Aggregation bias in regional impact analysis of trade policy

Extended Abstract

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Abstract

The aim of this paper is to demonstrate the importance of regional detail for impact analyses of changes in trading agreements using computable general equilibrium models (CGE). Taking the UK as a case study we compare the results from a UK national CGE model regionalised using simple regional Gross Value Added (GVA) shares with the results of models of the UK nations and regions. We begin by developing and applying a method to disaggregate the UK Input Output (IO) accounts into a set of consistent multi regional IO tables (MRIO). Using these accounts, we calibrate a set of CGE models that differ only from the regional disaggregation. In each model, we simulate an increase in openness to trade and calculate a series of bias measures reflecting spatial and temporal aspects. Results from simulations show that aggregated bias is relatively small and increases with the number of regions. The bias is larger for short-run results where constraints in supply drive a higher variation in prices. The aggregation bias is larger and more heterogeneous at the regional level. Regions which are less similar to the average (e.g. the East of England, Scotland and Northern Ireland) record larger regional aggregation bias measures than regions that are more similar to the average in the UK. The results support the development and use of region specific accounts for impact analysis of trade policy.

1 Introduction

The aim of this paper is to demonstrate the importance of regional detail for impact analyses of changes in trading agreements using computable general equilibrium modelling (CGE). Limitations in the availability of data at the regional level and computational issues have often led analysts to neglect the importance of detailed representation of regional economic structure in input-output (IO) and CGE models. However, growing interest in the spatial distributional impacts of trade agreements spurred by recent important development in international agreements including the decision of the UK to leave the European Union (Brexit) and the renegotiation of the North America Free Trade Agreement (NAFTA) have shed light on the importance of developing capacity for trade policy analysis at the regional level.

The issue of aggregation bias in the IO literature and the need for some level of aggregation is well documented especially with regards to sectoral aggregation (see for instance, Lahr and Stevens, 2002; Leontief, 1949; Llop and Manresa, 2014; Piñero et al., 2015). A seminal paper by Lahr and Stevens (2002) demonstrates that improper aggregation can lead to error in estimated impacts of up to 100%. Similar considerations have been made in the CGE literature. Brockmeier and Bektasoglu (2014) calibrates a CGE model to the Global Trade Analysis Project (GTAP) data to explore biases arising from data aggregatior on and model structure. They find that data aggregation impacts the results significantly more than the model structure. Britz and van der Mensbrugghe (2016) focus on techniques to improve efficiency in computation in order to reduce the need for spatial aggregation in the GTAP dataset. However, none of these CGE studies focus on sub-national issues.

In this paper, we aim to systematically explore biases in the estimation of trade impacts arising from subnational-level CGE analysis using the case of the UK. The focus on the UK is twofold. Firstly, in the aftermath of the 2016 Brexit referendum, a plethora of CGE studies have analysed the potential impacts of future trading relationships between the EU and the UK. However, the production of region-specific analysis was extremely limited (Duparc-Portier and Figus, 2022; Figus et al., 2018). When regional impacts were estimated, these were produced by apportioning national models' results using employment shares (Department for Business and Trade, 2021; Dhingra et al., 2017). These offer important insights into the type of impact that an important change in national policy may have on regions. However, these are subject to a series of limitations including the inability to capture the idiosyncratic characteristics of regional supply chains and their exposure to international trade. Secondly, the importance and need for regional modelling was reinforced by the trade modelling review expert panel report commissioned by the UK's Department for Business and Trade (2022) which explicitly invited for the development of regional models.

2 Methodology

2.1 Research design

The basic research design for this paper is straightforward. We develop a multi-regional dynamic CGE model of the UK economy that can be calibrated using data with different regional aggregation levels. We calibrate the model to reproduce three different regional aggregations: 1) single country UK, 2) the four UK nations (England, Scotland, Northern Ireland, Wales), 3) the twelve International Territorial Level 1 (ITL1) UK regions. We simulate a 1.5% illustrative trade shock to all imports and exports in the single country model and regionalise the results both at the UK Nations level and ITL1 level using regional gross value added shares as suggested in Dhingra et al. (2017) and Department for Business and Trade (2021). We then simulate the same trade shock to the two regional CGE models. Finally, we compare the regionalised national model results with the results of the actual regional models.

2.2 Data

Whilst The Scottish Government (2022) and Northern Ireland Statistics and Research Agency (2022) produce regional IO accounts, the UK does not have official multi-regional IO accounts. The Office for National Statistics (2023) publishes UK IO analytical tables. So as a first step for this paper, we use a top-down approach to disaggregate the UK IO table into a set of consistent multi-regional IO tables (MRIO).

We follow the method detailed in Jahn (2016) and Canning and Wang (2004) which relies on the Flegg local quotients method (Flegg et al., 2021; Flegg and Webber, 2000) to derive regional tables and on constrained optimization to produce a set of balanced accounts. We use data on regional Gross Value Added (GVA) employment shares and regional trade published by the Office for National Statistics and combine this with information from the existing regional IO accounts. The data is validated against the existing regional IO tables following Huang and Koutroumpis (2023). A full detailed account of the methodology will be provided with the full paper.

2.3 Model

The model describes the production activities of industries that use a combination of primary inputs, capital and labour, and intermediates to produce gross output. Intermediate inputs are either produced domestically or imported from the rest of the world. When the region is calibrated to MRIO the regions trade intermediate under the classical imperfect substitution Armington assumption.[1]

Households consume output from each of the industries and in each period in time are faced with a savings/investment decision. Following Devarajan and Go (1998) the intertemporal households' problem is derived

[1] A short account of the model is provided in this extended abstract. The model will be fully detailed in the paper.

by maximising the following expression:

$$U = \sum_{t=0}^{\infty} \beta^t \cdot u(C_t). \tag{1}$$

where eq. (1), $U : \mathbb{R}^\infty \to \mathbb{R}$ is the intertemporal utility function, $u : \mathbb{R}_+ \to \mathbb{R}$ is households utility, $C_t \in \mathbb{R}_+$ is households' aggregate consumption and $\beta \in (0, 1)$ is a discount factor, subject to a budget constraint (2):

$$II_t = uck_t \cdot KS_t + w_t \cdot LS_t + TR_t. \tag{2}$$

This states that households receive capital income (KS_t) at rate (uck_t), wage (w_t) income from labour (LS_t) and transfers from the government (TR_t).

3 Results

3.1 Quantifying the bias

To capture the difference between the GVA apportioning method and the multi-region CGE method we develop a simple distance measure in eq. (3):

$$D_t = \sum_{r,i} \frac{|\Delta O_{r,i,t}^{GVA} - \Delta O_{r,i,t}^{CGE}|}{\Delta O_{r,i,t}^{CGE} \cdot R \cdot I} \tag{3}$$

$\Delta O_{r,i,t}^{GVA}$ and $\Delta O_{r,i,t}^{CGE}$ are estimates of regional changes in output made using the GVA method and multi-region CGE model respectively. R is the number of regions and I is the number of sectors. $D_t \in \mathbb{R}_+$ is a measure of the average deviation between regional changes in output estimates made using the GVA method and the multi-region CGE model. As $D_t \to 0$, the results of the GVA method converge to those of the CGE method. As $D_t \to \infty$, the results of both methods diverge. Importantly, if $D_t = 1$, then the GVA method's estimation performance is qualitatively identical to estimating no change in output following the shock. In this paper, we will refer to D_t as aggregation bias.

3.2 Estimated aggregation bias

Number of regions/ time	**Short Run**	**Long Run**
4-region	0.16	0.04
12-region	0.16	0.07

Table 1: Aggregation bias for 4-region and 12-region model in the short and long run

Table 1 presents the estimated aggregation bias parameters depending on the number of regions in the short- and the long-run. Rows define the number of regions whilst columns define the period.

In the case of the 4-region model, $D_{SR} = 0.16$ and $D_{LR} = 0.04$. In the case of the 12-regions model, $D_{SR} = 0.16$ and $D_{LR} = 0.07$. These results have two key implications. First, short-run simulations are more prone to aggregation bias. In the short run factors of production are constrained and differences in regional prices increase deviation in the result. Second, finer levels of disaggregation are associated with higher levels of aggregation bias both in the short run and in the long run.

Importantly, the differences described occur even though most of the disaggregation procedure creating the regional Input-Output tables is based on the limited data available and relies on a top-down approach. Hence, we could expect differences to increase when more region-specific information is added.

3.3 Bias over time

$$A_t = \sum_{r,i} \frac{\Delta O^{GVA}_{r,i,t} - \Delta O^{CGE}_{r,i,t}}{\Delta O^{CGE}_{r,i,t} \cdot R \cdot I} \tag{4}$$

To determine the direction of the aggregation bias, eq. (3) is amended to exclude the absolute value symbol as presented in eq. (4). A_t is a measure of average absolute bias and is presented for the 4-region model in figure 1.[2]

Figure 1 demonstrates that, in the short run, Scotland's and Northern Ireland's output changes are overestimated by over 7% using the GVA apportioning method whilst England's and Wales' output changes are slightly underestimated. Over time, the over- and underestimations become less pronounced in all regions. Scotland's GVA apportioned output change estimate, in the long run, is lower than the CGE estimated result. This result indicates that the GVA method does not capture crucial general

[2] We report the results from the 4-region model for clarity. Similar results can be shown for the 12-region model.

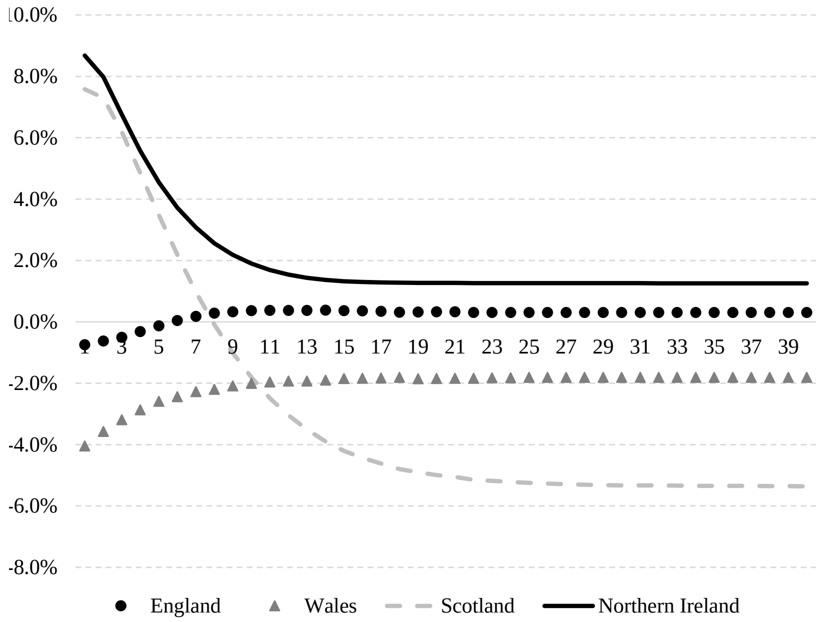

Figure 1: Aggregate output change bias over time

equilibrium effects for some regions.

3.4 Bias by region

Finally, we consider regional aggregation bias as measured using (5).

$$D_{r,t} = \sum_i \frac{|\Delta O^{GVA}_{r,i,t} - \Delta O^{CGE}_{r,i,t}|}{\Delta O^{CGE}_{r,i,t} \cdot R \cdot I} \tag{5}$$

Short run and Long run regional aggregation bias $D_{r,t}$ are presented in figure 2:

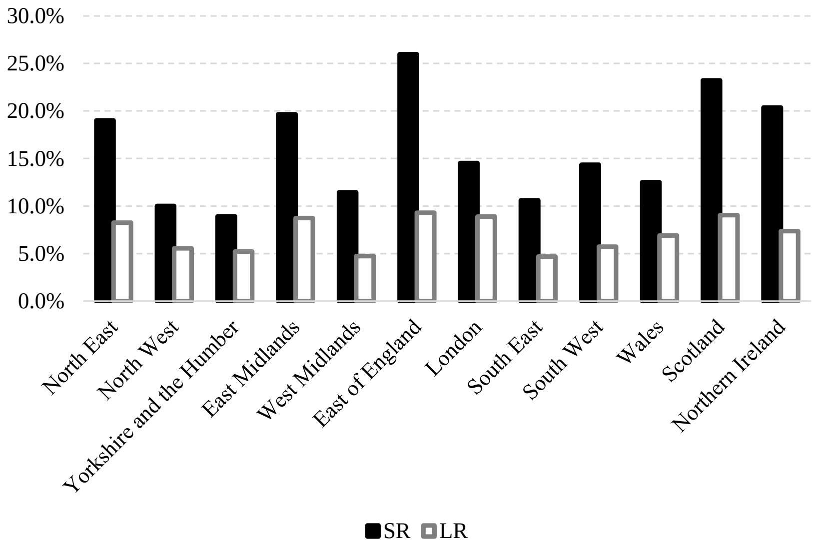

Figure 2: Aggregation bias in regional output changes

Figure 2 demonstrates the regional aggregation bias in output changes is heterogeneous at the regional level. Regions which are less similar to the average (e.g. the East of England, Scotland and Northern Ireland) record larger regional aggregation bias measures than regions more similar to the average in the UK. This is especially true in the short run. Based on this result, researchers should avoid using GVA shares to measure regional results if the underlying regional structure is very different to the country's structure.

4 Conclusion

In this paper, we have demonstrated the importance of using region-specific IO accounts for the calibration of CGE models with a focus on international trade policy. While apportioning the results from a national CGE model using GVA or labour shares could be a good approximation in certain cases our results suggest that this may lead to over or underestimating the impacts.

The bias tends to be higher for short-run estimations where supply constraints induce a greater price response. Results for regions that are more similar on average to the aggregated countries tend to lead to a relatively small bias. However, greater heterogeneity in regional structure increases the bias size. In the full paper, we will explore the implications of sectoral aggregation as well as regional aggregation at a more detailed level. In addition, we will show bias in the impact of other key variables such as employment and consumption.

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