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An empirical framework to study food labelling fraud: an application to the Italian extra-virgin olive oil market*

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The mislabelling of agricultural and food products is one of the most common types of food fraud. Despite the frequency with which labelling fraud occurs, there is no empirical framework to study its welfare implications, the probability that it may occur, and the measures that can limit its occurrence. We present an empirical framework to study the economic consequences of food labelling fraud in a differentiated products food market. Such framework requires the availability of sales data and the use of an 'attribute-space' demand model. The model is applied to the Italian extra-virgin olive oil market to simulate the occurrence of fraudulent '100 per cent Italian' claims. Our results indicate that potential consumer losses due to overpayments for a false claim are higher than manufacturer gains, suggesting that labelling fraud results in welfare losses and not just in welfare transfers. Simulation results indicate that the level of the current administrative fines is not likely to be effective to discourage '100 per cent Italian' labelling fraud. Imposing larger fines or other measures negatively affecting a firm's image could be more effective in deterring labelling fraud.

Key words: counterfactual simulation, extra-virgin olive oil, firm misconduct, food fraud, mislabelling.

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1. Introduction

Food fraud[1] can be defined as the intentional act of defrauding buyers of food or food ingredients for an economic gain, without placing at risk consumers' health (Spink and Moyer 2011). Having afflicted agri-food markets for centuries (Shears 2010), food fraud's incidence has increased in the last 20 years (Codex Alimentarius Commission 2017), affecting approximately one out of ten food products sold at the retail level, with a cost to the global agri-food industry ranging between \$10 and \$15 billion per year (GMA 2010). The incidence (and likely economic implications) of fraud varies both across agri-food supply chains (Moore *et al.* 2012) and within the same chain (Van Ruth *et al.* 2018). Food fraud can result in loss of consumer welfare due to the unjust payment of a price premium (Giannakas 2002) and lower consumers' trust in specific products/brands, in entire food supply chains and in the institutions that regulate them (Giannakas 2002; Baksi and Bose 2007; Charlebois *et al.* 2016).

A type of fraud particularly hard to detect, representing the majority of frauds in the agri-food sector, is product mislabelling, that is, the misrepresentation of some of a product's quality attributes; for example, selling conventional food as organic or the misuse of the designation of origin or animal welfare logos (European Parliament 2013; Charlebois *et al.* 2016; EU Food Fraud Network 2016; Whitworth 2017). In the EU alone frauds concerning the use of protected geographic indication (GI) logos affect approximately 9 per cent of all GI products and generate illegal revenues estimated at €2.3 billion due to the unjustified premium price paid by consumers (EUIPO 2016). Product mislabelling also affects the EU honey market where approximately 15 per cent of honey sold at the retail level is incorrectly labelled with regard to the botanical or geographical origins (Aries *et al.* 2016). According to a report by the U.S. Department of Agriculture (USDA), there have been 105 fraudulent organic certifications in the United States since 2006 (USDA 2018), placing at risk the trustworthiness of a market that is sized at \$47 billion (Whoriskey 2016). Also, mislabelling affects approximately 20 per cent of the seafood sold worldwide at the retail level; in the most common cases, the fraud involves the misuse of 'wild-caught' claims on farmed fish (FAO 2018). In the United States alone, sales of farmed salmon mislabelled as 'wild' led consumers to pay for unjustified premiums that generated illegal revenues for fraudulent firms for a total of nearly \$7 million per year (Cline 2012).

[1] Food fraud includes different intentional actions or 'opportunistic economic acts' (Hirschauer and Zwoll 2008). They fall under the categories of '… substitution, addition, tampering or misrepresentation of food, food ingredients, or food packaging, or false or misleading statement made about a product' (Spink and Moyer 2011, p. R158). Perpetrators of fraud benefit from the sale of low-quality products that resemble higher-quality ones (European Parliament 2013).

Economic research on food labelling fraud is limited, although a multitude of papers has studied agri-food labels. This literature has predominantly sidestepped fraud, focusing on offering guidelines for efficient labelling policies, assessing how different types of labelling schemes (private vs. public) and/or certification processes (voluntary vs. mandatory) reduce asymmetric information (Caswell and Mojduszka 1996) and their effects on welfare (Marette *et al*. 1999; Roe and Sheldon 2007). Other studies show how the certification process should be monitored (Zago and Pick 2004). A new branch of literature investigates how political processes can promote the emergence on the market of a type of label and/or a certification process (Zilbermann *et al*. 2018).

In spite of the large body of theoretical literature on food labels (see Bonroy and Constantatos (2015) for a review), only a few studies focus specifically on food fraud (Giannakas 2002; Hamilton and Zilberman 2006; Baksi and Bose 2007; Di Fonzo and Russo 2015). Some of these works found that third-party certification can lower the incidence of fraud, preventing consumers' welfare losses and reducing inspection costs (Giannakas 2002). This result holds even when certification is costly as long as certification cost offsets the 'incentive-to-cheat' (Baksi and Bose 2007) leading to the number of firms selling products with credence attributes being inversely related to the incentive of mislabelling (Hamilton and Zilberman 2006). The study by Di Fonzo and Russo (2015) who study GI consortia creation find instead that under certain conditions, labelling fraud can be rationally tolerated by all the other consortium members.

The empirical literature on agri-food labelling, which is plentiful, is mostly focused on label use and other consumer-related aspects of labelling (see, in the context of nutritional labels, the reviews by Drichoutis *et al*. (2011) and Kiesel *et al*. (2011)). The few empirical analyses focusing on agri-food fraud investigated fraudsters' behaviour (Hirschauer and Zwoll 2008; Gambelli *et al*. 2014; Lippert *et al*. 2014) and how fraud incidents affect consumer food choices (Yamoah and Yawson 2014; Agnoli *et al*. 2016). Hirschauer and Zwoll (2008) used a principal-agent model to explain fraudulent behaviour in the poultry sector and to determine the optimal level of fines offsetting illegally gained profits. Lippert *et al*. (2014) presented an econometric model to investigate non-compliance among organic farmers. Gambelli *et al*. (2014) studied how German and Italian farmers' characteristics affect their decisions to sell regular foodstuff as organic. Studying consumer behaviour after the horse meat scandal, Yamoah and Yawson (2014) found a decrease in retail sales of beef-based foods, especially for health-risk averse consumers. Agnoli *et al*. (2016) found that European consumers have strong preferences for ready-to-eat beef products made with 'national' beef as well as positive willingness to pay for products with enhanced food safety standards.

To the best of our knowledge, there is no general empirical framework of analysis proposed to assess how labelling fraud affects market outcomes, although exceptions based on case studies exist (e.g. Cicia, Del Giudice and Scarpa (2005) analysis of welfare losses due to lack of traceability in the Italian extra-virgin olive oil (EVOO) market). To fill this gap in the literature, we develop a framework which allows the simulation of consumers' welfare losses incurred by purchasing fraudulent food products and the extra profits internalised by the fraudulent manufactures. The estimates of producers' extra profits from fraud, along with different levels of fees/penalties and sales losses due to consumers' decreased trust in the fraudulent manufacturer, are used to simulate the probability level that a fraud is discovered which makes a manufacturer indifferent between committing labelling fraud and not. Thus, our framework could help policymakers design effective fee structures to deter fraud.

Our model adapts the framework developed by Bonanno *et al.* (2015) to measure welfare changes in the presence of untruthful health claims in a differentiated product market, to assess the effects of labelling fraud. We model the demand side of the market in 'attribute space', using a random coefficient logit model (Nevo 2000, 2001) to obtain estimates of the taste parameter for the attribute subject to fraud, and recover the supply side assuming manufacturers play a multi-product Nash-Bertrand game (Nevo 1998, 2000). We then simulate changes in consumer surplus due to consumers overpaying a premium for the fraudulent attribute, the extra profits from the fraudulent activity. Also, we assess the probability of committing fraud, given profits from fraud and the fines and other losses producers would incur if their fraudulent activity was revealed.

We apply our model to the Italian EVOO market, simulating fraud related to untruthful '100 per cent Italian' claims, using two years of monthly regional scanner data of EVOO sales from Italian hypermarkets and supermarkets. The fines used in the simulation are those implemented by the Ispettorato Centrale Repressione Frodi. The model is estimated using a generalised method of moment (GMM) estimator (Nevo 2000, 2001), with input (i.e. olive) prices from different sources used to correct for price endogeneity.

The Italian EVOO market represents an appropriate case study to show the usefulness of our framework. First, Italy is the second largest olive oil producing country in the world and olive oil is one of the agri-food products most at risk of fraud (Moore *et al.* 2012). Second, the Italian EVOO market has recently experienced several occurrences of labelling frauds where manufacturers have used non-Italian olives (or oils) in mixtures sold with the '100 per cent Italian' claim (as discussed in Section 2). Third, the Italian EVOO industry can be considered an oligopoly, as three producers (Deoleo, Ufi, and Monini) cumulatively control more than the 40 per cent of the market (Marchini and Diotallevi 2010).

This article proceeds as follows. In the next section, we present our framework to assess empirically welfare changes due to the presence of a 'false' attribute in the market and the threshold probability of fraud detection, which makes fraud not economically advantageous. In Section 3, we provide a description of the Italian EVOO market and a brief timeline of recent scandals concerning the mislabelling of non-Italian EVOO as ‘100 per cent Italian’ products, followed by a detailed description of the data used and the estimation method adopted in Section 4. The discussion of the estimation and simulation results follows (Section 5). We conclude with a discussion of policy implications, final remarks, limitations and opportunities for future research (Section 6).

2. An empirical economic model of labelling fraud

In this section, we develop an empirically tractable model to simulate consumers’ and manufacturers’ welfare changes due to labelling fraud, as well as the trade-off between different penalty structures and the probability that fraud occurs.

Our framework combines an oligopolistic supply side with a discrete choice demand model, following other analyses in the industrial organisation literature (Berry *et al.* 1995; Nevo 2001; Petrin 2002; Bonanno *et al.* 2015). The supply side considers firms as oligopolists following a two-stage decision process, deciding whether to commit labelling fraud first and then competing on prices, playing a Bertrand game. The demand side models the aggregation of consumers’ discrete choices where each product’s market share represents the probability that a product is chosen. Following the work of Bonanno *et al.* (2015), who simulated welfare changes in the presence of false health claims, we use the estimated demand coefficients and the calculated Nash - Bertrand short-run profits to determine the amount of consumers’ welfare losses incurred by overpayment for a false label and the resulting producer surplus. We then compare the counterfactual producer surplus to simulated gains from fraud, calculated using input price differential data, to present a range of the estimated extent of welfare losses due to fraud. Last, we use the estimated values of producer surplus, simulated fraud gains, and a schedule of fees and penalties to simulate the ‘threshold probability of fraud discovery’; that is, the lowest probability that a fraud is discovered which makes committing a fraud no longer an economically viable option.

2.1. The supply side

The supply side of the model considers food product manufacturers operating in an oligopoly and selling differentiated products. There are N manufacturers; the n^{th} manufacturer produces J_n products, for a total of J products in the market ($\mathrm{J} = \sum \mathrm{J_n}$). For simplicity of exposition, we assume that only one of the products sold has the attribute object of fraudulent activity (product f). It should be noted that we assume that (i) the number of products is given and (ii) the decision of producing the product with the fraudulent label (f) has already occurred. Given its portfolio of products, manufacturer n decides whether to perform fraud (fraud stage) and then it competes in price in the second stage (competition stage). We solve the competition stage first. Manufacturer n solves:

$$\max_{p_j} \pi_n = M \sum_{j \in J_n} S_j(p_j - c_j), \tag{1}$$

where M is market size, p_j is product j's price, c_j is its constant marginal cost, and S_j is its market share.

Following Nevo (1998, 2001), we assume that prices are the outcome of a multi-product Nash - Bertrand equilibrium. The profit maximisation in (1) leads to the following vector of first-order conditions:

$$p - c = -\Omega^{-1} S(.). \tag{2}$$

The $p - c$ and $S(.)$ are $(J \times 1)$ vectors of price cost margins (PCMs) and market shares, respectively. The elements of the matrix Ω are $\Omega_{jk} = \Omega^*_{jk} \Delta_{jk}$, where under the assumption of multi-product Nash - Bertrand behaviour:

$$\Omega^*_{jk} = \begin{cases} 1 & if \;\; k, j \in J_n \\ 0 & otherwise \end{cases}; \quad \text{and} \quad \Delta_{jk} = \frac{\partial S_j(.)}{\partial p_k}, \tag{3}$$

Ω^* is commonly referred to as the 'ownership matrix', whereas each element of Δ is a partial derivative of the demand (i.e. market share) for product j with respect to each price.

In the first stage, manufacturers decide whether or not to commit labelling fraud. For the fraudulent producer, the cost savings from using lower quality inputs to produce product f will lead to higher profits or:

$$\Delta\pi^{\mathrm{FR}}_{n,f} = \mathrm{MS}_f(p_f - c^{\mathrm{FR}}_f) - \mathrm{MS}_f(p_f - c_f) = \mathrm{MS}_f(c_f - c^{\mathrm{FR}}_f) > 0, \tag{4}$$

where the amount $\mathrm{MS}_f(c_f - c^{\mathrm{FR}}_f)$ is the economic gain from undertaking fraud. However, committing fraud may lead to incurring penalties and fines with some positive probability.

Let q be the probability of being found guilty of labelling fraud. The additional loss that the fraudulent manufacturer may incur because of loss of image or consumer trust if the fraud is discovered and made public is $\upsilon(\pi_n) = M \sum_{j \in J_n} \upsilon_j S_j(p_j - c_j)$, where $(0 \leq \upsilon_j \leq 1)$. Define G as the total amount of fines and penalties that a producer will be subject to if found guilty of fraud; penalties may include economic losses if the product gets seized by the anti-fraud authorities. Thus, let G_0 represent the 'fixed' administrative fines, and $G = G_0 + M \sum_{j \in J_n} \tau_j S_j(p_j - c_j)$, where $\tau_f = 1$ and $0 \leq \tau_j \leq 1$ for $j \neq f$. Larger τ_j indicates stronger penalties; that is, if all products are seized $\tau_j = 1 \quad \forall j$; if only sales of the specific products suspected of being fraudulent are blocked, $\tau_j = 0$ for $j \neq f$.

Given the framework illustrated above, a manufacturer will commit labelling fraud if the expected gains given all fines and penalties are strictly positive, or if:

$$(1 - q)\mathrm{MS}_f(c_f - c_f^{FR}) + q(-\upsilon(\pi_n) - G) > 0. \tag{5}$$

For any given value of expected gains, penalties and losses due to decreased consumer trust (i.e. demand losses), the manufacturer will have an economic incentive to commit fraud if the probability that the fraud is discovered, and therefore penalties are applied, is strictly lower than:

$$q^* = \frac{\mathrm{MS}_f(c_f - c_f^{\mathrm{FR}})}{\mathrm{MS}_f(c_f - c_f^{\mathrm{FR}}) + \upsilon(\pi_n) + G}. \tag{6}$$

We define q^* as the threshold probability of fraud discovery. The higher the q^*, the more likely a manufacturer will be to commit fraud. Consider an example: a $q^* = 0.95$ indicates that it would make economic sense for a manufacturer to commit fraud even if the probability of being caught is as large as 95 per cent. That is, the economic gain is large compared with the penalties that it will still be economically convenient to engage in labelling fraud even if a manufacturer were caught 19 times out of 20 inspections. $q^* = 0.05$ instead indicates that compared to the gains from fraud, penalties, and other expected losses are large enough to discourage committing fraud even if the fraud will only be discovered once out of 20 times that controls were performed. In section 2.3, we illustrate how to simulate different values of q^* from empirical welfare estimates.

2.2. The Demand Side

In order to capture consumers' taste for the attribute that can be the object of fraud, we use an attribute-space-based model; in this particular case, we use a discrete choice model framework (Berry 1994).[2] Assume there are t markets ($t = 1,\ldots,T$); each market is defined as a combination of a geographic area and a time period and contains I rational consumers indexed by i ($i = 1, \ldots,$

[2] We use a discrete choice demand model for three reasons. First, our approach requires the use of a demand model in attribute space. Since we follow Bonanno *et al.* (2015) closely, who also used a discrete choice demand model, we opted to use a model of the same family in our analysis. Second, even though using a model where demand is continuous would relax the assumption of unitary choices, Huang *et al.* (2008) found that discrete choice (logit) models can produce elasticity estimates closer to the 'true' values even when the data-generating process is not that of a discrete choice model. Third, Anderson and de Palma (1992) showed that discrete choice demand is consistent with the solution of a symmetric oligopoly supply side.

I_t). Consumer i chooses one unit of a product among $J_t + 1$ alternatives, where $j = 0$ indicates the outside option of not purchasing a product in the choice set captured by the data at the researcher's disposal.[3]

Following Berry (1994), we assume that each consumer's indirect utility is:

$$V_{ijt} = -\alpha_i p_{jt} + X_{jt}^{'}\beta + \xi_{jt} + e_{ijt}\, i = 1, \ldots, N, j = 1, \ldots, J, \tag{7}$$

where p_{jt} is the price of alternative j faced by all consumers in market t, X_j is a K-dimensional vector of observable characteristics of product j, α_i and β are, respectively, consumer i's taste parameter for price, and a conformable vector of taste parameters for the observable product characteristic, ξ_j indicates product j's unobserved (by the researcher, but known to the consumer) characteristics, and e_{ijt} is a mean-zero stochastic error term. Note that, for simplicity, we characterise consumers' heterogeneity in Equation (7) assuming that consumers value all product attributes equally, except price.

Equation (7) can then be rewritten as:

$$V_{ijt} = -\alpha_0 p_{jt} + X_{jt}\beta + \xi_{jt} - \alpha_1 v_i p_{jt} + e_{ijt} = \delta_{jt} + \mu_{ijt} + e_{ijt}, \tag{8}$$

where $\delta_{jt} = -\alpha_0 p_{jt} + X_{jt}\beta + \xi_{jt}$ is the mean utility of alternative j, while $\mu_{ijt} + e_{ijt}$ represents the deviation from the mean utility, including a random term to capture consumers' taste heterogeneity, or $\mu_{ijt} = -\alpha_1 v_i p_{jt}$.

As Berry (1994) and Berry *et al.* (1995) showed, to obtain an estimable form of (8), we assume that the term e_{ijt} is an independently and identically distributed extreme value type 1 across consumers and products. Thus, the probability of consumer i in market t choosing alternative j, conditionally on the random term v_i, is:

$$f_j(X, p_t, \delta_t; \theta) = \frac{\exp[-\alpha_0 p_{jt} + X_j\beta + \xi_j - \alpha_1 v_i p_{jt}]}{1 + \sum_{j=1}^{J} \exp[-\alpha_0 p_{jt} + X_j\beta + \xi_j - \alpha_1 v_i p_{jt}]}, \tag{9}$$

where θ is a vector including all the parameters in the model. Then, integrating Equation (3) over the distribution of the random term P_v:

$$s_t(X, p_t, \delta_t; \theta, P_v) = \int f_j\big(v_i, \delta_{jt}(X, p, \xi_j), X, p, \theta\big) P_v(\mathrm{d}v). \tag{10}$$

As discussed in the literature (Nevo 2000, 2001), the integral in Equation (10) has no closed form solution. However, using appropriate assumptions on the form of the unobserved heterogeneity, one can set up an

[3] Assuming that a consumer chooses only one unit of a product from a given choice set may be restrictive; however, it is necessary to use a discrete choice model (Berry *et al.* 1995; Nevo, 2001; Petrin, 2002).

'updating rule' so that the simulated shares match those observed in the data (see Nevo (2001) for a detailed illustration of the nested fixed point algorithm). More details on the estimation procedure are presented in Section 4.

2.3. Simulating the economic impact of labelling fraud

In this section, we employ the Bonanno *et al.* (2015) approach to simulating welfare losses for consumers in presence of labelling fraud, as well as a fraudulent producer's welfare gains. Let consumers' valuation of a given attribute L, potentially subject to labelling fraud, be β^L. On average, the amount that consumers would be overpaying for the fraudulent attribute L is $\beta^L/\bar{\alpha}$; $\bar{\alpha} = \frac{1}{R}\sum_{i=1}^{R}\alpha_i$, which also represents the average monetary value that consumers in the market attach to L.

Let p_j^0 be the (observed) price of product j carrying attribute L. Then:

$$p_j^{\mathrm{FR}} = p_j^o - \beta^L/\bar{\alpha}, \tag{11}$$

represents the price consumers should have paid for a product which did not contain L, but it was falsely represented as containing it.

Once values of p_j^{FR} are obtained, one can measure consumer welfare losses due to the overpayment for the fraudulent attribute. Given the demand model illustrated in the previous section (i.e. a random coefficient logit), the inclusive value function (IVF) for each consumer is (McFadden 1981):

$$V_i^{\mathrm{Scen}} = \ln\left(\exp\left(V_{ij}^{\mathrm{Scen}}\right)\right), \tag{12}$$

where Scen = {*0*, *FR*} where the superscript *0* indicates the IVF obtained with p^0, the observed price vector (i.e. the baseline scenario), and FR indicates the IVF obtained using p^{FR}, the vector of prices containing p_j^{FR} for each of the products assumed to have a fraudulent claim, otherwise p_j^0 is used. Welfare changes for each unit consumed by i are:

$$\mathrm{EV}_i = e(p^0, V_i^{\mathrm{FR}}) - e(p^{\mathrm{FR}}, V_i^{\mathrm{FR}}) = \frac{V_i^{\mathrm{FR}} - V_i^0}{\alpha_i}. \tag{13}$$

Total consumer welfare change is obtained by taking the average over the different values of α_i and multiplying Equation (13) times the size of the market M.

Let us now consider producer welfare. Once demand estimates are available, one can use the empirical counterpart of Equation (2) to determine profit margins and, as a result, producer surplus. Using Equation (11), we can calculate producer surplus (profits) that fraudulent manufacturers would have given up had they compensated consumers for the fraudulent attribute. Let S^0 be the vector of observed shares, and $I_{j,f}$ being an indicator variable representing products with the fraudulent attribute ($I_{j,f}$=1, for each i=f). One has:

$$\Delta\pi_n^{\mathrm{FR}^0} = M \sum_{j\in J_n} S_j^0 \frac{\beta^L}{\bar{\alpha}} I_{j,f}; \tag{14}$$

which is the reduction in producer surplus that a manufacturer would incur if it sold the products with the fraudulent claim at a lower price to consider the lower utility provided by the product to consumers. Because we model the market as an oligopoly, the amount in Equation (14) is likely to be lower than aggregate consumer losses due to overpayment, resulting in deadweight losses.

Equation (14) does not provide an estimate of the change in producer profits due to fraud, which is instead an empirical measure of $\mathrm{MS}_f(c_f - c_f^{\mathrm{FR}})$ (Equation (4)) which can be obtained in two ways. First, once c_j is estimated from Equation (2), one could regress it on a series of covariates, including an indicator variable for the fraudulent claim, other attributes, and additional cost variables, to obtain a ceteris paribus estimate of $c_f - c_f^{\mathrm{FR}}$ from the coefficient associated with the fraudulent claim. Alternatively, in the absence of product-specific cost data, one could use differences in prices of key inputs as a proxy for the differences in marginal costs for products with and without the attribute that can be subject of labelling fraud. In other words, using different values of input price differentials would provide a range of $c_f - c_f^{\mathrm{FR}}$, which, although not as accurate as an econometric estimate, can inform of the manufacturers' expected benefits from committing fraud.

Once an empirical measure of Equation (4) is available and estimates of profit margins are obtained using demand estimates and the Nash - Bertrand solution (Equation (2)), using a schedule of fines (G_0) different assumptions regarding the amount of product seized by the authorities (τ_j) and the loss of sales because of lower consumer trust (v_j), one can simulate different values of the threshold probability of fraud detection q^* (Equation (6)). The empirical exercise of obtaining ranges of q^* for different values of G_0, τ_j and v_j will inform on the trade-offs between different policy levers to make labelling fraud less likely.

3. The case study: The Italian EVOO market, incentives to mislabelling practices related to '100 per cent Italian' claims and recent related frauds

Italy is the second largest olive oil producing country in the world after Spain, with an average yearly production of 327,500 tons per year in the period 2014 - 2017. Seventy per cent of olive oil produced in Italy is classified as EVOO (ISMEA 2018). Because domestic demand of 535,000 tons per year in the period 2014 to 2017 exceeds production, Italy is a net importer of olives and olive oil from European and non-European countries such as

Spain, Greece, and Tunisia (ISMEA 2018). The Italian olive oil market is characterised by a high level of product differentiation in terms of credence attributes, with manufacturers offering a wide variety of products labelled as '100 per cent Italian', organic, and with geographical indications (GIs) logos such as protected designation of origins (PDOs).

There are three incentives for EVOO producers to improperly label foreign EVOO as '100 per cent Italian'. First, '100 per cent Italian' EVOO has been very successful in the marketplace. The retail price of '100 per cent Italian' EVOO ranges between 8 and 9 €/kg, for an average production cost of approximately 5 €/kg; EVOO of unspecified origin instead shows retail prices ranging between 4 and 5 €/kg (ISMEA 2018). Additionally, Italian consumers show strong preference for domestic EVOO, with a demand that has increased by 11 per cent since 2012. In 2014, the market for EVOO labelled '100 per cent Italian' reached a value of €111 million, twice as large as that of organic and other GI (PDO and PGI) EVOO combined (€31 and €18 million, respectively (Unaprol 2015)).

Second, the fines for intentionally mislabelling non-Italian EVOO as '100 per cent Italian' are low. The Italian regulation for the use of the '100 per cent Italian' claim also establishes administrative sanctions for voluntary mislabelling, which range between €2,000 and €12,000 (EU. Reg. 29/2012; Italian L.D. 103/2016). The fine may reach €18,000 when traceability records are also counterfeited to support the '100 per cent Italian' origin of the product (EU. Reg. 29/2012; Italian L.D. 103/2016).

Third, detecting the presence of non-Italian olive oil in a blend is only possible by means of DNA tests of recent development (Pasqualone *et al.* 2016). DNA-based testing methods are expensive and are not required as part of the routine checks performed by anti-fraud authorities. In fact, they are performed only if a manufacturer is suspected of mislabelling the product as '100 per cent Italian', after traceability documents are evaluated, and a budget is available for the tests to be performed (Italian Chamber of Deputy 2015). For these reasons, DNA-based tests have only recently been used by the national fraud repression authorities in some of their operations (Il Fatto Alimentare 2015; Il Sole 24 ore 2016).

The incidence of fraud related to the improper use of the '100 per cent Italian' claim on EVOO has increased since the inception of the label. The most recent example of this fraud (December 2015) involved olive oil originating from non-European countries, mainly from North Africa, mixed with domestic products and sold as '100 per cent Italian' (Il Fatto Alimentare 2015). The incident involved about 7,000 tons of product, for a value in the tens of millions of euros (Il Fatto Alimentare 2015). A few months later (February 2016), another investigation of the Ispettorato Centrale Repressione Frodi (the Italian central inspectorate for fraud repression and quality safeguarding of agri-food products) led to the discovery of more than 2,000 tons of EVOO originating from Spain and Greece sold as '100 per cent Italian' in 2014 and 2015, for values exceeding €13 million (Il Sole 24 ore 2016).

4. Data and estimation

4.1. Data and variables description

The database used for our empirical application contains 25 months (November 2012 - November 2014) of regional (17 regions) point-of-sale data representing EVOO sales from Italian hypermarkets and supermarkets, for a total of 425 geography/time combinations, each representing a 'market'. The data were supplied by Information Resources Inc. (IRI) and provided by the University of Foggia. The data are an unbalanced panel representing sales of 188 products, 45 of which carry the '100 per cent Italian' label. A total of 20,160 observations are included in the data used for the estimation.

The database includes information on volumes and values of sales in each market (region/month combination) used to calculate the products' price in €/L. Also, the IRI database contains a series of product characteristics which are included in the vector X_j of the demand equation. These characteristics are coded as binary indicator variables capturing, whether the product was sold with the '100 per cent Italian' origin label (*100 per cent Italian*), carrying a PDO label (*PDO*) or if it was produced using organic ingredients and process (*Organic*). Additionally, the data provide information on whether the oil had a fruity flavour (*Fruity*). The IRI data also report the package size of each product, information which we use to calculate the average volume (litres) per unit of product (*Average Vol. Unit.*) and an indicator variable to capture products that were sold in packages larger than 2 L (*Large_Package*).

Given the unbalanced nature of our panel and the large differences in the number of products sold in each market (ranging from a minimum of 25 to a maximum of 72 products), we follow Ackerberg and Rysman (2005) and include the natural log of the number of product sold in each market (*LnN Products*) to control for the negative effect of congestion on demand. Brand-specific variables were also added to control for other unobservable product features. Last, regional fixed effects are included in the model to control for time-invariant unobservables, as well as monthly dummies capturing potential seasonal variation in the demand for EVOO.

The total potential market size (M) used to compute market shares (including the outside option's share) is defined based on total potential consumption in volume. Market size is obtained by determining a proxy of capita consumption of EVOO times the population of each IRI region. According to the International Olive Oil Council (2018), annual consumption of olive oil in Italy was approximately 641.1 tons in the period 2013/14, which, considering the estimated Italian population (from ISTAT) of 60.79 million, results in a consumption of approximately 0.03 L per individual/per day, for an average of 3,350,274 L month/region.[4]

[4] We used a conversion factor of 1.1 (1 litre = 0.913 Kg http://www.centrafoods.com/blog/the-ultimate-list-of-olive-oil-conversions-calculations) to obtain the estimated market size in litres.

Table 1 reports the summary statistics for the estimation sample. The average price is 4.58 €/L. A total of 19.3 per cent of EVOO in our data carried the '100 per cent Italian' label. Also, we observe 3.2 and 2.6 per cent of products with the PDO and the organic label, respectively. A total of 5.1 per cent of EVOO in our sample had a 'fruity' taste, whereas the average packaging size was 1.055 L with 5.4 per cent of products being packaged in containers larger than 2 L. The average value of the natural log of the number of products sold in a market is 3.885, for an average of 48.65 products per market. The summary of the data presented in Table 1 masks the price disparity of EVOO sold in Italian market with a '100 per cent Italian' logo compared to others. The average prices of EVOO in our data (excluding PDOs) with and without the '100 per cent Italian' claim are 5.59 and 4.10 €/L, respectively, which are statistically different from one another, as illustrated in the box plots presented in Figure 1.

As illustrated in the previous section, in order to measure the economic gains due to the labelling fraud, one can either attempt to estimate the difference in marginal costs depicted in Equation (4) or infer it from data. For simplicity, we use the second approach. We calculate monthly values of price differentials between prices of Italian EVOOs at the origin and the average price of EVOO from Greece, Spain, and Tunisia, obtained from ISMEA, for the entire period under analysis. Figure 2 presents the values of these price differentials over time: the minimum price difference is €0.379 (October 2013); and the maximum is €1.28 (November 2014), for an average value of €0.687.

Table 1 Sample statistics ($N = 20{,}160$)

Variables	Mean	SD	Min	Max
Share	0.003	0.011	0.000	0.696
Price (€/litre)	4.581	1.593	1.405	17.037
100% Italian	0.193	0.394	0	1
PDO	0.032	0.176	0	1
Organic	0.026	0.162	0	1
Fruity	0.051	0.221	0	1
Average vol. unit	1.059	0.653	0.5	5
Package size > 2 litre	0.054	0.227	0	1
lnN products	3.884	0.223	3.218	4.276
Brand 1	0.179	0.384	0	1
Brand 2	0.092	0.289	0	1
Brand 3	0.130	0.336	0	1
Brand 4	0.083	0.276	0	1
Brand 5	0.027	0.161	0	1
Brand 6	0.049	0.216	0	1
Brand 7	0.099	0.298	0	1
Brand 8	0.036	0.185	0	1
Brand 9	0.039	0.193	0	1
Brand 10	0.045	0.208	0	1

Source: Author. elaboration from IRI data.

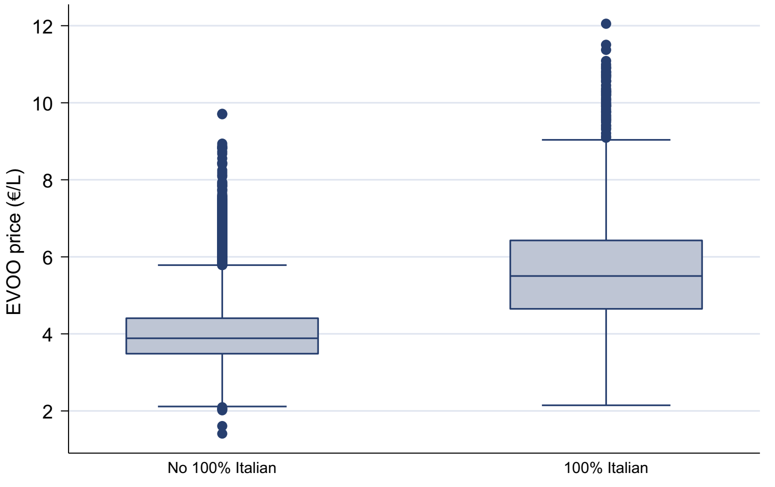

Figure 1 Boxplot of extra-virgin olive oil (EVOO) prices (excluding PDOs); product with and without the '100% Italian' label [Colour figure can be viewed at wileyonlinelibrary.com]

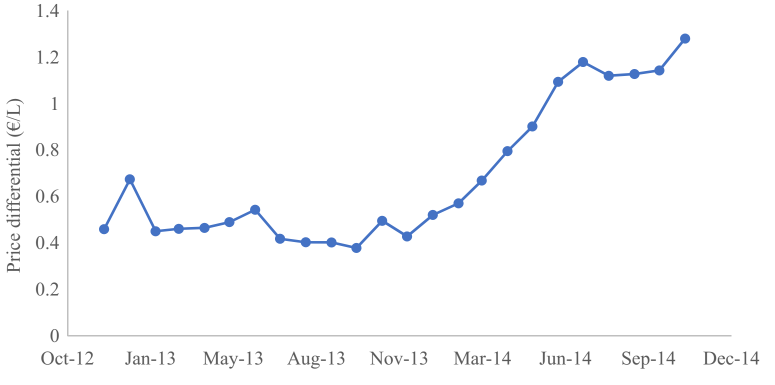

Figure 2 Price differential (at the origin) between Italian extra-virgin olive oil (EVOO) and average prices of products from Greece, Spain, and Tunisia (€/L).
Source: Authors' elaboration from data provided by ISMEA [Colour figure can be viewed at wileyonlinelibrary.com]

These three values (minimum, maximum and average price differentials) will be used to simulate a range of benefits of frauds.

4.2. Estimation

A common issue in the estimation of demand models for differentiated products is that price is likely correlated with unobservable product characteristics, which results in endogeneity bias. To account for price endogeneity, the random coefficient logit demand model is estimated using a GMM estimator (Nevo 2000, 2001) using origin prices of domestic and foreign EVOO (ISMEA 2018) interacted with indicator variables representing the product origin (i.e. Italian and foreign).

Following Nevo's (2001) notation, we define $Z = [z_1, \ldots, z_M]$, as a vector of instruments satisfying $E[Z'\omega(\theta*)] = 0$, where $\omega(\theta*)$ represents a function of the model parameters' true values $\theta*$. The vector of GMM-estimated parameters $\hat{\theta}$ solves:

$$\widehat{\theta} = \arg\min_{\theta} \omega(\theta)' Z A^{-1} Z' \omega(\theta), \tag{15}$$

where the matrix A represents a consistent estimate of $E[Z'\omega\omega' Z]$. In this case, $\omega(\theta*) = \xi_j$ represents the structural error in Equation (7), or the product-specific unobservable.

We use Hansen's (1982) J test, to test for the orthogonality of the exclusion restriction instrument, under the null of weak exogeneity; that is, that the overidentifying instruments are uncorrelated with the errors. Hansen's J statistic is distributed $\chi^2_{(k)}$, where k is the number of overidentifying restrictions. The instrument's strengths are assessed using Staiger and Stock's (1997) 'rule of thumb': the value of an F statistic for a test of the joint significance of the instruments' parameters in the first-stage regressions >10 is considered large enough to suggest the absence of weak instrument issues. Data manipulation and estimation were performed using STATA V. 14 and the simulations were performed in MATLAB 2018.

5. Empirical results

The estimated coefficients for the multinomial logit, with and without correcting for price endogeneity, as well as the random coefficient logit, are reported in the top panel of Table 2. Model diagnostics, which are reported in the bottom panel of Table 2, show that the value of Hansen's J test supports the validity of the overidentifying instruments used, given a statistic value of 1.59 for a p-value of 0.21. The F-statistic value capturing the joint significance of the instruments' coefficients in the first-stage regressions for price is 16.58, discarding weak instrument problems.

The estimated price coefficients are negative, as expected, and statistically significant in all the models, showing larger magnitude in those models where endogeneity is controlled for; in the random coefficient logit results, the estimated random parameter for price is also statistically significant, to indicate the presence of heterogeneity in price sensitivity among Italian consumers of EVOO. The demand results also indicate that Italian consumers of EVOO value the '100 per cent Italian' attribute, although the coefficients associated with this variable are only statistically different from zero at the 10 per cent level in the IV models. Interestingly, consumers show a strong preference for the PDO label (with coefficient values almost six times as large as those of '100 per cent Italian'), whereas the organic attribute surprisingly did not seem to be valued in a positive and statistically significant way by consumers, which is in contrast with findings from survey/experimental

Table 2 Selected econometric results

Variables	MNL OLS	MNL GMM	Random Coefficients Logit
Price	−0.430*** (0.008)	−0.588*** (0.156)	−0.698*** (0.206) 0.150*** (0.050)
100% Italian	0.138*** (0.022)	0.334* (0.193)	0.350* (0.191)
PDO	1.328*** (0.072)	2.186** (0.845)	1.981*** (0.707)
Organic	−0.007 (0.045)	0.278 (0.286)	0.280 (0.271)
Fruity	−0.904*** (0.033)	−0.858*** (0.058)	−0.848*** (0.061)
Average Vol. Unit	0.800*** (0.042)	0.731*** (0.079)	0.727*** (0.073)
Package Size > 2 litre	−2.933*** (0.107)	−2.840*** (0.139)	−2.841*** (0.125)
lnN Products	−2.268*** (0.129)	−2.218*** (0.135)	−2.336*** (0.119)
Constant	4.160*** (0.548)	4.609*** (0.738)	5.447*** (0.206)
Model diagnostics			
Pseudo R^2		0.335	
Hansen J (P-value $\chi^2_{(1)}$)		1.588	(0.207)
First Stage IV F		16.583	

Note: Standard errors in parenthesis; ***, ** and * indicate coefficients statistically different from 0 at the 1%, 5% and 10% level, respectively. Brand-level, region and month fixed effect coefficients omitted for brevity. *Hansen J*: test value and *P*-value in parenthesis under the null of overidentifying instruments being uncorrelated to the errors. *First Stage IV F*: *F* statistic for the test of joint significance of the IV coefficients in the first-stage regressions.

studies (Del Giudice *et al.* 2015). We find negative taste parameters for the fruity flavour, supporting previous findings that show Italian consumers have strong preferences for EVOO with a neutral taste while showing some degree of aversion for EVOO with fruity, bitter and pungent tastes (Cavallo *et al.*, 2018). Also, we find negative and statistically significant coefficients for large product packages (as one may expect) and for the natural log of the number of products sold in each market, consistent with the expectation of a ‘congestion’ in product space (Ackerberg and Rysman 2005).

The ranges of the estimated own-price elasticities, PCMs (in level and in percentage) and marginal costs are reported in Table 3. The own-price elasticities vary between −1.75 and −5.73, for an average value of −2.85. Given no other analysis of the EVOO market has been undertaken using a differentiated product demand framework (to the best of our knowledge), we cannot directly compare these estimates with other values, although they are in a range consistent with estimated elasticities for other shelf-stable differentiated food product markets.[5] The estimated profit margins vary from approximately €1.5 to €2.8 per litre of product, or from 18.23 per cent to 59.16 per cent, suggesting the existence of pricing power in the market in the

[5] Lopez & Fantuzzi (2012) found that the own-price elasticity of carbonated soft drinks ranged between −3.182 and −10.119. Richards and Hamilton (2015) instead found elasticities for the ready-to-eat breakfast cereals market varying from −1.622 to −2.920.

Table 3 Estimated own-price elasticities, profit margins and marginal costs

Variables	Minimum	Average	Maximum
Own-price elasticity	−5.730	−2.850	−1.749
PCM	1.494	1.640	2.798
PCM (%)	18.227	38.254	59.159
mc	1.055	3.003	11.773

Source: Authors' calculations from estimated parameters.

analysis. Last, all estimated constant marginal cost values are positive and vary between approximately €1.06 and €11.16 per litre.

The results of the simulated welfare effects of '100 per cent Italian' fraud are reported in Table 4. We randomly chose three of the leading EVOO producers in the Italian market, which we will refer to as Manufacturers A, B, and C, and simulate what would happen if their products carrying the '100 per cent Italian' label were fraudulent. The reader should keep in mind the illustrative nature of our example and that our results are not meant to quantify accurately the economic impact of the fraud occurring in the Italian EVOO market during the period under analysis.

The estimated average overpayment for the false '100 per cent Italian' label is €0.515/L; considering that the average price of '100 per cent Italian' EVOO in our sample is €5.59/L, this result indicates that about 9.22 per cent of the '100 per cent Italian' EVOO price is attributable to the label itself, which is lower than what was found in other research (+17 per cent €/L; Caporale *et al*. 2006).

The estimated decrease in (monthly) consumer surplus due to the overpayment for the false '100 per cent Italian' claims, presented in the left panel of Table 4, is equal to approximately €746,000 (or 1.18 per cent) for Manufacturer A, €146,000 (0.23 per cent) for Manufacturer B, and €115,000 (0.18 per cent) for Manufacturer C. By not selling the products with the fraudulent claims to consumers at a lower price, Manufacturer A had a (potential) gain of €148,000 (almost 1 per cent of its surplus), whereas for Manufacturers B and C, the amounts are even less (€35,334 and €25,643, respectively). In all cases, the overpayments incurred by consumers largely exceed gains in producer surplus, resulting in welfare losses ranging from €90,000 to €600,000. In the right panel of Table 4, we present simulated values of manufacturer gains from the labelling fraud, calculated using the EVOO price differentials for products with different origins, discussed in the previous sections. For Manufacturer A, the additional profits from engaging in fraud vary from €113,000 to €382,000; for Manufacturers B and C, additional profits range from €27,000 to €91,000 and €19,500 to €66,000, respectively. In all cases, the additional profits from fraud calculated at or above the average values of the input price differentials exceed the producer surplus from overcharging consumers for the fraudulent attribute. As a result, given that consumer welfare losses do not depend upon the cost

Table 4 Simulated welfare impacts of the presence of false 100% Italian claims in products from selected manufactures (values are in € thousands)

Products affected	Baseline (a)	Average premium	Δ Welfare: no premium (b)	%Δ Welfare [(a)−(b)]/(a)	Producers gains from fraud					
					Min		Average		Max	
					Δ Welfare	%Δ Welfare	Δ Welfare	%Δ Welfare	Δ Welfare	%Δ Welfare
Manufacturer A										
CS	63,166.51	0.515	−746.097	−1.18	−746.097	−1.18	−746.097	−1.18	−746.097	−1.18
PS	15,167.22		148.676	0.98	113.231	0.75	205.27	1.35	382.86	2.52
TW	78,333.73		−597.42	−0.76	−632.866	−0.81	−540.822	−0.69	−363.237	−0.46
Manufacturer B										
CS	63,166.51	0.515	−146.292	−0.23	−146.292	−0.23	−146.292	−0.23	−146.292	−0.23
PS	15,167.22		35.334	0.23	26.910	0.18	48.790	0.32	90.990	0.60
TW	78,333.73		−110.958	−0.14	−119.382	−0.15	−97.506	−0.12	−55.302	−0.07
Manufacturer C										
CS	63,166.51	0.515	−115.437	−0.18	−115.437	−0.18	−115.437	−0.18	−115.437	−0.18
PS	15,167.22		25.643	0.17	19.530	0.13	35.410	0.23	66.040	0.44
TW	78,333.73		−89.794	−0.11	−95.907	−0.12	−80.032	−0.10	−49.402	−0.06

Source: Authors' simulations from estimated parameters.

differential driving the extra profits for committing fraud, as the profits from the fraudulent activities increase, the deadweight losses due to fraud decrease. For example, in the case of Manufacturer A, the estimated welfare losses due to consumers' overpayments almost reach €600,000; at the highest values of the input price differentials, welfare losses are are estimated to be approximately €363,000.

Table 5 presents simulated values of the threshold probability of fraud detection that would deter an EVOO manufacturer from engaging in labelling fraud (Equation (6)) in function of the following: (i) the values of a one-time fine, G_0, ranging from the current minimum fine of €2,000 to €900,000, 50 times the largest fine currently imposed; (ii) losses due to products seized by the authorities, assuming either that no amount of product is seized ($\tau_f = 0$), or that only the fraudulent products are subject to being confiscated ($\tau_f = 1$; and $\tau_j = 0$ for $j \neq f$); (iii) sales lost due to diminished consumer trust, where we assume that there is either no loss in trust ($v_j = 0$) or increasing levels of trust leading to losses of 10 per cent ($v_j = 0.1$), 25 per cent ($v_j = 0.25$) or 50 per cent ($v_j = 0.5$); and (iv) per-unit benefits from perpetrating fraud (c–c^{FR}), calculated at the minimum, average and maximum values of the price differential between EVOO of Italian and foreign origin during the period under analysis. The simulation is performed focusing only on one manufacturer in our sample (Manufacturer B). Simulations for the other two Manufacturers (A and C) lead to similar results and are available upon request.

Table 5 Simulated probability of being found guilty of labelling fraud

Trust sales loss (v) / Product seized (τ)	Per-unit fraud benefit ($c_f - c_f^{FR}$)	One-time fines – fixed (G_0) – € thousands						
		2	12	18	90	180	360	900
$v_j = 0$	Minimum	0.889	0.571	0.470	0.151	0.081	0.042	0.017
$\tau_f = 0;\ \tau_j = 0\ j \neq f$	Average	0.925	0.682	0.591	0.235	0.135	0.073	0.031
	Maximum	0.964	0.818	0.750	0.375	0.231	0.130	0.057
$v_j = 0$	Minimum	0.033	0.032	0.032	0.028	0.024	0.019	0.012
$\tau_f = 1;\ \tau_j = 0\ j \neq f$	Average	0.058	0.057	0.056	0.049	0.043	0.034	0.021
	Maximum	0.104	0.102	0.101	0.089	0.077	0.061	0.038
$v_j = 0.1$	Minimum	0.027	0.026	0.026	0.023	0.021	0.017	0.011
$\tau_f = 1;\ \tau_j = 0\ j \neq f$	Average	0.047	0.046	0.046	0.041	0.037	0.030	0.019
	Maximum	0.085	0.084	0.083	0.075	0.067	0.054	0.035
$v_j = 0.25$	Minimum	0.021	0.021	0.020	0.019	0.017	0.014	0.010
$\tau_f = 1;\ \tau_j = 0\ j \neq f$	Average	0.037	0.036	0.036	0.033	0.030	0.025	0.017
	Maximum	0.067	0.066	0.066	0.061	0.055	0.046	0.032
$v_j = 0.5$	Minimum	0.015	0.015	0.015	0.014	0.013	0.011	0.008
$\tau_f = 1;\ \tau_j = 0\ j \neq f$	Average	0.027	0.027	0.027	0.025	0.023	0.020	0.015
	Maximum	0.050	0.049	0.049	0.046	0.043	0.037	0.027

Source: Authors' simulations from estimated parameters.
Note: The simulated probability is modeled as a function of (i) one-time fixed fines (G_0); (ii) losses due to seized products (τ); (iii) sales lost due to diminished consumer trust (v); and (iv) per-unit benefits from perpetrating fraud ($c_f - c_f^{FR}$). Manufacturer B only.

The simulated q^* ranges from 98.6 per cent to 0.8 per cent, for an average value of 13.3 per cent and a median value of 4.1 per cent. If no product is seized by the authorities, and there is no loss of image (top panel of Table 5), then our simulated threshold probabilities of fraud detection are very large (up to 98.6 per cent) at the current fine levels. If these conditions are maintained, fines need to be at least 20 times larger than the traceability fraud for q^* to reach values between 4 per cent and 13 per cent, and 50 times (€900,000) to reach values between 2 per cent and 6 per cent. If there is no loss in brand image/consumer trust (top two panels of Table 5) for the current levels of fines (€18,000 or less), then q^* will be lower than 5 per cent only at or above the average monetary benefits from committing fraud and if the fraudulent product is seized. As we illustrate below, it is possible for q^* to be much lower; however, this will require combinations of larger fines, including seizing fraudulent products, and, likely loss of image. q^* will reach values below 1 per cent only under extreme circumstances, that is, when the fine is very large (50 times the current maximum), lowest gains from fraud and loss of consumer trust resulting in 25 - 50 per cent decline in sales of other products produced by the fraudulent manufacturer.

The values in the bottom three panels show the importance of accounting for consumers' reactions to the announcement of labelling fraud on the decision of a manufacturer to commit the crime. Let us consider the current maximum level of fines (€18,000) and the authorities removing the fraudulent product from the market. The range of threshold probability of fraud detection spans from 3 per cent to 10 per cent if there is no decrease in sales due to consumers' loss of trust (third panel); 2 - 6.6 per cent if the manufacturer fears a sales decline of its other products by 25 per cent (fourth panel); and 1.4 - 4.9 per cent if the expected sales decline reaches 50 per cent (fifth panel). If fines were much larger, then the decline in the threshold probability of fraud detection due to loss of consumer trust is not as marked.

These results suggest the following: (i) manufacturers who invest in preserving their brand images will be less susceptible to the monetary penalties associated with being found guilty of fraud; (ii) losses of brand image may be a stronger deterrent not to commit to food fraud, particularly in the case of small penalties; and (iii) if the penalties are too low, and there is no loss of brand image manufacturers may still find fraud economically advantageous even if the probability of being discovered is high (that is, $q > 0.5$). Thus, policy measures based on informing the public about the perpetrator of food fraud that may result in loss of image for those found guilty of committing fraud can provide strong incentives against committing fraud.

6. Concluding remarks, model extensions and limitations

This paper proposes an empirical framework to analyse the effect of food labelling fraud using actual sales data, by means of a differentiated product demand model in attribute space and an oligopolistic supply side. The framework proposed allows quantification of consumers' welfare losses from overpayments for a product carrying a 'false' attribute as well as producers' extra profits from the fraudulent activities. The extra profits from fraudulent activities can then be used to simulate the (minimum) threshold probabilities of inspection and monitoring discouraging manufacturers from committing labelling fraud as a function of a fee schedule, whether the fraudulent product is seized, and different levels of consumers' loss of trust in the fraudulent manufacturer, captured by declines in sales. The latter may represent valuable information for policymakers in designing effective fee structures to deter fraudulent behaviours. For example, because in several EU member states the administrative fines associated with intentional mislabelling are not large enough to offset the profits from fraud, the European Parliament has proposed a revision of the magnitudes and types of fines to be imposed to agri-food companies that commit labelling fraud (European Parliament 2013).

Although this framework is useful in quantifying the economic effects of food labelling fraud, our analysis has limitations. However, it can be expanded/adapted to other contexts. First, in order to present an easy-to-use approach, our framework imposes some restrictive assumptions, such as that producers play a Bertrand - Nash pricing game, or the limiting assumptions on the distribution of consumer heterogeneity, captured by a random price coefficient. Thus, the findings we illustrate for the Italian EVOO market are only valid conditionally on the validity of the assumptions made. It may be that EVOO producers play a different game (i.e. Stackelberg) and/or that consumers' heterogeneity follows a more complex structure. As neither the Nash - Bertrand assumption nor the use of a random coefficient logit model is strictly necessary for our framework to work, future research could use different supply-side assumptions as well as alternative demand models to assess the economic impacts of labelling frauds.

Second, the way that we modelled the threshold probability of fraud detection does not take into account frequency of inspection and the possibility that larger fees and penalties can be applied to second-time or third-time offenders. It should be mentioned that data on the frequency of inspection are hard to obtain, particularly in some national contexts such as Italy, where the five different authorities devoted to fighting food fraud inspect food companies randomly and independently and not all of them disclose data on their fraud repression activities. Additionally, in some European countries, monetary sanctions do not change with multiple offenses. Modifying how q^* is determined, accounting for example how different probabilities of inspection, as well as a schedule of fines that changes conditionally on the number of prior offenses, can be the object of future research.

Third, the breadth of our simulated scenarios can be considerably expanded. In the first place, one could simulate a new market equilibrium where manufacturers found guilty of fraud sell the fraudulent products (either voluntarily or because mandated by the anti-fraud authorities) without the incriminated label. Additionally, although sales losses resulting from products being seized by the authorities are included in the calculation of the threshold fraud probability, we did not calculate the new equilibrium prices and quantities resulting from a market with fewer products. These two scenarios are similar to the de-labelling and product withdrawal scenarios considered in Bonanno *et al.* (2015) and could be easily included in future assessments of the economic effects of fraud.

Finally, as our simulations of the threshold probability of fraud detection show, increasing monetary sanctions may not be the only factor that lowers the incidence of fraud in the agri-food sector. Because our results show that non-monetary measures (lost sales due to decreased reputation) may be equally or even more effective in reducing rule-breaking behaviour, future research may focus on estimating empirically the exact extent of the trade-offs between administrative fines and loss of reputation. Existing literature suggests that non-monetary factors such as name-and-shame schemes generate effects similar to monetary schemes; they create opportunity costs for the firm (foregone profits) due to reputational losses that affect the firm's sales after fraud is disclosed (Alexander 1999; Karpoff *et al.* 2008). Such decrease in sales (and profits) from reputation loss can be even more severe that monetary sanctions imposed by regulatory frameworks and thus may work as a further disincentive for a firm not to break the rules. Future research may focus on studying how different methods of public disclosure of fraudulent activities may affect a product's sales, and how they could strategically be used to discourage labelling frauds.

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