ψ vs ECI: Cognitive–Institutional Capacity and Export Complexity as Predictors of Long-Run Growth

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Abstract

This paper compares the predictive power of a broad cognitive–institutional index ψ and the canonical Economic Complexity Index (ECI) for long-run GDP per capita growth. We construct a global country panel for 2000–2024 combining indicators of human capital, governance, digitalization, innovation and export complexity. The ψ-index is obtained as a latent factor from these variables, while ECI is taken from the standard HS92 export complexity dataset. We then build a 10-year growth panel and estimate a set of simple, transparent regressions. Three main findings emerge. First, ψ is a stable positive predictor of subsequent 10-year growth, explaining about 4–5% of the variance in a purely bivariate specification. Second, ECI shows a weak negative association with growth when used alone, but becomes a positive and significant predictor once ψ or initial income are controlled for—a pattern consistent with a classical suppressor effect. Third, robustness checks indicate that a version of ψ purged of log GDP per capita (ψ_{ng}) still retains strong predictive power, and that the joint ψ+ECI specification performs best in models with conditional convergence and year fixed effects. We interpret these results as evidence that export complexity has become a *conditional* engine of growth in the early 21st century: it matters most once a country has accumulated sufficient cognitive–institutional capacity.

1 Introduction

The ability of quantitative indicators to describe and predict long-run growth trajectories is a central concern of macroeconomics and development economics. Over the past two decades, one of the most visible attempts to link structural features of the economy to future growth has been the Economic Complexity Index (ECI) of Hidalgo and Hausmann (2009), widely used to measure the sophistication and diversification of countries' export baskets and, by implication, their productive capabilities.

In parallel, a growing literature has emphasized broader dimensions of development that extend beyond export structures: human capital, institutional quality, innovation capacity, digital infrastructure and social complexity. Rather than focusing on a single sectoral or trade-based metric, this work seeks composite measures capturing the *systemic* ability of a society to generate, diffuse and coordinate knowledge.

In this paper we contribute to this discussion by comparing the predictive power of two composite indices for long-run economic growth:

- a broad cognitive–institutional index, denoted ψ, constructed as a latent factor from multiple indicators of human capital, governance, innovation and digitalization; and
- the canonical export-based Economic Complexity Index (ECI), based on the HS92 product classification and widely used in the complexity literature.

Our core empirical question is straightforward: *Is ψ a more robust predictor of 10-year GDP per capita growth than ECI in the period 2000–2024?* We deliberately avoid claims of "revolution" or attempts to "replace" ECI. Instead, our goal is to estimate the comparative explanatory power of the two indices on a common panel, and to investigate whether they complement each other when used jointly.

Using a global panel of countries, we construct 10-year growth rates of log GDP per capita between 2000 and 2024 and estimate a set of simple OLS models. Three high-level findings stand out. First, ψ is a stable positive predictor of subsequent growth across the global sample. Second, ECI on its own exhibits a weak but statistically significant *negative* association with growth in this period, reflecting the fact that highly complex economies have tended to grow more slowly since 2000. Third, once we control for ψ or initial income, ECI becomes a positive predictor of growth—consistent with the idea that complexity acts as a "second-stage accelerator" conditional on cognitive–institutional capacity.

The contribution of this paper is threefold. First, we provide a transparent head-to-head comparison between ψ and ECI on the same 10-year growth panel, with all code and data-processing scripts openly available. Second, we document a robust suppressor pattern: ψ absorbs a large part of the level effect associated with income and institutions, after which ECI emerges as a positive predictor of growth. Third, by performing a series of robustness checks—including a version of ψ without income, conditional convergence specifications, year fixed effects, and a split between 2000–2010 and 2010–2024—we show that our results are not driven by a particular model choice or time window.

The remainder of the paper is structured as follows. Section 2 describes the data, the construction of ψ and ECI, and the 10-year growth panel. Section 3 presents the baseline regression results and associated visualizations. Section 4 reports robustness checks, including alternative index definitions and model specifications. Section 5 situates the findings within the broader literature on economic complexity, institutions and intangible capital. Section 6 concludes.

2 Data and Methods

2.1 Data sources

Our empirical analysis is based on a global country-year panel that combines standard macro, institutional, innovation and trade indicators. The main sources are:

- World Development Indicators (WDI): GDP per capita (current US$ and PPP), population, and a set of digitalization indicators (internet penetration, mobile broadband).
- UNDP Human Development Index (HDI).
- Barro–Lee educational attainment (years of schooling).
- Worldwide Governance Indicators (WGI): rule of law, government effectiveness, regulatory quality, control of corruption, voice and accountability.
- V-Dem electoral and liberal democracy indices.
- Patent data from WIPO (patents per million inhabitants).
- High-technology exports (WDI and related sources).
- KOF Globalisation Index.
- Export complexity: HS92-based ECI from the Harvard Growth Lab (Atlas of Economic Complexity).

The full list of variables, definitions and data sources is provided in an online supplement.

2.2 Construction of the ψ-index and ψ_{ng}

The ψ-index is designed to capture a broad cognitive–institutional capacity of a country. Conceptually, it aggregates information about:

- income level (log GDP per capita),
- human capital (years of schooling and related indicators),
- innovation (patents per million inhabitants),
- institutional quality (WGI and V-Dem),
- digitalization (internet penetration, mobile broadband),
- broader development and inequality metrics (e.g. HDI, inequality indices).

Technically, ψ is constructed via factor analysis on a standardized set of these indicators. We estimate a common factor model and apply varimax rotation, yielding factor loadings that reflect the empirical covariance structure of the data rather than ad hoc weights. The resulting factor scores are standardized to have mean zero and unit variance in the pooled panel.

Because log GDP per capita enters the construction of ψ, a natural concern is endogeneity: ψ may partially encode current income, which is itself strongly correlated with future growth via convergence effects. To address this, we construct an alternative version ψ_{ng} ("no-GDP") in which log GDP per capita is excluded from the factor model. The remaining variables (education, institutions, innovation, digitalization, etc.) are used to estimate the factor, and factor scores are again standardized. This allows us to separate the cognitive–institutional component from contemporaneous income.

2.3 Economic Complexity Index (ECI)

For export complexity we use the standard Economic Complexity Index (ECI) based on the HS92 product classification (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011). Annual ECI values are taken from the Harvard Growth Lab (Atlas of Economic Complexity) for 1995–2023, matched to our country codes, and standardized to zero mean and unit variance.

ECI is interpreted in the usual way: higher values indicate a more diversified and complex export basket, capturing the breadth and sophistication of productive capabilities embedded in a country's economy.

2.4 Ten-year growth panel

To compare the predictive power of ψ and ECI for long-run growth, we construct a 10-year growth panel. For each country i and initial year t we compute the average annual growth rate of log GDP per capita over a 10-year horizon:

$$g_{i,t,t+10} = \frac{\ln \mathrm{GDPpc}_{i,t+10} - \ln \mathrm{GDPpc}_{i,t}}{10}. \tag{1}$$

We restrict attention to horizons fully contained within the 2000–2024 period, which yields 3,802 observations with valid ψ and GDP data, and 2,969 observations with non-missing ECI. The intersection of the two samples (countries and years where both ψ and ECI are available) also contains 2,969 observations.

2.5 Baseline econometric specifications

Our baseline regressions are intentionally simple and transparent. We begin with three bivariate and multivariate OLS models:

$$\textbf{(1)}\quad g_{i,t,t+10} = \alpha + \beta_\psi\, \psi_{i,t} + \varepsilon_{i,t}, \tag{2}$$
$$\textbf{(2)}\quad g_{i,t,t+10} = \alpha + \beta_{\text{ECI}}\, \text{ECI}_{i,t} + \varepsilon_{i,t}, \tag{3}$$
$$\textbf{(3)}\quad g_{i,t,t+10} = \alpha + \beta_\psi\, \psi_{i,t} + \beta_{\text{ECI}}\, \text{ECI}_{i,t} + \varepsilon_{i,t}. \tag{4}$$

All models are estimated by OLS without weights. Standard errors are conventional (non-robust) unless otherwise stated; using heteroskedasticity-robust standard errors does not materially alter the results.

To probe robustness and address concerns about endogeneity and omitted variables, we later extend these specifications to include:

- the alternative index ψ_{ng};
- initial log GDP per capita (conditional convergence);
- year fixed effects $C(t)$ to absorb global shocks;
- a split of the sample into early (2000–2010) and late (2010–2024) periods.

These extended models are summarized in Table 1.

3 Results

3.1 Model (1): growth on ψ

Model (2) relates 10-year growth to the cognitive–institutional index ψ:

- $N = 3{,}802$ observations;
- $R^2 = 0.045$;
- $\hat{\beta}_\psi \approx 0.198$ ($p < 0.001$).

The association is positive, statistically strong, and persistent across the sample. A one-standard-deviation increase in ψ at time t is associated with roughly 0.2 percentage points higher annualized growth of GDP per capita over the subsequent decade. Figure 1 (left panel) shows the corresponding scatterplot with fitted regression line: despite wide dispersion, the upward-sloping trend is evident across income groups and regions.

3.2 Model (2): growth on ECI

Model (3) relates 10-year growth to export complexity:

- $N = 2{,}969$;
- $R^2 = 0.010$;
- $\hat{\beta}_{\text{ECI}} \approx -0.496$ ($p < 0.001$).

In contrast to the historical evidence for 1970–2000, ECI exhibits a weak *negative* association with growth over 2000–2024. Highly complex economies (high ECI) have tended to grow more slowly, while several fast-growing economies—India, Vietnam, Bangladesh, Ethiopia, Uzbekistan—display relatively low ECI in the early 2000s. Figure 2 (right panel) shows that the scatter of ECI versus growth is diffuse, with a slightly downward-sloping regression line.

3.3 Model (3): joint ψ + ECI and the suppressor effect

When we include both indices in a joint regression as in (4), we obtain:

- $N = 2{,}969$ (common sample);
- $R^2 = 0.056$;
- $\hat{\beta}_\psi \approx 0.266$ ($p < 0.001$);
- $\hat{\beta}_{\text{ECI}} \approx 0.605$ ($p < 0.001$).

Two features are noteworthy. First, ψ remains a positive and significant predictor, with a somewhat larger coefficient in the common sample. Second, the coefficient on ECI *switches sign*: from negative in the bivariate model to positive in the joint model. This is a textbook example of a suppressor effect: ψ absorbs the component of ECI that is correlated with income level and institutional capacity, allowing ECI to capture the residual variation associated with structural diversification at a given cognitive–institutional level.

Figure 3 presents a head-to-head visualization comparing ψ–growth and ECI–growth relationships on common axes. The left panel shows a clear upward slope for ψ, while the right panel shows a much weaker pattern for ECI. When partial regression plots are used (Figure 6), the residual association between ECI and growth conditional on ψ becomes clearly positive.

3.4 Visual summary

For completeness, we summarize the key figures here:

- **Figure 1**: scatterplot of 10-year growth versus ψ, with fitted OLS line.
- **Figure 2**: analogous scatterplot for ECI.
- **Figure 3**: side-by-side comparison of ψ and ECI as predictors of growth on common scales.
- **Figure 4**: bar chart of standardized coefficients for ψ, ψ_{ng} and ECI across multiple models.
- **Figure 5**: comparison of $\hat{\beta}_\psi$ and $\hat{\beta}_{\text{ECI}}$ in early (2000–2010) versus late (2010–2024) subsamples.

All underlying code for data processing and figure generation is available in the accompanying GitHub repository.

4 Robustness Checks

To assess whether our findings are driven by the inclusion of income in ψ, by sample composition, or by model specification, we estimate a set of additional regressions summarized in Table 1. We focus on eight benchmark models.

First, we reconstruct an alternative index ψ_{ng} that excludes log GDP per capita from the factor model. In a bivariate regression of growth on ψ_{ng}, the coefficient remains positive and highly significant:

- $N = 3{,}802$;
- $R^2 = 0.052$;
- $\hat{\beta}_{\psi_{ng}} \approx 0.82$ ($p < 0.001$).

This indicates that the predictive power of ψ is not mechanically driven by contemporaneous income.

Second, we estimate conditional convergence models by adding initial log GDP per capita ($\ln \mathrm{GDPpc}_{i,t}$). In a specification with ψ and $\ln \mathrm{GDPpc}$, the convergence term dominates the explained variance ($R^2 \approx 0.21$), with a strongly negative coefficient on initial income:

- $\hat{\beta}_{\ln \mathrm{GDPpc}} \approx -1.81$,
- $\hat{\beta}_{\psi} \approx -0.21$ (now negative),

reflecting the familiar fact that richer countries grow more slowly. When ECI is included along with ψ and $\ln \mathrm{GDPpc}$, ECI becomes strongly positive ($\hat{\beta}_{\mathrm{ECI}} \approx 1.11$) and remains highly significant, while convergence remains robust ($\hat{\beta}_{\ln \mathrm{GDPpc}} \approx -2.19$). This reinforces the interpretation of ECI as capturing conditional structural upgrading once income and institutional capacity are controlled for.

Third, models with year fixed effects $C(t)$ absorb common global shocks such as the commodity supercycle, the global financial crisis, and the COVID-19 pandemic. In a model with ψ and year fixed effects, the R^2 rises to about 0.43, and ψ remains positive and significant ($\hat{\beta}_{\psi} \approx 0.14$). An analogous model with ECI and year fixed effects yields a negative coefficient for ECI. In the joint specification with ψ, ECI and year fixed effects, both indices are positively associated with growth ($\hat{\beta}_{\psi} \approx 0.17$, $\hat{\beta}_{\mathrm{ECI}} \approx 0.23$), and the suppressor pattern persists.

Finally, we split the sample into two subperiods: 2000–2010 (early) and 2010–2024 (late). In the early period, both ψ and ECI are modestly predictive:

- $N = 2{,}191$, $R^2 \approx 0.083$;
- $\hat{\beta}_{\psi} \approx 0.30$, $\hat{\beta}_{\mathrm{ECI}} \approx 0.33$.

In the late period, the role of ψ becomes weaker while the conditional role of ECI increases:

- $N = 978$, $R^2 \approx 0.023$;
- $\hat{\beta}_{\psi} \approx 0.09$, $\hat{\beta}_{\mathrm{ECI}} \approx 0.81$.

Figure 5 illustrates this shift graphically. Overall, the results are consistent across alternative index definitions, convergence controls, year fixed effects and time splits.

Table 1: Regression robustness summary (10-year growth horizon)

Model	Specification	N	R^2	$\beta_{\psi/\psi_{\mathrm{ng}}}$	β_{ECI}
(1)	ψ only	3,802	0.045	$+0.198^{***}$	–
(2)	ECI only	2,969	0.010	–	-0.496^{***}
(3)	ψ + ECI	2,969	0.056	$+0.266^{***}$	$+0.605^{***}$
(4)	ψ_{ng} only (no GDP)	3,802	0.052	$+0.821^{***}$	–
(5)	ψ_{ng} + ECI	2,969	0.066	$+1.134^{***}$	$+0.730^{***}$
(6)	ψ + ECI + $\ln GDPpc$	2,969	0.246	-0.154^{***}	$+1.111^{***}$
(7)	ψ + ECI + FE(year)	2,969	0.401	$+0.165^{***}$	$+0.228^{**}$
(8)	Early / Late: ψ + ECI	2,191 / 978	0.083 / 0.023	$+0.304^{***}/+0.085^{***}$	$+0.330^{***}/+0.814^{***}$

Notes: Dependent variable is 10-year average annual growth of log GDP per capita. Coefficients are standardized. Convergence term $\beta_{\ln GDPpc}$ in model (6) is negative and highly significant (about -2.19). FE(year) denotes year fixed effects.
$^{**}p < 0.05$, $^{***}p < 0.01$.

5 Discussion

Our results speak directly to the ongoing debate on the relative roles of structural capabilities and institutional foundations in shaping long-run growth. The economic complexity literature (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011) argues that the diversity and sophistication of a country's export basket encode productive knowledge and should therefore be a powerful predictor of future income dynamics. This view was supported by strong empirical regularities for earlier periods, particularly the late-20th-century industrialization wave.

For the 2000–2024 window, however, our estimates suggest that export complexity alone is no longer sufficient. In a purely bivariate regression, ECI is weakly *negatively* related to 10-year growth. Once we condition on a broad cognitive–institutional index ψ or on initial income, ECI becomes a positive predictor, but its effect is clearly conditional. This pattern aligns with recent critiques that complexity measures increasingly capture what countries *have become* rather than what they are capable of becoming, unless one controls for underlying institutional and human capital conditions.

The performance of ψ is closely connected to the institutionalist perspective associated with Rodrik (2004, 2007), which emphasizes the interaction between incentives, governance and state capacity in enabling structural transformation. The ψ-index aggregates education, digital adoption, governance quality and innovation capacity—precisely the types of "embedded capabilities" that this literature views as prerequisites for successful upgrading. The fact that ψ_{ng}, which excludes income, remains strongly predictive supports the idea that these capacities are not mere reflections of GDP per capita, but independent determinants of growth potential.

Our findings also resonate with the macro-innovation literature on intangible capital and the changing nature of growth (Bloom and Jones, 2019; Jones, 2022). Modern growth increasingly depends on the accumulation of hard-to-measure assets: skills, R&D capability, digital infrastructure, managerial quality and absorptive capacity. ψ can be interpreted as a composite proxy for these intangible assets. The strong predictive performance of ψ_{ng} indicates that growth in the digital era is tightly linked to cognitive–institutional readiness rather than to export structure alone. In this environment, the marginal returns to export complexity depend on the ability to implement and scale complex technologies, which is precisely what ψ captures.

Finally, our time-split analysis connects to the observation of Szirmai (2012) that the drivers of development evolve across technological regimes. In the early 2000s, both ψ and ECI are modestly predictive of growth, reflecting the tail end of the export-led industrialization model. In the later period, ψ remains positive but weaker, while the conditional effect of ECI rises sharply once ψ is controlled for. This suggests that economic complexity has not "died" as a predictor of growth, but has become more evidently *conditional*: it operates as a second-stage accelerator once cognitive–institutional thresholds are reached.

Overall, our results support a hybrid interpretation. Export complexity remains relevant, but primarily in tandem with broader systemic capabilities captured by ψ. Rather than displacing the complexity paradigm, we refine it: structural sophistication amplifies growth conditional on cognitive–institutional maturity.

6 Conclusion

This paper has compared the predictive power of a broad cognitive–institutional index ψ and the Economic Complexity Index (ECI) for 10-year GDP per capita growth over 2000–2024. Three main conclusions emerge.

First, ψ exhibits a robust positive association with subsequent growth in a global panel of countries. This relationship persists when log GDP per capita is removed from the construction of ψ (ψ_{ng}), suggesting that the index captures genuine cognitive–institutional capacity rather than simply re-packaging income.

Second, ECI on its own shows a weak negative association with long-run growth in this period, consistent with the slowdown of highly complex economies and the rise of several less complex but rapidly growing economies. However, once we control for ψ or initial income, ECI becomes a positive and significant predictor. In joint models, ECI behaves as a suppressor-enhanced variable: its contribution becomes visible only after the cognitive–institutional component has been accounted for.

Third, the combination of ψ and ECI delivers the best predictive performance among our simple specifications, especially when conditional convergence and year fixed effects are included. This points to a complementary relationship: ψ captures broad systemic capabilities, while ECI captures structural export sophistication.

We refrain from strong causal claims. The regressions document robust empirical patterns rather than identificationally clean causal effects. Nonetheless, the patterns are stable across multiple robustness checks and time splits, and thus merit serious consideration. From a policy perspective, our results suggest that for low- and middle-income countries in the coming decades, building cognitive–institutional capacity—through education, digitalization, and improved governance—is at least as important as, and possibly a precondition for, efforts to upgrade export complexity. Export sophistication appears most growth-enhancing once a sufficient cognitive–institutional platform is in place.

Future work could extend this analysis by employing panel methods with country fixed effects, exploiting quasi-experimental shocks to institutional or digital variables, and conducting horse-race comparisons with other proposed indices (e.g. IQ measures, detailed human capital indices, digital adoption indices). It would also be valuable to explore explicit interaction terms between ψ and ECI, and to examine whether similar patterns hold at subnational or sectoral levels.

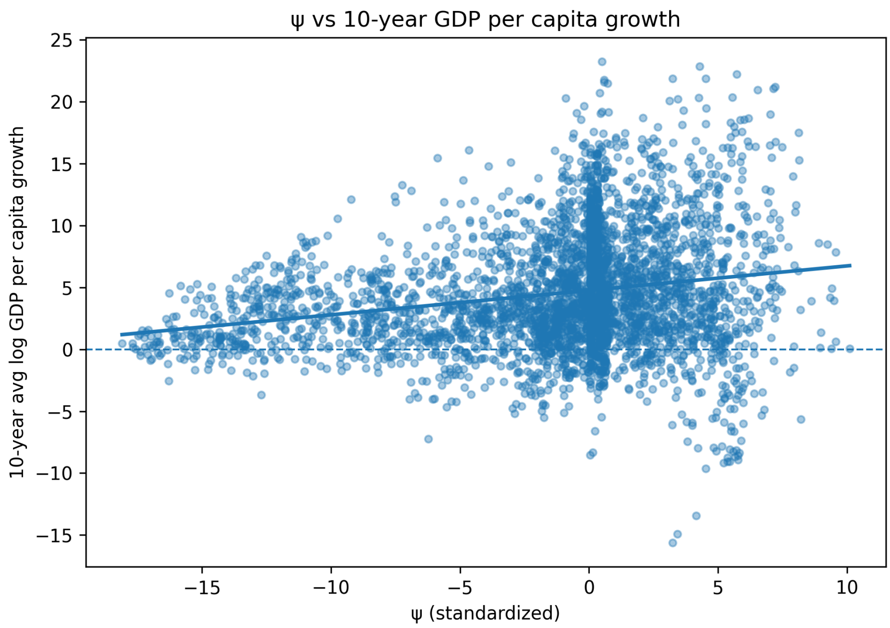

Figure 1: 10-year GDP per capita growth vs. ψ (scatterplot with fitted line).

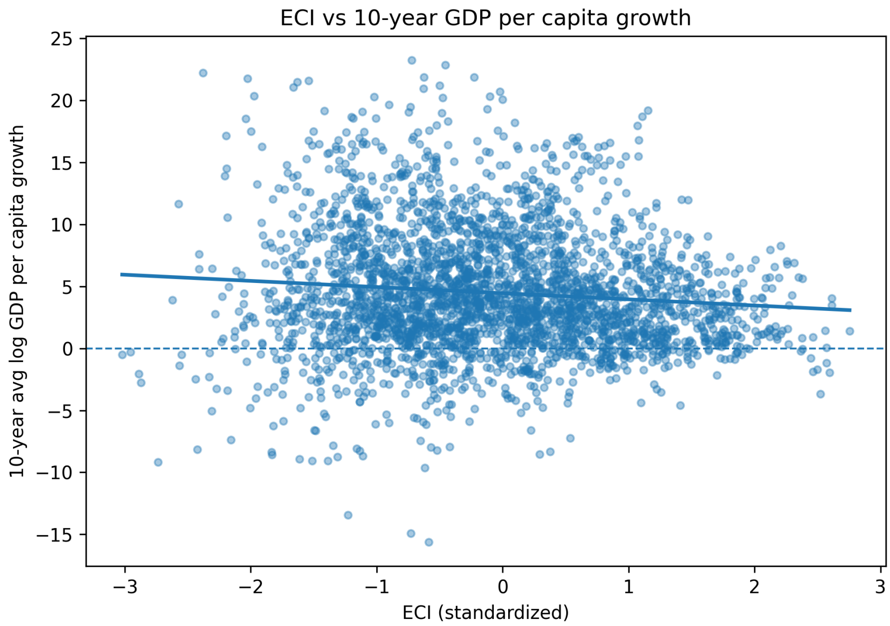

Figure 2: 10-year GDP per capita growth vs. ECI (scatterplot with fitted line).

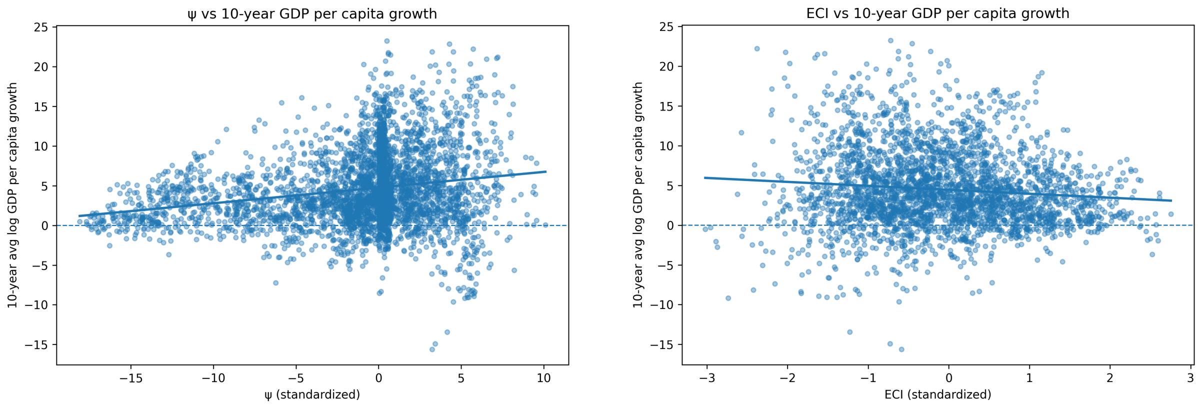

Figure 3: Head-to-head comparison: ψ (left) and ECI (right) as predictors of 10-year growth.

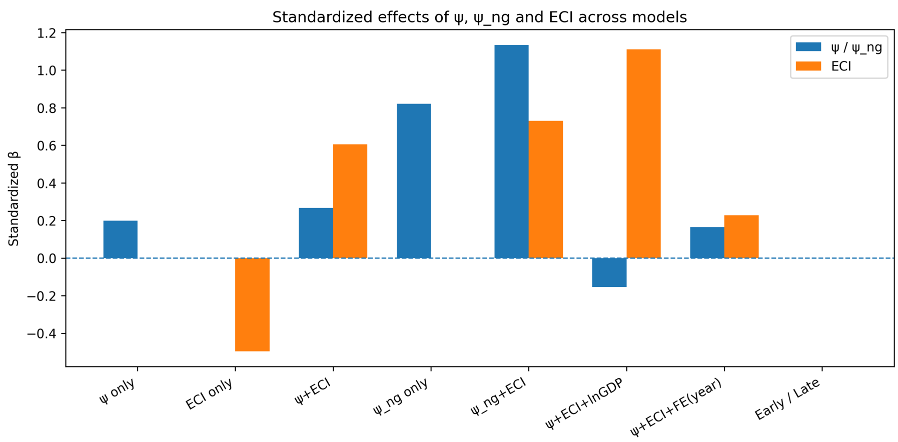

Figure 4: Standardized coefficients of ψ, ψ_{ng} and ECI across robustness models.

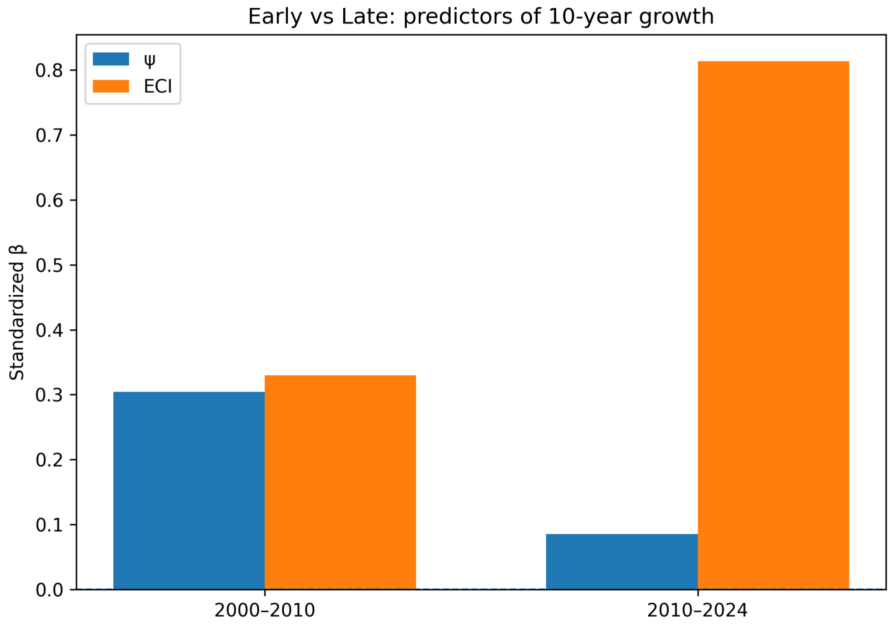

Figure 5: Early (2000–2010) vs. Late (2010–2024) predictors of long-run growth: ψ and ECI.

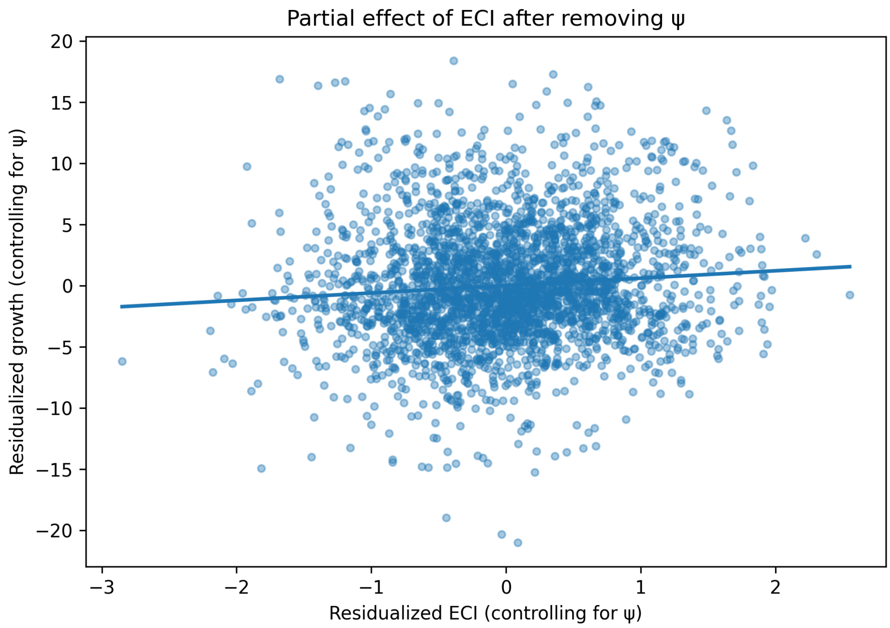

Figure 6: Partial regression plot: residualized ECI vs. residualized growth, controlling for ψ.

References

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26), 10570–10575.

Hausmann, R., & Hidalgo, C. A. (2011). The network structure of economic output. *Journal of Economic Growth*, 16(4), 309–342.

Rodrik, D. (2004). Industrial policy for the twenty-first century. *CEPR Discussion Paper* No. 4767.

Rodrik, D. (2007). *One Economics, Many Recipes: Globalization, Institutions, and Economic Growth*. Princeton University Press.

Bloom, N., & Jones, C. I. (2019). Seven facts about growth and technology. *NBER Working Paper* No. 25794.

Jones, C. I. (2022). The new Kaldor facts: Ideas, institutions, population, and human capital. *American Economic Journal: Macroeconomics*, 14(4), 220–256.

Szirmai, A. (2012). Industrialisation as an engine of growth in developing countries, 1950–2005. *Structural Change and Economic Dynamics*, 23(4), 406–420.