Input-Output Shock Propagation and Spectral Amplification

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Abstract

This paper studies how sector shocks spread through the 2018 production networks of France and Germany. We compare two simple input-output experiments. In the first, final demand in one sector is reduced by 25% and output is calculated with the static Leontief model. In the second, the short-run output limit of the shocked sector is reduced by 25% in a discrete-time model, while final demand stays at its baseline level. Because the two experiments change different parts of the model, their difference is treated as a scenario difference, not as pure dynamic amplification. We describe sector structure with the output multiplier, a forward-linkage index, and eigenvector centrality. The capacity experiment gives larger losses for suppliers, especially for the energy sector, while the C26 electronics shock has much smaller effects outside the shocked sector. France and Germany also have different network structures: energy has the highest eigenvector centrality in France, while business-service sectors have the highest values in Germany. The model follows changes in intermediate demand. It does not model physical input shortages, prices, inventories, substitution, or international trade.

Keywords: *input-output analysis, Leontief model, production networks, shock propagation, spectral centrality, capacity constraints, reshoring.*

1. Introduction

Sector shocks can spread through production networks from one industry to another. The pandemic, semiconductor disruptions, and the European energy crisis showed how important these links can be. In input-output analysis, it is important to separate a fall in final demand from a limit on production capacity, because these two cases answer different economic questions.

The classical input-output model, developed by Leontief [1], is the standard way to study how a change in final demand affects total output through intermediate inputs. Let A be the matrix of technical coefficients and d the vector of final demand. Sector output is then $x = (I - A)^{-1}d$. The model is simple and widely used, but it does not show how the economy adjusts over time and it does not include short-run production limits.

This paper compares the way shocks spread after a fall in final demand and after a fall in output capacity. We also study how the results are related to the position of the shocked sector in the production network. Following the network view of macroeconomic fluctuations [2], [3], we use three tools. First, we calculate standard input-output multipliers for France and Germany using OECD Inter-Country Input-Output data.

France and Germany are used as two comparison cases, not as examples that represent all of Europe. We choose them because they are large economies and because their network structures differ in the 2018 ICIO data. In 2025, Germany accounted for 23,8% of EU GDP and France for 15,8%, together making up 39,6% of the EU total [4].

Second, we use a simple discrete-time model with production limits: $x_{t+1} = \min\{\bar{x}, Ax_t + d_t\}$. Here, $\bar{x}$ is the vector of sector output limits. In the capacity experiment, the limit for the shocked sector is reduced to 75% of its baseline output. The limits for all other sectors stay at baseline, and final demand does not change. We therefore use baseline output as a simple proxy for short-run capacity. It is not meant to be an exact engineering maximum. Third, we describe each sector with the output multiplier, a forward-linkage index, and eigenvector centrality.

We apply both experiments to Electricity, gas, steam and air conditioning supply (sector D) and to Computer, electronic and optical equipment (sector C26). C26 is a broad electronics sector, not a pure semiconductor sector. We use it as a useful proxy in the context of the European Chips Act [5]. The energy experiment is motivated by the major European energy disruption in 2022 [6]. In the static benchmark, final demand in the selected sector falls by 25%. In the capacity experiment, the output limit of the selected sector falls by 25%.

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The results give four main points. First, the capacity experiment gives larger losses than the final-demand benchmark because it cuts gross output by 25%, while the static experiment cuts final demand by 25%. The difference should therefore not be called pure dynamic amplification of the same shock. Second, within each country and sector, the pattern of losses across sectors is close to a scaled version of the static result, so the capacity model changes the size of losses more than their ranking. Third, the energy shock has much larger effects on suppliers than the C26 shock. Fourth, the network measures differ clearly between France and Germany: energy has very high eigenvector centrality in France, while business-service sectors have the highest values in Germany.

2. Methodology

2.1 The Static Leontief Framework

Assume the economy has n sectors. Let $Z \in \mathbb{R}^{n \times n}$ be the matrix of transactions between sectors. The element Z_{ij} is the value of output from sector i used as an intermediate input by sector j. Let $x \in \mathbb{R}^n$ be the vector of gross sector output and $d \in \mathbb{R}^n$ the vector of final demand. The basic input-output identity is $x = Z1 + d$. The technical coefficient $a_{ij} = \frac{z_{ij}}{x_j}$ shows how much input from sector i is needed to produce one unit of output in sector j. Since $Z = A\,\mathrm{diag}(x)$, the Leontief solution is $x = (I - A)^{-1} d \equiv Ld$, where $L = (I - A)^{-1}$ is the Leontief inverse. Its column sums $m_j = \sum_i \ell_{ij}$ are output multipliers. They measure the total direct and indirect output created by one unit of additional final demand in sector j.

To model a final-demand shock, suppose sector j receives a shock of size $s_j \in [0,1]$. Its final demand becomes $d_j^{\text{shock}} = (1 - s_j)\, d_j$, and output becomes $x^{\text{shock}} = L\, d^{\text{shock}}$. The loss in sector i is $\text{loss}_i^{\text{FD}} = \frac{x_i^{\text{base}} - x_i^{\text{shock}}}{x_i^{\text{base}}} \cdot 100$. This is our final-demand benchmark. Other dynamic and network models show that adjustment limits and supply-chain links can change how shocks spread [7]-[9]. Our model below is simpler: it follows changes in intermediate demand to suppliers and does not model physical shortages of inputs.

2.2 A Dynamic Model with Capacity Constraints

We use a simple discrete-time model for the capacity experiment: $x_{t+1} = \min\{\bar{x}, Ax_t + d_t\}$. The minimum is applied to each sector. Here, Ax_t is intermediate demand from current production, d_t is final demand at time t, and $\bar{x}$ is the vector of output limits. The simulation starts from baseline output, and final demand stays at baseline. The shocked sector is limited to 75% of baseline output, while all other sectors stay at their baseline limits. Because the ICIO tables do not contain engineering capacity data, we use $\bar{x}$ as this simple short-run limit. When a sector produces less, it buys fewer intermediate inputs, so the effect moves upstream to its suppliers. The model does not represent physical input shortages moving downstream to customers.

If no capacity limit binds, the model converges to the static Leontief solution when the spectral radius of A is below 1. In the capacity experiment, the shocked sector reaches its limit immediately, while other sectors adjust as intermediate demand changes. More detailed models include additional channels [7]-[9]. The loss for sector i at the end of the simulation, period T, is $\text{loss}_i^{\text{cap}} = \frac{x_i^{\text{base}} - x_{i,T}}{x_i^{\text{base}}} \cdot 100$. The difference from the final-demand benchmark is $\text{gap}_i = \text{loss}_i^{\text{cap}} - \text{loss}_i^{\text{FD}}$. Since the two experiments change different parts of the model, a positive gap only means that the capacity case gives a larger loss. It does not prove that the static model underestimates the same shock.

2.3 Metrics of Systemic Importance

To describe each sector's place in the network, we use three measures. The first is the output multiplier, $m_i = \sum_i \ell_{ij}$, which measures backward links. The second is the forward-linkage index, $f_i = \sum_j \ell_{ij}$, which shows how strongly sector i appears in the total output needed across final-demand categories. The third is eigenvector centrality, based on the main right eigenvector of A [10]. This measure gives a high score to sectors that supply other central sectors. Let λ_1 be the largest eigenvalue of A, and let v_1 be its nonnegative right eigenvector, scaled so that its largest value is 1. The vector v_1 satisfies $v_{1,i} \propto \sum_j a_{ij} v_{1,j}$. This is a descriptive measure of supplier-side network position. It is different from the upstream effect produced by the dynamic model [2], [3].

Together, the three measures give different views of a sector's position in the network. They should not be treated as the same measure of risk. The output multiplier is directly linked to the effect of final-demand changes on suppliers. The forward-linkage index and eigenvector centrality describe other parts of the supply network. Differences between the measures are therefore useful information, not a contradiction.

3. Results

The analysis uses the 2021 edition of the OECD Inter-Country Input-Output (ICIO) tables [11]. These tables give harmonised data on production links within and between countries. We use France and Germany for the reference year 2018 because this is before the COVID-19 pandemic and the 2022 European energy crisis. The experiments should therefore be read as simulated shocks applied to the 2018 production structure. After sectors with zero output or empty rows and columns are removed, the sample contains 44 domestic sectors in each country.

For each country, we run two experiments for sector D and sector C26. The final-demand benchmark reduces final demand in the selected sector by 25%. The capacity experiment keeps final demand unchanged but reduces the selected sector's output limit by 25%. The two experiments therefore use the same 25% number but do not represent the same shock. C26 means the broad Computer, electronic and optical equipment sector, not a pure semiconductor sector. The dynamic simulations start from baseline output and run for 20 periods; the paths become stable within this period.

3.1 Systemic Importance and Network Structure

Before looking at the shocks, we first compare the positions of sectors in the two production networks. Table 1 shows the five sectors with the highest eigenvector centrality in each country, together with their output multipliers and forward-linkage values.

Country	Sector	Output multiplier	Forward linkage	Eigenvector centrality
France	D (Energy)	2,30	3,80	1,000
	M (Professional services)	1,64	4,98	0,223
	K (Financial services)	2,02	4,15	0,202
	N (Administrative services)	1,60	4,89	0,195
	G (Wholesale and retail)	1,65	4,76	0,104
Germany	M (Professional services)	1,61	4,27	1,000
	N (Administrative services)	1,58	3,52	0,526
	K (Financial services)	1,77	2,59	0,517
	L (Real estate)	1,39	2,62	0,465
	G (Wholesale and retail)	1,62	4,11	0,446

Table 1. Top five sectors by eigenvector centrality in France and Germany (2018)
Note: Sectors are ranked by eigenvector centrality of the technical coefficient matrix A, normalised so that the maximum value equals one. Output multiplier is the column sum of the Leontief inverse; forward linkage is its row sum. Own calculations based on OECD ICIO data

The two countries show a clear difference. In France, the electricity, gas and steam sector (D) has the highest output multiplier in the table, 2,30, and by far the highest eigenvector centrality, set to 1. The next sector, professional services (M), has a centrality of only 0,223. In Germany, professional services (M) is the most central sector, followed by administrative services (N), financial services (K), real estate (L), and wholesale and retail trade (G). The energy sector (D) is sixth, with a centrality of about 0,28. Energy is therefore especially important in the French centrality ranking, while service sectors hold most of the top positions in Germany.

These differences help explain the shock results, but no single measure is enough to predict losses. The capacity model passes lower intermediate demand upstream to suppliers, while eigenvector centrality gives a broader view of a sector's position in the supply network. We therefore use the measures together as descriptive indicators.

3.2 The Energy Shock

Table 2 shows the results of the energy-sector experiments. In the final-demand benchmark, a 25% fall in final demand for sector D reduces gross output in that sector by 10,98% in France and 11,59% in Germany. The output loss is smaller than 25% because final demand is only one part of the sector's total sales; demand from other sectors is not reduced directly. The largest secondary losses are found among suppliers to sector D. In France, coal mining loses 4,38% of output and oil and gas extraction loses 2,65%. In Germany, the corresponding losses are 6,89% and 1,83%. These numbers describe the 2018 input-output structure and should not be read as current energy-system data.

In the capacity experiment, the output limit of sector D is set to 75% of baseline, so the 25% loss of sector D is imposed directly. Lower output in sector D reduces its demand for intermediate inputs and therefore reduces output among its suppliers. In France, coal mining loses 9,96% in the capacity case, compared with 4,38% in the final-demand benchmark. Oil and gas extraction moves from 2,65% to 6,03%. The ratio between capacity losses and final-demand losses is about 2,28 for almost all reported French sectors. This almost constant ratio is not a separate amplification effect. With one binding capacity limit and linear input-output links, changing the size of the shock mainly scales the whole loss pattern. More generally, production-network research shows how input-output links spread sector shocks through the economy [2], [12].

Country	Sector	Static loss (%)	Dynamic loss (%)	Amplification (pp)
France	D (Energy, shocked)	10,98	25,00	14,02
	B05 (Coal mining)	4,38	9,96	5,58
	B06 (Oil and gas)	2,65	6,03	3,38
	B09 (Mining support)	0,47	1,07	0,60
	C19 (Coke, petroleum)	0,26	0,60	0,34
	E (Water, waste)	0,24	0,54	0,30
Germany	D (Energy, shocked)	11,59	25,00	13,41
	B05 (Coal mining)	6,89	14,86	7,97
	B06 (Oil and gas)	1,83	3,95	2,12
	C19 (Coke, petroleum)	0,42	0,91	0,49
	M (Professional services)	0,31	0,67	0,36
	C23 (Non-metallic minerals)	0,32	0,69	0,37

Table 2. Sectoral output losses from a 25% energy shock (sector D)
Note: Static losses are obtained from with shocked final demand. Dynamic losses are computed at from the constrained model. Amplification is the difference in percentage points.

Germany shows the same basic pattern. The loss of sector D is 25% by construction in the capacity experiment, while the coal-mining loss rises from 6,89% in the final-demand benchmark to 14,86% in the capacity case. The ratio is about 2,16 across the reported sectors, apart from rounding. The largest absolute differences appear in sectors that were already most exposed in the final-demand benchmark. Figure 1 shows this comparison. The main difference between the countries is therefore which suppliers are exposed and how strongly, not a separate country-specific dynamic amplification factor.

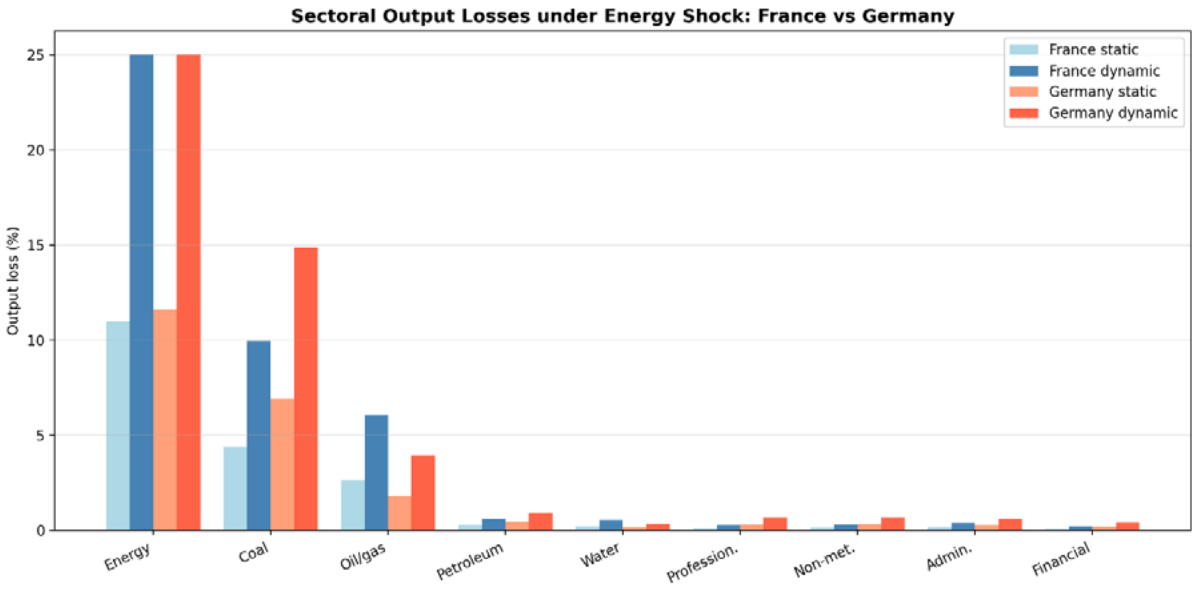


Figure 1. Sectoral output losses following a 25% energy shock in France and Germany, under the static Leontief model and the dynamic constrained model.

3.3 The C26 Electronics Shock

The C26 experiment gives a useful comparison because Computer, electronic and optical equipment has a much less central position in the reported network measures. In the final-demand benchmark, C26 output falls by 22,65% in France, close to the 25% fall in final demand. Losses in all other reported sectors stay below 0,4%. In the capacity experiment, C26 is forced to a 25% output loss, but effects on suppliers stay below 1%. Because the final-demand shock already gives a gross-output loss close to 25%, the two cases are much closer than in the energy experiment.

Country	Sector	Static loss (%)	Dynamic loss (%)	Amplification (pp)
France	C26 (Semiconductors, shocked)	22,65	25,00	2,35
	C25 (Fabricated metals)	0,38	0,42	0,04
	C24B (Non-ferrous metals)	0,31	0,34	0,03
	C22 (Rubber and plastics)	0,26	0,28	0,03
	C23 (Non-metallic minerals)	0,24	0,26	0,02
Germany	C26 (Semiconductors, shocked)	22,66	25,00	2,34
	C24B (Non-ferrous metals)	0,83	0,91	0,09
	H53 (Postal services)	0,69	0,76	0,07
	J62 63 (IT services)	0,37	0,41	0,04
	M (Professional services)	0,36	0,39	0,04

Table 3. Sectoral output losses from a 25% semiconductor shock (sector C26)
Note: Same specification as Table 2. Only the shocked sector and the top downstream sectors are reported.

Germany differs mainly in the size and spread of the supplier effects. The final-demand loss of C26 is 22,66%, while several other sectors have losses of about 0,3% to 0,9%. The capacity values are only slightly larger. The calculated eigenvector centrality of C26 is about 14 times higher in Germany than in France. In this model, however, the affected sectors are suppliers to C26 because lower C26 output reduces demand for intermediate inputs. The results should not be read as shortages in industries that use semiconductors. More generally, supply-chain studies show that network structure matters for the spread of shocks, although those studies use richer models than the simple model used here [8], [9].

3.4 Final-Demand Benchmark versus Capacity-Constrained Propagation

Across the four country-sector cases, the capacity experiment gives losses that are at least as large as the final-demand benchmark. This does not mean that the static Leontief model always underestimates the same shock, because the two experiments change different parts of the model. Within each case, the ratio of capacity loss to final-demand loss is nearly constant across affected sectors: about 2,28 for the French energy experiment, 2,16 for the German energy experiment, and about 1,10 for the C26 experiment in both countries. This shows that the current capacity model mainly changes the size of the static loss pattern rather than the ranking of affected sectors. Network structure determines which suppliers are exposed, while the size and type of the shock mainly determine the scale of the losses.

Figure 2 compares final-demand losses with capacity losses in all four cases. Points above the 45° line have larger losses in the capacity experiment. Because the two cases use different shocks, the distance from the line is a scenario difference, not a pure measure of dynamic amplification.

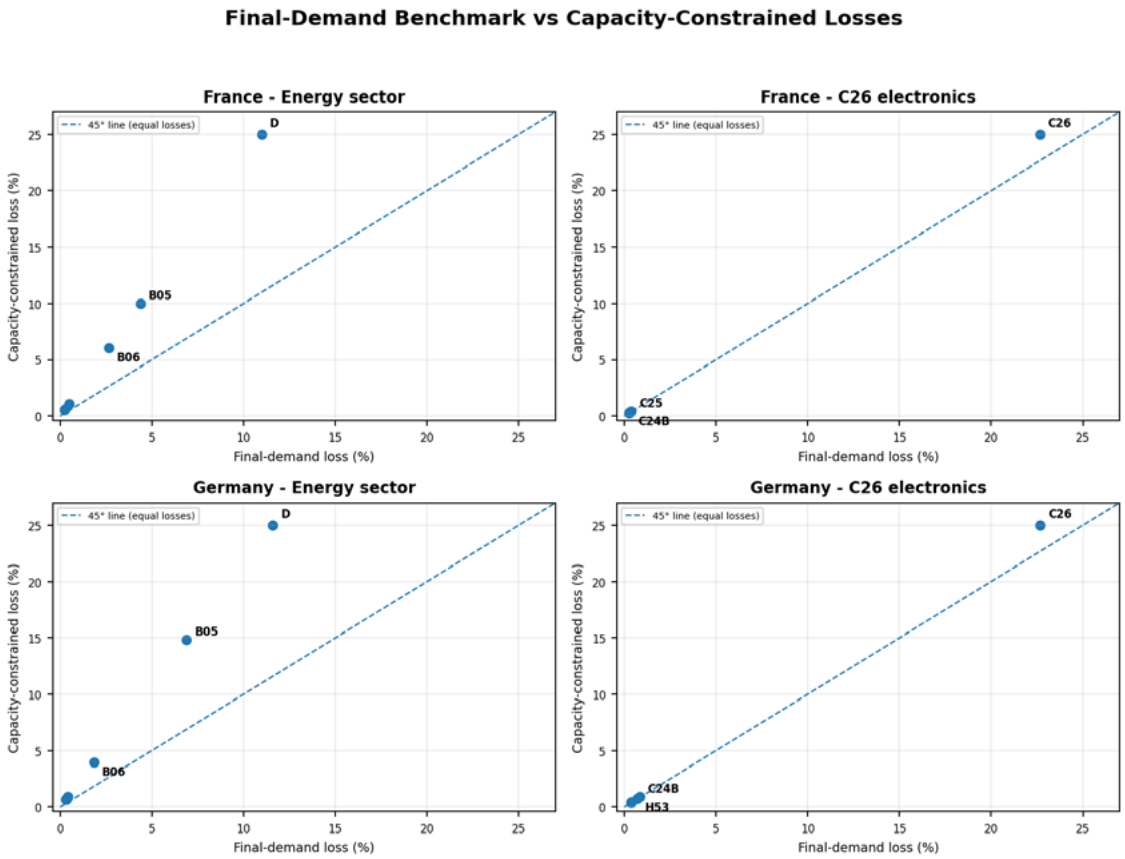


Figure 3 shows how output changes over time for the six most affected sectors in each capacity experiment. The effects on suppliers do not appear at once. Lower intermediate demand moves through the model over several periods before the system becomes stable. These paths show changes in demand for inputs, not physical shortages moving downstream

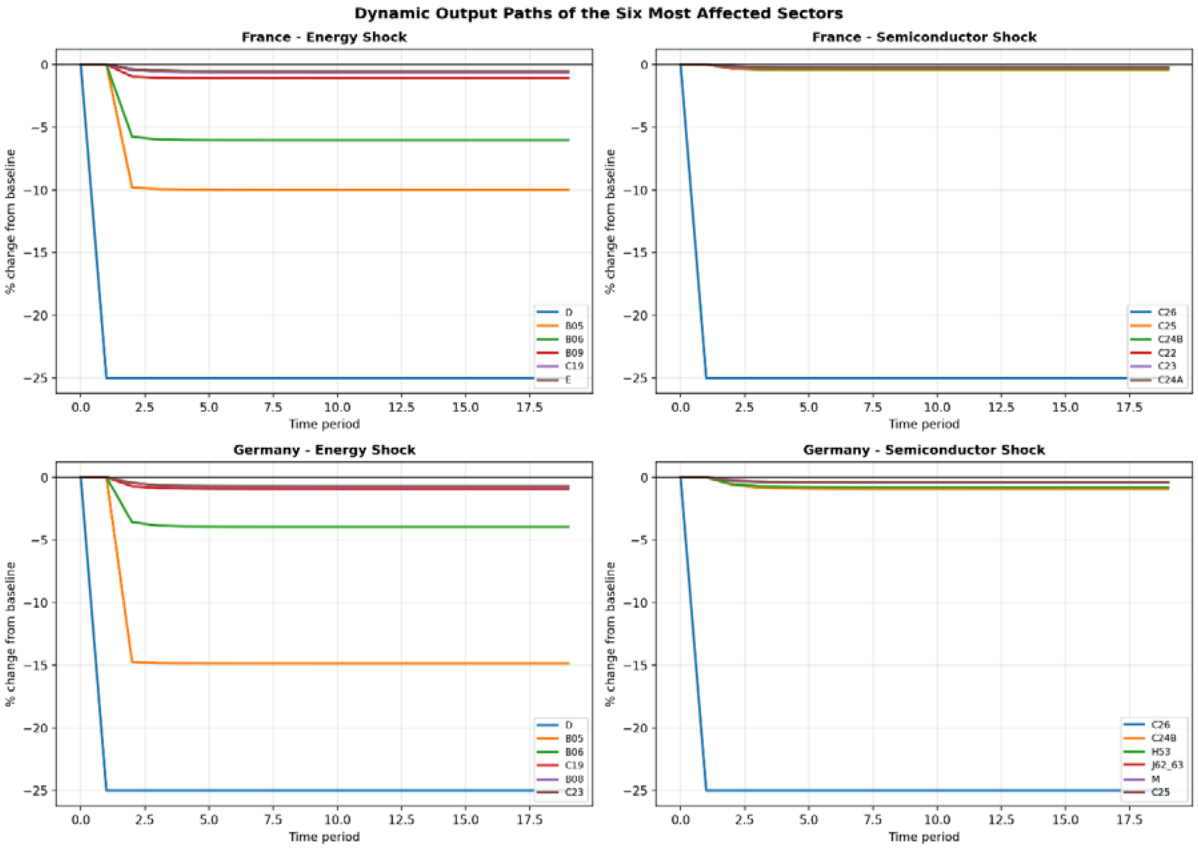


Figure 3. Simulated dynamic output paths for the six most affected sectors in each scenario over a 20-period horizon.

4. Discussion

The results give three broader points. First, the two experiments should be compared as two different shock definitions, not as a direct test of static versus dynamic accuracy. A 25% cut in gross-output capacity is stronger than a 25% cut in final demand when final demand is only part of the sector's sales. If the same negative final-demand shock is used in both models, the baseline output limit may not bind. When the spectral radius of the technical-coefficient matrix is below 1, the simple unconstrained dynamic model converges to the static Leontief result. A true comparison of dynamic amplification would therefore need the same outside shock in both models and extra features such as inventories, input bottlenecks, or explicit production functions, as in richer dynamic input-output models [7]. The static Leontief model still remains a useful accounting benchmark [13].

Second, the country comparison shows differences in supplier exposure in the 2018 ICIO structure. In France, the energy-sector shock gives sizeable losses for coal, oil and gas, and other suppliers. In Germany, the response of coal mining is especially strong. These results come from the 2018 input-output coefficients and should not be treated as statements about today's energy mix or energy policy without newer data.

Third, the C26 results do not prove either resilience or dependence on imports. The model uses domestic production links and does not model international sourcing directly. Weak domestic propagation therefore only means that supplier effects inside the modelled network are small. The European Chips Act aims to strengthen Europe's semiconductor sector [5], but studying how reshoring changes risk would require explicit trade links and a model in which input shortages can limit downstream customers. A possible 'reshoring paradox' should therefore be treated as a question for a larger model, not as a result proved by this analysis.

5. Conclusion

This paper combines the standard input-output model, a simple dynamic model with capacity limits, and network measures for France and Germany. Four conclusions follow. First, a 25% final-demand shock and a 25% output-capacity shock are different shocks, so the larger losses in the capacity case should not be called dynamic amplification of the same shock. Second, within each country and sector, the capacity loss pattern is close to a scaled version of the final-demand result, so the current model changes the size of losses more than their ranking. Third, the energy-sector shock has much stronger effects on suppliers than the C26 electronics shock. Fourth, France and Germany have different supplier-network structures: energy is especially central in France, while business-service sectors hold the highest centrality positions in Germany.

The model is intentionally simple. Useful next steps would be to use the same outside shock in different model versions, add inventories and limits on specific inputs, allow substitution and price changes, and include international trade directly. These additions would be needed to study physical supply shortages, downstream effects, or dependence on imports. In its current form, the model is best seen as a clear example of how lower intermediate demand can spread upstream through suppliers and how network structure differs between countries.

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THE USE OF AI TOOLS

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