Linking soy oil demand from the US Renewable Fuel Standard to palm oil expansion through an analysis on vegetable oil price elasticities

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Linking soy oil demand from the US Renewable Fuel Standard to palm oil expansion through an analysis on vegetable oil price elasticities

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Abstract

The United States (US) Renewable Fuel Standard and California's Low Carbon Fuel Standard support the use of soy biodiesel and renewable diesel in the transport fuel supply for climate mitigation. However, linkages between the markets for soy oil and palm oil, which is associated with very high land use change emissions, could negatively affect the climate performance of soy-based biofuels. This study estimates the own and cross-price elasticities for the supply of soy and palm oils in the US using country-level data from 1992 to 2016 under rational expectations, through a seemingly unrelated regressions system of equations. We find a positive cross-price elasticity of palm oil import with respect to soy oil price and a positive reaction of supply of soy oil to increase in prices of palm oil. These results suggest that US biofuel policies may underestimate substitution between soy and palm oils and thus overestimate the climate benefits from soy-based biofuel.

Key words: Biofuel; Price elasticity; Oils market; SURE.

JEL CODE: O13, P28, Q21, Q42

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1. Introduction

Biofuel policies in the United States (US), Europe, and other countries around the world have received great attention due to their potential market and environmental impacts (Sorda et al, 2010), including a significant increase in the amount of vegetable oil used in biodiesel and renewable diesel (US EIA, 2018; USDA FAS, 2017a). The significant increase in demand for these commodities (Gohin and Chantret, 2010; Chen and Onal, 2016) has likely increased prices of vegetable oils and other biofuel commodities and contributed to agricultural expansion globally; the resulting land-use change substantially increases the net GHG emissions from using biofuels (Malins et al., 2014). The net land use change emissions depend on the type of agricultural commodity whose production is expanding. Most notably, palm oil is generally associated with the highest land use change emissions of any biofuel feedstock (Valin et al., 2016; ARB, 2015; US EPA, 2012) because its expansion is strongly associated with the oxidation of carbon-rich peat soils (Miettinen et al., 2012; Page et al., 2011). However, an increase in the demand of one biofuel feedstock (for example, soy oil) does not affect the fundamentals (demand and supply) of that single feedstock market in isolation. If different types of agricultural commodities are substituted or complemented with one another, a change in the demand (and price) of a biofuel feedstock may change the supply (and price) of another commodity. Changes in price and demand are transmitted through markets, and the responsiveness of prices to demand (or supply) shocks can be inferred through analysis of price elasticity: thus, the characterization of price elasticities is fundamental to understanding the impacts of policy interventions in agricultural markets (Labandeira et al., 2017).

There are important climate and policy implications of cross-commodity interactions in biofuel feedstock markets. In particular, the US Renewable Fuel Standard (RFS) and California Low Carbon

Fuel Standard (LCFS) provide higher policy incentive value for biofuels with greater claimed GHG savings compared to petroleum (ARB, 2010, US EPA, 2010). Palm oil-derived biofuel does not qualify for any support in these policies (ARB, 2015, US EPA, 2012). Other vegetable oils, including soy and canola oil, qualify because the regulatory agencies administering these policies have assessed these feedstocks to have lower land use change emissions than palm oil (ARB, 2015, US EPA, 2010). As a result of these policy decisions, the US has experienced a dramatic increase in the use of soy oil in particular, and to a lesser extent, canola, corn and other oils over the past decade (Nelson & Searle, 2016). However, if the markets of these vegetable oils are linked with that of palm, the high demand for soy and other vegetable oils in US biofuel production could indirectly drive an increase in the production and supply of palm oil and associated land use change emissions.

Vegetable oil substitution is reflected in the regulatory analyses for these policies, but to a small degree; for example, the US Environmental Protection Agency's (EPA) analysis for the RFS found that only 3% of gross land expansion resulting from soy biodiesel demand is for new oil palm plantations, while 9% is for canola expansion and 73% is for soybean expansion (US EPA, 2010). If regulatory analyses underestimate the substitution effect between palm oil and other vegetable oils, they would underestimate the land use change emissions associated with those vegetable oils. The degree to which different vegetable oils substitute for one another is thus a critical factor in the overall climate impact of biofuel policies.

Substitution amongst vegetable oils can be reflected in the calculation of cross-price elasticities. Although the empirical literature on own-price and cross-price elasticities for vegetable oils in the US and in the EU is large (e.g. Labys, 1973, 1977; Goddard and Glance, 1989; Yen and Chern, 1992; Kojima *et al*., 2016; Cui and Martin, 2017), a vast majority of studies investigate the price elasticities of demand and there is little evidence available on price elasticities of supply. The literature provides mixed evidence on complementarity and substitutability effects in consumption. For instance, studies on cross-price elasticities of demand in the US market find palm and soy oils to be substitutes in consumption (Yen and Chern, 1992). In the EU market, studies have found the consumption of palm oil and soy oils to move together, with low and asymmetric cross-price elasticities (Labys, 1977). Moreover, there is evidence that US consumers tend to substitute canola oil and soy oil (Yen and Chern, 1992; Cui and Martin, 2017), while the consumption of soy oil and tallow move together (Labys, 1977; Goddard and Glance, 1989; Yen and Chern, 1992). The literature falls short on studies dedicated to the price elasticities of supply (PES).

The present study focuses on the US vegetable oil market. We examine how the supply of vegetable oils reacts to changes in prices in the US and quantify own-price and cross-price elasticities of supply. We use country-level data to estimate price elasticities using a Seemingly Unrelated Regression Equations (SURE) model, in a Two-Stage Least Square (2SLS) fashion using instrumental variables.

2. Trends in US vegetable oil markets (1992-2016)

Production and trade of US vegetable oils increased substantially over the period 1992-2016 (table 1). The US is a net importer of palm oil and does not have significant domestic production. Similarly, the US is a net importer of canola oil (17,920 Tg imported in 2016). On the other hand, the US is a large producer and net exporter of soybean oil.

TABLE 1 ABOUT HERE

Since the 1990s, the prices of soy, palm, and canola oils in the US market have followed a similar pattern, suggesting a high degree of market integration across commodities. The price of canola oil is highest and the price of palm oil is lowest among major vegetable oils traded in the US.

FIGURE 1 ABOUT HERE

Soy, palm, and canola are the three most heavily consumed oils/fats in the US, except for corn oil (table 2). We excluded corn oil from our analysis because it is a byproduct of corn starch production, representing only 5% of the corn grain by market value, and its supply is thus very unlikely to respond to changes in its price.

TABLE 2 ABOUT HERE

3. Methodological framework

3.1 The economic model

Our analysis is based on the standard profit-maximization theory of production, which assumes that producers aim to maximizing their profit. Key variables in producers' decision-making process include expectations on future prices. In particular, the supply quantity for good *i* may be described, *ceteribus paribus*, as a function of expected prices:

$$Q_i = f(E[P_i|\Omega\,], E[P_j|\Omega\,], \boldsymbol{Z})$$

where $E[\cdot]$ is the expectation operator, Ω stands for the information set (including all useful information to forecast prices that are available to producers), and $\boldsymbol{Z}$ is the matrix that collects all control factors. The economic theory predicts $f_{P_i}^{'}$ (the own-price elasticity) to be non-negative, and $f_{P_j}^{'}$ (the cross-price elasticity) to be negative (positive) for substitutes (complements) in production.

3.2 Estimation method

We estimate cross- and own-PES for different combinations of vegetable oils in the US markets. We use a 2SLS procedure following the approach of Dahl and Duggan (1996). We use instrumental variables (IVs) to forecast the variable (say, the variable A) with respect to which the elasticity will be estimated (say, the elasticity of B with respect to A), and then we use the predicted values (say, the forecasted A) to assess the PES (again, the elasticity of B with respect to A). The use of IVs allows us to deal with the identification problem that may affect the estimation of price elasticities (*cfr.* Angrist *et al.*, 1996; Imbens, 2014; Santeramo, 2015). Following Roberts and Schlenker (2013), we use weather-induced shocks, lagged yield and time trend as instruments for the supply[1]. The empirical specification of the first stage is as follows:

$$\ln\left(P_{i,t}^{k}\right) = \alpha_i + \beta_i \ln P_{i,t-1}^{k} + \sum\nolimits_{l=0}^{T} \gamma_{i,t}\, Weather\ shocks_{i,t-l}^{k} + \sum\nolimits_{n=1}^{2} \vartheta_n\ Time\ trend^{n} + \nu_i \tag{1}$$

where *i* and *k* index, respectively, the commodity and the market; the left hand side (LHS) is the logarithm of the price of the vegetable oil, $\ln\left(P_{i,t}^{k}\right)$; the right hand side (RHS) includes weather shocks (a flexible form for temperature and precipitation), lagged yield and a flexible form of time trend. The weather shocks are included following the approach in Roberts and Schlenker (2013).

The second stage assesses how changes in prices affect supply (the supply elasticity of B with respect to the forecasted A). We use a rational expectation framework (Nerlove, 1972, 1979): the expected prices equal realized prices with one period (one year) lag. The assumption is reasonable in that the planting decisions and the import decisions have different timing with respect to realized prices. In fact, planting decisions are made one year before harvest for the annual crops produced in the US (and very limited adjustments can be made to the planted area), while import decisions are made assuming that the price of imported commodities tend to reflect the expected price at the destination. The resulting econometric specification is as follows:

$$\ln\left(Q_i^k\right) = \varphi_i + \varepsilon_{i,i} \ln\left(E_{t-1}\left[\widehat{P_i^k}\right]\right) + \varepsilon_{i,j} \ln\left(E_{t-1}\left[\widehat{P_j^k}\right]\right) + CF + \nu_i \tag{2}$$

where the logarithm of the dependent variable (supply of the *i-th* commodity in market *k*), $\ln\left(Q_i^k\right)$, is regressed on the expected price (at time *t-1*) for the commodity *i*, $\ln\left(E_{t-1}\left[\widehat{P_i^k}\right]\right)$, and on the expected price (at time *t-1*) of the *j-th* commodity, $\ln\left(E_{t-1}\left[\widehat{P_j^k}\right]\right)$, and CF stands for control factors (following

[1] We gratefully acknowledge the suggestion of the reviewer to follow the approach of Roberts and Schlenker (2013).

Roberts and Schlenker, 2013) that we have excluded from stage-two (the lagged yield shocks which have been used as instruments). The prices of commodity *i* and commodity *j* are forecasted in the first stage (equation 1), and expressed in log form. The equation allows us to estimate the constant terms, φ_i, and the coefficients $\varepsilon_{i,i}$ and $\varepsilon_{i,j}$, which are, respectively, the own-PES and the cross-PES. The notation ν_i indicates the error term. The double-log specification allows us to interpret the estimated parameters ($\varepsilon_{i,i}$ and $\varepsilon_{i,j}$) directly as price elasticities (PES).

We opt for a Seemingly Unrelated Regression (SURE) system of equations to estimate the parameters of interest in a more efficient way compared to the estimates that would be provided through equation-by-equation OLS estimations. In fact, due to the correlation of the error terms, ν_i, the cross-equations relationships captured by the SURE system increase the efficiency of the estimates (Zellner, 1962). Based on equation (2), we derive the SURE system of interest:

$$\begin{cases} \ln(Q_1^{US}) = \varphi_1 + \varepsilon_{1,1}\ln\left(E_{t-1}\left[\widehat{P_1^{US}}\right]\right) + \varepsilon_{1,2}\ln\left(E_{t-1}\left[\widehat{P_2^{US}}\right]\right) + \varepsilon_{1,3}\ln\left(E_{t-1}\left[\widehat{P_3^{US}}\right]\right) + CF + \nu_1 \\ \ln(Q_2^{US}) = \varphi_2 + \varepsilon_{2,1}\ln\left(E_{t-1}\left[\widehat{P_1^{US}}\right]\right) + \varepsilon_{2,2}\ln\left(E_{t-1}\left[\widehat{P_2^{US}}\right]\right) + \varepsilon_{2,3}\ln\left(E_{t-1}\left[\widehat{P_3^{US}}\right]\right) + CF + \nu_2 \\ \ln(Q_3^{US}) = \varphi_3 + \varepsilon_{3,1}\ln\left(E_{t-1}\left[\widehat{P_1^{US}}\right]\right) + \varepsilon_{3,3}\ln\left(E_{t-1}\left[\widehat{P_3^{US}}\right]\right) + \varepsilon_{3,2}\ln\left(E_{t-1}\left[\widehat{P_2^{US}}\right]\right) + CF + \nu_3 \end{cases} \quad (3)$$

where the commodities are indexed by ordinal numbers in subscript: 1 stands for palm oil, 2 indicates soy oil, and 3 relates to canola oil.

3.3 Interpretation of own- and cross-PES

The price elasticities (PES) measure how supplied quantities react to changes in prices. The own-PES ($\varepsilon_{i,i}$) quantifies how the supply reacts to changes in its own price:

$$\varepsilon_{i,i} = \frac{\partial Q_i}{\partial P_i}\frac{P_i}{Q_i} \quad (5)$$

where $\varepsilon_{i,i}$ is the own-PES. The own-PES represents the percent change in the supplied quantity of a commodity due to a one percent change in the price of that same commodity. The cross-PES ($\varepsilon_{i,j}$) quantifies how the supply reacts to a change in price of a different commodity:

$$\varepsilon_{i,j} = \frac{\partial Q_i}{\partial P_j}\frac{P_j}{Q_i} \tag{6}$$

where $\varepsilon_{i,j}$ is the cross-PES. The cross-PES represents the percent change in supplied quantity of a commodity due to a one percent change in price of another commodity.

The supply is defined as price elastic when the percent change in supply induced by a one percent change in price is greater than one ($|\varepsilon| > 1$); *vice versa*, the supply is said to be price inelastic if the percent change in supply induced by a one percent change in price is smaller than one ($|\varepsilon| < 1$).

3.4 Data description

We use country-level data that covers 25 years from 1992 to 2016. The dataset includes data on soy oil, palm oil, and canola oil. The data for market fundamentals (in Tg) have been collected from the USDA FAS PSDO[2]. The net domestic consumption variable has been computed by summing production and imports and subtracting exports. The spot prices of vegetable oils are expressed in US$/Mt, and have been collected from the USDA Economics, Statistics and Market Information System[3]. Table 3 summarizes the descriptive statistics of key variables[4].

TABLE 3 ABOUT HERE

4. Results and discussion

4.1. Estimation of the supply elasticities

We find a high correlation between canola and soy oil prices (above 0.95) which could lead to collinearity in the analysis; we thus excluded canola oil and restricted the system of equations to focus

[2] Available at https://apps.fas.usda.gov/psdonline/app/index.html#/app/home, accessed in September 2016. Specifically, collected data concern annual production, domestic consumption, export and import, and oil crush, for the US.

3 Data on oil crops are available at http://usda.mannlib.cornell.edu/MannUsda

[4] Crush represents the total weight of the whole oilseeds, therefore the quantities shown for crush tend to be higher than those shown for production.

on the cross-price relationships between soy and palm oils. The system has been estimated by controlling for weather variables and time trends, as in Roberts and Schlenker, 2013. The results of the second stage of the 2SLS are reported in table 4. In line with economic theory, the own-PES for soy oil is positive and statistically significant. However, the quantity of palm oil imports does not react to changes in the US price of palm oil. The elasticity of palm oil supply to soy oil price is positive and above one (1.23), indicating that an increase in soy oil price results in a more than proportional increase in palm oil supply. The elasticity of soy oil supply to palm oil price is statistically significant, positive and below one (.142), suggesting that the soy oil supply reacts weakly to changes in palm oil price (table 4).

TABLE 4 ABOUT HERE

Our finding that soy oil supply is inelastic to price is logical because soy oil accounts for only around one-third of the total market value of soybeans; most of the value of soybeans is in the protein-rich meal (calculated with prices from USDA FAS, 2017b, and soybean meal yield from Purcell et al., 2000). Soybean expansion should thus be expected to respond mainly to soy meal price and only weakly to soy oil price. In contrast, the supply of palm oil, for which the US is a net importer, is more responsive to soy oil price changes.

In order to test the robustness of our results, we performed sensitivity analyses. First, we estimated the own-price elasticity for US soy oil (through a 2SLS procedure) with data at a higher frequency to test the robustness of data frequency. Second, we estimated the cross-price and own-price elasticities of vegetable oils in the US using an autoregressive distributed lag (ARDL) co-integration approach. Our findings confirm the results presented in the paper. The econometric results are omitted for brevity and available upon request.

5. Conclusion and Policy Implications

5.1. Policy implications of the results

The findings presented here suggest that an increase in the demand for soy oil driven by US biofuel policies (and the consequent increase in domestic price for soy oil) may result in a relatively modest increase in soy oil production compared to the change in palm oil imports. These results challenge those of the ARB LCFS and of the US EPA (2010): the latter projected that an increase in soy oil demand would result mostly in an increase in soy oil production. Notably, the US EPA (2010) results are ex-ante projections, while our results are an ex-post assessment of the policies.

The significant response of the palm oil market to changes in soy oil price suggests that support for soy biodiesel and renewable diesel in US federal and state policies is inadvertently exacerbating the environmental and climate damage from oil palm expansion. The palm oil industry has been expanding rapidly, and in addition to driving high GHG emissions from peat oxidation, leads to deforestation and a significant loss in biodiversity (Petrenko et al., 2016). The findings presented here suggest that the high land use change emissions associated with palm oil may be under-represented in regulatory analyses of US soy biofuel. The results presented here suggest that the net GHG emissions from soy biofuel demand are significantly higher than projected under current policies. The RFS and LCFS may thus overestimate the GHG savings from soy biodiesel and renewable diesel. In addition, these findings call into question EPA's determination that biomass-based diesel derived from soybean oil qualifies as an advanced renewable fuel (i.e., a fuel with at least 50% lower GHG emissions than petroleum diesel).

5.2 Final remarks

Our estimates of own- and cross-PES suggest that increases in the price of soy oil have a considerable impact on imports of palm oil but a limited effect on soy oil supply. We conclude that increasing soy oil demand due to US biofuel policies may be contributing to the expansion of oil palm plantations with associated high land use change emissions from deforestation and peat oxidation. US regulatory analyses do not appear to sufficiently account for the magnitude of this effect and may thus overestimate the GHG savings from soy biodiesel and renewable diesel. We recommend that US EPA redo its analysis of the GHG intensity of soy biodiesel taking into account the strong impact of soy oil demand on palm oil imports.

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Table 1. Production, imports, exports, and trade balance of vegetable oils in the US (annual averages, from 1992 to 2016).

	Unit	1992-2004				2005-2016			
		Production (A)	Exports (B)	Imports (C)	Trade Balance (B-C)	Production (A)	Exports (B)	Imports (C)	Trade Balance (B-C)
US									
Canola oil	Tg	2,423	958	4,877	-3,919	5,528	1,959	12,943	-10,984
Palm oil	Tg	0	51	1,731	-1680	0	221	10,397	-10,176
Soy oil	Tg	76,962	8,365	337	+8028	92,381	10,185	677	+9508

Source: Authors' elaboration on USDA FAS PSDO[5] (2016). Tg stands for 10^{12}g

Table 2 - 2017 statistics of major oils and fats in U.S. market

Commodity	Share of total U.S. oil/fat market	Share of total U.S. biodiesel production	Oil/fat as value share of main crop	Sources
Soybean oil	49%	55%	31%	USDA, EIA
Canola oil	14%	13%	67%	USDA, EIA
Corn oil	12%	14%	5%	USDA, EIA, ICF
Palm oil (including palm kernel oil)	10%	No data	95%	USDA, EIA, ICF
Tallow	5%	No data	1%	USDA, EIA, ICF

Sources: USDA, Oilcrops Yearbook; U.S. Energy Information Administration, Monthly Biodiesel Production Report with data for July 2018; ICF, Waste, Residue and By-Product Definitions for the California Low Carbon Fuel Standard.

[5] United States Department of Agriculture's Foreign Agricultural Service, Production, Supply, and Distribution Online.

Table 3. Descriptive statistics of the dataset

	Variable	Measure units	Min	Max	Median	Mean	Std. Dev.
Soy oil	Production	Tg	62.5	102.17	85.68	84.36	10.33
	Imports		0.05	1.39	0.37	0.50	0.39
	Exports		4.25	15.24	9.22	9.24	3.07
	Domestic consumption		58.57	93.21	76.43	77.18	9.73
	Net domestic consumption		55.92	92.87	74.98	75.63	10.10
	Crush		347.16	530.7	452.30	446.01	47.82
	Price	$/tonne	310.63	1,172.85	600.42	658.02	246.69
Palm oil	Production	Tg	0.00	0.00	0.00	0.00	0.00
	Imports		0.99	13.04	3.49	5.89	4.60
	Exports		0.02	0.42	0.09	0.13	0.11
	Domestic consumption		0.91	12.75	3.28	5.71	4.52
	Net domestic consumption		0.93	12.89	3.40	5.76	4.52
	Crush		0.00	0.00	0.00	0.00	0.00
	Price	$/tonne	235.00	1,154.00	523.00	586.13	245.51
Canola oil	Production	Tg	0.59	7.10	3.78	3.91	1.82
	Imports		3.96	17.92	5.55	8.75	4.77
	Exports		0.07	3.01	1.23	1.44	0.76
	Domestic consumption		4.50	23.72	8.49	11.22	6.27
	Net domestic consumption		4.48	23.71	8.05	11.22	6.23
	Crush		0.36	17.40	9.01	9.27	4.4
	Price	$/tonne	377.21	1,447.10	681.00	774.01	288.50

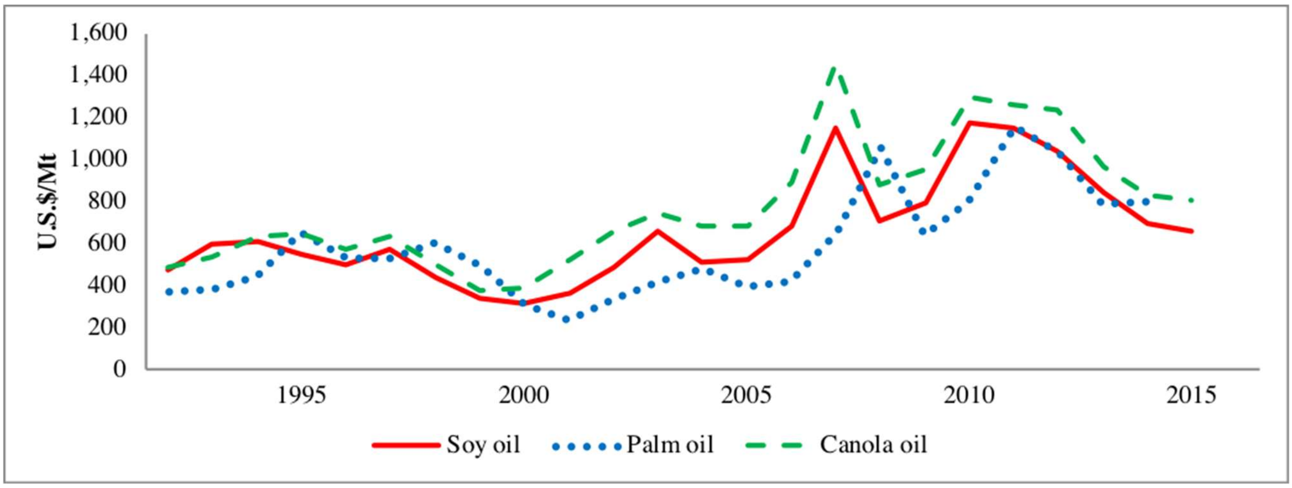
Tg stands for 1012g

Table 4. Own-price and cross-price elasticities of supply

		SUPPLIED QUANTITY	
		Soy oil	Palm oil
ESTIMATED PRICE	Soy oil	.189*** (.052)	1.23*** (.484)
	Palm oil	.142*** (.031)	.344 (.294)
	Control factors	YES	YES

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control factors include weather variables and time trends

Figure 1. Prices of vegetable oils in the US domestic market, from 1992 to 2016.



Source: Authors' elaboration on USDA AMS[6], USDA ERS[7] (2016).

[6] United States Department of Agriculture's Agricultural Marketing Service.

[7] United States Department of Agriculture's Economic Research Service.

Appendix

Table A - 2017 statistics of major oils and fats in U.S. market

Commodity	Share of total U.S. oil/fat market	Share of total U.S. biodiesel production	Oil/fat as share of main crop	Sources
Soybean oil	49%	55%	31%	USDA, EIA
Canola oil	14%	13%	67%	USDA, EIA
Corn oil	12%	14%	5%	USDA, EIA, ICF
Palm oil (including palm kernel oil)	10%	No data	95%	USDA, EIA, ICF
Tallow	5%	No data	1%	USDA, EIA, ICF

USDA, Oilcrops Yearbook, https://www.ers.usda.gov/data-products/oil-crops-yearbook/oil-crops-yearbook/#Soy%20and%20Soybean%20Products
U.S. Energy Information Administration, Monthly Biodiesel Production Report with data for July 2018, https://www.eia.gov/biofuels/biodiesel/production/biodiesel.pdf
ICF, Waste, Residue and By-Product Definitions for the California Low Carbon Fuel Standard, file:///Users/stephaniesearle/Downloads/LCFS_Biofuel_Categorization_Final_Report.pdf