Journal of Economic Behavior and Organization 225 (2024) 252–271

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Research paper

Growth volatility and trade: Market diversification vs. production specialization ☆

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ARTICLE INFO

JEL classification:
F15
F44
F61

Keywords:
Output volatility
Destination shocks
Origin shocks
Trade diversification
Specialization

ABSTRACT

We analyze how trade affects aggregate volatility using a multi-country, multi-industry, and multi-destination framework. We decompose aggregate output growth risk into destination risk, origin risk, and idiosyncratic risk (and their covariances). We then use this framework to run counterfactuals changing the degree of destination-market diversification (including home) and industry specialization. Using data on 19 industrial sectors, 34 countries, and 84 destination markets for the 1980–2011 period, we find that destination risk dominates, followed by idiosyncratic risk. From the counterfactuals, we find that the effect of increased destination-market diversification is quantitatively important in reducing aggregate volatility for high volatility countries. On the other hand, reducing specialization increases volatility.

1. Introduction

The role of international trade for macroeconomic volatility remains an important question for academics and policymakers alike. Recent episodes of price and output volatility fueled by international trade disruptions in the post-pandemic period have sparked renewed interest in the question of how exposure to trade can affect macroeconomic instability. Output volatility matters as, in the absence of complete international financial markets, it can lead to consumption volatility which reduces welfare for risk averse agents. This is, of course, not a new question. As emphasized by Caselli et al. (2020), a traditional view is that, by increasing production specialization, trade can increase vulnerability to sector-specific shocks. However, whether trade increases volatility depends not only on the pattern of specialization, but also on the geographical pattern of trade and the shocks that drive output volatility. For instance, a closed economy could face higher risks if shocks are mainly driven by national factors such as macroeconomic policies since all sales by national producers are domestic. A fully specialized economy, on the other hand, could face higher risks if most shocks are supply-side and sectoral in nature, or if macroeconomic shocks are highly correlated across destination markets for the sector in which the economy specializes.

☆ We would like to thank the Editor and two anonymous referees for their insightful comments. We thank Reshad Ahsan, Arpita Chatterjee, Diane Coyle, Anca Cristea, Qingyuan Du, Pedro Gomis-Porqueras, Andrei Levchenko, Volodymyr Lugovskyy, Jakob Madsen, Dennis Novy, Valérie Smeets, Frédéric Warzynski, and seminar participants at Kent, Reading, Jaume I, Birmingham, Texas Rio Grande, Asian Development Bank, and various conferences. We are grateful to Sabine Deij and Cynthia Huang for excellent research assistance. All remaining mistakes are ours.

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https://doi.org/10.1016/j.jebo.2024.07.001
Received 28 May 2023; Received in revised form 30 May 2024; Accepted 2 July 2024
Available online 25 July 2024
0167-2681/

We revisit the question of how trade affects aggregate volatility making use of an empirical multi-country, multi-sector, and multi-destination framework that can account for the role of output specialization and the market diversification of sales.

First, we propose a decomposition of aggregate output growth risk[1] into three elements: destination risk, origin risk, and idiosyncratic risk (and their covariances). Destination risk arises from product or aggregate shocks specific to the destination markets where products are sold (including the home market) independently of the country of origin. Origin risk arises from product or aggregate shocks specific to the producing country independent of the destination of sales. Idiosyncratic risk arises from shocks to the sales of one or all products exchanged between a producing country and a destination market. We also allow for the sources of these risks to co-vary. Our decomposition extends Koren and Tenreyro (2007) to a multi-destination market setting that enables us to analyze how the pattern of sectoral specialization and the diversification of sales across markets shape the exposure of different countries to these risks. An additional advantage of our approach is that it allows us to dive deeper into the sources of each risk. For instance, given the current structure of trade, is risk more influenced by the correlation of shocks across industries within a country or destination market, or that across markets within an industry? The flexibility of our methodology can shed light on these, more difficult, questions and provide important input for theoretical models studying the international transmission of shocks through trade.

Second, we use the results of our decomposition to carry out counterfactuals where we change the observed patterns of sectoral specialization and destination-market diversification to assess how they affect the three sources of risk and their covariances.

We carefully assemble a dataset of trade and output data for 34 countries, 84 destination markets, and 19 industries over the 1980–2011 period covering more than 80% of world output and exports. Using these data, we first estimate total risk and each of its risk components. We find that destination risk is the largest driver of total risk, followed by idiosyncratic risk, with origin risk coming last. For both destination and idiosyncratic risks, a key determinant is the *within-market* covariance of shocks *across industries*. That is, shocks to destination markets tend to affect simultaneously most of the sectors. The covariance components of total risk are consistently negative, acting as a risk absorption mechanism.

We then implement two trade counterfactuals: one in which we allow for increased destination-market diversification and allocate sales to each destination according to their GDP share in world GDP, and one in which we reduce the production specialization of all countries to resemble that of the global closed economy.

We find that the effect of *increased* diversification is quantitatively important in *reducing* aggregate volatility, especially for high volatility countries. The diversification effect reduces significantly both the destination and the idiosyncratic risks. Within destination risk, the most potent effect of diversification is reducing the within-market covariance of destination shocks across industries. A large part of this is driven by diversifying away from the home market.

On the other hand, and against conventional wisdom, we find that the effect of *reducing* specialization on volatility is *positive* and sizeable. Reducing specialization has a direct negative effect on volatility. However, our results show that it increases the correlation of origin-specific shocks across industries. In addition, it leads to a reduction in the negative covariance of shocks. The combination of these two effects outweighs the direct reduction in the volatility of origin-specific shocks, resulting in higher aggregate volatility when economies become less specialized.

Finally, we perform several robustness checks. First, we carry out our decomposition, separately, over a pre-globalization and a post-globalization period in order to test whether the sources of shocks have experienced significant changes with increased trade integration. We show that the results from this exercise are consistent with those based on the full sample period. In other words, most of the changes in risk in our sample are driven by changes in the exposure to shocks rather than changes in the nature of the shocks themselves. Second, we use an alternative decomposition allowing for a high degree of heterogeneity in terms of how shocks impact output. This richer specification does not change our decomposition results in a significant way. Third, we explore the robustness of our counterfactual results. Our diversification results are robust when we set sales diversification to the one observed pre-globalization (in 1980). For the specialization scenario, we show that our results are not driven by the sectoral specialization of the world post-globalization or larger economies.

Our paper relates, directly or indirectly, to three strands of the literature: a literature analyzing the link between openness measures and output volatility, a literature analyzing the shocks driving international business cycles, and a recent literature that analyzes the effects of Global Value Chains (GVC) on output and inflation risk. Di Giovanni and Levchenko (2009), for instance, study the relationship between trade and volatility and find that trade openness increases aggregate volatility. In general, however, the trade-volatility literature has yielded mixed results.[2] Our paper differs from these in several respects. First, we want to identify the channels through which trade drives aggregate volatility focusing on sectoral specialization and destination-market diversification. Second, our data allow us to analyze how the volatility-trade relationship is shaped by the combination of sources of risk, and trade and specialization structures. Third, our analysis allows for a more detailed understanding of the role of shock covariances among destination markets and among industries.

This paper also relates, albeit more indirectly, to the empirical literature on international business cycles. Kose et al. (2003a), Kose et al. (2008), and Hirata et al. (2013) use country-level data to decompose output fluctuations into global and country factors (risks). Karadimitropoulou and León-Ledesma (2013) extend this approach by considering industry, country, and global factors. A limitation of this decomposition is that, by considering the growth of a country's output in a given industry as the primary object

[1] Throughout the paper, we use the terms "aggregate volatility" and "total risk" interchangeably.

[2] For aggregate or industry studies see, among many others, Rodrik (1998), Cavallo (2008), Kose et al. (2003b), Loayza and Raddatz (2006), Karras and Song (1996), Bekaert et al. (2006), Calderón et al. (2005). For firm-level studies see Di Giovanni et al. (2014), Kurz and Senses (2016), Vannoorenberghe (2012), Nguyen and Schaur (2010), Buch et al. (2009).

of analysis, shocks specific to destination markets cannot be separately accounted for and thus might be attributed to country- or industry-specific shocks. For example, if the distribution of a country's sales across destination markets is similar across industries, shocks in any market could appear as country-specific shocks. Similarly, if destination markets are equally important in a given industry across countries, shocks in any market could appear as industry-specific shocks. We overcome this limitation by taking innovations in the growth rates of sales to all destination markets as the primitive and applying the methodology of Koren and Tenreyro (2007).

The supply disruptions experienced by the world economy during the pandemic and post-pandemic periods paved the way for a growing literature that analyzes the risks arising from exposure to Global Value Chains (GVCs). This literature is reviewed by Baldwin and Freeman (2022) within an optimal degree of openness framework. Recent contributions to this literature include Bonadio et al. (2021), Borin et al. (2021), D'Aguanno et al. (2021). These papers study the role of GVCs in shaping the response of economies to shocks. A key question of interest is whether "re-nationalization" of previously off-shored production would reduce exposure and hence the response to shocks. A common finding in these papers is that re-nationalization would not help reduce output volatility because, although it reduces exposure to external shocks, it increases exposure to domestic shocks by reducing diversification of input suppliers. Our result that diversification away from the home market reduces volatility echoes theirs. However, our focus is not on the off-shoring of intermediate inputs. Instead, our focus is on sales (which include both intermediates and final demand), identifying the sources of risk, and measuring how trade affects exposure to those risks. Furthermore, exposure to different risks in our paper stem from both international and domestic sales with purchases of intermediate inputs influencing the covariance of shocks within and across producing countries and destination markets.

More closely related to ours are the papers by Caselli et al. (2020) and Kramarz et al. (2020). Caselli et al. (2020) use a quantitative trade model to assess the importance of diversification and specialization channels in the relationship between trade and volatility. In their model, productivity shocks play a crucial role, with countries able to mitigate the country-specific component of these shocks through input imports. However, they remain vulnerable to the sectoral component of the same shocks due to persistent sectoral production patterns. In contrast, our decomposition framework imposes less structure on the data, allowing us to identify shocks that, while not directly mapping onto traditional structural shocks in macro models (such as productivity, tastes, or policy), are "deep" in the sense of being structurally identified using data on a country's domestic and international sales. This approach provides a richer set of insights that are directly relevant to policymakers and theoretical trade models of business cycle transmission.

Caselli et al. (2020) find that diversification of input sourcing can lower volatility by reducing the exposure to domestic productivity shocks. We also find that diversification lowers volatility but through the diversification of sales across markets.[3] In fact, our diversification counterfactual changes the destination of a country's sales, not the sourcing of inputs. The effect of input purchases on a country's production is kept to its observed value (through the covariance of origin shocks) as we only vary the sale share of an industry's gross output across destination markets. Importantly, the flexibility of our decomposition allows us to unveil how the various components of volatility change with trade.

Relative to Kramarz et al. (2020), we use less granular data but cover a larger set of countries and destination markets (including home) for three decades. Most importantly, our object of interest is total sales rather than export sales, which allows us to explore the role of the home market in explaining the diversification effects of trade.

In the next sections, we first present the empirical strategy, then discuss the data, our decomposition results and trade counterfactuals, and the robustness exercises. We conclude with a series of final remarks.

2. A decomposition of output volatility

We start by deriving a decomposition of output volatility at the aggregate level that accounts for the variation in industry-level sales due to shocks specific to destination markets, origin countries, and any destination-origin pairs. Our approach follows Koren and Tenreyro (2007) but with a couple of important differences. First, we consider the volatility of aggregate gross output rather than GDP per worker. That is because the former aggregates up observed sales to domestic and foreign markets. Second, our primary object of interest is the variation in industry-level sales to each destination market and not in industry-level gross output. Both these differences allow us to shed light on the effect of market diversification on aggregate volatility, in addition to the role of production specialization.

We then explain in detail how we identify the shocks underlying our components. That is, in fact, key to understanding what variation the estimated counterparts absorb. We use these insights to provide economic interpretations of the estimated risk and covariance components of output volatility, and a discussion of the role of trade.

2.1. Analytical derivation

First, because a country's gross output equals the sum of sales across all industries and destination markets, innovations in the growth rate of country c's gross output, q^c, can be expressed as a weighted sum of the innovations in the growth rate of industry i's sales in each of the destination markets $m = 1, \dots, M$ that c serves, y^c_{im}, as follows:

$$q^c = \sum_{i=1}^{I} \sum_{m=1}^{M} a^c_{im} * y^c_{im} \tag{1}$$

[3] See also Almunia et al. (2021) who show that Spanish firms used exports to diversify away from domestic demand shocks during the Great Recession.

where a^c_{im} is the share of industry i's sales to destination market m, S^c_{im}, in country c's total gross output, GO^c, i.e., $a^c_{im} = \frac{S^c_{im}}{GO^c}$. We should note that this weight can be conveniently rewritten as the product between the share of industry i's sales to m, $a^{ic}_m = \frac{S^c_{im}}{GO^c_i}$, and the share of i in total gross output, $a^c_i = \frac{GO^c_i}{GO^c}$, that is $a^c_{im} = \frac{S^c_{im}}{GO^c_i} * \frac{GO^c_i}{GO^c}$. In words, the weights in (1) are the product between two shares: one whose concentration captures the extent of *market diversification* at the industry-level, and the other whose concentration captures the extent of a country's industry *specialization*.

Second, we represent innovations in the growth rate of industry i's sales from c to m using the following factor decomposition:

$$y^c_{im} = \kappa_{im} + \gamma^c_i + \epsilon^c_{im} \tag{2}$$

where the first factor, κ_{im}, is specific to a destination-market-industry pair and it is independent of the origin country; the second factor, γ^c_i, is specific to a country of origin-industry pair, and independent of destination markets; and, ϵ^c_{im}, is the residual factor unexplained by the other two, i.e., picking up everything not accounted for by the other factors. Given the role of the residual factor, and that we place no restrictions on the covariance of these factors, (2) is a way of partitioning the data that constitutes an accounting identity.

In what follows, these factors are referred to as *shocks*. They capture the variation in sales due to different types of shocks (the exact nature of which we are agnostic about) that affect: some or all of the products purchased by a destination; some or all the products sold by an origin; and some or all the products sold by an origin to a given destination (including the home market).[4]

Last, we rewrite Eq. (2) using matrix notation as follows:

$$\boldsymbol{y^c} = \boldsymbol{\kappa} + \boldsymbol{\gamma^c} + \boldsymbol{\epsilon^c} \tag{3}$$

where $\boldsymbol{y^c}$ is the $(IM\text{x}1)$ vector of innovations y^c_{im}, $\boldsymbol{\kappa}$ is the $(IM\text{x}1)$ vector of destination-industry-specific shocks, $\boldsymbol{\gamma^c}$ is the $(IM\text{x}1)$ vector of origin-industry shocks (with each γ^c_i repeated M times), and $\boldsymbol{\epsilon^c}$ is the $(IM\text{x}1)$ vector of residual shocks. Using matrix algebra, we decompose the variance of q^c, $Var(q^c)$, as follows:

$$\begin{aligned} Var(q^c) = \boldsymbol{a^c}' E(\boldsymbol{y^c}\boldsymbol{y^c}')\boldsymbol{a^c} = \boldsymbol{a^c}'\boldsymbol{\Omega}_{\kappa}\boldsymbol{a^c} + \boldsymbol{a^c}'\boldsymbol{\Omega}_{\gamma^c}\boldsymbol{a^c} + \boldsymbol{a^c}'\boldsymbol{\Omega}_{\epsilon^c}\boldsymbol{a^c} + \\ + 2\boldsymbol{a^c}'\boldsymbol{\Omega}_{\boldsymbol{\gamma^c\kappa}}\boldsymbol{a^c} + 2\boldsymbol{a^c}'\boldsymbol{\Omega}_{\boldsymbol{\gamma^c\epsilon^c}}\boldsymbol{a^c} + 2\boldsymbol{a^c}'\boldsymbol{\Omega}_{\boldsymbol{\epsilon^c\kappa}}\boldsymbol{a^c} \end{aligned} \tag{4}$$

where $\boldsymbol{a^c}$ is the $(IM\text{x}1)$ vector that collects each destination market m's share in country c's total gross output at the industry level, $\frac{S^c_{im}}{GO^c}$; $\boldsymbol{\Omega}_{\kappa}$ is the variance–covariance matrix of destination-industry shocks, κ_{im}; $\boldsymbol{\Omega}_{\gamma^c}$ is the variance–covariance matrix of origin-industry-specific shocks, γ^c_i; $\boldsymbol{\Omega}_{\epsilon^c}$ is the variance–covariance matrix of residual shocks, ϵ^c_{im}; $\boldsymbol{\Omega}_{\boldsymbol{\gamma^c\kappa}}$ is the covariance matrix between origin-industry- and destination-industry-specific shocks; $\boldsymbol{\Omega}_{\boldsymbol{\gamma^c\epsilon^c}}$ and $\boldsymbol{\Omega}_{\boldsymbol{\epsilon^c\kappa}}$ are the covariance matrices of residual shocks with origin-industry- and destination-industry-specific shocks, respectively. The full derivation of this decomposition can be found in Online Appendix A.1.

2.2. Empirical implementation and economic interpretation

2.2.1. The shocks: identification

To quantify each of the components in Eq. (4), we first need estimators for destination-industry, origin-industry and residual shocks (κ_{im}, γ^c_i, and ϵ^c_{im}, respectively). For each origin country, industry, and destination market, we define innovations in sales, y^c_{imt}, as the deviation of the sales growth rate from its mean over time and we obtain the primitive shocks as follows:

$$\hat{\kappa}_{imt} \equiv \frac{1}{C}\sum_{c}^{C} y^c_{imt} \tag{5}$$

$$\hat{\gamma}^c_{it} \equiv \frac{1}{M}\sum_{m}^{M}(y^c_{imt} - \hat{\kappa}_{imt}) \tag{6}$$

$$\hat{\epsilon}^c_{imt} = y^c_{imt} - \hat{\kappa}_{imt} - \hat{\gamma}^c_{it} \tag{7}$$

As shown in Online Appendix A.2 the estimators in (5)–(7) are equivalent to those obtained from a restricted version of the following factor model:

$$y^c_{imt} = \sum_c\sum_i \gamma^c_{it} d_{ci} + \sum_m\sum_i \kappa_{imt} d_{im} + \epsilon^c_{imt} \tag{8}$$

with d_{im} and d_{ci} being indicator variables that take the value of 1 for industry-destination im and origin-industry ci, respectively, and estimated coefficients $\hat{\gamma}^c_{it}$, $\hat{\kappa}_{imt}$ and residuals $\hat{\epsilon}^c_{imt}$ being, respectively, the industry-destination im-specific shock, the origin-industry ci-specific-shock and the origin-industry-destination cim-specific shock at time t. The restriction that applies is that for each industry, the average across all countries of origin shocks equals zero, i.e., $\sum_c \gamma^c_{it} = 0$ for all i. This implies that we identify origin-industry-specific

[4] We also experimented with an alternative decomposition based on the following factor model for y^{ic}_m: $y^{ic}_m = \kappa_m + \gamma^{ic} + \epsilon^{ic}_m$. This specification allows us to focus on volatility aggregated at the industry-country level. However, results (available on request) suggest that industrial output volatility depends very little on industry-specific factors and that more interesting insights are obtained by focusing on volatility aggregated at the country level as in Eq. (1).

shocks relative to their average across all countries. Further, the model in (8) assumes that origin-, destination- and industry-specific shocks are zero, implying that origin-, destination- or industry-specific shocks are not identified separately from shocks specific to an origin-industry or destination-industry pair. Finally, controlling for origin-industry and destination-industry factors, the residual term contains shocks to y^c_{im} that affect some or all the products that an *origin* sells to a given *destination*, including the home market.

2.2.2. The shocks: interpretation

Our method does not allow us to identify shocks with a standard macro- or microeconomic interpretation of fundamental shocks (i.e., TFP, preferences, monetary policy, etc.). However, it allows us to identify shocks in a way that is crucial to understand how trade affects risk exposure. From the point of view of a policymaker, whether risk arises from, say, the demand for their products in specific markets (including the home market), or from factor markets and cost shocks, is important. Also, whether that risk is diversifiable is arguably more important than the (theoretically) fundamental nature of the shock. In this sense, our strategy follows Koren and Tenreyro (2007) but extends to a multi-sector and multi-destination setting.

According to the restricted model in Eq. (8), κ_{im} captures the variation in sales arising from shocks to destination preferences or technology that affect purchases of one or more products independent of their origin. Because, empirically, we are not able to disentangle destination-industry shocks from destination-specific shocks, κ_{im} also captures the variation in sales arising from any macroeconomic shocks in market m.

γ^c_i captures the variation in sales due to any shock that affects producers in one, several, or all industries of a country independent of the destination of their products. These shocks include not only technology, cost, factor markets, and macroeconomic shocks, but also shocks to global preferences due to, for instance, changes in the reputation of a country's products.

In essence, γ^c_i and κ_{im} both capture the variation in sales due to aggregate or industry-specific shocks. However, κ_{im} captures the variation arising from shocks that affect a destination's purchases across all sources, whereas γ^c_i captures the variation due to shocks that affect a country's sales across all markets.

The fact that we use sales across all destinations allows us to disentangle κ_{im} from γ^c_i also in the case in which the destination market is the home market. That is because the former captures variation from domestic shocks that affects purchases from all sources (including home). The latter, on the contrary, absorbs variation from shocks that affects sales across all destinations (including home).

ϵ^c_{im} captures the variation in sales not absorbed by κ_{im} and γ^c_i, which arises from shocks to some or all products sold from c to m. That is, those arising from changes in a destination market's preferences and policies that affect one, several, or all the products purchased from a particular origin. It can also capture changes in an origin's policies that affect sales of one, several, or all products sold to a particular destination, or changes in origin–destination-specific policy or bilateral exchange rates.

All the shocks in Eq. (2) can be correlated. Empirically, because κ_{im} and γ^c_i capture changes in sales due to macroeconomic or industry-specific conditions in country c and destination m, their covariance reflects, in part, the synchronization of business cycles between c and m. More generally, global shocks with asymmetric effects across countries and industries (that simultaneously affect countries' sales and purchases) create a correlation between κ_{im} and γ^c_i that the covariance absorbs. The extent to which some destinations are more sensitive to origin- or origin-industry-specific shocks, or some origins are more sensitive to destination- or destination-industry-specific shocks is, instead, captured by the covariance between ϵ^c_{im} and γ^c_i, and between ϵ^c_{im} and κ_{im}, respectively.

2.2.3. The risk components: estimation

Using the estimated shocks from Eqs. (5)–(7), we compute the associated variance–covariance matrices as follows: $\hat{\boldsymbol{\Omega}}_{\boldsymbol{\kappa}} = \frac{1}{(T-1)} \sum_{t=1}^{T} \boldsymbol{\Delta}\hat{\boldsymbol{\kappa}}_t \boldsymbol{\Delta}\hat{\boldsymbol{\kappa}}_t{}'$, $\hat{\boldsymbol{\Omega}}_{\boldsymbol{\gamma}^c} = \frac{1}{(T-1)} \sum_{t=1}^{T} \boldsymbol{\Delta}\hat{\boldsymbol{\gamma}}^c_t \boldsymbol{\Delta}\hat{\boldsymbol{\gamma}}^{c\prime}_t$, $\hat{\boldsymbol{\Omega}}_{\epsilon^c} = \frac{1}{(T-1)} \sum_{t=1}^{T} \boldsymbol{\Delta}\hat{\boldsymbol{\epsilon}}^c_t \boldsymbol{\Delta}\hat{\boldsymbol{\epsilon}}^{c\prime}_t$, $\hat{\boldsymbol{\Omega}}_{\gamma^c\kappa} = \frac{1}{(T-1)} \sum_{t=1}^{T} \boldsymbol{\Delta}\hat{\boldsymbol{\gamma}}^c_t \boldsymbol{\Delta}\hat{\boldsymbol{\kappa}}_t$, $\hat{\boldsymbol{\Omega}}_{\epsilon^c\kappa} = \frac{1}{(T-1)} \sum_{t=1}^{T} \boldsymbol{\Delta}\hat{\boldsymbol{\epsilon}}^c_t \boldsymbol{\Delta}\hat{\boldsymbol{\kappa}}_t{}'$, $\hat{\boldsymbol{\Omega}}_{\gamma^c\epsilon^c} = \frac{1}{(T-1)} \sum_{t=1}^{T} \Delta\hat{\gamma}^c_t \hat{\boldsymbol{\epsilon}}^{c\prime}_t$, where Δ represents deviations from the mean.

Combining the variance–covariance matrices of estimated shocks with observed sales shares at time t, a^c_{imt}, we obtain all the measures of risk that add up to total risk (aggregate volatility). More formally, we measure:

$$DR^c_t = \boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\kappa} \boldsymbol{a}^c_t \tag{9}$$

$$OR^c_t = \boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\gamma^c} \boldsymbol{a}^c_t \tag{10}$$

$$IDIOR^c_t = \boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\epsilon^c} \boldsymbol{a}^c_t \tag{11}$$

$$COV^c_{\boldsymbol{\gamma}^c\boldsymbol{\kappa}t} = 2\boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\gamma^c\kappa} \boldsymbol{a}^c_t \tag{12}$$

$$COV^c_{\boldsymbol{\epsilon}^c\boldsymbol{\kappa}t} = 2\boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\epsilon^c\kappa} \boldsymbol{a}^c_t \tag{13}$$

$$COV^c_{\boldsymbol{\gamma}^c\boldsymbol{\epsilon}^c t} = 2\boldsymbol{a}^{c\prime}_t \hat{\boldsymbol{\Omega}}_{\gamma^c\epsilon^c} \boldsymbol{a}^c_t \tag{14}$$

where DR^c_t, OR^c_t, and $IDIOR^c_t$ are the risk components of country c's output volatility at time t due to destination-specific, origin-specific and idiosyncratic shocks, respectively; $COV^c_{\boldsymbol{\gamma}^c\boldsymbol{\kappa}t}$ is twice the covariance between destination and origin shocks; $COV^c_{\boldsymbol{\epsilon}^c\boldsymbol{\kappa}t}$ and $COV^c_{\boldsymbol{\gamma}^c\boldsymbol{\epsilon}^c t}$ are twice the covariance between idiosyncratic and destination-specific shocks, and between idiosyncratic- and origin-specific shocks at time t, respectively.

2.2.4. The risk components: interpretation

The risk components obtained from Eqs. (9)–(14) have an intuitive interpretation. The first term, $\boldsymbol{a}^{c\prime}\hat{\boldsymbol{\Omega}}_{\kappa}\boldsymbol{a}^{c}$, captures what we refer to as *destination risk, DR*. For each country c, the *destination risk* relates to shocks that affect any destination's purchases of products independent of the origin country. The *destination risk* varies by origin country *only* in as much as the structure of sales across industries and destinations varies. This is because destination-specific shocks are common across origin countries and so are their variance–covariance matrix $\boldsymbol{\Omega}_{\kappa}$. Because of the level of aggregation we are working with, a country's destination risk is large if the country's sales are concentrated in: (i) destinations with high market volatility; (ii) markets with positively correlated destination-specific shocks across industries; (iii) industries whose sales across destinations are subject to positively correlated destination-specific shocks; and (iv) markets-industries with cross-industry, destination-specific shocks that are positively correlated across distinct destination markets. This can be clearly seen by rewriting the destination risk, $\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\kappa}\boldsymbol{a}^{c}$, as follows:

$$\begin{aligned}\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\kappa}\boldsymbol{a}^{c} &= \sum_{m}\sum_{i}(a^{c}_{im})^{2}E(\kappa^{2}_{im}) + 2\sum_{m}\sum_{i,j\neq i}a^{c}_{im}a^{c}_{jm}E(\kappa_{im}\kappa_{jm})+ \\ &+ 2\sum_{i}\sum_{m,m'\neq m}a^{c}_{im}a^{c}_{im'}E(\kappa_{im}\kappa_{im'}) + 2\sum_{i,j\neq i}\sum_{m,m'\neq m}a^{c}_{im}a^{c}_{jm'}E(\kappa_{im}\kappa_{jm'})\end{aligned} \tag{15}$$

where each term captures, respectively, the effect of the *volatility* of destination-specific shocks, the *within-market covariance* of destination-specific shocks *across industries*, the *within-industry covariance* of destination-specific shocks *across markets*, and the *covariance* of destination-specific shocks *across distinct industry-market pairs*. Note that this risk will depend on both the market diversification pattern and the industry specialization pattern through the shares a^{c}_{im}. To use an example, suppose a country, say India, produces textiles and computers which are sold in two destination markets, say, Belgium and Germany. Destination risk in India will be high: (i) if Germany and Belgium are subject to frequent and large shocks that affect their purchases in the textile and the computer industry; (ii) if shocks in the German (or Belgian) market tend to affect both their purchases of textiles and computers simultaneously (within-market covariance); (iii) if shocks to purchases of textiles (or computers) are highly correlated between Germany and Belgium (across-market covariance); (iv) if shocks to the purchases of textiles in Germany are correlated with shocks to the purchase of computers in Belgium (across industry-market pairs). Global value chains can play a role in these sub-components. Continuing with our example, suppose textiles are used in the production of cars. Shocks to German purchases of cars ($\kappa_{car,DEU}$) would be more likely to lead to changes in the purchase of textiles by Belgium ($\kappa_{tex,BEL}$) the larger the sales of Belgian cars to Germany. In this example the destination shocks are positively correlated. The extent to which they matter for India depends on the concentration of Indian car sales to Germany and that of Indian textiles to Belgium.

The second term, $\boldsymbol{a}^{c\prime}\hat{\boldsymbol{\Omega}}_{\gamma^{c}}\boldsymbol{a}^{c}$, is the *origin risk*, OR. This component is large if a country's output is concentrated in industries that receive large and frequent shocks, and these shocks are positively correlated across industries. This component captures the output risk a country faces given its *specialization* patterns. Formally, this can be seen by rewriting the origin risk $\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\gamma^{c}}\boldsymbol{a}^{c}$ as follows:

$$\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\gamma^{c}}\boldsymbol{a}^{c} = \sum_{i}(a^{c}_{i})^{2}E(\gamma^{c2}_{i}) + 2\sum_{i,j\neq i}a^{c}_{i}a^{c}_{j}E(\gamma^{c}_{i}\gamma^{c}_{j}), \tag{16}$$

where a^{c}_{i} is the share of industry i in country c's gross output, and each term captures the effect of the volatility of origin-specific shocks and the covariance of origin-specific shocks across industries, respectively. This risk will not depend on the market diversification pattern of sales, but only on the sectoral specialization pattern.[5] National input–output linkages between industries will affect the covariance of shocks across industries. This is important because this risk will not only be affected by the degree of sectoral specialization, but also whether the industries in which the country specializes co-move strongly with the rest. That is, using the example above, origin risk in India depends on the volatility of textile and computer production and whether shocks to these industries tend to be highly correlated. To the extent that GVCs affect the degree to which sectors are connected through forward and backward linkages *within* the producing country, this term will depend on the degree of the economy's integration in GVCs.

The third term, $\boldsymbol{a}^{c\prime}\hat{\boldsymbol{\Omega}}_{\epsilon^{c}}\boldsymbol{a}^{c}$, is the idiosyncratic risk (IDIOR). For each country c the idiosyncratic risk relates to shocks that affect some or all of c's products sold to any specific destination. This component is large if country c's sales are concentrated in: (i) destinations with high idiosyncratic volatility; (ii) markets with positively correlated idiosyncratic shocks across industries; (iii) industries whose sales across destinations are subject to positively correlated idiosyncratic shocks; and (iv) markets-industries with cross-industry idiosyncratic shocks that are positively correlated across distinct destination markets. Formally, the idiosyncratic risk, $\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\epsilon^{c}}\boldsymbol{a}^{c}$, can be rewritten as:

$$\begin{aligned}\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\epsilon^{c}}\boldsymbol{a}^{c} &= \sum_{m}\sum_{i}(a^{c}_{im})^{2}E((\epsilon^{c}_{im})^{2}) + 2\sum_{m}\sum_{i,j\neq i}a^{c}_{im}a^{c}_{jm}E(\epsilon^{c}_{im}\epsilon^{c}_{jm})+ \\ &+ 2\sum_{i}\sum_{m,m'\neq m}a^{c}_{im}a^{c}_{im'}E(\epsilon^{c}_{im}\epsilon^{c}_{im'}) + 2\sum_{i,j\neq i}\sum_{m,m'\neq m}a^{c}_{im}a^{c}_{jm'}E(\epsilon^{c}_{im}\epsilon^{c}_{jm'})\end{aligned} \tag{17}$$

where each term captures, respectively, the effect of the *volatility* of idiosyncratic shocks, the *within-market covariance* of idiosyncratic shocks *across industries*, the *within-industry covariance* of idiosyncratic shocks *across markets*, and the *covariance* of idiosyncratic shocks *across distinct industry-market pairs*.

[5] Even though the shares in the vector $\boldsymbol{a}$ are industry-origin–destination specific, in the calculation, the shares across destinations within industry are multiplied by the same expected values and can be aggregated up to the industry's share in total gross output.

The fourth and fifth terms, $COV^c_{\epsilon^c\kappa}$ and $COV^c_{\gamma^c\epsilon^c}$, summarize the effect on risk of the covariance of origin-specific shocks with destination-specific and idiosyncratic shocks, respectively. Focusing on the following decomposition of $COV^c_{\gamma^c\kappa}$:

$$2\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\gamma^c\kappa}\boldsymbol{a}^c = 2\sum_i\sum_m a^c_{im}a^c_i E(\kappa_{im}\gamma^c_i) + 2\sum_m\sum_{i,j\neq i} a^c_{im}a^c_j E(\kappa_{im}\gamma^c_j), \tag{18}$$

it is apparent that this term is large if countries' sales are concentrated in: (i) industries whose origin- and destination-specific shocks covary positively; and (ii) industry-pairs whose origin- and destination-specific shocks covary positively. This covariance can also be affected by GVC linkages. For instance, if there is a negative origin shock to the production of textiles in India and these are key inputs for production of cars in Belgium, the supply-chain disruption effect on Belgian production can affect its purchases of some or all goods/inputs from all countries, including India, creating co-movement between the origin and destination shocks. Similarly, $COV^c_{\gamma^c\epsilon^c}$ can be decomposed as follows:

$$2\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\gamma^c\epsilon^c}\boldsymbol{a}^c = 2\sum_i\sum_m a^c_{im}a^c_i E(\epsilon^c_{im}\gamma^c_i) + 2\sum_m\sum_{i,j\neq i} a^c_{im}a^c_j E(\epsilon^c_{im}\gamma^c_j). \tag{19}$$

The last term, $COV_{\epsilon^c\kappa}$, captures the effect on industrial risk of the covariance between destination-specific and idiosyncratic shocks. This component is larger the more concentrated sales are in destinations with high covariance between destination-specific and idiosyncratic shocks in the same industry or across industries. This can be seen by decomposing $COV_{\epsilon^c\kappa}$ as follows:

$$\begin{aligned}2\boldsymbol{a}^{c\prime}\boldsymbol{\Omega}_{\epsilon^c\kappa}\boldsymbol{a}^c &= 2\sum_i\sum_m (a^c_{im})^2 E(\kappa_{im}\epsilon^c_{im}) + 2\sum_m\sum_{i,j\neq i} a^c_{im}a^c_{jm}E(\kappa_{im}\epsilon^c_{jm}) + \\ &+ 2\sum_i\sum_{m,m'\neq m} a^c_{im}a^c_{im'}E(\kappa_{im}\epsilon^c_{im'}) + 2\sum_{i,j\neq i}\sum_{m,m'\neq m} a^c_{im}a^c_{jm'}E(\kappa_{im}\epsilon^c_{jm'})\end{aligned} \tag{20}$$

where the first two terms capture the effect of the *within-destination* covariance between destination-specific and idiosyncratic shocks *in each industry* and *across industries*, respectively; and the last two terms capture the *cross-destination* effect of the covariance between destination-specific and idiosyncratic shocks *in each industry* and *across industries*.

2.3. Leveraging the decomposition to understand the role of trade

The factor decomposition and risk measures presented above highlight the complex nature of the drivers of aggregate volatility in a multi-sector, multi-market world. According to the model, volatility is driven by a set of shocks (destination, origin, and idiosyncratic) and their co-movement. This co-movement may amplify risk (if positive) or insure against it (if negative).

Importantly, trade affects the exposure to different shocks (and their covariances) through two channels: sectoral production specialization, and market diversification. These are reflected in the share parameters, a^c_{im}, which arise from a combination of production specialization and destination-market diversification as shown by the identity:

$$a^c_{im} = \underbrace{\frac{S^c_{im}}{GO^c_i}}_{\text{diversification}} * \underbrace{\frac{GO^c_i}{GO^c}}_{\text{specialization}},$$

where $\frac{S^c_{im}}{GO^c_i}$ is the share of country c's gross output in industry i sold in market m or a^{ic}_m, and $\frac{GO^c_i}{GO^c}$ is the share of industry i's in the total gross output of country c or a^c_i. Given the variance–covariance matrices of shocks obtained before ($\hat{\boldsymbol{\Omega}}$'s), we can then change the weights vector to assess the effect of changes in market diversification and production specialization on total volatility and its components. The exercise assumes that the structure of trade weights is independent of the variance–covariance of shocks. This means that we are quantifying how changes to the *exposure* to different structural shocks affects aggregate volatility. In particular, we conduct two counterfactuals:

- *Diversification*: we first keep sectoral shares ($\frac{GO^c_i}{GO^c}$) as in the data, but change destination market shares so as to have weights that are just proportional to market m's GDP share in world GDP. We call this full market "diversification". This would represent a world where trade flows at the country level only depend on country size. That is, if $\bar{a}^c_{im}$ is the counterfactual share, we define: $\bar{a}^c_{im} = \frac{GDP_m}{\sum_m GDP_m} * \frac{GO^c_i}{GO^c}$. Note that, for many countries, this would imply a large diversification away from the *home* market. We thus also run a counterfactual to measure the extent to which the diversification effects are driven by the home market alone. In this case, we assign only the home market its GDP weight. The difference between the actual home market share and its GDP share is then allocated to the rest of the markets proportional to their *actual* shares such that we do not modify the relative importance of the rest of the markets. This is what we refer to as "home diversification".
- *No Specialization*: we then keep destination-market shares ($\frac{S^c_{im}}{GO^c_i}$) as in the data, but change sector shares to resemble a "closed" economy specialization. We call this the "no specialization" scenario. To do so, because the world economy is closed, we can use the shares of each sector in the world economy as a benchmark closed economy. To circumvent the fact that increased world trade may have affected world sectoral shares, we use world shares in 1980. That is, we define the counterfactual share $\bar{a}^c_{im}$ as: $\bar{a}^c_{im} = \frac{S^c_{im}}{GO^c_i} * \frac{\sum_c GO^{c,1980}_i}{\sum_c GO^{c,1980}}$. Note that this approximation to a closed economy specialization benchmark assumes that tastes and relative sectoral technologies are common across all producing countries.

Table 1
Producer Countries Summary Statistics.

	Income per Capita	Openness	Total Share of World	
			Non-oil Exports	GDP
Average	23 328.38	64.00	84.96	82.52
Std. Dev.	14 429.4	64.83	5.22	2.47
Min	1190.10	5.22	76.80	77.65
Max	82 491.78	621	95.40	85.86

Although none of these scenarios is likely to happen in reality, they help quantify the effects on volatility of these two different forces shaping the structure of trade. In a fully integrated market with no trade frictions and no preference heterogeneity, destination-market shares would be just a function of market size. The "no specialization" scenario, in contrast, quantifies the effect of the reduced specialization that would come about in a world without trade.

3. Data

Our empirical analysis uses annual production and bilateral trade data. Production data are from the CEPII TradeProd database, and UNIDO INDSTAT 4 databases. The TradeProd database is constructed by combining the World Bank dataset "Trade, Production and Protection" (Nicita and Olarreaga, 2007) with data from the OECD and the UNIDO (De Sousa et al., 2012). This dataset covers 26 manufacturing sectors at the 3-digit International Standard Industrial Classification (ISIC) Revision 2 level and 181 countries from 1980 to 2006. The INDSTAT 4 databases report production information at the ISIC Revision 3 and/or Revision 4 level for 147 countries from 1990 onward. Data are available at the 3-digit (Group) or 4-digit (Class) or both level of disaggregation. Integrating the INDSTAT 4 and the TradeProd database is not straightforward because INDSTAT 4 data for some countries are reported according to a non-standard ISIC Classification (ISIC combined codes), and the UNCTAD concordance tables across ISIC Revisions are only available at the 4-digit level, and not directly between Revision 4 and Revision 2. Online Appendix B.1 documents all the steps we followed to create a unique series of output data at the 3-digit ISIC level Revision 2 by country. The relevant code and our data quality checks are publicly available at https://l-puzzello.github.io/indstat-TPP/.

Trade data are from the CHELEM database, constructed by the CEPII and distributed by the Bureau van Dijk. The bilateral trade data is a balanced panel of 84 exporting and importing destinations at 4-digit ISIC Revision 3 level from 1967 to 2011. We prefer the CHELEM trade data to the trade data in the CEPII TradeProd database because their coverage allows for a finer disaggregation of destination markets.[6] We calculate domestic sales as the difference between gross output and exports (adjusted to account for re-exports). Online Appendix B.1 provides additional details on the data.

Because our methodology requires a balanced panel of producer countries and industries, we drop from our sample countries, industries, and years for which gross output data is sparse or missing in many consecutive years and then interpolate the missing values for less than 3% of all observations. At the country-industry level, and given the level of industry aggregation, there is no observation for which the production of an industry in a country is zero. Our bilateral trade data, however, contains 19% of zero flows across all country pairs, industries, and years. The percentage of zero trade flows varies across countries (i.e., from 0.12% for Germany to 67% for Bolivia). In the analysis, as well as in the relevant counterfactuals, a zero trade flow translates into a zero market share. When we calculate the shocks, there is a problem when consecutive flows are zero. To avoid division by zero, we replace zeros with a value of 0.0001.

Combining the production and trade data gives us a balanced panel of 34 producer countries, 84 destination markets (including an aggregate for the rest of the world), and 19 ISIC Revision 2 sectors from 1980 to 2011. The complete list of producer countries and destination markets is available in Online Appendix B.2.

Table 1 shows the representativeness of our sample of producer countries. Our sample covers countries with an income per capita that ranges from 1,190 to 82,492 real USD (PPP-adjusted). These countries, on average, account for more than 80% of global non-oil merchandise exports and GDP during the sample period.[7] Countries in the bottom 5% and the top 1% of the world income distribution, primarily African countries and oil exporting countries, are not covered by our sample. These countries, however, have less diversified production structures, exports and destination markets. In a nutshell, the producer countries in our sample provide more than enough variation to have confidence in our decomposition and counterfactual results.

4. Results

We now present a set of key results relating to the estimation of risks and their components as well as the counterfactual exercises. Due to the volume of results, we provide further plots and tables in the Online Appendix.

[6] For the subset of data common to the two datasets we verified a correlation of 0.9.

[7] To calculate GDP shares, we use GDP data in current USD from the World Development Indicators for all countries but Taiwan. For Taiwan, we sourced GDP data from the IMF.

Table 2
HHI: Mean and (Standard Deviation). Selected countries.

Country	Total HHI/ HHI m share of GO^c	Sectoral HHI/ HHI i share of GO^c	Market HHI/ HHI m share of GO_i^c
	(1)	(2)	(3)
Australia	0.07 (0.01)	0.10 (0.01)	0.78 (0.19)
Bulgaria	0.06 (0.02)	0.10 (0.01)	0.57 (0.23)
Canada	0.06 (0.01)	0.11 (0.01)	0.65(0.16)
Cyprus	0.12 (0.04)	0.15 (0.03)	0.73 (0.20)
China	0.07 (0.01)	0.09 (0.01)	0.73 (0.22)
Denmark	0.05 (0.01)	0.14 (0.03)	0.43 (0.18)
Germany	0.05 (0.01)	0.10 (0.01)	0.56 (0.20)
Ecuador	0.11 (0.03)	0.21 (0.04)	0.85 (0.17)
Finland	0.06 (0.01)	0.11 (0.01)	0.55 (0.21)
India	0.08 (0.01)	0.10 (0.00)	0.76 (0.23)
Japan	0.07 (0.01)	0.10 (0.01)	0.78 (0.20)
Korea	0.05 (0.01)	0.10 (0.01)	0.63 (0.24)
Mexico	0.07 (0.01)	0.11 (0.01)	0.65 (0.17)
Netherlands	0.05 (0.01)	0.12 (0.01)	0.40 (0.20)
Sweden	0.05 (0.01)	0.10 (0.01)	0.50 (0.20)
UK	0.06 (0.00)	0.09 (0.00)	0.63 (0.17)
Uruguay	0.10 (0.02)	0.21 (0.05)	0.68 (0.22)
USA	0.07 (0.00)	0.09 (0.00)	0.83 (0.11)
Average	0.07 (0.01)	0.12 (0.01)	0.64 (0.20)

Note. Total HHI is HHI of $a_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^c}{GO^c}$. Sectoral HHI is the HHI of $a_i^c = \frac{GO_i^c}{GO^c}$. Market HHI is the HHI of $a_m^{ic} = \frac{S_{im}^c}{GO_i^c}$. Average corresponds to the simple average for all 34 producing countries in our sample. HHI indexes for all countries are available in Table C.1 in Online Appendix C.

4.1. Shares and shocks: descriptive statistics

Key elements of our decomposition are the shares, a_{im}^c, innovations in the growth rate of output, y_{im}^c, and estimated shocks. The distribution of y_{im}^c is, by construction, symmetric around zero. So it is not particularly insightful. Hence, in this subsection we focus on shares and estimated shocks.

The shares a_{im}^c are calculated by taking the ratio of a country's sales to each market m in a particular industry i, S_{im}^c, to that country's total gross output, GO^c. Because of the magnitude of the denominator, most of these shares are small. Overall, more than 90% of all industry sales to specific markets account for less than 0.026% of a country's total gross output. Further, we exploit the identity $a_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^c}{GO^c}$ to understand the main source of variation in a_{im}^c, and the extent of market diversification and sectoral specialization in our sample. Indeed, we separately regress the logarithm of $\frac{S_{im}^c}{GO_i^c}$ and $\frac{GO_i^c}{GO^c}$ on the logarithm of a_{im}^c. Given the properties of the OLS estimator, estimated coefficients from each regression add up to one, with coefficients being the share of the overall variation in a_{im}^c due to each margin. More than 93% of the variation in a_{im}^c is due to the distribution of each industry's sales across markets, independent of whether we consider the overall variation, cross-country variation, or the time variation within country. The importance of this variation is confirmed when we calculate the Herfindhal-Hirchman Indexes (HHI) for a_{im}^c and its components. Table 2 shows our results for a selected group of countries in the interest of space.[8] At the aggregate level, sales concentration appears to be low (column (1)). Sectoral concentration varies more across countries, with commodity exporting countries such as Ecuador and Uruguay displaying a higher sectoral concentration (column (2)). With the possible exceptions of the Netherlands and Denmark, sales are highly concentrated by destination market at the industry level for all countries and exhibit higher dispersion within country (column (3)).

In Table 3 we report basic statistics about the distribution of the variances and covariances of estimated shocks. There are two findings to highlight. First, the volatility of shocks and their covariances within a destination market or origin country (in gray shaded cells) are relatively large and positive. Second, with the exception of the covariances between destination shocks, the distribution of all remaining covariances (in bold) is centered, almost symmetrically, around zero. Note, however, that this does not imply that the risk arising from these covariances is not important. The impact of covariances on volatility will also depend on the market and sector weights.

4.2. Decomposition

4.2.1. Total output risk

Fig. 1 plots *total output risk* for every country c and its dispersion across years (1981–2011) in descending order of the median over the time period. Total risk varies significantly across countries and appears to be negatively related to levels of development

[8] Full results for all countries can be found in Table C.1 in Online Appendix C.

Table 3
Shocks: Descriptive Statistics.

Panel A. Volatility and Covariance of destination-specific shocks				
	$E(k_{im}^2)$	$E(k_{im}k_{jm})$	$E(k_{im}k_{im'})$	$E(k_{im}k_{jm'})$
Mean	0.0461	0.0234	0.0083	0.0064
Median	0.0401	0.0170	0.0074	0.0058
% of negative observations	0.00	2.00	17.60	22.00
Standard Deviation	0.0267	0.0214	0.0104	0.0096
Panel B. Volatility and Covariance of origin-specific shocks				
	$E(\gamma_i^{c2})$	$E(\gamma_i^c\gamma_j^c)$		
Mean	0.0243	0.0044		
Median	0.0188	0.0034		
% of negative observations	0.00	18.00		
Standard Deviation	0.0259	0.0068		
Panel C. Volatility and Covariance of idiosyncratic shocks				
	$E((\epsilon_{im}^c)^2)$	$E(\epsilon_{im}^c\epsilon_{jm}^c)$	$E(\epsilon_{im}^c\epsilon_{im'}^c)$	$E(\epsilon_{im}^c\epsilon_{jm'}^c)$
Mean	0.581	0.045	**−0.007**	**−0.001**
Median	0.407	0.013	**−0.001**	**0.000**
% of negative observations	0.00	36.00	**51.25**	**50.06**
Standard Deviation	0.542	0.175	0.135	0.127
Panel D. Covariance between origin and				
	idiosyncratic shocks		destination shocks	
	$E(\epsilon_{im}^c\gamma_i^c)$	$E(\epsilon_{im}^c\gamma_j^c)$	$E(\kappa_{im}\gamma_i^c)$	$E(\kappa_{im}\gamma_j^c)$
Mean	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Median	**−0.0019**	**−0.0004**	**−0.0001**	**0.0001**
% of negative observations	**55.36**	**51.46**	**51.24**	**49.27**
Standard Deviation	0.0260	0.0237	0.0067	0.0063
Panel E. Covariance between destination-specific and idiosyncratic shocks				
	$E(\kappa_{im}\epsilon_{im}^c)$	$E(\kappa_{im}\epsilon_{jm}^c)$	$E(\kappa_{im}\epsilon_{im'}^c)$	$E(\kappa_{im}\epsilon_{jm'}^c)$
Mean	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Median	**−0.0043**	**−0.0003**	**−0.0001**	**−0.0001**
% of negative observations	**57.57**	**50.75**	**50.16**	**50.18**
Standard Deviation	0.0373	0.0343	0.0305	0.0302

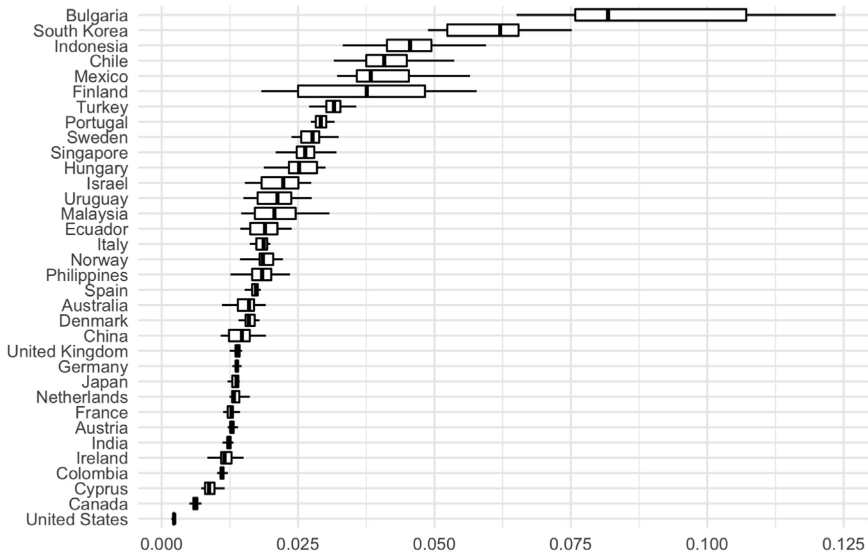
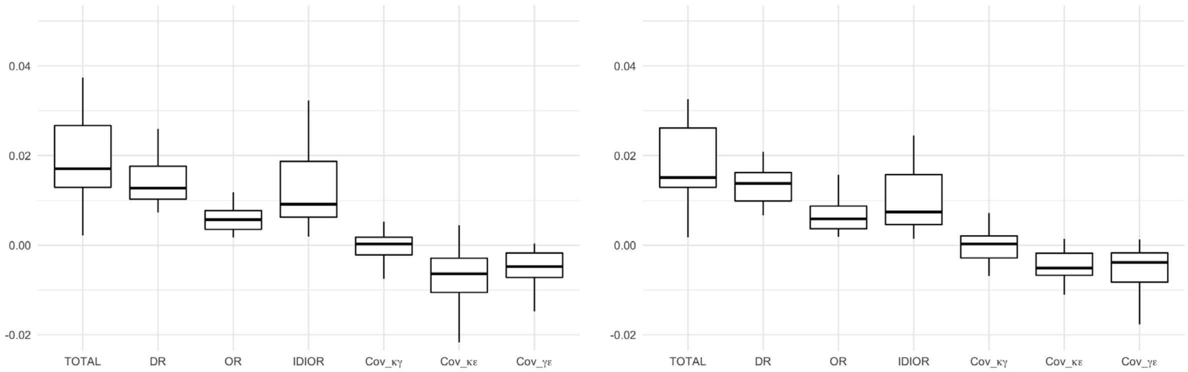


Fig. 1. Total output risk by country,1981–2011.

as in Koren and Tenreyro (2007).[9] High volatility tends to be associated with higher dispersion across years. This seems to be consistent with high volatility being associated with episodes of deep crises (i.e., South Korea, Indonesia, Chile, Mexico and Finland) and economic transformation (such as the case of Bulgaria). The USA, Canada, and most European countries display lower volatility levels and dispersion across years.

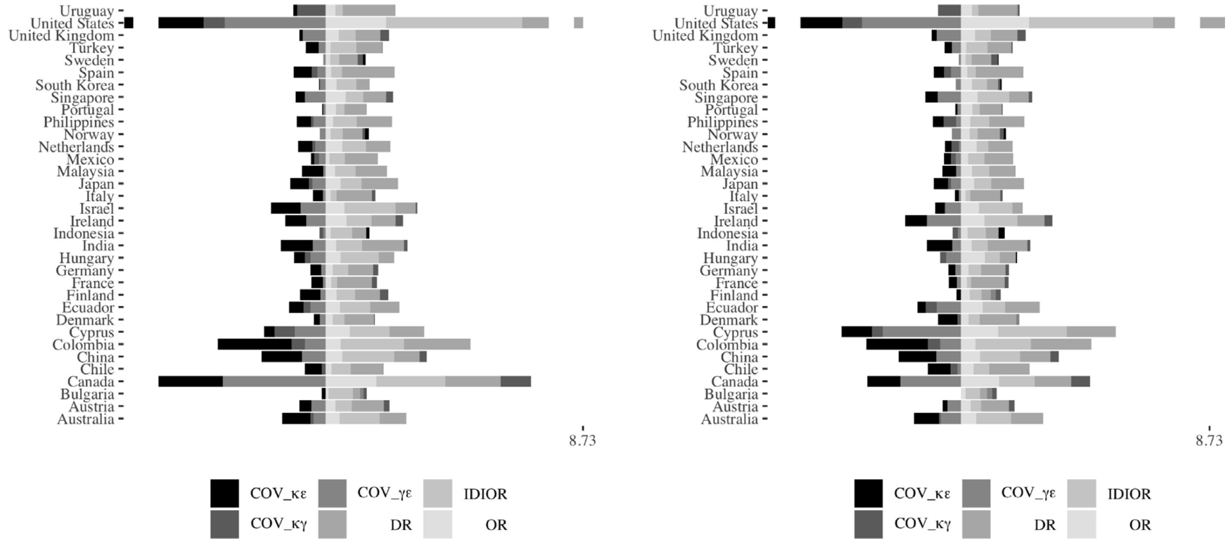
For the risk components, since we have a decomposition for every year, we will report results for 1981 and 2011 when necessary without loss of generality. In fact, the *ranking* of the risk components remains remarkably stable across the sample period which, in

[9] The R^2 of a regression on log GDP per capita and year fixed effects is 0.0454 with a negative slope.



(a) Year: 1981   (b) Year: 2011

Fig. 2. Total output risk decomposition.
Note. TOTAL is total output risk. DR stands for Destination Risk calculated according to Eq. (9). OR stands for Origin Risk calculated according to Eq. (10). IDIOR is for Idiosyncratic Risk from Eq. (11). $COV_{\gamma\kappa}$ is twice the covariance between origin and destination shocks as per Eq. (12). $COV_{\kappa\epsilon}$ is twice the covariance between destination and idiosyncratic shocks as per Eq. (13). $COV_{\gamma\epsilon}$ is twice the covariance between destination and idiosyncratic shocks as per Eq. (14).



(a) Year: 1981   (b) Year: 2011

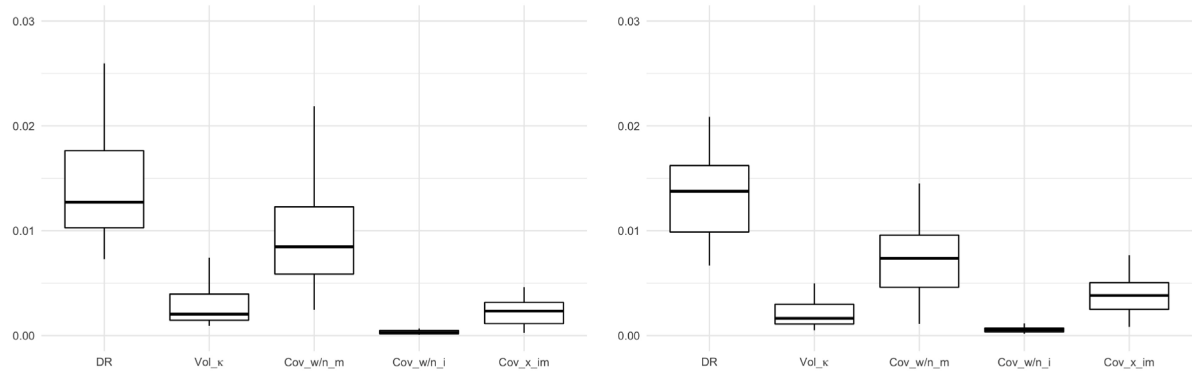
Fig. 3. Risk components contribution.
Note. DR stands for Destination Risk calculated according to Eq. (9). OR stands for Origin Risk calculated according to Eq. (10). IDIOR is for Idiosyncratic Risk from Eq. (11). $COV_{\gamma\kappa}$ is twice the covariance between origin and destination shocks as per Eq. (12). $COV_{\kappa\epsilon}$ is twice the covariance between destination and idiosyncratic shocks as per Eq. (13). $COV_{\gamma\epsilon}$ is twice the covariance between destination and idiosyncratic shocks as per equation. (14). Each graph is generated using the ggbreak R package developed by Xu et al. (2021).

itself, is an interesting result. Despite the rapid growth and transformation in international trade during these 30 years, the sources of volatility appear to have remained stable in relative terms.[10]

Fig. 2 presents a box-plot of total risk and its components as described in Eqs. (9)–(14) in 1981 and 2011. Although total risk is slightly lower in 2011,[11] in both periods destination risk dominates, followed by idiosyncratic risk. Origin risk is significant but relatively less important. That is, the risk arising from shocks that affect the destinations where output is sold (including the home

10 This result is robust when we allow the variance–covariance matrices to vary over time as shown in Section 5.

11 Total risk between 1981 and 2011 falls slightly for 23 of the 34 economies in our sample.



(a) Year: 1981 (b) Year: 2011

Fig. 4. Destination risk components.
Note. DR stands for Destination Risk calculated according to Eq. (9). Vol_$\kappa = \sum_m \sum_i (a^c_{im})^2 E(\kappa^2_{im})$ is the destination risk arising from the volatility of destination-industry shocks. Cov_w/n_m $= 2\sum_m \sum_{i,j\neq i} a^c_{im} a^c_{jm} E(\kappa_{im}\kappa_{jm})$ is the destination risk arising from the covariance of destination-industry shocks within-market across industries. Cov_w/n_i $=2\sum_i \sum_{m,m'\neq m} a^c_{im} a^c_{im'} E(\kappa_{im}\kappa_{im'})$ is the destination risk arising from the covariance of destination-industry shocks within-industry across markets. Cov_x_im $= 2\sum_{i,j\neq i} \sum_{m,m'\neq m} a^c_{im} a^c_{jm'} E(\kappa_{im}\kappa_{jm'})$ is the destination risk arising from the covariance of destination-industry shocks across distinct industry-market pairs.

market) dominates the risk arising from shocks at the origin-country-industry level. Noteworthy is the fact that covariances are negative, especially the covariances with idiosyncratic shocks. Given the distribution of covariances between shocks in Table 3, this implies that countries' sales are concentrated in markets whose idiosyncratic shocks are negatively correlated with destination and origin shocks.

Both the ranking of risks and the negative covariances appear to be consistent also across different countries. To see this, Fig. 3 presents the percentage contribution of each risk relative to total for each country in 1981 and 2011. It shows that covariances are negative for the practical totality of countries. In the USA and Canada, the proportional contribution of components appears to be large because of the low value of total risk. Nonetheless, it is the case that negative co-movement acts as a shock absorbing mechanism and this pattern is consistent across countries and periods.

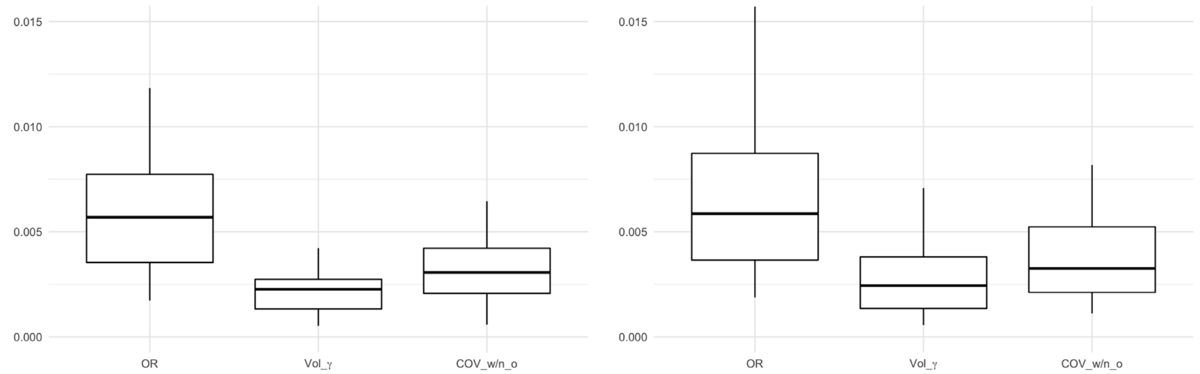
4.2.2. Risk components

As highlighted above, our decomposition allows us to dig deeper into the main drivers of each of these risk components. Due to their relevance, we will focus here on destination, origin, and idiosyncratic risk to understand the role of trade and specialization. In the interest of space, we present the decomposition of the covariance components in Online Appendix D.1.

Fig. 4 presents the different sub-components of the *destination risk* as per Eq. (15). To re-cap, destination risk does not only depend on the concentration of sales in destination-industry pairs with volatile shocks. It also depends on the concentration of sales in destination-industry pairs whose shocks co-vary within markets across industries, within industries across markets, and across industries and markets. A key result here is that the main driving force behind destination risk is the term related to covariance of destination shocks within-market across industries. Put another way, destination risk is large mainly because countries sell intensively to markets with positively correlated destination shocks across industries. This is consistent with the dominance of country-specific shocks found in the empirical international business cycles literature, i.e., shocks to market m that affect the demand for goods of all industries simultaneously. Thus, if sales are concentrated in a few markets where these shocks are dominant, destination risk will be large. This could be driven by the home market, for instance, which aligns with the result in Caselli et al. (2020) that trade can reduce exposure to aggregate domestic shocks. The term related to the covariance within industries across markets turns out to be a much smaller component. That is, the risk due to the concentration of an industry sales to destinations with strong co-movement appears to be small. Finally, the risk arising from the covariance across markets and industries is important and has increased during the sample period.

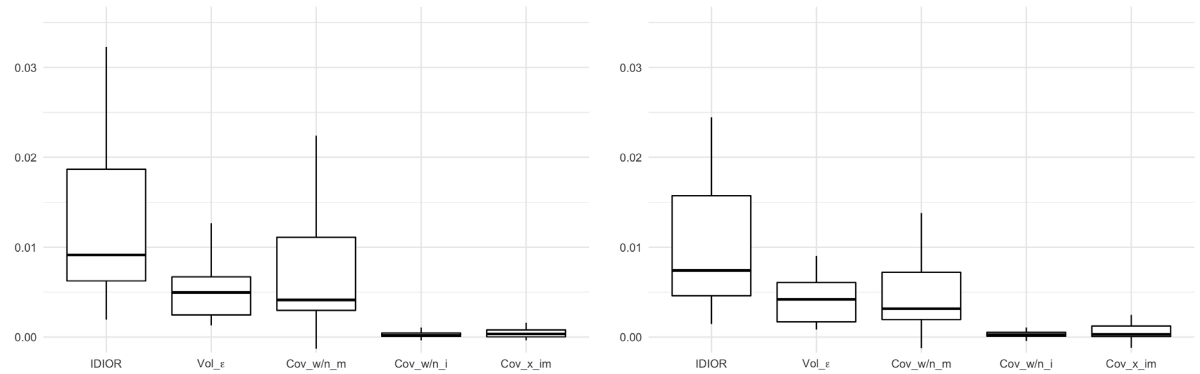
The decomposition of origin risk as per Eq. (16) is displayed in Fig. 5. In this case, both the *level* and the relative importance of sub-components is remarkably stable across years. The covariance across industries appears to be more important than the direct effect of variances. Rather than specialization in volatile sectors, what drives origin risk is primarily the fact that origin shocks co-move strongly across industries. Again, this is consistent with aggregate shocks (or shocks transmitted through input–output linkages) being more important than industry shocks (see Karadimitropoulou and León-Ledesma, 2013).

Fig. 6 shows the decomposition of *idiosyncratic risk* as per Eq. (17). Idiosyncratic risk is driven by the components related to the volatility and within-market covariance of shocks. The concentration of sales in markets with volatile shocks plays a much more important role for this risk than for the destination risk because idiosyncratic shocks are highly volatile. As shown in Panel C of Table 3, these shocks are, on average, an order of magnitude more volatile than destination shocks. As in the case of destination



(a) Year: 1981		(b) Year: 2011

Fig. 5. Origin risk components.
Note. OR stands for Origin Risk calculated according to Eq. (10). Vol_$\gamma = \sum_i (a_i^c)^2 E(\gamma_i^{c2})$ is the origin risk arising from the volatility of origin-industry-specific shocks. Cov_w/n_o=$2\sum_{i,j\neq i} a_i^c a_j^c E(\gamma_i^c \gamma_j^c)$ is the origin risk arising from the covariance of origin-industry shocks across industries within an origin.



(a) Year: 1981		(b) Year: 2011

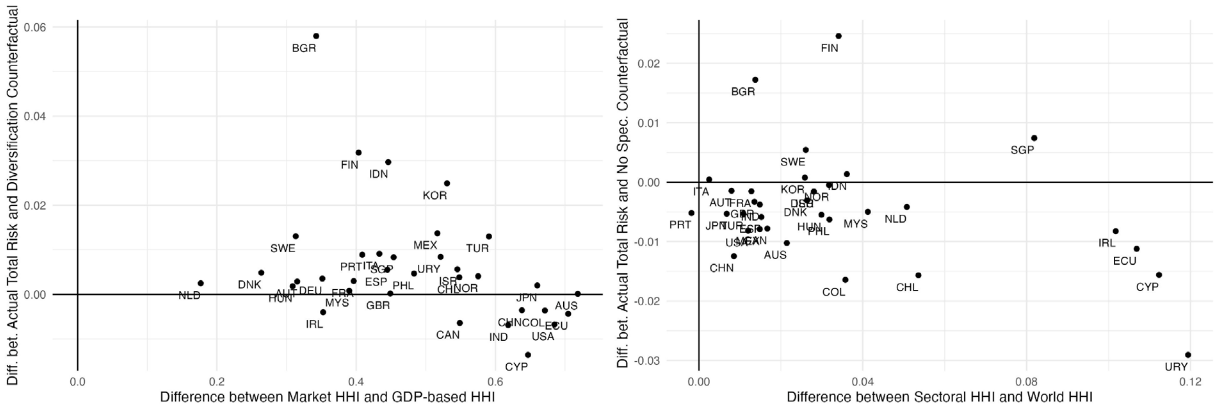
Fig. 6. Idiosyncratic risk components.
Note. IDIOR is for Idiosyncratic Risk from Eq. (11). Vol_$\epsilon = \sum_m \sum_i (a_{im}^c)^2 E((\epsilon_{im}^c)^2)$ is the idiosyncratic risk arising from the volatility of idiosyncratic shocks. Cov_w/n_m $= 2\sum_m \sum_{i,j\neq i} a_{im}^c a_{jm}^c E(\epsilon_{im}^c \epsilon_{jm}^c)$ is the idiosyncratic risk arising from the covariance of idiosyncratic shocks within-market across industries. Cov_w/n_i $= 2\sum_i \sum_{m,m'\neq m} a_{im}^c a_{im'}^c E(\epsilon_{im}^c \epsilon_{im'}^c)$ is the idiosyncratic risk arising from the covariance of idiosyncratic shocks within-industry across markets. Cov_x_im $= 2\sum_{i,j\neq i} \sum_{m,m'\neq m} a_{im}^c a_{jm'}^c E(\epsilon_{im}^c \epsilon_{jm'}^c)$ is the idiosyncratic risk arising from the covariance of idiosyncratic shocks across distinct industry-market pairs.

risk, the decomposition of idiosyncratic risk suggests that market diversification through international trade can potentially reduce total risk.

In Online Appendix D.1 we report box plots for the decomposition of the covariance terms as per Eqs. (18)–(20). The key finding regards the terms related to the covariance of idiosyncratic shocks with origin- and destination-specific shocks, respectively. Both these covariance terms are driven by the concentration of sales in markets and industries subject to origin or destination shocks that co-vary negatively with other industries' idiosyncratic shocks. The concentration of sales in the home market could explain these results to the extent that domestic shocks affect domestic sales relatively less than foreign ones.

These results thus offer a clear picture of the key sources of volatility in open economies. Destination and idiosyncratic risks, especially driven by the high co-movement between industries within destination markets, dominate. Origin risk, on the other hand, appears to be a less important source of risk.

All the components of total risk depend on the volatility and co-movement of shocks as well as the weights vector $\boldsymbol{a}^c$. However, while destination risk, idiosyncratic risk and all the covariance terms depend on both the markets and the industries in which a country specializes, origin risk only depends on industry specialization. Thus, we next carry out counterfactuals by changing the elements of $\boldsymbol{a}^c$ to isolate the effects of the trade structure from primitive shocks.



(a) (b)

Fig. 7. Changes in concentration under counterfactual scenarios.
Note. Panel (a) shows the change in the market HHI under the "diversification" scenario vs. the change in total risk for each country. Panel (b) shows the change in the sectoral HHI index under the "no specialization" scenario vs. the change in total risk for each country.

4.3. Counterfactuals: trade and volatility

In this section, we discuss our results on the effects of trade on aggregate volatility through sectoral specialization, and market diversification. We would expect an increase in trade intensity to increase the degree of sectoral specialization, but we would also expect an increase in market diversification through a larger dispersion in the vector of sale shares across markets. The counterfactuals allow us to isolate each of these channels. Indeed, Fig. 7 shows that the changes in sectoral and market concentration under our counterfactual scenarios are heterogeneous but consistent with the expected changes in market and sectoral concentration due to trade. Panel (a)'s x-axis shows that, under the diversification counterfactual, the market HHI falls for all countries. That is, our diversification experiment reduces sales concentration across markets at the industry level. This reduction is also substantial with an 85% fall on average. The change is heterogeneous with less diversified countries, such as Ecuador, the USA, and Australia, experiencing a larger fall, and more diversified countries, such as the Netherlands and Denmark, experiencing a smaller fall in concentration. The "no specialization" counterfactual also reduces sectoral concentration significantly as shown by the x-axis in Panel (b). The sectoral HHI falls by 20% on average. All countries experience a decrease in industry concentration except for Portugal for which there is a very small increase. Highly specialized countries such as Uruguay, Cyprus, and Ecuador experience the largest drops in concentration under this scenario.

In the remainder of this section we present the impact of the "diversification", "home diversification", and "no specialization" counterfactuals for all risks and their components. We present the results for 2011 here for conciseness. Results for other years are available and they are consistent with those for 2011. Fig. 8 plots total risk and counterfactual total risk under each scenario by country. Fig. 9 summarizes the same information using convenient yet insightful box-plots. Fig. 10 presents the effect of the three counterfactuals by risk component, whereas Fig. 11 presents the effect on the covariance terms. To shed light on the drivers of changes in destination, idiosyncratic, and origin risk, Figs. 12, 13, and 14 show the effect of the counterfactuals separately for the relevant sub-components as per Eqs. (15) to (17).[12]

4.3.1. Diversification counterfactual: results

In Fig. 8, the total risk under the diversification scenario (green triangle) is smaller than the actual total risk (red circle) for 26 of our 34 countries. Countries with the highest volatility in 2011, in the top rows of the plot, experience the largest decline in total risk due to market diversification. However, risk increases for countries such as the USA and Canada where total risk is lower. This is driven almost entirely by the effect of diversification away from the home market. More in general, independent of whether diversification lowers or increases total risk, a large part of the change is explained by diversifying away from the home market (in most rows of Fig. 8 the blue square and green triangle are close to each other). These results, again, point towards the importance of country-specific drivers of risk. Furthermore, given the negative association between risk and development, on average, it is poorer countries that experience a larger drop in volatility with diversification. A regression of the change in risk under this counterfactual on GDP per capita yields a significant but small coefficient of −0.0023.

Panel (a) in Fig. 7 shows that the gains from diversification appear to be small and negative for larger economies such as the USA, Japan, and India. These tend to be more closed economies where diversification implies large changes in destination-market concentration. However, they also display lower home market volatility and, hence, diversifying away from the home market

[12] Online Appendix D.1 reports the counterfactual results by sub-component for the covariance terms.

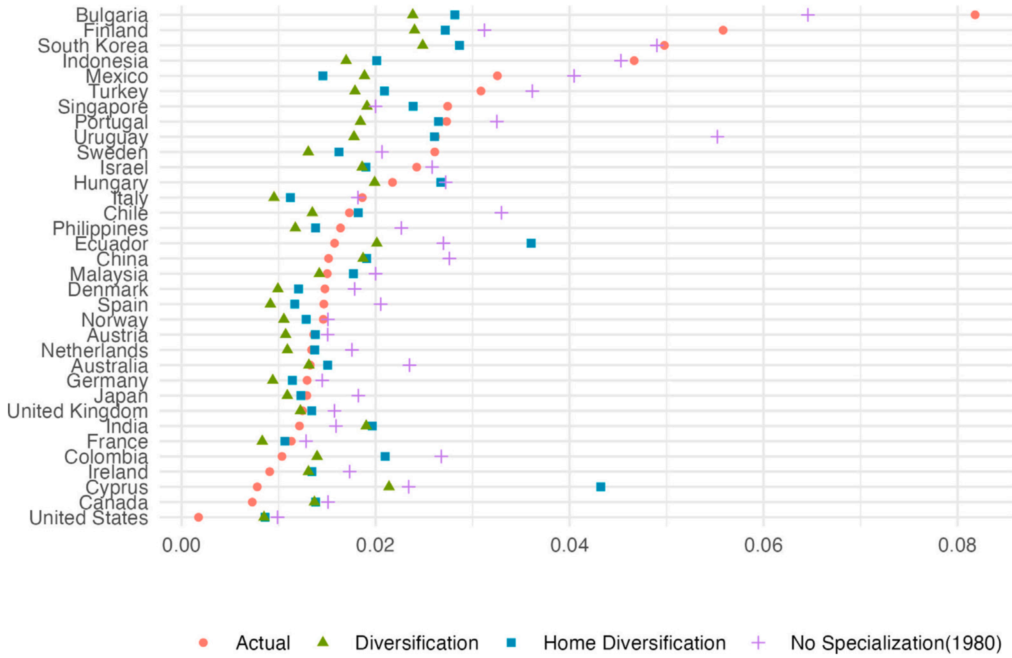


Fig. 8. Total risk under different counterfactual scenarios by country, 2011.
Note. Actual refers to the distribution of total risk computed using observed data. Countries are ranked in descending order of total risk in 2011.

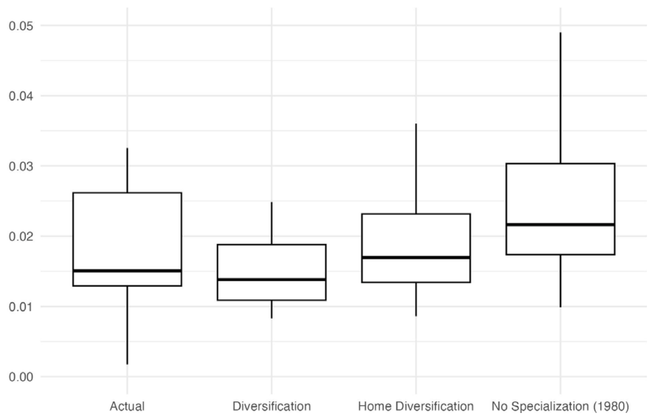


Fig. 9. Total risk under different counterfactual scenarios, 2011.**Note.** Actual refers to the distribution of total risk estimated using observed data.

increases risk. It is economies with relatively low destination- market concentration, such as Bulgaria, Finland and Korea (see Table 2), that experience the largest gains from further diversification. These countries have higher home market volatility and, hence, further diversifying away from the home market decreases risk.

Having said that, Fig. 8 also shows that diversifying away from home is not the whole story. For all countries that experience a drop in total risk because of diversification, except Mexico, diversification reduces total risk more than home diversification (the green triangle lies to the left of the blue square), leading us to conclude that diversification across foreign markets provides an additional hedging mechanism.

Fig. 9 summarizes the rich information in Fig. 8 conveniently showing a small decline in median total risk in the diversification scenario but a sizeable compression of its dispersion due to the large decline in volatility for high volatility countries. It also confirms that full diversification, on average, leads to further reduction in risk relative to home diversification. Onwards, we rely on box-plots to analyze large amounts of information while providing insights on the driving forces of our results.

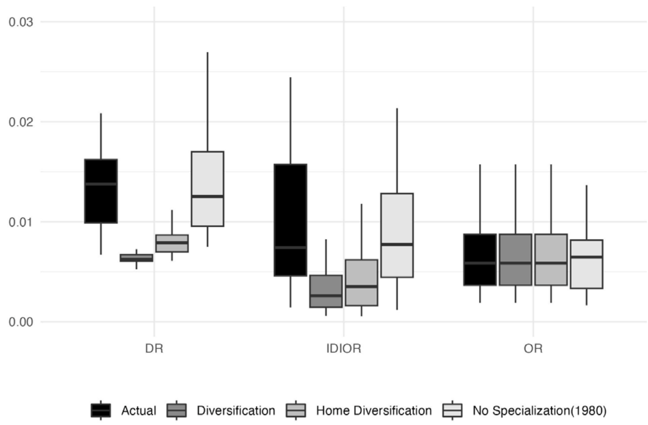


Fig. 10. Volatility components under counterfactual scenarios, 2011.
Note. DR stands for Destination Risk. OR stands for Origin Risk. IDIOR is for Idiosyncratic Risk. Actual refers to the distribution of each component estimated using observed data.

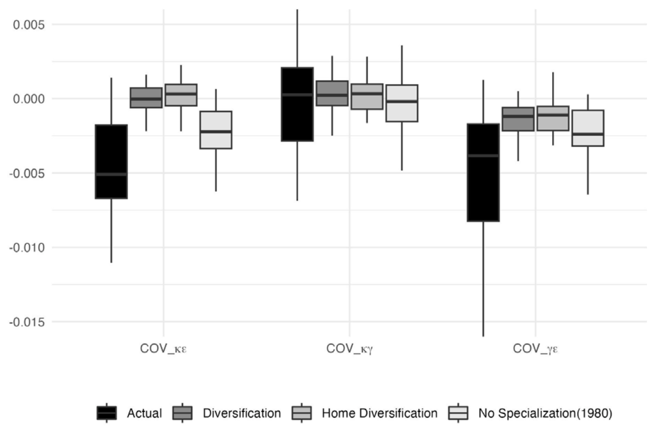


Fig. 11. Risk covariance terms under counterfactual scenarios, 2011.
Note. $COV\_\kappa\epsilon$ is twice the covariance between destination-industry and idiosyncratic shocks. $COV\_\kappa\gamma$ is twice the covariance between destination-industry and origin-industry shocks. $COV\_\gamma\epsilon$ is twice the covariance between origin-industry and idiosyncratic shocks.

Looking at Figs. 10 and 11, in the diversification scenario both the destination and the idiosyncratic risks drop substantially and, for the majority of countries, enough to more than make up for the increase in the covariance terms.[13] Figs. 12 and 13 provide additional insights on these results. The reallocation of market shares in the diversification scenarios reduces substantially the importance of the volatility and within-market correlation of destination and idiosyncratic shocks in total risk. As sales become less concentrated, each market, particularly the home market, becomes a less important source of risk. The increased importance of foreign markets causes an increase in the covariance terms due to the fact that a country's sales abroad are relatively more sensitive to domestic shocks than home sales.

4.3.2. No specialization counterfactual: results

Counter to conventional wisdom, Fig. 9 shows that the "no specialization" scenario implies a significant increase in volatility. This is the case for all but seven countries (Bulgaria, Finland, South Korea, Singapore, Sweden, Italy, and Indonesia).[14]

From Figs. 10 and 11, this increase in total risk in the "no specialization" scenario is primarily driven by two factors: higher origin risk and covariance terms. The reason behind the increase in origin risk is shown in Fig. 14, where the covariance across industries for origin risk increases. This suggests that countries are specialized in industries with a lower than average co-movement with other industries. And it is consistent with what one would expect given GVCs. In our counterfactual the covariances of origin

[13] The "home" diversification scenario has similar effects confirming that diversification away from the home market drives the diversification results. However, in the "home" diversification scenario, the drop in destination and idiosyncratic risks is not always enough to compensate for the increase in the covariance terms.

[14] See also Fig. 7 Panel (b).

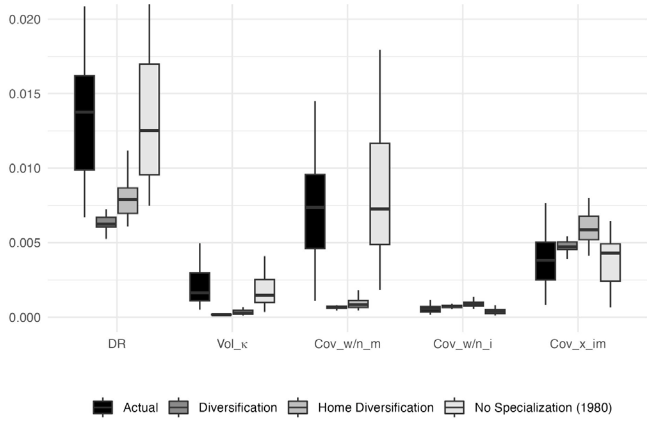


Fig. 12. Destination Risk components under different counterfactuals, 2011.
Note. DR stands for Destination Risk. Vol_κ is the destination risk arising from the volatility of destination-industry shocks. Cov_w/n_m is the destination risk arising from the covariance of destination-industry shocks within-market across industries. Cov_w/n_i is the destination risk arising from the covariance of destination-industry shocks within industry across markets. Cov_x_im is the destination risk arising from the covariance of destination-industry shocks across distinct industry-market pairs.

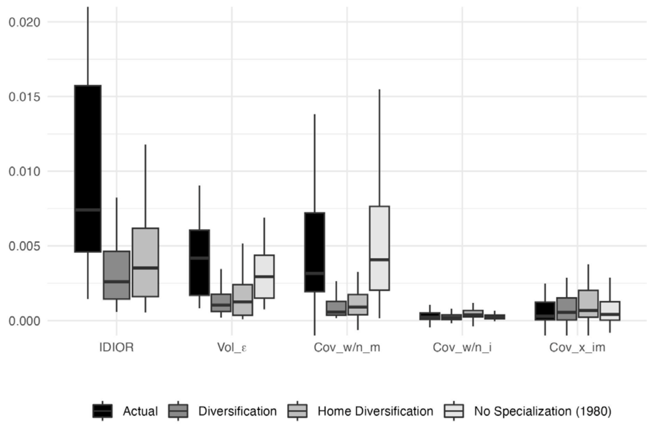


Fig. 13. Idiosyncratic Risk components under different counterfactuals, 2011.
Note. IDIOR is Idiosyncratic Risk. Vol_ϵ is the idiosyncratic risk arising from the volatility of idiosyncratic shocks. Cov_w/n_m is the idiosyncratic risk arising from the covariance of idiosyncratic shocks within-market across industries. Cov_w/n_i is the idiosyncratic risk arising from the covariance of idiosyncratic shocks within industry across markets. Cov_x_im is the idiosyncratic risk arising from the covariance of idiosyncratic shocks across distinct industry-market pairs.

shocks within country ($E(\gamma_i^c, \gamma_j^c)$) are fixed and the related covariance term only changes due to the counterfactual sectoral shares. Once countries specialize, they rely to a greater extent on other countries' inputs, thus becoming more integrated in GVCs. Exactly for this reason we observe a lower co-movement between sectors of specialization and other domestically integrated sectors. The no specialization counterfactual shifts the sectoral shares to sectors that are not integrated in GVCs, which display higher covariance with each other. The increase in the covariance terms is instead due to an increased concentration of sales in markets with larger covariances of destination and origin shocks with idiosyncratic shocks.

We should, however, note that the direct effect of reduced specialization on the diagonal elements of the origin risk is negative for the high origin risk countries (as shown by the compression in their distribution in Fig. 14). That is, the counterfactual reduces the concentration on high volatility sectors for these countries. This direct effect outweighs the effects on the covariances for some of them (see Fig. 8).

Our counterfactual results speak about the *potential* volatility effects of increased diversification and specialization. Throughout the sample period analyzed, all but one economy in our sample experienced a decline in destination-market concentration. This decline, however, was relatively small compared to our full diversification counterfactual (i.e., 22% average market HHI decline compared to 85% in the counterfactual). The change in sectoral concentration is even less pronounced. In fact, 10 out of our 34 economies experienced a decline in sectoral concentration. Given these small changes in the structure of trade despite rapid globalization, the actual volatility reduction effects of trade may be difficult to detect in the data when regressing volatility on openness measures, as seen in much of the previous literature.

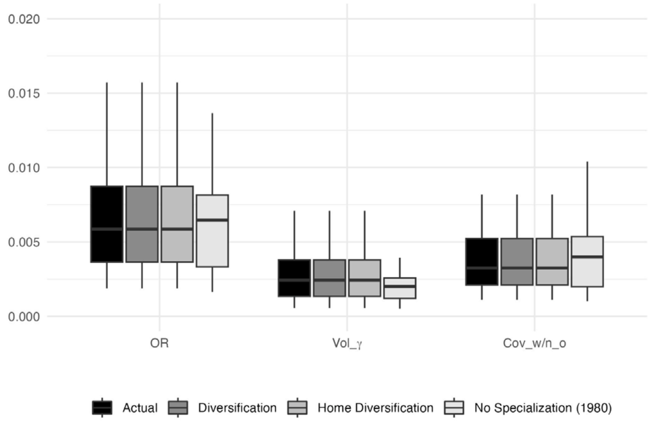


Fig. 14. Origin Risk components under different counterfactuals, 2011.
Note. OR stands for Origin Risk. Vol_γ is the origin risk arising from the volatility of origin-industry-specific shocks. Cov_w/n_o is the origin risk arising from the covariance of origin-industry shocks across industries within an origin.

5. Robustness

In the interest of space, we report the results referenced in this section in the Online Appendix.

5.1. Allowing for additional time variation

In our baseline decomposition, total risk and its components vary over time because the shares a vary over time. The variance and covariance of the shocks are kept constant because this allows us to reliably estimate them over the full sample period of 31 years. However, it is plausible that the increase in the pace of globalization in the mid-1990s might have changed those as well. To check whether there is any evidence for this, we compute the variance–covariance matrices of the shocks separately for the period 1981–1995, and 1996–2011. So that total risk and its components vary over the two sub-periods due to both the time variation in the a's and the period variation in the Ω's.

We find that the total risk ranking by countries remains stable. Importantly, when comparing 1981 and 2011, we observe similar patterns to the ones in the baseline decomposition (see Online Appendix Figure D. 5). That is, the change in the risk decomposition is driven mostly by changes in the industry and market shares rather than the Ω's. When comparing the same year using the results from the two decompositions (Online Appendix Figures D. 6 and D. 7), the ranking and sign of the different components does not change, although the results using only the first sub-period appear to display a higher dispersion. We use the results from the two period decomposition to explore any significant changes in the components of risk over time. We, thus, run simple regressions of each component on a constant and a dummy that equals one for the 1996–2011 period, and zero otherwise. We find that both destination and origin risk decrease and the idiosyncratic and covariance terms increase in the second sub-period. However, these changes cancel each other out leading to insignificant changes in total risk over the two sub-periods. We report all these results in Online Appendix D.2.

5.2. Alternative decomposition

We use the data partition in Eq. (2) in our baseline decomposition. Accordingly, innovations in the growth of sales at the origin-market-industry level are due to shocks specific to the destination-market-industry (κ_{im}), shocks specific to the origin-country-industry (γ_i^c), and shocks idiosyncratic to the origin-market-industry (ϵ_{im}^c). The latter thus captures any differential impact that shocks specific to the destination-market-industry have depending on the origin country of products purchased. They also capture any differential effect that shocks specific to the origin-country-industry have depending on the destination market of products sold. In this subsection we discuss the robustness of our results if we partition the data to remove these two sources of variation from ϵ_{im}^c using the following alternative factor decomposition:

$$y_{im}^c = B_c \kappa_{im} + b_m \gamma_i^c + \epsilon_{im}^c \tag{21}$$

where B_c is the exposure of origin country c to shocks specific to the destination-market-industry, and b_m is the exposure of destination market m to shocks specific to the origin country-industry. In matrix notation, the model in Eq. (21) becomes:

$$\boldsymbol{y}^c = B_c \boldsymbol{\kappa} + \boldsymbol{B} \boldsymbol{\gamma}^c + \boldsymbol{\epsilon}^c \tag{22}$$

where B_c is a constant and B is a $(IMxIM)$ diagonal matrix with b_m coefficients repeated I times on the diagonal. This model yields the following variance decomposition:

$$E(\boldsymbol{y}^c \boldsymbol{y}^{c'}) = B_c^2 \boldsymbol{\Omega}_\kappa + \boldsymbol{B}\boldsymbol{\Omega}_{\gamma^c} \boldsymbol{B}' + \boldsymbol{\Omega}_{\epsilon^c} + B_c \boldsymbol{B}\boldsymbol{\Omega}_{\gamma^c\kappa} + B_c \boldsymbol{\Omega}_{\epsilon^c\kappa} + B_c \boldsymbol{\Omega}'_{\gamma^c\kappa}\boldsymbol{B}' + \\ + \boldsymbol{\Omega}'_{\gamma^c\epsilon^c}\boldsymbol{B}' + B_c \boldsymbol{\Omega}'_{\epsilon^c\kappa} + \boldsymbol{B}\boldsymbol{\Omega}_{\gamma^c\epsilon^c} \tag{23}$$

Then, our risk and covariance terms change as follows:

$$\widetilde{DR}_t^c = \hat{B}_c^2 \boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{\Omega}}_\kappa \boldsymbol{a}_t^c \tag{24}$$

$$\widetilde{OR}_t^c = \boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{B}} \hat{\boldsymbol{\Omega}}_{\gamma^c} \hat{\boldsymbol{B}}' \boldsymbol{a}_t^c \tag{25}$$

$$\widetilde{IDIOR}_t^c = \boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{\Omega}}_{\epsilon^c} \boldsymbol{a}_t^c \tag{26}$$

$$\widetilde{COV}_{\gamma^c\kappa t}^c = 2\hat{B}_c \boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{B}} \hat{\boldsymbol{\Omega}}_{\gamma^c\kappa} \boldsymbol{a}_t^c \tag{27}$$

$$\widetilde{COV}_{\epsilon^c\kappa t}^c = 2\hat{B}_c \boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{\Omega}}_{\epsilon^c\kappa} \boldsymbol{a}_t^c \tag{28}$$

$$\widetilde{COV}_{\gamma^c\epsilon^c t}^c = 2\boldsymbol{a}_t^{c\prime} \hat{\boldsymbol{\Omega}}_{\gamma^c\epsilon^c} \hat{\boldsymbol{B}}' \boldsymbol{a}_t^c \tag{29}$$

To obtain the estimates coefficients $\hat{B}_c$ and $\hat{b_m}$ we estimate panel regressions of innovations in the growth of sales at the origin-market-industry level on the shocks obtained from Eqs. (5)–(6). We recalculate the residual, $\hat{\epsilon}_{im}^c = y_{im}^c - \hat{B}_c \hat{\kappa}_{im} - \hat{b}_m \hat{\gamma}_i^c$. The estimated components under this alternative factor model are very close to those under the baseline decomposition. That is, we find little evidence of heterogeneity in the response of both origin-countries to destination-market-industry shocks and destination markets to origin country-industry shocks. We report these results in Online Appendix D.3.

5.3. Alternative counterfactual specifications

We considered a different diversification scenario called “1980 Diversification” in which sale diversification is set to that in 1980. That is, we set the counterfactual shares to be $\bar{a}_{im}^c = \frac{S_{im1980}^c}{GO_{i1980}^c} * \frac{GO_i^c}{GO^c}$. This pre-globalization scenario captures a less geographically diversified trade structure. The results are available in Online Appendix D.4 and are consistent with our diversification results in that we find that less diversification increases total risk.

We also experimented with two alternative specialization scenarios.[15] In the first, we set the counterfactual shares to reflect the world specialization in 2011 rather than in 1980, that is $\bar{a}_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{\sum_c GO_i^{c,2011}}{\sum_c GO^{c,2011}}$. We do so to check whether changes in the sectoral specialization of the world following globalization affect our results. They do not. In the second, we set counterfactual shares to capture each country’s specialization in 1980, that is $\bar{a}_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^{c,1980}}{\sum_c GO^{c,1980}}$. In 1980 the majority of the countries in our sample had a less concentrated production structure. Our results are robust and reassure us that the “no specialization” results are not driven by the larger economies in our sample.

6. Conclusions

We revisit the question about how trade affects aggregate volatility using a multi-country, multi-industry and multi-destination empirical framework that allows us to isolate the effects of destination-market diversification and production specialization. Focusing on the growth of industry sales to different destination markets, we propose a decomposition of aggregate output growth risk into destination risk, origin risk, idiosyncratic risk, and their covariances. The pattern of specialization and destination-market diversification shapes the exposure of countries to these risks. Our approach allows us to dive deeper into the intricate mechanisms through which trade affects each risk. We then use the results of this decomposition to carry out counterfactuals where we measure how market diversification and production specialization shape the potential volatility effects of trade.

Using data on 19 industrial sectors, 34 countries, and 84 destination markets for the 1980–2011 period, we find that destination risk dominates, followed by idiosyncratic risk, with origin risk coming last. The covariance components are consistently negative, acting as a risk absorption mechanism.

From the counterfactual analysis, we find that the effect of increased destination-market diversification is quantitatively important in reducing aggregate volatility for high volatility countries. Diversification significantly reduces destination and idiosyncratic risks. Within the destination risk, this is mainly driven by a reduction of the cross-industry correlation arising from destination-market shocks. A large part of this is driven by diversifying away from the home market. On the other hand, and against conventional wisdom, reducing sectoral specialization increases volatility. This is driven by an increase in the correlation of origin shocks between industries within a country and an increase in the covariance of shocks.

[15] We report these results in Online Appendix D.5.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.07.001.

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