Energy Trade and Security: Scenario Simulation Comparison of Natural Gas Trade Using Computable General Equilibrium Models and Social Network Analysis

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Abstract. Energy supply chains are particularly volatile, with disruptions stemming from geopolitical tensions, technological changes, demand swings, and supply constraints. When disruptions do occur, they are more severe than in many other types of trade. Given this volatility and energy's importance not only for economic development but also for national security, predicting the impact of disruptions to the energy supply chain is crucial. This research compares computable general equilibrium (CGE) and social network analysis (SNA) scenario modeling to build a more accurate model by leveraging their complementarity. Our results show that combining the two models' predictions reduces the overall average error in predicting changes in market share.

Keywords: International Trade, Energy Security, Social Network Analysis

1 Introduction

Energy supply chains are particularly volatile, with disruptions stemming from geopolitical conflict, technological changes, demand swings, and supply constraints. Furthermore, disruptions in energy trade tend to be more severe than those in most other types of trade, given the relative concentration of trade flows and demand inelasticity [4]. Given this volatility and energy's importance not only for economic development but also for national security, predicting the likelihood and impact of energy supply chain disruptions is crucial. This research compares computable general equilibrium (CGE) and social network analysis (SNA) scenario modeling to identify their strengths and weaknesses and the ways they may complement one another.

CGE models are among the most commonly used for scenario simulation of trade disruptions. While regression analysis is more straightforward and has less complex data requirements, CGE models are better suited for scenario simulation due the inclusion of input-output data and price elasticities in nested substitution functions, allowing modelers to represent complex, multi-layered production processes (like combining labor, capital, and energy) more realistically and account for how substitutions occur at different levels (e.g., between capital and labor, or between domestic and imported fuels) to analyze economic policies and impacts better. However, CGE models do not capture structural interdependencies between actors at the network level.

SNA is also frequently used to simulate changes to a network and how they propagate through it. SNA's strength lies in not assuming independence between observations, as in regression analysis, and in offering additional insights into policy and other risk-mitigation responses to potential disruptions by controlling for the structural interdependence driven by complex geopolitical relationships that go beyond demand and price. These factors are especially important for energy, as seen in the increase in the United States' (US) energy exports to Europe following the initiation of conflict in Ukraine. SNA's weakness, however, is that its modeling options for incorporating price signals and other inputs are limited or overly complicated.

Our analysis uses the natural gas market to test the model's ability to predict the impact of disruption. Natural gas is frequently sold on the spot market to respond to changes in energy demand and supply, is bought and sold by countries with differing geopolitical goals, and is making up an increasing share of energy profiles, partially driven by its lower emissions compared to other fossil fuels. While other energy inputs, such as renewable energy sources, can be strategic for increasing energy security, given their intermittency and need for long-term planning, they are less likely to be used to address short-term disruptions in energy supply or demand during the time frame of our study.

2 Theory

2.1 CGE and Price Signals

The Computable General Equilibrium (CGE) framework is grounded in neoclassical economic theory. Markets clear through price adjustments. Its primary strength lies in the use of nested substitution functions that capture how producers and consumers respond to external market shocks. In the context of energy trade, CGE models simulate how a disruption in one region triggers price increases in other regions, prompting agents to substitute domestic production for imports or switch to alternative energy sources. A drawback of CGE models is that it is difficult to incorporate trade frictions caused by geopolitical alliances and other unobserved network features.

2.2 Social Network Analysis (SNA)

In the context of international trade, SNA treats trade as a system of interdependent relationships. The core of SNA in this study is that the network position of trading partners, rather than just relative prices and behavioral assumptions (elasticities), determines how trade flows are reconfigured during a crisis. Three features differentiate SNA from CGE in terms of predicting changes in flows between partners following a disruption. The first notion is that SNA captures higher-order dependencies between trading partners. For example, energy trade is not merely a series of bilateral transactions. Integrated production, extraction, and transportation infrastructure, along with geopolitical ties or barriers, also influence it. Second, through higher-order dependencies, SNA can account for the possibility that actors may prioritize energy security over cost minimization, explaining why trade might flow toward geopolitical allies during disruptions even though those transactions may cost more. Third, newer SNA models, such as the Additive and Multiplicative Effects Network (AMEN) model, can be extended to trade analyses to account for heterogeneity in how countries send and receive goods, thereby increasing the accuracy of out-of-sample predictions. We propose to integrate CGE and SNA models to leverage the qualities of both approaches, with the objective of increasing predictive accuracy.

3 Data and Research Design

3.1 Data

The data for the SNA models come from UN Comtrade trade data, and the time sample runs from 2017 to 2023. This period provides a base year before COVID-19-related disruptions and the 2022 invasion of Ukraine, which further disrupted energy markets. The trade data were subset to HS code 2711 for the analysis and include all countries engaged in natural gas trade. The analysis uses the US dollar (USD) value of natural gas trade, not volume.

For the CGE model, we use the standard GTAP model in GAMS and the GTAP 11 database, using 2017 as the base year. The simulation utilizes the GTAP 11 database, with global 2017 data aggregated into 45 composite regions (see Table 4 for regional definitions). The sectoral aggregations are used to compare the findings of the SNA and CGE model, but are not used when running the SNA mode.

3.2 Research Design

For our analysis, we test our model on the reduction in natural gas trade from Russia to countries subject to sanctions after the invasion of Ukraine. This scenario provides a back-check on the model, which can be compared with actual changes in the supply chain and supply decisions following this disruption were strongly influenced by geopolitical considerations.

***SNA Simulation Process*:**
We chose the Additive and Multiplicative Effects Network (AMEN) model for our SNA analysis for several reasons. First, in preliminary model testing, other

models failed to identify the structural parameters of energy trade and had poor model fit. ERGMs require user-specified terms, and for valued networks, there are a limited number of readily available options. These limitations do not mean that energy networks lack structural dependence, but instead that higher-order or more complex behavior is observed in the network than can be captured by simpler terms. AMEN models capture most forms of higher-order dependence and achieve better out-of-sample predictive performance than other network models [3]. Furthermore, it has been shown to better model actor-level out-degree and in-degree heterogeneity in economic networks [5].

We use the R 'amen' package to implement the network simulations in this paper [2]. However, the 'amen' package is not set up for direct scenario simulation analysis; instead, it only allows users to impute missing data and requires adaptation. For this adaptation, we follow three steps to simulate a new network post-disruption. The first step is to estimate the AMEN model with the sender and receiver effects as exogenous covariates for the 2017 base year, and to extract the additive and multiplicative effects matrix. We ran the model for 100,000 Markov chain iterations, using two dimensions of multiplicative effects and Poisson posterior inference for the parameters.

The second step is creating a new, disrupted matrix (DM) from the observed one that includes the simulated disruption and reduces the non-disrupted ties by the same total amount, relative to their observed percentage of remaining ties. The simulated disruption is an initial 50% drop in gas exports from Russia to all countries that imposed punitive sanctions against Russia. This group of geopolitical allies are listed in Table 1. The DM is used as the base to add post-disruption change flows. In parallel, the inverse matrix (IM) of non-disrupted ties is generated for the amount that is reduced in the DM. The IM is then multiplied by the EM, first converting the EM to a percentage of its maximum absolute value to create an additive matrix (AM). The AM is used to predict reallocation of disrupted trade flows based on network position. The IM has built-in structural zeroes, so reallocations can only occur within existing, positive ties in the AM. Note that network effects in the AM can be negative, so some flows are further reduced with a floor of zero.

The third step is to generate a disrupted gas trade matrix and then iteratively adjust the matrix using new gas prices and the effects matrix as covariates. The AM is iteratively added to the DM by five one-hundredths of a percent of the AM values, multiplying the AM by a randomly generated, uniformly distributed matrix of the same dimensions to introduce stochasticity in the process. This process is repeated until the sum of the new matrix reaches 95% of the original matrix, assuming a 5% efficiency loss. The process takes, on average, 50,000 iterations to reach the set value for this simulation. The final simulated matrix represents how flows would be reorganized under network pressure after a disruption.

GTAP Simulation Process The sectoral structure for the GTAP model is consolidated into 12 commodity groups, including key agricultural, extractive, manufacturing, and service activities. Natural Gas and Oil are in separate sectors. The Natural Gas sector includes both gaseous and liquid forms. The policy shocks were modeled using the standard GTAP model in GAMS [1], with comparative-static simulations and Constant-Difference-in-Elasticity (CDE) utility function. Sanctions on natural gas from Russia were introduced as changes to import taxes (imptx) on Natural Gas trade flows originating from region 27 (Russian Federation) toward specific destination regions (region 1, region 4, region 11, region 19, and region 26). Results are evaluated by changes in xw, which represents bilateral import demand across regions.

4 Results and Discussion

UN Comtrade and GTAP use different processes for compiling data, and therefore the values of trade between regions are not exactly the same. Therefore, we focus on differences in market-share predictions rather than volume changes. An additional reason for this choice is that both models are conservative and cannot capture volume changes driven by time trends. Between 2017 and 2023, natural gas trade grew over 14 billion cubic feet per day, or roughly 37% [6]. Figure 1 shows the distribution of market share prediction errors. The AMEN model has a smaller range of error, but is less concentrated around zero than the GTAP errors. This indicates that when accounting for structural dependence in an energy trade network, predictions are less likely to be overly wrong, but only when including input and price effects; the GTAP model, however, predicts substantial trade shifts that do not occur in practice.

In Figure 2, we show the expected changes in market share following the disruption. For the AMEN model, the general direction of realignment after disruption is that central actors increase their market share. In contrast, peripheral actors suffer a decrease in market share. We also see that the largest increase is between the US and Europe. In the GTAP model, realigned gas imports from Russia are replaced by imports from the US and Qatar. However, the realignment does not follow structural patterns. The 2023 benchmark is closer to the AMEN model than to the GTAP model, but is even closer to the combined average of AMEN and GTAP. The AMEN model corrects THE GTAP model's large errors, while the small, but frequent errors of the AMEN model are corrected by the GTAP model, indicating substantial complementarity between the two models.

In Table 2 and Table 3, we present a breakdown of the five biggest changes for of each model prediction for five of the largest exporters of natural gas. In general, we see that the AMEN model breakdown confirms what we visually saw in Figure 2. The USA increased exports to geopolitical allies such as Europe, Japan, and South Korea, and Russia decreased exports to these countries. However, the AMEN model is more conservative than the 2023 benchmark. The GTAP model predicts larger changes that are sometimes more accurate than the AMEN model, such as the decrease in exports from Russia to Europe. However, it frequently overshoots or misses the shift altogether, failing to account for geopolitical ties between gas sellers and buyers. For example, the GTAP predictions expect fewer relative exports from the US to South Korea and overshoot the increased exports from Russia to China. Both models still have shortcomings; neither predicted the increase in exports from Russia to India.

5 Conclusion and Future Steps

This study demonstrates that neither CGE nor SNA models alone are sufficient for accurately predicting the reallocation of natural gas trade flows following a major geopolitical disruption. While the GTAP model captures price-driven substitution effects with precision, it consistently fails to account for the structural and geopolitical constraints that govern real-world energy trade. Conversely, the AMEN-based SNA model preserves network topology and geopolitical dependencies but tends toward conservative predictions that underestimate the magnitude of trade shifts. When the predictions of both models are combined, the average market-share prediction error falls from 4.2% (AMEN) and 9.1% (GTAP) to just 0.68%, underscoring the strong complementarity between the two approaches. These results suggest that integrated hybrid modeling frameworks represent a promising frontier for energy security analysis, one capable of bridging the gap between economic theory and the complex geopolitical realities that shape global commodity flows.

Future work should focus on more tightly integrating the two modeling frameworks rather than relying on post-hoc averaging of their outputs. One productive avenue would be to use SNA-derived network statistics—such as centrality measures and latent geopolitical factors—as additional covariates within the CGE framework, or conversely, to use CGE-generated price signals to inform the construction of the disrupted network matrix in the SNA simulation. Extending the analysis to other energy commodities, such as other hydrocarbons or enriched uranium, and testing the model across a wider range of disruption scenarios would further validate its generalizability. Ultimately, a well-integrated hybrid model of this kind could serve as a practical tool for policymakers and analysts seeking to anticipate and mitigate the consequences of energy supply chain disruptions in an increasingly volatile geopolitical environment.

6 Tables and Figures

Table 1. Allied Countries that imposed Sanctions

Allied Countries
Australia, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia,Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway,Poland, Portugal, Romania, Singapore, Slovakia, Slovenia, South Korea,Spain, Sweden, North Macedonia, United Kingdom, USA

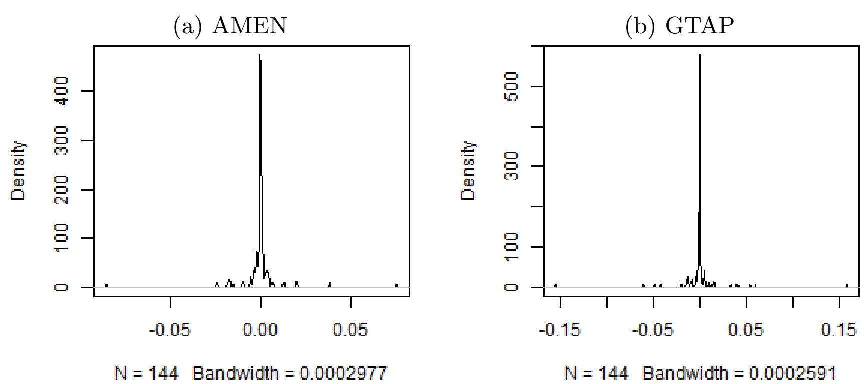

Fig. 1. Error Density of Market Share Predictions of Dyadic Regional Trade

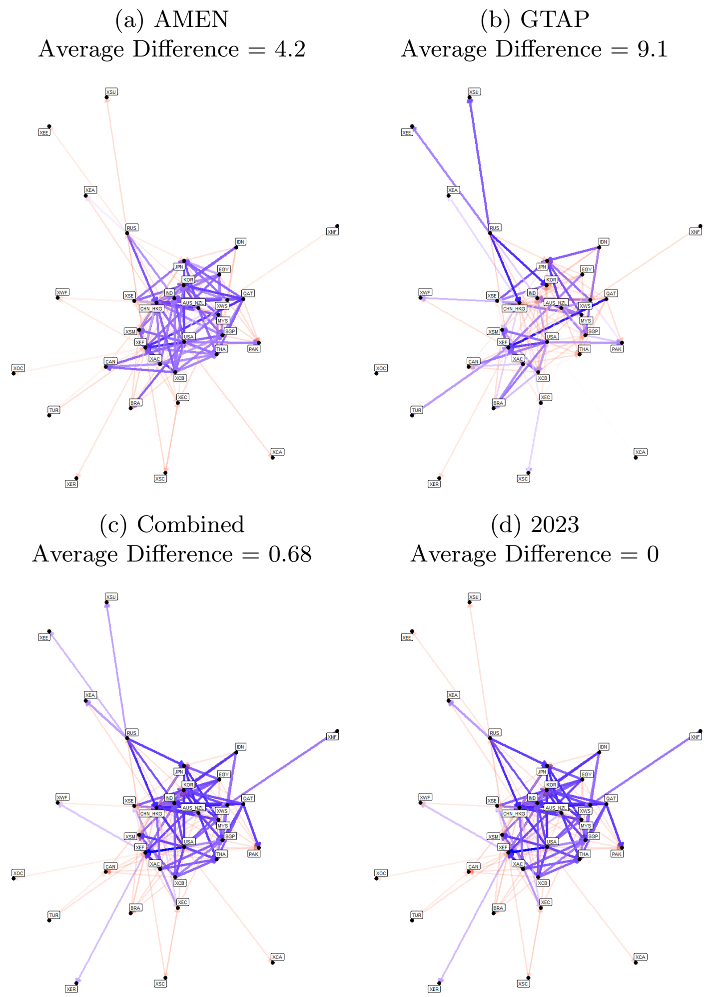

Fig. 2. Simulation Method Comparison: Change in Market Share. Red shows negative changes and blue shows positive changes. Line width and transparency indicate relative size of change. Average Difference refers to the absolute value of predicted changes versus the 2023 benchmark.

Table 2. Partner Changes for AMEN Model

Exporter	Rank	Importer	Base	Shock	2023
RUS	1st	XEF	7.15%	1.89%	4.27%
	2nd	JPN	1.98%	0.52%	2.02%
	3rd	CHN_HKG	0.73%	0.80%	2.51%
	4th	KOR	0.70%	0.19%	0.51%
	5th	USA	0.03%	0.01%	0.00%
AUS_NZL	1st	JPN	10.32%	10.95%	9.60%
	2nd	CHN_HKG	8.40%	9.14%	7.16%
	3rd	KOR	2.40%	2.63%	4.31%
	4th	MYS	1.11%	1.16%	0.69%
	5th	SGP	0.53%	0.57%	0.82%
USA	1st	XEF	8.47%	9.62%	18.14%
	2nd	KOR	1.40%	1.58%	2.00%
	3rd	JPN	1.16%	1.28%	1.63%
	4th	XSM	0.80%	0.85%	1.06%
	5th	IND	0.49%	0.54%	0.69%
QAT	1st	XEF	11.23%	12.24%	4.67%
	2nd	KOR	4.35%	4.73%	3.48%
	3rd	JPN	3.00%	3.18%	1.14%
	4th	CHN_HKG	2.99%	3.25%	5.05%
	5th	IND	2.81%	2.98%	3.16%
MYS	1st	JPN	2.89%	3.01%	3.36%
	2nd	CHN_HKG	1.72%	1.84%	2.03%
	3rd	KOR	1.34%	1.43%	1.96%
	4th	THA	0.75%	0.78%	0.48%
	5th	IND	0.07%	0.07%	0.00%

Table 3. Partner Changes for GTAP Model

Exporter	Rank	Importer	Base	Shock	2023
RUS	1st	XEF	19.23%	0.00%	4.27%
	2nd	XEE	3.16%	3.35%	0.00%
	3rd	CHN_HKG	1.52%	7.90%	2.51%
	4th	JPN	1.32%	0.00%	2.02%
	5th	KOR	0.32%	4.48%	0.51%
AUS_NZL	1st	JPN	12.96%	15.59%	9.60%
	2nd	KOR	3.24%	2.95%	4.31%
	3rd	CHN_HKG	3.16%	1.08%	7.16%
	4th	IND	0.99%	1.68%	0.10%
	5th	SGP	0.65%	0.73%	0.82%
USA	1st	CAN	3.89%	4.11%	0.02%
	2nd	KOR	1.10%	0.62%	2.00%
	3rd	XEF	1.07%	2.62%	18.14%
	4th	XWS	0.62%	0.52%	0.07%
	5th	JPN	0.59%	0.44%	1.63%
QAT	1st	XEF	9.69%	20.52%	4.67%
	2nd	KOR	4.19%	2.05%	3.48%
	3rd	IND	4.12%	3.76%	3.16%
	4th	JPN	4.00%	2.59%	1.14%
	5th	PAK	1.98%	2.07%	1.54%
MYS	1st	JPN	3.13%	3.81%	3.36%
	2nd	KOR	0.73%	0.67%	1.96%
	3rd	CHN_HKG	0.32%	0.11%	2.03%
	4th	IND	0.04%	0.07%	0.00%
	5th	SGP	0.04%	0.04%	0.03%

7 Appendix

Table 4. Regional Grouping

Aggregated Region	GTAP code	Names	Graph_Names
Region_1	AUS, NZL	Australia, New Zealand	AUS_NZL
Region_2	PYF, XOC	Rest of Oceania	XOC
Region_3	CHN, HKG	China, Hong Kong	CHN_HKG
Region_4	JPN	Japan	JPN
Region_5	KOR	Korea, Republic of	KOR
Region_6	MNG, XEA	Mongolia, Rest of East Asia	XEA
Region_7	TWN	Chinese Taipei	TWN
Region_8	IDN	Indonesia	IDN
Region_9	MYS	Malaysia	MYS
Region_10	PHL	Philippines	MYS
Region_11	SGP	Singapore	SGP
Region_12	THA	Thailand	THA
Region_13	VNM	Viet Nam	XSE
Region_14	LAO, BRN, KHM, BDI, XSE	Rest of Southeast Asia	XSE
Region_15	IND	India	IND
Region_16	PAK	Pakistan	PAK
Region_17	AFG, BGD, NPL, LKA, XSA	Afghanistan, Bangladesh, Nepal, Sri Lanka, Rest of South Asia	XSA
Region_18	CAN	Canada	CAN
Region_19	USA	United States of America	USA
Region_20	MEX	Mexico	MEX
Region_21	XNA	Rest of North America	XNA
Region_22	BRA	Brazil	BRA
Region_23	ARG, BOL, CHL ,COL, ECU, PRY, PER, URY, VEN, GUY, XSM	Argentina, Bolivia, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela (Bolivarian Republic of), Rest of South America	XSM

Aggregated Region	GTAP code	Names	Graph_Names
Region_24	CRI, GTM, HND, NIC, PAN, SLV, BLZ, XCA	Costa Rica, Guatemala, Honduras, Nicaragua, Panama, El Salvador, Rest of Central America	XCA
Region_25	DOM, HTI, JAM, PRI, TTO, BRB, XCB	Dominican Republic, Haiti, Jamaica, Puerto Rico, Trinidad and Tobago, Rest of Caribbean	XCB
Region_26	AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, GBR, CHE, NOR, ISL, XEF	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Switzerland, Norway, Rest of European Free Trade Association	XEF
Region_27	RUS	Russian Federation	RUS
Region_28	UKR	Ukraine	UKR
Region_29	ALB, SRB, BLR, XEE	Albania, Serbia, Belarus, Rest of Eastern Europe	XEE
Region_30	BIH, MKD, XER	Rest of Europe	XER
Region_31	KAZ, KGZ, TJK, UZB, XSU	Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, Rest of Former Soviet Union	XSU
Region_32	IRN	Iran, Islamic Republic of	IRN
Region_33	ISR	Israel	ISR
Region_34	OMN	Oman	OMN
Region_35	QAT	Qatar	QAT
Region_36	SAU	Saudi Arabia	SAU
Region_37	TUR	Turkey	TUR
Region_38	ARM, AZE, GEO, BHR, IRQ, JOR, KWT, LBN, PSE, SYR, ARE, XWS	Armenia, Azerbaijan, Georgia, Bahrain, Iraq, Jordan, Kuwait, Lebanon, Palestinian Territory, Occupied, Syrian Arab Republic, United Arab Emirates, Rest of Western Asia/Yemen	XWS
Region_39	EGY	Egypt	EGY

Aggregated Region	GTAP code	Names	Graph_Names
Region_40	DZA, MAR, TUN, XNF	Algeria, Morocco, Tunisia, Rest of North Africa	XNF
Region_41	BEN, BFA, CMR, CIV, GHA, GIN, MLI, NER, NGA, SEN, TGO, XWF	Benin, Burkina Faso, Cameroon, Côte d'Ivoire, Ghana, Guinea, Mali, Niger, Nigeria, Senegal, Togo, Rest of Western Africa	XWF
Region_42	AGO, CAF, TCD, COG, COD, GNQ, GAB, XAC	Central African Republic, Chad, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Rest of South and Central Africa	XAC
Region_43	COM, ETH, KEN, MDG, MWI, MUS, MOZ, RWA, SDN, TZA, UGA, ZMB, ZWE, XEC	Comoros, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Sudan, Tanzania, United Republic of Uganda, Zambia, Zimbabwe, Rest of Eastern Africa	XEC
Region_44	BWA, SWZ, NAM, ZAF, LSO, XSC	Botswana, Eswatini, Namibia, South Africa, Rest of South African Customs Union	XSC
Region_45	XTW	Rest of the World	XTW

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