# Uneven Wage Growth and Public Goods

The Case of US Public Education

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**Abstract**

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

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# 1 Working Notes

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

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

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

Items to be adjusted:

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

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

# 2 Introduction

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

## 2.1 Uneven Public Goods Expenditure

## 2.2 Uneven Wage Growth

## 2.3 Economic Health & The Elasticity of Public Education Expenditure

## 2.4 Risks for Increasing Inequality and Structural Transformation

**In many parts of the United States, local well-being is heavily cointegrated with industrial prosperity and stability, not least through the channel of public expenditure.**

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

A recent study by Resources for the Future found that US revenues from fossil fuels generated about $ 138 billion annually for US localities, states, tribes, and the federal government Raimi et al. (2022) . This amount is forecast to decline by 2050 even in a business-as-usual scenario assuming no changes in climate policy stringency. The study also finds that Wyoming, North Dakota, Alaska, and New Mexico are the states most dependent on fossil fuel revenues with at least 14% of state and local revenues generated from the fossil fuel industry (Wyoming's dependence is above 50%). The work makes a demonstrative statement about the link between this revenue stream and essential services like schools, public health, and infrastructure, but stops short of an empirical analysis into the impact of fossil fuel decline on revenues and associated expenditure.

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

**Furthermore, (adding insult to injury) community well-being and public expenditure in the US is already characterised by a high degree of spatial heterogeneity.** Not only does the US consistently rank among the top 5 most unequal OECD countries [1].

**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

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

school-age children. In 2019, governments around the US (including the federal government) spent a total of $870 billion on public education, roughly $17,013 per pupil National Center for Education Statistics (2023) . However, the quality of services delivered varies widely across the country. [2]

The quality of public education, especially at an early age, can have long-lasting consequences for personal and economic well-being over an individual's lifetime as well as generations following them Alfonso and DuPaul (2020) . Therefore, ensuring that local or regional economic decline does not disrupt or worsen the quality of education delivered to resource-dependent communities will be of paramount importance in a net-zero transition. [3]

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

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

*RQ1:* How does uneven industrial wage growth affect public education expenditure? *RQ2:* Do intergovernmental transfers alleviate wealth-driven inequalities in public ed exp? *RQ3:* Can accounting for non-constant

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

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

relationships between explanatory variables improve our understanding of the relationship between public goods and uneven economic growth?

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

# 3 Data

This work will make use of Willamette University's Annual Government Finance Database. This resource is a harmonised repository of the data collected annually as part of the US Census Bureau's Annual Survey of State & Local Government Finances, the 'only comprehensive source of information on the finances of local governments in the United States' Pierson, Hand, and Thompson (n.d.) . I aggregate school district measures up to the county-level to ensure the availability of adequate control and treatment variables. [4]

Thus, this dataset provides estimates in current $USD on total public school revenue disaggregated by source (federal, state, local intergovernmental versus own local sources) and expenditure disaggregated by item (level of schooling, teacher salaries, debt, etc.). Finally, I gather GDP control variables from the Bureau of Economic Analysis (BEA). This BEA data is only available after 2001, therefore the panel reported and used below is restricted to 2001-2021. This results in a complete and balanced panel of 2,710 of 3,143 US counties between 2001-2021. [5] [6]

```
Warning: The `size` argument of `element_line()` is deprecated as of ggplot2 3.4.0.
i Please use the `linewidth` argument instead.
```

```
[1] "Running analysis on CZs (cz_id)."
```

All data used is reported annually at the commuting zone level. [7]

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

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

[4] The database is provided for six different levels of government: state, county, municipal, township, special district, and school district. Reporting is only mandated in Census years (every five years), and even then missing data remains a challenge. This means that data provided at any other level of government suffers from significant levels of missing data, with a high level of selection bias correlated with administrative capacity. However, strengthened by a partnership with the National Center for Education Statistics, observations for US school districts exhibit near-complete coverage between 1997-2021 Pierson, Hand, and Thompson (n.d.) . I choose to conduct the analysis on the commuting zone level because of a lack of availability of control variables at a school district level.

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

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

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

**GDP Controls:** US Bureau of Economic Analysis. Values are also reported in current US dollars (real GDP values exist). The controls used in the below are total, private industry, and oil, gas, mining and quarrying commuting zone-level GDP.

**Population controls:** US Census Bureau.

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

## 3.1 Summary statistics

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

Table 1

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Enrollment | 13,356 | 62 | 170 | 0 | 3,170 |
| Population | 13,356 | 405 | 1,078 | 1 | 18,733 |
| Elem. Expenditure per pupil | 13,356 | 11 | 3 | 6 | 58 |
| Property Tax per pupil | 13,356 | 4 | 2 | 0 | 33 |
| IG Revenue per pupil | 13,356 | 7 | 2 | 1 | 28 |
| State IG Revenue per pupil | 13,356 | 7 | 2 | 1 | 26 |
| GDP per capita | 13,356 | 45 | 25 | 15 | 389 |
| GDP pc - Private Industry | 13,356 | 38 | 25 | 6 | 383 |
| House Price Index | 12,717 | 255 | 156 | 86 | 1,948 |

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

\footnote{Autor et al use a shift-share instrument to assess the effect of Chinese import competition on manufacturing employment in US counties Autor, Dorn, and Hanson (2013) . As an extension, Feler and Senses (2017) use a similar shift-share instrument to assess the effect of the same shock on the size of local government. Baccini and Weymouth (2021) employ a shift-share instrument for manufacturing layoffs to tease out the effect of a decline in manufacturing on both economically motivated and racial identity voting patterns in the US.}

Second, an additional popular indicator for modelling industrial shocks is *oil price* as values are often assumed to be exogenous to local and even national conditions Scheer et al. (2022) . Third, separate from specifically green transformation shocks, various indicators for measuring *deindustrialisation* have been proposed including the manufacturing share of employment, value added, and GDP Tregenna and Andreoni (2020). These deindustrialisation metrics could be used in combination with a shift-share instrument. Finally, in rare instances, exogeneity can be secured due to *geographical, climatological, or geological factors*. For example, Borge, Parmer, and Torvik (2015) obtain an exogenous measure of local revenue by "instrumenting the variation in hydropower revenue, and thus total revenue, by topology, average precipitation and meters of river in steep terrain." Certain authors have argued that the fact that the location of hydrocarbon deposits is dictated by geomorphological processes provides a plausible argument for exogeneity Chen et al. (2022).

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

# 4 Analysis

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

Considerable investigation uncovered the need for a regional or state–by-state estimation strategy to truly account for the heterogeneity across the units of observation. Therefore, the body of the analysis is dedicated to state-by-state estimation of the relevant econometric specifications. We dedicate majority of this manuscript to discussing the consequences of an uneven legislative landscape on educational expenditure outcomes.

## 4.1 Descriptive Regressions

### 4.1.1 Baseline

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

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

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

$Y_{it}$ is the natural logarithm of elementary (serving ages 6-12) education expenditure per pupil for county $i$ in year $t$. $\alpha_i$ and $\gamma_t$ represent county- and year-fixed effects, respectively, and $\varepsilon_{it}$ represents the error term. We control for enrollment to account for scaling factors in education expendture and intergovernmental transfers to account for the significant role of such transfers in funding education expenditure. Additionally, we optionally include a lagged dependent variable to account for the persistence of education expenditure. $X_{it}$ takes three forms represented by @ref(gdp_function), @ref(wage_function), @ref(hpi_function) where $h = [0, 2]$ in the specifications that incorporate time lagged variables. We estimate all equations in both levels and growth rates.

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

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

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

Education expenditure has a highly relevant time dependence. The effect of increases in GDP two years prior has the greatest effect on current education expenditure, implying a delayed effect of commuting zone-level economic growth on public education expenditure.

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

In the levels regressions, intergovernmental revenue per pupil emerges as the strongest and most consistent predictor of education expenditure. A 1% increase in intergovernmental transfers is associated with approximately a 0.35–0.38% increase in per-pupil education spending, controlling for unit and year fixed effects. This finding highlights the importance of state and federal aid in sustaining local education budgets. Lagged economic indicators, particularly private industry GDP and average weekly wages, are also positively and significantly associated with education spending. The magnitude of the coefficients increases with the number of lags, suggesting a gradual adjustment process by which local economic growth translates into higher public investment in education over time. For example, a 1% increase in lagged (t–2) real private GDP per capita is associated with a 0.14% increase in per-pupil spending, while lagged wage growth shows similar cumulative effects.

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

The growth rate regressions, while explaining less variance overall (as expected), largely confirm the patterns observed in the levels specifications. Intergovernmental revenue growth remains a strong and highly significant determinant of education expenditure growth, with coefficients ranging from 0.33 to 0.40. Lagged wage and GDP growth also emerge as important predictors, particularly at longer lags. Notably, wage growth two years prior is associated with a 0.31% increase in education spending growth, suggesting that labor market improvements take time to materialize in local education budgets. Growth in house prices also predicts increases in education spending, but these effects are concentrated in the contemporaneous and first-lag specifications.

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

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

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

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

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

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

| Dependent Variable: | (log) Elem.Ed.Exp.pp | | | | |
|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Funding Share_state | 1.141* | 0.6507 | -0.6806* | 0.0605 | -0.5615** |
| | (0.6255) | (0.5394) | (0.3990) | (0.3325) | (0.2522) |
| (log) Real GDP Priv. Industry pc | -0.2324*** | | | | |
| | (0.0753) | | | | |
| (log,l1) Real GDP Priv. Industry pc | 0.1055* | | | | |
| | (0.0596) | | | | |
| (log,l2) Real GDP Priv. Industry pc | 0.3441*** | | | | |
| | (0.0801) | | | | |
| Funding Share_state × (log) Real GDP Priv. Industry pc | 0.4109*** | | | | |
| | (0.1217) | | | | |
| Funding Share_state × (log,l1) Real GDP Priv. Industry pc | -0.1136 | | | | |
| | (0.0959) | | | | |
| Funding Share_state × (log,l2) Real GDP Priv. Industry pc | -0.4461*** | | | | |
| | (0.1221) | | | | |
| (log) Fed IG Rev. pp | -0.0026 | -0.0056 | -0.0166** | 0.0052 | -0.0023 |
| | (0.0092) | (0.0087) | (0.0077) | (0.0065) | (0.0059) |
| (log) Enrollment | -0.3327*** | -0.3522*** | -0.3881*** | -0.2252*** | -0.2470*** |
| | (0.0299) | (0.0294) | (0.0286) | (0.0187) | (0.0187) |
| Funding Share_state × (log) Fed IG Rev. pp | -0.0006 | 0.0071 | 0.0242** | -0.0099 | 0.0015 |
| | (0.0142) | (0.0135) | (0.0117) | (0.0101) | (0.0091) |
| Funding Share_state × (log) Enrollment | -0.0222 | 0.0032 | 0.0236 | 0.0147 | 0.0206 |
| | (0.0260) | (0.0255) | (0.0209) | (0.0166) | (0.0154) |
| (log) Annual Avg. Wkly. Wage | | -0.0206 | | -0.1824 | |
| | | (0.2234) | | (0.1576) | |
| (log, l1) Annual Avg. Wkly. Wage | | 0.2181 | | 0.4338** | |
| | | (0.1496) | | (0.1839) | |
| (log, l2) Annual Avg. Wkly. Wage | | 0.5060** | | 0.0489 | |
| | | (0.2274) | | (0.1333) | |
| Funding Share_state × (log) Annual Avg. Wkly. Wage | | 0.4959 | | 0.5470** | |
| | | (0.3515) | | (0.2458) | |
| Funding Share_state × (log, l1) Annual Avg. Wkly. Wage | | -0.0609 | | -0.4624 | |
| | | (0.2366) | | (0.2894) | |
| Funding Share_state × (log, l2) Annual Avg. Wkly. Wage | | -0.6423* | | -0.1810 | |
| | | (0.3562) | | (0.2158) | |
| (log) House Price Index | | | -0.0850 | | 0.0173 |
| | | | (0.1112) | | (0.0851) |
| (log, l1) House Price Index | | | 0.1626 | | 0.0712 |
| | | | (0.1357) | | (0.1759) |
| (log, l2) House Price Index | | | 0.3599*** | | 0.3197** |
| | | | (0.1019) | | (0.1552) |
| (log, l3) House Price Index | | | 0.0352 | | -0.1896 |
| | | | (0.1143) | | (0.1212) |
| (log, l4) House Price Index | | | -0.1431 | | -0.1233 |
| | | | (0.0926) | | (0.0991) |
| (log, l5) House Price Index | | | -0.0024 | | 0.0678 |
| | | | (0.0841) | | (0.0654) |
| Funding Share_state × (log) House Price Index | | | 0.4730*** | | 0.2378* |
| | | | (0.1741) | | (0.1310) |
| Funding Share_state × (log, l1) House Price Index | | | -0.1712 | | -0.0891 |
| | | | (0.2058) | | (0.2609) |
| Funding Share_state × (log, l2) House Price Index | | | -0.4792*** | | -0.4866** |
| | | | (0.1546) | | (0.2289) |
| Funding Share_state × (log, l3) House Price Index | | | -0.0245 | | 0.2783 |
| | | | (0.1783) | | (0.1861) |
| Funding Share_state × (log, l4) House Price Index | | | 0.2086 | | 0.1618 |
| | | | (0.1442) | | (0.1464) |
| Funding Share_state × (log, l5) House Price Index | | | -0.0623 | | -0.1219 |
| | | | (0.1314) | | (0.0993) |
| (l1, log) Elem.Ed.Exp.pp | | | | 0.5351*** | 0.5185*** |
| | | | | (0.0163) | (0.0146) |
| *Fixed-effects* | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 12,084 | 13,356 | 12,536 | 12,720 | 11,979 |

## 4.2 Instrumental Variable Approach

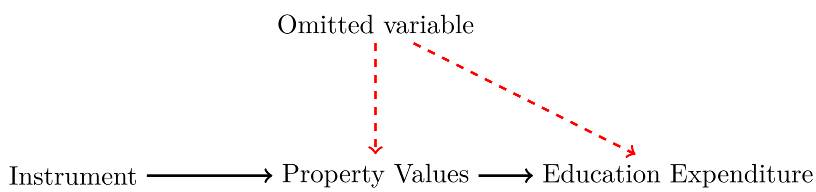
There is a significant endogeneity concern in using wage growth as the treatment variable. Therefore, I have tried two instrumental variable approaches below and aim to add results using production- and employment-based Bartik instruments.

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

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

As a reminder, the intuition behind the idea is

Figure 1: Instrumental Variable Path Diagram




As seen in Figure 1, I hypothesize that property taxes have an effect on education expenditure. However, there is significant concern of a reverse causal effect as higher income families likely gravitate towards school districts with higher levels of expenditure per pupil, driving up property values. However, we assume that coal mining activity has no other effect on education expenditure except through the channel of property taxes.

A more commonly used identification strategy is via a shift-share or Bartik instrument. A shift-share instrument interacts local industry shares with national industry-level growth rates to attain a plausibly exogenous local shock. In the context of this work, we intend to create a unit-specific time-varying treatment variable by interacting a unit-specific, time-invariant industrial employment share variable with a national-level time-varying wage growth rate.

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

The literature on Bartik instruments derives plausible exogeneity from two sources. First, authors argue that local industry shares are exogenous by imposing that shares be fixed to a particular base year and are therefore unable to adapt to changes in national-level growth rates. Such a shift-share instrument would look as follows:

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

where $S_{ij0}$ is the local share of unit $i$'s economy (potentially measured by metrics like employment, wages, revenue) in industry $j$ at a fixed base year $\tau$ and $G_{njt}$ is the growth rate of industry $j$ at a national level $n$ at time $t$.

Alternatively, authors may argue that the national-level growth rates are exogenous allowing the shares to vary over time, constructing the shift-share instrument as follows:

$$Z_{it} = \sum_{j=1}^{k} S_{ijt} G_{njt} \tag{7}$$

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

$$Z_{it} = \sum_{j=1}^{k} S_{0jt} G_{ojt} \tag{8}$$

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

$$X_{it} = \alpha_i + \beta \sum_{j=1}^{k} S_j G_j + \epsilon_{it} \tag{9}$$

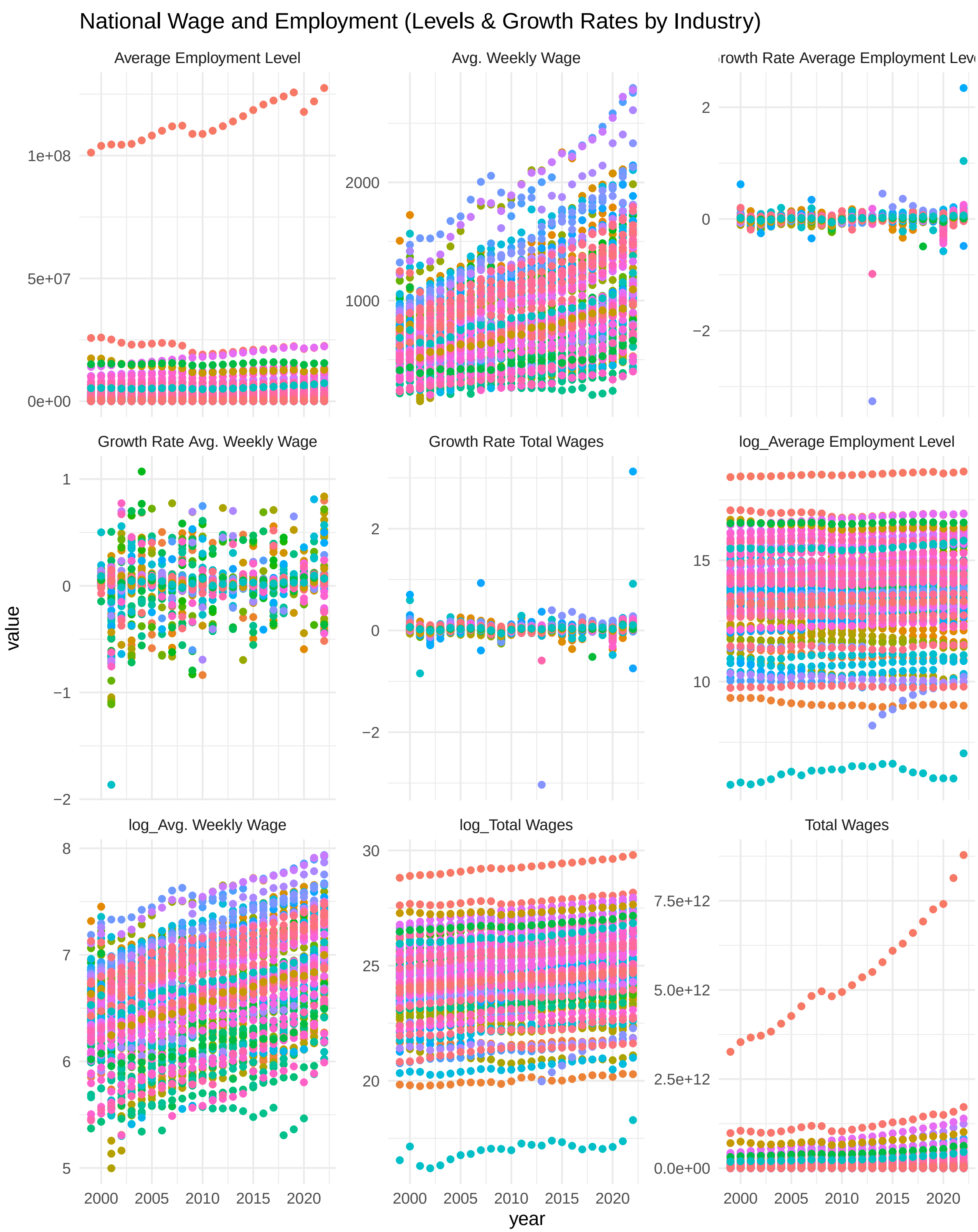
$$X_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j S_{\star j \star} G_{\star jt} + \epsilon_{it} \tag{10}$$

#### 4.2.1 Shift-share Instrument

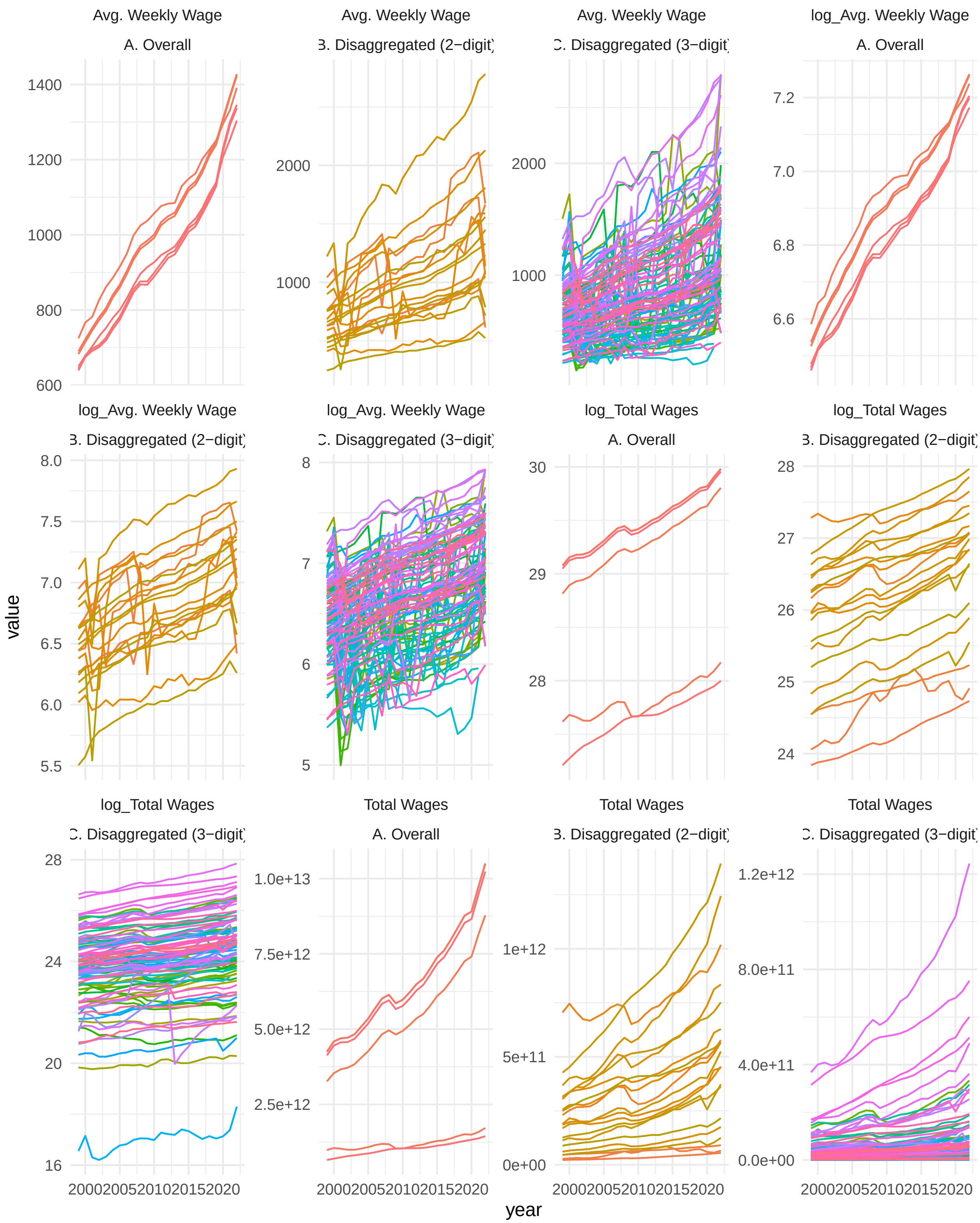
Finally, using data from the US Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), I have constructed a total of six shift-share Bartik instruments across two metrics (employment and wage) for three sectoral aggregations (oil and gas, coal, and all extractive industries) at the county-level. Equation 11 demonstrates the Bartik instrument as outlined in Ferri (2022) and Goldsmith-Pinkham, Sorkin, and Swift (2020) and defined in Bartik (1991) . $\Delta X_{t,s}$ represents national-level changes in either employment or wages in industry $s$ in time $t$ and $\frac{N_{i,\tau,s}}{N_{i,\tau}}$ represents the "sensitivity' ' of a county to these national shocks proxied by an initial share of local employment or wage in industry $s$ in a baseline time period $\tau$. The product of these two values defines the shift-share indicator $\tilde{X}_{i,t,s}$. In Figure XX, I demonstrate the wage- and employment-based shift-share instruments (each line represents a separate county) using a base period $\tau = 2001$. [8]

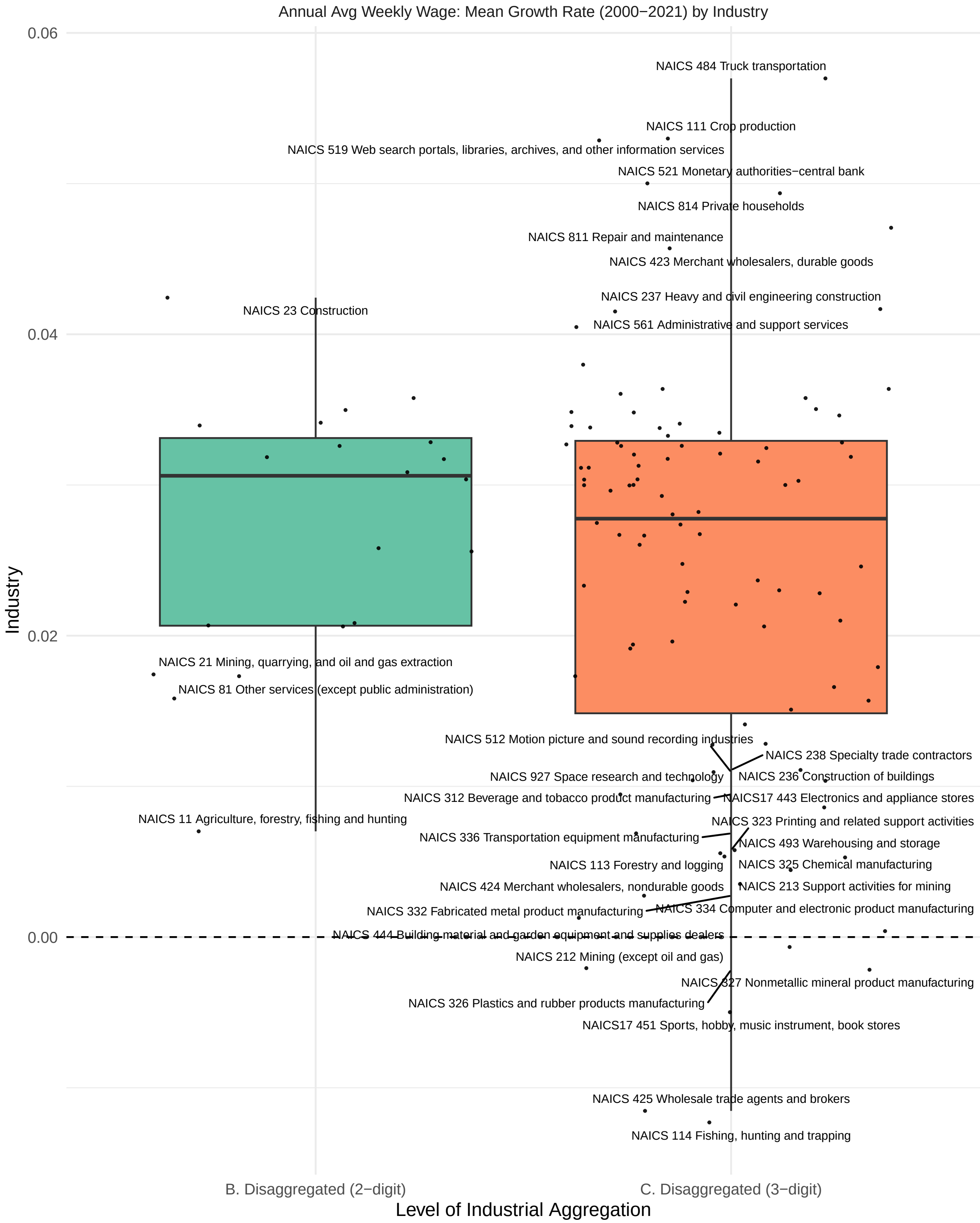
$$\tilde{X}_{i,t,s} = \Delta X_{t,s} * \frac{N_{i,\tau,s}}{N_{i,\tau}} \tag{11}$$

[8]We explore the sensitivity of results to the choice of base period $\tau$ by constructing the instrument for various base periods as well as a rolling window.



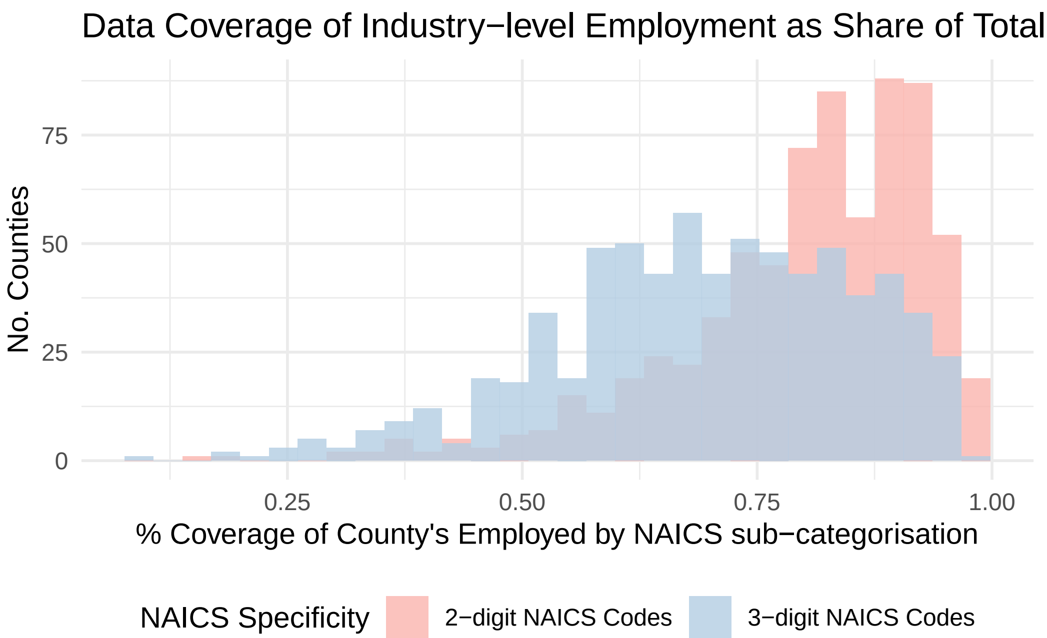
National Wage and Employment (Levels & Growth Rates by Industry)
Average Employment Level
Avg. Weekly Wage
rowth Rate Average Employment Leve
Growth Rate Avg. Weekly Wage
Growth Rate Total Wages
log_Average Employment Level
log_Avg. Weekly Wage
log_Total Wages
Total Wages
value
year
1e+08
5e+07
0e+00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


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




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

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

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




```
[1] TRUE
```

Fundamental to our identification strategy is the relationship between wages and property prices as well as real value added and property prices. We provide evidence of this relationship below.

#### 4.2.1.1 Industry-level Wages

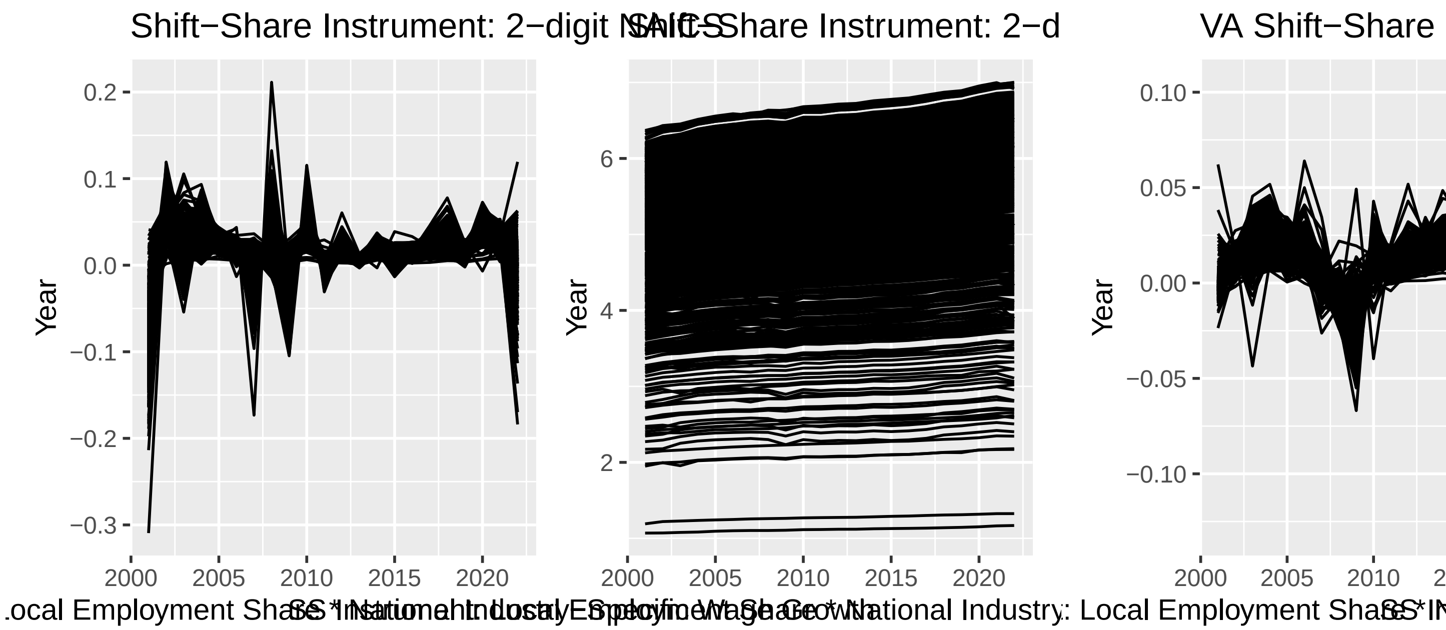
The two regression models show that wage levels and wage growth both play important roles in influencing house prices, but in different ways. The log-level model indicates that increases in average wages have a strong and persistent effect on the level of house prices, with significant positive effects extending up to four quarters. In contrast, the growth rate model suggests that house price growth responds primarily to contemporaneous wage growth, with little evidence of lagged effects. Together, these findings imply that while higher wages steadily raise housing values over time, short-term changes in wage growth influence house price dynamics more immediately but less durably. Together, they suggest that housing markets are more responsive to trends than to transitory shocks in wages.

| Dependent Variable: | (log) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (log) Annual Avg. Wkly. Wage | 0.9365*** |
| | (0.0643) |
| (log, l1) Annual Avg. Wkly. Wage | 0.0544*** |
| | (0.0137) |
| (log, l2) Annual Avg. Wkly. Wage | 0.0861*** |
| | (0.0146) |
| (log, l3) Annual Avg. Wkly. Wage | 0.0303* |
| | (0.0148) |
| (log, l4) Annual Avg. Wkly. Wage | 0.0863*** |
| | (0.0205) |
| (log, l5) Annual Avg. Wkly. Wage | 0.0261 |
| | (0.0153) |
| (log, l6) Annual Avg. Wkly. Wage | 0.0388 |
| | (0.0296) |
| (log, l7) Annual Avg. Wkly. Wage | 0.0222 |
| | (0.0224) |
| (log) Real GDP Priv. Industry pc | 0.0710*** |
| | (0.0112) |
| (log) Population | 0.4165*** |
| | (0.0594) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 12,570 |
| $R^2$ | 0.96815 |
| Within $R^2$ | 0.32132 |

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

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Annual Avg. Wkly. Wage | 0.3164*** |
| | (0.0635) |
| (GR, l1) Annual Avg. Wkly. Wage | 0.0040 |
| | (0.0168) |
| (GR, l2) Annual Avg. Wkly. Wage | 0.0242 |
| | (0.0157) |
| (GR, l3) Annual Avg. Wkly. Wage | 0.0035 |
| | (0.0205) |
| (GR, l4) Annual Avg. Wkly. Wage | 0.0263 |
| | (0.0232) |
| (GR, l5) Annual Avg. Wkly. Wage | $6.34 \times 10^{-5}$ |
| | (0.0199) |
| (GR, l6) Annual Avg. Wkly. Wage | -0.0118 |
| | (0.0216) |
| (GR, l7) Annual Avg. Wkly. Wage | -0.0093 |
| | (0.0234) |
| (GR) Real GDP Priv. Industry pc | 0.0078 |
| | (0.0107) |
| (GR) Population | 0.0063*** |
| | (0.0010) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 12,543 |
| $R^2$ | 0.39690 |
| Within $R^2$ | 0.02349 |

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




| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (GR) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|
| IV stages | First | Second | First | Second | First | Second |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| l(lev_ss_2d,1) | -0.5944$^{***}$ | | | | | |
| | (0.1041) | | | | | |
| (log) IG Revenue pp | 0.1805$^{***}$ | 0.3535$^{***}$ | 0.1723$^{***}$ | 0.3233$^{***}$ | 0.1723$^{***}$ | 0.1654$^{***}$ |
| | (0.0191) | (0.0349) | (0.0191) | (0.0363) | (0.0191) | (0.0303) |
| (log) Real GDP Priv. Industry pc | 0.2328$^{***}$ | 0.1701$^{***}$ | 0.2506$^{***}$ | 0.1261$^{***}$ | 0.2506$^{***}$ | 0.0872$^{**}$ |
| | (0.0265) | (0.0434) | (0.0269) | (0.0432) | (0.0269) | (0.0416) |
| (log) Enrollment | 0.3146$^{***}$ | -0.2889$^{***}$ | 0.2878$^{***}$ | -0.3395$^{***}$ | 0.2878$^{***}$ | -0.0055 |
| | (0.0315) | (0.0450) | (0.0309) | (0.0476) | (0.0309) | (0.0473) |
| (log) House Price Index | | 0.0611 | | 0.2364 | | -0.2446 |
| | | (0.1492) | | (0.1477) | | (0.1598) |
| l(ss_2d,1) | | | -0.4008$^{***}$ | | -0.4008$^{***}$ | |
| | | | (0.0581) | | (0.0581) | |
| *Fixed-effects* | | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 |
| $R^2$ | 0.96498 | 0.86692 | 0.96437 | 0.86874 | 0.96437 | 0.04049 |
| Within $R^2$ | 0.21946 | 0.30268 | 0.20588 | 0.31224 | 0.20588 | -0.03075 |
| F-test (1st stage) | 255.89 | | 44.628 | | 44.628 | |
| F-test (1st stage), (log) House Price Index | | 255.89 | | 44.628 | | 44.628 |
| F-test (1st stage), p-value | $5.18 \times 10^{-57}$ | | $2.49 \times 10^{-11}$ | | $2.49 \times 10^{-11}$ | |
| F-test (1st stage), p-value, (log) House Price Index | | $5.18 \times 10^{-57}$ | | $2.49 \times 10^{-11}$ | | $2.49 \times 10^{-11}$ |
| F-test (2nd stage) | | 0.97271 | | 2.5833 | | 2.9966 |
| F-test (2nd stage), p-value | | 0.32402 | | 0.10802 | | 0.08346 |
| Wu-Hausman | | 4.0636 | | 0.11774 | | 3.0318 |
| Wu-Hausman, p-value | | 0.04384 | | 0.73151 | | 0.08168 |
| Wald (IV only) | 32.611 | 0.16780 | 47.606 | 2.5607 | 47.606 | 2.3451 |
| Wald (IV only), p-value | $1.15 \times 10^{-8}$ | 0.68208 | $5.47 \times 10^{-12}$ | 0.10957 | $5.47 \times 10^{-12}$ | 0.12570 |

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

| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (GR) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|
| IV stages | First | Second | First | Second | First | Second |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| l(lev_ss_2d,1) | 0.0631$^{***}$ | | | | | |
| | (0.0183) | | | | | |
| (log) IG Revenue pp | -0.1551$^{***}$ | 0.2451$^{***}$ | -0.1851$^{***}$ | 0.4148$^{**}$ | -0.1851$^{***}$ | 0.1536 |
| | (0.0450) | (0.0331) | (0.0455) | (0.1609) | (0.0455) | (0.1081) |
| (log) Real GDP Priv. Industry pc | 0.1131$^{***}$ | 0.1691$^{***}$ | 0.1137$^{***}$ | 0.0650 | 0.1137$^{***}$ | -0.0602 |
| | (0.0272) | (0.0210) | (0.0270) | (0.0961) | (0.0270) | (0.0639) |
| (log) Enrollment | 0.1230$^{***}$ | -0.0304 | 0.1436$^{***}$ | -0.1619 | 0.1436$^{***}$ | -0.0890 |
| | (0.0108) | (0.0200) | (0.0080) | (0.1160) | (0.0080) | (0.0806) |
| (log) House Price Index | | 0.0414 | | 0.9553 | | 0.6173 |
| | | (0.1310) | | (0.8031) | | (0.5553) |
| l(ss_2d,1) | | | 0.2147 | | 0.2147 | |
| | | | (0.1732) | | (0.1732) | |
| *Fixed-effects* | | | | | | |
| year | Yes | Yes | Yes | Yes | Yes | Yes |
| state | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 |
| $R^2$ | 0.74522 | 0.70524 | 0.73946 | -0.03999 | 0.73946 | -2.5843 |
| Within $R^2$ | 0.45684 | 0.27039 | 0.44458 | -1.5743 | 0.44458 | -2.8302 |
| F-test (1st stage) | 274.09 | | 1.8203 | | 1.8203 | |
| F-test (1st stage), (log) House Price Index | | 274.09 | | 1.8203 | | 1.8203 |
| F-test (1st stage), p-value | $6.85 \times 10^{-61}$ | | 0.17730 | | 0.17730 | |
| F-test (1st stage), p-value, (log) House Price Index | | $6.85 \times 10^{-61}$ | | 0.17730 | | 0.17730 |
| F-test (2nd stage) | | 1.5672 | | 5.6628 | | 5.5013 |
| F-test (2nd stage), p-value | | 0.21064 | | 0.01734 | | 0.01902 |
| Wu-Hausman | | 3.5198 | | 4.6863 | | 5.2383 |
| Wu-Hausman, p-value | | 0.06066 | | 0.03042 | | 0.02211 |
| Wald (IV only) | 11.894 | 0.10000 | 1.5355 | 1.4147 | 1.5355 | 1.2357 |
| Wald (IV only), p-value | 0.00057 | 0.75184 | 0.21532 | 0.23431 | 0.21532 | 0.26633 |

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

#### 4.2.1.2 Industry-level GDP

The two regression tables investigate the relationship between real GDP per capita in the private industry and house prices. In the log-level specification, real GDP (including current and lagged values up to 7 periods) is positively and significantly associated with house prices. The contemporaneous coefficient (0.2411) is large and highly significant, and several lags (especially lags 1, 2, 3, and 5) are also positive and statistically significant, indicating a cumulative and persistent effect of GDP on housing values.

In contrast, the growth-rate specification shows a much weaker relationship. Most coefficients are small and not statistically significant, with the exception of lag 5, which shows a modest but significant positive association (0.0073). The $R^2$ values further support this contrast: the log-level model explains 96% of the variation in house prices (with a within $R^2$ of 0.203), while the growth-rate model explains only about 39% overall (and just 0.005 within variation).

Together, these findings suggest that levels (rather than short-run changes) in GDP are more systematically and substantially associated with house price dynamics. The stronger fit and significant lag effects in the log-level regression underscore the longer-term influence of economic fundamentals on housing markets.

| Dependent Variable: | (log) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (log) Real GDP Priv. Industry pc | 0.2411*** |
| | (0.0209) |
| l(log_real_gdp_priv_ind_pc,1) | 0.0276*** |
| | (0.0057) |
| l(log_real_gdp_priv_ind_pc,2) | 0.0204*** |
| | (0.0034) |
| l(log_real_gdp_priv_ind_pc,3) | 0.0199*** |
| | (0.0041) |
| l(log_real_gdp_priv_ind_pc,4) | 0.0045 |
| | (0.0031) |
| l(log_real_gdp_priv_ind_pc,5) | 0.0371*** |
| | (0.0052) |
| l(log_real_gdp_priv_ind_pc,6) | 0.0112* |
| | (0.0057) |
| l(log_real_gdp_priv_ind_pc,7) | 0.0060 |
| | (0.0063) |
| (log) Population | 0.5459*** |
| | (0.0499) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 12,570 |
| $R^2$ | 0.96261 |
| Within $R^2$ | 0.20336 |

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

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Real GDP Priv. Industry pc | 0.0161 |
| | (0.0162) |
| l(diff_log_real_gdp_priv_ind_pc,1) | 0.0093 |
| | (0.0057) |
| l(diff_log_real_gdp_priv_ind_pc,2) | 0.0062 |
| | (0.0043) |
| l(diff_log_real_gdp_priv_ind_pc,3) | -0.0009 |
| | (0.0034) |
| l(diff_log_real_gdp_priv_ind_pc,4) | -0.0025 |
| | (0.0024) |
| l(diff_log_real_gdp_priv_ind_pc,5) | 0.0070*** |
| | (0.0020) |
| l(diff_log_real_gdp_priv_ind_pc,6) | $8.67 \times 10^{-5}$ |
| | (0.0043) |
| l(diff_log_real_gdp_priv_ind_pc,7) | -0.0002 |
| | (0.0026) |
| (GR) Population | 0.0060*** |
| | (0.0011) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 12,542 |
| $R^2$ | 0.38588 |
| Within $R^2$ | 0.00564 |

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

| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (GR) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|
| IV stages | First | Second | First | Second | First | Second |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| l(lev_gdp_ss_2d,1) | -0.3555*** | | | | | |
| | (0.1323) | | | | | |
| (log) IG Revenue pp | 0.1757*** | 0.4073*** | 0.1724*** | 0.2561 | 0.1724*** | 1.139 |
| | (0.0192) | (0.0638) | (0.0192) | (0.3462) | (0.0192) | (1.860) |
| (log) Real GDP Priv. Industry pc | 0.2457*** | 0.2483*** | 0.2509*** | 0.0283 | 0.2509*** | 1.504 |
| | (0.0269) | (0.0904) | (0.0269) | (0.4988) | (0.0269) | (2.692) |
| (log) Enrollment | 0.3047*** | -0.1989** | 0.2890*** | -0.4521 | 0.2890*** | 1.625 |
| | (0.0320) | (0.0990) | (0.0310) | (0.5738) | (0.0310) | (3.102) |
| (log) House Price Index | | -0.2505 | | 0.6264 | | -5.891 |
| | | (0.3463) | | (1.978) | | (10.72) |
| l(gdp_ss_2d,1) | | | -0.0807 | | -0.0807 | |
| | | | (0.1461) | | (0.1461) | |
| *Fixed-effects* | | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 | 12,122 |
| $R^2$ | 0.96440 | 0.84227 | 0.96424 | 0.84169 | 0.96424 | -34.971 |
| Within $R^2$ | 0.20657 | 0.17354 | 0.20297 | 0.17053 | 0.20297 | -37.641 |
| F-test (1st stage) | 55.305 | | 0.36268 | | 0.36268 | |
| F-test (1st stage), (log) House Price Index | | 55.305 | | 0.36268 | | 0.36268 |
| F-test (1st stage), p-value | $1.1 \times 10^{-13}$ | | 0.54703 | | 0.54703 | |
| F-test (1st stage), p-value, (log) House Price Index | | $1.1 \times 10^{-13}$ | | 0.54703 | | 0.54703 |
| F-test (2nd stage) | | 3.5905 | | 0.14789 | | 14.186 |
| F-test (2nd stage), p-value | | 0.05814 | | 0.70056 | | 0.00017 |
| Wu-Hausman | | 10.777 | | 0.07212 | | 13.507 |
| Wu-Hausman, p-value | | 0.00103 | | 0.78828 | | 0.00024 |
| Wald (IV only) | 7.2235 | 0.52315 | 0.30531 | 0.10024 | 0.30531 | 0.30195 |
| Wald (IV only), p-value | 0.00721 | 0.46951 | 0.58058 | 0.75155 | 0.58058 | 0.58268 |

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

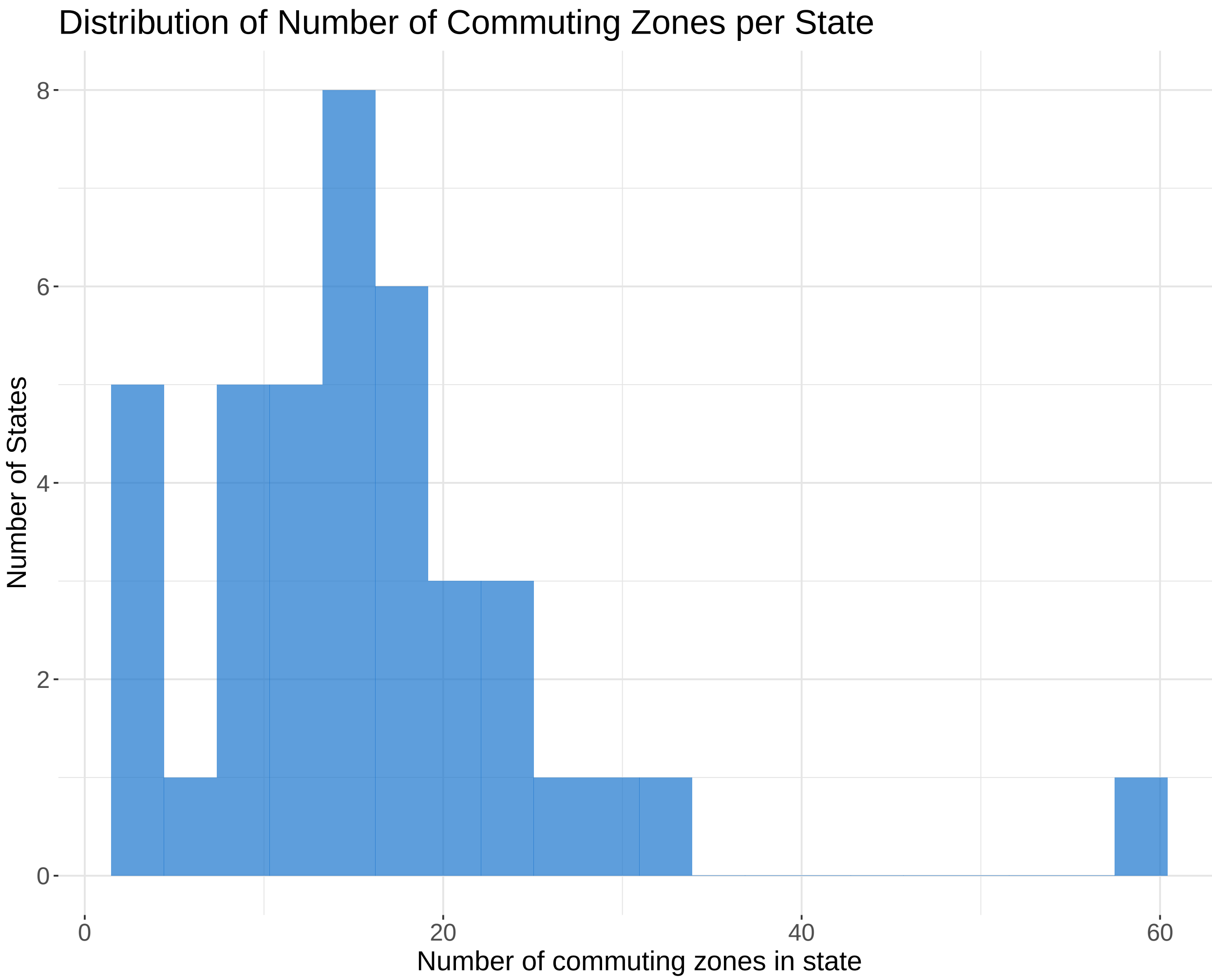
| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (GR) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|
| IV stages | First | Second | First | Second | First | Second |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| l(lev_gdp_ss_2d,1) | -0.3461*** | | | | | |
| | (0.1293) | | | | | |
| (log) IG Revenue pp | 0.1383*** | 0.2833*** | 0.1349*** | -24.99 | 0.1703*** | 1.182 |
| | (0.0186) | (0.0337) | (0.0186) | (2,972.5) | (0.0194) | (2.075) |
| (log) Real GDP Priv. Industry pc | 0.2211*** | 0.1798*** | 0.2260*** | -42.17 | 0.2502*** | 1.573 |
| | (0.0270) | (0.0542) | (0.0270) | (4,980.6) | (0.0269) | (3.032) |
| (l1, log) Elem.Ed.Exp.pp | 0.1551*** | 0.5870*** | 0.1558*** | -28.60 | | |
| | (0.0167) | (0.0391) | (0.0166) | (3,432.0) | | |
| (log) Enrollment | 0.3346*** | -0.0553 | 0.3192*** | -59.86 | 0.2903*** | 1.714 |
| | (0.0315) | (0.0717) | (0.0307) | (7,033.5) | (0.0309) | (3.519) |
| (log) House Price Index | | -0.3512 | | 187.0 | | -6.177 |
| | | (0.2203) | | (22,035.0) | | (12.11) |
| l(gdp_ss_2d,1) | | | 0.0012 | | -0.0749 | |
| | | | (0.1448) | | (0.1461) | |
| (GR, l1) Elem.Ed.Exp.pp | | | | | 0.0246** | 0.0724 |
| | | | | | (0.0098) | (0.2987) |
| *Fixed-effects* | | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 12,122 | 12,122 | 12,122 | 12,122 | 12,121 | 12,121 |
| $R^2$ | 0.96538 | 0.88407 | 0.96523 | -4,792.5 | 0.96428 | -38.439 |
| Within $R^2$ | 0.22851 | 0.39255 | 0.22508 | -25,115.6 | 0.20377 | -41.366 |
| F-test (1st stage) | 53.880 | | $8.63 \times 10^{-5}$ | | 0.31210 | |
| F-test (1st stage), (log) House Price Index | | 53.880 | | $8.63 \times 10^{-5}$ | | 0.31210 |
| F-test (1st stage), p-value | $2.27 \times 10^{-13}$ | | 0.99259 | | 0.57641 | |
| F-test (1st stage), p-value, (log) House Price Index | | $2.27 \times 10^{-13}$ | | 0.99259 | | 0.57641 |
| F-test (2nd stage) | | 10.091 | | 4.6001 | | 13.542 |
| F-test (2nd stage), p-value | | 0.00149 | | 0.03199 | | 0.00023 |
| Wu-Hausman | | 15.639 | | 4.4229 | | 12.905 |
| Wu-Hausman, p-value | | $7.71 \times 10^{-5}$ | | 0.03548 | | 0.00033 |
| Wald (IV only) | 7.1616 | 2.5417 | $7.2 \times 10^{-5}$ | $7.2 \times 10^{-5}$ | 0.26247 | 0.26022 |
| Wald (IV only), p-value | 0.00746 | 0.11090 | 0.99323 | 0.99323 | 0.60844 | 0.60998 |

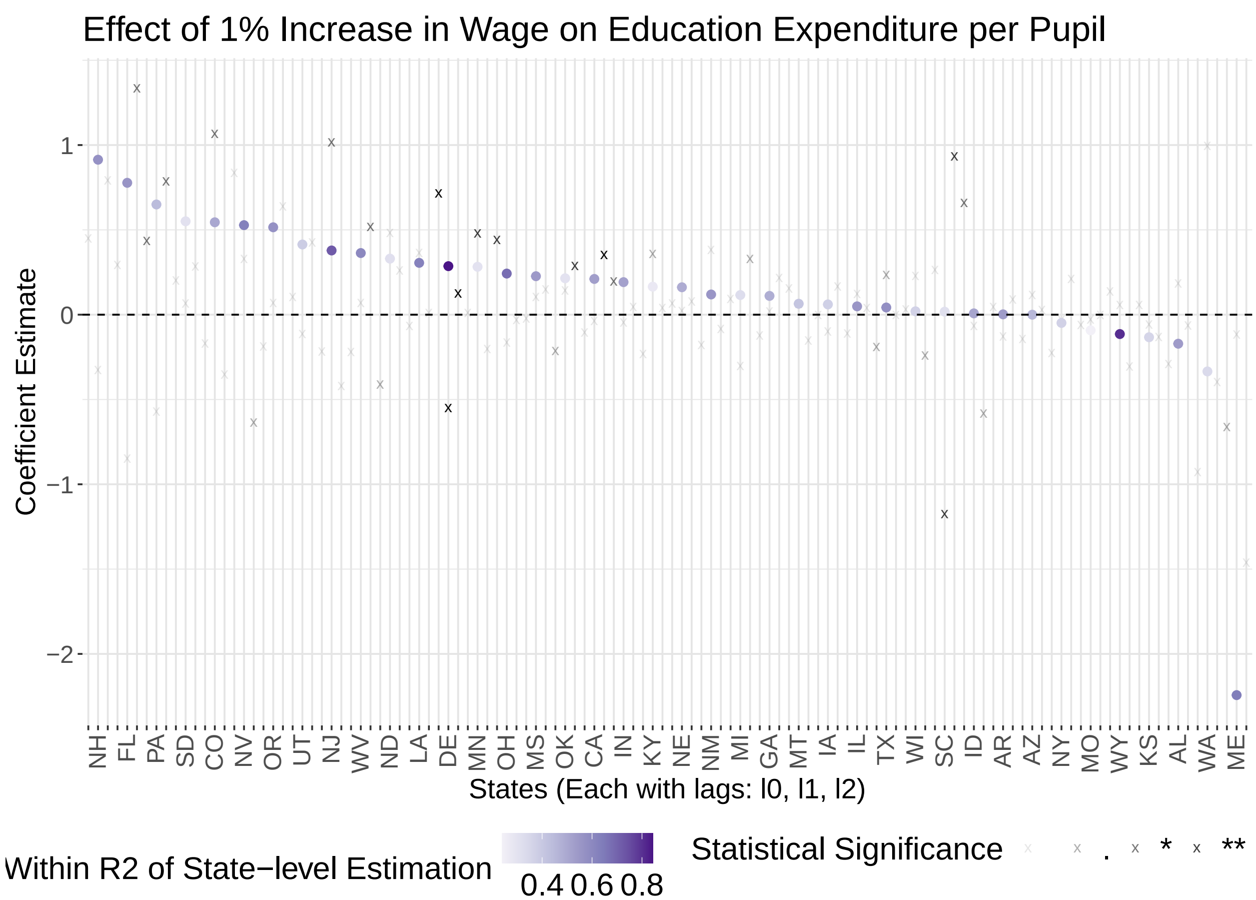
*Clustered (unit) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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

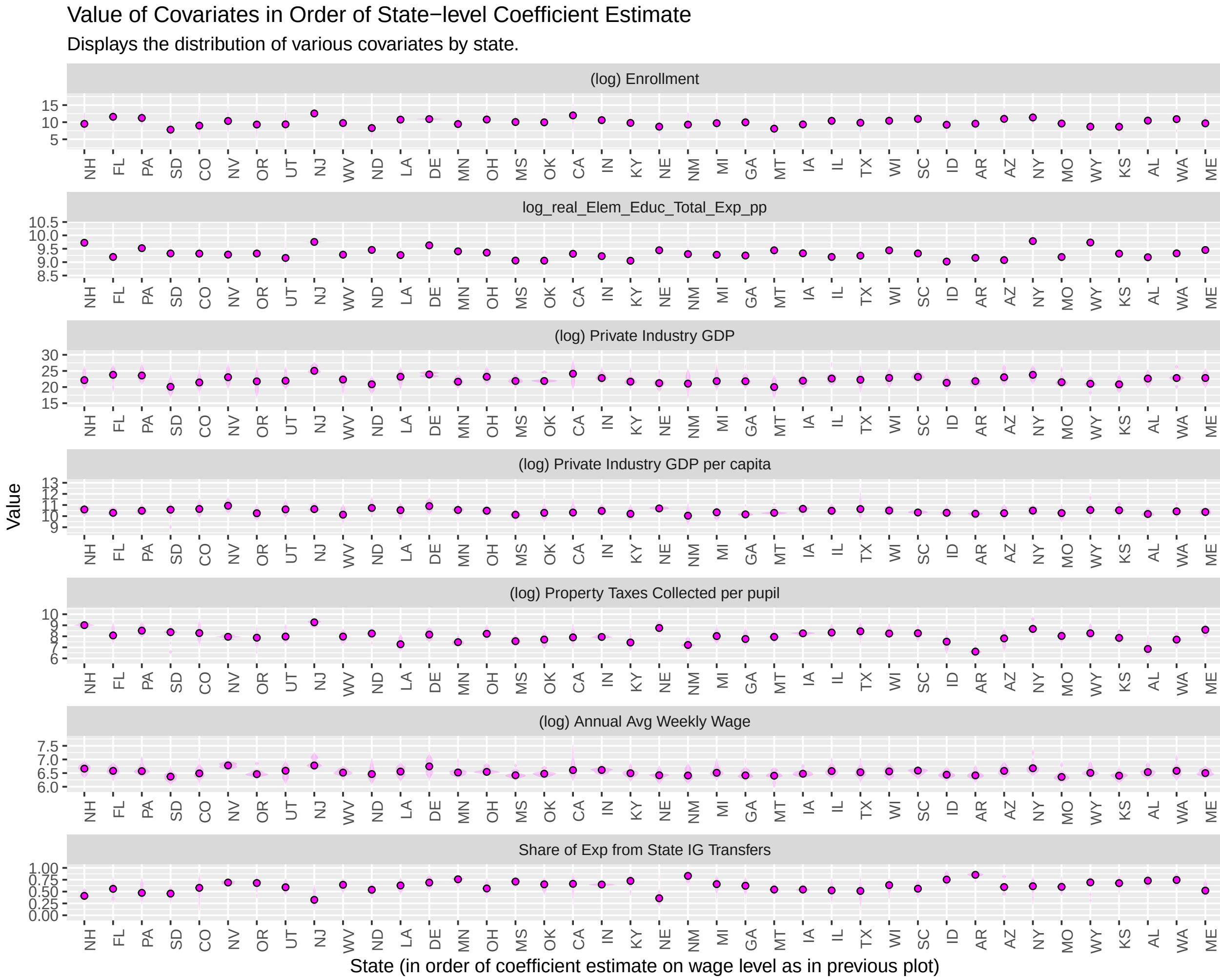
The lack of a causal link between housing wealth and public education spending highlights potential institutional rigidities in the fiscal transmission mechanism linking local economic conditions to public goods provision. In many U.S. localities, school finance systems remain only partially responsive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

#### 4.2.2 State-by-state estimation

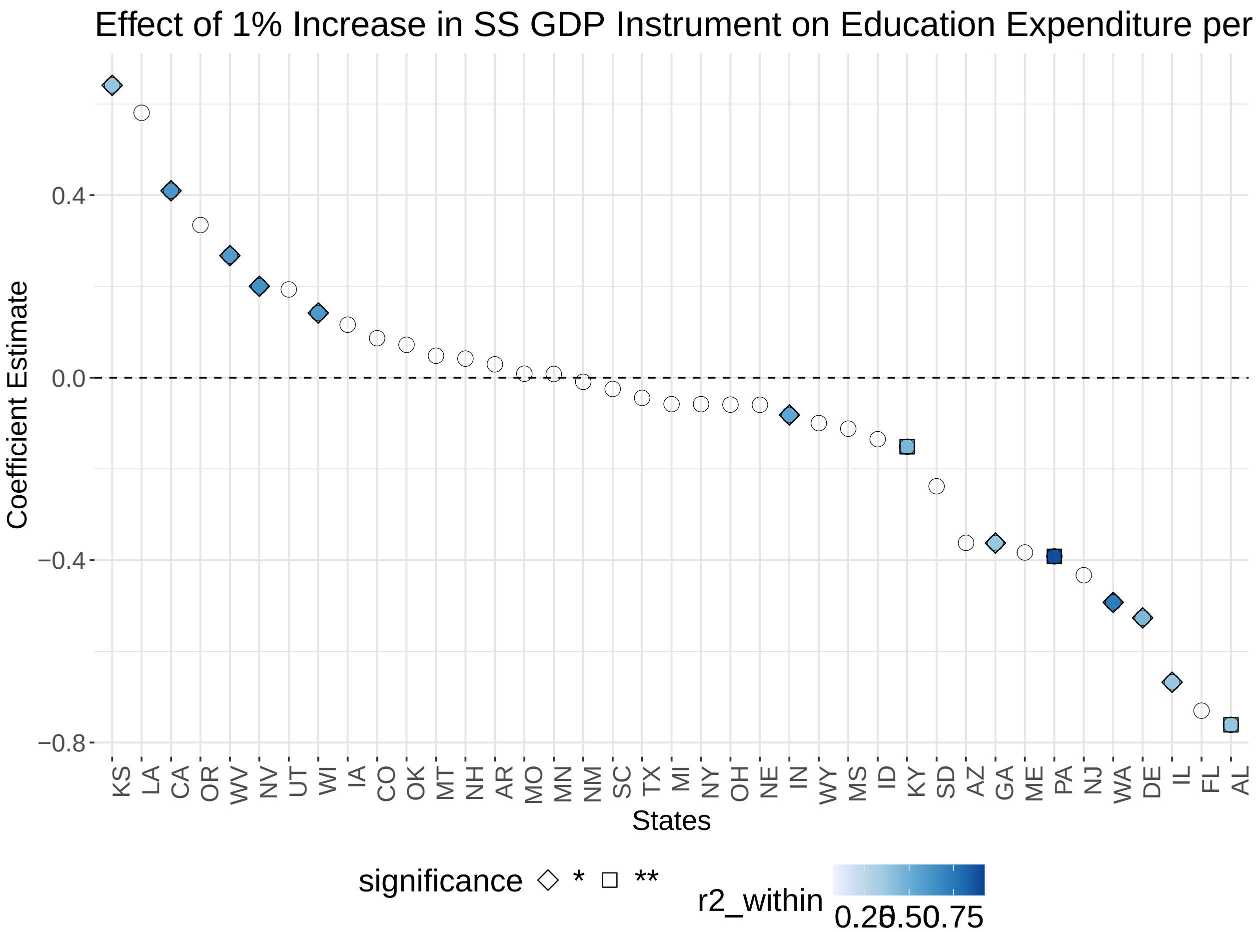




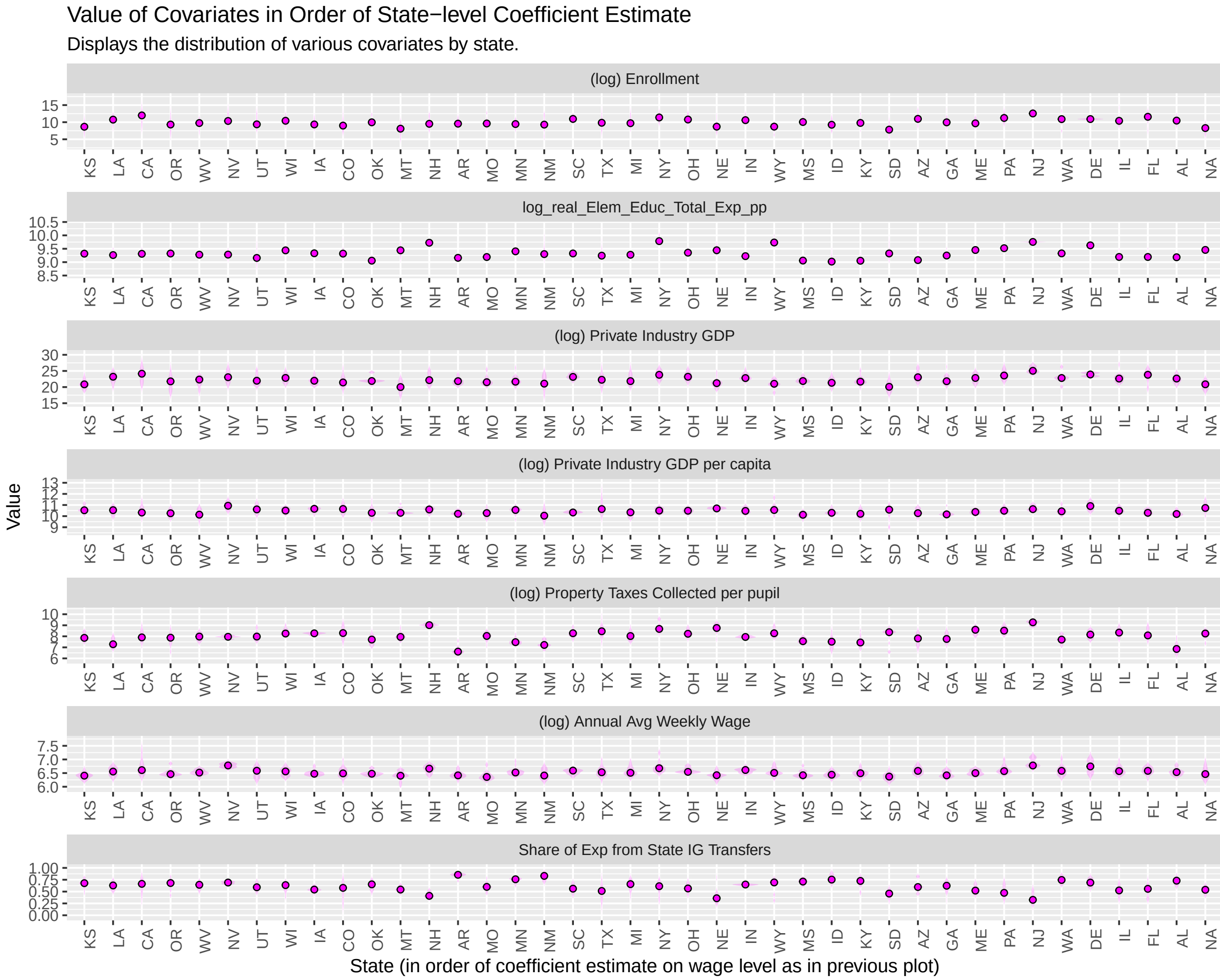

Effect of contemporaneous, l1, l2 lag of avg weekly wage on PP Education Expenditure controlling for enrollment, GDP, and intergovernmental transfers.
Each state has 3 lagged wage coefficients (l0, l1, l2).
Blue dots show total effect across lags, plotted at the l1 position.
Within R^2 of state−level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




#### 4.2.2.1 Shift-share



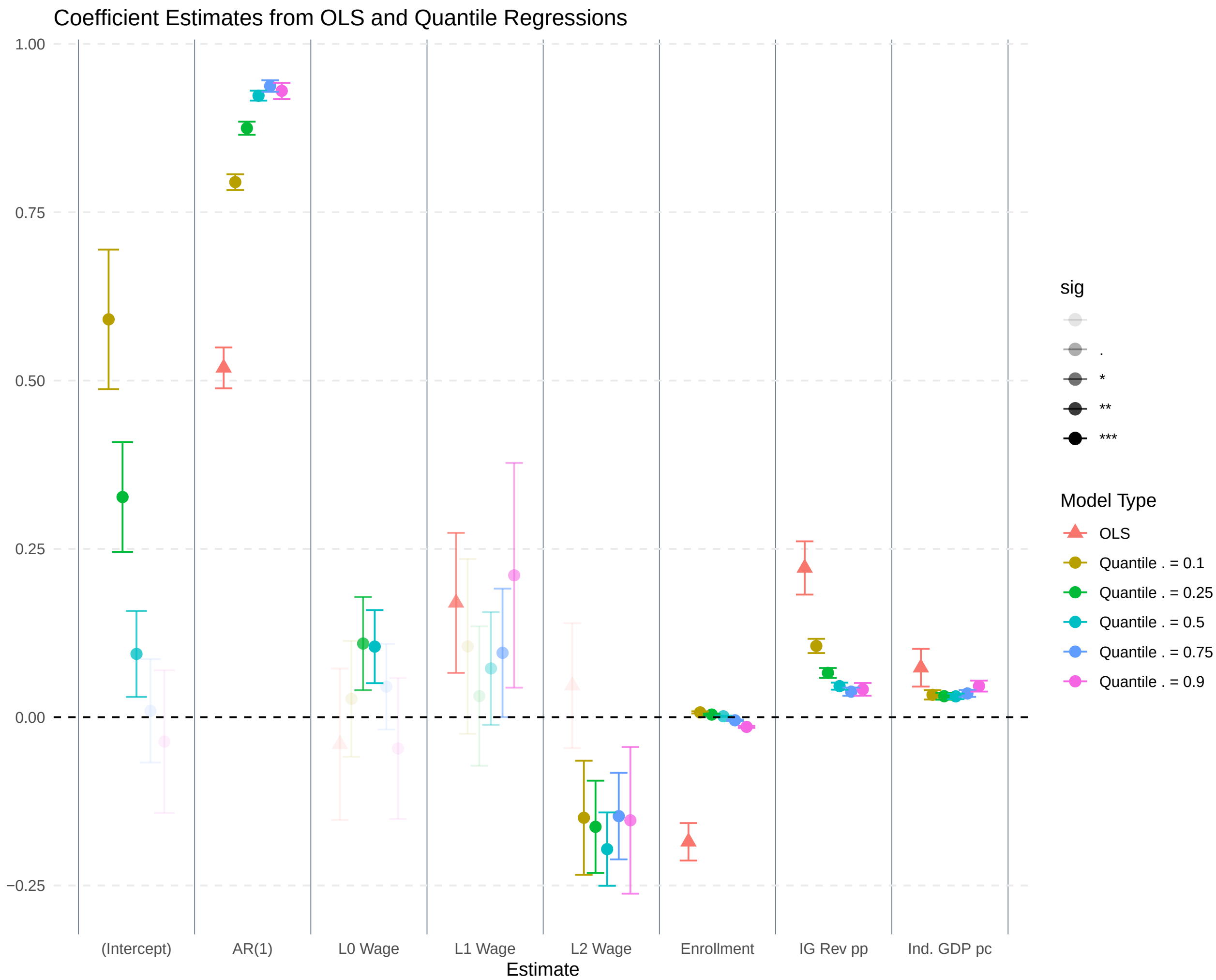
Effect of l1 of GDP SS Instrument on PP Education
Expenditure controlling for enrollment, GDP, and intergovernmental transfers and AR(1) term.
Within R^2 of state−level estimation reflected in color of point).




#### 4.2.2.1.1 Industry by Industry


Finance and
Agriculture, Forestry, Fishing,
Arts, Entertainment, and
Accommodation and
Other Services, except
Real Estate and Rental
Management of Companies and
Professional, Scientific, and
Administrative and waste
Health Care and Social
Industry

#### 4.2.3 Quantile Regression

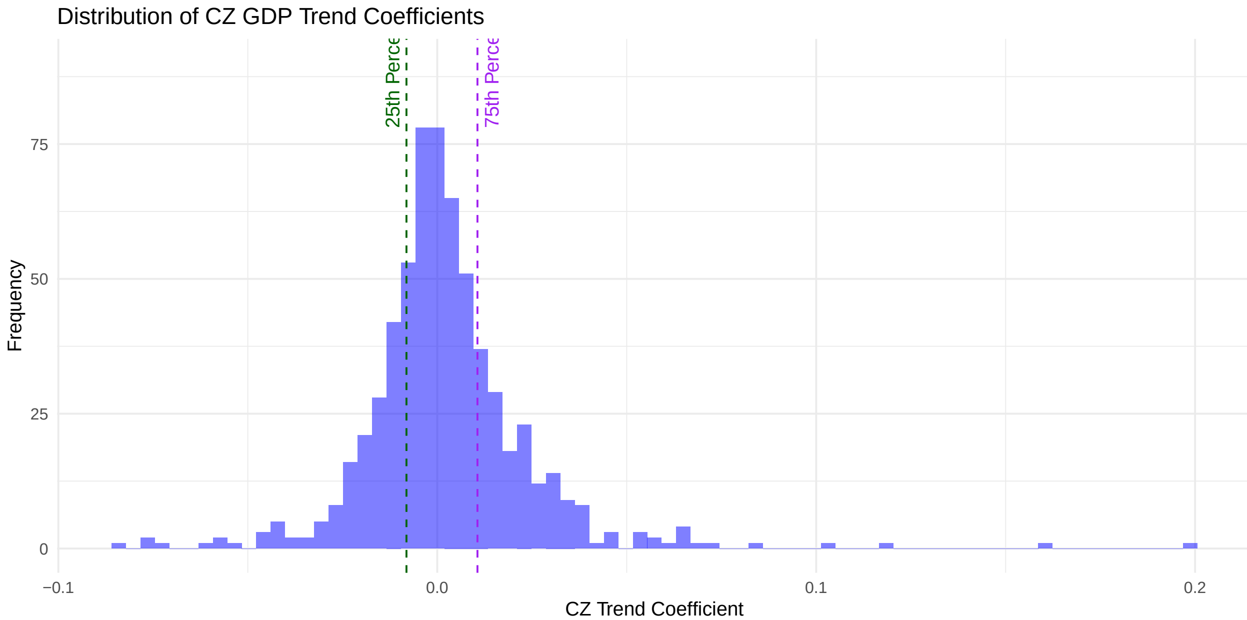


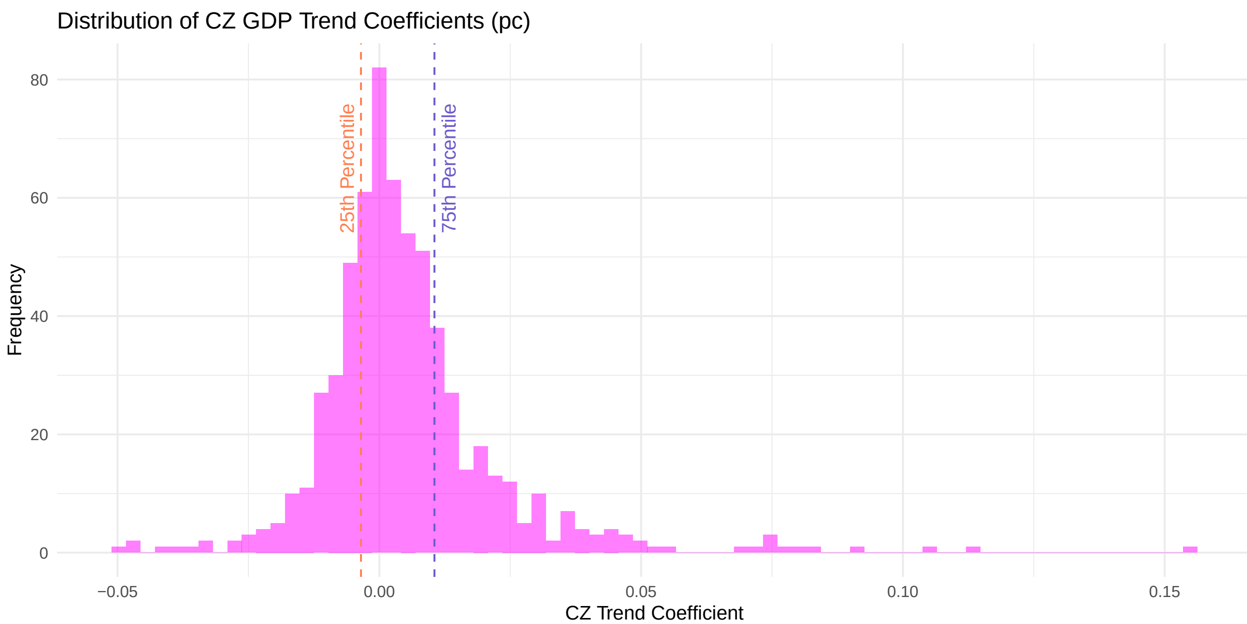

#### 4.2.4 Declining vs. Growing Regions

I identify declining vs. growing regions by estimating commuting-zone growth rates conditional on state and national level growth rates. Using this distinction (on both a per capita and total gdp bases and a lenient vs. stringent magnitude threshold), I rerun the key regressions identified in steps 2 and 3 on the subgroups (declining and growing regions).

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

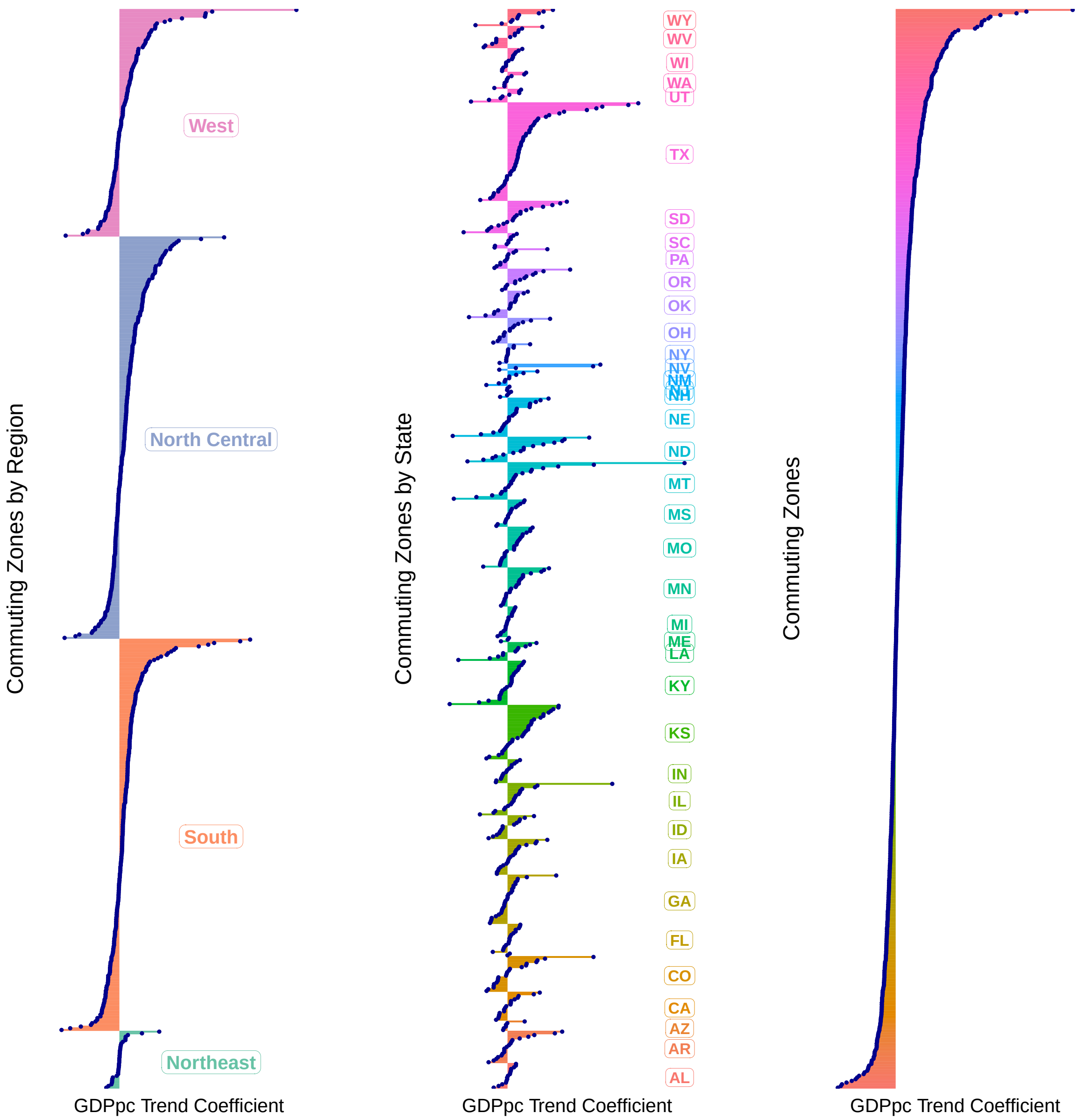
#### 4.2.5 CZ GDP growth conditional on state and national level



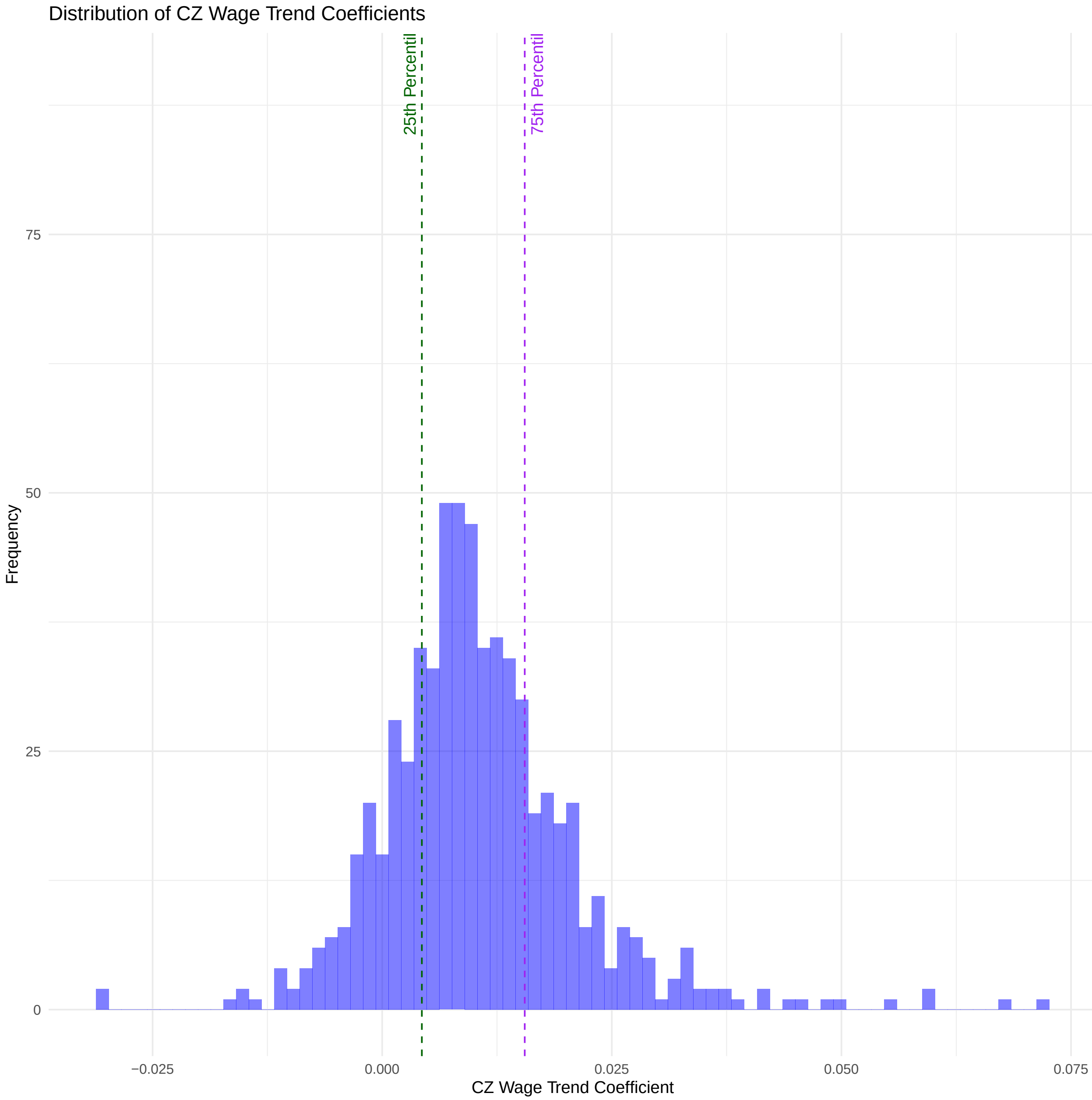




```
[1] 0.1965409

[1] 0.1383648

[1] 0.1100629
```

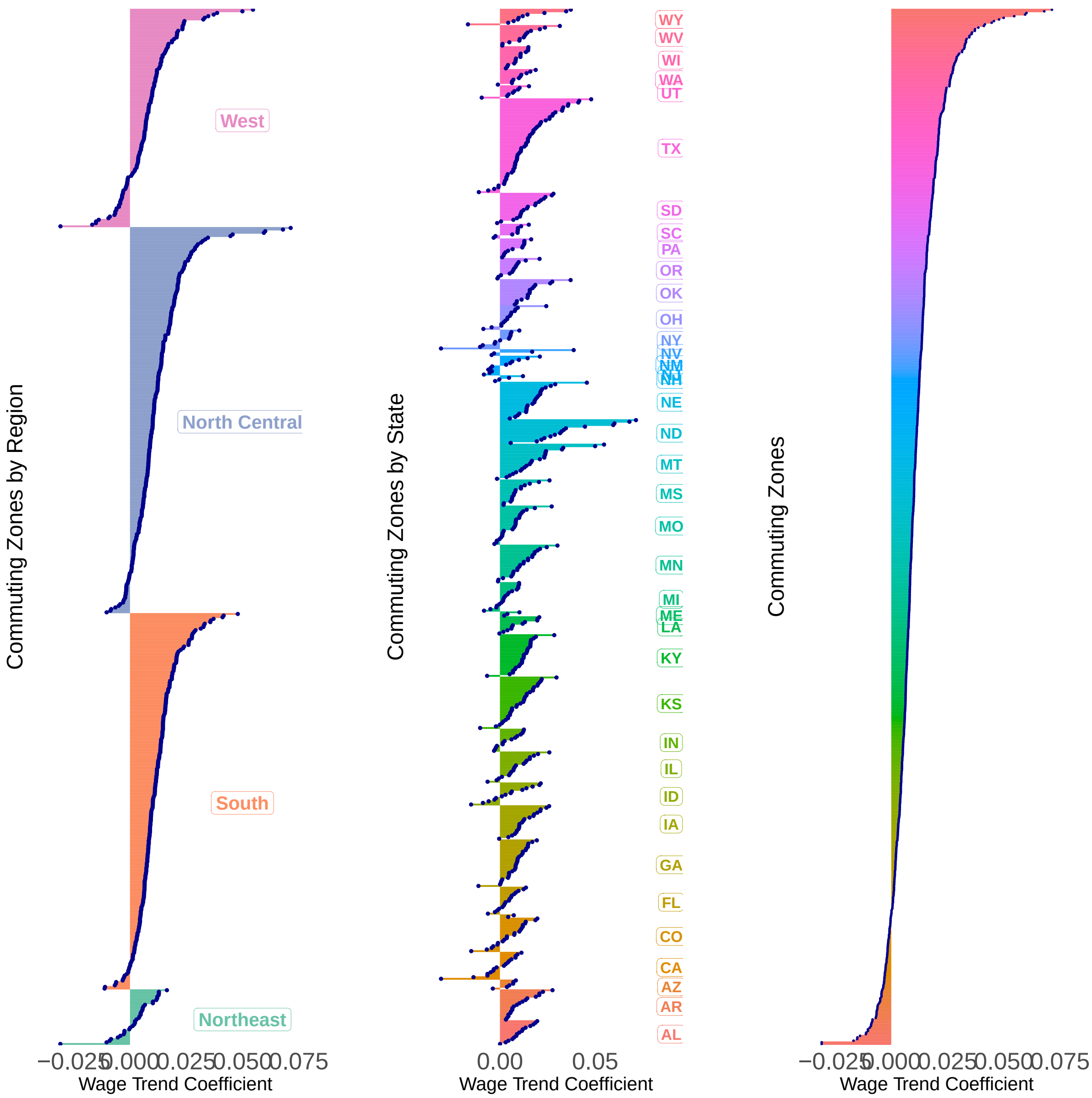
Commuting Zone GDP pc Growth Rate Controlling for National and State Level Tren
Calculated as mean of annual growth rate per commuting zone controlling for national and state

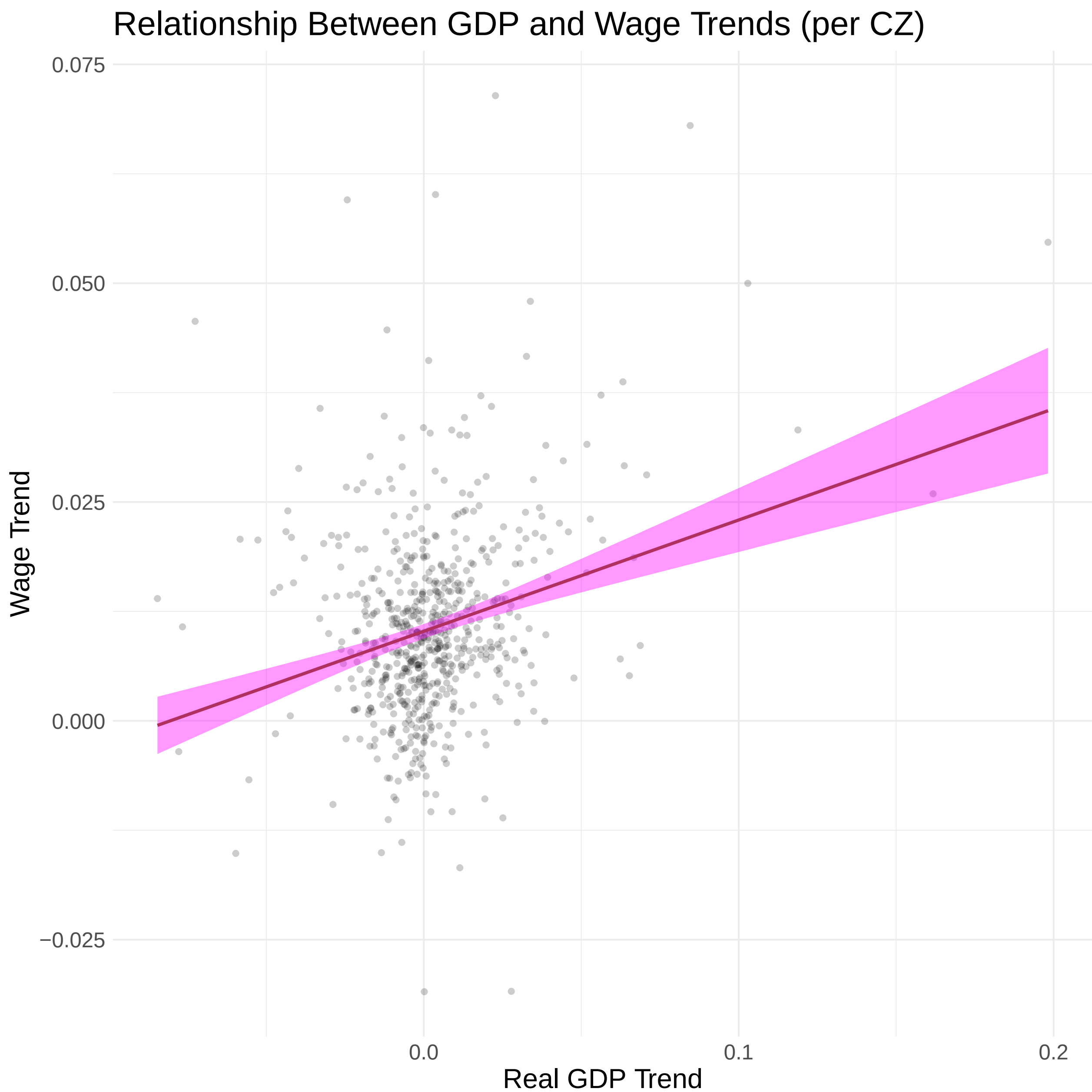


### 4.2.6 CZ Wage Growth

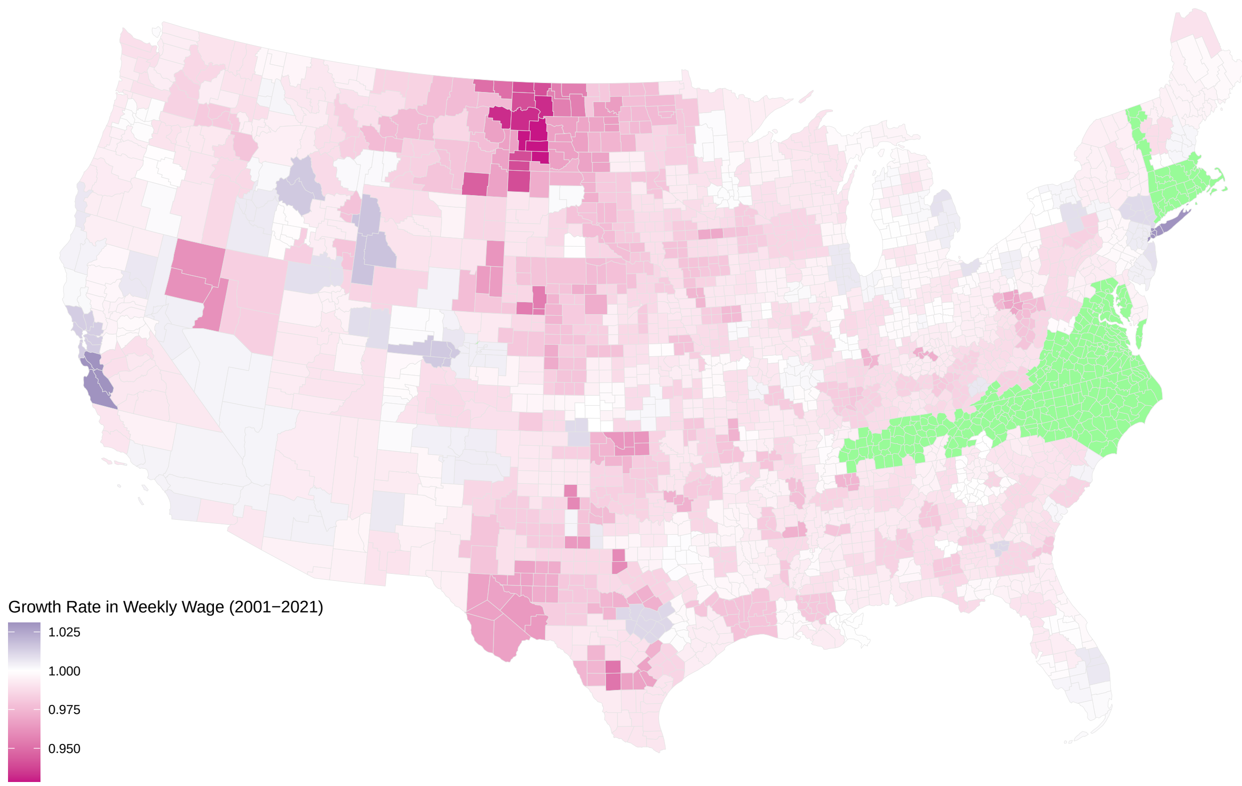


Commuting Zone Wage Growth Rate Controlling for National and State Level Trends
Calculated as mean of annual growth rate per commuting zone controlling for national and state

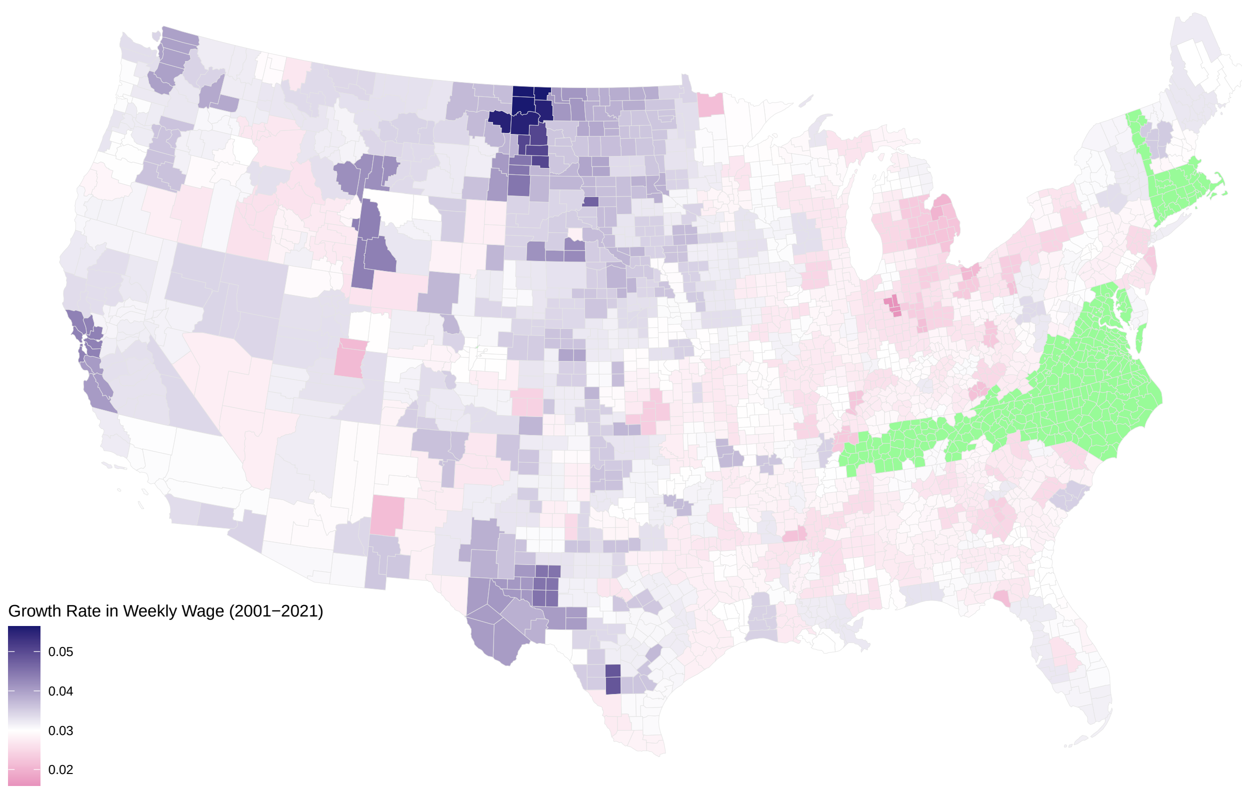



Relationship Between GDP and Wage Trends (per CZ)
0.075
0.050
0.025
0.000
−0.025
Wage Trend
0.0
0.1
0.2
Real GDP Trend

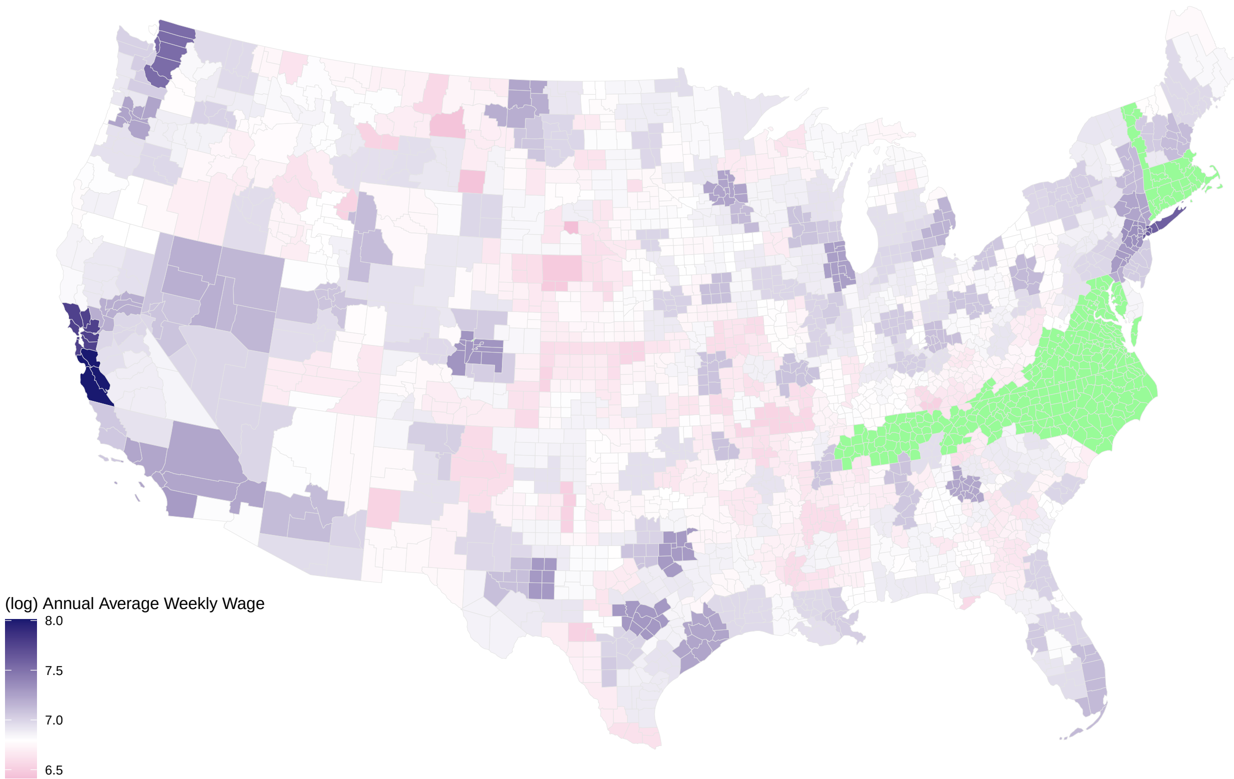
**Growth Rate of Weekly Wage in Relation to Median (CZ)**




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



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




#### 4.2.7 Running base models on declining vs. growing sub-groups

#### 4.2.8 Running IV models on declining vs. growing sub-groups

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

#### 4.2.9 Removing outliers - really high-income commuting zones!

As you can see in the scatterplot below, there is a somewhat non-linear relationship between property taxes and elementary expenditure as property taxes collected rise. This happens largely as a result of very high-income commuting zones. Therefore, I exclude any commuting zone that spends more than 28k per pupil to avoid any distorting effects. This removes 12 counties (~2% of the sample) This could benefit from more robust outlier detection. This outlier exclusion weakens our results (and the validity of our instrument choice) in the production-based IV regression. Worth noting and thinking about!!

Table 2: Declining

| Dependent Variable: | (log) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (log) Real GDP Priv. Industry pc | 0.0054 | | |
| | (0.0351) | | |
| (log,l1) Real GDP Priv. Industry pc | 0.0738*** | | |
| | (0.0242) | | |
| (log,l2) Real GDP Priv. Industry pc | 0.1024*** | | |
| | (0.0231) | | |
| (log) IG Revenue pp | 0.3722*** | 0.3729*** | 0.3541*** |
| | (0.0548) | (0.0520) | (0.0545) |
| (log) Annual Avg. Wkly. Wage | | 0.0871 | |
| | | (0.0969) | |
| (log, l1) Annual Avg. Wkly. Wage | | 0.1642** | |
| | | (0.0820) | |
| (log, l2) Annual Avg. Wkly. Wage | | 0.2610*** | |
| | | (0.0826) | |
| (log) House Price Index | | | 0.0386 |
| | | | (0.0431) |
| (log, l1) House Price Index | | | 0.0745** |
| | | | (0.0319) |
| (log, l2) House Price Index | | | 0.0239 |
| | | | (0.0318) |
| (log, l3) House Price Index | | | 0.1171*** |
| | | | (0.0350) |
| (log, l4) House Price Index | | | -0.0833** |
| | | | (0.0347) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 4,883 | 5,397 | 5,223 |
| $R^2$ | 0.85785 | 0.85948 | 0.86073 |
| Within $R^2$ | 0.22345 | 0.25049 | 0.22873 |

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

Table 3: Growing

| Dependent Variable: | (log) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (log) Real GDP Priv. Industry pc | 0.0206 | | |
| | (0.0243) | | |
| (log,l1) Real GDP Priv. Industry pc | $0.0622^{***}$ | | |
| | (0.0171) | | |
| (log,l2) Real GDP Priv. Industry pc | $0.1549^{***}$ | | |
| | (0.0323) | | |
| (log) IG Revenue pp | $0.3928^{***}$ | $0.3532^{***}$ | $0.3864^{***}$ |
| | (0.0359) | (0.0422) | (0.0406) |
| (log) Annual Avg. Wkly. Wage | | $0.2066^{***}$ | |
| | | (0.0776) | |
| (log, l1) Annual Avg. Wkly. Wage | | $0.1869^{***}$ | |
| | | (0.0582) | |
| (log, l2) Annual Avg. Wkly. Wage | | $0.2359^{**}$ | |
| | | (0.1161) | |
| (log) House Price Index | | | $0.1003^{***}$ |
| | | | (0.0309) |
| (log, l1) House Price Index | | | 0.0578 |
| | | | (0.0364) |
| (log, l2) House Price Index | | | $0.0553^{**}$ |
| | | | (0.0260) |
| (log, l3) House Price Index | | | 0.0145 |
| | | | (0.0255) |
| (log, l4) House Price Index | | | 0.0072 |
| | | | (0.0274) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 7,201 | 7,959 | 7,365 |
| $R^2$ | 0.85734 | 0.84617 | 0.85014 |
| Within $R^2$ | 0.28656 | 0.24697 | 0.23978 |

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

Table 4: Hyper-Declining

| Dependent Variable: | (log) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (log) Real GDP Priv. Industry pc | -0.0125 | | |
| | (0.0444) | | |
| (log,l1) Real GDP Priv. Industry pc | $0.0756^{**}$ | | |
| | (0.0295) | | |
| (log,l2) Real GDP Priv. Industry pc | $0.1095^{***}$ | | |
| | (0.0249) | | |
| (log) IG Revenue pp | $0.3183^{***}$ | $0.3276^{***}$ | $0.2935^{***}$ |
| | (0.0681) | (0.0660) | (0.0682) |
| (log) Annual Avg. Wkly. Wage | | 0.0659 | |
| | | (0.1231) | |
| (log, l1) Annual Avg. Wkly. Wage | | $0.1997^{*}$ | |
| | | (0.1013) | |
| (log, l2) Annual Avg. Wkly. Wage | | $0.2262^{**}$ | |
| | | (0.0911) | |
| (log) House Price Index | | | $0.0985^{*}$ |
| | | | (0.0510) |
| (log, l1) House Price Index | | | $0.0896^{**}$ |
| | | | (0.0408) |
| (log, l2) House Price Index | | | -0.0264 |
| | | | (0.0382) |
| (log, l3) House Price Index | | | $0.1484^{***}$ |
| | | | (0.0430) |
| (log, l4) House Price Index | | | $-0.1263^{***}$ |
| | | | (0.0452) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 3,021 | 3,339 | 3,173 |
| $R^2$ | 0.83249 | 0.83401 | 0.83486 |
| Within $R^2$ | 0.18513 | 0.21740 | 0.19832 |

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

Table 5: Hyper-Growing

| Dependent Variable: | (log) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (log) Real GDP Priv. Industry pc | 0.0105 | | |
| | (0.0299) | | |
| (log,l1) Real GDP Priv. Industry pc | 0.0569*** | | |
| | (0.0208) | | |
| (log,l2) Real GDP Priv. Industry pc | 0.1697*** | | |
| | (0.0393) | | |
| (log) IG Revenue pp | 0.3806*** | 0.3171*** | 0.3181*** |
| | (0.0567) | (0.0662) | (0.0681) |
| (log) Annual Avg. Wkly. Wage | | 0.1748 | |
| | | (0.1115) | |
| (log, l1) Annual Avg. Wkly. Wage | | 0.2536*** | |
| | | (0.0955) | |
| (log, l2) Annual Avg. Wkly. Wage | | 0.2795 | |
| | | (0.1696) | |
| (log) House Price Index | | | 0.1090** |
| | | | (0.0473) |
| (log, l1) House Price Index | | | 0.0844 |
| | | | (0.0525) |
| (log, l2) House Price Index | | | 0.0560 |
| | | | (0.0407) |
| (log, l3) House Price Index | | | -0.0058 |
| | | | (0.0337) |
| (log, l4) House Price Index | | | -0.0416 |
| | | | (0.0437) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 3,021 | 3,339 | 2,904 |
| $R^2$ | 0.79061 | 0.77279 | 0.77875 |
| Within $R^2$ | 0.28823 | 0.22654 | 0.16829 |

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

Table 6: Declining

| Dependent Variable: | (GR) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (GR) Real GDP Priv. Industry pc | 0.0238 | | |
| | (0.0299) | | |
| (GR,l1) Real GDP Priv. Industry pc | 0.0325 | | |
| | (0.0234) | | |
| (GR,l2) Real GDP Priv. Industry pc | 0.0039 | | |
| | (0.0084) | | |
| (GR) IG Revenue pp | 0.3390*** | 0.3086*** | 0.2965*** |
| | (0.0404) | (0.0342) | (0.0348) |
| (GR) Annual Avg. Wkly. Wage | | 0.0671 | |
| | | (0.1017) | |
| (GR, l1) Annual Avg. Wkly. Wage | | 0.1781** | |
| | | (0.0843) | |
| (GR, l2) Annual Avg. Wkly. Wage | | 0.2352*** | |
| | | (0.0671) | |
| (GR) House Price Index | | | 0.0619 |
| | | | (0.0429) |
| (GR, l1) House Price Index | | | 0.1467*** |
| | | | (0.0434) |
| (GR, l2) House Price Index | | | 0.0222 |
| | | | (0.0349) |
| (GR, l3) House Price Index | | | 0.0796* |
| | | | (0.0424) |
| (GR, l4) House Price Index | | | -0.0196 |
| | | | (0.0315) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 4,882 | 5,396 | 5,213 |
| $R^2$ | 0.18282 | 0.35298 | 0.36932 |
| Within $R^2$ | 0.11422 | 0.13625 | 0.13726 |

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

Table 7: Growing

| Dependent Variable: | (GR) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (GR) Real GDP Priv. Industry pc | -0.0005 | | |
| | (0.0157) | | |
| (GR,l1) Real GDP Priv. Industry pc | 0.0503*** | | |
| | (0.0193) | | |
| (GR,l2) Real GDP Priv. Industry pc | 0.0271*** | | |
| | (0.0101) | | |
| (GR) IG Revenue pp | 0.4316*** | 0.3442*** | 0.3574*** |
| | (0.0359) | (0.0291) | (0.0287) |
| (GR) Annual Avg. Wkly. Wage | | -0.0689 | |
| | | (0.0636) | |
| (GR, l1) Annual Avg. Wkly. Wage | | 0.1980*** | |
| | | (0.0616) | |
| (GR, l2) Annual Avg. Wkly. Wage | | 0.3412*** | |
| | | (0.0843) | |
| (GR) House Price Index | | | 0.0549* |
| | | | (0.0288) |
| (GR, l1) House Price Index | | | 0.0847** |
| | | | (0.0363) |
| (GR, l2) House Price Index | | | 0.0682*** |
| | | | (0.0247) |
| (GR, l3) House Price Index | | | -0.0101 |
| | | | (0.0323) |
| (GR, l4) House Price Index | | | 0.0605** |
| | | | (0.0276) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 7,201 | 7,959 | 7,322 |
| $R^2$ | 0.23645 | 0.34957 | 0.35888 |
| Within $R^2$ | 0.19246 | 0.15983 | 0.15699 |

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

Table 8: Hyper-Declining

| Dependent Variable: | (GR) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (GR) Real GDP Priv. Industry pc | 0.0148 | | |
| | (0.0363) | | |
| (GR,l1) Real GDP Priv. Industry pc | 0.0332 | | |
| | (0.0276) | | |
| (GR,l2) Real GDP Priv. Industry pc | 0.0096 | | |
| | (0.0102) | | |
| (GR) IG Revenue pp | 0.3811*** | 0.3209*** | 0.3120*** |
| | (0.0432) | (0.0456) | (0.0470) |
| (GR) Annual Avg. Wkly. Wage | | 0.0712 | |
| | | (0.1266) | |
| (GR, l1) Annual Avg. Wkly. Wage | | 0.1451 | |
| | | (0.1057) | |
| (GR, l2) Annual Avg. Wkly. Wage | | 0.1705** | |
| | | (0.0663) | |
| (GR) House Price Index | | | 0.0315 |
| | | | (0.0616) |
| (GR, l1) House Price Index | | | 0.1968*** |
| | | | (0.0603) |
| (GR, l2) House Price Index | | | -0.0251 |
| | | | (0.0423) |
| (GR, l3) House Price Index | | | 0.0983* |
| | | | (0.0546) |
| (GR, l4) House Price Index | | | -0.0170 |
| | | | (0.0427) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 3,020 | 3,338 | 3,166 |
| $R^2$ | 0.19624 | 0.34192 | 0.37036 |
| Within $R^2$ | 0.13578 | 0.13422 | 0.13878 |

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

Table 9: Hyper-Growing

| Dependent Variable: | (GR) Elem.Ed.Exp.pp | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| (GR) Real GDP Priv. Industry pc | -0.0012 | | |
| | (0.0191) | | |
| (GR,l1) Real GDP Priv. Industry pc | $0.0474^{**}$ | | |
| | (0.0238) | | |
| (GR,l2) Real GDP Priv. Industry pc | 0.0288 | | |
| | (0.0180) | | |
| (GR) IG Revenue pp | $0.4562^{***}$ | $0.3580^{***}$ | $0.3361^{***}$ |
| | (0.0560) | (0.0449) | (0.0444) |
| (GR) Annual Avg. Wkly. Wage | | -0.0596 | |
| | | (0.0973) | |
| (GR, l1) Annual Avg. Wkly. Wage | | $0.2442^{**}$ | |
| | | (0.0958) | |
| (GR, l2) Annual Avg. Wkly. Wage | | $0.3459^{**}$ | |
| | | (0.1359) | |
| (GR) House Price Index | | | 0.0024 |
| | | | (0.0482) |
| (GR, l1) House Price Index | | | $0.0913^{*}$ |
| | | | (0.0547) |
| (GR, l2) House Price Index | | | 0.0542 |
| | | | (0.0359) |
| (GR, l3) House Price Index | | | -0.0266 |
| | | | (0.0459) |
| (GR, l4) House Price Index | | | 0.0296 |
| | | | (0.0421) |
| *Fixed-effects* | | | |
| unit | Yes | Yes | Yes |
| year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 3,021 | 3,339 | 2,873 |
| $R^2$ | 0.23054 | 0.34754 | 0.34915 |
| Within $R^2$ | 0.19558 | 0.16349 | 0.13214 |

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

Table 10: Declining

| Dependent Variable: | (log) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (log) Annual Avg. Wkly. Wage | 0.6575*** |
| | (0.0778) |
| (log, l1) Annual Avg. Wkly. Wage | 0.2267*** |
| | (0.0686) |
| (log, l2) Annual Avg. Wkly. Wage | 0.2479*** |
| | (0.0466) |
| (log, l3) Annual Avg. Wkly. Wage | 0.0735* |
| | (0.0401) |
| (log, l4) Annual Avg. Wkly. Wage | 0.0320 |
| | (0.0483) |
| (log, l5) Annual Avg. Wkly. Wage | -0.0856 |
| | (0.0570) |
| (log, l6) Annual Avg. Wkly. Wage | -0.0840** |
| | (0.0423) |
| (log, l7) Annual Avg. Wkly. Wage | 0.1284* |
| | (0.0765) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 3,499 |
| $R^2$ | 0.98015 |
| Within $R^2$ | 0.22718 |

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

Table 11: Growing

| Dependent Variable: | (log) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (log) Annual Avg. Wkly. Wage | 0.5610*** |
| | (0.0591) |
| (log, l1) Annual Avg. Wkly. Wage | 0.2259*** |
| | (0.0435) |
| (log, l2) Annual Avg. Wkly. Wage | 0.2064*** |
| | (0.0600) |
| (log, l3) Annual Avg. Wkly. Wage | 0.0661 |
| | (0.0465) |
| (log, l4) Annual Avg. Wkly. Wage | 0.0270 |
| | (0.0495) |
| (log, l5) Annual Avg. Wkly. Wage | -0.0546 |
| | (0.0564) |
| (log, l6) Annual Avg. Wkly. Wage | -0.0276 |
| | (0.0578) |
| (log, l7) Annual Avg. Wkly. Wage | -0.1477* |
| | (0.0760) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 5,003 |
| $R^2$ | 0.97376 |
| Within $R^2$ | 0.16594 |

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

Table 12: Hyper-Declining

| Dependent Variable: | (log) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (log) Annual Avg. Wkly. Wage | 0.5745*** |
| | (0.0853) |
| (log, l1) Annual Avg. Wkly. Wage | 0.2655*** |
| | (0.0840) |
| (log, l2) Annual Avg. Wkly. Wage | 0.1877*** |
| | (0.0502) |
| (log, l3) Annual Avg. Wkly. Wage | 0.1265*** |
| | (0.0438) |
| (log, l4) Annual Avg. Wkly. Wage | 0.0161 |
| | (0.0529) |
| (log, l5) Annual Avg. Wkly. Wage | -0.0870 |
| | (0.0649) |
| (log, l6) Annual Avg. Wkly. Wage | -0.1118** |
| | (0.0488) |
| (log, l7) Annual Avg. Wkly. Wage | 0.1282* |
| | (0.0711) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 2,127 |
| $R^2$ | 0.97639 |
| Within $R^2$ | 0.26025 |

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

Table 13: Hyper-Growing

| Dependent Variable: | (log) House Price Index |
| --- | --- |
| Model: | (1) |
| *Variables* | |
| (log) Annual Avg. Wkly. Wage | 0.5194*** |
| | (0.0723) |
| (log, l1) Annual Avg. Wkly. Wage | 0.1717*** |
| | (0.0523) |
| (log, l2) Annual Avg. Wkly. Wage | 0.1825** |
| | (0.0828) |
| (log, l3) Annual Avg. Wkly. Wage | 0.0229 |
| | (0.0645) |
| (log, l4) Annual Avg. Wkly. Wage | 0.0560 |
| | (0.0728) |
| (log, l5) Annual Avg. Wkly. Wage | -0.0906 |
| | (0.0885) |
| (log, l6) Annual Avg. Wkly. Wage | 0.0789 |
| | (0.0770) |
| (log, l7) Annual Avg. Wkly. Wage | -0.2487** |
| | (0.1200) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 2,000 |
| $R^2$ | 0.97076 |
| Within $R^2$ | 0.16808 |

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

Table 14: Declining

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Annual Avg. Wkly. Wage | 0.3612*** |
| | (0.0547) |
| (GR, l1) Annual Avg. Wkly. Wage | 0.3075*** |
| | (0.0645) |
| (GR, l2) Annual Avg. Wkly. Wage | 0.2603*** |
| | (0.0390) |
| (GR, l3) Annual Avg. Wkly. Wage | 0.0505 |
| | (0.0358) |
| (GR, l4) Annual Avg. Wkly. Wage | -0.0370 |
| | (0.0459) |
| (GR, l5) Annual Avg. Wkly. Wage | -0.0942** |
| | (0.0470) |
| (GR, l6) Annual Avg. Wkly. Wage | -0.1156*** |
| | (0.0350) |
| (GR, l7) Annual Avg. Wkly. Wage | -0.0729* |
| | (0.0430) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 3,498 |
| $R^2$ | 0.60003 |
| Within $R^2$ | 0.09778 |

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

Table 15: Growing

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Annual Avg. Wkly. Wage | 0.3159*** |
| | (0.0505) |
| (GR, l1) Annual Avg. Wkly. Wage | 0.3214*** |
| | (0.0386) |
| (GR, l2) Annual Avg. Wkly. Wage | 0.1989*** |
| | (0.0494) |
| (GR, l3) Annual Avg. Wkly. Wage | 0.0777* |
| | (0.0426) |
| (GR, l4) Annual Avg. Wkly. Wage | 0.0274 |
| | (0.0579) |
| (GR, l5) Annual Avg. Wkly. Wage | -0.0722 |
| | (0.0580) |
| (GR, l6) Annual Avg. Wkly. Wage | -0.0423 |
| | (0.0473) |
| (GR, l7) Annual Avg. Wkly. Wage | -0.1538*** |
| | (0.0568) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 4,997 |
| $R^2$ | 0.41324 |
| Within $R^2$ | 0.05986 |

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

Table 16: Hyper-Declining

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Annual Avg. Wkly. Wage | 0.3151*** |
| | (0.0565) |
| (GR, l1) Annual Avg. Wkly. Wage | 0.3061*** |
| | (0.0825) |
| (GR, l2) Annual Avg. Wkly. Wage | 0.2185*** |
| | (0.0360) |
| (GR, l3) Annual Avg. Wkly. Wage | 0.0701* |
| | (0.0357) |
| (GR, l4) Annual Avg. Wkly. Wage | -0.0451 |
| | (0.0514) |
| (GR, l5) Annual Avg. Wkly. Wage | -0.0858* |
| | (0.0502) |
| (GR, l6) Annual Avg. Wkly. Wage | -0.0830** |
| | (0.0380) |
| (GR, l7) Annual Avg. Wkly. Wage | -0.1007** |
| | (0.0488) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 2,126 |
| $R^2$ | 0.58272 |
| Within $R^2$ | 0.10959 |

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

Table 17: Hyper-Growing

| Dependent Variable: | (GR) House Price Index |
|---|---|
| Model: | (1) |
| *Variables* | |
| (GR) Annual Avg. Wkly. Wage | 0.3493*** |
| | (0.0731) |
| (GR, l1) Annual Avg. Wkly. Wage | 0.2330*** |
| | (0.0501) |
| (GR, l2) Annual Avg. Wkly. Wage | 0.2029** |
| | (0.0808) |
| (GR, l3) Annual Avg. Wkly. Wage | 0.0618 |
| | (0.0650) |
| (GR, l4) Annual Avg. Wkly. Wage | 0.0930 |
| | (0.0846) |
| (GR, l5) Annual Avg. Wkly. Wage | -0.0640 |
| | (0.0876) |
| (GR, l6) Annual Avg. Wkly. Wage | 0.1175** |
| | (0.0591) |
| (GR, l7) Annual Avg. Wkly. Wage | -0.0784 |
| | (0.0873) |
| *Fixed-effects* | |
| unit | Yes |
| year | Yes |
| *Fit statistics* | |
| Observations | 1,997 |
| $R^2$ | 0.30943 |
| Within $R^2$ | 0.06094 |

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

## Table 18: lev_ss_2d

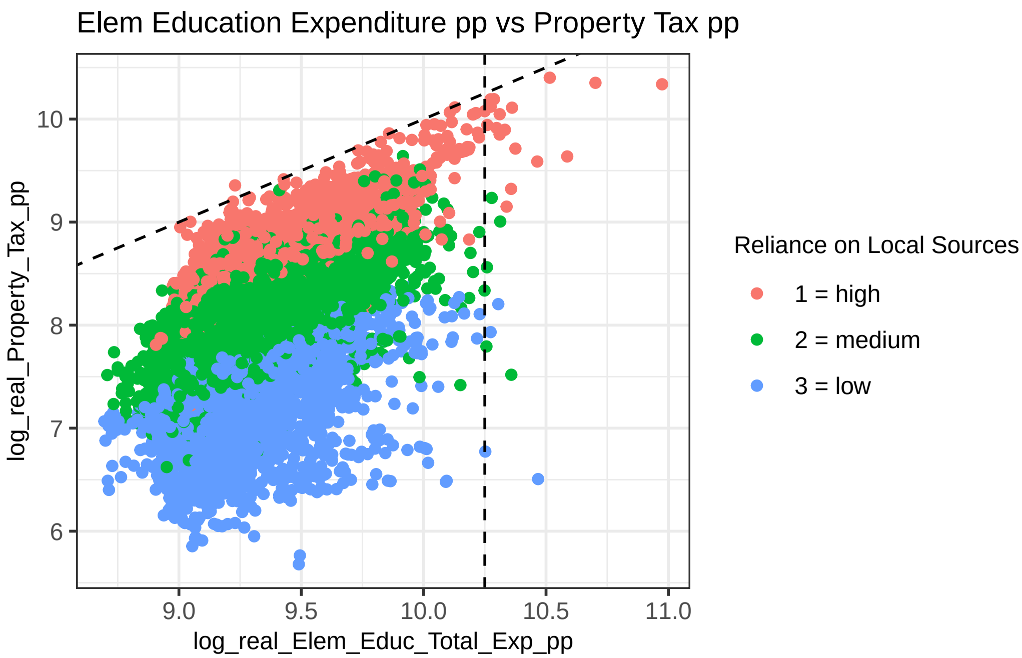
| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|---|---|
| | Declining | | Hyper-Declining | | Growing | | Hyper-Growing | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| SS (Lvl, 2d) | $0.7617^{***}$ | | $0.7629^{***}$ | | $0.7775^{***}$ | | $0.6990^{***}$ | |
| | (0.1513) | | (0.1850) | | (0.1424) | | (0.2543) | |
| (log) IG Revenue pp | $0.1568^{***}$ | $0.3614^{***}$ | $0.1638^{***}$ | $0.3269^{***}$ | $0.1123^{***}$ | $0.4126^{***}$ | $0.1029^{**}$ | $0.3782^{***}$ |
| | (0.0252) | (0.0560) | (0.0293) | (0.0751) | (0.0260) | (0.0387) | (0.0413) | (0.0648) |
| (log) Real GDP Priv. Industry pc | $0.3410^{***}$ | 0.1195 | $0.3171^{***}$ | 0.1441 | $0.2267^{***}$ | $0.1887^{***}$ | $0.1424^{***}$ | $0.2039^{***}$ |
| | (0.0521) | (0.0725) | (0.0674) | (0.0897) | (0.0277) | (0.0428) | (0.0251) | (0.0546) |
| (log) House Price Index | | 0.0642 | | -0.0339 | | 0.0088 | | -0.1664 |
| | | (0.1623) | | (0.2330) | | (0.1487) | | (0.2914) |
| *Fixed-effects* | | | | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 5,240 | 5,240 | 3,184 | 3,184 | 7,477 | 7,477 | 2,981 | 2,981 |
| $R^2$ | 0.96616 | 0.86142 | 0.95865 | 0.83107 | 0.95469 | 0.85491 | 0.94878 | 0.77980 |
| Within $R^2$ | 0.20062 | 0.23031 | 0.21519 | 0.17340 | 0.14249 | 0.27012 | 0.09780 | 0.18085 |
| F-test (1st stage) | 158.42 | | 97.123 | | 201.24 | | 54.190 | |
| F-test (1st stage), (log) House Price Index | | 158.42 | | 97.123 | | 201.24 | | 54.190 |
| F-test (1st stage), p-value | $8.29 \times 10^{-36}$ | | $1.37 \times 10^{-22}$ | | $4.32 \times 10^{-45}$ | | $2.35 \times 10^{-13}$ | |
| F-test (1st stage), p-value, (log) House Price Index | | $8.29 \times 10^{-36}$ | | $1.37 \times 10^{-22}$ | | $4.32 \times 10^{-45}$ | | $2.35 \times 10^{-13}$ |
| F-test (2nd stage) | | 0.68932 | | 0.10301 | | 0.01681 | | 1.3429 |
| F-test (2nd stage), p-value | | 0.40643 | | 0.74827 | | 0.89684 | | 0.24661 |
| Wu-Hausman | | 0.58584 | | 3.3194 | | 2.8246 | | 3.8590 |
| Wu-Hausman, p-value | | 0.44407 | | 0.06857 | | 0.09288 | | 0.04958 |
| Wald (IV only) | 25.355 | 0.15656 | 17.010 | 0.02117 | 29.833 | 0.00352 | 7.5530 | 0.32612 |
| Wald (IV only), p-value | $4.93 \times 10^{-7}$ | 0.69236 | $3.82 \times 10^{-5}$ | 0.88433 | $4.86 \times 10^{-8}$ | 0.95271 | 0.00603 | 0.56799 |

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

## Table 19: lev_ss_2d

| Dependent Variables: | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp | (log) House Price Index | (log) Elem.Ed.Exp.pp |
|---|---|---|---|---|---|---|---|---|
| | Declining | | Hyper-Declining | | Growing | | Hyper-Growing | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| SS (Lvl, 2d) | $1.054^{***}$ | | $0.9688^{***}$ | | $0.7566^{***}$ | | $0.8925^{***}$ | |
| | (0.2518) | | (0.1807) | | (0.1151) | | (0.2542) | |
| (log) IG Revenue pp | $0.0983^{***}$ | $0.3555^{***}$ | $0.1066^{***}$ | $0.4297^{***}$ | $0.1372^{***}$ | $0.3939^{***}$ | $0.1755^{***}$ | $0.3282^{***}$ |
| | (0.0347) | (0.0751) | (0.0266) | (0.0556) | (0.0219) | (0.0358) | (0.0447) | (0.0565) |
| (log) Real GDP Priv. Industry pc | $0.2891^{***}$ | $0.1485^{*}$ | $0.3102^{***}$ | 0.1003 | $0.2534^{***}$ | $0.1689^{***}$ | $0.1844^{***}$ | $0.1677^{***}$ |
| | (0.0711) | (0.0769) | (0.0534) | (0.0618) | (0.0284) | (0.0372) | (0.0341) | (0.0531) |
| (log) House Price Index | | 0.0849 | | 0.1351 | | 0.0348 | | -0.0760 |
| | | (0.2431) | | (0.1786) | | (0.1157) | | (0.2248) |
| *Fixed-effects* | | | | | | | | |
| unit | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 1,596 | 1,596 | 3,212 | 3,212 | 11,121 | 11,121 | 2,955 | 2,955 |
| $R^2$ | 0.96951 | 0.88239 | 0.96647 | 0.85954 | 0.95481 | 0.85046 | 0.93057 | 0.85752 |
| Within $R^2$ | 0.12795 | 0.23057 | 0.12632 | 0.26810 | 0.17429 | 0.26037 | 0.19823 | 0.20315 |
| F-test (1st stage) | 79.853 | | 144.25 | | 305.28 | | 92.517 | |
| F-test (1st stage), (log) House Price Index | | 79.853 | | 144.25 | | 305.28 | | 92.517 |
| F-test (1st stage), p-value | $1.1 \times 10^{-18}$ | | $1.56 \times 10^{-32}$ | | $1.86 \times 10^{-67}$ | | $1.39 \times 10^{-21}$ | |
| F-test (1st stage), p-value, (log) House Price Index | | $1.1 \times 10^{-18}$ | | $1.56 \times 10^{-32}$ | | $1.86 \times 10^{-67}$ | | $1.39 \times 10^{-21}$ |
| F-test (2nd stage) | | 0.69737 | | 3.0301 | | 0.37823 | | 0.54411 |
| F-test (2nd stage), p-value | | 0.40380 | | 0.08183 | | 0.53856 | | 0.46079 |
| Wu-Hausman | | 0.07573 | | 0.14927 | | 2.1958 | | 1.9181 |
| Wu-Hausman, p-value | | 0.78321 | | 0.69926 | | 0.13842 | | 0.16617 |
| Wald (IV only) | 17.514 | 0.12195 | 28.750 | 0.57152 | 43.178 | 0.09069 | 12.331 | 0.11418 |
| Wald (IV only), p-value | $3.01 \times 10^{-5}$ | 0.72698 | $8.82 \times 10^{-8}$ | 0.44971 | $5.22 \times 10^{-11}$ | 0.76331 | 0.00045 | 0.73546 |

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




### 4.3 Panel VAR Specification

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

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

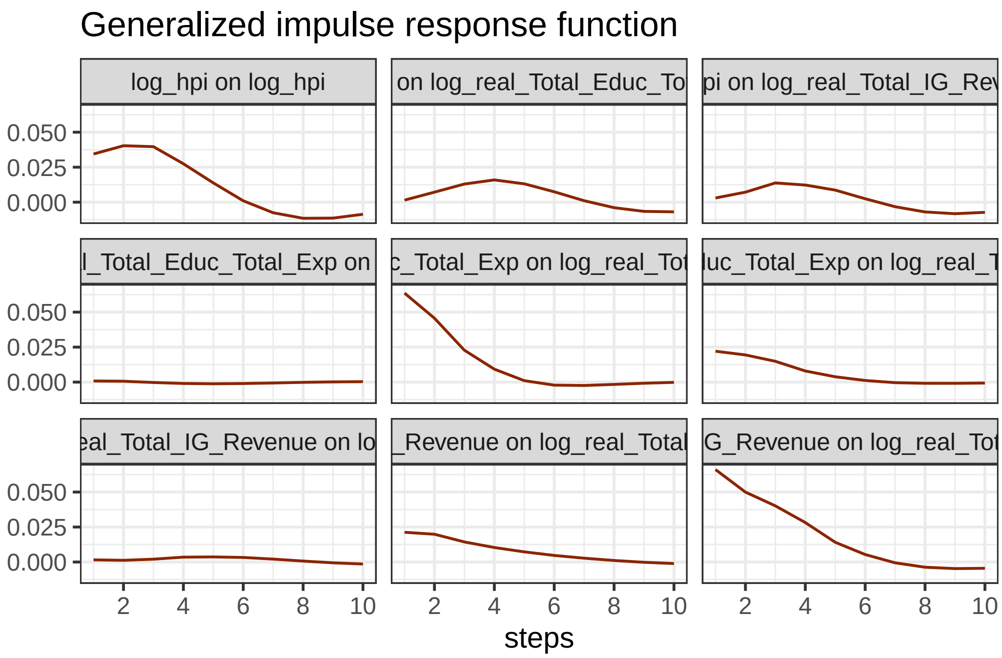
$$Y_{it} = \begin{bmatrix} \log(\text{real Total Educ. Exp.})_{it} \\ \log(\text{real Total IG Revenue})_{it} \\ \log(\text{HPI})_{it} \end{bmatrix}, \quad X_{it} = \begin{bmatrix} \log(\text{real GDP})_{it} \\ \log(\text{wage})_{it} \end{bmatrix}$$

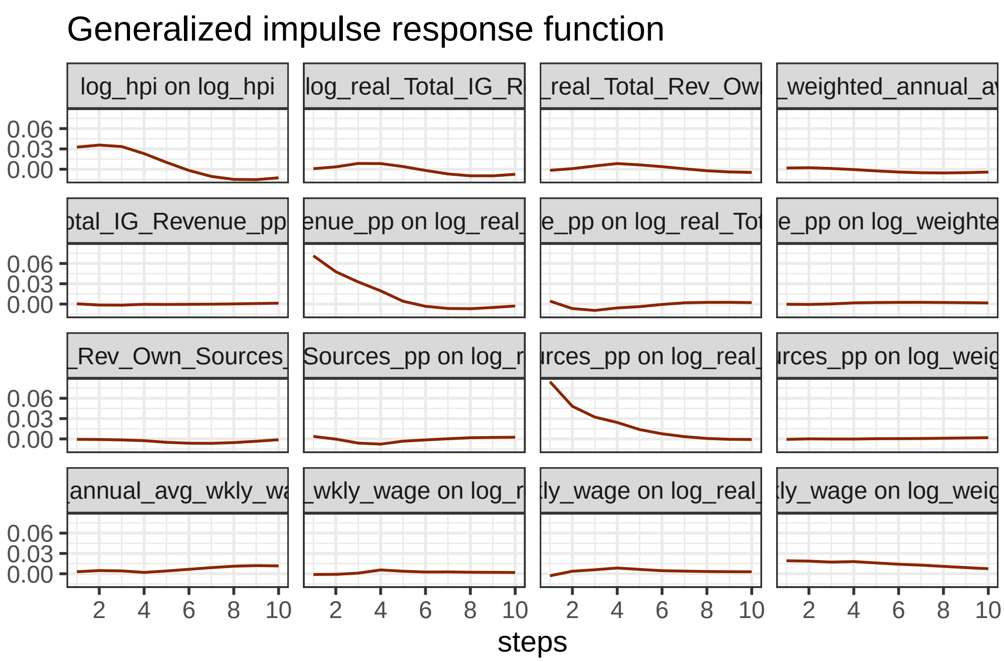
- $A_1, A_2, A_3, A_4$ are $3 \times 3$ coefficient matrices
- $\beta$ is a $3 \times 2$ matrix of coefficients on the exogenous variables
- $\alpha_i$ is a vector of unit fixed effects
- $\varepsilon_{it}$ is the error term

Where

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

- $A_1, A_2, A_3, A_4$ are $4 \times 4$ coefficient matrices
- $B$ is a $4 \times 1$ coefficient matrix
- $\alpha_i$ unit fixed effects
- $\varepsilon_{it}$ error term


Generalized impulse response function
log_hpi on log_hpi
on log_real_Total_Educ_To
pi on log_real_Total_IG_Rev
l_Total_Educ_Total_Exp on
c_Total_Exp on log_real_Tot
luc_Total_Exp on log_real_T
eal_Total_IG_Revenue on lo
_Revenue on log_real_Total
G_Revenue on log_real_Tot
0.050
0.025
0.000
2 4 6 8 10
steps


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

# 5 Property Prices

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

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

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

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

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

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

# 6 Results

# 7 Discussion

# 8 Conclusion

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

# 9 Appendix

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