrollment	0.0324	0.0342	1.0558
pct_black	pct_black	0.2205	0.2533	1.1492
pct_hispanic	pct_hispanic	0.2248	0.2232	0.9928

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 2.1 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0190	0.0183	0.9609
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0639	0.0638	0.9985
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0340	0.0331	0.9713
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0309	0.0318	1.0288
log_Enrollment	log_Enrollment	0.0234	0.0223	0.9523
pct_black	pct_black	0.1957	0.2155	1.1009
pct_hispanic	pct_hispanic	0.1690	0.1674	0.9903

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 2.8 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0219	0.0242	1.1039
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0602	0.0635	1.0555
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0273	0.0289	1.0592
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0162	0.0164	1.0107
log_Enrollment	log_Enrollment	0.0211	0.0220	1.0395
pct_black	pct_black	0.3369	0.3550	1.0538
pct_hispanic	pct_hispanic	0.1945	0.1896	0.9748

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1.5 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0282	0.0283	1.0037
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0804	0.0863	1.0738
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0394	0.0412	1.0458
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0173	0.0180	1.0380
log_Enrollment	log_Enrollment	0.0296	0.0301	1.0180
pct_black	pct_black	0.7404	0.8096	1.0934

```
pct_hispanic          pct_hispanic  0.2183    0.2279  1.0442
```

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 4.9 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0157	0.9981
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0485	0.0479	0.9878
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0216	1.0306
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0152	1.0574
log_Enrollment	log_Enrollment	0.0158	0.0157	0.9916
pct_black	pct_black	0.1886	0.2078	1.1019
pct_hispanic	pct_hispanic	0.1509	0.1485	0.9845

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1.5 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0266	0.0269	1.0090
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0683	0.0692	1.0132
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0336	0.0342	1.0197
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0234	0.0242	1.0376
log_Enrollment	log_Enrollment	0.0250	0.0250	0.9978
pct_black	pct_black	0.2594	0.3117	1.2016
pct_hispanic	pct_hispanic	0.2536	0.2613	1.0308

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 1 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0332	0.0361	1.0899
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0851	0.0896	1.0530
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0313	0.0329	1.0522
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0304	0.0355	1.1657
log_Enrollment	log_Enrollment	0.0343	0.0365	1.0648
pct_black	pct_black	0.3559	0.4287	1.2044
pct_hispanic	pct_hispanic	0.1887	0.2057	1.0901

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...
 Bootstrap completed in 4.3 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0173	0.0170	0.9825
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0535	0.0526	0.9830
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0238	0.0241	1.0138
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0151	0.0157	1.0408
log_Enrollment	log_Enrollment		0.0176	0.0174	0.9891
pct_black	pct_black		0.2254	0.2354	1.0446
pct_hispanic	pct_hispanic		0.1782	0.1804	1.0120

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...
 Bootstrap completed in 1.5 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0293	0.0298	1.0185
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0834	0.0868	1.0397
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0388	0.0405	1.0428
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0162	0.0174	1.0702
log_Enrollment	log_Enrollment		0.0335	0.0341	1.0185
pct_black	pct_black		0.5381	0.6185	1.1493
pct_hispanic	pct_hispanic		0.3026	0.3175	1.0491

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

All	Hyper-Declining (W..	Declining (Wage)	Group
All	Hyper-Declining (Wage)	Declining (Wage)	Group

Dependent Var.: (log) Elem.Ed.Exp.pp (log) Elem.Ed.Exp.pp (log) Elem.Ed.Exp.pp (log) Elem.Ed.Exp.pp
 (log) Elem.Ed.Exp.pp

(11, log) Elem.Ed.Exp.pp 0.5095*** 0.5132*** 0.5507*** 0.5030*** 0.5319 (**(0.0157)**) (**(0.0266)**) (**(0.0332)**)
(0.0174) (**0.0293**)

fitted_endog **0.2263** 0.3288*** 0.3420*** 0.2122*** 0.1548
 (0.0485) (0.0683) (0.0851) (0.0535) (0.0834)

(log) IG Revenue pp 0.2229*** 0.2803*** 0.2106*** 0.2243*** 0.1552 (**(0.0210)**) (**(0.0336)**) (**(0.0313)**)
(0.0238) (**0.0388**)

(log) Real GDP Priv. Industry pc **0.0662** 0.0156 0.0220 0.0703*** 0.0685 (**(0.0144)**) (**(0.0234)**)
(0.0305) (**0.0150**) (**0.0162**)

(log) Enrollment **-0.1955** -0.2275*** -0.2009*** -0.1938*** -0.2000** (**(0.0158)**) (**(0.0250)**) (**(0.0343)**)
(0.0176) (**0.0335**)

% Black 0.3328 0.2169 0.2131 0.3884 1.192
 (0.1886) (0.2594) (0.3559) (0.2254) (0.5381)
 % Hispanic 0.0484 0.2612 0.2542 0.0112 0.1339
 (0.1509) (0.2536) (0.1887) (0.1782) (0.3026)

Fixed-Effects: _____ unit Yes
 Yes Yes Yes Yes year Yes Yes Yes Yes _____

S.E.: Clustered by: unit by: unit by:

unit by: unit by: unit Observations 12,084 3,021 1,520 10,564 3,021 R2 0.90636 0.92102 0.94210 0.89805
0.90098 Within R2 0.51804 0.57170 0.58940 0.50753 0.50064 First-stage F 9.2412 5.3600 6.4764 10.356
2.7055 F p-value 4.22e-6 0.00111 0.00024 8.41e-7 0.04386 First-stage F (marginal) 15.675 5.6257 5.5599
19.379 11.901 F (marg) p-value 3.59e-10 0.00077 0.00086 1.59e-12 9.61e-8 Wu-Hausman 0.46756 0.06497
0.01588 0.58897 2.3350 WH p-value 0.49411 0.79880 0.89973 0.44282 0.12649 Sargan 66.871 42.439 34.534
38.772 11.434 Sargan p-value 3.01e-15 6.09e-10 3.17e-8 3.81e-9 0.00329 — Signif. codes: 0 ‘**0.001**’ ’0.01’
’0.05’ ’0.1’ ’1 All Hyper-Declining (Wage) Declining (Wage) Growing (Wage) Hyper-Growing (Wage) All
Hyper-Declining (Wage) Declining (Wage) Growing (Wage) Hyper-Growing (Wage) Dependent Var.: (log)
Annual Avg. Wkly. Wage (log) Annual Avg. Wkly. Wage (log) Annual Avg. Wkly. Wage (log) Annual
Avg. Wkly. Wage (log) Annual Avg. Wkly. Wage

VA SS (Lvl) -0.0203 -0.0218 0.1082 -0.0497 0.1516
(0.0353) (0.0529) (0.0716) (0.0410) (0.1059)

VA SS (Lvl, l1) -0.1831*** -0.1717* -0.3005*** -0.1466** -0.3541** (0.0448) (0.0673) (0.0893) (0.0521)
(0.1343)

VA SS (Lvl, l2) 0.1668*** 0.2313*** 0.2726*** 0.1188** 0.1489
(0.0391) (0.0602) (0.0826) (0.0446) (0.1119)

(log) IG Revenue pp 0.0143*** 0.0097** 0.0095* 0.0141*** 0.0161 (**0.0017**) (**0.0034**) (**0.0047**) (**0.0018**)
(**0.0038**)

(log) *Real GDP Priv. Industry pc* **0.0394** 0.0656*** 0.0633*** 0.0375*** 0.0313 (**0.0015**) (**0.0042**)
(**0.0056**) (**0.0016**) (**0.0026**)

(log) *Enrollment* **0.0099** 0.0175*** 0.0185** 0.0086** 0.0026
(0.0028) (0.0049) (0.0068) (0.0031) (0.0070)

% Black -0.1668*** -0.1666** -0.2457** -0.1323** -0.1830
(0.0450) (0.0624) (0.0950) (0.0505) (0.1513)

% Hispanic -0.0529* -0.0806* -0.0149 -0.0480* -0.0318
(0.0218) (0.0374) (0.0529) (0.0237) (0.0572)

(log, l1) Annual Avg. Wkly. Wage 0.7848*** 0.7824*** 0.8181*** 0.7784*** 0.7634*** (0.0051) (0.0108)
(0.0145) (0.0055) (0.0112)

Fixed-Effects: -----

	S.E.: Clustered by: unit by: unit by: unit by: unit by: unit									
Observations	12,084	3,021	5,016	7,068	3,021	R2	0.90636	0.90368	0.90765	0.90377
Within R2	0.51804	0.54245	0.55592	0.47980	0.48120	First-stage F	9.2412	7.9513	8.4961	5.0638
F p-value	5.5574	4.22e-6	2.81e-5	1.26e-5	0.00167	0.00084	First-stage F (marginal)	15.675	33.993	32.197
12.763	17.873	F (marg) p-value	3.59e-10	1.4e-21	1.35e-20	2.59e-8	1.72e-11	Wu-Hausman	0.46756	0.00585
0.00018	0.35284	1.2182	WH p-value	0.49411	0.93905	0.98939	0.55251	0.26971	Sargan	66.871
27.876	6.2101	Sargan p-value	3.01e-15	3.8e-15	4.95e-16	8.85e-7	0.04482	— Signif. codes:	0 ‘’ 0.001 ’’ 0.01	0.05 ‘’ 0.1 ‘’ 1
All Hyper-Declining (GDP)	Declining (GDP)	Growing (GDP)	Hyper-Growing (GDP)	All Hyper-Declining (GDP)	Declining (GDP)	Growing (GDP)	Hyper-Growing (GDP)	Dependent Var.:	(log)	Annual Avg.
Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)
Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)	Annual Avg.	Wkly.	Wage (log)
VA SS (Lvl)	-0.0203	-0.0986	-0.0993*	0.0801	0.2166*					
(0.0353)	(0.0508)	(0.0410)	(0.0560)	(0.0918)						
VA SS (Lvl, l1)	-0.1831***	-0.0678	-0.0692	-0.2708***	-0.3481**	(0.0448)	(0.0645)	(0.0521)	(0.0710)	(0.1165)
VA SS (Lvl, l2)	0.1668***	0.0549	0.0893	0.1859**	0.0437					
(0.0391)	(0.0584)	(0.0468)	(0.0602)	(0.0967)						
(log) IG Revenue pp	0.0143***	0.0098**	0.0117***	0.0136***	0.0107**	(0.0017)	(0.0030)	(0.0023)	(0.0023)	(0.0033)
(log) Real GDP Priv. Industry pc	0.0394***	0.0615***	0.0665***	0.0338***	0.0287	(0.0015)	(0.0040)			
(0.0033)	(0.0019)	(0.0025)								
(log) Enrollment	0.0099	0.0066	0.0100**	0.0127**	0.0047					
(0.0028)	(0.0050)	(0.0036)	(0.0040)	(0.0061)						
% Black	-0.1668***	-0.0178	-0.0446	-0.2890***	-0.4570**	(0.0450)	(0.0597)	(0.0481)	(0.0749)	(0.1520)
% Hispanic	-0.0529*	0.0061	0.0244	-0.0859**	-0.1211**	(0.0218)	(0.0453)	(0.0330)	(0.0285)	(0.0410)
(log, l1) Annual Avg. Wkly. Wage	0.7848***	0.7968***	0.7892***	0.7817***	0.7884***	(0.0051)	(0.0095)			
(0.0078)	(0.0069)	(0.0104)								
Fixed-Effects:	-----	-----	-----	-----	-----	-----	-----	-----	-----	-----
	- unit	Yes	Yes	Yes	Yes	Yes	year	Yes	Yes	Yes

	S.E. type									
Observations	12,084	3,021	5,016	7,068	3,021	R2	0.99247	0.99420	0.99450	0.99131
Within R2	0.77617	0.76424	0.74194	0.75790	0.75962	— Signif. codes:	0 ‘’ 0.001 ’’ 0.01 ’’ 0.05 ‘’ 0.1 ‘’ 1			

3.2.2 State-by-state estimation

Given the substantial heterogeneity in state-level economic makeup and public finance regimes, we investigate state-specific and industry-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.

Distribution of Commuting Zones per State

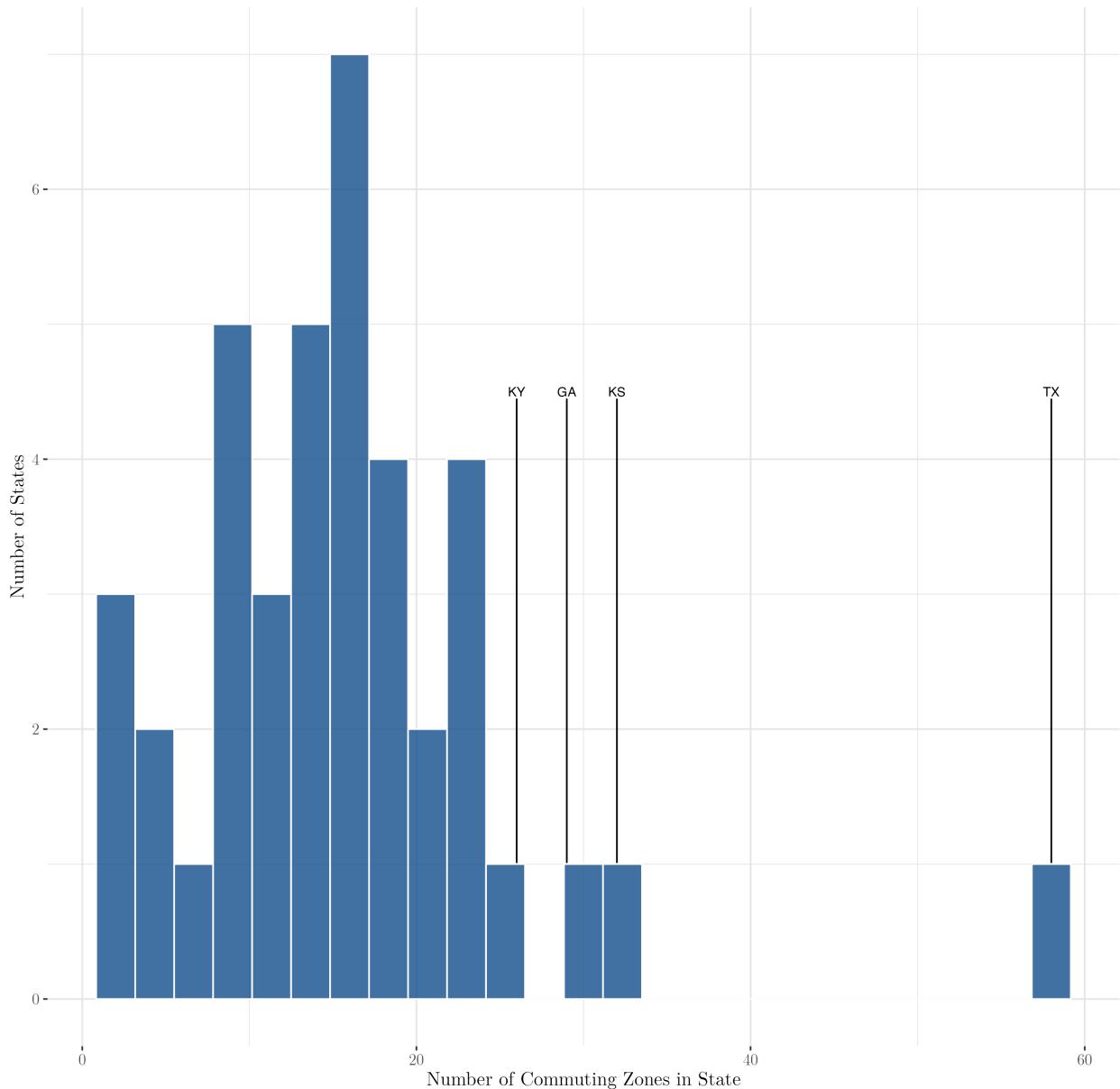


Figure 7: Histogram: Commuting Zones by State

Using our instrumental variable approach with a value-added based shift-share instrument, we corroborate the directionality and magnitude of the effect for 5 states: Ohio, Missouri, Arizona, Washington, Delaware, and New Hampshire. Delaware's sample size is so small that it's likely uninformative. However, the rest of the states provide interesting points of analysis.

```
Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.7 seconds
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==== Standard Error Comparison ===

Variable	Naive_SE	Bootstrap_SE	Ratio
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11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0828	0.0820	0.9906
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2358	0.2957	1.2542
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0758	0.1121	1.4795
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0664	0.0766	1.1529
log_Enrollment	log_Enrollment	0.0478	0.0852	1.7821
pct_black	pct_black	0.4877	0.6652	1.3640
pct_hispanic	pct_hispanic	1.0134	1.6274	1.6059

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0307	0.0341	1.1088	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1111	0.1551	1.3958	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0593	0.0617	1.0402	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0225	0.0355	1.5791	
log_Enrollment	log_Enrollment	0.0558	0.0772	1.3843	
pct_black	pct_black	1.0167	1.5378	1.5126	
pct_hispanic	pct_hispanic	1.1898	1.6291	1.3693	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0418	0.0502	1.2015	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2900	0.4376	1.5088	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0505	0.0817	1.6186	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0651	0.0922	1.4171	
log_Enrollment	log_Enrollment	0.0660	0.0875	1.3253	
pct_black	pct_black	3.4919	4.2659	1.2217	
pct_hispanic	pct_hispanic	1.7654	2.2551	1.2774	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.8 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0833	0.0910	1.0928	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.3199	0.3289	1.0279	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1813	0.1986	1.0952	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0227	0.0326	1.4397	
log_Enrollment	log_Enrollment	0.1289	0.1464	1.1358	
pct_black	pct_black	5.3774	5.9936	1.1146	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.9 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0189	0.0210	1.1088	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1214	0.1410	1.1613	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0342	0.0367	1.0730	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0241	0.0248	1.0278	
log_Enrollment	log_Enrollment	0.0484	0.0526	1.0862	
pct_black	pct_black	0.5782	0.6251	1.0810	
pct_hispanic	pct_hispanic	0.1872	0.2104	1.1240	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)....

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	fitted_endog	11_log_real_Elem_Educ_Total_Exp_pp	0.1009	0.0923	0.9139
log_real_Total_IG_Revenue_pp		log_weighted_annual_avg_wkly_wage	0.1992	0.2412	1.2111
log_real_gdp_priv_ind_pc		log_real_Total_IG_Revenue_pp	0.1096	0.1119	1.0212
log_Enrollment		log_real_gdp_priv_ind_pc	0.0639	0.0736	1.1526
pct_black		log_Enrollment	0.0578	0.0696	1.2050
pct_hispanic		pct_black	1.0817	1.5554	1.4379
		pct_hispanic	1.5902	2.2809	1.4343

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0602	0.0586	0.9728	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1675	0.1927	1.1508	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0876	0.0933	1.0657	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0621	0.0681	1.0975	
log_Enrollment	log_Enrollment	0.0771	0.0812	1.0535	
pct_black	pct_black	0.4397	0.5220	1.1871	
pct_hispanic	pct_hispanic	0.6489	0.8515	1.3123	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0825	0.0826	1.0015	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2315	0.4136	1.7866	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0906	0.0989	1.0910	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0493	0.0559	1.1346	
log_Enrollment	log_Enrollment	0.0867	0.1192	1.3744	
pct_black	pct_black	1.3732	2.6206	1.9085	
pct_hispanic	pct_hispanic	0.6220	1.0893	1.7512	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0451	0.0448	0.9938	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2153	0.2418	1.1230	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0722	0.0830	1.1496	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0667	0.0767	1.1503	
log_Enrollment	log_Enrollment	0.0784	0.0992	1.2643	
pct_black	pct_black	0.9171	1.2614	1.3754	
pct_hispanic	pct_hispanic	1.3127	1.5488	1.1799	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0987	0.0758	0.7676	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1928	0.3052	1.5827	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.2014	0.2185	1.0849	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0440	0.0650	1.4763	
log_Enrollment	log_Enrollment	0.1305	0.1349	1.0332	
pct_black	pct_black	7.8730	9.2173	1.1708	
pct_hispanic	pct_hispanic	0.7003	1.2096	1.7272	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0582	0.0609	1.0458	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1767	0.2583	1.4621	

log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1376	0.1608	1.1683
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0274	0.0506	1.8438
log_Enrollment	log_Enrollment	0.0853	0.1348	1.5797
pct_black	pct_black	0.8031	1.5408	1.9186
pct_hispanic	pct_hispanic	0.5048	0.9216	1.8255

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.1510	0.1460	0.9670
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1438	0.2073	1.4420
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1703	0.1778	1.0441
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0327	0.0518	1.5858
log_Enrollment	log_Enrollment	0.2072	0.2721	1.3136
pct_black	pct_black	0.9186	1.4489	1.5772
pct_hispanic	pct_hispanic	1.3516	1.5403	1.1396

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0508	0.0502	0.9890
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2014	0.2444	1.2136
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0535	0.0536	1.0017
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0158	0.0291	1.8404
log_Enrollment	log_Enrollment	0.0865	0.1211	1.3995
pct_black	pct_black	0.6081	1.0684	1.7571
pct_hispanic	pct_hispanic	0.5012	0.7538	1.5042

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0454	0.0439	0.9678
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2512	0.2751	1.0952
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0800	0.1198	1.4985
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0435	0.0569	1.3102
log_Enrollment	log_Enrollment	0.1060	0.1233	1.1630
pct_black	pct_black	1.0169	1.1314	1.1127
pct_hispanic	pct_hispanic	0.5690	0.8970	1.5764

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp		0.0755	0.0719	0.9526
fitted_endog	log_weighted_annual_avg_wkly_wage		0.3231	0.3894	1.2051
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.1173	0.1083	0.9236
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0759	0.0886	1.1673
log_Enrollment	log_Enrollment		0.0292	0.0604	2.0670
pct_black	pct_black		0.4306	0.6054	1.4060
pct_hispanic	pct_hispanic		0.8196	1.0248	1.2504

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.8 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp		0.0463	0.0469	1.0113
fitted_endog	log_weighted_annual_avg_wkly_wage		0.1630	0.1804	1.1064
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0155	0.0250	1.6137
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0426	0.0469	1.1001
log_Enrollment	log_Enrollment		0.0851	0.1124	1.3210
pct_black	pct_black		0.9989	1.3041	1.3056
pct_hispanic	pct_hispanic		0.4339	0.7530	1.7355

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp		0.0625	0.0747	1.1952
fitted_endog	log_weighted_annual_avg_wkly_wage		0.2356	0.2972	1.2614
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0943	0.1132	1.2002
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0680	0.1001	1.4721
log_Enrollment	log_Enrollment		0.0836	0.1157	1.3842
pct_black	pct_black		8.7309	9.0565	1.0373
pct_hispanic	pct_hispanic		0.4659	0.9220	1.9791

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0572	0.0603	1.0541
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.1581	0.2053	1.2986
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0939	0.1010	1.0750
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0544	0.0634	1.1671
log_Enrollment	log_Enrollment	log_Enrollment	0.1828	0.1993	1.0903
pct_black	pct_black	pct_black	5.2729	7.7322	1.4664
pct_hispanic	pct_hispanic	pct_hispanic	3.2408	3.9264	1.2116

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0476	0.0519	1.0902
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.1311	0.1445	1.1028
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0922	0.1069	1.1593
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0423	0.0706	1.6693
log_Enrollment	log_Enrollment	log_Enrollment	0.0743	0.1354	1.8225
pct_black	pct_black	pct_black	0.7356	1.1026	1.4990
pct_hispanic	pct_hispanic	pct_hispanic	0.1705	0.3492	2.0485

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0812	0.0814	1.0018
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.3058	0.3291	1.0761
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0833	0.1049	1.2588
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0869	0.1432	1.6491
log_Enrollment	log_Enrollment	log_Enrollment	0.1068	0.1372	1.2842
pct_black	pct_black	pct_black	2.9185	4.0778	1.3972
pct_hispanic	pct_hispanic	pct_hispanic	2.3520	4.5272	1.9248

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0694	0.0737	1.0621
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.3328	0.4512	1.3556
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0861	0.1149	1.3342

log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.1573	0.2105	1.3383
log_Enrollment	log_Enrollment	0.1180	0.1628	1.3790
pct_black	pct_black	7.2081	9.7263	1.3494
pct_hispanic	pct_hispanic	1.6041	2.2657	1.4125

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0848	0.0839	0.9898
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2973	0.5784	1.9453
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1561	0.1640	1.0505
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.1310	0.2351	1.7949
log_Enrollment	log_Enrollment	0.1284	0.2252	1.7533
pct_black	pct_black	0.2868	0.8952	3.1214
pct_hispanic	pct_hispanic	2.2453	3.0206	1.3453

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0488	0.0699	1.4318
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2168	0.2845	1.3123
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0370	0.0592	1.6008
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0831	0.0789	0.9489
log_Enrollment	log_Enrollment	0.1497	0.1675	1.1185
pct_black	pct_black	0.9380	1.3743	1.4652
pct_hispanic	pct_hispanic	0.8316	1.0216	1.2285

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0453	0.0503	1.1092
fitted_endog	log_weighted_annual_avg_wkly_wage	0.2164	0.2544	1.1758
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1197	0.1245	1.0394
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0603	0.0647	1.0738
log_Enrollment	log_Enrollment	0.0537	0.0606	1.1286
pct_black	pct_black	1.8178	2.2878	1.2586
pct_hispanic	pct_hispanic	0.5129	0.6426	1.2528

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0611	0.0774	1.2670
fitted_endog	log_weighted_annual_avg_wkly_wage		0.2870	0.3547	1.2358
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.1190	0.1356	1.1399
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.1071	0.1200	1.1198
log_Enrollment	log_Enrollment		0.0839	0.1083	1.2911
pct_black	pct_black		2.0604	3.1114	1.5101
pct_hispanic	pct_hispanic		1.0219	1.5203	1.4877

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.6 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0839	0.1259	1.5005
fitted_endog	log_weighted_annual_avg_wkly_wage		0.1003	1.2931	12.8930
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.1163	0.2210	1.8998
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.1245	0.3184	2.5571
log_Enrollment	log_Enrollment		0.0610	0.2012	3.3006
pct_black	pct_black		1.1858	11.1488	9.4018
pct_hispanic	pct_hispanic		0.5141	2.9674	5.7726

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0630	0.0805	1.2783
fitted_endog	log_weighted_annual_avg_wkly_wage		0.2402	0.3673	1.5293
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0799	0.1168	1.4624
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0671	0.1064	1.5855
log_Enrollment	log_Enrollment		0.0922	0.1487	1.6122
pct_black	pct_black		3.8518	5.1092	1.3264
pct_hispanic	pct_hispanic		0.4105	0.9871	2.4046

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0951	0.1145	1.2038
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.4829	0.5914	1.2246
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0540	0.1040	1.9236
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.2590	0.2638	1.0185
log_Enrollment	log_Enrollment	log_Enrollment	0.1015	0.1433	1.4120
pct_black	pct_black	pct_black	2.5749	6.0911	2.3655
pct_hispanic	pct_hispanic	pct_hispanic	0.5924	0.9599	1.6204

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.5 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0	0	0
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0	0	0
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0	0	0
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0	0	0
log_Enrollment	log_Enrollment	log_Enrollment	0	0	0
pct_black	pct_black	pct_black	0	0	0
pct_hispanic	pct_hispanic	pct_hispanic	0	0	0

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0439	0.0540	1.2306
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.0753	0.1346	1.7871
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0907	0.0915	1.0097
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0530	0.0559	1.0536
log_Enrollment	log_Enrollment	log_Enrollment	0.0838	0.1032	1.2313
pct_black	pct_black	pct_black	1.4006	1.8758	1.3393
pct_hispanic	pct_hispanic	pct_hispanic	0.5994	0.7433	1.2402

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0475	0.0492	1.0348
fitted_endog	log_weighted_annual_avg_wkly_wage	log_weighted_annual_avg_wkly_wage	0.1182	0.1552	1.3132
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0765	0.0804	1.0516

log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0465	0.0571	1.2256
log_Enrollment	log_Enrollment	0.0449	0.0538	1.1978
pct_black	pct_black	0.6467	0.7744	1.1975
pct_hispanic	pct_hispanic	0.6072	0.7327	1.2068

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 1 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0823	0.0886	1.0765
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1335	0.2628	1.9679
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0574	0.0614	1.0698
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0531	0.0650	1.2244
log_Enrollment	log_Enrollment	0.0372	0.0613	1.6470
pct_black	pct_black	1.1057	1.5499	1.4018
pct_hispanic	pct_hispanic	0.3126	0.3834	1.2266

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0739	0.0996	1.3465
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0654	1.0258	15.6932
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.1853	0.2601	1.4035
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.1562	0.5104	3.2678
log_Enrollment	log_Enrollment	0.1908	0.3536	1.8537
pct_black	pct_black	18.4631	20.7146	1.1219
pct_hispanic	pct_hispanic	6.3496	5.7274	0.9020

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...
 Using 8 cores for parallel bootstrap...
 Bootstrap completed in 0.8 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0596	0.0567	0.9509
fitted_endog	log_weighted_annual_avg_wkly_wage	0.1670	0.2233	1.3374
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0392	0.0442	1.1261
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0382	0.0362	0.9470
log_Enrollment	log_Enrollment	0.0550	0.0625	1.1363
pct_black	pct_black	1.3033	2.9727	2.2809
pct_hispanic	pct_hispanic	0.5592	0.7715	1.3795

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0692	0.0688	0.9936
fitted_endog	log_weighted_annual_avg_wkly_wage		0.3935	0.4117	1.0463
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0539	0.0597	1.1061
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0930	0.1075	1.1562
log_Enrollment	log_Enrollment		0.0506	0.1724	3.4050
pct_black	pct_black		2.2639	4.4535	1.9672
pct_hispanic	pct_hispanic		2.9480	3.5483	1.2036

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.6 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.1202	0.0872	0.7254
fitted_endog	log_weighted_annual_avg_wkly_wage		0.4355	1.1392	2.6161
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0892	0.0684	0.7667
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.2372	0.5029	2.1202
log_Enrollment	log_Enrollment		0.2905	0.2967	1.0212
pct_black	pct_black		1.0785	20.2451	18.7718
pct_hispanic	pct_hispanic		1.8186	14.7455	8.1083

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0738	0.0810	1.0972
fitted_endog	log_weighted_annual_avg_wkly_wage		0.1004	0.1461	1.4551
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0634	0.0904	1.4268
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0346	0.0497	1.4371
log_Enrollment	log_Enrollment		0.0842	0.1222	1.4527
pct_black	pct_black		1.6461	3.3732	2.0492
pct_hispanic	pct_hispanic		0.4142	0.6766	1.6333

Note: Ratio > 1 indicates naive SEs understate uncertainty

Computing bootstrap standard errors (399 replications)...

Using 8 cores for parallel bootstrap...

Bootstrap completed in 0.6 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.1106	0.2110	1.9075
fitted_endog	log_weighted_annual_avg_wkly_wage		0.2933	0.6300	2.1480
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.3651	0.4601	1.2603
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0859	0.2019	2.3497
log_Enrollment	log_Enrollment		0.3762	0.7519	1.9987
pct_black	pct_black		1.1707	10.2473	8.7533
pct_hispanic	pct_hispanic		0.8848	5.4958	6.2116

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.7 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0416	0.0425	1.0223
fitted_endog	log_weighted_annual_avg_wkly_wage		0.1342	0.1512	1.1263
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0596	0.0714	1.1994
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0215	0.0296	1.3745
log_Enrollment	log_Enrollment		0.0861	0.0999	1.1613
pct_black	pct_black		4.1979	4.5307	1.0793
pct_hispanic	pct_hispanic		2.0961	2.4774	1.1819

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 0.6 seconds

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.1859	0.2747	1.4780
fitted_endog	log_weighted_annual_avg_wkly_wage		5.3646	7.7871	1.4516
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0731	0.3001	4.1025
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.3006	2.1228	7.0620
log_Enrollment	log_Enrollment		0.1087	0.5270	4.8497
pct_black	pct_black		6.5807	61.3377	9.3209
pct_hispanic	pct_hispanic		34.5490	123.7798	3.5827

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Effect of 1% Increase in Wage (using SS GDP Instrument) on Education Expenditure per Pupil
 Displays only states whose second-stage coefficient is statistically significant at the 5% level and first-stage F statistic ≥ 6 and p-value < 0

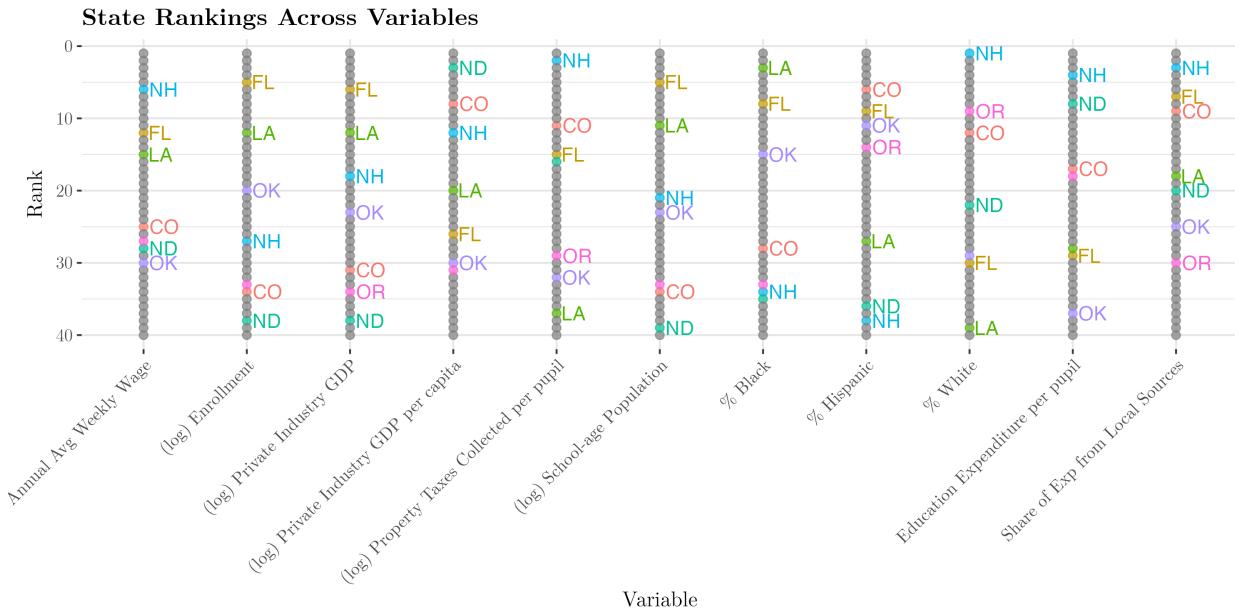
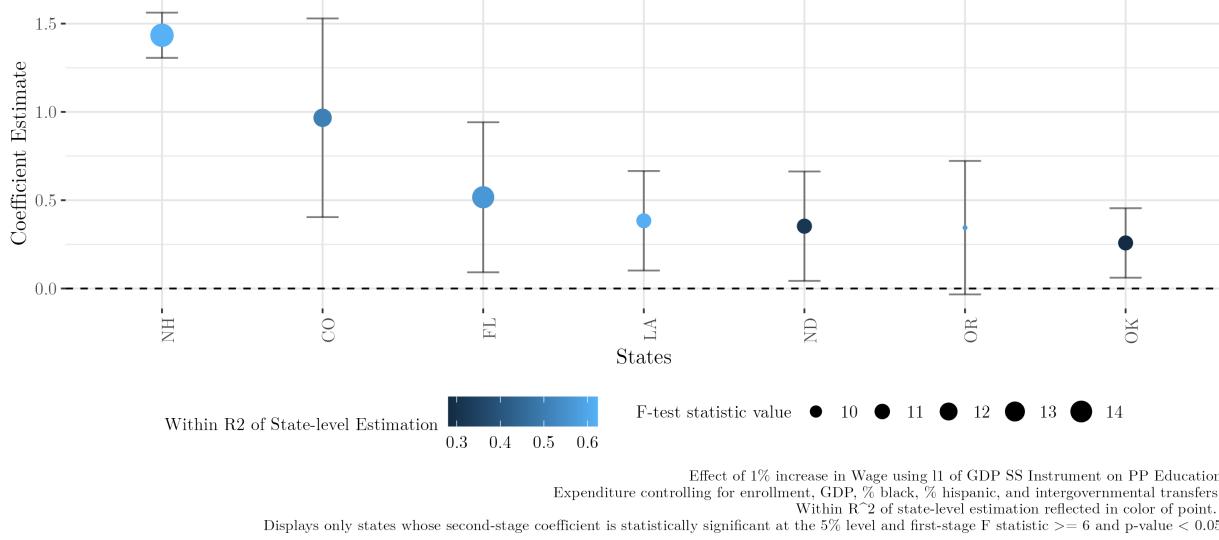
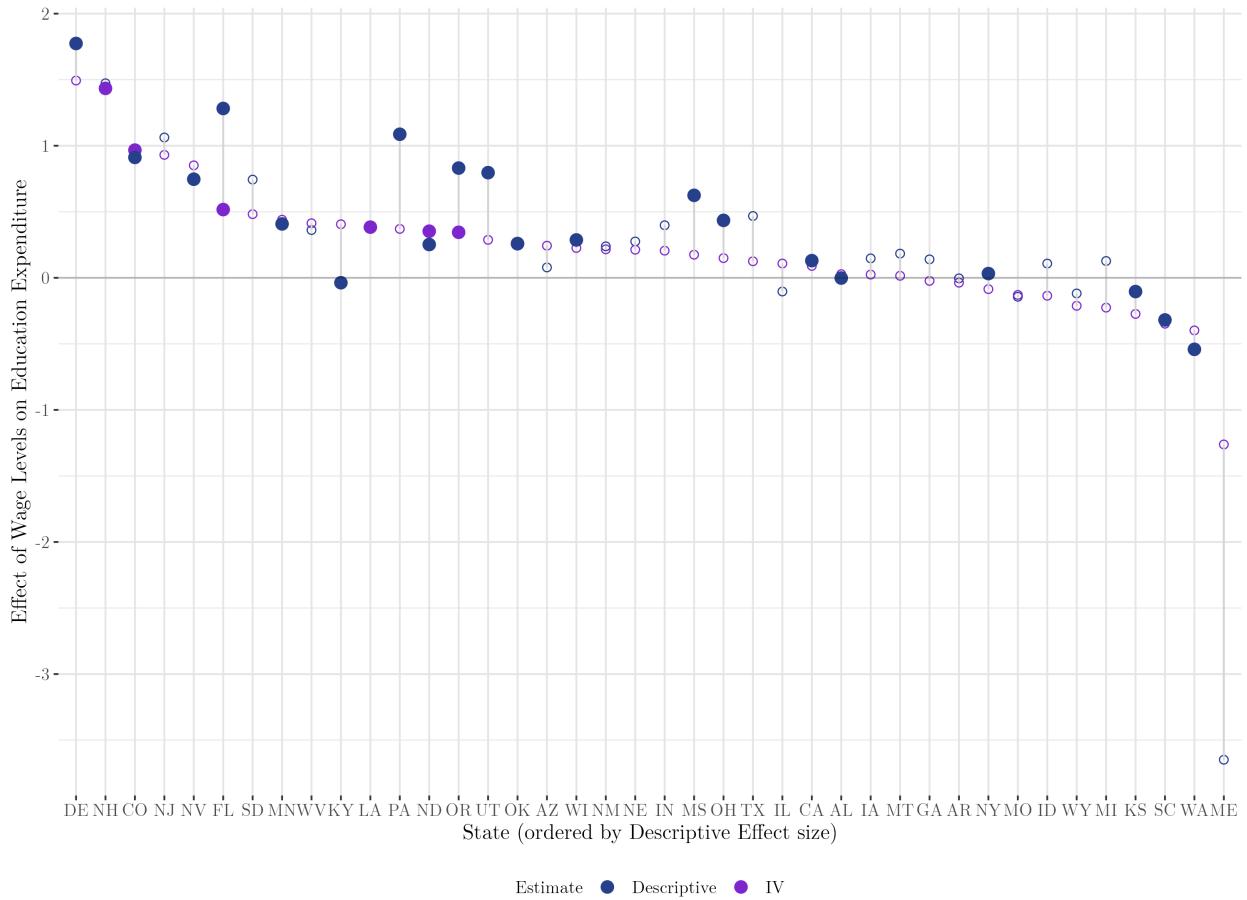


Figure 8: State-by-State Wage Effect Using SS GDP Shock

Placing the descriptive (linear combination of l0, l1, l2 lagged wage coefficient values) and causal estimates (second stage regression estimates - statistically significant second-stage estimates are represented by solid blue filled circles) side-by-side we can see an emerging pattern. First, positive wage-education relationships (Ohio, Arizona, New Hampshire) are corroborated more often than negative ones (WA). Among the well-identified relationships, only Mississippi and Missouri's relationship is revealed to be the opposite of what is suggested by the descriptive regression results.

Difference between Descriptive and IV Estimates by State

Filled blue circles represent the statistically significant estimate in IV regressions for DE, MO, OH, AZ, WA, NH.
We exclude MS as the statistically significant regression result is unreliable.



3.2.3 Industry by Industry

Second, given our shift-share instruments are the composite effect of shifts in industry-level wages and real value added, 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, our instrument is...

$$\tilde{Z}_{ijt} = G_{njt} * \frac{N_{ij\tau}}{N_{i\tau}} \quad (5)$$

...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 16 demonstrates the overall treatment effect of local wage changes instrumented via an industry-specific GDP shock.

```
Computing bootstrap standard errors ( 399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 23.9 seconds
```

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0162	1.0337	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0487	0.0448	0.9197	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0217	1.0330	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0146	1.0136	
log_Enrollment	log_Enrollment	0.0158	0.0145	0.9190	
pct_black	pct_black	0.1887	0.1906	1.0100	
pct_hispanic	pct_hispanic	0.1509	0.1566	1.0378	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 23.8 seconds

==== Standard Error Comparison ====

```

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0156	0.0154	0.9871
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0458	0.0441	0.9628
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0207	0.9881
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0143	0.0147	1.0321
log_Enrollment	log_Enrollment	0.0156	0.0153	0.9760
pct_black	pct_black	0.1883	0.1990	1.0570
pct_hispanic	pct_hispanic	0.1503	0.1528	1.0164

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 18.2 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
l1_log_real_Elem_Educ_Total_Exp_pp	l1_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0150	0.9543
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0487	0.0493	1.0108
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0216	1.0307
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0156	1.0807
log_Enrollment	log_Enrollment	0.0158	0.0161	1.0162
pct_black	pct_black	0.1886	0.2114	1.1212
pct_hispanic	pct_hispanic	0.1510	0.1517	1.0046

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.6 seconds

== Standard Error Comparison ==

	Variable	Naive_SE
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0485
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144
log_Enrollment	log_Enrollment	0.0158
pct_black	pct_black	0.1887
pct_hispanic	pct_hispanic	0.1510

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.4 seconds

==== Standard Error Comparison ===

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0157	1.0004
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0488	0.0493	1.0114
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0205	0.9789
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0150	1.0422
log_Enrollment	log_Enrollment		0.0158	0.0155	0.9790
pct_black	pct_black		0.1886	0.1922	1.0189
pct_hispanic	pct_hispanic		0.1511	0.1543	1.0211

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.2 seconds

==== Standard Error Comparison ===
```

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0155	0.9910
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0487	0.0496	1.0189
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0209	0.9954
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0152	1.0591
log_Enrollment	log_Enrollment		0.0158	0.0165	1.0478
pct_black	pct_black		0.1887	0.1938	1.0274
pct_hispanic	pct_hispanic		0.1512	0.1618	1.0701

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

```
Computing bootstrap standard errors ( 399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.3 seconds
```

==== Standard Error Comparison ====

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0158	1.0078	
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0488	0.0503	1.0308	
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0207	0.9862	
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0154	1.0688	
log_Enrollment	log_Enrollment	0.0158	0.0169	1.0714	
pct_black	pct_black	0.1885	0.2016	1.0692	
pct_hispanic	pct_hispanic	0.1511	0.1550	1.0261	

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors
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Set bootstrap_se = TRUE for corrected standard errors
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```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Computing bootstrap standard errors ( 399  replications)...
```

```
Using 8 cores for parallel bootstrap...
```

```
Bootstrap completed in 5.2 seconds
```

```
==== Standard Error Comparison ====
```

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0163	1.0368
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0488	0.0464	0.9516
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0218	1.0391
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0147	1.0216
log_Enrollment	log_Enrollment		0.0158	0.0153	0.9649
pct_black	pct_black		0.1887	0.2003	1.0615
pct_hispanic	pct_hispanic		0.1511	0.1532	1.0139

```
Note: Ratio > 1 indicates naive SEs underestimate uncertainty
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Set bootstrap_se = TRUE for corrected standard errors

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.2 seconds

==== Standard Error Comparison ===

          Variable Naive_SE Bootstrap_SE   Ratio
11_log_real_Elem_Educ_Total_Exp_pp 11_log_real_Elem_Educ_Total_Exp_pp  0.0157      0.0157  0.9993
fitted_endog                      log_weighted_annual_avg_wkly_wage  0.0487      0.0472  0.9687
log_real_Total_IG_Revenue_pp       log_real_Total_IG_Revenue_pp    0.0210      0.0221  1.0527
log_real_gdp_priv_ind_pc          log_real_gdp_priv_ind_pc     0.0144      0.0149  1.0354
log_Enrollment                     log_Enrollment                  0.0158      0.0145  0.9163
pct_black                          pct_black                    0.1886      0.1942  1.0295
pct_hispanic                       pct_hispanic                 0.1510      0.1466  0.9710

```

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

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Set `bootstrap_se = TRUE` for corrected standard errors

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Set `bootstrap_se = TRUE` for corrected standard errors

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Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstraps` as = TRUE for corrected standard errors.

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Sargan statistic = TRUE for all instruments

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Computing bootstrap standard errors ( 399 replications)...
```

```
Using 8 cores for parallel bootstrap...
```

```
Bootstrap completed in 5.1 seconds
```

```
==== Standard Error Comparison ===
```

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0154	0.9837
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0488	0.0485	0.9926
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0218	1.0423
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0150	1.0454
log_Enrollment	log_Enrollment		0.0158	0.0154	0.9771
pct_black	pct_black		0.1887	0.2015	1.0682
pct_hispanic	pct_hispanic		0.1511	0.1473	0.9746

```
Note: Ratio > 1 indicates naive SEs underestimate uncertainty
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5 seconds

==== Standard Error Comparison ====
                                         Variable Naive_SE Bootstrap_SE   Ratio
```

11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0150	0.9558
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0487	0.0508	1.0417
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0209	0.9929
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0144	1.0002
log_Enrollment	log_Enrollment	0.0158	0.0169	1.0699
pct_black	pct_black	0.1885	0.1827	0.9690
pct_hispanic	pct_hispanic	0.1511	0.1433	0.9486

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.2 seconds

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0159	1.0129
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0489	0.0488	0.9983
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0195	0.9268
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0141	0.9817
log_Enrollment	log_Enrollment	0.0158	0.0155	0.9802
pct_black	pct_black	0.1884	0.1879	0.9975
pct_hispanic	pct_hispanic	0.1512	0.1566	1.0359

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors


```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

```
Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.3 seconds
```

```
==== Standard Error Comparison ====
```

		Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp		0.0157	0.0156	0.9971
fitted_endog	log_weighted_annual_avg_wkly_wage		0.0487	0.0460	0.9446
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp		0.0210	0.0214	1.0200
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc		0.0144	0.0149	1.0356
log_Enrollment	log_Enrollment		0.0158	0.0159	1.0066
pct_black	pct_black		0.1887	0.1940	1.0280
pct_hispanic	pct_hispanic		0.1510	0.1523	1.0082

```
Note: Ratio > 1 indicates naive SEs underestimate uncertainty
```

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Set bootstrap_se = TRUE for corrected standard errors
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Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

```
Computing bootstrap standard errors ( 399  replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.3 seconds
```

==== Standard Error Comparison ===

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0160	1.0223
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0488	0.0514	1.0532
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0214	1.0223
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0143	0.9970
log_Enrollment	log_Enrollment	0.0158	0.0157	0.9975
pct_black	pct_black	0.1886	0.1928	1.0223
pct_hispanic	pct_hispanic	0.1512	0.1500	0.9924

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set `bootstrap_se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Computing bootstrap standard errors (399 replications)...
Using 8 cores for parallel bootstrap...
Bootstrap completed in 5.2 seconds

==== Standard Error Comparison ====

	Variable	Naive_SE	Bootstrap_SE	Ratio
11_log_real_Elem_Educ_Total_Exp_pp	11_log_real_Elem_Educ_Total_Exp_pp	0.0157	0.0154	0.9841
fitted_endog	log_weighted_annual_avg_wkly_wage	0.0487	0.0438	0.9003
log_real_Total_IG_Revenue_pp	log_real_Total_IG_Revenue_pp	0.0210	0.0216	1.0314
log_real_gdp_priv_ind_pc	log_real_gdp_priv_ind_pc	0.0144	0.0148	1.0260
log_Enrollment	log_Enrollment	0.0158	0.0155	0.9815
pct_black	pct_black	0.1890	0.1995	1.0557
pct_hispanic	pct_hispanic	0.1512	0.1517	1.0036

Note: Ratio > 1 indicates naive SEs underestimate uncertainty

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

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Set `bootstrap se = TRUE` for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Sargan statistic = TRUE for over-identifying restrictions

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Spherical errors TRUE for correlated endogenous regressors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Sargan statistic = TRUE for over-identifying restrictions

Using naive 2SLS standard errors (do not account for first-stage uncertainty)

```
Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors

Using naive 2SLS standard errors (do not account for first-stage uncertainty)
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Using naive 2SLS standard errors (do not account for first-stage uncertainty)
Set bootstrap_se = TRUE for corrected standard errors
```

Effect of 1% Increase in Wage on Ed. Exp. per Pupil Using Industry-Specific

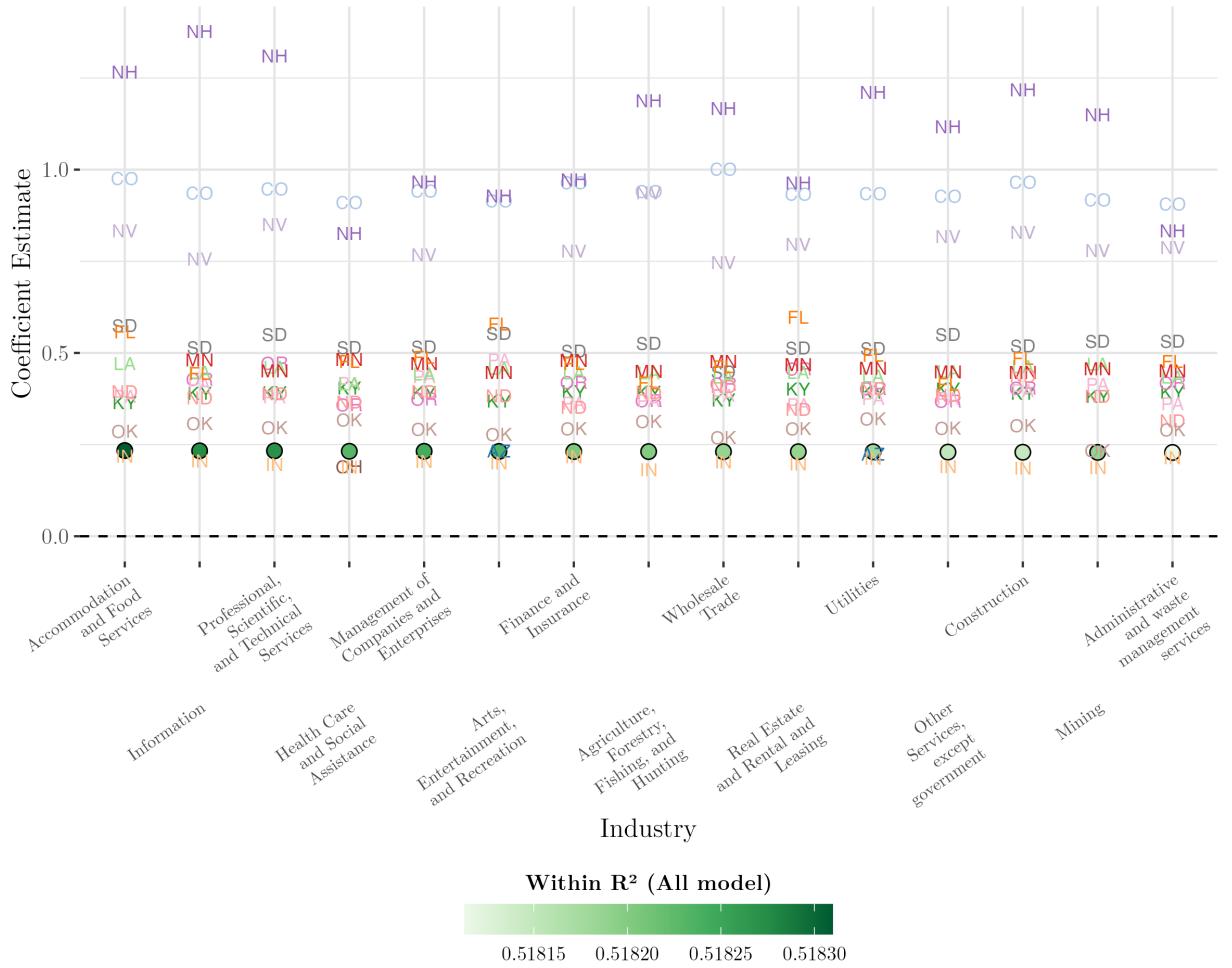


Figure 9: Wage Effect via Industry VA SS Shock

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 Discussion

...

5 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.

6 Data and Code Availability

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

7 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).

8 Acknowledgements

Appendices

A Modelling Challenges

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

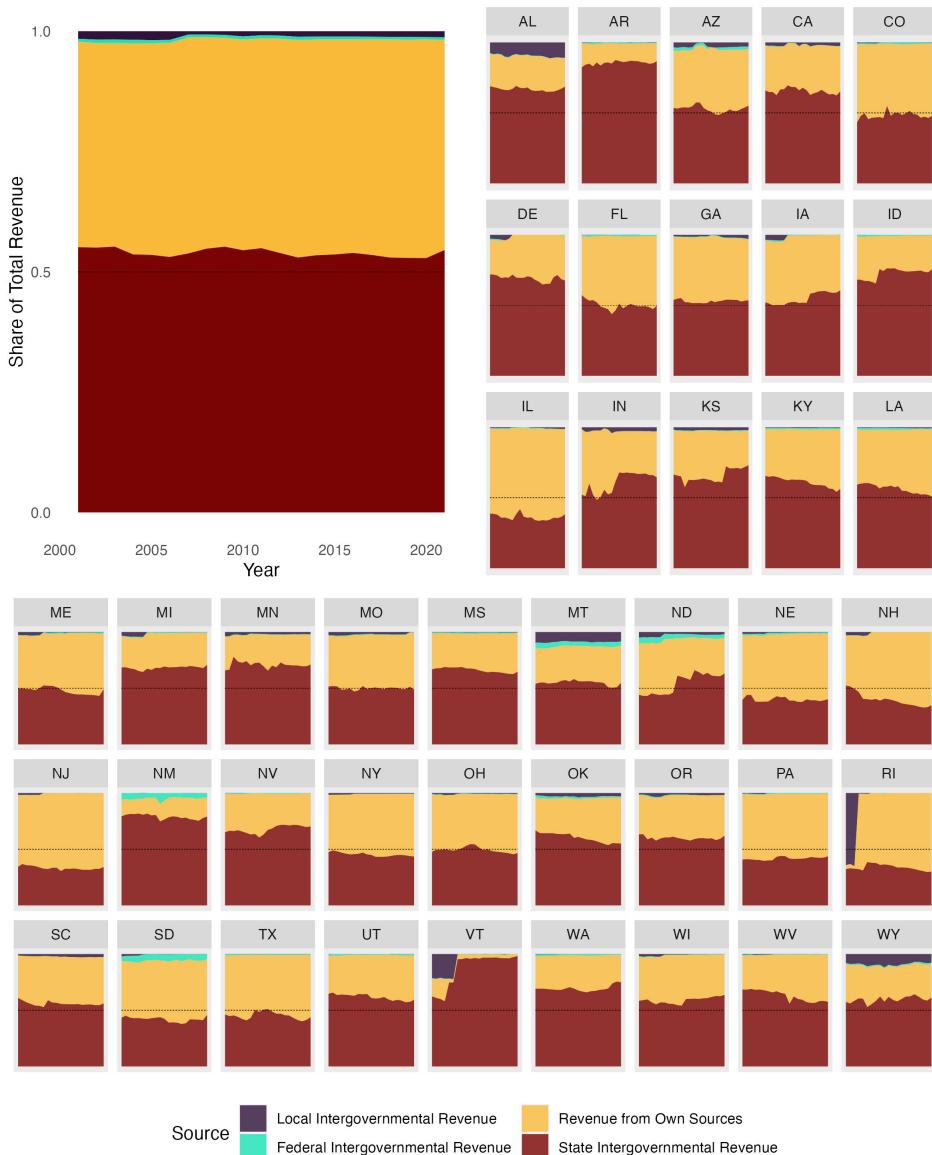
A.1 Structure of Financing for Local Public Education

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 10 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 10: Share of Revenue from Federal, State, Local Sources



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

Another factor that greatly impacts the data generating process in this study is that increasing recognition of the level of inequality of public education provision in the US has led to the implementation of several efforts to “equalise” public education by aiming for “per pupil” expenditure targets ?. The most significant change in this respect has been the creation of Educational Service Agencies (ESAs). These ESAs are apportioned state funding to serve multiple school districts in sub-regions of each state. Most of these ESAs were established around 2007 and persist to this day. ESAs are listed by state in Table 6. Currently, there are 553 agencies nationwide in 45 states. According to the Association of Educational Service Agencies (AES), 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 cyclicity.

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).

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Table 6: Educational Service Agencies by State

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

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

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