Biofuel Substitution in the U.S. Transportation Sector*

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Abstract:

We investigate biofuel substitution in the U.S. transportation sector, for the period from 1990 to 2017, using the normalized quadratic model. We relax the homoskedasticity assumption and instead assume that the covariance matrix of the errors of the flexible demand system is time-varying. We generate inference consistent with neoclassical microeconomic theory and the data generating process. Our results show that there is a small, but statistically significant substitution possibility between biofuel and natural gas, as well as between biofuel and oil, when the prices of fossil fuels change.

JEL classification: C32, Q42.
Keywords: Biofuels; Interfuel substitution; Normalized quadratic.

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1 Introduction

We present an econometric analysis of biofuel substitution in the United States transportation sector. An investigation of substitution between fuel ethanol (henceforth, biofuel) and fossil fuels (oil and natural gas) in the transportation sector has relevance, from both economic, energy, environmental, and policy related points of view. In 2017, the total transportation-related final demand in the United States was about $1.7 trillion, or 8.8% of GDP. This sector consumes about 14.02 million barrels of petroleum per day which accounts for about 71% of total U.S. oil consumption, and generates 28.5% of U.S. greenhouse gas (GHG) emissions (EPA, 2019). Consequently, efforts to promote biofuels consumption have intensified in the past few years, and the U.S. Congress and many states have adopted numerous biofuel policies, such as performance standards, subsidies, and mandates to increase the use of ethanol and biodiesel in the U.S. transportation sector — see Collins and Duffield (2005) for more details. As a result, interest in the use, and the substitution possibilities between biofuels and fossil fuels, is increasing and has attracted a great deal of attention.

There has been a large number of studies investigating interfuel substitution with most of these studies taking the approach of using a flexible functional form for the underlying aggregator function, following Diewert's (1971) influential paper. See, for example, Berndt and Wood (1975), Fuss (1977), Pindyck (1979), Considine (1989), Hall (1986), Serletis and Shahmoradi (2008), Serletis *et al.* (2010), Jadidzadeh and Serletis (2016), Hossain and Serletis (2017), and Serletis and Xu (2019), among others. However, most of the studies on sectoral interfuel substitution investigate the industrial sector while studies on the demand for energy and interfuel substitution in the transportation sector are scant — see Hossain and Serletis (2017) for a brief review of the literature. In fact, most of these earlier studies consider traditional fuels — coal, petroleum products, electricity, and natural gas — and do not include renewable energy.

In this regard, very few earlier studies that analyze renewable energy investigate the use of biomass as a residential fuel in developing countries — see, for example, Shukla and Moulik (1986) and Bhatia (1987), among others. On the other hand, recently Jones (2014) examines the biomass substitution in the U.S. industrial sector and Dumortier (2013) and Moore *et al.* (2013) examine the potential role of biomass as an alternative fuel for electric power generation for residential and other users. Also, Tsita and Pilavachi (2013) examine the use of gasified biomass in the transportation sector. However, very few studies deal with the demand and elasticities of substitution between traditional fossil fuels and biofuels in the transportation sector. Consequently, relatively little is known about this issue despite the increase in the number of studies on transportation energy demand. An exemption is Suh (2019), who uses the dynamic linear logit model, developed by Considine and Mount (1984), to provide estimates of elasticities of substitution between ethanol, biodiesel, natural gas, and petroleum in the U.S. transportation sector.

In this paper we are interested in biofuel substitution in the U.S. transportation sector, an issue that has become an important topic of inquiry in recent years as governments around the world seek to set policies that are intended to restrain carbon emissions or steer economies toward or away from certain fuels. We investigate biofuel substitution in the context of the locally flexible Normalized Quadratic (NQ) cost function, developed by Diewert and Wales (1988). We contribute to the literature by merging the interfuel substitution literature with the recent advances in financial econometrics. More specifically, we follow Serletis and Isakin (2017) and Serletis and Xu (2020), and relax the homoskedasticity assumption in the fuel demand system and allow the covariance matrix of the errors in the demand system to be time-varying. In doing so, we use the Baba, Engle, Kraft, and Kroner (BEKK) GARCH(1,1) representation for the conditional covariance matrix, and achieve superior modeling in the context of a parametric nonlinear fuel demand system that captures the uncertain nature of the fuel demand.

The main findings of the study are that interfuel substitution is generally low, but there exist substitution possibilities between biofuel and fossil fuels in the U.S. transportation sector. We find that a $0.20-per-gallon increase in the price of oil (holding the price of biofuel constant) leads to a 1.6% increase in the relative demand of biofuel. This is equivalent to an increase of about 21.8 million gallons in biofuel consumption in the U.S. transportation sector. These estimates can be critical for designing, implementing, and evaluating policies to promote the use of ethanol in the U.S. transportation sector.

The rest of the paper is organized as follows. Section 2 provides a brief description of the data. Section 3 describes related neoclassical microeconomic theory in the context of cost minimization. Section 4 presents the NQ cost function and discusses related econometric issues related to the estimation of the NQ fuel demand system with heteroskedastic disturbances and the imposition of the curvature conditions for theoretical regularity. Section 5 presents the full NQ fuel demand model with a BEKK specification for the covariance matrix. Estimation results, with a full set of elasticities of substitution, are discussed in Section 6. A conclusion and policy suggestions are given in the final section.

2 The Data

We use annual price and quantity data for one output — total transportation-related final demand, y — and three fuel inputs — biofuel (or fuel ethanol), b, natural gas, g, and oil (or motor gasoline), o — for the transportation sector in the United States, over the period from 1990 to 2017. The annual fuel specific price and consumption data are obtained from the Annual Energy Review published by the Energy Information Administration (EIA), with the exception of fuel ethanol for which the price series is obtained from the U.S. Department of Agriculture. Total transportation-related final demand (in billions of current dollars) is obtained from the Bureau of Transportation Statistics, and the GDP deflator (2012 = 100) was accessed from the FRED website. Based on the categories of the EIA, we define the quantity of biofuel as the fuel ethanol excluding denaturant consumed by the transportation sector whereas natural gas and oil is defined as the natural gas and motor gasoline consumed by the transportation sector, respectively.

The Energy Information Administration reports the quantities of the energy goods in different units. In particular, the quantity of fuel ethanol, natural gas, and motor gasoline is expressed in trillion Btu, billion cubic feet, and thousand barrels, respectively. On the other hand, the price of fuel ethanol, and motor gasoline is expressed in dollars per gallon while that of natural gas is expressed in dollars per thousand cubic feet. For comparability across disparate fuel types, we convert all the quantities in billion Btu, and the prices into cents per billion Btu (in real terms using the GDP deflator), using the EIA conversion rates as follows

General conversion:	1 barrel = 42 gallons
Ethanol:	1 barrel = 3,556,000 Btu
Natural Gas:	1 cubic foot = 1,029 Btu
Motor Gasoline:	1 gallon = 120,429 Btu.

The use of the three energy inputs (biofuel, natural gas, and oil) in the U.S. transportation sector, over the period 1990 through 2017, is given in Figure 1. As can be seen, the transportation sector is heavily dependent on the use of oil and the use of natural gas has been stable over the last few decades. On the other hand, biofuel use in this sector has increased sharply from 2002, and since 2008 the use of biofuel surpassed that of natural gas. Oil accounted for about 54% of total U.S. transportation sector energy consumption in recent times. However, biofuel is becoming increasingly popular as a fuel additive, and it has made a significant inroad into transport energy consumption over the past decade, and accounted for 5% of this sector's energy consumption while that of natural gas is 3% during this period. Figure 2 plots the retail prices of the energy inputs over time. The price of oil (refiner price of finished motor gasoline to end users) varies considerably during the sample period without any obvious long-run trend. The price of gas (citygate natural gas) is fairly stable during the whole sample period while that of biofuel (fuel ethanol) is consistently stable at a very low level. In general, the prices of natural gas and oil moved together and that of biofuel follows a similar trend.

3 Methodology

We follow Fuss (1977) and assume a production function that, in the general case with n energy inputs, is homothetically weakly separable in energy from the non-energy inputs as follows

$$Y = f\left(E\left(\boldsymbol{x}\right), \boldsymbol{M}\right) \tag{1}$$

where Y is gross output, $E(\cdot)$ is a homothetic aggregator function over the n energy goods, $\boldsymbol{x} = (x_1, ..., x_n)$, and $\boldsymbol{M}$ is a vector of other non-energy goods.

Using duality theory of cost and production functions [see Diewert (1974)] the corresponding weakly separable cost function is

$$C = g\left(P_E\left(\boldsymbol{p}\right),\ \boldsymbol{p}_z, Y\right)$$

where $\boldsymbol{p} = (p_1, ..., p_n)$ is the corresponding price vector of the n energy goods, $\boldsymbol{p}_z$ that of the non-energy goods, and $P_E(\cdot)$ is an energy price aggregator function which is a homothetic function and can be represented by a unit cost function as

$$C = C\left(\boldsymbol{p}, y\right) = yc\left(\boldsymbol{p}\right) \tag{2}$$

with the second equality assuming constant returns to scale. In equation (2), C is a non-decreasing, linearly homogeneous and concave function of prices, $\boldsymbol{p} > 0$, and $c\left(\boldsymbol{p}\right)$ is the corresponding unit cost function.

3.1 The NQ Cost Function

We follow Serletis *et al.* (2010), Jadidzadeh and Serletis (2016), Hossain and Serletis (2017), and Serletis and Xu (2019) and use a locally flexible functional form, the normalized quadratic (NQ) cost function, introduced by Diewert and Wales (1987). The NQ function can approximate an arbitrary twice continuously differentiable function to the second order at an arbitrary point in the domain. Moreover, the theoretical concavity (or curvature) conditions for this function can be imposed globally without losing its flexibility property. See Diewert and Wales (1987), Diewert and Fox (2009), and also Barnett and Serletis (2008) for more details regarding the NQ flexible functional form.

For a given level of output, y, and a price vector of energy goods, p, the NQ model for n energy inputs is given by

$$C(\boldsymbol{p}, y) = y \left[\sum_{i=1}^{n} b_i p_i + \frac{1}{2} \frac{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} p_i p_j \right)}{\left(\sum_{i=1}^{n} \alpha_i p_i \right)} \right] \tag{3}$$

where $\boldsymbol{b} = [b_1, b_2, \ldots, b_n]$ and the elements of the $n \times n$ matrix $\boldsymbol{B} \equiv [\beta_{ij}]$ are the unknown parameters to be estimated. We follow Feng and Serletis (2008) and impose the following two restrictions on the $\boldsymbol{B}$ matrix

$$\begin{aligned} \beta_{ij} &= \beta_{ji}, \qquad \text{for all } i, j; \\ \boldsymbol{B}\boldsymbol{p}^* &= \mathbf{0}, \quad \text{for some } \boldsymbol{p}^* > \mathbf{0} \end{aligned} \tag{4}$$

and treat the non-negative vector $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \ldots, \alpha_n]$ as predetermined so that $\sum_{i=1}^{n} \alpha_i = 1$ — see also Diewert and Fox (2009) for more details.

We apply Shephard's lemma to (3) to obtain the NQ energy demand system (in input-output form)

$$\frac{x_i}{y} = b_i + \frac{\left(\sum_{j=1}^{n} \beta_{ij} p_i \right)}{\left(\sum_{i=1}^{n} \alpha_i p_i \right)} - \frac{1}{2} \frac{\left(\alpha_i \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} p_i p_j \right)}{\left(\sum_{i=1}^{n} \alpha_i p_i \right)^2}. \tag{5}$$

3.2 Interfuel Substitution

The primary interest, central to this study, are the elasticities of substitution of fuel demand. Once the energy demand system is estimated, we can calculate several commonly used measures of elasticity of substitution to assess the substitutability/complementary relationship between the energy inputs. In particular, we use the Allen-Uzawa elasticities of substitution, Morishima elasticities of substitution, and the own- and cross-price elasticities.

The Allen-Uzawa elasticity of substitution between energy inputs i and j is given by

$$\sigma_{ij}^{a}\left(\boldsymbol{p},y\right)=\frac{C\left(\boldsymbol{p},y\right)C_{ij}\left(\boldsymbol{p},y\right)}{C_{i}\left(\boldsymbol{p},y\right)C_{j}\left(\boldsymbol{p},y\right)} \tag{6}$$

where the i,j subscripts refer to the first and second partial derivatives of $C\left(\boldsymbol{p},y\right)$ with respect to energy prices p_i and p_j. If $\sigma_{ij}^{a}>0$ (that is an increase in the jth price increases the optimal quantity of energy input i), the energy inputs i and j are Allen-Uzawa (net) substitutes. If $\sigma_{ij}^{a}<0$, they are Allen-Uzawa (net) complements.

However, the Allen-Uzawa elasticity of substitution may be uninformative in the case with more than two goods. In particular, as suggested by Blackorby and Russell (1989), when there are more than two goods, the relationship becomes complex and depends on things such as the direction taken toward the point of approximation. In that case, it is appropriate to use the Morishima elasticity of substitution, given by

$$\sigma_{ij}^{m}\left(\boldsymbol{p},y\right)=\frac{p_{j}C_{ij}\left(\boldsymbol{p},y\right)}{C_{i}\left(\boldsymbol{p},y\right)}-\frac{p_{j}C_{jj}\left(\boldsymbol{p},y\right)}{C_{j}\left(\boldsymbol{p},y\right)}. \tag{7}$$

If $\sigma_{ij}^{m}>0$ (that is, if increasing the j^{th} price increases the optimal quantity of energy input i relative to the optimal quantity of energy input j), then energy input j is a Morishima (net) substitute for energy input i. If $\sigma_{ij}^{m}<0$, energy input j is a Morishima net complement to energy input i.

Finally, the own- and cross-price elasticities, η_{ij}, can also be calculated as

$$\eta_{ij}=\frac{\partial x_{i}\left(\boldsymbol{p},y\right)}{\partial p_{j}}\frac{p_{j}}{x_{i}\left(\boldsymbol{p},y\right)} \tag{8}$$

or as $\eta_{ij}=s_{j}\sigma_{ij}^{a}$, where s_j is the cost share of energy input j in total production costs, and must satisfy the condition

$$\sum_{j=1}^{n}\eta_{ij}=0,\quad i=1,\ldots,n.$$

4 Econometric Issues

4.1 Theoretical Regularity

It is necessary to have a negative semidefinite $\boldsymbol{B}$ matrix in order to ensure the concavity of the cost function, $C\left(\boldsymbol{p},y\right)$, at every possible and imaginable point. In practice, the concavity of the cost function, $C\left(\boldsymbol{p},y\right)$, may not be satisfied if the estimated $\boldsymbol{B}$ matrix is not negative semidefinite. In this case, to ensure global concavity of the NQ cost function, we follow Diewert and Wales (1987) and Feng and Serletis (2008) and impose

$$\boldsymbol{B}=-\,\boldsymbol{K}\boldsymbol{K}' \tag{9}$$

where $\boldsymbol{K}$ is a lower triangular matrix which satisfies

$$\boldsymbol{K}'\boldsymbol{p}^{*}=\,\boldsymbol{0}_{n}. \tag{10}$$

Note that (10) and the lower triangular structure of $\boldsymbol{K}$ imply

$$\sum_{i=1}^{n} k_{ij} = 0, \qquad j = 1, ..., n. \tag{11}$$

It should be noted that in the case of the NQ cost model, concavity is imposed globally rather than locally at the reference point, and the curvature conditions can be imposed without destroying the flexibility of the functional form. See Diewert and Wales (1987) or Feng and Serletis (2008) for more details.

4.2 Stochastic Specification

To estimate the equation system (5), we add a stochastic component and write it as

$$\boldsymbol{x}_t = y\boldsymbol{\psi}\left(\boldsymbol{p}_t, \boldsymbol{\vartheta}\right) + \boldsymbol{\varepsilon}_t \tag{12}$$

where $\boldsymbol{\vartheta}$ is the vector of parameters to be estimated, $\boldsymbol{\varepsilon}_t$ is a vector of stochastic errors, and $\boldsymbol{\psi}(\boldsymbol{p}_t, \boldsymbol{\vartheta}) = \left(\psi_1\left(\boldsymbol{p}_t, \boldsymbol{\vartheta}\right), ..., \psi_n\left(\boldsymbol{p}_t, \boldsymbol{\vartheta}\right)\right)'$, with $\psi_i\left(\boldsymbol{p}_t, \boldsymbol{\vartheta}\right)$ given by the right-hand side of (5).

It is typically assumed that the disturbance vector $\boldsymbol{\varepsilon}$ is a classical disturbance term

$$\boldsymbol{\varepsilon}_t \sim N\left(\mathbf{0}, \boldsymbol{H}\right) \tag{13}$$

where $\mathbf{0}$ is a null matrix and $\boldsymbol{H}$ is the $n \times n$ symmetric positive definite error covariance matrix.

4.3 Heteroskedasticity

In this paper, we follow recent advances by Serletis and Isakin (2017) and Serletis and Xu (2020) and relax the homoskedasticity assumption (13) and instead assume that

$$\boldsymbol{\varepsilon}_t | \Psi_{t-1} \sim N\left(\mathbf{0}, \boldsymbol{H}_t\right) \tag{14}$$

where $\boldsymbol{H}_t$ is measurable with respect to information set Ψ_{t-1}. We also follow Serletis and Isakin (2017) and Hossain and Serletis (2017) and use (a restricted version of) the Baba, Engle, Kraft, and Kroner (BEKK) GARCH(p, q) representation for the covariance matrix with generality parameter K — see Engle and Kroner (1995). In particular, we assume a BEKK GARCH$(1, 1)$ with $K = 1$ representation for the covariance matrix of the errors as follows

$$\boldsymbol{H}_t = \boldsymbol{Q}\boldsymbol{Q}' + \boldsymbol{D}'\boldsymbol{H}_{t-1}\boldsymbol{D} + \boldsymbol{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\boldsymbol{A} \tag{15}$$

where $\boldsymbol{Q}$ is a lower triangular matrix containing the constant parameters in the conditional variance matrix, $\boldsymbol{D}$ indicates how current conditional variances and past conditional variances are correlated, and $\boldsymbol{A}$ captures the relationship between conditional variances and past residual terms. This specification allows past volatilities $\boldsymbol{H}_{t-1}$ and lagged values of $\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'}$ to show up in estimating current volatilities of each of the factor demands.

5 The NQ Model with BEKK Errors

In our case with three inputs ($n = 3$), the NQ factor demand system with a BEKK (1,1,1) specification for the covariance matrix, $\boldsymbol{H}_t$, consists of the following three conditional mean equations

$$\frac{x_1}{y} = b_1 + \frac{\left(\sum_{j=1}^{3} \beta_{1j} p_1\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)} - \frac{1}{2}\alpha_1 \frac{\left(\sum_{i=1}^{3} \sum_{j=1}^{3} \beta_{ij} p_i p_j\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)^2} + \varepsilon_1 \tag{16}$$

$$\frac{x_2}{y} = b_2 + \frac{\left(\sum_{j=1}^{3} \beta_{2j} p_2\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)} - \frac{1}{2}\alpha_2 \frac{\left(\sum_{i=1}^{3} \sum_{j=1}^{3} \beta_{ij} p_i p_j\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)^2} + \varepsilon_2 \tag{17}$$

$$\frac{x_3}{y} = b_3 + \frac{\left(\sum_{j=1}^{3} \beta_{3j} p_3\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)} - \frac{1}{2}\alpha_3 \frac{\left(\sum_{i=1}^{3} \sum_{j=1}^{3} \beta_{ij} p_i p_j\right)}{\left(\sum_{i=1}^{3} \alpha_i p_i\right)^2} + \varepsilon_3 \tag{18}$$

and the corresponding six conditional variance and covariance equations

$$\begin{aligned} h_{11,t} = {} & q_{11}^2 + d_{11}^2 h_{11,t-1} + d_{21}^2 h_{22,t-1} + d_{31}^2 h_{33,t-1} + 2d_{11}d_{21}h_{12,t-1} \\ & + 2d_{11}d_{31}h_{13,t-1} + 2d_{21}d_{31}h_{23,t-1} + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + a_{31}^2\varepsilon_{3,t-1}^2 \\ & + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \end{aligned} \tag{19}$$

$$\begin{aligned} h_{22,t} = {} & q_{12}^2 + q_{22}^2 + d_{12}^2 h_{11,t-1} + d_{22}^2 h_{22,t-1} + d_{32}^2 h_{33,t-1} + 2d_{12}d_{22}h_{12,t-1} \\ & + 2d_{12}d_{32}h_{13,t-1} + 2d_{22}d_{32}h_{23,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + a_{32}^2\varepsilon_{3,t-1}^2 \\ & + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{12}a_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \end{aligned} \tag{20}$$

$$\begin{aligned} h_{33,t} = {} & q_{13}^2 + q_{23}^2 + q_{33}^2 + d_{13}^2 h_{11,t-1} + d_{23}^2 h_{22,t-1} + d_{33}^2 h_{33,t-1} + 2d_{13}d_{23}h_{12,t-1} \\ & + 2d_{13}d_{33}h_{13,t-1} + 2d_{23}d_{33}h_{23,t-1} + a_{13}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{2,t-1}^2 + a_{33}^2\varepsilon_{3,t-1}^2 \\ & + 2a_{13}a_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{13}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{23}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \end{aligned} \tag{21}$$

$$\begin{aligned} h_{12,t} = {} & q_{11}q_{12} + d_{11}d_{12}h_{11,t-1} + d_{21}d_{22}h_{22,t-1} + d_{31}d_{32}h_{33,t-1} \\ & + (d_{11}d_{22} + d_{21}d_{12})\, h_{12,t-1} + (d_{11}d_{32} + d_{31}d_{12})h_{13,t-1} \\ & + (d_{22}d_{31} + d_{21}d_{32})\, h_{23,t-1} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + a_{21}a_{22}\varepsilon_{2,t-1}^2 \\ & + a_{31}a_{32}\varepsilon_{3,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\, \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + (a_{12}a_{31} + a_{11}a_{32})\, \varepsilon_{1,t-1}\varepsilon_{3,t-1} + (a_{21}a_{32} + a_{22}a_{31})\, \varepsilon_{2,t-1}\varepsilon_{3,t-1} \end{aligned} \tag{22}$$

$$\begin{aligned} h_{13,t} = {} & q_{11}q_{13} + d_{11}d_{13}h_{11,t-1} + d_{21}d_{23}h_{22,t-1} + d_{31}d_{33}h_{33,t-1} \\ & + (d_{11}d_{23} + d_{21}d_{13})\, h_{12,t-1} + (d_{11}d_{33} + d_{31}d_{13})h_{13,t-1} \\ & + (d_{21}d_{33} + d_{23}d_{31})\, h_{23,t-1} + a_{11}a_{13}\varepsilon_{1,t-1}^2 + a_{21}a_{23}\varepsilon_{2,t-1}^2 \\ & + a_{31}a_{33}\varepsilon_{3,t-1}^2 + (a_{11}a_{23} + a_{13}a_{21})\, \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + (a_{11}a_{33} + a_{13}a_{31})\, \varepsilon_{1,t-1}\varepsilon_{3,t-1} + (a_{21}a_{33} + a_{23}a_{31})\, \varepsilon_{2,t-1}\varepsilon_{3,t-1} \end{aligned} \tag{23}$$

$$
\begin{aligned}
h_{23,t} &= q_{12}q_{13} + q_{22}q_{23} + d_{12}d_{13}h_{11,t-1} + d_{22}d_{23}h_{22,t-1} \\
&+ d_{32}d_{33}h_{33,t-1} + \left(d_{12}d_{23} + d_{22}d_{13}\right) h_{12,t-1} + \left(d_{12}d_{33} + d_{32}d_{13}\right) h_{13,t-1} \\
&+ \left(d_{22}d_{33} + d_{23}d_{32}\right) h_{23,t-1} + a_{12}a_{13}\varepsilon_{1,t-1}^2 + a_{22}a_{23}\varepsilon_{2,t-1}^2 \\
&+ a_{32}a_{33}\varepsilon_{3,t-1}^2 + \left(a_{12}a_{23} + a_{13}a_{22}\right) \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\
&+ \left(a_{12}a_{33} + a_{13}a_{32}\right) \varepsilon_{1,t-1}\varepsilon_{3,t-1} + \left(a_{22}a_{33} + a_{23}a_{32}\right) \varepsilon_{2,t-1}\varepsilon_{3,t-1}. \qquad (24)
\end{aligned}
$$

In the general case with n factors, the NQ factor demand system with a BEKK (1,1,1) specification for the covariance matrix has $n\left(n+1\right)/2$ free parameters (that is, parameters estimated directly) in the mean equations (16)-(18) and $n\left(5n+1\right)/2$ free parameters in the variance and covariance equations (19)-(24). In our case with $n = 3$, we have 6 free parameters in the mean equations and 24 free parameters in the variance and covariance equations, for a total of 30 free parameters.

We estimate the model, consisting of equations (16)-(24) by full information maximum likelihood, avoiding Pagan's (1984) generated regressor problems associated with estimating the variance function parameters separately from the conditional mean parameters. The procedure is to maximize the log likelihood function with respect to the parameters, and the estimation is performed in ESTIMA RATS (version 9.0).

6 Empirical Evidence

6.1 ARCH Effects

We first estimate equations (16)-(18) under the homoskedasticity assumption in (13) and verify the presence of ARCH effects in the residuals of equations (16)-(18), $\hat{\varepsilon}_{biofuel}$, $\hat{\varepsilon}_{gas}$, and $\hat{\varepsilon}_{oil}$, respectively, by reporting the results of Lagrange multiplier (LM) tests for ARCH effects in Table 1. As can be seen in Table 1, the null hypothesis of no ARCH in each of $\hat{\varepsilon}_{biofuel}$, $\hat{\varepsilon}_{gas}$, and $\hat{\varepsilon}_{oil}$ is rejected with p-values less than 0.001. Moreover, in order to provide some perspective on the presence of ARCH effects, in Figure 3 we plot the estimated squared residuals, $\hat{\varepsilon}^2_{biofuel}$, $\hat{\varepsilon}^2_{gas}$, and $\hat{\varepsilon}^2_{oil}$.

6.2 Theoretical Regularity

We estimate the NQ model under the heteroskedasticity assumption in (14), assuming the BEKK specification (15) for the error covariance matrix, $\boldsymbol{H}_t$, that is, we estimate the model consisting of equations (16)-(24). In the second column of Table 2, we report a summary of the results from the unrestricted NQ demand system in terms of ML parameter estimates (with p-values in parentheses) for the mean equations (16)-(18) and the variance equations (19)-(24). We check the theoretical regularity conditions of positivity, monotonicity, and concavity as in Feng and Serletis (2008). In particular, positivity is checked by checking if the estimated fuel input demand is positive, $\hat{x}_i\left(\boldsymbol{p}, y\right) > 0$. Monotonicity is checked by computation of the values of the first gradient vector of the estimated cost function with respect to $\boldsymbol{p}$, and is satisfied if $\nabla_{\boldsymbol{p}}\hat{C}\left(\boldsymbol{p}, y\right) > 0$. Concavity is checked by examining whether the Hessian matrix derived from the cost function is negative semidefinite — see Feng and Serletis (2008) for more details.

We find that the unrestricted NQ model satisfies the positivity and monotonicity conditions, but concavity is violated at all sample observations. Because economic regularity has not been attained, we follow the suggestions of Barnett (2002) and, as in Feng and Serletis (2008), impose the concavity restrictions discussed in Section 4.2, to estimate the restricted NQ demand system and a BEKK(1,1,1) specification for the covariance matrix. The results are reported in the third column of Table 2 and indicate that imposing global concavity reduces the number of concavity violations to zero, without any induced violations of positivity and monotonicity. It is also to be noted that the imposition of the concavity constraints has not much influence on the flexibility of the NQ factor demand model as the log likelihood value decreases only slightly, suggesting that the concavity constrained NQ model can guarantee inference consistent with theory, without compromising much of the flexibility of the functional form.

6.3 Interfuel Substitution

In Table 3, we report the own- and cross-price elasticities of fuel demand, calculated at the (sample) mean of the data with p-values (based on the Delta method) in parentheses. They are based on the concavity restricted NQ model and a BEKK(1,1,1) specification for the covariance matrix as this model satisfies all the theoretical regularity conditions. As can be seen, all own-price elasticities are negative, as predicted by the theory, and are in absolute terms less than one. The own-price elasticity for oil, η_{33}, is the lowest ($\eta_{33} = -0.0156$ with a p-value of 0.000) while that of natural gas is the highest ($\eta_{22} = -0.2421$ with a p-value of 0.0006). In Table 3, a positive sign for the cross-price elasticities indicates that the factors are gross substitutes and a negative sign indicates that they are gross complements. As can be seen, all cross-price elasticities are in absolute values less than one. Table 3 also reveals that oil is a substitute to both biofuel and natural gas as indicated by the significant positive estimates of the cross price elasticities.

In addition to the own- and cross-price elasticities in Table 3, we report the symmetrical Allen elasticities of substitution, σ_{ij}^{a}, and the asymmetrical Morishima elasticities of substitution, σ_{ij}^{m}. In Table 4, we find all of the Allen own-price elasticities of substitution to be negative and mostly statistically significant. Again, the Allen own-price elasticity of substitution for natural gas is the highest ($\sigma_{22} = -6.0744$ with a p-value of 0.0011). However, as noted by Blackorby *et al.* (1989), the Allen elasticity of substitution produces ambiguous results for the cross-price elasticities of substitution, and for this reason we use the Morishima elasticity of substitution to investigate the substitutability/complementarity relation between inputs.

The asymmetrical Morishima elasticities of substitution, σ_{ij}^{m} ($i, j =$ biofuel, natural gas, and oil), are reported in Table 5 and give the percentage change in the x_i/x_j quantity ratio when the relative price p_j/p_i is changed by changing p_j and holding p_i constant. As can be seen in Table 5, all the fuels are Morishima substitutes, and the estimates are mostly statistically significant. The estimated Morishima elasticity of substitution between biofuel and natural gas when the price of natural gas changes is $\sigma_{12}^{m} = 0.1831$ (with a p-value of 0.0794), implying that a 1 % increase in the fuel price ratio p_2/p_1 will result in about a 0.18%

increase in the fuel use ratio (x_1/x_2). This suggests that biofuel is a Morishima substitute of natural gas when the price of natural gas changes. On the other hand, biofuel cannot be substituted with natural gas when the price of biofuel changes as indicated by the positive but insignificant estimate of $\sigma_{21}^m = 0.0508$ (with a p-value of 0.5322).

Similarly, biofuel and oil are substitutes to each when the price of oil changes only ($\sigma_{13}^m = 0.1613$ with a p-value of 0.0111) while the demand for oil is non-responsive to price changes in biofuel as indicated by the insignificant estimate of the σ_{31}^m elasticity ($\sigma_{31}^m = 0.0904$ with a p-value of 0.1737). Our estimate of $\sigma_{13}^m = 0.1613$ implies that a \$0.20-per-gallon increase in the price of oil relative to biofuel leads to a 1.6% increase in the quantity of biofuel demanded relative to oil. Finally, natural gas and oil are substitutes of each other, irrespective of which price changes, reflected by $\sigma_{23}^m = 0.2936$ (with a p-value of 0.0000) and $\sigma_{32}^m = 0.2539$ (with a p-value of 0.0005). Overall, Table 5 suggests that there exists relatively strong substitutability between natural gas and oil regardless of which price changes whereas biofuel is substitutable with both natural gas and oil to a lower degree only when the prices of natural gas and oil change.

In Figures 4-6 we graph the Morishima elasticities of substitution between biofuel and natural gas ($\sigma_{Biofuel,Gas}^m$ and $\sigma_{Gas,Biofuel}^m$), biofuel and oil ($\sigma_{Biofuel,Oil}^m$ and $\sigma_{Oil,Biofuel}^m$), and natural gas and oil ($\sigma_{Gas,Oil}^m$ and $\sigma_{Oil,Gas}^m$), respectively, at every point in the sample. In Figure 4, the Morishima elasticity of substitution between biofuel and natural gas when the price of natural gas changes, $\sigma_{Biofuel,Gas}^m$, varies between 0.07 (in 2012) and 0.36 (in 2001), whereas the Morishima elasticity of substitution between gas and biofuel when the price of biofuel changes, $\sigma_{Gas,Biofuel}^m$, is consistently below its counterpart with a maximum value of 0.13 (in 1991), indicating a very low substitutability between these two fuels, particularly when the price of biofuel changes. Similarly, Figure 5 shows that the Morishima elasticity of substitution between biofuel and oil when the price of oil changes, $\sigma_{Biofuel,Oil}^m$, varies between 0.09 (in 2017) and 0.29 (in 1991) whereas $\sigma_{Oil,Biofuel}^m$ shows very low substitution possibilities between biofuel and oil when the price of biofuel changes. The Morishima elasticities of substitution between natural gas and oil in Figure 6, confirm the general finding in Table 5 of significant and relatively higher substitution between the two energy goods. $\sigma_{Gas,Oil}^m$ varies between 0.13 (in 2012) and 0.53 (in 2001) whereas $\sigma_{Oil,Gas}^m$ varies between 0.11 (in 2012) and 0.49 (in 2001). To sum up, it is apparent from the relative high values of $\sigma_{Gas,Oil}^m$ and $\sigma_{Oil,Gas}^m$ in Figure 6 that, on average, natural gas and oil tend to exhibit higher potential for substitution as compared to biofuel. As for biofuel, the substitutability between biofuel and natural gas, and biofuel and oil, is only possible when the relative price of fossil fuels changes but the magnitude of such substitution is very low.

Finally, it is apparent from our analysis that the Morishima elasticities of substitution among the three energy goods are always positive but they exhibit a downward trend after 2005. For example, the Morishima elasticity of substitution between biofuel and natural gas when the price of gas changes, $\sigma_{Biofuel,Gas}^m$, declined from 0.29 in 2005 to 0.07 in 2012 while the Morishima elasticity of substitution between biofuel and oil when the price of oil changes, $\sigma_{Biofuel,Oil}^m$, declined rom 0.22 in 2005 to 0.09 in 2012. It is also important to note that, during that time, the transportation sector's dependency on oil started to decline gradually while the role of biofuel increased sharply (as can be seen in Figure 1). This lower substitutability between biofuel, and fossil fuels, together with the changing fuel consumption dynamics in the transportation sector, can be attributed partly to the Energy Policy Act of 2005. The

Energy Policy Act not only mandated the blending of renewable fuels with gasoline starting at 4 billion gallons in 2006 and reaching 7.5 billion gallons in 2012 but also included a variety of economic incentives, such as grants, income tax credits, subsidies and loans to promote biofuel research and development. This policy was further supported by the Energy Independence and Security Act of 2007 (EISA) to increase biofuel production to 36 billion gallons by 2022.

7 Conclusion

We investigate biofuel substitution in the U.S. transportation sector, for the period from 1990 to 2017, using the flexible demand systems approach. We generate inference, in terms of a full set of elasticities, consistent with neoclassical microeconomic theory and the data generating process. Our findings are as follows:

- The own-price elasticities are negative for all fuels.
- The Morishima elasticities of substitution among the energy goods are very low.
- Natural gas and oil have the highest potential for substitution.
- Biofuel and fossil fuels (natural gas and oil) are substitutes when the prices of fossil fuels change, reflecting the flexibility of the switch between these fuels.

Our findings of very low substitution between fuels are (in general) consistent with Suh (2019), the only other study that investigates biofuel substitution in the transportation sector. Our results also show that there is a small but statistically significant substitution possibility between biofuel and natural gas, as well as between biofuel and oil, when the prices of fossil fuels change. This finding differs significantly from Suh (2019) who finds a complementarity relationship between biofuel and natural gas.

Our estimates of the Morishima elasticities of substitution indicate that lowering the price of biofuel does not have any impact on the relative demand for natural gas and oil. However, policies that increase the price of natural gas and oil will have a significant positive effect on the demand for biofuel which is a lower carbon emitting fuel. For example, our estimate of $\sigma_{13}^m = 0.1613$ implies that a \$0.20-per-gallon increase in the price of oil relative to biofuel will increase the quantity of biofuel demanded relative to oil by 1.6%. Hence, rising fossil fuel prices will have a significant effect on the substitution of carbon intensive gas and oil for less carbon-intensive biofuel in the U.S. transportation sector. Finally, activist and aggressive price intervention in the natural gas market will also point the way to low-carbon biofuel, as indicated by the Morishima elasticity of substitution, $\sigma_{12}^m = 0.1831$.

The empirical analysis illustrates how the prices of fossil fuels affect biofuel usage in the transportation sector. Overall, biofuel has a significant though limited potential to displace fossil fuels as a source for transportation fuel in the near future. Given the low values of the elasticities of substitution, biofuel is unlikely to dominate the fuel supply despite having a steady growth in its usage in this sector. This information is critical for designing, implementing, and evaluating environmental policies in the U.S. transportation sector.

The market for biofuels is heavily dependent on federal incentives and regulations, such as federal tax credits, production credits, renewable fuel standards, and mandated minimum levels of consumption. Hence, policy intervention and a stronger enforcement mechanism are required to create the market conditions necessary for greater biofuel use in this sector. As a major contributor to greenhouse gas emissions and other pollutants, the transportation sector needs special attention, and governments around the world should consider the provision of infrastructure, taxes, and different subsidies to promote biofuels in their transportation sectors.

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Figure 1. Consumption of the energy goods (in quadrillion Btu)

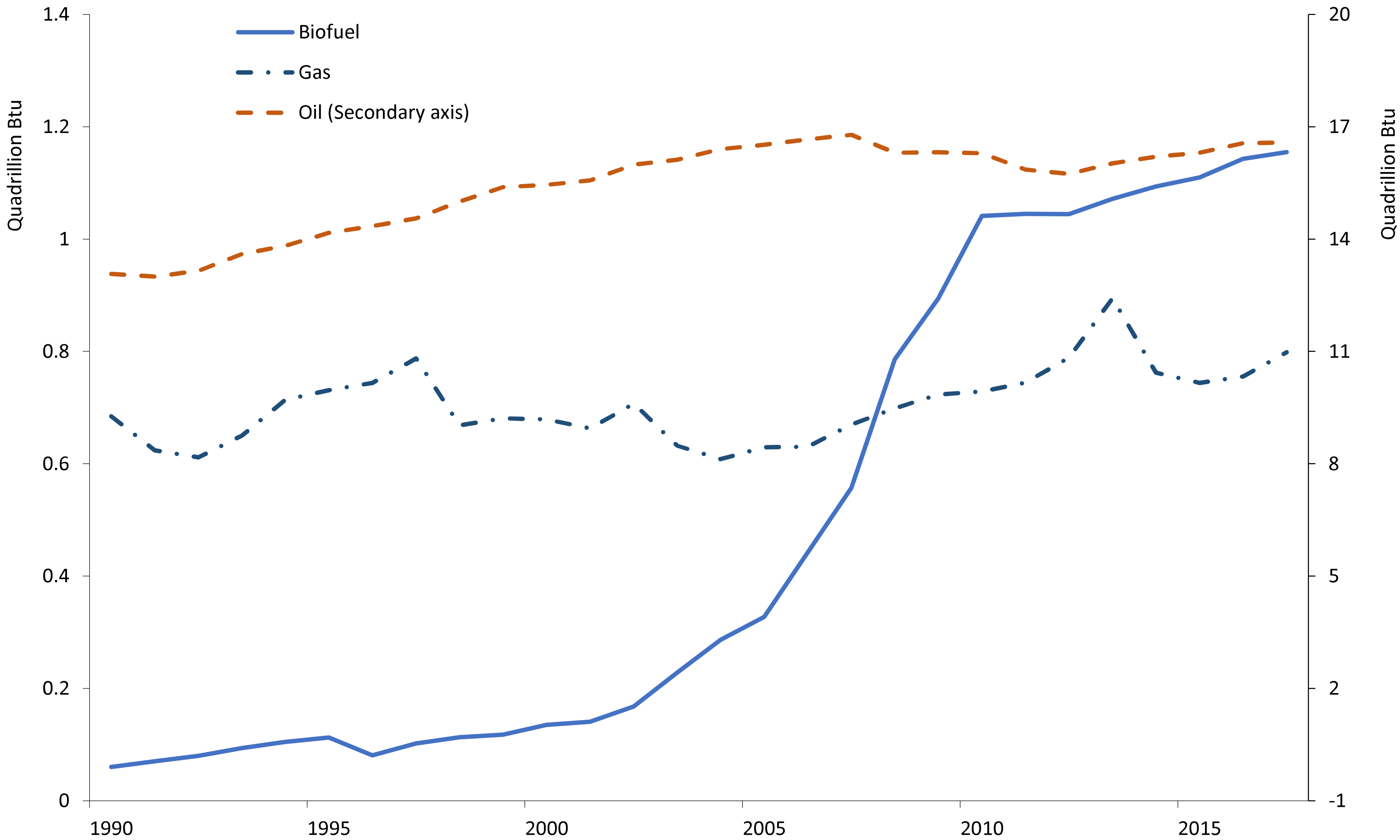

Figure 2. Prices of the energy goods (cents per billion Btu)

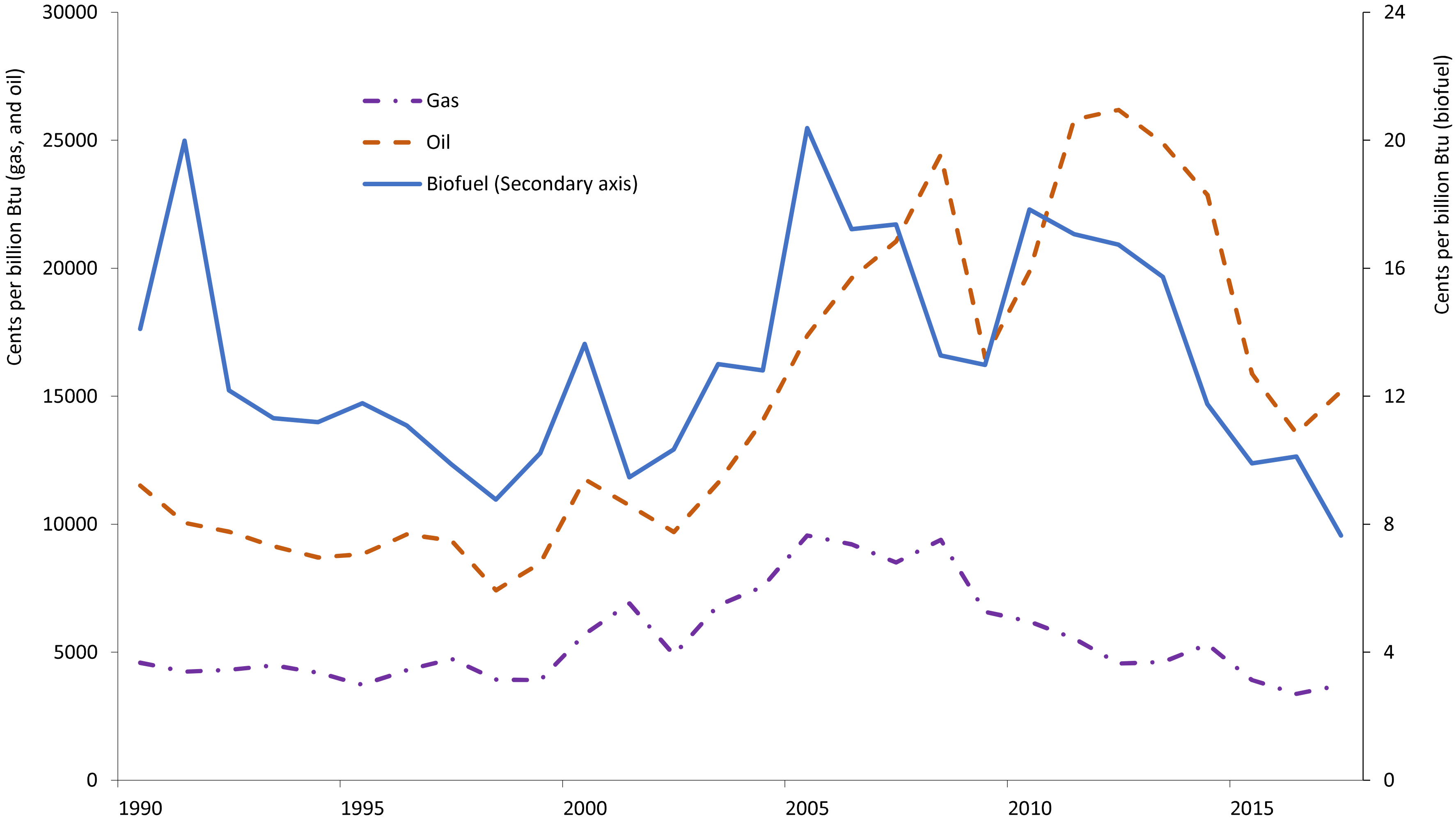

Table 1. ARCH tests in the residuals of the NQ model with homeskedasticity

Residual Series	LM Test Statistic (p-value)
Biofuel	19.442 (.0000)
Gas	20.512 (.0000)
Oil	17.552 (.0001)

Notes: Sample period, annual data 1990-2017 ($T = 28$).

Figure 3. Squared residuals of fuel demand equations

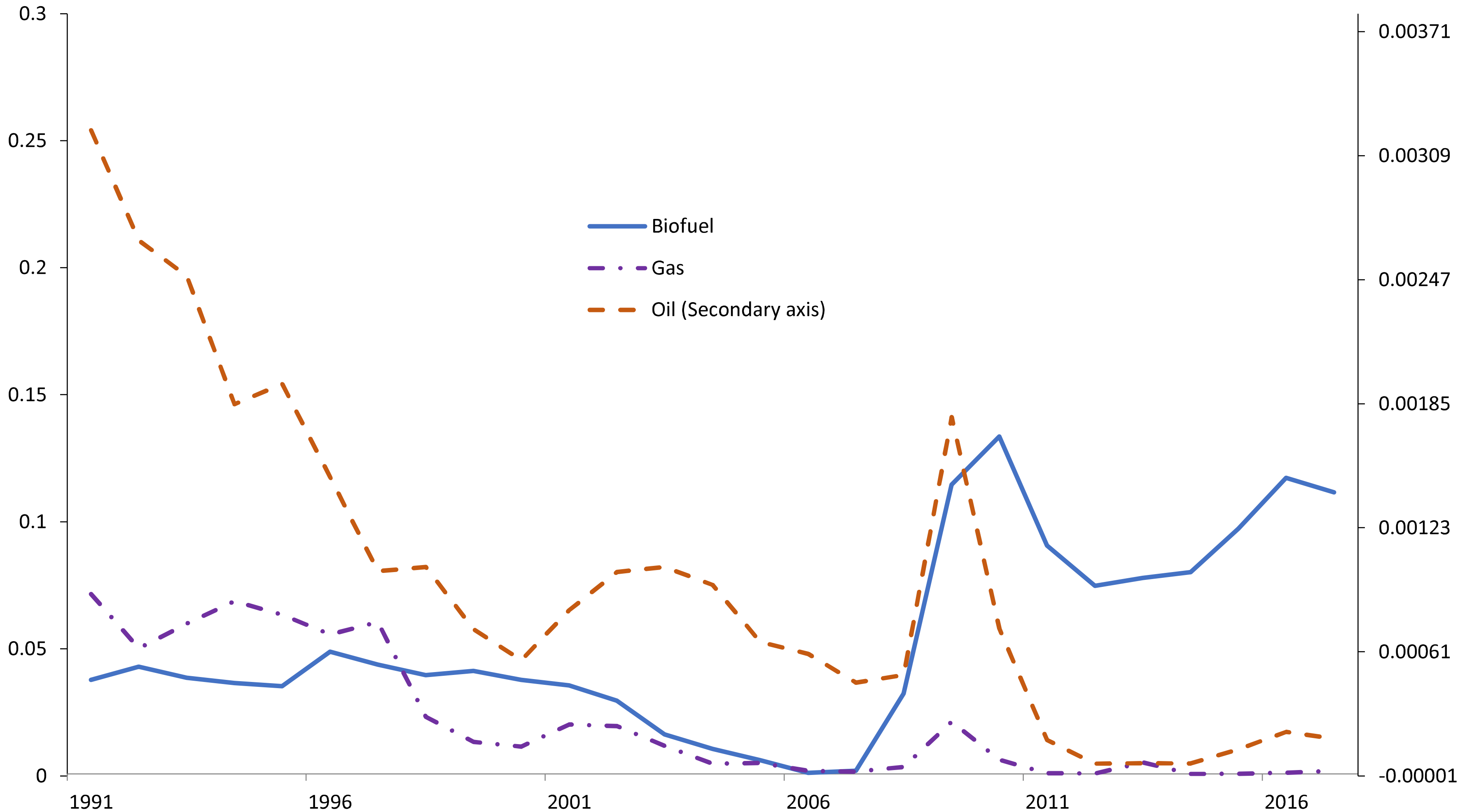

Table 2. Estimates of the NQ Model with BEKK Errors

Parameter	Model Unrestircted	 Restricted
Mean equations		
b_1	0.0489 (.0000)	0.0318 (.0000)
b_2	0.0347 (.1165)	0.0407 (.0000)
b_3	0.9163 (.0000)	0.9273 (.0000)
β_{11}	−0.0053 (.0712)	−0.0038 (.1943)
β_{12}	−0.0082 (.0000)	−0.0019 (.2420)
β_{13}	0.0135 (.2038)	0.0058 (.0369)
β_{22}	−0.0037 (.3139)	−0.0106 (.0004)
β_{23}	0.0119 (.8346)	0.0125 (.0000)
β_{33}	−0.0254 (.6646)	−0.0184 (.0000)
Variance equations		
q_{11}	0.0034 (.0000)	0.0000 (.9999)
q_{21}	0.0014 (.0024)	0.0000 (.9999)
q_{22}	−0.0000 (.9999)	−0.0000 (.9999)
q_{31}	0.0264 (.0006)	0.0000 (.9999)
q_{32}	−0.0000 (.9999)	−0.0000 (.9999)
q_{33}	0.0000 (.9999)	0.0000 (.9999)
a_{11}	1.3140 (.0000)	1.4762 (.0000)
a_{21}	−0.2802 (.0967)	0.4397 (.0000)
a_{31}	0.0512 (.0000)	0.0100 (.1955)
a_{12}	0.1404 (.0002)	0.0386 (.2318)
a_{22}	0.7404 (.0000)	0.3581 (.0071)
a_{32}	0.0328 (.0018)	0.0281 (.0020)
a_{13}	2.0695 (.0000)	1.3867 (.0034)
a_{23}	−3.2501 (.0333)	−0.2503 (.8677)
a_{33}	1.4942 (.0000)	1.0542 (.0000)
d_{11}	0.2535 (.0034)	−0.2254 (.0000)
d_{21}	−0.1253 (.0026)	−0.3388 (.0000)
d_{31}	0.0136 (.0000)	−0.0168 (.0000)
d_{12}	0.0291 (.3482)	−0.0360 (.0547)
d_{22}	0.0445 (.2943)	0.4163 (.0000)
d_{32}	0.0063 (.1700)	0.0043 (.0766)
d_{13}	0.0194 (.9467)	−1.8381 (.0000)
d_{23}	−1.0192 (.0391)	0.0737 (.9056)
d_{33}	0.3404 (.0000)	0.2366 (.0000)
Log L	235.80	232.36
Positivity violations	0	0
Monotonicity violations	0	0
Curvature violations	28	0

Notes: Sample period, annual data 1990-2017 ($T = 28$).
Numbers in parentheses are p-values.

Table 3. Own- and cross-price elasticities

Fuels
1 = Biofuel
2 = Gas
3 = Oil

Fuel i	Own- and cross-price elasticities		
	η_{i1}	η_{i2}	η_{i3}
(1)	−0.0867 (.1840)	−0.0589 (.2193)	0.1457 (.0216)
(2)	−0.0359 (.2219)	−0.2421 (.0006)	0.2780 (.0000)
(3)	0.0037 (.0287)	0.0118 (.0000)	−0.0156 (.0000)

Notes: Sample period, annual data 1990-2017. Numbers in parentheses are p-values.

Table 4. Allen elasticities of substitution

Fuels
1 = Biofuel
2 = Gas
3 = Oil

Fuel i	Allen elasticities of substitution		
	σ^a_{i1}	σ^a_{i2}	σ^a_{i3}
(1)	−3.5744 (.1759)	−1.4800 (.2178)	0.1556 (.0218)
(2)		−6.0744 (.0011)	0.2970 (.0000)
(3)			−0.0166 (.0000)

Notes: Sample period, annual data 1990-2017. Numbers in parentheses are p-values.

Table 5. Morishima elasticities of substitution

Fuels
1 = Biofuel
2 = Gas
3 = Oil

	Morishima elasticities of substitution		
Fuel i	σ_{i1}^{m}	σ_{i2}^{m}	σ_{i3}^{m}
(1)		0.1831 (.0794)	0.1613 (.0111)
(2)	0.0508 (.5322)		0.2936 (.0000)
(3)	0.0904 (.1737)	0.2539 (.0005)	

Notes: Sample period, annual data 1990-2017. Numbers in parentheses are p-values.

Figure 4. Morishima elasticities of substitution (Biofuel, Gas)

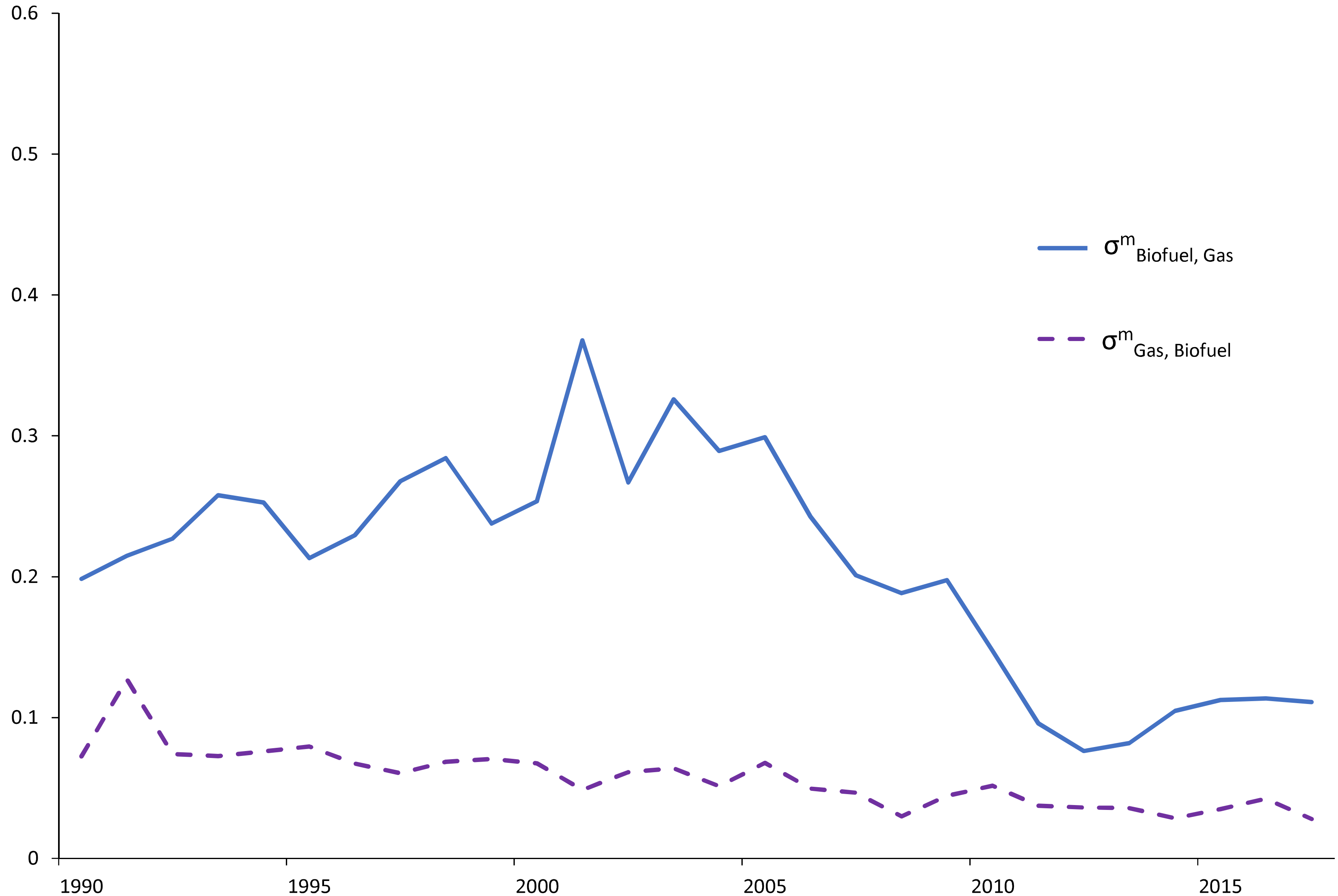

Figure 5. Morishima elasticities of substitution (Biofuel, Oil)

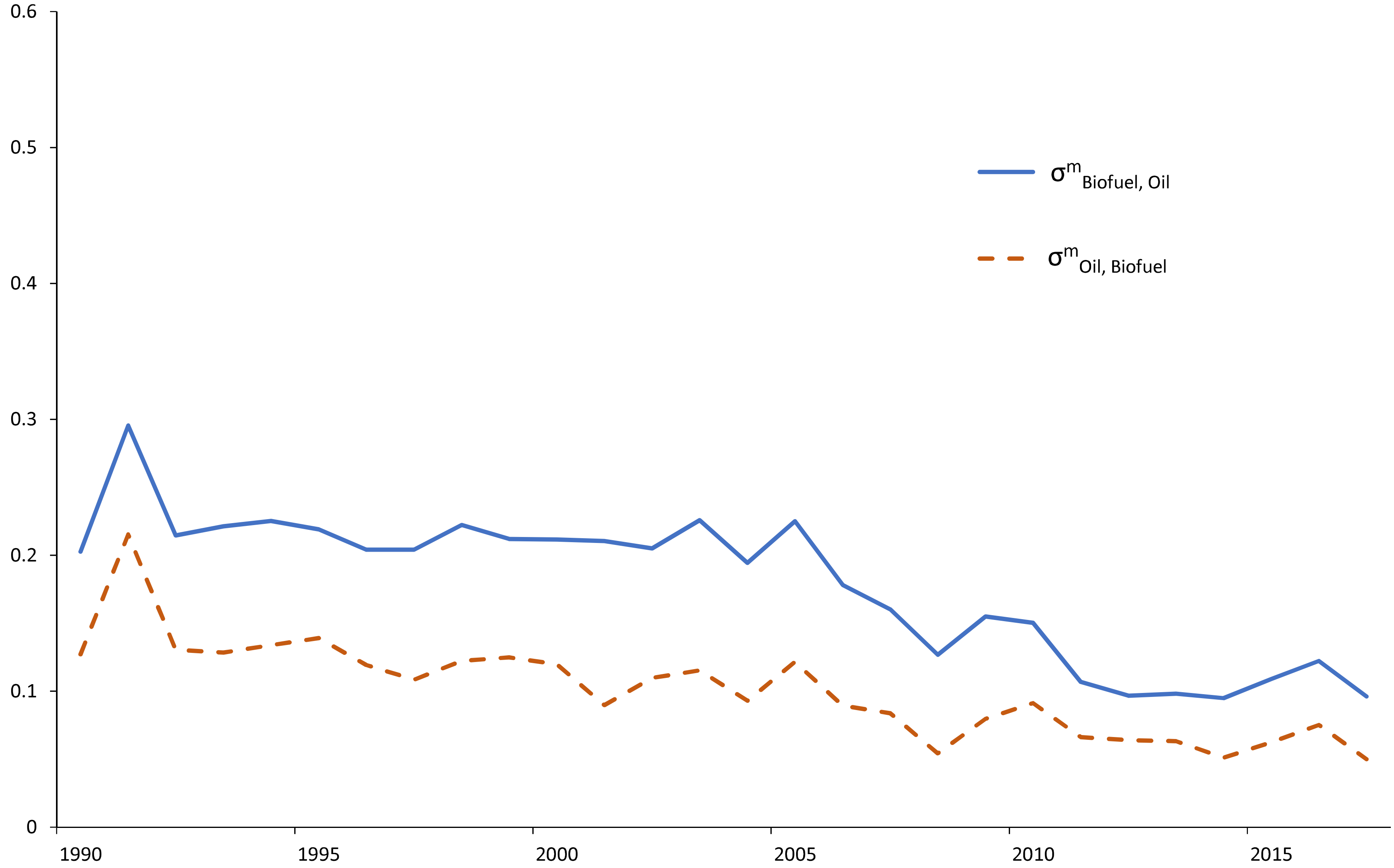

Figure 6. Morishima elasticities of substitution (Gas, Oil)