In Vino ‘No’ Veritas: impacts of fraud on wine imports in China

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China is one of the largest wine importing countries in the world and is poised for continued import growth in the future. Increased wine purchases throughout China have given rise to persistent fraud where fake wines are packaged and sold with counterfeit contents and labels. For exporting countries like France, counterfeit wines displace market share, damage foreign brand reputation, and cause distrust in consumers who are aware of counterfeiting problems throughout the country. We examine the impact of fraudulent wine events (as measured by negative media reports) on Chinese wine demand differentiated by supplying country. We employ the Rotterdam demand system and a switching regression procedure to estimate import demand and compare results across different media variable specifications. Results consistently show that negative reports disproportionately affect French wine regardless of how the media variable is specified. This is not surprising because most fraudulent events involve French wine counterfeits.

Key words: Australia, China, Counterfeit, demand, France, fraud, imports, media, wine.

1. Introduction

China is the third largest importer of bottled wine in the world (2016 data) and has grown in importance in the global wine market over the last decade (UN Comtrade 2018). Increasing disposable incomes, the rise of a more educated middle class, shifts towards Western lifestyles, increased gender equality and government promotion of wine as a healthy alternative to grain-based alcohol are key factors that caused substantial increased wine consumption in China (Balestrini and Gamble 2006; Liu and Murphy 2007; Mitry et al. 2009; Anderson and Wittwer 2013; Anderson and Wittwer 2015). Foreign wine is also perceived as prestigious and high quality, which has also contributed to the noteworthy growth in wine imports in China. However, increased consumption and demand for foreign varieties have given rise to persistent wine fraud where domestic firms often mimic foreign brands in the marketplace. Arguably, extensive fraud in China affects consumer preferences in ways that could ultimately affect wine exporting countries that

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increasingly rely on China for sales. In this study, we examine the effects of media reports about fraudulent wine events on wine import demand in China. We particularly focus on how these events affect wine exporting countries.

Domestic producers in China have supplied various forms of tainted wine where water, sugar and other substances are added to bulk wine prior to bottling (Coffey 2006; Dordevic et al. 2013; Muhammad et al. 2014; Wilkes et al. 2016). Counterfeiting also occurs with reused labelled bottles and fake foreign labels (Holmberg 2010). Black markets have emerged to supply various forms of counterfeit domestic and foreign wine to consumers. The presence of wine fraud in China ranges from activities that target collectors of high-end premium wine to general consumers of lower end wine (Holmberg 2010; Beconcini and Binion 2015). Quality, country of origin and branding are important factors affecting wine purchasing in China. However, fraudulent wine can damage foreign brands and capture market share from legitimate producers (Beconcini and Binion 2015).

Fraudulent events have been highlighted in the mainstream media, giving greater attention to the problem. A recent Forbes article describes this persistent fraud as an epidemic in the country, with claims that 50% of wine exceeding $35 per bottle in China is counterfeit, and that an estimated 30,000 bottles of bogus wine are sold every hour in China (Ambler 2017). Specific evidence of counterfeit wine includes more than 4,000 bottles confiscated from one operation in Shanghai in 2012, thousands of bottles of inexpensive Chinese wine mislabelled with fake foreign brands in a counterfeit operation in Yantai in 2013, and hundreds of fake wines identified by tourists throughout China (Balestrini and Gamble 2006). In 2011, Domaines Barons de Rothschild exported 200,000 bottles of Chateau Lafite Rothschild from France to China, yet evidence suggests that 600,000 bottles of this French wine were sold in China that year (Zhuoqiong and Xiangyi 2012). While Chateau Lafite has become one of the most counterfeited wines on the black market, other high-end French brands have also been counterfeited in China (Ambler 2017). The prevalence of wine fraud associated with French labels has been widely publicised, yet other European labels, as well as wines from Australia and other source countries have also been targets for fraudulent wine sales.

Given the importance of China to global wine trade and the potential impact of wine fraud on exporting countries, research on this issue is clearly warranted. Accordingly, we estimate the impacts of fraudulent events on wine import demand in China and examine whether these impacts are specific to exporting countries. While there is an extensive literature on the Chinese wine market (Balestrini and Gamble 2006; Liu and Murphy 2007; Anderson and Wittwer 2013; Muhammad et al. 2014; Anderson and Wittwer 2015), and the impacts of fraud on agricultural and food supply chains (Spink and Moyer 2011; Zhang and Xue 2016; Moyer et al. 2017; Kendall et al. 2018; van Ruth et al. 2018), this study is the first to estimate the impacts of wine fraud on Chinese wine demand, with a particular focus on supplying countries. This is an important contribution given the surge of fraudulent activity in the Chinese...
wine market and the growing importance of China as a global wine importer. We provide evidence that persistent wine fraud has impacted Chinese foreign wine demand with different effects across supplying countries.

In this study, we use the number of negative media reports relating to wine fraud activities in China as a measure of wine fraud prevalence. Our primary assumption is that consumers rely on, and are affected by, media information when making purchasing decisions (Just 2001). There is a robust literature investigating the effects of media coverage on consumer demand for a variety of food products in different countries (Kaabia et al. 2001; Verbeke and Ward 2001; Piggott and Marsh 2004; Yadavalli and Jones 2014). Following these studies, we derive a media index based on the number of reported articles containing key words and phrases linked to fraudulent wine events in China.

For the analysis, we employ the absolute-price version of the Rotterdam demand model (Theil 1980; Theil and Clements 1987) to estimate Chinese foreign wine demand by source (France, Italy, Spain, Australia, Chile, and the United States) and a switching regression procedure (Moschini and Meilke 1989; Ohtani et al. 1990) to examine if negative media events result in structural adjustments in the import demand coefficients. We use Nexus Uni™ to construct a media index based on the number of reported stories linked to fraudulent wine events in China. Model estimates are used to derive source-specific media elasticities. We also examine how negative media reports affected the allocation of total import expenditure across supplying countries.

2. Empirical model and methods

Following Seale et al. (2003), Carew et al. (2004), Muhammad (2011) and Muhammad et al. (2014), we model foreign wine demand assuming differentiation by source where Australian wine, French wine, etc., are treated as individual products. To limit the analysis to foreign or imported wine, we assume a multistage budgeting process where total expenditures are first allocated across all product groups and then group expenditures are allocated across the goods within each product group. In this context, foreign wine is treated as a product group where demand is determined in the first stage. Conditional on aggregate foreign wine expenditures, the demand for wine from each source is then determined in the second stage (Seale et al. 1992). Foreign wine preferences are assumed to be weakly separable or block-wise dependent, which implies that the utility interaction between foreign wine and other products is a matter of the product groups and not the individual goods within each group. We use the absolute-price version of the Rotterdam demand model in estimating import demand (Theil 1980; Theil and Clements 1987). As noted by Theil and Clements (1987), block-wise dependence (or weak separability of product groups) is sufficient for limiting analysis to goods within a product group when using the Rotterdam model.

Let $q$ and $p$ denote the quantity and price of imported bottled wine, and $i$ and $j$ denote the country of origin, and $n$ denote the number of source
countries. Given these terms, the demand for wine from the \(i\)th exporting source is specified as follows:

\[
wi,t \cdot d \log qi,t = \theta_i d \log Qt + \sum_{j=1}^{n} \pi_{ij} d \log pj,t + \tau_i \Delta MV_{t-1} + \mu_{i,t}.
\] (1)

Note that \(wi,t\) is the \(i\)th conditional budget share at time \(t\) defined as follows:

\[
wi,t = \frac{p_{i,t}q_{i,t}}{\sum_j p_{j,t}q_{j,t}}.
\]

\(\theta_i\) is the \(i\)th marginal budget share (total expenditure effect) and is defined as \(\theta_i = \frac{\partial(p_{i,t}q_{i,t})}{\partial(\sum_j p_{j,t}q_{j,t})}\). \(d \log Qt\) is the Divisia volume index:

\[
d \log Qt = \sum_i wi,t \cdot d \log qi,t,
\]

which is a measure of the change in real aggregate expenditures on foreign wine. \(\pi_{ij}\) is the Slutsky price coefficient or relative price effect, which measures the impact of the price of imported wine from the \(j\)th source on the quantity imported from the \(i\)th source. \(\mu_{i,t}\) is a random and normally distributed error term.

\(\Delta MV_{t-1}\) is the differenced media variable (\(MV\)), where \(MV\) is a measure of negative media reports. \(\tau_i\) measures the impact of fraudulent events (as defined by \(MV\)) on the quantity imported from the \(i\)th source. Note that we assume a one-period lag response to the media variable to account for lags in importer responsiveness. In equation (1), negative media coverage can have a direct impact on imports from a particular source. It is possible for negative media coverage to have no impact on an import \((\tau_i = 0)\), but it is also possible for negative media coverage to affect wine from all countries \((\tau_i < 0 \forall i)\). Since negative media reports will often mention wine from particular countries, it could be the case that \(\tau_i < 0\) for the countries mentioned in reports and \(\tau_i > 0\) for countries considered as viable alternatives.

\(\theta_i\), \(\pi_{ij}\) and \(\tau_i\) are treated as fixed parameters to be estimated. Demand theory requires the following constraints for adding up, homogeneity and symmetry: \(\sum_i \theta_i = 1\) and \(\sum_i \pi_{ij} = \sum_i \tau_i = 0\) (adding up); \(\sum_j \pi_{ij} = 0\) (homogeneity); and \(\pi_{ij} = \pi_{ji}\) (symmetry) (Seale et al. 1992).

Although equation (1) can account for the direct effect of negative media events on an import, structural adjustments in the marginal share and price coefficients due to negative media events are not accounted for. For instance, if negative press coverage is consistently about wine from a particular source, then consumers will likely allocate less expenditures to that source. In this instance, the marginal share \((\theta_i)\) for that source would no longer be constant but would vary based on the presence of negative media reports. To account for the possibility of structural change (i.e. nonconstant price and marginal share estimates), we model the impact of negative media reports using a switching regression procedure. Following the methodology of Moschini and Meilke (1989) and Ohtani et al. (1990), and the empirical applications of Gil et al. (2004) Peterson and Chen (2005), and Muhammad (2011), structural change in foreign wine demand is modelled assuming that all parameters are affected by a time-dependent variable \((h_t)\) that is a function of negative media reports in this instance. For instance, the most straight-forward approach would be to define
as a binary variable, where $h_t = 1$ for all observations with one or more negative media reports; $h_t = 0$ otherwise. Media variable specifications are discussed in the next section (3.2 Overview of media variable).

The switching regression version of the Rotterdam model is specified as follows:

$$w_{i,t}d\log q_{i,t} = \alpha_i + \xi^*_i h_t + (\theta_i + \theta_i^* h_t) d\log Q_t + \sum_{j=1}^{n} \left( \pi_{ij} + \pi_{ij}^* h_t \right) d\log p_{j,t} + \mu_{i,t}. \tag{2}$$

Given that the variables in equation (2) are in log differences, the added constant term ($\alpha_i$) is a measure of trending behaviour. Note that when $h_t \neq 0$, $\xi^*_i h_t$ measures the structural adjustment in the constant/trend, $\theta_i^* h_t$ measures the structural adjustment in the marginal share, and $\pi_{ij}^* h_t$ is the structural adjustment in the relative price effect. Structural change due to negative media coverage is based on the statistical significance of $\xi^*_i$, $\theta_i^*$ and $\pi_{ij}^*$. The joint hypothesis of no structural change ($\xi^*_i = \theta_i^* = \pi_{ij}^* = 0$) implies that negative media reports have no effect on the magnitudes of the constant, marginal share or price coefficients. This would imply, for instance, that consumer responsiveness to price changes does not vary with negative media coverage.

Given the added terms in equation (2), additional restrictions are required for adding up, homogeneity and symmetry: $\sum_i \xi^*_i = \sum_i \theta_i^* = \sum_i \pi_{ij}^* = 0$ (adding up); $\sum_i \pi_{ij}^* = 0$ (homogeneity); and $\pi_{ij}^* = \pi_{ji}^*$ (symmetry) (Peterson and Chen 2005; Muhammad 2011).

Of particular interest is the impact of structural change on the demand elasticities. The conditional expenditure elasticity, which is a measure of how a percentage change in total expenditures on imported wine affects wine from the $i$th source, is derived as follows:

$$\eta_i = \frac{d\log q_i}{d\log Q} = \frac{(\theta_i + \theta_i^* h_t)}{w_i} \tag{3},$$

note that this relationship is impacted by the significance and magnitude of $\theta_i^* h_t$. $\theta_i^* < 0$ indicates that negative media reports result in less expenditures being allocated to a particular source.

We can also derive the conditional Cournot (uncompensated) price elasticity with structural change:

$$\eta_{ij} = \frac{d\log q_i}{d\log p_j} = \frac{(\pi_{ij} + \pi_{ij}^* h_t)}{w_i} - \frac{(\theta_i + \theta_i^* h_t)}{w_i} \frac{w_j}{w_i}. \tag{4}$$

The first and second terms in equation (4) are the substitution and income effect of a price change in the $j$th source on imports from the $i$th source. $\pi_{ij}^* h_t$
and \( \theta_i h_t \) denote the structural change in this relationship and suggest that negative media reports could make consumers more or less responsive to price changes. Equations (3) and (4) are derived and statistically compared assuming the following: \( h_t = 0 \) and \( h_t \neq 0 \).

### 3. Data and estimation

#### 3.1. Chinese wine imports and prices

We obtained China Customs data on wine imports from the Global Trade Atlas®. Imports are defined according to the Harmonized Commodity Description and Coding System (HS) classification 220421, *wine of fresh grapes (excluding sparkling wine) in containers less than two litres*, which accounts for about 90% of total Chinese wine imports. Quantities are measured in litres (L), while values and prices are in U.S. dollars and include product cost, insurance and freight (CIF). The data are monthly and span the period January 2007-December 2017. To account for competition across supplying countries, we disaggregated imports by exporting country: Australia, Chile, France, Italy, Spain, United States and the *rest of the world* (ROW), which is an aggregation of the exporting countries not specified.

The six individual countries included in the analysis comprise nearly 93% of Chinese bottled wine imports. The annual market share and price for wine from each source are reported in Table 1. Australia and France are the two dominant wine suppliers to the Chinese market, with France maintaining the largest, yet declining market share over time as Australia gained a larger market share. In 2017, France comprised 41% of Chinese wine imports, while 27% of the market was held by Australia. Chile (11% market share) is the third largest supplier, followed by Spain (6%), Italy (5%) and the United States (3%). Along with Australia, there has been noteworthy growth in imports from Chile and a decrease in imports from France and the United States since 2011. Average prices per litre during 2007-2017 range from $2.86 (Spain) to $5.84 (Australia). Import prices in China varied over time from all sources, except for Chilean wine, which remained relatively consistent over the past decade. Average prices have risen substantially over time for Australian and U.S. wine, with modest increases in average prices for Italian wine. Australian wine had an average price of $5.02/L over the 2007-2012 period with average prices increasing by $1.79/L to $6.81/L during the 2012-2018 period. U.S. wine increased by $1.90/L over the same period: $3.95/L (2007-2012) to $5.85/L (2012-2017). By comparison, French and Spanish wines have decreased by $0.33/L and $0.83/L, respectively.

Chinese bottled wine imports have a 14% Most-favored-nation (MFN) tariff rate and a 10% excise (consumption) tax. Chile and Australia have preferential trade agreements with China. Accordingly, Chilean wines have been imported tariff free since 2015. Australia faced a 5.6% import tariff in 2017 that decreased to 2.8% on 1 January 2018 and will fall to 0% in 2019.
The United States and key European suppliers shared a level playing field from a market access perspective for the timeframe of this study. However, China imposed an additional 15% import tariff on U.S. wine starting in April 2018 as a result of the trade conflict with the United States that is expected to decrease U.S. wine export potential (Countryman and Muhammad 2006).

3.2. Overview of media variable

Using the Nexis Uni™ database, we conducted exact-phrase searches (e.g. *Chinese counterfeit wine*) of media reports on negative wine events in China. Nexis Uni™ contains media reports in all publication outlets ranging from newspapers, newswires, press releases and magazines to web-based publications, business reports, blogs, and online videos and images throughout the world. Along with the search terms *China* or *Chinese*, we searched the terms *fake wine(s)*, *counterfeit wine(s)*, *wine fraud*, *fraudulent wine(s)*, *bogus wine(s)*, *imitation wine(s)* and *replica wine(s)*. Exact-phrase searches required

| Year | Volume (million litres) | Value (million $U.S.) | Australia | Chile | France | Italy | Spain | United States | ROW |
|------|------------------------|-----------------------|-----------|-------|--------|-------|-------|----------------|-----|
| 2007 | 42.3                   | 184.1                 | 19.8      | 4.6   | 44.9   | 9.7   | 6.8   | 4.7            | 9.5 |
| 2008 | 57.6                   | 276.3                 | 19.9      | 5.2   | 45.9   | 7.8   | 4.3   | 5.3            | 11.5|
| 2009 | 91.1                   | 377.4                 | 21.2      | 6.4   | 48.0   | 6.0   | 3.6   | 5.5            | 9.2 |
| 2010 | 146.4                  | 657.4                 | 17.7      | 5.6   | 51.7   | 5.9   | 4.0   | 4.9            | 10.1|
| 2011 | 241.4                  | 1,274.3               | 15.2      | 5.4   | 55.4   | 6.1   | 4.9   | 4.2            | 8.8 |
| 2012 | 266.1                  | 1,375.8               | 15.1      | 6.3   | 52.9   | 5.7   | 5.7   | 4.8            | 9.6 |
| 2013 | 278.9                  | 1,382.5               | 16.4      | 7.2   | 47.6   | 6.5   | 6.6   | 5.3            | 10.4|
| 2014 | 288.1                  | 1,364.6               | 18.1      | 9.1   | 44.9   | 6.0   | 7.0   | 4.8            | 10.1|
| 2015 | 396.6                  | 1,879.8               | 23.4      | 9.1   | 46.2   | 4.4   | 6.0   | 2.7            | 8.2 |
| 2016 | 482.6                  | 2,197.4               | 24.7      | 9.5   | 44.0   | 5.2   | 6.5   | 2.4            | 7.7 |
| 2017 | 553.7                  | 2,553.6               | 26.7      | 10.5  | 41.1   | 5.4   | 5.9   | 3.0            | 7.4 |
| Average | 258.6                 | 1,229.4               | 19.8      | 7.2   | 47.5   | 6.2   | 5.6   | 4.3            | 9.3 |

Note: Chinese foreign wine imports are defined according to HS 220421: *wine of fresh grapes (other than sparkling wine)*, *containers of not over 2 litres*. ROW is rest of world. NA (not applicable). Source: Global Trade Atlas®, IHS Markit Inc.
that we obtain results for wine and wines separately and were used to avoid reports about other fraudulent activities affecting the wine market (e.g. counterfeit currencies). Using search terms like fake wine, counterfeit wine, bogus wine, etc., ensured that our search results were limited to media reports on fraudulent wine activities. We also reviewed the reports to ensure that all were related to negative wine events in China.

We found over 1,500 media reports globally during the period January 2007-December 2017, but when limiting the search output to media outlets in China and eliminating duplicate articles, the number of reported stories was significantly smaller (92 reported stories). The number of reported stories per month, as well as the cumulative number of stories over time, is shown in Figure 1. Overall, the intensity of reported stories increased over time and about 40% of all observations have at least one reported story. In China, one or two reported stories in a month appear to be the norm. About 8% of the observations had three or more reported stories. Furthermore, of the 92 reported stories employed in our analysis, there are 101 instances where a source country from our study is specifically mentioned in an article (See Table S1). France is the source country most often noted with 42 reports focused on fake French wine. Furthermore, French wines were the focus of negative media reports consistently throughout the timeframe considered for this analysis. While Australia was the second most noted source for wine fraud in China (21 reports), more than half of these reports occurred late in

![Figure 1](https://ssrn.com/abstract=3586845)
2017. The number of reports mentioning other exporting countries is significantly smaller by comparison (See Table S1).

We considered alternative specifications for the media variable \((MV)\) for the analysis. Let \(NM_t\) denotes the number of negative articles at time \(t\). We first considered a binary media variable defined as follows:

\[
MV_t = \begin{cases} 
1 & \text{if } NM_t \geq 1 \\
0 & \text{if } NM_t = 0 
\end{cases}
\]  

(5)

Note that \(MV_t = 1\) for all observations with at least one negative report; \(MV_t = 0\) when the number of negative reports is zero. Using equation (5) to estimate demand implies that individuals respond to the occurrence of negative media events regardless of the number of articles or reported stories. An obvious drawback to this approach is that \(NM\) could be directly related to the number of cases and how widespread wine fraud is in China; equation (5) cannot account for greater consumer responsiveness with the number of reported stories. A second drawback is that equation (5) ignores the possibility of past events affecting the present stock of knowledge. That is, individuals are assumed to return to their normal state during periods of nonoccurrence, even when following successive periods of negative media events.

We considered a count variable: \(MV_t = NM_t\), which is the number of reported stories at time \(t\). However, similar to equation (5), individuals are assumed to return to their normal state during periods of nonoccurrence. To account for past events on present choices, we considered a cumulative media variable: \(MV_t = \sum_{k=0}^{t-1} NM_{t-k}\) (Verbeke and Ward 2001; Sha et al. 2015). In this instance, however, individuals never return to a normal state.

An ideal media variable would account for past events while allowing for the possibility of returning to a normal state with successive nonoccurrence periods. We considered a weighted exponential moving average for this purpose (Holt 2004):

\[
MV_t = \delta [NM_t + (1 - \delta)NM_{t-1} + (1 - \delta)^2NM_{t-2} + (1 - \delta)^3NM_{t-3} + \ldots] 
\]  

(6)

Note that \(0 < \delta \leq 1\). As \(\delta \rightarrow 1\), \(MV_t \rightarrow NM_t\), indicating that the present stock of knowledge is most affected by recent reports. As \(\delta \rightarrow 0\), past reports have a greater impact on the present. For the analysis, we considered the following: \(\delta = 0.2\), \(\delta = 0.4\), \(\delta = 0.6\) and \(\delta = 0.8\). Media variable values derived using equation (6) are shown in Figure 2.

3.3. Estimation procedure

To estimate the Rotterdam model, continuous log differences are replaced with finite one-period log differences. Thus, the quantity and price terms in
equation (1) and (2) are approximated as \( d \log q_{i,t} \cong \log q_{i,t} - \log q_{i,t-1} \) and \( d \log p_{i,t} \cong \log p_{i,t} - \log p_{i,t-1} \). \( w_{i,t} \) is replaced with \( \bar{w}_{i,t} = \frac{1}{2}(w_{i,t} + w_{i,t-1}) \), which is the conditional budget share averaged over the periods \( t \) and \( t - 1 \). The Divisia volume index \( d \log Q_t \) is replaced with a discrete measure \( \Delta Q_t \) where \( d \log Q_t \cong \Delta Q_t = \sum \bar{w}_{i,t}(\log q_{i,t} - \log q_{i,t-1}) \) (Theil and Clements 1987).

The demand systems represented by equations (1) and (2) were estimated using the LSQ procedures in TSP (version 5.0), which uses the generalised Gauss–Newton method to estimate system parameters (Hall and Cummins 2009). We estimated models for each media variable (binary, count, cumulative and moving averages) separately. For equation (1), the media variable specification was differenced \( (\Delta MV_t = MV_t - MV_{t-1}) \) and then lagged one period \( (\Delta MV_{t-1}) \). For equation (2), we assumed the following: \( h_t = MV_t \). Results were compared across models and media variable specifications.

### 4. Results and discussion

Equation (1) was estimated separately for each media variable (binary, count, cumulative and moving averages: \( \delta = 0.2, \delta = 0.4, \delta = 0.6 \) and \( \delta = 0.8 \)) and compared based on log-likelihood values. We report the media elasticities and log-likelihood values from the estimations in Table 2. Here, we define the

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**Figure 2** Exponential moving averages based on the number of articles in Chinese media outlets: January 2007 - December 2017. Source: Calculations using data from Nexis Uni™.

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media elasticity as the percentage change in an import with respect to a 10-unit change in the number of reported stories. The log-likelihood is highest for the model with the count media variable ($MV_t = NM_t$).

The media elasticities are mostly significant and negative for French wine, and positive for Australian wine and to a lesser degree Italian wine, but are insignificant for all other countries. This is likely due to French and Australian wine dominating the Chinese market; the two countries have consistently accounted for about two-thirds of the foreign wine market in China (See Table 1). Previous research indicates that Chinese consumers prefer French and Australian wine, with an average of $0.48$ (U.S.) of every additional dollar spent on imports allocated to French wine and $0.20$ (U.S.) to Australian wine (Muhammad et al. 2014). Overall, results suggest that media reports on fraudulent events have a negative impact on French wine and a positive impact on Australian wine. The impacts range from $-0.12\%$ to $-0.94\%$ for French wine and $0.20\%$ to $1.20\%$ for Australian. According to media reports, French wines are particularly popular with fraudulent distributors and there is widespread understanding that the majority of fraud has been associated with French wine (Byrnes 2013). Reports also suggest that the prevalence of counterfeit wine in China has led to decreased demand for French wine (Lee 2013). This explains the negative media elasticity for French wine (a result that is consistent across media variable specifications). While the results suggest that Australian imports are a substitute for wine sourced from France, it is unclear if this is a direct result of a competitive relationship between the two countries, or if this is due to the persistent and growing demand for Australian wine in China, marketing initiatives by Australian producers, and the relative tariff advantage due to the China–Australia Free Trade Agreement (Boyce 2019). The positive results for Australian wine are similar to a finding in Verbeke and Ward (2001). They found that negative media coverage on meat consumption had a positive impact on pork products when the coverage primarily focused on mad cow disease and beef hormones. To further test the soundness of these results, we estimated the model using a media count variable specific to the exporting country (i.e. reports that mentioned French wine fraud versus reports that mentioned Australian wine fraud) (See Table S2). Results based on negative media reports specific to French wine are consistent with our overall findings.

We estimated a switching regression model, equation (2), for each media variable and conducted likelihood ratio tests to determine if structural change occurred based on negative media reports. The rational is that negative media reports could affect source-specific preferences, thereby affecting how expenditures are allocated across supplying countries and how buyers respond to source-specific prices.

For the structural change tests, we compared results from equation (2) without any parameter restrictions to several restricted models. Log-likelihood values and likelihood ratio test results for each model are reported in Table 3. Results show that the log-likelihood value is maximised when the
Table 2  Media elasticities† for Chinese foreign wine demand by county and media variable type

| Source country | Binary  | Count     | Cumulative | Moving average (δ = 0.2) | Moving average (δ = 0.4) | Moving average (δ = 0.6) | Moving average (δ = 0.8) |
|----------------|---------|-----------|------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Australia      | 0.42 (0.24)* | 0.20 (0.10)** | 0.20 (0.11)* | 1.20 (0.62)*              | 0.59 (0.30)**           | 0.38 (0.19)**           | 0.27 (0.13)**            |
| Chile          | 0.12 (0.31) | 0.13 (0.13) | 0.17 (0.14) | 0.83 (0.79)              | 0.40 (0.38)              | 0.26 (0.24)              | 0.18 (0.17)              |
| France         | −0.18 (0.14) | −0.12 (0.05)** | −0.15 (0.06)** | −0.94 (0.34)**           | −0.44 (0.16)**           | −0.27 (0.10)**           | −0.18 (0.07)**           |
| Italy          | −0.04 (0.43) | 0.33 (0.17)* | 0.22 (0.19) | 1.94 (1.08)*              | 0.94 (0.52)*             | 0.60 (0.33)*             | 0.43 (0.23)*             |
| Spain          | −0.41 (0.31) | −0.10 (0.13) | −0.07 (0.14) | −0.54 (0.82)              | −0.33 (0.39)             | −0.22 (0.25)             | −0.15 (0.17)             |
| U.S.           | 0.09 (0.61)  | −0.26 (0.25) | 0.14 (0.28) | 0.31 (1.58)              | 0.01 (0.75)              | −0.12 (0.47)             | −0.21 (0.33)             |
| ROW            | 0.17 (0.28)  | 0.06 (0.11)  | 0.02 (0.13) | 0.41 (0.72)              | 0.21 (0.34)              | 0.14 (0.22)              | 0.09 (0.15)              |
| Log-likelihood | 1,968.49    | 1,972.73    | 1,969.99    | 1,971.76                 | 1,972.13                 | 1,972.43                 | 1,972.59                 |

Note: ***0.01; **0.05; *0.10: Significance levels.

†Media elasticities are the %Δ in imports w.r.t. and 10-unit change in the number of articles. Asymptotic standard errors are in parentheses. ROW is rest of world.
media variable is specified as cumulative (2,035.32) or a weighted moving average (\(d = 0.2\) and \(d = 0.4\)) (2,030.01 and 2,015.86, respectively). Interestingly, it is only in these instances that structural change could not be rejected.

### Table 3 Log-likelihood values and likelihood ratio test results for switching regression models

| Model: media variable (MV) | Log-likelihood | Structural change test: \(\chi^2(4)\) | \(P\)-value |
|---------------------------|----------------|--------------------------------------|--------------|
| Binary MV                 | 1,995.42       | 31.63 (48)                           | 0.967        |
| Count MV                  | 2,003.88       | 48.56 (48)                           | 0.450        |
| Cumulative MV             | 2,035.32       | 111.43 (48)                          | 0.000        |
| Cumulative MV†            | 2,035.32       | 0.65 (6)                             | 0.995        |
| Moving average MV (\(d = 0.2\)) | 2,030.01       | 100.82 (48)                          | 0.000        |
| Moving average MV (\(d = 0.2\))† | 2,030.01       | 66.06 (42)                           | 0.010        |
| Moving average MV (\(d = 0.4\)) | 2,015.86       | 72.52 (48)                           | 0.013        |
| Moving average MV (\(d = 0.6\)) | 2,009.52       | 59.84 (48)                           | 0.117        |
| Moving average MV (\(d = 0.8\)) | 2,006.02       | 52.84 (48)                           | 0.293        |

Note: For the structural change tests, all media coefficients (constants, expenditure and price interactions) were set to zero unless otherwise noted.

†Media constant terms were set to zero only.
‡Media constant terms and price interactions were set to zero only.

### Table 4 Effects of media on expenditure elasticities†: switching regression model and cumulative media variable

| Country     | Pre-report | Post-report | Difference estimate |
|-------------|------------|-------------|---------------------|
| Australia   | 0.90 (0.08)*** | 1.10 (0.05)*** | 0.19 (0.07)*** |
| Chile       | 0.39 (0.10)*** | 0.68 (0.06)*** | 0.29 (0.08)*** |
| France      | 1.20 (0.04)*** | 1.09 (0.03)*** | -0.11 (0.04)*** |
| Italy       | 1.56 (0.13)*** | 1.07 (0.08)*** | -0.49 (0.11)*** |
| Spain       | 0.58 (0.10)*** | 0.90 (0.06)*** | 0.31 (0.09)*** |
| U.S.        | 0.59 (0.20)*** | 0.64 (0.12)*** | 0.05 (0.16) |
| ROW         | 0.75 (0.10)*** | 0.78 (0.06)*** | 0.02 (0.07) |

Note: ***0.01: Significance level.
†Elasticities are evaluated assuming the average value of the media variable. Asymptotic standard errors are in parentheses. ROW is rest of world.

### Table 5 Effects of media on expenditure elasticities†: switching regression model and exponential moving average media variable (\(d = 0.2\))

| Country     | Pre-report | Post-report | Difference estimate |
|-------------|------------|-------------|---------------------|
| Australia   | 1.07 (0.10)*** | 1.09 (0.07)*** | 0.02 (0.14) |
| Chile       | 0.38 (0.13)*** | 0.83 (0.08)*** | 0.45 (0.17)*** |
| France      | 1.18 (0.06)*** | 1.04 (0.04)*** | -0.14 (0.07)* |
| Italy       | 1.79 (0.17)*** | 0.84 (0.11)*** | -0.95 (0.22)*** |
| Spain       | 0.63 (0.13)*** | 0.98 (0.09)*** | 0.35 (0.17)*** |
| U.S.        | 0.15 (0.25) | 0.78 (0.17)*** | 0.63 (0.34)* |
| ROW         | 0.55 (0.12)*** | 0.95 (0.08)*** | 0.40 (0.16)*** |

Note: ***0.01; **0.05; *0.10: Significance levels.
†Elasticities are evaluated assuming the average value of the media variable. Asymptotic standard errors are in parentheses. ROW is rest of world.
For these models, the parameters do not remain constant in the presence of negative media reports. We also conducted structural change tests for the constants/trends ($\alpha_i^* = 0$), marginal share estimates ($\theta_i^* = 0$) and price coefficients ($\pi_{ij}^* = 0$), separately. We report the test result for no structural change in the constants/trends ($\alpha_i^* = 0$) when the media variable is specified as cumulative (See Cumulative MV$^a$ in Table 3). This constraint ($\alpha_i^* = 0$) could not be rejected. However, similar constraints on the marginal share ($\theta_i^* = 0$) and price coefficients ($\pi_{ij}^* = 0$) were rejected. For the moving average model ($\delta = 0.2$), we report the test results for no structural change in both the constants/trends and price coefficients ($\alpha_i^* = \pi_{ij}^* = 0$) (See Moving average MV$^b$ in Table 3). We could not reject this constraint indicating that structural change only occurred in the marginal share estimates ($\theta_i^*$) for this model.

The expenditure elasticities, equation (3), are derived using estimates from the two highest performing models: cumulative and moving average ($\delta = 0.2$); results are statically compared pre-report ($h_t = 0$) and post-report ($h_t \neq 0$). We set $h_t$ equal to the corresponding media variable average to derive the post-report estimates. The elasticities and corresponding difference estimates are evaluated at the mean (average budget share) using the ANALYZ procedure in TSP, which uses the delta method to calculate standard errors (Hall and Cummins 2009). Results are reported in Tables 4 and 5.

The switching regression results based on the cumulative media variable indicate that more countries are affected by negative media reports compared to the media estimates when structural change is not accounted for (See Table 4). Consistent with results reported in Table 2, the expenditure elasticities for Australia and France indicate that Australia is better off as a consequence of negative media coverage and that France is worse off. The pre- and post-report expenditure elasticities (0.90, 1.10) for Australia indicate a significant increase in expenditures being allocated to Australian wine with negative media reports. The opposite is the case for French wine (1.20, 1.09). What is interesting is that results also indicate that Chilean wine (0.39, 0.68) and Spanish wine (0.58, 0.90) also benefit from negative media coverage with increases even greater than Australian wine. However, both countries start from a more inelastic base. Inconsistent with previous results is the significant decline for Italian wine (1.56, 1.07), which is likely due to the declining share of Italian wine in the Chinese market rather than negative media coverage. Since 2007, the share of Italian wine in Chinese wine imports has persistently decreased from about 10% to about 5% in 2017 (See Table 1). Results for Italian wine could be, in part, due to this declining trend.

Findings are similar for the switching regression results when the media variable is specified as a weighted moving average ($\delta = 0.2$) (See Table 5). However, unlike the results for the cumulative media variable, the increase for Australian wine (1.07, 1.09) is not statistically significant. Additionally, the post-report expenditure elasticities are significantly higher for U.S. wine (0.15, 0.78) and ROW wine (0.55, 0.95). Similar to the cumulative results, the significant decline in the expenditure elasticity for Italian wine (1.79, 0.84) is
more likely the result of declining market share over time. What has been consistent throughout the study is the impact of negative media reports on French wine, as indicated by the significant decrease in the expenditure elasticity for French wine (1.18, 1.04).

5. Summary and conclusion

China is one of the fastest growing wine consuming countries in the world and an increasingly important market for foreign wine suppliers. The prevalence of fraudulent wine in the Chinese market creates uncertainty among consumers and can damage the reputation of foreign suppliers. In this study, we considered the impact of negative media coverage (reports on fraudulent activities) on Chinese foreign wine demand and find that negative media coverage has negatively impacted French wine in the Chinese market. This is not surprising because the majority of media reports on fraudulent activities were about French wine. Secondly, our results suggest that negative media coverage may have had a positive impact on imports from Australia. These results were consistent across media variable specifications.

The impacts of wine fraud on source countries may change in the future. As Australia’s market share has grown (see Table 1), counterfeiters are increasingly targeted Australian wine. Note the increased number of media reports that mention Australian wine in 2017 (see Table S1). With increased prevalence of Australian counterfeits in China, it is possible that wine fraud could negatively affect Chinese demand for Australian wine in the future.

This work contributes to the literature on the Chinese wine market, and the research investigating the impacts of fraud on agricultural and food supply chains, as this is the first study to estimate the impacts of wine fraud on Chinese import demand by source. However, there are limitations to our analysis. Our measurement of fraudulent activities is limited for two reasons. First, total wine fraud in China is difficult to quantify, given that activities often go unreported. Second, there may be underreporting of fraudulent events in the Chinese media, given censorships that exist in the Chinese press. However, to the degree that media reports appropriately capture wine fraud activities and overall consumer awareness of these activities, our results provide an accurate assessment of how these activities might be affecting the two dominant foreign wine suppliers in China.

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**Supporting Information**

Additional Supporting Information may be found in the online version of this article:

**Table S1.** Media report count by month and country of origin.

**Table S2.** Media elasticities† based on source-differentiated count media variable.