2023 ISDSA Presentation

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Overview

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Topic & Background

Topic: China's COVID-19 Lockdown Policy and Trade with US: A Deep Learning Time Series Approach

- International trade suffered from sizeable negative spillovers due to the COVID-19 shutdowns either from importer or exporter sides (Aiyar et al., 2022, Barbero et al., 2021, Berthou & Stumpner, 2022).
- The pandemic imposed uncommon magnitude on firms through the interruption of Global value chains (GVCs) (Verbeke, 2020, Ciravegna & Michailova, 2022).
- China's three-year lockdown policies have brought a huge impact on global trade and the economy (Bas et al., 2022, Liu et al., 2022).

Research Question & Hypotheses

Research Question & Hypotheses

As the United States' largest supplier of goods imports, what's the impact of China's three-year lockdown of borders and ports on U.S. trade and on U.S. firms?

- Hypothesis 1: China's COVID stringency has a negative impact on US imports from China.
- Hypothesis 2: China's COVID stringency has a negative effect on US exports to China.
- Hypothesis 3: China's COVID stringency negatively impacts US firms.
- Hypothesis 4: China's COVID stringency is more harmful to US firms that are more involved in global value chains.
- Hypothesis 5: China's COVID stringency has a different influence on different product sectors.

Research Design

Data & Variables

Monthly data on US trade flows with China at a Harmonized System (HS) product sector classification level, monthly moving average S&P 500 stock index, and the other related data between March 2010 and April 2023.

Data size: 1264 records, 14 variables

- **Dependent Variables (DVs)**
  1. US Imports from China (ln)
  2. US Exports to China (ln)
  3. S&P 500 Index (1d)

Data & Variables (Continued)

- **Independent Variables**
  1. China Stringency Index (1d)
  2. US Stringency Index (1d)
  3. Product Sector: seven most influential sectors and others
  4. Global Supply Chain Pressure Index (GSCPI) (1d)
- **Control Variables**
  1. US Producer Price Index (PPI) (1d)
  2. USD to CNY Exchange Rate (1d)
  3. 30-Day Average SOFR (the Federal Funds Rate) (2d)
  4. UK Stringency Index (1d)
  5. Mexico Stringency Index (1d)

Methods

Fixed-Effect Regression Analysis

- Fixed Year: 14 years from 2010 to 2023
- Fixed Product Sector: seven product sectors + Other sectors, such as Sector 16 (Electrical Equipment), Sector 19 (Arms and Ammunition), etc.

Counterfactual Analysis using Machine Learning and Deep Learning models

- Try 30 models for each DV, and the models include Gradient Boosting Machine (GBM), Extreme Gradient Boosting Models (XGBoost), Extremely Randomized Trees (XRT), Distributed Random Forest (DRF), General Linear Models (GLM), Stacked Ensemble Models, etc.
- Pick the best-performing models and predict DVs under a non-COVID-19 setting, then compare the difference verse real values

Results & Discussion

Fixed-Effect Regression Analysis

	M1 US Imports	M2 US Exports	M3 S&P 500
Global Supply Chain Pressure Index(GSCPI)(1d)	−0.046	−0.008	22.249***
	(0.031)	(0.106)	(6.151)
China Stringency Index(1d)	−0.003**	−0.004	3.126***
	(0.001)	(0.005)	(0.366)
US Stringency Index(1d)	−0.015***	0.040***	−8.217***
	(0.003)	(0.012)	(0.702)
Mexico Stringency Index(1d)	0.002	−0.005	0.731
	(0.002)	(0.008)	(0.454)
UK Stringency Index(1d)	−0.001	−0.009	1.938***
	(0.003)	(0.011)	(0.652)
SP500 Adj Price(1d)	−0.000	0.000	
	(0.000)	(0.001)	
US Producer Price Index(1d)	−0.008	−0.008	−3.945***
	(0.005)	(0.019)	(1.052)
Federal Funds Rate(2d)	0.075	0.523	216.583***
	(0.112)	(0.392)	(21.643)
Exchange Rate(1d)	0.069	1.590**	−429.985***
	(0.193)	(0.673)	(35.976)
GSCPI*China Stringency Index(1d)			−3.124***
			(0.435)
R^2	0.989	0.912	0.485
Adj. R^2	0.988	0.909	0.470
Num. obs.	1008	1008	1008

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 1 Fixed-Effect Regression Results (Numeric Variables)

Table 2 Fixed-Effect Regression Results (Categorical Variables)

	M1 US Imports	M2 US Exports	M3 S&P 500
Year 2011	0.025	0.439**	−24.789**
	(0.058)	(0.202)	(11.347)
Year 2012	0.071	0.374*	−2.699
	(0.058)	(0.203)	(11.443)
Year 2013	0.141**	0.451**	13.349
	(0.059)	(0.206)	(11.575)
Year 2014	0.084	0.138	10.972
	(0.058)	(0.204)	(11.482)
Year 2015	0.167***	0.249	−13.781
	(0.058)	(0.203)	(11.403)
Year 2016	0.065	−0.082	18.129
	(0.058)	(0.204)	(11.463)
Year 2017	0.084	0.356*	5.296
	(0.058)	(0.201)	(11.308)
Year 2018	0.155***	0.257	−4.518
	(0.058)	(0.204)	(11.480)
Year 2019	0.003	0.433**	38.497***
	(0.059)	(0.205)	(11.464)
Year 2020	0.004	0.131	50.476***
	(0.061)	(0.212)	(12.278)
Year 2021	0.125**	0.573***	61.494***
	(0.060)	(0.210)	(11.656)
Year 2022	0.051	−0.159	−55.768***
	(0.061)	(0.212)	(11.825)
Year 2023	−0.219***	−0.010	46.624***
	(0.083)	(0.288)	(16.576)
Product Sector 03	−7.630***	−7.250***	−0.508
	(0.042)	(0.148)	(8.337)
Product Sector 11	−1.144***	−3.594***	−7.023
	(0.042)	(0.147)	(8.282)
Product Sector 12	−1.863***	−6.487***	0.072
	(0.042)	(0.146)	(8.250)
Product Sector 16	0.675***	−0.972***	−3.749
	(0.043)	(0.149)	(8.376)
Product Sector 19	−6.596***	−12.411***	−3.941
	(0.042)	(0.146)	(8.202)
Product Sector 20	−0.763***	−4.931***	−4.865
	(0.042)	(0.146)	(8.216)
Product Sector 21	−6.278***	−6.929***	−4.516
	(0.042)	(0.148)	(8.312)
Numeric Variables	~	~	~
R^2	0.976	0.905	0.433
Adj. R^2	0.976	0.904	0.426
Num. obs.	2322	2322	2322

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3 Variable Importance Based on Fixed-Effect Regression Models

Variable Names / Models	Model 1 (US Imports)	Model 2 (US Exports)	Model 3 (S&P 500)
Global Supply Chain Pressure Index (GSCPI)(1d)	1.50	0.08	3.62
China Stringency Index(1d)	2.24	0.74	**8.53**
US Stringency Index(1d)	**4.36**	**3.31**	**11.71**
Mexico Stringency Index(1d)	1.06	0.57	1.61
UK Stringency Index(1d)	0.19	0.75	2.97
SP500 Adj Price(1d)	0.86	0.50	/
US Producer Price Index(1d)	1.54	0.42	3.75
Federal Funds Rate(2d)	0.67	1.33	**10.01**
Exchange Rate(1d)	0.36	2.36	1.95
GSCPI*China Stringency Index(1d)			7.18
Year 2011	0.43	2.17	2.18
Year 2012	1.22	1.84	0.24
Year 2013	2.40	2.19	1.15
Year 2014	1.43	0.68	0.96
Year 2015	2.88	1.23	1.21
Year 2016	1.12	0.40	1.58
Year 2017	1.46	1.77	0.47
Year 2018	2.65	1.26	0.39
Year 2019	0.05	2.12	3.36
Year 2020	0.07	0.62	4.11
Year 2021	2.08	2.73	5.28
Year 2022	0.83	0.75	4.72
Year 2023	2.65	0.03	2.81
Product Sector 03	**179.88**	**48.97**	0.06
Product Sector 11	27.14	24.43	**0.85**
Product Sector 12	44.38	44.29	0.01
Product Sector 16	15.83	6.53	0.45
Product Sector 19	**158.03**	**85.21**	0.48
Product Sector 20	18.25	33.80	**0.59**

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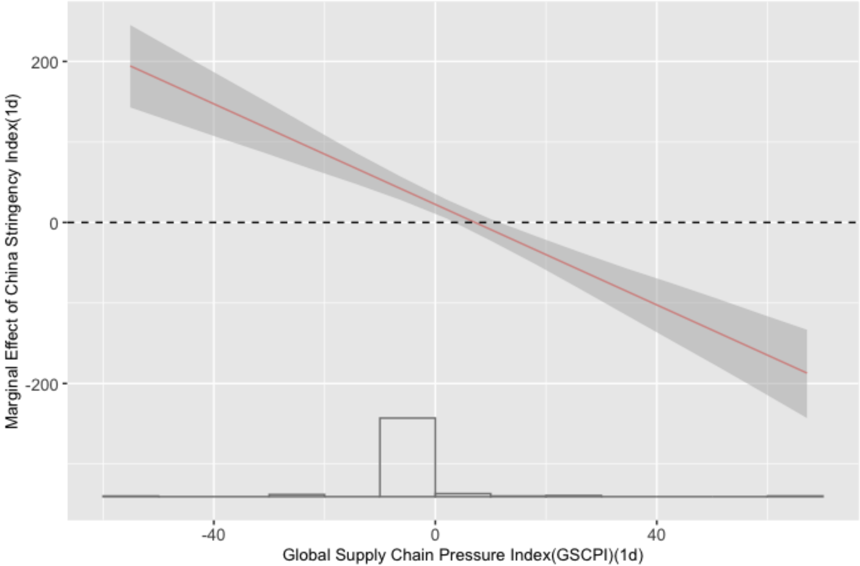
Interpret Fixed-Effect Regression Results

- **Model 1: US Imports from China**
  1. *China Stringency Index(1d)* negatively impacts DV –> Testify **hypothesis 1** that China's COVID lockdown harms US imports from China.
  2. *US Stringency Index(1d)* is more influential
  3. Heterogeneity exists in different product sectors –> supports **Hypothesis 5**
  4. Product Sectors are the most important variables affecting DV
- **Model 2: US Exports to China**
  1. *China Stringency Index(1d)* is not statistically significant –> **no evidence** for **Hypothesis 2**
  2. *US Stringency Index(1d)* is positively significant –> Do not impede US Exports to China
  3. *USD to CNY Exchange Rate* has a positive coefficient –> the appreciation of US Dollar against Chinese Yuan could lead to an increase in US Exports to China
  4. Heterogeneity also exists in different product sectors –> also supports **Hypothesis 5**
  5. Product Sectors are the most influential variables on DV

Interpret Fixed-Effect Regression Results (Continued)

- **Model 3: S&P 500 Stock Index**
  1. *China Stringency Index(1d)* positively correlates to DV –> **no evidence** for **Hypothesis 3**
  2. *US Stringency Index(1d)* has negative impacts on DV, three times compared to the effect of *China Stringency Index(1d)*
  3. *Federal Funds Rate(2d)* positively and *Exchange Rate(1d)* negatively affects DV
  4. *Federal Funds Rate(2d)*, *US Stringency Index(1d)* are the two most important variables, while neither of the product sectors are significant
  5. Interaction term *GSCPI(1d) * China Stringency Index(1d))* shows the marginal effect of China Stringency Index(1d) on the effect of GSCPI(1d) on DV (as shown in Figure 1) –> provides partial support for **Hypothesis 4**

Figure 1 Marginal Effect of China Stringency Index on GSCPI



Counterfactual Analysis Using ML & DL Models

Table 4 Machine Learning Model Outputs for US Imports from China

Model Name	RMSE	MSE
Stacked Ensemble All Models 1	0.2866127	0.08214687
Stacked Ensemble Best Of Family 1	0.2887900	0.08339967
XGBoost 3	0.2912866	0.08484787
XGBoost grid 1 model 3	0.2980404	0.08882808
XGBoost grid 1 model 2	0.2981007	0.08886401
XGBoost grid 1 model 7	0.2981757	0.08890878
XGBoost grid 1 model 1	0.3005206	0.09031266
GBM grid 1 model 2	0.3037550	0.09226709
XGBoost grid 1 model 4	0.3043604	0.09263524
XGBoost 1	0.3047184	0.09285329
XGBoost 2	0.3048350	0.09292435
GBM grid 1 model 5	0.3057125	0.09346014
GBM 3	0.3171580	0.10058922
GBM 2	0.3222319	0.10383342
GBM 1	0.3242554	0.10514156
GBM 5	0.3271882	0.10705213
GBM 4	0.3278621	0.10749355
GBM grid 1 model 4	0.3288419	0.10813701
GBM grid 1 model 1	0.3330015	0.11089002
DeepLearning grid 1 model 1	0.3384263	0.11453237
XGBoost grid 1 model 6	0.3390721	0.11496987
GLM 1	0.3523139	0.12412512
GBM grid 1 model 3	0.3535243	0.12497942
Deep Learning grid 2 model 1	0.3631232	0.13185844
Deep Learning grid 3 model 1	0.3866670	0.14951137
XGBoost grid 1 model 5	0.3880214	0.15056062
Deep Learning grid 1 model 2	0.3982622	0.15861281
DRF 1	0.6239557	0.38932074
Deep Learning grid 3 model 2	0.8053180	0.64853715
Deep Learning 1	0.8263134	0.68279385
Deep Learning grid 2 model 2	0.9746566	0.94995545
XRT 1	1.7566378	3.08577626

Table 5 Best Prediction Model for US Imports

Key	Value
Number of base models (used / total)	16/30
Number of GBM base models (used / total)	5/10
Number of XGBoost base models (used / total)	9/10
Number of Deep Learning base models (used / total)	2/7
Number of GLM base models (used / total)	0/1
Number of DRF base models (used / total)	0/2
Meta learner algorithm	GLM
Meta learner fold assignment scheme	$Random$
Meta learner nfolds	5
Meta learner fold column	NA
Custom meta learner hyper parameters	$None$

Table 6 List of ML & DL Models for US Exports

Model Name	RMSE	MSE
Stacked Ensemble Best Of Family 1	0.9865365	0.9732542
Stacked Ensemble All Models 1	0.9882620	0.9766617
XGBoost grid 1 model 2	1.0117982	1.0237356
GBM grid 1 model 2	1.0132849	1.0267463
GBM 4	1.0266991	1.0541110
GBM 2	1.0340456	1.0692504
Deep Learning grid 1 model 1	1.0367356	1.0748207
XGBoost grid 1 model 7	1.0388637	1.0792379
Deep Learning grid 1 model 2	1.0417290	1.0851994
GBM grid 1 model 5	1.0448477	1.0917066
GBM 5	1.0510447	1.1046949
GBM 3	1.0576939	1.1187163
XGBoost grid 1 model 5	1.0600774	1.1237641
XGBoost grid 1 model 1	1.0691573	1.1430974
DRF 1	1.0709706	1.1469781
XGBoost 1	1.0733685	1.1521198
XGBoost 3	1.0868586	1.1812616
XGBoost grid 1 model 3	1.0913843	1.1911197
XGBoost grid 1 model 4	1.0968599	1.2031017
GBM grid 1 model 3	1.1014629	1.2132205
XGBoost grid 1 model 6	1.1076824	1.2269604
Deep Learning grid 3 model 1	1.1079771	1.2276132
GBM grid 1 model 4	1.1098776	1.2318283
Deep Learning grid 2 model 1	1.1130012	1.2387717
XGBoost 2	1.1195827	1.2534654
GBM grid 1 model 1	1.1301963	1.2773437
GBM 1	1.1354005	1.2891342
GLM 1	1.1416664	1.3034022
XRT 1	1.3213085	1.7458561
Deep Learning grid 2 model 2	1.5702718	2.4657535
Deep Learning grid 3 model 2	1.6633787	2.7668287
Deep Learning 1	1.7708861	3.1360376

Table 7 Best Prediction Model for US Exports

Key	Value
Number of base models (used / total)	4/6
Number of GBM base models (used / total)	1/1
Number of XGBoost base models (used / total)	1/1
Number of Deep Learning base models (used / total)	1/1
Number of DRF base models (used / total)	1/2
Number of GLM base models (used / total)	0/1
Meta learner algorithm	GLM
Meta learner fold assignment scheme	$Random$
Meta learner nfolds	5
Meta learner fold column	NA
Custom meta learner hyper parameters	$None$

Table 8 List of ML & DL Models for S&P 500 Stock Index

Model Name	RMSE	MSE
Stacked Ensemble Best Of Family 1	0.9280165	0.8612146
Stacked Ensemble All Models 1	0.9383375	0.8804772
XGBoost grid 1 model 3	1.0761248	1.1580445
XGBoost grid 1 model 4	1.1410515	1.3019986
GBM 5	1.3505974	1.8241133
XGBoost 3	1.7063083	2.9114881
GBM grid 1 model 2	2.0223573	4.0899290
GBM grid 1 model 5	2.0975797	4.3998408
XGBoost grid 1 model 2	2.5187974	6.3443403
XGBoost 1	2.5971922	6.7454074
XGBoost 2	2.8570976	8.1630068
GBM 3	2.9283886	8.5754598
GBM 2	2.9817189	8.8906478
XGBoost grid 1 model 7	3.1011675	9.6172400
GBM 4	3.3480044	11.2091333
XGBoost grid 1 model 1	3.8210701	14.6005769
XGBoost grid 1 model 6	3.8932088	15.1570749
XGBoost grid 1 model 5	4.5019498	20.2675517
GBM grid 1 model 4	7.6059206	57.8500286
GBM grid 1 model 1	8.0902674	65.4524263
GBM grid 1 model 3	9.5561300	91.3196200
XRT 1	9.8925030	97.8616155
DRF 1	10.9131290	119.0963855
Deep Learning grid 2 model 1	30.3278762	919.7800725
Deep Learning grid 3 model 1	40.7346702	1659.3133555
Deep Learning grid 1 model 1	42.5497194	1810.4786228
Deep Learning grid 1 model 2	60.6225048	3675.0880872
GBM 1	62.4664186	3902.0534502
Deep Learning grid 3 model 2	63.6381056	4049.8084794
Deep Learning grid 2 model 2	65.2388067	4256.1018945
Deep Learning 1	70.6535934	4991.9302576
GLM 1	75.5887622	5713.6609736

Table 9 Best Prediction Model for S&P 500 Stock Index

Key	Value
Number of base models (used / total)	$2/6$
Number of GBM base models (used / total)	$1/1$
Number of XGBoost base models (used / total)	$1/1$
Number of DRF base models (used / total)	$0/2$
Number of Deep Learning base models (used / total)	$0/1$
Number of GLM base models (used / total)	$0/1$
Meta learner algorithm	GLM
Meta learner fold assignment scheme	$Random$
Meta learner nfolds	5
Meta learner fold column	NA
Custom meta learner hyper parameters	$None$

Best-Performing Models in Prediction

- **DV 1: US Imports from China**
  - Stacked Ensemble All Models performs best in the prediction of US Imports from China
  - 16 base models: 5 GBM base models, 9 XGBoost base models, and 2 DL base models
- **DV 2: US Exports to China**
  - Stacked Ensemble Best of Family Model is the best to predict US Exports to China
  - 4 base models: 1 GBM base model, 1 XGBoost base model, 1 DL base model, and 1 DRF base model
- **DV 3: S&P 500 Stock Index**
  - Stacked Ensemble Best of Family Model has the highest accuracy
  - 2 base models: 1 GBM base model and 1 XGBoost base model

Figure 2 Predicted US Imports under Non-COVID Setting vs Real US Imports

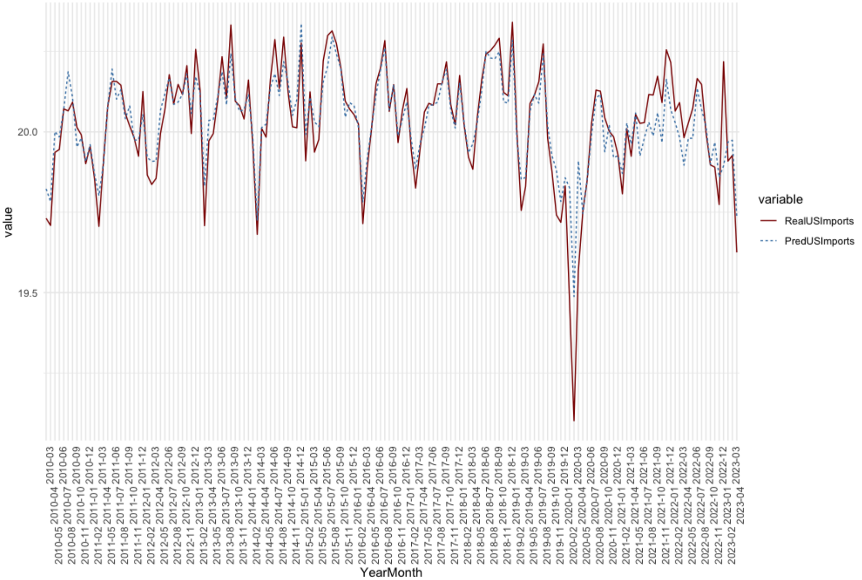


Figure 3 Predicted US Exports under Non-COVID Setting vs Real US Exports

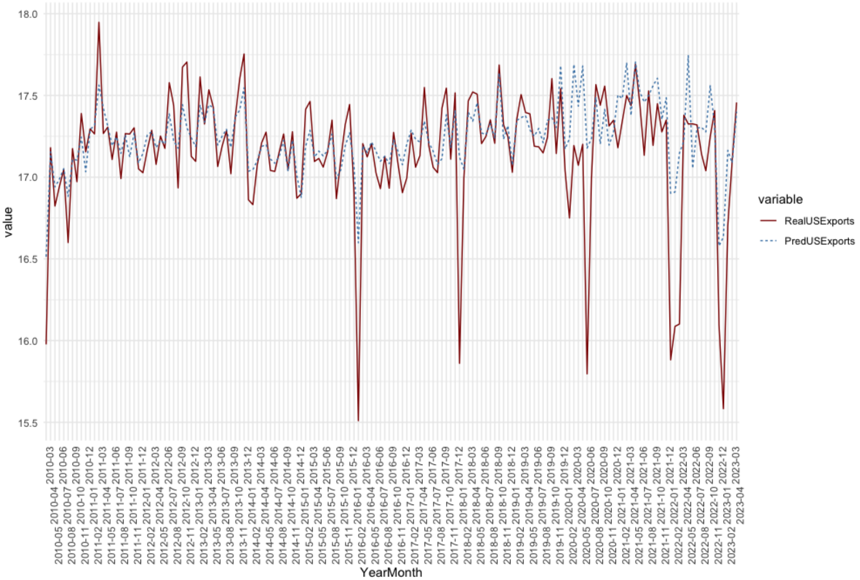
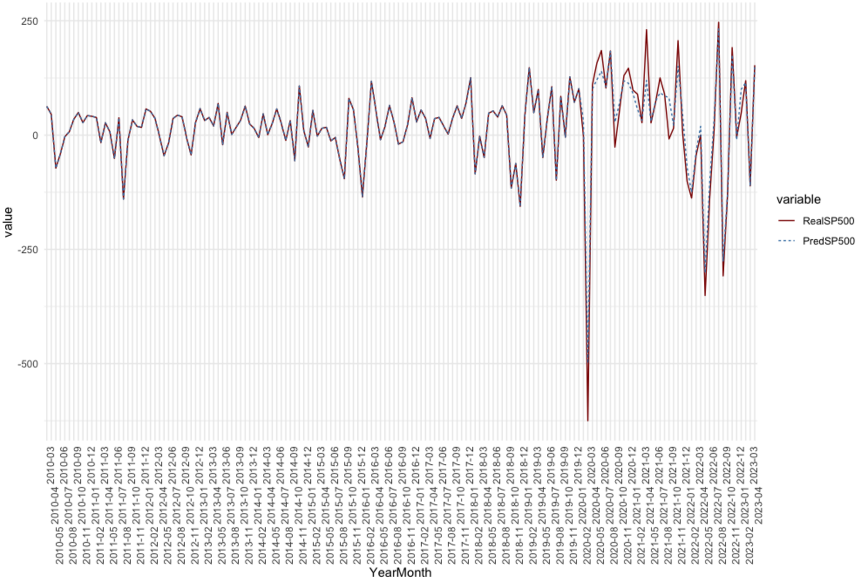


Figure 4 Predicted S&P 500 Stock Index under Non-COVID Setting vs Real Value



Interpret Plots of Predicted Values vs Real Values

- US imports from China was affected hugely at the beginning of the pandemic but returned to normal flow after June 2020
- The pandemic dramatically impacted US exports to China during the beginning of the pandemic, the end of 2021, and the end of 2022
- The COVID-19 pandemic does not affect the S&P 500 stock index obviously

Conclusion

Conclusion

- China Stringency Index (1d) affects US imports from China
- S&P 500 Stock Index is more sensitive to US domestic factors
- Heterogeneity exists in different product sectors
- China Stringency Index (1d) has a marginal effect on the impact of global supply pressure on US firms
- Counterfactual predictions are in line with model interpretation to some degree but need further exploration

Future Study

Drawbacks & Future Study

1. Roughness of monthly and product-sector-level data –> The future study could adopt data in smaller units to examine detailed effects
2. ML & DL Models used not advanced enough to cooperate with time series data –> long short-term memory (LSTM) could be applied in future study
3. Not accurate counterfactual setting –> A more detailed setting of counterfactual circumstances could be conducted in future study

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