Input-output network topology reveals persistent structural regimes in the global economy

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Outline

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Premise

The structure of production constrains future development. That structure lives in input-output data, but summary indicators average it away.

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Our claim

Production architecture is a distinct, measurable dimension of development. It is closely related to economic complexity ($\rho = 0.760$), yet not reducible to it.

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Complementary, not redundant

The Topological Development Index (TDI) tracks economic complexity closely ($\rho = 0.760$) while capturing a structurally distinct axis of production organization. It also carries information about subsequent GDP growth, which we examine in detail later.

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The gap

Economic complexity reads capabilities from *outputs*; value-chain measures quantify *flows*. We bring persistent homology to global input-output structure to recover a development dimension complementary to these.

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The key object—a *filtration*: $f_{\mathcal{G}} : \mathcal{V} \to \mathbb{R}$ or $f_{\mathcal{G}} : \mathcal{E} \to \mathbb{R}$ for node/edge filtration functions. Defining thresholds τ yields a chain of nested graphs:

$$\mathcal{G}_{\tau_1} \subseteq \mathcal{G}_{\tau_2} \subseteq \cdots \subseteq \mathcal{G}_{\tau_m}.$$

Superlevel filtration—early graphs contain the "strongest" nodes/links.

TDA — Persistent Homology (on Graphs)

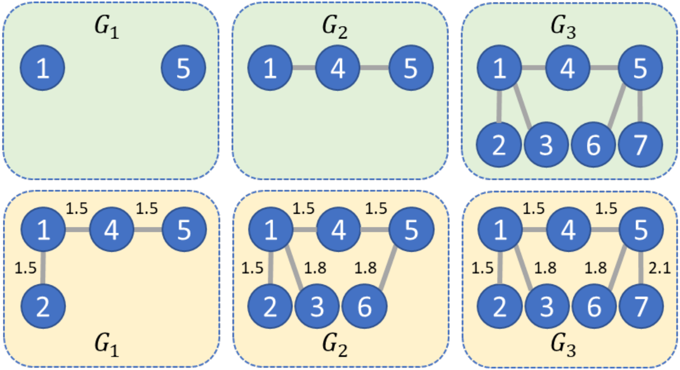

Figure: **Graph Filtration.** For $\mathcal{G} = \mathcal{G}_3$ in both examples, the top figure illustrates a *superlevel filtration using the node degree function* with thresholds $3 > 2 > 1$, where nodes of degree 3 are activated first, followed by those of lower degrees. Similarly, the bottom figure illustrates a *sublevel filtration based on edge weights* with thresholds $1.5 < 1.8 < 2.1$.

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$$\beta_0 = |C|, \qquad \beta_1 = |\mathcal{E}| - |\mathcal{V}| + \beta_0.$$

Then for the specified graph filtration $\mathcal{G}_{\tau_1} \subseteq \mathcal{G}_{\tau_2} \subseteq \cdots \subseteq \mathcal{G}_{\tau_m}$ at each $\mathcal{G}_{\tau_i}$ we can compute β_0^i and β_1^i yielding *Betti Vectors*

$$\mathcal{G}_{\tau_1} \subseteq \mathcal{G}_{\tau_2} \subseteq \cdots \subseteq \mathcal{G}_{\tau_m} \qquad \rightarrow \qquad \begin{matrix} \begin{bmatrix} \beta_0^1 & \beta_0^2 & \cdots & \beta_0^m \end{bmatrix} \\ \\ \begin{bmatrix} \beta_1^1 & \beta_1^2 & \cdots & \beta_1^m \end{bmatrix} \end{matrix}$$

OECD ICIO Networks

- 81 Countries (80 + 1 for RoW), 50 Sectors, from 1995–2022[1]

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- Final 1-hop CS graph has ~ 300 nodes, $\sim 63,000$ edges

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OECD — Country-Year Subgraph Construction

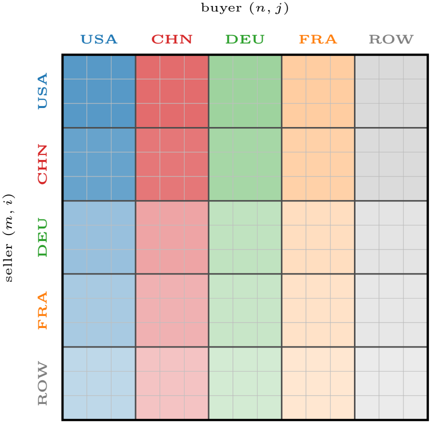

Figure: OECD Z Matrix (raw)

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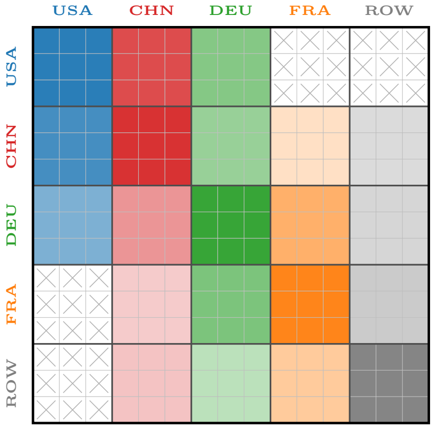

Figure: $Z \to \Omega$ Construction

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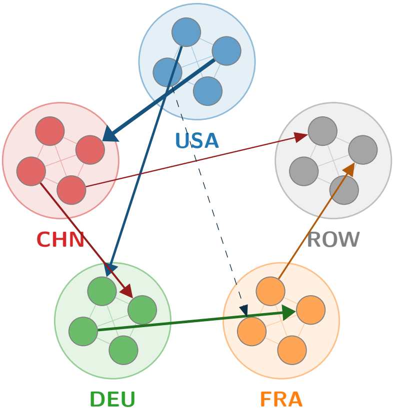

Figure: $\Omega \rightarrow$ Full Network

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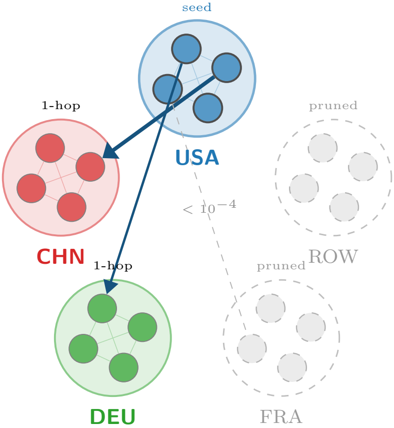

Figure: Full Network → USA 1-hop $\mathcal{G}$

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yielding topological summary $\mathbf{b} := [\mathbf{b}^I; \mathbf{b}^X; \mathbf{b}^D] \in \mathbb{R}^{120}$.

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- Repeating over all countries and all years yields $80 \times 28 = 2,240$ vectors—our dataset.

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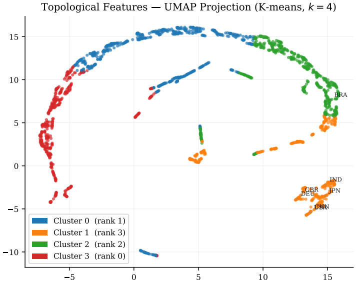

Figure: Topological features visualized with coloring by cluster/regime. The regimes lie on a near one-dimensional spine.

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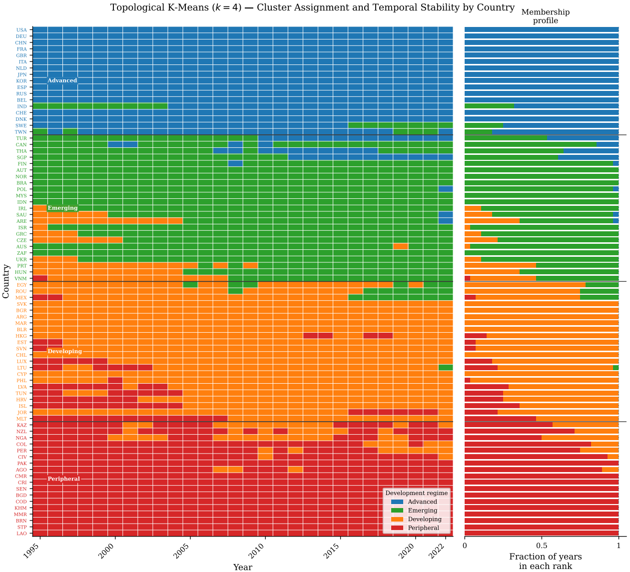

TDI — Why Topology Features?

Feature space	Dim.	Silhouette ↑	DB ↓	CH ↑
Topological	120	**0.549**	**0.543**	**9,735**
Spectral	48	0.464	0.696	5,239
Joint (T+S)	168	0.456	0.701	6,489
Graph-statistic	25	0.239	1.408	547

Table: Cluster quality metrics for a variety of extracted features—topology remains the most informative across three different metrics: Silhouette, Davies-Bouldin, and Calinski-Harabasz.

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Topological Development Index (TDI)

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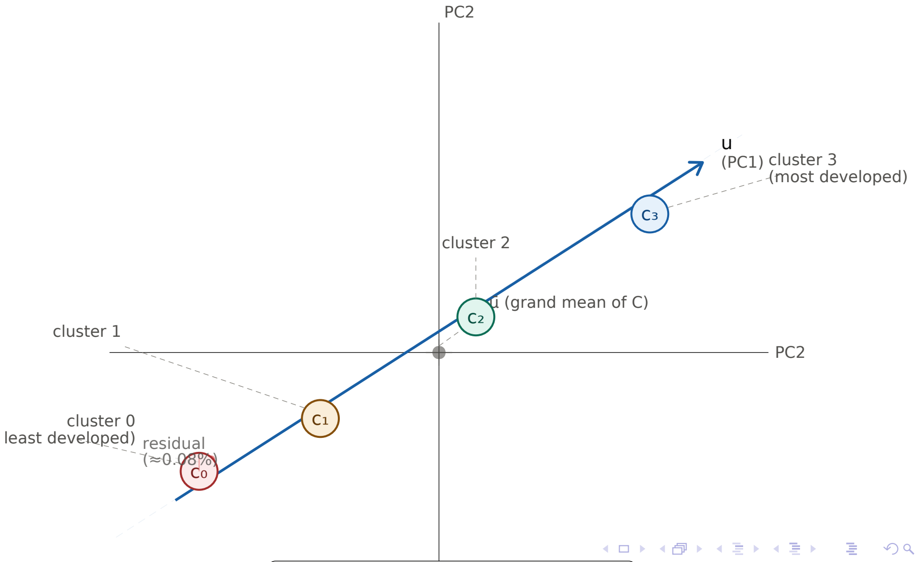
TDI — Results

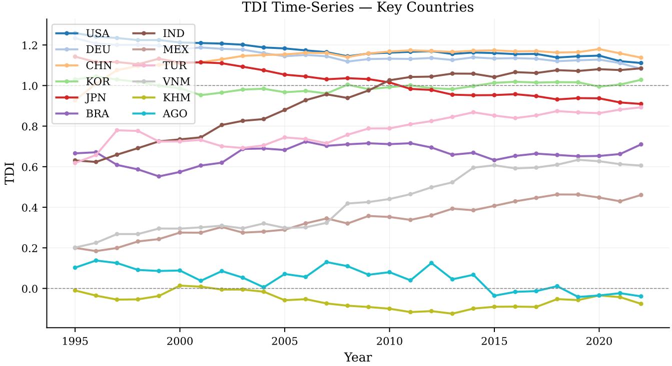


PC2
u
(PC1)
cluster 3
(most developed)
C₃
cluster 2
ū (grand mean of C)
C₂
cluster 1
PC2
C₁
cluster 0
least developed)
residual
(≈0.08%)
C₀

TDI — Results

The four regime centers span the unit interval, we retain values outside of $[0, 1]$ rather than clipping them:

Min	Max	Mean	Std. Dev	Q1	Median	Q3
-0.323	1.259	0.450	0.379	0.138	0.406	0.744



TDI — Results

USA
DEU
CHN
FRA
GBR
ITA
NLD
JPN
KOR
ESP
RUS
BEL
IND
CHE
DNK
SWE
TWN
TUR
CAN
THA
SGP
FIN
AUT
NOR
BRA
POL
MYS
IDN
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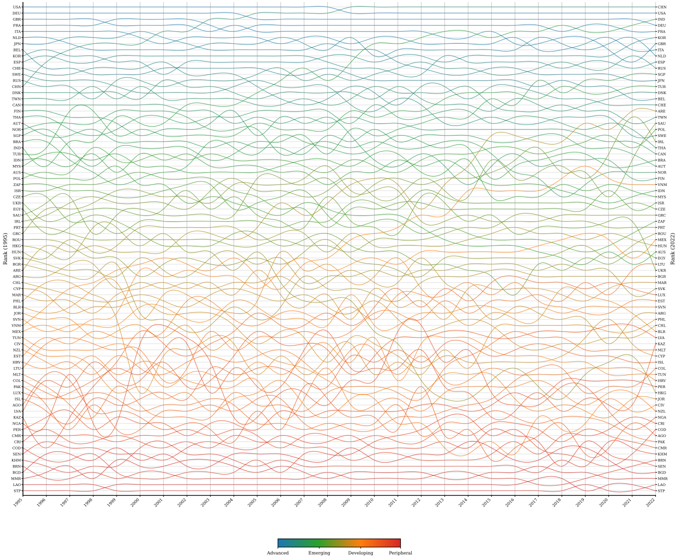
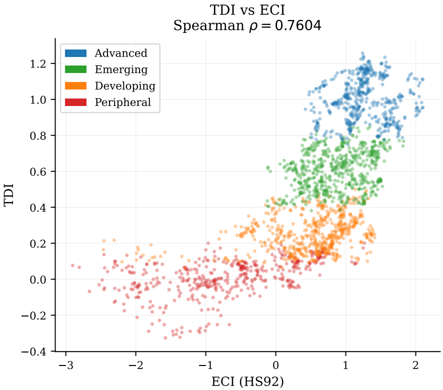
SEN
BGD
COD
KHM
MMR
BRN
STP
LAO
TDI
1.0
0.5
0.0
1995
2005
2015
2022
Peripheral (rank 0)
Developing (rank 1)
Emerging (rank 2)
Advanced (rank 3)
Year

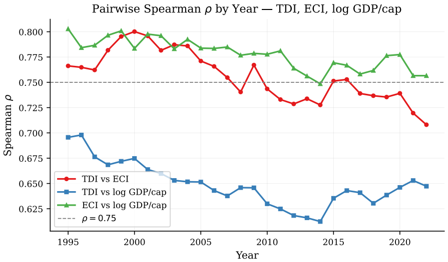
TDI — Results



Rank (1995)
USA DEU GBR FRA ITA NLD JPN BEL KOR ESP CHE SWE RUS CHN DNK TWN CAN FIN THA AUT NOR SGP BRA IND TUR IDN MYS AUS POL ZAF ISR CZE UKR EGY SAU IRL PRT GRC ROU HKG HUN SVK BGR ARE ARG CHL CYP MAR PHL BLR JOR SVN VNM MEX TUN CIV NZL EST HRV LTU MLT COL PAK LUX ISL AGO LVA KAZ NGA PER CMR CRI COD SEN KHM BRN BGD MMR LAO STP
Rank (2022)
CHN USA IND DEU FRA KOR GBR ITA NLD ESP RUS SGP JPN TUR DNK BEL CHE ARE TWN SAU POL SWE IRL THA CAN BRA AUT NOR FIN VNM IDN MYS ISR CZE GRC ZAF PRT ROU MEX HUN AUS EGY LTU UKR BGR MAR SVK LUX EST SVN ARG PHL CHL BLR LVA KAZ MLT CYP ISL COL TUN HRV PER HKG JOR CIV NZL NGA CRI COD AGO PAK CMR KHM BRN SEN BGD MMR LAO STP
1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Advanced
Emerging
Developing
Peripheral

TDI — Correlations





Average correlation values:

TDI vs log GDP per capita: $\rho = 0.628$

TDI vs ECI (HS92): $\rho = 0.760$

TDI — Growth Predictor

- Looking at 5-year growth predictions
- Linear Regressions:
  - Broad Search ($\sim 3,840$ specs): For $p < 0.05$, 33 specs excl small countries, 10 specs full data
  - Excluding small countries, performance $\uparrow\uparrow$
  - Best results with Country-Year Fixed Effects, MYS+lgdppc for controls, and excluding small countries

Year Sample	ECI	n	TDI Coef	TDI p	ECI Coef	ECI p	R^2
Full Panel	eci exp	1865	0.041	0.041	-0.012	0.580	0.649
Every 5-year	eci exp	373	0.052	0.039	-0.023	0.416	0.664

- Non-Linear ML:
  - Excluding small countries increases performance, but no strong results
- Shift from predicting growth to *classifying* growth..

TDI – Growth Predictor

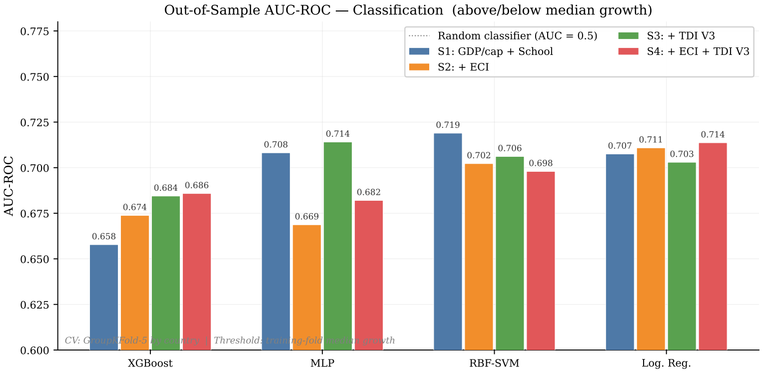


Figure: TDI improves performance across ML models for binary (above/below median growth) classification.

Questions?