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Fiscal Discipline and Foreign Direct Investment among India's Top 10 FDI-Receiving States: A Computational Panel Analysis, FY 2019-20 to FY 2023-24

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Abstract

Foreign direct investment (FDI) is highly concentrated across Indian states, raising the question of whether differences in state fiscal conditions are associated with investment outcomes. This study examines the relationship between fiscal discipline and FDI among ten major FDI-receiving states in India over FY 2019–20 to FY 2023–24. Fiscal discipline is measured using fiscal deficit, public debt, own tax revenue, and capital expenditure, each expressed relative to GSDP. Using fiscal data for 50 state-year observations compiled from official government sources, with FDI outcomes available for 48, the study combines fixed-effects and pooled regression models with rank correlation, LASSO, Elastic Net, and SHAP-based random-forest analysis. Across the empirical specifications, public debt emerges as the strongest fiscal variable associated with cross-state differences in FDI. However, this association is predominantly between states rather than within states over time. Further analysis shows that regional differences account for a substantial share of the observed variation in public debt, and the debt–FDI association becomes statistically indistinguishable from zero after accounting for regional effects. The analysis also finds no robust relationship between fiscal indicators and GSDP growth after controlling for year-specific shocks. The study's key contribution is to demonstrate how computational and panel-based analysis can distinguish cross-sectional associations from within-state dynamics, thereby preventing overinterpretation of fiscal indicators as causal determinants of FDI. The findings provide a reproducible analytical framework for examining sub-national fiscal conditions and investment patterns and highlight the need for a broader state panel to identify causal relationships.

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1. INTRODUCTION

Foreign investment in India is highly concentrated. Of the Rs 3.68 lakh crore of FDI equity that entered the country in FY 2023-24, the ten states examined in this paper accounted for roughly 84 per cent, with Maharashtra, Karnataka and Gujarat alone taking about 65 per cent (Department for Promotion of Industry and Internal Trade [DPIIT], 2024, 2025). State governments compete for these flows openly. Their budgets are also scored in public: NITI Aayog's (2025) Fiscal Health Index ranks eighteen major states on spending quality, revenue mobilisation, fiscal prudence and debt, and a good position in such a ranking is easily taken as a sign that a state is attractive to investors. We have not found a study that checks this inference against state-level FDI data.

Checking it runs into a data constraint. A state-wise FDI series, audited fiscal ratios and a consistent GSDP series exist together for just five years, FY 2019-20 to FY 2023-24, and FY 2020-21 was dominated by the pandemic. With ten states observed for five years, the choice of standard errors, of model or even of cross-validation scheme can change a conclusion. Feature-importance tools add a further risk, because with so few units a model can score well by learning which state an observation comes from. Decisions taken on such evidence need a method that shows which findings hold up and which are produced by the shape of the data.

We propose such a method and use it to study four indicators of fiscal discipline: outstanding debt, the fiscal deficit, a capital-expenditure proxy and own tax revenue, all scaled by GSDP. Their association with FDI, and with GSDP growth, is estimated twice, once with panel econometrics and once with regularised regression and tree ensembles. Only a result on which the two approaches agree is carried forward, and that result is then confronted with region and year effects, the confounds most likely to mimic it. The study contributes in two ways. It sets audited Finance Commission ratios against DPIIT's state-wise FDI series, a pairing we did not find in the studies reviewed in Section 2, and it offers a workflow for short panels that guards against feature leakage and against composite indices that are never validated.

2. LITERATURE REVIEW

Theory does not give public finance a single sign. Barro (1990) shows that tax-financed productive spending can raise the long-run growth rate, whereas Fischer (1993) reports that countries with large budget deficits grow more slowly, partly because such deficits erode

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macroeconomic stability and private investment. For Indian states the evidence concerns growth more than investment: panel studies by Trivedi and Rajmal (2011) and by Panda and Sahay (2022) find that higher deficits are followed by slower growth, while Misra et al. (2023) assess the sustainability of state debt. Foreign investment does not appear as an outcome in any of them.

Studies of FDI location build on Dunning's (1993) framework of ownership, location and internalisation advantages, and Blonigen's (2005) survey finds that market size, infrastructure, labour costs and institutional quality recur as determinants. Fiscal federalism suggests why the finances of a host government could also count, since mobile firms and households compare jurisdictions (Oates, 1972; Tiebout, 1956), and Feld et al. (2024) find across countries that sub-national governments with more control over their own taxes attract more cross-border acquisitions. Indian states make a useful test case: they share a currency, a central bank and, since 2017, a goods and services tax, so any fiscal effect could not operate through exchange rates or monetary credibility.

Our methods draw on work that treats machine learning as a partner to econometrics rather than a substitute for it (Athey & Imbens, 2019; Varian, 2014). Mullainathan and Spiess (2017) stress that good prediction does not imply reliable coefficients, a warning that matters most in small samples. We combine the LASSO of Tibshirani (1996), the Elastic Net of Zou and Hastie (2005), the random forest of Breiman (2001) and the SHAP attributions of Lundberg and Lee (2017). Applications of these tools to panels with as few as ten units are rare, and we found none on Indian state finances.

3. DATA

Our ten states fall into four regions. Maharashtra and Gujarat form the west; Karnataka, Tamil Nadu and Telangana the south; Haryana, Rajasthan and Uttar Pradesh the north; and West Bengal and Jharkhand the east. They are the ten states with the largest cumulative FDI equity inflow from October 2019 to March 2024 among those for which the Sixteenth Finance Commission (FC-16) publishes fiscal data. Delhi receives more FDI than most of them, yet the FC-16 annexures carry no data for it, which is why West Bengal is included instead.

Fiscal deficit, outstanding liabilities and own tax revenue, each as a percentage of GSDP, are taken from Volume II of the FC-16 Report (Government of India, 2025), whose figures rest on audited State Finance Accounts. The annexures do not report capital expenditure, so we use a proxy obtained by subtracting the revenue deficit from the gross fiscal deficit. By the accounting identity this proxy equals capital outlay plus net lending, less

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miscellaneous capital receipts; it is not reported capital expenditure, and we call it the capex proxy throughout. A script in our repository compares all 200 fiscal values with the published annexures, and every value matches. FDI, here and throughout, is the FDI equity inflow in DPIIT's state-wise series, in rupees crore (DPIIT, 2024); because it begins in October 2019, the FY 2019-20 observation covers half a year, a level difference that year effects remove. GSDP at current prices on the 2011-12 base comes from the Ministry of Statistics and Programme Implementation (MoSPI, 2024), and we compute its annual growth rate. Census 2011 literacy and urbanisation rates serve as controls in cross-state models only, since they are fixed over the period. All 50 state-years have fiscal data, whereas FDI is available for 48, as DPIIT reports Uttar Pradesh on its own only from FY 2021-22; the two missing cells are left out of every FDI model rather than imputed. Summary statistics appear in Table 1.

Table 1. Summary statistics, 50 state-years (FDI observed in 48)

Variable	Mean	SD	Median	Min	Max
Gross fiscal deficit, % of GSDP	2.82	1.26	3.10	−0.70	5.40
Outstanding liabilities, % of GSDP	28.82	6.55	29.55	17.60	42.50
Own tax revenue, % of GSDP	6.47	0.80	6.30	5.20	8.20
Capex proxy, % of GSDP	2.27	1.01	1.90	0.10	4.60
FDI equity inflow, Rs crore	31,194	43,933	12,884	44	163,795
GSDP growth, nominal %	10.39	7.35	11.41	−4.38	26.76

Note. FC-16 Volume II annexures, DPIIT and MoSPI; authors' calculations. Capex proxy: gross fiscal deficit less revenue deficit (capital outlay plus net lending, less miscellaneous capital receipts).

Splitting the variance of each series into its between-state and within-state components reveals a contrast that drives the rest of the analysis. For debt, 91.5 per cent of the variance is between states, leaving 8.5 per cent within. For GSDP growth the split is reversed, with 98.3 per cent of the variance occurring within states. Over this window debt is close to a fixed characteristic of each state, while growth moves mostly with the calendar, and an estimator that mixes the two sources of variation can credit a fiscal variable with what is really a difference between states or between years.

4. EMPIRICAL STRATEGY

The analysis follows the sequence in Figure 1. Both tracks use the same observations but rely on different assumptions, so agreement between them carries information. A result

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counts only if the tracks match on its sign and on its rank among the indicators; it is then tested for regional and temporal confounding. The rule is a robustness screen, not a test. The two tracks estimate different quantities, conditional associations on one side and predictive importance on the other, so we ask only whether they agree on direction and ordering. Agreement cannot rule out a confound that affects both, which is why the audit follows.

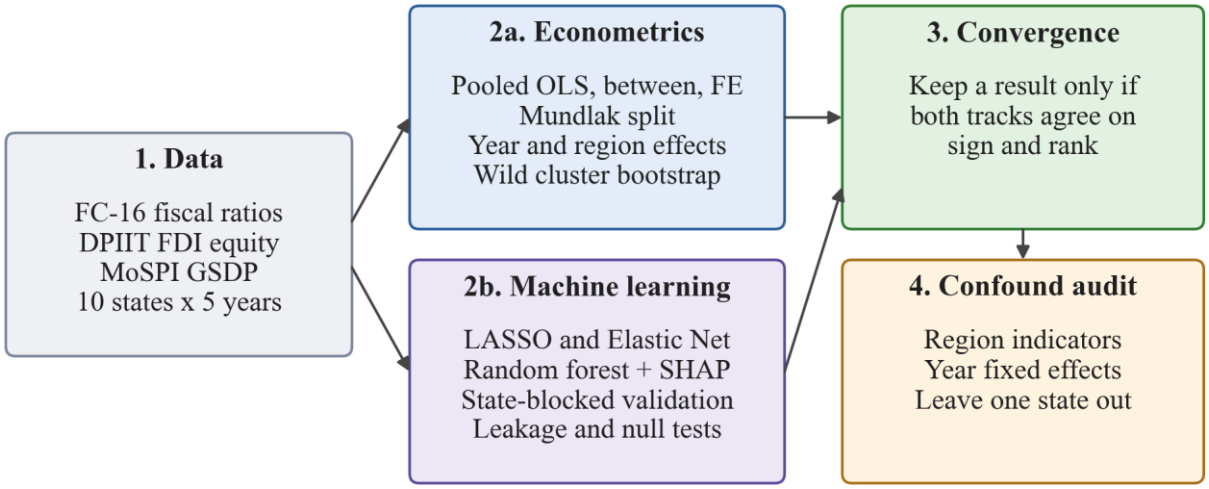


Figure 1. Study workflow: two tracks, a convergence rule and a confound audit

Econometric track. For state i in year t we estimate

$$\ln \mathbf{FDI}_{it} = \alpha_i + \beta_1 \mathbf{DEBT}_{it} + \beta_2 \mathbf{FD}_{it} + \beta_3 \mathbf{OTR}_{it} + \beta_4 \mathbf{CAPEX}_{it} + \gamma \mathbf{COVID}_t + u_{it} \quad (1)$$

in which (DEBT) denotes outstanding liabilities, (FD) the gross fiscal deficit, (OTR) own tax revenue and (CAPEX) the derived capital-expenditure proxy, each in per cent of GSDP, while COVID is a dummy for FY 2020-21. Including the state effects α restricts identification to changes within a state, and we pair this estimator with Driscoll and Kraay (1998) standard errors. Without the state effects, and with literacy and urbanisation added, pooled OLS mainly compares states with one another. The device of Mundlak (1978) bridges the two: each regressor enters as its state average and as the yearly departure from that average, and a test of equal coefficients shows whether the two kinds of variation tell the same story. Asymptotic cluster-robust inference is unreliable with ten clusters, so each key coefficient is also tested with a wild cluster bootstrap that draws Rademacher weights (Cameron et al., 2008). For growth, the same right-hand side is used with nominal GSDP growth as the dependent variable.

Machine-learning track. Penalties for the LASSO and the Elastic Net are set by leave-one-state-out cross-validation, and a random forest of 1,000 trees, limited to depth three with at least four observations in each leaf, is explained with SHAP values; all random seeds are fixed in the code. We adapt the track to a ten-unit panel in four ways. Validation folds hold out entire states, which stops a state from informing predictions about itself. Variables that never

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change within a state are left out: when the Census controls were included in an early run, urbanisation dominated the SHAP ranking (mean |SHAP| of 1.30, with debt at 0.25) simply because it identifies states, and we report that episode as a result in its own right. Rankings are judged against a null distribution generated by permuting the outcome across whole states 500 times. Lastly, both methods are re-estimated on data demeaned by state, giving the track its own within-state test.

Composite index. Many published indices aggregate fiscal indicators into one ranking without checking it against any outcome. We construct a similar index by averaging the four indicator ranks with equal weights, so that a state ranks as more disciplined when its deficit and debt are lower and its own tax revenue and capex proxy are higher, and compare it with each state's five-year FDI using Spearman's rank correlation.

5. FINDINGS

5.1 Cross-state versus within-state variation

The debt coefficient from each econometric specification is collected in Table 2. Pooled across the 48 state-years with Census controls, it equals −0.176 (cluster-robust SE 0.062), which implies that one percentage point less debt goes with roughly 19 per cent more FDI, since exp(0.176) − 1 = 0.19. The cluster-robust p-value is 0.007; the wild bootstrap gives 0.057, narrowly above the 5 per cent threshold. Replacing the COVID dummy with year effects enlarges the coefficient to −0.244 (bootstrap p = 0.019), and controlling for log GSDP as a proxy for market size leaves it at −0.173 (bootstrap p = 0.087). Dropping the six-month FY 2019-20 observations raises it to −0.237 (39 state-years, bootstrap p = 0.079), and the between estimator, fitted to the ten state averages of the four fiscal indicators, also gives −0.237.

The sign reverses inside states. In the Mundlak equation the state-average term is −0.256 and the within-state term +0.370, and the bootstrap rejects their equality (p = 0.015, or 0.043 with year effects). The positive within-state relation reflects the pandemic year: debt ratios rose everywhere in FY 2020-21 and stayed high through the FDI recovery, so within each state the high-debt years are also the recovery years. With year effects in the fixed-effects model the estimate is +0.332 and no longer significant (bootstrap p = 0.234), and restricting the sample to FY 2021-22 onwards, still with year effects, turns it negative at −0.452 (bootstrap p = 0.075). The pattern is consistent with FDI tracking persistent differences between states rather than year-to-year changes in debt, and Section 5.3 shows that those differences cannot be separated from geography.

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The composite index fares poorly: its rank correlation with five-year FDI is only −0.255 (p = 0.476). Uttar Pradesh accounts for much of the shortfall, topping the index while recording the least FDI, a total depressed by its two unreported years. Debt by itself does much better, with ρ = −0.842 (p = 0.002).

Table 2. Coefficient on debt-to-GSDP in models of log FDI

Model	Coefficient	Bootstrap p	Cluster p
Pooled: Census controls, COVID dummy	−0.176	0.057	0.007
Pooled: Census controls, year effects	−0.244	0.019	0.001
Pooled: Census controls, log GSDP	−0.173	0.087	0.003
Pooled: Census controls, region effects	−0.036	–	0.365
Mundlak: state-average component	−0.256	–	<0.001
Mundlak: within-state component	+0.370	–	<0.001
Between estimator, state averages	−0.237	–	0.022
Fixed and year effects, all years	+0.332	0.234	0.098
Fixed and year effects, from FY 2021-22	−0.452	0.075	0.008

Note: Bootstrap p is from a wild cluster bootstrap with 1,999 Rademacher draws; cluster p uses standard errors clustered by state; – = not computed. The between estimator uses the four fiscal indicators only. The two Mundlak components differ at bootstrap p = 0.015. Every model uses the 48 state-years with FDI data except the between estimator (ten state means) and the last row (30 state-years).

5.2 What the machine-learning track adds

The estimates in Table 3 order the indicators the same way. Along the LASSO path debt acquires a non-zero coefficient first, at a penalty of 1.016, against 0.609 for the capex proxy and 0.375 for the fiscal deficit, and its standardised coefficient is the largest under both penalised regressions. The random forest gives debt a mean |SHAP| of 1.029, almost five times the 0.219 of the fiscal deficit, and debt stays first when each state is dropped in turn. Rank alone is weak evidence, though: under the state-block permutation null, debt still comes first 38 per cent of the time, since forests favour regressors with large variance. Its margin is the stronger result, because a lead as large as the observed one occurs in only 3.8 per cent of permuted samples (p = 0.038). With state-demeaned data debt again leads, but its LASSO coefficient becomes positive (+0.441), the same reversal the econometric track found. The capex proxy carries a negative sign that we do not interpret causally: it includes net lending, and revenue-surplus states such as Uttar Pradesh show inflated values. Reported capital outlay

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is available from state budget documents for just two years, FY 2022-23 (actual figures) and FY 2023-24 (revised estimates). Swapping it for the proxy in a pooled model with Census controls on those 20 state-years leaves the debt coefficient negative and significant (−0.321, cluster p = 0.004). The sample is too short to compare this estimate directly with Table 2, so it serves only as a check on the sign.

Table 3. Indicator importance in the machine-learning track (outcome: log FDI)

Indicator	Entry penalty	LASSO	Elastic Net	SHAP, pooled	SHAP, within
Debt-to-GSDP	1.016	−1.376	−1.280	1.029	0.274
Capex proxy	0.609	−0.553	−0.562	0.136	0.031
Fiscal deficit	0.375	0.563	0.488	0.219	0.119
COVID year	0.316	0.129	0.161	0.007	0.001
Own tax revenue	0.138	0.039	0.098	0.208	0.037

Note: LASSO and Elastic Net columns are standardised coefficients with penalties chosen by state-blocked cross-validation; the entry penalty is where each indicator joins the LASSO path. SHAP columns are mean absolute SHAP values in log-FDI units from the pooled and the state-demeaned forest; the within values describe demeaned data and are not comparable in size with the pooled ones.

Prediction tests point to the same caution. Holding out one observation at a time, the four models explain between 40 and 51 per cent of the variance in log FDI; holding out a whole state, they explain between 9 and 24 per cent. Most of the apparent accuracy therefore comes from recognising persistent state characteristics. The LASSO degrades least and the two tree ensembles most, consistent with a roughly linear relationship, so we read the SHAP rankings as support for the linear estimates. None of the models is fit for forecasting FDI.

5.3 Testing the result against region and time

Figure 2 shows why the regional confound matters. States with low debt and high FDI lie in the west and south; those with high debt are in the north and east. Debt averages 20.6 per cent of GSDP across the western pair, against 26.2 per cent for the southern states, 33.1 for the northern and 34.5 for the eastern, so region accounts for 72 per cent of the variation in debt across the ten states. On their own, region dummies explain more of log FDI ($R^2 = 0.60$) than debt does ($R^2 = 0.31$). Adding them to the pooled model moves the debt coefficient to −0.036 (p = 0.365), indistinguishable from zero, and removing regional means from both series reduces

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the rank correlation to −0.285 (p = 0.425). With four regions and ten states, fiscal and regional explanations cannot be told apart.

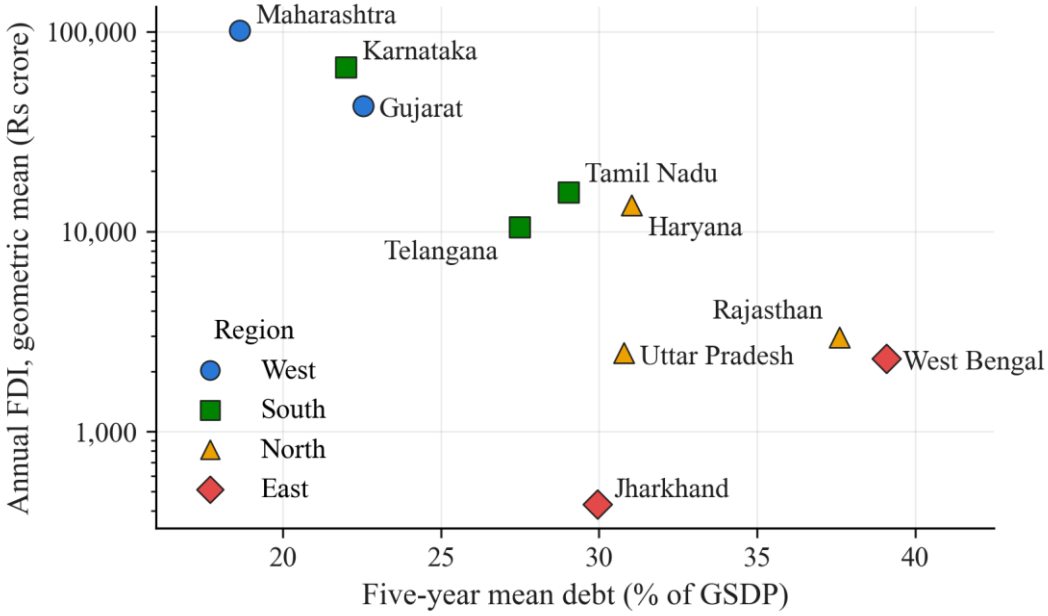


Figure 2. Five-year mean debt and typical annual FDI by state, marked by region (geometric-mean FDI on a log scale; Uttar Pradesh over its three reported years)

The growth results do not survive the same scrutiny. In fixed-effects models of nominal GSDP growth with only a COVID dummy, the coefficients on debt (+1.097) and on own tax revenue (+4.083) are both significant. Once each year has its own effect, the own-tax coefficient is no longer distinguishable from zero (bootstrap p = 0.61), while debt turns negative (−0.689, bootstrap p = 0.088). The earlier estimates were picking up the common post-pandemic recovery, and we find no evidence that these fiscal indicators are related to growth. Variance inflation factors lie between 1.33 and 1.69, so collinearity among the regressors does not explain any of these patterns.

6. LESSONS FOR DATA-DRIVEN DECISION MAKING

Three practical lessons follow for analysts in government and business. The first concerns the level at which a pattern holds. A chart in which low-debt states receive more FDI is a fair description of the data, but it offers no support for the claim that cutting a deficit will raise next year's inflows. Panels of firms, branches or customers raise the same issue, and a Mundlak decomposition, which needs only one additional regression, shows whether a relationship lives between units or within them.

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Explanations produced by explainable-AI tools need validation of their own. Urbanisation topped the SHAP ranking only because it identifies states, and any variable that is constant within units can do the same. Holding out whole units during validation, permuting outcomes across units and refitting without each unit in turn are inexpensive checks, and the fall in accuracy from row-wise to unit-wise validation is a convenient measure of how much a model has memorised rather than learned.

Indices raise a related issue. A composite fiscal score, like many corporate scorecards, can look rigorous while predicting the outcome less well than one of its inputs. Every index deserves a test against the outcome it is supposed to guide, with the result published whether or not it flatters the index. For investment-promotion agencies the conclusion is modest: persistently low debt goes with a strong standing among FDI destinations, but in these data that cannot be distinguished from the advantages of the western and southern regions, such as ports, established industrial clusters and large metropolitan markets.

7. CONCLUSION

Econometric and machine-learning methods, resting on different assumptions, agree that public debt is the fiscal indicator most closely associated with FDI among India's ten largest recipient states. The association is a difference between states, not a response within states to changes in debt, and it disappears when regional controls are added. Growth shows no stable relation to any fiscal indicator once year effects are included. These are findings about the limits of what a short sub-national panel can identify, and the same workflow can be applied to other problems with few units and few periods.

Several caveats apply. FDI is observed in only 48 state-years. DPIIT allocates investment to the state where the receiving company has its registered office, so states hosting many corporate headquarters may appear to receive more than they do. Off-budget borrowing is missing from the debt measure, growth is nominal, and the design cannot identify causal effects. A wider cross-section is the most promising next step. For the 26 states covered by both FC-16 and DPIIT's cumulative FDI table, region accounts for 35 per cent of the variance in debt rather than 72 per cent, and an exploratory regression on these states yields a negative debt coefficient even with regional controls (-0.143, $p = 0.056$). A larger sample may therefore be able to separate the fiscal and regional explanations that this one cannot.

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DATA AND CODE AVAILABILITY

The data, code and output files that reproduce every table, figure and number in this paper are publicly available at https://github.com/fbivinay/BMS-Conference. The command python code/run_all.py reruns the analysis and compares each reported value with the regenerated output.

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