Transformation towards sustainable and resilient societies in Asia and the Pacific

Technical Annexes

UNITED NATIONS ESCAP
Economic and Social Commission for Asia and the Pacific

ADB

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Technical Annex for Chapter 1

Examining the Resilience of Agricultural and Food Commodity Trade Networks in the Asia and Pacific Region

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Report Summary

With the increasing effects of globalization and the interdependence of nations through cross-border movement of goods, global commodity trade networks represent one of the most critical networks for sustainable development. A significant benefit of globalization has been the ability of an increasing percentage of the world's population to rely more on dynamic trade networks to meet their staple food demands. Given the future uncertainties of regional crop yield loss due to climate change and an increasing global population, the role of trade for food security is anticipated to be further enhanced. However, due to the complexities of commodity trade networks, this increasing reliance of food security on trade networks also results in the vulnerability to the propagation of natural and economic shocks through global supply and demand chains. From this background, research on the resilience of food and agricultural commodity trade networks has gained increasing attention by policymakers.

A promising a research approach for identifying the system-level properties of a network is the ecological network analysis. Rooted in observations from natural ecological networks, this approach reveals a tradeoff between 'network efficiency' and the resilience of networks. Network efficiency reflects the degree of articulation or constraints of flows in a network. Previous research has indicated that similar to natural systems, between 1996 to 2012 global commodity trade sectors exhibited higher growth rates with higher levels of network efficiency while sectors with lower levels of efficiency, i.e., more redundant networks, exhibited higher resilience of growth after the 2009 global economic crisis.

Using the ecological network analysis, this report examines the trends of the network efficiency of 74 critical staple agricultural commodities in the Asia and Pacific region from 1986 to 2013. Results indicate that the majority (73%) of critical food and agricultural networks have exhibited a positive trend in their network efficiencies. A comparison of the yearly standard deviation of each network relative to all other food and agricultural networks may reveal excessive network efficiency and a lower capacity to maintain resilience to natural and economic disruptions.

An important driver of the increase in the network efficiency of the examined networks can be related to the decreasing rate of tariffs due to trade liberalization, especially through proliferation of preferential trade agreements (PTAs). A fixed effects model regression of overlapping food and agricultural networks and their weighted average preferential tariff rates imposed by UN-ESCAP member countries confirms the existence of a strong negative relationship between preferential tariff rates and trade network efficiency. These results were confirmed while considering for average imports and Most Favored Nations (MFN) tariffs as control variables.

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The results of this report indicate the need for more research on the network dynamics of critical commodities (such as food commodities) and development of indicators based on the ecological network analysis to guide resilient sectoral and trade policies. Countries need to put in more thought on how to integrate strategic provisions within trade agreements, especially PTAs, to ensure greater resilience of their trade networks. Countries need to examine closely the previous responses of trade networks to shocks and disruptions and generate high-frequency data on trade flows to enable such analysis.

1. Introduction

Global commodity trade is the most critical network of our modern age and as reflected in the Sustainable Development Goals [1], to accommodate growing populations, overcome poverty, and end hunger, the sustainable growth of global trade networks is a priority for humankind. Global trade is not only vital to economic development and as countries increasingly rely on international trade to meet their growing demand for agricultural commodities, global trade is also vital to food security. Agricultural trade is essential in maintaining supplies, stabilizing prices, and providing alternative food options – most importantly for vulnerable regions. Between 1985 and 2011, the total value of global agricultural exports has tripled in real terms, from around $ 250 billion USD to more than $ 750 billion USD [2]. As a result of global food trade, around 80% of humans now live in net-food-importing countries [3].

Given the expansion of globalization over the last century, commodity trade networks have grown in volume, complexity, and are increasingly vulnerable to the propagation of shocks throughout their supply and demand chains. As countries and regions become more reliant on international trade for their food security, they will be vulnerable to the network propagation of risk. In a highly interconnected global network, local or global shocks, e.g., economic crises, political instability, and climatic disaster, can be propagated faster and adversely affect the production, export, and import of traded goods. A prominent example was the 2009 global economic crisis which drastically impacted the necessary trade and investment for sustaining food and agricultural systems – especially in the emerging and least developed countries [4]. Therefore, the resilience of trade networks and the need to address system-level risks has become a subject of increasing attention in recent years by both policymakers and business practitioners. In this avenue, researchers have focused on understanding the structure of economic networks and their capacity to respond to shocks and stresses.

Given the evolutionary history of natural systems over centuries and millennia [5], new insights arising from our understanding of the resilience of natural networks can be useful to understand the resilience of food trade networks. In this avenue, the ecological network analysis is a promising approach for identifying holistic properties based on an analysis of the network flows of material, energy, or information. The ecological network analysis has revealed a fundamental tradeoff between 'network efficiency' and 'network redundancy', where networks exhibit higher growth with higher levels of efficiency and higher resilience with higher levels of redundancy. While systems in the long-term exhibit a potential to increase their efficiency at the expense of redundancy [6], [7], the relative dominance of these two system variables varies based on the system's environmental constraints and decisions of its agents.

Network efficiency reflects the degree of articulation or constraints to network flows. Efficiency tends to increase naturally in systems where agents select preferential interactions with other agents using a combination of competition and cooperation to develop pathways with higher intensity and specialization of resource flows. In global trade systems, preferential interactions are largely determined by locational proximity, cultural links, and strategic partnerships supported, for example, through targeted trade agreements. Network redundancy, on the other hand, reflects the degree of freedom or overhead in the network of flows. Redundancy is exhibited as the diversity of pathways and is critical for a system's capacity for innovation and ability to adapt to changing environmental conditions arising from shocks and disturbances. In global trade systems, the ability to choose from different agents of supply and demand is central to free-market principles and enables maneuverability in supply. Previous research has indicated that similar to natural systems, between 1996 to 2012 global commodity trade sectors exhibited higher growth rates with higher levels of network efficiency while sectors with higher levels of network redundancy exhibited higher resilience of growth after the 2009 global economic crisis [8].

1.1. Research Questions

This report examines the trends of the network configurations of 74 critical staple agricultural commodities in the Asia and Pacific region (see Appendix 1 for a list of regions). By doing so, this report seeks to answer the following research questions:

a. How have network configurations impacting the resilience of critical food agricultural commodities evolved over the years from 1986 to 2013?
b. What has been the role of preferential trade agreements (PTAs) in the observed network configuration trends?

The examined critical food and agricultural commodities not only feed billions of individuals but also indirectly affect the production and consumption of other food and energy systems across the region. Given the growing uncertainty to meet future demand for staple foods and loss of production yields due to climate change [9], the role of trade in balancing agricultural commodity market disparities is further enhanced.

One of the most influential mechanisms in shaping future trade networks are preferential trade agreements (PTAs). PTAs are strategic instruments leveraged towards the reduction or elimination of barriers to the flow of commodity goods. The Asia-Pacific region has been a major contributor to the growth of PTAs, where, currently, 167 PTAs, 63% of the global total, are established [10]. The increasing growth of PTAs increases the drive towards further regional trade liberalization. In this avenue, further research on the influence of PTAs on the network configuration of agricultural and good trade networks is warranted.

2. Data and Methodology

The data of this study were derived from the United Nations – Food and Agriculture Organization (UN-FAO) dataset. This dataset includes annual cross-border trade flows of food and agricultural products by all countries in the world. For the purposes of this research the import and export values of (74) commodity networks among the Asian, Pacific, and all other countries were examined between from 1986 to 2013. Each of these agricultural and food commodity networks represents a densely interconnected network of international trade within the Asia and Pacific region. Weighted average preferential tariff rates imposed by UN-ESCAP member countries were derived from the World Integrated Trade Solutions (WITS) database. Table 1 displays a list of all commodity networks and Appendix 1 displays a list of all Asia and Pacific regions examined for this research.

In the interest of repeating our results, the following technical issues should be mentioned. Firstly, it is not uncommon to see a directed trade flow reported twice in the database with a large difference between the two values, i.e., one by an importing country and one by an exporting country. This difference may be due to the fact that the data reported by the importer is based on Cost, Insurance, and Freight (CIF) accounting whereas the data reported by the exporter is based on Free-On-Board (FOB) accounting. With the assumption that imports are carefully scrutinized for taxing purposes and therefore more accurate, primacy was given to the importer's reports when available. Secondly, the reported flows are based on nominal US dollar values and therefore were adjusted to real values using US dollar Commodity Price Index (CPI) inflation data from the U.S. Bureau of Labor Statistics.

3. Results

The slopes of the linear trend-lines reveal the long-term network efficiency of the food and agricultural commodity trade networks (Table 1). Out of the 74 examined networks, the majority of networks, i.e. 54 networks or 73% of all examined networks, exhibited a positive trend in their network efficiency while only 24 exhibited a negative trend. Among all networks, 17 networks, maintaining a trend-line slope between 0.003 and -0.003, did not exhibit any major discernable long-term change. Among the 24 networks with a negative trend-line slope, only 10 networks exhibited a discernable decreasing trend-line slope between -0.003 and -0.0151. Networks maintaining a trend-line slope between 0.003 and 0.0150 exhibited positive long-term growth of their network efficiency. Finally, 13 networks exhibited significant growth in their long-term network efficiency with trend-line slopes higher than 0.150. A time fixed effects model also confirms the initial observation of an overall increase in efficiency among all networks (P>0.00). See Appendix 2 for full results. These findings are in line with observations in other natural and social networks, whereby in the long-term, systems tend to increase their efficiency at the expense of their redundancy [6].

A detailed examination of the trend of the network efficiency and the yearly standard deviation relative to all networks reveals interesting observations (Figure 1). As an example, we examine one critical staple commodity within each trend-line category: soybeans (decreasing trend); rice (flat trend); wheat flour (increasing trend); and wheat (high increase trend).

In the soybean trade network, the network efficiency fluctuates between a high level of .15 and .23 nats from 1986 to the early 1990's and continues to gradually decrease and settle down to a lower range of around .05 nats. This indicates the gradual decrease of the constraints of the soybean trade network and reflects the increasing production and trade of soya in the Asia and Pacific regions. The standard deviation of the network efficiency of soybean trade begins at -1 late 1980's and decreases to a lower basin of -2 in the later years. This indicates that in comparison to other trade agricultural and food commodity trade networks, soybean trade has expanded its diversity and flexibility of trade pathways.

In the rice trade network, we observe a steady fluctuation of network efficiency for the majority of years between 1986 and 2013 and with no noticeable trend. The standard deviation of rice trade has also remained steady for the majority of years and fluctuating between .05 and -0.05. This indicates an average level of network efficiency of rice trade in comparison to other commodities. These results reflect the fact that rice remains one of the most protected agricultural food commodities and is produced locally with extremely low levels of global import and export [11].

The flour wheat trade network has gradually increased its network efficiency, starting from levels of around 1.0 nats in the late 1980's and early 1990s to a higher level of 1.4 nats in 2013. Despite its sudden drop in 2008-2010, reflecting the global economic and food crises of 2009, the wheat flour trade network resumed its long-term increasing trend. Wheat flour is one of the most heavily traded agricultural commodities globally and also within the Asia and Pacific region. This critical staple commodity network has maintained an above average standard deviation for the majority of years and even reaching a high standard deviation of 3 in more recent years. These results indicate that, in comparison to other agricultural and food commodity networks, the wheat flour trade network is becoming increasingly constrained and therefore brittle in the Asia and Pacific region.

Among the critical staple commodity trade networks, wheat trade exhibits one of the highest increases in its network efficiency level. This trade network maintained network efficiency levels of 0.2 nats in the early 1990’s and a rise and settlement to a higher basin of network efficiency around 0.6 nats. The standard deviation of rice trade has also seen a shift; beginning with a standard deviation in the range of -1 until the mid-1990’s and shift to a higher standard deviation range of 0.5 in more recent years. Similar to wheat flour, these results indicate that the trade network of wheat, in comparison to other networks, is increasingly becoming constrained.

One of the main drivers of network efficiency within trade networks can be due to preferential trade and more specifically tariffs imposed by countries on imported goods. To examine such a relationship, a fixed effect model regression was conducted between 33 food and agriculture product networks and their matching weighted average preferential tariff rates imposed by UNESCAP member countries. The fixed effects model results revealed a strong negative relationship between preferential tariff rates and network efficiency ($p>0.05$). When considering the average imports and also Most Favored Nations (MFN) tariff rates as control variables in the fixed effects model, results confirm the initial findings with no significant change in coefficient or significance of the preferential (PRF) tariff rates. A separate fixed effects model between 33 food and agricultural product networks and their matching Most Favored Nations (MFN) tariff rates did not reveal any significant relationship. See Appendix 3 for full results.

4. Discussion

Research on highly interconnected agriculture and food commodity trade networks emphasizes the importance of system-level network properties for informing relevant policy and practices. While the majority of previous research on international trade networks has focused on un-weighted binary relations among regions, new insights on global and regional trade dynamics can be achieved by taking under consideration the weights and intensity of trade flows. Towards this end, as countries and regions become more reliant on international trade for their food security, the ecological network analysis can reveal system-level network configurations relevant to the resilience of these trade networks to the potential shocks and disturbances.

Evolutionary and natural ecological traits can advance our ability to better situate the concept of resilience to commodity trade networks and inform policies and strategies relevant to sustainable development. In this report, the ecological network analysis was utilized to examine the network properties of 74 critical agricultural and food commodity networks between 1983 and 2013. Similar to natural ecological systems, the majority of these agricultural and food commodity trade networks exhibited a tendency to increase their network efficiency over the long-term, whereby regions select preferential interactions with other regions to develop pathways with higher intensity and specialization of trade flows.

4.1. Role of preferential trade agreements (PTA)

Trade liberalization can take several forms, however, countries and regions tend to lower their import tariffs concurrently with their trade partners. Such liberalizations can be in the form of preferential trade agreements (PTAs) among a group of countries. The main characteristic of a PTA is that lower tariffs are imposed on commodity goods produced in member countries than to those produced outside. As the Asia Pacific region continues to increasingly pursue the growth of PTAs, it is warranted to investigate their effects on the network configuration of critical food and agriculture products. Results from the fixed effects model regression of the food and agricultural networks and their corresponding weighted average tariffs rate confirm that tariffs are an important driving force in increasing the network efficiency of the examined trade networks.

The above results were re-confirmed when considering average imports and Most Favored Nations (MFN) tariff rates as control variables in the fixed effects model[2]. The inclusion of the control variables indicate that preferential (PRF) tariff rates made possible through the growth of PTAs in the Asia Pacific region have played a major contribution in the increase of efficiency in the examined networks from 1986-2013. Furthermore, the results also indicate that the increase of network efficiency was not driven by a reduction of MFN tariff rates made possible through the general multilateral trade liberalization over the years.

Given these results, it is evident that through lower tariff rates the cost of higher magnitude flow relationships are lowered and consequently the network efficiency is increased. Conversely, it can be assumed that through higher tariff rates the cost of higher magnitude flows increase and therefore network efficiency is decreased. While the increase in network efficiency may be in line with intuitive economic thinking suggesting the need to shorten supply and demand chains and the need to constrain the trade network to fewer and more economically advantageous regions. However, under the increasing network constrain, trade networks may be more vulnerable to the risk of becoming brittle and less flexible in their capacity to recover in the aftermath of trade shocks, such as, for example, a supply disruption or excessive price increase.

5. Conclusions

The ecological network analysis of the 74 critical agricultural and food commodity networks reveals the need for reconsidering the importance of maneuverability and flexibility of supply and demand partners for resilient trade. Preferential trade agreements, for example, through bilateral tariff reductions, can encourage more trade optimization and trade growth. However, the excessive focus of these strategies may lead towards overly constraining the trade networks and decreasing the network's capacity for resilience in the face of shocks. Therefore, it is essential to maintain a strategy which does not excessively encourage the efficiency of trade networks and where network redundancies are also encouraged. Lower levels of network efficiency entail more redundancy in trade and can be enhanced through the diversification of production among more regions for more export and import partners and trade flows with higher intensities.

Agricultural and food commodity trade networks encompass complex interactions among farmers, businesses, and public organizations. A multi-stakeholder initiative raising the awareness of the risk of excessive network efficiency can lead to better management and contingency plans for the diversification of trade among suppliers and consumers of agricultural and food commodities. To improve the precision of relevant policies and strategies, more research is warranted in simulating and quantifying the impact of shocks on these critical commodity networks. This can be achieved by collecting more precise datasets on commodity trade networks and examining the response of the network to previous shocks and disruptions at higher temporal granularities including quarterly, monthly, and real-time data. Most importantly, Countries need to put in more thought on how to

[2] For future research, a robustness check and possible corrections for collinearity can be conducted.

integrate strategic provisions within trade agreements, especially PTAs, to ensure greater resilience of their trade networks.

Table 1 Efficiency trendline slopes for agricultural and food networks (1986-2013).

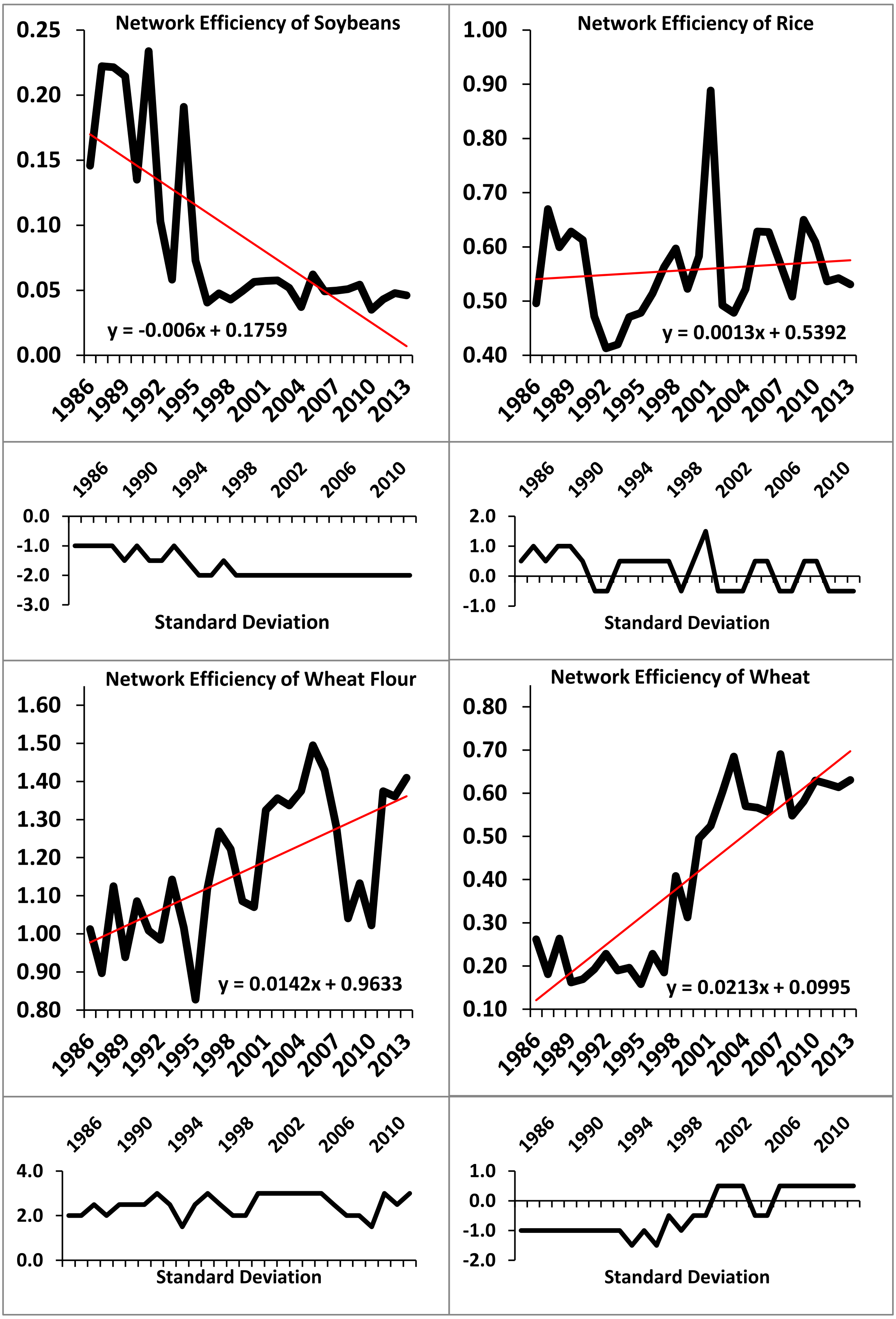
	Name of Network	Trendline
Decreasing Trend	Cotton, carded, combed	-0.0037
	Potatoes	-0.0044
	Oil, palm	-0.005
	Coffee, roasted	-0.0052
	Soybeans	-0.006
	Cocoa, beans	-0.0064
	Cocoa butter	-0.007
	Cheese, sheep milk	-0.0073
	Oil, olive, virgin	-0.0099
	Flour, pulses	-0.0131
	Lard	-0.0151

	Name of Network	Trendline
No Discernable Change – (flat slopes)	Flour, potatoes	0.0028
	Cocoa, paste	0.002
	Oil, soybean	0.002
	Oil, coconut (copra)	0.002
	Butter, cow milk	0.0019
	Rice	0.0013
	Meat, chicken	0.0011
	Meat, cattle	0.0001
	Oranges	-0.0004
	Plantains	-0.0006
	Cotton lint	-0.0008
	Flour, roots & tubers	-0.0008
	Apples	-0.001
	Meat, pork	-0.0014
	Coffee, green	-0.0016
	Juice, orange single strength	-0.0022
	Flour, cereals	-0.0027

	Name of Network	Trendline
Highly Increasing Trend	Sugar beets	0.0436
	Sweet potatoes	0.0309
	Meat, beef, preparations	0.0278
	Goats	0.0269
	Flour, mixed grain	0.0232
	Pigs	0.0229
	Bread	0.0217
	Wheat	0.0213
	Bananas	0.0193
	Oil, rapeseed	0.0192
	Bulgur	0.0183
	Milk, whole fresh cow	0.0161
	Chick peas	0.0161

	Name of Network	Trendline
Increasing Trend	Eggs, hen, in shell	0.015
	Flour, wheat	0.0142
	Eggs, dried	0.0137
	Sugar refined	0.0132
	Eggs, liquid	0.0127
	Millet	0.0122
	Cottonseed	0.0105
	Buckwheat	0.0104
	Oil, maize	0.0102
	Cheese, processed	0.0102
	Barley	0.0096
	Cotton waste	0.0096
	Meat, cattle, boneless	0.009
	Chickens	0.0089
	Juice, orange, concentrated	0.0086
	Sheep	0.0086
	Oats	0.0085
	Lentils	0.0083
	Duck	0.0081
	Sorghum	0.0074
	Oil, palm kernel	0.0071
	Oil Sunflower	0.006
	Meat pig	0.0054
	Maize	0.0051
	Cattle	0.005
	Cheese, whole milk cow	0.0047
	Cocoa, powder & cake	0.0047
	Cotton linter	0.0047
	Potato, frozen	0.0042
	Flour, maize	0.0042
	Cassava dried	0.0039
	Sugar Raw Centrifugal	0.0035
	Tea	0.0034

Figure 1: Network efficiency trends and corresponding standard deviation (relative to all networks) for soybeans, rice, wheat flour, and wheat.



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Appendix 1: List of UN-ESCAP regional and economic classifications and corresponding ISO3 and UN-FAOSTAT country codes.

UN-ESCAP Regions - Official Names	ISO3	FAOSTAT
The Islamic Republic of Afghanistan	AFG	2
the Republic of Armenia	ARM	1
Australia	AUS	10
the Republic of Azerbaijan	AZE	52
the People's Republic of Bangladesh	BGD	16
the Kingdom of Bhutan	BTN	18
Brunei Darussalam	BRN	26
the Kingdom of Cambodia	KHM	115
the People's Republic of China	CHN	41
the Republic of Fiji	FJI	66
Georgia	GEO	73
the Republic of India	IND	100
the Republic of Indonesia	IDN	101
the Islamic Republic of Iran	IRN	102
Japan	JPN	110
the Republic of Kazakhstan	KAZ	108
the Republic of Kiribati	KIR	83
the Democratic People's Republic of Korea	PRK	116
the Republic of Korea	KOR	117
the Kyrgyz Republic	KGZ	113
the Lao People's Democratic Republic	LAO	120
Malaysia	MYS	131
the Republic of Maldives	MDV	132
the Republic of the Marshall Islands	MHL	127
the Federated States of Micronesia	FSM	145
Mongolia	MNG	141
the Republic of the Union of Myanmar	MMR	28
the Republic of Nauru	NRU	148
the Federal Democratic Republic of Nepal	NPL	149
New Zealand	NZL	156
the Islamic Republic of Pakistan	PAK	165
the Republic of Palau	PLW	180
Independent State of Papua New Guinea	PNG	168
the Republic of the Philippines	PHL	171
the Russian Federation	RUS	185
the Independent State of Samoa	WSM	244
the Republic of Singapore	SGP	200
Solomon Islands	SLB	25
the Democratic Socialist Republic of Sri Lanka	LKA	38
the Republic of Tajikistan	TJK	208
the Kingdom of Thailand	THA	216
the Democratic Republic of Timor-Leste	TLS	176
the Kingdom of Tonga	TON	219
the Republic of Turkey	TUR	223
Turkmenistan	TKM	213
Tuvalu	TUV	227
the Republic of Uzbekistan	UZB	235
the Republic of Vanuatu	VUT	155
the Socialist Republic of Viet Nam	VNM	237
Niue	NIU	160
Cook Islands	COK	47

Appendix 3:

Results from the fixed effects model regression for 33 food and agriculture product networks and their corresponding weighted average MFN tariff rates.

Fixed-effects (within) regression Number of obs = 763
Number of product network groups = 33
R-sq: within = 0.0000 Obs per group: min = 12
between = 0.0854 avg = 23.1
overall = 0.0329 max = 24
F(1,729) = 0.01
corr(u_i, Xb) = 0.2074 Prob > F = 0.9039

Efficiency	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
MFN-Tariffs	0.0000	0.0003	-0.1200	0.9040	-0.0007	0.0006
_cons	0.4647	0.0065	71.1400	0.0000	0.4519	0.4776

sigma_u | .22015665
sigma_e | .12307666
rho | .76188898 (fraction of variance due to u_i)

F test that all u_i=0: F(32, 729) = 61.00 Prob > F = 0.0000

Results from the fixed effects model regression for 33 product networks and their weighted average preferential (PRF) tariffs practiced by UNESCAP regions.

Fixed-effects (within) regression Number of obs = 477
Number of product network groups = 33
R-sq: within = 0.0127 Obs per group: min = 7
between = 0.1523 avg = 14.5
overall = 0.0119 max = 24
F(1,443) = 5.72
corr(u_i, Xb) = -0.1882 Prob > F = 0.0172

Efficiency	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
PRF-Tariffs	-0.0026	0.0011	-2.3900	0.0170	-0.0048	-0.0005
_cons	0.4778	0.0071	67.2700	0.0000	0.4639	0.4918

sigma_u | .23068972

```
sigma_e |  .10103684
    rho |  .83905005   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------------------
F test that all u_i=0:     F(32, 443) =    50.87            Prob > F = 0.0000
```

Results from the fixed effects model regression for 33 product networks and matching weighted average PRF rates, while considering average imports as a control variable.

```
Fixed-effects (within) regression        Number of obs        =    477
Number of product network groups   =      33
R-sq:  within  = 0.0202                  Obs per group: min =    7
      between = 0.1986                         avg = 14.5
      overall = 0.0118                         max = 24
F(2,442)          =      4.56
corr(u_i, Xb)  = -0.2028     Prob > F          =    0.0109
------------------------------------------------------------------------------------------------------
```

Efficiency	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
PRF-Tariffs	-0.0025	0.0011	-2.2700	0.0240	-0.0046	-0.0003
Average Imports	0.0000	0.0000	1.8400	0.0670	0.0000	0.0000
_cons	0.4743	0.0073	64.5600	0.0000	0.4598	0.4887

```
------------------------------------------------------------------------------------------------------
sigma_u |  .23125203
sigma_e |  .10076677
    rho |  .84042572   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------------------
F test that all u_i=0:     F(32, 442) =    51.15           Prob > F =    0.0000
```

Results from the fixed effects model regression for 33 food and agriculture product networks and their matching weighted average preferential tariff rates while considering the average imports and MFN tariffs as control variables.

```
Fixed-effects (within) regression          Number of obs      =      469
Number of product network groups   =      33
R-sq:  within  = 0.0246                  Obs per group: min =        7
between = 0.0046                          avg =      14.2
overall = 0.0045                           max =       24
F(3,433) =  3.63
corr(u_i, Xb)  = -0.0199                  Prob > F          =    0.0130
------------------------------------------------------------------------------------------------------
```

Efficiency	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]

PRF-Tariffs	-0.0024	0.0011	-2.1800	0.0290	-0.0045	-0.0002
Average Imports	0.0000	0.0000	1.9200	0.0550	0.0000	0.0000
MFN-Tariffs	-0.0004	0.0003	-1.2500	0.2120	-0.0011	0.0002
_cons	0.4849	0.0093	52.1100	0.0000	0.4666	0.5032

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sigma_u | .23006857
sigma_e | .10045621
rho | .83987669 (fraction of variance due to u_i)

F test that all u_i=0: F(32, 433) = 45.10 Prob > F = 0.0000

Technical Annex for Chapter 2

Table A1. Analysis of Correlations between selected development indicators and disaster losses

Section 2.4 Flooding explains that impacts of extreme hazard events are aggravated by increasing exposure and vulnerability. Rapid urbanization and coastal development in developing countries are usually not complemented by infrastructure and social services leading to increased risks. Activities, investments, and policies that lower risks and increase resilience are expected to minimize disaster impact.

Using available data, the correlation between risk factors (exposure and vulnerability), infrastructure availability, and disaster losses were examined using the following variables:

- *Access to electricity, percentage of paved roads, road density,* and the *percentage of urban populations living in slums* suggest levels of access to infrastructure: better access means better resilience.
- *Percentages of populations in urban agglomerations* and *in low-lying areas* measure exposure levels of populations to disaster risks: higher exposure levels mean higher risks.
- *Literacy rates* and *government spending on education and health* measure investments in human capital resilience.

Disaster losses are measured by deaths, damages, and affected population. To standardize across various population and economy sizes, deaths are measured per million population, affected population are measured per 1000 population, and damages are measured as a percentage of GDP.

Values used are 1990-2016 averages.

Two sets of data are used:

- Mortality rates, damages, and affected population from *floods*; and
- Mortality rates, damages, and affected population from *floods and storms* combined.

The following countries and territories are covered: Afghanistan, Bangladesh, Bhutan, Cambodia, China, Hong Kong, China, India, Indonesia, Iran, Korea DPR, Korea Republic, Lao PDR, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Sri Lanka, Thailand, Timor Leste, Turkey, and Viet Nam.

Correlation coefficients between the variables representing losses and the risks factors (exposure and vulnerability) are shown in Table A1.

Table A1. Correlation Coefficients between Risk and Resilience Indicators, and Disaster Losses

Indicators that influence resilience	Losses from Floods			Losses from Floods and storms		
	Deaths	Economic damages	Affected population	Deaths	Economic damages	Affected population
Access to electricity (% of population)	(0.452)***	(0.387)*	(0.194)	(0.318)	(0.398)	(0.071)
% of urban population living in slums	0.560 ***	0.297	0.321	0.281	0.317	0.400*
% of population living in urban agglomerations	(0.343)	(0.144)	(0.347)	(0.222)	(0.150)	(0.238)
% of population in low-lying areas	(0.220)	0.012	0.126	0.162	0.028	0.063
% of paved roads to total roads	(0.290)	(0.377)	(0.582)**	(0.174)	(0.407)	(0.749)***
Road density (km per sq km)	(0.284)	(0.134)	0.148	(0.048)	(0.142)	0.035
Literacy rate	(0.559)***	0.262	0.107	(0.138)	0.269	0.302
Government education spending (% of GDP)	0.094	(0.451)**	(0.536)**	(0.374)*	(0.510)**	(0.357)
Public health spending (% of GDP)	0.401*	(0.247)	(0.258)	(0.361)	(0.401)*	(0.119)

Sources: Deaths, Affected population, Economic damages: ESCAP online statistical database (http://data.unescap.org/escap_stat); risk and resilience indicators: World Development Indicators (2017) and International Road Federation (2016).

Notes:

Countries and territories in this analysis include Afghanistan, Bangladesh, Bhutan, Cambodia, China, Hong Kong, China, India, Indonesia, Islamic Republic of Iran, Democratic People's Republic of China, Republic of Korea, Lao People's Democratic Republic, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Philippines, Sri Lanka, Thailand, Timor Leste, Turkey, and Viet Nam

Figures enclosed in parentheses indicate negative values.

A small p-value (typically ≤ 0.05) indicates the strong evidence against the null hypothesis; a large p-value indicates weak evidence against the null hypothesis (so it is not rejected).

**** Coefficient is significant at the 0.01 level; p-value ≤ 0.01*
*** Coefficient is significant at the 0.05 level; p-value ≤ 0.05*
** Coefficient is significant at the 0.10 level; p-value ≤ 0.10*

Table 2. Regression Analysis: Economic Impact of Oil and Gas Prices in Four Central Asian Economies

Section 2.4 Commodity Shocks discusses how the oil price shocks from 2004, with deep dives around 2009 and 2015, have affected Central Asian countries. The vulnerability of the Central Asian economies to external shocks is due to its dependence on extractive industries (minerals, natural gas, and oil) and remittances. In 2000-2014, almost 30% of the GDPs of Azerbaijan and Turkmenistan depended on natural resource rents; and almost 20% of the GDPs of Kazakhstan and Uzbekistan. Fuel exports make up 92% of Azerbaijan's and 70% of Kazakhstan's merchandise exports. Slowdowns in the economies of Russia and China are also affecting the Central Asia's exports and remittances.

Using regression analysis (time series), the impact of changing oil prices (for Azerbaijan and Kazakhstan) and changing natural gas prices (for Turkmenistan and Uzbekistan) on the following economic variables were measured:

- Gross Domestic Product (GDP)
- Per capita GDP
- Reserves
- Household expenditure
- Depth of food deficit

Crude oil prices are measured in $ per barrel and natural gas prices are measured in $ per million BTU. Price data was sourced from the World Bank Commodity Price Data (The Pink Sheet) at http://www.worldbank.org/en/research/commodity-markets.

The use of natural logarithm (LN) in regression analysis translates coefficients of dependent variables into percentage changes; for every one percentage change in the commodity price, the coefficient is interpreted as the percentage change of the respective dependent variable in each equation.

Time series analysis covered the period 1992-2016.

Regression coefficients and corresponding standard errors are shown in Tables A2a (Azerbaijan), A2b (Kazakhstan), A2c (Turkmenistan), and A2d (Uzbekistan).

Table A2a. Regression Analysis: Effects of oil prices in Azerbaijan					
	Independent variable: LN (Crude oil, average in $/barrel)				
	(Eq. 1)	(Eq. 2)	(Eq.3)	(Eq. 4)	(Eq. 5)
Dependent variables	Regression coefficients				
LN GDP (constant 2010 US$)	1.047***				
Standard error	0.100				
LN GDP per capita (constant 2010 US$)		0.933***			
Standard error		0.088			
LN household final consumption expenditure (constant 2010 US$)			0.944***		
Standard error			0.062		
LN total reserves (includes gold, current US$)				3.265***	
Standard error				0.538	
LN depth of the food deficit (kilocalories per person per day)					(1.531)***
Standard error					0.164

Sources: World Bank Commodity Price Data (The Pink Sheet). http://www.worldbank.org/en/research/commodity-markets; World Development Indicators. http://databank.worldbank.org/data/home.aspx

Note:

A small p-value (typically ≤ 0.05) indicates the strong evidence against the null hypothesis; a large p-value indicates weak evidence against the null hypothesis (so it is not rejected).

**** Coefficient is significant at the 0.01 level; p-value ≤ 0.01*

*** Coefficient is significant at the 0.05 level; p-value ≤ 0.05*

** Coefficient is significant at the 0.10 level; p-value ≤ 0.10*

Table A2b. Regression Analysis: Effects of oil prices in Kazakhstan					
	Independent variable: LN (Crude oil, average in $/barrel)				
	(Eq. 1)	(Eq. 2)	(Eq. 3)	(Eq. 4)	(Eq. 5)
Dependent variables	Regression coefficients				
LN GDP (constant 2010 US$)	0.616***				
Standard error	0.065				
LN GDP per capita (constant 2010 US$)		0.581***			
Standard error		0.052			
LN household final consumption expenditure (constant 2010 US$)			0.583***		
Standard error			0.085		
LN total reserves (includes gold, current US$)				1.911***	
Standard error				0.175	
LN depth of the food deficit (kilocalories per person per day)					0.186*
Standard error					0.097

Sources: World Bank Commodity Price Data (The Pink Sheet). http://www.worldbank.org/en/research/commodity-markets; World Development Indicators. http://databank.worldbank.org/data/home.aspx

Note:

A small p-value (typically ≤ 0.05) indicates the strong evidence against the null hypothesis; a large p-value indicates weak evidence against the null hypothesis (so it is not rejected).

**** Coefficient is significant at the 0.01 level; p-value ≤ 0.01*
*** Coefficient is significant at the 0.05 level; p-value ≤ 0.05*
** Coefficient is significant at the 0.10 level; p-value ≤ 0.10*

Table A2c. Regression Analysis: Effects of natural gas prices in Turkmenistan					
	Independent variable: LN (Natural gas, Europe, $/million BTU)				
	(Eq. 1)	(Eq. 2)	(Eq. 3)	(Eq. 4)	(Eq. 5)
Dependent variables	Regression coefficients				
LN GDP (constant 2010 US$)	0.749***				
Standard error	0.134				
LN GDP per capita (constant 2010 US$)		0.594***			
Standard error		0.114			
LN household final consumption expenditure (constant 2010 US$)			no data		
Standard error					
LN total reserves (includes gold, current US$)				no data	
Standard error					
LN depth of the food deficit (kilocalories per person per day)					(0.517)***
Standard error					0.084

Sources: World Bank Commodity Price Data (The Pink Sheet). http://www.worldbank.org/en/research/commodity-markets; World Development Indicators. http://databank.worldbank.org/data/home.aspx

Note:
British Thermal Unit (BTU) is a unit of measurement for natural gas; it measures the amount of heat in fuel.

A small p-value (typically ≤ 0.05) indicates the strong evidence against the null hypothesis; a large p-value indicates weak evidence against the null hypothesis (so it is not rejected).

**** Coefficient is significant at the 0.01 level; p-value ≤ 0.01*
*** Coefficient is significant at the 0.05 level; p-value ≤ 0.05*
** Coefficient is significant at the 0.10 level; p-value ≤ 0.10*

Table A2d. Regression Analysis: Effects of natural gas prices in Uzbekistan					
	Independent variable: LN (Natural gas, Europe, $/million BTU)				
	(Eq. 1)	(Eq. 2)	(Eq. 3)	(Eq. 4)	(Eq. 5)
Dependent variables	Regression coefficients				
LN GDP (constant 2010 US$)	0.661***				
Standard error	0.111				
LN GDP per capita (constant 2010 US$)		0.485***			
Standard error		0.085			
LN household final consumption expenditure (constant 2010 US$)			no data		
Standard error					
LN total reserves (includes gold, current US$)				no data	
Standard error					
LN depth of the food deficit (kilocalories per person per day)					0.602***
Standard error					0.202

Sources: World Bank Commodity Price Data (The Pink Sheet). http://www.worldbank.org/en/research/commodity-markets; World Development Indicators. http://databank.worldbank.org/data/home.aspx

Note:
British Thermal Unit (BTU) is a unit of measurement for natural gas; it measures the amount of heat in fuel.

A small p-value (typically ≤ 0.05) indicates the strong evidence against the null hypothesis; a large p-value indicates weak evidence against the null hypothesis (so it is not rejected).

**** Coefficient is significant at the 0.01 level; p-value ≤ 0.01*

*** Coefficient is significant at the 0.05 level; p-value ≤ 0.05*

** Coefficient is significant at the 0.10 level; p-value ≤ 0.10*