Meta Response Surface Design for General and Partial Equilibrium Models

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Abstract:

A Meta-Analysis of potential Doha Development Agenda outcomes has identified characteristics of models, data and policy experiments that influence simulated welfare changes across a wide range of modelling frameworks. This analysis by Hess and von Cramon-Taubadel (2008) was based on 5800 observations from 110 studies. Meta-regressions produce plausible results and explain a significant proportion of the variation within the dependent variable. However, due to the complexity of the general and partial equilibrium models within the literature sample, explanatory variables in this analysis are mostly binary and do not allow for detailed assessments of the role of individual parameters across different models. Therefore, the partial equilibrium model "GSIM" and a single country CGE for Canada are employed in order to generate meta-data out of synthetic scenarios. These scenarios are based on randomly specified combinations of base data, elasticities and tariff changes that a software routine has selected from previously specified, plausible ranges that were obtained from the literature sample of Doha assessments. The meta-regression based on these synthetic meta-data thus combines two different trade models into one econometric response surface meta-model. Further development of this approach may potentially enable simultaneous sensitivity assessments of scenarios from both models as well as predictions of model outcomes from alternative base data and parameter specifications.

Keywords: General Equilibrium, Partial Equilibrium, Response Surface Design, Meta-Analysis

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1 Introduction

Economists employ applied trade models to generate empirical estimates of the gains and losses that would accrue to specific interest groups, countries and regions as a result of trade liberalization and domestic policy changes, especially with regard to Agriculture. However, applied trade models are frequently criticized as having weak empirical foundations (Alston et al., 1990; McKitrick, 1998; Anderson and Wincoop, 2001) and as being insufficiently transparent (Ackerman, 2005; Piermartini and Teh, 2005). Furthermore, different models often produce trade simulation results that "… differ quite widely even across similar experiments" (Charlton and Stiglitz, 2005).

These problems complicate an already controversial debate on trade liberalization. They are water on the mills of critics who question the ability of economists to accurately estimate the benefits of liberalization, or who question the existence of these benefits in the first place.

Conventional sensitivity analysis of simulation results, typically with regard to a small number of parameters or exogenous policy variables may yield important insights (e.g. Westhoff et al. 2008); however, there are no general rules for the conduction of sensitivity analyses and modelers might feel inclined to report only 'robust' findings. In addition, conventional sensitivity analysis is not well-suited to comparing simulation results across models.

Qualitative reviews of published studies (e.g. Charlton and Stiglitz, 2005; Piermartini and Teh, 2005) have been used to compare results across models, typically grouping them according to selected model characteristics (e.g. 'dynamic vs. static'), or types of liberalization experiment. However, such essentially bivariate comparisons cannot control for simultaneous variation in the other many factors listed above, and this limitation can produce misleading results (Harrison et al., 1997).

Recently, meta-analysis (Stanley 2001) has been used by various authors to improve exogenous model input (e.g. Boys and Florax 2007, Disdier and Head 2006), or to provide explanations for differences of results across applied trade models: Cipollina and Salvatici (2006) meta-analyze gravity models; Hess and von Cramon-Taubadel (2008) investigate whether meta-analysis can contribute to explaining variation of welfare effects in quantitative trade policy model simulations. However, these meta-analyses are based on information that has been retrieved from literature samples and are therefore potentially prone to measurement error. Particularly with regard to a comparison of simulation output from applied trade models this measurement error might be severe due to the complexity of the models involved. Therefore, in this paper we present the results of a meta-analysis which is based on a synthetic dataset of several thousand simulation scenarios that we generate using two ‘typical’ models, one partial equilibrium (PE) and the other a single country general equilibrium (GE). As discussed below, this meta-analysis can be interpreted as an extensive, econometric sensitivity analysis, which is also often referred to as meta-modeling or response surface analysis (Kleijnen et al. 2005). Section 2 introduces the methodological framework of response surface analysis; section 3 presents results which are discussed in section 4; section 5 concludes.

2 Meta-analysis of synthetic data from applied trade models (response surface analysis)

2.1 Concept and experimental design

Response surface estimation typically aims to assess the robustness of complex models with many interacting variables. Estimating econometric response surfaces for such models is common in many areas such as engineering, natural sciences and, in economics, especially for agent-based simulations and can be seen as an extensive, econometric sensitivity analysis of the simulation models to be assessed (Kleijnen et al. 2005).

Response surface estimation for a model typically involves an experimental design that generates combinations of the *k* exogenous model input variables ($X_1, \dots X_k$) and plugs each combination into the model to simulate a corresponding value of the output variable (Y). This procedure is repeated to generate a ‘synthetic meta-dataset’ that is then used to estimate Y as a function of

($X_1, \ldots X_k$) econometrically. If a second-order polynomial provides a reasonable approximation, then a suitable econometric response surface model with k factors is a linear model with quadratic and interaction terms (Kutner et al. 2005):

$$E\{Y\} = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \beta_{11} X_1^2 + \ldots + \beta_{kk} X_k^2 + \beta_{12} X_1 X_2 + \ldots + \beta_{k-1,k} X_{k-1} X_k \qquad (1)$$

In this model, the coefficients $\beta_1 \ldots \beta_k$ are the linear, $\beta_{11} \ldots \beta_{kk}$ the quadratic and $\beta_{12} \ldots \beta_{k-1,k}$ the interaction term effects. In total, equation (1) requires the estimation of $p=(k+1)(k+2)/2$ parameters. The synthetic meta-dataset for response surface estimation must contain at least three expressions of each variable X to permit estimation of the quadratic terms.

For statistical inference it would be ideal if the synthetic meta-dataset included all possible combinations of the k effects (saturated design). However, for $k = 10$ the minimum three observations for each factor alone would require a design with $3^{10} = 59049$ combinations of model scenarios to generate the synthetic meta-dataset; at two minutes each this would require one computer to work for roughly 82 days.

Kutner et al. (2005) as well as Kleijnen et al. (2005) therefore outline practical strategies for less demanding experimental designs. We adopt an experimental design that is similar to a Latin hypercube sampling (LHS) strategy, where each combination of factors exists only once. In our context this reduces the computational cost significantly, albeit at the cost of the efficiency of the response surface estimates.

Furthermore, in case of applied trade models the hypothesis that first- and second-order polynomials provide a reasonable approximation for the response surface is questionable as these models are often highly non-linear.[2] While literature-based meta regression models typically explain the variance of the dependent variable at an aggregated level for which linear and quadratic approximations are sufficient (Stanley 2001), meta-modeling of applied trade models should anticipate the potential existence and significance of non-linear model response. As a

[2] Note, for example, that the systematic sensitivity analysis tool of the standard GTAP model assumes a 3rd degree polynomial approximate model behavior (Arndt 1996).

suitable econometric modeling framework for this purpose, we employ a generalized additive model (GAM) of the following form (Wood, 2006):

$$g(m_i) = \beta_0 + \boldsymbol{\beta}_n \boldsymbol{X}_{ni} + f_1(\boldsymbol{X}_{qi}) + f_2(\boldsymbol{X}_{r-1\,i}, \boldsymbol{X}_{ri}) + \ldots + \varepsilon_i, \qquad (2)$$

where m_i = E(Y_i), and for the application to applied trade models it is assumed that $Y_i \sim N(0, \sigma^2)$, the $\boldsymbol{X}_n$, $\boldsymbol{X}_q$ and $\boldsymbol{X}_r$ are vectors of explanatory variables, and f_1 and f_2 are smooth functions. The number of model input factors to be included in the response surface is $k=n+q+r$. Through specification of the link function g as Gaussian, the parametric parts of the model in the first three terms provide a linear framework that reduces to a generalized linear model (GLM) and, under standard assumptions, is equivalent to the OLS regression model. Note that similar to equation (1), the vector X_n, may also be specified to include interaction effects and/or quadratic terms. The non-parametric parts of the GAM, the functions f_1 and f_2 in equation (2), are estimated using penalized splines (Wood 2006). The procedure applied for this is penalized iteratively re-weighted least squares (P-IRLS), which we perform using the *mgcv* package of the statistical programming language R. Note that the function f_2 represents a non-parametric interaction term of two explanatory variables.

For response surface modeling of applied trade models, the non-parametric components of equation (2) are important because they facilitate detection and comparison of alternative specifications of functional forms and interaction effects in a unified econometric modeling framework. Similar to meta-regression analysis, the coefficient of determination (adjusted R^2) provides a transparent and well-known criterion for the selection of response surfaces. In addition, an econometric response surface can easily be benchmarked by comparing predicted values against actual simulation results from the trade model in question.

In the following we estimate response surfaces for two applied models of moderate complexity that are calibrated to base data from Canada as an example of an industrial economy with protection of various agricultural products. For each model, a Visual-Basic software routine is used generate randomly selected combinations of exogenous parameter values chosen from specified ranges (see below). Then, the routine solves the model with these values and saves the model input data and the corresponding output values (simulation results) into a database. The next section describes the models and the specific experimental design that is used.

2.2 The models used

The Global Simulation Model (GSIM) is a partial equilibrium trade model with Armington-product differentiation at the regional level. It was developed by Francois and Hall (2003) as a flexible modeling approach that yields insights into trade policy with modest data and parameter requirements (Francois 2007). For this paper, the model is calibrated to base data and tariffs for wheat trade between Canada, USA, EU and the Rest of the World (ROW). Trade flows and bilateral tariffs are obtained from the GTAP-5 dataset.

To generate the synthetic meta-data, all elasticities are allowed to vary between |0.01| and |5|. Trade flows are allowed to vary between 0 and 20 billion US$, and tariff changes for each generated scenario are allowed to vary between 0 to 100% of the original bilateral GTAP-5 tariffs. This implies that simulated ordinary tariff changes for Canada are in the range of -80% to +60% for imported wheat, depending on the initial bilateral tariff level that has been obtained from the GTAP-5 database.

The second model used for response surface generation is a single country CGE model benchmarked to GTAP-5 pre-release data for Canada. The model was developed by van der Mensbrugghe (2000) to facilitate flexible trade policy analysis in a general equilibrium framework. The model contains many features of a typical single country CGE such as production nests based on CES functions, Armington product differentiation for domestic and imported products on the demand side, private consumption based on an extended linear expenditure system, etc.

The model covers only two aggregated sectors, all agricultural (AGR) and all other non-agricultural (OTH) products produced and consumed in Canada. In the experimental design, tariffs and export subsidies/taxes are allowed to vary +/-100% around the default GTAP tariffs.

Again, trade parameters for input substitution, export substitution and export demand in AGR and OTH, respectively, are allowed to vary between 0.01 and up to 5 times their original values. Finally, variability is also introduced into the model's social account matrix (SAM). Thorbecke (2001) suggests that due to measurement and aggregation error it would be more convincing to consider the SAM as a stochastic rather than as a deterministic depiction of the input-output relationships in an economy. It is not clear exactly how uncertainty in SAMs could be incorporated in response surface estimation, but as a first attempt the following procedure is applied to the SAM for Canada in the single country CGE model: Table 3 presents the SAM entries that have been allowed to vary within a range of +/- 50% about their original values (obtained from the GTAP dataset). An iterative Visual Basic routine then adjusts the remaining SAM entries to ensure that the accounting restriction $\Sigma_{rows} - \Sigma_{columns} = 0$ is maintained and the relative magnitude different SAM accounts is approximately kept. While somewhat *ad hoc*, this procedure nevertheless makes it possible to estimate the sensitivity of the CGE model with respect to moderate changes in the base data composition. Such changes could be results of yearly fluctuations in prices, trade flows, etc., or of inaccuracies that are introduced when data for real SAMs are assembled (Thorbecke 2001). On the other hand, it has to be noted that this approach only maintains the condition that a SAM is balanced overall; it does not ensure that various sub-relationships within the SAM necessarily hold (compare e.g. Reinert and Roland Holst 1997). The single country CGE is solved for a smaller sample of 1000 scenarios under default solver settings, and for more conservative solver[3] settings each model has been solved about 10 000 times.

[3] This more conservative specification of the Excel solver involves 1000 iterations; accuracy 10^{-6}, tolerance 10^{-5} %; convergence 10^{-8}; automatic scaling; cubic estimates; Newton.

3 Results

The GSIM model converges for all scenarios. The single country CGE fails to converge for about 0.3% of the simulation runs. Scenarios that did not converge are eliminated from the synthetic meta-dataset. The coefficient of determination is, depending on model specification, about 10% to 15% lower when less restrictive solver settings are used, while estimated coefficients do not change fundamentally.

For the PE as well as for the CGE model, equation (3) is first estimated with only first order terms and without interaction effects; due to the Gaussian link function it is therefore identical to an OLS linear regression. This regression produces an adjusted R^2 for the PE (CGE) model of 77% (49%). Starting from these response surfaces, all exogenous parameters in each model are next estimated using penalized splines to detect higher order functional forms. The base- and smoothing parameters of these penalized splines are specified according to standard assumptions (see R *mgcv* package by Wood 2006).

If only polynomial forms of the model response are modeled this way, but interaction effects are ignored, the adjusted R^2 only increases from 77 to 78.9% for GSIM; for the CGE it increases from 49 to 55%. In both models, up to fourth-order polynomials are detected. Alternatively, if interaction terms between independent variables are added to the model, the adjusted R^2 increases to 87% for GSIM and to 80% for the CGE. Furthermore, if all non-parametric splines are removed from the model and instead squared terms for tariffs are included along with the most significant interaction effects, the adjusted R^2 does not drop for GSIM (see Table 1). In the case of the CGE, squared terms for tariffs, and those elasticities for which higher order polynomials were indicated, are included in the response surface equation. Altogether, eight variables are included: import tariffs (AGR, OTH), export taxes (AGR, OTH), import- and export substitution elasticities (AGR, OTH) and transformation elasticities between import and export supply (AGR, OTH). To keep the regression model parsimonious only the most significant interaction effects are retained. Consequently, the adjusted R^2 drops from 80 to 70% (see Table 2).

[Table 1:]

The resulting response surface models in Tables 1, 2 and 3 provide first- and second-order approximations to each model response $E\{Y_i\}$ while retaining a major advantage of parametric regression (i.e. convenient interpretation of marginal effects). In the following we highlight several key results of the response surface estimations:

[Table 2:]

Both sets of results confirm that simulated GDP and welfare effects can vary widely for the same tariff reduction experiment depending on the values of other parameters in the model; an illustration for this is presented in Figure 1, where predicted values from the CGE response surface are shown. Figure 1 illustrates the relationship between tariff changes and predicted GDP changes from the response surface results in Table 2 under different assumptions regarding the size of the elasticities in the model (utilizing sample averages for all other variables except the tariff cuts displayed in Figure 1).

[Figure 1:]

As one would expect, the effect of tariff cuts in agriculture and/or in the other sectors is strictly positive for Canada's GDP. When other elasticities are high, higher welfare effects result from a given tariff change than when the other elasticities are low. However, reducing agricultural tariffs alone affects GDP only moderately compared with tariff reductions in the rest of the economy. When both agricultural and other tariffs are reduced simultaneously, the predicted change in GDP is almost identical to that when other tariffs are reduced alone in OTH. Finally, the effect of simultaneous changes in both agricultural and other tariffs are smaller than the sum of the effects of individual reductions in agricultural and other tariffs.

At the same time, the high R^2 values in Tables 1, 2 and 4 (in the range of 70-80%) confirm that exact knowledge of all model characteristics and other factors that go into a trade policy simulation makes it possible to explain a large proportion of this variance in simulation outcomes; however, although the models are strictly deterministic, no perfect fit of the econometric model could be obtained. In this regard, solver accuracy seems to play a key role.

The results in Table 1 confirm that GSIM results are fundamentally driven by initial tariff levels and that welfare effects based on calculations of economic rents are related to the square of the tariff change. With regard to magnitude and sign of the coefficients it is not immediately clear why Canada only experiences a net welfare gain when it or any other country reduces its tariffs vis-à-vis ROW, while tariff cuts vis-à-vis any other trade partner are net welfare decreasing. The reason is that in this experimental setting, high and low initial tariffs are not altered proportionally. Instead, all tariffs are subject to the same range of random changes. Whenever initial bilateral tariffs are below the average new tariff, this results on average across the meta-dataset in a tariff increase, while only countries that initially show tariffs higher than average experience on average a net tariff cut.

Table 2 presents the response surface for the single country CGE model, with the exception of the estimated coefficients for the SAM base data which are presented in Table 3. With regard to the magnitude of estimated coefficients Table 2 shows that in general changes in variables related to AGR have a much smaller effect on GDP in Canada, signaling – as one would expect – that GE effects even from an aggregated agricultural sector play a minor role in the overall Canadian economy.

The estimated coefficients for SAM base data in Table 3 indicate by how much Canada's real GDP in million US$ changes if the corresponding SAM entries change by 1 million US$ Interestingly, the largest coefficients are for government expenditure on agriculture and income tax revenues from agriculture. However, these effects are not or only just significant at conventional levels, but are suggestive of the especially distortive impact of agricultural policies and the economic burden that agriculture places on the economy as a whole. With regard to the statistical significance levels it should be emphasized that due to the synthetic structure of the meta-dataset (e.g. the arbitrarily chosen number of simulation runs), a conventional interpretation of t-values is not possible. Furthermore, within this reasoning no effort has (yet) been made to apply robust standard errors to the estimated coefficients.

[Table 3:]

In both models, interaction effects between key input parameters account for much more of the variance in the dependent variable than higher-order (greater than 2) polynomial effects. Moreover, this impact of interaction effects is much stronger in the CGE model than in the PE.

So far, both trade models have been analyzed separately, and the estimated response surfaces provide more or less the same insights that a thorough and comprehensive sensitivity analysis could. In the spirit of meta-analysis we next attempt to estimate a joint response surface for both models. The dependent variable in GSIM is the change in consumer and producer rents (the GSIM model does not incorporate tax revenue into the welfare measure), while the single country CGE is solved for changes in GDP. To merge the individual synthetic meta-datasets from these models, the simulated change in consumer surplus is taken from the GSIM results, and simulated change in consumer utility is taken from the single country CGE[4]. The result is a new dependent variable labeled 'Welfarechange'. However, it should be noted that the question which variables compare from a theoretical point of view best to each other do not affect the question whether a meta response surface estimation for both models is feasible or not: To control for differences between the underlying measures, a dummy variable (PE=1 if the observation in questions stems from GSIM) is included in the regression. For all explanatory variables that are included in one but not the other model, missing values are imputed using sample means (see e.g. Greene, 2003; Little, 1992).

[Table 4:]

[4] Alternatively, one may argue that the entire welfare measure from GSIM should be compared to changes in Utility; for a discussion see e.g. Mas-Colell et al. 1995.

Table 4 presents estimation results for this combined synthetic meta-dataset: The coefficient of determination as well as the signs, magnitudes and significance levels of most explanatory variables are similar to those in Tables 5 and 6. The coefficient of the PE dummy shows that after controlling for all other effects that are captured by the explanatory variables, the measure of consumer surplus from the GSIM model is *ceteris paribus* 4.7 billion US$ higher (with a standard error of 118 million US$) than the change in consumer utility in the CGE model. This indicates that the joint estimation of one response surface for both models is feasible and able to generate econometric measures of the difference between simulation output from two very distinct applied trade models.

5 Conclusion

Meta-analysis with synthetic data (econometric sensitivity- or response surface analysis across models) – if computationally manageable – provides a methodological alternative that can enable both direct comparison of output and input from different models and detailed quantitative assessment of the impact of individual modeling frameworks, parameters and base data specifications on simulation results. The response surface analysis presented above can clearly be refined and better tailored to specific tasks, e.g. through more clearly defined policy scenarios or through the use of more sophisticated non-parametric estimation techniques. The trade-off between the complexity of a response surface and ease of interpretation should be kept in mind when pursuing the latter. A related question is whether it is possible to develop response surfaces that could offer a low-cost alternative to modeling, at least up to a first degree of approximation. Exercises of this nature can be especially beneficial for least developed countries, which often cannot afford to maintain sophisticated own modeling capacities and dedicate highly trained personnel to the comparison and assessment of different and often conflicting model results. In closing it is important to stress that our results only assess the effect of various data-, parameter,- and theoretical assumptions on simulation results- they cannot shed any light on what is the ‘right’ model.

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Table 1: Response surface estimates for GSIM (partial equilibrium model)

Estimate	*Coefficient*	*Std.*	*t-value*	*Pr(>|t|)*	*Signif.*
Intercept	148.163	183.304	0.808	0.42	
Tradevolume USACanada * ΔTariff	0.075	0.007	10.457	0.00	***
Tradevolume USAEU * ΔTariff	0.114	0.012	9.557	0.00	***
Tradevolume USAROW * ΔTariff	-1.022	0.012	-87.275	0.00	***
Tradevolume CanadaUSA * ΔTariff	0.165	0.018	9.313	0.00	***
Tradevolume CanadaEU * ΔTariff	0.109	0.012	9.343	0.00	***
Tradevolume CanadaROW * ΔTariff	-0.954	0.015	-65.574	0.00	***
Tradevolume EUUSA * ΔTariff	0.184	0.018	10.366	0.00	***
Tradevolume EUCanada * ΔTariff	0.085	0.009	9.065	0.00	***
Tradevolume EUROW * ΔTariff	-1.021	0.012	-84.955	0.00	***
Tradevolume ROWUSA * ΔTariff	0.224	0.018	12.456	0.00	***
Tradevolume ROWCanada * ΔTariff	0.071	0.009	7.632	0.00	***
Tradevolume ROWEU * ΔTariff	0.100	0.012	8.346	0.00	***
Tradevolume ROWROW * ΔTariff	-1.011	0.014	-73.817	0.00	***
Tradevolume EUEU	-0.021	0.005	-4.570	0.00	***
(Tradevolume USAEU * ΔTariff)^2	0.00001	0.00000	2.289	0.02	*
(Tradevolume USAROW * ΔTariff)^2	0.00001	0.00000	3.677	0.00	***
(Tradevolume CanadaUSA * ΔTariff)^2	0.00000	0.00000	2.068	0.04	*
(Tradevolume Canada EU	0.00000	0.00000	-0.482	0.63	
(Tradevolume Canada ROW * ΔTariff)^2	0.00002	0.00000	7.667	0.00	***
(Tradevolume EUUSA * ΔTariff)^2	-0.00001	0.00000	-4.098	0.04	***
(Tradevolume EUCanada * ΔTariff)^2	0.00000	0.00000	-1.623	0.10	
(Tradevolume EUROW * ΔTariff)^2	0.00002	0.00000	8.497	0.00	***
(Tradevolume ROWUSA * ΔTariff)^2	-0.00001	0.00000	-5.291	0.00	***
(Tradevolume ROWCanada * ΔTariff)^2	0.00000	0.00000	-2.834	0.00	**
(Tradevolume ROWEU * ΔTariff)^2	-0.00001	0.00000	-3.752	0.00	***
(Tradevolume ROWROW * ΔTariff)^2	0.00001	0.00000	5.948	0.00	***
Demand elasticity USA	-810.961	17.300	-46.876	0.00	***
Supply elasticity USA	3.619	18.012	0.201	0.84	
Substitution elasticity USA	-12.069	17.915	-0.674	0.50	
Demand elasticity Canada	147.739	17.410	8.486	0.00	***
Supply elasticity Canada	-67.984	17.285	-3.933	0.00	***
Substitution elasticity Canada	-52.583	17.490	-3.006	0.00	**
Demand elasticity EU	277.268	17.502	15.842	0.00	***
Supply elasticity EU	-162.872	17.522	-9.296	0.00	***
Substitution elasticity EU	-40.369	18.151	-2.224	0.03	*
Demand elasticity ROW	43.436	18.936	2.294	0.02	*
Supply elasticity. ROW	-223.931	18.863	-11.871	0.00	***
Substitution elasticity ROW	93.536	18.072	5.176	0.00	***

F-statistic: 1789 on 38 and 10011

Multiple R-Squared: 0.87 Adjusted R-squared: 0.87

*Note: *, ** and *** refer to significance at the 10, 5 and 1 per cent levels, respectively.*

Table 2: Single country CGE response surface for Canada

Variable	*Coeff.*	*Std. error*	*t-value*	*Pr(>|t|)*	*Signif.*
Intercept	-4025.8	807.8	-4.98	0.000	***
Δ Tariff Other Sectors (Oth)	44411.48	2783.8	15.95	0.000	***
Δ Tariff Agriculture (Agr)	-6766.8	5668.1	-1.19	0.233	
'Armington' CES parameter for substitution imports/domestic products 'Other Sectors': σ_m_Oth	-71.18	38.0	-1.87	0.061	
CET parameter exports/domestic production 'Other Sec's': σ_x_Oth	91.38	36.2	2.52	0.012	*
CET parameter exports/domestic production Agriculture: σ_x_Agr	9.1	35.0	0.26	0.795	
'Armington' CES parameter for substitution imports/domestic products Agriculture: σ_m_Agr	-8.5	35.0	-0.24	0.809	
Δ Export Tax Agr	-4288.1	3982.6	-1.08	0.282	
Δ Export Tax Oth	-32028.6	8138.3	-3.94	0.000	***
$(\Delta \text{ Export Tax Agr})^2$	40306.9	19511.3	2.07	0.039	*
$(\Delta \text{ Export Tax Oth})^2$	-251701.4	84071.1	-2.99	0.003	**
$(\Delta \text{ Tariff Agr})^2$	2107.2	9782.1	0.22	0.830	
$(\Delta \text{ Tariff Oth})^2$	101486.7	2994.6	33.89	0.000	***
Elasticity of foreign export demand Agr	83.9	56.1	1.50	0.135	
Elasticity of foreign export demand Oth	1465.7	56.1	26.13	0.000	***
$(\text{Elasticity of foreign export demand Agr})^2$	-6.8	3.3	-2.07	0.039	*
$(\text{Elasticity of foreign export demand Oth})^2$	-69.8	3.3	-21.09	0.000	***
Δ Tariff Oth * σ_m_Oth	-1285.7	188.2	-6.83	0.000	***
Δ Tariff Oth * σ_m_Oth	701.8	178.0	3.94	0.000	***
σ_m_Oth * σ_x_Oth	-40.8	4.3	-9.49	0.000	***
σ_x_Agr * σ_m_Agr	-0.7	4.0	-0.17	0.869	
σ_x_Agr * Δ Tariff Agr	995.7	362.1	2.75	0.006	**
σ_m_Agr * Δ Tariff Agr	661.0	351.8	1.88	0.060	.
Δ Export Tax Agr * Δ Export Tax Oth	-83283.5	81587.4	-1.02	0.307	
El.'s foreign exp dem. (Agr * Oth)	7.6	3.0	2.53	0.012	*
ΔTariff Oth * σ_m_Agr * σ_x_Oth	-526.4	21.1	-24.96	0.000	***
ΔTariff Agr * σ_x_Agr * σ_m_Agr	-101.2	40.0	-2.53	0.011	*

Estimated Coefficients for the SAM entries are displayed in Table 3

Residual standard error = 5570

Multiple R^2 = 0.7018, adjusted R^2 = 0.7005

F-statistic: 559.8 on 44 and 10468

*Note: *, ** and *** refer to significance at the 10, 5 and 1 per cent levels, respectively.*

Table 3: Estimated coefficients for the SAM base data, single country CGE for Canada. (Note that these coefficients are part of the regression in Table 2)

Variable	*Coefficient*	*Std. error*	*t-value*	*Pr(>|t|)*	*Signif.*
Agric. – Agric.	-0.0317	0.0149	-2.1220	0.0339	**
Agric. – Other Sectors	0.0157	0.0067	2.3350	0.0196	**
Agric – Labor	-0.0241	0.0144	-1.6740	0.0942	
Agric. – Capital	-0.0380	0.0171	-2.2180	0.0266	**
Agric. – Other Factors	0.0100	0.0335	0.2990	0.7646	
Agric. – Income Tax	0.1012	0.0563	1.7990	0.0720	*
Agric. – Government	-0.2749	0.1712	-1.6060	0.1083	
Agric. – Tariff Revenue	-0.0689	0.9346	-0.0740	0.9413	
Other Sec's – Agric.	-0.0073	0.0056	-1.3120	0.1897	
Other Sec's – Other Sec's	0.0011	0.0003	4.1970	0.0000	***
Other Sec's – Labor	0.0042	0.0004	10.4780	0.0000	***
Other Sec's – Capital	0.0031	0.0006	5.4450	0.0000	***
Other Sec's – Other Factors	-0.0527	0.0223	-2.3630	0.0181	**
Other Sec's – Income Tax	-0.0004	0.0093	-0.0460	0.9631	
Other Sec's – Government	0.0025	0.0033	0.7740	0.4390	
Other Sec's – Tariff Rev.	0.0624	0.0120	5.2170	0.0000	***
ROW – Other Sec's (Imp.)	-0.0068	0.0012	-5.6410	0.0000	***
ROW – Agric. (Imports)	0.0113	0.0525	0.2160	0.8290	

*Note: *, ** and *** refer to significance at the 10, 5 and 1 per cent levels, respectively.*
The abbreviations label SAM entries 'expenses on sector/factor/tax' – by sector '…'.

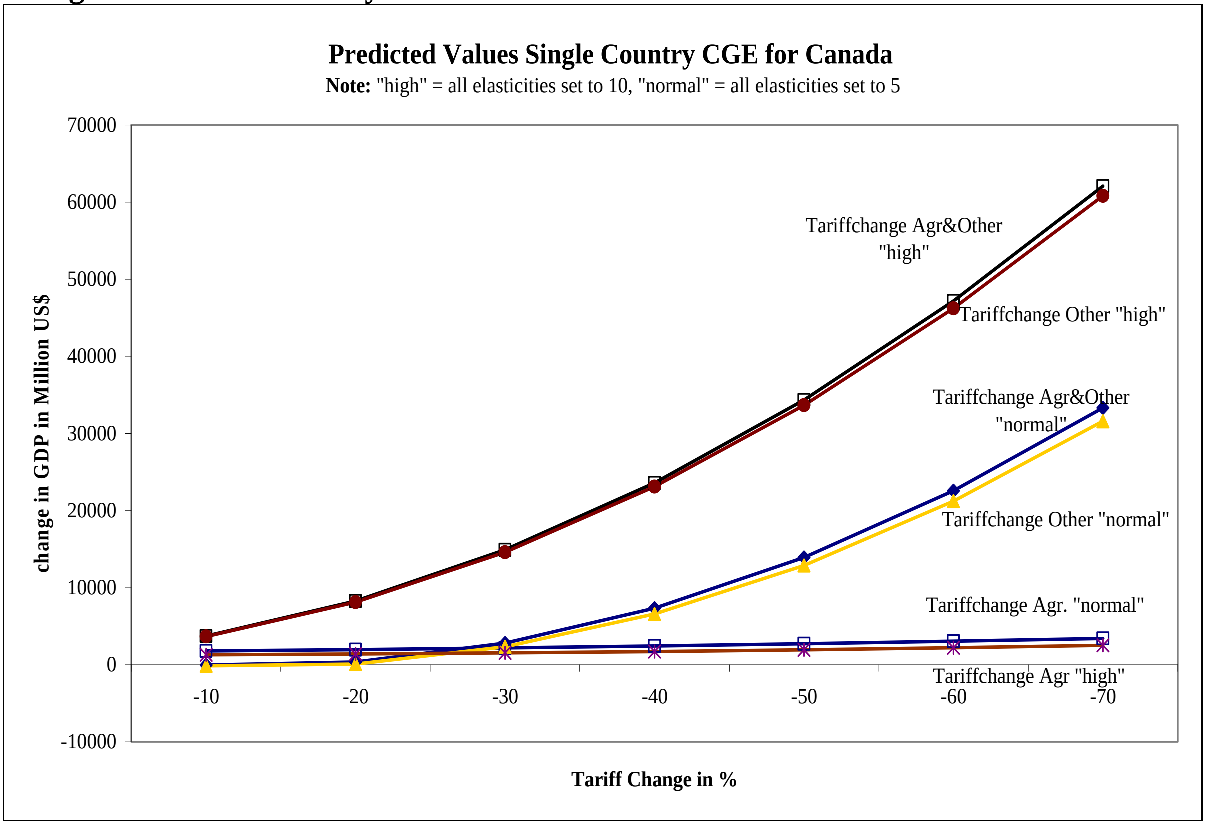
Table 4: Changes in consumer utility (CGE) and consumer surplus (PE) jointly estimated using synthetic data from both models

Variable	Coeff.	Std. Err.	t- value	Pr(>|t|)	
Intercept	-12483.788	525.639	-23.750	0.000	***
Tradevolume USACanada * ΔTariff	-1.115	0.009	-121.080	0.000	***
Tradevolume USAEU * ΔTariff	0.129	0.015	8.440	0.000	***
Tradevolume USAROW * ΔTariff	0.101	0.015	6.732	0.000	***
Tradevolume CanadaUSA * ΔTariff	-0.059	0.023	-2.612	0.009	**
Tradevolume CanadaEU * ΔTariff	-0.002	0.015	-0.129	0.897	
Tradevolume CanadaROW * ΔTariff	-0.031	0.019	-1.673	0.094	.
Tradevolume EUUSA * ΔTariff	0.174	0.023	7.669	0.000	***
Tradevolume EUCanada * ΔTariff	-0.952	0.012	-78.611	0.000	***
Tradevolume EUROW * ΔTariff	0.112	0.015	7.227	0.000	***
Tradevolume ROWUSA * ΔTariff	0.177	0.023	7.664	0.000	***
Tradevolume ROWCanada * ΔTariff	-0.947	0.012	-79.607	0.000	***
Tradevolume ROWEU * ΔTariff	0.064	0.015	4.180	0.000	***
Tradevolume ROWROW * ΔTariff	0.102	0.018	5.797	0.000	***
Tradevolume EUEU	-0.020	0.006	-3.443	0.001	***
(Tradevolume USAEU * ΔTariff)2	0.000	0.000	1.471	0.141	
(Tradevolume USAROW * ΔTariff)2	0.000	0.000	-0.288	0.773	
(Tradevolume CanadaUSA * ΔTariff)2	0.000	0.000	3.916	0.000	***
(Tradevolume CanadaEU DelTarCanadaEU)2	0.000	0.000	0.722	0.471	
(Tradevolume CanadaROW * ΔTariff)2	0.000	0.000	-2.061	0.039	*
(Tradevolume EUUSA * ΔTariff)2	0.000	0.000	-2.142	0.032	*
(Tradevolume EUCanada * ΔTariff)2	0.000	0.000	15.276	0.000	***
(Tradevolume EUROW * ΔTariff)2	0.000	0.000	1.489	0.136	
(Tradevolume ROWUSA * ΔTariff)2	0.000	0.000	-1.555	0.120	
(Tradevolume ROWCanada * ΔTariff)2	0.000	0.000	12.733	0.000	***
(Tradevolume ROWEU * ΔTariff)2	0.000	0.000	-3.737	0.000	***
(Tradevolume ROWROW * ΔTariff)2	0.000	0.000	1.533	0.125	
Demand elasticity USA	-508.669	22.230	-22.882	0.000	***
Supply elasticity USA	55.393	23.145	2.393	0.017	*
Substitution elasticity USA	1.915	23.020	0.083	0.934	
Demand elasticity Canada	-142.034	22.371	-6.349	0.000	***
Supply elasticity Canada	-21.978	22.210	-0.990	0.322	
Substitution elasticity Canada	114.747	22.474	5.106	0.000	***
Demand elasticity EU	243.997	22.489	10.850	0.000	***
Supply elasticity EU	-29.461	23.324	-1.263	0.207	
Substitution elasticity EU	-162.094	22.514	-7.200	0.000	***
Demand elasticity ROW	75.884	24.332	3.119	0.002	**
Supply elasticity ROW	25.046	23.222	1.079	0.281	
Substitution elasticity ROW	-192.945	24.238	-7.960	0.000	***
Δ Tariff Other Sectors (‘Oth’)	-49.418	15.796	-3.129	0.002	**
Δ Tariff Agricultural Sector (‘Agr’)	-54.221	21.550	-2.516	0.012	*
‘Armington’ CES parameter import/dom: σ_m_Oth	8.717	20.555	0.424	0.672	
CET parameter export/dom. production: σ_x_Oth	31.370	19.857	1.580	0.114	
CET parameter export/dom :production σ_x_Agr	30.360	19.864	1.528	0.126	
‘Armington’. CES parameter import/dom: σ_m_Agr	-51.673	32.162	-1.607	0.108	
Δ Export Tax Agr	1682.763	2259.840	0.745	0.456	
Δ Export Tax Oth	59534.159	4617.855	12.892	0.000	***
(Δ Export Tax Agr)2	-5489.364	11071.195	-0.496	0.620	
(Δ Export Tax Oth)2	-708193.487	47704.099	-14.846	0.000	***
(Δ Tariff Agr)2	-0.451	0.555	-0.812	0.417	
(Δ Tariff Oth)2	2.896	0.170	17.044	0.000	***
Elasticity of foreign export demand Agr	-44.784	31.824	-1.407	0.159	
Elasticity of foreign export demand Oth	1252.610	31.833	39.349	0.000	***
(Elasticity of foreign export demand Agr)2	4.147	1.881	2.205	0.027	*
(Elasticity of foreign export demand Oth)2	-52.962	1.879	-28.191	0.000	***
Agric. – Agric.	0.003	0.008	0.377	0.706	
Agric. – Other Sectors	0.009	0.004	2.399	0.016	*
Agric – Labor	-0.006	0.008	-0.699	0.484	
Agric. – Kapital	-0.001	0.010	-0.131	0.895	
Agric. – Other Factors	0.025	0.019	1.303	0.193	

Table 4 continued:					
Variable	*Coeff.*	*Std. Err.*	*t- value*	*Pr(>|t|)*	
Agric. – Income Tax	0.021	0.032	0.643	0.520	
Agric. – Government	-0.002	0.097	-0.022	0.983	
Agric. – Tariff Revenue	0.128	0.530	0.241	0.810	
Other Sec's – Agric.	-0.012	0.003	-3.957	0.000	***
Other Sec's – Other Sec's	-0.001	0.000	-7.437	0.000	***
Other Sec's – Labor	0.008	0.000	33.486	0.000	***
Other Sec's – Kapital	0.007	0.000	21.416	0.000	***
Other Sec's – Other Factors	-0.014	0.013	-1.110	0.267	
Other Sec's – Income Tax	0.001	0.005	0.192	0.848	
Other Sec's – Government	0.009	0.002	4.896	0.000	***
Other Sec's – Tariff Rev.	-0.212	0.007	-31.274	0.000	***
ROW – Other Sec's (Imp.)	-0.003	0.001	-4.183	0.000	***
ROW – Agric. (Imports)	-0.051	0.030	-1.717	0.086	.
PE dummy (1 if GSIM partial equilibrium model)	4762.391	118.781	40.094	0.000	***
Δ Tariff Oth * σ_m_Oth	-11.204	1.068	-10.491	0.000	***
Δ Tariff Oth * σ_m_Oth	10.085	1.010	9.984	0.000	***
σ_m_Oth * σ_x_Oth	-12.142	2.438	-4.981	0.000	***
σ_x_Agr * σ_m_Agr	-3.482	2.276	-1.530	0.126	
σ_x_Agr * Δ Tariff Agr	6.298	2.055	3.065	0.002	**
σ_m_Agr * Δ Tariff Agr	4.867	1.996	2.438	0.015	*
Δ Export Tax Agr * Δ Export Tax Oth	68165.836	46294.738	1.472	0.141	
El.'s foreign exp dem. (Agr * Oth)	-1.627	1.713	-0.950	0.342	
ΔTariff Oth * σ_m_Agr * σ_x_Oth	-0.487	0.120	-4.072	0.000	***
ΔTariff Agr * σ_x_Agr * σ_m_Agr	-0.748	0.227	-3.299	0.001	***
F-statistic: 862.6 on 83 and 20479 DF, p-value: < 0.0000					
Adjusted R-Squared:	0.7776	Residual standard error: 3161 on 20479 deg. of f.			

*Note: *, ** and *** refer to significance at the 10, 5 and 1 per cent levels, respectively.*

Figure 2: Predicted values for the single country CGE for Canada as a function of tariff changes and other elasticity values



Note: High = all elasticities set to 10; normal = all elasticities set to 5.