Phyloeconomic Trade Diversity: a Study of the Impact of Diversification on Firms' Export Volatility for 63 Developing Countries

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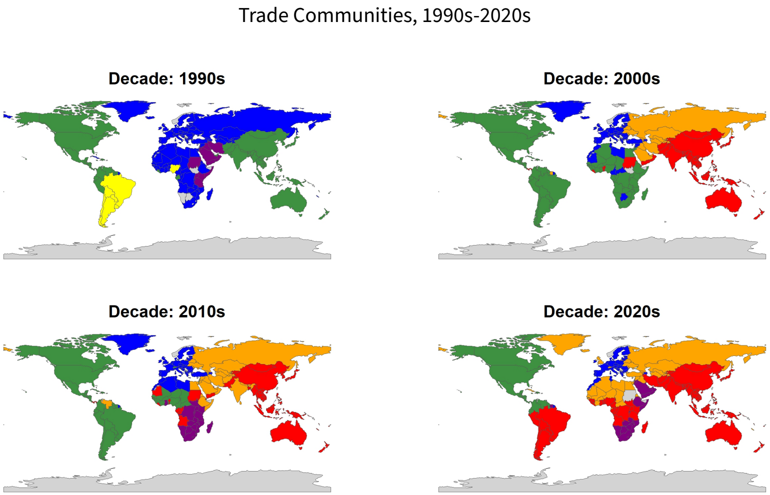
Context, Motivation & Puzzle

Trade volumes remain resilient, but markets are more fragmented



Source: Artuc, Goldberg, Lasso, Taglioni (2025, work in progress). **Notes:** Authors' calculation using UN COMTRADE total bilateral data. Community detection with Greedy Modularity Algorithm (networkX, Hagberg et al., 2008). Each color represents a trade community.

Diversification: does destination market similarity matter?

- This paper asks whether **diversification still stabilizes firm exports** when markets may become increasingly **dissimilar**.
- Standard intuition:
  - More markets $\Rightarrow$ better risk sharing
  - More destinations and more balanced portfolios $\Rightarrow$ less volatility.
- But is something missing?
  - The standard intuition implicitly assumes that **markets are interchangeable**.
  - Meanwhile, we also see that firms exporting to **more heterogeneous sets of destinations** can experience **higher volatility**.

Literature on why trade diversification matters for firms

+ Larger firms with more customers have less volatile output (Herskovic et al. 2020; di Giovanni et al. 2014, 2018; Kramarz et al. 2020)
+ Firms with more diversified input sources have better performance (Goldberg et al. 2010; Topalova and Khandelwal 2011; Pierola et al. 2017)
+ Exporting to foreign countries allows firms to hedge against idiosyncratic demand shocks (as in classical asset portfolio theory; Esposito 2022)

- Some firms—especially smaller exporters—experience higher export volatility when diversifying across destinations (Vannoorenberghe 2012; Vannoorenberghe et al. 2016)

Measuring trade diversification

- Most empirical studies proxy export diversification using:
  - the **number of destination markets**
  - **concentration indices** (Herfindahl–Hirschman, Theil)

- These measures do not condition on the correlation structure of shocks across markets.

- This limitation becomes more relevant in a fragmented or geopolitically polarized trade environment (non-random changes to markets' exposition to correlated vs. uncorrelated shocks).

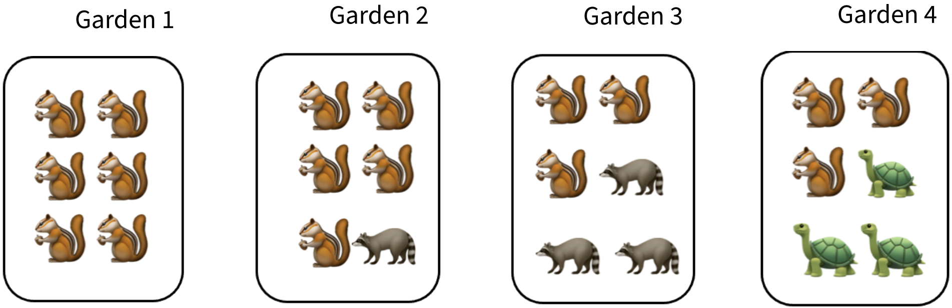
$\Rightarrow$ We need diversification measures that encompass all three margins: how rich, how balanced, and how similar/dissimilar trading partners are.

This paper

- Export diversification has **three distinct dimensions**: **richness**, **evenness**, and **disparity**, which are typically bundled together in the literature
- To separate these margins, we adapt **phylogenetic measures of biodiversity** and construct a firm-level indicator of **phyloeconomic trade diversity**
- Using customs data for over **900,000 firms in 63 emerging economies**, we ask which diversification margin drives **export volatility**
- **Key finding:** once margins are separated, they work in **opposite directions**:
  - More destinations and more balanced portfolios **reduce** volatility
  - Conditional on richness and balance levels, greater destination **dissimilarity increases volatility**

Bio-diversity and economic-diversity

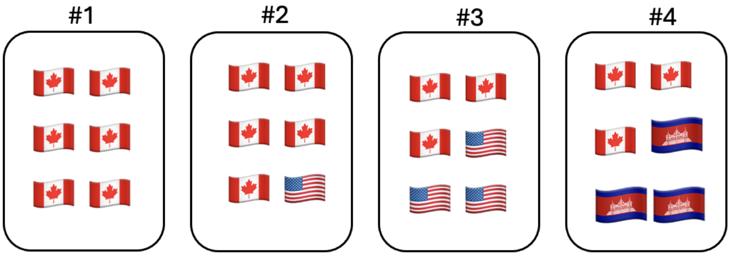
From biodiversity to export portfolios: three dimensions of diversification



- Biodiversity combines:
  - **Richness** (how many species)
  - **Evenness** (how balanced the ecosystem is)
  - **Disparity** (how different species are)

~~Phylogenetic~~ Phyloeconomic diversity across firms

- Trade analogy: export portfolios differ in **how many**, **how balanced**, and **how dissimilar** destination markets are.



- Diversity of exports of firm #4 is greatest because the economic disparity between Canada and Cambodia is larger than the disparity between Canada and the US.
- Two firms can export to the same number of markets with the same concentration, yet face different risk because destinations differ in **disparity**.

Phyloeconomic diversity:
a measurement framework to
separate diversification margins

Phyloeconomic diversity index Φ_i

- We adapt a phylogenetic diversity index (Leinster & Cobbold, 2012) to trade.
- Firm *i*'s diversification across destination markets is an average of the similarity between countries in firm *i*'s portfolio of trade partners:

$$\Phi_i = \left(\sum_{c=1}^{C} p_{ic} \, (Zp)_{ci} \right)^{-1}, \qquad (Zp)_{ci} = \sum_{c'=1}^{C} z_{cc'} \, p_{ic'} .$$

- c is a country and i is a trading firm
- p_{ic} = share of destination country c in firm i trade (exports or imports)
- $z_{cc'}$ = similarity between destination countries c and c' (inverse function of bilateral "distance" between countries)

How Φ_i captures export diversification (relative to standard measures)

- Standard measures:
  - **Number of destinations** captures **richness**
  - **Concentration / entropy measures** (HHI, Shannon, Theil) capture **evenness**

- Φ_i integrates all three dimensions of diversification:
  - **Richness**: more destination markets
  - **Evenness**: more balanced export shares
  - **Disparity**: similarity/ dissimilarity in destination markets

- Formally, $\Phi_i \geq 1$, is **increasing** in the number of partners ($\#Dest_i$) and **decreasing** in export concentration (HHI_i), **but varies across firms with same** $\#Dest_i$ **and** $\textbf{HHI}_i$.

- $\Phi_i = 1$ for a single-destination exporter.

Operationalizing similarity across markets

- We construct Φ using two alternative similarity matrices Z:
  - **Geography:** similarity falls with bilateral distance
  - **Business cycles:** similarity rises with correlation in GDP per-capita growth
- Results are robust across both definitions.

▸ A1: Index Details ▸ A2: Similarity Definition ▸ A3: Geo ▸ A4: Cycles

Data

Data: firm-level customs exports for 64 economies

- Universe of transaction-level customs data from the Exporter Dynamics Database (Fernandes, Freund, Pierola, 2016).
- Coverage: **63** emerging/developing economies; **1996–2019** (varying by country).
- Variables: exporting firm unique identifier, destination country, HS 6-digit, product, export value, year
- We aggregate those to **firm** $\times$ **HS2** $\times$ **destination** $\times$ **year**; $N \approx$ **915k** firm-product pairs.
- We compute Φ at the firm-product-year level using geography- and cycle-based Z matrices.

Understanding sources of variation in diversity indicators

	Adjusted R^2 from variance decomposition			
Matrix Z:	Geographic Proximity		Business cycle	
Sample:	All firms	Firms with $\Phi > 1$	All firms	Firms with $\Phi > 1$
Fixed effects	(1)	(2)	(3)	(4)
Firm	0.344	0.475	0.307	0.401
Year	0.005	0.015	0.001	0.002
Country	0.035	0.102	0.021	0.070
Product	0.012	0.023	0.007	0.011
Year + Country + Product	0.045	0.117	0.028	0.081
Country-Year	0.037	0.108	0.023	0.076
Product-Year	0.020	0.043	0.010	0.017
Country-Product	0.069	0.144	0.047	0.102
Country-Year + Product-Year + Country-Product	0.072	0.151	0.049	0.109

- Variation in diversity indicators is primarily driven by **firm-level heterogeneity**, rather than country, product, or time effects.
- At the same time, diversity varies **within firms over time**, which we exploit for **within-firm identification** in the regressions.

Does diversification reduce export volatility? Firm-level evidence

Econometric specification

$$\ln(Vol_{i,T}) = \alpha + \beta \ln(\Phi_{i,T_0}) + \delta \ln(HHI_{i,T_0}) + \gamma \ln(\#Dest_{i,T_0}) + \eta \ln(Dist_{i,T_0}) + FE + \varepsilon_{iT}.$$

- T = 3-year volatility windows (benchmark), from 1996-1998 to 2014-2016.
- FE: country$\times$product$\times$period (between) and + firm (within).
- $Dist_{i,T_0}$: average distance of firm i to its destination markets (so to measure dissimilarity beyond remoteness).

Measuring export volatility

- For each firm, de-trend exports within each period:

$$x_{it} = \alpha_i + \beta_i Trend_t + \varepsilon_{it}.$$

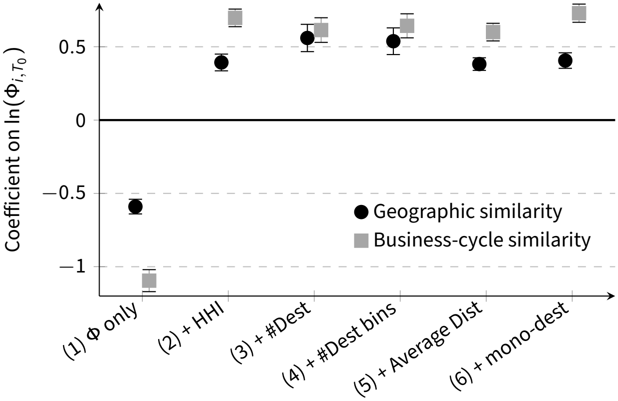
- Volatility: computed as Root Mean Square Error (RMSE) around the firm-specific trend, scaled by average firm exports ($\bar{x}_i$) over the period T:

$$Vol_{i,T} = \frac{RMSE_{i,T}}{\bar{x}_i}.$$

- Requires firms observed **continuously** within each period (requirement that eliminates one-time exporters and smaller firms).

Disentangling the diversification margins: between-firm evidence

Baseline results — across firms within country×product×period



Specification: Export volatility and diversity (between-firm)

(95% confidence intervals shown).

Core findings

Holding constant the number of destinations, export concentration (HHI), **and average distance to markets**, greater destination dissimilarity (Φ) **increases** export volatility.

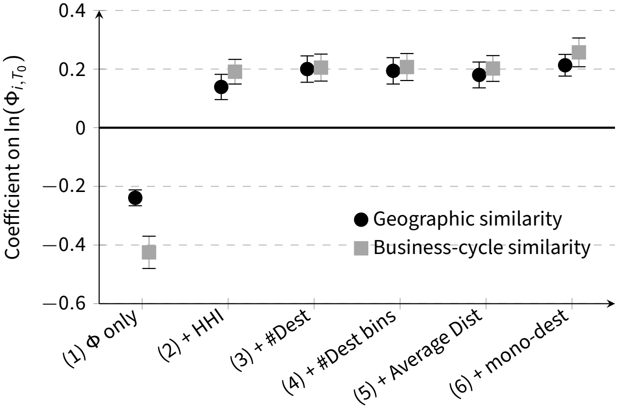
Richer and more even portfolios **reduce** volatility.

Results robust to business cycle-based similarity.

▸ Tables

Disentangling the diversification margins: within-firm evidence

Baseline results — firm fixed effects (changes within firm over time)



Specification: Export volatility and diversity (within-firm)

(95% confidence intervals shown).

Netting-out firm traits (size, capabilities, baseline riskiness)

The sign flip survives **firm fixed effects**.

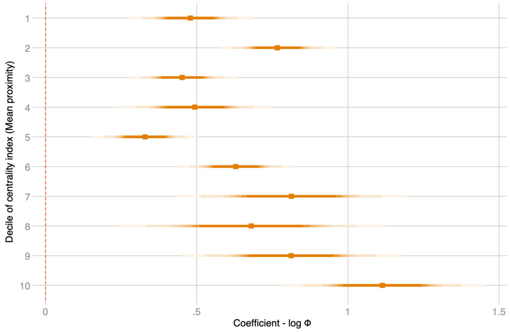
Additional insight: when a firm increases **destination dissimilarity** (higher Φ), its export volatility **rises**, even after controlling for changes in #destinations, concentration (HHI), and average distance to markets.

Interpretation: the sign flip is not driven by cross-firm selection into "exotic" portfolios; it reflects **within-firm portfolio reconfiguration**.

Results are robust to different similarity concepts.

Tables

Where diversification becomes destabilizing: the role of market access



- Geography links disparity across destinations to distance from origin (ϕ is gravity-consistent).
- **Effect strongest for firms in central countries**, where diversification mechanically implies reaching farther, more peripheral, riskier markets.
- For firms in peripheral countries, marginal increases in disparity do not change risk too much.

Why can higher disparity increase volatility?
Evidence from simulations

Why the sign flips: hedging vs. risk-taking

- Think of total exports as a portfolio:

$$Var(X_i) = \sum_c p_{ic}^2 Var(x_{ic}) + \sum_c \sum_{c' \neq c} p_{ic} p_{ic'} Cov(x_{ic}, x_{ic'}).$$

- Disparity can reduce covariance (hedging) …
- **But** reaching dissimilar markets often means reaching **more distant** markets, where firm-destination demand is harder to stabilize (higher variance).
  - For our core finding to be verified, the greater variance effect needs to dominate
  - Intuition relies on role of gravity forces and trade costs that increase with distance from the home country

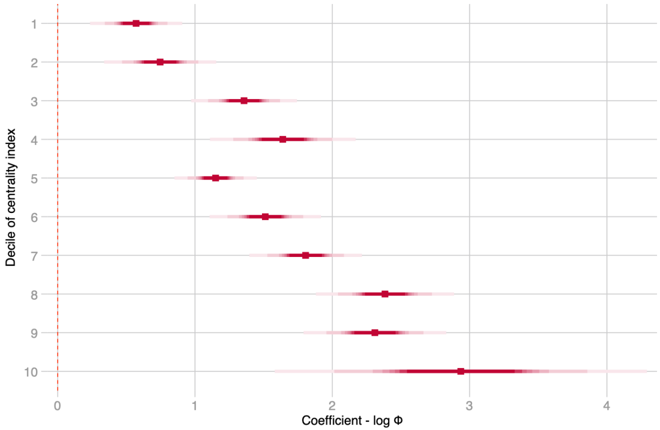
Simulations: when does disparity hedge vs. amplify risk?

- We simulate a Melitz-type model with **firm-destination demand shifters** and destination attractiveness parameters.
- Three shock environments:
  - No spatial structure (benchmark)
  - Spatially correlated macro shocks (disparity hedges)
  - **Higher volatility in distant markets** (disparity amplifies volatility)
- **Key point:** the paradox emerges when **demand volatility increases with distance** — consistent with exporter dynamics evidence.

Key point explained

- Positive coefficient on Φ in firm volatility regression results from two ingredients:
  - For a given number of destinations, firms with more diverse destinations tend to choose destinations more distant from home
  - Regardless of home, sales in destinations more distant from home are more volatile and face larger shocks (to firm-destination demand)
    - Establishing stable exports is harder in more distant markets: e.g., Chaney (2014), Morales et al. (2019)

Why destination dissimilarity can increase export volatility: evidence from simulations



Simulation: Scenario 3 (paper Figure 14c))

Mechanism

To reach more **dissimilar** destinations, firms must reach **more distant and difficult markets**.

Firm–destination demand shocks are more volatile in such markets, raising overall export volatility.

This mechanism reproduces the **positive coefficient on Φ** conditional on richness and evenness.

Consistent with literature: establishing stable exports is harder in more distant markets: e.g., Chaney (2014), Morales et al. (2019)

Implications for diversification strategies under fragmentation

- Diversification is **not one-size-fits-all**: richness and balance hedge risk, but destination dissimilarity can raise volatility.
- **Who** firms diversify towards matters as much as **how many** markets they serve.
- Diversification becomes stabilizing when accompanied by **lower trade costs and lower uncertainty** in distant markets (e.g. trade facilitation, finance, insurance).

Takeaway

- Export diversification has **three margins**: **richness**, **evenness**, and **disparity**.
- Richer and more balanced portfolios **reduce** export volatility, but greater destination dissimilarity **increases** it.
- **Bottom line:** diversification **without reducing trade frictions** can increase volatility.

Appendix: Methods and robustness

Appendix A1: Zoom in on the Φ_i indicator

$$\Phi_i = \left(\sum_{c=1}^{C} p_{ic} \left[(Zp)_{ci} \right] \right)^{-1}, \qquad (Zp)_{ci} = \sum_{c'=1}^{C} z_{cc'}\, p_{ic'}$$

$$\Phi_i^{-1} = \begin{pmatrix} p_1 & p_2 & \cdots & p_{c'} & \cdots & p_N \end{pmatrix} \begin{pmatrix} 1 & z_{1,2} & \cdots & z_{1,c'} & \cdots & z_{1,N} \\ z_{2,1} & 1 & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ z_{c',1} & \cdots & \cdots & 1 & \cdots & z_{c'N} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{N,1} & \cdots & \cdots & z_{N,c'} & \cdots & 1 \end{pmatrix} \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_{c'} \\ \vdots \\ p_N \end{pmatrix}$$

- Z contains similarities between destination pairs; $(Zp)_{ci}$ is the weighted average similarity of c relative to the firm's portfolio.

back

Appendix A2: Measuring similarity across markets (Z) and role of home country

- $z_{cc'}$ measures similarity across destination countries c and c'.
- “Similarity” can be defined along multiple dimensions:
  - Geographic proximity (inverse of physical distance) ▸ geo
  - Business-cycle synchronicity (correlation in GDP-per-capita growth) ▸ cycle
  - (Other options: income distance, UN voting, language/culture, etc.)

- Φ_i is based on similarity **between partner markets**, not similarity to the home market.
  - Including the home market would require firm-level domestic sales.
  - Excluding it improves cross-country comparability of Φ_i.

▸ back

Appendix A3: Z matrix based on geography

- Similarity falls with bilateral distance:

$$z_{cc'}^{dist} = \exp\left(-\frac{dist_{cc'}}{\overline{dist}}\right),$$

- $\overline{dist}$ is the average distance across country pairs; $z_{cc'}^{dist} \in [0, 1]$ and $z_{cc}^{dist} = 1$.

back

Appendix A4: Z matrix based on business-cycle synchronicity

- Similarity rises with correlation in GDP-per-capita growth:

$$z_{cc'}^{bc} = \frac{1 + \mathrm{Corr}(g_{ct}, g_{c't})}{2},$$

- g_{ct} is annual growth in GDP per capita over the chosen sample window; $z_{cc'}^{bc} \in [0, 1]$.

back

Appendix B1: Baseline regression tables (between-firm)

	(1)	(2)	(3)	(4)	(5)	(6)
Z = Geographic similarity						
$\ln(\Phi_{i,T_0})$	-0.590^a	0.393^a	0.560^a	0.538^a	0.382^a	0.406^a
	(0.050)	(0.057)	(0.093)	(0.091)	(0.043)	(0.053)
$\ln(HHI_{i,T_0})$		0.454^a	0.005	0.036	0.005	-0.006
		(0.018)	(0.029)	(0.027)	(0.025)	(0.023)
$\ln(\#Dest_{i,T_0})$			-0.508^a			-0.389^a
			(0.017)			(0.012)
$\ln(Dist_{i,T_0})$					0.078^a	0.068^a
					(0.014)	(0.011)
FE hs2$\times$cty$\times$T	✓	✓	✓	✓	✓	✓
#Dest bins				✓		✓
Sample	#Dest>1	#Dest>1	#Dest>1	#Dest>1	#Dest>1	all firms
Obs.	670060	670060	670060	670060	670060	1304967
Z = Business-cycle similarity						
$\ln(\Phi_{i,T_0})$	-1.095^a	0.697^a	0.614^a	0.643^a	0.600^a	0.729^a
	(0.075)	(0.060)	(0.084)	(0.082)	(0.060)	(0.062)
$\ln(HHI_{i,T_0})$		0.465^a	-0.016	0.020	0.013	0.017
		(0.021)	(0.031)	(0.029)	(0.028)	(0.027)
$\ln(\#Dest_{i,T_0})$			-0.495^a			-0.388^a
			(0.016)			(0.011)
$\ln(Dist_{i,T_0})$					0.096^a	0.077^a
					(0.016)	(0.013)
FE hs2$\times$cty$\times$T	✓	✓	✓	✓	✓	✓
#Dest bins				✓		✓
Sample	#Dest>1	#Dest>1	#Dest>1	#Dest>1	#Dest>1	all firms
Obs.	668217	668217	668217	668217	668217	1296460

Notes: clustered SEs at country$\times$period and hs2$\times$period. Signif.: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

back

Appendix B2: Baseline regression tables (within-firm)

	(1)	(2)	(3)	(4)	(5)	(6)
Z = Geographic similarity						
$\ln(\Phi_{i,T_0})$	-0.239^a	0.139^a	0.200^a	0.194^a	0.180^a	0.213^a
	(0.027)	(0.043)	(0.045)	(0.045)	(0.044)	(0.037)
$\ln(HHI_{i,T_0})$		0.167^a	0.033^b	0.046^a	0.044^a	0.052^a
		(0.015)	(0.014)	(0.014)	(0.014)	(0.013)
$\ln(\#Dest_{i,T_0})$			-0.251^a			-0.194^a
			(0.015)			(0.012)
$\ln(Dist_{i,T_0})$					0.027^a	0.020^a
					(0.009)	(0.006)
FE hs2$\times$cty$\times$T	✓	✓	✓	✓	✓	✓
FE firm	✓	✓	✓	✓	✓	✓
#Dest bins				✓		✓
Obs.	380144	380144	380144	380144	380144	752241
Z = Business-cycle similarity						
$\ln(\Phi_{i,T_0})$	-0.425^a	0.191^a	0.205^a	0.207^a	0.202^a	0.257^a
	(0.055)	(0.042)	(0.046)	(0.046)	(0.044)	(0.049)
$\ln(HHI_{i,T_0})$		0.167^a	0.025^c	0.039^a	0.039^a	0.050^a
		(0.011)	(0.015)	(0.014)	(0.014)	(0.013)
$\ln(\#Dest_{i,T_0})$			-0.248^a			-0.193^a
			(0.014)			(0.012)
$\ln(Dist_{i,T_0})$					0.029^a	0.024^a
					(0.009)	(0.008)
FE hs2$\times$cty$\times$T	✓	✓	✓	✓	✓	✓
FE firm	✓	✓	✓	✓	✓	✓
#Dest bins				✓		✓
Obs.	379167	379167	379167	379167	379167	747168

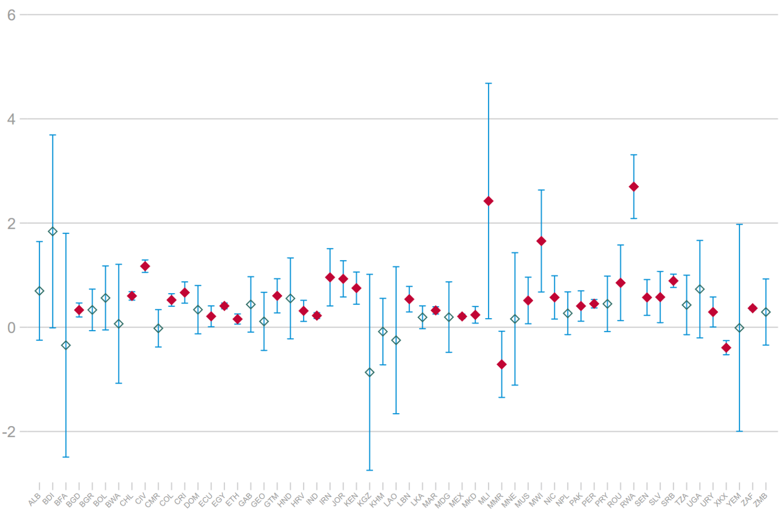
Notes: clustered SEs at country$\times$period and hs2$\times$period. Signif.: $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

back

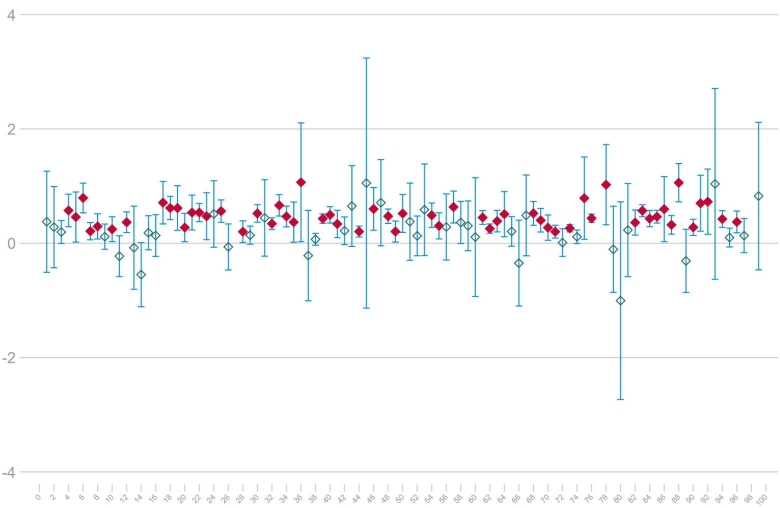
Appendix C0: Robustness and heterogeneity (navigation)

- Baseline robustness checks (tables): ▸ between-firm ▸ within-firm
- Country-by-country and product-by-product coefficients: ▸ by country ▸ by product
- Heterogeneity across subsamples: ▸ heterogeneity

Appendix C1: Between-firm estimates by country (geography)

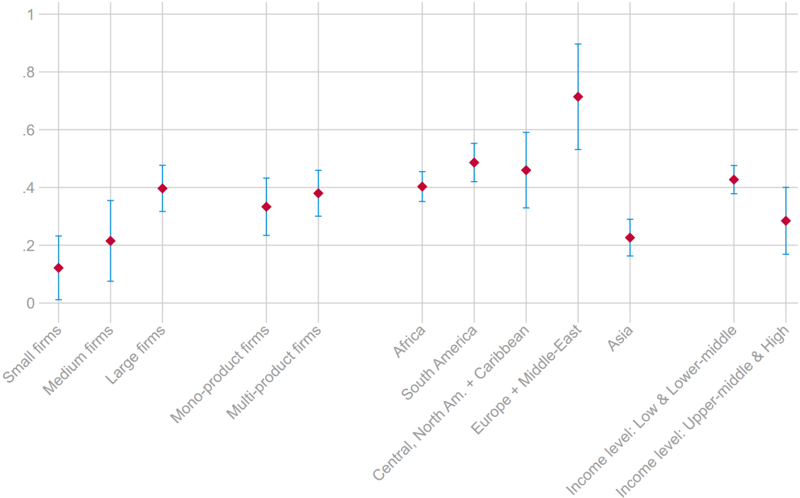


Appendix C2: Between-firm estimates by HS2 product (geography)



Appendix C3: Heterogeneity in the Φ–volatility relationship

Coefficients on ln(Φ) across subsamples



Appendix C4: Robustness checks – between-firm (Table 4)

	(1)	(2)	(3)	(4)	(5)
Dep var:	Vol	$\ln(\nu)$	$\ln(Vol)$	$\ln(Vol_{\Delta T})$	$\ln(Vol)$
T:	3y	3y	5y	3y	3y
Sample:	#Dest>1	#Dest>1	#Dest>1	#Dest>1	#Dest>4
Z = Geographic similarity					
$\ln(\Phi)$	0.058^a	0.485^a	0.382^a	0.363^a	0.370^a
	(0.010)	(0.043)	(0.040)	(0.056)	(0.035)
$\ln(HHI)$	-0.012	0.025	0.025	-0.046	0.073^a
	(0.010)	(0.024)	(0.029)	(0.029)	(0.028)
$\ln(Dist)$	0.024^a	0.075^a	0.075^a	0.087^a	0.078^a
	(0.004)	(0.013)	(0.014)	(0.014)	(0.024)
Z = Business-cycle similarity					
$\ln(\Phi)$	0.058^a	0.485^a	0.605^a	0.541^a	0.763^a
	(0.010)	(0.043)	(0.066)	(0.082)	(0.069)
$\ln(HHI)$	-0.012	0.025	0.045	-0.039	0.092^a
	(0.010)	(0.024)	(0.039)	(0.034)	(0.030)
$\ln(Dist)$	0.024^a	0.075^a	0.098^a	0.104^a	0.118^a
	(0.004)	(0.013)	(0.012)	(0.017)	(0.026)

Notes: clustered SEs at country$\times$period and hs2$\times$period. $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$. ▸ back

Appendix C5: Robustness checks – within-firm (Table 5)

	(1)	(2)	(3)	(4)	(5)
Dep var:	Vol	$\ln(\nu)$	$\ln(Vol)$	$\ln(Vol)$	$\ln(Vol)$
T:	3y	3y	5y	3y	3y
Sample:	#Dest>1	#Dest>1	#Dest>1	#Dest>1	#Dest>4
Z = Geographic similarity					
$\ln(\Phi)$	0.005	0.160^{a}	0.129^{a}	0.260^{a}	0.104
	(0.008)	(0.040)	(0.034)	(0.061)	(0.064)
$\ln(HHI)$	-0.003	0.039^{b}	0.047^{a}	-0.010	0.071^{a}
	(0.005)	(0.016)	(0.012)	(0.022)	(0.020)
$\ln(Dist)$	0.006^{a}	0.024^{a}	0.001	0.038^{a}	0.025
	(0.002)	(0.007)	(0.009)	(0.013)	(0.017)
Z = Business-cycle similarity					
$\ln(\Phi)$	0.010^{b}	0.201^{a}	0.136^{a}	0.293^{a}	0.092
	(0.005)	(0.025)	(0.044)	(0.087)	(0.094)
$\ln(HHI)$	-0.001	0.053^{a}	0.045^{a}	-0.014	0.063^{a}
	(0.004)	(0.014)	(0.015)	(0.028)	(0.022)
$\ln(Dist)$	0.007^{a}	0.015^{c}	0.010	0.045^{a}	0.018
	(0.002)	(0.008)	(0.007)	(0.015)	(0.020)

Notes: clustered SEs at country × period and hs2 × period. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$. ▸ back

Appendix C6: Additional robustness (Tables 8–9)

- Additional checks (paper Appendix): winsorizing volatility, controlling for initial exports, restricting to large country$\times$product cells, dropping largest countries.

	(1) Wins.	(2) +ln X_0	(3) $>$500 firms	(4) Drop big C
Between-firm, Z = Geographic				
ln(Φ)	0.272^a	0.246^a	0.343^a	0.475^a
	(0.030)	(0.052)	(0.041)	(0.032)
Within-firm, Z = Geographic				
ln(Φ)	0.130^a	0.119^a	0.190^b	0.149^a
	(0.030)	(0.046)	(0.087)	(0.041)

(Full tables for both Z matrices in paper Appendix Tables 8–9.) back