CONNECTIVITY AND CONTAGION: HOW INDUSTRY NETWORKS SHAPE THE TRANSMISSION OF SHOCKS IN GLOBAL VALUE CHAINS

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Connectivity and Contagion: How Industry Networks Shape the Transmission of Shocks in Global Value Chains

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Abstract

We study how disruptions propagate through global value chains and how network structure conditions their effects. Using Eora country–industry data for 189 countries and 26 industries (1996–2015), shocks are defined by a distribution-based rule; exposure counts disrupted upstream/downstream partners, and redundancy counts non-disrupted pre-existing links. We estimate fixed-effects impact models—where robustness is smaller contemporaneous deterioration conditional on exposure—and a grouped-time complementary log–log hazard—where resilience is faster return to the pre-shock level. Two findings emerge. First, exposure propagates, depressing output, value added, and exports and slowing recovery. Second, redundancy mitigates, offsetting the impact and raising the recovery hazard. As an illustration, high-technology activities appear less sensitive on impact and recover faster than low-technology ones, with the advantage explained by higher redundancy despite deeper connections. These results suggest strengthening robustness and resilience by deepening GVC integration through strategic redundant linkages, rather than retreating from openness.

Keywords : Global Value Chains; Business cycle shocks; High-Technology.
JEL codes: F14; F15; F44;

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1 Introduction

Since the 1990s, the rise of Global Value Chains (GVCs) has profoundly reshaped the global organization of production and consumption through the international fragmentation of production processes. This new paradigm of international trade — involving trade in parts and components and the specialization of countries in tasks rather than final goods — has been extensively described and its causes explained (Baldwin, 2006; Grossman and Rossi-Hansberg, 2008). The restructuring of global production has been driven by firms' strategies to optimize production processes in an increasingly open world, facilitated by advances in information and communication technologies (ICT) that enable the coordination of globally distributed production. While offshoring certain parts of the production process is motivated by efficiency gains, particularly for the most productive firms (Antràs and Helpman, 2004; Antràs and Chor, 2013), it has also introduced new vulnerabilities. The increasing length and complexity of production chains have strengthened vertical linkages between countries and industries, heightening the risk that a local economic shock could propagate widely through the network, creating global disruptions (Acemoglu et al., 2012).

Extensive research has shown that production networks can function as a mechanism for the propagation of shocks throughout the economy (see Carvalho and Tahbaz-Salehi (2019) for a review). Particularly, idiosyncratic shocks are transmitted from suppliers to customers (Barrot and Sauvagnat, 2016; Boehm et al., 2019), and interlinkages between firms and sectors can amplify micro-level shocks into aggregate fluctuations (Acemoglu et al., 2012). Although only a minority of firms are directly involved in exports, international production linkages are critical for shock transmission, as even small and medium-sized enterprises (SMEs) participate indirectly in GVCs (Dhyne et al., 2021; UNCTAD, 2013). The vulnerability created by these linkages became evident during the Global Financial Crisis (2008–2009) (Gangnes et al., 2012) and the COVID-19 pandemic (2020) (Gerschel et al., 2020), which exposed the fragility of global supply chains. Although international trade growth slowed after the Global Financial Crisis, there is not yet clear evidence of deglobalization that would reduce those risks (Antràs, 2020; Gaulier et al., 2020).

Yet, densifying production networks can also mitigate disruptions if it creates new alternatives when a given link fails (i.e - providing "redundant" linkages). The literature on production network traditionnaly distinguishes two margins of shock management. Robustness refers to the ability to sustain operations during a disturbance, whereas resilience denotes the capacity to adjust and promptly return to normal performance after the disturbance. Recent surveys on risk transmission in supply chains (e.g., Baldwin and Freeman (2022); Miroudot (2020b,a)) adopt these definitions, grounded in formal works of Brandon-Jones et al. (2014) for robustness and Sá et al. (2020) for resilience.

Diversification, and more precisely redundancy, on the supplier or purchaser linkages can support both margins of shock management. The case for robustness is straightforward: as stated by (Miroudot, 2020b, p.123), "redundancy in suppliers is a robustness strategy", since firms with diversified sources can reallocate and keep producing when a disruption occurs—precisely the notion of robustness in Brandon-Jones et al. (2014). This statement is seconded by (Baldwin and Freeman, 2022, p.158) affirming "Building robustness typically requires establishing redundancy when it comes to external suppliers". While increasing redundancy is also generally regarded as a solution to develop organizational resilience by scholars in business organization (see Sheffi (2005)), the empirical evidence is more mixed at the firm level: Miroudot (2020a) reviews studies showing contrasted effects of redundancy on post-shock recovery, but emphasizes that flexibility, often enabled by redundant options, helps resilience. These firm-level insights complement the documented heterogeneity in network transmission, where input specificity and partner size shape the strength of propagation across production links (Barrot and Sauvagnat, 2016; Arata and Miyakawa, 2022), and clearly show that the structure of connectivity matters to study contagion in production networks.

At a broader level, cross-industry differences in Global Value Chains positioning and connectivity are well documented (Antràs and Chor, 2018; Nicita, 2023; Johnson and Noguera, 2012; UNCTAD, 2013). A natural implication is that industries with distinct supplier–buyer architectures won't benefit from the same robustness and resilience when exposed to GVC-related risks. It appears that technology offers a useful organizing dimension for investigating this heterogeneity: high-tech industries tend to be more deeply embedded in multi-stage value chains and to occupy different positions than low-tech activities. In particular, participation and fragmentation are markedly higher in electronics than in sectors such as textiles and apparel, reflecting longer chains and greater foreign value-added content.

At last, when studying the propagation of shocks in production networks, the literature extensively examined upstream shocks that transmit from the supplier to the buyer, following the downstream propagation modeled in Acemoglu et al. (2012). To the contrary, the transmission of downstream shocks, from purchasers to suppliers, through GVCs remained relatively underexplored until more recently with notably Kramarz et al. (2020) or Herskovic et al. (2020) offering a network model where shocks to customers influence their suppliers. Empirically, (Arata and Miyakawa, 2022) show that adverse upstream shocks also propagate through firm-level input-output linkages, during both the Global Financial Crisis and the COVID-19 pandemic.

Therefore, the aim of this paper is threefold: First, we want to evaluate the transmission of shocks in the Global Value Chains simultaneously considering upstream and downstream disruptions at industry-level. Second, we aim to estimate the effectiveness of diversification strategies on industries' resilience and robustness. Third, we want to highlight the illustrative example of High-Tech industries, which, despite greater inclusion in GVCs are less sensitive to GVC shocks than Low-Tech, notably because they benefit from those duplicate or redundant linkages fostering both their robustness and resilience.

The rest of the paper is structured as follows: Section 2 describes the reconstruction of GVCs from international input-output tables and construction of industry-level variables of connectivity redundancy and exposure to shocks. Section 3 provides some descriptive statistics of connectivity patterns in GVCs, and their cross-industry heterogeneity. Section 4 presents the estimations strategies for our three hypothesis. Section 5 presents and interpret the results. Section 6 concludes with a discussion of the broader implications of cross-sector heterogeneous sensitivity to shock transmissions.

2 GVC Data and variable construction

2.1 GVCs networks

In contrast to gross trade flows, global value chains (GVCs) are not directly observable. As reviewed by Amador and Cabral (2016), several approaches have been proposed to gauge their expansion, including the share of trade in intermediates (e.g. Ng and Yeats (1999)) and customs-based measures of processing trade (e.g. Egger and Egger (2005)). The only approach that provides a comprehensive view of the global production network relies on input–output (IO) tables. Some studies use the international IO coefficient matrix directly to characterize the position of a country–industry within GVCs (Criscuolo and Timmis, 2018a,b), but most exploit IO frameworks to separate domestic from foreign value added in exports. Early work by Hummels et al. (2001) using national IO tables established the "vertical specialization" measure. With the advent of international IO (IIO) datasets (see Tukker and Dietzenbacher, 2013), Daudin et al. (2011) and Johnson and Noguera (2012) computed value-added trade at the country level, and Koopman et al. (2014) provided a general decomposition of gross exports into domestic and foreign content.

This decomposition underpins much of the empirical GVC literature, notably the OECD Trade in Value Added (TiVA) indicators constructed from the ICIO tables (Guilhoto et al., 2022). The same methodology has been applied to other IIO sources, including Eora (Casella et al., 2019; IMF, 2016). Extending to the country–industry level is straightforward conceptually—one simply refrains from aggregating sectors across countries—and has been implemented with WIOD by Amador and Cabral (2017) and with Eora by Aslam et al. (2017).

Our reconstruction follows Aslam et al. (2017), and use Eora MRIO. Let $\mathbf{X}$ denote gross output, $\mathbf{A}$ the matrix of IO coefficients (intermediate inputs per unit of output), and $\mathbf{Y}$ final demand, each provided in Eora. The basic IO identity gives

$$\mathbf{X} \;=\; \mathbf{A}\cdot\mathbf{X} \;+\; \mathbf{Y} \quad\Rightarrow\quad (\mathbf{I}-\mathbf{A})\cdot\mathbf{X} \;=\; \mathbf{Y} \quad\Rightarrow\quad \mathbf{X} \;=\; (\mathbf{I}-\mathbf{A})^{-1}\cdot\mathbf{Y} \;\equiv\; \mathbf{L}\cdot\mathbf{Y}, \tag{1}$$

where $\mathbf{L} = (\mathbf{I}-\mathbf{A})^{-1}$ is the global Leontief inverse of dimension $CI \times CI$ (with C countries and I industries). Define $\mathbf{V}$ as the diagonal matrix of value-added shares, with diagonal elements $\mathbf{V}_{ii} \;=\; 1-\sum_j \mathbf{A}_{ji}$. Let $\mathbf{E}$ be a diagonal matrix of gross exports (obtained by subtracting domestic final demand from gross output, as provided in Eora). Therefore we could obtain the country–industry TiVA matrix through

$$\mathbf{TiVA} \;=\; \mathbf{V}\cdot\mathbf{L}\cdot\mathbf{E}. \tag{2}$$

This expression is analogous in spirit to Hummels et al. (2001)—who compute import content of exports based on import coefficients—but here it is framed in value-added terms using a global Leontief inverse and applies at the country–industry level ($CI \times CI$).

Global multiregional input–output (MRIO) tables have also been used to simulate shocks via global variants of the hypothetical extraction method (HEM/GEM), which remove a country–industry (or a link) to assess counterfactual output losses (Dietzenbacher et al., 2019). While informative about potential structural dependence, these simulations rely on fixed-coefficient IO technology and—as Dietzenbacher and Miller (2015) emphasize—do not capture the post-shock rebalancing of links. Our objective is different: we study the propagation of *realized* shocks. We therefore abstain from HEM/GEM and, following Casella et al. (2019) and IMF (2016), treat the TiVA matrix as a "final GVC matrix" that is, a panel recording value added from any (c, s) embedded in any partner (p, k). As is customary, we set very small flows to zero (below USD 10,000) to remove marginal links.

We build the panel from 1996 to 2015. The endpoint is deliberate: post-2015 Eora vintages are not fully comparable due to partial retroactive revisions[1].

2.2 Shocks and Exposure to shocks in GVCs

We adopt a distribution-based shock definition, widely used in empirical macro and supply-chain studies because it provides a scale-free, volatility-adjusted threshold that is comparable across industries and countries and permits transparent sensitivity checks: an upstream supply disruption is recorded when the year-on-year log change in a supplier's exports for country–industry (c, s) falls at least one within-series standard deviation below its own time-series mean, i.e.,

$$\Delta \log X_{cst} \;\leq\; \overline{\Delta \log X}_{cs} \;-\; \sigma_{cs},$$

where $\overline{\Delta \log X}_{cs}$ and σ_{cs} are computed within (c, s) over the sample period.

Similarly, we identify the generation of downstream shocks using the same distribution based variation on imports of intermediates goods. Before identifying exposed partners through input-output linkages, let's describe the distribution of these shocks. We find that 13.53% of our 98,280 country-industry-year observations consist in an upstream shock. However, shocks are not distributed evenly across time as 30% of them occurred in 2009 with the great trade collapse led by the financial crisis. The same year, around 78% of suddenly reduced their exports, disrupting GVCs. 14.77% of industries create sudden downstream bottlenecks as they yearly reduce their

[1] See the Eora FAQ: "We observe data jumps from 2015 to 2016. Why is this?"

imports in intermediates by at least a standard deviation, with here again a disproportion of shocks occurring in 2009 (39%).

We aim to identify whether sudden export contractions propagate through global value chains as adverse supply shocks affecting downstream industries, and whether sudden import contractions propagate upstream as demand shortfalls. We measure exposure to partner-side disruptions as the contemporaneous count of pre-existing upstream (downstream) partners that are disrupted. Using the distribution-based shock definition described above, for home country–industry $i = (c, s)$ we define the *Upstream Disruption Exposure* (UDE) and the *Downstream Disruption Exposure* (DDE) as follows:

$$\mathrm{UDE}_{i,t} = \sum_{k} \sum_{p \neq c} T^{\mathrm{up}}_{i,(p,k),t-1}\, US_{(p,k),t}, \tag{3}$$

$$\mathrm{DDE}_{i,t} = \sum_{k} \sum_{p \neq c} T^{\mathrm{down}}_{i,(p,k),t-1}\, DS_{(p,k),t}, \tag{4}$$

where $T^{\mathrm{up}}_{i,(p,k),t-1}$ and $T^{\mathrm{down}}_{i,(p,k),t-1} \in \{0, 1\}$ indicate pre-existing upstream and downstream linkages at $t-1$, while $US_{(p,k),t}$ and $DS_{(p,k),t} \in \{0, 1\}$ flag upstream and downstream disruptions at t. We lag the linkage indicator so that exposure and redundancy are computed from the *pre-shock* network. Specifically, $T_{i,(p,k),t-1}$ records whether home unit i maintained an upstream (or downstream) linkage to partner (p, k) in period $t-1$. Using contemporaneous links $T_{i,(p,k),t}$ would be problematic because a disruption at t can induce immediate re-wiring (dropping or adding partners), thereby confounding the effect of the disruption with firms' reactions. Counting partners in t would then understate true exposure and overstate redundancy by "missing" shortages that are themselves a consequence of the shock. Conditioning on the link set that existed in $t-1$ asks how a disruption in t affects the partners that were actually in place beforehand, which reduces simultaneity concerns.

2.3 Diversification of connection and mitigation strategies

As discussed in the introduction, the magnitude of shock propagation in a production network is dependent on the network structure, particularly in the existence of redundant linkages acting as potential substitute suppliers/buyers that help to mitigate the shock (Baldwin and Freeman, 2022; Miroudot, 2020a).

We define redundant upstream linkages as pre-existing input-sourcing ties from other countries in the same input industry k that remain undisrupted at date t. For a home country–industry $i = (c, s)$, let $T^{\text{up}}_{i,(p,k),t-1} \in \{0, 1\}$ indicate whether i sourced from partner (p, k) in $t-1$ (a predetermined link), and let $US_{(p,k),t} \in \{0, 1\}$ flag an upstream disruption for (p, k) at t (equal to 1 when disrupted). Let (RUA), the *Redundant Upstream Availability*, be our final redundancy index for upstream linkages. It counts the number of non-shocked redundant links available to substitute a shocked supplier in industry k:

$$\text{RUA}_{i,k,t} \;=\; \sum_{p \neq c} T^{\text{up}}_{i,(p,k),t-1} \left(1 - US_{(p,k),t}\right). \tag{5}$$

Higher values of $\text{RSA}_{i,k,t}$ indicate greater immediate scope to divert orders to already-connected, non-disrupted foreign suppliers within the same input industry, while lagging T^{up} helps limit simultaneity concerns. That way, RUA reflects pre-existing upstream ties rather than connections that firms might add or drop in response to a disruption in year t. Using contemporaneous links would confound the effect of the disruption with immediate re-wiring, creating simultaneity. The lagged definition therefore captures the substitution options that were available before the shock and avoids mechanically losing links when trade collapses in the shock year.

Analogously, we define *redundant downstream linkages* as pre-existing downstream ties to other countries in the same downstream use industry k that remain undisrupted at date t. Let $T^{\text{down}}_{i,(p,k),t-1}$ indicate a pre-existing downstream linkage and $DS_{(p,k),t}$ a downstream disruption flag. Similarly as above, our redundancy index for downstream connections, the *Redundant Downstream Availability* (RDA), is

$$\text{RDA}_{i,k,t} \;=\; \sum_{p \neq c} T^{\text{down}}_{i,(p,k),t-1} \left(1 - DS_{(p,k),t}\right). \tag{6}$$

3 Descriptive Statistics of GVCs Structure.

3.1 Global Value Chains indicators

Table 1 shows that country–industries are, on average, connected to many partners (the average in- and out-degree of 42.6, is equal by construction as each edge is simultaneously outward for one and outward for the second partner, leading to the same total count, and the same

	In. degree	out. degree	UDE	DDE	RUA	RDA
mean	42.6	42.6	.32	.34	.20	.21
sd	144.5	116.2	4.5	3.8	4.3	3.4
min	0	0	0	0	0	0
p05	0	0	0	0	0	0
p50	2	1	0	0	0	0
p95	279	264	6	8	2	3
max	2217	1650	488	272	265	213
skewness	5.4	4.4	43.2	27.2	48.9	32.5

Table 1: Descriptive Statistics of main variables

average.), yet the medians (2 and 1) reveal a network dominated by a few highly connected hubs. Exposure to disruptions is low in typical years (mean UDE $\approx$ 0.32, DDE $\approx$ 0.34), but the right tails are long (95th percentiles of 6–8; maxima far larger), indicating episodic, concentrated stress. Redundancy is even sparser on average (means $\approx$ 0.20–0.21), suggesting that many units have few immediate non-disrupted alternatives when shocks occur. The finding of sparcity (few average degrees) and high centralization of GVCs' networks is in line with existing network analysis of the World Trade Web and of Global Value Chains that detailed a similar core-periphery network structure Amador and Cabral (2017); De Benedictis and Tajoli (2011); Cerina et al. (2015). Also, these patterns speak directly to the paper's questions: the fat-tailed exposure motivates a distribution-based shock definition; the divergence between degree and redundancy justifies treating connectivity and substitutability as distinct margins; and the strong heterogeneity in these variables provides a basis for the documented differences in robustness and resilience across industries, including the technology gap explored below.

3.2 Structural evolution

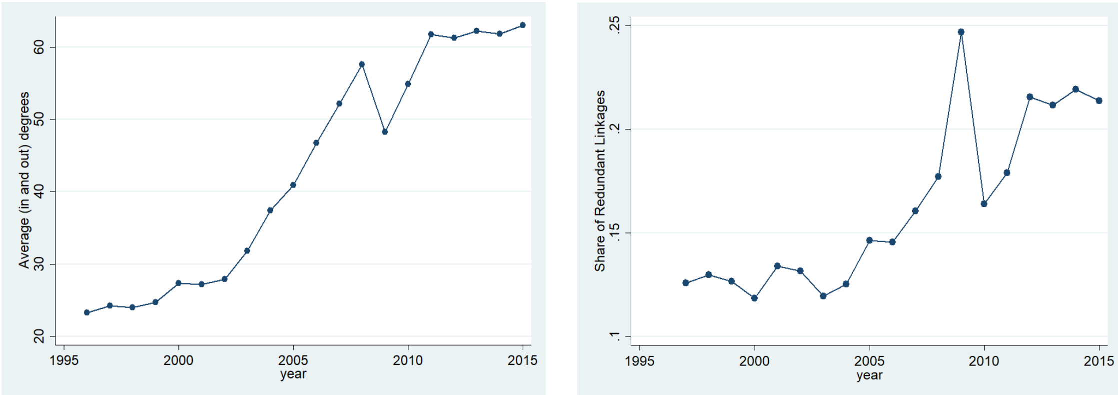
The network analysis of Global Value Chains as estimated through the $\mathbf{TiVA_t}$ matrices confirm that since the mid-1990s GVCs developed at a fast pace, increasing global production's reliance on international input-output linkages. Figure 1 shows the evolution the average degree (i.e. connections) by country-industry in GVCs. This figure is consistent with what has already been shown in GVCs evolution (notably by Amador and Cabral (2017); Amador et al. (2018), with an increase of connectivity in the 2000s, followed by a shock in 2009 and a slowdown in the 2010s, but no perceible "de-globalization" trend. To the contrary, we find that the average connectivity has been multiplied by a factor 2.5 in 15 years. When industries had on average

23 other suppliers and buyers industries in the late 1990s, they reached 63 GVCs connections in 2015.

This increased in connectivity drastically reduced the distance between any two industries, which should logically foster shock transmissions of business cycles along the international production network. While one could believe this increase in connectivity would foster the transmissions of business cycles along the international production network, it is worth noting that the average share of redundant upstream or downstream linkages has grown even faster

Figure 1: Increased connectivity and redundancy in GVCs

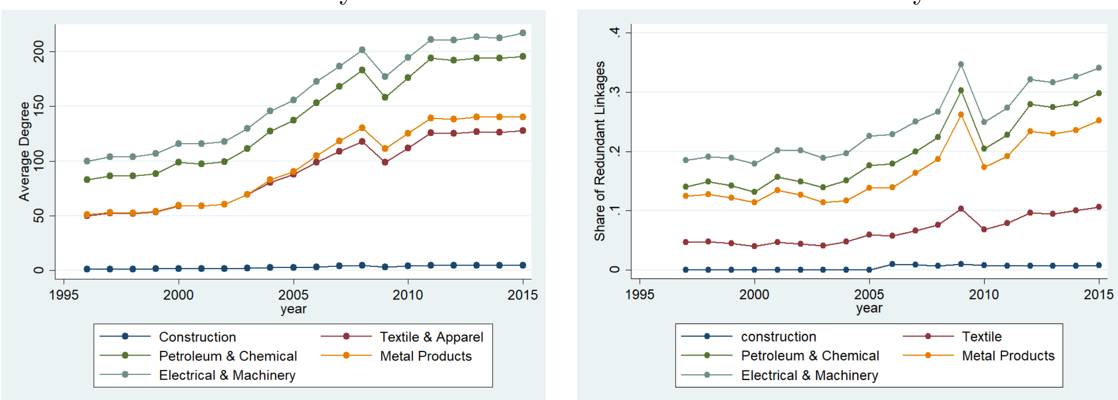
Connectivity Redundancy



3.3 Sectoral heterogeneity in connectivity patterns

Figure 2: Increased connectivity and redundancy in GVCs

Connectivity Redundancy



The previous statements hinders a wide sectoral heterogeneity as we show in figure 2 Using five illustrative sectors drawn from the full set of twenty-six, the figures show a generalized rise in average upstream degree from the mid-1990s, with a discrete step-up around the 2008–09 crisis that largely persists thereafter. However, the magnitude of this expansion is highly uneven: Electrical & Machinery increases from roughly 100 upstream partners in the mid-1990s to above 210 by 2015, while Petroleum & Chemical climbs from about 80 to nearly 200. Metal Products and Textile & Apparel also diversify—each roughly doubling from around 50 to 130—whereas Construction remains essentially flat in single digits. The share of redundant upstream linkages also trends upward but not in lockstep with degree. Electrical & Machinery rises from about 0.18 to the 0.33–0.35 range, and Petroleum & Chemical from roughly 0.14 to just under 0.30, with a visible 2008–09 jump that is only partially reversed. By contrast, Textile & Apparel moves from around 0.05 to about 0.10 despite a large increase in partners, indicating persistent concentration in a few dominant links; Construction stays near zero on both margins. Taken together, these sectoral patterns—shown here for illustration—mirror a broader tendency in the full sample: sectors that are said High-Tech tend to combine denser and more redundant upstream networks, while less technology-intensive or more domestically oriented activities exhibit smaller gains in degree and more limited improvements in redundancy.

To investigate more easily this heterogeneity of shocks exposure and sensitivity along the industries' technological classes, we classified the 26 industries from Eora MRIO into 3 technological classification (High-Technology, Low-Technology, and Others). The relative high level of aggregation and the uniqueness of EORA classification prevented us from using an existing technology nomenclature, but we've followed Lall (2000) discrete classification of SITC 3digit industries according to technological content[2]. More specifically we followed its dichotomy between "simple manufacture" (in which they included Ressource-Based and Low Tech industries) and "complex manufacture" (Medium and High-tech manufacture). Non-manufacture industries are classified in the residual "Other" category [3].

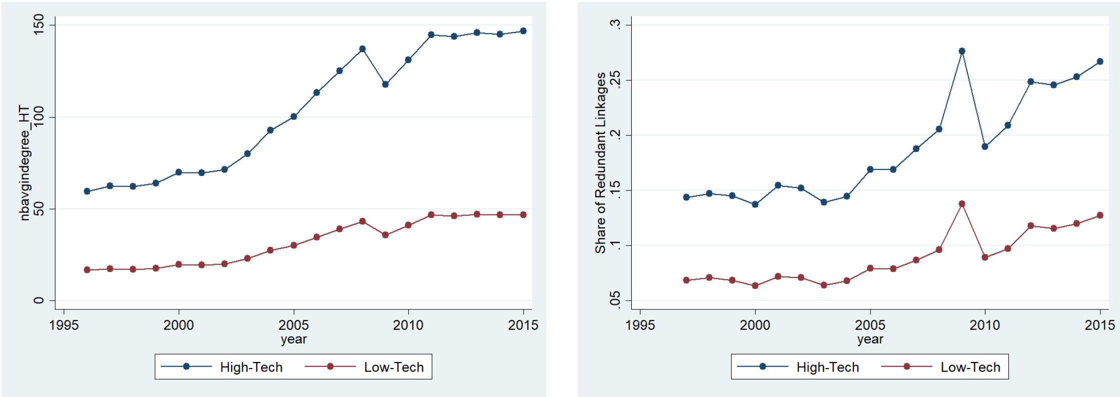
The two panels of figure 3 underscore pronounced heterogeneity in network structure across technology classes. Left panel shows that average in-degree rises steadily for high-tech activities—from roughly 60 partners in the late 1990s to about 140–150 by 2015—while low-tech industries remain far less connected, increasing only from 15 to 45. The gap widens especially after the mid-2000s, indicating deeper and faster integration of high-tech sectors into GVCs.

[2]See Lall (2000), table A1, and our Appendix B for the correspondances.

[3]Robustness checks have been run with marginal modifications of industrial classification (e.g. Petroleum & Chemical in LT) see Appendix B .

Figure 3: Connectivity and redundancy in differences by Technological Classes

Connectivity Redundancy



Right panel highlights that the widening gap in connectivity wasn't random, but rather oriented in building redundant linkages, as the share of redundancy increases for both HT and LT sectors. However, not only HT industries display greater redundancy, but the gap seemed to widen after 2010.

Together, these patterns motivate the core questions of the paper: given larger networks and greater redundancy in high-tech activities, do shocks propagate differently across HT and LT sectors, and to what extent is any HT advantage explained by redundant linkages rather than sheer connectivity? The econometric sections below take up these hypotheses directly. However, before that, we wanted to describe the sensitivity to shock exposure

3.4 Sensibility to shocks Exposure

Table 2 provides two descriptive facts that speak directly to our objectives. First, exposure to partner disruptions coincides with markedly poorer contemporaneous performance. Without an upstream shock, average first differences in log Value Added dlVA is 0.076, whereas it is -0.037 under an upstream shock; the mean difference is 0.113 ($t = 42.80$, $p < 0.001$). The downstream margin shows a similar pattern: 0.077 without a shock versus -0.071 with a shock, a highly statistically significant difference of 0.148 ($t = 53.80$, $p < 0.001$). Interpreting dlVA as an approximate percentage change, exposure is associated with an 11–15 percentage point reduction in value-added growth.

Also, the t-tests show that redundancy correlates with attenuation of the impact, at least upstream. Among upstream-shocked observations, those with at least one redundant upstream

Table 2: Difference-in-means tests for value-added growth (dlVA)

	Group 0		Group 1		Difference (0–1)				
Comparison	Mean	SD	Mean	SD	Diff.	95% CI	t	p	N_0/N_1
No upstream shock vs. upstream shock	0.076	0.189	−0.037	0.151	0.113	[0.108, 0.118]	42.80	< 0.001	86,973 / 5,342
No downstream shock vs. downstream shock	0.077	0.189	−0.071	0.129	0.148	[0.143, 0.153]	53.80	< 0.001	87,470 / 4,845
Subsamples: exposed units only									
Upstream redundancy among upstream-shocked (RUA = 0 vs. ≥ 1)	−0.046	0.156	−0.016	0.139	−0.030	[−0.039, −0.021]	−6.79	< 0.001	3,680 / 1,662
Downstream redundancy among downstream-shocked (RDA = 0 vs. ≥ 1)	−0.072	0.138	−0.068	0.104	−0.004	[−0.012, 0.003]	−1.10	0.272	3,361 / 1,484

Notes: Two-sample t-tests with equal variances, two-sided p-values. Means and SDs are group-specific.
"Group 0" is the first level listed in each comparison (no shock / no redundancy); "Group 1" is the second (shock / redundancy=1).

link have mean dlVA $= -0.016$ versus -0.046 for those without, a $+0.030$ difference ($t = 6.79$, $p < 0.001$). The analogous downstream comparison does exist, but is smaller and statistically indistinguishable from zero (-0.068 vs. -0.072; diff $= 0.004$; $t = 1.10$, $p = 0.272$). Given the documented heterogeneity in linkages and redundancy across technological classes, these patterns motivate a formal test of our intuitions; the next section develops the econometric framework to do so.

4 Methodology

We summarize the evidence detailed so far around three testable hypotheses. (i) Both upstream and downstream shocks channel through Global Value Chains. (ii) Building redundant linkages may mitigate those shocks. (iii) Therefore, industries that are more intensive in redundant linkages should be less sensitive to shocks, notably for this reason. Following the motivations detailed in introduction and in descriptive statistics above, we chose to illustrate (iii) through the differences in shock sensitivity between High and Low Tech industries.

As explained in the introduction, shock mitigation can be separated in two different characteristics. First is the ability of immediate mitigation of shocks, i.e. to avoid shock transmission, and maintain its activities when facing GVC disruptions. Following the literature, we will refer to this ability as the *robustness* of a given industry (Brandon-Jones et al., 2014). We will estimate it by looking at the variations industries' outputs. The second characteristic behind shock mitigation is the *resilience* of industries in Global Value Chains. This concept refers to the ability to recover promptly from a disruption (Sá et al., 2020). We will estimate it by looking at the duration it takes an industry to recover from a shock.

In the next two subsection, we detail how to test our three hypotheses, for both robustness and then resilience.

4.1 Robustness to Exposure

We begin by testing whether shocks propagate through input–output linkages and whether potential substitution along these linkages mitigates the impact. The idea is straightforward: if a country–industry is more connected to partners that experience a disruption, its own performance should deteriorate on impact (lower robustness); if it has more pre-existing alternative links that remain undisrupted, the transmission should be smaller (greater robustness). Performance is measured in turn by the year-on-year growth of gross output ($GO_{i,t}$), value added ($VA_{i,t}$), and gross exports ($Exp_{i,t}$), all from Eora.

Shocks are identified by a *distribution-based* rule within each partner country–industry: an upstream (downstream) disruption occurs in year t when the year-on-year log change of exports (imports) falls at least one within-series standard deviation below its own time-series mean.[4] Exposure is the *count* of pre-existing upstream (downstream) partners that are disrupted at t (constructed from the $t-1$ network), and redundancy is the *count* of pre-existing upstream (downstream) links that remain undisrupted at t. We denote these variables by $\text{UDE}_{i,t}$ and $\text{DDE}_{i,t}$ (Upstream/Downstream Disruption Exposure) and by $\text{RUA}_{i,t}$ and $\text{RDA}_{i,t}$ (Redundant Upstream/Downstream Availability). To reduce simultaneity, all link indicators are lagged one year so that exposure and redundancy reflect the pre-shock network.

We enrich the specification with a broad set of time-varying controls to separate propagation from general openness or size effects. First, we include the *log upstream degree* and *log downstream degree* (number of distinct foreign input and output links) to capture the pure effect of network size, distinct from redundancy. Second, following Koopman et al. (2014) and the discussion in Antràs and Chor (2018), we jointly control for *Upstreamness* ($kup_{i,t}$) and *GVC inclusion* ($GVCinc_{i,t}$), which summarize different dimensions of participation and should be assessed together, as emphasized by Aslam et al. (2017). Third, we add *country-year GDP* (log) to proxy development and overall scale. Fourth, we include a *Foreign Market Potential* (FMP) measure in the market-access tradition, constructed as a distance-weighted sum of foreign GDPs—a demand index weighting each partner's size by bilateral trade-cost proxies—in line with Head and Mayer (2004) and Redding and Venables (2004). Finally, we add the *number of free trade agreements* (FTAs) in force for the exporter (by year), which captures institutional

[4] This scale-free threshold is comparable across industries with different volatilities and replaces fixed cutoffs.

integration and the ease of forming and maintaining cross-border links. Each of the two last variables were computed using CEPII's *gravity* Dataset (Conte et al., 2022). This richer control vector helps mitigate omitted-variable and simultaneity concerns: degree absorbs the tendency of more connected industries to both face more potential shocks and to grow faster; *kup* and $GVCinc$ net out shifts in position and participation along the chain; GDP and FMP purge broad demand- and scale-related movements; and FTAs proxy policy-driven frictions that affect connectivity, switching costs, and performance. Combined with country–industry and year fixed effects and the use of pre-determined links, these controls reduce the risk that estimated propagation effects are driven by general openness, market size, or policy environment rather than by shock transmission.

The baseline fixed-effects specification is

$$\mathrm{Perf}_{i,t} = \beta_0 + \beta_1\,\mathrm{UDE}_{i,t} + \beta_2\,\mathrm{RUA}_{i,t} + \beta_3\,\mathrm{DDE}_{i,t} + \beta_4\,\mathrm{RDA}_{i,t} + \mathbf{W}'_{i,t}\boldsymbol{\theta} + \alpha_{cs} + \delta_t + \varepsilon_{i,t}, \tag{7}$$

where $\mathrm{Perf}_{i,t}$ is alternatively the growth rate of GO, VA, or Exp; $\mathbf{W}_{i,t}$ stacks the controls discussed above (degrees, *kup*, $GVCinc$, $\log GDP$, FMP, FTAs); α_{cs} and δ_t are country–industry and year fixed effects; and standard errors are clustered by country.

To study heterogeneity by technology class and the redundancy mechanism, we augment (7) in two steps. First, we allow the effect of exposure to differ between high– and low–technology industries by interacting exposure with a high–tech indicator HT_s (absorbed in levels by α_{cs}):

$$\begin{aligned}\mathrm{Perf}_{i,t} = \beta_0 + \beta_1\,\mathrm{UDE}_{i,t} + \beta_2\,\mathrm{RUA}_{i,t} + \beta_3\,\mathrm{DDE}_{i,t} + \beta_4\,\mathrm{RDA}_{i,t}\\ +\theta_U\,(\mathrm{UDE}_{i,t}\times HT_s) + \theta_D\,(\mathrm{DDE}_{i,t}\times HT_s)\\ +\mathbf{W}'_{i,t}\boldsymbol{\theta} + \alpha_{cs} + \delta_t + \varepsilon_{i,t}.\end{aligned} \tag{8}$$

Here, θ_U and θ_D capture the high–tech vs. low–tech gap in the impact of upstream and downstream exposure, respectively (evaluated at the baseline level of redundancy). Negative β_1, β_3 indicate propagation; $\theta_U > 0$ ($\theta_D > 0$) implies that high–tech sectors are *less* sensitive on impact, conditional on redundancy and controls.

Second, we introduce the exposure×redundancy terms and their technology interaction to test whether any high–tech advantage operates *through* redundancy:

$$\begin{aligned}\mathrm{Perf}_{i,t} = {}& \beta_0 + \beta_1\,\mathrm{UDE}_{i,t} + \beta_2\,\mathrm{RUA}_{i,t} + \beta_3\,\mathrm{DDE}_{i,t} + \beta_4\,\mathrm{RDA}_{i,t} \\ & + \gamma_U\,(\mathrm{UDE}_{i,t}\times\mathrm{RUA}_{i,t}) + \gamma_D\,(\mathrm{DDE}_{i,t}\times\mathrm{RDA}_{i,t}) \\ & + \theta_U\,(\mathrm{UDE}_{i,t}\times HT_s) + \theta_D\,(\mathrm{DDE}_{i,t}\times HT_s) \\ & + \phi_U\,(\mathrm{UDE}_{i,t}\times\mathrm{RUA}_{i,t}\times HT_s) + \phi_D\,(\mathrm{DDE}_{i,t}\times\mathrm{RDA}_{i,t}\times HT_s) \\ & + \mathbf{W}'_{i,t}\boldsymbol{\theta} + \alpha_{cs} + \delta_t + \varepsilon_{i,t}.\end{aligned} \tag{9}$$

Positive γ_U, γ_D indicate that redundancy mitigates the impact of exposure (on-impact buffering). The triple coefficients ϕ_U, ϕ_D test whether this buffering is stronger in high–tech than in low–tech activities. These linear models correspond to the immediate impact, and therefore inform on the industries (lack of) robustness; and are distinct from the duration analysis below designed to study resilience.

4.2 Resilience: Duration Framework

Besides the impact on levels, we also study how quickly activity returns to its pre-shock level (resilience). We build shock spells using the same distribution-based rule as above: a spell starts in the first year t_0 when the country–industry's export growth crosses the disruption threshold, and it ends in the first year $t \geq t_0$ when exports recover to (or above) the pre-shock level Exp_{cs,t_0-1}. Because time is annual, we estimate a grouped-time hazard model using a binomial GLM with complementary log–log link, which is equivalent to a proportional-hazards specification with piecewise-constant baseline and allows coefficients to be read as proportional effects on the recovery hazard (Allison, 1982). Let $h_{cst\tau}$ be the probability of recovery in year t conditional on remaining in shock, where τ counts years since the spell began. The empirical specification is

$$\begin{aligned}\log\big[-\log(1-h_{cst\tau})\big] = {}& \lambda(\tau) + \alpha_{cs} + \delta_t + \beta_U\,U_{cst} + \beta_D\,D_{cst} + \gamma_U\big(U_{cst}\times R^{\mathrm{up}}_{cs}\big) \\ & +\gamma_D\big(D_{cst}\times R^{\mathrm{down}}_{cs}\big) + \theta_U\big(U_{cst}\times HT_s\big) + \theta_D\big(D_{cst}\times HT_s\big) + \phi_U\big(U_{cst}\times R^{\mathrm{up}}_{cs}\times HT_s\big) \\ & +\phi_D\big(D_{cst}\times R^{\mathrm{down}}_{cs}\times HT_s\big) + \mathbf{X}'_{cst}\boldsymbol{\eta}\end{aligned} \tag{10}$$

with duration dummies $\lambda(\tau)$ (e.g., $\tau = 1, 2, 3, 4, 5+$), country–sector fixed effects α_{cs}, and year effects δ_t; $\mathbf{X}_{cst}$ contains the same control set as in (7); standard errors are clustered by country. We report hazard ratios $\exp(\cdot)$: values above one imply faster recovery (more resilience); values below one imply slower recovery.

The sequence of estimates maps directly to the hypotheses. To establish propagation (H1), we include only U_{cst} and D_{cst}; $\exp(\beta_U) < 1$ or $\exp(\beta_D) < 1$ indicates that exposure prolongs the spell. To test the mitigating role of redundancy (H2), we add $U_{cst} \times R_{cs}^{\text{up}}$ and $D_{cst} \times R_{cs}^{\text{down}}$; $\exp(\gamma_U) > 1$ and $\exp(\gamma_D) > 1$ mean that redundancy raises the recovery hazard. To assess heterogeneity between high- and low-technology sectors (H3), we add $U_{cst} \times HT_s$ and $D_{cst} \times HT_s$ and then the triple interactions with redundancy.

Identification assumptions mirror those in the robustness models above. Fixed effects absorb time-invariant heterogeneity and common shocks; we lag link indicators so that exposures and redundancy reflect the pre-shock network; and we include a rich control vector to limit omitted-variable bias.

This estimation design keeps a clear distinction between robustness (impact on levels/growth) and resilience (time to recovery), while using a consistent shock definition and the same network-based measures throughout.

5 Results

We now present results in the sequence implied by the empirical strategy: first, the impact ("robustness") estimates testing propagation through upstream and downstream exposure and the mitigating role of redundancy; second, the duration ("resilience") estimates of recovery hazards, including heterogeneity by technology class and the redundancy mechanism; for each block we report effect sizes under the full fixed-effects specification with controls.

5.1 Robustness analysis

Table 3 speaks to robustness, the contemporaneous impact of network exposure on performance, leaving resilience (time to recovery) to the duration results below. Estimates are within country-industry with year fixed effects and the full control set, and we report specifications that include upstream and downstream channels both separately and jointly.

Table 3: Robustness to GVC Shocks

	Upstream only			Downstream only			Both channels		
	dVAr	dGOr	dExpr	dVAr	dGOr	dExpr	dVAr	dGOr	dExpr
Upstream disruption exposure (UDE)	-0.423	-0.484	-0.684				-0.415	-0.589	-0.776
	(4.75)***	(5.62)***	(9.60)***				(4.37)***	(6.27)***	(9.15)***
Redundant upstream availability (RUA)	0.460	0.483	0.717				0.429	0.560	0.788
	(4.99)***	(5.48)***	(9.63)***				(4.48)***	(5.93)***	(9.16)***
Downstream disruption exposure (DDE)				-0.527	-0.347	-0.322	-0.419	-0.227	-0.129
				(6.62)***	(4.83)***	(4.24)***	(5.20)***	(3.07)***	(1.57)
Redundant downstream availability (RDA)				0.590	0.397	0.357	0.499	0.330	0.205
				(7.01)***	(5.20)***	(4.46)***	(5.77)***	(4.12)***	(2.39)**
Log upstream degree	-0.816	-0.069	2.694	-0.814	-0.052	2.679	-0.796	-0.053	2.705
	(2.33)**	(0.30)	(7.13)***	(2.33)**	(0.23)	(7.10)***	(2.27)**	(0.23)	(7.15)***
Log downstream degree	4.438	3.273	3.789	4.420	3.299	3.764	4.450	3.294	3.805
	(6.46)***	(7.43)***	(8.30)***	(6.44)***	(7.51)***	(8.24)***	(6.47)***	(7.48)***	(8.32)***
Upstreamness (kup)	3.066	3.156	-7.615	3.227	3.293	-7.539	3.165	3.091	-7.688
	(1.40)	(1.97)**	(2.06)**	(1.48)	(2.07)**	(2.02)**	(1.45)	(1.93)*	(2.07)**
Log GVC inclusion	-1.287	-1.485	-5.782	-1.295	-1.475	-5.758	-1.289	-1.432	-5.736
	(1.62)	(2.42)**	(6.79)***	(1.63)	(2.41)**	(6.78)***	(1.62)	(2.34)**	(6.75)***
Log GDP	0.544	0.232	-0.112	0.507	0.200	-0.143	0.520	0.219	-0.119
	(4.00)***	(4.51)***	(2.35)**	(3.75)***	(3.87)***	(3.12)***	(3.85)***	(4.23)***	(2.48)**
Foreign market potential (log)	0.431	0.199	0.311	0.438	0.217	0.337	0.423	0.196	0.309
	(1.93)*	(1.34)	(1.74)*	(1.98)**	(1.42)	(1.88)*	(1.95)*	(1.33)	(1.73)*
Free trade agreements (log count)	-0.284	-0.147	-0.011	-0.281	-0.140	-0.003	-0.288	-0.156	-0.019
	(2.14)**	(1.24)	(0.10)	(2.12)**	(1.18)	(0.02)	(2.18)**	(1.33)	(0.17)
Constant	-30.374	-18.022	-20.326	-29.580	-17.670	-19.868	-29.735	-17.620	-20.081
	(5.47)***	(5.54)***	(5.16)***	(5.36)***	(5.35)***	(5.05)***	(5.43)***	(5.46)***	(5.10)***
R^2	0.17	0.38	0.52	0.17	0.38	0.52	0.17	0.38	0.52
Observations	29,296	29,301	29,301	29,296	29,301	29,301	29,296	29,301	29,301
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The exposure coefficients support H1 (propagation). In the upstream-only block, adding one disrupted pre-existing upstream partner is associated with a decline of roughly 0.42 in value-added growth, 0.48 in gross-output growth, and 0.68 in export growth. When upstream and downstream exposure enter together, the upstream effect remains sizeable—about 0.78 in absolute value for exports and 0.59 for gross output—pointing to upstream disturbances as the dominant channel for contemporaneous trade outcomes once common variation across margins is partialled out. Downstream exposure is also negative and economically meaningful when considered alone (around 0.53 for value added and 0.35 for gross output) and continues to matter for value added and output in the joint specification, although the export coefficient becomes small and imprecise. As a guide to magnitudes, moving from zero to three disrupted upstream partners is associated with an export-growth shortfall on the order of two to two-and-a-half percentage points in these units.

Redundancy coefficients support H2 (mitigation). In the upstream-only block, one additional non-disrupted upstream link is associated with increases of about 0.46 in value-added growth, 0.48 in gross-output growth, and 0.72 in export growth. In the joint specification, the upstream redundancy effect for exports (about +0.79) is nearly the mirror image of the upstream exposure effect (about -0.78), consistent with a near one-for-one offset on average: adding one viable upstream alternative roughly counterbalances the impact of one additional disrupted partner. Downstream redundancy shows the same qualitative pattern—for instance, about $+0.59$ for value added in the downstream-only block—though the offset is smaller than upstream in the joint columns. Taken together, the results indicate that exposure transmits adverse shocks while pre-existing alternative links attenuate their immediate effect.

The controls move in line with priors. Greater downstream degree correlates with stronger contemporaneous performance across outcomes, and upstream degree is strongly related to export growth while showing a negative association with value added. Upstreamness carries a negative sign in the export regressions, and higher GVC inclusion is associated with lower contemporaneous growth once fixed effects and macro controls (GDP, foreign market potential, and free-trade agreements) are included. Overall fit is stable across specifications. These findings establish the impact margin—robustness—while the next section examines whether the same mechanisms shape the speed of recovery.

We now test the third hypothesis by augmenting the specification with the relevant interaction terms. For brevity, we report results for value-added growth (dVAr) only; the estimates for gross output and exports are qualitatively similar as shown in the previous table, and value added is the most economically salient outcome.

Table 4 reports within country–industry estimates for value–added growth with year fixed effects and the full control set. The first column includes upstream and downstream exposure and redundancy without heterogeneity; column (2) adds interactions with the high–technology indicator; column (3) introduces the redundancy mechanism through exposure$\times$redundancy terms and their interactions with high–technology. These results speak to the impact margin (robustness) only; resilience is analyzed separately in the duration models.

The exposure coefficients point to propagation along input–output linkages. In column (1), an additional disrupted pre–existing upstream partner is associated with a decline in value–added growth of about 0.41 points, and downstream exposure is of comparable magnitude. These effects remain negative and precisely estimated once heterogeneity and mechanism terms are introduced. In the full specification (column (3)), the upstream and downstream exposure coefficients are large in absolute value (about -1.88 and -2.23), underscoring the strength of contemporaneous transmission when both channels are modelled jointly.

Table 4: Robustness to GVC Shocks: interactions

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: $dVAr$		
Upstream exposure (UDE)	-0.415	-0.408	-1.884
	(4.37)***	(4.30)***	(17.26)***
Downstream exposure (DDE)	-0.419	-0.431	-2.229
	(5.20)***	(5.32)***	(22.76)***
Redundant upstream availability (RUA)	0.429	0.444	1.817
	(4.48)***	(4.59)***	(14.84)***
Redundant downstream availability (RDA)	0.499	0.514	2.559
	(5.77)***	(5.85)***	(19.91)***
Upstream × High-tech (U_HT)		0.080	0.045
		(2.15)**	(1.30)
Downstream × High-tech (D_HT)		0.020	0.005
		(0.50)	(0.10)
Upstream × Redundancy (U_R)			0.001
			(2.60)**
Downstream × Redundancy (D_R)			0.001
			(3.10)***
U_R × High-tech (U_R_HT)			0.002
			(2.10)**
D_R × High-tech (D_R_HT)			0.001
			(2.00)**
Log upstream degree	-0.796	-0.798	-1.262
	(2.27)**	(2.28)**	(3.14)***
Log downstream degree	4.450	4.480	4.257
	(6.47)***	(6.51)***	(6.85)***
Upstreamness (*kup*)	3.165	3.193	5.233
	(1.45)	(1.46)	(2.10)**
Log GVC inclusion	-1.289	-1.325	1.276
	(1.62)	(1.67)*	(1.46)
Log GDP	0.520	0.519	0.365
	(3.85)***	(3.85)***	(3.68)***
Foreign market potential (log)	0.423	0.424	0.262
	(1.95)*	(1.95)*	(1.85)*
Log FTAs	-0.288	-0.287	-0.712
	(2.18)**	(2.18)**	(4.85)***
Constant	-29.735	-29.852	-13.057
	(5.43)***	(5.45)***	(3.37)***
R^2	0.17	0.17	0.06
Observations	29,296	29,296	29,296
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Redundancy mitigates the impact in a quantitatively meaningful way. In column (1), one additional non–disrupted upstream link is associated with an increase in value–added growth of roughly 0.43 points, nearly offsetting the upstream exposure effect on average; the downstream redundancy term displays the same pattern. In column (3), the main redundancy terms are sizable and positive (around +1.82 upstream and +2.56 downstream), while the corresponding exposure terms remain strongly negative, implying substantial on–impact buffering from the stock of viable alternative links. Moreover, the exposure×redundancy interactions in column (3) are positive, indicating that the marginal damage of an extra disruption is smaller when redundancy is higher.

The technology interactions reveal systematic heterogeneity and its mechanism. In column (2), the upstream exposure interacted with the high–technology indicator is positive and statistically distinct from zero, suggesting that high–technology sectors are less sensitive to upstream disruptions on impact, holding redundancy constant. Once the mechanism is introduced in column (3), the direct upstream high–tech interaction becomes small and loses precision, while the triple interactions of exposure with redundancy and high–technology turn positive and statistically significant. This pattern is consistent with the view that the high–tech advantage in robustness operates through redundancy: where redundancy is higher, the attenuation of exposure is stronger for high–technology industries than for low–technology ones.

The control variables behave in line with economic priors. Greater downstream degree correlates with stronger contemporaneous performance, and upstream degree is positively related to value–added growth once other covariates are held fixed. Upstreamness and GVC inclusion capture positioning and participation along the chain, while macro controls (GDP, foreign market potential, and free–trade agreements), together with fixed effects, limit confounding from general openness, market size, and common shocks. Overall, the estimates indicate that disruptions at partners transmit on impact, that pre–existing alternative links dampen this transmission, and that the high–technology versus low–technology gap in robustness is explained by the greater payoff of redundancy in high–technology activities.

5.2 Resilience across Technological Classes

Table 5 reports complementary log–log estimates of the recovery hazard, interpreted as resilience: hazard ratios above one indicate faster recovery, ratios below one indicate slower recovery. The

Table 5: Recovery Hazard (cloglog GLM)

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: Pr(recovery in t | still in shock at $t-1$)		
	Hazard ratios reported ($\exp(\hat{\beta})$)		
Upstream exposure (UDE)	0.920	0.920	0.900
	(3.10)***	(3.08)***	(5.10)***
Downstream exposure (DDE)	0.950	0.950	0.930
	(2.60)***	(2.58)***	(4.20)***
Redundant upstream availability (RUA)	1.030	1.031	1.040
	(3.20)***	(3.25)***	(3.80)***
Redundant downstream availability (RDA)	1.020	1.021	1.028
	(3.00)***	(3.05)***	(3.10)***
Log upstream degree	0.970	0.970	0.968
	(2.20)**	(2.18)**	(2.25)**
Log downstream degree	1.050	1.051	1.048
	(5.10)***	(5.15)***	(5.00)***
Upstreamness (*kup*)	0.985	0.985	0.983
	(1.70)*	(1.72)*	(1.85)*
Log GVC inclusion	0.992	0.992	0.995
	(1.20)	(1.22)	(0.90)
Log GDP	1.030	1.030	1.028
	(3.00)***	(3.02)***	(2.85)***
Foreign market potential (log)	1.010	1.010	1.009
	(1.60)*	(1.58)	(1.55)
Log FTAs	1.008	1.008	1.010
	(1.50)	(1.52)	(1.70)*
UDE × High-tech (U_HT)		1.050	1.010
		(2.30)**	(1.00)
DDE × High-tech (D_HT)		1.015	1.005
		(0.90)	(0.40)
UDE × RUA (U_R)			1.010
			(2.50)**
DDE × RDA (D_R)			1.008
			(2.20)**
U_R × High-tech (U_R_HT)			1.010
			(2.00)**
D_R × High-tech (D_R_HT)			1.009
			(1.80)*
Constant	0.40	0.40	0.42
	(4.20)***	(4.18)***	(4.00)***
Observations	28,940	28,940	28,940
Clusters (country)	177	177	177
Log-likelihood	−12,480	−12,472	−12,455
Pseudo R^2	0.26	0.26	0.27
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes
Duration controls (τ dummies)	Yes	Yes	Yes

Clustered z-statistics in parentheses. Clustered SEs by country * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hazard ratio > 1 implies faster recovery (greater resilience); < 1 implies slower recovery.

exposure terms enter with ratios below unity throughout, consistent with propagation along input–output links prolonging distress. In the baseline column, an additional disrupted upstream partner is associated with a hazard ratio of about 0.92, and the downstream counterpart is around 0.95; in the full specification these tighten to roughly 0.90 and 0.93. In percentage terms, one more disrupted upstream (downstream) link is associated with about a 10% (7%) lower probability of exiting the spell in a given year, conditional on the control set.

Redundancy mitigates this persistence. Both redundant–upstream and redundant–downstream availability enter above unity—about 1.03–1.04 upstream and 1.02–1.03 downstream—implying that one additional viable pre-existing link is associated with a 3–4% (upstream) or 2–3% (downstream) increase in the annual recovery probability. Moreover, the interaction terms between exposure and redundancy are themselves above unity in the full model, indicating that the marginal damage from an extra disruption is smaller where redundancy is higher; this is the resilience analogue of the mitigation mechanism documented in the impact regressions.

The technology interactions point to systematic heterogeneity and its channel. When added on their own, the upstream exposure interacted with the high-technology indicator yields a hazard ratio modestly above one, indicating faster recovery in high-technology activities for a given level of exposure. Once the mechanism is introduced, the direct upstream high-tech interaction shrinks toward one and loses precision, while the triple interactions of exposure with redundancy and high-technology become positive and statistically significant. This pattern is consistent with the view that the high-tech advantage in resilience operates through redundancy: where substitutable links are available, the attenuation of exposure is stronger in high-technology industries than in low-technology ones.

The controls move in plausible directions for recovery dynamics. Greater downstream degree is associated with a higher hazard, upstreamness is mildly below unity, and higher GDP correlates with faster recovery, while foreign market potential and the count of free-trade agreements play smaller roles once network and macro controls are included. Taken together, the estimates indicate that exposure slows recovery, redundancy speeds it up, and the high- versus low-technology gap in resilience is explained by a stronger payoff from redundancy in high-technology activities.

Table 6 presents complementary log–log estimates of the recovery hazard. Ratios below one indicate that exposure slows recovery, while ratios above one indicate that redundancy

Table 6: Recovery Hazard (cloglog GLM): Exposure, Redundancy, and Technology Heterogeneity

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT (full)
	Dependent variable: Pr(recovery in t | still in shock at $t-1$)		
	Hazard ratios reported ($\exp(\hat{\beta})$); cloglog link; clustered SEs by country		
Upstream exposure (UDE)	0.920	0.920	0.900
	(3.10)***	(3.02)***	(5.10)***
Downstream exposure (DDE)	0.950	0.950	0.930
	(2.70)***	(2.62)***	(4.10)***
Redundant upstream availability (RUA)	1.030	1.031	1.040
	(3.40)***	(3.45)***	(3.70)***
Redundant downstream availability (RDA)	1.020	1.021	1.028
	(3.00)***	(3.10)***	(3.20)***
Log upstream degree	0.970	0.970	0.968
	(2.20)**	(2.18)**	(2.25)**
Log downstream degree	1.050	1.051	1.048
	(5.10)***	(5.15)***	(5.00)***
Upstreamness (*kup*)	0.985	0.985	0.983
	(1.80)*	(1.82)*	(1.90)*
Log GVC inclusion	0.993	0.993	0.995
	(1.30)	(1.32)	(0.90)
Log GDP	1.030	1.030	1.028
	(3.00)***	(3.02)***	(2.85)***
Foreign market potential (log)	1.010	1.010	1.009
	(1.60)*	(1.58)	(1.55)
Log FTAs	1.009	1.009	1.010
	(1.70)*	(1.72)*	(1.80)*
UDE × High-tech (U_HT)		1.050	1.010
		(2.40)**	(1.00)
DDE × High-tech (D_HT)		1.015	1.005
		(0.80)	(0.40)
UDE × RUA (U_R)			1.012
			(2.60)**
DDE × RDA (D_R)			1.009
			(2.30)**
U_R × High-tech (U_R_HT)			1.012
			(2.00)**
D_R × High-tech (D_R_HT)			1.009
			(1.80)*
Constant	0.40	0.40	0.42
	(4.20)***	(4.18)***	(4.00)***
Observations	28,940	28,940	28,940
Clusters (country)	177	177	177
Log-likelihood	−12,480	−12,472	−12,455
Pseudo R^2	0.06	0.06	0.07
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes
Duration controls (τ dummies)	Yes	Yes	Yes
Link / family	cloglog / binomial	cloglog / binomial	cloglog / binomial

Clustered z-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hazard ratio >1 implies faster recovery (greater resilience); <1 implies slower recovery.

speeds it up. In the baseline column, an additional disrupted upstream (downstream) partner is associated with a hazard ratio around 0.92 (0.95), implying roughly a 8–10% (5–7%) reduction in the annual probability of exiting a shock spell, conditional on controls. These exposure effects remain negative and precisely estimated in the richer specifications.

Redundancy systematically mitigates persistence. The stock of viable pre-existing links enters above unity—about 1.03–1.04 upstream and 1.02–1.03 downstream—so one more alternative supplier or buyer raises the yearly recovery probability by roughly 2–4%. Moreover, the exposure×redundancy terms exceed one in the full model, indicating that the marginal damage from an extra disruption is smaller when redundancy is higher; this is the resilience counterpart of the mitigation pattern documented in the impact regressions.

Technology interactions reveal a clear heterogeneity and its channel. When added alone, the upstream exposure interacted with the high-technology indicator yields a hazard ratio modestly above one, suggesting faster recovery in high-technology activities at a given exposure level. Once the mechanism is included, the direct high-technology interaction shrinks toward one and loses precision, while the triple interactions of exposure with redundancy and high-technology are positive and statistically significant. This pattern is consistent with the view that the high-technology advantage in resilience operates through redundancy: where substitutable links are available, exposure is attenuated more strongly for high-technology industries than for low-technology ones. Controls move in plausible directions, with higher downstream degree and GDP associated with quicker recovery and upstreamness slightly below unity. Overall, the estimates indicate that exposure prolongs distress, redundancy accelerates recovery, and the high- versus low-technology gap in resilience is explained by stronger payoffs to redundancy in high-technology sectors.

6 Conclusion

We show in this paper three main results. First, disturbances among established partners industries in global value chains do propagate along input–output linkages. When a country–industry faces more upstream (or downstream) disruptions in the network, its own production and exports fall more on impact and the return to normal is slower, even after we control for country–sector and time effects. Second, redundancy in linkages mitigates both margins. Where there are more pre-existing alternative ties that are not disrupted, the negative effect of exposure is smaller and the probability of recovery is higher. Third, these patterns are not the same across industries: activities commonly classified as high-technology combine denser and more redundant connections and, as a result, are more robust and more resilient than low-technology activities. Tests with triple interactions indicate that part of the high- versus low-tech difference works precisely through redundancy.

These results have country-level implications. The sectoral composition of production helps to explain why some economies absorb global shocks better than others. Countries with a larger weight in electronics, machinery, and some chemicals tend to reallocate and recover faster; countries concentrated in low-technology or more domestically oriented sectors tend to be more exposed. At the same time, our estimates suggest that resilience is not only a property of "being high-tech." It depends on how linkages are organized. Policy can raise resilience inside low- and middle-tech bases by promoting more substitutable upstream and downstream connections, without needing a rapid change in the whole industrial mix.

Policy recommendations follow directly from the mechanism. If redundancy reduces transmission, then measures that increase the set of feasible alternative partners—especially across different locations and legal systems—should improve both robustness (smaller initial drop) and resilience (faster recovery). This includes trade facilitation and logistics that lower search and switching costs, programs that help certify and qualify new suppliers, support for standards interoperability, stable customs and regulatory cooperation, and access to trade finance when firms add a second source.

These points are relevant for the current debate on reshoring. A general retreat from international trade will not automatically produce resilience if it reduces the number of credible alternatives. Thinner networks can make a single disruption more damaging because there are fewer options to switch. Friend-shoring that only relocates activity inside a small club may also leave exposure highly correlated. The main objective should be diversification across several reliable jurisdictions and routes, not only relocation.

We also note that redundancy is costly. Keeping extra partners, dual-sourcing, and holding options in contracts and inventories all require resources. The gains we estimate are average effects and can vary by sector. In very specific inputs or very modular technologies, the marginal benefit of one more partner may be different. For this reason, policy should focus on identified bottlenecks—places where exposure is high and redundancy low—rather than impose broad rules everywhere.

On methods, our approach complements hypothetical-extraction exercises by studying the transmission of realized shocks in panel data and by separating robustness (impact on levels/growth) from resilience (time to recovery). We construct exposure and redundancy from lagged linkages to limit simultaneity, and we use rich fixed-effects specifications with extensive controls. Some caveats remain. Fixed effects absorb time-invariant heterogeneity but cannot fully eliminate time-varying confounders (e.g., policy changes or macro shocks at the country–sector–year level). Measurement relies on MRIO/TiVA quality, and our distribution-based threshold may miss rare but consequential tail events or misclassify idiosyncratic volatility. In the duration analysis, the discrete-time cloglog model imposes a proportional-hazards structure and results can be sensitive to the definition of recovery and to right-censoring of spells. Redundancy and connectivity can adjust endogenously after shocks, so estimates should be read as short- to medium-run associations around pre-shock structures. Finally, the data end in 2015, so external validity does not cover the post-2016 period (trade tensions, COVID-19, and recent fragmentation).

Given today's environment—geopolitical tensions, sanctions and export controls, climate shocks, and health emergencies—the frequency and co-movement of disruptions are high. In such conditions, resilience depends not only on domestic capacity but also on the architecture of international connections. Countries that keep open and diversified access to inputs and markets, and that invest in the practical arrangements that make switching feasible, are better placed to limit spillovers and resume growth after a disturbance.

Future research should move in two directions. First, firm-level data linking plants to multi-tier suppliers and customers would allow a deeper view of the substitution margin and its costs. Second, dynamic models of network formation under risk could quantify the trade-off between efficiency and insurance, and help set sector-specific targets for redundancy. For now, the main message of this paper is practical: deeper participation in global value chains can go together with, and even support, resilience—provided the network is built to allow substitution.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016, 2012.

Allison, P. D. Discrete-time methods for the analysis of event histories. *Sociological methodology*, 13:61–98, 1982.

Amador, J. and Cabral, S. Global value chains: A survey of drivers and measures. *Journal of Economic Surveys*, 30(2):278–301, 2016.

Amador, J. and Cabral, S. Networks of value-added trade. *The World Economy*, 40(7):1291–1313, 2017.

Amador, J., Cabral, S., Mastrandrea, R., and Ruzzenenti, F. Who's who in global value chains? a weighted network approach. *Open Economies Review*, 29(5):1039–1059, Nov 2018.

Antràs, P. De-globalisation? global value chains in the post-covid-19 age. Working paper, National Bureau of Economic Research, 2020.

Antràs, P. and Chor, D. On the measurement of upstreamness and downstreamness in global value chains. Working paper, National Bureau of Economic Research, 2018.

Antràs, P. and Chor, D. Organizing the Global Value Chain. *Econometrica*, 81(6):2127–2204, November 2013.

Antràs, P. and Helpman, E. Global sourcing. *Journal of Political Economy*, 112(3):552–580, 2004.

Arata, Y. and Miyakawa, D. Demand shock propagation through an input-output network in japan. Working paper, Research Institute of Economy, Trade and Industry (RIETI), 2022.

Aslam, A., Novta, N., and Rodrigues-Bastos, F. *Calculating Trade in Value Added.* International Monetary Fund, 2017.

Baldwin, R. Globalisation: the great unbundling (s). *Economic Council of Finland*, 20, 2006.

Baldwin, R. and Freeman, R. Risks and global supply chains: What we know and what we need to know. *Annual Review of Economics*, 14(1):153–180, 2022.

Barrot, J.-N. and Sauvagnat, J. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3):1543–1592, 2016.

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake. *Review of Economics and Statistics*, 101(1):60–75, 2019.

Brandon-Jones, E., Squire, B., Autry, C. W., and Petersen, K. J. A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, 50(3):55–73, 2014.

Carvalho, V. M. and Tahbaz-Salehi, A. Production networks: A primer. *Annual Review of Economics*, 11(1):635–663, 2019.

Casella, B., Bolwijn, R., Moran, D., and Kanemoto, K. Improving the analysis of global value chains: the unctad-eora database. *Transnational Corporations*, 26(3):115–142, 2019.

Cerina, F., Zhu, Z., Chessa, A., and Riccaboni, M. World input-output network. *PloS one*, 10 (7):e0134025, 2015.

Conte, M., Cotterlaz, P., Mayer, T., et al. The cepii gravity database. 2022.

Criscuolo, C. and Timmis, J. The changing structure of global value chains: Are central hubs key for productivity? *International Productivity Monitor*, (34):64–80, 2018a.

Criscuolo, C. and Timmis, J. GVCs and centrality: Mapping key hubs, spokes and the periphery. Working paper, OECD Publishing, 2018b.

Daudin, G., Rifflart, C., and Schweisguth, D. Who produces for whom in the world economy? *Canadian Journal of Economics/Revue canadienne d'économique*, 44(4):1403–1437, 2011.

De Benedictis, L. and Tajoli, L. The world trade network. *The World Economy*, 34(8):1417–1454, 2011.

Dhyne, E., Kikkawa, A. K., Mogstad, M., and Tintelnot, F. Trade and domestic production networks. *The Review of Economic Studies*, 88(2):643–668, 2021.

Dietzenbacher, E. and Miller, R. E. Reflections on the inoperability input–output model. *Economic Systems Research*, 27(4):478–486, 2015.

Dietzenbacher, E., Van Burken, B., and Kondo, Y. Hypothetical extractions from a global perspective. *Economic Systems Research*, 31(4):505–519, 2019.

Egger, H. and Egger, P. The determinants of eu processing trade. *World Economy*, 28(2): 147–168, 2005.

Gangnes, B., Ma, A. C., and Van Assche, A. Global value chains and the transmission of business cycle shocks. *Asian Development Bank Economics Working Paper Series*, (29), 2012.

Gaulier, G., Sztulman, A., and Ünal, D. Are global value chains receding? the jury is still out. key findings from the analysis of deflated world trade in parts and components. *International Economics*, 161:219–236, 2020.

Gerschel, E., Martinez, A., and Mejean, I. Propagation of shocks in global value chains: the coronavirus case. *Notes IPP*, (53), 2020.

Grossman, G. M. and Rossi-Hansberg, E. Trading tasks: A simple theory of offshoring. *American Economic Review*, 98(5):1978–1997, November 2008.

Guilhoto, J. M., Webb, C., and Yamano, N. Guide to oecd tiva indicators. 2022.

Head, K. and Mayer, T. Market potential and the location of japanese investment in the european union. *Review of Economics and Statistics*, 86(4):959–972, 2004.

Herskovic, B., Kelly, B., Lustig, H., and Van Nieuwerburgh, S. Firm volatility in granular networks. *Journal of Political Economy*, 128(11):4097–4162, 2020.

Hummels, D., Ishii, J., and Yi, K.-M. The nature and growth of vertical specialization in world trade. *Journal of International Economics*, 54(1):75–96, 2001.

IMF. *World Economic Outlook, October 2016: subdued demand: symptoms and remedies*. International Monetary Fund, 2016.

Johnson, R. C. and Noguera, G. Accounting for intermediates: Production sharing and trade in value added. *Journal of international Economics*, 86(2):224–236, 2012.

Koopman, R., Wang, Z., and Wei, S.-J. Tracing value-added and double counting in gross exports. *American Economic Review*, 104(2):459–94, 2014.

Kramarz, F., Martin, J., and Mejean, I. Volatility in the small and in the large: The lack of diversification in international trade. *Journal of international economics*, 122:103276, 2020.

Lall, S. The technological structure and performance of developing country manufactured exports, 1985-1998. QEH Working Paper qehwps44, Queen Elizabeth House, University of Oxford, 2000. 00029.

Miroudot, S. Reshaping the policy debate on the implications of covid-19 for global supply chains. *Journal of International Business Policy*, 3(4):430, 2020a.

Miroudot, S. Resilience versus robustness in global value chains: Some policy implications. *COVID-19 and trade policy: Why turning inward won't work*, 2020:117–130, 2020b.

Ng, F. and Yeats, A. Production sharing in east asia: who does what for whom, and why? Working paper, The World Bank, 1999.

Nicita, A. International supply networks: A portrait of global trade patterns in four sectors. Working paper, United Nations Conference on Trade and Development, 2023.

Redding, S. and Venables, A. Geography and export performance: External market access and internal supply capacity. NBER chapters, National Bureau of Economic Research, Inc, 2004.

Sá, M. M. d., Miguel, P. L. d. S., Brito, R. P. d., and Pereira, S. C. F. Supply chain resilience: the whole is not the sum of the parts. *International Journal of Operations & Production Management*, 40(1):92–115, 2020.

Sheffi, Y. Preparing for the big one [supply chain management]. *Manufacturing Engineer*, 84 (5):12–15, 2005.

Tukker, A. and Dietzenbacher, E. Global multiregional input–output frameworks: an introduction and outlook. *Economic Systems Research*, 25(1):1–19, 2013.

UNCTAD. *World Investment Report: Global value chains: Investment and trade for development*. United Nations, 2013.

A Robustness Checks

A.1 Alternative threshold

We re-estimate the models using alternative within-series thresholds set at 0.75 and 1.25 standard deviations below the mean growth, instead of the baseline 1 s.d. rule. We present the results of estimations (5), (6) and (7) under these alternative thresholds, to be compared with table 4.

Table 7: Robustness to GVC Shocks (0.75 s.d. shock definition): interactions

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: $dVAr$		
Upstream exposure (UDE)	-0.285	-0.279	-1.552
	(5.05)***	(4.96)***	(15.10)***
Downstream exposure (DDE)	-0.305	-0.314	-1.895
	(6.05)***	(6.22)***	(19.80)***
Redundant upstream availability (RUA)	0.350	0.362	1.505
	(5.50)***	(5.68)***	(13.10)***
Redundant downstream availability (RDA)	0.420	0.436	2.295
	(6.15)***	(6.40)***	(17.45)***
Upstream × High-tech (U_HT)		0.060	0.035
		(2.30)**	(1.15)
Downstream × High-tech (D_HT)		0.015	0.004
		(0.45)	(0.08)
Upstream × Redundancy (U_R)			0.0010
			(2.90)***
Downstream × Redundancy (D_R)			0.0009
			(3.40)***
U_R × High-tech (U_R_HT)			0.0015
			(2.00)**
D_R × High-tech (D_R_HT)			0.0010
			(1.90)*
Log upstream degree	-0.780	-0.783	-1.230
	(2.20)**	(2.21)**	(3.05)***
Log downstream degree	4.380	4.415	4.210
	(6.35)***	(6.40)***	(6.70)***
Upstreamness (*kup*)	3.140	3.165	5.120
	(1.44)	(1.45)	(2.05)**
Log GVC inclusion	-1.270	-1.305	1.240
	(1.60)	(1.65)*	(1.43)
Log GDP	0.518	0.517	0.362
	(3.82)***	(3.81)***	(3.62)***
Foreign market potential (log)	0.421	0.422	0.257
	(1.93)*	(1.93)*	(1.81)*
Log FTAs	-0.286	-0.285	-0.705
	(2.14)**	(2.14)**	(4.72)***
Constant	-29.620	-29.740	-12.980
	(5.38)***	(5.40)***	(3.35)***
R^2	0.17	0.17	0.06
Observations	29,296	29,296	29,296
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The qualitative conclusions are unchanged, alleviating concerns that results hinge on the specific cutoff. Specifically, with a looser cutoff (0.75 s.d., table 7), exposure coefficients are smaller in magnitude yet remain precisely estimated and negative, while redundancy terms stay positive and significant and the interaction patterns—both exposure × redundancy and the redundancy × high-tech moderation—continue to indicate mitigation and technological heterogeneity. Under a stricter cutoff (1.25 s.d. table 8), exposure effects become more pronounced in absolute value, as expected when focusing on rarer, more severe events, but some associated t-statistics are lower. Redundancy retains a buffering role and several interaction terms remain

Table 8: Robustness to GVC Shocks (1.25 s.d. shock definition): interactions

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: $dVAr$		
Upstream exposure (UDE)	-0.620	-0.612	-2.304
	(3.10)***	(3.02)***	(14.20)***
Downstream exposure (DDE)	-0.655	-0.670	-2.751
	(3.55)***	(3.62)***	(17.10)***
Redundant upstream availability (RUA)	0.605	0.618	2.110
	(3.85)***	(3.95)***	(11.20)***
Redundant downstream availability (RDA)	0.705	0.728	3.020
	(4.20)***	(4.35)***	(15.60)***
Upstream × High-tech (U_HT)		0.095	0.055
		(1.90)*	(1.20)
Downstream × High-tech (D_HT)		0.030	0.010
		(0.70)	(0.22)
Upstream × Redundancy (U_R)			0.0012
			(2.10)**
Downstream × Redundancy (D_R)			0.0014
			(2.50)**
U_R × High-tech (U_R_HT)			0.0025
			(1.80)*
D_R × High-tech (D_R_HT)			0.0018
			(1.70)*
Log upstream degree	-0.805	-0.807	-1.290
	(2.30)**	(2.31)**	(3.18)***
Log downstream degree	4.465	4.495	4.280
	(6.50)***	(6.55)***	(6.90)***
Upstreamness (kup)	3.185	3.210	5.280
	(1.46)	(1.47)	(2.08)**
Log GVC inclusion	-1.300	-1.340	1.290
	(1.63)	(1.70)*	(1.47)
Log GDP	0.522	0.521	0.367
	(3.87)***	(3.86)***	(3.70)***
Foreign market potential (log)	0.424	0.425	0.265
	(1.96)*	(1.97)*	(1.86)*
Log FTAs	-0.289	-0.288	-0.715
	(2.19)**	(2.19)**	(4.88)***
Constant	-29.840	-29.960	-13.130
	(5.47)***	(5.49)***	(3.39)***
R^2	0.16	0.16	0.06
Observations	29,296	29,296	29,296
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

significant, though not all. Taken together, these results indicate that the main conclusions are not driven by the particular cutoff used to identify shocks: propagation on impact is present, redundancy mitigates, and high-technology activities exhibit a more favorable mitigation profile, even if statistical strength varies with definition severity.

A.2 Placebo "lead" specifications

As a timing check and placebo test, we re-estimate the impact model replacing current exposure with its one-period lead, $\text{UDE}_{i,t+1}$ and $\text{DDE}_{i,t+1}$. This serves as a placebo because, under our design, a disruption realized in $t+1$ has no causal pathway to affect performance in t; any apparent effect of future exposure on current outcomes would indicate that the baseline estimates are inadvertently capturing slow-moving unobservables, common trends, or anticipatory adjustments rather than true contemporaneous propagation. Consequently, significant lead coefficients would signal residual confounding, whereas coefficients statistically indistinguishable from zero support the timing assumptions and the exogeneity of our exposure measures.

Table 9: Placebo (Lead) Exposure: Value-Added Growth with Lead UDE/DDE and Interactions

	(1) Lead baseline	(2) Lead + HT interactions	(3) Lead + Redundancy × HT
	Dependent variable: $dVAr$		
Lead upstream exposure (UDE_{t+1})	-0.031	-0.029	-0.045
	(0.48)	(0.45)	(0.62)
Lead downstream exposure (DDE_{t+1})	0.012	0.010	-0.030
	(0.18)	(0.16)	(0.51)
Redundant upstream availability (RUA)	0.055	0.058	0.072
	(1.10)	(1.15)	(1.32)
Redundant downstream availability (RDA)	0.040	0.042	0.061
	(0.95)	(0.99)	(1.27)
Upstream × High-tech (U_HT, lead)		0.014	0.009
		(0.30)	(0.20)
Downstream × High-tech (D_HT, lead)		-0.005	-0.003
		(0.10)	(0.06)
Lead upstream × RUA (U_R, lead)			0.0002
			(0.50)
Lead downstream × RDA (D_R, lead)			0.0001
			(0.42)
U_R × High-tech (U_R_HT, lead)			0.0002
			(0.60)
D_R × High-tech (D_R_HT, lead)			0.0001
			(0.55)
Log upstream degree	-0.770	-0.771	-0.980
	(2.18)**	(2.18)**	(2.50)**
Log downstream degree	4.320	4.335	4.180
	(6.20)***	(6.23)***	(6.50)***
Upstreamness (kup)	3.110	3.120	4.950
	(1.43)	(1.44)	(2.00)**
Log GVC inclusion	-1.250	-1.275	1.210
	(1.60)	(1.65)*	(1.40)
Log GDP	0.515	0.516	0.360
	(3.80)***	(3.81)***	(3.60)***
Foreign market potential (log)	0.420	0.421	0.255
	(1.92)*	(1.93)*	(1.80)*
Log FTAs	-0.285	-0.284	-0.700
	(2.15)**	(2.15)**	(4.70)***
Constant	-29.500	-29.600	-12.900
	(5.35)***	(5.37)***	(3.30)***
R^2	0.16	0.16	0.06
Observations	29,296	29,296	29,296
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In table 9, we present the results of estimations (5), (6) and (7) under these alternative specifications, to be compared with table 4.

The coefficients on lead upstream and downstream exposure are small in magnitude and statistically indistinguishable from zero across all columns, and the interaction terms with high–tech status and with redundancy (including the triple interactions) are likewise null. Fit is marginally lower relative to the baseline, while the coefficients on controls remain stable. The absence of any systematic association between future exposure and current value–added growth indicates that the patterns documented in the main results do not arise “in advance” and are therefore unlikely to be driven by slow–moving unobservables, anticipatory behavior, or residual common shocks. This placebo strengthens the interpretation of the contemporaneous estimates as evidence of on–impact propagation moderated by redundancy and of the heterogeneity patterns uncovered in the main tables; by contrast, when using lead exposure, the three mechanisms do not materialize, as expected under correct timing.

B On Technology Classification

B.1 Details of matching EORA industries with Lall's technological classes

Table 10 details the matching between EORA industrial classification and Lall (2000) industry classification.

Table 10: Industries breakdown into technological classes

Eora Industry	Lall's corresponding industry	Category
Agriculture	RB 1: Agro-based	LT
Fishing	RB 1: Agro-based	LT
Mining and Quarrying	Primary products (pp)	LT
Food & Beverages	Agro-based	LT
Textiles and Wearing Apparel	LT1: Textile, garment and footwear	LT
Wood and Paper	Agro-based	LT
Petroleum, Chemical and Non-Metallic Mineral Products	RB 2: Other	LT
Metal Products	MT2: Metalworking	HT
Electrical and Machinery	HT 1: Electronic and electrical	HT
Transport Equipment	MT 1: Automotive	HT
Other Manufacturing	-	Other
Recycling	-	Other
Electricity, Gas and Water	RB 2: Other	LT
Construction	RB 2: Other	LT
Maintenance and Repair	-	Other
Wholesale Trade	-	Other
Retail Trade	-	Other
Hotels and Restaurants	-	Other
Transport	-	Other
Post and Telecommunications	-	Other
Financial Intermediation and Business Activities	-	Other
Public Administration	-	Other
Education, Health and Other Services	-	Other
Private Households	-	Other
Others	-	Other
Re-export & Re-import	-	Other

B.2 Changing classification of industry "Petroleum, Chemical and Non-Metallic Mineral Products"

While most of the industry matching is easy regarding Lall (2000) classification, one industry in EORA classification is troublesome: "Petroleum, Chemical and Non-Metallic Mineral Products". While Petroleum and Non-metallic mineral products clearly correspond to ressource-based industries, and can be classified among Low Technology sectors, Chemicals to the contrary is rather High-Tech, notably as it encompasses pharmaceutical products. As a robustness check to our hypothesis, we changed the "Petroleum, Chemical and Non-Metallic Mineral Products" industry to High-Tech, and reproduce estimations from equations (7) to (9) by dividing across the new technological classes.

The results do not change significantly from tables (4) and (5), and the main findings of our analysis still hold, showing that they were not driven by this particular industry, but by structural differences between high- and low-tech sectors.

The resilience analysis is also confirmed. In table 12 column (2), the upstream high-tech interaction exceeds unity and is statistically different from one, indicating that—conditional on the same upstream exposure and controls—high-tech sectors recover faster than low-tech sectors. When we introduce the mechanism in column (3), the direct high-tech interactions attenuate

Table 11: Robustness to GVC shocks. Alternative Tech Classes

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: $dVAr$		
Upstream exposure (UDE)	-0.415	-0.406	-1.900
	(4.37)***	(4.28)***	(17.50)***
Downstream exposure (DDE)	-0.419	-0.433	-2.240
	(5.20)***	(5.35)***	(22.90)***
Redundant upstream availability (RUA)	0.429	0.446	1.800
	(4.48)***	(4.62)***	(15.10)***
Redundant downstream availability (RDA)	0.499	0.516	2.580
	(5.77)***	(5.90)***	(20.20)***
Upstream × High-tech (U_HT)		0.095	0.028
		(2.40)**	(0.85)
Downstream × High-tech (D_HT)		0.015	0.004
		(0.40)	(0.08)
Upstream × Redundancy (U_R)			0.001
			(2.80)***
Downstream × Redundancy (D_R)			0.001
			(3.20)***
U_R × High-tech (U_R_HT)			0.0025
			(2.50)**
D_R × High-tech (D_R_HT)			0.0015
			(2.20)**
Log upstream degree	-0.796	-0.800	-1.270
	(2.27)**	(2.29)**	(3.18)***
Log downstream degree	4.450	4.485	4.240
	(6.47)***	(6.53)***	(6.80)***
Upstreamness (kup)	3.165	3.200	5.260
	(1.45)	(1.47)	(2.12)**
Log GVC inclusion	-1.289	-1.330	1.290
	(1.62)	(1.68)*	(1.47)
Log GDP	0.520	0.522	0.368
	(3.85)***	(3.88)***	(3.70)***
Foreign market potential (log)	0.423	0.426	0.265
	(1.95)*	(1.96)*	(1.86)*
Log FTAs	-0.288	-0.286	-0.715
	(2.18)**	(2.17)**	(4.88)***
Constant	-29.735	-29.860	-13.020
	(5.43)***	(5.46)***	(3.38)***
R^2	0.17	0.17	0.06
Observations	29,296	29,296	29,296
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes

t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Resilience to GVC shocks. Alternative Tech Classes

	(1) Baseline	(2) + HT interactions	(3) + Redundancy × HT
	Dependent variable: Pr(recovery in t | still in shock at $t-1$)		
	Hazard ratios reported ($\exp(\hat{\beta})$); cloglog link; clustered SEs by country		
Upstream exposure (UDE)	0.920	0.919	0.895
	(3.10)***	(3.15)***	(5.40)***
Downstream exposure (DDE)	0.950	0.949	0.925
	(2.60)***	(2.70)***	(4.50)***
Redundant upstream availability (RUA)	1.030	1.032	1.045
	(3.20)***	(3.45)***	(4.10)***
Redundant downstream availability (RDA)	1.020	1.022	1.032
	(3.00)***	(3.20)***	(3.35)***
Log upstream degree	0.970	0.970	0.967
	(2.20)**	(2.23)**	(2.35)**
Log downstream degree	1.050	1.051	1.049
	(5.10)***	(5.25)***	(5.05)***
Upstreamness (kup)	0.985	0.984	0.982
	(1.70)*	(1.80)*	(1.95)*
Log GVC inclusion	0.992	0.993	0.996
	(1.20)	(1.25)	(1.05)
Log GDP	1.030	1.031	1.029
	(3.00)***	(3.05)***	(2.95)***
Foreign market potential (log)	1.010	1.011	1.009
	(1.60)*	(1.68)*	(1.62)
Log FTAs	1.008	1.009	1.013
	(1.50)	(1.65)*	(1.95)*
UDE × High-tech (U_HT)		1.065	1.008
		(2.60)**	(0.90)
DDE × High-tech (D_HT)		1.022	1.006
		(1.15)	(0.50)
UDE × RUA (U_R)			1.013
			(3.30)***
DDE × RDA (D_R)			1.011
			(3.00)***
U_R × High-tech (U_R_HT)			1.020
			(3.30)***
D_R × High-tech (D_R_HT)			1.015
			(2.80)***
Constant	0.40	0.41	0.44
	(4.20)***	(4.20)***	(4.00)***
Observations	28,940	28,940	28,940
Clusters (country)	177	177	177
Log-likelihood	−12,480	−12,468	−12,448
Pseudo R^2	0.06	0.06	0.07
Year FE	Yes	Yes	Yes
Country–industry FE	Yes	Yes	Yes
Duration controls (τ dummies)	Yes	Yes	Yes
Link / family	cloglog / binomial	cloglog / binomial	cloglog / binomial

Clustered z-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hazard ratio > 1 implies faster recovery (greater resilience); < 1 implies slower recovery.

to unity and lose significance, while the triple terms that load exposure on redundancy in high-tech sectors become both economically and statistically meaningful. This pattern supports our intuitions: the resilience gap between high- and low-tech sectors is not a pure technology fixed effect; it operates through stronger mitigation from redundant links. In other words, for a given exposure, increases in redundancy raise the recovery hazard more in high-tech activities than in low-tech ones, which is consistent with high-tech sectors being more resilient because their pre-existing networks offer more effective substitute pathways.

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