How strong is the UK's preference for more variety?

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Abstract

Use of modern trade specifications which account for new trade theory and gains from increasing variety, such as Krugman (1980) and Melitz (2003), remains in its infancy in CGE modelling. Central to determining the gains from new product varieties and the impacts on welfare, trade patterns and factor returns is the elasticity of substitution between varieties. Thus, this paper develops the research underpinning these trade specifications by assessing a range of approaches for estimating substitution elasticities at the GTAP sector level.

Soderbery (2015) showed that previous estimates of the elasticity of substitution were significantly biased in the US context. We apply this approach to produce estimates for the UK, extending it to provide estimates at the product and GTAP sector level. Our results corroborate Soderbery's (2015), with our estimates between 15% and 39% lower than previous UK estimates, suggesting they understated the gains from product variety in the UK. Investigating the importance of aggregation, we find that estimates are sensitive to the level of aggregation methodology, with product level estimates significantly higher than their GTAP counterparts. Using CGE simulations, we demonstrate the importance of estimating parameters at the same level of aggregation as modelling is carried out on.

1. Introduction

As the number of free trade agreements has increased in recent decades, computable general equilibrium (CGE) models have become a central tool in analysing their economy-wide impacts (Hertel et al, 2007). Standard CGE modelling in trade relies on the Armington assumption, whereby products are imperfect substitutes depending on their origin. In this setup, trade policy changes result in efficiency gains from reallocation of factors across sectors and terms-of trade changes. However, new trade theory provides additional avenues for gains from trade in the form of scale economies and a greater number of varieties through an increase in imports. Beyond this, Melitz (2003) has also emphasised the importance of firm heterogeneity in capturing gains from trade in such a context.

Whilst the international trade literature has found substantial evidence for these new channels of gains from trade, the question on whether and how to include imperfect competition, scale economies and firm heterogeneity in CGE models remains unanswered in academic circles (Nilsson, 2019). Part of the reluctance to move to incorporating these features in CGE modelling may stem from the lack of empirical evidence on some of the key parameters governing the gains from trade in these models, particularly on elasticities, which Hillberry and Hummels (2013) and Nilsson (2019) emphasise are central to the results of CGE modelling on welfare, trade patterns and factor returns.

This paper seeks to develop the research underpinning trade specifications incorporating new trade theory and gains from increasing variety by estimating one of the key elasticities in such models, the elasticity of substitution between varieties. Using a constant elasticity of substitution (CES) utility function, Feenstra (1994) demonstrates this parameter is central to

[1] The views expressed in this paper are the authors' and do not represent the views of the UK Department for International Trade.

determining the gains from new product varieties through trade. With a high elasticity of substitution among varieties, the potential for gains from variety are small, yet if the elasticity of substitution among varieties is low, the potential for gains from variety are high, demonstrating the importance of using frameworks that allow for variety gains in CGE modelling of trade policy.

Previous studies estimating the elasticity of substitution rely on restricting identifying assumptions, as in the case of Romer (1994) and Hummels (1999), or result in an estimator with substantial biases, such as in Broda and Weinstein (2006). More recent research from Soderbery (2015) proposes an alternative estimator to reduce the biases in Broda and Weinstein (2006), but only applies this to data from the US. As these parameters can differ substantially by country, we apply the Soderbery (2015) method to sectors within the UK economy. Previous literature has confined estimates to HS6 or CN8 products. Given the frequency with which the GTAP database is used in CGE modelling, we extend the previous research to provide results at the GTAP sector level, providing a valuable contribution in improving the foundations of CGE models in new trade theory and thus the robustness of the results.

Our findings support Soderbery's (2015) conclusion that the Broda and Weinstein (2006) estimators produce biased elasticities, with our median elasticities between 15% and 39% lower than previous UK estimates. This suggests previous estimates significantly understated the benefits from additional product variety to the UK economy. Our results also provide evidence that the elasticity of substitution is sensitive to aggregation, with significant differences between the network level and GTAP estimations across the 47 GTAP sectors. This finding is important given the conclusions of McDaniel & Balistreri (2003) that elasticities should be estimated at a level close to that of simulation and demonstrates the importance of estimating parameters at the GTAP level used in CGE modelling. Using a Krugman style CGE model, we simulate unilateral tariff liberalisation for the UK, comparing across different sets of elasticities to highlight the differences in overall welfare. The stark differences in the results between the sets of elasticities estimated at different aggregations reinforces our argument that aggregation matters. Consequently, if modellers aim to run simulations based on New Trade Theory in a CGE framework, they should aim to estimate a set of elasticities at same aggregation as their model, in this instance, the 65 GTAP sectors.

The structure of the paper will be as follows: section 2 outlines the key theoretical and empirical literature, section 3 describes the methodology, section 4 explains the estimation procedure applied, section 5 gives a description of the dataset used for both the CN8 network and GTAP sector level analysis, and section 6 outlines and compares the key results from both analyses, before section 7 concludes.

2. Literature review

2.1 Monopolistic Competition and New Trade Theory

The movement towards trade models of monopolistic competition and increasing returns to scale, first formally introduced by Dixit and Stiglitz (1977) and Krugman (1980), marked an important shift away from perfectly competitive and constant returns models toward more realistic production processes. Monopolistic competition accounts for firms who enjoy some market power, as there are many firms in a market creating different varieties of the same good. These markets create intra-industry trade between countries due to "love of variety" demand functions, and therefore better explain the pattern of world trade which has occurred over recent decades.

Dixit and Stiglitz (1977) argue that a love for variety is already inherent in the assumption of monotonic preferences present in a typical CES utility function. It is widely agreed that increasing returns are apparent in production, and therefore firms cannot sustain pricing equal to marginal cost. Firms thus price a mark-up above their marginal cost to cover the fixed cost to enter the market; however, as entry is free, there are zero profits in equilibrium. As each firm operates under increasing returns, it does not make sense to produce identical goods across firms, but instead specialise in a distinct variety, creating some degree of market power. Firms are assumed to have the same cost structures (fixed and variable) and thus price similarly. It can be shown that the larger the population, the larger the number of available varieties and consumers always prefer an average of two products to extremes of either. Therefore, as shown in Dixit and Stiglitz (1977), utility is strictly increasing in the number of varieties within an industry and even more so with a lower elasticity of substitution between varieties, σ.

Krugman (1980) bases his model of international trade and monopolistic competition on Dixit and Stiglitz (1977). He sheds light on observed intra-industry trade between similar countries and the positive correlation between the size of exports and domestic markets. He builds on ideas from Balassa (1967) and Grubel (1967) to present a formal analysis of trade in the context of imperfect competition, differentiated products and economies of scale. In contrast to Armington (1969), firms incur fixed costs to produce and the total number of varieties is no longer exogenously set. In this context, Krugman (1980) identifies a gain from trade through a ‘love of variety’. Consumers who are exposed to the same goods from abroad, though differentiated products, will shift purchases away from their autarky basket to one with greater variety. This utility maximising tendency produces the same outcomes as Armington (1969), cross-border trade of the same good; however, instead of assuming one representative good per industry there exists a continuum of differentiated goods.

Krugman (1980) illustrates how economies of scale rewards industries that reside within the nation with the greatest demand for that good: an industry’s competitiveness depends on domestic demand for the good under autarky. Increased domestic demand allows firms to benefit from economies of scale and increasing productivity, thus gaining a substantial share of global trade of the good once economies open to trade. The key parameter affecting gains from trade in Dixit and Stiglitz (1977) and Krugman (1980) is the elasticity of substitution between varieties within an industry, σ. It is therefore imperative for users of modern multi-sector multi region trade models, dependant on these micro foundations, to estimate such parameters robustly.

2.2 Empirical Literature

Feenstra (1994) argues that models which allow for product differentiation and whose results are reliant on increasing varieties as a result of trade lack empirically founded elasticities of substitution. He derives the CES model and importantly includes the impact of new varieties on the price index. In the conventional price index, all new product varieties are homogenous and perfect substitutes for existing ones and so there is no price fall from additional varieties. This highlights the shortcomings of Armington-based trade specifications in CGE models, which do not recognise this channel of impact in international trade and only differentiate imports by country, not firm. Using a panel of US import data from various partners across six manufactured products between 1964 and 1987, he estimates the elasticity of substitution between varieties using a supply and demand equilibrium. His findings show that correcting the price index for increasing varieties reduces the income elasticity of import demand, especially in developing countries.

Hummels (1999) estimates elasticities of substitution as part of research analysing barriers to trade. He takes a gravity approach to estimation, estimating the trade-distance relationship to infer an elasticity of substitution. Using data from the US and Latin America, a one sector model produces estimates ranging from 2-5.26, significantly lower than the estimates from the multi-sector model, where estimates range from 3-8. The results also suggest that the level of aggregation affects the elasticity, with a narrower definition of a good resulting in a higher substitution elasticity.

Broda and Weinstein (2006) take a different approach to estimating the elasticity of substitution in research on the impact of variety on welfare. They argue that Hummels' (1999) approach relies on extreme identifying assumptions, such as trade costs being completely passed on to consumers and changes in trade costs being unaffected by changes in import demand. Thus, they instead present a model of import demand and supply equations to estimate the elasticity of substitution, adapting a method based on Feenstra (1994) that provides estimates robust to simultaneity bias and measurement error. Using US data from 1972-2001, Broda and Weinstein (2006) estimate almost 30,000 elasticities at the lowest level of disaggregation available. Similar to Hummels (1999), they find varieties are increasingly substitutable at lower levels of disaggregation, with an average elasticity of 12 for 8-digit goods compared to 6 at the 3-digit good level. They also find the elasticity of substitution has decreased over time, implying increasing differentiation among traded goods. They use their elasticity of substitution estimates to demonstrate how the 4-fold increase in global varieties over the period substantially increased US welfare, confirming the importance of using the Dixit-Stiglitz framework in international trade.

In a subsequent paper, Broda et al (2006) use the same method to estimate elasticities of substitution for approximately 200 3-digit sectors across 73 countries. They find that the typical country has a median elasticity of 3.4 and mean elasticity of 6.8, with the latter higher as the elasticity has a lower bound of 1. For the UK, they estimate a median elasticity of substitution of 2.4, indicating that the UK tends to value variety more than the typical country.

Soderbery (2015) argues that the structural estimator developed by Feenstra (1994) and adapted by Broda and Weinstein (2006) to estimate the elasticity of substitution has substantial biases, particularly in small samples. Instead, Soderbery (2015) proposes using a hybrid estimator based on limited information maximum likelihood (LIML). Using Monte Carlo analysis, Soderbery (2015) shows that the standard estimator is biased because it overweights outlier observations, a problem reduced using the hybrid estimator. Converting to the hybrid estimator reduces the median elasticity of substitution for HS8 products imported by the US from 1993 to 2007 by 35%. As a result, Soderbery (2015) shows the bias in the standard estimator underestimates consumer gains from variety by a factor of 6 over the period.

However, in a subsequent paper using data on all global trade flows at HS4 level from 1991 to 2007, Soderbery (2018) uses an approach similar to Broda and Weinstein (2006) because of the computationally intensive nature of LIML. The results indicate a global median elasticity of substitution of 2.88, compared to a median of 2.98 for the UK, slightly higher than the median estimate in the Broda et al (2006) study.

In a recent study, Ahmad and Riker (2019) note that the method of estimating elasticities of substitution using a system of demand and supply equations developed by Feenstra (1994) and adapted by Broda and Weinstein (2006) and Soderbery (2015) relies on the assumption of uncorrelated supply and demand errors, alongside the small sample biases identified by Soderbery (2015). Thus, they take a different approach to estimation, relying on the structural relationship between the price-cost mark-up and the elasticity of substitution in industries operating under monopolistic competition. Using US manufacturing data from 2012, they compute elasticities of substitution at differing levels of aggregation. At the 3-digit industry level, their estimates range from 1.8 to 7, with a median elasticity of 2.6. They also find that elasticity estimates are similar at different levels of industry aggregation, in contrast to Broda and Weinstein (2006) who find that elasticity estimates depend on the level of aggregation specified.

Overall, whilst the empirical literature has developed to address substantial biases in early estimates, it is limited in country and aggregation scope, particularly in relation to the GTAP sector aggregation widely used in CGE modelling.

3. Methodology

Our contribution is to apply the approach of Soderbery (2015) to data for the UK economy. This allows us to run Krugman style trade models of the UK economy and to assess how the results that Soderbery (2015) finds for the US are robust to changes in country sample.

This approach works by deriving theoretical estimation equations from the monopolistic competition framework of Krugman (1979). In this, a constant elasticity of substitution utility function is used to specify preferences across a variety of products produced by different exporters. This leads to the level of competition between varieties in each sector being determined by the elasticity of substitution between these products; in cases where varieties are perfectly substitutable, competition is perfect, whilst decreasing the elasticity of substitution introduces degrees of imperfection in that competition.

The innovation of Soderbery (2015) is to show, both theoretically and empirically, that earlier approaches to estimating this elasticity parameter (such as Feenstra (2004) and Broda and Weinstein (2006)) suffer from bias and proposes an alternative estimation procedure based on limited information maximum likelihood methods. This is applied to data for the United States[2] to estimate substitution elasticities for a large range of imported products. Our research examines how the substitution elasticities for the US and the UK differ, offering important lessons on the extent to which researchers need to replicate the analysis for their countries of interest to ensure robust inference.

Furthermore, Broda and Weinstein (2006) raise important points about the previous literature on variety. The fact that previous studies have only estimated one or two elasticities of substitution, and that “all varieties enter into the utility function with a common elasticity” leads to three key issues. Firstly, that it leads to the assumption that consumers value variety the same for all types of goods, secondly, that they value variety the same across different goods as they do across different countries exporting the same good and thirdly, that the aggregation bias can lead to meaningless estimates as it averages the impact of a price change across different countries and commodities. Therefore, our research endeavours to estimate and compare the substitution elasticities at two levels of aggregation, the 8-digit commodity code level and the GTAP 65 sector level. As Broda and Weinstein (2006) have shown, the level of aggregation is important, and that intuitively the more disaggregate the data, the greater the substitution elasticity. GTAP is the level of

[2] Due to data constraints in this type of analysis firm level data on different varieties of products is not available, so a good is defined as the 8-digit product and a variety of that good is defined as the origin of that 8-digit product, also known as the Armington assumption (1969).

aggregation which will be used to simulate overall welfare impacts using a CGE model and because these models rely so heavily on these trade elasticities, it is important to shed light on the differences between pre and post estimation aggregation.

4. Estimation procedure

4.1 Deriving a theoretically consistent form for the estimation equation

The theoretical framework used to derive the supply and demand equations for estimation follow Feenstra (1994), Broda and Weinstein (2006) and Soderbery (2015). They set up a standard model of trade, maximising a consumer's CES utility function and deriving a demand equation. On the supply side, firms who export operate under monopolistic competition and have upward sloping export supply curves. Our focus in this paper is on the demand side elasticities which reflect the extent to which consumers prefers more variety in imported goods[3]. Below we present an extremely reduced-form derivation of the key equations as we want to avoid repetition of the work already published in the literature, for the full detail please refer to Feenstra (1994). To estimate the demand and supply elasticities, quantities are converted into their respective market shares for variety v of good g in time t[4]. This produces two structural equations and before combining both, we follow Feenstra (1994) to eliminate time and product specific unobservables present in supply and demand. To remove the good specific shocks, he presents both equations in logs and takes first differences. He then differences again, to remove time-specific unobservables, using a reference variety k (i.e. from a specific country). This brings us to equations (1) and (2) from Soderbury (2015):

$$\Delta^k lns_{gvt} \equiv \Delta lns_{gvt} - \Delta lns_{gkt} = -(\sigma_g - 1)\Delta^k \ln(p_{gvt}) + \varepsilon^k_{gvt} \tag{1}$$

$$\Delta^k lnp_{gvt} \equiv \Delta lnp_{gvt} - \Delta lnp_{gkt} = \left(\frac{\omega_g}{1+\omega_g}\right)\Delta^k \ln(s_{gvt}) + \delta^k_{gvt} \tag{2}$$

$$\text{Where } \varepsilon^k_{gvt} = \Delta^k \ln(b_{gvt}) \text{ and } \delta^k_{gvt} = \Delta^k\left(\frac{\eta_{gvt}}{1+\omega_g}\right)$$

Where σ is the elasticity of substitution to be estimated, ε^k_{gvt} and δ^k_{gvt} are unobservable demand and supply shocks. They include η_{gvt}, a random technology factor, $\omega_g \geq 0$ the inverse export supply elasticity and b_{gvt} a random taste parameter.

Feenstra (1994) lastly takes the above system of equations, multiplies the demand and supply shocks together, scales and rearranges to produce equation (3) below to be estimated:

$$Y_{gvt} = \theta_{1g}X_{1gvt} + \theta_{2g}X_{2gvt} + u_{gvt} \tag{3}$$

Where:

$Y_{gvt} \equiv (\Delta^k lnp_{gvt})^2, X_{1gvt} \equiv (\Delta^k lns_{gvt})^2, X_{2gvt} \equiv (\Delta^k lns_{gvt})(\Delta^k lnp_{gvt}), u_{gvt} = \frac{\varepsilon^k_{gvt}\delta^k_{gvt}}{(1-\rho_g)}$, $\rho_g = \frac{\omega_g(\sigma_g-1)}{1+\omega_g\sigma_g}$ and θ_{1g} and θ_{2g} are non-linear functions of σ_g and ρ_g.

[3] Varieties are differentiated by their country of origin.

[4] For a detailed derivation please refer to Feenstra (1994).

4.2 A hybrid estimator

Following Soderbery (2015), we estimate equation (3) using limited information maximum likelihood methods. This two-stage approach uses a set of country fixed-effects in its first stage to isolate the country-specific factors that influence the relative quantity and value of trade (θ_{1g} and θ_{2g} respectively). The second stage of the approach weights the fitted values from the first stage using the t-statistic to give greater power to more tightly identified estimates. Given the a-priori theory that demand elasticities should be negative and supply elasticities should be positive, the estimators are obtained using a grid-search technique that constrains the estimates to align with their theoretically feasible values.

This estimator was shown by the Monte Carlo analysis of Soderbery (2015) to be superior to previous approaches which took a 2SLS approach. In samples which differ by the number of years used, LIML estimates outperform 2SLS estimates in terms of bias and in terms of the fraction of estimates that fall into the theoretically infeasible regions, prior to constraints being set.

5. Data

The methodology of Soderbery (2015) requires data on just two fundamental variables, trade values and trade quantities. Import value and quantity data is obtained from the UK customs authority, HMRC OTS (Her Majesty's Revenue and Customs Overseas Trade Statistics) and we download these at the 8-digit commodity code level across 12 years from 2009 to 2020. As these CN8 commodity codes change over the period of interest, we use the HMRC concordance tables to aggregate this data to networks of CN8 codes that are consistent over the time period. A number of products at this level of aggregation are suppressed due to their sensitive nature and so we do not estimate elasticities covering this data.

5.1 CN8 Network Level Analysis

For the network level analysis, data on trade values and weights are used to calculate unit value indices for each observation. Following Soderbery, observations where trade value and weights are zero are excluded from the estimation as unit value indices cannot be calculated for these. This reduces the number of observations from 25,558,848 to 2,045,298, removing almost 92% of the observations.

5.2 GTAP Sector Level Analysis

For the GTAP sector level analysis, the above CN8 network level data on trade values and weights is used to generate data at the GTAP level of aggregation. Trade data is usually mapped to GTAP sectors using the standard GTAP-HS6 concordance tables. However, as the aggregation to networks of products that are consistent over time can lead to products from different GTAP sectors being grouped, networks are allocated to GTAP sectors based on whichever sector has the highest proportion of the networks trade.

To ameliorate the issue of bias that occurs when using unit value indices in place of survey-based price data, GTAP sector level price data is obtained by calculating price indices using network level unit values as elementary indices, rather than creating GTAP level unit value indices. This creates an issue that is not present in the network level analysis; where the network level regressions can easily drop zero trade observations with its impact isolated to that country-time observation in that network only, the creation of price indices requires price information on all networks relevant to a GTAP sector for each country-time observation to ensure comparability between observations[5]. One approach would be to drop the sector level country-time observation in instances where any of the underlying networks for those observations are missing, leading to an approach comparable to that of the network level analysis with missing observations simply being dropped from the estimation stage. However, given the greater possibility that there would be at least one missing network for each country-time observation, this approach results in significant proportions of missing observations in the dataset.

To avoid this issue, we employ the standard technique used by statistical agencies to fill in required data that is missing and impute the CN8 network price observations where required. To control the proportion of the data that is being imputed, we first identify the proportion of network-time observations that are missing from each GTAP sector and choose a threshold of countries to include, based on the proportion of data available[6]. To investigate the extent to which results are sensitive to the method of imputation, we then follow two alternative approaches.

In the first approach, we solely use data from related observations to fill in gaps. Once a set of countries to be included has been chosen, we then impute within-network price data by chaining available observations for a country-product across years[7]. This allows us to fill missing observations where a product is temporarily missing, in line with the suggestion of IMF handbook of importer price indices[8]. For products that are missing across all of the years studied, we then move to impute where the price of similar goods is available. Specifically, when a product network is entirely non-traded with a partner across all time periods, the unit price for that partner is taken from the HS6 product that the majority of that CN8 network's trade falls into[9]. For observations that are still missing, the price is then taken from the HS4, or HS2 product sequentially. Finally, any remaining missing data are imputed using the corresponding network-year average across all available countries. Through this process we ensure that all missing price observations are imputed using the most relevant available data. The proportion of the data that is created by each stage of this approach is shown in Table 1.

In the second approach, we supplement the above process using XGBoost (Chen & Guestrin, 2016), a gradient boosting machine learning technique, as an extra stage of imputation after the price data has been chained across years. This technique uses a gradient boosted trees-based regressor to estimate missing data with dummy variables formed from the corresponding observation's year, network, and country. We use grid-search to tune the hyperparameters (number of estimators and maximum depth). The proportion of the data that is created by each stage of this approach is shown in Table 2.

[5] This can create serious issues of inconsistency for the estimation. For example, if a missing price was assumed to be 0 (i.e. is left out of the calculated price index for that sector level observation) it would bias the index downward and make it appear that the price fell in that period. However, given the fact that no units of that network's product was sold in that observation, this would indicate an incorrect demand relationship where fewer units of a product are demanded as its price falls.

[6] A cap of 80% of a partner's potential observations across products and years is used. This was chosen to reflect a good proportion of major trade partners.

[7] This is to say, when observations are available for some years for a given product and country, we use those existing unit price observations to impute data for the remaining years of that product for that country.

[8] IMF(2009)

[9] This is to say, if 60% of a particular CN8 network's trade falls into a particular HS6 sector, that HS6 sector's trade value and quantity is used to calculate a unit price which is then applied to the CN8 network for each year.

Table 1: Cumulative proportion of non-missing data after each stage of imputation (without machine learning stage)

GTAP Sector	Before Imputation	Chaining Across Time	HS6	HS4	HS2	Average Across countries
BPH	45.2%	71.0%	72.7%	91.7%	100.0%	100.0%
B_T	38.9%	67.8%	83.8%	92.7%	99.5%	100.0%
CHM	45.9%	71.8%	77.3%	92.7%	99.8%	100.0%
CMT	43.1%	71.7%	84.0%	97.7%	100.0%	100.0%
COA	50.4%	82.7%	86.4%	89.1%	100.0%	100.0%
CTL	26.2%	47.1%	52.7%	63.8%	100.0%	100.0%
C_B	53.3%	86.7%	86.7%	97.0%	100.0%	100.0%
EEQ	58.7%	85.8%	88.3%	96.7%	100.0%	100.0%
ELE	54.2%	80.9%	83.0%	91.8%	99.8%	100.0%
ELY	83.3%	100.0%	100.0%	100.0%	100.0%	100.0%
FMP	57.0%	83.9%	86.8%	93.4%	98.5%	100.0%
FRS	36.2%	66.1%	74.4%	93.1%	98.5%	100.0%
FSH	34.5%	63.9%	69.3%	94.3%	99.4%	100.0%
GAS	50.3%	66.7%	66.7%	96.9%	100.0%	100.0%
GDT	41.7%	100.0%	100.0%	100.0%	100.0%	100.0%
GRO	44.6%	73.3%	77.6%	91.5%	100.0%	100.0%
I_S	41.1%	74.7%	81.8%	94.7%	100.0%	100.0%
LEA	47.6%	71.0%	76.3%	82.9%	94.2%	100.0%
LUM	38.9%	66.1%	71.9%	92.5%	98.8%	100.0%
MIL	47.1%	72.8%	93.7%	97.3%	100.0%	100.0%
MVH	46.6%	71.1%	80.8%	92.1%	100.0%	100.0%
NFM	44.8%	74.5%	77.2%	86.7%	99.1%	100.0%
NMM	47.1%	77.2%	81.1%	87.9%	100.0%	100.0%
OAP	32.2%	64.6%	68.6%	81.6%	98.3%	100.0%
OCR	42.1%	68.0%	75.3%	87.9%	99.0%	100.0%
OFD	41.8%	67.0%	81.7%	96.3%	99.7%	100.0%
OIL	32.2%	65.2%	75.1%	75.6%	98.0%	100.0%
OME	51.1%	80.2%	83.1%	93.2%	99.9%	100.0%
OMF	55.7%	84.0%	86.1%	91.7%	99.0%	100.0%
OMT	50.6%	76.7%	86.6%	97.8%	100.0%	100.0%
OSD	44.7%	73.0%	76.9%	86.2%	99.9%	100.0%
OTN	36.8%	66.2%	73.0%	82.5%	98.7%	100.0%
OXT	40.0%	71.0%	72.1%	78.7%	99.8%	100.0%
PCR	48.1%	85.9%	98.7%	100.0%	100.0%	100.0%
PDR	59.2%	96.0%	98.7%	99.7%	100.0%	100.0%
PFB	39.4%	81.2%	86.3%	92.9%	100.0%	100.0%
PPP	47.7%	74.6%	77.2%	87.7%	97.9%	100.0%
P_C	45.8%	74.4%	89.9%	96.6%	100.0%	100.0%
RMK	61.8%	88.9%	94.8%	99.7%	100.0%	100.0%
RPP	57.4%	82.5%	85.6%	93.8%	99.6%	100.0%
SGR	46.5%	74.2%	85.1%	97.6%	100.0%	100.0%
TEX	47.5%	78.0%	80.3%	93.4%	99.9%	100.0%
VOL	41.3%	69.9%	81.9%	92.2%	100.0%	100.0%

V_F	47.0%	71.1%	76.3%	90.6%	100.0%	100.0%
WAP	63.3%	88.8%	93.2%	98.5%	99.8%	100.0%
WHT	43.7%	79.5%	83.2%	97.5%	99.1%	100.0%
WOL	39.5%	75.2%	81.7%	86.9%	99.5%	100.0%

Table 2: Cumulative proportion of non-missing data after each stage of imputation (with machine learning stage)

GTAP Sector	Before Imputation	Chaining Across Time	XGBoost	HS6	HS4	HS2	Average Across Countries
BPH	45.2%	71.0%	100.0%	100.0%	100.0%	100.0%	100.0%
B_T	38.9%	67.8%	100.0%	100.0%	100.0%	100.0%	100.0%
CHM	45.9%	71.8%	99.4%	99.4%	99.5%	100.0%	100.0%
CMT	43.1%	71.7%	94.8%	97.5%	99.9%	100.0%	100.0%
COA	50.4%	82.7%	100.0%	100.0%	100.0%	100.0%	100.0%
CTL	26.2%	47.1%	92.9%	92.9%	93.8%	100.0%	100.0%
C_B	53.3%	86.7%	100.0%	100.0%	100.0%	100.0%	100.0%
EEQ	58.7%	85.8%	100.0%	100.0%	100.0%	100.0%	100.0%
ELE	54.2%	80.9%	99.5%	99.5%	100.0%	100.0%	100.0%
ELY	83.3%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
FMP	57.0%	83.9%	96.6%	97.0%	97.9%	99.2%	100.0%
FRS	36.2%	66.1%	100.0%	100.0%	100.0%	100.0%	100.0%
FSH	34.5%	63.9%	96.5%	97.0%	100.0%	100.0%	100.0%
GAS	50.3%	66.7%	100.0%	100.0%	100.0%	100.0%	100.0%
GDT	41.7%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
GRO	44.6%	73.3%	100.0%	100.0%	100.0%	100.0%	100.0%
I_S	41.1%	74.7%	100.0%	100.0%	100.0%	100.0%	100.0%
LEA	47.6%	71.0%	98.9%	99.3%	99.5%	99.8%	100.0%
LUM	38.9%	66.1%	98.8%	98.9%	100.0%	100.0%	100.0%
MIL	47.1%	72.8%	97.1%	99.6%	99.8%	100.0%	100.0%
MVH	46.6%	71.1%	97.8%	98.4%	99.3%	100.0%	100.0%
NFM	44.8%	74.5%	100.0%	100.0%	100.0%	100.0%	100.0%
NMM	47.1%	77.2%	100.0%	100.0%	100.0%	100.0%	100.0%
OAP	32.2%	64.6%	97.1%	97.1%	98.6%	99.9%	100.0%
OCR	42.1%	68.0%	100.0%	100.0%	100.0%	100.0%	100.0%
OFD	41.8%	67.0%	99.3%	99.3%	100.0%	100.0%	100.0%
OIL	32.2%	65.2%	100.0%	100.0%	100.0%	100.0%	100.0%
OME	51.1%	80.2%	99.4%	99.4%	99.4%	99.9%	100.0%
OMF	55.7%	84.0%	99.6%	99.6%	99.8%	100.0%	100.0%
OMT	50.6%	76.7%	99.5%	99.5%	99.9%	100.0%	100.0%
OSD	44.7%	73.0%	100.0%	100.0%	100.0%	100.0%	100.0%
OTN	36.8%	66.2%	93.5%	93.6%	95.8%	99.1%	100.0%
OXT	40.0%	71.0%	98.0%	98.0%	98.0%	100.0%	100.0%
PCR	48.1%	85.9%	100.0%	100.0%	100.0%	100.0%	100.0%
PDR	59.2%	96.0%	100.0%	100.0%	100.0%	100.0%	100.0%

PFB	39.4%	81.2%	100.0%	100.0%	100.0%	100.0%	100.0%
PPP	47.7%	74.6%	100.0%	100.0%	100.0%	100.0%	100.0%
P_C	45.8%	74.4%	96.6%	98.9%	99.7%	100.0%	100.0%
RMK	61.8%	88.9%	100.0%	100.0%	100.0%	100.0%	100.0%
RPP	57.4%	82.5%	100.0%	100.0%	100.0%	100.0%	100.0%
SGR	46.5%	74.2%	100.0%	100.0%	100.0%	100.0%	100.0%
TEX	47.5%	78.0%	100.0%	100.0%	100.0%	100.0%	100.0%
VOL	41.3%	69.9%	99.3%	99.5%	99.9%	100.0%	100.0%
V_F	47.0%	71.1%	100.0%	100.0%	100.0%	100.0%	100.0%
WAP	63.3%	88.8%	100.0%	100.0%	100.0%	100.0%	100.0%
WHT	43.7%	79.5%	100.0%	100.0%	100.0%	100.0%	100.0%
WOL	39.5%	75.2%	100.0%	100.0%	100.0%	100.0%	100.0%

Following imputation of the elementary unit value indices, laspeyres indices are calculated to obtain price data at the GTAP level. When comparing prices of imported goods across countries, it is important to ensure that comparable baskets of goods are used. As import bundles might differ across certain countries, the weights for the basket of goods are calculated as the proportion of each network product that is imported across all partners as a proportion of total imports from that GTAP sector.

Total trade value for each GTAP sector is calculated by summing the trade values of each network by GTAP sector and total trade quantity is obtained by deflating this value by the above price index.

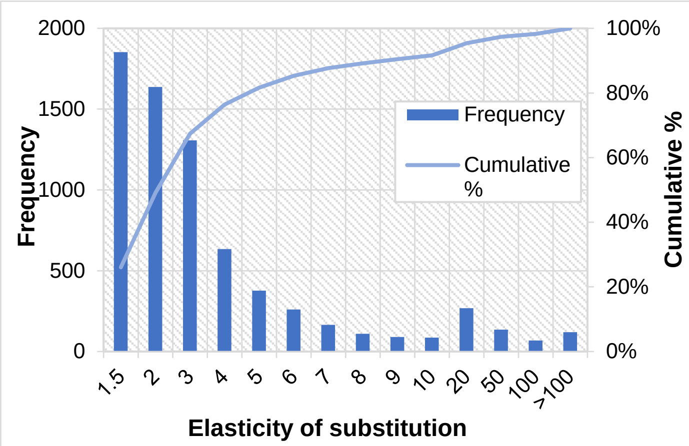
Given the use of imputation to fill in missing price data that underpins the sector level price indices, it is possible to run the sector level regressions including observations where traded value is zero. To further investigate the sensitivity of results, we test how elasticity estimates are affected by the inclusion of these zero trade observations. Removing zero trade observations has the benefit of removing observations where all the underlying elementary unit value indices are imputed and hence which are potentially of a lower reliability, whilst including zero trade observations has the benefit of including additional information if the imputation is deemed reliable. This gives four aggregate datasets that results are estimated on: the first imputation approach above, both with and without zeros, and the second imputation approach above, both with and without zeros.

6 Results

6.1 CN8 Network level results

Estimating the elasticities at the CN8 network level results in 7,110 estimations from 8,451 networks.[10] Whilst it is infeasible to report all estimated elasticities, row 1 of table 1 contains summary statistics[11]. As the elasticities of substitution have a lower bound of 1 but no upper bound in calculation, the mean is higher than the median, at 6.33 compared to 2.03. Figure 1 illustrates the distribution of the network level elasticities, showing that almost 50% of the elasticities are less than 2, with a small number of outliers greater than 100.

Figure 1: Histogram: network level elasticities of substitution



The median estimate is over 18% lower than other UK estimates of the elasticity of substitution using the previous estimator developed by Feenstra (1994) and Broda and Weinstein (2006). Thus, our results confirm Soderbery's (2015) finding that previous estimates significantly overestimate the elasticity of substitution, understating the consumer gains from variety. Compared to the median elasticity of substitution for the US estimated by Soderbery (2015) of 1.86, our median is slightly higher, suggesting that the UK values additional varieties less than the US. This is consistent with previous estimations suggesting that the elasticity of substitution is higher in the US than the UK.

Network level elasticities of substitution were assigned to GTAP sectors following the method outlined in section 5, with each elasticity trade weighted according to the proportion of trade it accounted for within a GTAP sector. Column 3 in Table 3 displays the results for each GTAP sector, illustrating that the elasticity of substitution varies significantly dependent on sector. By a significant margin, the sector with the highest elasticity of substitution is plant-based fibres. This appears to be driven by a specific network within the GTAP sector, with the median elasticity within the sector 2.03. Other sectors with high elasticities include oil and meat sectors. In particular, the commodity nature of the oil sector suggests this is intuitive, as varieties in commodity sectors are likely to matter less.

In contrast, sectors with low elasticities of substitution, thus suggesting additional varieties matter more, include energy sectors such as electricity, gas and coal. This appears contradictory to other commodity sectors which have higher elasticity values but is likely influenced by the low number of networks which map into each GTAP sector, with only one network mapped to the electricity sector and two mapped to the gas sector.

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[10] It was not possible to estimate an elasticity of substitution for all networks, as for some the number of country pairs and/or periods with positive trade values were insufficient. This is similar to Soderbery (2015), in which around 10% of goods did not have sufficient data to estimate an elasticity of substitution.

[11] Following Soderbery (2015), elasticities are censored at 131.05 for exposition. This is due to increases in already large elasticities having little significance for estimated variety gains, an issue outlined in footnote 21 in Broda and Weinstein (2006). Out of 7,110 estimations, 103 were censored.

Table 3: Summary statistics

	Observations	Mean	St dev	Min	Max	Median
$\sigma_{Network}$	7,110	6.33	17.93	1.00	131.05	2.03
$\sigma_{GTAP\ Imp\ 1}$	41	6.27	9.90	1.04	55.01	1.82
$\sigma_{GTAP\ Imp\ 2}$	41	5.65	8.02	1.04	41.02	2.43
$\sigma_{GTAP\ ML\ 1}$	40	8.12	20.84	1.04	131.05	1.63
$\sigma_{GTAP\ ML\ 2}$	40	5.35	8.51	1.04	40.76	1.85

Table 4: Estimated elasticities of substitution, GTAP sectors

GTAP sector name	Code	Network	GTAP Imp 1	GTAP Imp 2	GTAP ML 1	GTAP ML 2
Bovine cattle, sheep and goats, horses	CTL	3.96	1.75	1.75	1.49	1.49
Animal products n.e.c (not elsewhere classified)	OAP	2.45			1.53	1.53
Bovine meat products	CMT	11.18	1.81	1.81	1.96	1.96
Meat products n.e.c	OMT	12.94	1.05	1.05	1.05	1.05
Fishing	FSH	2.27	1.04	1.04	1.58	1.58
Food products n.e.c	OFD	7.91	5.33	5.33	5.92	5.92
Raw milk	RMK	1.51	7.23	7.23	10.99	10.99
Dairy products	MIL	4.19				
Manufactures n.e.c	OMF	7.16	1.05	1.05	2.16	2.16
Crops n.e.c	OCR	4.63	1.05	1.05	1.05	1.05
Vegetables, fruit, nuts	V_F	3.87	1.06	1.06	1.10	1.10
Wheat	WHT	6.72	8.36	15.60	8.37	15.61
Cereal grains n.e.c	GRO	7.90	1.53	1.53	1.23	1.23
Paddy rice	PDR	2.25	2.50	2.51	8.25	2.39
Processed rice	PCR	4.90	26.26	26.26	37.39	37.39
Oil seeds	OSD	3.26	1.98	1.98	9.26	9.26
Vegetable oils and fats	VOL	5.46	1.22	1.22	1.32	1.32
Sugar cane, sugar beet	C_B	1.98	12.87	8.83	13.96	7.85
Forestry	FRS	2.31	1.82	2.19	1.62	1.75
Basic pharmaceutical products	BPH	5.25	6.97	6.97	1.75	1.75
Chemical products	CHM	3.52	1.04	1.04	1.04	1.04
Sugar	SGR	8.86	1.11	1.11		
Beverages and tobacco products	B_T	3.06	3.49	3.49	3.74	3.74
Other Extraction	OXT	3.27	12.30	12.30	1.46	1.46
Mineral products n.e.c	NMM	3.30	1.14	1.14	1.08	1.08
Ferrous metals	I_S	2.77	5.22	5.22	3.87	3.87
Metals n.e.c	NFM	4.52	7.30	7.30	1.64	1.64
Coal	COA	1.30	55.01	2.43	138.10	2.44
Petroleum, coal products	P_C	9.06	24.98	24.98		
Gas manufacture, distribution	GDT	1.97	1.23	3.23	1.23	3.23
Crude Oil	OIL	11.03	21.17	41.02	21.19	40.76
Gas	GAS	1.95	1.36	3.25	1.41	2.26
Electricity	ELY	1.16				
Rubber and plastic products	RPP	4.49	1.45	1.45	1.24	1.24
Paper products, publishing	PPP	2.52	1.20	1.20	1.60	1.60
Manufacture of electric equipment	EEQ	7.08				
Leather products	LEA	3.37	1.07	1.07	1.07	1.07

Wearing apparel	WAP	5.20	1.08	1.08	1.08	1.08
Wood products	LUM	10.09	3.58	3.58	3.66	3.66
Metal products	FMP	5.86				
Wool, silk-worm cocoons	WOL	7.74	5.99	5.99	11.04	11.04
Textiles	TEX	4.87	7.44	7.44	10.41	10.41
Plant-based fibres	PFB	106.70	1.29	1.29	1.46	1.46
Machinery and equipment n.e.c	OME	4.66	1.44	1.44	1.44	1.44
Transport equipment n.e.c	OTN	10.91	7.73	7.73	8.70	8.70
Motor vehicles and parts	MVH	10.50				
Computer, electronic and optical products	ELE	5.69	4.42	4.42	3.26	3.26

6.2 GTAP Results

Table 3 includes summary statistics for the four estimations run on the GTAP sector aggregation, where GTAP Imp refers to the dataset created using the first imputation method detailed above and GTAP ML refers to the dataset created using second approach. Both datasets were created accounting for zero trade value observations differently, with method 1 including zero trade observations in the dataset and method 2 dropping any zero trade observations. Whilst removing observations with zero trade values is consistent with Soderbery (2015) and the estimation run at the network level, removing these observations potentially excludes useful information from the estimation if the price data is deemed reliable.

Comparing the median estimates, Table 3 shows that the methods that exclude observations with zero trade result in higher medians both for the imputation and machine learning based datasets. All median estimates except for imputation these two sets of estimates are lower than previous estimates for the UK using the Feenstra/Broda & Weinstein estimator, supporting Soderbery's (2015) finding that the estimator overestimates the elasticity of substitution.

Columns 4-7 in Table 4 display the GTAP sector elasticity estimates across methods. We note that elasticities of substitution across the four methods are broadly similar across sectors, particularly on the pattern of sectors with the highest and lowest elasticities of substitution. A notable exception is coal, in which the machine learning method with zero trade value observations included gives a substantially higher elasticity than other methods. The similarity of these results gives an important insight into the approach that modellers should take when constructing their data. Where the differences in the aggregate and network level results highlight the importance of estimating elasticities at the level of simulation, the concern of economists must then turn to the method by which the data is aggregated. The lack of sensitivity that is evidenced in Tables 3 and 4 indicate that results are invariant to the assumptions used in aggregation process and that the choice of approach is therefore of less concern. In light of this, we focus our analysis on the estimates in column 4, namely those produced using the first imputation method and including observations with zero trade values in the dataset. This method is chosen as it includes a large set of information in the parameter estimates, as well as involving less data processing in the imputation process compared to the machine learning approach.

Focusing on the column 4 estimates, sectors with the highest elasticities of substitution and thus indicating that additional varieties matter less, include energy sectors such as coal, petroleum and crude oil. This demonstrates the homogeneous nature of these commodities and is consistent with findings from Broda and Weinstein (2006) that commodity goods are more likely to have higher elasticities of substitution.

In contrast, sectors with the lowest elasticities of substitution include chemical products, fishing, other meat products and other crops. As the other crops sector includes products such as plants used in perfumery or pharmacy, living plants, cut flowers, and spice and aromatic crops, it is likely that these will have much lower levels of elasticity than in standard commodity crops. This hypothesis is consistent with agricultural sectors that have higher elasticities of substitution, which include more homogeneous crops such as wheat and sugar cane, alongside raw milk.

6.3 Comparison of Results

Comparing across median elasticities of substitution, the level of aggregation has a significant influence on the estimates, with a higher median under the network level estimation compared to the primary GTAP sector estimation (GTAP Imp 1). This implies consumers value variety less at lower levels of aggregation, likely driven by the relative ease at which consumers can substitute between disaggregated products compared to highly aggregated sectors. This finding of different elasticities of substitution depending on the level of aggregation supports that of Hummels (1999) and Broda and Weinstein (2006) yet contradicts that of Ahmad and Riker (2019), who conclude that changing the aggregation level does not change the estimated elasticities.

However, using a central elasticity of substitution risks obscuring significant differences between sectors, as table 3 illustrates. For the 41 sectors where both network level and GTAP sector estimations were obtained, over 66% of sectors had higher elasticities of substitution under the network level estimation compared to the GTAP estimation, with network level estimates over 4 times higher than GTAP estimates on average. This suggests that estimating elasticities at the most disaggregated level available and trade weighting estimates to produce a GTAP sector value risks overestimating the elasticity of substitution, highlighting the importance of estimating model parameters at the level of aggregation used in modelling.

6.4 CGE Simulation Results

To understand the impact that each parameter estimation technique has at the macro level we simulate UK unilateral tariff liberalisation using a Krugman style CGE model developed by Thomas Rutherford and Christoph Böhringer. This structure builds on the GTAPinGAMS framework, extending the basic Armington trade structure to include imperfectly competitive sectors and increasing aggregate productivity linked to the number of firms (varieties) in an industry, as shown in the Dixit-Stiglitz model. The model follows that of Balistreri, Böhringer and Rutherford (2018) [12], with the ability to exogenously define the Dixit-Stiglitz elasticity of substitution between varieties, σ. Using the GTAP10A database we aggregate up to 6 regions and 62 sectors (see Annex, table 2), remove UK defensive tariffs across imports from all regions and run the model using different elasticities of substitution, σ, shown in

[12] We follow the same model structure and assumptions as used in Balistreri, Böhringer and Rutherford (2018). Note that not all sectors operate under increasing returns to scale; see the Annex, table 2 for a mapping of these sectors.

table 5[13]. As we have not been able to estimate services sectors due to data constraints, we assign all services sectors elasticities to the median estimate for that method.

Table 5: CGE Simulation Results

Estimate	Value	Overall Welfare Gain
Authors network level estimates trade weighted to GTAP 65 sectors	Differentiated by sector, ranging 1.16 – 20	0.01%
Authors GTAP level estimates	Differentiated by sector, ranging 1.04 – 20	0.19%
Authors Network level estimates median	2.03	0.11%
Authors GTAP level estimates median	1.82	0.16%
Broda and Weinstein (2006) UK median	2.4	0.07%
Soderbery (2018) UK median	2.98	0.04%
Balistreri, Böhringer and Rutherford (2018)[14]	3	0.04%

The simulations show positive welfare gains across all sets of elasticities and the lower the median value of sigma, the higher the welfare gains. This is intuitive because a lower value of sigma implies that new varieties are valued more by consumers and therefore the introduction of new, differentiated varieties due to UK import liberalisation provides higher overall welfare gains.

We include the median estimates from alternative estimation techniques used in Soderbery (2018) and Broda and Weinstein (2006) for comparison. The welfare results in table 5 corroborates the argument that the LIML estimator used in this analysis (which produces lower elasticity values) reduces the risk of underestimating the welfare gains from trade liberalisation, with higher welfare gains under the network and GTAP level medians compared to those from previous literature. Our results also show that the simulations which apply differentiated elasticities by sector result in the highest and lowest welfare gains across all methods, with the network level gain significantly lower than that of the GTAP level. This relates to the fact that estimating the variety elasticity at a more disaggregated level (i.e., the network level) generates higher values as consumers do not value different varieties as much. In doing this and trade weighting up to the 62-sector aggregation used in the CGE modelling, on average larger elasticities are simulated across sectors and we therefore risk underestimating the gains from liberalisation in the modelled sectors.

7 Conclusion

Despite evidence for new theories of trade, most CGE modelling relies on standard Armington theory to demonstrate the effects of trade policy. The move towards incorporating new trade theory in CGE modelling has likely been slow due to the lack of evidence on some of the key parameters governing the gains from trade in these models, such as the elasticity of substitution, which determines the extent to which new varieties benefit consumers.

Thus far, literature on estimating the elasticity of substitution has primarily focused on the US, with approaches providing estimates for wider sets of countries, including the UK, suffering from substantial biases. Sectoral aggregation is also limited to CN8 products or HS

[13] For computational reasons, we constrain the upper bound of the elasticity at 20; this only affects two sectors.
[14] This is not estimated econometrically rather it is the default value for the elasticity recommended by the authors who developed the CGE model in use.

sectors. Given that most CGE modelling is confined to 65 sectors[15], modellers are faced with using arbitrary parameters or parameters estimated at different levels of aggregation to their modelling. By estimating the elasticity of substitution between varieties across UK GTAP sectors, this paper develops the research underpinning the use of new trade theory specifications in CGE modelling.

Our results first contribute to the recent literature arguing previous elasticity of substitution estimates suffer from significant upward biases, with our median elasticity estimates between 15% and 39% lower than previous UK estimates[16]. This implies that previous estimates significantly understated the benefits from additional product variety to the UK economy.

Furthermore, our results provide evidence that the elasticity of substitution is sensitive to aggregation, with significant differences between the network level and GTAP estimations across the GTAP sectors. On average, across sectors, network level estimates are over 4 times higher than GTAP level estimates, indicating the importance of estimating parameters at the level of aggregation used in CGE modelling. To demonstrate this further, we use a Krugman style CGE model to run a unilateral tariff liberalisation simulation for the UK. This results in starkly different results dependent on the estimates used, with network level estimates producing a welfare gain that is approximately 1/20th of the gain under the GTAP level estimates. Considering the importance of aggregation to estimates, we go a step further by investigating multiple approaches to aggregation, demonstrating that elasticity estimates are largely insensitive to the assumptions required when constructing GTAP level price data. These findings are important to modellers who are interested in conducting Krugman style CGE modelling of their own country, showing the necessity of using aggregate estimates whilst reassuring modellers that results are robust to assumptions used in the data cleaning process.

In future, the research could be further developed in two directions. Firstly, although we have provided estimates for elasticities of substitution across GTAP sectors, there is no consensus in the literature on which sectors should be defined as imperfectly competitive and thus benefit from Krugman variety effects depending on the magnitude of the elasticity of substitution. Increased evidence on the classification of individual GTAP sectors would greatly improve the accuracy of CGE modelling in a Krugman style model structure.

Secondly, future research could use the elasticity of substitution estimates to establish how product variety has contributed to welfare in the UK, similar to Broda and Weinstein (2006), who use elasticity estimates to calculate how growth in product variety from US imports impacted US welfare. This would illustrate the magnitude of the mechanism by which trade increases product variety and welfare in the UK, thus determining the importance of including such mechanisms in CGE modelling of trade policy.

[15] This also includes services sectors, which we were unable to provide estimates for due to data availability.
[16] Based on the network level estimation or our primary GTAP level estimation, GTAP Imp 1.

References

Ahmad, S. and Riker, D. 2019. *A method for estimating the elasticity of substitution and import sensitivity by industry*. Washington: US International Trade Commission.

Armington, P. 1969. A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers, 16(1), pp. 159-178.

Balassa, B. 1967. *Trade Liberalisation among industrial countries*, New York.

Balistreri, E., Böhringer, C. & Rutherford, T. 2018. *Quantifying Disruptive Trade Policies.* CESifo Working Paper Series 7382. CESifo.

Broda, C. and Weinstein, D. E. 2006. Globalization and the gains from variety. *The Quarterly Journal of Economics,* 121(2), pp. 541-585.

Broda, C., Greenfield, J., Weinstein, D. 2006. *From groundnuts to globalization: a structural estimate of trade and growth*. NBER Working Paper Series No 12512. Cambridge MA: NBER.

Chen, T. & Guestrin, C. 2016. XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22md ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 785-794.

Dixit, A. & Stiglitz, J. 1977. Monopolistic Competition and Optimum Product Diversity. *The American Economic Review,* 67(3), pp. 297-308.

Feenstra, R. C. 1994. New product varieties and the measurement of international prices. *The American Economic Review,* 84(1), pp. 157-177.

Grubel, H. 1967. Intra-Industry Specialisation and the Pattern of Trade, *The Canadian Journal of Economics and Political Science,* 33(3), pp. 374-388.

Hertel, T., Hummels, D., Ivanic, M., Keeney, R. 2007. How confident can we be of CGE-based assessments of Free Trade Agreements? *Economic Modelling*, 24, pp. 611-635.

Hillberry, R. & Hummels, D. 2013. Trade Elasticity Parameters for a Computable General Equilibrium Model, pp, 1213-1269 in Dixon, P. & Jorgenson, D. (eds), *Handbook of Computable General Equilibrium Modeling, Volume 1,* Amsterdam: Elsevier.

Hummels, D. 1999. *Toward a Geography of Trade Costs*. GTAP Working Papers 1162, Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University.

International Monetary Fund 2009. *Export and Import Price Index Manual*, Report, 71-90.

Krugman, P. 1979. Increasing returns, monopolistic competition, and international trade. *Journal of International Economics,* 9(4), pp. 469-479.

Krugman, P. 1980. Scale Economies, Product Differentiation, and the Pattern of Trade. *The American Economic Review,* 70(5), pp. 950-959.

McDaniel, C. & Balistreri, E. 2003. A Review of Armington Trade Substitution Elasticities. *Economie Internationale*, 23(3), pp. 301-313.

Melitz, M. 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica,* 71(6), pp. 1695-1725.

Nilsson, L. 2019. Reflections on the economic modelling of free trade agreements. *Journal of Global Economic Analysis,* 3(1), pp. 156-186.

Romer, P. 1994. New Goods, Old Theory, and the Welfare Costs of Trade Restrictions. *Journal of Development Economics,* 43(1), pp. 5-38.

Soderbery, A. 2015. Estimating import supply and demand elasticities: analysis and implications. *Journal of International Economics,* 96, pp.1-17.

Soderbery, A. 2018. Trade elasticities, heterogeneity, and optimal tariffs. *Journal of International Economics,* 114, pp.44-6.

Annex

Table 1: GTAP estimation summary statistics

		Mean		St. dev of the mean		Mean of the st. dev	
GTAP	**Unit**	**Without ML**	**With ML**	**Without ML**	**With ML**	**Without ML**	**With ML**
B_T	Price	440	449	1,378	1,416	1,045	1,070
B_T	Value	248,721,233	234,964,169	298,778,355	296,990,861	52,269,131	43,311,036
B_T	Weight	21,879,681	23,063,817	34,206,990	36,361,122	13,037,656	12,790,044
BPH	Price	351	342	634	630	150	148
BPH	Value	760,161,615	751,355,414	1,110,598,313	1,110,672,673	244,066,254	239,682,379
BPH	Weight	4,905,748	5,229,769	6,718,759	7,265,325	1,921,971	2,042,884
C_B	Price	61	66	61	57	80	82
C_B	Value	4,565,262	4,575,716	6,956,303	6,968,026	4,078,673	4,085,803
C_B	Weight	142,060	142,647	164,979	181,277	154,188	156,637
CHM	Price	10,718	10,699	27,949	27,864	24,792	24,851
CHM	Value	1,119,731,191	1,030,562,240	1,260,723,778	1,220,410,008	204,605,300	169,789,504
CHM	Weight	5,882,110	7,168,843	7,581,729	9,643,765	3,197,575	3,627,027
CMT	Price	14	13	20	20	16	17
CMT	Value	129,855,071	123,788,489	208,675,258	205,358,540	22,092,931	21,456,992
CMT	Weight	27,726,799	27,138,691	52,999,453	51,248,388	4,214,205	4,525,770
COA	Price	70	17	171	43	109	15
COA	Value	114,339,578	123,725,759	180,516,366	195,841,154	77,775,884	84,659,535
COA	Weight	1,223,887,604	608,384,758	2,387,016,624	939,860,358	907,958,308	543,229,305
CTL	Price	995	1,148	1,934	2,195	1,590	1,827
CTL	Value	41,396,785	35,730,313	91,378,394	78,147,170	10,336,880	8,196,586
CTL	Weight	221,621	170,495	501,768	387,627	138,436	104,263

EEQ	Price	1,443	1,448	9,000	9,095	1,369	1,376
EEQ	Value	352,666,452	347,268,223	629,951,888	631,455,282	80,204,769	78,321,467
EEQ	Weight	11,111,771	11,563,946	50,557,415	51,850,043	3,541,381	3,439,490
ELE	Price	934	936	2,502	2,522	1,489	1,500
ELE	Value	750,074,197	742,987,136	1,568,671,666	1,566,008,960	168,295,135	166,511,700
ELE	Weight	3,043,235	3,046,942	8,188,616	8,217,772	855,516	852,423
ELY	Price	20,983,229	20,983,229			7,777,137	7,777,137
ELY	Value	251,097,959	251,097,959			98,480,746	98,480,746
ELY	Weight	12	12			1	1
FMP	Price	285	271	1,202	1,152	74	51
FMP	Value	194,152,280	190,546,577	316,723,926	317,762,535	64,230,947	63,079,846
FMP	Weight	10,122,776	9,957,542	41,068,831	38,170,329	3,576,251	3,510,702
FRS	Price	370	350	1,189	1,177	924	894
FRS	Value	3,133,542	2,977,028	2,444,409	2,393,661	2,331,169	2,286,372
FRS	Weight	900,661	745,081	1,358,007	898,776	892,480	731,043
FSH	Price	1,093	1,156	2,136	436	1,458	1,291
FSH	Value	58,478,074	43,718,616	67,999,127	49,246,359	23,014,000	17,990,431
FSH	Weight	2,845,162	1,903,955	3,759,689	2,530,924	2,879,544	3,021,311
GAS	Price	402,759	427,783	1,099,688	1,168,062	1,395,134	1,481,841
GAS	Value	620,205,771	794,524,035	1,148,379,211	1,224,640,115	359,095,219	421,808,734
GAS	Weight	4,309,581,493	3,159,082,599	8,171,420,011	5,678,875,419	1,853,450,889	1,385,786,104
GDT	Price	382	382	636	636	405	405
GDT	Value	37,034	37,034	61,872	61,872	17,156	17,156
GDT	Weight	16,264	16,264	40,511	40,511	9,232	9,232
GRO	Price	3	2	3	2	2	1
GRO	Value	19,228,834	15,582,763	33,162,074	26,973,711	10,547,141	7,664,288
GRO	Weight	57,763,138	17,703,919	180,741,711	37,041,401	48,015,104	13,542,908
I_S	Price	50	45	45	44	24	22
I_S	Value	232,828,566	217,460,439	188,749,561	182,388,249	49,914,620	45,526,783
I_S	Weight	11,798,353	13,761,423	14,555,995	18,853,395	6,174,526	6,772,709
LEA	Price	70	70	54	53	44	44

LEA	Value	116,032,355	115,093,936	276,277,674	276,393,053	32,826,840	32,489,616
LEA	Weight	5,807,617	5,843,608	22,916,628	23,298,325	1,550,758	1,549,063
LUM	Price	100	93	134	141	140	137
LUM	Value	165,716,545	147,292,004	187,820,162	157,980,728	47,536,464	43,560,312
LUM	Weight	25,081,016	24,978,659	40,413,503	38,781,336	13,435,666	13,219,058
MIL	Price	8	6	12	6	5	4
MIL	Value	233,033,619	218,606,217	199,921,198	194,576,070	36,127,257	33,417,954
MIL	Weight	48,637,740	48,176,539	43,466,700	44,247,902	15,820,913	15,131,523
MVH	Price	221	162	572	449	383	246
MVH	Value	1,352,404,658	1,263,499,780	3,088,592,893	3,046,576,047	335,778,071	310,727,238
MVH	Weight	69,579,069	78,039,148	166,205,152	196,399,582	42,484,682	42,604,441
NFM	Price	5,287	6,109	7,388	8,053	6,571	7,188
NFM	Value	1,089,944,291	1,022,726,859	1,516,536,619	1,452,142,325	821,460,755	793,633,254
NFM	Weight	301,341	249,767	404,772	364,101	191,887	170,719
NMM	Price	119	81	92	73	76	46
NMM	Value	100,770,402	95,145,766	145,732,186	146,556,138	22,919,467	19,369,957
NMM	Weight	4,602,825	10,853,291	14,937,138	43,993,232	2,819,127	3,474,915
OAP	Price	558	376	700	510	729	434
OAP	Value	31,565,335	33,724,642	30,891,683	28,356,723	7,143,693	7,864,325
OAP	Weight	730,932	786,074	1,597,010	1,199,267	501,995	268,156
OCR	Price	93	90	163	158	167	164
OCR	Value	55,567,000	53,091,178	139,928,232	139,039,515	8,573,697	7,528,791
OCR	Weight	4,360,790	6,865,184	14,802,024	27,073,723	1,982,973	2,377,465
OFD	Price	11	11	14	14	3	3
OFD	Value	702,697,569	668,912,412	565,484,575	560,890,711	127,991,160	123,909,779
OFD	Weight	121,715,104	134,523,316	113,774,885	134,818,242	37,597,895	44,487,338
OIL	Price	21	5	91	22	26	6
OIL	Value	928,964,484	858,523,892	2,023,000,281	1,991,152,351	601,964,590	551,183,399
OIL	Weight	2,256,626,752	2,127,078,689	5,275,003,583	5,138,730,066	1,082,854,721	1,020,667,056
OME	Price	242	222	187	157	165	159

OME	Value	624,993,838	602,245,966	956,859,183	962,003,651	111,165,684	105,952,787
OME	Weight	7,216,894	7,892,817	16,601,885	17,528,735	2,751,893	3,386,877
OMF	Price	9,561	9,633	29,141	29,395	8,875	8,963
OMF	Value	346,672,323	339,501,698	695,451,301	697,788,024	86,674,437	81,846,463
OMF	Weight	464,488	424,141	1,523,058	1,486,513	484,773	447,604
OMT	Price	15	16	29	32	31	32
OMT	Value	325,896,040	309,590,989	302,440,507	284,511,318	51,594,846	49,818,598
OMT	Weight	82,286,964	82,626,813	93,753,432	94,897,396	22,051,927	22,146,336
OSD	Price	18	12	24	19	22	17
OSD	Value	14,469,768	14,339,822	15,514,917	14,592,185	9,096,076	8,741,180
OSD	Weight	7,498,235	9,231,736	13,118,250	13,032,499	6,540,204	6,874,128
OTN	Price	150,106	155,094	522,190	542,714	30,868	29,048
OTN	Value	863,270,889	827,896,872	1,402,898,549	1,395,397,085	352,528,130	316,818,148
OTN	Weight	1,472,739	1,344,535	2,605,466	2,673,166	611,755	495,898
OXT	Price	179,962	191,396	386,935	415,763	81,075	84,726
OXT	Value	150,895,061	128,439,801	236,915,052	209,648,079	77,137,449	71,265,252
OXT	Weight	36,180	34,639	52,204	47,494	40,059	32,358
P_C	Price	232	17	459	21	495	15
P_C	Value	708,555,252	664,478,161	707,433,430	684,509,680	278,881,540	258,649,539
P_C	Weight	148,989,135	223,652,131	198,780,375	298,389,520	101,155,099	131,471,180
PCR	Price	2	2	1	1	1	1
PCR	Value	17,187,226	16,186,984	26,136,268	25,313,040	4,942,571	4,540,656
PCR	Weight	21,578,461	20,782,756	38,183,439	37,116,193	7,592,193	7,403,314
PDR	Price	2	3	2	2	2	3
PDR	Value	555,705	555,483	798,188	798,338	395,027	395,696
PDR	Weight	427,367	420,591	492,595	496,075	307,885	306,941
PFB	Price	73	71	88	96	51	45
PFB	Value	1,383,913	1,121,981	1,125,537	815,618	777,383	707,729
PFB	Weight	110,038	82,132	149,692	100,864	55,071	45,755
PPP	Price	105	93	260	239	122	106
PPP	Value	199,776,705	187,801,608	262,716,302	262,402,172	33,305,287	29,513,353
PPP	Weight	15,967,169	17,083,552	31,176,955	33,650,018	8,802,377	9,614,480

RMK	Price	13	11	20	20	6	4
RMK	Value	10,177,771	10,048,032	18,933,230	18,937,829	4,334,179	4,245,997
RMK	Weight	4,888,067	5,072,538	11,711,674	12,423,187	2,780,239	2,616,839
RPP	Price	49	48	103	103	69	69
RPP	Value	241,131,692	236,888,481	400,364,392	401,100,367	49,915,711	48,409,697
RPP	Weight	26,942,622	29,419,550	74,260,541	81,720,935	10,182,993	10,814,912
SGR	Price	18	18	38	39	12	12
SGR	Value	21,645,679	20,870,692	40,227,157	39,936,462	5,831,732	5,558,621
SGR	Weight	14,424,321	15,085,271	26,968,624	29,238,245	7,141,499	6,973,368
TEX	Price	57	56	62	60	39	38
TEX	Value	208,616,161	204,448,695	308,187,963	308,549,689	67,201,514	66,455,602
TEX	Weight	16,701,876	16,628,920	42,788,379	43,473,923	4,951,637	4,813,896
V_F	Price	5	6	4	5	4	4
V_F	Value	188,674,755	174,510,123	265,073,664	261,543,224	38,497,137	35,537,277
V_F	Weight	70,333,815	65,852,340	109,865,367	117,595,249	20,633,150	18,046,815
VOL	Price	18	19	42	45	14	14
VOL	Value	114,321,387	104,012,815	128,827,912	124,859,475	24,491,741	22,996,182
VOL	Weight	37,674,530	37,153,166	68,422,132	71,359,168	9,939,606	9,813,682
WAP	Price	84	84	75	74	61	61
WAP	Value	252,748,124	250,731,911	534,271,865	534,227,383	60,946,198	60,285,468
WAP	Weight	11,150,797	11,105,065	35,827,680	35,877,977	3,186,449	3,169,163
WHT	Price	3	3	6	6	2	2
WHT	Value	12,423,402	11,620,632	22,357,499	21,276,868	7,616,607	7,047,161
WHT	Weight	39,310,614	43,005,693	77,751,613	85,072,097	26,898,226	29,696,629
WOL	Price	217	212	456	442	165	158
WOL	Value	12,531,679	11,583,910	12,934,598	12,808,327	3,779,884	3,309,239
WOL	Weight	287,434	269,516	387,019	378,602	93,321	80,332

Table 2: CGE simulation regional aggregation

Country Code	Country Name
TPP	9 CPTPP members
ROW	Rest of World
CHN	China
USA	United States
REU	EU 27

GBR	Great Britain

Table 3: CGE simulation Sectoral and IRTS/CRTS mapping

Sector code	Sector Name	IRTS or CRTS
ric	Rice	CRTS
wht	Wheat	CRTS
gro	Cereal grains nec	CRTS
v_f	Vegetables, fruit, nuts	CRTS
osd	Oil seeds	CRTS
c_b	Sugar cane, sugar beet	CRTS
pfb	Plant-based fibers	CRTS
ocr	Crops nec	CRTS
ctl	Bovine cattle, sheep and goats, horses	CRTS
oap	Animal products nec	CRTS
rmk	Raw milk	CRTS
wol	Wool, silk-worm cocoons	CRTS
frs	Forestry	CRTS
fsh	Fishing	CRTS
col	Coal	CRTS
crg	Crude oil and gas	CRTS
oxt	Other Extraction (formerly omn Minerals nec)	CRTS
cmt	Bovine meat products	CRTS
omt	Meat products nec	CRTS
vol	Vegetable oils and fats	CRTS
mil	Dairy products	CRTS
sgr	Sugar	CRTS
ofd	Food products nec	IRTS
b_t	Beverages and tobacco products	IRTS
tex	Textiles	IRTS
wap	Wearing apparel	IRTS
lea	Leather products	IRTS
lum	Wood products	IRTS
ppp	Paper products, publishing	IRTS
oil	Oil	CRTS
chm	Chemical products	IRTS
bph	Basic pharmaceutical products	IRTS
rpp	Rubber and plastic products	IRTS
nmm	Mineral products nec	IRTS
i_s	Ferrous metals	IRTS
nfm	Metals nec	IRTS
fmp	Metal products	IRTS
CEO	Computer, electronic and optical products	IRTS
eeq	Manufacture of electric equipment	IRTS
ome	Machinery and equipment nec	IRTS
mvh	Motor vehicles and parts	IRTS
otn	Transport equipment nec	IRTS

omf	Manufactures nec	IRTS
ele	Electricity	CRTS
gdt	Gas manufacture, distribution	CRTS
ser	Water and dwellings	CRTS
cns	Construction	IRTS
trd	Wholesale and Retail Trade	IRTS
afs	Accommodation, Food and service activities	IRTS
otp	Transport nec	CRTS
wtp	Water transport	CRTS
atp	Air transport	CRTS
whs	Warehousing and support activities for transportation	CRTS
cmn	Communication	IRTS
ofi	Financial services nec	IRTS
ins	Insurance (formerly isr)	IRTS
rsa	Real estate activities	IRTS
obs	Business services nec	IRTS
ros	Recreational and other services	IRTS
osg	Public Administration and defense	CRTS
edu	Education	CRTS
hht	Human health and social work activities	CRTS