Disaggregating Input-Output Tables: A novel approach applied to the EU transition to electric vehicles

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European Commission Joint Research Centre

32nd International Input-Output Association Conference, Seville, 22nd - 26th June 2026

Outline

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Motivation

Input-Output (IO) tables:

Provide a detailed "map" of inter-industry linkages revealing:

- which sectors are key suppliers or users of others' outputs
- how production is organized across the economy

Well suited for analysing a wide range of socioeconomic aspects of globalization and input dependency in production

However, many policy questions hinge on the heterogeneity hidden when sectors are highly aggregated (e.g., product targeted subsidies)

- need for disaggregation

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Literature (non-exhaustive)

Disaggregating IO tables:

- Wolsky (1984): Theoretical foundation of industry disaggregation
  - limited to *two* subsectors
  - initial guess + set of distinguishing vectors: set of admissible technical coefficients that preserve the aggregate IO relationship

- Lindner et al. (2012): Generalisation of Wolsky (1984)
  - generalisation to n subsectors
  - initial seed + random walk exploration of the feasible coefficient space
  - limited ability to reveal deep heterogeneity in subindustry technologies

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Our methodology: In a nutshell

- Disaggregates *sector N* into *n subsectors*
- Uses econometric techniques to estimate the technical coefficients that preserve the aggregate IO relationships over a period of time t (exploiting time variation)
- Requires complementary *production* and *trade* data at the desired level of disaggregation, for a period of time t (with $t > n$)
- Advantage: obtains point estimates that allow to uncover the heterogeneity of subsectors through proxies (production and trade data)
- Limitation: imposes the technical coefficients, reflecting consumption and production patterns, to be fixed over period t. Therefore, t should be relatively short

  Balances efficiency vs IO structure invariance

Our methodology: Framework

Define a multi-country economy with:

- K countries $(k, l = 1, \ldots, K)$
- N sectors $(i, j = 1, \ldots, N)$
- and a global matrix of technical coefficients $\mathbf{A}$, as follows:

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} & \ldots & \mathbf{A}^{1K} \\ \mathbf{A}^{21} & \mathbf{A}^{22} & \ldots & \mathbf{A}^{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{K1} & \mathbf{A}^{K2} & \ldots & \mathbf{A}^{KK} \end{bmatrix}, \quad \mathbf{A}^{kl} = \begin{bmatrix} a^{kl}_{11} & a^{kl}_{12} & \ldots & a^{kl}_{1N} \\ a^{kl}_{21} & a^{kl}_{22} & \ldots & a^{kl}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a^{kl}_{N1} & a^{kl}_{N2} & \ldots & a^{kl}_{NN} \end{bmatrix}$$

$$\text{with } \mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$$

Our methodology: The disaggregation problem (I)

Assume sector N is disaggregated into $n > 1$ subsectors for each country

Define a new augmented technical coefficient matrix $\mathbf{A}^{*kl}$ of size $(N-1+n) \times (N-1+n)$ where s_p is the disaggregated sector with $p = 1, 2, ..., n$

$$\mathbf{A}^{*kl} = \begin{bmatrix} a^{*kl}_{11} & a^{*kl}_{12} & \cdots & a^{*kl}_{1(N-1)} & a^{*kl}_{1s_1} & \cdots & a^{*kl}_{1s_n} \\ a^{*kl}_{21} & a^{*kl}_{22} & \cdots & a^{*kl}_{2(N-1)} & a^{*kl}_{2s_1} & \cdots & a^{*kl}_{2s_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ a^{*kl}_{(N-1)1} & a^{*kl}_{(N-1)2} & \cdots & a^{*kl}_{(N-1)(N-1)} & a^{*kl}_{(N-1)s_1} & \cdots & a^{*kl}_{(N-1)s_n} \\ a^{*kl}_{s_1 1} & a^{*kl}_{s_1 2} & \cdots & a^{*kl}_{s_1(N-1)} & a^{*kl}_{s_1 s_1} & \cdots & a^{*kl}_{s_1 s_n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ a^{*kl}_{s_n 1} & a^{*kl}_{s_n 2} & \cdots & a^{*kl}_{s_n(N-1)} & a^{*kl}_{s_n s_1} & \cdots & a^{*kl}_{s_n s_n} \end{bmatrix}$$

Our methodology: The disaggregation problem (II)

Introduce two sets of shares, recoverable from observable data (production and bilateral trade):

- *The output share* of subsector s_p in total output of sector N in country l:

$$\alpha^l_{s_p} = \frac{x^{*l}_{s_p}}{x^l_N}, \qquad \text{with} \quad \sum_{p=1}^{n} \alpha^l_{s_p} = 1, \tag{1}$$

- *The consumption share* of subsector s_p from total flow of sector N from country k to l:

$$\beta^{kl}_{s_p} = \frac{x^{*kl}_{s_p}}{x^{kl}_N}, \qquad \text{with} \quad \sum_{p=1}^{n} \beta^{kl}_{s_p} = 1, \tag{2}$$

Our methodology: The disaggregation problem (III)

Conservation of flows yields the following constraints for each country pair (k, l):

$$a_{i,j}^{kl} = \begin{cases} \sum_{p=1}^{n} \alpha_{s_p}^{l} \, a_{i,s_p}^{*kl} & \text{if } i \in \{1, \cdots, N-1\},\ j = N, \\ \sum_{p=1}^{n} \beta_{s_p}^{kl} \, a_{s_p,j}^{*kl} & \text{if } i = N,\ j \in \{1, \cdots, N-1\}, \\ \sum_{p=1}^{n} \sum_{p'=1}^{n} \alpha_{s_p}^{l} \beta_{s_{p'}}^{kl} \, a_{s_{p'},s_p}^{*kl} & \text{if } i = N,\ j = N. \end{cases} \tag{3}$$

$$b_N^{kl} = \sum_{p=1}^{n} \beta_{s_p}^{kl} \, b_{s_p}^{*kl}. \tag{4}$$

$$\text{with} \quad a_{i,s_p}^{*kl} \geq 0, \quad a_{s_p,j}^{*kl} \geq 0, \quad a_{s_p,s_{p'}}^{*kl} \geq 0, \quad b_{s_p}^{*kl} \geq 0, \qquad \forall\, i, j, p, p', k, l. \tag{5}$$

Our methodology: Generalisation to panel data

- Add the time dimension t to all variables ($t = 1, \ldots, T$, with $T > n$)
  Taking IO tables and complementary production and trade data over time as a *panel of country-industry-year observations*

$$a_{i,j}^{kl}(t) = \begin{cases} \sum_{p=1}^{n} \alpha_{s_p}^{l}(t)\, a_{i,s_p}^{*kl}(t) & \text{if } i \in \{1, \cdots, N-1\},\ j = N, \\ \sum_{p=1}^{n} \beta_{s_p}^{kl}(t)\, a_{s_p,j}^{*kl}(t) & \text{if } i = N,\ j \in \{1, \cdots, N-1\}, \\ \sum_{p=1}^{n} \sum_{p'=1}^{n} \alpha_{s_p}^{l}(t) \beta_{s_{p'}}^{kl}(t)\, a_{s_{p'},s_p}^{*kl}(t) & \text{if } i = N,\ j = N. \end{cases} \tag{6}$$

$$b_N^{kl}(t) = \sum_{p=1}^{n} \beta_{s_p}^{kl}(t)\, b_{s_p}^{*kl}(t). \tag{7}$$

Our methodology: Estimation in four steps

- Assume time-invariant technology and preferences
  technical coefficients are treated as constant over the estimation period
- Estimate by OLS
  panel data with temporal variation in production and trade shares provides the identifying variation
- Enforce non-negativity
  ensure non-negative coefficients by selecting the zero-restriction pattern that minimises the estimation error
- Restore accounting consistency via RAS
  iteratively rescale estimated coefficients to satisfy the row and column constraints of the IO framework

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Application to the automotive sector: Motivation

- Electrification is reshaping EU automotive supply chains
  ICEs and EVs differ in production technology, inputs, and sourcing patterns
- Foreign dependence is a first-order policy concern
  batteries and semiconductors concentrate risk in a small number of non-EU suppliers
- IO analysis can map these dependencies
  but only if EVs and ICEs are treated as distinct sectors
- Standard IO tables do not allow this distinction
  EVs and ICEs are aggregated into a single sector (C29): our methodology fills this gap

Application to the automotive sector: Background (I)

Growing reliance on Extra-EU imports of cars and components, mainly from China

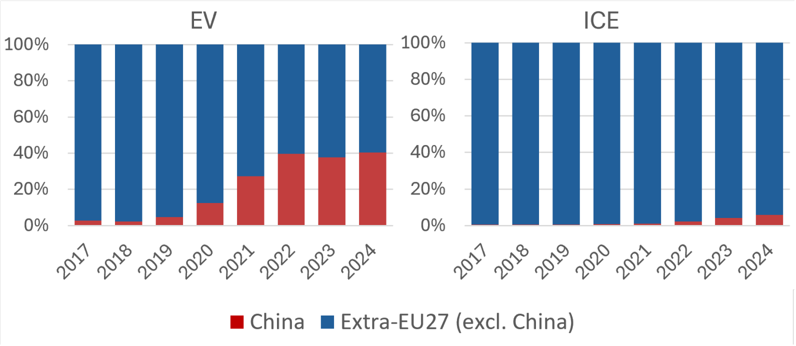

Figure 1: Extra-EU imports of vehicles: EVs and ICEs (share of value)

Application to the automotive sector: Background (II)

Aggregate IO data from the car manufacturing industry show that the EU local content has declined by just 3 p.p. in the last decade

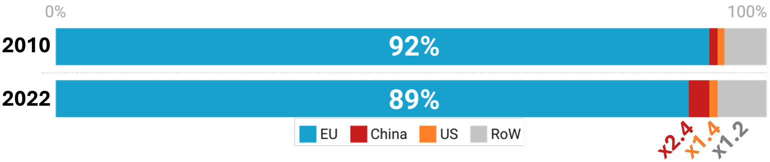

Figure 2: Origin of the value content of the EU car industry

This raises the following questions:

- Does the exposure to imported components differs between ICEs and EVs?
- To which extent the transition to EVs has influenced the decrease in the share of locally manufactured inputs in EU car manufacturing?

Application to the automotive sector: Data

FIGARO: Annual EU inter-country Input-Output tables (2017 – 2022)

Geographical coverage:

- The EU 27 Member States
- 18 main EU trading partners
- An aggregate with the rest of the world (RoW)

Sectoral coverage:

- 64 industry sectors (NACE 2-digit level)
  - C29, Manufacture of motor vehicles, trailers, and semitrailers

Production and trade data: PRODCOM, COMEXT (2017 – 2022)

Application to the automotive sector: Results (I)

Apply the methodology to three subsectors of the automotive industry:

- ICEs: internal combustion engine and mild hybrid vehicles
- EVs: battery electric and plug-in hybrid electric vehicles
- Parts: automotive parts

We find a higher import dependence for EVs (29%) than for ICEs (13%)

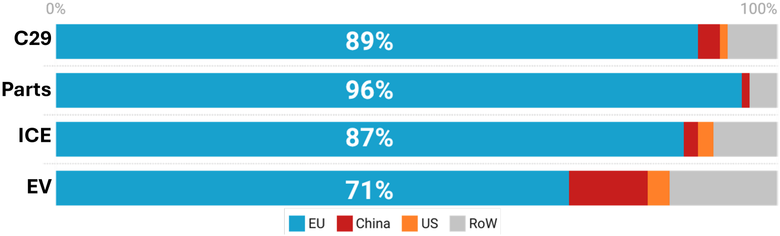

Figure 3: EU value content by industry segment (2022)

Application to the automotive sector: Results (II)

EVs rely more on inputs where the EU faces a technology-driven competitive disadvantage and less on those where the EU holds a dominant position (e.g. automotive manufacturing)

Technological gap

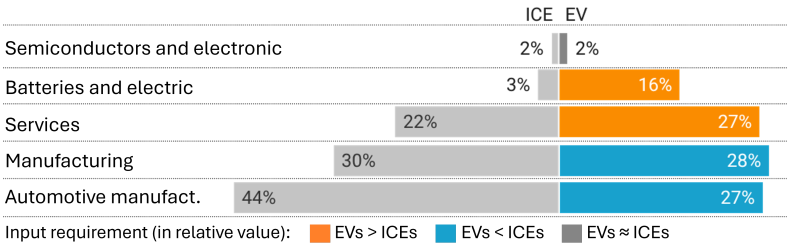

Figure 4: Shift in production technology from ICE to EV (relative value, 2022)

Application to the automotive sector: Results (III)

The transition from ICEs to EVs has come with significant additional outsourcing across all sectors of the value chain

Value chain shift

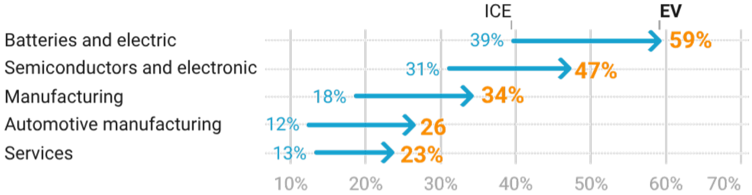

Figure 5: Input import dependence in ICE and EV production (2022)

Application to the automotive sector: Results (IV)

The shift in global value chains is the main reason (80%) behind the local content gap between EVs and ICEs

Which is the most important channel?

Figure 6: EV counterfactual scenario

Counterfactual analysis: keeping the same EU local content across the different sectors of the value chain for EVs as ICEs

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Main takeaways

- A new methodology to uncover hidden heterogeneity in IO tables
  easy to implement, uses publicly available data
- EVs are more import-dependent than ICEs
  disaggregating industry C29 reveals heterogeneity across the two segments
- The gap is mainly driven by sourcing choices, not a technology disadvantage
  around 80% reflects greater outsourcing by EV producers and only 20% a technology-driven competitive disadvantage
- Policy implication
  strengthening EU strategic autonomy calls for reducing outsourcing and boosting competitiveness in EV supply chains

Limitations and further work

Limitations:

The newly developed methodology:

- assumes that the production technology and foreign sourced input portfolio remain unchanged over the estimation period
- has difficulty identifying reliable coefficients when data collinearity is relatively high

Further work:

- Explore robustness of the estimation methodology
- Exploit geographical dimension (beyond time dimension) to potentially shorten the estimation period
- Application to other sectors (e.g. critical sectors/technologies)
- Explore heterogenous indirect effects of the value chain

References

- Wolsky, A. (1984) Disaggregating Input–Output Models. The Review of Economics and Statistics, 66, 283–291
- Lindner, Legault, and Dabo Guan (2012). Disaggregating input-output models with incomplete information. In: Economic Systems Research 24.4, pp. 329-347

Thank You!

Any questions or comments?

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