General Equilibrium Impact Of **India**'s Acession Into **CPTPP** Using **Structural Gravity Model**

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Presentation Overview

Intro

- **CPTPP** : Comprehensive & Progressive Agreement for Trans-Pacific Partnership
  - The FTA was initiated on 30th December 2018
  - On July 16, 2023, U.K. signed an Accession Protocol with CPTPP11. [1]
  - 12 Member Countries:

Australia	Mexico
Brunei	New Zealand
Canada	Peru
Chile	Singapore
Japan	United Kingdom
Malaysia	Vietnam

- **CPTPP+** : CPTPP with India **(Hypothetical Scenario)**

[1] The CPTPP becomes effective for the U.K. upon full ratification by all members including U.K.. If not fully ratified by October 16, 2024, 6 CPTPP11 members and the U.K. must ratify for the Accession Protocol to take effect.

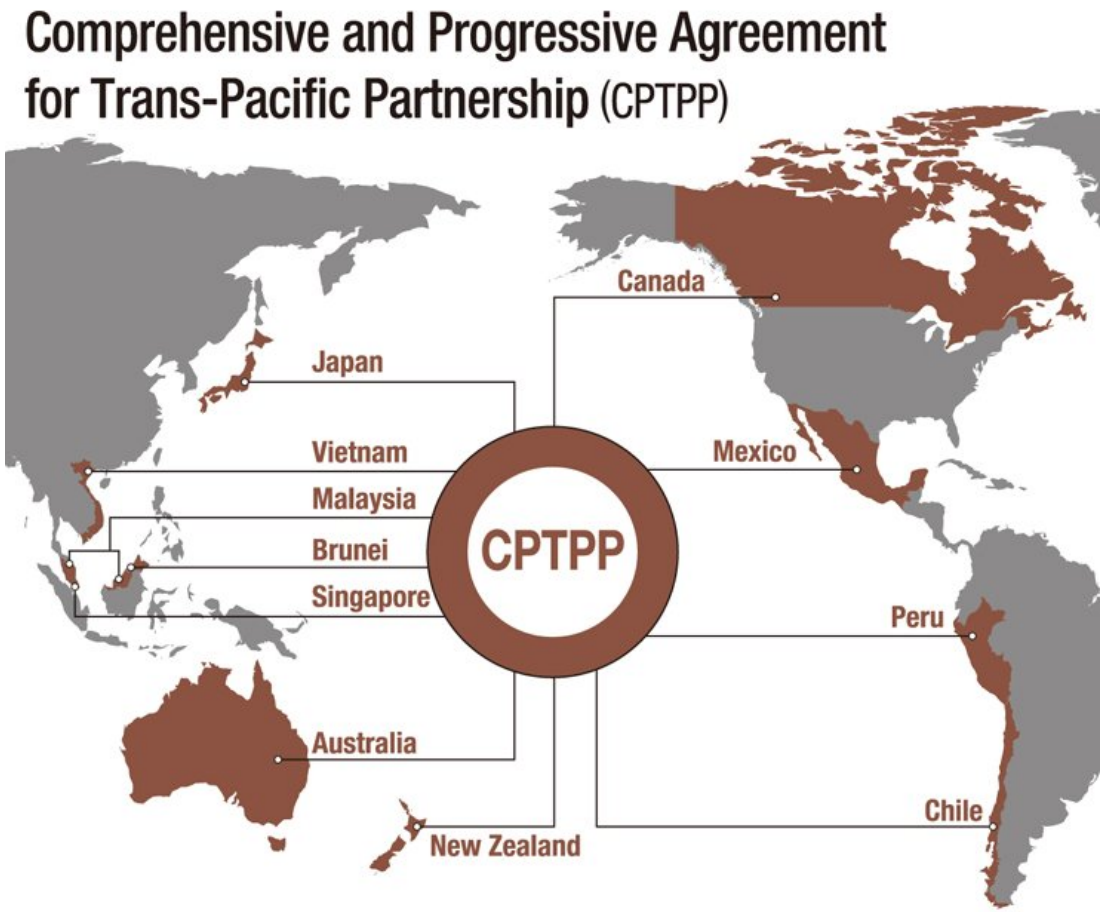

Figure: CPTPP11 [2]

[2] Cho Sang Won KOTRA

- World GDP in 2022: 101.003 Trillion US$

Country	GDP (in billion US$)	GDP share of the world
Australia	1675,419	1.6588
Brunei	16,682	0.0165
Canada	2139,840	2.1186
Chile	301,025	0.2980
Japan	4231,141	4.1891
Malaysia	0,406	0.0004
Mexico	1414,187	1.4001
New Zealand	0,247	0.0002
Peru	0,243	0.0002
Singapore	0,467	0.0005
U.K.	3070,668	3.0402
Vietnam	0,409	0.0004
Σ_i	11909.065	12.7231

Table: 2022 GDP data[3]

- Total CPTPP Population = 518 million[4] ($\approx$ 6.5% of world Pop.)

[3] World Bank

[4] World Economics - The Global Authority on Geographic Investability

Entry into Force of the CPTPP / Implementation of the CPTPP

Date(s) of entry into Force:

- 30 December 2018 for Australia, Canada, Japan, Mexico, New Zealand, and Singapore
- 14 January 2019 for Viet Nam
- 19 September 2021 for Peru
- **29 November 2022 for Malaysia**
- 21 February 2023 for Chile

Snapshot: CPTPP Market

CPTPP Population: 514 million (6.6% of world population)
CPTPP GDP: US$11.7 trillion (12.2% of world GDP)
CPTPP Total Trade: US$6.6 trillion (14.7% of total world trade)
CPTPP Exports: US$3.4 trillion (15.2% of world exports)
CPTPP Imports: US$3.2 trillion (14.3% of world imports)

Figure: CPTPP11 at one glance[5]

[5] MALAYSIA'S FREE TRADE AGREEMENTS Last updated : 02-10-2023

India's Economy

- **A "FORCE" to reckon with!**

GDP GDP Rank	3.736 trillion (nominal) :: 13.033 trillion (PPP) 5th (nominal) :: 3rd (PPP)
Population	1.417 billion
Trade (2021)	Exports: 420 billion USD :: Imports: 612 billion USD

Table: India at a Glance (2022)[6]

- 17.76 % of World Population [7]
- 3.4% of World GDP (2022)

- **India Joining CPTPP Should have Considerable Impact on the CPTPP members !!**

[6] wikipedia
[7] worldometer

Countries to be considered in the analysis ...

- **12 Member Countries**:

Australia	Mexico
Brunei	New Zealand
Canada	Peru
Chile	Singapore
Japan	United Kingdom
Malaysia	Vietnam

- **8 Nonmember Countries**:

USA	France
China	Italy
Germany	Brazil
India	Russia

- Total 20 Countries $\equiv (11 + \text{UK} + \text{India} + 7)$

Sl. No.	World Rank[8]	Country	GDP8[0]	Share of World GDP[9]
1	1	USA	$25.463 trillion	25.32%
2	2	China	$17.963 trillion	17.86%
3	3	Japan	$4.231 trillion	4.21%
4	4	Germany	$4.072 trillion	4.05%
5	5	India	$3.385 trillion	3.37%
6	6	UK	$3.071 trillion	3.05%
7	7	France	$2.783 trillion	2.77%
8	8	Russia	$2.240 trillion	2.23%
9	9	Canada	$2.140 trillion	2.13%
10	10	Italy	$2.010 trillion	2.00%
11	11	Brazil	$1.920 trillion	1.91%
12	12	Australia	$1.675 trillion	1.67%
13	14	Mexico	$1.414 trillion	1.41%
14	34	Singapore	$467 billion	0.46%
15	36	Vietnam	$409 billion	0.41%
16	37	Malaysia	$406 billion	0.40%
17	46	Chile	$301 billion	0.30%
18	51	New Zealand	$247 billion	0.25%
19	52	Peru	$243 billion	0.24%
20	129	Brunei	$16.68 billion	0.02%

Table: GDP wise sorting of the 20 Countries. BLUE → CPTPP Member Country & GREEN → Non-Member Country

[8] worldbank 2022 data

[9] worldometer GDP 2022 data

: Objective :

1. Analysing the GE impacts on **All the CPTPP members** when **India joins CPTPP**
2. & its **GE Impact on top 10 GDP Countries**

- I will be applying **NLS** [Herman, 2021] **solving strategy**.

Dataset

- I have considered **Cross Sectional** data for the year 2021

Serial No.	Variables	Sources
1	**Trade among countries**	WITS
2	**Export & Import Of a Country**	WITS
3	**PTA**	WITS
5	Common Language	CEPII
4	Contiguity	CEPII
6	Distance	CEPII
7	International Trade	WITS

Table: Data Sources

- For Missing Trade data I have considered the Latest Available data.[For Brunei - Mexico : 2020 data; Brunei- Peru - 2019 data; Peru - Brunei - 2019 data; Peru - Peru - 2020 data]
- Overall there are 20 countries so we will have $20^2 = 400$ **rows** and there are 11 **Columns**.
- $400X11$ **dataset.**

	A	B	C	D	E	F	G	H	I	J	K
1	exporter	importer	year	trade	Y	E	pta	contiguity	common_language	lndist	international
2	Australia	Mexico	2021	2485957.01	342036103.27	506565459.47	1	0	0	14359	1
3	Canada	Mexico	2021	20453800.09	501538854.87	506565459.47	1	0	0	3604	1
4	Chile	Mexico	2021	1139794.39	94676809.21	506565459.47	1	0	0	7353	1
5	Japan	Mexico	2021	5062543.94	757066261.25	506565459.47	1	0	0	10791	1
6	New Zealand	Mexico	2021	85753.55	44325287.82	506565459.47	1	0	0	11103	1
7	Peru	Mexico	2021	1335838.55	56260115.20	506565459.47	0	0	1	4708	1

Figure: The Dataset for the Herman's code to run [Herman, 2021]

1. `exporter` → Exporting Country
2. `importer` → Importing Country
3. `year` → Year for the data. (in our case its 2021)
4. `trade` → **Trade (in thousand USD)** between `exporter` and `importer` country
5. `Y` → **Total export (in thousand USD)** of the exporting country
6. `E` → **Total import (in thousand USD)** of the importing country
7. `pta` → Whether there is any Trade Agreement between the `exporter` and the `importer` country
8. `contiguity` → whether the countries share land border or not
9. `common_language` → whether the countries have a common language or not
10. `lndist` → Distance between the Exporting and the importing country **(in km)**
11. `international` → Whether the two country trade with each other or not

The Structural Gravity Model [Anderson and van Wincoop, 2003]

$$X_{ij} = \frac{Y_i E_j}{Y}\left(\frac{t_{ij}}{\Pi_i P_j}\right)^{1-\sigma} \quad (1a)$$

$$\Pi_i^{1-\sigma} = \sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} \frac{E_j}{Y} \quad (1b)$$

$$P_j^{1-\sigma} = \sum_i \left(\frac{t_{ij}}{\Pi_i}\right)^{1-\sigma} \frac{Y_i}{Y} \quad (1c)$$

$$p_i = \left(\frac{Y_i}{Y}\right)^{1-\sigma} \frac{1}{\alpha_i \Pi_i} \quad (1d)$$

$$E_i = \phi_i Y_i \equiv \phi_i p_i Q_i \quad (1e)$$

$$E_j = \Sigma_i X_{ij}$$
$$Y_i = \Sigma_j X_{ij} \quad (2)$$

1. X_{ij}: nominal trade volume from i to j
2. E_j: total expenditure of **importer j**
3. Y_i: total production in **exporter i**
4. Y: world output
5. t_{ij}: **bilateral trade costs** between i and j
6. σ: **elasticity of substitution** for goods of different countries ($\sigma > 1$)
7. α_i: CES preference parameter
8. P_j: **Importer Multilateral Resistances**
9. Π_i: **Exporter Multilateral Resistances**
10. p_i: **factory-gate price** for each variety of goods of origin country i
11. Q_i: quantity supplied of each variety of goods of country i
12. ϕ_i: an exogenous parameter that defines the relation between the value of output and aggregate expenditure

Conditional General Equilibrium Effect [Yotov et al., 2016]

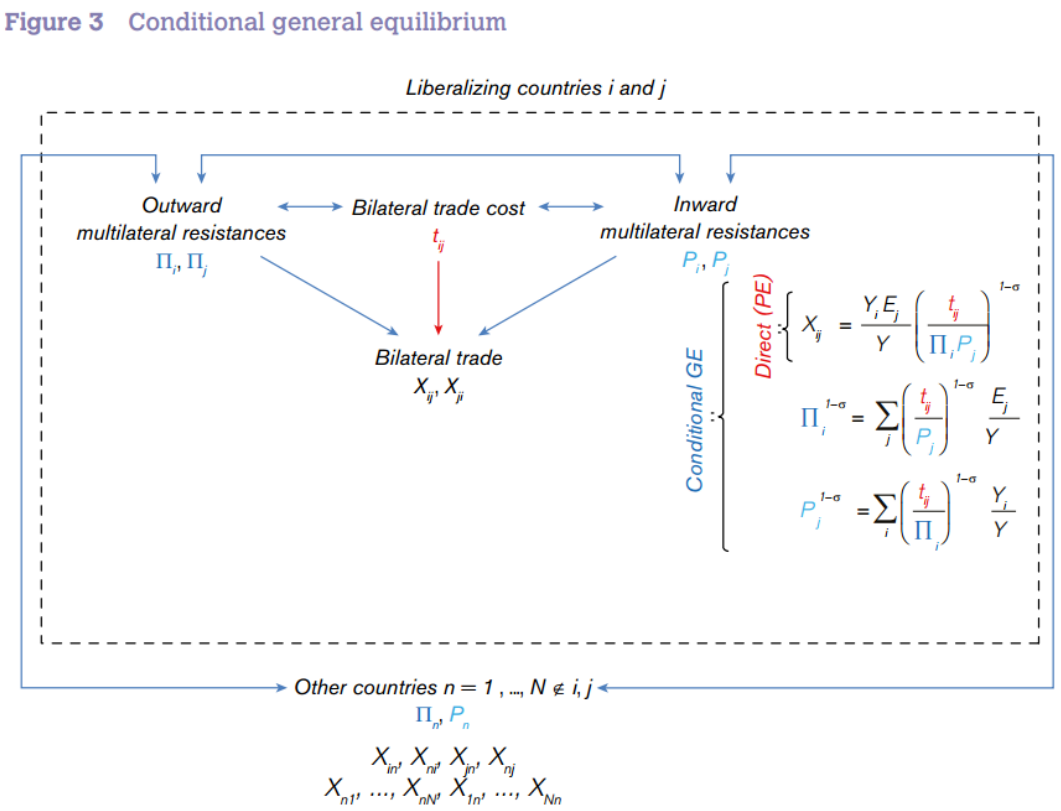

Figure: How changes are propagated in the SGM (For Conditional GE case) [Yotov et al., 2016]

Full Endowment General Equilibrium Effect[Yotov et al., 2016]

- Will solve all the SGM equations ((1a) to (1e)) simultaneously
  - $Q_i \rightarrow$ constant.
  - $t_{ij} \rightarrow$ variable.
  - changes is propagated to all the SGM equations ((1a) to (1e)) simultaneously .

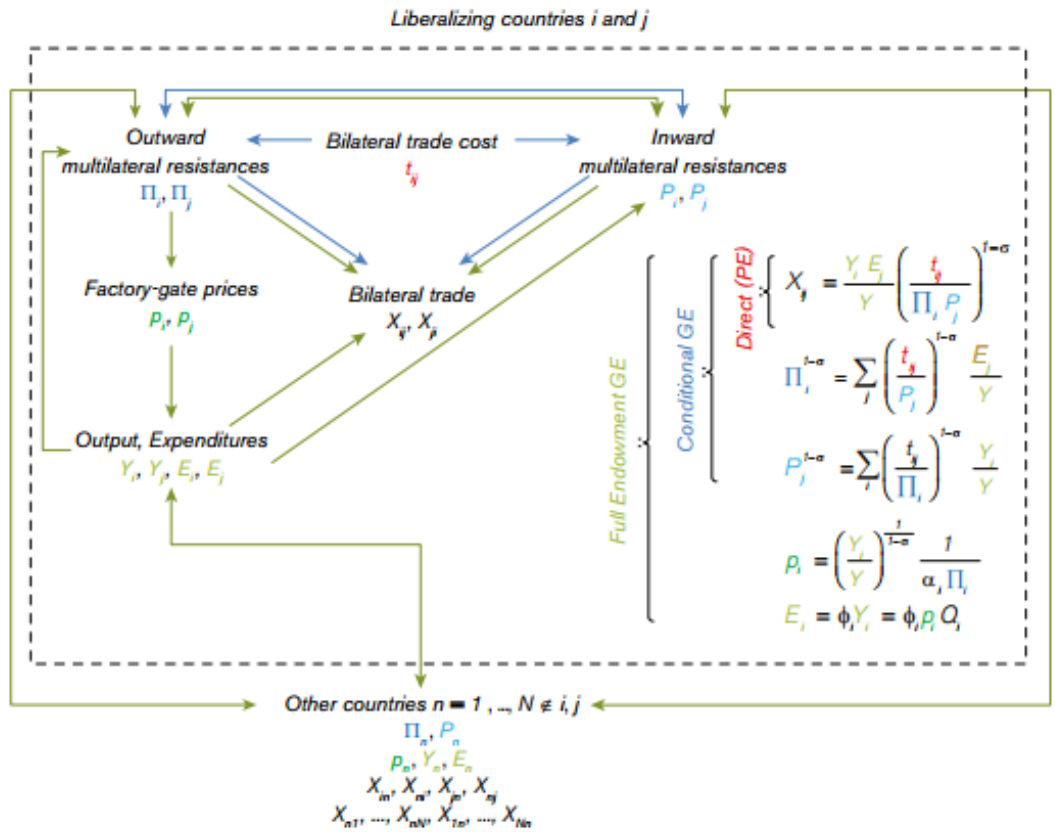

Figure: How changes are propagated in the SGM (For GE case) [Yotov et al., 2016]

- **Empirical Gravity Model** :

$$\ln X_{ij,t} = \pi_{i,t} + \chi_{i,t} + \mu_{ij} + \beta.\boldsymbol{T_{ij,t}} + \ln \epsilon_{ij,t} \tag{3}$$

$\pi_{i,t} \rightarrow$ Exporter Time Fixed Effect
$\chi_{i,t} \rightarrow$ Importer Time Fixed Effect
$\mu_{ij} \rightarrow$ Pair Fixed Effect
$\boldsymbol{T_{ij,t}} \rightarrow$ **Trade Policy Vector**
$\beta \rightarrow$ Parameter
$\epsilon_{ij,t} \rightarrow$ Error Term

- $\boldsymbol{T_{ij,t}} = (RTA_{ij,t}, ES_{i,t}.INTL_{ij}, MFN_{j,t}.INTL_{ij})^{\top}$
$RTA_{ij,t} \rightarrow$ RTA between Countries $i\&j$ at time t
$ES_{i,t} \rightarrow$ Export Subsidies by Country i
$MFN_{j,t} \rightarrow$ MFN tariff by country j
$INTL_{ij} \rightarrow$ 1 for inter-national trade & 0 for intra-national trade

Solving Strategies [Herman, 2021]

- Packages (only) for robust and fast **econometric estimation** of gravity models
  - **STATA** : `ppml` [10] , `ppmlhdfe` [11], & `ppml_panel_sg` [12]
  - **R** : `R_glmhdfe` [13] & `gravity` [14]
  - **Python** :`gme` [15]
- Tools for **"Full Fledged" Gravity Analysis** (along with CFLs):
  - **STATA** :
    - the readymade **.do** file provided in [Yotov et al., 2016] employs **GEPPML algo**
    - `GE_gravity` package[16]
  - **Python** : `gegravity` package by [Herman, 2021]
    - it solves GE gravity models and conducts CFL experiments, using econometrically estimated parameter values from `gme` package. `gegravity` Employs **NLS algo**

[10] Santos Silva, J. M. and S. Tenreyro (2015). PPML: Stata module to perform Poisson pseudo-maximum likelihood estimation.

[11] Correia, S., P. Guimar aes, and T. Zylkin (2019). ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects.

[12] Larch, M., J. Wanner, Y. V. Yotov, and T. Zylkin (2019). Currency unions and trade: A ppml re-assessment with high-dimensional fixed effects.

[13] Hinz, J., A. Hudletz, and J. Wanner (2019). Separating the wheat from the chaff: Fast estimation of GLMs with high-dimensional fixed effects.

[14] Woelwer, A.-L., J. P. Burgard, J. Kunst, M. Vargas, R. Francois, L. Henry, and H. Doytchinova (2020). gravity: Estimation Methods for Gravity Models. R package version 0.9.9.

[15] Herman, P. R., S. Ahmad, S. Shikher, T. Gurevich, G. Kenneally, S. Schreiber, C. Payan, and R. Ubee (2018). gme: Gravity Modeling Environment. Python package version 1.2.

[16] Zylkin, T. (2019). GE GRAVITY: Stata module to solve a simple general equilibrium one sector Armington-CES trade model.

The GEPPML Algo [Yotov et al., 2016]

- **STEP 1: Solving the Baseline Model**

Step1.a Estimation of (3) using PPML

$$\hat{\pi}_{i,t} = \ln\left(\frac{Y_{i,t}}{\hat{\Pi}_{i,t}^{1-\sigma}} E_{R,t}\right) \tag{4a}$$

$$\hat{\chi}_{j,t} = \ln\left(\frac{E_{j,t}}{\hat{P}_{j,t}^{1-\sigma}} \frac{1}{E_{R,t}}\right) \tag{4b}$$

$$\hat{\mu}_{ij} = \pi_i + \chi_i + \beta_1 \ln DIST_{ij} + \beta_2 CNTG_{ij} + \beta_3 . LANG_{ij} + \beta_4 . CLNY_{ij} + \ln \epsilon_{ij} \tag{4c}$$

Step1.b Constructing the Baseline MTRs:

$$[\hat{\Pi}_{i,t}^{1-\sigma}]^{\text{BLN}} = \frac{Y_{i,t}}{e^{\hat{\pi}_{i,t}}} . E_{R,t} \tag{5a}$$

$$[\hat{P}_{j,t}^{1-\sigma}]^{\text{BLN}} = \frac{E_{j,t}}{e^{\hat{\chi}_{j,t}}} \cdot \frac{1}{E_{R,t}} \tag{5b}$$

- **STEP 2: Defining Counterfactual Scenario.**
  - India joining CPTPP (earlier India was outside CPTPP)
  - Changes in Trade Policy vector $\boldsymbol{T}_{\boldsymbol{ij,t}}^{\text{CFL}} \implies$ Changes in Trade Costs $[t_{ij,t}]^{\text{CFL}}$
- $[t_{ij,t}]^{\text{BLN}} \rightarrow [t_{ij,t}]^{\text{CFL}}$ Introduces The "Shock" !
- CFL Empirical Gravity Model

$$\ln X_{ij,t} = \pi_{i,t}^{\text{CFL}} + \chi_{i,t}^{\text{CFL}} + \bar{\mu}_{ij} + \bar{\boldsymbol{\beta}}.\boldsymbol{T}_{\boldsymbol{ij,t}}^{\text{CFL}} + \ln \epsilon_{ij,t}^{\text{CFL}} \tag{6}$$

NOTE: $\bar{\mu}_{ij} \equiv \mu_{ij}$ & $\bar{\boldsymbol{\beta}} \equiv \boldsymbol{\beta}$ of equn (3)

- **STEP 3: Solving the CFL Scenario.**

Step3.a Solving For The Conditional General Equilibrium [Figure 4]

- Solving equation (6)
- Obtaining "Conditional" CFL MTR terms

$$[\hat{\Pi}_{i,t}^{1-\sigma}]_{\text{CDL}}^{\text{CFL}} = \frac{Y_{i,t}}{e^{\hat{\pi}_{i,t}^{CFL}}} . E_{R,t} \tag{7a}$$

$$[\hat{P}_{j,t}^{1-\sigma}]_{\text{CDL}}^{\text{CFL}} = \frac{E_{j,t}}{e^{\hat{\chi}_{j,t}^{CFL}}} \cdot \frac{1}{E_{R,t}} \tag{7b}$$

$\hat{\pi}_{i,t}^{CFL}$ & $\hat{\chi}_{j,t}^{CFL}$ are PPML estimator of $\pi_{i,t}^{\text{CFL}}$ & $\chi_{i,t}^{\text{CFL}}$ of equn (6)

Step3.b Solving For The Full Endowment General Equilibrium [Figure 5]

The GEPPML Algo (contd.) [Yotov et al., 2016]

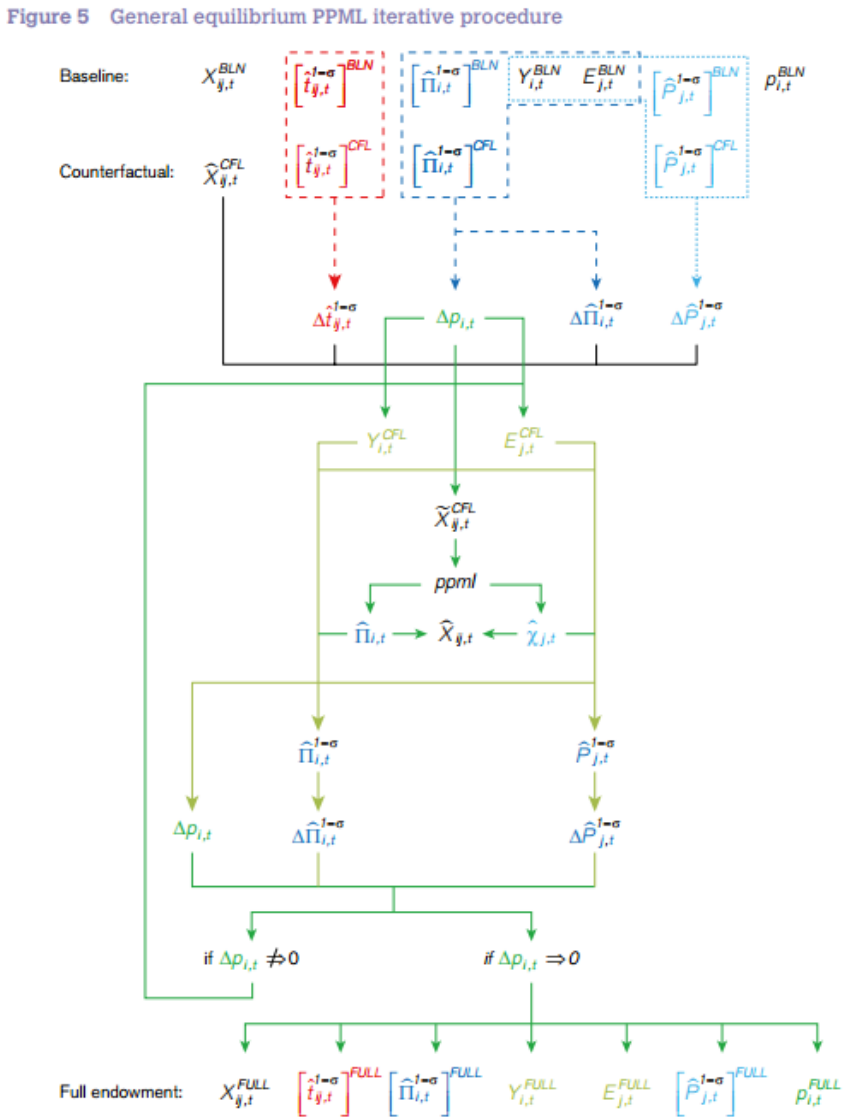

Figure: 4 Step Iterative Solving Procedure [Yotov et al., 2016]

IM_Step1 Changes in Factory gate prices $p_{i,t}$:

$$\Delta p_{i,t}^{CFL} = \frac{p_{i,t}^{CFL}}{p_{i,t}} = \left(\frac{\exp\left(\hat{\pi}_{i,t}^{CFL}\right) / E_{R,t}^{CFL}}{\exp\left(\hat{\pi}_{i,t}\right) / E_{R,t}} \right)^{\frac{1}{1-\sigma}} \tag{8}$$

IM_Step2 Changes in Income/Output, Expenditure, and Trade flow terms ($Y_{i,t}^{CFL}$, $E_{j,t}^{CFL}$ & $X_{ij,t}^{CFL}$)

$$Y_{i,t}^{CFL} = \frac{p_{i,t}^{CFL}}{p_{i,t}} Y_{i,t} \tag{9a}$$

$$E_{j,t}^{CFL} = \frac{p_{j,t}^{CFL}}{p_{j,t}} E_{j,t} \tag{9b}$$

$$X_{ij,t}^{CFL} = \frac{\left[\hat{t}_{ij,t}^{1-\sigma}\right]^{CFL}}{\hat{t}_{ij,t}^{1-\sigma}} \times \frac{Y_{i,t}^{CFL} E_{j,t}^{CFL}}{Y_{i,t} E_{j,t}} \times \frac{\Pi_{i,t}^{1-\sigma}}{\left[\Pi_{i,t}^{1-\sigma}\right]^{CFL}} \times \frac{P_{j,t}^{1-\sigma}}{\left[P_{j,t}^{1-\sigma}\right]^{CFL}} \times X_{ij,t} \tag{9c}$$

IM_Step3 Repeat [Step3] and [IM_Step1] & [IM_Step2] until Convergence is achieved ie $\Delta p_{i,t} \approx 1$

IM_Step4 **"Final Result"**

The FE General Equilibrium MTR terms

$$[\hat{\Pi}_{i,t}^{1-\sigma}]_{\text{FULL}}^{\text{CFL}} = \frac{Y_{i,t}^{\text{FULL}}}{e^{\hat{\pi}_{i,t}^{FULL}}} . E_{R,t}^{FULL} \tag{10a}$$

$$[\hat{P}_{j,t}^{1-\sigma}]_{\text{FULL}}^{\text{CFL}} = \frac{E_{j,t}^{\text{FULL}}}{e^{\hat{\chi}_{j,t}^{FULL}}} . \frac{1}{E_{R,t}^{FULL}} \tag{10b}$$

$\hat{\pi}_{i,t}^{FULL}$&$\hat{\chi}_{j,t}^{FULL}$ are the latest value.

$$\begin{aligned}
\frac{p_{i,t}^{FULL}}{p_{i,t}^{BLN}} &= \left(\frac{\exp\left(\hat{\pi}_{i,t}^{FULL}\right) / E_{R,t}^{FULL}}{\exp\left(\hat{\pi}_{i,t}^{BLN}\right) / E_{R,t}^{BLN}} \right)^{\frac{1}{1-\sigma}} \\
Y_{i,t}^{FULL} &= \frac{p_{i,t}^{FULL}}{p_{i,t}^{BLN}} \times Y_{i,t}^{BLN} \\
E_{i,t}^{FULL} &= \varphi_i Y_{i,t}^{FULL} \\
X_{ij,t}^{FULL} &= \frac{Y_{i,t}^{FULL} E_{j,t}^{FULL}}{Y^{FULL}} \frac{\left(\hat{t}_{ij,t}^{CRL}\right)^{1-\sigma}}{\left[\hat{\Pi}_{i,t}^{1-\sigma}\right]_{FULLL}^{CFL} \left[\hat{P}_{j,t}^{1-\sigma}\right]_{FULL}^{CFL}}
\end{aligned} \tag{11}$$

The GEPPML Algo(contd.)[Yotov et al., 2016]

- **STEP 4:**
  $|\text{Baseline Indexes} - \text{CFL CDL Indexes}| \rightarrow$ CDL GE effect of CPTPP+
  $|\text{Baseline Indexes} - \text{CFL Full Indexes}| \rightarrow$ *FE GE effect* of CPTPP+
- **STEP 5:** Construction Of Confidence Intervals of the parameters.

Implementation [Yotov et al., 2016]

- **STEP 1: Solving the Baseline Model**

Step1.a Estimation of (3) using PPML
Step1.b Constructing the Baseline MTRs:

- **STEP 2: Defining Counterfactual Scenario**
- **STEP 3: Solving the Counterfactual Scenario**
- **STEP 4: Computing the changes in the indexes**
- **STEP 5: Constructing the confidence interval of the Parameters**

NLS Algorithm [Herman, 2021]

- Offers an alternative approach to solving GE gravity models compared to the custom iterative method `GEPPML` outlined by [Yotov et al., 2016]
- Instead of custom iterations, NLS algorithm harnesses standard nonlinear solvers provided by the `scipy` package in Python, specifically using the `root` function
- [Herman, 2021] Implemented the algorithm in `.py` in the `gegravity` package
  - The `gegravity` package simplifies the process of solving GE gravity models and conducting counterfactual experiments based on parameter values estimated using econometric techniques from other packages.

Package Overview

- **Dependencies**:
  - `gme`: Gravity modeling tools for data structuring, econometric model definition, and PPML estimation.
  - `pandas`: Data manipulation and analysis.
  - `scipy` and `numpy`: Numerical and scientific computing.
- **Key Classes**:
  - `OneSectorGE`: Methods for solving the baseline model and conducting counterfactual scenarios.
  - `MonteCarloGE`: Conducts Monte Carlo counterfactual simulations, providing results with statistical precision metrics.

Implementation [Herman, 2021]

- **Link to the Entire code** [Herman, 2021]
  `https://github.com/debmanna/ECO412_Project/blob/main/Herman.ipynb`
  - The Raw code is there in the ”Synopsis (Remastered)”

Modified Herman's Code [Herman, 2021]

```
## IMPORTING LIBRARIES

import gegravity as ge
import pandas as pd
import gme as gme

# Increase number of columns printed for a pandas DataFrame
pd.set_option("display.max_columns", None)
pd.set_option('display.width', 1000)
```

```
## LOADING DATASET

gravity_data_location = "CPTPP_modified_main.csv"
grav_data = pd.read_csv(gravity_data_location)

print(grav_data.head())
```

```
## PREPARE DATASET AND ECONOMETRIC INPUTS FOR GE MODEL

# Define GME Estimation Data
gme_data = gme.EstimationData(grav_data, # Dataset
                              imp_var_name="importer", # Importer column name
                              exp_var_name="exporter", # Exporter column name
                              year_var_name = "year",  # Year column name
                              trade_var_name="trade")  # Trade column name

 # Create Gravity Model
 gme_model = gme.EstimationModel(gme_data, # Specify data to use
                                 lhs_var="trade",                                  # dependent, "left hand side"
                                       variable
                                 rhs_var=["pta","contiguity","common_language", # independent variables
                                          "lndist","international"],
                                 fixed_effects=[["exporter"],["importer"]])      # Fixed effects to use
```

```python
## ESTIMATING THE GRAVITY MODEL WITH PPML

gme_model.estimate()
# Print econometric results table

print(gme_model.results_dict['all'].summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  trade   No. Observations:                  400
Model:                            GLM   Df Residuals:                      356
Model Family:                 Poisson   Df Model:                           43
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:            -1.7401e+09
Date:                Thu, 16 Nov 2023   Deviance:                   3.4801e+09
Time:                        12:02:19   Pearson chi2:                 3.76e+09
No. Iterations:                    10   Pseudo R-squ. (CS):              1.000
Covariance Type:                  HC1
==============================================================================
```

Figure: The estimated gravity model results

	coef	std err	z	P>|z|	[0.025	0.975]
pta	0.0622	0.237	0.263	0.793	-0.402	0.526
contiguity	1.1767	0.242	4.856	0.000	0.702	1.652
common_language	-0.6698	0.235	-2.855	0.004	-1.130	-0.210
lndist	1.204e-05	2.21e-05	0.544	0.586	-3.13e-05	5.54e-05
international	-2.7103	0.377	-7.185	0.000	-3.450	-1.971
exporter_fe_Australia	18.3632	0.529	34.700	0.000	17.326	19.400
exporter_fe_Brazil	17.5486	0.497	35.329	0.000	16.575	18.522
exporter_fe_Brunei	14.8607	0.661	22.484	0.000	13.565	16.156
exporter_fe_Canada	18.1358	0.473	38.336	0.000	17.209	19.063
exporter_fe_Chile	16.1176	0.528	30.515	0.000	15.082	17.153

Figure: Coefficients of the estimated gravity model

```
## DEFINING A GE MODEL

ge_model = ge.OneSectorGE(gme_model,              # gme gravity model
                    year = "2021",                # Year to use for model
                    expend_var_name = "E",        # Expenditure column name
                    output_var_name = "Y",        # Output column name
                    reference_importer = "India",   # Reference importer
                    sigma = 5)                    # Elasticity of substitution
```

- The Reference Country is `India`
- The `year` is 2021

```
## SOLVING THE BASELINE GE MODEL

ge_model.build_baseline(omr_rescale=100)
# Examine the solutions for the baseline multilateral resistances
print(ge_model.baseline_mr.head(20))
```

```
Solving for baseline MRs...
The solution converged.
             baseline omr  baseline imr
country
Australia        1.942819      1.070281
Brazil           1.840491      1.054386
Brunei           1.808422      1.091267
Canada           1.797318      1.051717
Chile            1.866900      1.064646
China            1.620557      0.894584
France           1.849611      0.968671
Germany          1.693060      0.964329
India            1.787515      1.000000
Italy            1.769935      1.024815
Japan            1.776661      1.013177
Malaysia         1.944037      1.025192
Mexico           1.774734      0.999787
New Zealand      1.991070      1.120847
Peru             1.878647      1.056136
Russia           1.869219      0.961785
Singapore        1.892056      1.043771
UK               1.840134      1.075487
USA              1.547719      1.004403
Vietnam          1.765015      0.977437
```

Figure: Baseline Multilateral Resistance Terms(Output of the just above block of code)

```
## SOLVING THE COUNTERFACTUAL GE MODEL

# Create a copy of the baseline data
exp_data = ge_model.baseline_data.copy()

# Modify the copied data to reflect a counterfactual experiment in which India and CPTPP12 countries sign a
      preferential trade agreement (pta)

exp_data.loc[(exp_data["importer"] == "Australia") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Australia"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Brunei") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Brunei"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Canada") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Canada"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Chile") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Chile"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Japan") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Japan"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Malaysia") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Malaysia"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Mexico") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Mexico"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "New␣Zealand") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "New␣Zealand"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Peru") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Peru"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "Singapore") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Singapore"), "pta"] = 1

exp_data.loc[(exp_data["importer"] == "UK") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "UK"), "pta"] = 1
```

```
exp_data.loc[(exp_data["importer"] == "Vietnam") & (exp_data["exporter"] == "India"), "pta"] = 1
exp_data.loc[(exp_data["importer"] == "India") & (exp_data["exporter"] == "Vietnam"), "pta"] = 1

# Define the experiment within the GE model
ge_model.define_experiment(exp_data)
# Examine the baseline and counterfactual trade costs
print(ge_model.bilateral_costs.head())

##
# Simulate the counterfactual model
##
ge_model.simulate()
# Examine the counterfactual trade flows predicted by the model.
print(ge_model.bilateral_trade_results.head())
```

```
                    baseline trade cost  experiment trade cost  trade cost change (%)
exporter  importer
Australia Australia             0.511798               0.511798                    0.0
          Brazil                0.043678               0.043678                    0.0
          Brunei                0.037968               0.037968                    0.0
          Canada                0.042951               0.042951                    0.0
          Chile                 0.082502               0.082502                    0.0
Solving for conditional MRs...
The solution converged.
Solving full GE model...
The solution converged.
                    baseline modeled trade  experiment trade  trade change (percent)
exporter  importer
Australia Australia           6.592889e+07      6.592200e+07               -0.010436
          Brazil              4.754732e+06      4.759726e+06                0.105038
          Brunei              1.732759e+05      1.734580e+05                0.105073
          Canada              9.691082e+06      9.695803e+06                0.048709
          Chile               3.667270e+06      3.671082e+06                0.103943
```

Figure: Counterfactual Results (Output of the just above block of code)

```
## ACCESSING and EXPORTING THE RESULTS

##
# Retrieve many of the different sets of model results
##
# A collection of many of the key country-level results (prices, total imports/exports, GDP, welfare, etc.)
country_results = ge_model.country_results
# The bilateral trade results
bilateral_results = ge_model.bilateral_trade_results
# A wider selection of aggregate, country-level trade results
agg_trade = ge_model.aggregate_trade_results
# country multilateral resistance (MR) terms
mr_terms = ge_model.country_mr_terms
# Get the solver diaganoistics, which is a dictionary containing many types of solver diagnostic info
solver_diagnostics = ge_model.solver_diagnostics

##
# Export results
##
# Export the results to a collection of spreadsheet (.csv) files and add trade values in levels to the outputs.
ge_model.export_results(directory="./Sample_result",name="India_CPTPP_PTA_experiment", include_levels = True)
# It is also possible to add alternative country identifies such as full country names using the country_names
      argument.
# See the technical documentation for details
```

- Generates two `csv` file:
  `India_CPTPP_PTA_experiment_bilateral_results.csv` → **Bilateral Trade Results**
  `India_CPTPP_PTA_experiment_country_results.csv` → **Impact on the individual countries**
- The results of the above code capture the GE impact of INDIA joining CPTPP on all the 20 countries
- LINK to the Fully Functional Code and all the files

Results

1. The Estimated gravity models and their coefficients
2. Impact at Individual Country level
3. Bilateral Trade Results

- I will keep special emphasis on the **Impact of India's trade relation** with the rest of the 19 countries involved in the analysis.

Estimated Gravity Model

```
Estimation began at 12:02 PM  on Nov 16, 2023
Omitted Regressors: ['importer_fe_Vietnam']
Estimation completed at 12:02 PM  on Nov 16, 2023
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                    trade   No. Observations:                  400
Model:                              GLM   Df Residuals:                      356
Model Family:                   Poisson   Df Model:                           43
Link Function:                      Log   Scale:                          1.0000
Method:                            IRLS   Log-Likelihood:           -1.7401e+09
Date:                 Thu, 16 Nov 2023   Deviance:                  3.4801e+09
Time:                         12:02:19   Pearson chi2:                3.76e+09
No. Iterations:                      10   Pseudo R-squ. (CS):             1.000
Covariance Type:                    HC1
==============================================================================
                             coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
pta                        0.0622      0.237      0.263      0.793      -0.402       0.526
contiguity                 1.1767      0.242      4.856      0.000       0.702       1.652
common_language           -0.6698      0.235     -2.855      0.004      -1.130      -0.210
lndist                 1.204e-05   2.21e-05      0.544      0.586   -3.13e-05    5.54e-05
international             -2.7103      0.377     -7.185      0.000      -3.450      -1.971
```

Figure: Estimated Gravity Model Results

- `pta` has a +ve coeff (**0.0622**) and it's statistically significant, indicating a strong positive impact on TRADE.

- `contiguity` has a +ve coeff. (**1.1767**), indicating that neighboring countries trade more and it is statistically significant ($p < 0.05$)
- `lndist` has very small +ve coefficient but it is statistically insignificant which is counterintuitive as the increase in dist trade should reduce, but in reality, larger economies do trade with each other.
- `international`: Counterintuitively International trading relations has a -ve coefficient **(-2.7103)**, but it's not statistically significant.
- `common_language` Counterintuitively common language has a -ve coefficient (**-0.6698**), but it's not statistically significant.

This suggests that in this modern interconnected world countries always trade irrespective of whether them having international trading relations or a common language or not.

Impact at Individual Country level

When **India Joins the CPTPP** the following dominant changes are observed:

- **Factory Gate Price** changes:
  are **+ve for all countries** $\Rightarrow$ India's accession into CPTPP could lead to increased demand for certain goods that India was importing, causing an increase in prices. The entry of India into CPTPP drives prices up and leads to a realignment of trade relations.

	factory gate price change (percent)
USA	0.0776
China	0.0726
Japan	0.0746
Germany	0.0752
India	0.1516
UK	0.0983
France	0.0764
Russia	0.0734
Canada	0.1006
Italy	0.0747
Brazil	0.0737
Australia	0.0713
Mexico	0.0744
Singapore	0.0763
Vietnam	0.1216
Malaysia	0.0761
Chile	0.0731
New Zealand	0.1166
Peru	0.1431
Brunei	0.0739

Figure: Changes in Factory Gate Prices

- **GDP** Change:
  1. **-ve GDP change for Non-Member countries** show that India's entry into CPTPP led to loss of economic integration benefits, such as reduced trade flows, investment, and cooperative economic activities. Negative Change for non-member countries shows that when India joins CPTPP, both India and non-members may look to strengthen bilateral trade relations, potentially increasing trade within the CPTPP bloc.
  2. **+ve GDP change for Countries** implies that India's entry to CPTPP is of benefit to such countries. They gain perhaps because of increased market size and ability to charge a higher markup. A considerable increase in GDP can happen when India joins CPTPP.

	GDP change (percent)
USA	-0.0019
China	-0.0077
Japan	-0.0049
Germany	-0.0035
India	0.1516
UK	0.0387
France	-0.0023
Russia	-0.0040
Canada	0.0400
Italy	-0.0049
Brazil	-0.0077
Australia	0.0181
Mexico	-0.0053
Singapore	-0.0027
Vietnam	0.0385
Malaysia	-0.0041
Chile	-0.0081
New Zealand	0.0659
Peru	0.0602
Brunei	-0.0075

Figure: Changes in GDP

- **welfare statistic** likely measures the economic well-being of each country The marginal positive values in the welfare statistic column could indicate that, according to this model, the countries listed experience a slight increase in economic welfare when India joins CPTPP.
  The reason is may be due to trade diversion to other countries, resource allocation from India to other countries, leading to a small welfare gain and exit of a major economy like India could open up market opportunities for smaller countries .

	welfare statistic
USA	1.00002
China	1.00008
Japan	1.00005
Germany	1.00004
India	0.99849
UK	0.99961
France	1.00002
Russia	1.00004
Canada	0.99960
Italy	1.00005
Brazil	1.00008
Australia	0.99982
Mexico	1.00005
Singapore	1.00003
Vietnam	0.99962
Malaysia	1.00004
Chile	1.00008
New Zealand	0.99934
Peru	0.99940
Brunei	1.00007

Figure: Changes in Welfare Stats

- The **OMR** (Outward Multilateral trade Resistance term) changes **are -ve** for all countries, which suggests that these countries are facing decreased resistance to exporting goods after India joins the bloc. This could be due to enhanced trade synergies, and weakened logistic costs.

	baseline omr	experiment omr	omr change (percent)
USA	1.5477	1.5465	-0.0776
China	1.6206	1.6194	-0.0725
Japan	1.7767	1.7753	-0.0746
Germany	1.6931	1.6918	-0.0751
India	1.7875	1.7848	-0.1514
UK	1.8401	1.8383	-0.0983
France	1.8496	1.8482	-0.0763
Russia	1.8692	1.8678	-0.0733
Canada	1.7973	1.7955	-0.1005
Italy	1.7699	1.7686	-0.0746
Brazil	1.8405	1.8391	-0.0736
Australia	1.9428	1.9414	-0.0712
Mexico	1.7747	1.7734	-0.0743
Singapore	1.8921	1.8906	-0.0762
Vietnam	1.7650	1.7629	-0.1215
Malaysia	1.9440	1.9426	-0.0760
Chile	1.8669	1.8655	-0.0731
New Zealand	1.9911	1.9888	-0.1165
Peru	1.8786	1.8760	-0.1429
Brunei	1.8084	1.8071	-0.0738

Figure: Changes in OMR term for all the countries

- The **IMR** (Inward Multilateral trade Resistance term) changes **are +ve** which suggest the countries might adjust their trade agreements making it harder for countries to import from each other or from alternative partners and so their is an increase in resistance.

	baseline imr	experiment imr	imr change (percent)
USA	1.0044	1.0052	0.0795
China	0.8946	0.8953	0.0803
Japan	1.0132	1.0140	0.0795
Germany	0.9643	0.9651	0.0787
India	1.0000	1.0000	0.0000
UK	1.0755	1.0761	0.0596
France	0.9687	0.9694	0.0787
Russia	0.9618	0.9625	0.0774
Canada	1.0517	1.0524	0.0606
Italy	1.0248	1.0256	0.0796
Brazil	1.0544	1.0552	0.0814
Australia	1.0703	1.0708	0.0531
Mexico	0.9998	1.0006	0.0797
Singapore	1.0438	1.0446	0.0790
Vietnam	0.9774	0.9782	0.0831
Malaysia	1.0252	1.0260	0.0802
Chile	1.0646	1.0655	0.0813
New Zealand	1.1208	1.1214	0.0507
Peru	1.0561	1.0570	0.0828
Brunei	1.0913	1.0922	0.0813

Figure: Changes in IMR term for all the countries

- **Net Foreign Export** & **Net Foreign Import** The baseline modeled trade, which represents the initial trade flows as per the model before any changes, and the experiment trade simulates the counterfactual scenario where India joins CPTPP.

	baseline modeled foreign exports	experiment foreign exports	foreign exports change
USA	614914430.590	615314535.694	0.065
China	1877863683.599	1878956906.473	0.058
Japan	534693507.758	535063317.705	0.069
Germany	1025298144.715	1026004915.641	0.069
India	314402395.666	315417176.739	0.323
UK	286911644.703	287497163.926	0.204
France	430392216.610	430706406.494	0.073
Russia	445554813.030	445885084.760	0.074
Canada	390487649.088	391078120.052	0.151
Italy	482527677.809	482870345.876	0.071
Brazil	251238326.159	251421687.304	0.073
Australia	284954374.731	285208087.764	0.089
Mexico	409503646.498	409797622.012	0.072
Singapore	357779314.903	358041887.171	0.073
Vietnam	305699774.806	306129936.881	0.141
Malaysia	262635449.319	262829159.119	0.074
Chile	91756588.914	91824870.555	0.074
New Zealand	43338738.083	43395122.102	0.130
Peru	55956569.323	56042162.915	0.153
Brunei	11287528.158	11295936.250	0.074

(a) Net Foreign Export

	baseline modeled foreign imports	experiment foreign imports	foreign imports change
USA	1749406904	1750681835	0.073
China	1112954958	1113395971	0.040
Japan	530321056	530676393	0.067
Germany	772066896	772565023	0.065
India	479778418	481033514	0.262
UK	492429138	493209969	0.159
France	544950969	545346075	0.073
Russia	234003889	234161304	0.067
Canada	367376866	367939695	0.153
Italy	418888617	419175944	0.069
Brazil	197850599	197989804	0.070
Australia	195657494	195843298	0.095
Mexico	408680322	408965519	0.070
Singapore	295094606	295306510	0.072
Vietnam	291973777	292381367	0.140
Malaysia	193914839	194056458	0.073
Chile	86821813	86884698	0.072
New Zealand	47088335	47148667	0.128
Peru	49418929	49493995	0.152
Brunei	8518050	8524406	0.075

(b) Net Foreign Import

- From the above data it appears that for most country pairs, trade volumes increase when India joins CPTPP, which is expected as the addition of a major economy like India would typically disrupt existing trade patterns and increase the overall trade volumes due to the massive size of its market.

Bilateral Trade Results

- **Impact on India's Export to the CPTPP and Nonmember countries**

exporter	importer	baseline modeled trade	experiment trade	trade change (percent)	baseline observed trade	experiment observed trade	trade change (observed level)
India	USA	36797564.7488	36746297.9970	-0.1393	30123681.0400	30081712.4127	-41968.6273
India	China	129040904.8493	128859031.3061	-0.1409	64498538.4300	64407632.5445	-90905.8855
India	Japan	19213763.3352	19186462.6191	-0.1421	8335076.3700	8323233.1121	-11843.2579
India	Germany	27343381.5737	27303797.4902	-0.1448	3451637.7800	3446640.9614	-4996.8186
India	India	90623586.6007	90276857.9283	-0.3826	175588331.1400	174916524.7015	-671806.4385
India	**UK**	**10689278.5406**	**11353226.5369**	**6.2113**	**3629393.5500**	**3854827.7143**	**225434.1643**
India	France	14137646.2842	14117315.3328	-0.1438	2240375.5100	2237153.6890	-3221.8210
India	Russia	5560393.3119	5551945.3603	-0.1519	5360774.0800	5352629.4115	-8144.6685
India	**Canada**	**7293187.3749**	**7746657.5512**	**6.2177**	**841600.5000**	**893928.8864**	**52328.3864**
India	Italy	13993736.9826	13973890.4790	-0.1418	2883945.8600	2879855.7272	-4090.1328
India	Brazil	7634930.3893	7624572.9546	-0.1357	1333708.6800	1331899.3903	-1809.2897
India	**Australia**	**3984701.7986**	**4229957.4638**	**6.1549**	**8185672.8300**	**8689495.3835**	**503822.5535**
India	Mexico	13339515.2913	13320609.2044	-0.1417	18956.3400	18929.4732	-26.8668
India	Singapore	6351561.9633	6342518.7031	-0.1424	7551444.8900	7540693.2542	-10751.6358
India	Vietnam	6893760.5650	6888172.6998	-0.0811	436925.0600	436570.9023	-354.1577
India	Malaysia	6001516.9882	5993230.6924	-0.1381	5385446.2900	5378010.6032	-7435.6868
India	Chile	3181313.1190	3176962.6368	-0.1368	87830.6000	87710.4906	-120.1094
India	**New Zealand**	**948076.0069**	**1006787.7898**	**6.1927**	**135730.8800**	**144136.3263**	**8405.4463**
India	Peru	1715605.7272	1714564.9644	-0.0607	1697309.0900	1696279.4267	-1029.6633
India	Brunei	281556.8156	281174.9573	-0.1356	424230.4600	423655.1021	-575.3579

Figure: India's Export to the other countries

- Observe that the **trade change** is +ve only for **UK, Canada, Australia & New Zealand** $\Rightarrow$ India's export to these 4 CPTPP countries increases when India joins the trading block.

- For rest of the 16 countries **trade change** is -ve $\Rightarrow$ India's export with these counutry decreases. Perhaps the export gets rerouted to **UK, Canada, Australia & New Zealand**

- **Impact on India's Import from the CPTPP and Nonmember countries**

exporter	importer	baseline modeled trade	experiment trade	trade change (percent)	baseline observed trade	experiment observed trade	trade change (observed level)
USA	India	18676020.0761	18645849.0911	-0.1615	36889355.8300	36829761.3235	-59594.5065
China	India	246905007.6315	246543344.7729	-0.1465	69373320.2100	69271703.1811	-101617.0289
Japan	India	25202376.7508	25163919.1285	-0.1526	6710011.1100	6699771.9538	-10239.1562
Germany	India	45189386.0018	45119663.7876	-0.1543	1694942.8900	1692327.7810	-2615.1090
India	India	90623586.6007	90276857.9283	-0.3826	175588331.1400	174916524.7015	-671806.4385
UK	**India**	**8748349.7172**	**9289344.4488**	**6.1840**	**5248351.4600**	**5572907.5856**	**324556.1256**
France	India	11928436.8471	11909602.9482	-0.1579	418514.7000	417853.9040	-660.7960
Russia	India	19847788.9507	19818244.4178	-0.1489	4700401.7300	4693404.9217	-6996.8083
Canada	**India**	**8984202.6548**	**9539129.7114**	**6.1767**	**2423641.0000**	**2573341.9827**	**149700.9827**
Italy	India	20324321.5811	20293272.0580	-0.1528	3217664.0300	3212748.3956	-4915.6344
Brazil	India	12002045.3192	11984062.2320	-0.1498	2434929.2000	2431280.8598	-3648.3402
Australia	India	8519460.9661	8507320.5754	-0.1425	7254797.0500	7244458.8289	-10338.2211
Mexico	India	18299884.5480	18272106.0284	-0.1518	5243013.1200	5235054.4281	-7958.6919
Singapore	India	9724695.3956	9709367.2152	-0.1576	12624314.7000	12604416.1051	-19898.5949
Vietnam	India	9895150.7401	10499743.3289	6.1100	689537.5300	731668.1949	42130.6649
Malaysia	India	7058642.9290	7047562.1744	-0.1570	4984843.2800	4977018.0045	-7825.2755
Chile	India	4371344.0710	4364870.2551	-0.1481	5606.3900	5598.0871	-8.3029
New Zealand	**India**	**1203071.1347**	**1276770.4653**	**6.1259**	**383135.2200**	**406605.8266**	**23470.6066**
Peru	**India**	**2510712.9283**	**2662403.8378**	**6.0417**	**1397850.9900**	**1482305.6027**	**84454.6127**
Brunei	India	387519.6461	386937.1892	-0.1503	380150.1400	379578.7598	-571.3802

Figure: India's Import from other countries

- Observe that the **trade change** is +ve only for **UK, Canada, New Zealand & Peru** $\Rightarrow$ India's import from these 4 CPTPP countries increases when India joins the trading block.

- For rest of the 16 countries **trade change** is -ve $\Rightarrow$ India's import with these counutry decreases. It is highly likely that India will become more depended on **UK, Canada, New Zealand & Peru** to meet its deficient import demand.

Conclusion

1. India's accession into CPTPP has overall +ve Welfare Impacts (as is observed in the 14)on all the countries under consideration
2. The **Inward Trade Resistance term** (IMR) of all the countries increases and the **Outward Trade Resistance term** (OMR) of all the countries decreases $\Rightarrow$ All the countries becomes more resistant towards import and favors export (ie **the countries adopt policy so as to promote their export**)

   We see a decrease in shipment volumes due to the loss of a major trading partner. This would be reflected in lower imports from India and potentially lower exports to India
3. India's market is substantial, and its accession into CPTPP would enhance the size of the CPTPP market, leading to significant changes in trade volumes for member countries as well as Non-members countries.

- **Therefore India's accession into CPTPP is very favourable.**

References

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THANKS !