Shifting Alliances – Friendshoring in Agricultural Trade

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Selected presentation for the International Agricultural Trade Research Consortium's (IATRC's) 2023 Annual Meeting: The Future of (Ag-) Trade and Trade Governance in Times of Economic Sanctions and Declining Multilateralism, December 10-12, 2023, Clearwater Beach, FL.

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2023 IATRC Annual Meeting
Dec 10-12, Clearwater Beach FL

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Outline

Background

Uncertainties

- → Uncertainty about the future has significant impact on the economy - investment, output, trade ...
- → Uncertainty can arise from various sources - conflicts (political/armed/trade), economic, ...

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- Machine Learning vs. traditional methods ...

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→ Machine Learning vs. traditional methods ...

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ARTICLE

Anomalies in agricultural trade: A Bayesian classifier approach

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Abstract
This study examines the uncertainty-agricultural trade nexus. Uncertainty effects on macroeconomic indicators such as consumption and investment have been well studied. However, less is known about the relationship between uncertainty and international trade, particularly the heterogeneity of that linkage across sectors. Application of a novel data-driven methodology—anomaly detection and classification via a Naïve Bayesian Classifier—to monthly data at the HS-4 level finds that agricultural imports are reduced when economic policy uncertainty is high. The effects of policy-related uncertainty are more persistent than that of supply-side fluctuations. Anticipatory stock-piling occurred when uncertainty is specific to trade policy.

KEYWORDS
anomaly detection, machine learning, policy uncertainty

JEL CLASSIFICATION
F14, C45, Q17

Friendshoring

→ **Three Cs: consequences and considerations**
- COVID - Severe disruptions to the supply/demand sides
- Conflict - Escalating political and armed disputes
- Climate Change - Ongoing discussions about the future of production and distribution

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→ **Additional uncertainties** $\Longrightarrow$ Restructuring of supply chains: rivals $\rightarrow$ allies

Friendshoring

- → **Three Cs: consequences and considerations**
  - ◇ COVID - Severe disruptions to the supply/demand sides
  - ◇ Conflict - Escalating political and armed disputes
  - ◇ Climate Change - Ongoing discussions about the future of production and distribution
- → **Additional uncertainties** $\implies$ Restructuring of supply chains: rivals $\rightarrow$ allies
- → **Resiliency vs. Efficiency/Costs**
  - ◇ $\approx$ 5% drop in global production (WTO)
  - ◇ $\approx$ 2% drop in global economic output (IMF)

Background

MITSloan Management Review

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MAGAZINE SUMMER 2020 ISSUE / FRONTIERS

Is It Time to Rethink Globalized Supply Chains?

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Willy Shih • March 19, 2020 Reading Time: 7 min

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Biden's Trade Challenge: Kicking the China Dependency Habit

Officials want to avoid trade deals whose rules boost China's role in supply chains

By Greg Ip Follow

June 22, 2023 12:01 am ET

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U.S., Allies Weigh How to Reduce Economic Ties With China

Countries seek to lessen dependence on China but maintain global trade, investment

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Updated April 17, 2023 5:14 pm ET

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"Rather than being highly reliant on countries where we have geopolitical tensions and can't count on ongoing, reliable supplies, we need to really diversify our group of suppliers. "

Janet Allen, US Treasury Secretary (2022)

"We have no eternal allies, and we have no perpetual enemies. Our interests are eternal and perpetual, and those interests it is our duty to follow. "

Lord Palmerston, UK Prime Minister (1848)

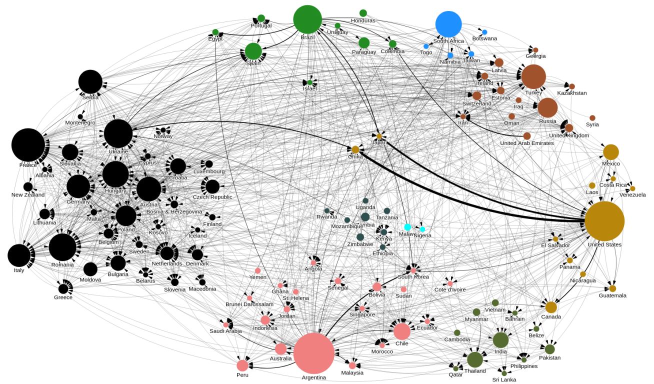
Data and Methods

Data

Data Summary

Product	HS4-Code	2021 Trade Value (billions of USD)	Source
Meats			
Fresh/chilled Beef	HS-0201	28.8	IHS Markit
Frozen Beef	HS-0202	32.8	IHS Markit
Pork	HS-0203	36.9	IHS Markit
Sheep/Goat	HS-0204	10.5	IHS Markit
Chicken	HS-0207	30.6	IHS Markit
Grains and Legumes			
Wheat	HS-1001	61.8	UN-Comtrade
Corn	HS-1005	52.3	IHS Markit
Rice	HS-1006	28.4	UN-comtrade
Soybean	HS-1201	78.5	IHS Markit
Edible Oils			
Soybean Oil	HS-1507	17.1	IHS Markit
Peanut Oil	HS-1508	0.713	IHS Markit
Palm Oil	HS-1511	51.1	IHS Markit
Sunflower Oil	HS-1512	16.7	IHS Markit
Rapeseed Oil	HS-1514	12.3	IHS Markit

Network Approach



Corn Trade Network for 2022

→ Nodes (countries) and Edges (trade)

→ Networks dynamics for analyses and prediction

◇ *Centrality Measures, Community Detection, Global Clustering*

Centrality Measures

→ **Degree Centrality**

- Measures connections to other nodes
- Higher degree centrality $\implies$ trades with more partners
- eg: more friends on Facebook
- In directed networks, in-degree = imports partners & out-degree = exports partners
- $D_i = \sum_j e(i,j)$, where $e(i,j) = 1$ if link present, 0 otherwise

→ **Betweenness Centrality**

- Measures connections facilitated between other nodes
- Higher betweenness centrality $\implies$ acts like a bridge
- eg: mutual friends with lots of people
- $B_i = \sum_{a,b} \frac{n_{aib}}{n_{ab}} =$ fraction of optimal paths between a and b passing through i

→ **Laplacian Centrality**

- Measures global influence on the network
- Higher Laplacian centrality $\implies$ large change in the network if removed
- eg: friends with *popular* people
- $L_i = \frac{E_L(G) - E_L(G_i)}{E_L(G)}$, $E_L(G) =$ Laplacian Energy & $E_L(G_i)$ Laplacian Energy with i removed

Community Detection

→ Community = groups of nodes that are densely interconnected.

→ More connections within communities and few between communities.

→ Identified by maximizing ***modularity***: (Zhu, Chen, and Zeng, 2020)

$$Q = \sum_{c=1}^{N} \left[\frac{L_c}{m} - \lambda \left(\frac{k_c^{in} k_c^{out}}{2m} \right) \right],$$

L_c = number of intra-community links in community c,
m = number of edges in community,
λ = resolution limit,
k_c^{in}, k_c^{out} = sums of in- and out-degrees of nodes in community c,

→ To detect optimal communities for each commodity for each year:
- ⋄ assign each node to its own community
- ⋄ join pairs of communities such that modularity is maximized
- ⋄ conclude when no further modularity increase is possible

Clustering

→ Measures tendency of connectivity within a network.

→ Function of *triangles* observed in a network vs. total *triangles* possible.

→ For a weighted directed network, clustering coefficient of each node i:

$$i_c = \frac{N_i}{2(deg^{tot}(i)(deg^{tot}(i)-1)-2deg^{false}(i))} \qquad \frac{\Delta\text{s observed}}{\text{total }\Delta\text{s possible}}$$

N_i = number of directed triangles through node i,
deg_i^{tot} = sum of in- and out-degrees of node i,
deg_i^{false} = number of "false" triangles through node i

→ The global clustering coefficient of the whole network is the average of clustering coefficient for all nodes:

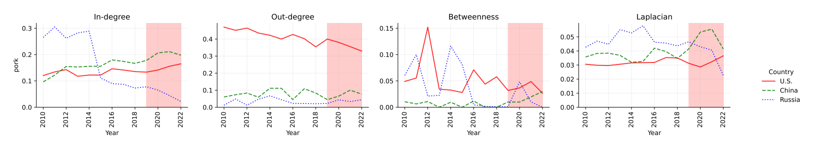
$$\text{Average Clustering Coefficient}(G_c) = \frac{1}{I}\sum_i^I t_i,$$

I = number of nodes in the network,
t_i = clustering coefficient for each node i

Results

Centrality Changes - Pork

Centrality Changes for Pork



→ China now imports from more partners.

→ US exporting to fewer partners, Russian imports have collapsed.

→ Betweenness decreasing for all countries.

→ China's influence on global network is remarkably higher compared to the US.

Community Detection - Pork

	Average Number of Communities					
Commodity	**1995-1999**	**2000-2004**	**2005-2009**	**2010-2014**	**2015-2019**	**2020-2022**
Pork	6.6	6.6	6.4	7.6	8.4	8.67

→ Number of communities increasing $\Longrightarrow$ network more divided

Community Detection - Pork

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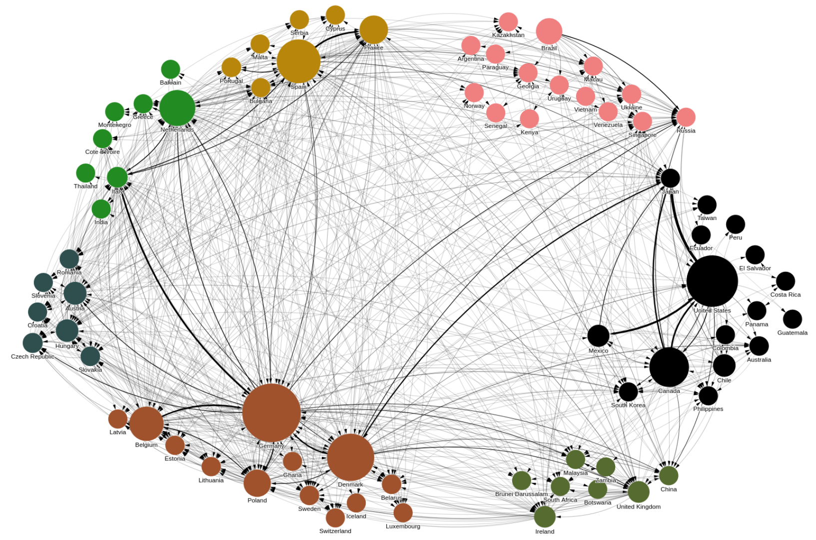
→ Number of communities increasing $\Longrightarrow$ network more divided

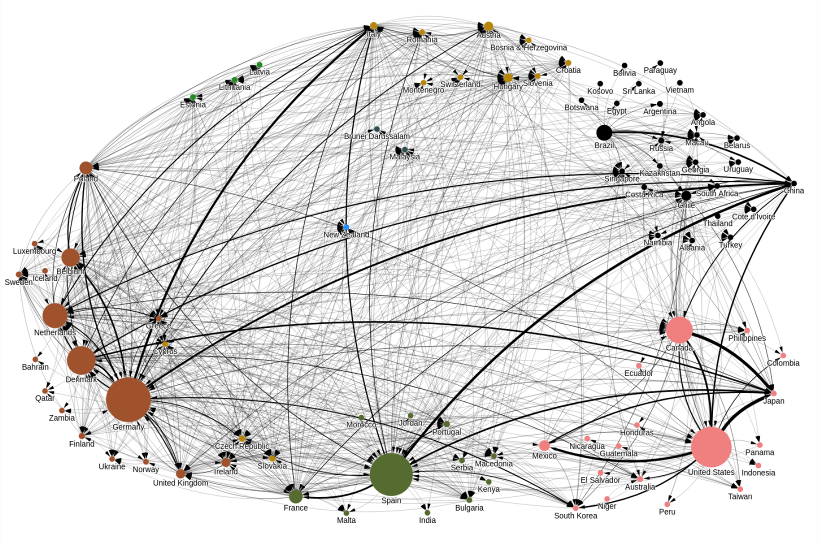
Year	China community	imps	exps	US community	imps	exps	Russia community	imps	exps
2011	Australia, Canada, Chile, China, Colombia, Costa Rica, Indonesia, Japan, Mexico, Peru, Philippines, South Korea, Taiwan, United States ... (20)	10.61	8.64	Australia, Canada, Chile, China, Colombia, Costa Rica, Indonesia, Japan, Mexico, Peru, Philippines, South Korea, Taiwan, United States ... (20)	10.61	8.64	Argentina, Brazil, Ecuador, Egypt, Georgia, Kenya, Macau, Paraguay, Russia, Senegal, Singapore, Ukraine, Uruguay, Venezuela, Vietnam (15)	2.78	0.85
2013	Botswana, Brunei Darussalam, China, Ireland, Malaysia, Namibia, South Africa, United Kingdom, Zambia (9)	2.51	0.67	Australia, Canada, Chile, Colombia, Indonesia, Japan, Mexico, Peru, Philippines, South Korea, Taiwan, United States ... (21)	8.56	7.46	Argentina, Brazil, Egypt, Georgia, Kazakhstan, Kenya, Macau, Norway, Paraguay, Russia, Senegal, Singapore, Ukraine, Uruguay, Venezuela, Vietnam (16)	3.04	0.96
2015	Bolivia, Chile, China, Costa Rica, Peru, South Korea	3.02	0.73	Belize, Canada, Colombia, Ecuador, El Salvador, Guatemala, Honduras, Indonesia, Japan, Mexico, Nicaragua, Panama, Taiwan, United States (12)	6.92	6.81	Argentina, Australia, Belarus, Brazil, Congo, Egypt, Malaysia, Paraguay, Russia, Senegal, Serbia, Singapore, Thailand, Ukraine, UAE, Uruguay, Vietnam ... (21)	2.09	1.26
2017	China, Ireland, Qatar	2.35	0.34	Canada, Colombia, Ecuador, El Salvador, Ghana, Guatemala, Honduras, Indonesia, Japan, Mexico, Nicaragua, Panama, Philippines, Taiwan, United States (15)	8.46	7.59	Argentina, Australia, Belarus, Brazil, Cote d'Ivoire, Egypt, Kazakhstan, Mozambique, Nigeria, Paraguay, Russia, Singapore, South Africa, Ukraine, Uruguay, Venezuela ... (23)	2.06	1.46
2019	Argentina, Belarus, Brazil, Chile, China, Egypt, Georgia, Paraguay, Russia, Singapore, South Africa, Sri Lanka, Thailand, Turkey, Uruguay, Vietnam ... (22)	5.73	1.93	Australia, Canada, Colombia,Guatemala, Indonesia, Japan, Mexico, Peru, Philippines, South Korea, Taiwan, United States ... (15)	10.14	7.63	Argentina, Belarus, Brazil, Chile, China, Egypt, Georgia, Paraguay, Russia, Singapore, South Africa, Sri Lanka, Thailand, Turkey, Uruguay, Vietnam ... (22)	5.73	1.93
2021	Argentina, Brazil, China, Egypt, France,Kenya, Paraguay, Portugal, Serbia, Singapore, Spain, Uruguay, Vietnam ... (24)	12.03	10.55	Canada, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Japan, Mexico, Nicaragua, Panama, Philippines, Thailand, United States (13)	9.36	9.72	Belarus, Russia	0.12	0.08

Notes: All imports and exports figures are in billions of US$. Numbers in parentheses at the end of the community column represent the number of members in the community.

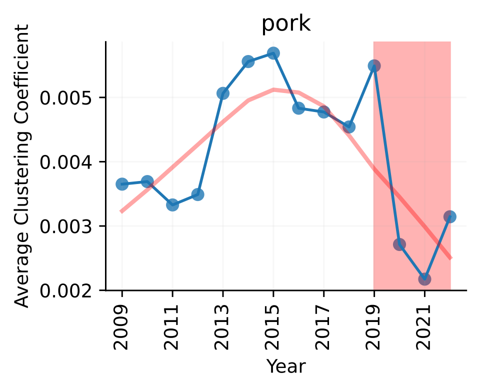
Communities - Pork (2013)



Communities - Pork (2019)



Clustering - Pork

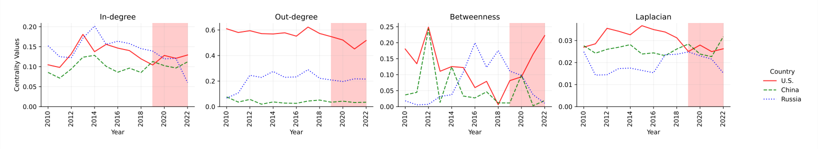


→ Declining clustering coefficient $\implies$ decline in network stability (less interconnected than before)

→ Same pattern is observed in other food commodities.

Centrality Changes - Corn

Centrality Changes for Corn



→ China's now imports from more partners.

→ US not exports to fewer partners.

→ Betweenness decreasing for all countries, US trends upwards after Phase One agreement and COVID recovery.

→ US's influence on global network is declining.

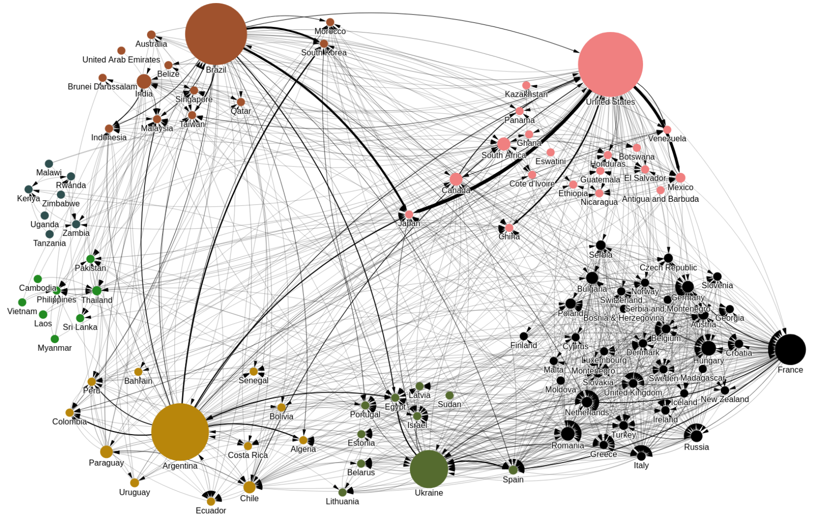
Community Detection - Corn

	Average Number of Communities					
Commodity	**1995-1999**	**2000-2004**	**2005-2009**	**2010-2014**	**2015-2019**	**2020-2022**
Corn	7.0	7.2	6.6	7.2	6.8	7.33

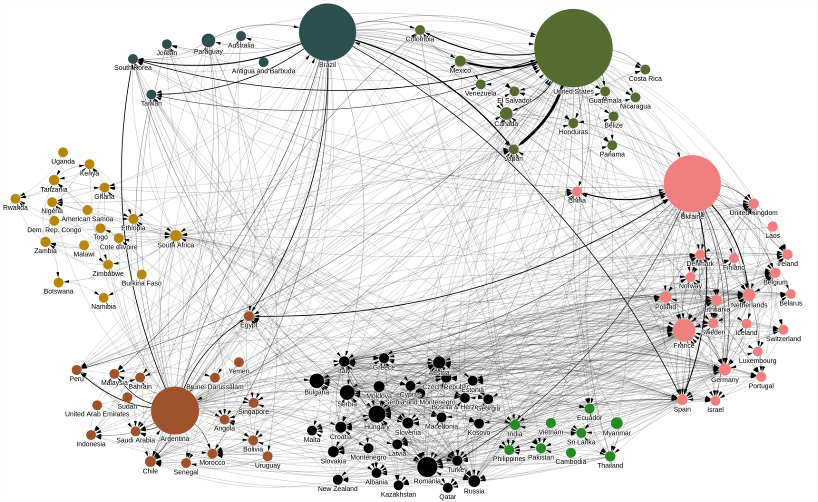
Year	China community	imps	exps	US community	imps	exps	Russia community	imps	exps
2011	Australia, Canada, China, Ghana, Guatemala, Honduras, Japan, Mexico, Namibia, Nicaragua, South Africa, South Korea, United States ... (22)	13.18	15.59	Australia,Canada, China, Ghana, Guatemala, Honduras, Japan, Mexico, Namibia, Nicaragua, South Africa, South Korea, United States ... (22)	13.18	15.59	Albania, Austria, Belgium, France, Germany, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Syria, Turkey, United Kingdom ... (36)	7.20	6.56
2013	Canada, China, Ghana, Japan, Mexico, Nicaragua, South Africa, United States, Venezuela ... (19)	10.97	8.02	Canada, China, Ghana, Japan, Mexico, Nicaragua, South Africa, United States, Venezuela ... (19)	10.97	8.02	Austria, Belgium, France, Georgia, Germany, Greece, Hungary, Ireland, Italy, Netherlands, New Zealand, Norway, Poland, Romania, Russia, Serbia, Sweden, Switzerland, Turkey, United Kingdom ... (36)	7.29	7.11
2015	China, Egypt, Estonia, Israel, Kazakhstan, Laos, Lithuania, Myanmar, Portugal, Ukraine (10)	3.66	3.77	Bolivia, Canada, Colombia, Japan, Mexico, Peru, United States, Venezuela ... (15)	9.08	9.68	Belarus, Belgium, Bulgaria, France, Georgia, Germany, Greece, Hungary, Italy, Netherlands, New Zealand, Norway, Poland, Romania, Russia, Spain, Sweden, Switzerland, Turkey, United Kingdom ... (37)	7.06	5.92
2017	Belgium, China, Denmark, Finland, France, Germany, Ireland, Israel, Netherlands, Norway, Poland, Portugal, Qatar, Spain, Ukraine, United Kingdom ... (22)	6.46	5.74	Canada, Colombia, Japan, Kazakhstan, Mexico, Peru, United States, Venezuela ... (16)	8.99	10.36	Albania, Australia, Georgia, Macedonia, Montenegro, Russia, Serbia, Serbia and Montenegro, South Korea, Turkey ... (14)	2.69	1.24
2019	Belarus, Belgium, China, France, Germany, Iceland, Israel, Netherlands, Poland, Spain, Ukraine, United Kingdom ... (22)	8.61	7.77	Belize, Canada, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Japan, Mexico, Nicaragua, Panama, United States, Venezuela (14)	8.15	7.99	Austria, Bulgaria, Croatia, Cyprus, Georgia, Greece, Hungary, Italy, Kazakhstan, New Zealand, Qatar, Romania, Russia, Serbia, Turkey ... (28)	3.62	4.12
2021	Canada, China, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Japan, Mexico, Panama, United States, Venezuela (12)	19.69	17.81	Canada, China, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Japan, Mexico, Panama, United States, Venezuela (12)	19.69	17.81	Georgia, Iran, Iraq, Ireland, Russia, Singapore, Turkey, UAE, United Kingdom (20)	5.09	3.65

Notes: All imports and exports figures are in billions of US$. Numbers in parentheses at the end of the community column represent the number of members in the community.

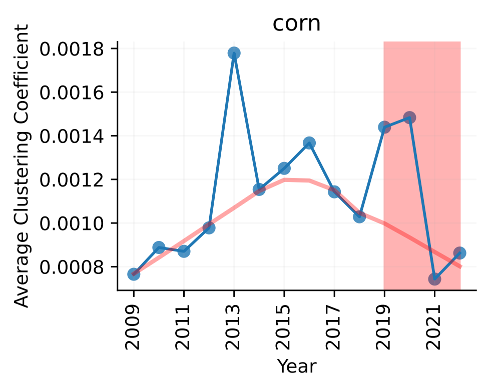
Communities - Corn (2013)



Communities - Corn (2019)

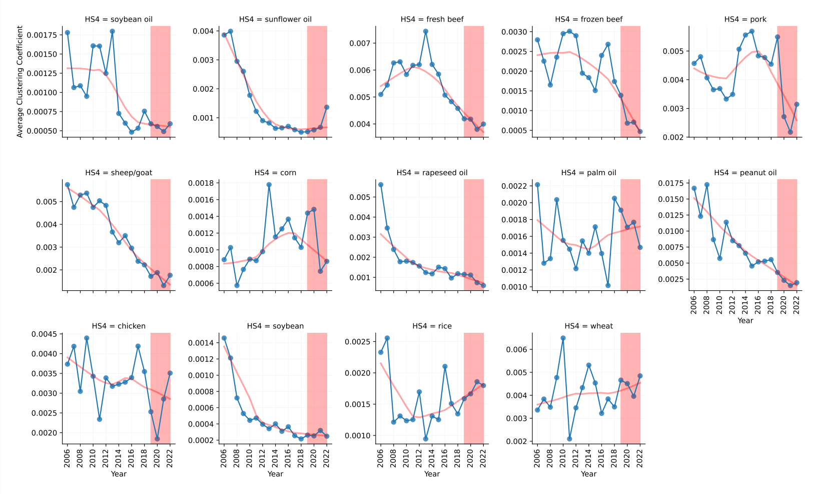


Clustering (Corn)



→ Declining clustering coefficient, similar to pork and other commodities.

Clustering


HS4 = soybean oil
HS4 = sunflower oil
HS4 = fresh beef
HS4 = frozen beef
HS4 = pork
HS4 = sheep/goat
HS4 = corn
HS4 = rapeseed oil
HS4 = palm oil
HS4 = peanut oil
HS4 = chicken
HS4 = soybean
HS4 = rice
HS4 = wheat
Average Clustering Coefficient
Year

Takeaways

Takeaways and Future

→ Food supply chains are changing: new influencers, more sub-chains, tendency towards deglobalization.

→ Friendshoring in early stages...

→ Resiliency and safeguards are major thrust areas.

→ Food security is under threat if supply chains deglobalize (availability and access issues).

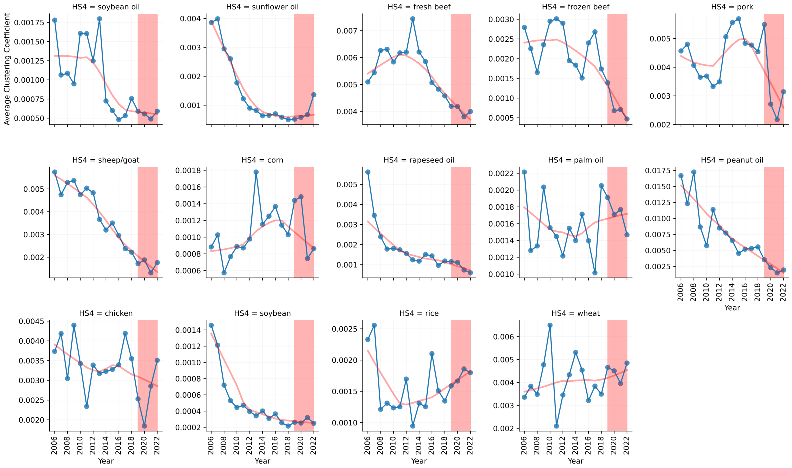
Appendix

Centrality Measures

Community Detection

Commodity	Average Number of Communities					
	1996-2000	2001-2005	2006-2010	2011-2014	2015-2019	2020-2022
Meats						
Fresh/chilled beef	4.8	6.6	9.4	8.4	8.6	7.00
Frozen beef	6.0	7.8	5.4	7.2	7.2	8.33
Pork	6.6	6.6	6.4	7.6	8.4	8.67
Sheep/goat	6.2	6.4	6.0	7.6	9.4	7.33
Chicken	6.0	7.0	6.4	7.2	8.4	7.33
Grains and Legumes						
Wheat	7.0	8.6	8.2	7.8	8.4	9.0
Corn	7.0	7.2	6.6	7.2	6.8	7.33
Rice	8.4	9.8	9.0	8.2	8.8	9.33
Soybean	8.8	8.2	7.2	8.0	8.6	11.33
Edible Oils						
Soybean Oil	6.0	7.0	9.4	9.6	9.2	9.33
Peanut Oil	4.6	5.2	4.6	5.8	5.4	5.0
Palm Oil	8.8	11.0	9.4	11.4	11.8	13.33
Sunflower Oil	5.2	7.6	8.2	8.8	9.0	9.0
Rapeseed Oil	5.0	7.2	7.0	7.4	7.6	6.67

Clustering



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Average Clustering Coefficient
Year