The following publication Liu, X., Liu, A., Jiao, X. and Liu, Z. (2024), "The impact of policy intervention on international wine demand", International Journal of Contemporary Hospitality Management, Vol. 36 No. 8, pp. 2728-2751 is published by Emerald and is available at https://doi.org/10.1108/IJCHM-08-2023-1275.

The Impact of Policy Intervention on International Wine Demand

----The Short- and Long-run Impact of the Anti-dumping Duties on Imported Australian Wine to China

Abstract

Purpose: The purpose of the study is to investigate the impact of implementing anti-dumping duties on imported Australian wine to China in the short- and long-run, respectively.

Methodology: First, the Difference-in-Differences (DID) method is utilized in this study to evaluate the short-run causal effect of implementing anti-dumping duties on imported Australian to China. Second, a Bayesian ensemble method is employed to predict 2023-2025 wine exports from Australia to China. The disparity between the forecasts and counterfactual prediction which assumes no anti-dumping duties represents the accumulated impact of the anti-dumping duties in the long run.

Findings: The anti-dumping duties resulted in a significant decline in red & rose, white, and sparkling wine exports to China by 92.59%, 99.06%, and 90.06% respectively, in 2021. In the long run, wine exports to China are projected to continue this downward trend, with an average annual growth rate of -21.92%, -38.90%, and -9.54% for the three types of wine, respectively. In contrast, the counterfactual prediction indicates an increase of 3.20%, 20.37%, and 4.55% for the respective categories. Consequently, the policy intervention is expected to result in a decrease of 96.11%, 93.15%, and 84.11% in red & rose, white, and sparkling wine exports to China from 2021 to 2025.

Originality: The originality of this study lies in the creation of an economic paradigm for assessing policy impacts within the realm of wine economics. Methodologically, it also represents the pioneering application of the DID and Bayesian ensemble forecasting methods within the field of wine economics.

Keywords: Anti-dumping Duties, Australian Wine, China, DID, Bayesian Ensemble Forecast

1. Introduction

The global wine market constitutes a substantial and diverse economic sector, with wine production spanning across numerous countries worldwide, consistently captivating a growing consumer base. According to the International Organisation of Vine and Wine (OIV), global wine exports reached 1,070 million liters, achieving a record value of 37.6 billion EUR in 2022 (OIV, 2023). Given the planting and brewing cycle in the downstream grape market, the unpredictable impact of weather on supply and quality, and the restricted shelf life of the ordinary wine, disparities between supply and demand frequently arise.

The unanticipated policy intervention exacerbates this mismatch even further. Taking Australian wine exports to China as an illustration, while the UK and the USA have traditionally been the largest markets, China has emerged as a pivotal contributor to Australia's market expansion since the signing and enactment of the China-Australia Free Trade Agreement in 2015 (Wine Australia, 2022). According to DB (2022), Australian wine exports to China surged by 221% between 2015 and 2019. However, escalating trade tensions between the two nations led to the imposition of punitive tariffs on various Australian imports.

In early 2021, the Ministry of Commerce of the People's Republic of China announced an escalation in anti-dumping duties on imported Australian wines, raising the rate from 116.2% to 218% over the subsequent five years. Consequently, reported annual wine exports from Australia to China plummeted to a mere $12 million in 2022, accounting for just 1% of the market value prior to the implementation of the duty policy (The Guardian, 2023).

Due to the changeable trade policy and strong export orientation of the major producing country, this trade dispute has placed the bilateral wine industries between Australia and China under unprecedented uncertainties (Mariani et al., 2012). Such uncertainties shape the current competitive international wine market and form the basis for future market development. Most existing literature has primarily discussed the factors influencing international wine trade based on demand theory, highlighting the impact of macroeconomic variables such as price, income, and exchange rates on wine imports and exports. Additionally, some studies have employed time series models using these variables to predict wine demand in different regions (e.g., Fogarty, 2010; Liu and Song, 2021; Storchmann, 2012). From consumers' perspective, behavioral theories including theory of planned behaviour and goal framing theory explain the influence of policy on individual purchasing decisions (Taghikhah et al., 2020). However, individual decisions in response to policy have not been expanded and reflected at a macro level on wine demand overall through rigorous analytical framework. The influence of policy interventions on wine demand has been largely disregarded and existing studies mainly focus on the domestic markets in Europe and the Americas (Carbone, 2021; Meloni et al., 2019; Pomarici and Sardone, 2020). Compared to the domestic wine demand, international wine trade is influenced by more factors, making the impact of policy intervention more complicated. To fill the research gap, this study aims to contribute to understanding the short-term effects of policy interventions and forecasting long-term counterfactual consequences of the anti-dumping duties on Australian wine exports to China, focusing on 2021 and the period 2023 to 2025, respectively.

The novelty of this study lies in the proposition of a rigorous economic paradigm for evaluating policy impacts on international wine demand, which can be regarded as a generic analytical framework that has wide applicability to the wine literature. Methodologically, it represents the first endeavor to investigate the causal effect of policy intervention on wine demand using the Difference-in-Differences (DID) method within the wine economics literature. Furthermore, this study pioneers the utilization of counterfactual prediction and the Bayesian ensemble method to assess policy impact, offering a more dependable and robust evaluation of future consequences of policy intervention. As a result, this research provides valuable insights for both the demand and supply facets of the wine industry. International wine traders can refer to the results to restructure their supply chains and diversify target markets, while winemakers can use the forecasts to fine-tune their production and inventory strategies for optimal operations.

The subsequent sections of the study are as follows: The second part reviews policy implications and demand forecasting studies within the wine field. The third section introduces the methodology and data employed in this research. The ensuing section presents the findings. The concluding section wraps up the study.

2. Literature review

2.1 The wine sector and policy

The wine industry constitutes a complex system encompassing both the production and consumption of wine, along with intricate product and service chains involving numerous stakeholders (Anastasiadis and Alebaki, 2021). Consequently, the wine sector is highly responsive to policy alterations, historically being subject to extensive public control and stringent policies and constraints (Meloni et al., 2019). Such policies and restrictions encompass production subsidies, price guarantees, market stabilizers, and plantation limitations (Carbone, 2021). Given the intricate nature of the wine industry and its global sensitivity to policies and restrictions, academics from various disciplines have increasingly directed their attention towards analyzing the impact of these policies and restrictions on the industry, consumers, and trade, all with broader implications for overall welfare and taxation (Carbone, 2021).

These policies have influenced both the supply and demand sides of the wine sector. For instance, the EU's wine policy has been extensively examined in prior literature (Meloni et al., 2019; Pomarici and Sardone, 2020, 2022; Schulz et al., 2022). It has led to substantial imbalances with surplus supply and limited export opportunities under the initial framework of the Common Agricultural Policy (CAP), designed to maintain farmer income through market intervention and higher prices (Carbone, 2021). More recently, the EU's wine policy has evolved to incorporate environmental and social objectives, leading to constraints on cultivation and measures for consumer protection, such as wine labeling regulations (Pomarici & Sardone, 2020). Noev (2006) conducted a descriptive and explanatory analysis of the Bulgarian wine sector's development in response to policies related to land reform, vine area ownership, and state support over time.

Another type of policy often examined in wine research is taxation policy, imposed on consumption due to the health impacts of alcoholic beverages, as well as value-added tax (VAT) or import tariffs, primarily focusing on their influence on the demand side of the wine sector. Given that taxes can be quantified directly, studies on wine taxation frequently employ quantitative methods to assess their impact on wine demand. For instance, Anderson (2010) presented estimates of consumer tax equivalents for wine, beer, and spirits taxes as of 2008 across various high-income and developing countries, offering descriptive evidence of the influence of diverse taxes on the prices of these alcoholic beverages. The impact of taxes on the elasticity of wine demand was explored in Cho et al. (2007), who investigated changes in demand elasticity in Canada using the Kalman filter method and the Chow test, finding that government taxation can effectively impact consumption. Similarly, Özdemir (2015) examined the repercussions of high taxation policies on Anatolian wine demand and price elasticity in Turkey, using standard ordinary least squares and maximum likelihood regressions, revealing significant policy effects on wine demand and price elasticity in Turkey.

While studies have examined the relationship between policy interventions and wine demand, these studies have primarily focused on domestic wine demand, with limited attention given to the impact of policies on international wine trade. Furthermore, although a few studies have utilized econometric methods, there remains a lack of evidence to discuss the causal relationship between policies and wine demand. This study marks the initial endeavor to evaluate the impact of anti-dumping duties on Australian wine exports by utilizing the DID method within a quasi-experimental design. While previous studies in commodities and services estimated policy impacts by controlling for individual and time-fixed effects (Kohl et al., 2016; Gao and Su, 2019), this approach may be insufficient due to potential endogeneity, failing to adequately account for unobservable factors that vary over time among individuals. Building upon the model design by Gobillon and Magnac (2016), this research design not only incorporates individual fixed effects and time-fixed effects but also integrates interactive individual-time fixed effects. This inclusion captures the time-dependent impact of unobservable factors across countries (regions) and delivers robust findings.

2.2 Determinants of Wine Demand

Although research on wine demand is a relatively nascent field, it has extended beyond the scope of wine agriculture economics to encompass adjacent fields such as trade, finance, and environmental economics (Storchmann, 2012). Scholars have identified numerous factors that can influence wine demand or the prices of wine-related assets.

In the economics literature, wine consumption follows the fundamental laws of demand theory. Both domestic wine consumption and international wine trade are related to prices and income. A pivotal discovery in previous research is that the wine demand tends to be more elastic compared to other alcoholic beverages (Fogarty, 2010).

This signifies that individuals are more likely to adjust their consumption patterns in response to changes in the price or availability of wine (i.e., own- and substitute-price effects). When discussing international wine trade, some macroeconomic factors, including exchange rates between exporting and importing countries (Anderson and Wittwer, 2013), money supply, and interest rates (Jiao, 2017), indirectly influence wine prices. Hence, they are also identified as factors affecting wine demand. Income is another factor that has been extensively examined in previous research on wine consumption. Results have demonstrated that income elasticity can vary depending on the type of wine and the market it is being sold in (Muhammad et al., 2014; Capitello et al., 2015; Liu and Song, 2021).

Literature in the field of consumer behavior suggests that due to the experiential nature of wine consumption, its demand is often intertwined with factors that are challenging to quantify, such as consumers' lifestyles and "expert opinions" on quality and aging potential. Brunner and Siegrist (2011), based on a postal survey in the German-speaking part of Switzerland, discovered that individuals with better wine knowledge tend to consume more wine. The influence of expert opinions on other consumers' wine consumption was confirmed by Hilger et al. (2011) through an experimental approach conducted in a retail grocery chain. Taste trends have been recognized as influential factors in modeling and forecasting developments in the global wine market (Anderson et al., 2001). Choice experiments have also examined wine consumption to assess consumer preferences for various wine attributes, revealing a range of attributes that impact consumer choices, such as firm reputation, origin, and grapevine variety (Hertzberg and Malorgio, 2008). Therefore, wine demand is primarily influenced by price and income, along with additional social psychological factors, resulting in the sensitivity to external factors. However, to date, there has been little empirical research testing the impact of policies on wine demand. In fact, the implementation of certain policies can directly influence wine prices and consumer expectations and purchasing behaviour, especially in the international wine trade, thus having a significant impact on overall wine demand.

2.3 Wine demand forecasting

While wine is a fairly common agricultural commodity, research in wine forecasting remains underdeveloped, with only a few studies primarily focusing on specific wine price ranges and their financial value. Among the most prominent topics in wine demand forecasting is the prediction of Bordeaux wine prices, carried out using univariate models (Bazen and Cardebat, 2018) and econometric models incorporating meteorological variables (Ashenfelter, 1989; Ashenfelter, 2008; Oczkowski, 2010). Another branch of studies, based on cross-sectional analyses, delves into the financial performance of fine wine investments, generating forecasts through financial pricing and machine learning models in recent studies (Yeo et al., 2015; Fernandez-Perez et al., 2019). However, these forecasts have been limited to wines at the high end of the market, lacking generalizability to the broader wine market, which is characterized by large volume and high frequency trading.

The literature concerning macro-level wine demand quantity forecasting remains underdeveloped. Bazen and Cardebat (2018) highlighted the lag in methodological development for wine forecasting compared to research in other commodities. Moreover, the accuracy of employed forecasting methods has been overlooked, as no studies have assessed their accuracy against actual numbers. In a recent study, Bargain (2020) utilized the gravity model to explore Chinese wine demand for various French wine-growing regions. Employing the autoregressive distributed lag (ADL) model, Liu and Song (2021) estimated and forecasted China's demand for imported bottled, bulk, and sparkling wines based on country of origin from 2019 to 2023. However, although the ADL model offers flexible forecasting without strict assumptions (e.g., fixed prices or macroeconomic conditions), its model selection process is susceptible to volatility among the data, potentially impacting forecasting performance (Athanasopoulos et al., 2018).

To address this issue, this study employs a Bayesian ensemble method to enhance the ADL model and generate robust forecasts for Australian wine exports to China. The bootstrap aggregation (bagging) method introduced by Breiman (1996) aims to ensemble multiple predictors calculated from bootstrapped series, thereby significantly enhancing forecasting decisions of base models. Bagging has been widely employed by scholars to estimate and forecast inflation growth (Rapach and Strauss, 2010), stock prices (Hillebrand and Medeiros, 2010), and tourism demand (Athanasopoulos et al., 2018; Song et al., 2021). To optimize the ensemble, the Bayesian model combination (BMC) is implemented in this study to further refine the bagging process. Dating back to the 1970s, the Bayesian model average or combination methods were first used to measure the parameter uncertainty and simulation uncertainty (Corlu et al., 2020).

Given a few candidate models from the bagging process, the posterior probabilities of the candidate models are used to quantify their likelihood with real-world data (Wasserman, 2000). The BMC method can overcome the limitation of direct bagging by determining the candidate model combination with appropriate posterior distributions. This way, models with higher marginal likelihoods are assigned greater weights in aggregation.

To the best of the author's knowledge, neither DID nor the Bayesian ensemble method has been employed in wine economics. This research aims to generate novel economic paradigm to assess policy impact on wine demand, providing valuable industry insights to anticipate trends in Australian wine demand taking into account the long-term impact of policy—critical for business planning and decision-making.

3. Methodology and data

This study aims to assess the impact of anti-dumping duties on Australian wine exports to China and provide comprehensive forecasts for Australian red & rose, white, and sparkling wine exports spanning from 2023 to 2025. Specifically, the DID method is employed to evaluate the short-term policy impact of the duty policy. To estimate long-term losses, the findings from the causal inference are utilized as adjustments for 2021 Australian wine exports to China, enabling counterfactual forecasting by assuming the absence of the duty policy. In addition to the counterfactual prediction, the Bayesian ensemble forecasting method is employed to generate *ex-ante* forecasts for Australian wine exported to China.

3.1 DID model for policy assessment

To identify the impact of China's anti-dumping duties on Australian wine exports, the DID model is specified as follows:

$$\begin{aligned} lnExport_{i,t} &= \alpha_0 + \beta_1 TW_i \times Post_t + \beta_2 lnY_{i,t} \\ &+ \beta_3 lnRP_{i,t} + \beta_4 D_{CAFTA} + \mu_i + \gamma_t + \mu_i\gamma_t + \varepsilon_{i,t} \end{aligned} \quad (1)$$

where $\ln Export_{i,t}$ represents the natural logarithm of the quantity of Australian wine exported to region i in time t. The $TW_i \times Post_t$ term is an independent variable introduced to account for the intervention of China's anti-dumping duties on Australian wine exports, where TW_i and $Post_t$ are dummy variables indicating China and the the time of policy intervention, which occurred in the first quarter of 2021, respectively.

The coefficient β_1 measures the net effect of this intervention on Australian wine exports to China.

Following the demand theory, the model also incorporates the effects of income and relative prices, with $lnY_{i,t}$ representing income and $lnRP_{i,t}$ representing relative prices—the price ratio between the imported and exported markets adjusted by the exchange rate (Hummels and Klenow, 2005; Martins et al., 2017). The coefficient β_2 and β_3 correspond to the income and relative price elasticities, respectively.

To account for potential "shocks" from other policies in the DID estimation, a dummy variable D_{CAFTA} is introduced to neutralize the impact of the China-Australia Free Trade Agreement.

To exclude other policies "shocks" from the DID estimation, a dummy variable is included to offset impact of the China-Australia Free Trade Agreement (D_{CAFTA}). In addition to individual (μ_i) and time (γ_t) fixed effect terms, an interactive fixed effects term ($\mu_i \times \gamma_t$) is incorporated to further address endogeneity concerns in causal analyses (Bai, 2009). $\varepsilon_{i,t}$ and α_0 represent the model's residual and constant term, respectively.

Parallel trends test

The estimated DID model needs to satisfy the parallel trend assumption, implying that the experimental and control groups should exhibit similar trends. This study draws upon Beck et al. (2010) and extend the subsequent dynamic model by introducing pre- and post-dummy variables of the policy shock:

$$\ln Export_{it} = \alpha_0 + \sum_{a=2019Q1}^{a=2021Q4} \beta_a TD_a \times TW_i + \beta_2 X_{it} + \mu_i + \gamma_t + \mu_i \gamma_t + \varepsilon_{it} \quad (2)$$

where the TD_a is the dummy variables that encompass the two years preceding the policy's implementation and all subsequent periods thereafter (Ferrara et al., 2021). Furthermore, interaction terms between the policy and these dummy variables are formulated. If the interaction term between the pre-policy period and the policy is statistically insignificant, it implies that the dependent variables of both the experimental and control groups exhibit parallel development. Similarly, the interaction term between the post-policy period and the policy offers insights into the treatment effect of China's implementation of anti-dumping charges on Australian imported wine from a dynamic standpoint. The term X_{it} denotes the control variables in equation (1).

Placebo tests

It is important to acknowledge that the estimates of the DID model might potentially be influenced by other unobservable variables. In this study, a placebo test is employed to evaluate the credibility of the estimation outcomes of the DID model for causal inference (Liu & Lu, 2015). The placebo test is structured as follows:

$$\hat{\beta} = \beta + \sigma \frac{cov(TW \times Post, \varepsilon | W)}{var(TW \times Post | W)} \quad (3)$$

where $\hat{\beta}$ represents the estimated coefficient of the policy in equation (1). σ denotes the impact of unobservable factors on Australia's wine exports to mainland China. Moreover, W stands for the control variables and fixed effects within the model. A σ value of zero indicates an unbiased estimation of $\hat{\beta}$. However, confirming whether σ is truly zero is practically unfeasible. The typical approach involves randomizing the timing and location of policy implementation. In this study, a fabricated TW' and $Post'$ are introduced to replace the independent variable in the DID model. This involves randomly selecting a country (region) as the experimental group and assigning the timing of policy implementation. As TW' and $Post'$ are generated at random, the coefficient of the policy, denoted as β, should theoretically equal zero. Furthermore, if the estimated $\hat{\beta}$ equals zero, it can be inferred that σ is also zero, indicating that the anti-dumping tariff policy remains unaffected by unobservable factors.

3.2 Bayesian ensemble forecasting

Building on prior research in wine economics (Liu and Song, 2021), this study takes into account several influential factors for the modeling and forecasting of wine demand. For predicting wine demand in the Chinese market, the model can be formulated as follows:

$$Export_t = A\left(Y_t^{\gamma} EP_t^{\delta} S_t^{\theta}\right) e_t, \quad (4)$$

where $Export_t$ represents the quantity of wine exported to China in period *t*. Y_t denotes the income level of Chinese consumers in period *t*. EP_t stands for the export price of Australian wine to China, adjusted by the real exchange rate. S_t represents the substitution price or demand for other alcoholic beverages such as beer and spirits within China. *A* represents the constant term and e_t signifies the current error term.

Given that Equation (4) does not incorporate any policy variable, the trade price can be considered independent of other determinants. Additionally, as the trade price holds greater significance as a determinant of demand, it is more appropriate to utilize the trade price rather than a general relative price in Equation (1) for predicting future wine demand.

The ADL model, as introduced by Hendry (1995), is employed to capture the dynamics of demand for Australian wine in this study. By applying the natural logarithm and extending the consideration of substitutions involving the consumption of beer and spirits within Equation (2), an ADL model of order *(P, Q, N, M)* for China can be written as:

$$lnExport_t = \alpha + \sum_{p=1}^{P} \beta_p lnExport_{t-p} + \sum_{q=0}^{Q} \gamma_{1,q} lnY_{t-q} + \sum_{n=0}^{N} \delta_n lnEP_{t-n} + \sum_{m=0}^{M} \theta_{1,m} lnBeer_{t-m} + \sum_{k=0}^{K} \theta_{2,K} lnSpirit_{t-k} + \zeta D_t + \varepsilon_t \quad (5)$$

where D represents the dummy variable accounting for seasonality and special events like the 2008 financial crisis and the COVID-19 pandemic. The maximum lagged orders *P, Q, N, M,* and *K* are each set to 4 to align with the quarterly frequency of the data. The determination of lagged order selection is based on the Akaike Information Criterion, aiming to identify the optimal equilibrium between the goodness of fit and model complexity.

The Bayesian ensemble forecasting generates multiple ADL forecasts using a Bayesian approach, and then combines these Bayesian forecasts based on each model's Bayes factor. To begin, in order to enhance the sample size, the training data is replicated 50 times using the historical wine demand data, employing the time series bootstrapped method proposed by Bergmeir et al. (2016). Subsequently, given the bootstrapped training data X_n, a set of Bayesian models $\Theta_n \sim p_n(Export|\boldsymbol{\eta_n}, X_n^*)\pi_n(\boldsymbol{\eta_n}|X_n^*), n = 1, \ldots, 50$ is constructed. Each of these models conditionally consist of a likelihood p_n and a prior π_n to estimate the bootstrapped posterior distribution of parameters $\boldsymbol{\eta_n}$.

Based on the log marginal likelihood, a Bayes factor is computed to distinguish the performance of each bootstrapped model, facilitating the assignment of higher weight to the model demonstrating better performance (Kass and Raftery, 2019; Steel, 2020).

The Bayes factor between two models with equal priors is specified as

$$Bayes\ factor_{i,j} = logp_i(Export|\boldsymbol{\eta_n}, X_i^*) - logp_j\left(Export\middle|\boldsymbol{\eta_n}, X_j^*\right) \quad (6)$$

After eliminating all spurious models with unreasonable signs, the ultimate model is consolidated through Bayesian model combination, using each set of parameters and its corresponding Bayes factor as the weighting factor.

3.3 Data and model evaluation

The wine exports utilized in this study encompass quarterly volumes of Australian wine exports to the top 20 markets spanning from 2005 to 2022. These markets include the US, Canada, New Zealand, the UK, the Netherlands, Belgium, Denmark, Germany, Sweden, Finland, France, Ireland, China, Hong Kong SAR, Chinese Taipei, Singapore, Japan, South Korea, the UAE, and Thailand. The data source is the Australian Bureau of Statistics and comprises exports of red & rose, white, and sparkling wine[1].

Regarding explanatory variables, income is gauged by the real GDP index of these 20 import markets. GDP and CPI and exchange rates which are used to calculate relative price are all sourced from the International Monetary Fund. The export price, EP, is calculated by dividing the exported value by the exported volume, adjusted by the real effective exchange rate. To account for scale differences, all variables are transformed into indices relative to their 2010 levels.

In order to assess the fitting capabilities of the forecasting models, the Bayesian ensemble forecasting model is juxtaposed with four benchmark models. These benchmarks encompass three time series models—Seasonal Naïve, ETS, and SARIMA—as well as one econometric model, which is the ADL model. The comparison is based on their ex-post forecasting performance. The forecasting validation pertains to data spanning from the first quarter of 2007 to the third quarter of 2022.

[1] The Australian Bureau of Statistics aggregates the export data for red and rose wine into a single category. Consequently, the red & rose wine category encompasses commodity IDs 22042902, 22042991, 22042992, 22042935, and 22042965. Similarly, white wine consists of commodity IDs 22042901, 22042934, and 22042964. Sparkling wine is represented by commodity IDs 22040110, 22041011, 22041090, and 22041091. It's worth noting that the data might exhibit variations when compared with statistics published by different departments due to differing statistical scopes.

To gauge model performance, the following metrics are employed: root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute scaled error (MASE). These metrics are calculated using the ensuing formulas:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

$$MASE = \frac{\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|}{\frac{1}{N-s}\sum_{i=s+1}^{N}|y_i - \hat{y}_{i-s}|} \tag{9}$$

where y_i and $\hat{y}_i$ denote the actual and forecasted values for the training period, with a data point length of *N*. RMSE and MAPE assess the average absolute and squared errors, respectively, by which the estimates deviate from the actual values. Employing the mean absolute error of the seasonal naïve forecasts on the training set as the denominator, the seasonal MASE measurement provides a scale-free ratio that compares model performance against a baseline error (Hyndman and Koehler, 2005). In the assessment of forecasting methods, preference is given to the method exhibiting the lowest RMSE, MAPE, and MASE.

4. Empirical results

4.1 Short-run effect

DID analysis was utilized to evaluate the short-run impact of the anti-dumping duties on wine imported from Australia to China, encompassing the main DID results, parallel trend test, and placebo test, respectively.

The results of DID models

First, the net impact of China's anti-dumping tariff on Australian wine exports is assessed, and the results are presented in Table 1. Models 1 to 3 sequentially examine the impact of the anti-dumping duties on the export of red & rose, white, and sparkling wine from Australia to China. In Model 1, the coefficient of *TW*×*Post* is -2.6023 with a significance level of 1%, indicating a significant decline of 92.59% in Australia's red

& rose wine exports to China due to the implementation of anti-dumping duties[2]. The outcomes of Models 2 and 3 indicate substantial decreases of 99.06% and 90.06% in Australia's exports of white and sparkling wines to China, respectively. These reductions were statistically significant at the 10% and 1% significance levels, respectively. The estimated impacts of the anti-dumping duties are highly consistent with the statistics in relevant reports and news which record 99% slashes of total wine trade values in 2021 (The Guardian, 2023; Wine Australian, 2022). The results also correspond to the influence of policy on consumer behaviour, which can be further aggregated into a significant drop in wine exports to China at the macro level (Taghikhah et al., 2020). Both empirical evidence and previous literature findings suggest the reliability of the DID results.

In terms of control variables, income significantly influences wine consumption of red & rose wine (Model 1), aligning with demand theory. However, income's effect on the purchase of white (Model 2) and sparkling wine (Model 3) is not statistically significant. This discrepancy could be attributed to the limited exports of the latter two types of wine compared to red & rose wine. Interpretation of the relative price effect requires caution. The positive coefficients in Models 1 and 2 do not imply Australian wine is inferior. As the trade price was substantially impacted by the anti-dumping duties, it is not included as a primary control variable in the model to ensure the independence of the DID term. Thus, the relative price is introduced solely to control for potential influences of price level and exchange rate, respectively.

The China-Australia Free Trade Agreements' impact on Australia's wine exports to mainland China is positive and statistically significant at the 1% level. This suggests that the China-Australia Free Trade Agreements positively boosted Australia's wine exports to mainland China during the study period.

Table 1 Results of DID models

Variables	Model 1 ln*rr_Export*	Model 2 ln*w_Export*	Model 3 ln*s_ Export*
TW×*Post*	-2.6023***	-4.6660*	-2.3087***
	(0.3770)	(2.5972)	(0.5008)
ln*Y*	1.9558***	2.1901	0.5428
	(0.7253)	(1.4902)	(0.5523)

[2] The model's dependent variable is in logarithmic form, and the independent variable is the dummy variable. Therefore, according to the estimation results, the actual effect of the independent variable on the dependent variable is exp (β_1)-1.

ln*RP*	1.5669**	3.2656***	-0.0667
	(0.7545)	(1.1613)	(0.5195)
D_{CAFTA}	0.6154	2.3750*	-0.0241
	(0.5644)	(1.2753)	(0.2995)
Cons	-2.6023***	-4.6660*	-2.3087***
	(0.3770)	(2.5972)	(0.5008)
Country/region FE	YES	YES	YES
Period FE	YES	YES	YES
Interactive FE	YES	YES	YES
R^2	0.4976	0.4176	0.5848
N	1360	1360	1360

Notes: 1. The values in parentheses represent standard errors; 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results of Parallel trend tests

If, before the implementation of China's anti-dumping duty policy on Australian wine exports, the Australian wine exports to China had deviated significantly from their historical trend compared to other countries (regions), this could potentially influence the model's estimation results. To test the presence of systematic differences in the outcome variables between the experimental and control groups before the policy intervention, a parallel trend test is conducted. The results are presented in Figure 1, where the estimated coefficients of β_a fall within the 95% confidence intervals of their significance, based on the results of equation (2).

The subplots illustrate the outcomes for the exports of red & rose wine, white wine, and sparkling wine as the dependent variables, respectively. It is evident that the majority of the coefficient β_a estimates remain insignificant across the periods preceding the policy implementation, regardless of the dependent variable. This indicates that, for most of the periods leading up to the policy's implementation, there was no substantial divergence in the exports of various types of Australian wine to China compared to the wine exports to other control group countries (regions). This observation is consistent with the parallel trend assumption.

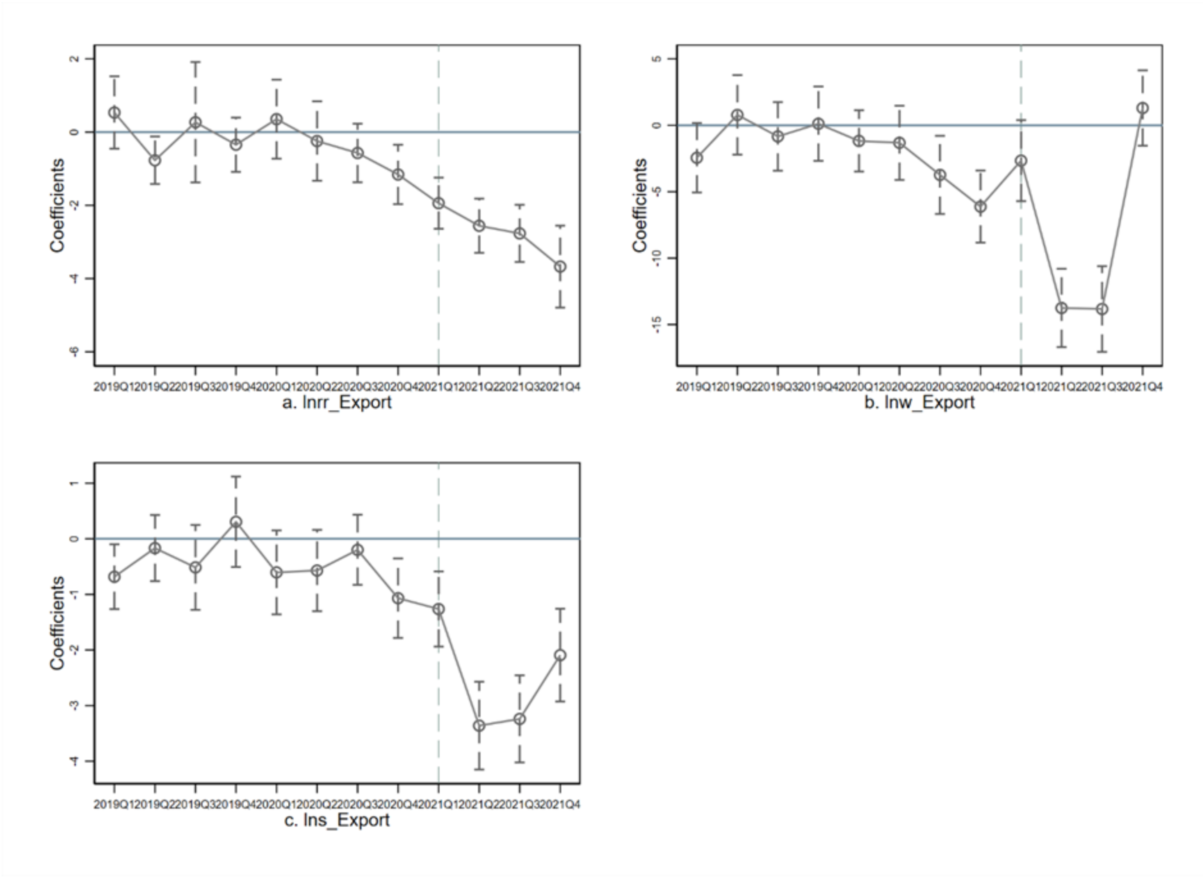

Fig. 1. Parallel Trend Tests

In Figure 1, it is evident that the interaction terms associated with the fourth quarter of 2020 exhibit significant negative values. This implies that the effects of the policy became noticeable during this period. In other words, there was an anticipatory effect of the policy shock on Australian wine exports. This finding is consistent with established research that has observed anticipatory effects of economic policies (Buettner and Madzharova, 2021), as many policies are developed, passed, and implemented gradually over time.

For this study, it is important to note that while the policy intervention officially took effect in the first quarter of 2021, the investigation initiated by the Ministry of Commerce of the People’s Republic of China began in August 2020, followed by an official statement. This sequence of events likely introduced uncertainty to the Chinese market regarding the importation of wine from Australia well in advance.

This research also incorporates Baidu Search Enquiry Index data for each quarter preceding and following the fourth quarter of 2020. As illustrated in Figure 3, there was a noticeable increase in the search volume for "Australian wine" in China during the fourth quarter of 2020. Subsequently, there was a decline in the search volume, indicating the proactive response of the Chinese market in anticipation of the policy's implementation.

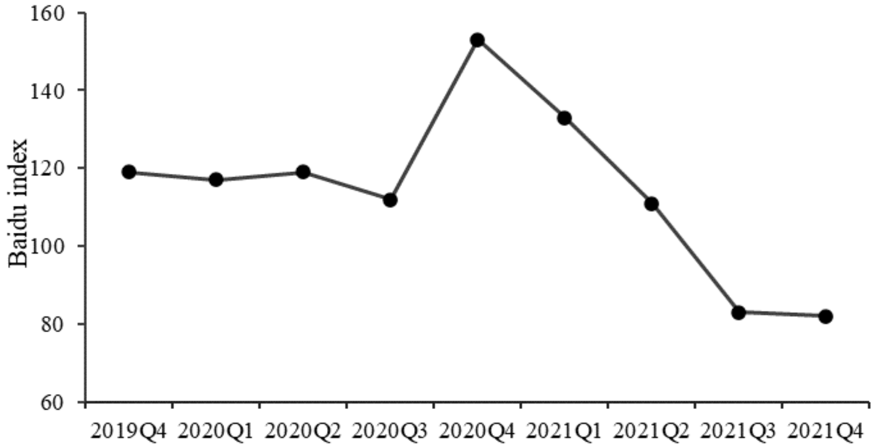

Fig. 2 Baidu Search Enquiry Index of "Australian Wine"

Regarding red & rose wine, the policy's negative impact becomes evident as early as the first quarter of 2021, and this impact is projected to persist over time as illustrated in Figure 1. Given that red wine constitutes the largest proportion of the total quantity, its dynamic response to the policy can serve as an indicator of the overall declining trend in the quantity of Australian wine exports to China. In contrast, the negative impact of the policy on white and sparkling wines is more pronounced in the second and third quarters of 2021, with the effects tapering off in subsequent periods.

In summary, despite the anticipatory effects of the policy, the estimation results successfully pass the parallel trend tests. This indicates that the observed changes in the quantity of wine exported from Australia to China can be attributed to the policy itself rather than other influencing factors. Following the policy's implementation, Australia's wine exports to China experienced a significant and adverse impact.

The results of placebo tests

In spite of the inclusion of various control variables and fixed effects in the DID model, it remains essential to assess the potential impact of unobservable factors on the policy evaluation outcomes. To address this, placebo tests are employed in this study to determine whether other random factors might account for the aforementioned estimation results (Ferrara et al., 2012; Liu and Lu, 2015).

Following equation (3), this study conducted 500 regressions with the dependent variables encompassing the three distinct types of wine, resulting in 500 hypothetical $\hat{\beta}$ coefficients for each case. Subsequently, a kernel density plot was generated to visualize the distribution of their estimated coefficients and their significance, as depicted in Figure 3. The solid line on the X-axis represents the genuine effect of the policy on Australian wine exports to China, while the dashed line on the Y-axis signifies the 95% confidence interval. The three subplots correspond to the density function of red & rose, white, and sparkling wine, respectively.

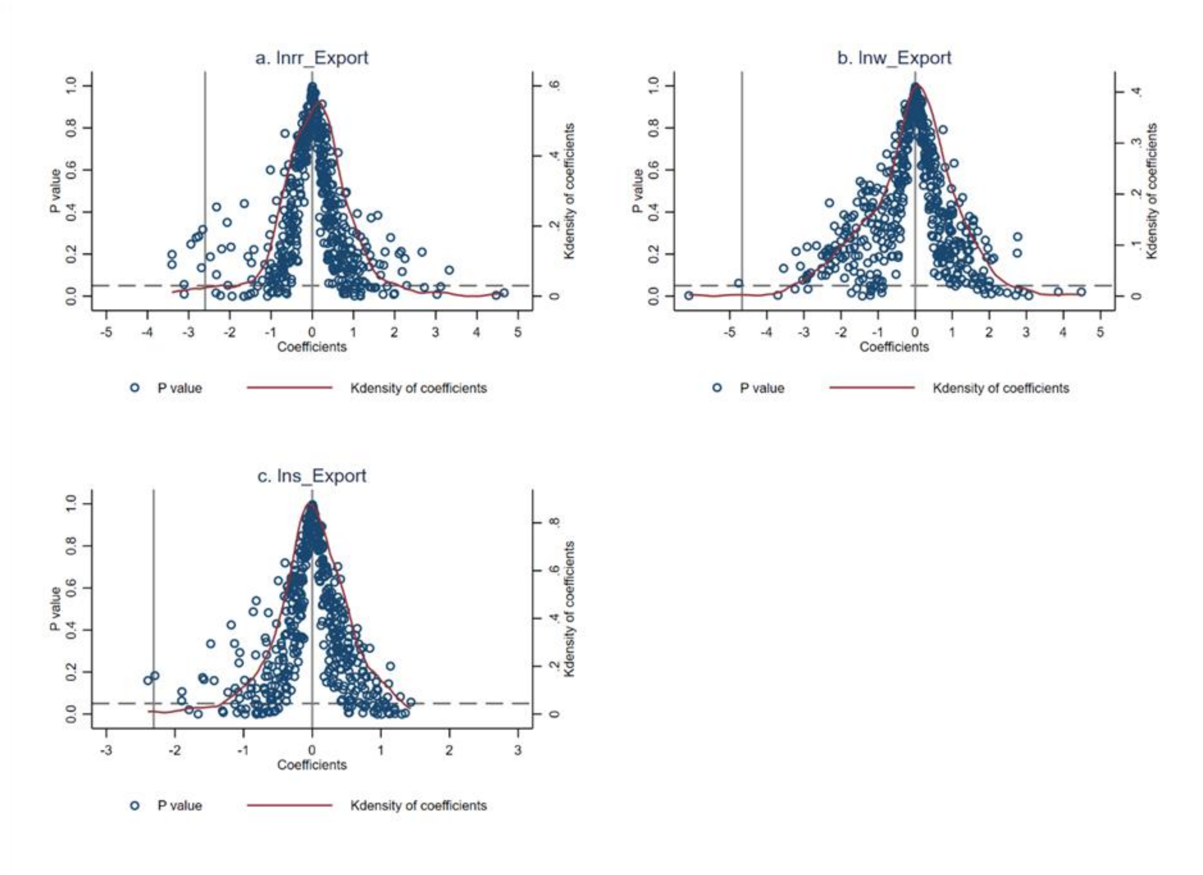

Fig. 3. Placebo tests

As per Figure 3, the estimated coefficients of $\hat{\beta}$ are primarily concentrated around 0 and exhibit a normal distribution. The results from the two-sided test indicate that, for different dependent variables, the probabilities of the hypothetical $\hat{\beta}$ being larger than the actual policy effects are only 3.2%, 0.2%, and 0.4% for red & rose, white, and sparkling wine, respectively. These probabilities are all indicative of low likelihood events. The p-values corresponding to the hypothetical $\hat{\beta}$ obtained from most regression models are greater than the 0.05 significance level, as depicted in Figure 3.

Given that the actual policy effects presented in Table 1 deviate significantly from the results of the placebo test, it can be inferred that the influence of other unobservable factors on the policy evaluation can be discounted.

The aforementioned outcomes highlight that Australia's wine exports to China underwent a substantial decline compared to other countries (regions) subsequent to China's increase in anti-dumping duties on Australian wines. Notably, considering the coefficient magnitudes, it is evident that the policy shock had the most pronounced impact on the quantity of white wines, experiencing a decrease of 99.06%. This was followed by red & rose wine (92.59%) and sparkling wine (90.06%). Throughout the study period, it was observed that red & rose wine exports constituted approximately 77% of Australia's total wine exports to China. Consequently, the exports of red & rose wine exhibited the most considerable decline in absolute terms.

4.2 Long-run effect

To explore the prospective influence of the anti-dumping duties on wine imports from Australia to China, the study employed a Bayesian ensemble method to forecast Australian wine exports to China up to the year 2025. Additionally, the investigation delved into the demand elasticities the three categories of wine.

Unit root and cointegration tests

To assess the integration order of all variables suitable for the ADL model, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are employed. These tests are used to analyze the export volumes and prices of the three types of Australian wine, as well as Chinese GDP, beer, and spirits consumption in logarithmic scale.

The null hypothesis of the ADF and PP tests is that the data contains unit roots, indicating non-stationarity. Conversely, the null hypothesis of the KPSS test is that the data is stationary. The integration order can be determined if more than two tests yield consistent results. Following the first difference, the stationarity of each variable is assessed to categorize them as $I(0)$, $I(1)$, or higher orders. The outcomes of the unit root tests are presented in Table 3. Nearly all variables exhibit unit roots at the level but become stationary at the first difference, implying that most integration orders do not exceed one. Hence, this study utilizes bound tests to evaluate the cointegration relationship between wine exports and its explanatory variables (Pesaran et al., 2001).

The bounds test, proposed by Pesaran et al. (2001), is employed to examine the cointegration relationship between the dependent variable and independent variables. In this process, all long-term coefficients are subjected to a joint test that assesses whether they significantly differ from zero, with the null hypothesis implying the absence of a long-term relationship. After conducting the general-to-specific estimation, the coefficients of lagged dependent variables are also scrutinized. The identification of a cointegration relationship between the dependent variable and its explanatory variables occurs when the null hypothesis is rejected based on *F*-statistics and *t*-statistics surpassing the upper bound threshold (Song and Lin, 2010).

Notably, the *F*- and *t*-statistics of Australian white and sparkling wine exports surpass the upper bound at the 1% significance level, indicating the presence of a long-term relationship. However, for red & rose wine exports, the model does not reject the null hypothesis of the bound test, suggesting that the long-run relationship between red & rose wine exports and influencing factors remains unclear. This could be attributed to the substantial decreases resulting from the imposition of anti-dumping duties on wine imported from Australia and the considerable fluctuations in international wine trade. Consequently, the findings regarding red & rose wine exports necessitate cautious interpretation.

Table 2. Results of unit root and cointegration tests

Unit root test	Red & rose volume			White volume			Sparkling volume		
	Level	Diff		Level	Diff		Level	Diff	
ADF	-0.902	-4.288 ***		-3.092	-4.056 **		-1.323	-4.683 ***	
PP	-17.353 *	-38.512 ***	*I*(1)	-32.153 ***	-39.912 ***	*I*(1)	-32.886 ***	-54.870 ***	*I*(1)
KPSS	0.338	0.226		0.349 *	0.125		0.479 **	0.395 *	
	Red & rose price			White price			Sparkling price		
	Level	Diff		Level	Diff		Level	Diff	
ADF	-2.890	-4.736 ***		-2.677	-4.342 ***		-1.387	-6.324 ***	
PP	-40.817 ***	-36.425 ***	*I*(1)	-36.948 ***	-46.278 ***	*I*(1)	-48.060 ***	-62.523 ***	*I*(1)
KPSS	0.610 **	0.067		0.592 **	0.108		0.492 **	0.280	
	GDP			Beer			Spirits		
	Level	Diff		Level	Diff		Level	Diff	
ADF	-2.086	-4.624 ***		-2.945	-5.559 ***		-1.798	-3.895 **	
PP	-46.290 ***	-23.522 **	*I*(1)	-3.556	-18.729 *	*I*(1)	1.514	-12.312 ***	*I*(1)
KPSS	1.649 ***	0.678 **		0.407 *	0.540 **		0.744 ***	0.976 **	
Cointegration test	Red & rose exports (k = 9)			White exports (k = 7)			Sparkling exports (k = 7)		
F-statistic		2.803			17.531 ***			19.782 ***	
t-statistic		-3.250			-6.904 ***			-7.748 ***	

Notes: 1. All the variables are tested in logarithmic scale; 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Australian wine export elasticities

The statistically significant demand elasticities between the three types of wine and their influential variables from the ADL modeling are presented in Table 3. Following the principles of demand theory, a positive correlation is expected between income level and demand, resulting in positive income elasticities. Conversely, price elasticities are anticipated to be negative. However, due to the significant impact of the anti-dumping duties' implementation, it is not statistically viable to establish a positive relationship between the decline in Australian wine exports and an increase in Chinese income. Among the income and price elasticities, the price elasticities are significant in two out of the three models, emphasizing the pivotal role of price in wine export (Liu and Song, 2021). Moreover, these price elasticities also provide insights into the market positions of different wine categories. Specifically, the demand for Australian white wine is more responsive to price changes compared to that of sparkling wine, underscoring the preference for sparkling wine among Chinese consumers.

The negative elasticities observed in beer consumption suggest that Chinese consumers perceive red & rose and white wine similarly to beer in their daily alcoholic beverage consumption habits. This drinking behaviour aligns with the findings of Liu & Song (2021). However, sparkling wine is regarded as a complementary option to beer. The elasticity indicates that a 1% increase in beer consumption leads to a 3.07% rise in the demand for Australian sparkling wine. The positive elasticities associated with spirit consumption are significant, at least at the 5% level. This strongly implies that Chinese consumers view consuming foreign liquor as a symbol of social status, reserving them for special occasions alongside spirits (Liu and Song, 2021; Lin and Tavoletti, 2013).

Table 3. Demand Elasticities of Australian Wine Exports to China

	GDP	Price	Beer	Spirit
Red & rose	-	-	-13.962 ***	8.947 ***
White	-	-2.433 ***	-9.245 *	4.566 **
Sparkling	-	-0.710 ***	3.065 **	3.203 ***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Model performance evaluation

In terms of the in-sample forecasting performance, Table 4 displays the modeling accuracies across the five import markets for the three types of wine, measured by

RMSE, MAPE, and MASE. In general, these three accuracy metrics yield consistent results. The Bayesian ensemble model demonstrates the highest forecasting accuracy in predicting red & rose and sparkling wine exports to China. While the Bayesian ensemble model's accuracy is slightly lower than that of the ADL model in estimating white wine, it still significantly outperforms the other three time series models. To assess the overall forecasting accuracy, the average performance of each model in predicting demand across all wine types has been evaluated. Here, the Bayesian ensemble model surpasses nearly all other benchmarks based on the three accuracy measurements. This overall superior forecasting performance underscores the reliability of predicting wine demand from 2023 to 2025, considering the implementation of anti-dumping duties and the impact of COVID-19.

Table 4. *Ex-post* Forecasting Accuracy.

	SNaïve	ETS	SARIMA	ADL	Bayes.ensemble
Red & Rose					
RMSE	1.114	0.765	0.765	0.628	**0.613**
MAPE	6.225	4.287	4.235	3.713	**3.551**
MASE	1.000	0.690	0.681	0.897	**0.860**
White					
RMSE	1.979	1.559	1.452	**0.787**	0.803
MAPE	12.996	10.203	9.608	**5.061**	5.185
MASE	1.000	0.772	0.724	**0.444**	0.454
Sparkling					
RMSE	1.041	0.810	0.851	0.428	**0.347**
MAPE	7.129	5.734	5.533	2.673	**2.388**
MASE	1.000	0.787	0.756	0.446	**0.391**
Average					
RMSE	1.378	1.045	1.023	0.614	**0.588**
MAPE	8.784	6.742	6.459	3.816	**3.708**
MASE	1.000	0.750	0.720	0.595	**0.568**

Note: Values in bold represent the lowest value of accuracy measurements for each model, indicating the model with the best model fitness.

Ex-ante forecasts

The Bayesian ensemble model was employed to generate *ex-ante* quarterly wine demand forecasts for the three types of wines in the Chinese market from 2023 to 2025. Additionally, counterfactual forecasts were generated from 2022 to predict how anti-dumping duties would impact wine demand. The scenario assumes the absence of anti-dumping duties. In practice, the quarterly impacts of the anti-dumping duties are added back to the 2021 Australian wine exports to China, based on the DID estimations in Fig. 1. To prevent the tariff from affecting wine trading prices in the counterfactual forecasting, export prices after 2021 are extended using the univariate forecasting model based on the normal period. Fig. 4 illustrates the quarterly historical data, *ex-ante* forecasts, and counterfactual predictions from 2017 Quarter 1 to 2025 Quarter 4, while Table 5 presents the annual forecasts and the calculated average annual growth rate (AAGR). Overall, most wine demand forecasts exhibit significant fluctuations due to the implementation of anti-dumping duties on imported wine from Australia to China.

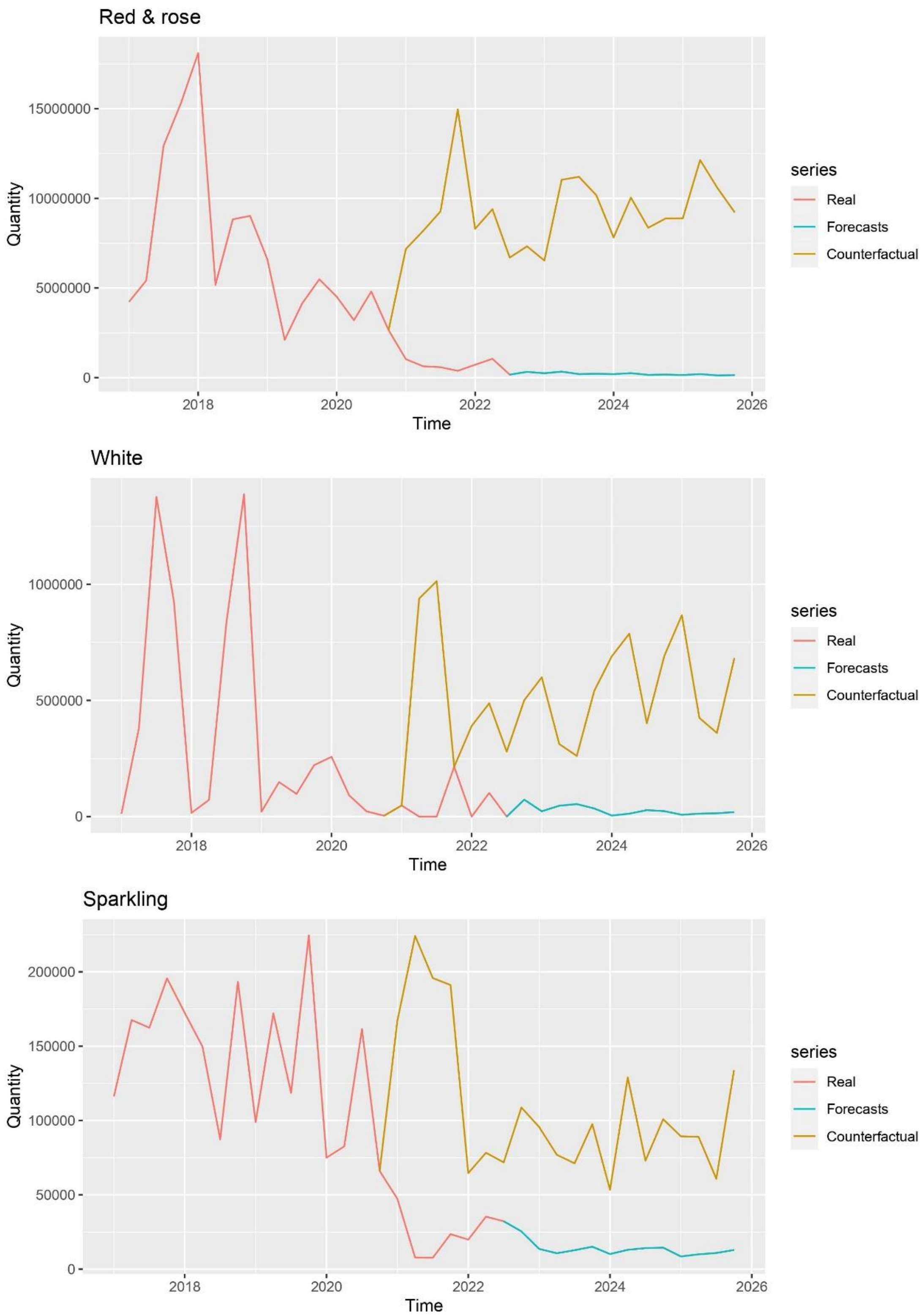

Fig. 4. Historical, *Ex-ante* forecasting, and Counterfactual Forecasts of Imported Australian Wine from 2017 to 2025.

In terms of the *ex-ante* forecasts, the wine demand for all three types of wine is expected to remain at a low level since the anti-dumping duties were initiated in 2021, and it is projected to continuously decrease with an Average Annual Growth Rate (AAGR) of -21.92%, -38.90%, and -9.54%, respectively. This indicates a substantial impact due to the anti-dumping duties. According to the counterfactual predictions, the demand for red & rose wine in the Chinese market could increase to nearly 40.83 million, with an AAGR of 3.2%. Meanwhile, white wine demand might experience an average annual growth rate of 20.37%, reaching 2.33 million in 2025. The demand for sparkling wine in the Chinese market appears to be more stable than the other two types of wines, both historically and in terms of predictions. However, a notable level shift occurs in the counterfactual predictions compared to the original forecasts. In this way, the accumulated losses caused by the implementation of anti-dumping duties from 2021 to 2025 are 96.11%, 93.15% and 84.11% for red & rose, white and sparkling wine, respectively.

Table 5. *Ex-ante* and Counterfactual Australian Wine Demand Forecasts.

	Red & rose		White		Sparkling	
Year	*Ex-ante*	Counterfactual	*Ex-ante*	Counterfactual	*Ex-ante*	Counterfactual
2019	18,318,737.40	-	488,622.00	-	614,019.85	-
2020	15,183,267.40	-	375,254.50	-	385,103.50	-
2021	2,629,177.70	39,609,491.00	262,428.00	2,213,973.90	86,289.15	778,308.40
2022	2,262,182.78	31,725,559.60	174,962.03	1,658,001.41	112,792.18	323,470.81
2023	992,871.89	38,958,984.79	158,656.53	1,714,522.71	52,116.52	341,255.75
2024	771,148.29	35,104,254.28	68,620.32	2,570,817.21	51,752.48	356,184.12
2025	605,311.53	40,826,881.00	54,172.56	2,334,103.00	42,235.57	373,038.41
AAGR 2023-2025	-21.92%	3.20%	-38.90%	20.37%	-9.54%	4.55%
Accumulated loss (%)		96.11%		93.15%		84.11%

Note: Accumulated loss= 1-(Ex-ante/Counterfactual)

5. Conclusions

Discussion

To conclude, this study utilized the DID methodology to investigate the short-run effect of anti-dumping duties on Australian wine exports to China, and a Bayesian ensemble ADL model was employed to predict the continuous long-run effect up to 2025. Parallel and placebo tests were conducted in the DID analysis to examine the robustness of the results. The imposition of anti-dumping duties on imported Australian wine led to a significant decline in red & rose, white, and sparkling wine exports to China in 2021, with decreases of 92.59%, 99.06%, and 90.06%, respectively, compared to a scenario without such policy intervention. The significant drop corresponds to the previous literature related to the responsiveness and sensitivity of overall wine demand to policy (Carbon, 2021), and indirectly reflects potential disturbances in individual purchasing behaviour (Taghikhah et al., 2020) that aggregated to the reduction of wine demand at the macro level. Consistent with the industrial news and reports, this policy had a substantial impact on freezing wine exports from Australia to China (The Guardian, 2023; Wine Australian, 2022).

Turning to the long-run effect, alongside co-integration tests and elasticity analysis, the forecasting performance of the proposed Bayesian ensemble method was evaluated by generating *ex-post* forecasts and comparing them with results from various benchmark forecasting models. The findings demonstrate that, on average, the Bayesian ensemble method exhibited the highest accuracy in forecasting Australian wine exports to China. According to the *ex-ante* forecasts, influenced by the anti-dumping duties, wine exports to China will continue to decline with average annual growth rates of -21.92%, -38.90%, and -9.54% for red & rose, white, and sparkling wines, respectively, from 2023 to 2025. Counterfactual predictions suggest that, without anti-dumping duties, red & rose, white, and sparkling wine exports to China would increase by 3.20%, 20.37%, and 4.55%, respectively. By quantifying the difference between actual and counterfactual forecasts, the continuation of the anti-dumping duty policy could lead to decreases of 96.11%, 93.15%, and 84.11% in red & rose, white, and sparkling wine exports to China between 2021 and 2025.

Considering that Australian white and sparkling wines hold limited market shares and that the accumulated decrease in red & rose wine amounts to 96.11%, this suggests that Australian wine could nearly exit the Chinese market within the next three years. Although neither China nor Australia is each other's top wine trade partner, the quantity and value of trade significantly contribute to both countries' international wine business markets.

Research significance

Differing from other macro-level studies, this research incorporates policy factors into the analysis framework of wine demand. It was found that the implementation of anti-dumping tax policies significantly reduced Australia's wine exports to China. It implies that when forecasting wine demand for a country or region, it's crucial to consider not only market factors but also policy factors, thereby enriching the literature in this field. This study also makes the following two empirical contributions. First, differing from the previous commodities and services studies that independently consider the individual- and time-fixed effects when using the DID method for policy assessment, this study is the first to address the potential endogeneity in the international trade markets by incorporating the individual and time effects as well as their interactive terms. This DID quasi-experimental design provides guidelines for policy evaluation in a complex market environment where the time-dependent impact of unobservable factors occurs. Second, this study introduces a novel forecasting method, the Bayesian ensemble, to improve time series forecasting performance with fluctuating data. The Bayesian ensemble method is robust and superior because it integrates multiple Bayesian estimations from bootstrapped series according to their Bayesian factors.

Practically, policy impact analysis can assist the wine industry in better preparing for changes, especially during turbulent periods. Although the movement to end the tariff on Australian barley exports by China starting from Aug 2023 provides a positive perspective for Australian wine export, both countries are planning to diversify markets and explore substitute markets to meet demand and manage supply. Therefore, New World wines such as Chilean and New Zealand wines should strategically develop plans to expand the market share in China. New World winemakers and merchants should organize more promotional activities for Chinese customers. The government should endeavour to engage with China under the One Belt One Road scheme to reduce wine tariffs. There is also an opportunity to promote domestic wine to Chinese consumers. Addressing the challenge of high costs, including production techniques and taxation, could involve government interventions like tax deductions or subsidies to promote domestic wine and fill the demand gap created by the absence of Australian wine. For Australia, wine traders should explore markets in other countries and regions, seeking new trading partners to diversify the destination markets of Australian wine exports, thus reducing the vulnerability to overwhelmingly influences from policy changes in one particular destination.

Research prospects and limitations

This study advances the wine economic literature by applying cutting-edge causal inference and Bayesian ensemble methods to investigate policy intervention impacts on international wine demand. It establishes a rigorous economic framework to assess policy impacts in the short and long run, contributing to the wine economic literature. This framework can be extended to other wine markets to explore potential future market fluctuations caused by external shocks such as carbon-neutral policies.

One limitation of this study is the scope of analysis due to data availability constraints. Future studies could broaden the analysis to encompass the global wine market, developing a more comprehensive framework for policy impact analysis. Additionally, this study did not account for potential simultaneous impacts, like the pandemic's influence on international wine demand, in the short-run analysis. In the future, advanced causal inference methods could be integrated to identify the effects of various external shocks occurring simultaneously on international wine demand.

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