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Growth Volatility and Trade: Market Diversification vs. Production Specialization*

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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 85 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.

JEL Classification: F15, F44, F61.

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1 Introduction

The role of international trade for macroeconomic volatility remains an important question for academics and policymakers alike. As emphasized by Caselli et al. (2020), a popular view is that, by increasing production specialization, trade can increase fragility. In the absence of complete insurance markets, this could lead to a reduction in the welfare gains from trade. However, whether trade increases economic risk 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 would face higher risks if shocks are mainly driven by national factors such as macroeconomic policies since all producers' sales are domestic. A fully specialized economy, on the other hand, would face higher risks if most shocks are supply-side and sectoral in nature, or if macroeconomic shocks are highly correlated across destination markets.

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.

We first propose a decomposition of aggregate output growth risk into three components: destination risk, origin risk, and idiosyncratic risk (and their covariances). Destination risk arises from shocks to the destination markets where products are sold (including the home market) independently of the country of origin. Origin risk arises from shocks specific to the producing country/industry independent of the destination of sales. Idiosyncratic risk is the residual. 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. The pattern of specialization and the diversification of sales across markets will shape the exposure of different countries to these risks. An added advantage of our approach is that it allows us to dive deeper into the mechanisms through which trade affects each risk. For instance, the destination risk depends not only on whether a country's sales are concentrated in markets with high volatility. It also depends on whether the country's output is concentrated in industries whose sales across destinations are subject to positively correlated shocks, and whether sales are concentrated in markets with positively correlated shocks across industries. Likewise, origin risk depends on whether countries specialize in highly volatile industries, but also on how shocks co-vary between industries within a country. Our methodology is able to shed light on these, more intricate, channels linking trade and volatility.

Secondly, we use the results of our decomposition to carry out counterfactuals where we change the observed patterns of sectoral specialization and market diversification. This allows us to assess how these two channels shape the potential volatility effects of trade. That is, we test how the geographical pattern of sales and production specialization affect each of the three sources of risk and their constituent components.

We carefully assemble a dataset of trade and output data for 34 countries, 85 destination markets, and 19 industries over the period 1980–2011. Using these data we first estimate total risk and each of its sub-components. We find that destination risk is the most important component, 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*. 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 according to GDP weights, and one in which we reduce production specialization to resemble a 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 by reducing the within-market covariance of destination shocks across industries. A large part of this is driven by diversifying away from the home market.[1]

On the other hand, and against conventional wisdom, the effect of reducing specialization on volatility is positive and sizeable. Reducing specialization has a direct negative effect on volatility. However, it increases the correlation of shocks between industries. In addition, both the diversification and specialization counterfactuals lead to a reduction in the negative covariance of shocks. The combination of these effects and the increase in the correlation of shocks across industries outweigh the direct reduction in volatility leading to higher total volatility when economies become less specialized. Taken together, the results indicate that trade diversification can lead to sizeable volatility reduction effects and that specialization could potentially decrease rather than increase volatility.

Our paper relates, directly or indirectly, to two strands of the literature: a literature analyzing the link between openness measures and output volatility, and a literature analyzing the shocks driving international business cycles. 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.

[1] This home market effect, however, displays more heterogeneity across countries.

[2] For aggregate or industry studies see, among many others, Rodrik (1998); Cavallo (2008); Kose, Prasad and Terrones (2003); Loayza and Raddatz (2006); Karras and Song (1996); Bekaert et al. (2006);

First, we want to identify the channels through which trade drives aggregate volatility focusing on production specialization and 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, Otrok and Whiteman (2003), 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 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 Koren and Tenreyro (2007)'s methodology.

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 model of trade to assess the importance of the diversification and specialization channels, and find that trade can lower volatility by reducing the exposure to domestic shocks.[3] In a similar fashion, Kramarz et al. (2020) derive a decomposition of *export sales* volatility at the firm level and apply it to the universe of French firms and their exports to the European Union. They find that the lack of diversification in exports is a key driver of volatility. Our approach complements these two papers. We impose less structure on the data and allow risks to co-vary independently of the trade and specialization patterns. Our decomposition allows for a rich set of relevant facts for theoretical trade models. Although the shocks we identify are not "structural" in the traditional modelling sense, they are relevant measures of risk from the point of view of sectors or firms. Also, we use less granular data than Kramarz et al. (2020) but cover

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).

[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.

a large set of countries and destination markets (including home) for three decades and the object of interest is gross output rather than export sales.

In the next sections we first present the empirical strategy, then discuss the data, and present our decomposition results and trade counterfactuals. We finish with a set of concluding 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 $m = 1, ..., M$ that c serves, y^c_{im}, as follows:

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

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, $a_i^c = \frac{GO_i^c}{GO^c}$, that is $a_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^c}{GO^c}$. 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 model:

$$y_{im}^c = \kappa_{im} + \gamma_i^c + \epsilon_{im}^c \tag{2}$$

where the first disturbance, κ_{im}, is specific to a destination market-industry pair and it is independent of the origin country; the second disturbance, γ_i^c, is specific to a country of origin-industry pair, and independent of destination markets; and, ϵ_{im}^c, is the residual disturbance unexplained by the other two.

In what follows, these disturbances are referred to as *shocks*. These factors capture the variation in sales due to different types of disturbances (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).

Last, we rewrite the model in equation (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 (IMx1) vector of innovations y_{im}^c, $\boldsymbol{\kappa}$ is the (IMx1) vector of destination-industry specific disturbances, $\boldsymbol{\gamma^c}$ is the (IMx1) vector of origin-industry disturbances (with each γ_i^c repeated M times), and $\boldsymbol{\epsilon^c}$ is the (IMx1) vector of residual disturbances. Using matrix algebra, we decompose the variance of q^c, $Var(q^c)$, as follows:

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

where $\boldsymbol{a^c}$ is the (IMx1) vector that collects each destination market m's share in country c's total gross output at the industry level, $\frac{S_{im}^c}{GO^c}$; $\boldsymbol{\Omega_{\kappa}}$ 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_i^c; $\boldsymbol{\Omega_{\epsilon^c}}$ is the variance-covariance matrix of residual disturbances, ϵ_{im}^c; $\boldsymbol{\Omega_{\gamma^c\kappa}}$ is the covariance matrix between origin-industry and destination-industry specific shocks; $\boldsymbol{\Omega_{\gamma^c\epsilon^c}}$ and $\boldsymbol{\Omega_{\epsilon^c\kappa}}$ 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 estimate each of the components in equation (4), we first need estimators for destination-industry, origin-industry and residual shocks (κ_{im}, γ_i^c, and ϵ_{im}^c, respectively). For each origin country, industry, and destination market, we define innovations in sales, y_{imt}^c, as the deviation of the sales growth rate from its mean over time and we estimate the primitive shocks as follows:

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

$$\hat{\gamma}_{ict} \equiv \frac{1}{M}\sum_{m}^{M}(y_{imt}^c - \hat{\kappa}_{imt}) \tag{6}$$

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

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

$$y_{imt}^c = \sum_{c}\sum_{i}\gamma_{it}^c d_{ci} + \sum_{m}\sum_{i}\kappa_{imt} d_{im} + \epsilon_{imt}^c \tag{8}$$

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 $\hat{\gamma_{it}^c}$, $\hat{\kappa}_{imt}$ and residuals $\hat{\epsilon}_{imt}^c$ being, respectively, the industry-destination im-specific shock, the origin-industry-ci-specific-shock and the cim-origin-industry-destination-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., $\sum_c \gamma_{it}^c = 0$ for all i. This implies that we identify origin-industry specific 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 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_{im}^c that affect some or all the products that an *origin* sells to a given *destination*, including the home market.

2.2.2 The Estimated 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 the risk and diversification effects of trade. From the point of view of a firm or sector, 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 extended to a multi-sector and multi-destination setting.

According to the restricted model in equation (8), our estimates of κ_{im} capture the variation in sales arising from shocks to destination preferences, costs, 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, our estimates for κ_{im} also capture the variation in sales arising from any macroeconomic shocks in market m.

Our estimates of γ_i^c, capture 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_i^c 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_i^c 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_i^c 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).

Our estimates of ϵ_{im}^c capture the variation in sales not absorbed by κ_{im} and γ_i^c, 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 disturbances in equation (2) can be correlated. Empirically, because the estimated κ_{im} and γ_i^c capture changes in sales due to macroeconomic or industry-specific conditions in country c and destination m, the estimated 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_i^c that our estimated 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 estimated covariance between ϵ_{im}^c and γ_i^c, and between ϵ_{im}^c and κ_{im}, respectively.

2.2.3 The Components: Estimation

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

Combining the variance-covariance matrices of estimated shocks with observed sales shares at time t, a_{imt}^c, we obtain all the measures of risk that comprise aggregate volatility. More formally, we measure:

$$DR_t^c = \boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\kappa} \boldsymbol{a_t^c} \tag{9}$$

$$OR_t^c = \boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\gamma^c} \boldsymbol{a_t^c} \tag{10}$$

$$IDIOR_t^c = \boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\epsilon^c} \boldsymbol{a_t^c} \tag{11}$$

$$COV_{\boldsymbol{\gamma^c \kappa} t}^c = 2\boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\gamma^c \kappa} \boldsymbol{a_t^c} \tag{12}$$

$$COV_{\boldsymbol{\epsilon^c \kappa} t}^c = 2\boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\epsilon^c \kappa} \boldsymbol{a_t^c} \tag{13}$$

$$COV_{\boldsymbol{\gamma^c \epsilon^c} t}^c = 2\boldsymbol{a_t^{c\prime}} \hat{\boldsymbol{\Omega}}_{\boldsymbol{\gamma^c \epsilon^c}} \boldsymbol{a_t^c} \tag{14}$$

where DR_t^c, OR_t^c, and $IDIOR_t^c$ are the risk components of country c's output volatility at time t due to destination-specific, origin-specific and idiosyncratic shocks, respectively; $COV_{\boldsymbol{\gamma^c \kappa} t}^c$ is twice the covariance between destination and origin shocks; $COV_{\boldsymbol{\epsilon^c \kappa} t}^c$ and $COV_{\boldsymbol{\gamma^c \epsilon^c} t}^c$ 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 Estimated Components: Interpretation

The estimated components of industrial volatility in equation (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 is 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*. Global value chains can play an important role in these sub-components. For instance, if an industry has concentrated sales in destinations with highly integrated value chains, then this will increase the within-industry, across-markets covariance due to global value chain spillovers between those destinations. Note that this risk will depend on both the market diversification pattern and the industry specialization pattern through the shares a^{c}_{im}.

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:

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

where a_i^c 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 specialization pattern.[4] National input-output linkages between industries will affect the covariance of shocks across industries. This is important because this risk will not only be impacted by the degree of specialization, but also whether the industries in which the country specializes co-move strongly with the rest.

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:

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

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*.

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

[4] 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.

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

it is apparent that this term is large if countries' sales are concentrated in: (i) industries whose origin- and destination-specific shocks covary positively; (ii) industry-pairs whose origin- and destination-specific shocks covary positively. Global value chains can affect these components too. For example, consider a reduction in computer chips production in Taiwan. This can lead to an increase in the cost of producing cars and electronics that reduces purchases of car and electronics components of several car- and electronics- producing countries. The same shock might have increased the demand for other industries' output if consumers in some countries changed their spending patterns in response to the shock. Similarly, $COV^c_{\boldsymbol{\gamma^c\epsilon^c}}$ 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, $COV_{\boldsymbol{\epsilon^c\kappa}}$, 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 $COV_{\boldsymbol{\epsilon^c\kappa}}$ as follows:

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

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 Taking stock: The role of trade

The factor model and risk measures presented above highlight the complex nature of the drivers of aggregate volatility in a multi-sector, multi-market world. In particular, the role of trade in shaping volatility.

According to the model, volatility will be 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). The trade structure may change the exposure to these shocks and also their co-movement.

Importantly, trade affects the exposure to different shocks (and their covariances) through two channels: production specialization, and market diversification. These will be reflected in the share parameters (a_{im}^c) which arise from a combination of production specialization (a_i^c) and market diversification (reflected in the a_m^{ic}'s). We would expect an increase in trade intensity to increase the degree of specialization in the vector of a_i^c's, but we would also expect an increase in diversification through a larger dispersion in the vector of a_m^{ic}'s. For instance, we can think of a closed economy with no specialization and where all destination shocks originate from domestic sales. If this economy opens up to trade, the effect on volatility will depend on the sector in which it specializes; whether the markets to which it exports have higher or lower combined volatility than the domestic market; and the covariance between these effects.

In order to ascertain the role of production specialization and market diversification, we run counterfactual exercises in which we assume that the industry shares correspond to a notional closed economy (no specialization) and the market shares are proportional to GDP shares (full diversification). This allows us to analyze the effect of trade on each relevant component. By implication, it allows us to understand the *channels* through which trade can affect volatility.

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 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/.

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.

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 85 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.[5] We calculate domestic sales as the difference between gross output and exports (adjusted to account for re-exports). Online Appendix B provides additional details on the data.

Combining the production and trade data gives us a balanced panel of 34 producer countries, 85 destination markets (including an aggregate for the rest of the world), 19 ISIC Revision 2 sectors over 32 years from 1980 to 2011.

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.

4.1 Shares and Shocks: Descriptive Statistics

Key elements of our decomposition are the shares, a^c_{im}, innovations in the growth rate of output, y^c_{im}, and estimated shocks. The distribution of y^c_{im} 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^c_{im} are calculated by taking the ratio of a country's sales to each market m in a particular industry i, S^c_{im}, to that country's total gross output, GO^c. Because of the

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

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, the identity $a^c_{im} = \frac{S^c_{im}}{GO^c_i} * \frac{GO^c_i}{GO^c}$ provides the basis for a regression decomposition of these market shares. We separately regress the logarithm of $\frac{S^c_{im}}{GO^c_i}$ and $\frac{GO^c_i}{GO^c}$ on the logarithm of a^c_{im}. 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^c_{im} due to each margin. More than 93% of the variation in a^c_{im} 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.

In Table 1 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 market or origin (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

Figure 1 plots *total output risk* for every country c and its dispersion across years (1981–2011) in descending order of the median. Total risk varies significantly across countries and appears to be negatively related to levels of development as in Koren and Tenreyro (2007).[6] 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 US, Canada, and most European countries display lower volatility levels and dispersion across years.

For risk components, since we have a decomposition for every year, we will report results for 1981 and 2011 when necessary in the interest of readability. Note, however, that the *ranking* of the risk components remains remarkably stable across the sample period which, in itself, is an interesting result. Despite the rapid growth and transformation

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

Table 1: 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

in international trade during these 30 years, the sources of volatility appear to have remained stable in relative terms. Furthermore, on average, volatility levels have not changed substantially during this period.[7]

Figure 2 presents a box plot of total risk and its components as described in equations (9)–(14) in 1981 and 2011. Although total risk is slightly lower in 2011, in both periods

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

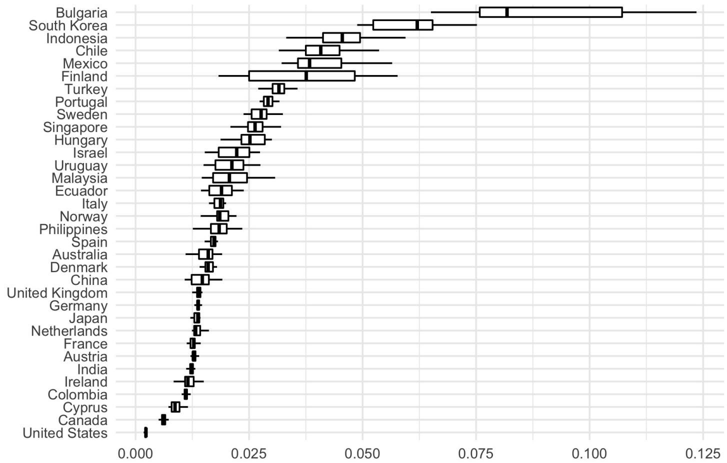
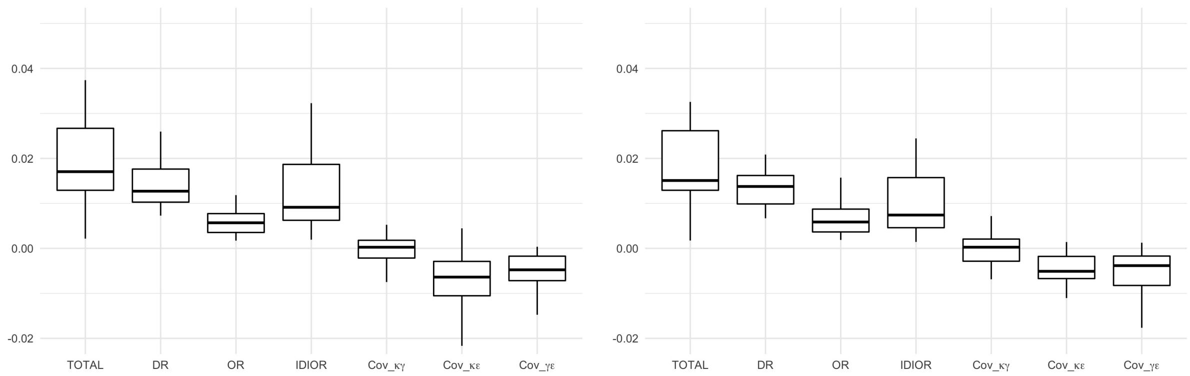


Figure 1: Total Output Risk by country, 1981–2011

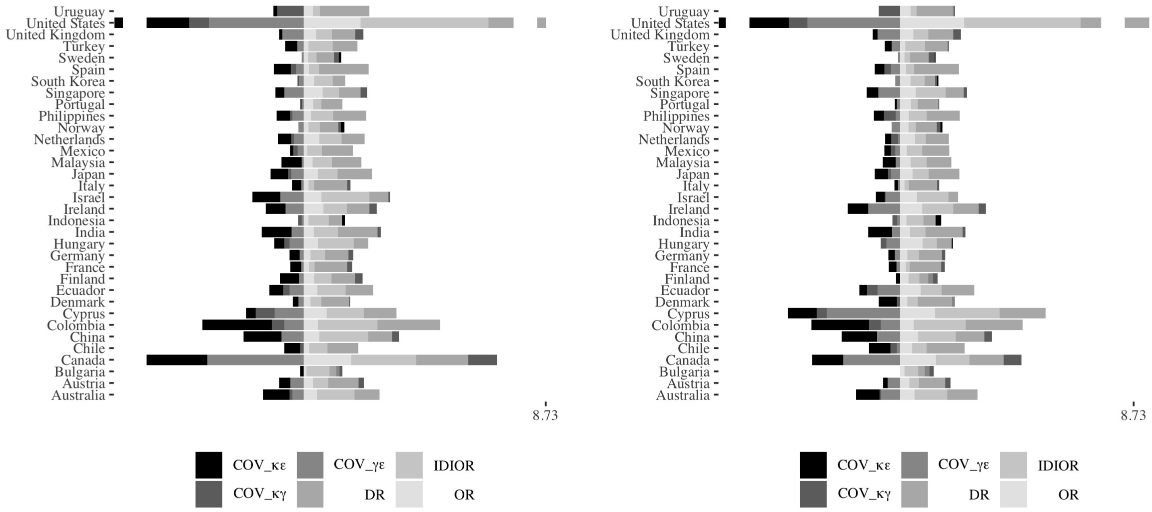


(a) Year: 1981 (b) Year: 2011

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

Figure 2: Total Output Risk Decomposition

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 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 1, this implies that countries' sales are concentrated in markets whose idiosyncratic shocks are negatively correlated with destination and origin shocks. The counterfactual results in section 4.3 provide some insights on how much of this pattern is due to the home market.



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

Note. DR stands for Destination Risk calculated according to equation (9). OR stands for Origin Risk calculated according to equation (10). IDIOR is for Idiosyncratic Risk from equation (11). $COV_{\gamma\kappa}$ is twice the covariance between origin and destination shocks as per equation (12). $COV_{\kappa\epsilon}$ is twice the covariance between destination and idiosyncratic shocks as per equation (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).

Figure 3: Risk Components Contribution

Both the ranking of risks and the negative covariances appear to be consistent also across different countries. To see this, Figure 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 US 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.

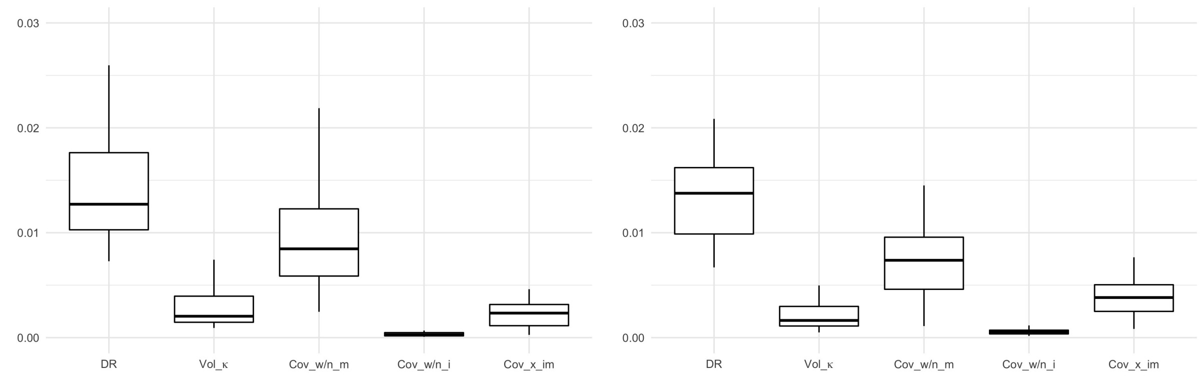
4.2.2 Risk Components

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 C.

Figure 4 presents the different sub-components of the estimated *destination risk* as per equation (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 (i.e., shocks that are highly correlated across industries that sell intensively to a particular market). 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 equation (16) is displayed in Figure 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 networks) being more important than industry shocks (see Karadimitropoulou and León-Ledesma, 2013).

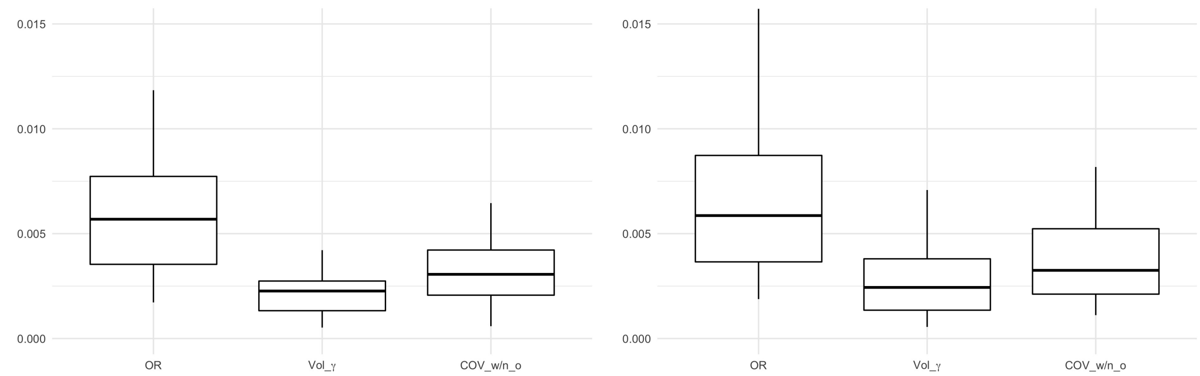
Figure 6 shows the decomposition of *idiosyncratic risk* as per equation (17). Idiosyncratic risk is driven by the components related to the volatility and within-market covariance of shocks. The concentration of sales in markets with volatile shocks plays a much more important role for this risk than for the destination risk because idiosyncratic



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

Note. DR stands for Destination Risk calculated according to equation (9). Vol_κ=$\sum_m \sum_i (a^c_{im})^2 E(\kappa^2_{im})$ 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.

Figure 4: Destination Risk Components

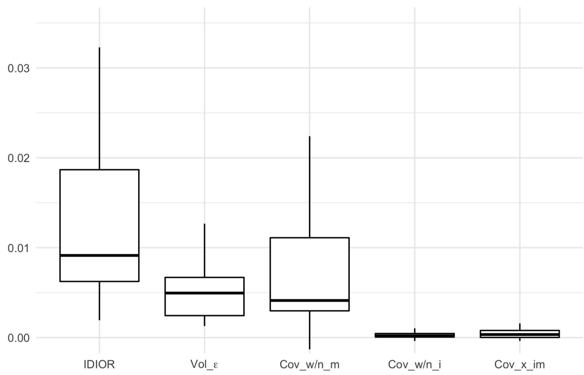


(a) Year: 1981 (b) Year: 2011

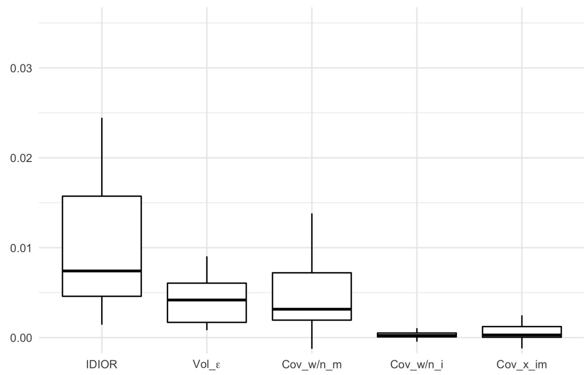
Note. OR stands for Origin Risk calculated according to equation (10). Vol_γ=$\sum_i (a^c_i)^2 E(\gamma^{c2}_i)$ is the origin risk arising from the volatility of origin-industry-specific shocks. Cov_w/n_o=$2\sum_{i,j\neq i} a^c_i a^c_j E(\gamma^c_i \gamma^c_j)$ is the origin risk arising from the covariance of origin-industry shocks across industries within an origin.

Figure 5: Origin Risk Components

shocks are highly volatile. As shown in Panel C of Table 1, these shocks are, on average, an order of magnitude more volatile than destination shocks. As in the case of destination risk, the decomposition of idiosyncratic risk suggests that market diversification through international trade can potentially reduce total risk.



(a) Year: 1981



(b) Year: 2011

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

Figure 6: Idiosyncratic Risk Components

In Online Appendix C we report box plots for the decomposition of the covariance terms as per equations (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 trade structure from primitive shocks.

4.3 Counterfactuals: Trade and volatility

We want to understand how specialization patterns and market concentration affect volatility. To do so, we make use of the decomposition of the weights presented in section 2.1. To recap, note that:

$$a_{im}^c = \underbrace{\frac{S_{im}^c}{GO_i^c}}_{\text{diversification}} * \underbrace{\frac{GO_i^c}{GO^c}}_{\text{specialization}},$$

where $\frac{S_{im}^c}{GO_i^c}$ is the share of industry i in country c output sold in market m, and $\frac{GO_i^c}{GO^c}$ is the share of industry i's sales in country c's gross output. Given the estimated variance-covariance matrices of shocks ($\hat{\mathbf{\Omega}}$'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. In particular, we present two counterfactuals:

- *Diversification*: we first keep sectoral shares ($\frac{GO_i^c}{GO^c}$) as in the data, but change market shares so as to have weights that are just proportional to market m's GDP share in all 85 m markets.[8] We call this full market "diversification".[9] This would represent a world where we remove all trade costs making trade flows at the country level only proportional to country size. That is, if $\bar{a}_{im}^c$ is the counterfactual share, we define: $\bar{a}_{im}^c = \frac{GDP_m}{\sum_m GDP_m} * \frac{GO_i^c}{GO^c}$. 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 then call "home" diversification.

- *Specialization*: we then keep market shares ($\frac{S_{im}^c}{GO_i^c}$) 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. That is, we define the counterfactual share $\bar{a}_{im}^c$ as: $\bar{a}_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{\sum_c GO_i^c}{\sum_c GO^c}$. Note that this

[8] We used GDP data from the World Development Indicators for all countries but Taiwan. For Taiwan, we sourced GDP data from the IMF. GDP is measured in current USD.

[9] We also run a scenario where market weights were uniformly distributed. However, this would imply that the market share of large and small countries would be the same leading to *too much* diversification.

approximation to a closed economy specialization benchmark assumes that tastes and relative sectoral technologies are common across all producing countries.

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.

Given that destination and idiosyncratic risk, which both depend on destination, dominate origin risk, which is independent of markets, we should expect changes in destination weights to have a larger effect on each of these risk components. As mentioned above, 93% of the variability in the elements of $\boldsymbol{a^c}$ can be attributed to the variability in $\frac{S^c_{im}}{GO^c_i}$. This can also be seen when analyzing concentration measures of the $\boldsymbol{a^c}$ vector. Table 2 presents Herfindhal-Hirchman Indexes (HHI), for different components of the weights vector for a few selected countries.[10] At the aggregate level, market concentration appears to be low (column (1)). Sectoral concentration varies more by country, with commodity exporting countries such as Chile and Ecuador displaying a higher sectoral concentration (column (2)). The market concentration is very high (column (3)) at the industry level. With the possible exceptions of Sweden and Germany, sales are highly concentrated by destination market at the industry level for all countries.

Under the diversification counterfactual, the market concentration HHI at the country and industry level falls for all countries as expected. That is, our diversification experiment reduces sales concentration at the market level. This reduction is also substantial with an 85% fall on average at the industry level. The change is heterogeneous with less diversified countries, such as Ecuador, the US, 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 industry concentration significantly on average. The HHI falls by 20% on average. All countries experience a decrease in industry concentration except for Italy and 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.

We now present the impact of the "diversification", "home" diversification, and "no specialization" counterfactual 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

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

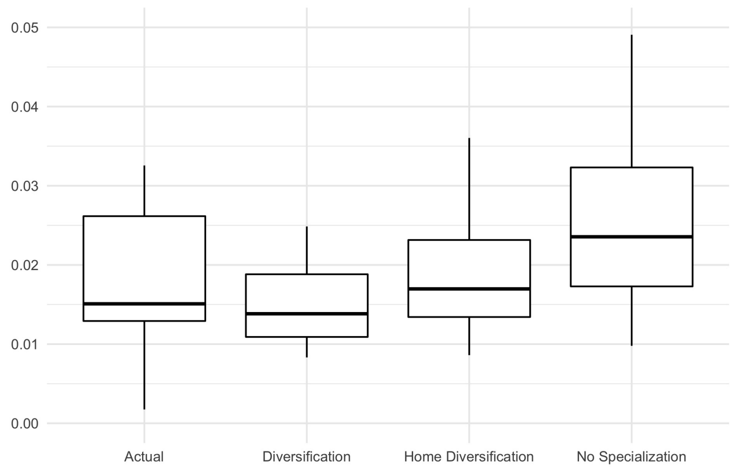
Table 2: Herfindahl-Hirschman Indexes (HHI): Mean and (Standard Deviation)

Country	HHI m share of GO^c (1)	HHI i share of GO^c (2)	HHI m share of GO_i^c (3)
Australia	0.0694 (0.0077)	0.0961 (0.0116)	0.7820 (0.1896)
Canada	0.0616 (0.0057)	0.1056 (0.0090)	0.6471(0.1563)
Cyprus	0.1229 (0.0356)	0.1490 (0.0340)	0.7292 (0.2004)
China	0.0665 (0.0103)	0.0900 (0.0053)	0.7322 (0.2242)
Denmark	0.0488 (0.0118)	0.1406 (0.0262)	0.4302 (0.1781)
Germany	0.0504 (0.0064)	0.1018 (0.0094)	0.5589 (0.1954)
Ecuador	0.1096 (0.0316)	0.2072 (0.0402)	0.8452 (0.1709)
India	0.0806 (0.0086)	0.0994 (0.0041)	0.7582 (0.2287)
Japan	0.0679 (0.0081)	0.0993 (0.0070)	0.7808 (0.1968)
Korea	0.0513 (0.0082)	0.0972 (0.0135)	0.6281 (0.2413)
Mexico	0.0709 (0.0096)	0.1055 (0.0141)	0.6547 (0.1694)
Netherlands	0.0464 (0.0090)	0.1242 (0.0063)	0.3974 (0.1977)
Sweden	0.0461 (0.0051)	0.0981 (0.0060)	0.4967 (0.2045)
UK	0.0565 (0.0048)	0.0888 (0.0034)	0.6333 (0.1682)
Uruguay	0.0969 (0.0206)	0.2064 (0.0500)	0.6782 (0.2225)
USA	0.0732 (0.0038)	0.0907 (0.0028)	0.8253 (0.1085)
Average	0.0683 (0.0124)	0.1185 (0.0140)	0.6364 (0.1992)

Note. HHI m share of GO_c is the HHI of $a_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^c}{GO^c}$. HHI i share of GO^c is the HHI of $a_i^c = \frac{GO_i^c}{GO^c}$. HHI m share of GO_i^c 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 D.1 in Online Appendix D.

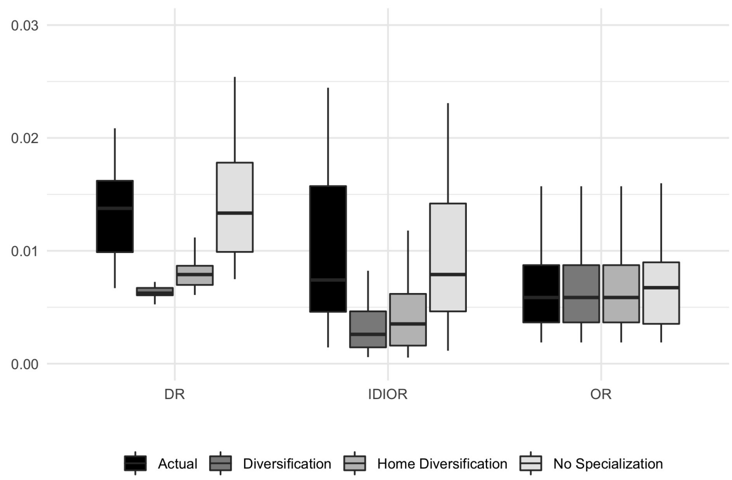
with those for 2011. In each figure, we present a box plot of the actual risk side-by-side with the risk under the three different counterfactuals.

Figure 7 presents the effect on *total* risk of each scenario. The diversification counterfactual shows a small decline in median volatility but a sizeable reduction in volatility for the high volatility percentiles of the cross-sectional distribution of countries. When looking at individual countries, diversification leads to a reduction in volatility for 26 of the 34 countries in the sample. These are usually the countries with the highest total risk. However, risk increases for countries such as the USA and Canada where total risk is lower. This is driven mostly by the effect of diversification away from the home market. For countries that experience a large reduction in risk from diversification, the majority of it is explained by the home market effect. The same goes for countries that experience an increase in total risk from diversification: diversifying away from a low risk home market may lead to an increase in risk, albeit small quantitatively. These results point towards



Note. Actual refers to the distribution of total risk estimated using observed data.

Figure 7: Total risk under different counterfactual scenarios, 2011

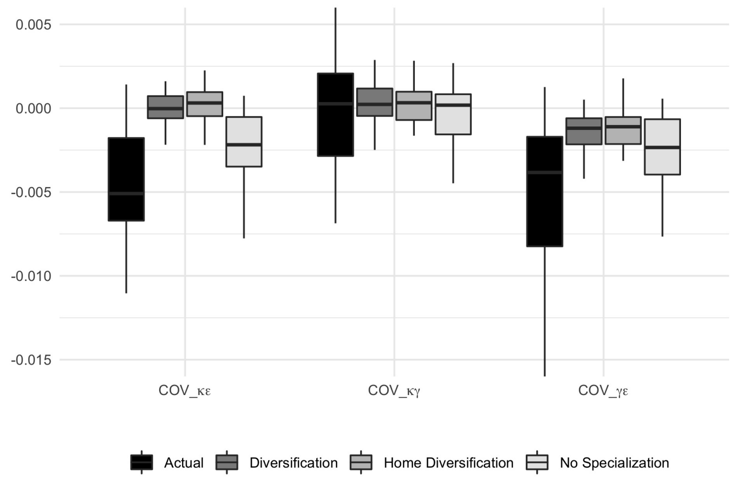


Note. DR stands for Destination Risk. OR stands for Origin Risk. IDIOR is for Idiosyncratic Risk. Actual refers to the distribution of each component estimated using observed data.

Figure 8: Volatility components under counterfactual scenarios, 2011

the importance of country-specific drivers of risk, as found in previous literature. Counter to conventional wisdom, the "no specialization" scenario shows a significant increase in volatility. This is the case for all but five countries (Bulgaria, Finland, South Korea, Singapore, and Sweden). The reasons behind this increase will become evident when we look at the individual components.

Figure 8 presents the effect of the three counterfactuals by risk component, whereas Figure 9 presents the effect on the covariance terms. To shed light on the drivers of

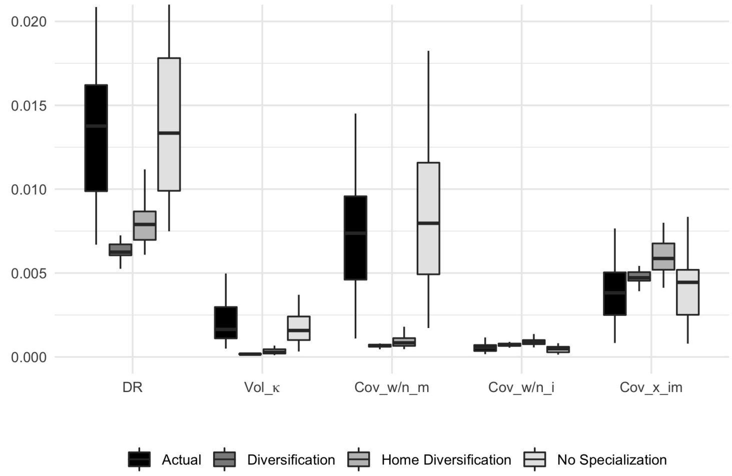


Note. COV$\kappa\epsilon$ is twice the covariance between destination-industry and idiosyncratic shocks. COV_$\kappa\gamma$ is twice the covariance between origin-industry and destination-industry shocks. COV_$\gamma\epsilon$ is twice the covariance between origin-industry and idiosyncratic shocks.

Figure 9: Risk covariances under counterfactual scenarios, 2011

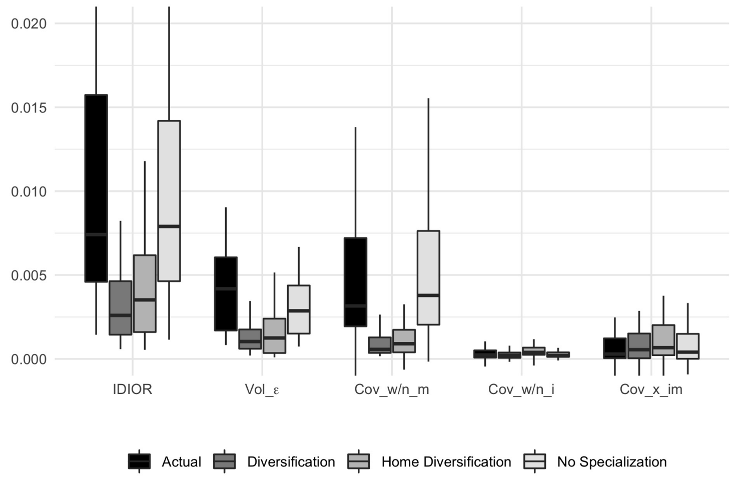
changes in destination, idiosyncratic, and origin risk Figures 10, 11, and 12 show the effect of the counterfactuals separately for the relevant sub-components as per equations (15) to (17).[11] In the diversification scenario both the destination and the idiosyncratic risks drop substantially and, for the majority of countries, enough to more than make up for the increase in the covariance terms. The "home" diversification scenario has similar effects suggesting 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 enough to compensate for the increase in the covariance terms. Figure 13 presents the percentage change in total risk in the full diversification scenario versus the home market diversification and a 45^o line. It shows that these two counterfactuals are highly correlated suggesting a large role for home market diversification. For all countries except Mexico, however, diversification drops total risk more than home diversification. Put simply, diversification across foreign markets provides an additional hedging mechanism. The reallocation of market shares in the diversification scenarios reduces 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.

[11] Appendix C reports the counterfactual results by sub-component for the covariance terms.



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.

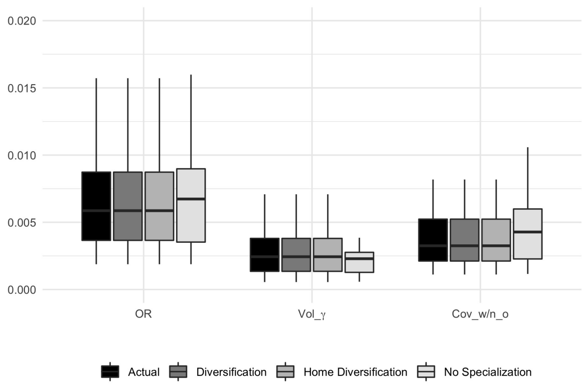
Figure 10: Destination Risk components under different counterfactuals, 2011



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.

Figure 11: Idiosyncratic Risk components under different counterfactuals, 2011

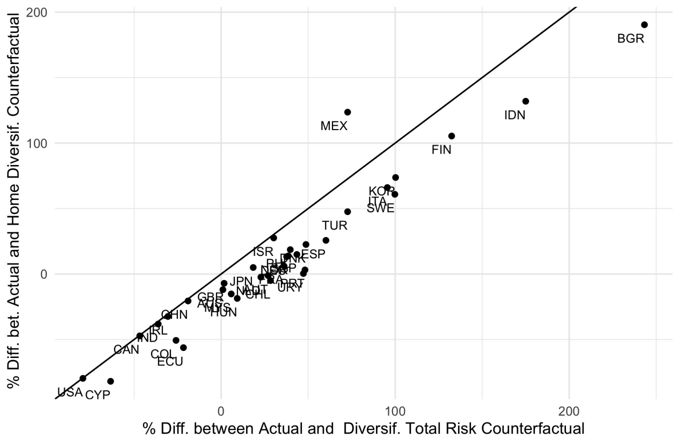
The increase in total risk in the “no specialization” scenario is driven by two factors. First, as shown in Figure 12 the covariance across industries for origin risk increases. This suggests that countries are specialized in industries with a lower than average co-movement with other industries. Second, there is an increased concentration of sales in markets with larger covariances of destination and origin shocks with idiosyncratic shocks (Figure 9). This is due to the lower concentration of the shares of sales in total gross output across destinations. Reduced industrial specialization, however, leads to smaller reallocation of sales across markets than the diversification scenarios and, thus, to smaller increases in the covariance terms.[12] The combination of these effects is sufficient to increase total risk. Note that the direct effect of reduced specialization on the diagonal elements of the origin risk is negative for the high origin risk volatility countries (Figure 12). That is, the counterfactual reduces the concentration on high volatility sectors. However, this direct effect, is outweighed by the covariance effects above. That is, the conventional argument that specialization increases fragility appears not to hold in our data.



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.

Figure 12: Origin Risk components under different counterfactuals, 2011

[12]Destination and idiosyncratic risks are not affected significantly in this scenario as the home market remains the main destination of a country’s sales.



Note. The X-axis presents the percentage change in total risk under the diversification scenario. The Y-axis shows the percentage change in total risk under the *home* diversification scenario. 45^o is the line.

Figure 13: Total Risk Diversification and Home Diversification Counterfactuals, 2011

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 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 the rapid globalization process, the actual volatility reduction effects of trade may be hard to detect in the data.

5 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 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 85 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 specialization increases volatility. This is driven by an increase in the correlation of shocks between industries and an increase in the covariance of shocks.

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Online Appendix

A Derivation and Estimation of the Decomposition

A.1 Derivation of Decomposition

According to equation (3) $\boldsymbol{y^c}$ is represented by the following model:

$$\boldsymbol{y^c} = \boldsymbol{\kappa} + \boldsymbol{\gamma^c} + \boldsymbol{\epsilon^c} \tag{A1}$$

From equation (A1), the product of $\boldsymbol{y^c}$ with its transpose is:

$$\begin{aligned}\boldsymbol{y^c y^{c\prime}} &= (\boldsymbol{\kappa} + \boldsymbol{\gamma^c} + \boldsymbol{\epsilon^c})(\boldsymbol{\kappa'} + \boldsymbol{\gamma^{c\prime}} + \boldsymbol{\epsilon^{c\prime}}) = \\ &= \boldsymbol{\kappa\kappa'} + \boldsymbol{\gamma^c\kappa'} + \boldsymbol{\epsilon^c\kappa'} + \boldsymbol{\kappa\gamma^{c\prime}} + \boldsymbol{\gamma^c\gamma^{c\prime}} + \boldsymbol{\epsilon^c\gamma^{c\prime}} + \boldsymbol{\kappa\epsilon^{c\prime}} + \\ &+ \boldsymbol{\gamma^c\epsilon^{c\prime}} + \boldsymbol{\epsilon^c\epsilon^{c\prime}}\end{aligned} \tag{A2}$$

Taking expectations in equation (A2) and defining: $\boldsymbol{\Omega}_{\kappa} = E(\boldsymbol{\kappa\kappa'})$, $\boldsymbol{\Omega}_{\gamma^c} = E(\boldsymbol{\gamma^c\gamma^{c\prime}})$, $\boldsymbol{\Omega}_{\epsilon^c} = E(\boldsymbol{\epsilon^c\epsilon^{c\prime}})$, $\boldsymbol{\Omega_{\gamma^c\kappa}} = E[\boldsymbol{\gamma^c\kappa'}]$, $\boldsymbol{\Omega_{\epsilon^c\kappa}} = E[\boldsymbol{\epsilon^c\kappa'}]$, and $\boldsymbol{\Omega_{\gamma^c\epsilon^c}} = E[\boldsymbol{\gamma^c\epsilon^{c\prime}}]$ we obtain:

$$\begin{aligned}E(\boldsymbol{y^c y^{c\prime}}) = \boldsymbol{\Omega}_{\kappa} + \boldsymbol{\Omega_{\gamma^c}} + \boldsymbol{\Omega}_{\epsilon^c} + \boldsymbol{\Omega_{\gamma^c\kappa}} + \boldsymbol{\Omega_{\epsilon^c\kappa}} + \boldsymbol{\Omega_{\gamma^c\kappa}}' + \\ + \boldsymbol{\Omega'_{\gamma^c\epsilon^c}} + \boldsymbol{\Omega'_{\epsilon^c\kappa}} + \boldsymbol{\Omega_{\gamma^c\epsilon^c}}\end{aligned} \tag{A3}$$

The variance of q^c can then be expressed as follows:

$$\begin{aligned}Var(q^c) = \boldsymbol{a^{c\prime}} E(\boldsymbol{y^c y^{c\prime}})\boldsymbol{a^c} = \boldsymbol{a^{c\prime}}\boldsymbol{\Omega}_{\kappa}\boldsymbol{a^c} + \boldsymbol{a^{c\prime}}\boldsymbol{\Omega}_{\gamma^c}\boldsymbol{a^c} + \boldsymbol{a^{c\prime}}\boldsymbol{\Omega}_{\epsilon^c}\boldsymbol{a^c} + \\ + 2\boldsymbol{a^{c\prime}}\boldsymbol{\Omega_{\gamma^c\kappa}}\boldsymbol{a^c} + 2\boldsymbol{a^{c\prime}}\boldsymbol{\Omega_{\gamma^c\epsilon^c}}\boldsymbol{a^c} + 2\boldsymbol{a^{c\prime}}\boldsymbol{\Omega_{\epsilon^c\kappa}}\boldsymbol{a^c}\end{aligned} \tag{A4}$$

A.2 Equivalence of Estimators

This section shows the equivalence between the cross-sectional mean estimators (5)–(6) and the regression estimator (8).

The coefficients from estimating model (8) solve the following least-squares problem:

$$\begin{aligned}&\min_{\kappa,\gamma} \quad \left[\boldsymbol{Y} - \boldsymbol{D}\begin{pmatrix}\kappa \\ \gamma\end{pmatrix}\right] \\ &\text{subject to} \quad (\boldsymbol{I_I} \otimes \boldsymbol{1'_C})\gamma = 0\end{aligned} \tag{A5}$$

where $\boldsymbol{Y}$ is the $(IMC\text{x}1)$ vector of shocks to sales. The matrix $\boldsymbol{D}$ is the $(IMC\text{x}(IM + IC))$ matrix of industry-destination and origin-industry indicators. Accounting for the constraints, $\boldsymbol{D}$ can be written as follows:

$$\boldsymbol{D} = \left[\boldsymbol{1}_C \otimes \boldsymbol{I}_{IM} \quad \left(\boldsymbol{I}_{IC} - \frac{1}{C}\boldsymbol{1}_C \otimes (\boldsymbol{I_I} \otimes \boldsymbol{1'_C})\right) \otimes \boldsymbol{1_M}\right]$$

The minimization problem (A5) gives the following first order conditions:

$$\boldsymbol{D'D}\begin{pmatrix}\kappa\\ \gamma\end{pmatrix} = \boldsymbol{D'Y} \tag{A6}$$

$$(\boldsymbol{I_I} \otimes \boldsymbol{1'_C})\gamma = 0 \tag{A7}$$

Now, let $\boldsymbol{l} = \sum_c \boldsymbol{y^c_{im}}$ denote the $(IM\text{x}1)$ vector of the sum of shocks across countries within an industry-destination im, $\boldsymbol{m} = \sum_m \boldsymbol{y^c_{im}}$ be the $(IC\text{x}1)$ vector of the sum of shocks across markets with an origin-industry ci, and $\boldsymbol{g} = \sum_m \sum_c y^c_{im}$ be the $(I\text{x}1)$ vector that sums shocks over all destinations and origins. Then, we can rewrite estimated shocks as follows:

$$\hat{\boldsymbol{\kappa}} = \frac{\boldsymbol{l}}{C} \tag{A8}$$

$$\hat{\gamma} = \frac{1}{M}(\boldsymbol{m} - \frac{\boldsymbol{1_C} \otimes \boldsymbol{g}}{C}) \tag{A9}$$

Also, given the definition of $\boldsymbol{D}$:

$$\boldsymbol{D'D} = \begin{bmatrix} C\boldsymbol{I}_M & 0 \\ 0 & M\Big(\boldsymbol{I}_{IC} - \frac{1}{C}\boldsymbol{1}_C \otimes (\boldsymbol{I_I} \otimes \boldsymbol{1'_C})\Big) \end{bmatrix}$$

Thus,

$$\boldsymbol{D'D}\begin{pmatrix}\hat{\kappa}\\ \hat{\gamma}\end{pmatrix} = \begin{pmatrix}\boldsymbol{l}\\ \boldsymbol{m} - \frac{\boldsymbol{1_C}\otimes\boldsymbol{g}}{C}\end{pmatrix} = \begin{pmatrix}\sum_c \boldsymbol{y^c_{im}}\\ \sum_m \boldsymbol{y^c_{im}} - \frac{1}{C}\boldsymbol{1_C} \otimes \sum_m\sum_c \boldsymbol{y^c_{im}}\end{pmatrix} \tag{A10}$$

At the same time,

$$\boldsymbol{D'Y} = \begin{pmatrix}\sum_c \boldsymbol{y^c_{im}}\\ \sum_m \boldsymbol{y^c_{im}} - \frac{1}{C}\boldsymbol{1_C} \otimes \sum_m\sum_c \boldsymbol{y^c_{im}}\end{pmatrix} = \begin{pmatrix}\boldsymbol{l}\\ \boldsymbol{m} - \frac{\boldsymbol{1_C}\otimes\boldsymbol{g}}{C}\end{pmatrix} \tag{A11}$$

Condition (A6) is thus satisfied. Noticing that $(\boldsymbol{I_I} \otimes \boldsymbol{1'_C})\hat{\gamma} = \boldsymbol{g} - \frac{C}{C}\boldsymbol{g} = 0$ the constraint in (A7) is also satisfied.

B Data

Data on production are from the TradeProd and the UNIDO INDSTAT 4 database. The TradeProd database is constructed by combining the World Bank dataset "Trade, Production and Protection" (Nicita and Olarreaga, 2006) 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 onwards. 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 correspondence tables across ISIC Revisions are only available at the 4-digit level,[13] and not direct between Revision 4 and Revision 2. We follow these steps to create a unique series of output data at the 3-digit ISIC level Revision 2 by country:

1. **Pre-process INDSTAT 4 data.** In this step, we deal with two issues:
   - The data for some countries are reported according to a customized ISIC classification. We use the UNIDO correspondence tables between this classification and the standard ISIC Revision 3 or Revision 4,[14] to obtain production at the Class level. When one ISIC combined code matched to many standard ISIC codes we uniformly split the value at the combined code across standard codes.
   - UNCTAD correspondence tables are only available at the Class level. This complicates the concordance process in a few instances. In some cases, production is only available at the Group level. In these cases, we uniformly split the value at the Group level across its Classes. In other cases, the Group value does not match the value obtained by summing-up production across Classes within that Group. If the Group value is greater than the value aggregated across its Classes, we take the difference and split it uniformly across Classes within the Group. If the Group value is smaller than the value aggregated across its Classes, we replace the former with the latter.

2. **Concord INDSTAT 4 data and create output series at the 3-digit ISIC Revision 2.** Once the INDSTAT 4 data are available at the Class level, we use UNCTAD Correspondence Tables. The correspondence table between ISIC Revision 3 and Revision 2 is direct, and when one code in Revision 3 matches to many in Revision 2 we split the corresponding output value uniformly. The correspondence table between ISIC Revision 4 and Revision 2 is not available, and to get it we use correspondence tables between Revision 4 and Revision 3.1, between Revision 3.1 and Revision 3, and between Revision 3 and Revision 2. A before, one to many matches are dealt by splitting uniformly the relevant output value. After concording the production data at the Class level, we aggregate them up at the Group level.

3. **Integrate TradeProd and INDSTAT 4 data.** Because of the overlap of some data across datasets we are able to verify that the quality of our series, in the aggregate and by sector, is high for the countries included in our sample.

The code implementing steps 1–3 and our data quality checks are publicly available at https://l-puzzello.github.io/indstat-TPP/.

[13] https://unstats.un.org/unsd/classifications/Econ#corresp-isic-un

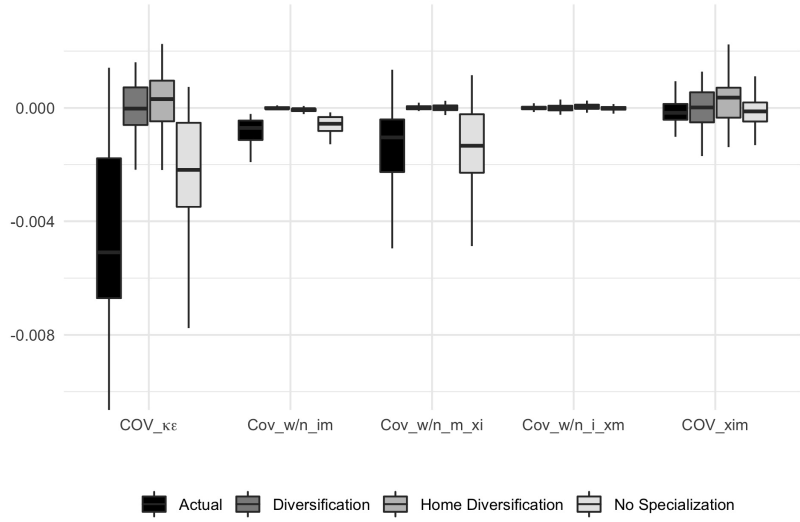
[14] https://stat.unido.org/metadata

In our efforts to obtain a balanced panel of producer countries and industries, we restrict our sample by dropping countries, industries, and years for which gross output data are sparse or missing in many consecutive years. As a consequence, our sample contains 34 producer countries, 19 3-digit ISIC Revision 2 sectors, and 32 years from 1980 to 2011, which yields 646 observations in any given year. This panel contains 2.45% missing gross output data. Among the 34 countries in our sample, 8 countries do not have missing gross output data. The remaining 26 countries report missing gross output data for a fraction of years and sectors which range between 0.16% (i.e., one observation) to 15.6% (i.e., 95 observations) of the total number of observations for each country (i.e., 608 observations). We interpolate the logarithm of gross output for these remaining missing values.

Trade data are from the CHELEM database, constructed by the CEPII and distributed by the Bureau van Dijk. The bilateral trade dataset is a balanced panel of 85 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. For the subset of data common to the two datasets we verified a correlation of 0.9. We use UNCTAD correspondence tables to bring the trade data at the 3-digit ISIC Revision 2.

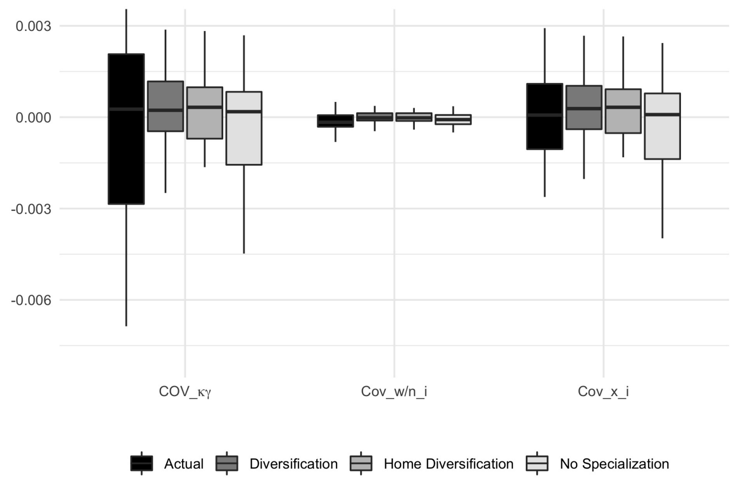
We compute domestic sales at the industry-level by taking the difference between a country's gross output and exports at the industry-level. To reduce the incidence of negative domestic sales we eliminate re-exports from exports. More precisely, we adjust all export values following the methodology proposed by GTAP and calculate country c's re-exports in industry i, RX^c_{it}, as follows: $RX^c_{it} = \frac{M^c_{it}}{M^c_{it}+GO^c_{it}} * X^c_{it}$, where M^c_{it} are country c's imports of good i; GO^c_{it} is country c's gross output of good i; and X^c_{it} are country c's exports of good i. Intuitively, a country can either export its production or its imports. So, if no information is available, the best guess is that a given unit of good i's exports is a re-export with probability equal to the share of imports of good i in the total availability of good i in the country.

C Covariance decompositions under different counterfactual scenarios



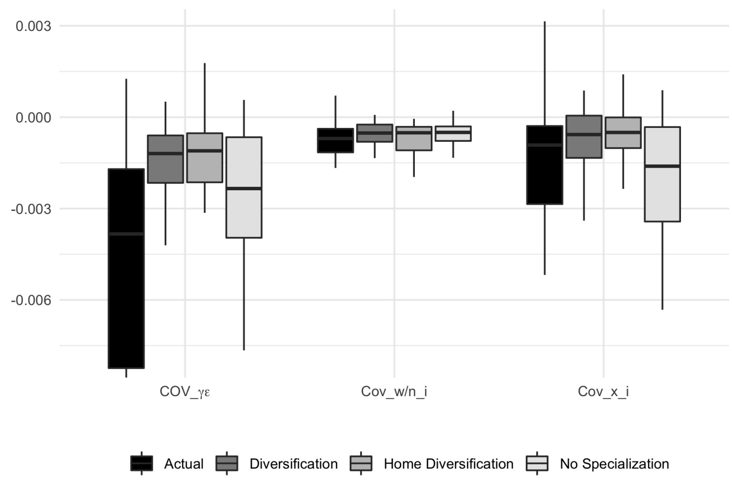
Note. COV_$\kappa\epsilon$ is twice the covariance between destination and idiosyncratic shocks. Cov_w/n_im arises because of the covariance of destination and idiosyncratic shocks within an industry-market pair. Cov_w/n_m_xi is the term related to the covariance of destination and idiosyncratic shocks within a market across industries. Cov_w/n_i_xm is the term related to the covariance of destination and idiosyncratic shocks within industry across countries. Cov_xim is the term related to the covariance of destination and idiosyncratic shocks across distinct industry-market pairs. Actual refers to the distribution of each component estimated using observed data.

Figure C. 1: Destination-Idiosyncratic Covariance, 2011



Note. COV_$\kappa\gamma$ is twice the covariance between destination and origin shocks. Cov_w/n_i is the term related to the within-industry covariance of destination and origin shocks. Cov_x_i is the term related to the covariance of destination and origin shocks across industries. Actual refers to the distribution of each component estimated using observed data.

Figure C. 2: Destination-Origin Covariance, 2011



Note. COV_$\gamma\epsilon$ is twice the covariance between origin and idiosyncratic shocks. Cov_w/n_i is the term related to the within-industry covariance of origin and idiosyncratic shocks. Cov_x_i is the term related to the covariance of origin and idiosyncratic shocks across industries. Actual refers to the distribution of each component estimated using observed data.

Figure C. 3: Origin-Idiosyncratic Covariance, 2011

D HHI indexes: full list of countries

Table D.1: Herfindahl-Hirschman Indexes: Mean and (Standard Deviation)

Country	HHI m share of GO^c	HHI i share of GO^c	HHI m share of GO_i^c
Australia	0.0694 (0.0077)	0.0961 (0.0116)	0.7820 (0.1896)
Austria	0.0415 (0.0075)	0.0838(0.0039)	0.4919 (0.1832)
Bulgaria	0.0629 (0.0224)	0.0984 (0.0140)	0.5704 (0.2341)
Canada	0.0616(0.0057)	0.1056(0.0090)	0.6471(0.1563)
Chile	0.0985 (0.0240)	0.1512(0.0266)	0.7463 (0.2260)
China	0.0665 (0.0103)	0.0900 (0.0053)	0.7322 (0.2242)
Colombia	0.1118 (0.0179)	0.1286 (0.0190)	0.7945 (0.1686)
Cyprus	0.1229 (0.0356)	0.1490 (0.0340)	0.7292 (0.2004)
Germany	0.0504 (0.0064)	0.1018 (0.0094)	0.5589 (0.1954)
Denmark	0.0488 (0.0118)	0.1406 (0.0262)	0.4302 (0.1781)
Ecuador	0.1096 (0.0316)	0.2072 (0.0402)	0.8452 (0.1709)
Finland	0.0577 (0.0095)	0.1122 (0.0093)	0.5492 (0.2136)
France	0.0615 (0.0098)	0.0990 (0.0131)	0.5852 (0.1780)
Hungary	0.0596 (0.0191)	0.1139 (0.0148)	0.5663 (0.2104)
India	0.0806 (0.0086)	0.0994 (0.0041)	0.7582 (0.2287)
Indonesia	0.0513 (0.0105)	0.0941 (0.0075)	0.5913 (0.2674)
Ireland	0.0679 (0.0152)	0.1768 (0.0148)	0.4835 (0.2187)
Israel	0.0713 (0.0121)	0.1087 (0.0051)	0.6944 (0.2282)
Italy	0.0486 (0.0028)	0.0821 (0.0029)	0.5737 (0.1890)
Japan	0.0679 (0.0081)	0.0993 (0.0070)	0.7808 (0.1968)
Korea	0.0513 (0.0082)	0.0972 (0.0135)	0.6281 (0.2413)
Mexico	0.0709 (0.0096)	0.1055 (0.0141)	0.6547 (0.1694)
Malaysia	0.0505 (0.0126)	0.1550 (0.0250)	0.5284 (0.2255)
Netherlands	0.0464 (0.0090)	0.1242 (0.0063)	0.3974 (0.1977)
Norway	0.0759 (0.0071)	0.1115 (0.0066)	0.6697 (0.1956)
Phillipines	0.0702 (0.0183)	0.1277 (0.0110)	0.6241 (0.2545)
Portugal	0.0592 (0.0097)	0.0908 (0.0102)	0.6047 (0.2199)
Singapore	0.0873 (0.0204)	0.2091 (0.0399)	0.5527 (0.1779)
Spain	0.0650 (0.0080)	0.0942 (0.0039)	0.6806 (0.1545)
Sweden	0.0461 (0.0051)	0.0981 (0.0060)	0.4967 (0.2045)
Turkey	0.0643 (0.0070)	0.0948 (0.0058)	0.7528 (0.1737)
Uruguay	0.0969 (0.0206)	0.2064 (0.0500)	0.6782 (0.2225)
UK	0.0565 (0.0048)	0.0888 (0.0034)	0.6333 (0.1682)
USA	0.0732 (0.0038)	0.0907 (0.0028)	0.8253 (0.1085)
Average	0.0683 (0.0124)	0.1185 (0.0140)	0.6364 (0.1992)

Note. HHI m share of GO_c is the HHI of $a_{im}^c = \frac{S_{im}^c}{GO_i^c} * \frac{GO_i^c}{GO^c}$. HHI i share of GO^c is the HHI of $a_i^c = \frac{GO_i^c}{GO^c}$. HHI m share of GO_i^c is the HHI of $a_m^{ic} = \frac{S_{im}^c}{GO_i^c}$.