



Forecasting China's Merchandise Export Growth with Import and Exchange-Rate Changes

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Abstract

This study forecasts the annual growth rate of China's merchandise exports measured in current US dollars. The target variable is calculated from World Bank WDI merchandise export values [1]. The predictors include lagged export growth, import growth, exchange-rate change, China's GDP growth, and world GDP growth. The variable design reflects trade-flow persistence, external demand, and price-conversion channels discussed in the international trade literature [3, 4, 5]. The training sample is 1996-2018, and the test sample is 2019-2024. The results show that export persistence and import growth are informative, but large external shocks make the forecast errors larger than those in the GDP and consumption papers.

Keywords: merchandise exports; import growth; exchange rate; world GDP; random forest

1. Research Question and Data

The analysis focuses on a single trade variable: the annual growth rate of China's merchandise exports in current US dollars. The target is narrower than trade competitiveness or industrial upgrading, but it is suitable for testing whether lagged public indicators contain short-run forecasting information. The data come from the World Bank WDI database [1]. Merchandise exports and imports are converted into annual growth rates. The exchange-rate variable is the annual percentage change in the official RMB per US dollar exchange rate. China's GDP growth and world GDP growth are also included as broad domestic and external-demand indicators.

The target is export-value growth rather than export-volume growth. This distinction matters because current-dollar export values are affected by quantities, prices, exchange rates, and product composition [4, 10]. The results are therefore interpreted as export-value forecasts.

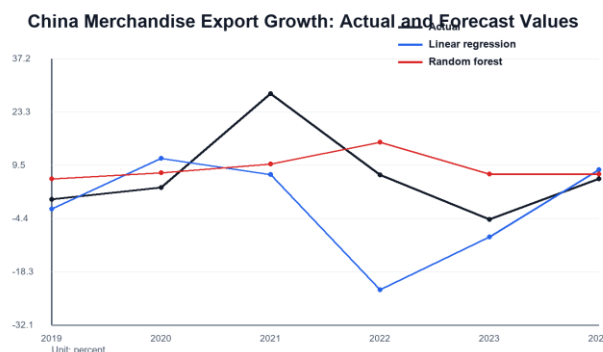


Figure 1. Actual and forecast merchandise export growth, 2019-2024

Source: World Bank WDI; author's calculation using one-year lagged predictors.

2. Variable Construction

All predictors are lagged by one year. This design avoids using information from the forecast year itself. It also makes the forecasting task harder, because trade flows can change quickly within a year. Lagged export growth captures trade persistence. Lagged import growth may reflect processing trade and domestic activity. Exchange-rate change captures a price-conversion channel. China GDP growth reflects domestic production conditions, while world GDP growth approximates external demand [4, 5]. This variable set follows a trade-flow logic rather than a domestic-demand logic. Imports are included because intermediate inputs and processing trade can move with later exports. The exchange-rate variable is included because current-dollar export values may change even when the physical volume response is smaller. World GDP growth is a rough demand proxy, not a substitute for destination-market data. The test period from 2019 to 2024 includes trade tensions, the pandemic shock, global inventory changes, and the 2024 recovery. These events make the export series more volatile than GDP or household consumption growth.

Table 1. Recent data used in the merchandise export forecast

Year	Export	Import	Exchange rate	China GDP	World GDP
2019	0.51	-2.69	4.42	6.07	2.68
2020	3.62	-0.60	-0.11	2.34	-2.90
2021	28.03	29.69	-6.55	8.57	6.41
2022	6.89	1.01	4.47	3.13	3.40
2023	-4.67	-5.53	5.15	5.41	2.95
2024	5.85	1.09	1.60	4.98	2.87

3. Model Design

The paper compares a historical mean, a linear regression model, and a random forest [11]. Export growth is more volatile than the other two targets, so a linear model may be strongly affected by extreme years. The random forest can represent simple nonlinear splits, although it remains limited by the small sample. MAE and RMSE are used to evaluate forecast accuracy [14]. Since the target is current-dollar export growth, errors can arise from price and exchange-rate movements even when the model captures the general direction of external demand.

The model is intentionally modest. It does not use deep learning, large language models, or high-dimensional trade data. The aim is to produce a replicable small empirical exercise based on open data.

4. Forecasting Results

The forecast plot shows that export growth is highly volatile in the test period. The models lag behind the strong rise in 2021 and the decline around 2023. This is expected because annual lagged variables cannot fully capture global inventory cycles, freight rates, commodity prices, or trade-policy changes. Compared with GDP and household consumption, export forecasting produces larger errors. This is not a failure of calculation. It reflects the fact that export values respond to more external and price-related factors.

Table 2. Forecast errors for merchandise export growth, test period 2019-2024

Model	MAE	RMSE
Historical mean	11.896	12.531
Linear regression	11.321	15.389
Random forest	8.204	9.949

China Merchandise Export Growth: Random-Forest Variable Importance



Note: normalized split-gain importance from the random-forest model.

Figure 2. Variable importance in the merchandise export forecast

Source: World Bank WDI; author's calculation using one-year lagged predictors.

The random-forest importance figure suggests that lagged export growth and lagged import growth are important predictors. This is plausible because export activity has persistence and because imports are linked to processing trade and domestic production activity. World GDP growth contributes to the model, but it is too broad to capture the composition of China's export destinations and products. A stronger trade model would use partner-country demand or product-level export data, following the logic of gravity and heterogeneous trade-flow models [2, 3, 7]. The error table confirms that export growth is a difficult annual forecasting target. The model can organize some information from lagged indicators, but it should not be read as a complete trade-cycle forecasting system.

5. Discussion

The main strength of the paper is clarity. It defines the export measure, states that the target is current-dollar value growth, and reports the limitations of annual lagged predictors. The results should therefore be read as forecast evidence rather than as causal evidence on export competitiveness.

The findings also suggest a practical extension. If monthly customs data are available, the same design can be applied to a narrower export category, such as automobiles, electronic products, or textiles. That would reduce aggregation and make the forecast more informative. The trade interpretation is different from the GDP and consumption papers. Here, the forecast error is not only a domestic macro problem. It may reflect foreign demand, global inventories, shipping conditions, commodity prices, exchange-rate valuation, and partner-country policy. A broad export variable is useful for demonstration, but product-level data would be better for policy or business decisions. Different export sectors have different price, demand, and exchange-rate sensitivities.

6. Limitations and Replication

The replication files include `export_raw_wdi.csv`, `export_model_data.csv`, and `export_predictions.csv`. The WDI indicator codes are `TX.VAL.MRCH.CD.WT`, `TM.VAL.MRCH.CD.WT`, `PA.NUS.FCRF`, and `NY.GDP.MKTP.KD.ZG`. World GDP growth uses the WLD country aggregate. Export and import growth are calculated from current-dollar values. Exchange-rate change is calculated from the annual official exchange rate. The random seed is fixed at 20260620, and the random-forest settings are the same as in the GDP and consumption papers.

The main limitation is that current-dollar export values combine quantity and price effects. The model also ignores partner-country composition and product structure. These limitations should be stated clearly in any submission version. Another limitation is that world GDP growth is too broad to represent external demand for Chinese exports. Demand from the United States, the European Union, ASEAN economies, and emerging markets may move differently. A single global aggregate hides those differences.

The model also omits shipping costs, commodity prices, tariff changes, and inventory cycles. These

factors can move export values quickly, especially during periods of global disruption. Their omission helps keep the exercise simple but reduces explanatory detail.

A stronger extension would use customs data by product group and destination market. The same random-forest framework could then be applied to a narrower target, such as automobile exports or electronics exports, where the economic interpretation would be sharper.

7. Conclusion

Lagged imports, lagged exports, exchange-rate changes, and GDP indicators provide some information for forecasting China's merchandise export-value growth, but the test-period errors remain large. The study is useful as a small open-data exercise. It shows the mechanics of constructing a target variable, building lagged predictors, comparing models, and explaining random-forest importance. The main practical message is caution. A machine-learning model can summarize lagged trade and macro indicators, but export values are exposed to global shocks that are not fully visible in annual public data. The model should therefore be used as a baseline, not as a complete forecasting system. The narrow design is still valuable. It makes the target variable explicit, separates value growth from volume growth, and shows exactly where the forecast performs poorly. Future work should move from total exports to a product-destination panel. A model that forecasts, for example, electric-vehicle exports to several major markets would have a clearer trade mechanism and a more useful policy interpretation than an aggregate annual value forecast.

References

- World Bank. (2026). World Development Indicators database. <https://api.worldbank.org/>
- Tinbergen, J. (1962). *Shaping the World Economy: Suggestions for an International Economic Policy*. Twentieth Century Fund.
- Anderson, J. E. (1979). A theoretical foundation for the gravity equation. *American Economic Review*, 69(1), 106-116.
- Goldstein, M., & Khan, M. S. (1985). Income and price effects in foreign trade. In R. W. Jones & P. B. Kenen (Eds.), *Handbook of International Economics*, Vol. 2 (pp. 1041-1105). Elsevier.
- Anderson, J. E., & van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1), 170-192. <https://doi.org/10.1257/000282803321455214>
- Eaton, J., & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741-1779. <https://doi.org/10.1111/1468-0262.00352>
- Helpman, E., Melitz, M., & Rubinstein, Y. (2008). Estimating trade flows: Trading partners and trading volumes. *Quarterly Journal of Economics*, 123(2), 441-487. <https://doi.org/10.1162/qjec.2008.123.2.441>
- Baier, S. L., & Bergstrand, J. H. (2007). Do free trade agreements actually increase members' international trade? *Journal of International Economics*, 71(1), 72-95. <https://doi.org/10.1016/j.jinteco.2006.02.005>
- Rose, A. K. (2000). One money, one market: Estimating the effect of common currencies on trade. *Economic Policy*, 15(30), 8-45. <https://doi.org/10.1111/1468-0327.00056>
- Feenstra, R. C. (2004). *Advanced International Trade: Theory and Evidence*. Princeton University Press.
- Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5-32. <https://doi.org/10.1023/A:1010933404324>
- Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, 28(2), 3-28. <https://doi.org/10.1257/jep.28.2.3>
- Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253-263. <https://doi.org/10.1080/07350015.1995.10524599>
- Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4), 679-688. <https://doi.org/10.1016/j.ijforecast.2006.03.001>
- Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice* (3rd ed.). OTexts.