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European regional resilience to supply shocks diffused through global value chains

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Abstract

The aim of this paper is to quantitatively assess the propagation of supply shocks across European regions, triggered by the COVID-19 pandemic and diffused through Global Value Chains (GVCs). By taking advantage of the cross-country variation in policy responses to the pandemic, as well as the heterogeneity in regional productive structures, we document how downstream transmission of shocks via GVC-induced backward linkages yields differences in terms of regional resilience. By combining and adapting datasets at the NUTS2 level, classifying EU regions according to the risk of falling into a development trap, and embedding inter-regional, inter-industry indicators in a regression model estimated with a local projection method, we show that regional responses of real value added to foreign (i.e., inter-country) and domestic (i.e., intra-country yet inter- and intra-regional) shocks are far from homogeneous. The nuanced picture emerging from our findings warns against withdrawing from GVCs as an attempt to insulate from foreign shocks, as this might hamper the very forces that allow dynamic regions to withstand them.

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Non-Technical Summary

Recent years have exposed the European economy to a sequence of concurrent crises—ranging from the COVID-19 pandemic to geopolitical tensions, supply disruptions, and climate-related risks. These shocks have highlighted the deep interconnectedness of European regions through global value chains (GVCs). This paper asks a crucial policy question: How do global supply shocks affect European regions differently, and what makes some regions more resilient than others?

Using the COVID-19 pandemic as a real-world stress test, the study examines how supply disruptions originating abroad spread through global and domestic production networks and how they ultimately affected regional economic activity across Europe. Importantly, the analysis moves beyond national averages and focuses on regional outcomes, recognising that European regions differ widely in their economic structures, capabilities, and degree of integration into global markets.

A central insight of the paper is that exposure to global shocks via high integration in global value chains is not, by itself, a weakness. While highly connected regions experienced sharper initial disruptions during the pandemic, many of them also recovered more quickly. Their ability to rebound was linked to strong local capabilities: Diversified production structures, higher technological intensity, and capacity to adapt when supply links were interrupted. In these regions, global integration went hand-in-hand with resilience.

By contrast, regions with weaker economic foundations—particularly those at risk of falling into a "development trap"—fared much worse. These regions are typically characterised by lower productivity growth, limited technological upgrading, and a reliance on labour-intensive activities. Although they were initially less exposed to foreign shocks because of their weaker global integration, this insulation did not translate into better long-term outcomes. Instead, their limited economic dynamism meant that domestic shocks had persistent negative effects, and recovery was slow or incomplete. In other words, avoiding exposure did not guarantee resilience.

The evidence suggests that resilience is less about retreating from global connections and more about building the internal capacities that allow regions to adjust when shocks occur. Regions that combined global openness with strong local capabilities followed a "pain shared is pain reduced" dynamic: Although shocks were transmitted quickly through global networks, recovery was also faster because adjustment mechanisms were already in place.

These results carry important implications for current debates on European industrial policy and strategic autonomy. There is growing pressure to re-shore or near-shore production and reduce dependence on foreign suppliers in the name of security and resilience. While these strategies may reduce exposure in specific sectors, the paper warns that a broad withdrawal from global value chains risks undermining the very forces that support long-term regional resilience. In particular, policies that prioritise insulation over capability-building may leave weaker regions even more vulnerable to future shocks.

Instead, the findings point to an alternative policy direction. Strengthening regional resilience requires sustained investment in economic dynamism, including skills, innovation, and technological upgrading. Diversifying supply bases—rather than simply shortening them—and reinforcing intra-regional capabilities can help regions respond more effectively to disruptions without sacrificing the benefits of openness. Place-based policies that recognise different regional starting points are especially important, as one-size-fits-all approaches are unlikely to address Europe's deep-seated regional inequalities.

Overall, the paper shows that resilience in the face of global shocks is fundamentally a question of capabilities rather than exposure. Europe’s challenge is not simply how to shield regions from global shocks and disengage from global value chains, but how to ensure that all regions have the capacity to adapt when those shocks inevitably occur. Strategies focused narrowly on reshoring or reducing international linkages risk overlooking the deeper sources of vulnerability. Instead, strengthening resilience requires sustained investment in innovation, skills, and diversification—especially in lagging regions—so that all parts of Europe can participate in global value chains in ways that support long-term development and stability.

European regional resilience to supply shocks diffused through global value chains

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Abstract

The aim of this paper is to quantitatively assess the propagation of supply shocks across European regions, triggered by the COVID-19 pandemic and diffused through Global Value Chains (GVCs). By taking advantage of the cross-country variation in policy responses to the pandemic, as well as the heterogeneity in regional productive structures, we document how downstream transmission of shocks via GVC-induced backward linkages yields differences in terms of regional resilience. By combining and adapting datasets at the NUTS2 level, classifying EU regions according to the risk of falling into a development trap, and embedding inter-regional, inter-industry indicators in a regression model estimated with a local projection method, we show that regional responses of real value added to foreign (i.e., inter-country) and domestic (i.e., intra-country yet inter- and intra-regional) shocks are far from homogeneous. The nuanced picture emerging from our findings warns against withdrawing from GVCs as an attempt to insulate from foreign shocks, as this might hamper the very forces that allow dynamic regions to withstand them.

Keywords: Global Value Chains; inter-regional connectivity; regional economic resilience; COVID-19 pandemic supply shocks; regional development trap risk.

JEL classifications: C32, C67, F62, R11, R15.

1. Introduction

In the current geoeconomic and geopolitical context, European countries are facing what has been labelled as a "polycrisis", characterised by the occurrence of simultaneous exogenous shocks that

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lead to domino effects and are channelled by the interconnectivity across countries and regions (Tooze, 2022; Lawrence et al., 2024; Soete and Stierna, 2023).

Soete and Stierna (2023) argue that the recent “cascading crises” - involving the new geopolitical tension that have led to an increase in military and security investments (European Commission, 2024), health outbreaks such as the COVID-19 pandemic, the looming effects of climate change and natural disasters on economies and societies – all resonate with the historical period of high turbulence that Schumpeter lived while developing his seminal ideas. In revisiting Schumpeter’s insights, they argue that the resilience of the European Union (EU, hereinafter) to the polycrisis should rely on *a place-based focused policy* and one that pays attention to the *interconnectivity between global and regional levels*. The two ingredients are intertwined: achieving EU’s regional resilience requires unpacking the channels through which the global polycrisis spreads across countries and regionally within countries. In addition, the polycrisis in Europe is likely to affect more adversely areas that are comparatively more stagnant and with a higher level of vulnerability (Rodriguez-Pose, 2018, Diemer et al., 2022).

These arguments are particularly timely and relevant in a context where the debate on industrial policy is drifting away from a ‘place-based focus’ and is increasingly crafted in terms of strategic autonomy and national economic security (Guerrieri and Padoan, 2024; Fontana and Vannuccini, 2024). Such narrative on achieving resilience to external shocks by trading less and relying on domestic sourcing might be a backlash for the most vulnerable countries and regions.

For instance, albeit not from a regional perspective, Bonadio et al. (2021) have looked at the effects of COVID-19-induced lockdown based on cross-country differences in stringency measures, the share of the work that could be shifted to remote working, and – most importantly – the density of foreign backward linkages versus domestic ones. They find that the counterfactual of foreign backward linkages fully shifting to domestic ones –the *renationalisation*[5] of global supply - does not increase resilience. Replacing reliance on foreign suppliers with domestic ones, for instance by re-shoring or near-shoring, does not necessarily increase resilience to global shocks. Baldwin and Evenett (2020) reach the same conclusion, arguing that ‘turning inwards’ would not only be

[5] This can now be identified with the notion of economic security in the European debate (Guerrieri and Padoan, 2024).

ineffective in terms of increasing resilience to shocks, but would be harmful, particularly to those countries that are most vulnerable, such as lower- and middle-income countries.

While there is growing evidence of how shocks propagate along GVCs at the country and industry level (see, for instance, Joya and Rougier, 2019, Acemoglu et al., 2016, Schwellnus et al., 2023), there is a dearth of empirical evidence on the extent to and the conditions under which global shocks trickle down at the subnational level.

Indeed, identifying suitable place-based policies to increase resilience to global shocks requires a careful analysis of: (i) the 'initial conditions', underpinning existing European regional asymmetries and vulnerabilities in terms of lack of dynamism and inefficient specialisation; (ii) how global connectivity via global value chains makes polycrisis' shocks percolate to different regions, depending on their interregional connectivity; (iii) how regions with different initial conditions perform in terms of resilience, i.e., the speed of recovery after the shock.

It is in the context of this broad research agenda that this paper aims to locate its contribution. Considering the existing asymmetries across EU regions, how do global and regional interconnectivity affect the propagation of shocks? Do regions with different initial conditions respond differently to different types of shocks? Do different degrees of resilience to shocks risk exacerbating the existing EU regional imbalances?

The paper contributes to different streams of literature.

First, a large and consolidated literature has looked at European regional imbalances in terms of growth and development (among others, Bathelt et al., 2024; Diemer et al., 2022) and inequalities in employment and earnings (among others, Rodriguez-Pose, 2018; Wirkierman et al., 2025). Diemer et al. (2022), which we build upon in our empirical analysis, borrow from the concept of middle-income trap (Eichengreen, Park, and Shin 2014) and apply it to European regions. Based on a synthetic indicator of income, productivity and employment growth dynamism, they define regions in (or at risk of falling into) a development trap, and argue that trapped regions are those receiving little policy attention, being caught between national policies targeting the wealthiest and most dynamic places, and the EU cohesion policy targeting the least developed regions.[6] Wirkierman et al. (2025) take a step forward and also consider EU regional trade-linkage centrality (see also Bathelt et al., 2024). They make sense of EU regional asymmetries in employment growth by considering technological dependency and regional trade centrality, finding that a necessary condition for technological strength to contribute to employment growth is the trade centrality of core regional EU blocks. Hence, Europe's regional imbalances reflect a core-periphery structure of technological dependency and high-tech trade centrality.

Second, the literature on *global connectivity* and the role of GVCs as potentially amplifying existing inequalities, with global interconnectivity vehiculating the domino effects of polycrises across countries, has in general been blind to their regional effects, with few exceptions (see Comotti et al., 2020; Crescenzi and Harman, 2023; Almazán-Gómez et al. 2025, Boschma, 2024; Kimino, 2025). These studies have highlighted the importance of adding a subnational or regional lens to the research on GVCs (Comotti et al. 2020; Crescenzi and Harman, 2023), have built on the evolutionary economic geography literature to better understand the ability of regions to develop new and upgrade existing GVCs (Boschma, 2024), have studied the territorial effects of trade policy (Almazán-Gómez et al. 2025) and have explored the intricate relationship between Foreign Direct Investment (FDI) and spatial knowledge within EU subnational regions (Kimino, 2025).

We contribute to this literature by offering a novel framework and method to capture the propagation of an external shock via global (i.e., GVC-induced) and regional interconnectivity across European regions. We consider one of the most emblematic examples of the recent global polycrisis, the COVID-19 pandemic, and the variation in policy response across the world, that has been transmitted downstream across regional sectors via GVC-induced backward linkages and has yielded different effects in terms of regional resilience. In particular, we explicitly build on the concept of regional developmental trap (Diemer et al. 2022) to consider the 'initial conditions' of

[6] This argument resonates with the notion of 'places that do not matter', put forward by Rodriguez-Pose and co-authors (2018, 2021), who suggest that the struggling regions are those that are not supported by EU cohesion policies, and neither they are able to benefit from national policies that mainly support the most dynamic regions. This has generated a hyped debate in the aftermath of Brexit and the raise of other forms of populism in Europe and the US (Rodriguez-Pose et al., 2021).

regional vulnerability, and we study how the COVID-19 pandemic shock has propagated across GVCs affecting regions' performance in terms of income generation in real terms.

There are specific characteristics of regions that feed our interpretative framework: (i) the heterogeneity of initial conditions, that is, the diversity in regional dynamism and the risk of development trap, as in Diemer et al. (2022), in addition to the extent to which each region is insulated or exposed to foreign shocks, which in turn depends on (ii) the intensity of backward linkages with regional, domestic (that is, national), European and extra-EU regions; (iii) the above dimensions lead to regional differences in the opportunity and speed of re-adjustment in the post-shock period, that is the degree of resilience to external shocks.

We employ a range of data sources in our analysis. First, we construct backward GVC participation measures based on FIGARO-REG for 2017, which we combine with information from EUREGIO to further disaggregate the manufacturing, mining and utilities sectors and maximise accuracy of our measurement approach. We then combine these with measures of COVID-19 shocks, which rely on the Oxford COVID-19 Government Response Tracker compiled by Hale et al. (2021) and data on industry's face-to-face contact intensity from Famiglietti et al. (2020). Finally, we draw on measures of real value added from ARDECO, which we temporally decompose with information on turnover indexes from Eurostat. We then resort again to ARDECO to retrieve information on labour productivity, income and occupation rate dynamics to compute development trap risk measures, following Diemer et al. (2022). Our final dataset focuses on European regions at 2 digits of the NUTS 2016 classification, which we use to study how COVID-19 shocks from January 2020 to December 2022 affect output dynamics. We distinguish between foreign and domestic shock by estimating impulse response functions through a local projection model (Jordà, 2005, Teulings and Zubanov, 2014).

We find that dynamic regions, mainly those that are at low risk of development trap, are those that are most integrated within GVCs and source relatively more from extra-EU inputs but also are structurally self-reliant in high-tech inputs. This group of regions have therefore been significantly hit from the initial foreign shock but have been able to recover fast enough and adjust to it. Conversely, regions at medium risk of development trap, that are not necessarily all stagnant, mainly rely on domestically – rather than extra-EU – sourced inputs. This means that foreign shocks are mediated by the indirect linkages of national trade partners with foreign suppliers (from where the initial shock originated) and are, therefore, lagged, with a post-shock recovery that is sluggish. Finally, the group of regions at high risk of development trap are also those that have been the most insulated from foreign shocks, having a relatively weaker integration to GVCs (which does not preclude them from having a *high* dependence on intra-EU foreign inputs which may be substituted), and a higher share of labour inputs on the value of gross output. Here the foreign shock hits the least, as it is mediated by domestic linkages, though it translates in a poor post-shock resilience. We argue that the poor resilience is linked to the propagation of supply shocks to labour compensation which hit final demand, negatively affected by the lack of dynamism and the potential job losses following from the fall in production.

Overall, it seems that a high exposure to foreign shocks coupled with strong initial conditions has led to higher post-shock resilience than a low(er) exposure to foreign shocks when this is combined with an initial lack of dynamism. Regional resilience is hence a 'pain shared-pain halved' story, when foreign exposure is associated with (and possibly be a co-determinant of) high regional dynamism.

We draw implications of our findings for policy by reflecting on the extent to which the parabola of foreign shocks has led to a misplaced tendency to drive industrial policy's objectives towards autonomy and economic security, while focusing on regional internal upgrading – not necessarily withdrawing from economic integration – might be an alternative, safer strategy for European regions in terms of resilience.

The remainder of the paper is structured as follows. The next section focuses on our empirical strategy, explains the formulation of our indicators and their operationalisation into empirical variables, offering descriptive evidence of the regional heterogeneity in initial conditions, foreign and domestic connectivity, and a map of regional resilience to shocks. The following section assesses through econometric methods our research questions and further discusses the results. The final section offers concluding remarks and policy implications.

2. Empirical strategy and descriptive evidence

2.1 How to measure GVC shocks across regions

We look at the propagation of shocks through GVCs across regions by building upon and adapting the national-level analysis of Acemoglu et al. (2016) and Auer et al. (2019). The core intuition of these contributions is that the impact of a supply shock to industry i on industry j is mediated by the importance of industry i in the input structure of industry j.

In line with Acemoglu et al. (2016), we argue that when an industry experiences a negative supply shock, this will be passed on to its customers, who will in turn pass it *downstream* to their customers and so forth. The extent to which the shock propagates depends on how reliant the customers are on the industry that has experienced the shock.

We therefore build a matrix of weights linking EU regional industries with suppliers, both European (identified at the country, region, industry level) and extra-EU (only identified at the country-industry level), relying on information from FIGARO-REG.[7] The dataset is only available for a cross-section of NUTS2 regions for 2017, so in our analysis we assume inter-sectoral and inter-regional linkages to be fixed in time, i.e., they represent truly *structural* proportions. We follow Borin and Mancini (2019) and construct a backward GVC participation indicator between source industry i in region s of country c and destination sector j in region r of country k:

$$backward_{isc,jrk} = V\hat{B}^{(-isc)}E \tag{1}$$

Where V is a diagonal matrix of value-added shares per unit of output and E is a diagonal matrix of gross exports by regional industry of origin, that is the portion of gross output of each regional industry absorbed – that is, demanded – by foreign intermediate *and* final demand. $\hat{B}^{(-isc)}$ is a modified version of the Leontief inverse (Miller and Blair, 2022, p. 21): following Borin and Mancini (2019) this is the inverse of $(I - A^{(-isc)})$, where $A^{(-isc)}$ is a matrix of global input

[7] The dataset is available at https://data.jrc.ec.europa.eu/dataset/dff29c8d-b85b-41fa-9cb7-7289c7324937. As we discuss in the Appendix A, we combine information from FIGARO-REG with EUREGIO, to further increase granularity of our data.

sourcing per unit of gross output (A), from which the row identifying the export of intermediate goods for regional industry isc has been set to zero to avoid double-counting. [8]

This measure links gross exports of each industry-region-country jrk to the value-added contributions coming from each industry-region-country isc. We discuss the details of how we compute this matrix of weights in Appendix A.[9]

We then combine information on regional industries' reliance on their suppliers with measures of upstream shocks, following Schwellnus et al. (2023). We choose the exogenous shocks related to lockdowns and restriction of mobility that countries deployed between January 2020 and December 2022. To compute this, we combine the country-level data from the Oxford COVID-19 Government Response Tracker compiled by Hale et al. (2021) with data on industry's face-to-face contact intensity from Famiglietti et al. (2020):[10]

$$covid\ shock_{ic(m)} = \Delta stringency_{c(m)} * FaceToFace_i \tag{2}$$

where $\Delta stringency_{c(m)}$ of country c in month m measures the monthly change in the stringency index, which ranges from 0 to 100 and "measures the extent of school, workplace and public transport closures, restrictions to public events, gatherings and internal movements, requirements to stay at home, controls of international travel and public information campaigns" (Schwellnus et al., 2023, p. 15).

[8] While we refer the interested reader to the discussion in Borin and Mancini (2019), the intuition here is that the Leontief inverse connects *final* output to the primary factors producing it. Backward GVC participation, instead, considers foreign value added in *all* (i.e., both final and intermediate) goods and services that exit a country. The authors propose a methodology to properly disentangle this.

[9] This measure captures for each unit of export of a region-industry the amount of value added required from each supplier. We choose to look at value added embodied in gross exports, rather than gross output for two reasons. First, we wish to remain consistent with the broad literature on GVC participation and, second, we wish to avoid any mechanical relationship between our explanatory variable and our outcome variable in the econometric analysis in section 3.

[10] A brief discussion on notation is in order at this point. Subscripts isc refer to the industry of origin i in region s of country c (the supplier), whereas subscripts jrk refer to destination sector j in region r of country k (the buyer). In our framework, the granular unit of analysis is destination sector jrk, which receives shocks originating (directly or indirectly) from all its suppliers. Such shocks vary over time; and we report all time-related notation in brackets, in this case, month (m).

Instead, $FaceToFace_i$ of source industry *i* ranges from 0 to 100 and is obtained by aggregating – across occupations within each industry – individual, survey-level responses to the extent that a job requires to perform tasks in close physical proximity to others.[11]

The data on stringency of COVID-19 restrictions is provided daily, and we aggregate it to months (m) for each country (*c*)*;* the data on face-to-face contact is provided for the NAICS industry classification, which we translate into the NACE Rev. 2 industry classification (subscript *i*). The shock therefore captures the *increase*[12] in COVID-19 restrictions ($\Delta stringency_{c(m)}$) combined with an indicator of exposure to such measures across industries ($FaceToFace_i$).

Starting from equations (1) and (2) we compute a measure of COVID-19 shocks for each industry-region-country by looking at the average COVID-19 policy restriction of its suppliers (including itself), weighted by the importance of each supplier:

$$COVID_{jrk(m)} = \sum_{isc} w_{isc,jrk}^{t0} * covid\ shock_{ic(m)} \qquad (3)$$

$w_{isc,jrk}^{t0} = \frac{backward_{isc,jrk}}{\sum_{isc} backward_{isc,jrk}}$ is a time invariant weight (measured in $t0 = 2017$) based on backward GVC participation, i.e., flows of value added from *isc* to exports of *jrk*.

Our approach provides us with a disaggregation of shocks across regions, countries, time, and industries. This is important since industries are affected by COVID-19 stringency policies to a different degree and they also have different patterns of GVC integration, so it is crucial to account for these heterogeneities. As we discuss further down in this section, our outcome variable does not vary at the industry level and requires us to aggregate our $COVID_{jrk(m)}$ measure across

[11] Possible survey answers and corresponding individual scores in parenthesis are: 'I don't work near other people (beyond 100 ft.)' (score = 0), 'I work with others but not closely (e.g., private office)' (score = 25), 'Slightly close (e.g., shared office)' (score = 50), 'Moderately close (at arm's length)' (score = 75), 'Very close (near touching)' (score = 100). See Famiglietti et al. (2020) for details.
[12] The stringency measure from Hale et al. (2021) starts on January 1st, 2020. In order not to lose January 2020 from our analysis we could assume that the measure in December 2020 was equal to 0 everywhere. Looking at the data, it seems that in the early days of 2020 this was still the case across most countries, however the data also shows that China and Hong Kong already have non-zero values for the early days of January, and we know that these countries had already started introducing restrictions in December 2019. To account for this, we resort to imputing the value for December 2019 as the average of the first ten days of January 2020, while we assume that policy stringency was equal to 0 until November 2019 for all countries.

destination industries j, using information on GDP shares from the European Commission's Annual Regional Database (ARDECO) for the year y:[13]

$$COVID_{rk(m,y)} = \sum\nolimits_j \frac{GDP_{jrk(y)}}{\sum_h GDP_{hrk(y)}} * COVID_{jrk(m,y)} \tag{4}$$

Hence, our final measure combines (i) information on the variation in policy stringency to counter the COVID-19 pandemic, (ii) the intensity of backward GVC linkages and (iii) the industrial structure of each region in terms of GDP shares.

Equation (4) reports the average shock that a region receives through its backward participation to GVCs from *all* industries that supply value added to it. This includes both the region's own inter-industry linkages, the input linkages with the domestic economy and those with foreign suppliers. By selectively setting to zero the appropriate weights we can retrieve two kinds of shocks:

1. $COVIDf_{rk(m,y)}$ – the COVID-19 shock to region *r* in country k induced by foreign suppliers.
2. $COVIDd_{rk(m,y)}$ – the COVID-19 shock to region *r* in country k coming from domestic suppliers.[14]

This refinement therefore distinguishes between regions' foreign (i.e., inter-country) and domestic (i.e., intra-country yet inter- and intra-regional) COVID-19 shocks. Crucially, our measure fully accounts for the geographic origin of shocks at a regional level: to highlight this we can focus on January 2020 in which most countries had not introduced any restriction to counter the COVID-

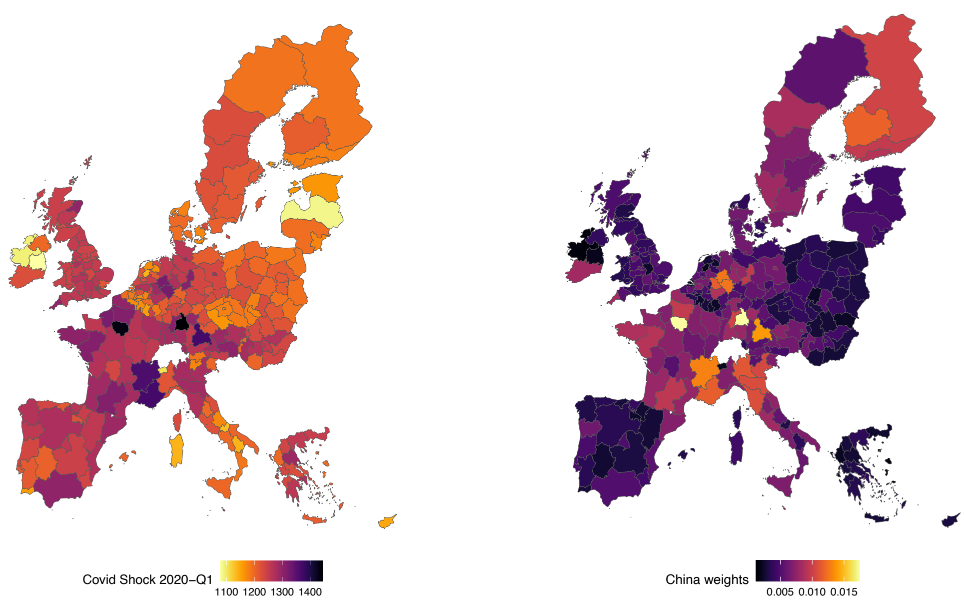
[13] To clarify, index h in the summation in the denominator of the equation is an index that iterates over destination industry. It is different from *j* to avoid confusion in the nested summation. By using h, we make clear that one can take the denominator term outside of the main summation (the one over *j*), and still obtain the same result.

[14] For domestic shocks, the country of origin is the same as that of destination, so $c = k$. Specifically, $COVIDd_{rk(m)}$ is equal to: $COVIDd_{rk(m)} = \sum_j \frac{GDP_{jrk(y)}}{\sum_h GDP_{hrk(y)}} \sum_{isc} w^0_{isc,jrk} * covid\ shock_{ic(m,y)}$, with $c = k$. It is important to note that $covid\ shock_{ic(m,y)}$ does not vary across regions within the same country. However, it does vary across *industries* of origin i by country c and so do the weights $\sum_{isc} w^0_{isc,jrk}$, as well as the region's economic structure, captured by $\frac{GDP_{jrk(y)}}{\sum_h GDP_{hkr(y)}}$. So, domestic COVID-19 shocks will vary across regions within the same country to the extent that regions differ from each other in terms of their linkages with other domestic industries and in terms of their economic structure.

19 pandemic, except China (and to a lesser extent Hong Kong and Mongolia). Figure 1 reports our foreign COVID-19 shock measure in January 2020 (left-hand side map) and the weights given to China based on equation (1) (right-hand side map).

Our measure accurately captures that in January 2020 the regions that suffered the largest COVID-19 shocks are also those that imported the largest shares of value added from China, notably, Stuttgart, Munich, Dusseldorf, Île de France and Rhône-Alpes, Provence-Alpes-Côte-d'Azur, as well northern Italy. These are for the most part manufacturing regions that import components from China for both machineries, automotive and textile industries.

Figure 1 – Foreign COVID-19 shocks in January 2020 (left panel) and backward GVC participation weights for China (right panel).



Source: Authors' calculations based on FIGARO-REG and ARDECO databases, EUROSTAT, Oxford COVID-19 Government Response Tracker and Famiglietti et al. (2020).

2.2 Outcome variable: monthly real value added across regions

To study the effect of monthly COVID-19 shocks on EU regions we look at the dynamics of real value added between January 2020 and December 2022. We therefore combine information on annual real value added at the regional level from ARDECO for the years 2012 to 2022 and couple this with information from real monthly turnover indexes from Eurostat. We use the Denton-Cholette method (Dagum and Cholette, 2006),[15] using regional annual information as benchmark and national monthly measures as a time-varying indicator to obtain regional monthly measures of real value added for the industrial sector.[16] Eurostat monthly turnover index provides a measure of volume trend in value added for the industrial sector, so our outcome variable only captures value-added dynamics in these industries. We focus here on the industrial sector because it is the one that is the most integrated within GVCs, while still accounting for a significant portion of the European economy.[17]

Figure 2 reports the monthly dynamics of regional real value added in different EU countries. As expected, we observe a significant contraction of real value-added growth after February 2020 (identified by the vertical dashed line) which then bounces back by the summer of 2020.

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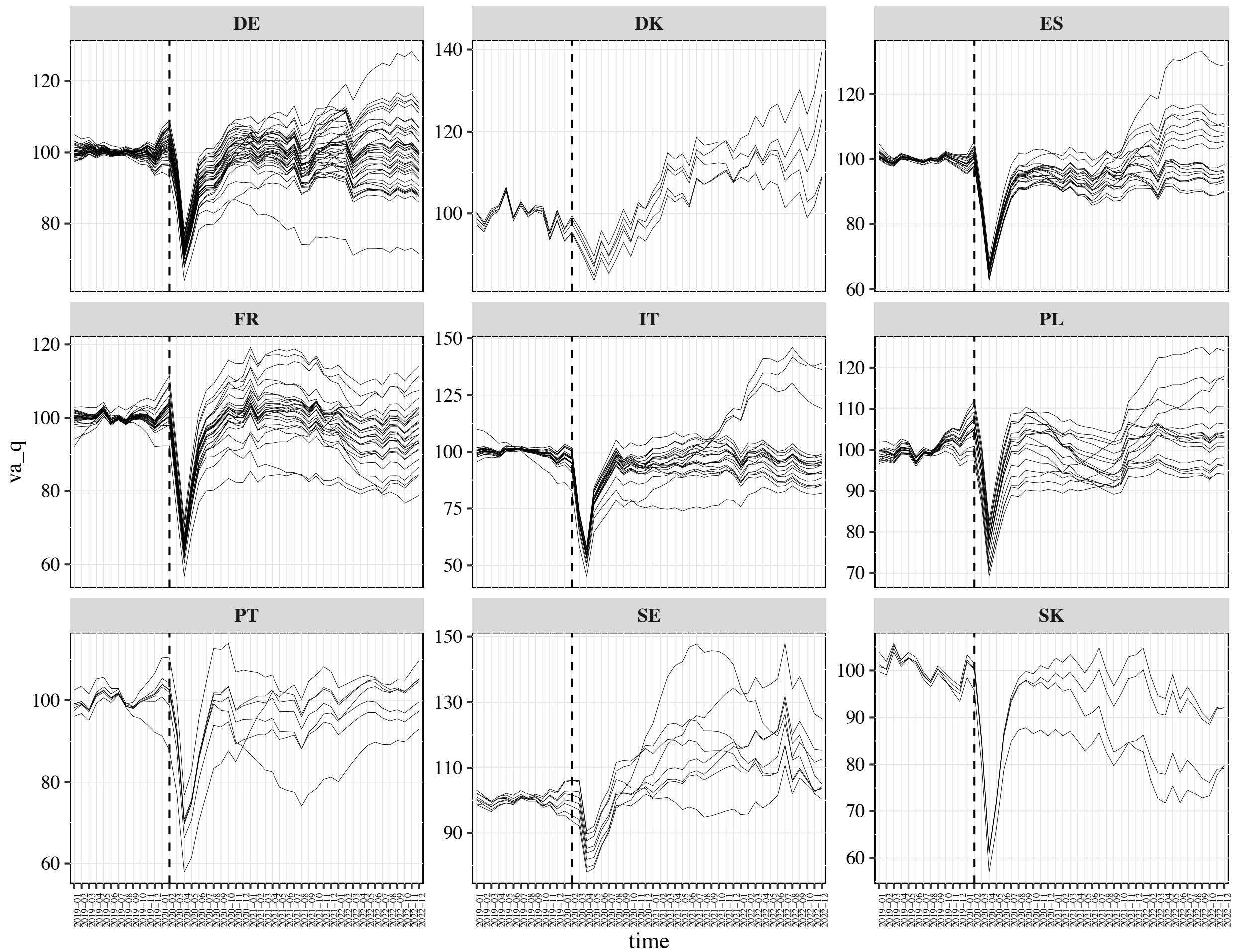
[15] This method allows combining information on monthly dynamics which is constrained to annual levels provided by ARDECO. Crucially, we have annual information all the way through 2022, which means we do not need to use monthly indicators to extrapolate, but to simply perform a temporal disaggregation.

[16] This covers mining and quarrying (B), manufacturing (C) as well as energy (D) and water and waste management (E). This is because EU regional data from the ARDECO dataset only provides information for the industrial sector (B-E) as a whole. It is important to highlight that the volume indexes for the B-E aggregate, which we rely on, are largely driven by the dynamics of the manufacturing sector, which accounts for the largest share of value produced.

[17] Eurostat does not provide monthly turnover indexes for the total economy, but only for broad sectors. We therefore refrain from performing aggregations across industries, to minimise noise in our estimates.

Figure 2 – Real GVA of the industrial sector across EU regions, monthly dynamics, 2019 = 100.



Notes: Time period from 2019-01 to 2022-12. EU countries in each panel identified by their ISO2 country acronym.
Source: Authors' calculation on Eurostat short term statistics, production in industry, monthly data.

Two remarks are in order here. First, we do not observe large wide-spread contractions in real value-added growth in the following months despite restrictions being put back in place in winter 2020, suggesting that production processes have somewhat adjusted after the first shock. Second, after the first shock, the dynamics of real value-added exhibits much more cross-regional heterogeneity, suggesting that not all regions have recovered at the same speed. We explore this further in our econometric analysis, when looking at differences of the impact of the COVID-19 shock across regions at different risks of being in a development trap, borrowing from Diemer et al. (2022).

2.3 The initial conditions: Regional heterogeneity in the risk of development trap and resilience to foreign and domestic shocks

As mentioned in the previous section, the literature on economic geography has shown that regions differ in terms of growth and development (among others, Bathelt et al., 2024; Diemer et al., 2022), employment and earnings inequalities (among others Rodriguez-Pose, 2018), technology and trade centrality (Wirkierman et al., 2025). This geographical heterogeneity may also affect the regional capability to react to domestic and foreign shocks.

Among the local characteristics that may affect resilience, we focus on regional dynamism as a key determinant of being at risk of falling into a development trap, following the approach developed in Diemer et al. (2022). We update their results by looking at the 2011-19 period, broadly following their methodological approach, by relying on data on income (GDP per capita at constant prices), labour productivity (gross value added per worker at constant prices) and employment-to-population ratio. We describe how we compute the risk of a region falling into a development trap in detail in the Appendix C. At any rate, the intuition of this indicator is to compare a region's dynamism with respect to national and EU levels along the three above-mentioned dimensions (per-capita GDP, labour productivity and employment intensity). The measure will therefore capture whether a region is growing faster (or slower) than the rest of the EU.

The development trap risk (DTR) indicator developed by Diemer et al. (2022) that we adopt is bound between 0 and 1, allocating to each region a probability of falling into a development trap. The higher the value of the indicator, the higher the probability. The full set of values across regions may be considered as a distribution of the risk of being trapped. We then classify regions according to their position in the distribution of the (time-)averaged 'risk of being trapped' (DTR) indicator, according to four possibilities:[18]

[18] Our approach (slightly) differs from the one introduced by Diemer et al. (2022), where regions above Quartile 3 are considered 'in a development trap' (which corresponds to our 'high risk' category) and regions between Quartile 2 and Quartile 3 are considered 'at risk of becoming trapped' (which corresponds to our 'mid-high risk' category). Instead, we allocate a risk of being trapped to all regions (from low to high), so that also regions between Quartile 1 and Quartile 2 – considered not-at-risk for Diemer et al. (2022) – are allocated a 'mid-low risk' of being trapped, whereas those regions below Quartile 1 we classify as being at 'low risk' of being trapped. The rationale for this classification is that regions slightly above or slightly below Quartile 2 (i.e., the median) may not be so different from each other, so by explicitly considering regions at the two extremes of the distribution - those at low risk, below Quartile 1 and those at high risk, above Quartile 3 - we aim to contrast and highlight their diverging trajectories and structural configuration.

(i) At *low* development trap risk (below Quartile 1);

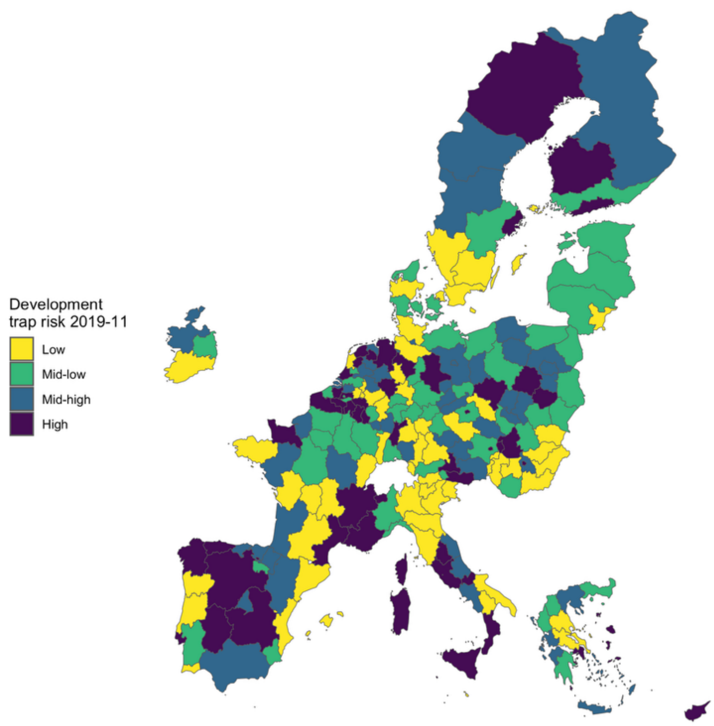
(ii) At *medium-to-low* (‘mid-low’) development trap risk (between Quartile 1 and Quartile 2);

(iii) At *medium-to-high* (‘mid-high’) development trap risk (between Quartile 2 and Quartile 3);

(iv) At *high* development trap risk (above Quartile 3).

Figure 3 depicts a map of European regions, classified according to categories (i)-(iv) detailed above.

Figure 3 – Development trap risk across regions over the period 2011-19.



Source: Authors’ calculations based on ARDECO database.

Results highlight significant heterogeneity across regions within countries. For example, Italy shows a divide between North and South but also the presence of some dynamic regions in the South, France is also affected by large disparities, with both Southern and Northern regions at high risk of being in a development trap. The same goes for Eastern regions in the Netherlands. It is important to stress that development trap is measured only in dynamic terms, i.e., as an inverse measure of overall economic dynamism. It is therefore interesting to compare it with more structural measures, which we know affect how COVID-19 shocks propagate.

We start by comparing dynamics (captured by the DTR indicator) with levels of per capita income. In Table 1 we tabulate development risk with the same classification of income used in Diemer et al. (2022), i.e., we consider high income regions above the EU average, low income regions with income less than 75% of the EU average and middle income those in between.[19] For simplicity, we lump mid-low and mid-high risk regions into a unique category.[20]

Table 1 – European regions across development risk and income levels.

Development trap risk	High income	Mid income	Low income	Total
Low	0.42	0.23	0.35	1.00
Mid	0.41	0.23	0.37	1.00
High	0.47	**0.33**	**0.20**	1.00
Total	0.43	0.25	0.32	1.00

Source: Authors' calculations based on ARDECO database.

Table 1 evinces that economic dynamism does not map uniquely into income levels, in line with Diemer et al. (2022). Across *all* levels of development trap risk, just under half of the regions are high-income: economic dynamism varies essentially irrespectively of high-income status. Mid-income regions are however overrepresented in the group of regions at high development trap risk, accounting for 33% of regions at high risk, against an average share of 25%. Conversely, low-income regions are underrepresented among those at high risk, which account for only 20% of them, against an average of 32%.

[19] We measure income here in terms of GDP per capita, since we are no longer looking at changes over time but comparisons across countries, we rely here on GDP per capita at purchasing power parity, also sourced from ARDECO.
[20] Hence, the mid-risk aggregated category comprises all regions between Quartile 1 and Quartile 3 of the distribution of the risk of being trapped.

This evidence underscores two points, crucial for our study. First, high per capita income is not necessarily representative of economic dynamism; the latter, in turn, is key to explain a region's ability to overcome external shocks. Second, in line with the growing literature on regional development trap, mid-income regions appear to have a structurally vulnerable position: they are dynamic enough to have moved -- in many cases -- beyond a low-income status, yet not sufficiently resilient to withstand adverse shocks. Taking this heterogeneity in economic dynamics becomes crucial to understand how regions react to external shocks.

To further pursue this, we examine other key structural features of regions across development trap risk groups in Table 2. Low risk regions not only have higher economic dynamism but also consume a larger share of high-tech intermediates (col. 1) and source a larger share of intermediates from within themselves (col. 2). They are also integrated internationally, especially with countries outside of the European Union and China (col. 5 and 6, respectively). These are signals of regions that have access to a varied array of productive capabilities locally, specialised in technology-intensive activities and with a high participation in global value chains.

We do not expect these features to insulate them from external shocks: Figures 1 and 3 indeed show that many of the regions that are most exposed to China and have been hit by large shocks in January 2020 are also among those with low development trap risk. However, the characteristics that emerge from Table 2 suggest that these regions are likely to bounce back and recover from external shocks.

Table 2 – European regions across development trap risk levels and intermediate consumption patterns

Dev. trap risk	**Shares of intermediate consumption (%)**						**LC/GO (%)**
	High-tech (1)	Regional (2)	Domestic extra-region (3)	Foreign (4)	Extra-EU (5)	China (6)	(7)
Low	**7.28**	**23.65**	44.73	31.62	**3.57**	**0.81**	29.54
Mid	5.77	19.86	**50.87**	29.26	2.86	0.55	31.65
High	5.51	19.70	47.60	**32.70**	3.02	0.59	**33.82**

Source: Authors' calculations on ARDECO data and FIGARO-REG. LC/GO = labour compensation to gross output ratio as a percentage; We focus on C26 to C30 as high-tech and overlook C20-21 since these are mixed with C19, manufacturing of coke and petroleum. The table reports unweighted averages by development trap risks. For each column we report the largest value in bold.

Regions at medium risk of development trap exhibit a rather different profile. They have the lowest average share of foreign intermediates (col. 4 to 6), and the largest share of intermediates sourced from the domestic (i.e., national) economy but not from the same region. Note that Table 2 reports shares of *direct* intermediate consumption, while our COVID-19 shock indicator relies on the Leontief inverse and, therefore, accounts for both direct and indirect flows of value added. So, focussing on direct purchases is informative of *how*, rather than *how much*, each region is integrated with the rest of the global economy. The strong direct linkages that mid-risk regions have with the rest of their domestic economy suggests that their exposure to foreign shocks might be indirect and, therefore, manifest with a lag.

Finally, regions with a high risk of development trap also import intermediates from abroad, but they are less integrated with extra-EU partners and consume fewer high-tech intermediates (cols. 4, 6 and 1, respectively). This suggests that they may be less exposed to foreign shocks, since they rely less on non-EU suppliers providing specialised high-tech inputs and can rely on smoother intra-EU trade relationships. At the same time, high-risk regions display the highest labour-compensation-to-gross-output ratio (col. 7). This indicates a cost structure skewed towards local wage payments, while sourcing relatively few inputs from their own regional economy (col. 2) and, overall, exhibiting lower roundaboutness. Such a structure can further insulate these regions from foreign shocks but makes them more vulnerable to domestic ones. In particular, domestic shocks can propagate not only through supply channels but also through demand channels, if wage contractions reduce local demand, as we surmise when interpreting our econometric results in the following section.

3. Econometric analysis

We have described above how we compute foreign and domestic COVID-19 shocks. These are continuous variables that take values zero before January 2020 and then observe a large increase, in a rather synchronous way, in the first months of 2020, with more modest variation from the second half of 2020 through the end of 2022. We relate these measures to changes in real value added across regions. We know that shocks along GVCs are not always immediate and that it might take some time for them to propagate (Schwellnus et al., 2023). This setup lends itself well to be studied in terms of impulse response functions with a local projection method (Jordà, 2005, Teulings and Zubanov, 2014). We follow the approach in Schwellnus et al. (2023), although we focus here on backward shocks, distinguishing between foreign and domestic ones. We therefore estimate the equation below at a monthly frequency over the course of 12 months:

$$\ln(y)_{r(t+k)} - \ln(y)_{r,t-1} = \alpha + \beta_1^k COVIDf_{kr(t)} + \varphi^k \sum_{f=1}^{k} COVIDf_{kr(t+f)} + \\ + \beta_2^k COVIDd_{kr(t)} + \delta^k \sum_{f=1}^{k} COVIDd_{kr(t+f)} + \rho_r + \tau_t + \varepsilon_{rt} \quad (5)$$

For each time t, we study how the COVID-19 domestic and foreign shocks affect the change in the log of real value added of the industrial sector of region *r* from the previous period $y_{r,(t-1)}$ and that of the k^{th} following month.[21] When looking at the effect of shocks over time it is important to account for both past and intervening shocks, both foreign and domestic ($\varphi^k \sum_{f=1}^{k} COVIDf_{kr(t+f)}$ and $\delta^k \sum_{f=1}^{k} COVIDd_{kr(t+f)}$, respectively). We also include fixed effects for regions and time, ρ_r and τ_t, and cluster our standard errors by region.

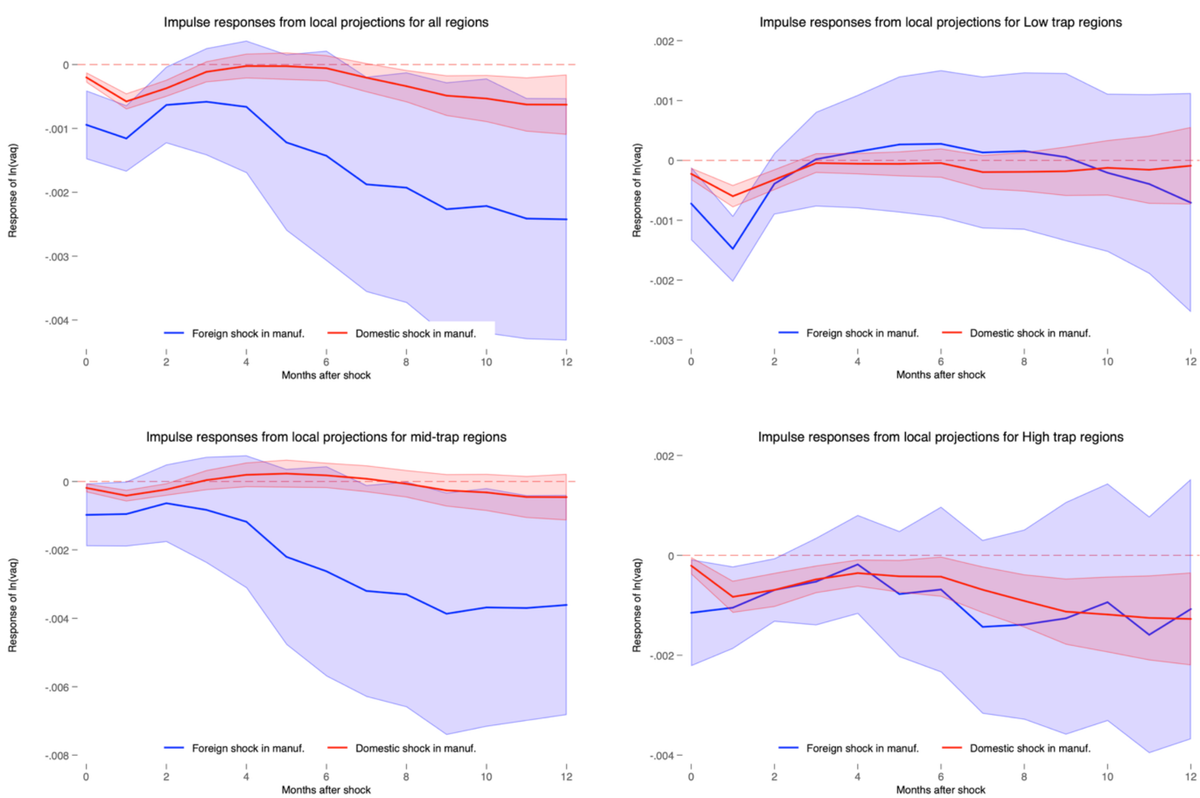
We run our econometric analysis on a broad sample of regions from EU countries, excluding only a few smaller economies for which we have no regional breakdown or present highly volatile data.[22] Furthermore, our preferred estimation relies on regional shocks that are weighted averages

[21] Please note that in this section (differently from the previous one), subscript *k* refers to a parameter going from 0 to 12 indicating our time horizon.

[22] Our final sample includes Austria, Belgium, Czechia, Germany, Denmark, Spain, Finland, France, Hungary, Italy, the Netherlands, Poland, Portugal, Sweden and Slovakia. We exclude Cyprus, Estonia, Luxembourg, Malta, Latvia (these smaller countries do not offer a regional NUTS 2-digit breakdown), Bulgaria, Croatia, Romania, Slovenia (for which no regional breakdown is available in FIGARO-REG). We also exclude Greece and Ireland, which are affected by well-known reliability issues concerning national accounts, especially for Ireland due to how multinational companies report their activities. However, in Appendix D, we report results with the full sample of countries, i.e. excluding only Bulgaria, Croatia, Romania and Slovenia. Results are broadly consistent.

of COVID-19 shocks endured by manufacturing industries alone, but originating across all industries and countries. This is because manufacturing production has been affected the most by supply chain disruptions. Furthermore, our outcome variable is changes in real value added in the industrial sector of which manufacturing is by far the largest component, in addition to mining and utilities[23]. In Appendix D, we run extensive robustness checks, by including shocks from all industries, expanding our sample and weighting our results on regions' value added to capture their economic size. Results are largely consistent as we further discuss in Appendix D. Figure 4 reports the effect of both domestic and foreign shocks over time, while we report regression tables in Appendix D.

Figure 4 – COVID-19 shocks, foreign and domestic



Source: Authors' calculation. Graphs report estimates and 95% confidence intervals for a local projection model used to estimate impulse response functions for domestic and foreign shocks. To facilitate interpretation, shocks have been rescaled by 100. Shocks are based on regional averages of the manufacturing sector.

[23] We opt to exclude these industries from our preferred shock measures because they are both prone to measurement error both in the compiling of input-output linkages and in estimating face-to-face interactions, which would affect our variables. As we discussed further in our text we do run a battery of robustness checks including all industries and find consistent results.

We find that overall COVID-19 shocks, both domestic and foreign, have a significant and rapid effect, even from the first month following the shock. Coefficients are small but not economically negligeable either, looking at the first month for all regions (upper left panel in Figure 4) the coefficient implies that a change of 100 in the COVID-19 shock would correspond to a reduction of real gross value added growth of 0.12%.[24] Interestingly, we find that both foreign and domestic COVID-19 shocks have lasting effects over time, imposing a significant drag on output growth over the following year. To quantify this, we can take the coefficient corresponding to foreign COVID-19 shocks at the ninth month, equal to 0.0023 in Table A3.a in Appendix D; if we scale this by the standard deviation in our sample reported in Table A.2 in the Appendix, we find that a one standard deviation increase in the COVID-19 foreign shock reduces real value added cumulatively over 10 months by approximately 1.23% relative to its value at month t-1.[25] To put this into perspective, we can compare this with the average monthly growth (as delta log of real value added) in the 2016-2019 period which in our sample is equal to 0.00154 (approximately 0.154%). It then follows that a 1-standard-deviation foreign shock is associated to a –1.23% cumulative change over 10 months. Since normal monthly growth is only about 0.15%, this shock is economically equivalent to wiping out roughly 8 months of normal economic growth.

These results for all regions mask significant heterogeneity, which we explore in the other three panels of Figure 4. The most dynamic regions, at low risk of development trap, seem to recover quite quickly from both – foreign and domestic – shocks. They are more strongly affected than the full sample, but by month 2 foreign shocks lose statistical significance and the same occurs for domestic shocks by month 3. Overall, these regions seem to be able to bounce back rapidly, relying on their strong economic dynamism and, as discussed in the previous section, on their ability to source a large share of intermediates from within themselves.

[24] To see where this figure comes from, note that we have rescaled our explanatory variables by 100 to make results easier to interpret. As we show in Table A2 of Appendix B, our COVID-19 foreign shocks in 2020 have a median value of 115.9, with an average of 335.73, making a quantification based on a $COVIDf_{kr(t)}$ increase by 100 quite reasonable. Now, recall we have a log-level model, where the percentage change in the outcome variable is equal to $100*\beta_1^k COVIDf_{kr(t)}$. As we show in Table A3.a of Appendix D, the foreign shock has a coefficient of -0.0012, which means that a one unit increase in the foreign shock (rescaled by 100) is equal to a decrease of 0.12% of gross value-added growth. Finally, it’s also important to stress that these estimates only capture partial equilibrium effects, without accounting for broader general equilibrium dynamics.

[25] Again, to clarify, this is 0.0023 * 533.3489, which we rescale by 100 and obtain -0.0023 * 5.333489 ≈ -0.0123, i.e., -1.23%.

On the other hand, regions at a medium risk of development trap experience a consistently negative foreign shock, although this is only statistically significant from month 6. This reflects the fact that supply-chain shocks often manifest with a delay (Schwellnus et al., 2023) and that these regions are particularly well embedded within the domestic economy (see Table 2), meaning that they are likely to having been hit by foreign COVID-19 shocks mostly indirectly. However, they also struggle to diversify and endure longer effects of the shock, compared to regions at low risk of development trap, hence showing a lower resilience.

Finally, the regions at high risk of development trap exhibit yet a different pattern. They recover rather quickly from foreign shocks, while in contrast they endure long-lasting negative effects from domestic shocks. As hinted in the previous section, this can be explained considering that these regions are relatively more labour intensive with a cost structure skewed towards wage payments rather than intermediate inputs (see Table 2). Hence, their production processes are less roundabout and, therefore, more at risk of being unable to recover from domestic shocks. This can, in turn, be explained through a Keynesian mechanism of decreasing income (i.e., value added, of which wages are a key component), leading to lower final demand (which, to a sizeable extent, depends on consumption financed out of wages), further leading to lower output and lower income. Therefore, these regions manage to recover quickly from foreign shocks due to their relatively lower connectivity to extra-EU regions, higher integration with European foreign suppliers and their input cost structure biased towards wages, as discussed in Table 2. However, their reliance on wages makes it harder to recover from domestic shocks, as these hit both the supply and demand side: lower wages not only disrupt production but also reduce domestic income and, as a result, demand for final output.

These results have significant implications for the economic performance of European regions, both in absolute and relative terms. First, we show that all regions are affected by both domestic and foreign shocks, and that in a highly economically integrated continent such as Europe, a relatively lower *direct* import intensity of intermediates offers little shelter from GVC shocks. However, the regions' ability to recover from such shocks is significantly affected by their own economic dynamism. Regions growing fast can bounce back quickly, while laggards are often saddled with a lasting drag on their output growth. More specifically, regions at a medium risk of development trap see their output being negatively affected by foreign shocks with a delay due to the indirect import of inputs, while regions trapped – or at a high risk of being trapped – are largely vulnerable to domestic shocks due to their cost structure biased towards wage costs rather than intermediate inputs and to the lack of local economic dynamism.

Overall results (top left panel of Figure 4) are led by those for regions at mid-risk of development trap, that is the group with the highest number of regions. This is in itself indicative of the state of European resilience to foreign shocks: the dependence on extra-EU foreign suppliers is not in itself a symptom of vulnerability, whereas the lack of dynamism and of high-tech inter-regional trade centrality (in the sense of Wirkierman et al., 2025) are perhaps more so.

4. Concluding remarks

The current historical phase of polycrisis, as we have argued, may generate several collateral effects on EU regional cohesion that extend well beyond the immediate impact of individual shocks. These effects risk reshaping policy priorities—for instance, by weakening the emphasis on place-based and EU regional cohesion policies (Rodríguez-Pose, 2025), or by shifting both the policy discourse and financial resources toward economic security concerns and away from interventions aimed at industrial upgrading and employment growth.

This paper has sought to provide evidence that warrants caution before moving decisively in either of these directions. Focusing on one of the emblematic contributors to the polycrisis—the COVID-19 shock—we show that addressing the persistent lack of dynamism in many European regions may constitute a necessary precondition for effectively responding to future foreign (and domestic) shocks and for securing a more sustainable form of resilience.

We pursue this objective by introducing a novel methodological framework and presenting new empirical evidence that examines regional and global interconnectivity—an aspect that is central to understanding the transmission and amplification of shocks.

Using the supply-side restrictions associated with the COVID-19 pandemic as an illustrative case, we analyse how regions respond to major economic shocks. Our findings show that these responses are far from homogeneous: initial structural conditions and underlying economic dynamism play a critical role in shaping regional resilience to shocks.

Dynamic regions, that combine GVC integration with extra-EU partners and sourcing of high-tech inputs with strong intra-regional capabilities, experience the strongest initial disruption but also mounted the fastest recovery. Regions at medium risk of development trap, by contrast, display a more limited international orientation and rely primarily on domestic (though inter-regional) and intra-EU input sourcing. Here, the transmission of foreign shocks occurred indirectly and with delay, leading to a slower recovery. Meanwhile, the most vulnerable regions, at high risk of falling into a development trap, were relatively insulated from the initial foreign shock due to lower global (extra-EU) integration, but this insulation offered little advantage in the longer run. Coupled with lower economic dynamism, higher dependence on labour-intensive production, they have limited capacity to rebound, resulting in persistently negative consequences from domestic shocks.

All in all, our results paint a nuanced picture of the initial conditions of regions at different risks of development trap. High-income status is not, *per se*, associated with either higher or lower risk of being in a development trap, nor is integration with foreign suppliers. This can in fact be compatible with economic resilience to shocks, provided regions have the necessary initial capabilities to adapt. Resilience in this context is therefore less about avoiding exposure and more about having the capacity to absorb and reconfigure. In this sense, regional resilience operates according to a "pain shared is pain reduced" mechanism, provided that external exposure is matched with, and may co-evolve with, robust regional economic dynamism.

These findings offer new and relevant insights for the debate on European industrial policy and strategic autonomy. The current focus on prioritising autonomy and security as a strategy to shield from external shocks risks overlooking the structural and, perhaps, more sustainable sources of regional resilience, such as economic dynamism, a diversification of intermediates' suppliers and intra-regional high-tech capabilities, allowing to rapidly readjust in the post-shock period. Withdrawing from global value chains or reconfiguring them via re-shoring or near-shoring in the attempt to insulate from foreign shocks, might hamper the very forces that allow dynamic regions to withstand external shocks. Conversely, focusing on internal upgrading, building new capabilities, and diversifying regions' supplier base can offer the necessary conditions to increase resilience without sacrificing economic openness.

While the paper advances a spatially grounded understanding of regional exposure and resilience, some limitations can be mentioned, that open important avenues for further research.

First, the analysis focuses on the COVID-19 shock as a paradigmatic example of the polycrisis; however, different types of shocks—energy, geopolitical, climatic—may interact with regional structures through different regional mechanisms, limiting the generalisability of our findings.

Second, despite incorporating key indicators of regional dynamism and global integration, our framework does not fully capture the institutional, political–economic and social underpinnings that contribute to the understanding of how regions mediate and respond to shocks. These dimensions are particularly relevant when we mention the polycrisis, as the co-occurrence of different shocks implies also all the different realms involved.

Third, the empirical evidence relies on existing multi-regional input–output and GVC datasets that, while informative, provide only partial account of firm-level heterogeneity. Future research could extend the analysis by comparing multiple types of shocks, integrating richer institutional and behavioural data, and exploiting more granular spatial or firm-level sources to deepen understanding of how regional resilience in an evolving global economic geography can be achieved.

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Appendixes

Appendix A – Regional input-output tables and backward participation to GVCs

Our effort to devise measures of COVID-19 shocks diffused through GVCs relies on having high-quality and granular data. Regional input-output data present several challenges in this respect. First, and foremost, the FIGARO-REG database offers only a coarse industrial disaggregation bundling manufacturing together with mining and utilities (letters B to E in the NACE Rev.2 classification). However, these industries have radically different patterns of integration in GVCs and therefore exposure to upstream shocks. To properly account for this, we disaggregate the information in FIGARO-REG with data from its predecessor, i.e., EUREGIO, which offers a richer industry disaggregation but only up to 2010. We therefore use EUREGIO's shares to disaggregate FIGARO-REG as reported in the Table A.1 below:

Table A1 – EUREGION to FIGARO-REG industry crosswalk

EUREGIO industry code (2010)	EUREGIO Industry descriptor (2010)	FIGARO-REG industries (2017)	Disaggregated industry (2017)
ss1	Agriculture	A	A
ss2	Mining quarrying and energy supply	B-E	B
ss3	Food beverages and tobacco	B-E	C10T12
ss4	Textiles and leather etc	B-E	C13T18
ss5	Coke refined petroleum nuclear fuel and chemicals etc	B-E	C19T21
ss6	Electrical and optical equipment and Transport equipment	B-E	C26T30
ss8	Other manufacturing	B-E	CX
ss9	Construction	F	F
ss10	Distribution	G-I	G
ss11	Hotels and restaurant	G-I	I
ss12	Transport storage and communication	G-I	H
ss13	Financial intermediation	K	K
ss14	Real estate renting and business activities	M_N	M_N
ss15	Non-Market Service	O-Q	O-Q
ss14	Real estate renting and business activities	J	J
ss14	Real estate renting and business activities	L	L
ss15	Non-Market Service	R-U	R-U

EUREGIO also works with a different vintage of the NUTS regional classification, so we rely on conversion tables provided by the Joint Research Centre of the European Commission within the R-package *nuts*. By performing classification conversions across both industries and regions, we alter the dimensions of all main matrices and vectors: for the matrix A containing inter-industry, inter-regional input flows we deploy a generalised RAS (GRAS) algorithm (Miller and Blair, 2022, p. 430) to reconcile the new column and row totals and obtain a new A matrix which is consistent with the new disaggregation.

After these manipulations we have a standard set of input-output accounts and we can start from the usual setup (Miller and Blair, 2022, p. 12), where production is given by:

$$x = (I - A)^{-1} f = Bf \tag{1.A}$$

where x is the gross output column vector – i.e., including both production of intermediate and final goods and services – produced by all industry × region × country combinations (an industry-region-country); f is a vector of final output by industry-region-country of origin. B is the Leontief inverse, whose typical element $b_{isc,jrk}$ represents the total (direct and indirect) input requirements by destination sector *j* in region *r* of country *k* sourced from industry *i* in region *s* of country *c*, per unit of final output of sector *j* in region *r* of country *k*.

The Leontief inverse allows us to trace the inter-country intersectoral relationships, taking the example of three countries *a, b,* and *c* (and, for illustrative purposes, assuming one region and one product in each country)*:*

$$(I - A)^{-1} = B = \begin{pmatrix} b_{aa} & b_{ab} & b_{ac} \\ b_{ba} & b_{bb} & b_{bc} \\ b_{ca} & b_{cb} & b_{cc} \end{pmatrix} \tag{2.A}$$

Each *column* in this matrix represents a value chain and the distribution of the values of each $b_{c,k}$ can be used to capture the structure of the GVC. This approach has been used extensively in the literature on GVCs to capture countries' participation in GVCs. We follow here Borin and Mancini (2019) and compute a bilateral (industry-region-country to industry-region-country) measure of backward participation that isolates foreign value added that enters an industry-region-country and is then re-exported. Formally this is:

$$backward_{c,k} = V\hat{B}^{(-c)}E \tag{3.A}$$

As we discuss in the main text, $\hat{B}^{(-c)}$ is a modified version of the Leontief inverse, $(I - A^{(-c)})^{-1}$ where we zero out from A all intermediate exports, i.e., for countries a, b, and c, respectively:

$$A_a^{(-c)} = \begin{pmatrix} a_{aa} & 0 & 0 \\ a_{ba} & a_{bb} & a_{bc} \\ a_{ca} & a_{cb} & a_{cc} \end{pmatrix}$$

$$A_b^{(-c)} = \begin{pmatrix} a_{aa} & a_{ab} & a_{ac} \\ 0 & a_{bb} & 0 \\ a_{ca} & a_{cb} & a_{cc} \end{pmatrix} \tag{4.A}$$

$$A_c^{(-c)} = \begin{pmatrix} a_{aa} & a_{ab} & a_{ac} \\ a_{ba} & a_{bb} & a_{bc} \\ 0 & 0 & a_{cc} \end{pmatrix}$$

By removing from each country its intermediate exports row, we avoid double counting when we then multiply $\hat{B}^{(-c)} =, \left(I - A^{(-c)}\right)^{-1}$by , V and, crucially the vector of gross exports E, which contains all gross exports, both of intermediate (which would have been included in A) and final products.

Appendix B – COVID-19 shocks

As mentioned in the main text, our COVID-19 shock relies on the interaction between a country-level, time-varying indicator of COVID-induced restrictions and an industry-level, time-invariant measure of face-to-face interaction intensity. Here we describe in more detail both measures and what they capture.

Hale et al. (2021) provide a range of measures of government response, which they classify as follows:

- C - containment and closure policies
- E - economic policies
- H - health system policies
- V - vaccination policies

Each of these four classes contains a range of indicators which the authors combine to produce indexes ranging from 0 to 100. We focus here on what the authors refer to as a stringency index which combines information on all containment and closure policies: (i) school closing, (ii) workplace closing (iii) cancelled public events (iv) restrictions on gathering size (v) closed public transport (vi) stay-at-home requirements (vii) restriction on internal movement, (viii) restrictions on international movement and also includes (ix) public information campaigns from the Health system policies group. We are aware that efforts in quantifying policy responses are often fraught with measurement errors as policy initiatives do not lend themselves easily to this kind of exercises. However, the database has been used extensively in the policy debate, and we are also confident that, by looking at the aggregate measure of stringency, measurement errors should be minimised; whereas looking at changes -- rather than levels -- of this index further mitigates possible measurement errors.

The data compiled by Hale et al. (2021) provides information on countries' response to COVID-19, in terms of containment measures. To accurately capture how this has affected economic activity, it is important to introduce a sectoral dimension, since policies are likely to affect industries to different degrees. We incorporate this by interacting changes in the stringency index from Hale et al. (2021) with an indicator of face-to-face intensity developed by Famiglietti et al. (2020). The authors produce an industry-level indicator classified according to the NAICS classification, which we manually convert to NACE Rev. 2. They start from information on industries' contact intensity from O*NET for workers between the age of 25 and 64, which identifies which occupations require physical proximity to carry out work. They then combine this occupational level information from O*NET with employment data from the 2017 American Community Census to compute industries' contact intensity.

Finally, we report in Table A2 main descriptive statistics for our measures of foreign and domestic COVID-19 shocks. It is immediate to see that the bulk of the shock occurs in 2020, as all countries moved to restrict movement and deploy containment policies to halt the spread of the virus.

Table A2 – Descriptive statistics of COVID-19 shocks

	Mean	St. dev.	min	p10	p25	p50	p75	max
Foreign shocks	21.02	533.35	-740.82	-443.71	-282.74	-60.44	102.31	2,407.16
Domestic shocks	20.59	683.62	-1,633.76	-627.43	-266.31	-10.54	94.58	3,634.58
2020								
Foreign shocks	335.73	790.86	-724.19	-480.29	-258.78	115.90	565.05	2407.16
Domestic shocks	354.52	1000.79	-1633.76	-733.00	-188.99	84.71	668.65	3634.58

Source: Authors' calculations. The table reports main descriptive statistics for foreign and domestic shocks computed on a sample of 6984 observations used for the results discussed in the main text. The lower panel reports the same statistics for 2020 only, relying on 2328 observations.

It is worth noting that the policy stringency itself only varies from 0 to 100, but we exploit *changes* in this measure: these range from -45.44 to 78.04, but the top and bottom quartiles are 3.96 and 1.60, respectively with an interquartile range of only 5.56. This measure is then interacted with the face-to-face measure from Famiglietti et al. (2020), which ranges from 49.73 (for financial services) to 79.74 (for personal laundry services). This highlights how strong the COVID-19 shocks have been during 2020, especially compared to the other years and why it is important to interpret the results by dividing our measures by 100, since a change in one unit of our COVID-19 measure would have corresponded to a very tiny change in policy stringency and therefore in the economic shock ensuing from that.

Appendix C – Development trap risk

Our measure to classify regions in terms of development trap risk follows closely the approach of Diemer et al. (2022). While we refer the interested reader to their paper, we reprise here the main approach and discuss the variables used in this paper.

The key idea is to compare a region's compound annual growth rate (CAGR) with the national and the European averages across three dimensions:

1. Income: we rely on GDP per capita at constant 2005 prices, from ARDECO.
2. Labour productivity: we rely on gross value added per worker at constant 2005 prices, from ARDECO.
3. Employment-to-population ratio, which we compute by combining Total Employment (workplace based, employed persons) over total population, also from ARDECO.

For each of these three measures, v, we then compute for each region i and time t the CAGR over a five-year period – similarly to Diemer et al. (2022), who construct a set of dummies focussing on the years 2011-19:

1. $DR_{i,t}^{v}$ takes value 1 if acceleration in variable of interest v in region i at time t is positive.
2. $DC_{i,t}^{v}$ takes value 1 if acceleration in variable of interest v in region i at time t is larger than the national level.
3. $DE_{i,t}^{v}$ takes value 1 if acceleration in variable of interest v in region i at time t is larger than the European average.

For Estonia, Luxembourg, Latvia, Malta and Cyprus we do not have a regional disaggregation, therefore we only compute indicators $DR_{i,t}^{v}$ and $DE_{i,t}^{v}$, and we then compute the following measure for region *i* in a given year *t*:

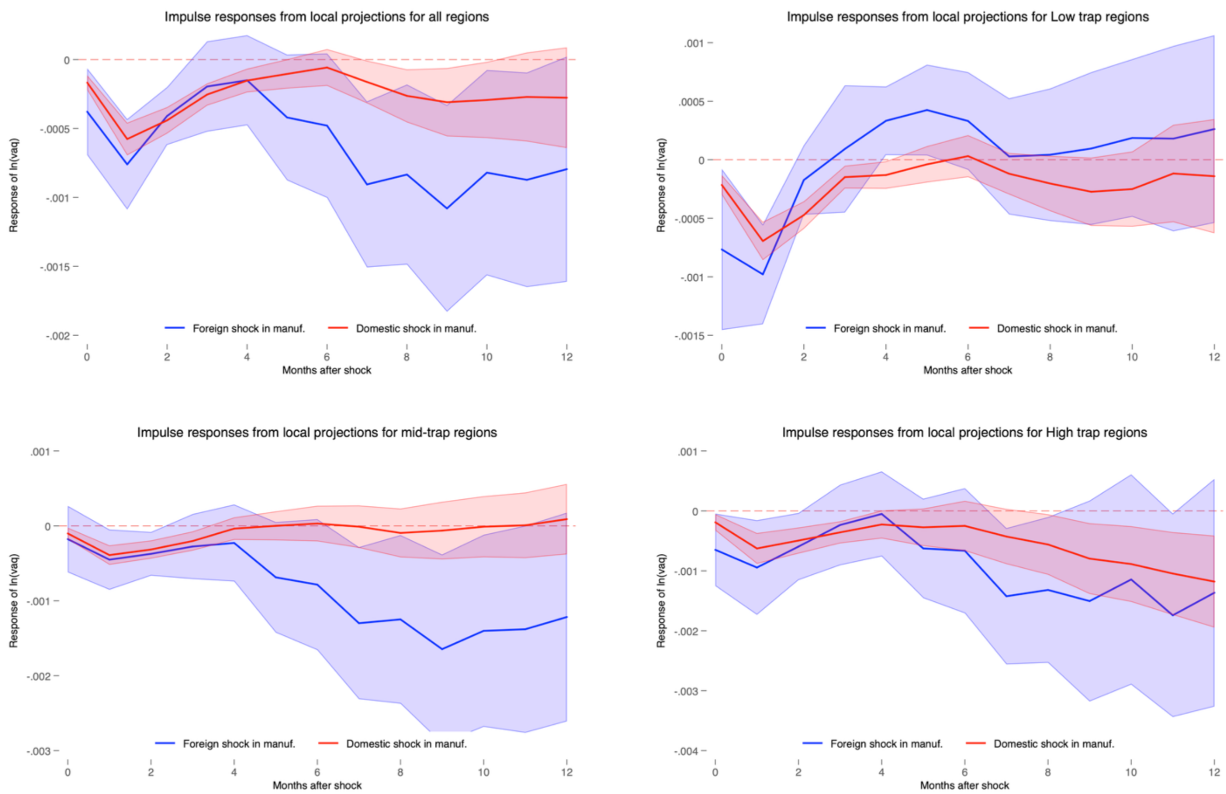
$$DTR_{i,t} = \begin{cases} 1 - \dfrac{\sum_v DR_{i,t}^v + \sum_v DC_{i,t}^v + \sum_v DE_{i,t}^v}{9}; if\ regional\ data\ is\ available \\ 1 - \dfrac{\sum_v DR_{i,t}^v + \sum_v DE_{i,t}^v}{6}; if\ regional\ data\ it\ not\ available. \end{cases} \quad (5.A)$$

This measure is bounded between 0 and 1, as discussed in the main text, with higher values signalling a higher probability of a region falling into a development trap.

Appendix D – Extensions and robustness checks

In the figures below we report results for different variations of our preferred specification. Overall, our results are robust. In Figure A1 we make sure that our results are not driven by small regions, we weight results by regions' value added measured at the annual level and averaged over the 2011-19 period, the same time span over which we compute our regional development trap risk measure. We find our results to be starker, if anything, although coefficients are somewhat smaller. This is to be expected, since we are giving larger weights to larger regions, whose value added is likely to experience smaller fluctuation, in percentage terms, over time.

Figure A1 – COVID-19 shocks, foreign and domestic, size-weighted results

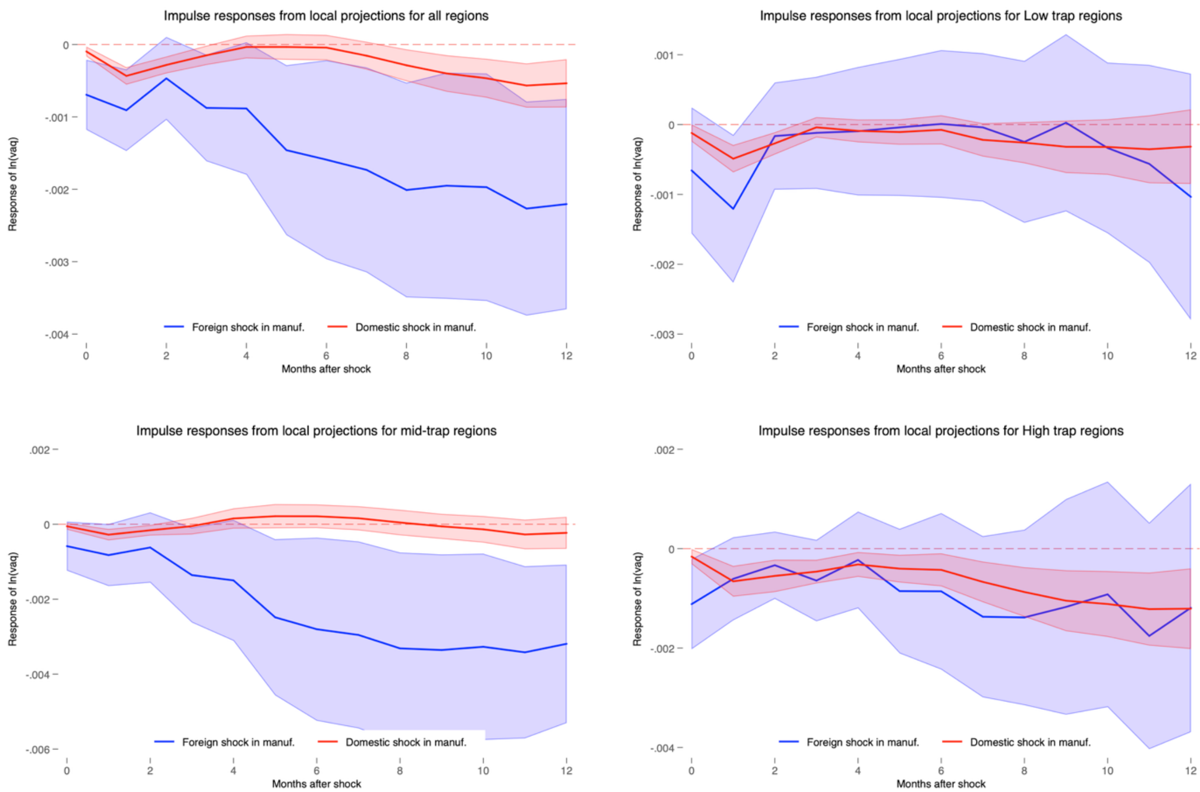


Source: Authors' calculations. Graphs report estimates and 95% confidence intervals for a local projection model used to estimate impulse response functions for domestic and foreign shocks. To facilitate interpretation shocks have been rescaled by 100. Shocks are based on regional averages of the manufacturing sector. Results are weighted by regions' average total annual value added, measured as an average over 2011-19.

Figure A2 expands our sample by including smaller countries for which we have no regional breakdown and that are often affected by large volatility in their national accounts and measures of value added and input-output tables. These are, in particular, Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and

Malta. Results remain overall robust, although we observe a loss of significance for trapped (i.e., at high risk) regions concerning the foreign shock.

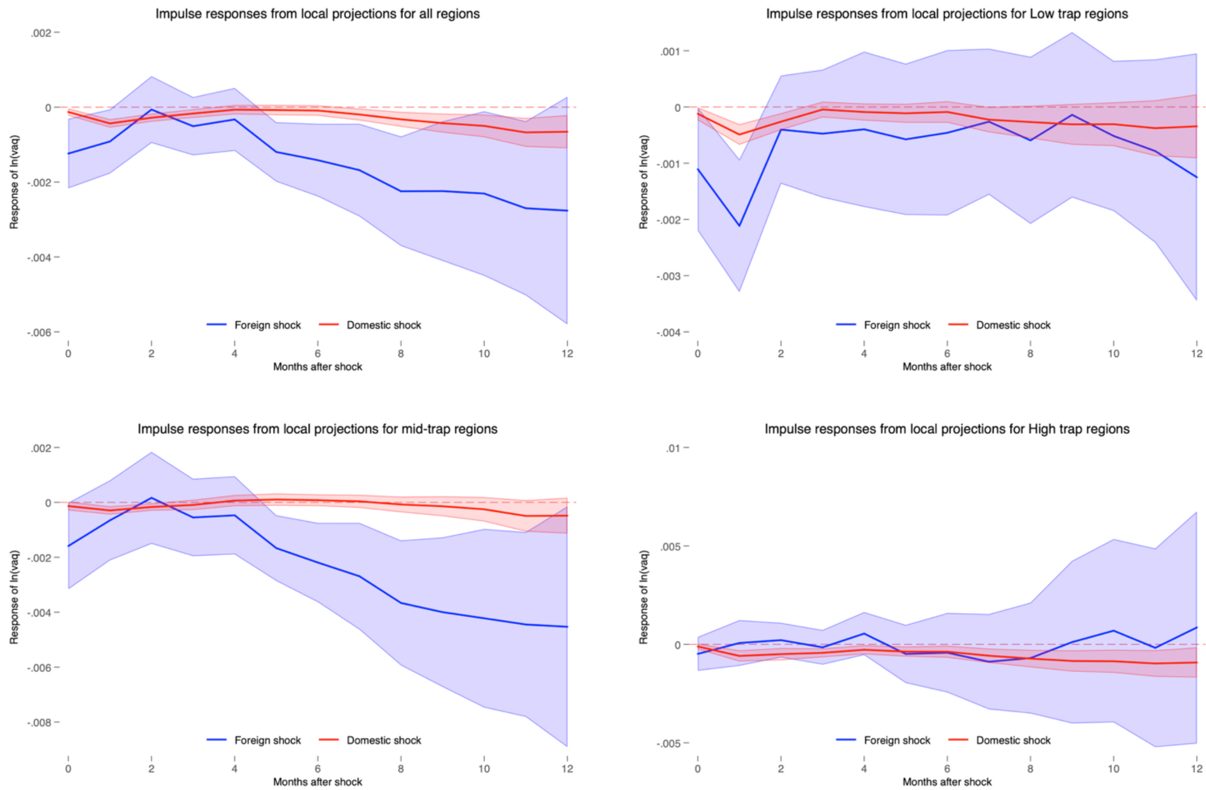
Figure A2 – COVID-19 shocks, foreign and domestic, expanded sample



Source: authors' calculation. Graphs report estimates and 95% confidence intervals for a local projection model used to estimate impulse response functions for domestic and foreign shocks. To facilitate interpretation shocks have been rescaled by 100. Shocks are based on regional averages of the manufacturing sector. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta.

In Figure A3 we look not only at the broader sample but also compute shocks looking at all industries within a region, as discussed in equation (4) in the main text. To clarify this means that the COVID-19 shock endured by a region is the weighted average of the shocks received by all the industries, not just the manufacturing sector, using value added shares as weights. Again, results are overall consistent with our preferred sample, although we see once again no statistically significant relationship between foreign shocks and growth in real value added for trapped (i.e., at high risk) regions. This can be explained by the fact that we know these regions are often high-income but weakly integrated within European value chains, with a productive structure tilted towards labour intensive industries, largely relying on regional wages both as a source of inputs and income for the local demand. This explains why we still find strong evidence of the negative impact that domestic shocks have while that is not the case for foreign shocks.

Figure A3 – COVID-19 shocks, foreign and domestic aggregated across all industries for the expanded sample



Source: authors' calculation. Graphs report estimates and 95% confidence intervals for a local projection model used to estimate impulse response functions for domestic and foreign shocks. To facilitate interpretation, shocks have been rescaled by 100. Shocks are based on regional averages of all industries.Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta and shocks are computed for all industries.

Finally, in Figure A4, we report results for the same expanded sample, weighting these by regional size in terms of annual value added, as discussed above. Results are essentially consistent, if not starker. For completeness we also report the tables with the econometric results graphically plotted in the main text and above. The tables A3.a and A3.b report the results from Figure 4 in the main text, while tables A4.a to A7.b report results discussed in this section of the Appendix from Figures A1 to A4.

Figure A4 – COVID-19 shocks, foreign and domestic aggregated across all industries, for the expanded sample and size weighted

Source: authors' calculation. Graphs report estimates and 95% confidence intervals for a local projection model used to estimate impulse response functions for domestic and foreign shocks. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta and shocks are computed for all industries. To facilitate interpretation shocks have been rescaled by 100. Shocks are based on regional averages of all industries. Results are weighted by regions' average total annual value added, measured as an average over 2011-19.

Table A3.a – COVID-19 shocks, foreign and domestic, for all regions and low-risk subsample

VARIABLES	(1) month=0	(2) month=1	(3) month=2	(4) month=3	(5) month=4	(6) month=5	(7) month=6	(8) month=7	(9) month=8	(10) month=9	(11) month=10	(12) month=11	(13) month=12
							All regions						
Foreign shock	-0.0009***	-0.0012***	-0.0006**	-0.0006	-0.0007	-0.0012*	-0.0014*	-0.0019**	-0.0019**	-0.0023**	-0.0022**	-0.0024**	-0.0024**
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Domestic shock	-0.0002***	-0.0006***	-0.0004***	-0.0001	-0.0000	-0.0000	-0.0001	-0.0002*	-0.0003***	-0.0005***	-0.0005***	-0.0006***	-0.0006***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0220***	-0.0431***	-0.0567***	-0.0677***	-0.0763***	-0.0878***	-0.1021***	-0.1175***	-0.1355***	-0.1574***	-0.1748***	-0.1924***	-0.2029***
	(0.0025)	(0.0046)	(0.0058)	(0.0065)	(0.0068)	(0.0073)	(0.0077)	(0.0082)	(0.0089)	(0.0096)	(0.0100)	(0.0102)	(0.0105)
Constant	0.1403***	0.2753***	0.3618***	0.4321***	0.4892***	0.5644***	0.6590***	0.7591***	0.8762***	1.0182***	1.1304***	1.2425***	1.3179***
	(0.0157)	(0.0294)	(0.0369)	(0.0413)	(0.0432)	(0.0462)	(0.0489)	(0.0521)	(0.0571)	(0.0618)	(0.0638)	(0.0649)	(0.0678)
Observations	6,984	6,790	6,596	6,402	6,208	6,014	5,820	5,626	5,432	5,238	5,044	4,850	4,656
R-squared	0.5509	0.5955	0.6016	0.6002	0.6002	0.6105	0.6212	0.6393	0.6642	0.6865	0.7119	0.7413	0.7621
							Low risk regions						
Foreign shock	-0.0007**	-0.0015***	-0.0004	0.0000	0.0001	0.0003	0.0003	0.0001	0.0002	0.0001	-0.0002	-0.0004	-0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)
Domestic shock	-0.0002***	-0.0006***	-0.0003***	-0.0000	-0.0001	-0.0001	-0.0000	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Value added (ln,t-1)	-0.0366***	-0.0687***	-0.0876***	-0.1000***	-0.1020***	-0.1113***	-0.1238***	-0.1381***	-0.1571***	-0.1766***	-0.1910***	-0.2023***	-0.2104***
	(0.0036)	(0.0063)	(0.0074)	(0.0077)	(0.0075)	(0.0078)	(0.0086)	(0.0101)	(0.0125)	(0.0142)	(0.0154)	(0.0158)	(0.0163)
Constant	0.2372***	0.4453***	0.5673***	0.6481***	0.6638***	0.7262***	0.8107***	0.9068***	1.0328***	1.1632***	1.2612***	1.3376***	1.3969***
	(0.0235)	(0.0408)	(0.0476)	(0.0499)	(0.0486)	(0.0504)	(0.0558)	(0.0657)	(0.0823)	(0.0946)	(0.1049)	(0.1100)	(0.1173)
Observations	1,836	1,785	1,734	1,683	1,632	1,581	1,530	1,479	1,428	1,377	1,326	1,275	1,224
R-squared	0.7332	0.8029	0.8194	0.8247	0.8079	0.7934	0.7928	0.8012	0.8191	0.8367	0.8593	0.8779	0.8907
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A3.b – COVID-19 shocks, foreign and domestic, for mid- and high-risk subsample

VARIABLES	(1) month=0	(2) month=1	(3) month=2	(4) month=3	(5) month=4	(6) month=5	(7) month=6	(8) month=7	(9) month=8	(10) month=9	(11) month=10	(12) month=11	(13) month=12
Mid-risk regions													
Foreign shock	-0.0010**	-0.0010*	-0.0006	-0.0008	-0.0012	-0.0022*	-0.0026*	-0.0032**	-0.0033*	-0.0039**	-0.0037**	-0.0037**	-0.0036**
	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0010)	(0.0013)	(0.0016)	(0.0016)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0016)
Domestic shock	-0.0002***	-0.0004***	-0.0002**	0.0000	0.0002	0.0002	0.0002	0.0001	-0.0001	-0.0003	-0.0003	-0.0005	-0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Value added (ln,t-1)	-0.0171***	-0.0347***	-0.0451***	-0.0550***	-0.0662***	-0.0790***	-0.0939***	-0.1093***	-0.1267***	-0.1494***	-0.1691***	-0.1897***	-0.2027***
	(0.0032)	(0.0065)	(0.0079)	(0.0092)	(0.0105)	(0.0116)	(0.0124)	(0.0127)	(0.0130)	(0.0139)	(0.0139)	(0.0139)	(0.0138)
Constant	0.1093***	0.2216***	0.2871***	0.3503***	0.4243***	0.5072***	0.6045***	0.7048***	0.8160***	0.9605***	1.0837***	1.2088***	1.2972***
	(0.0206)	(0.0410)	(0.0501)	(0.0582)	(0.0663)	(0.0734)	(0.0781)	(0.0803)	(0.0830)	(0.0881)	(0.0871)	(0.0852)	(0.0849)
Observations	3,384	3,290	3,196	3,102	3,008	2,914	2,820	2,726	2,632	2,538	2,444	2,350	2,256
R-squared	0.4617	0.4863	0.4886	0.4864	0.5094	0.5477	0.5739	0.6006	0.6295	0.6547	0.6813	0.7160	0.7413
High risk regions													
Foreign shock	-0.0012**	-0.0010**	-0.0007**	-0.0005	-0.0002	-0.0008	-0.0007	-0.0014	-0.0014	-0.0013	-0.0009	-0.0016	-0.0011
	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0008)	(0.0009)	(0.0010)	(0.0012)	(0.0012)	(0.0012)	(0.0013)
Domestic shock	-0.0002**	-0.0008***	-0.0007***	-0.0005***	-0.0004**	-0.0004**	-0.0004**	-0.0007***	-0.0009***	-0.0011***	-0.0012***	-0.0013***	-0.0013***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Value added (ln,t-1)	-0.0215***	-0.0412***	-0.0563***	-0.0673***	-0.0746***	-0.0857***	-0.1001***	-0.1152***	-0.1330***	-0.1553***	-0.1720***	-0.1902***	-0.1987***
	(0.0040)	(0.0069)	(0.0091)	(0.0100)	(0.0103)	(0.0113)	(0.0124)	(0.0142)	(0.0164)	(0.0183)	(0.0202)	(0.0218)	(0.0239)
Constant	0.1353***	0.2598***	0.3544***	0.4236***	0.4729***	0.5449***	0.6385***	0.7345***	0.8476***	0.9903***	1.0992***	1.2181***	1.2845***
	(0.0250)	(0.0432)	(0.0573)	(0.0626)	(0.0646)	(0.0711)	(0.0784)	(0.0900)	(0.1041)	(0.1158)	(0.1275)	(0.1370)	(0.1519)
Observations	1,764	1,715	1,666	1,617	1,568	1,519	1,470	1,421	1,372	1,323	1,274	1,225	1,176
R-squared	0.6191	0.6985	0.7089	0.7134	0.6893	0.6711	0.6656	0.6721	0.6924	0.7130	0.7385	0.7631	0.7798
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A4.a – COVID-19 shocks, foreign and domestic, size-weighted results, for all regions and low-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
							All regions						
Foreign shock	-0.0004**	-0.0008***	-0.0004***	-0.0002	-0.0001	-0.0004*	-0.0005*	-0.0009***	-0.0008**	-0.0011***	-0.0008**	-0.0009**	-0.0008*
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Domestic shock	-0.0002***	-0.0006***	-0.0004***	-0.0003***	-0.0002***	-0.0001*	-0.0001	-0.0002**	-0.0003***	-0.0003**	-0.0003**	-0.0003	-0.0003
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0202***	-0.0375***	-0.0481***	-0.0569***	-0.0628***	-0.0708***	-0.0812***	-0.0923***	-0.1049***	-0.1210***	-0.1346***	-0.1486***	-0.1589***
	(0.0028)	(0.0047)	(0.0058)	(0.0065)	(0.0067)	(0.0070)	(0.0072)	(0.0075)	(0.0081)	(0.0084)	(0.0083)	(0.0084)	(0.0082)
Constant	0.1450***	0.2700***	0.3457***	0.4092***	0.4539***	0.5126***	0.5894***	0.6699***	0.7607***	0.8771***	0.9741***	1.0737***	1.1497***
	(0.0198)	(0.0338)	(0.0414)	(0.0466)	(0.0479)	(0.0501)	(0.0518)	(0.0542)	(0.0583)	(0.0608)	(0.0604)	(0.0611)	(0.0600)
Observations	6,984	6,790	6,596	6,402	6,208	6,014	5,820	5,626	5,432	5,238	5,044	4,850	4,656
R-squared	0.7376	0.8014	0.8112	0.8121	0.7837	0.7655	0.7587	0.7609	0.7706	0.7805	0.7995	0.8190	0.8336
							Low risk regions						
Foreign shock	-0.0008**	-0.0010***	-0.0002	0.0001	0.0003**	0.0004**	0.0003	0.0000	0.0000	0.0001	0.0002	0.0002	0.0003
	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Domestic shock	-0.0002***	-0.0007***	-0.0005***	-0.0001***	-0.0001**	-0.0000	0.0000	-0.0001	-0.0002*	-0.0003*	-0.0003	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0389***	-0.0671***	-0.0807***	-0.0920***	-0.0915***	-0.0956***	-0.1018***	-0.1067***	-0.1162***	-0.1270***	-0.1352***	-0.1427***	-0.1491***
	(0.0029)	(0.0047)	(0.0057)	(0.0061)	(0.0062)	(0.0066)	(0.0068)	(0.0070)	(0.0078)	(0.0086)	(0.0091)	(0.0098)	(0.0096)
Constant	0.2948***	0.5086***	0.6111***	0.6966***	0.6950***	0.7286***	0.7779***	0.8174***	0.8904***	0.9730***	1.0347***	1.0881***	1.1347***
	(0.0219)	(0.0359)	(0.0434)	(0.0466)	(0.0473)	(0.0496)	(0.0514)	(0.0526)	(0.0586)	(0.0654)	(0.0692)	(0.0747)	(0.0737)
Observations	1,836	1,785	1,734	1,683	1,632	1,581	1,530	1,479	1,428	1,377	1,326	1,275	1,224
R-squared	0.7786	0.8566	0.8745	0.8885	0.8889	0.8848	0.8880	0.8950	0.9041	0.9104	0.9212	0.9299	0.9347
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results are weighted by regions' average total annual value added, measured as an average over 2011-19. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A4.b – COVID-19 shocks, foreign and domestic, size-weighted results, for mid- and high-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
							Mid-risk regions						
Foreign shock	-0.0002	-0.0005**	-0.0004**	-0.0003	-0.0002	-0.0007*	-0.0008*	-0.0013**	-0.0012**	-0.0016**	-0.0014**	-0.0014*	-0.0012*
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
Domestic shock	-0.0001**	-0.0004***	-0.0003***	-0.0002***	-0.0000	0.0000	0.0000	-0.0000	-0.0001	-0.0001	-0.0000	0.0000	0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0142***	-0.0278***	-0.0368***	-0.0439***	-0.0514***	-0.0616***	-0.0736***	-0.0873***	-0.1025***	-0.1211***	-0.1380***	-0.1562***	-0.1691***
	(0.0033)	(0.0063)	(0.0080)	(0.0092)	(0.0100)	(0.0109)	(0.0115)	(0.0123)	(0.0131)	(0.0137)	(0.0133)	(0.0130)	(0.0124)
Constant	0.0992***	0.1946***	0.2572***	0.3073***	0.3620***	0.4348***	0.5205***	0.6167***	0.7217***	0.8524***	0.9702***	1.0945***	1.1854***
	(0.0233)	(0.0438)	(0.0563)	(0.0647)	(0.0704)	(0.0761)	(0.0806)	(0.0862)	(0.0925)	(0.0966)	(0.0944)	(0.0922)	(0.0885)
Observations	3,384	3,290	3,196	3,102	3,008	2,914	2,820	2,726	2,632	2,538	2,444	2,350	2,256
R-squared	0.7435	0.7907	0.7932	0.7838	0.7391	0.7142	0.7035	0.7044	0.7151	0.7283	0.7549	0.7829	0.8044
							High risk regions						
Foreign shock	-0.0006**	-0.0009**	-0.0006**	-0.0002	-0.0001	-0.0006	-0.0007	-0.0014**	-0.0013**	-0.0015*	-0.0011	-0.0017**	-0.0014
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0009)	(0.0010)
Domestic shock	-0.0002***	-0.0006***	-0.0005***	-0.0004***	-0.0002*	-0.0003*	-0.0003	-0.0004*	-0.0006**	-0.0008**	-0.0009***	-0.0010***	-0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Value added (ln,t-1)	-0.0163***	-0.0315***	-0.0419***	-0.0503***	-0.0577***	-0.0673***	-0.0794***	-0.0925***	-0.1070***	-0.1259***	-0.1423***	-0.1593***	-0.1680***
	(0.0033)	(0.0058)	(0.0078)	(0.0087)	(0.0106)	(0.0129)	(0.0151)	(0.0178)	(0.0203)	(0.0217)	(0.0215)	(0.0206)	(0.0206)
Constant	0.1139***	0.2198***	0.2920***	0.3509***	0.4047***	0.4730***	0.5598***	0.6512***	0.7525***	0.8844***	0.9999***	1.1212***	1.1892***
	(0.0227)	(0.0400)	(0.0542)	(0.0606)	(0.0737)	(0.0898)	(0.1054)	(0.1246)	(0.1424)	(0.1526)	(0.1518)	(0.1464)	(0.1487)
Observations	1,764	1,715	1,666	1,617	1,568	1,519	1,470	1,421	1,372	1,323	1,274	1,225	1,176
R-squared	0.7163	0.7792	0.7843	0.7819	0.7499	0.7276	0.7191	0.7208	0.7312	0.7477	0.7730	0.7964	0.8169
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results are weighted by regions' average total annual value added, measured as an average over 2011-19. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5.a – COVID-19 shocks, foreign and domestic, expanded sample, for all regions and low-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
							All regions						
Foreign shock	-0.0007***	-0.0009***	-0.0005	-0.0009**	-0.0009*	-0.0015**	-0.0016**	-0.0017**	-0.0020***	-0.0020**	-0.0020**	-0.0023***	-0.0022***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)
Domestic shock	-0.0001***	-0.0004***	-0.0003***	-0.0001**	-0.0000	-0.0000	-0.0000	-0.0002	-0.0003**	-0.0004***	-0.0005***	-0.0006***	-0.0005***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0282***	-0.0523***	-0.0672***	-0.0784***	-0.0840***	-0.0950***	-0.1057***	-0.1153***	-0.1344***	-0.1558***	-0.1739***	-0.1888***	-0.1963***
	(0.0030)	(0.0052)	(0.0063)	(0.0069)	(0.0066)	(0.0069)	(0.0070)	(0.0073)	(0.0077)	(0.0082)	(0.0086)	(0.0090)	(0.0097)
Constant	0.1767***	0.3274***	0.4205***	0.4914***	0.5290***	0.5995***	0.6687***	0.7316***	0.8532***	0.9908***	1.1074***	1.2027***	1.2593***
	(0.0190)	(0.0324)	(0.0396)	(0.0429)	(0.0411)	(0.0428)	(0.0433)	(0.0455)	(0.0480)	(0.0513)	(0.0536)	(0.0563)	(0.0609)
Observations	7,740	7,525	7,310	7,095	6,880	6,665	6,450	6,235	6,020	5,805	5,590	5,375	5,160
R-squared	0.5082	0.5665	0.5830	0.5837	0.5847	0.5962	0.6129	0.6318	0.6592	0.6840	0.7144	0.7411	0.7582
							Low risk regions						
Foreign shock	-0.0007	-0.0012**	-0.0002	-0.0001	-0.0001	-0.0000	0.0000	-0.0000	-0.0002	0.0000	-0.0003	-0.0006	-0.0010
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0009)
Domestic shock	-0.0001*	-0.0005***	-0.0003***	-0.0000	-0.0001	-0.0001	-0.0001	-0.0002*	-0.0003*	-0.0003	-0.0003	-0.0004	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Value added (ln,t-1)	-0.0420***	-0.0761***	-0.0961***	-0.1083***	-0.1062***	-0.1130***	-0.1216***	-0.1288***	-0.1470***	-0.1648***	-0.1780***	-0.1855***	-0.1901***
	(0.0038)	(0.0061)	(0.0069)	(0.0072)	(0.0074)	(0.0079)	(0.0093)	(0.0130)	(0.0138)	(0.0147)	(0.0149)	(0.0168)	(0.0191)
Constant	0.2705***	0.4907***	0.6194***	0.6986***	0.6873***	0.7334***	0.7912***	0.8401***	0.9596***	1.0785***	1.1678***	1.2210***	1.2616***
	(0.0248)	(0.0393)	(0.0444)	(0.0461)	(0.0475)	(0.0508)	(0.0599)	(0.0848)	(0.0905)	(0.0963)	(0.1000)	(0.1140)	(0.1301)
Observations	1,980	1,925	1,870	1,815	1,760	1,705	1,650	1,595	1,540	1,485	1,430	1,375	1,320
R-squared	0.6794	0.7676	0.7941	0.8003	0.7821	0.7697	0.7724	0.7785	0.8003	0.8210	0.8490	0.8634	0.8701
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5.b – COVID-19 shocks, foreign and domestic, expanded sample, for mid- and high-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
	Mid-risk regions												
Foreign shock	-0.0006*	-0.0008*	-0.0006	-0.0014**	-0.0015*	-0.0025**	-0.0028**	-0.0030**	-0.0033**	-0.0034**	-0.0033**	-0.0034***	-0.0032***
	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0008)	(0.0011)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0011)
Domestic shock	-0.0001	-0.0003***	-0.0002**	-0.0001	0.0002	0.0002	0.0002	0.0002	0.0000	-0.0001	-0.0001	-0.0003	-0.0002
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0258***	-0.0475***	-0.0604***	-0.0714***	-0.0792***	-0.0920***	-0.1030***	-0.1113***	-0.1310***	-0.1533***	-0.1745***	-0.1909***	-0.1978***
	(0.0047)	(0.0081)	(0.0098)	(0.0109)	(0.0109)	(0.0116)	(0.0117)	(0.0112)	(0.0111)	(0.0118)	(0.0122)	(0.0120)	(0.0120)
Constant	0.1601***	0.2948***	0.3745***	0.4438***	0.4939***	0.5757***	0.6453***	0.6997***	0.8236***	0.9647***	1.0972***	1.1968***	1.2466***
	(0.0288)	(0.0499)	(0.0607)	(0.0677)	(0.0671)	(0.0716)	(0.0717)	(0.0689)	(0.0682)	(0.0722)	(0.0736)	(0.0706)	(0.0698)
Observations	3,852	3,745	3,638	3,531	3,424	3,317	3,210	3,103	2,996	2,889	2,782	2,675	2,568
R-squared	0.4157	0.4561	0.4702	0.4703	0.4967	0.5351	0.5681	0.5956	0.6271	0.6547	0.6862	0.7175	0.7383
	High risk regions												
Foreign shock	-0.0011**	-0.0006	-0.0003	-0.0006	-0.0002	-0.0009	-0.0009	-0.0014	-0.0014	-0.0012	-0.0009	-0.0018	-0.0012
	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0012)	(0.0012)	(0.0013)
Domestic shock	-0.0002**	-0.0007***	-0.0005***	-0.0005***	-0.0003**	-0.0004***	-0.0004**	-0.0007***	-0.0009***	-0.0010***	-0.0011***	-0.0012***	-0.0012***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Value added (ln,t-1)	-0.0229***	-0.0434***	-0.0580***	-0.0684***	-0.0749***	-0.0858***	-0.0983***	-0.1121***	-0.1302***	-0.1520***	-0.1689***	-0.1872***	-0.1972***
	(0.0041)	(0.0071)	(0.0092)	(0.0099)	(0.0100)	(0.0111)	(0.0121)	(0.0137)	(0.0158)	(0.0176)	(0.0193)	(0.0206)	(0.0222)
Constant	0.1417***	0.2689***	0.3592***	0.4240***	0.4669***	0.5360***	0.6157***	0.7031***	0.8177***	0.9555***	1.0647***	1.1845***	1.2595***
	(0.0255)	(0.0442)	(0.0569)	(0.0612)	(0.0621)	(0.0687)	(0.0749)	(0.0849)	(0.0984)	(0.1093)	(0.1199)	(0.1279)	(0.1391)
Observations	1,908	1,855	1,802	1,749	1,696	1,643	1,590	1,537	1,484	1,431	1,378	1,325	1,272
R-squared	0.6032	0.6823	0.6977	0.7023	0.6751	0.6569	0.6549	0.6648	0.6863	0.7073	0.7353	0.7607	0.7791
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to manufacturing industries alone for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A6.a – COVID-19 shocks, foreign and domestic aggregated across all industries for the expanded sample, for all regions and low-risk subsample

VARIABLES	(1) month=0	(2) month=1	(3) month=2	(4) month=3	(5) month=4	(6) month=5	(7) month=6	(8) month=7	(9) month=8	(10) month=9	(11) month=10	(12) month=11	(13) month=12
All regions													
Foreign shock	-0.0012***	-0.0009**	-0.0001	-0.0005	-0.0003	-0.0012***	-0.0014***	-0.0017***	-0.0022***	-0.0022**	-0.0023**	-0.0027**	-0.0028*
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0010)	(0.0011)	(0.0012)	(0.0016)
Domestic shock	-0.0001***	-0.0004***	-0.0003***	-0.0002***	-0.0001	-0.0001	-0.0001	-0.0002**	-0.0003***	-0.0004***	-0.0005***	-0.0007***	-0.0007***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0279***	-0.0522***	-0.0673***	-0.0788***	-0.0845***	-0.0953***	-0.1060***	-0.1154***	-0.1347***	-0.1561***	-0.1740***	-0.1897***	-0.1971***
	(0.0030)	(0.0052)	(0.0064)	(0.0070)	(0.0068)	(0.0071)	(0.0072)	(0.0074)	(0.0079)	(0.0085)	(0.0089)	(0.0095)	(0.0099)
Constant	0.1752***	0.3273***	0.4213***	0.4935***	0.5317***	0.6019***	0.6716***	0.7349***	0.8589***	0.9991***	1.1130***	1.2127***	1.2665***
	(0.0187)	(0.0323)	(0.0397)	(0.0437)	(0.0422)	(0.0441)	(0.0450)	(0.0471)	(0.0511)	(0.0557)	(0.0580)	(0.0614)	(0.0641)
Observations	7,740	7,525	7,310	7,095	6,880	6,665	6,450	6,235	6,020	5,805	5,590	5,375	5,160
R-squared	0.5099	0.5686	0.5848	0.5847	0.5843	0.5960	0.6133	0.6326	0.6610	0.6878	0.7195	0.7491	0.7666
Low risk regions													
Foreign shock	-0.0011*	-0.0021***	-0.0004	-0.0005	-0.0004	-0.0006	-0.0005	-0.0003	-0.0006	-0.0001	-0.0005	-0.0008	-0.0012
	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0011)
Domestic shock	-0.0001**	-0.0005***	-0.0003***	-0.0000	-0.0001	-0.0001	-0.0001	-0.0002*	-0.0003*	-0.0003*	-0.0003	-0.0004	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Value added (ln,t-1)	-0.0415***	-0.0751***	-0.0952***	-0.1073***	-0.1053***	-0.1118***	-0.1204***	-0.1278***	-0.1464***	-0.1653***	-0.1787***	-0.1869***	-0.1913***
	(0.0038)	(0.0060)	(0.0068)	(0.0071)	(0.0074)	(0.0079)	(0.0091)	(0.0128)	(0.0138)	(0.0147)	(0.0150)	(0.0165)	(0.0183)
Constant	0.2680***	0.4842***	0.6132***	0.6924***	0.6821***	0.7261***	0.7849***	0.8354***	0.9583***	1.0857***	1.1776***	1.2373***	1.2775***
	(0.0243)	(0.0387)	(0.0439)	(0.0459)	(0.0479)	(0.0509)	(0.0593)	(0.0842)	(0.0916)	(0.0976)	(0.1019)	(0.1139)	(0.1276)
Observations	1,980	1,925	1,870	1,815	1,760	1,705	1,650	1,595	1,540	1,485	1,430	1,375	1,320
R-squared	0.6804	0.7698	0.7954	0.8013	0.7823	0.7701	0.7731	0.7786	0.8006	0.8222	0.8506	0.8659	0.8732
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to all industries for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A6.b – COVID-19 shocks, foreign and domestic aggregated across all industries for the expanded sample, for mid- and high-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
Mid-risk regions													
Foreign shock	-0.0016*	-0.0007	0.0002	-0.0006	-0.0005	-0.0017***	-0.0022***	-0.0027***	-0.0037***	-0.0040***	-0.0042**	-0.0044**	-0.0045**
	(0.0008)	(0.0007)	(0.0009)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0010)	(0.0012)	(0.0014)	(0.0017)	(0.0017)	(0.0022)
Domestic shock	-0.0001*	-0.0003***	-0.0002**	-0.0001	0.0001	0.0001	0.0001	0.0000	-0.0001	-0.0001	-0.0003	-0.0005*	-0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Value added (ln,t-1)	-0.0253***	-0.0477***	-0.0609***	-0.0724***	-0.0797***	-0.0923***	-0.1034***	-0.1119***	-0.1321***	-0.1542***	-0.1748***	-0.1929***	-0.2009***
	(0.0045)	(0.0080)	(0.0099)	(0.0116)	(0.0114)	(0.0120)	(0.0122)	(0.0117)	(0.0120)	(0.0132)	(0.0136)	(0.0141)	(0.0137)
Constant	0.1574***	0.2961***	0.3774***	0.4485***	0.4968***	0.5779***	0.6499***	0.7078***	0.8387***	0.9845***	1.1119***	1.2201***	1.2719***
	(0.0279)	(0.0498)	(0.0615)	(0.0711)	(0.0696)	(0.0741)	(0.0754)	(0.0737)	(0.0782)	(0.0877)	(0.0899)	(0.0925)	(0.0901)
Observations	3,852	3,745	3,638	3,531	3,424	3,317	3,210	3,103	2,996	2,889	2,782	2,675	2,568
R-squared	0.4197	0.4609	0.4734	0.4720	0.4943	0.5308	0.5650	0.5953	0.6292	0.6619	0.6971	0.7332	0.7548
High risk regions													
Foreign shock	-0.0005	0.0001	0.0002	-0.0002	0.0005	-0.0005	-0.0004	-0.0009	-0.0007	0.0001	0.0007	-0.0002	0.0009
	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0006)	(0.0008)	(0.0010)	(0.0012)	(0.0014)	(0.0021)	(0.0024)	(0.0026)	(0.0030)
Domestic shock	-0.0001	-0.0006***	-0.0005***	-0.0004***	-0.0003**	-0.0004***	-0.0004**	-0.0006***	-0.0007***	-0.0008***	-0.0009***	-0.0010***	-0.0009**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Value added (ln,t-1)	-0.0231***	-0.0437***	-0.0584***	-0.0688***	-0.0752***	-0.0857***	-0.0979***	-0.1121***	-0.1300***	-0.1516***	-0.1677***	-0.1855***	-0.1951***
	(0.0042)	(0.0072)	(0.0093)	(0.0099)	(0.0101)	(0.0111)	(0.0121)	(0.0137)	(0.0157)	(0.0174)	(0.0191)	(0.0204)	(0.0218)
Constant	0.1427***	0.2705***	0.3609***	0.4258***	0.4689***	0.5356***	0.6124***	0.7003***	0.8101***	0.9417***	1.0380***	1.1485***	1.2121***
	(0.0257)	(0.0444)	(0.0572)	(0.0615)	(0.0627)	(0.0688)	(0.0749)	(0.0843)	(0.0955)	(0.1037)	(0.1098)	(0.1129)	(0.1165)
Observations	1,908	1,855	1,802	1,749	1,696	1,643	1,590	1,537	1,484	1,431	1,378	1,325	1,272
R-squared	0.6004	0.6801	0.6967	0.7019	0.6744	0.6570	0.6540	0.6615	0.6824	0.7032	0.7302	0.7558	0.7728
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to all industries for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A7.a – COVID-19 shocks, foreign and domestic aggregated across all industries, for the expanded sample and size weighted, for all regions and low-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
							All regions						
Foreign shock	-0.0012**	-0.0021***	-0.0012***	-0.0010**	-0.0011*	-0.0013***	-0.0014***	-0.0011***	-0.0019***	-0.0022***	-0.0017***	-0.0020***	-0.0019***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Domestic shock	-0.0002***	-0.0006***	-0.0004***	-0.0002***	-0.0002***	-0.0002***	-0.0001**	-0.0002**	-0.0004***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Value added (ln,t-1)	-0.0275***	-0.0473***	-0.0602***	-0.0685***	-0.0686***	-0.0759***	-0.0827***	-0.0850***	-0.0998***	-0.1173***	-0.1356***	-0.1457***	-0.1491***
	(0.0038)	(0.0056)	(0.0070)	(0.0072)	(0.0055)	(0.0056)	(0.0054)	(0.0063)	(0.0065)	(0.0065)	(0.0064)	(0.0069)	(0.0080)
Constant	0.1990***	0.3418***	0.4349***	0.4956***	0.4976***	0.5526***	0.6026***	0.6201***	0.7270***	0.8602***	0.9967***	1.0715***	1.1002***
	(0.0275)	(0.0405)	(0.0510)	(0.0520)	(0.0396)	(0.0399)	(0.0389)	(0.0470)	(0.0478)	(0.0478)	(0.0485)	(0.0515)	(0.0563)
Observations	7,740	7,525	7,310	7,095	6,880	6,665	6,450	6,235	6,020	5,805	5,590	5,375	5,160
R-squared	0.6476	0.7437	0.7704	0.7722	0.7449	0.7369	0.7409	0.7448	0.7599	0.7797	0.8091	0.8245	0.8314
							Low risk regions						
Foreign shock	-0.0021**	-0.0027***	-0.0011	-0.0011	-0.0011	-0.0008	-0.0008	0.0000	-0.0011	-0.0009	-0.0005	-0.0008	-0.0008
	(0.0009)	(0.0010)	(0.0009)	(0.0010)	(0.0012)	(0.0009)	(0.0007)	(0.0003)	(0.0007)	(0.0006)	(0.0005)	(0.0006)	(0.0005)
Domestic shock	-0.0002***	-0.0007***	-0.0004***	-0.0001	-0.0003***	-0.0001*	-0.0001	-0.0002**	-0.0004**	-0.0006***	-0.0005***	-0.0005**	-0.0006**
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0438***	-0.0720***	-0.0898***	-0.0986***	-0.0887***	-0.0912***	-0.0920***	-0.0844***	-0.0976***	-0.1137***	-0.1301***	-0.1315***	-0.1291***
	(0.0023)	(0.0031)	(0.0048)	(0.0045)	(0.0048)	(0.0048)	(0.0059)	(0.0106)	(0.0094)	(0.0064)	(0.0055)	(0.0067)	(0.0080)
Constant	0.3360***	0.5531***	0.6896***	0.7572***	0.6822***	0.7032***	0.7096***	0.6523***	0.7547***	0.8877***	1.0191***	1.0334***	1.0219***
	(0.0176)	(0.0242)	(0.0375)	(0.0350)	(0.0369)	(0.0373)	(0.0470)	(0.0852)	(0.0760)	(0.0484)	(0.0416)	(0.0494)	(0.0564)
Observations	1,980	1,925	1,870	1,815	1,760	1,705	1,650	1,595	1,540	1,485	1,430	1,375	1,320
R-squared	0.6671	0.7866	0.8272	0.8412	0.8302	0.8336	0.8454	0.8527	0.8713	0.8933	0.9190	0.9251	0.9246
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to all industries for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results are weighted by regions' average total annual value added, measured as an average over 2011-19. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A7.b – COVID-19 shocks, foreign and domestic aggregated across all industries, for the expanded sample and size weighted, for mid- and high-risk subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	month=0	month=1	month=2	month=3	month=4	month=5	month=6	month=7	month=8	month=9	month=10	month=11	month=12
						Mid-risk regions							
Foreign shock	-0.0009	-0.0018***	-0.0014**	-0.0012**	-0.0012**	-0.0018***	-0.0021***	-0.0018**	-0.0029***	-0.0037***	-0.0035***	-0.0037***	-0.0035***
	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0008)	(0.0006)	(0.0007)	(0.0007)	(0.0008)	(0.0009)
Domestic shock	-0.0001***	-0.0005***	-0.0004***	-0.0002***	-0.0002*	-0.0001	-0.0001	-0.0000	-0.0002	-0.0002	-0.0002	-0.0003	-0.0002
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Value added (ln,t-1)	-0.0223***	-0.0386***	-0.0500***	-0.0571***	-0.0592***	-0.0695***	-0.0786***	-0.0843***	-0.1018***	-0.1219***	-0.1434***	-0.1588***	-0.1660***
	(0.0053)	(0.0079)	(0.0101)	(0.0107)	(0.0090)	(0.0094)	(0.0093)	(0.0096)	(0.0100)	(0.0102)	(0.0102)	(0.0098)	(0.0096)
Constant	0.1565***	0.2709***	0.3509***	0.4017***	0.4170***	0.4919***	0.5570***	0.5975***	0.7208***	0.8689***	1.0249***	1.1329***	1.1855***
	(0.0370)	(0.0555)	(0.0709)	(0.0754)	(0.0627)	(0.0658)	(0.0653)	(0.0674)	(0.0702)	(0.0728)	(0.0743)	(0.0713)	(0.0681)
Observations	3,852	3,745	3,638	3,531	3,424	3,317	3,210	3,103	2,996	2,889	2,782	2,675	2,568
R-squared	0.6386	0.7239	0.7457	0.7375	0.6984	0.6870	0.6901	0.6955	0.7116	0.7369	0.7737	0.7972	0.8108
						High risk regions							
Foreign shock	-0.0004	-0.0009*	-0.0002	0.0000	0.0004	-0.0005	-0.0005	-0.0013	-0.0012	-0.0010	-0.0006	-0.0013	-0.0010
	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0007)	(0.0008)	(0.0009)	(0.0014)	(0.0016)	(0.0015)	(0.0016)
Domestic shock	-0.0001*	-0.0005***	-0.0004***	-0.0003***	-0.0002*	-0.0003*	-0.0002	-0.0004*	-0.0005**	-0.0007**	-0.0007**	-0.0009***	-0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Value added (ln,t-1)	-0.0170***	-0.0325***	-0.0430***	-0.0514***	-0.0582***	-0.0671***	-0.0778***	-0.0904***	-0.1050***	-0.1238***	-0.1398***	-0.1570***	-0.1673***
	(0.0034)	(0.0060)	(0.0080)	(0.0088)	(0.0103)	(0.0124)	(0.0144)	(0.0169)	(0.0191)	(0.0202)	(0.0200)	(0.0196)	(0.0195)
Constant	0.1180***	0.2262***	0.2983***	0.3573***	0.4067***	0.4709***	0.5480***	0.6353***	0.7353***	0.8646***	0.9733***	1.0950***	1.1723***
	(0.0234)	(0.0417)	(0.0554)	(0.0608)	(0.0715)	(0.0862)	(0.1004)	(0.1176)	(0.1344)	(0.1433)	(0.1440)	(0.1425)	(0.1442)
Observations	1,908	1,855	1,802	1,749	1,696	1,643	1,590	1,537	1,484	1,431	1,378	1,325	1,272
R-squared	0.7030	0.7671	0.7756	0.7743	0.7425	0.7207	0.7134	0.7147	0.7248	0.7409	0.7673	0.7916	0.8116
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impulse response function with local projections method. COVID-19 shocks to all industries for our preferred sample of countries. Each column refers to the time horizon considered, measured in number of months The explanatory variables have been divided by 100 to facilitate interpretation of the results. Results are weighted by regions' average total annual value added, measured as an average over 2011-19. Results now include Cyprus, Estonia, Greece, Ireland, Luxembourg, Latvia and Malta. The vector of lags and leads of shocks is omitted for space's sake, full results are available upon request. Standard errors are robust and clustered at the regional level, in parentheses *** p<0.01, ** p<0.05, * p<0.1