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RESEARCH ARTICLE

Assessing the economy-wide impact of food fraud: A SAM-based counterfactual approach

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Abstract

This paper proposes a social accounting matrix (SAM)-based, counterfactual approach to assess the economy-wide impact of food fraud in a given country and applies it to the Italian economy. The empirical application uses primary data collected by the authority in charge of the monitoring and repression of fraud in food value chains between the years 2007 and 2015. This is a unique dataset to analyze the issue, although it includes only data on food fraud within the country. The results of the SAM simulations show that the share of economy directly and indirectly linked to the supply of irregular food products accounts for 0.5% of the total value of output and is able to activate up to 156 thousand labor units. The net impact of food fraud on output and employment in the whole economy is negative, with losses averaging up to 1.8 billion euros of output and of 20,000 jobs per year, with a relative impact significantly larger in agriculture than in the food industry. These figures reveal an intrinsic fragility of the agri-food system, especially in those subsectors featuring relatively large price elasticities such as quality products (e.g., wine, olive oil, cheese). The overall conclusion is that food fraud is not only a source of unfair competition to regular production activities but also has an overall contractionary impact on the whole economy due to its directly unproductive rent-seeking nature. [EconLit classifications: C67, L66, Q13].

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1 | INTRODUCTION

Food fraud problem, which has been known about since ancient times (Shears, 2010) that has only recently been conceptualized as a policy issue (Lord, Flores Elizondo, & Spencer, 2017; Manning & Soon, 2016; Spink & Moyer, 2011). The pressure of recurrent food incidents such as the melamine contaminated milk in China and the European horsemeat scandal has contributed to this recognition. Indeed, the risk of food fraud is growing in terms of both the danger it presents and the concern it generates (Avery, 2014; Spink & Moyer, 2011). This is related to the increasing complexity of food supply chains under globalization, with companies having less visibility and control of key processes, and monitoring agencies having less ability to detect fraud incidents. More recently, this situation has been exacerbated by the global recession as suppliers, squeezed by costs, have had stronger incentives to surrender to temptation to commit food fraud (GMA, 2010). At the same time, more effective regulatory environments, broader media coverage, and growing consumer advocacy and government scrutiny have all contributed to an increase in public awareness and concern (Avery, 2014; Deloitte, 2017; Elliot, 2014).

It is no surprise, then, that scholarly debate on food fraud ensued (Manning & Soon, 2016). Most of this debate initially focused on formally defining the concept of food fraud which is currently defined as “any intentional illegal acts made by food value chain operators for [the] sake of illegal economic gains” (Spink & Moyer, 2011),[1] identifying the different food fraud types and clarifying the difference between food fraud and other intentional food crimes such as food defence risks, which are deliberate or intentional acts of contamination or tampering to harm public health (FDA, 2018; Global Food Safety Initiative, 2014; Manning & Soon, 2016).

More recently, the debate has turned toward the characterization and analysis of food fraud episodes. This strain of literature focused on the systematic identification of the different food fraud types (Everstine, Spink, & Kennedy, 2013; Shears, 2010; Spink & Moyer, 2013) as well as who commits food fraud (Manning, Smith, & Soon, 2016; Spink, Moyer, Park, & Heinonen, 2013), what their motivations are (Spink et al., 2013) and their methods (Lord, Flores Elizondo, et al., 2017; Lord, Spencer, Albanese, & Flores Elizondo, 2017; Manning & Soon, 2016 and Manning et al., 2016). To do this, conceptual frameworks have been developed from the contributions of parent disciplines such as food policy, food technology, business and behavioral sciences, and criminology (Lord, Flores Elizondo, et al., 2017, Lord, Spencer, et al., 2017; Manning & Soon, 2016; Smith, Manning, & McElwee, 2017; Spink, 2011; Spink & Moyer, 2011, 2013). Particularly, criminology has significantly contributed to the explanation of the drivers behind food fraud, using both “traditional criminology” (i.e., how to reduce crime by understanding the motivations of the human actors) and “environmental criminology” (i.e., how to reduce the crime opportunity by reducing the physical attributes of time and space from the environment where the perpetrator of food fraud operates) (Spink & Moyer, 2011). Specifically, analyses that integrate “enterprise theory” with “situational prevention theory” are proven very useful in developing “an understanding of how food frauds are situated actions, shaped by contingent enterprise conditions that influence how food frauds are organized and why decisions to offend become rational” (Lord, Spencer, et al., 2017: 483).

This debate has had far-reaching consequences in terms of analytical content, shifting the focus of food fraud risk from prevention to vulnerability reduction (Spink, Ortega, Chen, & Wu, 2017; van Ruth, Huisman, & Luning, 2017; van Ruth, Luning, Silvis, Yang & Huisman, 2018). The debate has also impacted evidence-based policy-making and regulation through intelligence-building (Moore, Spink, & Lipp, 2012), modeling to predict the occurrence of food fraud incidents (Bouzembrak & Marvin, 2016; FDA, 2015; NSF, 2014), building surveillance systems (CDC, 2018; EU Commission, 2018b) and developing systems of food fraud prevention for the food chain operators (USP, nd; GSFI, 2014; SSAFE, 2015). For instance, several databases, such as the EU Rapid Alert System for Food and Feed (EU Commission, 2018a) and the United States Pharmacopeial Convention food fraud database (USP, 2012), have been created to document food fraud incidents.

[1]The difficulty in achieving a consensus on a food fraud definition was partly due to the differences existing among various regulatory systems (e.g., EU vs. USA), partly because of the multi-stakeholder nature of the platforms where this concept should be used and partly due to the intrinsically multifaceted nature of the concept itself encompassing many different illegal acts as different as substitution, addition, tampering or misrepresentation of food, food ingredients or food packaging, labeling, product information.

Quite surprisingly, the aforementioned efforts have not been paralleled by an effort to provide a systematic account of the socioeconomic impact of food fraud, although the latter is a source of unfair competition and may result in a food safety or public health risk events with significant economic consequences for a company, the food industry, consumers, and society at large. According to the last Operation Opson (Interpol-Europol, 2017), the largest internationally coordinated effort to fight against food fraud involving the police and regulatory bodies from 65 countries, the value of food and beverage seizures was estimated to be as high as €235 million (ca. $270 million at the current exchange rate) over a short period of 4 months (from December 2016 to March 2017). The UK Food Safety Agency estimates that food fraud may affect approximately 10% of all commercially sold food products (Everstine & Kircher, 2013). The overall cost to global industry is estimated to range between $10–15 billion (Johnson, 2014) and $30–40 billion (Rey, 2014).[2] In terms of impact on people's wellbeing, one single episode such as the melamine contamination of milk and infant formula affected about 300,000 Chinese infants and young children, with 52,000 people hospitalized and six reported deaths. The estimated total cost of this scandal was $10 billion, including the costs associated with product recalls and withdrawals, incident investigation, lost sales, decreases in shareholder value, and adverse health consequences (GMA, 2010).

These estimates, however, are likely to represent only a fraction of the true cost, because the full scale of food fraud "may be unknown or even possibly unknowable" (Spink & Fejes, 2012: 265) since the goal of fraudsters is not to be detected. Generally, the fraud databases "do not provide an overall estimate… (and)… the variability in the methods used by individual industries or commissions in the elaboration of their data makes a meta-analysis complex or impossible" (Spink & Fejes, 2012: 250). As a result, most estimates reported in the literature on the economic impact of food fraud are limited in scope, being based on anecdotal evidence of single episodes and generally based on expert guesses (Moyer, DeVries, & Spink, 2017). Even when there is an attempt to get estimates based on harmonized data (e.g., OECD-EUIPO, 2016), the estimates usually refer only to the *market value of seizures* rather than *assessing the impact* of fraudulent activities on the relevant economies. To the best of our knowledge, the only study trying to make this assessment is CENSIS (2012), which uses input–output tables to simulate the impact of counterfeiting on the Italian economy. The main limitation of this study is that it looks only at the aggregate food sector. Specifically, the "food and beverages" industry is not broken down into subcomponents (e.g., the various food and beverage subsectors). Moreover, the data on fraud are partially imputed (i.e., not actually recorded) data, retrieved adopting average parameters estimated for OECD countries. In short, there is a lack of a systematic and rigorous account of the socioeconomic impact of food fraud.

This paper aims at contributing to this literature, proposing a method that makes possible the assessment of the economy-wide impact of food fraud in a given country by measuring it in a rigorous, counterfactual framework. The approach uses a social accounting matrix (SAM) to simulate the effect on some key economic variables—namely the value of output, employment, value added and household income—determined by food fraud carried out *within* a country.

This impact assessment will be carried out with specific reference to Italy, which is indeed an excellent case study. In fact, the food sector is one of the most important parts of the so-called "Made in Italy"[3] and represents one of the most profitable sectors for fraudulent activities (Eurispes, 2011), with the revenue from food counterfeiting estimated at 15.7% of total counterfeiting activities in the country (CENSIS, 2012). Furthermore, the provision of the primary data on seizures and irregularities detected by the authority in charge of the monitoring and repression of fraud in food value chains—that is the Central Inspectorate for Agri-food Quality Protection and

[2]The Grocery Manufacturer Association estimates that one adulteration incident averages between 2% and 15% of a company's annual revenue in terms of lost sales as well as possible bankruptcies if adverse public health consequences occur. For example, "this could translate to a $400 million impact for a $10 billion company, or a $60 million impact for a $500 million company" (GMA, 2010: 6). These figures are likely to represent a lower bound of the economic impact of a food incident because they consider only direct cost to a given company not accounting for the spillover effects due to the consumer confidence and trust loss across countries and sectors (Meerza & Gustafson, 2018).

[3]According to the EU Commission (2019), Italy is the EU country with the largest number of registered protected agri-food products that by the end of 2018 accounted for 299 protected designations of origin (PDOs), protected geographic indications (PGIs), and traditional specialties guaranteed (TSGs) and 526 registered protected denominations and geographic indications wines (DOCG, DOC, and IGT).

Fraud Repression (ICQRF)—offers a unique opportunity to shed some light on the evolution of food fraud over the years 2007–2015 and to assess the impact of this fraud on the Italian economy.

In pursuing the above objective, the paper is organized as follows: Section 2 provides an overview of food fraud committed in Italy between 2007 and 2015. Section 3 introduces the adopted methodology showing how an impact evaluation of food fraud can be modeled in a counterfactual framework. Section 4 shows how a SAM of the Italian economy has been developed to obtain a model suitable to perform the impact evaluation analysis. Section 5 discusses the results of such analysis, first assessing the output and employment activated by fraudulent activities in the food sector, and secondly carrying out a counterfactual analysis of the impact of food fraud on the Italian economy. Section 6 summarizes the main findings and discusses the policy implications.

2 | FOOD FRAUD IN ITALY

2.1 | Inspections and seizures in Italian food value chains

Although many bodies are involved in the repression of agri-food fraud in Italy, the ICQRF is the only authority performing systematic inspections based on representative samples that cover all food value chains within the country. The information of ICQRF inspection activities are disaggregated per geographic area (regions and provinces) and at agri-food subsector level, spanning over the period 2007–2015 (ICQRF, 2016). When a fraud is detected, the consequence might be either the seizure of the relevant product and/or the payment of a fine. The ICQRF refers to both cases as "irregularities". Therefore, the set of seized products is just a subset of irregular products.

In this paper, we adopt a broad definition of food fraud, as proposed by Spink and Moyer (2011), including any kind of fraudulent action such as food alteration, adulteration, sophistication, and falsification of agri-food products as well as counterfeiting, that is the falsification of their trademarks including those related to the indication of geographical origin. Operationally, this means that a food fraud exists whenever an ICQRF-inspected product features any kind of irregularity no matter if it leads to the product seizure or to other administrative penalties such as fines and warnings. Therefore, any product featuring any type of fraud is identified as "irregular product", while the agent that commits fraud is called "irregular establishment."

A summary of inspection activities and outcomes performed by ICQRF is reported in Table 1. Wine is the most inspected product, accounting for more than 30% of total inspections, followed by olive oil, horticultural and dairy products, accounting for 14%, 13%, and 11%, respectively. The same ranking largely applies also to establishments. In terms of proportions of irregularities on the number of inspections, wine also ranks first: 14% in terms of products and 26% in terms of establishments. Other important subsectors are fish, other drinks, animal feeds and olive oil, all ranging between 10% and 12% in terms of irregular products and around 12–13% in terms of irregular establishments.

2.2 | Regional and subsector disaggregation of food fraud

To get some insights on the intensity of irregularities, we look at the ratio of seized products to irregular ones as well as the ratio of irregular products to inspected ones. The upper panel of Figure 1 plots the two ratios against each other, with the black lines representing the national averages. The figure shows that fraud is more intense in Veneto, Lazio, Piedmont, Lombardy, and Puglia regions, followed by Sicily, Tuscany, Campania, and Friuli V.G. The lower panel of Figure 1 plots the ratio of irregular establishments to inspected ones against the ratio of inspected establishments to active establishments in each region. It shows that Piedmont, Lazio, and Lombardy have been underinspected, while regions such as Molise, Marche, Sardinia, Basilicata, and Calabria are overinspected.

We performed the same analysis to assess the intensity of irregularities per subsector (Figure 2). In terms of products (upper panel), the picture shows that the intensity of irregularities is higher than the average for wine,

TABLE 1 Summary of the ICQRF inspections by subsector over 2007–2015

Subsectors	Number of inspections		Distribution of inspections		% of irregularities/inspections	
	Products	Establishments	Products (%)	Establishments (%)[a]	Products (%)	Establishments (%)
Meat products	29,698	13,026	5.8	12.0	9.2	13.83
Fish products	1,280	884	0.3	0.8	12.4	12.10
Olive oil	70,419	26,882	13.8	24.8	8.5	12.71
Other foods	40,332	18,363	7.9	17.0	7.7	11.41
Horticultural products	68,086	21,670	13.4	20.0	5.1	9.95
Dairy products	57,703	19,554	11.3	18.1	6.8	11.81
Cereal products	47,335	17,699	9.3	16.4	6.9	11.43
Animal feed	29,169	9,013	5.7	8.3	9.3	12.06
Wine	150,889	33,504	29.7	31.0	13.9	25.51
Other drinks	13,669	5,867	2.7	5.4	10.3	13.81
Total	508,580	108,203	100.0	153.8	9.4	21.07

Abbreviation: ICQRF, Central Inspectorate for Agri-food Quality Protection and Fraud Repression.
[a]The proportions of inspected establishments do not sum to 100% because some of them (e.g., retailers, processors and wholesalers) supply products belonging to different value chains.
Source: ICQRF (2016).

fish, other drinks, and olive oil. All the other subsectors show an intensity of irregularities lower than the average. In terms of establishments, wine and olive oil seem to be well monitored while the ones toward the bottom left corner (e.g., animal feed and other food producers) appear to require more attention by the monitoring body.

A prima facie conclusion would be that a redistribution of inspection activities across regions and subsectors may lead to an improvement in the ICQRF performance through shifting resources from regions/subsectors that seem to be overinspected/less prone to irregularities to those underinspected/more prone to irregularities. While this might be the case in principle, it is worth noting that data reported in Figures 1 and 2 are averages that can hide a lot of heterogeneity across regions and products. In fact, we do not have background information about the operational efficiency across ICQRF's regional offices or about misreporting rates across regions. It might also be that it is easier to detect fraud for one product concentrated in a given region than another. Furthermore, a diversity of characteristics affecting the likelihood of food fraud may also exist within product categories (such as in the case of vertical quality differentiation using denomination of origin or organic certifications) or within regions (due, e.g., to the structure of the supply chain in different territories). Therefore, to provide greater evidence to support countermeasures against food fraud, a more in-depth analysis of the situation on the ground in each specific region and value chain would be required. This might be also done considering the theoretical and empirical literature in kindred disciplines, such as the agro-environmental literature on effectiveness of monitoring design.[4]

2.3 | Value of seized and irregular food products

To assess the value of irregular products, we need to first estimate these figures at the sample level and then expand them to the population level. At both levels, we have two different figures that can be meant as a lower and an upper bound of detected food fraud. In fact, the ICQRF database includes figures both for seized products

[4]There are indeed dynamic monitoring schemes based on targeting those who did not comply in previous periods that have proved to be more cost-effective than simple random monitoring (see, e.g., Fraser, 2004). However, the discussion of this schemes is beyond the aims of this study.

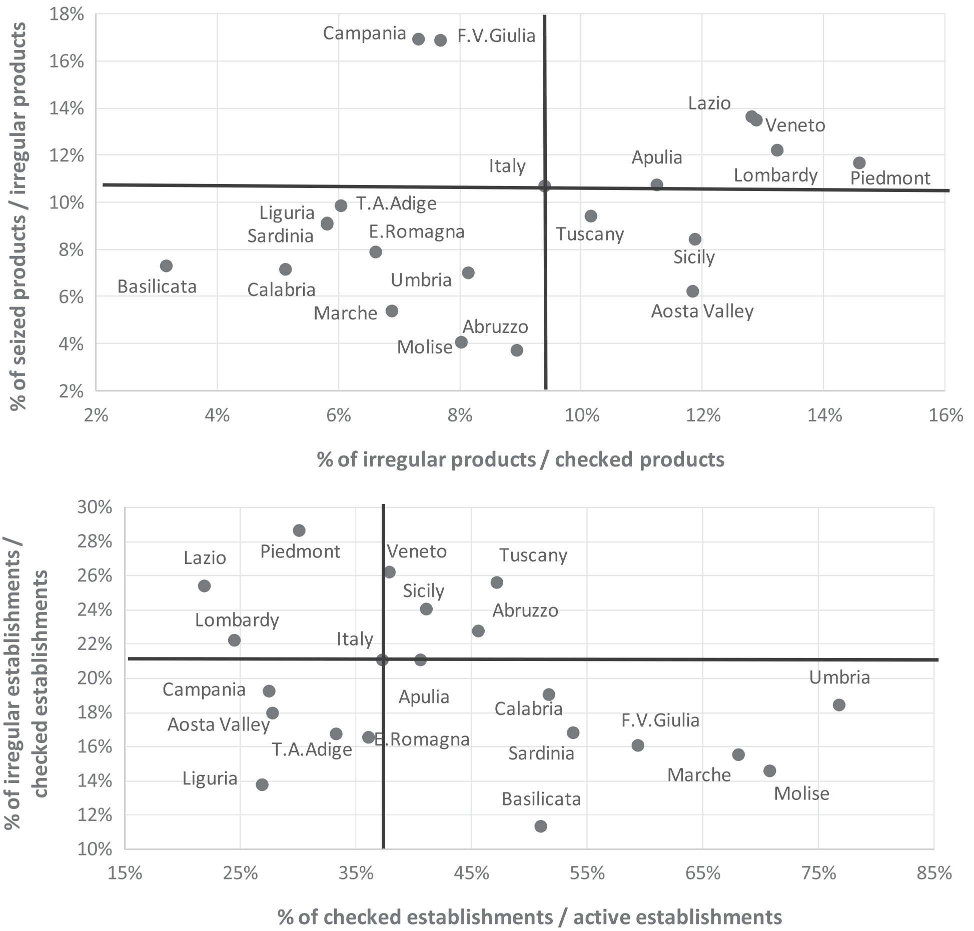

FIGURE 1 Intensity of food frauds per regions: products (upper panel) and establishments (lower panel). Source: authors' elaboration from ICQRF (2016) and ISTAT (2014). ICQRF, Central Inspectorate for Agri-food Quality Protection and Fraud Repression

(the lower bound), and for the total of irregular products detected by inspection activity (the upper bound). Seized products being only a subset of irregular products, the latter is the relevant concept in our analysis.

While in the case of seized products, the database reports both quantities and their estimated monetary values, in the case of irregular products the ICQRF database reports only quantities. Therefore, we need to estimate the monetary value of irregular products detected by ICQRF inspections. This sample-level estimation is performed adopting a two-step procedure: first we calculate the ratios of the number of seized products to the irregular products ("expansion rate" column in Table 2), and then we divide the value of seized products by this rate to yield the value of irregular products at the sample level. This procedure rests on the implicit assumption that the composition of seizures is representative of the whole set of irregular products. At the same time, we acknowledge that seizures refer to more serious infringements to the rules and norms (e.g., food adulteration that can have harmful effects) than, for example, mere administrative noncompliance not subject to seizure. This carries an important information content in analyzing food fraud that we think is important to disclose to the interested reader. Therefore, we perform the analysis for both categories of products, that is, seized and irregular products.

Furthermore, frauds are modeled as exogenous shocks on the final demand in the proposed analytical framework (cf. Section 3). Therefore, food fraud data have been transformed as if it referred to products for final

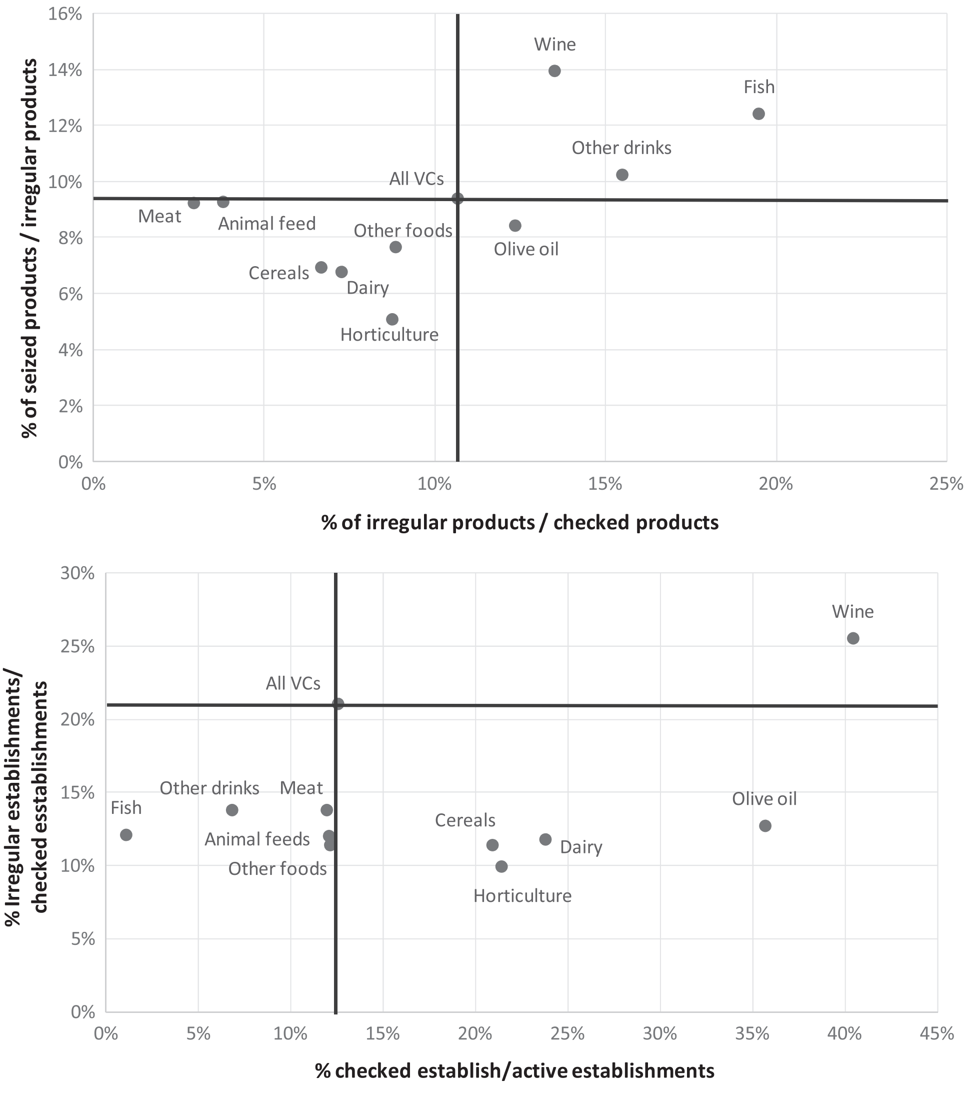

FIGURE 2 Intensity of food frauds per subsectors: products (upper panel) and establishments (lower panel). Source: authors' elaboration from ICQRF (2016) and ISTAT (2014). ICQRF, Central Inspectorate for Agri-food Quality Protection and Fraud Repression

consumption, using proper technical coefficients specific for the subsector considered and the stage within the value chain where the fraud is detected. For example, if wine grapes are detected as irregular, the quantity of grapes have been first transformed into wine equivalent quantities using the technical conversion coefficients; then the resulting quantities have been multiplied by the consumer price of wine.

Finally, for the purpose of assessing food fraud impact on the whole Italian economy, we need to expand the figures estimated at sample level to the level of the whole Italian food industry, that is, population level. This expansion is performed adopting a two-step procedure. First, we calculate the sampling rates, that is, the ratios of the number of inspected establishments to the number of active establishments ("ICQRF sampling rate" column in Table 2). Then we compute the values of seized and irregular products at the population level by dividing sample values of these groups of products by the sampling rates. This procedure seems adequate as inspection activities are designed by ICQRF to control a representative sample of all active establishments.

TABLE 2 Values of seized and irregular products: population level estimation (constant 2009 euro)

	Sample level			Population level		
Sector	Values of seizures (000 euro)	Expansion rate (%)	Values of Irregularities (000 euro)	ICQRF sampling rate (%)	Values of seizures (000 euro)	Values of irregularities (000 euro)
Meat products	55	3.3	1,675	2.0	2,803	85,121
Fish products	29	17.9	161	0.2	19,188	107,049
Olive oil	2,748	15.9	17,306	6.3	43,577	274,433
Other foods	278	9.6	2,890	2.2	12,555	130,298
Horticultural products	964	8.4	11,462	3.8	25,588	304,352
Dairy products	430	8.2	5,233	4.8	9,056	110,179
Cereal products	614	5.6	10,921	3.7	16,678	296,530
Animal feed	106	6.8	1,561	61.4	172	2,544
Wine	39,030	17.8	219,292	8.3	470,740	2,644,843
Other drinks	212	18.9	1,126	1.0	21,844	115,818
Total	44,467	–	271,627	–	622,201	4,071,167

Abbreviation: ICQRF, Central Inspectorate for Agri-food Quality Protection and Fraud Repression.
Source: Authors' elaboration on ICQRF (2016) and ISTAT (2014).

Table 2 presents the average yearly value[5] of seized and irregular products per each subsector expressed in constant monetary terms at 2009 prices, which is the SAM reference year. The average yearly value of food fraud ranges from €0.6 billion, when only seizures are accounted for, to €4.0 billion, when total irregular products are considered. These lower and upper bounds define a range consistent with the estimates provided for the period 2008–2010 by CENSIS (2012), which assessed the market value of food counterfeit products in Italy as high as €1.15 billion (at 2009 prices). As expected, wine is by far the largest subsector both in terms of value of seizures and irregular products, with olive oil, horticultural products and cereal products playing an important role as well.

3 | MODELING THE IMPACT OF FOOD FRAUD IN A SAM FRAMEWORK

A SAM is a representation of the economic flows within an exchange economy in a matrix form (Miller & Blair, 2009) accounting for the interrelationships among production activities, income distribution among factors and institutions, final consumption, and capital formation. Each row of a SAM shows the receipts of a specific sector while the corresponding column lists the sector expenditures. There are several accounts in the rows of the matrix, namely: production activities; factors of production; institutions' current accounts such as households, firms, government; the capital formation account; and the account for exchanges of the economy with the rest of the world. The same structure holds for the columns of the matrix. As in any double entry accountancy system, the corresponding rows and column totals must balance.

The first step in SAM modeling is the identification of endogenous and exogenous accounts. Usually, for small economies, the government and the rest of the world are considered as exogenous as the model does not explain

[5]We consider the yearly average of fraud committed over the whole reference period (2007–2015) to reduce the likelihood of using a biased figure due to interannual variability of the number of controls as well as their subsector composition, as might be the case when considering the food fraud committed only in one specific year. In other words, the resulting figure better represents the average actual composition of fraud in the Italian agri-food system.

the behavior of those accounts. The process of capital formation can be also considered as exogenous when the research question does not focus on dynamic impacts.

The model can be represented in a compact form as a set of equations representing the balance of the accounts for the endogenous components (production activities, factors of production, households, and firms) as follows. Let **B** be the matrix of expenditure coefficients for endogenous accounts, that is the matrix of coefficients obtained dividing each single entry of the matrix by the corresponding column/row total. Then:

$$\mathbf{y} = \mathbf{B}\mathbf{y} + \mathbf{x}, \tag{1}$$

where **y** is the vector of nominal income of endogenous accounts (output of production activities, factor earnings, and gross income for institutions), and **x** is the vector of exogenous inflows toward endogenous accounts (foreign trade, savings and capital formation, transactions between institutions and the government).

The solution of the system (1) maps the vector **x** of exogenous component of the system to the vector **y** of totals through the matrix **M** of SAM multipliers:

$$\mathbf{y} = (\mathbf{I} - \mathbf{B})^{-1}\mathbf{x} = \mathbf{M}\mathbf{x}, \tag{2}$$

where **I** is the identity matrix. SAM-based models are typically demand-driven, that is the activation of the economy depends on the magnitude of a vector of exogenous inflows, **x**, toward endogenous accounts, **y**, via post-multiplication to the matrix of multipliers, **M**. Being a linear model, Equation (2) holds also in difference, providing a straightforward way to simulations:

$$d\mathbf{y} = \mathbf{M}d\mathbf{x}, \tag{3}$$

where $d\mathbf{x}$ is a vector of changes in exogenous injections, representing a given scenario to be assessed. The SAM multipliers are Leontievian–Keneysian multipliers insofar as the households' accounts are endogenous thus *closing* the model to final consumption. Therefore, SAM multipliers account not only for the interindustry effects—as is the case of standard input–output multipliers—but also for the additional demand generated by households' consumption as a result of the distribution of value added (Miller & Blair, 2009: 518).

There are two ways to carry out an impact assessment of food fraud in a SAM framework, each referring to either of the right-hand side terms in Equation (3). A first approach simply estimates the impact of the final demand of seized or irregular products (representing the lower and upper bounds of food fraud, respectively) supplied by the current configuration of the Italian agri-food system. To do this, Equation (3) is used with $d\mathbf{x}$ being the vector of the estimated values of seized and other irregular food products keeping **M** constant. This assesses the share of the economy directly and indirectly relying (throughout the interdependencies among production activities, income distribution, and consumption expenditure) on food fraud activities. We interpret the results of this simulation as a measure of vulnerability of the agri-food production system. Indeed, food fraud brings about an inherent risk of consumers losing trust should a food scandal/scare happen. In this case, the larger the share of the final demand supplied by fraudulent products, the higher the risk of a system disruption.

A more accurate analysis can be carried out adopting a counterfactual approach that requires some manipulations of the matrix **M**. The SAM represents the *actual* flows in the economy, including both regular and irregular food production activities. The SAM direct expenditure coefficients used to derive the matrix **M** reflect the *average* structure of intermediate consumptions of food subsectors, including both regular and irregular activities. However, the structure of costs of a production unit not complying with regulations and standards is different from that of a fully compliant production unit. We expect that an irregular food would be obtained increasing the ratio between value added and intermediate costs and increasing the share of profits in the primary distribution of value added to factors. Such a different configuration of costs decreases the backward linkages of the irregular production activity, reducing its ability to stimulate the economic system through industrial interdependencies. The increased share of distributed profits, however, will affect the economy via the changes in income distribution and increase the final consumption expenditure. The net result of these two effects—that is, the decrease of backward linkages and the increase in profit—depends on the structure of costs and income distribution in the industries affected by fraud that will determine the final impacts on the whole economy in terms of output, employment, and distribution of income across household deciles. In conclusion, a counterfactual analysis of the impact of irregular activities should compare the total activity of the actual economy represented in the SAM, with that of a hypothetical economy of fully compliant firms (i.e., those not committing fraud).

Suppose a matrix $\mathbf{B}^*$ of SAM-based direct expenditure coefficients representing a fully compliant production system is available. The corresponding matrix $\mathbf{M}^*$ of SAM multipliers could be calculated. Then, the total impact of irregular production activities could be estimated as follows:

$$\mathbf{c} = (\mathbf{M} - \mathbf{M}^*)\mathbf{x} = \mathbf{y} - \mathbf{y}^*, \tag{4}$$

where, $\mathbf{x}$ is the vector of actual (i.e., SAM-based) exogenous inflows toward all endogenous accounts, $\mathbf{y}$ is the vector of totals of actual endogenous accounts, $\mathbf{y}^*$ is the vector of totals of endogenous accounts that would be observed should the production system be fully compliant, and $\mathbf{c}$ estimates the impacts of irregular activities expressed as changes, that is, actual minus fully compliant, in the totals of endogenous accounts.

Such a counterfactual analysis requires additional data on how noncompliance affects the vector of costs of production activities in each food subsector. Let $\mathbf{A}_f$ be the matrix of expenditure coefficients for irregular production activities and $\mathbf{f}$ the vector of total values of irregular productions. The commodity by industry use matrix $\mathbf{Z}_f$ representing total intermediate consumptions for irregular production activities can be calculated as follows:

$$\mathbf{Z}_f = \mathbf{A}_f\hat{\mathbf{f}}, \tag{5}$$

where the hat indicates the diagonalization of vector $\mathbf{f}$. The use matrix for fully compliant production activities can be obtained by the difference:

$$\mathbf{Z}_r = \mathbf{Z} - \mathbf{Z}_f, \tag{6}$$

where, $\mathbf{Z}$ is the use matrix in the original SAM.

Finally, matrix $\mathbf{A}^*$ can be obtained dividing the elements of $\mathbf{Z}_r$ by the total value of regular products:

$$\mathbf{A}^* = \mathbf{Z}_r\left(\widehat{\mathbf{y} - \mathbf{f}}\right)^{-1}. \tag{7}$$

Matrix $\mathbf{B}^*$ representing the "fully compliant" (i.e., counterfactual) economy is obtained substituting the "modified" matrix $\mathbf{A}^*$ for the matrix of direct expenditure coefficients of production activities in matrix $\mathbf{B}$ obtained from the original SAM.

4 | A SAM FOR THE ANALYSIS OF THE AGRI-FOOD SECTOR IN ITALY

To perform the analysis, a suitable SAM of the Italian economy, fully representing the agri-food system and its relationships with the rest of the economy, is needed (cf. Appendix A for details). To build the SAM, the input–output (I–O) table of the Italian economy for the year 2009 (ISTAT, 2016) was disaggregated to include eight farming typologies and 10 different groups of food processing. All these activities produce a set of 11 different commodities. The disaggregated I–O table was then merged with a SAM of the Italian economy developed by the Tuscany Regional Institute for Economic Planning with reference to the same year (IRPET, 2016). The final SAM includes a total of 183 accounts including 64 commodities, 54 industries, 12 accounts for primary income distribution, 23 final consumptions functions, 18 accounts for current income use by institutions, nine accounts to represent capital formation, and three accounts for flows with the rest of the world. Households are disaggregated into 10 groups according to deciles of equivalent per capita available income. Institutions purchase bundles of goods and services corresponding to 23 final consumption functions. Agriculture and food industries sell their products to consumers according to the first two functions, that is, purchases of food and beverages. The model closure assumes Government, capital formation, and rest of the world as exogenous accounts.

Developing a counterfactual in a SAM framework requires additional information on fraud that is difficult to obtain. Considering the huge diversification of production processes in the food industry, getting the relevant information would require an extensive survey. An alternative, adopted in this study, is to ask food sector experts and key informants working in organizations in charge of inspections in the agri-food sector to provide their best guess on the cost structure of the most common irregular production processes. This would make possible to build matrix $\mathbf{B}^*$ according to the procedure summarized in Section 3 (cf. Appendix B for details).

This procedure deserves specific attention for the wine and the olive oil industries, two subsectors that are strategic for the Italian food system and most targeted by fraudsters (ISMEA, 2019a, 2019b). In these two cases, the experts and key informants were asked to provide first a description of the most common frauds in each subsector, taking also into account the different possible configurations of the process in different typologies of production units (for instance farm-based or industrial production activities). Then, they were asked to modify the $\mathbf{B}$ matrix elements to better represent the cost vector of each fraudulent activity.

For other food subsectors, we assumed that the adoption of irregular practices in production was able to determine the same advantages enjoyed on average by the operators in the wine and olive oil industry. Specifically, we assumed that the adoption of irregular practices in production and trade was able to triple the value of output with the same expenditure for input purchase (cf. Appendix B). Only the cost of professional and legal services was assumed to maintain the same share of gross output value as in the average activities represented in the SAM. These hypotheses are quite heroic. However, the analysis can still provide useful insights on the economics of food fraud in Italy, considering that the share of irregular products other than wine and olive oil is only 27% of the total irregular products value.

5 | RESULTS AND DISCUSSION

5.1 | The vulnerability of Italian economy to food fraud

In this section, we report the results of the first approach, that is, the vector of seized and irregular product as an exogenous shock $d\mathbf{x}$ in Equation (3), to assess the share of economic activities directly and indirectly activated by the final demand actually met by supply of fraudulent food products. In doing so, we model the fraud as an exogenous component of the final demand of commodities, similar to export and inventory changes.

The production that has been activated between 2007 and 2015 amounts to a value ranging on average between €1.9 billion per year, if only seizures are considered, and €13.9 billion per year, in the case that total irregular products are accounted for (Table 3). These figures clearly show the importance of food fraud in the Italian economy. In the reference period, between 0.1% and 0.5% of value added (a proxy of GDP) was generated by food fraud. The share of total employment directly and indirectly activated by the final demand supplied by food fraud is up to 0.6% or 156,000 labor units when all irregular products are considered.

The impact is much larger when considering as reference only the agri-food system (Figure 3). The size of production activated by the final demand of fraudulent food products varies across subsectors but is particularly important (more than 25% when considering all irregular products) for wine and the related activity of specialized permanent crops farms (11.3%). Overall, the total output driven by food fraud accounts for 3.2% of agri-food output and 5.8% of total employment in agri-food sectors.

TABLE 3 Share of total economy activated by the final demand for irregular food products (value/year in €2009, average 2007–2015)

	Only seized products		All irregular products	
Type of impact	Absolute value	Share (%)	Absolute value	Share (%)
Total value of food frauds (M€)	622		4,693	
Total output (M€)	1,858	0.06	13,879	0.48
Total employment (000 LU)	22	0.09	156	0.65
Value added (M€)	795	0.06	5,828	0.45
Households' gross income (M€)	715	0.04	4,754	0.29

Source: Authors' elaboration.

These figures provide a measure of the agri-food production system vulnerability to food scares and scandals. This is a highly policy-relevant result, though not yet a genuine measure of the impact of agri-food fraud on the economy. In fact, despite being a potential source of instability, the irregular food production activities generate and distribute (illegal) incomes and stimulate the economy throughout backward and forward linkages that are not accounted for by the analysis above. To capture these impacts, a counterfactual analysis is needed.

5.2 | The impact of agri-food fraud on the Italian economy

What would be the level of activation of the Italian economy if all production activities were carried out fully complying with regulations and standards? Table 4 shows that food fraud contributes to a reduction of the total level of activity in the economy: up to €1.8 billion of total output in all sectors of the Italian economy are potentially lost, corresponding to about 20,000 full time labor units with respect to a fully compliant economy. In times of high unemployment, this is a striking figure. The income distributed to households shrinks too (up to −0.01%). Interestingly, the net impact on value added is positive though small, due to the increased share of profits produced by fraudulent activities. These profits partially offset the contractionary impact of fraud, but forward linkages as represented by the SAM coefficients are not able to stimulate the economy (throughout final demand) to generate enough employment and income to compensate for the losses due to the weakening of backward linkages. The total amount of profits distributed by fraudulent activities (not shown in Table 4) amounts to €2.17 billion, a figure showing the extent of the area of *rents from fraud* negatively affecting the viability of the Italian economic system. In

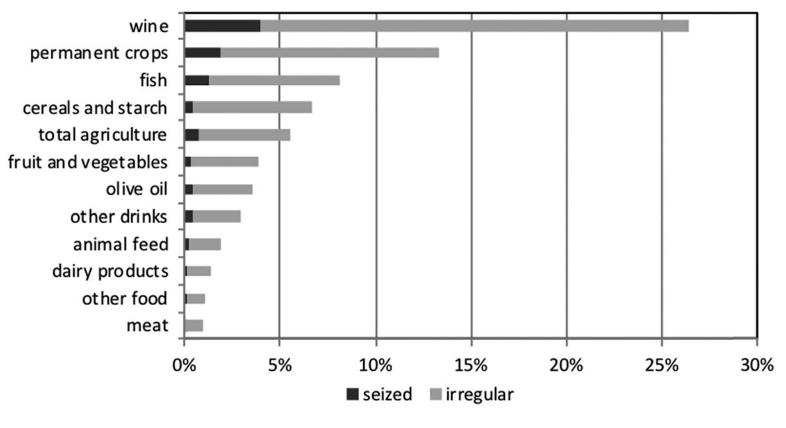

FIGURE 3 Share of the output of agro-food subsectors activated by food frauds. Source: authors' elaboration

TABLE 4 Impact of irregular production activities (value/year in €2009, average 2007–2015)

	Only seized products		All irregular products	
Type of impact	Absolute value	% impact	Absolute value	% impact
Total output (M€)	−139	0.00	−1,827	−0.06
Total employment (000 LU)	−2	−0.01	−20	−0.08
Value added (M€)	6	0.00	87	0.01
Households' gross income (M€)	−16	0.00	−174	−0.01

Source: Authors' elaboration.

the case of fraud, the largest part of these profits is likely to be sterilized into unproductive assets and/or transferred outside the national economy. In fact, the increased profit share is generally obtained by selling irregular products whose price is higher than their intrinsic lower quality would fetch in the market that do not require specific investments to be produced.

As expected, the relative impact on the agri-food system is much larger. The relative impact on output is far more important in agriculture (up to −1%) than in the food industry (between −0.03% and −0.33%; Figure 4). The lower intrinsic quality of irregular food production is mainly due to the lower value of agricultural input used per unit of processed food. This in turn decreases the backward impacts toward agriculture generated by food production activities.

The larger impact on agriculture crucially depends on the typology of food fraud in the most important Italian agri-food value chains. The Italian food products targeted by fraudsters are generally heavily dependent on the domestic agricultural production, that is most fraud is committed through false claims about the quality/origin of the raw material used by the food industry.

In the wine industry, for instance, the most common fraud refers to adopting irregular wine-making practices (e.g., use of wood chips to provide flavors to young wine) and noncompliance with the rules on process documentation and quality certification (e.g., denomination of origin). In both cases, the frauds have a backward impact up to the production of grapes, whose quality and/or origin is not as expected by the wine production codes. In fact, the cost coefficients of agricultural production in the case of these two fraudulent activities are one half and one sixth, respectively, of the SAM coefficient of agricultural production cost for the wine industry (cf. Table B.1).

The same arguments can be advanced for the olive oil industry, where the frauds mostly refer to the quality (extra-virgin vs. virgin or lower quality oil) and origin (Italian vs. non-Italian oil) of the raw material. Again, the fraud

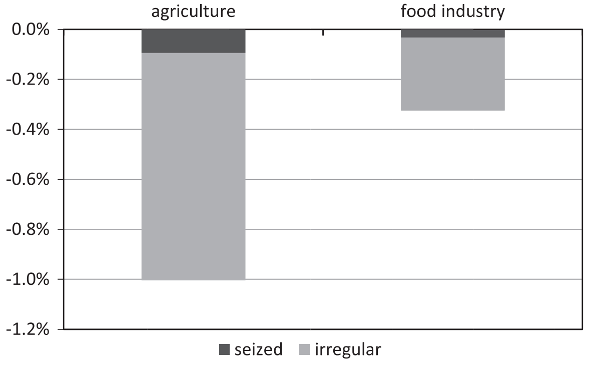

FIGURE 4 Impact on total output in the agro-food sectors (percentage changes, yearly average 2007–2015). Source: authors' elaboration

TABLE 5 Impact on output and employment in the agro-food sectors (percentage changes and absolute values, yearly average 2007–2015)

	Impact of all irregular products on			
	Output		Labor units	
Subsectors	M€	%	n.	%
Meat and production of meat products	−34	−0.16	−102	−0.17
Processing and preserving of fish, crustaceans and molluscs	−24	−1.30	−74	−1.36
Production of olive oil	−12	−0.48	−15	−0.48
Manufacture of other food products	−75	−0.17	−368	−0.17
Manufacture of processed vegetables and fruits products	−20	−0.22	−63	−0.22
Manufacture of dairy products	−59	−0.37	−192	−0.38
Manufacture of grain mill products, starches and starch products	−33	−0.74	−72	−0.77
Manufacture of prepared animal feed	−37	−0.78	−90	−0.79
Production of wine	−67	−1.07	−218	−1.21
Manufacture of other beverages	−22	−0.25	−77	−0.25
Specialist fields crop	−103	−1.04	−2,681	−1.04
Specialist permanent crops	−130	−1.01	−5,335	−1.10
Total agriculture	−468	−1.01	−12,507	−1.05
Total food industry	−382	−0.33	−1,271	−0.29

Source: Authors' elaboration.

committed by plants performing the whole process (i.e., pressing, refinery, and packaging), olive oil mills, and packaging companies heavily impact the olive production: the cost coefficient of the agricultural production in these three types of firms is 25%, 40%, and nil, respectively, as compared to the SAM cost coefficient for the olive oil industry (cf. Table B.2).

This is largely consistent with the findings of scholars who analyzed the vulnerability of various supply chains to food fraud, highlighting the key factors in terms of opportunities, motivations, and control measures (van Ruth et al., 2017, 2018). For instance, van Ruth, Luning, Silvis, Yang, and Huisman (2018) found that the top food fraud factors for the olive oil industry are mostly related to the raw materials.[6] Furthermore, in the case of the Italian olive oil industry, the opportunities offered by the very high payoff in a profitable industry and some structural features of the production units—specifically, small-medium size firms—can explain the lack of hard (i.e., technical) and soft (i.e., managerial) control systems to prevent food fraud.

Table 5 shows the breakdown of the estimated impacts by subsector when the value of total irregular production is considered. Overall, the agri-food sector loses more than 850 M€ of output and 13,700 labor units, mostly concentrated in agriculture, a combined effect of a larger output loss and a more labor-intensive production technology in agriculture. The impact on output is different across the various production activities, ranging from 0.17% in the "other food" subsector to 1.30% in the "fish processing and preservation" industry. As expected, the wine sector is one of the most impacted by fraud with a contraction of 1.07% of its output and a loss of 218 labor units (−1.21%). Coupling this result with that of specialized permanent crops, which includes a relevant share of

[6]The factors that were identified by van Ruth et al. (2018) as highly important in determining the vulnerability of the olive oil industry to fraud are the following: among the opportunities, "fraud detectability in raw materials," "fraud detectability in final products," and "historical evidence of fraud in raw materials"; among the motivations, "valuable components or attributes" and "level of competition branch of industry"; and among control measures, "verification of fraud monitoring system raw materials," "fraud monitoring system final products," "verification of fraud monitoring system final products," "information system own company," "tracking and tracing system own company," and "whistle blowing own company".

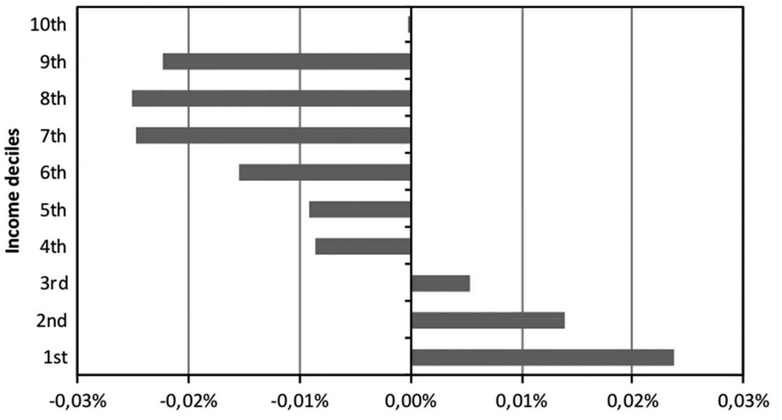

FIGURE 5 Impact on households' gross income (percentage changes by income deciles, yearly average 2007–2015).Source: authors' elaboration

farms directly producing wine (and olive oil), the picture is even gloomier: this component of agriculture loses 1.01% of its potential output and more than 5,300 labor units (−1.10%) because of food fraud.

A further interesting result concerns the redistributive effect of these impacts. Table 4 shows that food fraud decreases the gross income earned by households up to €174 million. This aggregate impact results from the combined effect of the average composition of fraud (in terms of industries affected) and the distributive features of the agri-food sector. The aggregate negative impact on the households' incomes is due to the lower backward linkages of irregular activities overriding the positive multipliers effect of additional final demand generated by the increased share of (illegal) profit distributed to households.

The aggregate gross income change is not equally distributed across households. Figure 5 shows how such an impact is distributed among deciles of equivalent per capita income. The impact seems to be slightly progressive, benefitting the lowest deciles and negatively affecting the middle and high-income deciles. A notable exception is represented by the highest decile, whose income is virtually unaffected. However, the overall change of household groups' relative position in income distribution is likely to be small.

6 | CONCLUDING REMARKS

The main contribution of this study is to propose an approach to carry out an economy-wide evaluation of the socioeconomic impact of food fraud in a given economy in a SAM-based, counterfactual framework. Building a suitable SAM of a given economy, with a complete and consistent set of accounts properly disaggregated to get a detailed representation of the agri-food system, makes possible the assessment of the share of the economy, which depends on the final demand supplied by irregular activities. The counterfactual approach we propose can be easily implemented to any country, provided that data on seized or irregular products is available along with a SAM of its economy. We implemented this approach with reference to Italy, a country featuring a highly competitive quality-oriented agri-food system where the incentives to commit food fraud are rampant. SAM simulations show that the share of the Italian economy directly and indirectly linked to supply of irregular food products accounts for 0.5% of the total value of output and 0.6% of total employment. Focusing solely on the agri-food sector, the total output activated by irregular product demand is much higher, accounting for 3.2% of output and 5.8% of employment. The heavy dependence of some value chains on the demand met by irregular production makes them vulnerable to the shocks deriving from food scandals/scares, especially if they feature relatively large price elasticities. Wine seems to be the most fragile value chain in Italy, considering that irregular products met roughly one fourth of its demand. Olive oil is also significantly prone to food fraud as almost 4% of its final demand is met by irregular products. These activities, through backward linkages, account also for 13% of the demand for permanent crop products.

Results from the counterfactual analysis show that the net impact of food fraud on the Italian economy is negative, leading to a loss of output and employment, while the impact on GDP is positive though very small. Looking at the agri-food system, the relative impact on output is far more important in agriculture (−1%) than in the food industry (−0.33%). The overall conclusion is that food fraud is not only a source of unfair competition to regular production activities, but also has an overall contractionary impact on the whole economy due to its character of directly unproductive rent-seeking activities (Bhagwati, 1982; Krueger, 1974).

Our analysis has two main policy implications. The large share of production activities reveals an intrinsic fragility of the system, especially in those subsectors featuring relatively large price elasticities such as quality products. Quite paradoxically, it is the attempt to vertically differentiate food products, for example through certification of geographic origin, which makes these value chains more vulnerable to the risk of fraud, as fraudsters can exploit the complexity of implemented quality assurance systems. Simplifying administrative procedures and designing an effective and efficient system of controls are key components of any policy for ensuring food safety and quality.

A second policy implication emerges from the counterfactual analysis. More effective approaches/tools to combat food fraud is not only a measure to increase the agri-food sector competitiveness in the global markets, but is also an effective pro-growth policy that is likely to produce positive impacts on employment in the short-run.

Although the proposed approach makes possible a systematic and rigorous assessment of the socioeconomic impact of food fraud in a given economy, it is worthwhile to emphasize the major limitations of our empirical application that could hopefully be addressed in future studies. Our dataset includes only data on food fraud *within* the country. Therefore, the impact of food counterfeiting of Italian products abroad, as in the case of the so-called "Italian sounding," is not accounted for: if considered, it would significantly increase the estimated impacts. These illegal activities can be easily included in the proposed framework through a change in the vector of the exogenous injection (i.e., export decrease due to the crowding out of Italian products in foreign markets generated by fraud) should reliable data on this food fraud be available.

A second limitation refers to the negative impact of food fraud on the reputation of products, thereby reducing consumers' willingness to buy those products or their willingness to pay for higher-quality products such as PGIs and PDOs (NFU Mutual, 2018). This negative effect on honest producers and the overall market has not been considered in the analysis because of lack of suitable data.[7] Should this data be available, it could be easily accommodated in the analysis modifying the vector of final demand for food products.

A final limitation is related to the linear nature of the SAM model, where consumption behavior is modeled through the average propensity to consumption of the different income groups. The inclusion of marginal propensities in the model, moving towards a so-called "fixed price" version of the linear model (Pyatt & Round, 1979) or toward the construction of a computable general equilibrium model, may allow a more accurate estimation of impacts, especially in subsectors featuring high demand elasticities such as those of quality differentiated products (e.g., wine, oil, cheese).

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[7]This results in a reduced estimate of the impact of food frauds as we assessed it. We thank the editor for highlighting this issue.

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APPENDIX A: BUILDING A SAM FOR THE ANALYSIS OF FOOD FRAUD IN ITALY

ISTAT provides both supply and use tables for the Italian economy, which are consistent with the System of National Accounts. Current price tables are available from 1995 onward and are based on the NACE rev. 1 classification for industries and CPA (Statistical Classification of Products by Activity) classification of products. We disaggregated the ISTAT 2009 table (ISTAT, 2016), which details 59 industries and corresponding products. In this table, agriculture and food industry are represented each by one production account. Furthermore, the commodity classification adopted in the ISTAT table includes only two products, namely "agricultural products" and "food products," produced by the corresponding industries.

In order to get a more detailed breakdown of the agro-food system that is consistent with available statistical information, we proceeded as follows:

- disaggregate the agro-food industry into 11 subsectors;
- disaggregate food commodity into 11 products, consistent with the food industry disaggregation;
- disaggregate agriculture into eight subsectors producing both the single "agricultural commodity" already present in the original SAM and the 11 food products according to the new disaggregation;
- include the disaggregated supply and use tables within the SAM of the Italian economy provided by IRPET for the same reference year (2009).

The original food industry branch (column in the use matrix) and the corresponding product (row in the supply table) were disaggregated into 11 more detailed branches/products, namely:

- Production of meat products,
- processing and preserving of fish, crustaceans, and molluscs,
- production of olive oil (virgin and refined),
- manufacture of other food products (vegetable oils and fats, sugar, bakery, and farinaceous products),
- manufacture of processed vegetables and fruits products,

- manufacture of dairy products,
- manufacture of grain mill products, starches, and starch products,
- manufacture of prepared animal feed,
- production of wine,
- manufacture of beverages,
- manufacture of tobacco products.

Within the supply and use framework the “use” (or “make”) table provides the production account for the whole economy disaggregated by groups of production units classified according to the nature of economic activity (industries). Each column of the use table shows the value at purchasing prices of goods and services used by each industry in the production process. So, the original overall values composing the aggregated food industry column represent a set of row constraints for the estimation of the 69 × 11 matrix of the disaggregated “use” account for the food industry (58 rows of non-food products plus 11 new rows replacing the original single “food” product).

Further information on the cells of the matrix to be estimated was collected from the following sources:

- EUROSTAT structural business statistics database (https://ec.europa.eu/eurostat/web/structural-business-statistics/data/database), which provides at the proper NACE disaggregation the values for total output, value added, wages and salaries for each year;
- ISTAT survey on industrial enterprises accounts (https://www.istat.it/it/archivio/13635), which is a yearly business survey which provides data on aggregated intermediate consumption and labor input as well as specific inputs such as energy consumption, transportation and commercial services, legal services, and so on;
- ISMEA 2003 use matrix of the Italian food system (ISMEA, 2009), which provides interindustry flows for the food industry at a disaggregated level, although using a classification not completely consistent with NACE: for example, while it provides a separate industry for olive oil it aggregates other vegetable and animal oils and fats to the other food product industry.

Building on the above-mentioned sources, we first made a tentative disaggregation of each cell of the original column into the 11 cells of each row of the 69 × 11 matrix. We got reliable disaggregated estimates of aggregated intermediate consumption by both ISTAT and Eurostat and we knew the row totals from the original ISTAT table. It was possible to use a bi-proportional procedure (the so-called rAs method; cf. Bacharach, 1965) to get more accurate and consistent estimates for the intermediate consumption use submatrix of the food industry. Wages were disaggregated building on Eurostat data.

The single row for food in the original 59 × 59 supply table was replaced by a 11 (commodity) rows by 69 (industry) columns matrix, with the inclusion of further columns for final uses, namely household consumption, gross investments, and exports. The estimates of interindustry flows were mainly based on data from the ISMEA matrix. Household consumption was disaggregated building on estimates from the ISTAT household budget survey, which was available at the micro level. We used a correspondence table to reallocate consumption based on the Classification of Individual Consumption by Purpose classification to the corresponding items of the CPA nomenclature. Export by individual food industries were directly obtained by export statistics at FOB prices by CPA from ISTAT, whereas gross investments were disaggregated proportional to the totals of the other components.

The disaggregation of agriculture was carried out on the supply and use table already including the subsectors of food industry and the disaggregated classification of food products. Given the focus on processed food, agriculture was disaggregated only as an industry, that is all eight subsectors composing agriculture in the disaggregated supply and use table provide only one “agricultural product” commodity.

The disaggregation of agriculture in the use table was based on microdata from the Farm Business Survey (FBS) carried out by ISTAT on a sample of representative farms of Italian agriculture. The survey is designed to support national accounts estimates for agriculture and includes information on the intermediate consumptions and labor inputs of farms. Farms were classified into eight subsectors according to the Type of Farming classification adopted at the European level within the Farm Accountancy Data Network (EU Regulation 2003/369) as follows:

- Specialized field crops,
- specialized horticulture,
- specialized permanent crops,
- specialized grazing livestock,
- specialized granivores,
- mixed cropping,
- mixed livestock,
- mixed crops-livestock.

The 69 × 8 matrix of estimates of intermediate consumptions for the subsectors of agriculture based on FBS data was used to disaggregate by row the single entries of the "Agriculture" column of the original use matrix. A similar approach was used to disaggregate entries referred to factors use (wages for employed labor, mixed income of self-employed labor) as well as net indirect taxes on production.

Farms are typically multi-product production units where the diversification of farm activity increased also the share of nonagricultural goods and services (e.g., processed food, tourism, etc.) supplied by farms. Furthermore, in the Italian agriculture, a considerable share of wine and olive oil production is produced and traded by farms. In the disaggregated version of the supply and use table, the eight subsectors corresponding to different Types of Farming supply a mix of agricultural products as well as other goods and services, including processed foods and restaurant and accommodation services. Therefore, the disaggregation of agriculture output in the supply table was based on additional information of products sold by different Types of Farming provided as Standard Results by the Farm Accounting Data System public database (http://ec.europa.eu/agriculture/rica/index.cfm.)

The SAM of the Italian economy provided by IRPET for the reference year (2009) included a supply and use table based on the ISTAT 2009 supply and use table. The industry and commodity classifications are consistent even though less disaggregated. Furthermore, despite little discrepancies due to the balancing of the matrix after the inclusion of the "social" component (i.e., income distribution and final consumption), the values of total output of industries and total supply of commodities are very close to those in the original supply and use ISTAT table. Therefore, the inclusion of the disaggregated supply and use table was quite straightforward, requiring only some simple adaptations.

Accounts for industries and commodities (except for agriculture and food industry and products) were reaggregated where necessary to make them consistent with the IRPET matrix disaggregation. Eventually, the SAM supply and use part includes 54 industries producing 64 commodities. In the original IRPET SAM, institutions purchase bundles of goods and services corresponding to 23 final consumption functions. Agriculture and food industry sell their products to consumers throughout the first two functions referred to purchases of food and beverages. Therefore, it was not necessary to disaggregate final consumption according to the new classification of commodities in the supply and use table.

The new accounts for agriculture and food industry subsectors in the SAM were balanced adjusting the value of depreciation in the disaggregation of value added, while the accounts for new food commodities were balanced adjusting variations in stocks. The final SAM includes a total of 183 accounts, namely: 64 commodities, 54 industries, 12 accounts for primary income distribution, 23 final consumptions functions, 18 accounts for current income use of institutions, nine accounts for capital formation, and three accounts for the rest of the world.

APPENDIX B: IRREGULAR ACTIVITIES' COST STRUCTURE ESTIMATION

The information needed to estimate the $\mathbf{A_f}$ matrix of expenditure coefficients for irregular production activities is difficult to obtain through a direct survey. Firms, by definition, disguise their noncompliance and are unlikely to provide insights on their costs and profits. This is the reason why, in building a "counterfactual" SAM referring to a hypothetical fully compliant agri-food system, we estimated the $\mathbf{A_f}$ matrix using information provided by 15 key informants who lead key functions within control bodies (the Central Inspectorate for Quality Protection and Fraud Repression in Agro-Food Products and the Agro-food Unit of the Italian Forest Service), research institutions (Council for Agricultural Research and Analysis of Agricultural Economics), producers associations (Italian Olive Consortium), and freelance professionals specialized in specific industries (wine and olive oil).

All the key informants are experts of the organization of production in the agri-food system across the country and can rely on the knowledge their own institutions and network of officers in decentralized offices of the institution they belong to. We did not try to get differentiated information on specific regional contexts (despite the fact that production conditions may differ among different areas) essentially because the SAM used in the analysis refers to Italy as a whole, that is it does not allow for disaggregation of expenditure coefficients (and the related impacts) at the subnational level. Furthermore, as emerged by the informants' answers, most fraud refers to "paper fraud" (e.g., incomplete or false documentation in the use of quality marks, such as PDO labels). The impact of these types of fraud on the production cost structure is likely to be the same across different regions.

A separate estimation of expenditure coefficients for irregular production activities was carried out only for the wine and olive oil industries that accounts for about two-third of detected irregularities and frauds. The elicitation of expert estimates entails the following steps:

- key informants were asked to qualitatively describe the most important frauds in the production of wine and olive oil,
- they were then asked to modify the wine and olive oil average cost structures (i.e., the SAM cost structures) to better represent the production activities of different production units;
- finally, they were asked to further modify the vector of costs to better represent cost structure of an average noncompliant production unit.

The expert estimates were averaged and the resulting vectors were sent back to them for a double check before being used in building the counterfactual model.

Starting from the expenditure coefficients of the "Wine industry" subsector of the SAM, the cost structure for irregular activities was estimated (Table B.1) for two most common types of fraud, namely wine produced adopting irregular wine-making practices (such as the use of wood chips to provide flavors to young wine) and wine marketed and not complying with administrative rules on process documentation and quality certification. Actually, the largest part of fraud in the wine supply chain may be described as a combination of these two forms of irregularities. As a result, in calculating the matrix of multipliers for the counterfactual "fraud-free" wine sector, we assumed that the structure of costs of the irregular activities was the simple average of the last two columns in Table B.1.

We assume these coefficients as representative of the average structure of costs in irregular wine production irrespective of the specific producing unit (e.g., farms or winery) where winemaking takes place. Farms included in the "specialized permanent crops" subsector are assumed to afford the same cost vector in processing grapes, wine ageing and bottling, although expenditure coefficients in the corresponding column of the SAM include also the costs for the "agricultural" part of wine production (vineyard cultivation). This assumption seems reasonable for two reasons. First in the disaggregation of production accounts to build the SAM each production unit is classified under a given "industry" according with a "prevalence" criterion in production. Activities included in the "wine industry" produce for the largest part wine, despite they might supply also other outputs, possibly including agricultural products. Second, wine processing (like other bio-based activities traditionally carried out also at the farm level) is a process with limited

TABLE B.1 The structure of costs in the production of wine
SAM average coefficients and irregular activities (% of the output value)

		Irregular activities	
	Wine industry SAM coefficients (%)	Irregular wine processing (%)	Administrative frauds (%)
Intermediate consumption			
Agricultural products	18.30	9.10	3.70
Wine	5.80	2.90	1.20
Electric power, natural gas, water	3.60	3.60	0.70
Chemical products	3.10	3.10	0.60
Non-metallic minerals	2.50	2.50	0.50
Financial services	5.60	2.80	1.10
Legal, professional and administrative services	9.60	9.60	9.60
Other goods and services	35.10	35.10	7.00
Wages	8.10	8.10	1.60
Profits	8.30	23.20	74.00

Abbreviation: SAM, social accounting matrix.

economies of scale compared to other manufacturing activities. Even though the production units classified under the "Wine industry" account in the SAM are likely to be larger than farms, it is reasonable to assume that the structure of production costs may be not so different when compared to that of wine production activities carried out in "specialized permanent crops" farms (the second most important subsector producing wine according to the SAM).

Different plants operate in the olive oil supply chain: whole-process plants, where all the phases of the production process are realized (extraction, refinery, and packaging); olive oil mills producing virgin olive oil (for final consumption or to be further processed in refineries); and packaging plants purchasing olive oil and marketing packed products (mostly represented in the wholesale trade service). The vectors of expenditure coefficients for these activities cannot be directly derived from the SAM. Oil extraction and packaging are simply parts of the activities in industries (such as "specialized permanent crops" and "wholesale trade services") where also several other production processes are carried out. We used secondary information on production costs (ISMEA, 2014, 2015, 2016) and assessments provided by key informants to "adjust" the structure of costs of the "olive oil industry" (the only sector in the SAM where production of olive oil is the prevalent activity) to better represent also other activities delivering olive oil to the market. Table B.2 shows the estimated cost structure of irregular activities in the three different production unit types, contrasting them with the average SAM coefficients resulting from the "olive oil industry" column.

In the derivation of the "counterfactual" matrix, we assumed that the three cost vectors in Table B.2 represent irregular olive oil in industrial activities ("olive oil industry" subsector), farm-based activities (all the subsectors of agriculture in the SAM producing olive oil), and the "wholesale trade service industry" of the SAM, respectively.

Regarding the other food subsectors (which account for a minor share of fraud), we assumed that the adoption of irregular practices in production and trade was able to determine the same advantages enjoyed on average by the operators in the wine and olive oil industry, tripling the value of output keeping constant the production cost (a conservative value, considering that according to experts' assessment the frauds in the wine and olive oil sectors can actually be as high as five times the value of output). Consequently, all coefficients representing the composition of intermediate consumption were divided by three. Only the cost for "professional and legal services" was assumed to be equal to that of the "averages" activities represented in the SAM.

TABLE B.2 The structure of costs in the production of olive oil
SAM average coefficients and irregular activities (% of the output value)

		Irregular activities		
	Olive oil industry SAM coefficients (%)	Whole-process plants (%)	Olive oil mills (%)	Packaging plants (%)
Intermediate consumption				
Agricultural products	33.90	8.50	13.40	0.00
Olive oil, virgin and refined	10.90	2.70	0.00	12.20
Electric power, natural gas, water	9.80	2.50	0.70	0.40
Waste management and remediation activities	0.90	0.20	0.10	0.00
Wholesale trade	4.60	1.20	0.20	0.20
Retail trade	2.60	0.60	0.10	0.10
Land transport and transport via pipelines	1.70	0.40	0.10	0.10
Warehousing and support activities for transportation	2.50	0.60	0.10	0.10
Other goods and services	29.40	7.30	2.20	1.10
Wages	3.50	0.90	1.90	0.10
Profits	0.20	75.00	81.30	85.70

Abbreviation: SAM, social accounting matrix.

A sensitivity analysis was carried out replicating the counterfactual analysis according to different hypotheses on the structure of costs in irregular activities, respectively, halving ("best" case) and doubling ("worst" case) the output value to intermediate costs ratio, relative to the "reference" estimate based on the expert estimates for wine and olive oil and our assumptions for other sectors. Figure B.1 shows how the results of the analysis change switching from the worst to the best-case scenario: the total output change of the whole economy generated by frauds ranges from −0.02% to −0.07% as compared to a reference estimate of 0.06%.

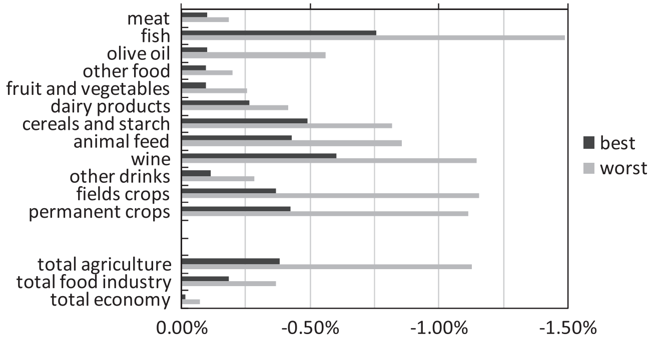

FIGURE B.1 Sensitivity analysis