Methodological Options for Estimating the Causal Impacts of the UK's Trade Remedies on Trade and Economic Performance

Grant Thornton

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1. Executive Summary

Purpose of this report

1.1 This report aims to facilitate the Trade Remedies Authority's ("TRA") evaluation of its existing and future trade measures. It does this by investigating the strengths and weaknesses of the application of methodological tools to estimate the causal impacts of the UK's trade remedy measures. These tools are investigated using case studies on trade patterns and the performance of the UK industries.

1.2 **The report is not intended to provide commentary or evaluate existing trade remedy measures, but instead provide a toolkit for future policymakers to draw upon when undertaking their own evaluations. The case studies contained in the report are wholly illustrative – and in some cases based on synthetic data to help illustrate the analysis – meaning that they should not be read as providing an assessment of the impacts of the remedies described.**

Summary of tools used in trade evaluation

1.3 The main focus of this report is investigating evaluation models which have been based on econometric methods, where differences pre-and post- a trade remedy are observed, whilst also taking into account what might have happened in the absence of the trade remedy (for example using some sort of 'control' group). This begins with a literature review of evaluation approaches undertaken within the academic literature and by policymakers. The key econometric methods considered in this report are:

- **Gravity models.** Gravity models form the seminal trade literature and the foundation to capture the conceptual determinants of bilateral trade. At their heart, they explain bilateral trade flows as a function of size of economies and the distance between economies, sector specific factors (e.g. technological innovation within industry) and trade remedy. When observations before and after a trade remedy are available, gravity models can be used to detect changes in trade flows as a result of trade remedies.
- **Difference-in-differences (diff-in-diff).** Diff-in-diff seeks to identify the impact of trade remedies by comparing actual outcomes (import volumes, firms profits and so forth) to those in a counterfactual scenario i.e. the scenario that would have occurred absent the trade remedy. In essence, the approach looks at the change in outcome (e.g. import volumes) before and after a trade remedy for a 'treated' group (i.e. a group of companies/sectors subject to a trade remedy). It then 'nets off' (subtracts) the change the same outcome (e.g. import volumes) for a 'control' group (i.e. a group not affected by the trade remedy; e.g. a group in an adjacent sector or the same sector in a different country). By seeking to take account of what would have happened absent the intervention (by looking at a 'control' group), the technique is intended to provide confidence that the identified impact is truly 'causal'.
- **Synthetic control (SCM).**[1] Akin to diff-in-diff, SCM seek to isolate causal impacts by focussing on a counterfactual scenario (i.e. absent the trade remedy). Unlike diff-in-diff, and as the name suggests, the SCM involves constructing an artificial counterfactual. In particular, SCM creates a counterfactual by weighting a number of unimpacted "units" that are combined to form a counterfactual. The units used often come from a wider pool of potential units, denoted the "donor pool". In the context of trade remedies, this means predicting an outcome (e.g. import volumes) as if the trade remedy had not been imposed.

[1] Synthetic control is sometimes referred to as Synthetic Control Method *("SCM").* For the purpose of this report, these terms are used interchangeably.

- **Event studies.** Event study methodologies can be used to estimate the impact of a specific change. They work similarly to SCM in that the counterfactual model is created to estimate the evolution of the variables of interest across time. Once this is complete, the event study method directly computes an "event day" impact, that is the difference between the estimated counterfactual and the observed variable on an event day. This methodology works well for single events or multiple discrete events. However, this methodology is not best placed to estimate contemporaneous factors, such as trade remedies.
- **Bayesian methods (BCI).** Bayesian econometrics is based on Bayes theorem,[2] and posits an alternative interpretation method for results of empirical estimations. The methodology involves specifying a likelihood function which incorporates the probability of observing your data given the model specification and specifying so-called "*priors*". These priors reflect beliefs of parameters before observing the data. This can be based on prior knowledge or one can allow for the data to dominate.

1.4 There are occasions when econometric methods are not suitable, or it is not possible to implement such approaches. For example, in instances where data is not available or time/resources are limited. In these circumstances, it may be appropriate to use simple empirical approaches such **before-during-after** analysis (where variables of interest are compared before and after the imposition of a trade remedy) or **trend analysis** (which investigates changes in variables over time and examines changes in trajectories and fluctuations).

1.5 In some circumstances it may not be possible to observe the response of variables of interest to the imposition of a trade remedy at all. For example, data may be completely absent, or the remedy may simply be to 'do nothing' (e.g. to retain an existing trade remedy). In this case, data-driven approaches may not be suitable (or possible) for evaluating trade remedies. In these circumstances, techniques based on **economic theory** (sometimes called simulation methods) may help shed light the impacts of trade remedies. Some of the some of the most widely deployed approaches are as follows include Computable General Equilibrium (CGE) models and microeconomic models (e.g. 'new trade' models essentially which essentially model how firms compete in the marketplace).

Evaluation framework

1.6 With the different evaluation tools and techniques in place, the question becomes: under what circumstances should the different approach be deployed? To allow for this question to be answered, a guiding framework for methodology selection has been developed: a key output of this research. The framework is not meant to be a prescriptive "must follow" approach but gives an initial indication of methodologies that one may wish to consider. The framework is given in two forms: a tabular format and a decision-tree format.

Tabular format

1.7 The tabular version of the framework proceeds through two steps: one that helps identify which methods are feasible; and a second that helps identify the appropriateness of different feasible methodologies (depending on data and other consideration factors).

1.8 Table 1 below identifies the main considerations for feasibility across the methodologies. The table identifies whether a methodology is feasible if the answer is "Yes" to the question (with red meaning "not viable", amber meaning "potentially viable" and green meaning "viable"). For example, if there are no valid comparators, then diff-in-diff, synthetic control, Bayesian methods and event studies are all unlikely to be feasible. Likewise, if only pre-initiation data is available (and no post- trade remedy initiation data is available) then economic theory (simulation) methods may be the only option available.

[2] Bayes, T., 1763. LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, FRS communicated by Mr. Price, in a letter to John Canton, AMFR S. *Philosophical transactions of the Royal Society of London*, (53), pp.370-418.

Table 1: Consideration of factors that make econometric methodologies feasible

General approach	Method	Only pre-initiation is data available?	No change to Trade Remedy?	No valid comparators?	Data only contains a few time periods?
Quasi-experimental	Bayesian Methods (BCI)				
Quasi-experimental	Synthetic Control				
Quasi-experimental	Diff-in-diff				
Quasi-experimental	Event Study				
Non-quasi experimental	Gravity Model				
Non-quasi experimental	Trend analysis				
Non-quasi-experimental	Before-during-after				
Non-counterfactual	Economic theory (simulation) methods				

Notes: Dark grey indicates "Not Viable" if answer to question is "Yes"; light grey indicates "Potentially Viable" if answer to question is "Yes"; and white indicates "Viable" if answer to question is "Yes".
Source: GT Analysis.

1.9 Once Table 1 has been used to identify feasible methodologies, further data specific factors should be considered when making a choice between methodologies. These considerations are indicated in Table 2 below. The colours illustrate the circumstances in which the methods may be most appropriately deployed. For example, Bayesian methods maybe the most appropriate approach if data is very noisy and contains structural breaks, interpreting the results of the analysis as genuinely causal is an important factor to consider and ample time is available. Conversely, if time is of the essence and there is less of a desire to test whether a trade remedy has truly caused an impact, then a before-during-after comparison may suffice.

Table 2: Consideration of factors that make a particular method appropriate, conditional on the method being feasible

General approach	Method	Noisy data/ structural breaks?	Few comparators available?	Important that interpretation is causal?	Time is limited and/or complexity is to be avoided?
Quasi-experimental	Bayesian Methods (BCI)				
Quasi-experimental	Synthetic Control				
Quasi-experimental	Diff-in-diff				
Quasi-experimental	Event Study				

General approach	Method	Noisy data/ structural breaks?	Few comparators available?	Important that interpretation is causal?	Time is limited and/or complexity is to be avoided?
Non-quasi-experimental	Gravity Model				
Non-quasi-experimental	Trend analysis				
Non-quasi-experimental	Before-during-after				
Non-counterfactual	Economic theory (simulation) methods	Some simulation models can be entirely theoretical and do not need data (i.e. except for calibration).			

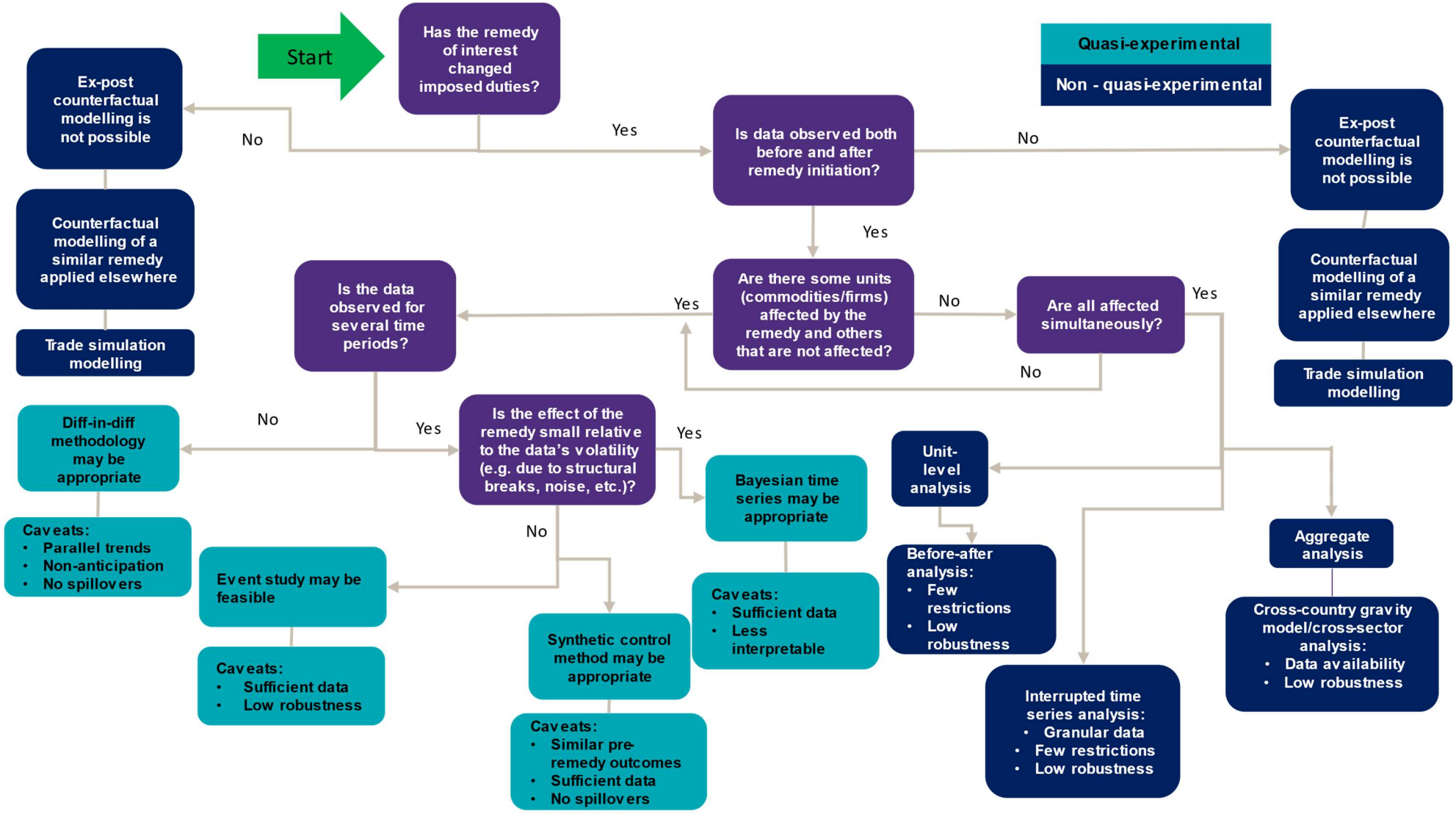
Notes: White means that the methodology copes well, light grey means that the methodology can be adapted to accommodate the factor, and dark grey means that the methodology cannot be adapted with the relevant factor.
Source: GT Analysis.

Decision tree format

1.10 The principles expressed in the above tables can be presented in the form of a decision tree: the following diagram how the factors in Table 1 and Table 2 should be navigated when the TRA is deciding on a suitable model. It expresses method selection as flow of thought; the method of choice is a terminal node that follows naturally from conditions that have been satisfied in previous nodes. It begins by considering fundamental features of the data and the prevailing context, and thereafter leads the user through more nuanced details such that the remaining set of viable models is more tailored to the situation at hand. The conclusions of the decision tree and those in Table 1 and Table 2 regarding model suitability in a given context are consistent as they are governed by the same principles.

1.11 Table 1, Table 2, and Figure 1 are not intended to be read prescriptively. It is not being proposed that a particular methodology be used with certainty and exclusivity, but rather, it is conditional on the necessary circumstances warranting it. It is to be read as general guidance for the contexts and constraints that make some methodologies more suitable for a given problem, and which methodologies may struggle with the data or context

Figure 1: Decision tree for methodology selection



Source: GT Analysis.

Illustrative case study applications

1.12 With the above framework for methodology selection in place, four case studies were undertaken intended to:

- illustrate how the above framework can be applied in practice to make choices between methods;
- show why the selection of the appropriate method is so important (and that selecting an inappropriate method can result in misleading results);
- illustrate some of the practical challenges that may be encountered in pursuing these approaches and how they can be overcome; and
- uncover important practical lessons-learned for evaluating the impact of trade remedies.

1.13 The case studies do not evaluate the true impact of the trade remedies in question. In fact, case study 3 and 4 even use synthetic data. Therefore, the focus should not be on the results of the models but rather on the process of selecting the appropriate evaluation method based on contextual factors and issues that may arise during impact estimation.

Illustrative Case Study 1 – AD0012 Aluminium Extrusions from the People's Republic of China (PRC)

Context

1.14 This case study covers the application of ex-post counterfactual analysis to assess the impact of imposition of a new anti-dumping measure in the UK. The trade remedy is an anti-dumping measure applied to Aluminium Extrusions imported from the PRC. The TRA initiated an investigation into the matter on 21 June 2021 and later concluded in its provisional and final determinations, dated 17 August 2022 and 16 December 2022 respectively, that these goods were being dumped into the UK and this was causing injury to UK industry.[3] The impact of the trade remedy on the import volumes of nine target commodities was assessed.

Analytical approach

1.15 The data used to assess the impact of the trade remedy was trade data at the 8-digit commodity-level obtained from UK Trade Info.[4] Although the trade remedy was applied to commodities at the 10-digit level, the data that was available was at the 8-digit level (i.e. several 10-digit commodity codes fall into a single 8-digit commodity code). Therefore, the affected commodities were matched to their nearest 8-digit level commodity code and analysis was undertaken at this level. Following the methodology selection framework above – and noting the abundance of data and potential to construct a useful control group – the methodologies used to estimate the causal impact of the trade remedy were the Synthetic Control Method (i.e. SCM) and Bayesian methods (i.e. BCI).

Results

1.16 The results from the analysis are shown in the tables below.

Table 3: Estimated effect for each commodity using synthetic control method (SCM)

Commodity	Aggregated Treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76041090	-6.83	-81.8	0.000

[3] https://www.trade-remedies.service.gov.uk/public/case/AD0012/submission/58db49f3-2ec8-4b8d-9acc-82d85bb69037/
[4] https://www.uktradeinfo.com/ is HM Revenue & Customs' gateway for official UK trade data.

Commodity	Aggregated Treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76081000	-0.44	-61.3	0.000
76082089	-1.19	-76.3	0.000
76042910	-3.24	-75.5	0.000
76082081	-0.13	-25.5	0.349
76042100	-1.50	-33.8	0.005
76041010	0.00	-0.6	0.095
76109090	12.94	64.2	0.001
76042990	-59.06	-52.4	0.017

Notes: This table presents the results from using the SCM for each commodity. The first column shows the aggregate impact of the trade remedy on the volume of imports in kilotons (i.e. the sum of the impact of the trade remedy in each quarter). The second column shows the average impact as a proportion of the predicted imports for every quarter in the post-initiation period. The final column shows p-value associated with the average impact of the trade remedy. Values below 0.05 indicate that the average impact is statistically significant at the 5% significance level.
Source: GT analysis.

Table 4: Estimated effect for each commodity using Bayesian causal impact (BCI)

Commodity	Aggregated Treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76041090	-6.83	-81.8	0.000
76081000	-0.44	-61.3	0.000
76082089	-1.19	-76.3	0.000
76042910	-3.24	-75.5	0.000
76082081	-0.13	-25.5	0.349
76042100	-1.50	-33.8	0.005
76041010	0.00	-0.6	0.095
76109090	12.94	64.2	0.001
76042990	-59.06	-52.4	0.017

Notes: This table presents the results from using the BCI for each commodity. The first column shows the aggregate impact of the remedy on the volume of imports in kilotons. The second column shows the average impact as a proportion of the predicted imports for every quarter in the post-initiation period. The final column shows p-value associated with the average impact of the remedy. Values below 0.05 indicate that the average impact is statistically significant at the 5% significance level.
Source: GT analysis.

1.17 These models led to similar findings with respect to certain commodities: the trade remedy led to a notable and statistically significant reduction in the volume of imports. However, the findings of models diverged with respect to other commodities. In particular, BCI was able to estimate causal impacts more precisely and thus detected statistically significant trade remedy impacts for a greater number of commodities. This may be due to the ability of the BCI to generate more precise and less biased estimates of causal impacts when the underlying data is noisy.

Key lessons

1.18 Additional themes that were captured within this case study include:

- **Counterintuitive trade remedy impacts.** Evidence was found of the trade remedy having the potentially counterintuitive impact of increasing imports for some commodities that should have been made relatively more expensive as a result of the anti-dumping measure. This is likely due to imperfect coverage between the unit of analysis (i.e. the 8-digit level commodity codes) and the unit targeted by the measure (i.e. the 10-digit commodities). Notably, some the 10-digit commodities within the 8-digit classifications investigated were within the scope of the trade remedy while others were out of scope. Therefore, some of the estimates reported at the 8-digit level were a combination of impacts due to the trade remedy and import movements for commodities not targeted by the trade remedy. Import movements for non-targeted commodities may be due to (i) substitution between the targeted commodity and the non-targeted commodities; (ii) attempts by importers to circumvent the trade remedy or (iii) exogenous factors unrelated to the trade remedy. Further analysis of import behaviour at the 10-digit level is required to both empirically separate the true impact of the trade remedy from external factors, and to understand the mechanisms driving the imports of non-targeted commodities within the same 8-digit level commodity code as targeted commodities.
- **Anticipation effects.** Evidence was found of importers anticipating the trade remedy and adjusting their importing behaviour in response to the trade remedy prior to the initiation date. The initiation of a similar EU trade remedy investigation prior to the initiation date of the corresponding trade remedy investigation of the UK may have led importers to pre-empt the trade remedy taking effect in the UK. It is suggested that the initiation date is back dated within the analysis in order to capture these anticipation effects within the causal impact estimates. The approach taken by the evaluator to uncover causal impacts would be different if the pre-initiation effects were found to be due to exogenous factors unrelated to the trade remedy.
- **Comparator commodities poorly predicting observable imports.** Results showed that the BCI was unable to accurately predict observed imports during the pre-initiation period due to poor explanatory power of the comparator commodities. Including variables that may explain some of the variation of in import volumes (e.g. exchange rates or more qualitatively similar commodities) could reduce the noise in the model and generate more precise estimates of the trade remedy impact.
- **Substitution and complementary effects.** Comparator commodities that may have been affected by the trade remedy because they are substitutes of or complements for the target commodity should be removed from the sample. Efforts were made to minimise the number of commodities that were affected by spillovers, but there is evidence to suggest that not all such commodities were. The conceptual and quantitative measures to minimise the number of comparator commodities that may be impacted by spillovers and the recommended process is detailed in Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC.

Illustrative Case Study 2 – TD0014 Heavy Plate from the PRC

Context

1.19 This case study illustrates how models from economic theory can be used to explore the impact of trade remedies when there is no observable counterfactual from real-world data (e.g. because there has been no recent change in remedy or data is not available).

1.20 To illustrate the application of these models, the case study considers duties imposed by the UK on Heavy Plate from the PRC. An import tariff of around 70% has been imposed on these imports since 2017. Importantly, TRA's conclusion through its transition review was not to change the scope/form/level of the measure, meaning that it is not possible to observe changes in demand, market share and so forth. This means that econometric approaches to evaluation are not suitable.[5] More information about the case is available in the TRA's recommendation to the

[5] More information about the case is available in the TRA's recommendation to the Secretary of State (TRA, 2023). https://www.trade-remedies.service.gov.uk/public/case/TD0014/submission/ddae82b4-c854-4721-ae2b-c6cda678f18d/

Secretary of State (TRA, 2023). The case study focuses on the impact on market share but other variables such as profits, consumer welfare and so forth can also be explored through these models.

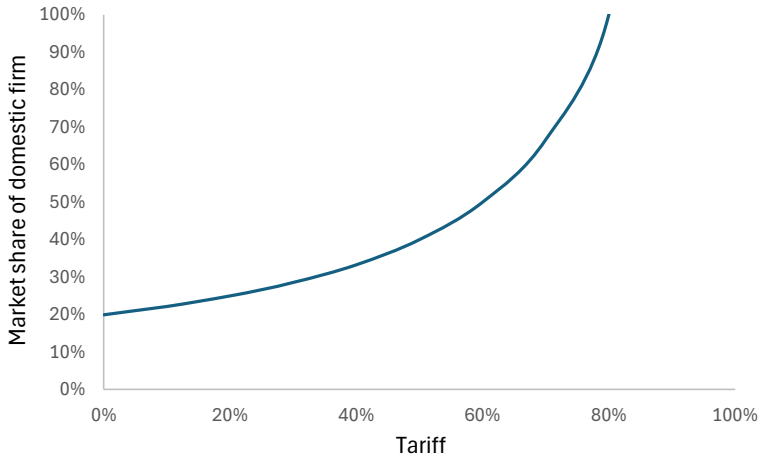
Analytical approach

1.21 The case study uses a variant of the models developed by authors including Brander, Spencer and Krugman in the early 1980s (part of the 'New Trade Theory' literature). Essentially, a Cournot oligopoly model (adapted to capture international trade and tariffs) is constructed to simulate how firms compete in the domestic market. This model is then 'calibrated' with real-world information (for example about existing prices, firms' costs and market shares) to explore the impact of trade remedies (in particular, the effect of retaining an import tariff).

Results

1.22 The relationship between the import tariff and the market share of the domestic firm can be plotted, by calibrating the model with real world data. As the import tariff rises it increases the foreign firm's effective costs in the domestic market, giving a competitive advantage to the domestic firm. The domestic firm's market share rises and the foreign firm's market share falls (Figure 2).

Figure 2: Impact of an import tariff



Source: GT Analysis.

1.23 This information can be used to derive an illustration of the impact of retaining the import tariff in this setting. The import tariff being applied is circa 70%, resulting in a domestic firm market share of around 67% (as per the TRA findings). The model can then be used to construct a counterfactual – and estimate the market share – for other tariff levels to help evaluate the impact of the import tariff. For example:

- in a counterfactual where a 50% tariff was applied (for example if 50% was the most-favoured nation (MFN) tariff), the model would imply a domestic market share of 40%. This would imply that, compared to that counterfactual, the impact of retaining the import tariff is to uphold the market share of the domestic firm by around 27 percentage points.
- in a counterfactual where the import tariff is removed altogether, the implied domestic market share would fall (a difference of almost 50 percentage points). In other words, according to the model, retaining the import tariff results in around half of the market purchasing from the domestic producer that would otherwise procure from the foreign supplier.

Key lessons

1.24 Models from economic theory can help give useful indications of the impacts of trade remedies, and illustrate the economic mechanisms through which trade remedy affects variables of interest. They may be especially useful where data is not available to construct a counterfactual scenario. However, the models are inevitably oversimplifications of real-world dynamics. In addition, different theoretical models serve different purposes and calibrating them is fraught with uncertainty. As a result, they may be best thought of tools to help illustrate impacts and give an indication of possible size of effects in the context of significant uncertainty (rather than techniques capable of providing precise estimates of trade remedy impacts).

Illustrative Case Study 3 – TD0004 and TS0005 Biodiesel from United States and Canada

Context

1.25 This case study pertained to the UK changing the scope of two trade remedies imposed by the European Commission: an anti-dumping measure (i.e. TD0004) and a countervailing measure (i.e. TS0005). The initial measures began in July 2009 and imposed anti-dumping and countervailing duties on imports of biodiesel originating in the US and consigned from Canada. On 11 August 2020, the TRA initiated a transition review of the original EU measure to assess whether the measure should be varied or revoked in the UK.[6,7] The recommendation revoked the measure in relation to HVO biodiesel but it maintained the measure with relation to FAME biodiesel, and this change in scope was instated from 30 January 2021.[8]

Analytical approach

1.26 This case study uses synthetic firm-level data as real-world firm-level data was not available due to confidentiality issues. However, in collaboration with the TRA, synthetic firm-level data was create, resembling the data that the TRA would have access to when it undertakes its investigations. The synthetic data attempted to mirror this real-world data by containing similar variables and a realistic level of granularity and frequency. The synthetic data was a quarterly sample spanning from 2010 to 2023, contained firm-level variables such as costs, sales, revenues and profit, and consisted of one firm that was exposed to the trade remedy and, depending on the specification, between 10-30 comparator firms that were not exposed to the trade remedy.

1.27 The impacts of the trade remedy were estimated using the SCM and BCI (following the methodology selection framework above). However, these impacts were known beforehand as they were constructed as part of the data. The performance of the methodology was assessed by measuring how close the estimates were to the true impact of the trade remedy.

Results

1.28 The baseline case investigates the impact of the trade remedy with 10 firms, assuming the effect of the trade remedy was constant over time and the underlying volatility in the data was relatively low. The results from estimating the SCM and BCI on this data are summarised in the tables below. The reported results are the true and estimated aggregate impact of the trade remedy in the entire post-initiation period and the average proportional impact of the trade remedy.

[6] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[7] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[8] Biodiesel from United States and Canada - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Table 5: SCM results with constant trade remedy impact and low volatility

Outcome	True Aggregated Impact	Estimated Aggregated Impact	Estimated True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-91	-10.0	-9.15	0.455
Costs (trimmed sample)	-100	-181	-10.0	-16.68	0.833
Demand	3,927	3,642	23.5	21.36	0.364
Demand (trimmed sample)	3,927	5,369	23.5	35.04	0.667
Profit	13,320	11,829	11.1	9.74	0.545
Profit (trimmed sample)	13,320	20,071	11.1	17.73	0.667
Revenue	146,516	124,909	11.1	9.31	0.545
Revenue (trimmed sample)	146,516	220,775	11.1	17.73	0.667

Notes: This table shows the impact of the trade remedy on the synthetic firm assuming that the impact of the trade remedy reduces cost by 10% and is constant over time. The columns indicating the aggregate effect show the true and estimated aggregate impacts of the trade remedy (i.e. the sum of the impact of the trade remedy in each quarter). The columns indicating the proportionate impact of the trade remedy show the impact of the trade remedy as a percentage across each quarter in the post-initiation period. The p-value represents the statistical precision of the estimate produced by the model. Values below 0.05 indicate that the estimate of the average impact of the trade remedy is statistically significant, whereas numbers above 0.05 indicate that the estimate of the average impact is not statistically different from 0.
Source: GT Analysis.

Table 6: BCI results with constant trade remedy impact and low volatility

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-149	-10.0	-14.16	0.0640
Costs (trimmed sample)	-100	-111	-10.0	-10.95	0.0002
Demand	3,927	3,978	23.5	23.89	0.0568
Demand (trimmed sample)	3,927	4,071	23.5	24.57	0.0002
Profit	13,320	11,877	11.1	9.79	0.0167
Profit (trimmed sample)	13,320	13,476	11.1	11.26	0.0002
Revenue	146,516	130,647	11.1	9.79	0.0163
Revenue (trimmed sample)	146,516	148,234	11.1	11.26	0.0002

Notes: This table shows the impact of the trade remedy on the synthetic firm assuming that the impact of the trade remedy reduces cost by 10% and is constant over time. The columns indicating the aggregate effect show the true and estimated aggregate impacts of the trade remedy (i.e. the sum of the impact of the trade remedy in each quarter). The columns indicating the proportionate impact of the trade remedy show the impact of the trade remedy as a percentage across each quarter in the post-initiation period. The p-value represents the statistical precision of the estimate produced by the model. Values below 0.05 indicate that the estimate of the average impact of the trade remedy is statistically significant, whereas numbers above 0.05 indicate that the estimate of the average impact is not statistically different from 0.
Source: GT Analysis.

Key lessons

1.29 The SCM and BCI to were implemented on synthetic firm-level under varying scenarios. The scenarios investigated included: (i) low versus high data volatility; (ii) a constant trade remedy impact versus a time-varying trade remedy impact; (iii) 10 comparator firms vs 30 comparator firms; and (iv) a sample consisting of some unsuitable comparators versus a sample consisting of no unsuitable comparator. The results showed that the best performing model in terms of both accuracy and precision across the board was the BCI, and that a sample with no unsuitable comparators yielded the best results. This finding was robust to all the modifications made to the underlying data. This result is likely due to the ability of the BCI to generate more precise estimates of causal impacts despite the underlying data being noisy or the true impact of the trade remedy being small and time-varying.

1.30 This case study also underscored the importance of removing unsuitable comparators from the sample before undertaking causal analysis. Keeping unsuitable comparators in the sample generates bias that may even cause models that are highly robust to noise (i.e. the BCI) to perform poorly, especially as the data becomes noisier, the number of comparators changes and as the impact of the trade remedy becomes more complex.

Illustrative Case Study 4 – TS0023 Stainless Steel Bars and Rods from India

Context

1.31 This case study is based on a trade remedy initially imposed by the EU on Stainless Steel Bars and Rods originating in India, which was revoked after a TRA transition review.[9] The case study illustrates an approach to evaluating trade remedies when data is limited and explores some of their key challenges.

Analytical approach

1.32 Since the case study data is limited to just a small number of periods, the methodology selection framework above reveals that some of the more advanced techniques (e.g. SCM and BCI) are unlikely to be suitable. Nevertheless, potential data on comparators does exist, so a difference-in-differences ("diff-in-diff") estimation is employed. As with Case Study 3, a synthetic data set was constructed for sales (since it was not possible for TRA to share data owing to confidentiality considerations).

1.33 Diff-in-diff estimators rely on the parallel trends assumption. This assumption states that the pre-trade remedy trends of the comparator and treated firm are parallel. This assumption is necessary to interpret causal impacts from a diff-in-diff estimation.

Results

1.34 The results for this case study are estimated in three scenarios:

- Parallel trend;
- Parallel trend with noise; and
- Non-parallel trend.

1.35 Data was constructed to create an actual drop in sales of £10,500.

1.36 The estimation results for the parallel trends estimation are presented below.

[9] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Table 7: Estimation results for the parallel trends analysis

	Sales
(Intercept)	50.76***
	(0.2598)
Treated	-2.0495**
	(0.3674)
After	0.9115
	(0.00942)
Treated x After	-10.4661***
	(0.6364)
R-squared	0.9975
Adj R-squared	0.9937
F-statistic	265.2***
Residual standard error	0.3674

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05**
Standard errors are reported in parentheses.
Source: GT Analysis.

1.37 When the pre-trade remedy trends are parallel, estimation yields a close to accurate estimation of the fall in sales. When noise is added into the estimation, the results of the estimation are further from the actual drop. The results from the noisier estimation are presented below.

Table 8: Estimation results for diff-in-diff with a parallel trend and noise

	Sales
(Intercept)	50.9446***
	(0.4891)
Treated	-2.3956**
	(0.6917)
After	0.7353
	(0.8471)
Treated x After	-10.6277**
	(1.1980)
R-squared	0.992
Adj R-squared	0.98
F-statistic	82.56**
Residual standard error	1.246

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05**
Standard errors are reported in parentheses.
Source: GT Analysis.

1.38 The results identify a fall in sales, but of £10,630 rather than £10,500. This occurs as the level of noise is comparable to the underlying trend, and with only three observations, it is more difficult to identify the underlying trend. Significant noise will interfere with identifying an underlying trend, unless the frequency or quantity of observations is large enough to ascertain a trend despite the noise.

1.39 The analysis is also conducted for a comparator firm that does not have a pre- trade remedy parallel trend. The results of this estimation are presented below.

Table 9: Diff-in-diff estimation with non-parallel trends

	Sales
(Intercept)	50.079 ***
	(1.386)
Treated	-5.519
	(1.960)
After	5.961
	(2.401)
Treated x After	-15.589**
	(3.395)
R-squared	0.9711
Adj R-squared	0.9266
F-statistic	22.36*
Residual standard error	1.960

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05**

Standard errors are reported in parentheses.

Source: GT Analysis.

1.40 This estimation results in an estimated fall in sales of £15,590. This is significantly larger than the actual drop of £10,500. This highlights the importance of the parallel trends assumption holding.

Key lessons

- Whilst diff-in-diff estimations require minimal data, there are still strict criteria that must be met for the interpretation of diff-in-diff to be causal.
- If there is significant noise, the trend may be more difficult to identify. This can be solved by obtaining more data, or more frequent data.
- If there is no appropriate comparator or the parallel trends assumption does not hold, then alternative methods should be undertaken, or further data should be collected.

Key lessons and recommendations

1.41 The key aim of this report was to develop a framework for evaluation methodology selection that the TRA can use to select suitable approaches for the causal analysis of trade remedies in a way that is tailored to the various contexts that the TRA are likely to encounter. The methodology selection framework presented above (and detailed in Section 6) was developed with this aim in mind. This framework delivers the TRA with more than just a toolkit for causal analysis; it provides the TRA with a guide for selecting the right tools for the right task.

1.42 The case studies illustrate how this framework can be applied to four scenarios to which the TRA applies trade remedies. Each case study was unique in terms of the context of the trade remedy that was applied, the nature of the counterfactual problem implied by the trade remedy and the data that was available for analysis. In each case, the framework was used to guide the selection of the methodology. When comparison of multiple methodologies was undertaken, the methodology that was deemed most suitable by the framework delivered the best results.

1.43 The high-level take-away from these results is that the framework can be relied upon to choose causal approaches, from a suite of feasible methodologies, that are tailored to the nuances of the context. However, the framework should not be read prescriptively; the framework and its proposed methodologies should not be followed blindly and judgement is necessary. Further, the framework should not be interpreted as proposing a particular method to be used with certainty and exclusivity. Specifically:

- Methodologies within the framework have assumptions that must be met for causal impacts of trade remedies to be identified; and
- If these assumptions are not met, other methodologies should be considered.

1.44 The framework is intended to serve as general guidance for the contexts and constraints that make some methodologies more suitable and others less so.

1.45 In practice, conditional on a set of methods being feasible, it would be ideal to apply all of them and use the findings of each method to triangulate the most credible answer. This can be done by implementing multiple methodologies, where feasible, and then:

- Assessing the degree of similarity in their findings;
- Identifying potential factors that drive differences in results, should divergences arise;
- Evaluating the importance of each finding based on the merits and limitations of each approach in light of the context;
- Being transparent with any assumptions that have been made due to limited evidence;
- Being transparent with all shortcomings in the methodologies considered and caveat results accordingly; and
- Coming to a reasonable and well-balanced conclusion.

1.46 The fourth point is particularly important when the TRA is led by the framework to use approaches that are less capable of producing causal estimates but are the most suitable due to time and complexity constraints. The framework has been endowed with the flexibility of proposing approaches that the TRA can use to deliver expedient results when there is a shortage of time, data or expertise. However, these approaches tend to be less able to produce causal findings when compared to more robust yet resource intensive alternatives. The TRA may wish to ensure that all results are caveated appropriately when endeavouring to use the framework to deliver results at pace. Furthermore, in cases where the TRA relies of purely theoretical approaches, they could view the findings of these approaches as illustrative rather than precise and causal.

Data collection considerations

1.47 Situations may arise when methodologies that would be most capable of delivering causal estimates will be infeasible due to data constraints, and the TRA may be limited to second-best alternatives that produce less reliable and robust results. The TRA faces many data constraints that can be inflexible in the short-term, particularly with respect to firm-level data. The TRA's database of firm-level information has historically depended on the voluntary data contributions of domestic importers, domestic like-good producers, and firms in the wider supply chain of domestic producers and importers. The nature of the data that TRA acquires for investigations is sparce, and usually consists of a small number of firms with limited time periods. This heavily limits the methodologies that the TRA can feasibly apply when investigating trade remedies; data-hungry approaches such as the SCM and BCI would likely unworkable.

1.48 The following recommendations could potentially help the TRA enhance their data capabilities:

- Collect more granular data or for longer time periods: increasing the number of time periods that can be assessed will create opportunities for the TRA to implement a greater number of robust approaches for causal inference. This can be done either by collecting data at a higher frequency (e.g. at the monthly or quarterly level) or by incorporating a greater number of pre-trade remedy years into the sample. It may be possible for the TRA to encourage participation of firms to cooperate with greater data demands by stressing the importance of data in coming to sound determinations;
- Encouraging firms to participate: Whilst compelling firms to participate may not be possible, strong encouragement of participation could lead to better insights from the data. However, there may be an argument for this in scenarios where the trade remedy in under review is likely to have widespread and significant effects on UK industry and the wider economy. In such cases, making correct deductions about the impact of a trade remedy can have large

economic ramifications on the UK and it would allow the TRA to give make the best approaches feasible by having ample data; and

- Make the most of what is available: if the TRA were able to harmonise all the data that has been collected from previous investigations into a single database, it may be able to leverage this information in future investigations. This may allow the TRA to increase the number of time periods and comparators contained in future data samples by appending relevant information from prior investigations. In theory, this could expand the data available to the TRA in the long-term without jeopardizing the participation of its questionnaires' respondents in the short-term.[10]

Practical considerations for causal analysis

1.49 The framework provides the TRA with guidance for how to select feasible and suitable methodological approaches for the causal assessment of trade remedies in subject to various contexts and constraints. However, there are many considerations that the TRA must bear in mind when practically undertaking causal analysis with these approaches in order to meaningfully interpret their findings. These considerations include many of the key lessons gleaned from the case studies within this report but also go beyond them. They include:

- **The unit of treatment and unit of analysis:** in general, there can be a divergence between how the trade remedy is implemented practice and how this is captured in the data. For instance, the trade remedies are imposed at the 10-digit commodity code level, whilst analysis was undertaken at the 8-digit level. This resulted in counterintuitive findings for commodities that had imperfect overlap between these two levels of classification with respect to trade remedy exposure. Such divergences must be identified and addressed, or the results must be caveated accordingly;
- **Pre-initiation effects:** effects of a trade remedy that materialise prior to the initiation of the trade remedy investigation may be indicative of factors that must be accounted for in causal analysis;
- **Spillover effects:** these may arise when commodities that are out of scope for a trade remedy are impacted due to substitution effects, complementary effects or other effects connected to the trade remedy. Failing to account for spillover effects may result in the estimated impact of the trade remedy being heavily biased;
- **Volatility matters:** the underlying volatility of the data has implications for the performance of the many of the methodologies considered within this report. Numerous ways to mitigate the amount of noise in the data were proposed and executed in this report; and
- **Sample selection:** the TRA gathers its firm-level data on a volunteer basis. This creates sample selection issues of varying degrees. Sample selection occurs when the sample is not representative of the general market or population of interest. In its most extreme form, sample selection can render ex-post counterfactual analysis infeasible because there are no comparators for the firms that are affected by the trade remedy. The only recourse in such a situation would be to rely on empirical or theoretical methods that do not rely on a counterfactual. Less extreme forms of sample selection can be overcome by implementing approaches that are robust to sample selection (these are beyond the scope of this report) or caveating the findings and resulting conclusions appropriately.

[10] The TRA will need to ensure that it adheres to any data storage and utilisation terms within the data provision agreements it made with respondents from past investigations.

2. Introduction

Purpose of this Report

2.1 This report aims to facilitate the Trade Remedies Authority's ("TRA") evaluations of its existing and future operational practices. It endeavours to do this by investigating the strengths and weaknesses of applications of methodological tools to estimate the causal impacts of the UK's trade remedy measures. These tools are investigated using four case studies that consider different types of trade remedy measures: a) a new UK measure, b) an EU measure transitioned by the UK and scope unchanged following transition review, c) an EU measure transitioned by the UK and scope changed following transition review, d) EU measure transitioned by the UK and revoked following transition review.

2.2 The report is not expected to provide commentary or evaluate existing trade remedy measures, but instead provide a toolkit for future policy-makers to draw upon when undertaking their own evaluation. It will do this by commenting on the existing trade literature landscape, detailing the suite of analytical tools currently used for the evaluation of trade policy and understanding their feasibility in the context of the TRA's work.

2.3 The report also discusses the impacts of the UK's unique circumstance, in which it has transitioned a number of trade remedy measures that previously applied to the whole EU28, and particularly how the UK can mitigate the challenges of a structural break in its time-series. This also extends to how future policy-makers should overcome the challenges of COVID-19 pandemic, which are likely to have distorted trade patterns materially from historical trends.

2.4 At its core, this report will provide an approach for the systematic evaluation of the impacts of the UK's trade remedy measures on imports and the performance of UK producers and importers of goods covered by these duties and other firms involved in the supply chain.

Scope of this Report

2.5 The scope of this report is as follows. It begins by setting out the existing academic literature exploring trade remedies and the various methodological approaches that have been employed to estimate their causal impact. Thereafter, the methodologies themselves are covered in greater detail and categorised into causal methodologies, non-causal methodologies, and simulation-based methodologies.[11] The methodologies are then used to develop the selection framework and the framework is applied to the case studies. The report is concluded by covering the key lessons from the case studies and recommendations for the TRA as it implements the framework in future investigations. The conclusion of the document is followed by appendices reporting extended results and discussing the data adjustments undertaken in analysis in further detail. Thereafter, there is a glossary that defines key terms and concepts to make the report more accessible to readers with non-econometric backgrounds.

[11] We use the following terms interchangeable within this report: causal methodologies and quasi-experimental methodologies, non-causal methodologies and non-quasi-experimental methodologies, and simulation-based methodologies and non-counterfactual methodologies. This correspondence is because quasi-experimental methods are generally better suited for causal analysis than non-quasi-experimental approaches; hence quasi-experimental approaches are generally also causal approaches. Further, simulation-based approaches are generally used in cases where there is no suitable counterfactual for a particular remedy, hence being labelled non-counterfactual. We expand on both points later in the report.

3. Applications of evaluation tools in trade literature

Summary

3.1 This literature review outlines the direct and indirect impacts of trade on the domestic and international markets in two distinct areas: quantitative and qualitative. This is considered as:

- an explanation of how causal impact methodologies are used for evaluating the impact of trade remedies; and
- a discussion of the use of causal impact methodologies within the trade literature.

Impacts of trade remedy measures

3.2 The core aim of any trade remedy measure is to protect domestic industries from unfair trade practices. However, trade remedies will also directly and indirectly affect international and domestic stakeholders. For the purpose of this analysis, stakeholders include producers, exporters, importers, companies in the supply chain of the trade remedy-applied good and consumers. The theoretical impacts that are most likely to arise as a consequence of trade remedies will be covered in the following section. Moreover, this discussion will be used as means of understanding which effects should be the focus of any evaluation.

Domestic impacts

Trade impacts

3.3 The primary impact of any trade remedy is likely to be a reduction in imports from the targeted country and/or firm. Literature has noted the direct impacts of trade remedies, in particular citing a decline in imports from the moment an investigation is launched and prior to any imposition of a trade remedy, the so-called “chilling effect”. It is also noted in these papers that imports from the targeted country often do not return to pre-trade remedy levels even after the expiration of the trade remedy.[12]

3.4 Two effects are at play here where both the announcement of an investigation coupled with the imposition of a trade remedy are likely to shape trading patterns. This dual effect is notable and suggests consideration may also be given to the extent time horizons shape the conclusions of any evaluation (i.e. baseline pre-announcement vs pre-trade remedy).

Direct impacts

3.5 In addition to the volume of trade, there are also likely to be direct price effects. The price of imported goods is expected to rise as a consequence of trade remedies.[13] This is because import tariffs are likely to be passed onto the consumers or other producers that use the good as part of their supply chain in a competitive market. This is expected as a direct impact from tariffs. The direct price impact may be inferred using quantitative methods, but price increases can materialise through indirect effects described below. The type of product impacted by the import tariff should also be considered, with some products having more of a direct consumer impact, e.g. ironing boards versus intermediate steel products.

[12] Carter, C.A. and Steinbach, S., 2018. *Trade diversion and the initiation effect: a case study of US trade remedies in agriculture* (No. w24745). National Bureau of Economic Research.
[13] Sandkamp, A., 2020. The trade effects of antidumping duties: Evidence from the 2004 EU enlargement. Journal of International Economics, 123, p.103-307.

3.6 Domestic price levels will also be shaped by UK manufacturers, whom as a result of less competition, supply at a price closer to the target price, which inevitably are likely to be higher than those prior to the trade remedy.[14] This effect can be most closely assessed by considering the competitive structure of the market pre- and post- trade remedy. Davies and Carr (2022)[15] assess the effects of trade on market structure utilising trade and domestic production data over time to understand how the concentration of markets vary when exposed to trade. A market that is shaped by competitive forces is likely to have an unconcentrated market structure, measured using the Herfindahl-Hirschman Index[16] or other metrics. The mechanisms behind price rises are likely to be shaped by a variety of factors. Further analysis to determine the data requirements and availability of evidence will shape the extent to which a quantitative or qualitative approach would work best for assessing price impacts.

3.7 Trade remedy measures can also lead to an increase in employment and domestic output in the protected sector.[17] Domestic output may be best inferred by looking at how market shares within the domestic economy vary pre and post trade measures. The analysis will focus on the 15 injury factors that are considered by the TRA when conducting trade remedy investigations. These are defined as:[18]

- **Actual and potential decline in:**
  - Sales;
  - Profits;
  - Output;
  - Market share;
  - Productivity;
  - Return on investment; and
  - Utilisation of capacity;
- **Factors affecting domestic prices of the like goods;**
- **In the case of dumping:**
  - Magnitude of the margin of dumping;
- **Actual and potential negative effects on:**
  - Cash flow;
  - Inventories;
  - Employment;
  - Wages;
  - Growth, and;
  - The ability to raise capital or investments.

3.8 The causal impacts of a trade remedy on these injury factors, conditional on suitable data being available, can be quantitatively measured.[19] However, it may be possible to complement quantitative analysis with qualitative analysis to better understand the underlying mechanisms driving quantitative results and have a more holistic view of trade remedy impacts overall. For example, suppose that a quantitative analysis determined that the trade remedy generated greater

[14] Marsh, S.J., 1998. Creating barriers for foreign competitors: a study of the impact of anti-dumping actions on the performance of US firms. *Strategic Management Journal*, *19*(1), pp.25-37.
[15] Carr, J. and Davies, S., 2022. Seller versus Producer concentration: incorporating the impact of foreign trade, CCP Working Paper 22-05
[16] The Herfindahl-Hirschman Index measures concentration within a market by squaring the market share of each firm within market and summing the shares. The values can take a range from close to 0 to 10,000 (Monopoly). Increases in the values may signify a decrease in competitive forces.
[17] De Souza, G. and Li, H., 2022. The employment consequences of anti-dumping tariffs: Lessons from Brazil.
[18] For more information, see: How we assess injury - GOV.UK (www.gov.uk)
[19] Carr, J. and Davies, S., 2022. Seller versus Producer concentration: incorporating the impact of foreign trade, CCP Working Paper 22-

employment in the domestic industry of the like-good targeted by the trade remedy. This may be a useful finding in isolation, but it may benefit from qualitative analysis to aid in determining how this additional employment was created and what it comprised of. For instance, qualitative analysis may help to determine, among other things, if: (i) the increased employment arose from increased production due to a decline in competitive pressure from overseas; (ii) what type of employment increased (e.g. high wage jobs or low wage jobs); or (iii) whether this increase was at the intensive margin (i.e. more working hours) or extensive margin (i.e. more jobs created). Qualitative analysis can be used alongside quantitative investigations to gain further insight into the exact changes in employment resulting from a trade remedy and how they came about. This will give a greater understanding of the causal impact of the trade remedy overall.

Indirect impacts

3.9 Indirect impacts, or third party effects, of trade remedies include impacts on upstream and downstream industries, substitute and complimentary goods and any employment multiplier effects. These effects can occur due to factors and circumstances that are unique to individual industries, or due to changes in trade patterns arising from a trade protection measure. They can arise as unforeseen impacts on economic variables that are unrelated to the targeted industry and are often referred to as the unintended policy impact. For example, the reduction in FDI,[20] and the increase in exporting wages that followed after Brazil's announcement of a currency devaluation in 1999.[21]

International impacts

Spillover trade and price impacts

3.10 An impact on international trade can be seen through indirect trade impacts that take the form of changes in exports from non-targeted countries or firms. This could be akin to firms in closely related industries within a targeted country pre-emptively reducing their trading activity and/or diversion effects to third countries.[22] These impacts most commonly impact substitute or complimentary goods industries, upstream and downstream industries. These indirect impacts could be quantitatively assessed by investigating patterns of trade with other countries not targeted by the specific trade remedy measure. For example, if a trade remedy measure is implemented and restricts imports from the PRC, importers of the restricted good may look to an alternative overseas producer, and hence imports from other countries could increase.

3.11 Indirect price increases may also be another form of indirect trade effects. This is where non-targeted goods and industries from targeted countries pre-emptively raise prices to prevent further trade remedy measures being implemented. Given the multitude of factors affecting international price setting, a more focussed approach to appraising price spillover effects such as these may require a qualitative approach.[23]

3.12 The imposition of a trade remedy itself may not be the trigger for trade remedy impacts. The structure of implementation by a trade remedy will have both direct and indirect impacts, and the approach to trade remedy implementation may influence the timing of observed trade remedy impacts. For example, if lobbyists petition the government to take anti-dumping action, these can have an impact on the sector before any trade remedy measure is implemented.[24] The threat of implementing a trade remedy measure can impact producers as they may change their behaviour before implementation of the measure (chilling effect).[25] There are additional challenges, such as

[20] Haaland, J.I. and Wooton, I., 1998. Antidumping jumping: Reciprocal antidumping and industrial location. *Weltwirtschaftliches Archiv*, *134*(2), pp.340-362.
[21] Araújo, B.C. and Paz, L.S., 2014. The effects of exporting on wages: An evaluation using the 1999 Brazilian exchange rate devaluation. *Journal of Development Economics*, *111*, pp.1-16.
[22] Park, S., 2009. The trade depressing and trade diversion effects of antidumping actions: The case of China. *China Economic Review*, *20*(3), pp.542-548.
[23] Jabbour, L., Tao, Z., Vanino, E. and Zhang, Y., 2019. The good, the bad and the ugly: Chinese imports, European Union anti-dumping measures and firm performance. Journal of International Economics, 117, pp.1-20.
[24] Lee, S.Y. and Jun, S.H., 2004. On the Investigation Effects of United States Anti-dumping Petitions. *J. World Trade*, *38*, p.425.
[25] Herander, M.G. and Schwartz, J.B., 1984. An empirical test of the impact of the threat of US trade policy: The case of antidumping duties. *Southern Economic Journal*, pp.59-79.

identifying the time delay between the trade remedy measure implementation and measurement that require qualitative consideration of quantitative evidence.

Types of trade evaluation tools

3.13 There are two types of evaluation that are useful for assessing the impact of trade remedy measures: qualitative and quantitative. This section will start discussing qualitative tools and their use, and then discuss further quantitative tools to evaluate the impact of trade remedies and trade remedies in general.

3.14 This report focusses on quantitative tools, but it is noted that qualitative tools should be considered alongside quantitative analysis.

Qualitative tools

3.15 Qualitative tools are used to investigate the impacts of trade remedies that are less amenable to quantifiable analysis. Qualitative information that may be collected before implementation of a trade remedy includes firm-level, worker-level and consumer-level perspectives on trade remedies, and preferences for possible trade remedies. After a trade remedy is implemented, further information could be collected on the impacts of the trade remedy. This could be in conjunction with quantitative analysis, to give further context of results, or to identify impacts when quantitative analysis is not possible.

3.16 Survey data is the most common qualitative tool used to assess the impact of trade remedies. These surveys are used in various contexts, for example to identify the distributional impacts of trade policy,[26] assess the distortionary impact of trade remedy measures, and measure perceptions of trade remedies.[27]

3.17 Chilling effects could be identified quantitatively,[28] but could also be discussed on a case-by-case basis, particularly for those who are directly impacted by trade remedies. The literature is limited, but survey methodology or stakeholder consultation on those identified to be impacted is broadly considered to be the best methodology to identify these impacts.

3.18 The UNCTAD has published a useful guide to approaching trade policy impact assessment, which outlines useful qualitative approaches to social impact, human rights impact, environmental impact, and economic impact assessment.[29] This report suggests that: “The choice of methods and approaches needs to be flexible. It depends on country conditions, the answers sought, the stage of negotiations, and the data availability. The choice of methodology and the subject of the study will then determine the tools for data collection and analysis and the data sources to be assessed. The choice of tools will also depend on the data sources available.”

3.19 The qualitative assessment suggested by the UNCTAD includes five main areas that should be considered:

- Economic Impact;
- Social Impact;
- Human Rights Impact;
- Environmental Impact; and
- Stakeholder Consultation

[26] Porto, G.G., 2006. Using survey data to assess the distributional effects of trade policy. *Journal of International Economics*, *70*(1), pp.140-160.
[27] Anderson, K., 2003. Measuring Effects of Trade Policy Distortions: How Far Have We Come?. *World Economy*, *26*(4), pp.413-440.
[28] Vandenbussche, H. and Zanardi, M., 2010.
The chilling trade effects of antidumping proliferation. *European Economic Review*, *54*(6), pp.760-777. Sun, J.Y., 2020. The Chilling Trade Effects of Provisional Anti-dumping Duties: The Case of Korea. *Journal of Korea Trade*, *24*(3), pp.1-19.
[29] Guidebook on Trade Impact Assessment (unctad.org)

Quantitative tools

3.20 This section is focussed on trade literature and methodologies used within the trade literature, and how they have been applied to identify causal impacts of trade remedies, with little focus on how these methodologies are applied.

3.21 There are a handful of causal impact methodologies that are already used extensively in the context of trade remedies or trade remedies. This section explains the conventional methodologies that are employed, and the benefits and drawbacks of each methodology, particularly pertaining to the ability to deal with two particularly relevant events for the UK policy landscape; COVID-19 pandemic and Brexit.

3.22 Quantitative tools are useful for estimating causal impacts of trade remedies. These estimation methods are necessary for calculating impacts on economic variables, such as domestic production output, employment and monetary impacts. These impacts would otherwise be unobservable, due to inter-dependencies on exogenous variables, including but not limited to cost and other policy interactions. For example, implementation of a trade remedy measure, and a change in the exchange rate will both lead to different impacts on imports. One cannot simply state that any observed reduction of imports is due to the implementation of the trade remedy measure.

3.23 Another consideration for quantitative methodologies is the trade remedy implementation process. The process of trade remedy implementation may have impacts on the suitability and interpretation of all quantitative methodologies. Some methodologies struggle to cope with anticipation impacts, which may be present if an investigation is announced before a trade remedy measure is implemented. For example, if an anti-dumping investigation is started, any firm that could be viewed as dumping has an incentive to raise prices to reduce the possibility of an anti-dumping measure being implemented. This means that before the trade remedy measure is decided, there is an incentive to change behaviour. For each of these methods, careful consideration of the date of the intervention (trade remedy measure) is necessary.

3.24 The remainder of this section summarises the literature in the trade landscape that uses the quantitative models to identify trade remedy impacts. For a more in-depth explanation of each of the identified methods, see section 3 below.

Gravity Models

3.25 Gravity models in the trade literature are often carefully calibrated and can be used in conjunction with different econometric methods to allow causal interpretation. For example, Felbermayr and Sandkamp (2020) exploit firm-level differences within products to estimate the impact of anti-dumping remedies.[30] Other literature modifies the gravity model to estimate the impact of Non-tariff trade remedy in the EU-South Korea Agreement.[31]

3.26 Whilst modifications can be made to gravity models to identify causal impacts of trade remedy measures by including a careful selection of controls,[32] these models require sufficient controls for other impacts, such as breaks in trend. Existing literature combines the gravity model with a differences-in-differences approach,[33] or control for the break in trend directly.[34] These approaches require external variation or very careful controlling of the cause of the break in trend. For some periods, particularly during the COVID-19 pandemic, this may be inherently difficult and cause data limitations. Additionally, the initial specification of gravity models has endogeneity concerns, so controls need to be carefully selected to ensure there is no bias present. These models also rely on large amounts of data, which may not be available at sufficient detail to

[30] Felbermayr, G. and Sandkamp, A., 2020. The trade effects of anti-dumping duties: Firm-level evidence from China. *European Economic Review*, *122*, p.103-367.
[31] Grübler, J. and Reiter, O., 2021. Non-tariff trade policy in the context of deep trade integration: an ex-post gravity model application to the EU-South Korea agreement. *East Asian Economic Review*, *25*(1), pp.33-71.
[32] Controls is a term used in econometrics to describe variables (or economic indicators) currently not used in analysis that are added to isolate the impact of the trade remedy.
[33] Felbermayr, G. and Sandkamp, A., 2020. The trade effects of anti-dumping duties: Firm-level evidence from China. *European Economic Review*, *122*, p.103-367.
[34] Zainuddin, M.R.K.V., Shukor, M.S., Zulkifli, M.S. and Abdullah, A.H., 2021. Dynamics of Malaysia's bilateral export post COVID-19: A gravity model analysis. *Jurnal Ekonomi Malaysia*, *55*(1), pp.51-69.

perform analysis. Consideration should be given to whether implementation of a trade remedy measure itself leads to a break in trend. Other trends or breaks such as the COVID-19 pandemic and Brexit, and time-varying changes would require careful consideration of a set of controls.

3.27 The modifications necessary to gravity models often mean that there is an increased burden placed on data. As more controls are included, more data is needed, and the burden on data increases, and combining approaches such as gravity models and difference-in-differences lead to further data requirements. This makes them less attractive for use in a trade remedy landscape.

3.28 However, controls must be chosen carefully to avoid reverse causality. Reverse causality refers to a situation whereby a dependent variable causes the independent variable.[35] For example, to estimate the impact of a trade remedy on trade flows, including variables to control for Brexit could lead to reverse causality if the trade remedy case was initiated following Brexit. Possible ways to address this include use of proxies (instrumental variables), including individual characteristics or factors that vary with time (time fixed effects), or a difference-in-difference approach.[36] However, these estimations are more difficult with a change in trend.

Differences-in-Differences (diff-in-diff):

3.29 Existing literature has used diff-in-diff methodology to estimate the impact of anti-dumping measures on target industry prices,[37] and on other outcomes, including targeted exporters, local producers, and other impacted exporters.[38] Similarly, Dettmer (2014)[39] investigate the impact of implementation of the EU's single market on reallocation of trade. This methodology is sometimes combined with other methodologies, such as propensity score matching, to avoid selection bias.[40] Endogeneity bias is also a common theme, with concerns directly controlling for endogeneity of trade agreements.

3.30 Natural experiments can provide a source for variation for estimation, for example the 2004 EU enlargement has been used to identify the impact of anti-dumping measures on exporters' prices.[41] This natural variation cannot be constructed, and so is often not a choice for estimation. However, existence of a natural experiment should be considered.

Synthetic Control

3.31 Abadie (2021) provides guidance for the feasibility, data requirements and methodological considerations of synthetic control methods.[42] This paper should guide the basis of the decision on whether the synthetic control methodology is appropriate. These requirements include having sufficient data pre- and post-intervention.

[35] A dependent variable is the variable being estimated, independent variable refers to variables included to estimate the dependent variable.
[36] For an application of fixed effects and instrumental variables in the context of gravity models, see Jochmans, K. and Verardi, V., 2022. Instrumental-variable estimation of exponential-regression models with two-way fixed effects with an application to gravity equations. *Journal of Applied Econometrics*, *37*(6), pp.1121-1137.
[37] Sandkamp, A., 2020. The trade effects of antidumping duties: Evidence from the 2004 EU enlargement. *Journal of International Economics*, *123*, p.103-307.
[38] Jabbour, L., Tao, Z., Vanino, E. and Zhang, Y., 2019. The good, the bad and the ugly: Chinese imports, European Union anti-dumping measures and firm performance. *Journal of International Economics*, *117*, pp.1-20.
[39] Dettmer, B., 2015. Trade effects of the European Union's service directive: Contrasting ex ante estimates with empirical evidence. *The World Economy*, *38*(3), pp.445-478.
[40] The TRA may wish to identify the impact of a trade remedy on domestic producers of the like-good. A diff-in-diff would compare the change in outcomes of domestic like-good producers to domestic producers of other goods not impacted by the trade remedy. However, like-good producers may be very different to firms in other industries (e.g. they may be smaller, have different cost structures or produce highly different products). Therefore, the parallel trends assumption may not hold as the treated and control firms are too dissimilar and, therefore, incomparable. Propensity score is a quantitative technique used to match firms impacted by a trade remedy to firms in the wider economy on the basis of their similarity in terms of pre-determined characteristics (e.g. firm size, cost structure and good similarity). Propensity score matching is particularly useful when there are several dimensions upon which treated and control units could be matched (e.g. firm size, cost structure, operating sector, and others) as it reduces all of these dimensions into a single propensity score and matches treated and control units on the basis of this score. Matching may improve the ability of diff-in-diff to produce causal estimates because matching may make the parallel trends assumption more likely to hold.
[41] Sandkamp, A., 2020. The trade effects of antidumping duties: Evidence from the 2004 EU enlargement. *Journal of International Economics*, *123*, p.103-307.
[42] Abadie, A. 2020. Using Synthetic Controls: Feasibility,Data Requirements, and Methodological Aspects. Mimeo. Article prepared for the Journal of Economic Literature

3.32 Existing literature has estimated the impacts of free trade agreements on GDP in the US,[43] the impact of a North American Free Trade Agreement on high-fructose corn syrup supply in Canada,[44] the cost of Brexit,[45] and of the EU-Turkey Customs Union on GDP.[46] The National Board of Trade of Sweden uses this methodology to estimate the impact of anti-dumping policies in the EU.[47] This methodology has been used to find the causal impact of tobacco policy changes.[48]

3.33 Synthetic control is also well suited for estimating temporal impacts, and can be used for longer-term estimations, such as for six months post policy implementation. This is because the synthetic control by design incorporates intertemporal impacts and incorporates any market-specific factors into the estimation. Additionally, by design the synthetic control can be estimated for as long as necessary, with the difference being able to be monitored across time, in contrast to diff-in-diff or gravity models where the estimation may be limited to one day (e.g. after six months) in the period of interest. The synthetic control instead allows for a view of the intertemporal impacts and when and how the impacts occurred.

3.34 A particularly interesting study using this methodology is Garcia-Lembergman et al (2018). The authors construct a synthetic control from a donor pool of 170 countries prior to quantitative restrictions imposed on Bolivia. This provides a novel solution to a break in trend and enables the use the country prior to imposition of a policy as the control. Such implementation could be possible for Brexit, but might struggle to deal with intertemporal impacts, or longer-term effects such as the COVID-19 pandemic, particularly if impacts differ between comparators. For example, when considering a washing machine, other white goods (e.g. fridges) might be a good comparator, because impacts do not differ.

3.35 Ritzel and Kohler (2017) incorporates this methodology into a diff-in-diff estimation strategy.[49] This estimation method requires external variations to be feasible, which are impossible to manufacture.

Event Study

3.36 Existing literature has used event study methodology to estimate the impact of anti-dumping remedies and investigations into dumping on the performance of US firms.[50] This approach involves using three different event dates: the date of a petition being filed in relation to anti-dumping, the date of International Trade Commission ("ITC") determination and the date of the final *ITC* determination. This particular approach does not allow for an estimation of the impact of trade remedy measures on trade flows, however alternative literature provides estimations on ex-post stock prices[51] and other events such as the impact of Russian invasion on Ukraine grain and oilseed trade.[52]

3.37 This approach could be applied to estimate the ex-post impact on trade but would require careful consideration of functional form, specifically suitable control variables for counterfactual estimation, similar in nature to synthetic control estimation. This would require similar level data to

[43] Colla-De-Robertis, E. and Garduño Rivera, R., 2021. The effect of a free trade agreement with the United States on member countries' per capita GDP: A synthetic control analysis. *Regional Science Policy & Practice*, *13*(4), pp.1129-1145.
[44] Barlow, P., McKee, M., Basu, S. and Stuckler, D., 2017. Impact of the North American Free Trade Agreement on high-fructose corn syrup supply in Canada: a natural experiment using synthetic control methods. *Cmaj*, *189*(26), pp.E881-E887.
[45] Springford, J., 2021. The cost of Brexit, January 2021: The end of transition edition. *Centre for European Reform Insight, March*. Also, see Serwicka, I. and Tamberi, N., 2018. Not backing Britain: FDI inflows since the Brexit referendum. *UK Trade Policy Observatory Briefing Paper*, *23*.
[46] Aytuğ, H., Kütük, M.M., Oduncu, A. and Togan, S., 2017. Twenty years of the EU-Turkey Customs Union: A synthetic control method analysis. *JCMS: Journal of Common Market Studies*, *55*(3), pp.419-431.
[47]Kommerskollegium. (2022). The Economics of the EU's Trade Defence Instruments: Winners and Losers of Anti-Dumping Policies. Access from The Economics of EU's anti-dumping measures | Kommerskollegium
[48] Abadie, A., Diamond, A. and Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, *105*(490), pp.493-505.
[49] Ritzel, C. and Kohler, A., 2017. Protectionism, how stupid is this? The causal effect of free trade for the world's poorest countries: Evidence from a quasi-experiment in Switzerland. *Journal of Policy Modeling*, *39*(6), pp.1007-1018.
[50] Prusa, T.J., 2001. On the spread and impact of anti-dumping. *Canadian Journal of Economics/Revue canadienne d'économique*, *34*(3), pp.591-611.
[51] Egger, P.H. and Zhu, J., 2020. The US–Chinese trade war: an event study of stock-market responses. *Economic Policy*, *35*(103), pp.519-559.
[52] Ahn, S., Kim, D. and Steinbach, S., 2023. The impact of the Russian invasion of Ukraine on grain and oilseed trade. *Agribusiness*, *39*(1), pp.291-299.

the synthetic control methodology, as it requires creating a comparator. However, in contrast to synthetic control where the impact is considered across time, the impact is measured on a date, the so-called *event day.* Event studies are not designed to account for impacts across time. As trade flow impacts, and any subsequent impacts on injury factors due to implementation of a trade remedy would not be expected to be instant (or quick), it may be difficult to use an event study to gain an understanding of temporal impacts.

3.38 Combining this methodology with qualitative analysis can aid understanding of the temporal impacts, in addition to understanding quantitative impacts at time intervals specified by the evaluator.

Bayesian Econometrics (BCI)

3.39 The literature on trade has used Bayesian econometrics methodology as early as 2012, including to estimate the effect of preferential trade agreements on trade flows with a gravity model.[53] It is noted that this paper uses Bayesian model averaging, which weights Bayesian models. This is a complex form of estimation, and it is important to understand a single Bayesian model before achieving this.

3.40 Recent literature (within the last two years) has investigated the impact of US trade policy uncertainty (related to the US-China trade war) on the PRC's output, consumption and net exports using a Bayesian VAR Model.[54] This estimation is a good fit for Bayesian econometrics, as uncertainty is a concern.

3.41 Policy impacts have also been investigated with Bayesian econometrics, including the impact of regulatory policy on UK gas use,[55] the impact of unconventional monetary policy in the Euro Area,[56] and the impact of anti-dumping measures on international wine demand.[57]

3.42 The literature also discusses extensions of the gravity model that incorporate Bayesian inference, specifically to overcome issues such as misspecification of gravity model equations, incorporation of contracting costs into the gravity model, and country specific effects.[58] Additionally, the proposed model has the benefit of correctly weighting zero-values and reducing bias as a result.[59] Similar approaches using Bayesian modified gravity models have been used to estimate the impact of non-tariff measures on Sri Lankan tea trade.[60]

3.43 This model has been specifically designed for estimating volumes of trade and could be useful to overcome the issues relating to breaks in trend. Similar models adapted to causal impacts, such as Google's causal impact model,[61] can be used to estimate the impact of trade remedies. The methodology usually requires some knowledge, or belief of the model parameters. This can include, but is not limited to, information from previous studies about the distribution of parameters of interest, subjective priors based on beliefs of parameters, or objective priors, which are chosen based on statistical properties. In the context of anti-dumping duties, if a similar trade remedy has

[53] Eicher, T.S., Henn, C. and Papageorgiou, C., 2012. Trade creation and diversion revisited: Accounting for model uncertainty and natural trading partner effects. *Journal of Applied Econometrics*, *27*(2), pp.296-321.
[54] Yan, H., Xiao, W., Deng, Q. and Xiong, S., 2022. Analysis of the Impact of US Trade Policy Uncertainty on China Based on Bayesian VAR Model. *Journal of Mathematics*, *2022*
[55] Elwell, C.A., Biddulph, P., Lowe, R. and Oreszczyn, T., 2015. Determining the impact of regulatory policy on UK gas use using Bayesian analysis on publicly available data. *Energy Policy*, *86*, pp.770-783.
[56] Evgenidis, A. and Papadamou, S., 2021. The impact of unconventional monetary policy in the euro area. Structural and scenario analysis from a Bayesian VAR. *International Journal of Finance & Economics*, *26*(4), pp.5684-5703.
[57] Liu, X., Liu, A., Jiao, X. and Liu, Z., 2024. The impact of policy intervention on international wine demand. *International Journal of Contemporary Hospitality Management*.
[58] Ranjan, P. and Tobias, J.L., 2007. Bayesian inference for the gravity model. *Journal of Applied Econometrics*, *22*(4), pp.817-838.
[59] This was done by using a Tobit threshold model. A Tobit model is a specification that intends to handle deal with outcomes that are highly non-linear; especially outcomes with that have a large proportion of observations with zero values. The motivation for using a Tobit model arises from the fact that linear specifications, those used most frequently within event studies, perform poorly when handling non-linear outcomes. In particular, when the outcome is non-linear because of many zero-values this causes the estimated impact to be biased towards zero (i.e. attenuation bias). Tobit models account for these non-linearities in the outcome variable and reduce the attenuation bias created by linear specifications.
[60] Khadka, S., Gopinath, M. and Batarseh, F.A., 2023. Anomalies in agricultural trade: A Bayesian classifier approach. *Journal of the Agricultural and Applied Economics Association*.
[61] Brodersen, K.H., Gallusser, F., Koehler, J., Remy, N. and Scott, S.L., 2015. Inferring causal impact using Bayesian structural time-series models.

had a significant impact previously, then you could use a prior distribution for the trade remedy impact that reflects the previously estimated parameter.

3.44 To illustrate the differences between Bayesian estimations and frequentist (conventional) estimation methods, Iacovone et al (2023) estimate the impact of a Colombian government programme aimed at increasing imports.[62] This paper provides estimations for Bayesian and traditional frequentist approaches, and finds that the statistical precision with which the Bayesian approach produces its estimates almost perfectly coincides with the precision of frequentist approaches.[63]

Trade Remedies Evaluation

3.45 The literature on ex-post trade evaluation methods specific to trade remedy measures is scarce. Most common recent approaches recently involve synthetic control methodologies (popularised by Abadie, 2021), such as those used by Lehtimäki et al. (2023)[64] and the National Board of Trade of Sweden.[65]

3.46 Bayesian approaches are appearing within the literature, most commonly with adaptions to the gravity model, such as Ranjan and Edirisinghe (2020)[66] and Ranjan and Tobias (2007).[67]

[62] Iacovone, L., McKenzie, D. and Meager, R., 2023. Bayesian Impact Evaluation with Informative Priors.
[63] More specifically, the Bayesian's posterior intervals update to overlap almost completely overlap with standard frequentist confidence intervals.
[64] Lehtimäki, J. and Sondermann, D., 2022. Baldwin versus Cecchini revisited: the growth impact of the European Single Market. *Empirical Economics*, *63*(2), pp.603-635.
[65] Kommerskollegium. (2021). EU Trade Defence. Accessed at EU Trade Defence (kommerskollegium.se)
[66] The Impact of Non-Tariff Measures on Sri Lankan Tea Trade: A Bayesian Inference of the Gravity Model
[67] Ranjan, P. and Tobias, J.L., 2007. Bayesian inference for the gravity model. *Journal of Applied Econometrics*, *22*(4), pp.817-838.

4. Econometric methods

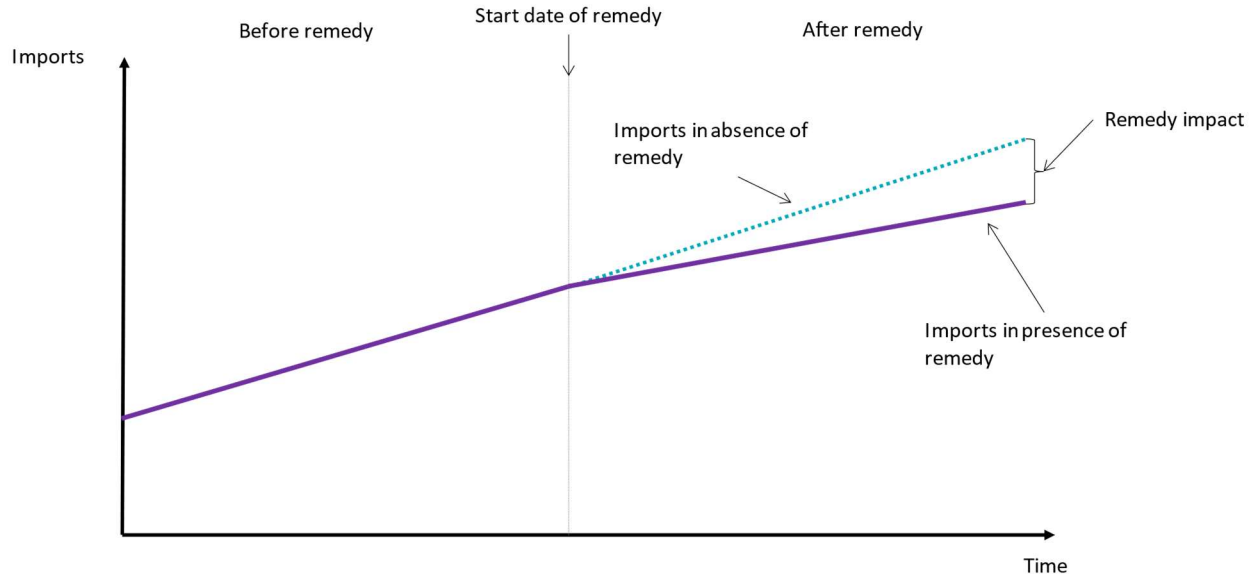
4.1 Econometric methods are used to empirically estimate causal impacts by undertaking ex-post counterfactual analysis. Causal ex-post counterfactual analysis refers to any approach that tries to estimate the impact of a particular event after it has already occurred. The key requirements that must be met by the data in order for these methodologies to be applied are (i) that the event causing the impact of interest resulted in an observable change in regime; and (ii) that the outcome that has been impacted by the event is observed prior to and after the commencement of the event.68 Once feasible, these approaches aim to estimate the causal impact of the event on the outcome.

4.2 Trade specific causal impact estimations have been conducted extensively in the literature, as outlined in Chapter 2. This section aims to intuitively explain the various causal impact methodologies that exist in the context of trade policy, and their respective difficulties for estimating trade remedy impacts.

The Identification Problem

4.3 Consider the following hypothetical scenario. Suppose that a new trade remedy was imposed on the imports of a particular commodity X. The commodity impacted by the measure is referred as the treated commodity because it has undergone the 'treatment' of the measure. To perfectly estimate the impact of the measure on the level of imports of X., it would be necessary to observe the import volumes of X after measure was imposed under two different scenarios: (i) when the trade remedy is present (i.e. the new measure is imposed); and (ii) when the trade remedy is absent (i.e. the new measure is not imposed). Once the imports in these two scenarios have been identified, the impact of the trade remedy is simply the difference between the imports in the two scenarios. This is illustrated graphically for this hypothetical commodity in Figure 3.

Figure 3: Illustration of identification problem for commodity X



Source: GT Analysis.

[1] Assumption (i) refers to events that are represented by some observable change in the regime associated with the event. As it pertains to trade remedies, examples include a new measure being put in place, an existing measure being changed in scope, or an

existing measure being revoked. Events that do not result in some observable change in regime (e.g. a trade remedy investigation resulting in no measures being imposed, changed or revoked) may not be assessed by such approaches.

4.4 The figure shows a plot of the import volumes of commodity X over time. The grey dashed line represents the commencement of the trade remedy, with the region to the left of this line signifying pre-trade remedy period and the region to the right representing the post- trade remedy period. The solid purple line prior to the trade remedy represents the observed pre-trade remedy imports of commodity X. The solid purple line beyond the start date of the trade remedy represents the import volumes of commodity X in the scenario that the trade remedy occurred. These are simply the observed import volumes in the post- trade remedy period, as the trade remedy did in fact occur. The dashed blue line represents the post- trade remedy imports that would have been observed had the trade remedy not taken place. These imports are called the unobserved counterfactual because they are not observed due to the scenario, they are observed in not happening in reality (i.e. the trade remedy did happen in reality, so the import volumes that would have arisen if the trade remedy did not take place are not observed or known). The true impact of the trade remedy on import volumes is the difference between the observed import volumes and the import volumes that would have arisen in the unobserved counterfactual (i.e. the gap between the solid purple line and the dashed blue line).

4.5 Identifying the true impact of the trade remedy requires the evaluator to observe both observed imports and imports under the unobserved counterfactual. Given that the import volumes under the unobserved counterfactual are, by nature, unobserved, it is impossible to know the true impact of the trade remedy with certainty. This is what is called the counterfactual problem or the identification problem; identifying true causal impacts perfectly is impossible because it requires information on something that is not known or observed. However, ex-post counterfactual approaches try to estimate causal impacts by predicting this unobserved counterfactual. While it is impossible to predict these outcomes with absolute certainty, these approaches endeavour to estimate them with a reasonable degree of confidence and, thus, derive an estimate of the true impact of the trade remedy. The more effectively an approach can estimate the unobserved counterfactual, the more credibly the approach will estimate causal impacts.

4.6 The discussion of causal ex-post counterfactual methods and their relative performance in estimating the causal impacts within the case study will, explicitly or implicitly, hinge upon how well these approaches can overcome the identification problem. The case studies will exhibit contexts where various ex-post counterfactual approaches are feasible and will explore why certain approaches overcome this problem more effectively than others when applied in the same context.

Causal Methodologies

4.7 Causal methodologies, otherwise known as quasi-experimental methodologies, are those specifically designed to overcome the identification problem and estimate the causal impact of trade remedies. They do this by providing credible estimates of the unobserved counterfactual.

4.8 These methods can be juxtaposed to less sophisticated approaches to identifying the impact of a trade remedy; such as a simple comparison of outcomes observed pre- and post- the initiation of a trade remedy investigation. This calculation would not identify the causal impact of the trade remedy measure as it may conflate true causal impacts with several other factors (e.g. confounding events,[69] time related trends, or seasonality). For example, if a trade remedy reduced trade flows by 10 units but at the same time the COVID-19 pandemic reduced trade flows by 100 units, failure to account for the COVID-19 pandemic would lead to attributing a fall in 110 units to the trade remedy. This would over-estimate the impact of the trade remedy. Hence, identifying a causal impact from a change in measure requires the use of econometric tools that capture the unobserved counterfactual and estimate impacts that are as close as possible to the true causal impacts.

[69] Confounding events are events that occur within a similar timeframe as the event of interest, and have an impact on the variable of interest. If not correctly controlled for, causal impacts may be over- or under-estimated.

4.9 To discuss causal methodologies, there are a few factors that should be considered for plausibility. Table 10 below indicates the main considerations.

Table 10: Key considerations for methodology choice

Factor	Measure
Data Limitations	Ability for the methodology to deal with limited data, and data requirements for estimation. For example, is the methodology possible with limited data?
Causal Interpretation	Ability of methodology to enable causal interpretation, and any concerns for causal interpretation. For example, Is there an endogeneity concern?
Difficulty	Difficulty of methodology in terms of interpretation and implementation, and whether the difficulty is necessary for causal interpretation. For example, is there a simple interpretation and could the methodology be explained to anyone?
Feasibility	Are econometric requirements met to conduct the analysis. For example, for difference-in-differences, does a suitable control group exist? Do you have the skills required to conduct the analysis?
Limitations	Any methodology limitations, particularly regarding causal impacts. For example, are strict criteria required for causal inference, or is prior knowledge required?
Data Limitations	Ability for the methodology to deal with limited data, and data requirements for estimation. For example, is the methodology possible with limited data?
Causal Interpretation	Ability of methodology to enable causal interpretation, and any concerns for causal interpretation. For example, Is there an endogeneity concern?
Difficulty	Difficulty of methodology in terms of interpretation and implementation, and whether the difficulty is necessary for causal interpretation. For example, is there a simple interpretation and could the methodology be explained to anyone?

Source: GT Analysis

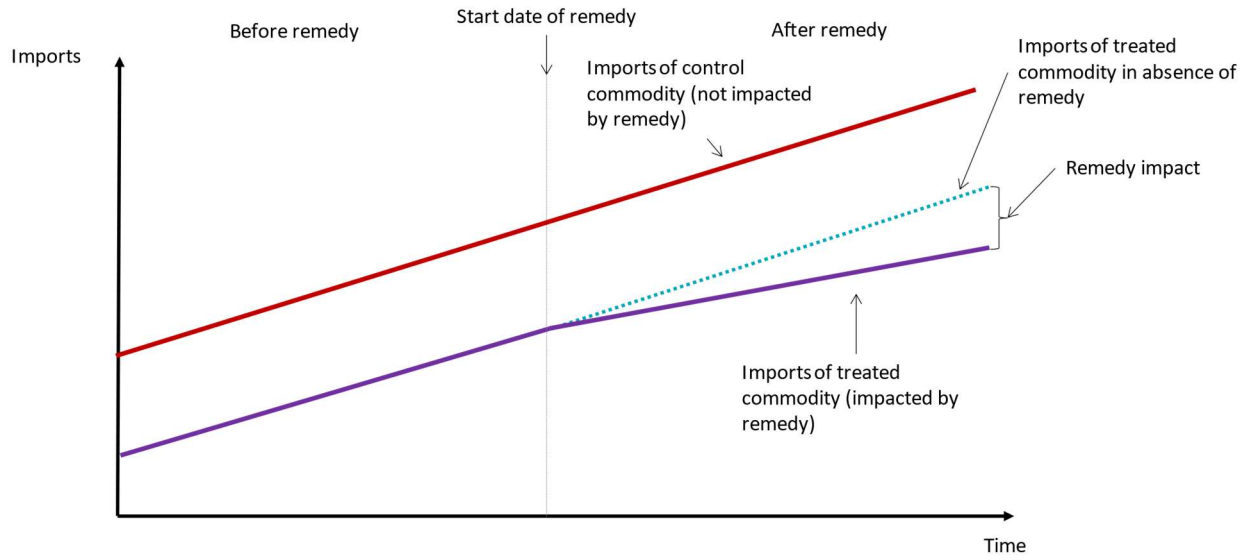
4.10 This section is structured by first outlining the potential methodology choices for causal interpretation and followed by table illustrating the considerations in Table 10 for each methodology.

Differences-in-differences

4.11 To understand this methodology, it is imperative that one understands the concept of a counterfactual. The term “counterfactual” denotes the unobserved scenario that should be considered when calculating a causal impact. In the case of identifying a causal impact of a trade remedy measure on trade flows, the counterfactual would be the trade flows if the measure was not applied.

4.12 Differences-in-differences (diff-in-diff or DiD) describes a causal estimation technique that uses a comparator to estimate the counterfactual. This technique requires taking the difference between pre-trade remedy and post-trade remedy observations of a combination of variables for a trade remedy applying nation and non-trade remedy applying nation. These differences are compared, and the difference is attributed to the causal impact.

Figure 4: A Difference-in-Difference estimation illustrated



Source: GT Analysis

4.13 Figure 4 above shows how a causal impact can be estimated from the diff-in-diff methodology. This methodology hinges on the trends of the two countries being parallel for the duration of the analysis, this is often referred to as "the parallel trends assumption." The parallel trends assumption requires the pre-intervention (in this case, pre- trade remedy) trend of the control group and treated group are parallel. If this condition does not hold, then estimates will be biased. With the impact of COVID-19 pandemic and varying trade remedies, diff-in-diff estimations would struggle to identify the causal impact.

4.14 Additionally with the break in trend caused by Brexit, the parallel trends assumption may not hold and will thus cause biased estimates, particularly during the period of analysis that is impacted by the break in trend. Hence, any analysis conducted using this period should include sufficient testing of the parallel trends assumption. This includes cases whereby both the trade remedy-impacted good and the comparator are both impacted by Brexit, as the change in trend could be independent for each good. The parallel trend period should be at least as long as the trade remedy evaluation wishes to be, but this should be considered on a case-by-case basis. With longer pre-intervention training data (in this case, pre-trade remedy data), the likelihood of a difference in trend falls.

4.15 Use of diff-in-diff relies heavily on a defined control group. With instances of trend-altering events, such as the financial crisis, the COVID-19 pandemic and Brexit, a control group is not easily found, as Brexit is a country specific factor (and also interacted with similar, geographically adjacent countries) and the COVID-19 pandemic had impacts worldwide. This methodology is not recommended for no defined control group. In addition, these models rely heavily on the parallel trends assumption. If this does not hold, the estimations will be biased.

4.16 This methodology works well for scenarios where the control group (products, firms and nations not impacted by the trade remedy) is well defined, and for which the parallel trends assumption holds. However, this model may struggle with anticipation impacts. Careful consideration of the intervention date (i.e. 'Start date of trade remedy' in Figure 4) is necessary.

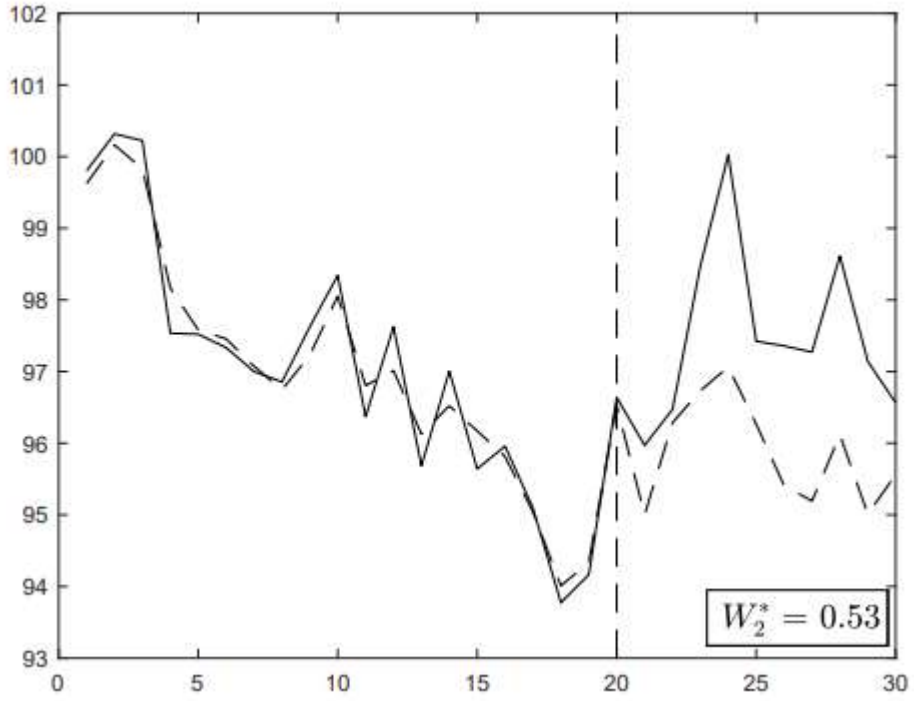
4.17 Diff-in-diff requires data at the level you wish to investigate, and data from a suitable control group at the same level of granularity at the level you wish to investigate. The data must consist of at least three periods, and you must observe before and after the trade remedy implementation.

Synthetic Control

4.18 Synthetic control methods create a counterfactual by weighting a number of unimpacted "units" that are combined to form a counterfactual. The units used often come from a wider pool of

potential units, denoted the “donor pool.” In the context of trade remedies, this methodology assigns weights to each of the comparator units in the donor pool in such a way that their weighted sum closely mimics the impacted unit in the period prior to the trade remedy. The idea is that if this estimated counterfactual closely matches the outcomes (e.g. sales, import volumes, prices, etc.) of the impacted unit prior to the trade remedy, then it will be a good proxy for the counterfactual scenario of the impacted unit (i.e. the outcomes of the impacted unit if the trade remedy was not implemented) during and after trade remedy. The impact of the trade remedy on an outcome of interest would simply be the difference between the outcome of the impacted unit and the synthetic unit in the period following the trade remedy. How well the synthetic unit matches the impacted unit can be tested for goodness-of-fit using in-sample estimations. At the product level, a counterfactual product can be estimated using a combination of comparator products.

Figure 5: An illustration of synthetic control methodology



Notes: The solid line represents the treated unit, and the dashed line represents the synthetic control. The vertical dashed line indicates the treatment. The X-axis indicates time, and the Y-axis is the measure of interest.
Source: Abadie, A. and Vives-i-Bastida, J., 2022. Synthetic controls in action. arXiv preprint arXiv:2203.06279.

4.19 This methodology does not rely on the parallel trends assumption, but instead requires large amounts of data, which may not be feasible for estimation. Data is required at the same level as conclusions wish to be drawn at, for example for individual commodity codes to estimate the impact on an individual commodity’s trade flow. Data required includes trade data, at individual product levels for suitable comparators. This includes data for the 8- and 10-digit level commodity codes, and output levels for individual businesses. This data allows for an estimation of a comparator that has likeness to the good that trade remedies were applied for. It is noted that even when using the 8- and 10-digit level commodity codes, isolating individual commodities may not be possible. A case-by-case approach should be taken to identify any possible spillovers and interactions.

4.20 For example, for estimation of the output of domestic firms, a combination of other goods may be used to form the synthetic control, or a combination of unique factors about the good. These should be carefully chosen such that no substitute goods are included, as these would experience a change in demand after the trade remedy is imposed.

4.21 Synthetic control methodologies can also be difficult to calibrate. Conditional on the data being available, it may still prove difficult to aggregate the comparator nations or products into a counterfactual that closely mimics the outcome of a trade remedy-applying nation or trade remedy-impacted product. However, testing can be done to identify the fit of the pre-trade remedy period, and out-of-sample testing to ensure how well the method may predict the counterfactual outcomes post-trade remedy. It is assumed that these tests hold post- trade remedy, but these cannot be tested (as by nature, the counterfactual is not observable). In practice, incorporating a number of controls and being creative with the specification should be taken into consideration. Consideration of each explanatory variable and its explanatory power and potential to cause reverse causality will be necessary. In the context of trade remedies, country specific factors may not be captured sufficiently in a synthetic control estimation.[70]

4.22 Structural breaks are particularly difficult to address when these impacts are experienced by other countries that would usually form part of the control, such as in the case of COVID-19 pandemic. These events introduced significant amounts of volatility and noise, which has been shown to reduce the performance of synthetic control methodology.[71]

4.23 Various factors may lead to the donor pool (available comparator units) being very small. The donor pool must not consist of commodities that are substitutes or complements of the targeted commodity, or commodities that could be used to circumvent the trade remedy. All such commodities must be removed from the sample. Furthermore, commodities impacted by trade remedy investigations that would not have impacted the targeted commodity in absence of the trade remedy must be removed. Both factors can reduce the size of the sample and reduce the statistical power of the synthetic control estimates. The granularity of the data may also influence the number of available comparators. Country-level analysis may be difficult to perform analysis using a synthetic control because the number of suitable comparator countries in the donor pool may be limited, especially as data collection standards may vary from country to country. However, if analysis is performed at the commodity level, then it is more likely that a sufficient number of appropriate comparators will be identified to form part of the donor pool.

4.24 For a robust synthetic control, you must observe the unit of interest across a period of time, alongside comparators. These comparators, combined to build the so-called “donor pool”, must not be impacted by the trade remedy, but must be sufficiently similar to the unit of interest (e.g. a comparable firm of similar size, profits, …) The comparators should be observed before and after the trade remedy implementation, such that the synthetic variable can be constructed to form the counterfactual.

4.25 This approach requires a relatively large amount of data to perform well. It requires the data to have more time periods than diff-in-diff and gravity models, as a greater number of time periods reduces the bias of its estimates. Furthermore, a large number of comparators in the donor pool are needed for estimates to be precise.[72]

Event Study

4.26 Event study methodologies require similar level of data to synthetic control methodologies, but have typically been used with data containing fewer time periods than synthetic control.

4.27 Event study methodologies can be used to estimate the impact of a specific change. It works similarly to synthetic control methodology in that the counterfactual model is created to estimate

[70] See Abadie, Alberto. "Using synthetic controls: Feasibility, data requirements, and methodological aspects." *Journal of Economic Literature* 59, no. 2 (2021): 391-425 for an exhaustive list of the assumptions and data requirements that are needed for SCM.
[71] Ebell, M. and Warren, J., 2016. The long-term economic impact of leaving the EU. *National Institute Economic Review*, *236*(1), pp.121-138.
[72] There are generally no rules of thumb regarding a suitable number of time periods, as the number of time periods required for credible estimation also varies with the volatility of the outcome and how well the comparators predict the outcome of the treated unit in the synthetic control. For instance, if the data contains structural breaks, using all time periods may generate more bias that restricting the sample to time periods following the structural break. The number of comparators is mechanically related to the statistical precision of the estimates because the statistical significance of the causal impact (i.e. whether it can be concluded that the estimate is different from zero due to factors other than statistical uncertainty) is based on how many units, treated and control, are in the sample. Therefore, a sample of 20 comparators at minimum is required to determine whether the estimated causal impact is statistically significant at the 5% significance level. A 5% significance level is used to determine statistical significance because it is the convention among economists and social scientists.

the evolution of the country of interest across time. Once this is complete, the event study method directly computes an "event day" impact, that is the difference between the estimated counterfactual and the observed variable on an event day. This methodology works well for single events, but is not best placed to estimate contemporaneous factors, such as trade remedies. This methodology was designed to investigate one-off impacts, however for trade remedies that stay in place or have longer term impacts then synthetic control methodology would be more appropriate.

4.28 This methodology can be employed for trade remedies, but would require understanding of the lag between trade remedy measure implementation and impacts on trade volumes and value.

4.29 As discussed previously, the implementation process of trade remedies can also be crucial for the reaction of producers and may cause complications with this methodology. Anticipation effects should be expected, and with event study methodology, it may be necessary to remove the dates in this period from data used to estimate the counterfactual ("the training data"), which may cause a significant lag between the training data and the event, depending on the length of the investigation period. Similarly, if the event date was to include anticipation effects, the chosen event study date would capture the threat of trade remedy impacts rather than to the actual trade remedy impacts. This means that event dates must be chosen with consideration for anticipation effects.

4.30 Multiple event dates could be considered, but each event window and specification would have to be individually calibrated. Without this, event studies would need to be conducted for many dates, or for a large prediction window which could be time consuming and resource intensive and limit the predictive power of the event study. The larger prediction frames are compared to the training period, the lower predictive power of the event study. Additionally, noise, further impacts or confounders can impact the results of the event study. For example, interactions with other trade remedies, other firm changes, or legislation changes.

Bayesian Econometrics (BCI)

4.31 The term "Bayesian econometrics" describes any model that is estimated using Bayesian statistics. It does not refer to a particular model, but an entirely distinct philosophical approach to statistical inference that differs to the diff-in-diff, event studies, synthetic control and gravity models. This form of econometrics can be applied to a multitude of models, however, can be more econometrically involved than diff-in-diff, synthetic control, event studies and gravity models, with the requirement of correct prior assumptions. These assumptions can cause specification issues, and lead to biased results if not formed appropriately. Familiarity with appropriate assumptions and their meanings for the outcome of the estimation method is required for correct specification. The term "Bayesian inference" is used to describe using Bayesian econometrics to infer statistical inference from an econometric estimation.

4.32 Bayesian econometrics is based on Bayes theorem,[73] and posits an alternative interpretation method for results of empirical estimations. Whilst it is not a direct estimation method, it is an alternative method for interpreting results. The methodology involves specifying a likelihood function which incorporates the probability of observing your data given the model specification and specifying so-called "priors". These priors reflect beliefs of parameters before observing the data. This can be based on prior knowledge or one can allow for the data to dominate.

4.33 This can then be combined with Markov Chain Monte Carlo simulation[74] to iteratively sample values of parameters given the observed data. This gives rise to estimation of the model parameters.

4.34 Once these estimations have been made, there are a number of econometric tests that can be conducted post-estimation, including convergence tests, point estimates and sensitivity analysis.

[73] Bayes, T., 1763. LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, FRS communicated by Mr. Price, in a letter to John Canton, AMFR S. *Philosophical transactions of the Royal Society of London*, (53), pp.370-418.

[74] Markov Chain Monte Carlo (MCMC) is a computational technique used to approximate complex probability distributions (likelihoods of different outcomes). It involves combining random sampling (using the Monte Carlo method) and a mathematical system (Markov Chains).

4.35 The advantages of this method involve allowing for explicit modelling of uncertainty, which allows for more accurate parameter estimation with limited or spare data and more accurate estimates in data sets with large amounts of uncertainty, without overfitting. This methodology is also useful for estimating parameters with heterogenous outcomes.

4.36 This is a departure from frequentist (traditional) econometrics, that fits the data to existing models, without prior assumptions.

4.37 Priors can also be created using the data, by using an "Empirical Bayes approach". This approach involves stating a prior, and subsequently updating the prior using Bayes' theorem, based on observed data. The Empirical Bayes approach is used when information about the parameters is limited before estimation. However, this must be carefully validated, as priors can impact Bayesian estimations significantly.

4.38 An empirical approach is recommended when information is not known about parameters. The use of Bayesian econometrics requires careful use of econometrics and is recommended for estimations of data with large amounts of noise.

4.39 A variety of data sources are useful for Bayesian econometrics, but these methodologies are usually employed with limited data or with particularly noisy data. However, observations before and after would be required. In practice, this is likely to be combined with other models, for example in Google's causal impact method.[75]

[75] https://google.github.io/CausalImpact/CausalImpact.html

Summary of causal methodologies

Table 11: A Summary of the methodological considerations and recommended approaches

	Ability to make causal inference	Ability to deal with i.) limited and ii.) missing data	Ability to deal with i.) COVID-19 pandemic and ii.) Brexit	Input Requirements	Outputs	Scope for Modelling	Other considerations	In-Scope
Gravity Models	Only when combined with other methodologies	i.) Limited – requires large scale data for modelling and causal methodologies often require more data. ii.) Limited – missing data would require assumptions, or a specific methodological approach.[76]	Gravity models are not designed to cope with breaks in trend. Instead, a segmented or time-series analysis, or combination with diff-in-diff would have to be considered to address the break in trend.	GTAP data. Appropriate controls to avoid reverse causality.	Models changes to the value of trade and output (GVA) for 65 goods and services across 141 regions measured at the ISIC 4 level. Outputs only possible combined with other methodologies or segmented time series analysis and appropriate controls. This often requires large numbers of observations.	CGE modelling, requires specialist input software and dated assumptions, e.g. global database representing economy for a reference year, most recent is 2014.		Not recommended for this analysis.
Differences-in-differences	Only under parallel trends assumptions.	i.) Limited – requires suitable control group. ii.) Limited- if significant data is missing from the control, this methodology is not recommended.	i.) If COVID-19 pandemic impacts the data, then this will need to be accounted for. ii.) Brexit may causa a break in trend and this would need to be accounted for.	Suitable control group. Inputs include a treatment dummy, exporter and product fixed effect. E.g. company size etc.	Domestic production output: Changes in value/volume of trade, domestic market share/turnover identified by the causal impact are only possible if a control group exists or is well defined, and no structural breaks or variations in trend for the control group exist.	Suitable control groups are situational, as is the impact from Brexit and COVID-19 pandemic, depending on the trade remedy measure implementation dates. This should be considered on a case-by-case basis.	Trade remedy measures themselves changes could lead to a break in trend.	Not recommended for this analysis.

[76] Shen, G. and Aydin, S.G., 2014. Origin–destination missing data estimation for freight transportation planning: a gravity model-based regression approach. *Transportation Planning and Technology*, *37*(6), pp.505-524.

	Ability to make causal inference	Ability to deal with i.) limited and ii.) missing data	Ability to deal with i.) COVID-19 pandemic and ii.) Brexit	Input Requirements	Outputs	Scope for Modelling	Other considerations	In-Scope
Synthetic Control Method	When synthetic control is close to the actual outcomes.	i.) Can require large amounts of data to construct the control. ii.) Individual missing data can be mitigated by other observations.	i.) COVID-19 pandemic can be accounted for if it impacts comparators in different ways – e.g. trade difficulties between certain dates due to boarder rules. ii.) Brexit would need to be accounted for, but as all comparator firms also experienced Brexit, this should not pose a large issue. Reverse causality will be tested (i.e. test whether trade remedy was implemented in part due to Brexit).	Data available on comparators, including in sufficient detail – in practice this involves access to 8- and 10-digit level commodity code trade data, which may not be available for analysis.	Identification of causal changes in value/volume of trade and domestic market share/ turnover are possible during Brexit periods, but COVID-19 pandemic periods may be difficult to control for if there are heterogenous impacts.	With code specific data available, and sufficient comparators.	Appropriate comparators for the good should be available, with comparators not being substitutes.	This is the recommended approach.
Event Study	For single events.	i.) Requires sufficient data for a training period. ii.) Missing data may bias estimates, but individual observations are not necessarily problematic .	i.) COVID-19 pandemic can be built in if it impacts the comparators, but care should be taken to address heterogeneity. ii.) Brexit would need to be accounted for, but as all comparator firms also experienced Brexit, this should not pose a large issue.	Data available for a suitable training period, sufficient controls for heterogenous impacts of COVID-19 pandemic.	Event day estimations can be obtained, similarly to synthetic control. Contemporaneous estimations would instead benefit from synthetic control estimation.	For on-day impacts only. Timelines for impacts would need to be known- and this would not accurately capture any impacts over time.	Methodology struggles with contemporaneous impacts.	This methodology is not recommended for this analysis due to the contemporaneous impacts. This could lead to under or over estimation.

	Ability to make causal inference	Ability to deal with i.) limited and ii.) missing data	Ability to deal with i.) COVID-19 pandemic and ii.) Brexit	Input Requirements	Outputs	Scope for Modelling	Other considerations	In-Scope
			Reverse causality will be tested.					
Bayesian Econometrics	Only with careful priors.		i.) Copes well with small data sets and is designed to work with small data sets. ii.) Missing data can cause bias and imprecision in estimation but can be mitigated by augmenting the approach and selecting suitable priors.[77]	i.) COVID-19 heterogenous impacts can be incorporated. Whilst controlling is still necessary, Bayesian econometrics is particularly good at dealing with uncertainty. ii.) Brexit would need to be accounted for, but as all comparator firms also experienced Brexit, this should not pose a large issue. Reverse causality will be tested.	Knowledge on prior distributions, controls for heterogenous impacts of COVID-19 and Brexit	Identification of causal changes in value/volume of trades is possible but depends on the methodology. This is not a "methodology" per se, but an alternate school of statistical thought that differs from frequentist statistics.		Functional form would need to be discussed as Bayesian econometrics can be applied to many contexts. It should be noted that this is not a "methodology" per se, but more a technique for inferring statistical inference

Source: GT Analysis

[77] See Geweke, J., 2005. Contemporary Bayesian econometrics and statistics. *John Wiley & Sons*.

Non-Causal Methodologies

4.40 There are a number of methodologies that can be employed when causal methodologies are infeasible due to data constraints or other limiting factors. The alternative methodologies discussed are generally unsuitable for causal analysis as their required assumptions are violated in most cases. Hence, these methodologies are classed as 'non-causal methodologies' within this report. However, these approaches may be used to gain insight into observed differences in outcomes over time, or they may be combined with other methodologies in order to yield causal estimates.

Gravity Models

4.41 Gravity models form the seminal trade literature and the foundation to capture the conceptual determinants of bilateral trade. This method requires calibrating a novel estimation method and adjusting it for the scenario studied. Later, this report discusses how existing gravity models can be used to assess possible impacts of a trade remedy (Chapter 7).

4.42 The traditional form of a gravity model is the so-called "gravity equation," which takes the following functional form:

$$Ln\ Y_{jhft} = \beta_0 + V_{jhf} + V_{jht} + V_{hf} + firm\ size_{jf} + distance_{jfh} + \varepsilon_{jhft} \quad (1)$$

Where $Ln\ Y_{jhf}$ is the natural logarithm of exports (this can be value or quantity) at the firm level, V_{jhf}, V_{jht} and V_{hft} are country-product-firm, country-product-time and product-firm-time fixed effects respectively. The variable $firm\ size_{jf}$ is a measure of firm size, usually turnover or a similar measure, $distance_{jf}$ is the distance between the two countries and ε_{jhft} is the error term. The subscripts represent different levels of granularity, j is country, h is product, and f is firm, t is time. This specification itself does not include ability to determine causal ex-post trade remedy implementation impacts.

4.43 Gravity models benefit from understanding the mutual benefits of trade and explaining the volume of trade experienced between two countries. The foundation model is based on size of economies and the distance between economies, as well as trade costs and sector specific factors, e.g. technological innovation within industry or transportation costs.

4.44 The traditional forms of these models lack causal explanatory power as they do not incorporate policy impacts. The incorporation of trade remedy measures into the model may introduce bias arising from reverse causality between trade flows and the measure. This is because the implementation of a trade remedy is likely to be dependent on the trade flows of the respective good. Likewise, trade flows will also change depending on the trade remedy implemented. This should be accounted for in the econometric specification.

4.45 To identify causal impacts, sufficient controls must be incorporated into the model; including country fixed effects, product level fixed effects, firm fixed effects, time fixed effects, other trade remedies, distance, market size and product characteristics. Nevertheless, these controls may be insufficient to remove all reverse causality that may be present. Additionally, techniques for coping with reverse causality place more weight on necessity of detailed data. This can be costly and make estimation difficult.

4.46 While gravity models in their solitary and basic form are generally unsuitable for causal inference, they can be modified to identify causal impacts. This can be done through introducing of fixed effects to control for time-invariant impacts, or by combining gravity models with other methodologies such as diff-in-diff.

4.47 Generally, the data required for firm level estimation of gravity models is a variety of firm level data, of profits, exports, locations and various other firm specific data. This data should be accompanied by firm level and country level fixed effects, or data for a control group to allow

reduction of endogeneity. This methodology would require observations before, during and after trade remedy imposition.

Before-During-After Analysis

4.48 This approach is commonly used to assess the impact of interventions over time. This is conducted by separating the data into three main time periods:

- Before: the period of time before the trade remedy is imposed;
- During: the period of time during which the trade remedy is imposed; and
- After: the period of time following the imposition of the trade remedy.

4.49 In principle, this approach compares the average outcome during the period that the trade remedy is in place to the average outcome outside of the trade remedy period and ascribes any differences in the averages to the trade remedy. The periods during and after are designed to evaluate the short-term and long-term impacts of imposing a trade remedy measure, respectively.[78] This conceptually simple approach can be enhanced by the inclusion of time-varying factors that may be correlated with the trade remedy; as the omission of such factors would bias the estimated impact of trade remedy.

4.50 Whilst it is possible to uncover causal impacts from this analysis, this is only attained under the strong assumption that all factors that may bias the estimates are included in the model. This assumption is untestable and often violated by the fact that it is often impossible to account for every single factor that may bias identification. Furthermore, the data requirements for this approach can be substantial. Numerous time periods and observations are needed for causal inference. Moreover, this approach seeks to leverage cross sectional variation in the data (i.e. differences between different participants at a fixed point in time), so several comparators are also required to achieve the best results. Gathering and preparing this data is likely to be time and resource intensive, especially with attrition and loss of participants during long-term data collection.

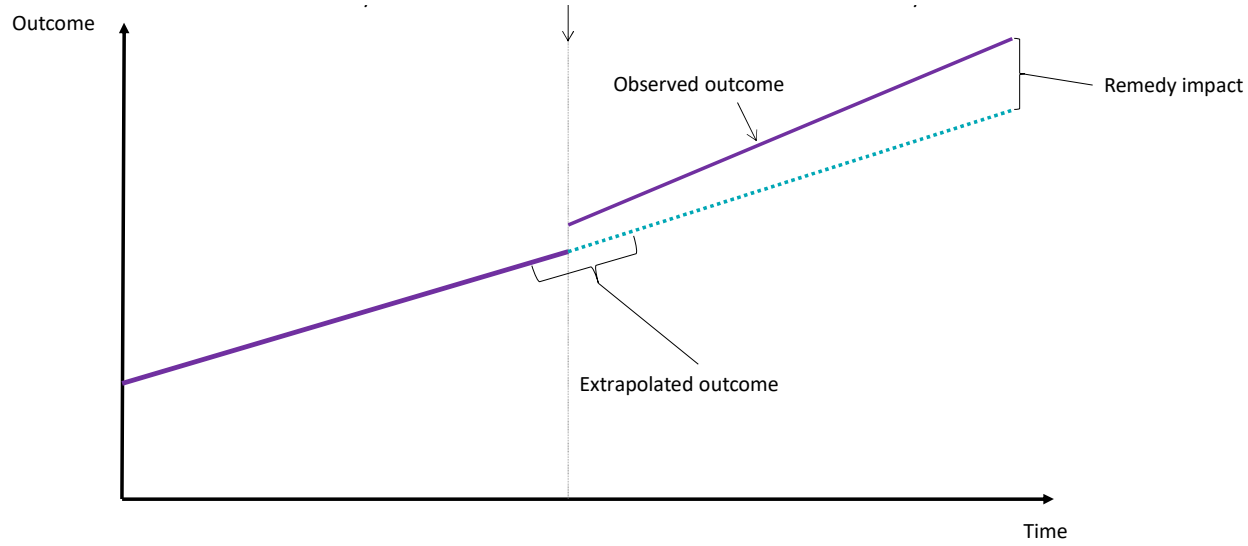
4.51 Given this restriction, it is unlikely that this methodology can be used for causal inference in the context of trade remedies. However, this methodology could be used as an alternative when sufficient data is available and the requirements for other methodologies are not met.

Trend Analysis/Interrupted Time Series

4.52 Trend analysis investigates changes in variables over time and examines changes in trajectories and fluctuations. This approach uses the trend in the outcome of interest prior to the trade remedy to estimate what the trend would have been in the periods following the imposition of trade remedy, had the trade remedy not been imposed. The pre- trade remedy trajectory is used to estimate the unobserved counterfactual and the difference between the post- trade remedy outcomes and the extrapolated trend is the estimated impact of the trade remedy. This is illustrated in the figure below.

[78] Suppose that a trade remedy is imposed for a set number of years and is revoked thereafter. This creates three distinct time periods; the period before the trade remedy was imposed (i.e. 'before'), the period during which the trade remedy was imposed (i.e. 'during') and the period after the trade remedy's revocation (i.e. 'after'). How the 'after' period is treated empirically depends on prior assumptions about the impact of the trade remedy. It is possible for there to be no distinction between the 'before' and 'after' periods. In this case, the effect of the trade remedy would be the difference between average outcome 'during' period and the average outcomes in the 'before' and 'after' periods. Such an approach would assume that the impact of the trade remedy ceased once the 'during' period ended. However, if the impact of the trade remedy is assumed to have lasted longer than the 'during' period, the periods 'before' and 'after' periods are treated separately. The short-term impact of the trade remedy is the difference in average outcomes between the 'before' and 'during' periods, and the long-term impact of the trade remedy is the difference in the average outcomes in the 'before' and 'after' periods.

Figure 6: Illustration of trend analysis



Source: GT Analysis

4.53 The figure above shows that the observed outcome shifts upwards and has a change in its slope following the remedy. Trend analysis extrapolates the trend of the outcome into the post-remedy period and treats this extrapolated outcome as a proxy for the unobserved counterfactual. This approach provides insights into patterns of change and is particularly useful when the underlying data exhibits seasonal variations and cycles. A key benefit of this approach is that it may be used when there are no comparators available.

4.54 However, this approach does rely on large amounts of historical across time data which, in practice, may be limited in scope or quality. Additionally, this approach requires the assumption of continuity; namely, that trends and patterns that were present prior to the trade remedy will continue after the trade remedy investigation is initiated. However, as is often the case with trade remedies, it may be that changes in the trend following initiation are influenced by factors unrelated to the trade remedy, such as COVID-19 pandemic and Brexit. Failing to account for these factors would bias the estimates produced by trend analysis. While there are mitigations for this, the evaluator should take caution when interpreting estimates produced by this approach as causal.

5. Simulation methods

5.1 This section outlines the methods that should be considered when data or the policy scenario does not allow for econometric methods. These methods can be more flexible with regard to data than econometric methods, that may need specific data.

5.2 The previous chapter stressed the importance of assessing the counterfactual. Many of the econometric methods above (e.g. diff-in-diff, SCM and BCI) take a 'data-driven' approach to the counterfactual: they observe how variables (e.g. import volumes or profits) evolve in the 'treatment' group (i.e. in firms/sectors that are subject to the trade remedy) and compare that evolution to the same variables for a 'control group.'[79]

5.3 However, it will sometimes be the case that no such control group can be observed, meaning that it is not possible to deploy econometric methods to construct a counterfactual. There are various reasons why it may not be possible to observe such a control group / counterfactual, for example:

- insufficient time has passed since the imposition of a trade remedy such that impacts are yet to be observed;
- the trade remedy is so broadly defined across commodities that there are no comparators outside of the scope of the intervention (so all relevant commodities are 'treated', with none left to act as a 'control');
- the candidates for control commodities / sectors all behave sufficiently differently from the affected group in general, meaning that there is no valid control; and
- the trade remedy did not change, such that the unobserved counterfactual is difficult to construct.

5.4 In these circumstances, non-econometric methods can be used to evaluate the possible impact of the trade remedy. The key difference between the econometric and non-econometric approaches is how they arrive at the counterfactual. In particular, non-econometric approaches construct the counterfactual not by looking at data on a control group (e.g. on closely related commodities) but instead using established tools from economic theory to predict how the variables of interest (e.g. imports, profits or costs) would have evolved with and without the intervention. A key difference of these approaches is that the implied impact of a trade remedy is driven by the assumptions of the underlying economic model (and not by observing changes in real world data, for example changes in import volumes and market shares).

5.5 Various techniques could be used for such an exercise, but the some of the most widely deployed are as follows:

- Gravity model;
- Computable General Equilibrium models (CGE); and
- 'New trade' models (or more generally partial equilibrium models considering firms' behaviours in particular markets).

5.6 The remainder of this section describes the different approaches, explores some of their pros and cons and considers the circumstances in which they are most relevant.

Gravity Models

5.7 The last chapter describes how gravity models could be used – in the presence of data on 'treated' and 'untreated' sectors/commodities by trade remedies – to estimate an equation that would assess the impact of that particular trade remedy. Additionally, gravity models can also be used to assess the possible impact of a trade remedy when there is no data on the observed outcome. In particular, the (very extensive) gravity model literature contains estimates of how trade, all else equal, responds to the raising of trade barriers (both tariff and non-tariff) and trade remedies in

[79] The precise way in which the control group is constructed depends on the technique.

particular. These relationships are embodied in elasticity and other parameter estimates. These elasticity estimates can be combined with information on the trade remedy (e.g. the level of the import tariff) to estimate an impact on trade volumes.

5.8 The key point here (and a key difference in how gravity models are used in this context compared to the discussion in the last chapter) is that the impact of any trade remedy is based on the elasticity/parameter estimates from the literature, rather than directly observing changes as a result of an intervention.

5.9 Whilst using gravity models in this way may be appropriate in certain circumstances (e.g. if data and time is limited), the approach does have its limitations. For example, the approach says nothing about the precise mechanism through which the trade remedy has an impact (the impact is just based on general relationships observed in the literature). Additionally, since gravity models tend to be aggregated (often considering whole-economy or sector-level trade flows, rather than disaggregated commodity-level flows), they can fail to pick up nuances around the particular goods concerned. Gravity models also only directly consider the impact on imports and exports (ignoring effects on other variables, e.g. profit).

Computable General Equilibrium Models

5.10 Computable General Equilibrium (or CGE) models are used extensively in academia, government and international organisations to assess the impact of policy interventions.

5.11 In essence, they contain equations describing how consumers, firms and governments interact in an economy in their consumption and supply of goods, services, labour and capital. As explained further below, they tend to operate at fairly aggregate levels rather than at the level of an individual industry/commodity.

5.12 A CGE model is designed to allow policy interventions – everything from taxes to trade remedies – to be simulated, assessing how they 'flow through' the economy. For example, in a CGE environment, an import tariff on an imported commodity would have the effect of increasing the price of those imports faced by consumers in the domestic economy. This would result in a substitution of demand towards domestic production. In turn, this could increase demand for domestic labour in the sector, putting upward pressure on wages in that sector. This, in turn, could dampen the effects of the initial tariff. Likewise, this policy could also increase costs to domestic consumers and businesses who use the commodity as an input. The range of different effects and feedback loops from this initial intervention in a CGE model is, in effect, infinite. As impacts dissipate through the economy – becoming smaller as they move from one market to another – the economy described in a CGE model eventually reaches a new 'general equilibrium.' The term general equilibrium denotes the scenario by which markets reach an equilibrium, where demand and supply are matched. It is then possible to compare key variables of interest (imports, exports, firm profits, GDP, the price level or jobs) in the 'original' (pre trade remedy) and 'new' (post trade remedy) equilibria, to assess the impact of the trade remedy on those variables.

5.13 CGE models have a number of benefits. They illustrate how a trade policy intervention may flow through the economy in ways that are important but not immediately obvious, helping understand the economic mechanisms at play. In doing so, they can approximate the impact on a whole range of different variables of interest (not just imports, but things like profits, wages and jobs). However, even the most sophisticated CGE models are crude representations of reality, and their track-record of reproducing real-world results is somewhat mixed. As with all non-econometric methods discussed here, their results are driven by (a very large number of) assumptions within the model, and not by direct observation of the impacts of a trade remedy (or any other policy intervention). And like gravity models, they tend to be highly aggregated in nature (for example, a typical sector in a CGE model might be 'metals', without differentiating types of metals, such as steel and aluminium, or different types of steel) and usually analyse a few dozen sectors at most. Therefore, they may struggle to isolate all but the most broad-brush of trade policy interventions.

New Trade Models

5.14 New trade models apply concepts from industrial organisation and competition economics to international trade. In particular, they model trade through the activities of individual firms competing across borders in an oligopoly environment (for example, competition between Boeing and Airbus has long been studied through the lens of these models). Firms' behaviours are assumed to be driven by the desire to maximise profit. There are several different assumptions that can be made, including: a) the number of firms interacting in the market; b) whether firms compete on quantities (Cournot competition) or price (Bertrand competition); c) whether imported and domestic goods are identical or differentiated; and d) whether firms have first-mover advantages. All of these assumptions have significant implications for the results of any analysis.

5.15 As with the CGE approach, the models can used to test the impacts of trade remedies. Unlike CGE models, new trade models, since they are microeconomic models of firms' interactions, can assess the impacts on quantities supplied by individual firms, as well as the impacts on profits and so forth. Whilst new trade models offer the most granular non-econometric approach to assessing the impacts of trade remedies, as with all non-econometric approaches they rely on external assumptions (rather than direct observation of the impacts of the trade remedy).

6. Taxonomy of methodologies

6.1 This section outlines an initial taxonomy of methodologies, followed by a guiding framework for methodology selection. This is not meant to be a prescriptive "must follow" diagram but gives an initial indication of methodologies that are possible to implement. The summary is given in two forms: firstly, a set of two tables that can be used to determine feasibility, and secondly, a flow diagram indicating appropriateness of methodologies depending on data and other consideration factors.

6.2 Feasibility is required for a methodology to be conducted. For example, you cannot conduct causal analysis with no post-remedy applied data. This is indicated in Column 3 of Table 12 below. Table 12 identifies the main components for feasibility across the taxonomy of methodologies. For example, if only pre-initiation data is available (and no post-initiation data is available) then non-counterfactual methodologies should be considered. The colours relate to answering "Yes" to the above questions. For example, the "No valid comparators?" answering "Yes" would mean that you would prefer to conduct and interrupted time-series, before-after comparison or simulation methods. This table is intended to indicate feasibility of models only and is intended to capture the most common scenarios for analysis.

Table 12: Consideration of factors that make econometric methodologies feasible

General approach	Method	Only pre-initiation is data available?	No change to the remedy?	No valid comparators?	Data only contains a few time periods?
Quasi-experimental	Bayesian Methods (BCI)				
Quasi-experimental	Synthetic Control				
Quasi-experimental	Diff-in-diff				
Quasi-experimental	Event Study				
Non-quasi experimental	Gravity Model				
Non-quasi experimental	Trend analysis				
Non-quasi-experimental	Before-during-after				
Non-counterfactual	Economic theory (simulation) methods				

Notes: Dark grey indicates "Not Viable" if answer to question is "Yes"; light grey indicates "Potentially Viable" if answer to question is "Yes"; and White indicates "Viable" if answer to question is "Yes".
Source: GT Analysis.

6.3 Where methodologies are indicated as amber, it may be possible to conduct analysis, but the analysis would need to be carefully tested. For example, an event study with short periods may

need to be tested with in-sample testing or careful consideration of the event window and/or the estimation window.

6.4 Once feasible methodologies have been considered by consulting Table 12, further data specific factors should be considered when making a choice between methodologies. These considerations are indicated in Table 13 below.

Table 13: Consideration of factors that make a particular method appropriate, conditional on the method being feasible

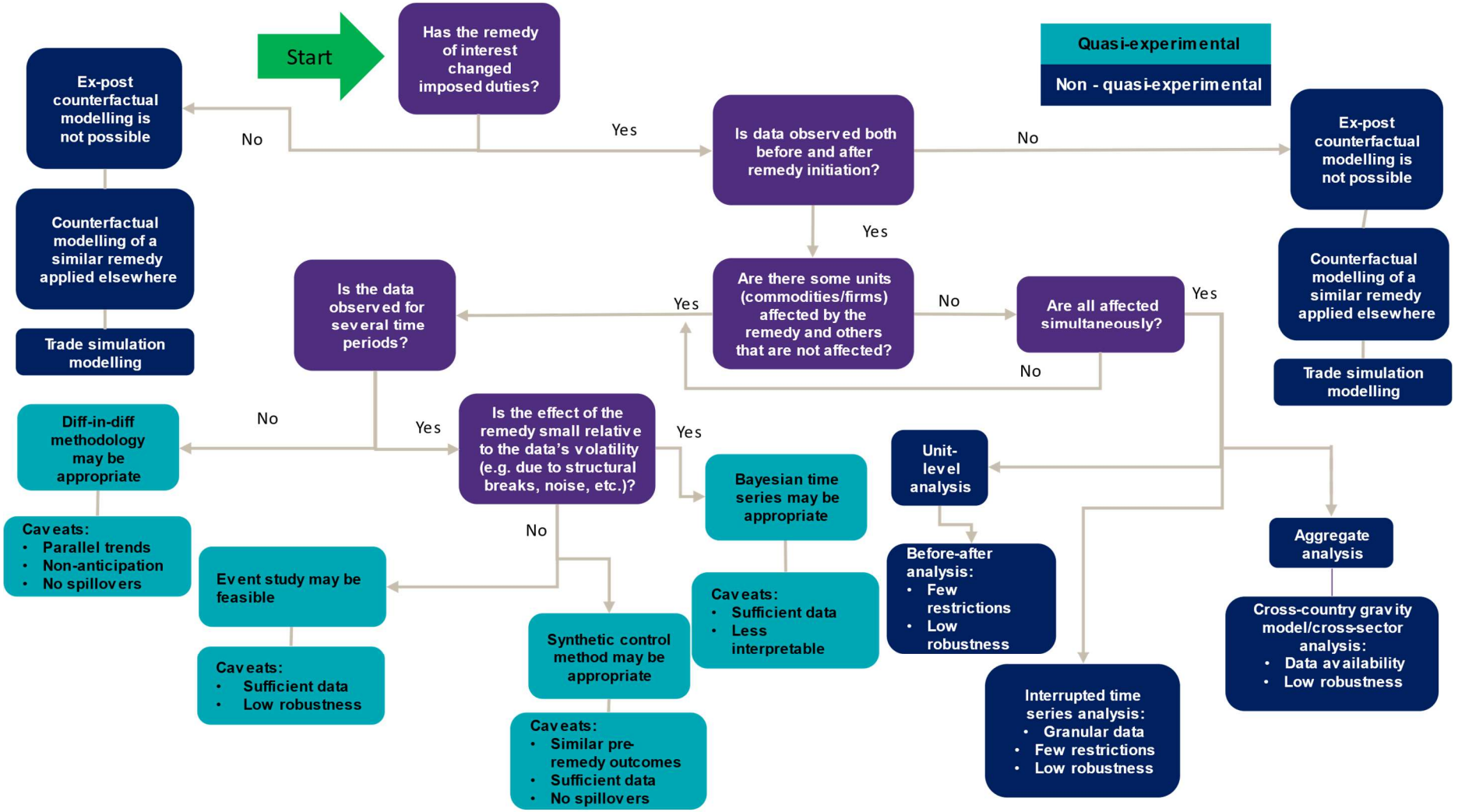
General approach	Method	Noisy data/ structural breaks?	Few comparators available?	Important that interpretation is causal?	Time is limited and/or complexity is to be avoided?
Quasi-experimental	Bayesian Methods (BCI)				
Quasi-experimental	Synthetic Control				
Quasi-experimental	Diff-in-diff				
Quasi-experimental	Event Study				
Non-quasi-experimental	Gravity Model				
Non-quasi-experimental	Trend analysis				
Non-quasi-experimental	Before-during-after				
Non-counterfactual	Economic theory (simulation) methods	Some simulation models can be entirely theoretical and do not need data (i.e. except for calibration).			

Notes: White means that the methodology copes well, light grey means that the methodology can be adapted to accommodate the factor, and dark grey means that the methodology cannot be adapted with the relevant factor.
Source: GT Analysis.

6.5 This table is intended to aid choice of methodologies but is not intended to rule out methodologies. For example, whilst before-after comparison is difficult with noisy data and structural breaks, this does not mean that additional trend analysis and consideration of noise cannot aid explanatory power if no other methodologies are available.

6.6 To further illustrate the taxonomy of methodologies, an alternative illustration to aid choice of methodologies is included below.

Figure 7: Decision tree for methodology selection



Source: GT Analysis

6.7 The decision tree above is an alternative representation of how the factors in Table 12 and Table 13 should be navigated when the TRA is deciding on a suitable model. It expresses model selection as flow of thought; the model of choice is a terminal node that follows naturally from conditions that have been satisfied in previous nodes. It begins by considering fundamental features of the data and the prevailing context, and thereafter leads the user through more nuanced details such that the remaining set of viable models is more tailored to the situation at hand. The conclusions of the decision tree and those in Table 12 and Table 13 regarding model suitability in a given context are consistent as they are governed by the same principles.

6.8 Table 12 and Table 13, and are not intended to be read prescriptively. The framework does not propose that a particular methodology must be used with certainty and exclusivity, conditional on the necessary circumstances warranting it. It is to be read as general guidance for the contexts and constraints that make some methodologies more suitable for a given problem and others less so.

6.9 In practice, conditional on a set of methods being feasible, it would be ideal to apply each of them and triangulate a final result by: (i) assessing the degree of similarity in each model's findings; (ii) identifying potential factors that determine major divergences in the results should divergences arise; and (iii) evaluating the importance of each model's finding in order to come to a final, well-balanced conclusion. This would be the preferred approach as it would ensure that the final conclusions are robust, well-balanced, and made from varied evidence and perspectives.

6.10 Some situations will not permit the approach proposed above. For example, in situations where results are required quickly and there is insufficient time to consider all methods that may be viable. In such instances, the above framework can lead the TRA to expedient solutions that are less resource-intensive and can be applied with relative speed and ease. However, in such situations the TRA must be wary of the weaknesses that the framework associates with a particular approach and caveat the breadth and robustness of its conclusions accordingly.

6.11 To illustrate how to use the framework, case studies are used.

6.12 To illustrate how this framework is used, an understanding of the trade remedy landscape is necessary. The following sections outline the characteristics of the trade remedy landscape within the UK and discuss case studies to illustrate use of the framework.

7. Characteristics of trade remedies

7.1 The evaluation of a particular trade remedy will be materially influenced by the circumstances in which it is applied. This section first starts by outlining the trade remedy decision timeline, and then discusses the characteristics of trade remedies considered for case studies.

Trade remedy decision making process

7.2 It is important to understand the trade remedy implementation process before discussing the econometric estimation process.

7.3 The UK TRA conducts trade remedy investigations for a number of reasons, including (but not limited to):

- A new investigation into unfair trading practice (for example, dumping) that leads to a new trade remedy measure being imposed.
- A review of an existing trade remedy, which includes transition reviews, expiry reviews and interim reviews.

7.4 Once an investigation has begun, a Notice of Initiation is published on the TRA's public file.[80] A case timeline is also published, indicating the deadline for Provisional Determination (if necessary), Statement of Essential Facts and Final Recommendation. In between each of these stages, stakeholders have the opportunity to comment on and respond to documents (for example, questionnaires produced by the TRA and filled in by other stakeholders) published on the public file and the online Trade Remedies Service. When the Final Recommendation is reached, it is submitted by the TRA to the Department for Business and Trade (DBT) where the Secretary of State can accept or reject the TRA's recommendation. Depending on the evidence gathered during an investigation, it is possible that the TRA may not always recommend a trade remedy measure.

7.5 Understanding the process of how trade remedies are implemented is instrumental for correctly incorporating key dates into the econometric analysis. In particular, the announcement of an investigation may lead to domestic agents pre-empting the imposition of a trade remedy at a later date and cause them to adjust their behaviour beforehand. This can lead to the trade remedy having an impact on key performance indicators prior to the date of the trade remedy's imposition. Such effects are called anticipation effects because they occur prior to the imposition of a trade remedy and in anticipation of the trade remedy. Failing to account for these effects when estimating the impact of the trade remedy results in biased estimates. Therefore, the initiation date is treated as the commencement of the trade remedy in the econometric specifications in order to account for any anticipation effects arising from the announcement of the investigation.[81]

7.6 For the purposes of the econometric analysis, each relevant case will have three main dates to consider:

- Date of initiation;
- Date of preliminary decision; and
- Date of final determination.

[80] https://www.gov.uk/government/organisations/trade-remedies-authority

[81] It is possible for anticipation effects to materialise prior to the initiation date that signifies that announcement of an investigation. These effects are discussed in great detail in the case studies. Furthermore, it may be the case that there are no anticipation effects arising from the announcement of the investigation. However, the initiation date is used in order to be conservative.

These key dates will be integral to ensuring robust analysis.

Trade remedies characteristics

7.7 This chapter explores a taxonomy of trade remedies and details the relative differences and commonalities in evidence that exist across these different categories. In doing so, it also details how this evidence may affect the type or detail of any evaluation.

7.8 The TRA is in a unique position of currently performing 'transition reviews' which examine the existing programme of trade remedy measures that remain in place following the UK's departure from the European Union. This report will consider three case studies pertaining to the possible transition review scenarios, and one case study pertaining to encapsulate new measures that could be implemented.

Taxonomy of trade remedy landscape

7.9 In consultation with the TRA, there are four main case studies to be used for the remainder of the analysis. These case studies are as follows:

Table 14: A short summary of selected case studies

Title	Description	EU's Investigation Date(s)	TRA's Investigation Initiation Date	Associated Counterfactual	Case Study Number
AD00012 – Aluminium Extrusions from the PRC	New UK measure	Not applicable	21 June 2021	No investigation initiated and no measure implemented	1
TD0014 – Heavy Plate from the PRC	EU measure transitioned by the UK and scope unchanged	06 October 2016 investigation with 27 February 2017 policy date[82]	25 January 2022	No obvious calculatable counterfactual	2
TD0004 and TS0005 – Biodiesel from the USA and Canada	EU measure transitioned by the UK and scope changed	11 March 2009 provisional countervailing measure with 07 July 2009 policy date	11 August 2020	EU measure transitioned and scope unchanged	3
TS0023 – Stainless Steel Bars and Rods from India	EU measure transitioned by the UK and revoked	27 April 2016 initiation date for the expiry review on provisional countervailing measure, with 27 June 2016 being determination to maintain countervailing measures through to 2022	21 June 2022	EU measure maintained by UK following transition review	4

Source: GT Analysis with consultation from the TRA.

7.10 The case studies each represent a unique scenario in the trade remedy landscape. Four main categories are considered on the basis of the UK's recent departure from the European Union:

- New UK trade remedies: Trade remedies implemented that are new to the UK;
- Unchanged trade remedies: Trade remedies that have been transitioned from the EU and the scope has remained unchanged;

[82] Where the 'policy date' for the EU investigation refers to the date that the remedy was imposed in the EU.

- Changed trade remedies: Trade remedies that have been transitioned from the EU and the scope has been modified during transition review; and
- Revoked remedies: Trade remedies that have been revoked following transition review.

7.11 In order to identify the relevant causal impact that is aimed to be estimated by the case studies, it is important to define the counterfactual. The counterfactual is used to describe the alternative scenario that would have arisen, had what happened in reality not materialised. The counterfactual scenario is then compared to the actual scenario to estimate the causal impact the trade remedy. It is important to define the counterfactual to identify and understand the causal impact of interest. For example, if the TRA imposed a trade remedy that resulted in a new UK measure, the counterfactual would be what would have materialised if the new measure was never imposed.

7.12 The counterfactual is a pre-requisite for causal analysis and must be determined upon before selecting an appropriate method for causal analysis. This is in addition to the feasibility and suitability conditions illustrated earlier in Table 12 and Table 13. Once case studies and their relevant counterfactuals are decided, the consideration should move to the nature of the evaluation exercise.

Nature of evaluation exercise

7.13 Trade remedies can impact a number of different outcomes that may be of interest to the TRA. This section outlines these variables and sorts them according to the granularity of data. This is done to identify the granularity of data needed to carry out the analysis.

7.14 This report considers two main factors; the 15 injury factors discussed earlier in section 2, and trade flow impacts.

7.15 The level of disaggregation that is seen in data reflects the level of disaggregation in the conclusions of causal analysis. For example, if the data covers outcomes at the 8-digit commodity code-level, it is possible to estimate the impact of the trade remedy on an 8-digit commodity code by using other 8-digit commodity codes as comparators. However, if the data consist of firm-level sales, employment and wages, then the evaluator may undertake firm-level analysis but would require access to data from comparable firms that were not impacted by the trade remedy. The level of disaggregation and the nature of the data that is available must be considered when determining the feasibility of econometric analysis and the conclusions that can be drawn from the analysis.

7.16 With trade being the focus of this case study evaluation exercise, careful consideration of spillover effects should be undertaken. Spillover effects are inadvertent impacts arising from a trade remedy that may bias the estimation of the trade remedy's causal impact. Spillovers are considered in greater detail within the case studies. Furthermore, the impact of other trade remedies and remedies on the comparator group, whether commodities or firms, should also be considered within the analysis.[83]

Sources of evidence

7.17 Trade data for this report has been sourced from HMRC at the commodity code 8-digit level.[84] For each case study, data is collected for the affected commodities, and commodities in the relevant HS 2-digit chapter for the country of interest. This is combined with relevant comparator codes, which are indicated below under each relevant case study.

7.18 Due to confidentiality of the data gathered as part of trade remedy investigations, the TRA is unable to share firm level data with Grant Thornton. Hence, to ensure that this report can illustrate the methodologies appropriate at the firm level, the TRA provided an indication of what the data

[83] To be specific, the impact of remedies on the comparator group should be accounted for if those very trade remedies would not have impacted the impacted commodity or firm in absence of the trade remedy. If the trade remedies in question would have also influenced the impacted commodity or firm had the trade remedy not taken place, then no adjustments need to be made to the empirical approach because the comparators would be capturing events that would have arisen in the unobserved counterfactual.
[84] https://www.uktradeinfo.com/trade-data/ots-custom-table/

relates to and level of data that is accessible. A synthetic data set is then created to illustrate the case study. Details of the synthetic data construction are included below.

8. Illustrative case studies

8.1 This section applies the methodology selection framework developed in the previous chapter to a number of case studies. These case studies are framed within trade remedies that were recommended by the TRA in various contexts and cover four main types of trade remedy investigations:

- Trade remedy investigations that result in a new UK measure;
- Trade remedy investigations involving a transitioned EU measure that had a change in scope;
- Trade remedy investigations involving a transitioned EU measure that had its scope unchanged; and
- Trade remedy investigations that resulted in an EU measure being revoked.

8.2 The setting of the case study in terms of the nature of the trade remedy and the data that was available had implications for the methodology suggested by the selection framework. Both trade analysis using real trade data and firm-level analysis using synthetic data were undertaken. Furthermore, it is shown how traditional econometric approaches can be applied to contexts where ex-post counterfactual analysis is feasible (i.e. a trade remedy investigation causes an explicit change in imposed duties resulting from a new or changed trade remedy). These approaches include the SCM, the BCI and the diff-in-diff. It is also illustrated how more theoretical, non-econometric approaches can be applied to contexts where ex-post counterfactual analysis is not feasible (i.e. a trade remedy investigation did not result in an explicit change in imposed duties). These approaches include theoretical models derived from academic literature.

8.3 Each case study covers the following:

- A description of the background;
- Data sources and evidence base;
- The identification problem that must be addressed in order to undertake causal analysis;
- The methodologies selected on the basis of the methodology selection framework;
- The results and key findings; and
- The conclusion.

8.4 The results presented in the following sections (e.g. aggregated and average impacts) are not representative of the true impacts of those specific trade remedies on trade patterns and firms' performance. Rather, the goal of the case studies is to demonstrate how one could apply the framework and obtain various types of results using different models, depending on the context.

8.5 The following sections begin by outlining the general identification problem that must be addressed when undertaking causal ex-post counterfactual analysis, when this is feasible, and then cover the case studies.

Illustrative Case Study 1: AD0012 – Aluminium Extrusions from the People's Republic of China (PRC)

Introduction

8.6 This case study will cover the application of ex-post counterfactual analysis to assess the impact of imposing a new anti-dumping measure in the UK. The specific trade remedy in question pertained to anti-dumping measures that were applied to Aluminium Extrusions imported from the PRC. The case study assesses the impact of the trade remedy on the import volumes of the commodities that were targeted by the trade remedy; of which there were nine targeted commodities in total, classified using 8-digit commodity codes. The data used to assess the impact of the trade was trade data with commodities defined at the 8-digit level obtained from HMRC. The methodologies used to estimate the causal impact of the trade remedy were the SCM and BCI. The remainder of the case study is set out as follows:

- A brief background to the specifics of the measure and how it was applied;
- A description of how the data to undertake the analysis is set-up;
- The conceptual framework that governed the analysis; with particular focus on the counterfactual problem that must be overcome in order to identify the causal impact of the trade remedy;
- An explanation of how the methodology selection framework was applied to determine which methodologies were used to estimate the causal impacts; and
- Presentation of the outcomes and discussion of the key themes that emerged from the analysis and that can be applied to other case studies.

Background

8.7 The anti-dumping investigation discussed in this case study pertained to Aluminium Extrusions imported from the PRC. This was initially triggered by an application lodged by Hydro Aluminium UK Ltd alleging that certain Aluminium Extrusions imported into the UK from the PRC were being dumped and causing injury to the UK industry.[85] This resulted in the TRA initiating an investigation into the matter on 21 June 2021.[86] There The TRA later concluded in its provisional and final determinations, dated 17 August 2022 and 16 December 2022 respectively, that these goods were indeed being dumped into the UK and this was causing injury to UK industry with respect to those goods.[87]

8.8 The key dates for this case study are as follows:

- Date of initiation: 21 June 2021;
- Date of provisional determination: 17 August 2022; and
- Date of final determination: 16 December 2022.

8.9 The provisional determination resulted in the imposition of a provisional anti-dumping duty on UK imports of these goods from the PRC and these duties were recommended in the final determination. The provisional and final duties are indicated in the table below.

[85] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[86] https://www.trade-remedies.service.gov.uk/public/case/AD0012/submission/58db49f3-2ec8-4b8d-9acc-82d85bb69037/
[87] https://www.trade-remedies.service.gov.uk/public/case/AD0012/submission/3f3d3876-1284-46f0-85a2-22d0ce5d09aa/ ; TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Table 15: Provisional and final anti-dumping duties

Exporter/Producer	Provisional duty (Imposed 17 August 2022)	Final duty (Imposed 16 December 2022)
Press Metal International Group	22.35%	15.06%
Shandong Nanshan	9.50%	0.00%
Haomei Group	19.93%	11.40%
Non-sampled, co-operating exporters	20.86%	15.40%
Non co-operating exporters	128.17%	35.10%

Source: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

8.10 The trade remedy pertained to commodities that fell within HS2 digit classification of 76: a category of commodities defined as containing "Aluminium and articles thereof". This categorisation of commodities can be subdivided into increasingly granular classifications at the 4-digit, 6-digit, 8-digit and 10-digit levels. The trade remedy was applied to a collection of 10-digit commodities.

Data

General data setting

8.11 Estimating the causal impact of the trade remedy on trade flows requires trade data that captures imports of commodities imported from the PRC at a level of granularity that permits analysis of each of the affected commodities. Ideally, commodities would to be defined at the 10-digit level, as this is the level at which the measure was imposed, and there would be available trade data for both commodities targeted by the trade remedy and commodities that were out of scope of the trade remedy. The former (i.e. imports of targeted commodities) would be the outcome of interest under assessment and the latter (i.e. imports of out-of-scope commodities) would be used as comparators measured against the outcome of interest.

8.12 The analysis used data obtained from HMRC.[88] This database contains the recorded history of commodity trade flows between the UK and its international trade partners from as early as the year 2000. It is comprised of information on the despatch country (for imports), destination country (for exports), total value, and net mass (in kilograms) of trade for each commodity.

8.13 However, the most granular definition of commodities within this database is the 8-digit level; this is a higher level of aggregation than the 10-digit level. Therefore, the analysis used data at the 8-digit level as a second best alternative and did so as follows. It used the 8-digit commodity codes in which the targeted 10-digit commodities fell under and considered these 8-digit codes to be proxies for the targeted commodities. Additionally, each 8-digit commodity within the HS 2-digit classification of 76 was used as candidate comparator commodities.

8.14 The resulting 8-digit commodity codes and their correspondence with the 10-digit codes that were within the trade remedy's scope are summarised Plot of pre-trends assuming parallel trends assumption is violated within the Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC. The table shows that there is an imperfect correspondence between the 10-digit codes targeted by the trade remedy and the associated 8-digit code that is the unit of the analysis. Notably, there are three 8-digit codes (i.e. 76109090, 76082081 and 76082089) that are within scope that contain 10-digit codes that are outside of the scope of the trade remedy. This partial coverage between the unit of the analysis and the unit of the trade remedy has implications for the analysis and will be further discussed within the results subsection of this case study.

[88] Overseas trade data table - UK Trade Info

8.15 The analysis involved assessing the impact of the trade remedy on nine targeted commodities.[89] A distinct dataset for each affected commodity was created, resulting in nine datasets in total, used to undertake analysis for each commodity. For a given target commodity, a dataset consisted of the imports of the targeted commodity in question and the imports of all comparator commodities.

8.16 Adjustments were made to the data before conducting the analysis. The main adjustments included (i) removing non-targeted commodities that may have been impacted by the trade remedy or by remedies other than the trade remedy in question; (ii) aggregating the data from the monthly level to the quarterly level; (iii) trim the first months in the sample for each commodity dataset; and (iv) transforming import volumes from kilograms to the inverse hyperbolic sine of kilograms during estimation.[90] These adjustments are described in detail in Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC.[91] The final results are reported in kilotons and as percentages for ease of interpretation.

8.17 For this case study, it is assumed that the impacts of the trade remedy first emerged on of the initiation 21 June 2021. It is understood that the corresponding duty for this trade remedy was only imposed after this date. However, the impacts started to be measured from this date to capture any anticipation or trade remedy threat impacts. Therefore, the trade remedy is evaluated at Q2 2021 given the aggregation to the quarterly level. It is assumed that the targeted commodities were only impacted by the duty in Q2 2021 and the following periods, and that the non-targeted commodities remaining in the dataset were not impacted by the trade remedy or another remedies.

Data set-up: Synthetic Control Method

8.18 The key step in the generation of a synthetic control is the calculation of the weights that are assigned to the non-target commodities. The weights are calculated such that the pre-initiation characteristics of the synthetic control match the same pre-initiation characteristics of the target commodity as closely as possible. These characteristics can be specified by the researcher. The characteristics were the entire history of pre-initiation imports. In particular, the weights were created such that the observed imports of the synthetic control closely match the observed imports of the targeted commodity in each pre-initiation quarter. This matching could have been done on other outcomes, such as the average imports observed over the entire pre-initiation period, or even the average price per kilogram of imports in the pre-initiation period. However, given that the imports of the synthetic control match the imports observed in each pre-initiation quarter, no other characteristics can be used in the matching process because all the variation has already been captured by the history of pre-initiation imports.

Data set-up: Bayesian Causal Impact

8.19 The BCI specification predicted counterfactual imports using two sources of information: (i) the comparator commodities and (ii) time-varying characteristics of the targeted commodity's imports. Both the SCM and BCI use comparator commodities to predict the counterfactual imports of the targeted commodity. However, the key difference between how the SCM and the BCI undertake this process is that the BCI estimates the relationship between the targeted commodity and the comparator commodities more flexibly. The SCM generally places more restrictions in this relationship (e.g. the targeted commodity's imports are a weighted sum of the comparator

[89] Despite the remedy targeting more than nine commodities at the 10-digit, these commodities fell into nine 8-digit codes. As only 8-digit codes are observed in the HMRC data, the analysis only focused on these nine 8-digit codes. These nine 8-digit codes are referred as commodities throughout this chapter for the sake of ease.
[90] The inverse hyperbolic sine refers to a transformation that can be applied to a variable before undertaking causal analysis. Please refer to Appendix 1 for a more detailed discussion of this transformation, why it was used and the implications of using it on analysis and the interpretation of the result.
[91] Suppose that there is a remedy other than the Aluminium Extrusions remedy that is the focus of this case study. Let this other remedy be referred to as an 'external remedy', and the Aluminium Extrusions remedy as the 'remedy of interest'. The reference to 'remedies other than the one in question' within point (i) refers to the fact that suitable comparators should not be impacted by the treatment of interest (i.e. the remedy of interest) or external treatments (i.e. external remedies) that the treated commodity would not have been impacted by in the absence of treatment of interest. If a particular comparator commodity is within the scope of an external remedy and the treated commodity would not have been impacted by in absence of treatment of interest, then the comparator commodity is no longer a suitable comparator for the treated commodity. Our reference to 'other remedies' in reference to suitable comparators refers to this fact.

commodities' imports), whereas the BCI uses Bayesian econometric modelling to define this relationship in a less restrictive manner. This can improve how precisely the BCI estimates counterfactual imports. The BCI also captures time-varying characteristics identified in the pre-initiation imports of the targeted commodity and this further enhances performance. The BCI specification used in this case study assumed that the relationship between target commodity imports and comparator commodity imports was stable over time and made no prior assumptions about the nature of the relationship between target commodity imports and comparator commodity import.[92] .

Conceptual framework and model choice

8.20 The purpose of this case study is to provide methodologies that estimate the impact of the trade remedy on the imports of each of the commodities targeted by the trade remedy. To perfectly estimate the impact for a given targeted commodity, it would be necessary to observe the import volumes of this commodity in the post-initiation period under two different scenarios: (i) when the trade remedy is present (i.e. if the measure was imposed); and (ii) when the trade remedy is absent (i.e. if the measure was not imposed). Once the observed outcome and the counterfactual scenario have been identified, the impact of the trade remedy is simply the difference between the outcomes in the two counterfactuals. The outcomes in both counterfactual scenarios are observed because the analysis uses synthetic data (i.e. the outcomes with and without the trade remedy are known because they are pre-defined). However, in reality the only outcomes that would be observable are those that arise in the presence of the trade remedy. The unobservability of the counterfactual in absence of the trade remedy creates an identification problem; outcomes that are unobserved must be identified to estimate the true impact of the trade remedy.

8.21 The methodologies explored will try to overcome the identification problem estimating the outcomes that would have prevailed in the unobserved counterfactual (i.e. in absence of the trade remedy if the new measure on Aluminium Extrusions was not imposed) and thereby allow the true impact of the trade remedy to be estimated.

Methodology selection

8.22 Analysis was conducted using a synthetic control method (SCM) and a Bayesian causal impact (BCI) model. For a given target commodity, the time periods considered and the non-target commodities that were used to construct the counterfactual were the same across methodologies in order to enable comparison across models.

8.23 The decision to use these models was arrived at by applying the methodology selection framework outlined in previous sections. As a reminder, there are two variants of this framework; a tabular framework set out in Table 12 and Table 13, and a decision tree in Figure 7. The selection of the most appropriate methods is consistent across both variants of the framework. This case study will illustrate how both the tabular framework and the decision tree can be used. First, the application of the tabular framework will be outlined, followed by an outline of the application of the decision tree.

8.24 The first step in applying the tabular framework is to determine whether a methodology is feasible by assessing whether the context meets the criteria outlined by the column headings in Table 12. In this particular case, the trade remedy investigation did result in an observable change in the duties imposed by the TRA; as there was a new UK measure that was imposed. The data available had both pre-initiation and post-initiation data, consisted of several time periods and there were several valid comparators in the pool of control commodities that were used to generate the counterfactual.[93] Therefore, all the listed methodologies would be feasible in this case.

[92] The most simplistic and basic specification of this approach is used as outlined in the technical documentation published by its original creators. This method can be further sophisticated by the inclusion of more components; however, this has not been attempted. For more details, please refer to the documentation published by the authors of this package on the following link: https://google.github.io/CausalImpact/CausalImpact.html.
[93] The length of the panels varied with the commodities in question. Panel length ranged from 35 to 84 quarters. The number of comparator commodities ranged from 42 to 44 commodities.

8.25 The second step is to determine which methodologies are suitable by assessing the criteria outlined by the column headings in Table 13. The first thing considered is the ease of causal interpretation to ensure that the methodologies chosen are capable of delivering results that can be interpreted as causal. The best methodologies for causal interpretation according to the framework are BCI, the SCM and the diff-in-diff method. Thereafter the number of comparators is considered. The comparator pool is quite large and therefore all three methods are suitable. Time and complexity were not considered to be constraints in this case, as to the aim was to illustrate alternatives that can be pursued by TRA that has both the time and expertise to execute all the methodologies.

8.26 The final consideration made was the extent of noise within the underlying data due to volatility and structural breaks. It was already discussed the volatility of the underlying monthly data and measures to mitigate this by aggregating the data and transforming import volumes by taking the inverse hyperbolic sine. However, the data remains relatively volatile for several of the commodities. Therefore, the framework would recommend that BCI would be most suitable for this case study, as synthetic control methods and difference-in-differences can be quite sensitive to noisy data.

8.27 The decision tree in Figure 7 can also be used to arrive to similar conclusion. The first step was to ask whether the trade remedy investigation resulted in a change in imposed duties and work through the tree until arriving at a node or a set of nodes that meet the criteria of the context. The framework has been applied as follows:

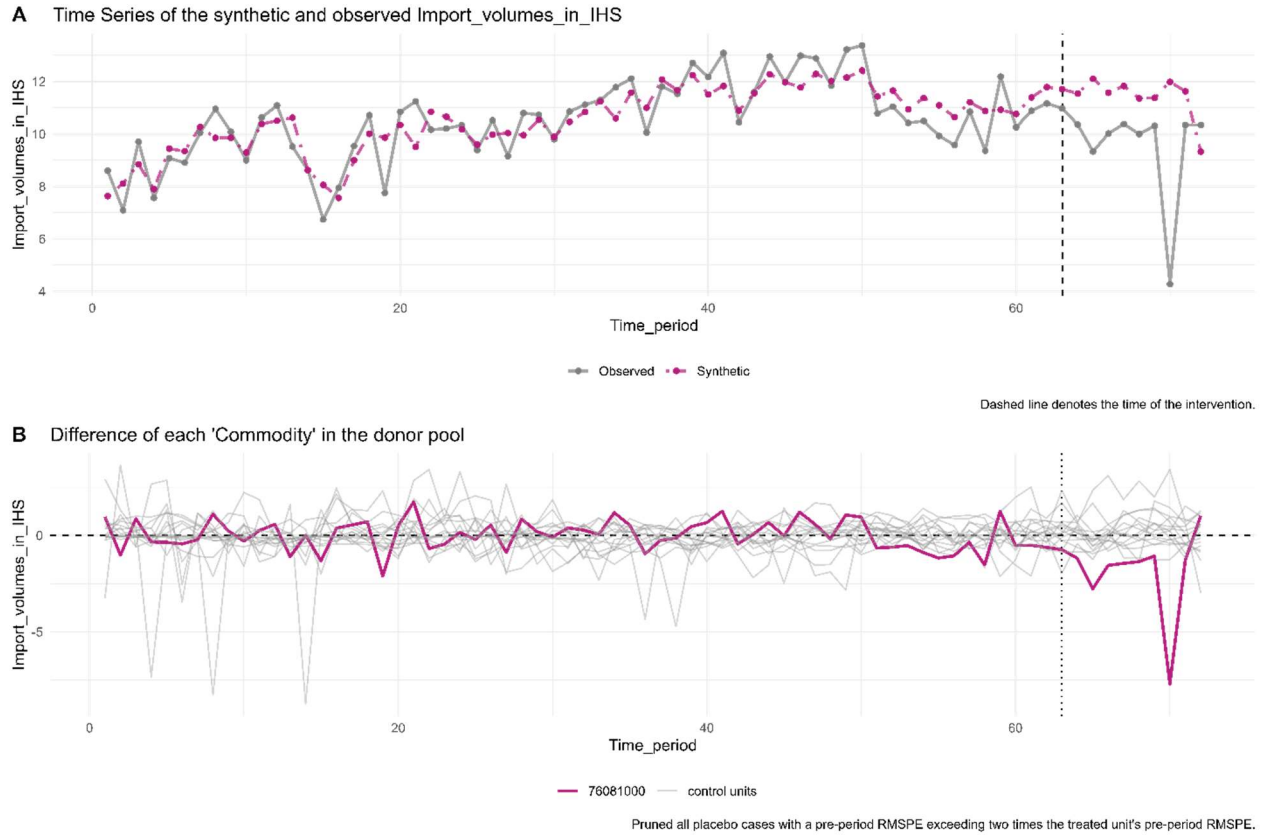
- The trade remedy investigation did result in a change in imposed duties. Follow “yes” to the next node;
- There is data available for the period before and after the initiation. Follow “yes” to the next node;
- There are some commodities that are affected by the trade remedy and others that are not. Follow “yes” to the next node;
- The data is observed for several time periods. Follow “yes” to the next node;
- Data is noisy, so it may be the case that the impact of the trade remedy is small relative to the volatility in the data. Follow “yes” to the next node; and
- The result is that BCI may be the most appropriate approach. The caveats of this approach are that there is sufficient data, which there is in this case, and that these methods are less interpretable with respect to the individual relationships between the affected commodity and the comparator commodities. Namely, ascertaining how the import volumes of a specific comparator commodity impact the import volumes of the affected commodity is less clear cut with BCI than it is with a synthetic control method or an event study, for instance. However, these methods can still be used to understand the causal impact of the trade remedy on the import volumes of the targeted commodity because they can be used to construct a good proxy for what the import volumes of the target commodity would have been in absence of the trade remedy.

8.28 It has been shown how the tabular framework and the decision tree framework can be applied and how they should lead to consistent conclusions regarding the most appropriate model for the task at hand. The BCI approach was chosen because the framework would suggest that it would be most appropriate for this case study. However, a second analysis was conducted using the SCM approach to better understand and illustrate how the results can converge or diverge across methodologies. The concluding remarks aim to explain some of the reasons behind any divergences and provide guidance on how a multiplicity of approaches can be evaluated to triangulate. In this instance, the volatility of the data may impair the ability of the SCM to estimate causal impacts. Therefore, any notable divergences that are uncovered by this investigations and the importance attributed to the findings of these methodologies will be viewed with this mind.

Results

8.29 The results produced by the SCM and the BCI lead to similar conclusions for some of the commodities. In general, both approaches predict that the trade remedy led to a notably reduction in import volumes for a number of the targeted commodities. This similarity in findings can be illustrated graphically with respect to commodity 76081000. The figure below shows the estimated impact of the trade remedy on this commodity using the SCM.

Figure 8: The impact of trade remedy on imports of commodity 76081000 using synthetic control method (SCM)



Notes: Panel A shows the predicted and observed imports of commodity over time using the SCM. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the time periods denominated by an index. The initiation date is signified by the black vertical dashed line close to the end of the time series. Panel B shows the difference between the observed and predicted imports for commodity 76081000 over time. The y-axis corresponds to the difference between the two plots shown in Panel A and also represents the effect of the trade remedy in each period. The pink line represents the targeted commodity and the grey lines correspond to the placebo treatment effects of each comparator commodity used to generate the predicted imports. Source: GT Analysis using tidysynth.R package in R.

8.30 The top panel, Panel A, plots the observed and predicted import volumes for this commodity over time. The imports are in terms of the inverse hyperbolic sine of total import weight in kilograms, so the key findings that can be taken from this figure are limited to the sign, general magnitude, and statistical significance of the treatment effects. The direct interpretation of the treatment beyond will be discussed later. The graph shows that predicted imports closely followed observed imports until the initiation date of the trade remedy investigation signified by the vertical dashed line.

Beyond this date, predicted imports remain consistently higher than observed imports, signifying that the trade remedy reduced imports.[94]

8.31 Panel B plots the difference between observed imports and predicted imports over time for both the target commodity and the control commodities. In particular, the pink line shows this difference for the target commodity. This difference corresponds to the effect of the trade remedy in a given period. The plot in panel B tells a similar story to the plot in panel A. Predicted imports closely followed observed imports until the initiation date, hence a treatment effect that is close to 0 during this period. However, observed imports begin to fall below predicted imports after the initiation date, hence a negative treatment effect during this period. There is also a notable dip in observed imports following the trade remedy that occurs for one quarter which exacerbates the generally negative treatment effect.

8.32 The grey lines in Panel B represent the placebo plots, illustrating the estimated treatment effects for the control commodities. These treatment effects are generated by repeating the synthetic control analysis but only for the control commodities. For each control commodity, a synthetic control is generated using the other control commodities. Thereafter, the difference between predicted imports and observed imports in each period is calculated for every control commodity (i.e. the treatment effect is calculated for each control commodity) and this is plotted against the corresponding differences (i.e. the treatment effects) for the targeted commodity. The effects for the control commodities are called placebo effects because no notable impacts due to the trade remedy are to be expected. These placebo effects should be close to zero if the assumption that the trade remedy did not impact any of the control commodities is satisfied.

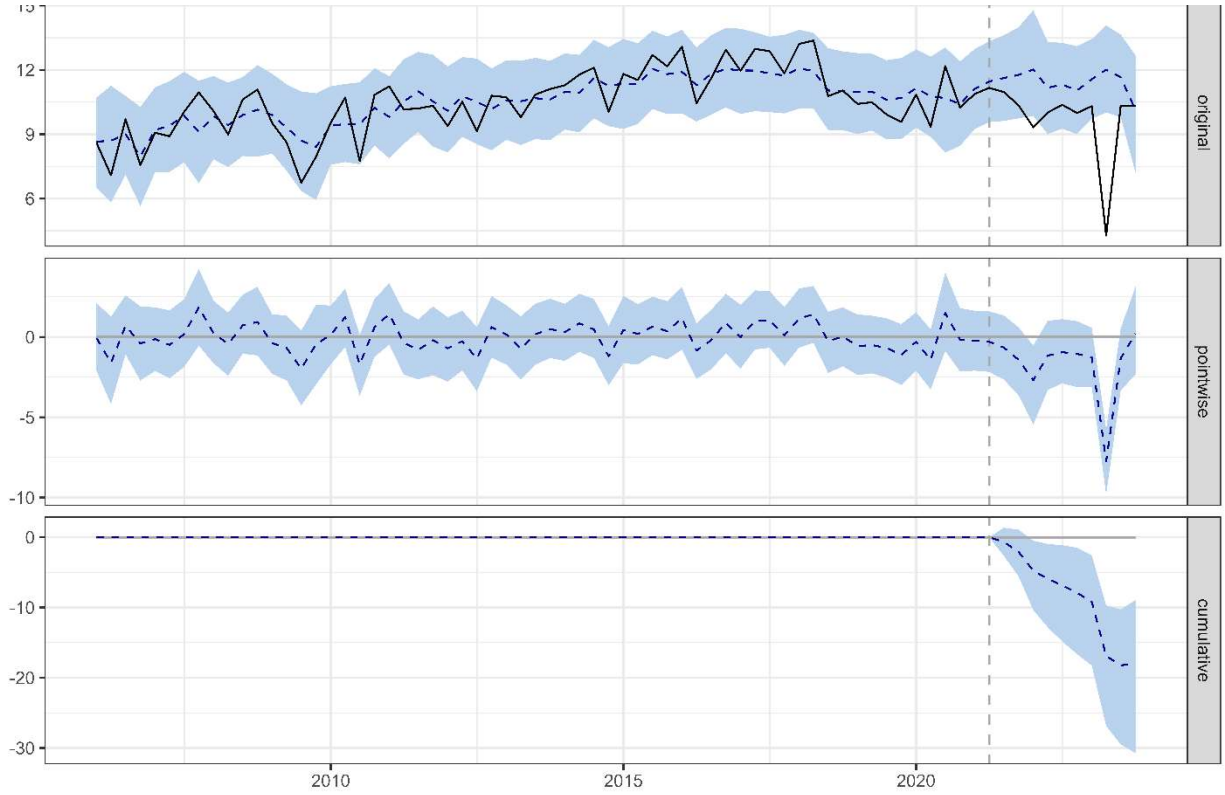
8.33 The placebo effects are intended to display impacts arising purely due to statistical uncertainty. They are used to give an indication of whether the impacts observed for the treated commodity are large enough to be considered above normal and therefore statistically significant. If the treatment effects for the target commodity are notably higher than the placebo effects, then it suggests that these impacts are likely to be driven by the trade remedy and more than statistical uncertainty. However, if the treatment effects for the target commodity are less than many of the placebo effects then the impact of the trade remedy cannot be distinguished from statistical error, and it must be concluded that the trade remedy had no statistically significant impacts. In this case, the average treatment effect for the target commodity is notably higher than the average placebo treatment effects so it can be concluded that the impact of the trade remedy is statistically significant.[95]

8.34 The aforementioned findings are closely mirrored by the findings produced by the BCI. The figure below shows the treatment effects of the trade remedy for commodity 76081000 estimated using this approach.

[94]It was outlined in the introduction of this case study that the commencement of the trade remedy impacts in the empirical investigation corresponded with the initiation date of the trade remedy investigation. Any references to the 'initiation date' when referring to the commencement of trade remedy impacts within this case study and other case studies are to be understood as the initiation date of the trade remedy investigation.

[95] Statistical significance is determined by assessing whether the impact lies outside of the 95% confidence interval. In particular, statistical significance is defined based on the 5% significance level.

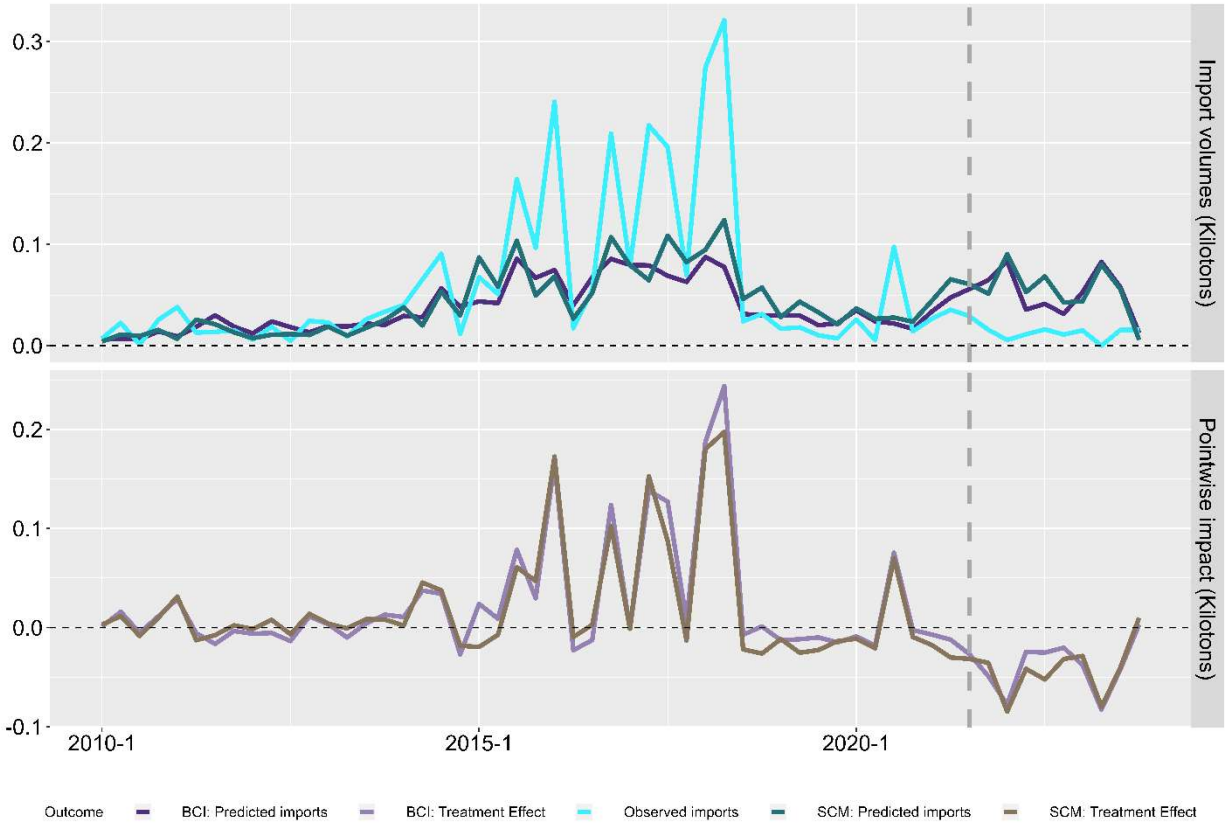
Figure 9: The impact of trade remedy on imports of commodity 76081000 using Bayesian causal impact (BCI)



Notes: The first panel from the top shows the predicted (dashed line) and observed (solid line) imports of commodity 76081000 over time using the BCI. The light blue shading represents the 95% confidence interval around the predicted imports. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line close to the end of the time series. The second panel the difference between the observed and predicted imports for commodity 76081000 over time. The light blue shading represents that 95% confidence interval around the estimated treatment effect. The y-axis corresponds to the difference between the two plots shown in the first panel and also represents the effect of the trade remedy in each period. The third panel represents the accumulated treatment effect: it is the sum of the treatment effect from the initiation date going forwards. The y-axis shows the accumulated treatment effect in terms of the inverse hyperbolic sine of import volumes. The light blue shading represents that 95% confidence interval around the estimated accumulated treatment effect.
Source: GT Analysis using CausalImpact.R package in R.

8.35 The layout of the results follows those of the SCM. The first panel shows the predicted and observed import volumes over time, the second panel shows the treatment effect over time and the third panel shows the accumulated treatment effect from the date of the trade remedy going forward. All findings are in terms of the inverse hyperbolic sine of import volumes. Much like the SCM, predicted imports closely align with observed imports prior to the initiation date, but observed imports fall below predicted imports in subsequent periods. The BCI also reports pointwise 95% confidence intervals for the treatment effect in each period. This allows for the statistical significance to be determined for the treatment effect in each period, as opposed to the SCM that only performs inference for the average treatment effect. The impact of the trade remedy is statistically significant for two quarters in the post-initiation period, and the average impact of the trade remedy is also statistically significant. The findings of both approaches are compared in the figure below.

Figure 10: Comparison of SCM and BCI for commodity 76081000



Notes: The first panel from the top shows the predicted imports for the SCM, the predicted imports from the BCI and observed imports of commodity 76081000 over time. The y-axis shows import volumes in kilotons while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line close to the end of the time series. The second panel the difference between the observed and predicted imports using the SCM and BCI for commodity 76081000 over time. The y-axis corresponds to the difference between the predicted imports and observed imports shown in the first panel and represents the effect of the trade remedy in each period.
Source: GT Analysis.

8.36 The above figure compares the findings of the SCM and BCI for commodity 76081000. The predicted imports and associated treatment effects are in terms of kilotons. An observation that can be made when comparing this figure to the figures that show the corresponding impacts in terms of the inverse hyperbolic sine is that the relative magnitudes of the predicted imports and the treatment effects appear to be different. In Figure 10, observed imports in kilotons appear to display a high degree of volatility between the years 2015-2018 while the same volatility is not observed when looking at the inverse hyperbolic sine of import volumes in Figure 8 or Figure 9. Moreover, the seemingly large one-period decline in observed imports following the initiation shown in Figure 8 and Figure 9 is much less pronounced than what is shown in Figure 10. These discrepancies are due to the nature of the inverse hyperbolic sine transformation: this transformation forces large quantities of imports to be closer to smaller quantities of imports, and this tendency becomes more extreme with larger values.[96]

8.37 The detailed results for this commodity and all other target commodities using both approaches are summarised in the tables below.

[96] See Appendix 1 for an illustrative example of this.

Table 16: Estimated effect for each commodity using synthetic control method (SCM)

Commodity	Aggregated treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76041090	-13.54	-89.5	0.023
76081000	-0.46	-49.5	0.023
76082089	-1.54	-79.9	0.023
76042910	-4.09	-86.5	0.045
76082081	-0.94	-68.0	0.114
76042100	-1.69	-36.8	0.136
76041010	-0.41	-44.4	0.250
76109090	5.47	26.2	0.295
76042990	22.78	93.4	0.750

Notes: This table presents the results from using the SCM for each commodity. The first column shows the aggregate impact of the trade remedy on the volume of imports in kilotons (i.e. the sum of the impact of the trade remedy in each quarter). The second column shows the average impact as a proportion of the predicted imports for every quarter in the post-initiation period. The final column shows p-value associated with the average impact of the trade remedy. Values below 0.05 indicate that the average impact is statistically significant at the 5% significance level.
Source: GT Analysis.

Table 17: Estimated effect for each commodity using Bayesian causal impact (BCI)

Commodity	Aggregated Treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76041090	-6.83	-81.8	0.000
76081000	-0.44	-61.3	0.000
76082089	-1.19	-76.3	0.000
76042910	-3.24	-75.5	0.000
76082081	-0.13	-25.5	0.349
76042100	-1.50	-33.8	0.005
76041010	0.00	-0.6	0.095
76109090	12.94	64.2	0.001
76042990	-59.06	-52.4	0.017

Notes: This table presents the results from using the BCI for each commodity. The first column shows the aggregate impact of the trade remedy on the volume of imports in kilotons (i.e. the sum of the impact of the trade remedy in each quarter). The second column shows the average impact as a proportion of the predicted imports for every quarter in the post-initiation period. The final column shows p-value associated with the average impact of the trade remedy. Values below 0.05 indicate that the average impact is statistically significant at the 5% significance level.
Source: GT Analysis.

8.38 The columns indicate the commodity, the total impact of the trade remedy in Kilotons (i.e. the cumulative impact in each post-initiation quarter), the impact of the trade remedy in each post-initiation quarter as a proportion of the predicted imports and the final impact indicates the statistical significance of the average impact. For illustrative purposes, the impacts for commodity 76081000 using the SCM can be interpreted as follows. The first column shows that trade remedy is predicted to reduce the total volume of imports over the entire post initiation period (i.e. Q2 2021 – Q4 2023) by 0.46 kilotons. The second column states the trade remedy caused imports to be

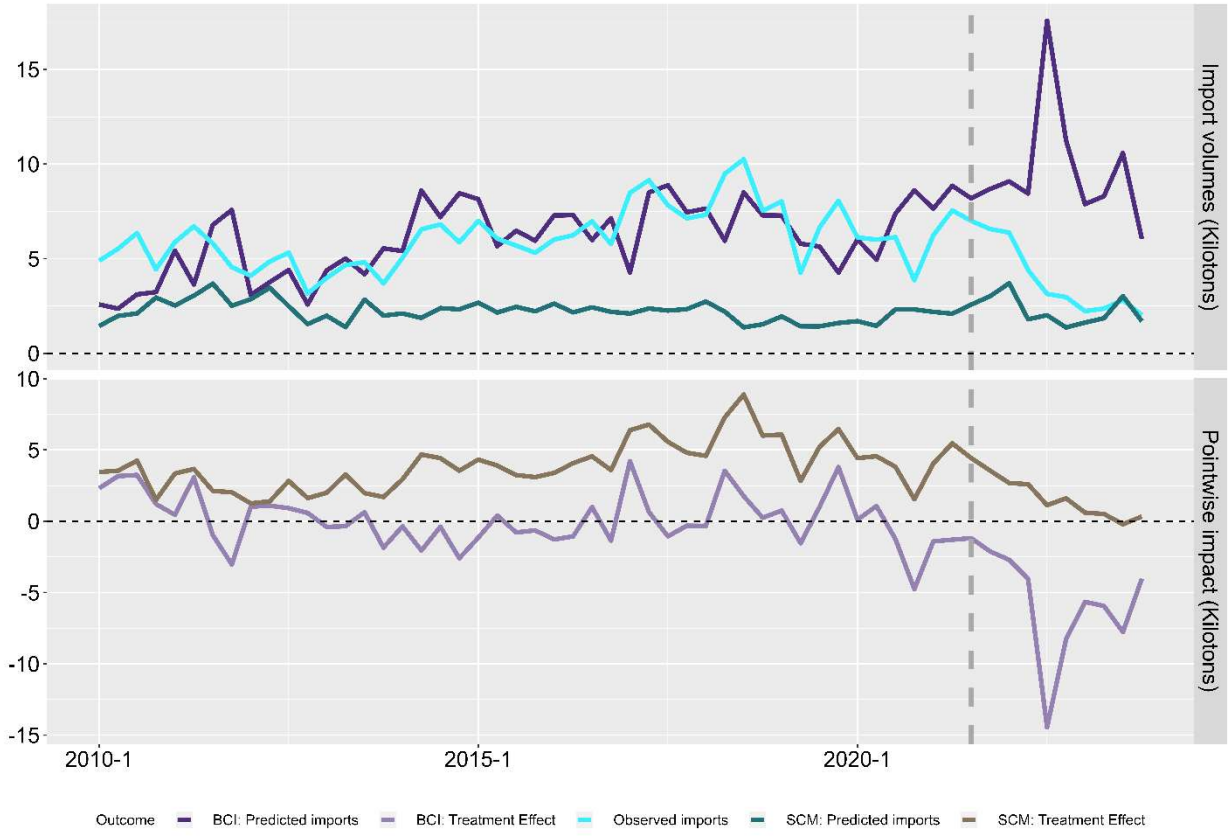
49.5% lower than what they would have been in the absence of the trade remedy on average for the post-initiation period. The final column states that the average impact of the trade remedy had a p-value that corresponds to 0.023. As this value is less than 0.05, it can be concluded that the average impact is statistically significant at the 5% significance level. The corresponding interpretation of the results using the BCI are that the trade remedy reduced import volume by 0.44 kilotons, resulted an average 61.3% reduction in import volumes in each post-initiation quarter, and the average impact was found be statistically significant at 5%.

8.39 The estimated impacts of the trade remedy for the first four of the commodities listed in Table 16 and Table 17 (i.e. 76041090, 76081000, 76082089 and 76042910) are roughly similar across approaches. The trade remedy is estimated to have reduced imports for all commodities and the average impact is statistically significant at the 5% level. The results vary with respect to the aggregated impact, as the SCM is generally found to predict larger impacts in absolute terms. However, the proportionate impacts are more similar within commodities but vary across commodities; the predicted reductions in imports per quarter range between 50%-90%.

8.40 However, the effects estimated by the approaches diverge with respect to the magnitude, sign and precision for the remaining commodities. The estimated impacts predicted by the SCM are found to be statistically insignificant at the 5% significance level for the five remaining commodities, while the BCI predicts statistically significant impact for three of them (i.e. 76042100, 76109090 and 76042990). This, in tandem with the fact that the p-values for BCI estimates are smaller than the SCM for the first four commodities, indicates that the BCI is estimating causal impacts more precisely than the SCM.

8.41 A stark distinction between the two sets of findings is highlighted in the results for commodity 76042990; the commodity in the final row of both results tables. The SCM predicts that the trade remedy increased aggregate imports by 17 kilotons, but this impact is estimated very imprecisely; this is indicated by the very small p-value associated with this corresponding impact. However, the BCI predicts that total imports following the trade remedy fell by 56 kilotons, the largest reduction reported among all commodities, and this impact is statistically significant. The difference can be illustrated in the figure below.

Figure 11: Comparison of SCM and BCI for commodity 76042990



Notes: The first panel from the top shows the predicted imports for the SCM, the predicted imports from the BCI and observed imports of commodity 76042990 over time. The y-axis shows import volumes in kilotons while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line close to the end of the time series. The second panel the difference between the observed and predicted imports using the SCM and BCI for commodity 76042990 over time. The y-axis corresponds to the difference between the predicted imports and observed imports shown in the first panel and represents the effect of the trade remedy in each period.
Source: GT Analysis.

8.42 The figure above compares the predicted imports and corresponding trade remedy impacts estimated using the SCM and BCI for commodity 76042990. The plots clearly show that the predicted imports from the BCI align with observed imports more closely than the SCM predictions in the pre-initiation period. The SCM predictions systematically underestimate observed imports. This divergence in predicted imports carries forward to the post-initiation period. The BCI predicts that counterfactual imports in the post-initiation period would have exceeded observed imports in the presence of the trade remedy, while the SCM predicts the near opposite.

8.43 The predictive power of the two models in the pre-initiation period has direct implications for their ability to estimate counterfactual imports in the post-initiation period and identify the causal impact of the trade remedy. If a model's predicted imports closely match observed imports in the pre-initiation period, then it is more tractable that the model will produce accurate predictions of counterfactual imports post-initiation. Therefore, the causal impact of the trade remedy that is estimated by the model is also likely to be valid. Conversely, if the model is unable to generate accurate predictions of pre-initiation imports, then it's ability to generate valid predictions of post-initiation imports and resulting causal impacts is questionable. For these reasons, the causal impacts estimated by the BCI are likely to be more credible in this particular case.

8.44 The only commodity that is estimated to have experienced a statistically significant increase in imports is commodity 76109090. This increase is statistically significant for the BCI only. This finding is counterintuitive because the trade remedy imposed new anti-dumping duties which

should, in theory, reduce the imports of the targeted commodities because they have become more expensive. This finding is discussed in more detail later in the report.

8.45 The differences in estimated impacts can be traced back to features of the relative merits of these methodologies; particularly their ability to detect causal impacts in the presence of noisy data. When the two methodologies estimate statistically significant impacts, they report findings that are highly similar. However, the BCI is able to estimate causal effects more precisely in general and is also able to detect statistically significant impacts more frequently than the SCM when dealing with noisy data. This can have massive implications on the conclusions that are made about the effect of a trade remedy.

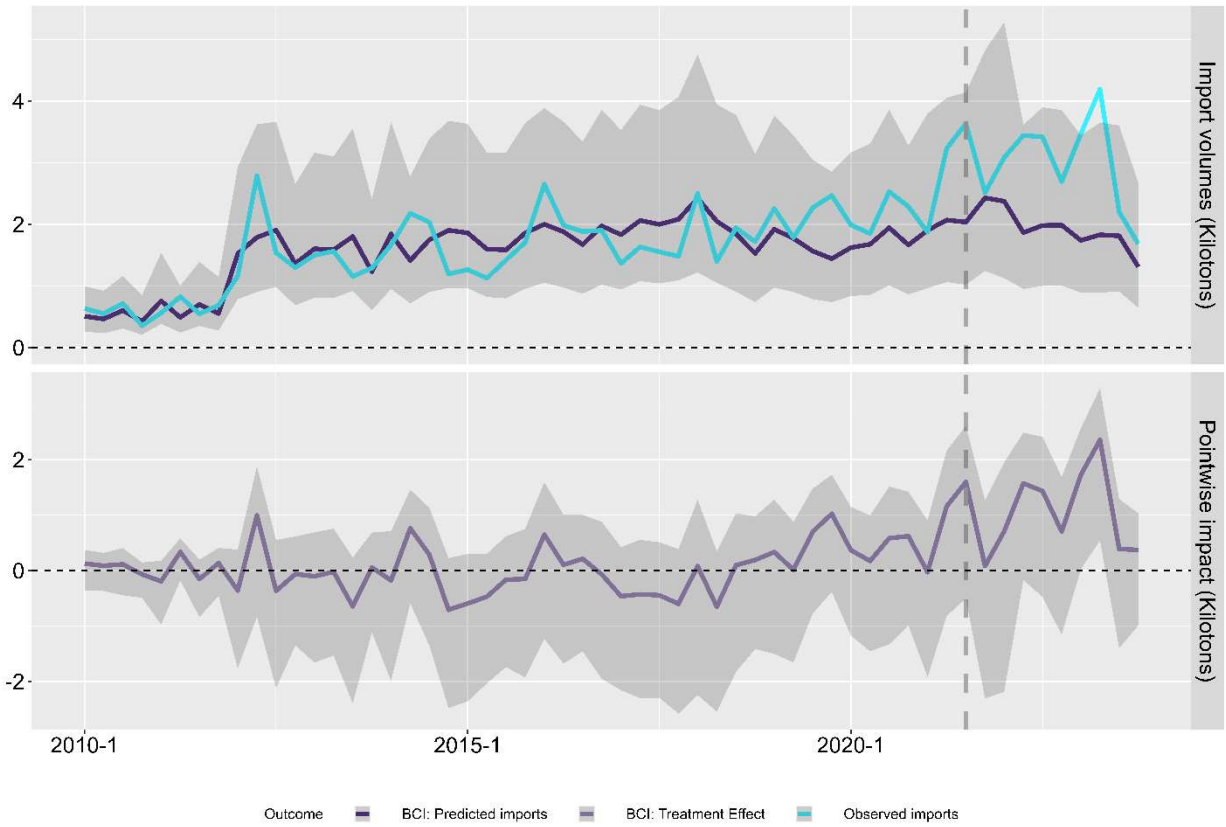
8.46 Most notably, the SCM detects no statistically significant impact of the trade remedy on imports of commodity 76042990 while the BCI predicts that the trade remedy resulted in the largest reduction of imports of this commodity in absolute terms. This is likely because the BCI predicted observed imports in the pre-initiation period quite well and produced more valid estimates of counterfactual imports in the post-initiation period despite the data being noisy. Conversely, it can be argued that the noisy data led to the SCM's predictions of pre-initiation imports being relatively poor and its estimates of counterfactual imports being unreliable as result.[97] This reiterates the importance of selecting the appropriate for the given circumstances and further illustrates how the methodology selection framework can allow the TRA to identify the most appropriate model.

Counterintuitive trade remedy impacts

8.47 The results for commodity 76109090 were somewhat counterintuitive. Both the SCM and BCI predicted that the trade remedy had a positive impact on imports of this commodity, and this positive impact was statistically significant using the BCI. The results for this commodity using the BCI are illustrated in the figure below.

[97] Further inspection of the model outputs reveals that the BCI's superior performance in the pre-initiation period was likely due it being better able to model a structural break in the data. These model outputs are shown in Appendix 1. Both figures clearly show a structural break in the time series of observed imports just prior to 2010. However, the BCI's predicted imports still closely aligned with observed imports following the structural break while the SCM's predicted imports fell below observed imports for the remainder of the pre-initiation period. These discrepancies carried forward into the post-initiation period and had implications on the estimated treatment effects as a result.

Figure 12: Trade remedy impact for commodity 76109090 using Bayesian causal impact (BCI)



Notes: The first panel from the top shows the predicted imports for the BCI and observed imports of commodity 76109090 over time. The y-axis shows import volumes in kilotons while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line and the grey boundaries around the plots in the top and bottom panel constitute the 95% confidence interval around the estimated BCI estimated imports and treatment effects, respectively. The second panel the difference between the observed and predicted imports using the BCI for commodity 76109090 over time. The y-axis corresponds to the difference between the predicted imports and observed imports shown in the first panel and represents the effect of the trade remedy in each period.
Source: GT Analysis.

8.48 This result is counterintuitive because the new import tariff increases the volume of imports. One would expect imports for this commodity to fall following the trade remedy because they have become relatively more expensive. However, the opposite result was found. Discussions with TRA suggest that this finding may be driven by the imperfect correspondence between the unit of the analysis (i.e. the 8-digit level commodity codes) and the unit that the trade remedy was applied to (i.e. the 10-digit level commodity codes). The 8-digit commodity code 76109090 used in the analysis consists of four 10-digit commodity codes: 7610909010, 7610909091, 7610909092 and 7610909095. All imports made under the 8-digit level commodity code are treated as being within scope of the trade remedy, however only one of the 10-digit level commodity codes that this code is comprised of was within scope for the trade remedy (i.e. 7610909010) while the remaining three were not.

8.49 This means that only a fraction of the imports under the 8-digit level commodity code and, therefore, the corresponding estimated impacts, can be ascribed to the trade remedy. An observed increase in imports coming under the 8-digit level commodity code 76109090 may be the net outcome of a reduction in imports for the commodity 7610909010 (which is in scope of the anti-dumping measure) and simultaneous increase in imports for commodities 7610909091, 7610909092 and 7610909095 (which are out of scope of the anti-dumping measure). It was not

possible to test this hypothesis empirically because 10-digit level trade data was not available, but it is plausible.

8.50 A further theme to be considered within this narrative are the drivers for fluctuations in the imports of the commodities that are out of scope. Assuming that the trade remedy reduced or, at the very least, halted the imports of the targeted commodity, the positive trade remedy impacts observed would be increasing imports for the out of scope commodities. Plausible reasons for this increase in imports may be driven by three sources:

- Factors unrelated to the trade remedy (e.g. the sectors that rely on these commodities are growing, leading to greater imports volumes for these commodities);
- Substitution effects resulting from importers of the targeted commodity importing more of the commodities that are out of scope because these commodities are interchangeable with the targeted commodity and are relatively cheaper due to not being impacted by the trade remedy; and
- Importers attempting to circumvent the trade remedy: this may be done through intentionally mislabelling the targeted commodity and importing it erroneously under a commodity code belonging to one of the out of scope commodities. Other ways of circumventing the trade remedy include importing from the PRC but executing shipment via third countries that are not impacted by the trade remedy, or re-processing the targeted commodity so that it arrives in the UK under a commodity code that is out of scope. The circumvention of trade remedies is a matter of ongoing debate and research.[98]

8.51 It is not possible to attribute the findings to any of these mechanisms nor is it is possible to distinguish these mechanisms from the true impacts of the trade remedy within the analysis as it pertains to this commodity. Identifying the causal impact of the trade remedy on the targeted commodity alone would require trade data at the 10-digit level, not available when writing this report. Therefore, the estimated causal impacts for this commodity must treated with caution as there may be other factors confounding the true impact. On the contrary, it is likely that the estimated impacts serve as upper bounds for the true effect. The confounding factors likely drove up imports and counteracted the intuitively negative impact of the trade remedy. The true impact of the trade remedy is likely to be lower (i.e. negative) than the aggregate effect that is reported.

8.52 Commodity 76109090 is not the only 8-digit commodity code with the issue of imperfect coverage; one of the five 10-digit commodities within 76082089 are out of scope, and one of the three 10-digit commodities within 76082081 are out of scope. Therefore, conclusions for 76109090 naturally extend to these commodities. In particular, the estimates likely represent upper bounds of the true effect. This finding is especially useful for the interpretation of the reported effects for commodity 76082089, which had a reported impact that was not statistically significant for both the SCM and BCI. This result may not be indicative of the trade remedy having no impact on the imports of this commodity; rather, it may be that the true impact is being understated (i.e. being made to look less negative and more positive) because of the import flows of the 10-digit commodity that is out of scope.

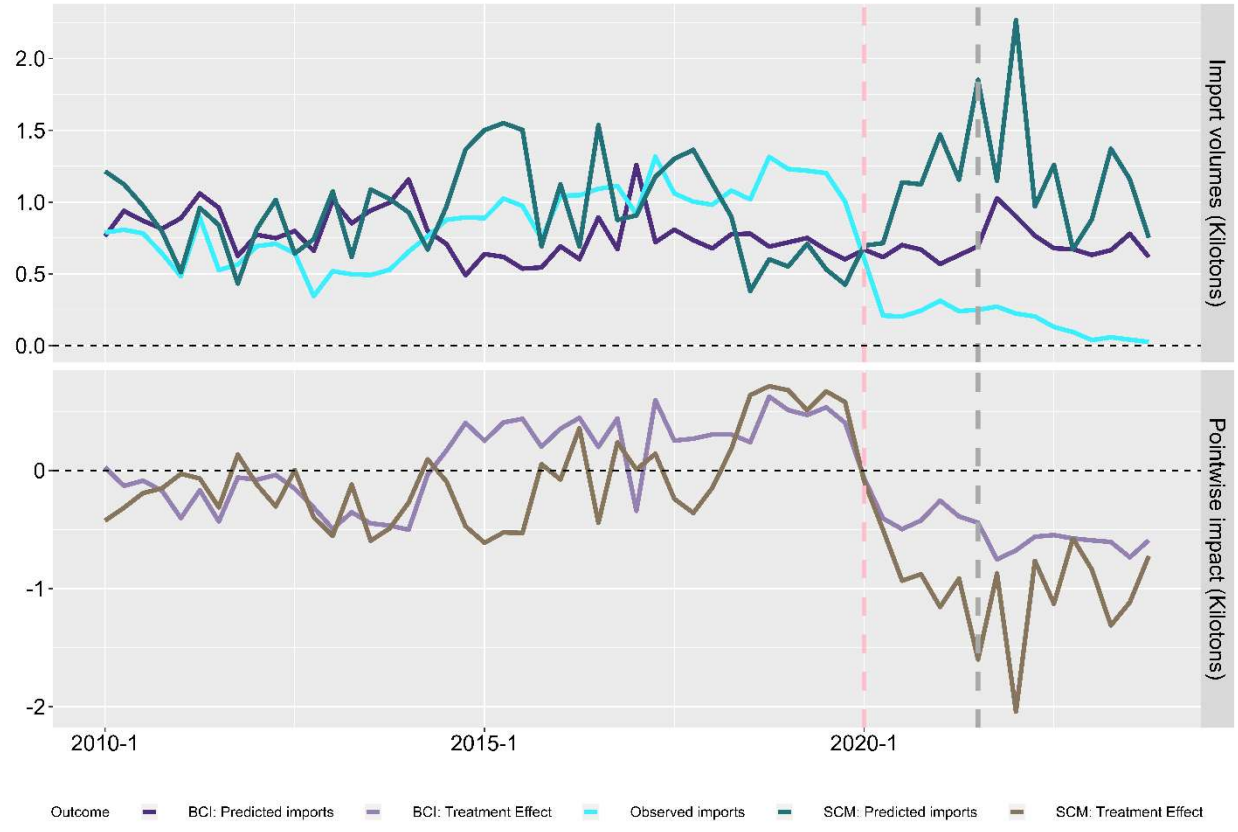
Anticipation effects

8.53 Before continuing with this subsection, the distinction between anticipation effects and pre-initiation effects should be made clear. Anticipation effects are trade remedy effects that are observed prior to initiation because economic agents pre-empt the trade remedy and adjust their behaviour accordingly beforehand. These are effects that are solely due to the trade remedy because they are driven by anticipation of the trade remedy. Pre-initiation effects are any large and atypical movements in imports that are observed prior to initiation. Pre-initiation effects can, in principle, be caused by anything; they can be due to anticipation effects, but they may also include other events that are external to the trade remedy. Anticipation effects are a consequence of the trade remedy and are a subset of pre-initiation effects, but pre-initiation effects may also consist of factors that are unrelated to the trade remedy.

[98] See Economic research into the circumvention of trade remedies

8.54 The analysis for commodity 76041090 uncovered potential pre-initiation effects that may be due to either anticipation effects driven by the trade remedy or factors unrelated to the trade remedy. The figure below displays this.

Figure 13: Comparison of SCM and BCI for commodity 76041090



Notes: The first panel from the top shows the predicted imports for the SCM, the predicted imports from the BCI and observed imports of commodity 76041090 over time. The y-axis shows import volumes in kilotons while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line and the date that the anticipation effects seem to first appear is signified by the vertical dashed pink line. The second panel the difference between the observed and predicted imports using the SCM and BCI for commodity 76041090 over time. The y-axis corresponds to the difference between the predicted imports and observed imports shown in the first panel and represents the effect of the trade remedy in each period. Source: GT Analysis.

8.55 The figure above shows the import volumes predicted by the SCM and BCI and the corresponding estimated impacts. The grey vertical line indicates the initiation date and the pink vertical line indicates the Q1 2020. From the figure, it appears as though observed imports began falling prior to the initiation date with the decline appearing to have begun in Q1 2020. This result may be due to anticipation effects (i.e. that importers pre-empted the commencement of the trade remedy prior to the initiation date and adjusted their imports accordingly) or pre-initiation effects that are unrelated to the trade remedy. Understanding the source of pre-initiation effects (i.e. determining whether they due to anticipation effects or other factors unrelated to the trade remedy) is important as it has implications for what can be interpreted from the results and what steps can be taken to reach this interpretation. There are a few key steps that must be taken by the evaluator when pre-initiation effects are suspected:

- The source of the pre-initiation effects must be identified: there must be reasonable conceptual and, where possible, statistical evidence to ascribe pre-initiation effects to either anticipation effects or specific exogenous factors;

- If anticipation effects have been identified as the source of the pre-initiation effects, then changes must be made to the empirical set-up so as to aggregate these effects into the total effect of the trade remedy; and
- If factors external to the trade remedy have been identified as the source of the pre-initiation effects, then this indicates that a crucial identification assumption may have been violated. Large deviations between observed imports and predicted imports that arise in the pre-initiation period due to factors that are unrelated to the trade remedy (e.g. COVID-19 pandemic) suggest that there are unique drivers of the targeted commodity's imports that are not being captured by the comparators' imports. This suggests that comparator commodity imports are a poor proxy for the targeted commodity's imports, and that the predicted imports in the post-initiation period do not capture counterfactual imports in absence of the trade remedy. This implies that the impacts estimated by the models may not be indicative of true causal impacts. If this has been determined to be the case, then there one of two options that can be pursued:
    - The evaluator can try to separate these external effects from the trade remedy impacts and identify the trade remedy impacts in isolation; and
    - If the evaluator is unable to separate the trade remedy impacts from the exogenous pre-initiation effects, it is not possible to identify the true impact of the trade remedy and the results must be caveated accordingly.

8.56 Each point is considered in turn as it relates to this case study.

Identifying the source of the pre-initiation effects

8.57 First, the argument for the pre-initiation effects being due to anticipation of the trade remedy will be considered. The EU announced its own of initiation of an anti-dumping proceeding concerning imports of Aluminium Extrusions originating in the PRC at a time that roughly coincides with the beginning of the pre-initiation effects in the data. This proceeding was announced in February 2020 and targeted all the commodities that were within scope for the UK investigation discussed in this case study. It may be that UK importers of commodity 76041090 foresaw that an investigation in the UK would be imminent following the EU's investigation and adjusted their behaviour accordingly. The one issue with this theory is that the EU's investigation included all the commodities targeted by this trade remedy, but anticipation effects for are only seen for this commodity and none of the others. This could be explained by a heterogeneous response from importers across commodities. For instance, it may be that importers believed that the UK would be more likely to investigate this commodity, or that demand for this commodity is more sensitive to price shocks, such that the anticipation effect was larger for this commodity relative to others.

8.58 It may also be that the pre-initiation effects were driven by events unrelated to the trade remedy. Such an event would be the effect of the COVID-19 pandemic and the economic slowdown that followed on from the lockdowns that roughly began in Q1 2020. A potential counterpoint to this argument is that the impact of the pandemic was systemic and should, in theory, have been felt simultaneously across all commodities. However, pre-initiation effects are only observed for this commodity and none of the others. It can be argued that the absence of pre-initiation effects in any of the other targeted commodities is evidence that the pre-initiation effects observed for this commodity are too localised to be attributed to the pandemic. Namely, if the pandemic were responsible for these pre-initiation effects, one would expect to see them in at least some of the other targeted commodities given how widespread the impacts of the COVID-19 pandemic were.[99]

8.59 The underlying mechanisms of potential pre-initiation effects are a subject of further research and are beyond the scope of this study. Nevertheless, it is important to understand how these pre-initiation effects may be influencing the estimated trade impacts of the trade remedy and what causal effects can be uncovered in light of them. The first step is understanding the source of

[99] A counterpoint to this is that it may still be plausible for the pandemic to be responsible for these pre-initiation effects if the effects of the pandemic were uniquely large for this commodity and none of the other target commodities. For example, if production of this commodity was atypically concentrated in a single area and production in this area stopped during the pandemic, then the COVID-19 pandemic impacts for this commodity may be notably higher than the remaining commodities.

potential pre-initiation effects. The next section illustrates the steps that follow from the insights yielded in this step.

Pre-initiation effects due to anticipation effects

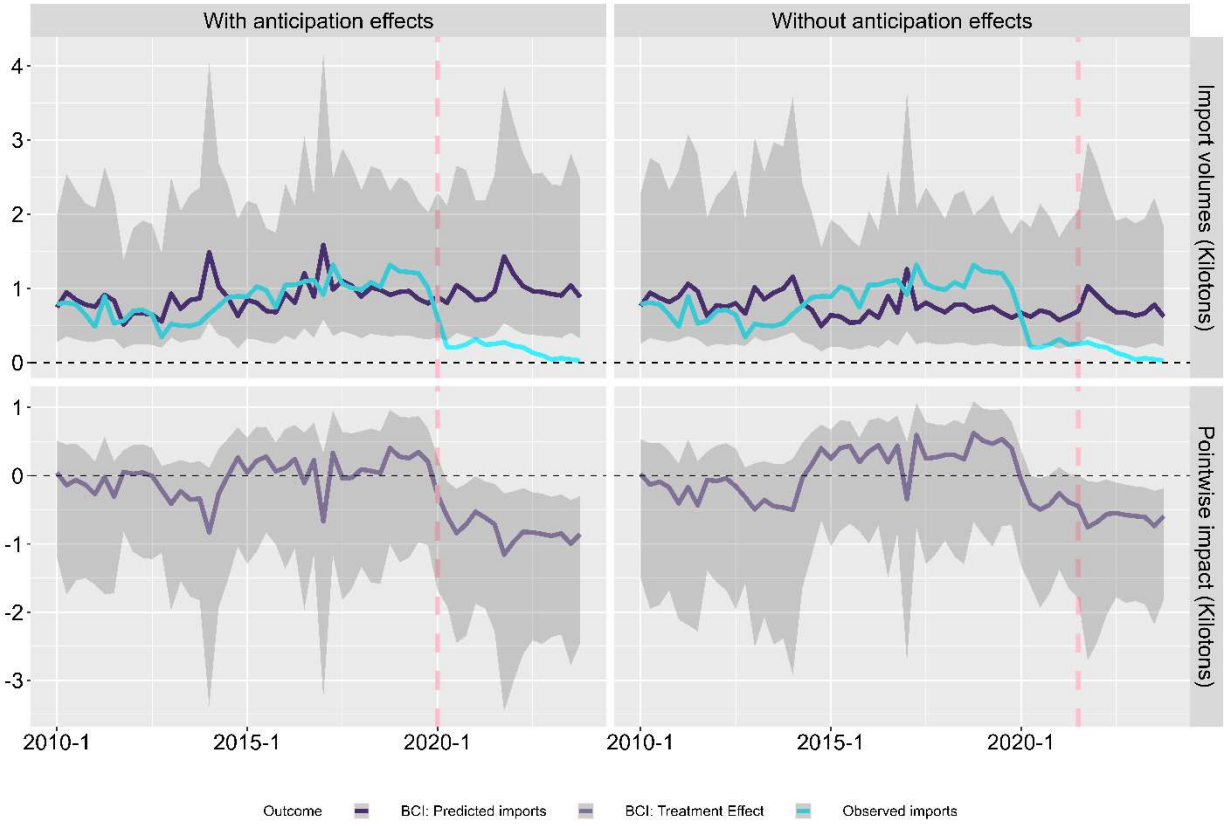
8.60 If pre-initiation effects are due to importers anticipating the trade remedy and adjusting their behaviour beforehand, then these anticipation effects are part and parcel of the overall effects of the trade remedy and must be accounted for in the econometric approach. Failing to account for valid anticipation effects underestimates the impact of the trade remedy on imports in at least two ways:

- The periods prior to the initiation date are not included when calculating the effects of the trade remedy. However, if anticipation led to imports responding sooner than the initiation date, the analysis is not including effects that should be included; and
- The model, whether SCM, BCI or another model, estimates the predicted value of imports in absence of the trade remedy using all the data in the pre-initiation period. If anticipation effects begin before the initiation date, then the model falsely ascribes the anticipation effects as being a natural part of the data. Thus, the model incorporates these effects into the estimated counterfactual, and this forces the predicted imports to be closer to observed imports than the true counterfactual imports would have been in in the post-initiation period.[100]

8.61 Altogether, anticipation effects should be considered as part of the total impact of the trade remedy and should be accounted for in the calculations. This can be done by estimating the model using only data prior to the date that the anticipation effects began. For ease, the date that the anticipation effects began is referred as the anticipation date. This is juxtaposed to the current approach where the model is estimated by using all data prior to the initiation date. Thereafter, the model should be used to predict import volumes following the anticipation date and the difference between predicted and observed import volumes in the period after the anticipation date constitutes the impact of the trade remedy. This is illustrated in the figure below.

[100] True counterfactual imports refer to the imports that would have been observed if the remedy did not take place.

Figure 14: Trade remedy impact for commodity 76041090 using BCI with and without anticipation effects



Notes: The two plots in the top left and top right panels show the predicted imports for the SCM BCI and observed imports of commodity 76041090 over time. The y-axis shows import volumes in kilotons while the x-axis shows the date for both plots. The plot in the top left panel shows predicted imports assuming the trade remedy began from the anticipation date and the plot in the top right shows the predicted imports assuming the trade remedy began on the initiation date. The anticipation date and the anticipation date are signified by the pink vertical dashed line for the two figures in the left panels and the two plots in the right panels, respectively. The two plots in the bottom left and bottom right panels panel the difference between the observed and predicted imports using the BCI for commodity 76042990 over time. The y-axis corresponds to the difference between the predicted imports and observed imports shown in corresponding plots in the top left and the top right panels. From the bottom left panel to the bottom right panel, these represent the effect of the trade remedy in each period assuming the trade remedy began on the anticipation date and on the initiation date, respectively.
Source: GT Analysis.

8.62 The figure above shows the estimated impact of the trade remedy for commodity 76041090 using the BCI in a specification that accounts for anticipation effects and a specification that does not account for them. The specification that accounts for anticipation effects estimates the model in the period prior the anticipation date and estimates treatment effects for the period following the anticipation date. The specification without anticipation effects carries out the corresponding analysis using the initiation as previously done. A key observation is that the treatment effect is larger when anticipation effects are accounted for. This is shown more explicitly in the table below that compares the effect of the trade remedy with and without anticipation effects.

Table 18: Impacts with and without anticipation effects

Scenario	Aggregated Treatment effect (Kilotons)	Average Impact (%)	P-value for Average Impact
Anticipation effects present	-9.50	-86.11	0.000
Anticipation effects absent	-6.83	-81.80	0.000

Source: GT Analysis.

8.63 The results in the table above show that the impact of the trade remedy is higher when anticipation effects are accounted for, especially with respect to the aggregate impact. The analysis shows that failing to account for anticipation effects caused the BCI to underestimate the aggregate impact by 28% (i.e. the aggregate impact without anticipation effects is 28% lower than the aggregate impact with anticipation effects). This highlights that failing to account for anticipation effects can have drastic impacts on the estimated impact of a trade remedy.

Pre-initiation effects due to exogenous factors

8.64 If the pre-initiation effects are driven by confounding events such as COVID-19 pandemic, the approach taken with anticipation effects outlined above would not be appropriate. The change in imports was driven by an event other than the trade remedy; therefore, the effect trade remedy must be separated from the effect of the confounding event for the true causal impact of the trade remedy to be identified. In theory, movements in imports driven by such confounding events should be captured by the comparator commodities. SCM and BCI are meant to use the control commodities to create a counterfactual of the target commodity that already accounts for confounding events in order for these approaches to be valid.

8.65 If the combination of comparator commodities does not capture these events, then they may not be suitable comparators for counterfactual analysis. In this case, an advisable first step would be to look through all the comparator commodities and restrict the set of comparator commodities to those that most closely align with the target commodity in terms of the descriptions associated with their 8-digit commodity codes and in terms of import volumes and prices over time.[101] This is done with the aim of limiting the comparators to those that are most likely to also have been affected by the exogenous factor and thus enable for the true impact of the trade remedy to be identified. If this proves to be ineffective, it may be necessary to identify other variables that are both exogenous (i.e. unrelated to the trade remedy) and capture the impact of the shock.

8.66 Regardless of which route is taken, the only way to identify the impact of a trade remedy in the midst of a confounding shock is to ensure that the comparators used to predict the counterfactual capture this shock in some way. Failing this, it would not be possible to perfectly detangle the impact of the trade remedy from the impact of the shock within the pre-initiation effects. If the evaluator is unable to separate the impact of the trade remedy from the impact of the pre-initiation effects, then it may be possible to report the aggregate effect of trade remedy and caveat the interpretation of the results accordingly. The degree to which this exercise is informative is contingent upon the sign (i.e. positive or negative) of the impact of the shock and the hypothesised sign of the trade remedy impact.

8.67 For example, if the trade remedy is hypothesised to reduce imports and the pre-initiation effects are known to increase imports, then the negative impact of the trade remedy would be understated (i.e. the negative impact of the trade remedy is made less negative by the pre-initiation effects). The interpretation of the aggregate impact in such a scenario would be that it is a conservative estimate of the impact of the trade remedy. The pre-initiation effects would be acting against the

[101] For example, the evaluator may limit the pool of comparators to commodities that share the same 4-digit or 6-digit commodity code. The evaluator may also compare the time series of the prices and import volumes of the comparators to the targeted commodity, and limit the comparator set to N (where N is some arbitrary but large number) commodities that are closest to the targeted commodity on average. Additionally, each 2-digit, 4-digit, 6-digit and 8-digit classification has a corresponding description that explains what kind of commodities fall within the categorisation.

trade remedy impacts; therefore, the aggregate impact would indicate an upper bound of the true impact (i.e. the true impact would be more negative than the aggregate impact).

8.68 The interpretation of the aggregated impact becomes more ambiguous if the impact of the trade remedy and the pre-initiation effects have the same sign. For instance, suppose that both the hypothesised trade remedy impacts and the pre-initiation effects negative. The aggregate impact may be the product of one of three outcomes:

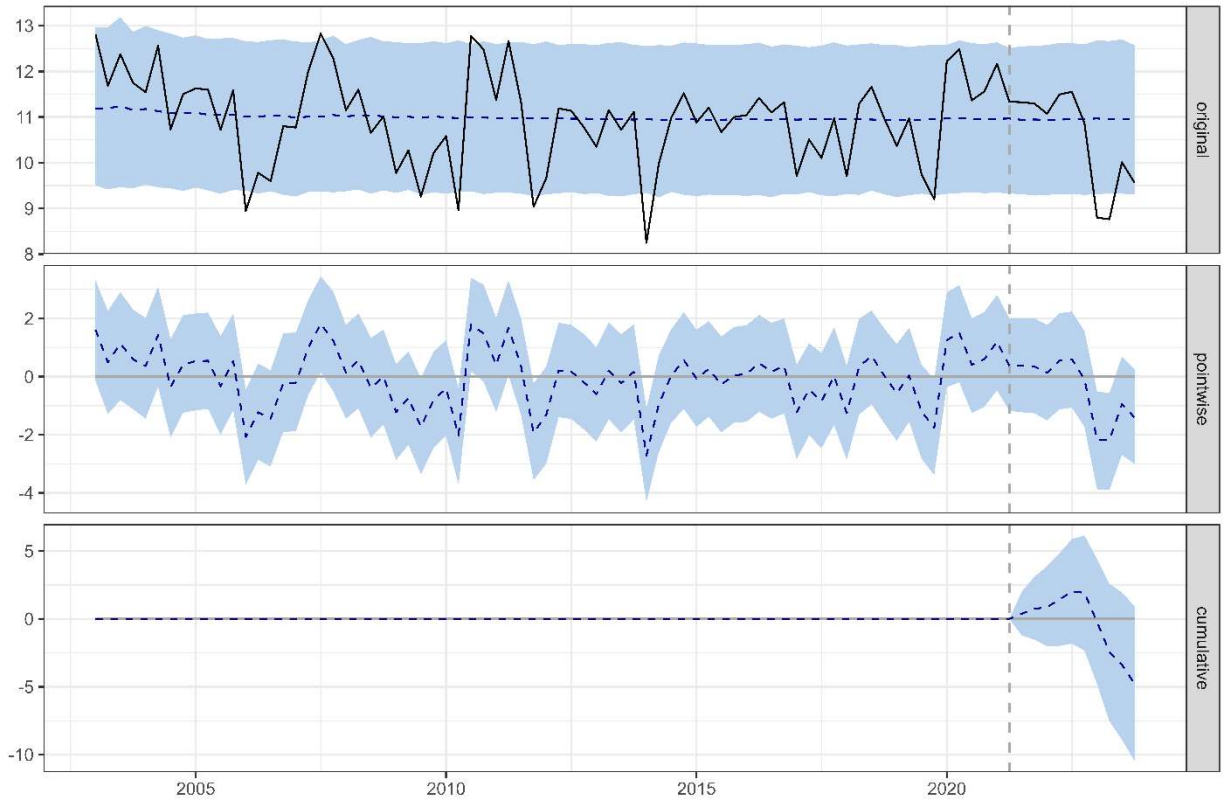
- the trade remedy had a negative impact that was reinforced by the negative pre-initiation effects;
- the trade remedy had no impact and the aggregate impact is solely driven by pre-initiation effect; or
- the trade remedy had a positive impact that is being counteracted by the pre-initiation effects.

8.69 The available data would not allow the evaluator to discern which of these reasons is driving the results, thus the aggregate impacts would be difficult to interpret. In any case, bounding of the true impact is contingent upon having realistic prior assumptions about the sign of the trade remedy impact and the sign of the impact of the exogenous factors driving the pre-initiation effects. If this information is not known, then very little can be said regarding the interpretation of the estimated effects.

Comparator commodities poorly predicting observed imports

8.70 A key finding was identified when using the BCI for commodity 76041010. In particular, the predicted imports were almost completely stable over both the pre-initiation and post-initiation periods. This is shown in the figure below.

Figure 15: Trade remedy impact for commodity 76041010 using Bayesian causal impact (BCI)

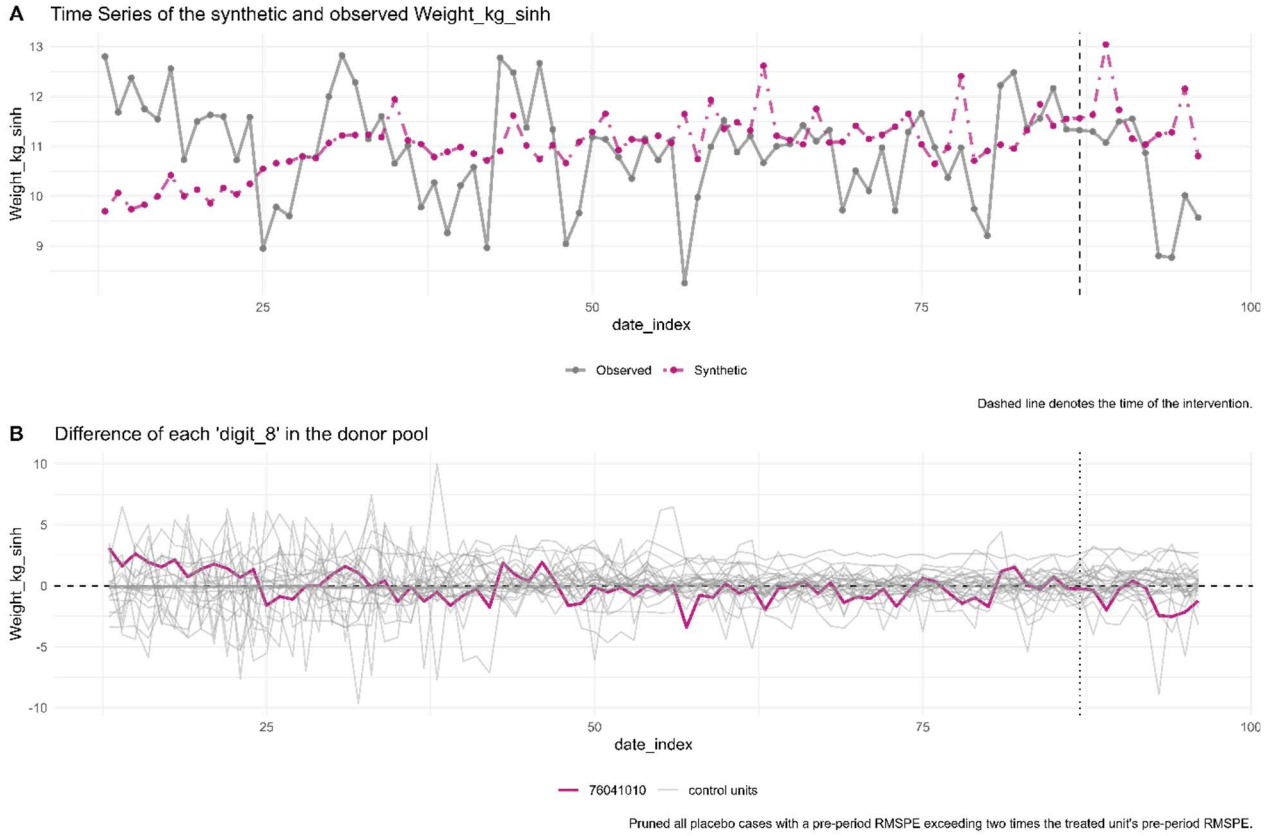


Notes: The first panel from the top shows the predicted (dashed line) and observed (solid line) imports of commodity 76041010 over time using the BCI. The light blue shading represents the 95% confidence interval around the predicted imports. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line close to the end of the time series. The second panel the difference between the observed and predicted imports for commodity 76041010 over time. The light blue shading represents that 95% confidence interval around the estimated treatment effect. The y-axis corresponds to the difference between the two plots shown in the first panel and also represents the effect of the trade remedy in each period. The third panel represents the accumulated treatment effect: it is the sum of the treatment effect from the initiation date going forwards. The y-axis shows the accumulated treatment effect in terms of the inverse hyperbolic sine of import volumes. The light blue shading represents that 95% confidence interval around the estimated accumulated treatment effect.
Source: GT Analysis using CausalImpact.R package in R.

8.72 The figure above shows that the predicted imports using the BCI are equal to a constant value for the entire sample. This suggests that the comparator indices are not explaining any variation in observed imports. This could be due to observed imports being so noisy that the BCI interprets observed imports to be an unpredictable, random sequence that is centred on the average value of imports in the pre-initiation period. The inability to distinguish meaningful variation in imports from random noise is expressed by the fact that the average impact of the remedy is found to be statistically insignificant (i.e. the p-value for the average impact in Table 18 is above 0.05).

8.73 The finding of the BCI is somewhat mirrored in the results using the SCM. The figure below shows the predicted imports and estimated impact of the trade remedy using the SCM. Predicted imports appear to be somewhat less static than with the BCI, but they still appear to be stable and centred around the mean level of imports in the pre-initiation period. There does appear to be a small spike in predicted imports immediately after the initiation date, but the average impact of the trade remedy is not statistically different from zero.

Figure 16: Trade remedy impact for commodity 76041010 using synthetic control method (SCM)



Notes: Panel A shows the predicted and observed imports of commodity over time using the SCM. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the time periods denominated by an index. The initiation date is signified by the black vertical dashed line close to the end of the time series. Panel B shows the difference between the observed and predicted imports for commodity 76081000 over time. The y-axis corresponds to the difference between the two plots shown in Panel A and also represents the effect of the trade remedy in each period. The pink line represents the targeted commodity and the grey lines correspond to the placebo treatment effects of each comparator commodity used to generate the predicted imports. Source: GT Analysis using tidysynth.R package in R.

8.74 Both methods appear to suggest that the import data for this targeted commodity is so noisy that the comparators are unable to predict any meaningful variation from the time series. The key solution to this issue is to introduce comparators that possess more explanatory power to the models. This can be achieved by identifying other commodities that are likely to be more closely aligned to the target commodities' 8-digit description and adding them to the sample of comparators, or identifying macro variables that may explain some of the variation in the target commodities' imports. Some macro variables include the exchange rate between the British pound and the major global currencies that are used to facilitate purchases of this import (e.g. the Chinese yuan or the US dollar). These macro variables can be used to reduce the noise in the data and improve the predictive power of the model. This may in turn enable the models to estimate the impacts of the trade remedy with greater precision.

Substitution and complementary effects

8.75 A key assumption that must be satisfied in order for both the SCM and BCI to estimate the causal impact of the trade remedy is that none of the comparator commodities are impacted by the trade remedy itself. While the trade remedy was only targeted at a specified group of commodities, it may have inadvertently impacted the imports of commodities that are outside of the scope of the trade remedy. These effects are called spillover effects, and two notable spillover effects are substitution effects and complementary effects. These effects can be described as follows:

- Substitution effects occur when the trade remedy impacts import volumes of non-targeted commodity because the non-targeted commodity is a substitute for the targeted commodity. This means that an increase in the price of the targeted commodity will result in an increase in the imports of the non-targeted commodity because the two goods are used interchangeably. For example, if a non-target commodity is a substitute for the target commodity, then the increase in the import price of the target commodity caused by the trade remedy will result in an increase in the import volumes of the non-target commodity (e.g. butter and margarine).
- Complementary effects occur when the trade remedy impacts the imports of a non-targeted commodity because the non-targeted commodity is a complement of the targeted commodity. This means that an increase in the price of the targeted commodity due to the trade remedy will result in a reduction in the imports of the non-targeted commodity because the two goods are used in alongside one another. For example, if a non-target commodity is a complement for the target commodity, then the increase in the import price of the target commodity caused by the trade remedy will result in a decrease in the import volumes of the non-target commodity (e.g. tennis rackets and tennis ball).

8.76 The presence of substitution and complementary effects in certain comparator commodities will mean that these commodities will give a misleading impression of what the imports of the target commodity would have been in absence of the trade remedy and will cause the estimated treatment impacts to be biased. Therefore, it is essential that all commodities that are contaminated by spillover effects are removed from the set of comparator commodities that are used to predict counterfactual imports. Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC outlines the issue of spillover effects and attempts to mitigate this. However, due to time constraints, the analysis does not include results for the preferred strategy for identifying comparator commodities that may be influenced by spillover effects and removing them from the sample. Thus, it is possible that the analysis may be impacted by substitution and complementary effects.

8.77 There is no definitive way of identifying the influence of substitutes of complementary commodities on the current results. Visual inspection of the treatment effects of some commodities may allude to the presence of spillover effects. For instance, Figure 11 displaying the impact of the trade remedy for commodity 76042990 shows that the BCI predicted a strong an abrupt spike in imports in the post-initiation period. Similarly, Figure 13 displaying the impact of the trade remedy for commodity 76041090 shows that the BCI predicted a strong upward spike in imports immediately following the initiation date while the SCM shows a more extreme and persistent spike following the anticipation date. These spikes appear to be atypical when compared to the levels of observed imports prior to initiation. Therefore, it is possible that set of comparator commodities consists of substitutes and that the spike in predicted imports is being driven by a surge in demand for these substitutes in the wake of the trade remedy.

8.78 Conversely, these spikes may be an artefact of the inverse hyperbolic sine transformation imposed on imports when conducting the analysis. The inverse of the hyperbolic sine is a transformation brings large values and small values of import volumes closer together. This tendency becomes more extreme for larger values of the import volumes. Therefore, when import volumes are transformed back into kilograms following the analysis, the reported results can show spikes and abnormalities that were not present in the analysis beforehand.[102] For instance, when Figure 11 is reconfigured to show the impact of the trade remedy on commodity 76042990 in terms of the inverse hyperbolic sine, the spike in the post-initiation period is not as visually prominent.[103] However, this explanation is not wholly sufficient as notable spikes in predicted imports do appear at times even when imports are in terms of the inverse hyperbolic sine.[104]

8.79 The concern of spillovers biasing the estimated impact of the trade remedy is one that must be taken seriously. Therefore, a step-by-step process has been outlined. This could be used by the TRA to minimise the number of comparator commodities that may have experienced spillover

[102] See Appendix 1 for a discussion on the inverse hyperbolic sine transformation and how it differentially impacts numbers of varying sizes.
[103] This is shown in Appendix 1.
[104] This is illustrated with the SCM output of the trade remedy impact on commodity 76109090 shown in Appendix 1.

effects from the trade remedy due to substitution effects or complementary effects, or commodities that may have been disproportionately influenced events external to the policy itself (e.g. they may be the target of other remedies). Such commodities may be inappropriate comparators for estimating the impact of the trade remedy on target commodities.

Conclusion

8.80 This case study focused on the imposition of a new UK measure in a context where there is an abundance of data in terms of the number of time periods and the number of comparators. This illustrate how both the tabular format and the decision tree format of the methodology selection framework can be applied to select the appropriate models for estimating causal impact of the trade remedy. The models implemented were the SCM and BCI. These models led to similar findings with respect to certain commodities; the trade remedy led to a notable and statistically significant reduction in the volume of imports. However, the findings of models diverged with respect to other commodities. In particular, the BCI was able to estimate causal impacts more precisely and thus detected statistically significant trade remedy impacts for a greater number of commodities. This may be due to the ability of the BCI to generate more precise and less biased estimates of causal impacts when the underlying data is noisy.

8.81 Additional themes that were captured within this case study include:

- Counterintuitive trade remedy impacts: results suggested that the trade remedy resulted in increased imports for commodities that should have been made relatively more expensive as a result of the anti-dumping measure. Most likely, this is due to imperfect coverage between the unit of analysis (i.e. the 8-digit level commodity codes) and the unit targeted by the measure (i.e. the 10-digit level commodity codes). Notably, some of the estimates reported at the 8-digit level were a combination of impacts due to the trade remedy and import movements for commodities not targeted by the trade remedy. Further analysis of import behaviour at the 10-digit commodity code level is required to both empirically separate the true impact of the trade remedy from external factors, and to understand the mechanisms driving the imports of non-targeted commodities within the same 8-digit classification as targeted commodities;
- Anticipation effects: results suggested that importers anticipated the trade remedy and adjusted their importing behaviour in response to the trade remedy investigation prior to the initiation date. The initiation of a similar EU trade remedy prior to the initiation date of the corresponding trade remedy investigation of the UK may have led importers to pre-empt the trade remedy taking effect in the UK. Backdating the initiation date within the analysis could capture these anticipation effects within the causal impact estimates. The approach taken by the evaluator to uncover causal impacts would be different if the pre-initiation effects were found to be due to exogenous factors unrelated to the trade remedy;
- Comparator commodities poorly predicting observable imports: the BCI was not able to accurately predict observed imports in the pre-initiation period because the explanatory power of the comparator commodities was poor. Including additional explanatory variables (e.g. exchange rates or more qualitatively similar commodities) could reduce the noise in the model and generate more precise estimates of the trade remedy impact; and
- Substitution and complementary effects: comparator commodities that may have been affected by the trade remedy because they are substitutes of or complements for the target commodity should be removed from the sample. Erratic jumps shortly following the initiation date suggest that did not all commodities affected by spillovers were removed. There are several conceptual and quantitative measures that could minimise the number of comparator commodities that may be impacted by spillovers. This are presented in Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC.

Illustrative Case Study 2: TD0014 Heavy Plate from the PRC

Introduction

8.82 This case study illustrates how models from economic theory can be used to explore the impact of trade remedies when there is no observable counterfactual from real-world data (e.g. because there has been no recent change in policy or data is not available).

8.83 The case study uses a variant of the models developed by authors including Brander, Spencer and Krugman in the early 1980s (part of the 'New Trade Theory' literature). Essentially, a Cournot oligopoly model (adapted to capture international trade and tariffs) is constructed and then 'calibrated' with real-world information to explore the impact of trade remedy measure (in particular, the effect of retaining an import tariff).[105] This model was chosen because, in a Cournot model, firms are assumed to compete on quantities (rather than price) which is consistent with an anti-dumping environment (see below). It is also a relatively simple model, which could easily be adapted to other settings.

8.84 To illustrate the application of these models, the case study considers duties imposed by the UK on Heavy Plate from the PRC. An import tariff of around 70% has been imposed on these imports since 2017. Importantly, TRA's conclusion through its transition review was not to change the scope/form/level of the measure, meaning that the unobserved counterfactual is not well defined. This means that econometric approaches to evaluation are not suitable[106]. The case study focuses on the impact on market share (but other variables such as profits, consumer welfare and so forth can also be explored through these models).

Putting it into practice

8.85 The model here is a simple Cournot model in which firms compete on quantity (specifically, they choose how much of the commodity to supply to the domestic market taking as given the amount supplied by other firms). The products of the foreign and domestic firms are assumed to be identical, and there is no cooperation between firms. A full description and derivation of the model is described in Appendix 2: Derivations for illustrative Case Study 2: TD0014 Heavy Plate from the PRC.

8.86 The model gives rise to an equation for the domestic firm's market share as a function of price (p), the domestic firm's marginal cost (c_i), the foreign firm's marginal cost (c_j) and the import tariff (t):

$$s_i = \frac{p - c_i}{2p - c_i - c_j - t} \tag{2}$$

8.87 This equation is intuitive. Note that t appears in the denominator with a negative sign, meaning that a higher tariff increases the domestic market share. Note also that if the import tariff is zero $(t = 0)$ and the firms have the same marginal cost $c_i = c_j$ the market share becomes $s_i = 0.5$ or 50%: since the firms have the same marginal costs in the domestic market and no tariff is applied, the market is split equally between the two firms.

[105] A Cournot oligopoly model is a theoretical formulation of strategic interactions between profit-maximising firms competing for a limited market. The objective of firms in this formulation is to maximise their profits by setting production quantities that allow this while also accounting for the quantities set by their competitors.
[106] More information about the case is available in the TRA's recommendation to the Secretary of State (TRA, 2023). TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Calibrating the model

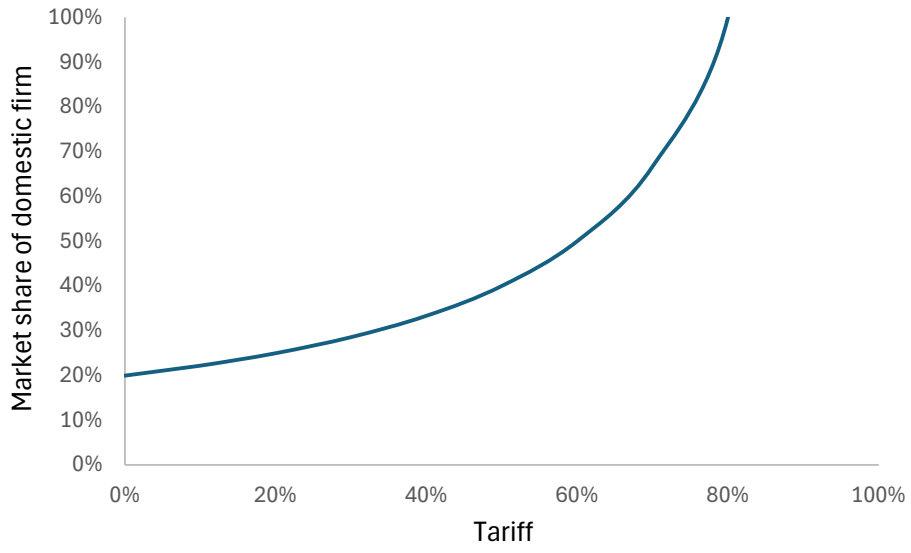
8.88 In order to use this framework to understand the possible impact of an import tariff, the model had to be 'calibrated' (i.e. choose values for parameters in the equation above that are broadly representative of the real-world):

- Price. A useful starting point is to 'normalise' the price level p: since prices are just arbitrary numbers that could be expressed in any currency (pounds, dollars, millions of pounds or any other currency); one approach is to the price equal to 1 and express all other parameters relative to that price. This is a common technique when calibrating models like this one;
- Marginal cost of the domestic firm, c_i. Various studies have considered price-cost-margins in the steel industry and suggest that margins may be around 5% to 20% (see for example Matsuoka (2003) and Flath (2009)[107]). Assuming the higher value (which might be reasonable since the only interest is in marginal costs), this would imply $c_i = 0.8$; and
- Marginal cost of the foreign firm, c_j. As an illustration of how to calibrate this, at the current tariff level (of around 70%), the market share of the domestic firm is two-thirds (TRA, 2023).[108] Using equation (8) with $t = 0.7$, $s_i = 0.67$ and $c_i = 0.8$, the implied marginal cost of the foreign firm is $c_j = 0.2$.

Results

8.89 Figure 17 plots the relationship between the import tariff and the market share of the domestic firm. As the import tariff rises it increases the foreign firm's effective costs in the domestic market, giving a competitive advantage to the domestic firm. The domestic firm's market share rises (and the foreign firm's market share falls).

Figure 17: Impact of an import tariff



Source: GT Analysis.

Table 19: Import tariff and implied market share

Import tariff	0%	10%	20%	30%	40%	50%	60%	70%	80%

[107] It is acknowledged that these papers are relatively old, and the context is by no means a perfect match for the UK steel market. They may nevertheless be useful in understanding the approximate magnitudes of some of the parameters. Of course, the case study's purpose is to illustrate the process of using models from economic theory in an evaluation context (rather than providing a precise estimate of the impact). A fuller study could seek to explore a fuller range of sources.
[108] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Implied market share	20%	22%	25%	29%	33%	40%	50%	67%	100%

Source: GT Analysis.

8.90 This information can be used to derive an illustration of the impact of retaining the import tariff in this setting. The import tariff being applied is circa 70%, resulting in a domestic firm market share of around 67% (as per the TRA finding). The model can then be used to construct a counterfactual – and estimate the market share – for other tariff levels to help evaluate the impact of the import tariff. For example:

- in a counterfactual where a 50% tariff was applied ($t = 0.5$) (for example if 50% was the most-favoured nation (MFN) import tariff),[109] the model would imply a domestic market share of $s_i = 40\%$. This would imply that, compared to that counterfactual, the impact of retaining the import tariff is to uphold the market share of the domestic firm by around 27 percentage points.
- in a counterfactual where the import tariff is removed altogether ($t = 0$), the implied domestic market share would fall all the way to $s_i = 20\%$ (a difference of almost 50 percentage points). In other words, according to the model, retaining the import tariff results in around half of the market purchasing from the domestic producer that would otherwise procure from the foreign supplier.

8.91 As a sense-check, the domestic market share prior to the imposition of the import tariff (before 2017) was 30% to 40% (according to the TRA).[110] This suggests that the model is potentially yielding broadly credible results (albeit potentially, but not necessarily, over-predicting the impact of removing the import tariff somewhat).

Practical considerations

8.92 The above gives an illustration of how models from economic theory can be used to generate a counterfactual in circumstances where it is not possible to observe real-world changes as a result of a trade policy.

8.93 It should be noted that the model could be adapted to different circumstances. For example, this case study has considered the simplest case of one domestic and one foreign firm. But this could be generalised to any number of firms (although the model clearly becomes more complex).

8.94 More generally, there are several different directions in which modelling of this type could go. Some important practical considerations when undertaking modelling of this type are:

- **Choice of model.** The example above uses a simple oligopoly model (specifically a Cournot model, following the literature of Brander (1981) and others) since it captures some of the key features of the market in question. However, there is a very wide range of models that could be drawn from that have different features and lend themselves to different circumstances (and which, inevitably, give different results to one another). Some key questions for consideration in the choice of model include:
  - Do firms compete on quantity, price or other variables? If firms compete on quantity, Cournot type models may be most suitable (they have been designed precisely for this purpose). However, price competition may be better approximated by Bertrand or differentiated product Bertrand models (in these models, firms explicitly choose price rather than quantity).
  - Is firm entry/exit likely? If the number of firms is fixed, oligopoly models (e.g. Cournot or Bertrand) may be appropriate: these models assume a fixed number of firms, by construction. If firms are likely to enter or exit the market as a result of trade policy,

[109] In the context of trade remedies, the trade remedy is sometimes applied over and above the most favoured nation (MFN) tariff. If an MFN tariff exists, the model could be used to evaluate the trade remedy simply by comparing the outcomes of interest assuming the MFN tariff and MFN tariff plus any additional tariff as a result of the remedy.
[110] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

models of Chamberlinian monopolistic competition may be more suitable (in these models, firms enter/exit the market until so that (economic) profit is eroded to zero).

- How differentiated are the goods of different (especially foreign versus domestic) producers? Many standard models (e.g. Cournot) assume identical products. But other models recognise differences between domestic and foreign firms' wares and incorporate 'love of variety' (e.g. those of Krugman (1979, 1980)) in consumers' preferences.
- Is it more relevant to look at firm-level or economy / sector-wide effects? Firm level effects may be best described through microeconomic models of oligopoly and/or monopolistic competition (as above). If wider macroeconomic effects are the topic of interest, Computable General Equilibrium (CGE) models may be better suited.

- **Choice of parameters / calibration.** As illustrated above, in using models from economic theory to assess the implications of trade policy, it is necessary to 'calibrate' key parameters so that models simulate the real-world as closely as possible. Calibrating these parameters normally requires desk-based (or even primary) research. Data to calibrate models is often very 'patchy': it's rarely the case that perfect information is available and normally judgement is needed. The table below sets out some of the most common parameter types and example sources of information that can be used to calibrate them. There is typically a great deal of uncertainty around parameter choice, with information on parameter values often being scarce or contradictory. In that context, when undertaking analysis of this type it is important to explain the limitations of the analysis and undertake sensitivity testing (i.e. by using estimates from various data sources to test the range of possible outcomes).

Table 20: Parameters and sources

Parameter type	Example sources of evidence
Market level demand elasticities for a particular industry	Academic literature, industry intelligence
Marginal costs (either in absolute terms or relative to the price level)	Company accounts, academic literature, surveys, industry intelligence
Consumers' utility and firms' production functions (including elasticities of substitution)	Input-output and supply-use tables, academic literature, industry intelligence
Firm numbers, market shares	Trade associations, market research organisations, TRA or other investigation, surveys, industry intelligence
Quantities supplied	Trade associations, market research organisations, TRA or other investigation, surveys, industry intelligence

Source: GT Analysis.

8.95 Overall, models from economic theory can help give useful indications of the impacts of trade remedies, and illustrate the economic mechanisms through which policy affects variables of interest. They may be especially useful where real-world data is not available to construct a counterfactual scenario. However, the models are inevitably oversimplifications of real-world dynamics. In addition, different theoretical models serve different purposes and calibrating them is fraught with uncertainty. As a result, they may be best thought of tools to help illustrate impacts and give an indication of possible size of effects in the context of significant uncertainty (rather than techniques capable of providing precise estimates of trade remedy impacts).

Illustrative Case Study 3: TD0004 and TS0005 – Biodiesel from the USA and Canada

Introduction

8.96 This case study pertained to two trade remedy investigations that involved the UK changing the scope of transitioned EU measures upon completing transition reviews. Both measures were applied to the biodiesel industry; with one being an anti-dumping measure (i.e. TD0004) and the other being a countervailing duty measure (i.e. TS0005). The initial measure began in July 2009 and imposed anti-dumping duties on imports of biodiesel originating in the US and consigned through Canada. On 11 August 2020, the TRA initiated a transition review of the original EU measure to assess whether the measure should be varied or revoked in the UK.[111] The investigation drew a distinction between "renewable diesel" or "Green diesel" (referred to as HVO in the final determination) and other kinds of diesel-goods (referred to as FAME). In particular, the final recommendation revoked the measure in relation to HVO but it maintained the measure with relation to FAME, and this change in scope was imposed from 30 January 2021.[112] The details of the specific commodities and exporters to which the duties were applied are contained in Appendix 3: Model outputs for illustrative Case Study 3: TD0004 and TS0005 Biodiesel from the USA and Canada.

Key dates

8.97 The key dates for this case study are as follows:

- Date of initiation: 11 August 2020. This date will mark as the commencement of the revocation in order to ensure that any anticipation effects that occur prior to the trade remedy's enactment will be captured in the analysis.
- Date of revocation of anti-dumping and countervailing duty measures for HVO goods: 30 January 2021. This date will not inform the analysis in any way.

Synthetic data construction

8.98 The analysis of this case study uses synthetic firm-level data because firm-level data was unavailable due to confidentiality considerations. However, in collaboration with the TRA, synthetic firm-level data was created. This closely resembles the data that the TRA would have access to when it undertakes its investigations. The synthetic data attempted to mirror this real-world data by containing similar variables and a realistic level of granularity and frequency. The data was constructed in the following steps:

- Nature of the trade remedy impact: this case study aims to estimate the impact of the trade remedy on a hypothetical firm that imports and uses HVO biodiesel products.[113] The impacts are only estimated for firms that were exposed to the revocation of the anti-dumping measure. Therefore, the impact results from a reduction in cost for an importing firm following the revocation of the anti-dumping measure. In the basic set-up, the impact of the trade remedy is defined as a permanent 10% reduction in the unit-costs of the importing firm that begins on the initiation date.[114] Other specifications covered in the report will allow for this effect to vary with time. For ease of reference, the firm that is impacted by the trade remedy is defined as

[111] TD0004 Notice of Initiation: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk); TS0005 Notice of Initiation: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[112] TD0004 Final determination: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk); TS0005 Final determination: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[113] While many of the governing principles used to assess the impact of the trade remedy on importers can be carried over into the assessment of producers and upstream/downstream firms, the approach taken would need to be adjusted and tailored to the nature of the problem and the data that is available.
[114] It is equally possible to model the impact of the trade remedy pertaining to the revocation of the countervailing duty measure as an increase in costs following the initiation date. However, the general approach taken to identify causal impacts that is outlined in this subsection remains largely unchanged.

the treated firm; this is because it experienced the 'treatment' of being impacted by the measure.

- Number of time periods: the analysis uses quarterly data spanning from January 2010 to December 2023 (i.e. 56 quarters in total);
- Number of firms: one specification includes 11 firms: one impacted firm and 10 comparator firms; a second analysis includes 31 firms: one impacted firm and 30 comparator firms;
- Costs: firm-level costs are defined only as unit-costs that were generated using basic assumptions.[115] The selection of these parameters does not accurately portray the costs of biodiesel to importers in the UK, but ensures that there was a significant amount of variation across firms in the synthetic data; [116]
- Prices: firm-level prices were treated as a simple 10% mark-up of the underlying unit costs estimated for every firm;
- Demand/Sales: firm-level demand (or sales) was defined a linear combination of a fixed amount (this can be conceptualised as brand loyalty because it is constant over time and is independent of price), the price set by the firm and, where appropriate, the price set by other firms. The sales function was defined in terms of logs;[117] and
- Revenues and profit: revenues are defined as firm-level sales multiplied by firm level price, while profit is defined as total revenue minus total costs (where total costs are total firm-level sales multiplied by firm-level unit costs).

Defining treatment and the treatment group

8.99 In general, the definition of a treated unit when undertaking firm-level analysis differs to the definition in commodity-level analysis undertaken in Case Study 1. Exposure to treatment (i.e. the trade remedy) in the commodity-level analysis is somewhat binary; a commodity code is either in scope or out of scope of a trade remedy. Commodities that are in scope are the treated units while commodities that are out of scope are the control units.[118]

8.100 Treatment is relatively simple and binary at commodity level; a commodity that is within scope is treated while a commodity that is out of scope is untreated. The nature of treatment becomes more nuanced at the firm-level. Primarily, firm-level exposure to the trade remedy based on how firms interact with the treated commodities in the product market. In particular, exposure to the trade remedy will vary depending on whether the firm in question is (i) an importer of the impacted good, (ii) a producer of a like good, or (iii) is in the general supply chain of an importer or like-good producer. The nature of this firm-level interaction with the product market will in turn inform the approach used to investigate the causal impact of the trade remedy. The approach for assessing

[115] In particular, unit-costs are set to be a linear combination of a constant drawn from a uniform distribution, unit-costs from the previous quarter (i.e. a one-period lag), time trends until the fourth polynomial (i.e. linear, quadratic, cubic and quartic time trends) and random noise.

[116] Unit costs are specified in the equation below.

$$cost_{it} = \alpha + \beta_1 cost_{it-1} + \delta_1 t + \delta_2 t^2 + \delta_3 t^3 + \delta_4 t^4 + \varepsilon_{it}$$

Where $cost_{it}$ represents the unit cost of firm i in quarter t, α represents a fixed part of unit-costs, $cost_{it-1}$ represents the unit cost of firm i in quarter $t-1$ (with β_1 representing the influence of past costs on present costs) and $\delta_1 - \delta_4$ represent the coefficients associated with the various polynomials of time trend. ε_{it} represents random noise. α, β_1 and $\delta_1 - \delta_4$ were varied to produce a wide range of unit-costs for the firms in the sample.

[117] Demand is specified in the equation below.

$$\log(sales)_{it} = \alpha + \beta_1 \log(price)_{it} + \beta_2 \log(\text{price})_{\text{jt}} + \varepsilon_{it}$$

Where $\log(sales)_{it}$ represents the log sales for firm i in quarter t, $\log(price)_{it}$ represents the log price set by firm i in quarter t and $\log(\text{price})_{\text{jt}}$ represents price set by firm j in quarter t. β_1 represents firm i's own price elasticity (i.e. the impact of firm i's price on it's own sales) and β_2 represents the cross price elasticity of firm i with respect to firm j (i.e. the effect of firm j's price on firm i's sales).

[118] This definition of the control group comes with the caveat that some control units withing the control group may have been affected due to substitution and complementary effects. The choice of whether these should be included depends on the question of interest to the evaluator.

the impact of the trade remedy will differ depending on which group is the subject of the analysis.[119] The discussion will focus on the impact of the trade remedy on domestic importers.

8.101 The key step in assessing the impact of the trade remedy on domestic importers is to identify which firms have been exposed to the trade remedy through imports (i.e. the treated group) and those which have not (i.e. the control group). Defining these two groups is not trivial and must account for the input mixes (i.e. the resources and factors of production) that firms operate with both before and after and the trade remedy. How the treatment group is defined will have implications on (i) how a suitable control group is selected, and (ii) the interpretation of the estimated trade remedy impacts.

8.102 To illustrate this point, consider a hypothetical economy consisting of three firms: Firm A, Firm B and Firm C. Suppose that a trade remedy investigation is initiated and results in countervailing duty measures being imposed on the imports of commodity X (i.e. the cost of importing commodity X declines). Suppose all three firms have different input mixes and that the firms in this economy can access commodity X only through importing. Suppose that the pre- and post-initiation import behaviours and trade remedy exposures of each firm are summarised in the table below.

Table 21: Hypothetical trade remedy exposure and treatment status

Firm	Commodity X imports pre-initiation	Commodity X imports post-initiation	Trade remedy exposure pre-initiation	Trade remedy exposure post-initiation	Pre-initiation treatment status	Post-initiation treatment status
A	High	High	High	High	Treated	Treated
B	Low	Low	Low	Low	Treated	Treated
C	None	Medium	None	Medium	Not treated	Treated

Source: GT Analysis.

8.103 Suppose Firm A's production process relied heavily upon commodity X prior to the trade remedy. It follows that Firm A would have relatively high level of exposure to the trade remedy as a large proportion of its costs are directly impacted by the trade remedy. Hence, high pre- and post-initiation imports led to exposure to the trade remedy both pre- and post-initiation.

8.104 Conversely, suppose Firm B relied less heavily upon commodity X prior to initiation. Firm B would be less exposed to the trade remedy than Firm A but, nonetheless, exposed to the trade remedy both pre- and post-initiation. Finally, suppose firm C did not import commodity X at all prior to initiation but began importing and utilising commodity X it after initiation by changing its production process. While Firm C had no exposure to the trade remedy pre-initiation, it became increasingly exposed to the trade remedy post-initiation.

8.105 It may be of interest to assess the impact of the trade remedy for all pre-initiation importers of commodity X. The treatment group in this case would be all firms that imported a positive amount of commodity X prior to initiation; Firm A and Firm B. The control group must therefore consist of comparator firms that would be good proxies of Firm A and Firm B in absence of the trade remedy. Notably, Firm C should not be included in this group of comparators because it was impacted by the trade remedy following the initiation. Additionally, firms that may be impacted by any substitution or complementary spillover effects resulting from the trade remedy should not be included in the control group.

8.106 The definition of the treatment group also has implications for how the treatment effect is interpreted. With application to the case above, defining the treatment group as firms that were importers of commodity X pre-initiation would mean that the estimated impact would only be

[119] Another way in which firm-level treatment is non-binary is that firm-level exposure is contingent upon how much a firm interacts with the treated commodity, conditional on how it interacts with it in the first place. For instance, importing firms that import proportionately high amounts of the treated commodity will be more exposed to the trade remedy than firms that import relatively small amounts of the good. This topic will not be explored further within this report but is worth mentioning.

applicable to such firms. It is not necessarily the case that these impacts are generalisable to firms that were not importers of commodity X pre-initiation but became importers of commodity X post-initiation (i.e. Firm C). It may be suitable to define a separate treatment group specifically for such firms and undertake the analysis to identify the impact of the trade remedy on this group. This would also imply that the interpretation of the trade remedy impacts would change; the estimated impacts would only be applicable to post-initiation importers of commodity X that were not importers pre-initiation.

8.107 This simple illustration highlights some key lessons to bear in mind when defining treatment exposure and the treatment group when it comes to firm level analysis. Firstly, treatment exposure is not binary but can vary in intensity and with time depending on the input mix of the firms in the sample. Secondly, the definition of the treatment group will have implications for how a suitable control group is defined and the comparator firms that can be included in the control group. Finally, the definition of the treatment and control groups will have implications for the interpretation of the causal impacts that are identified.[120]

Conceptual framework and model choice

8.108 The purpose of this case study is to provide methodologies that estimate the impact of the trade remedy on the synthetic importing firm's costs, sales, revenue and profit. To estimate this impact perfectly, each of these outcomes would need to be observed for the importing firm in the post-initiation period both in the presence of the trade remedy (i.e. if the measure was revoked) and in absence of the trade remedy (i.e. if the measure was not revoked). Once the outcomes in these two counterfactual scenarios have been identified, the impact of the trade remedy is simply the difference between the outcomes in the two counterfactuals. The outcomes in both counterfactual scenarios are observed synthetic data is being used (i.e. the outcomes with and without the trade remedy are known because they are pre-defined). However, in reality the only outcomes that would be observable are those that arise in the presence of the trade remedy. The unobservability of the counterfactual in absence of the trade remedy creates an identification problem; to estimate the true impact of the trade remedy, outcomes that are unobserved must be identified.

8.109 The methodologies explored will try to overcome the identification problem estimating the outcomes that would have prevailed in the unobserved counterfactual (i.e. if the measure was not revoked for HVO diesel goods but remained as it was when transitioned from the EU) and thereby allow the true impact of the trade remedy to be estimated.

8.110 The methodology selection framework to choose the most appropriate methodology was applied. The particularities of the data and the context of this case study are highly similar to those in Case Study 1. Therefore, the selected method was the BCI and the reasons for its selection according to the framework are highly similar. First, the tabular framework's feasibility criteria in Table 12 is used. The trade remedy resulted in a change in imposed duties, and the data covers both the pre-initiation and post-initiation time periods, consisted of several time periods and several firms. Therefore, all the listed methodologies are feasible in this case. The suitability criteria in Table 13 is then applied. The chosen methods had ease of causal interpretation, were not constrained by time or complexity, and were robust to noise. Therefore, the BCI would be the best option. Application of the decision tree framework in a similar way to Case Study 1 yields identical conclusions. The analysis also presents the results from the SCM to compare the performance of the two methodologies and illustrate why the BCI may be preferred.

[120] The approach to this case study is solely focused on the impact of the trade remedy on importers of the affected commodities. It may be of interest to understand how shifting focus to domestic producers of the like good would change the conceptual and analytical approach and recommendations outlined in this case study. Exposure to treatment would be conceptually similar to this case study in that it will also vary with intensity. However, the extent of treatment exposure for would now depend on the extent of overlap between the range of goods produced by the domestic producer and the targeted commodity. For instance, producers with product ranges that largely consist of close substitutes to the targeted commodities are likely to be more exposed to the trade remedy than firms that produce goods that are less substitutable. The key principles for identifying the causal impact of the trade remedy, however, will remain broadly consistent with those outlined in this case study. However, the mechanisms through which the trade remedy will impact domestic producers will differ to domestic importers, and this will need to be reflected in how the counterfactual is defined and how the results are interpreted.

Unsuitable comparators

8.111 The robustness of the applied methodologies was investigated when unsuitable comparator firms are present in the sample. Unsuitable comparators are defined as comparator firms that may have been inadvertently influenced by the trade remedy in some way (i.e. spillover effects) or are influenced by external factors (e.g. other remedies) that would not have affected the treated firm in absence of the trade remedy. Such spillover effects were discussed in Case Study 1 and include substitution effects, complementary effects or any other effects arising from the trade remedy either directly or indirectly. Having unsuitable comparator firms in the sample can produce biased estimates of the causal impact of the trade remedy because they give misleading impressions of what the outcomes of the treated firm would have been in the absence of the trade remedy. Therefore, removal of unsuitable comparator firms from the sample may lead to more accurate estimates of the true causal impact of the trade remedy.

8.112 Unsuitable comparator firms were introduced to the data in three ways. The first way was by reducing or increasing the costs of some comparator firms in the post-initiation period. This was intended to capture any direct spillovers resulting from the trade remedy or external events that arise simultaneously with the trade remedy. The second way was by modelling substitutionary and complementary relationships into firm-level sales. The sales of some comparator firms were modelled to be positively or negatively related to the price of the treated firm. For comparator firms that sell products that are substitutes for the treated firm's products, the price of the treated firm is positively related to the sales of the comparator firms' products. The opposite is true for comparator firms that sell complements of the treated firm's products. Altogether, 40% of the comparator firms were modelled as being unsuitable comparators for the treated firm due to one of the three factors listed above (i.e. substitution effects, complementary effects and direct effects of the trade remedy).

8.113 Results from analysis carried out on the full sample of comparators were compared to results from analysis on a trimmed sample that excluded the unsuitable comparators. The implications of using unsuitable comparators are then discussed.

Results

8.114 The analysis was carried out using the SCM and BCI methodologies using both the full and trimmed sample. The sensitivity of the findings to adjustments in the underlying data is assessed by adjusting the data in three ways:

- Number of comparator firms: one specification had 10 comparator firms and a second specification had 30 comparator firms. Correspondingly, the number of unsuitable comparator firms was either 4 or 12 (40% of the sample in either case);
- Volatility of the data: there were low volatility and high volatility scenarios. The variance of the error components in the cost and sales functions were 10 times higher in the high volatility scenario than the corresponding variances in the low volatility scenario; and
- Magnitude of the true trade remedy impact: there were two variants of the trade remedy impact. The first variant had a constant trade remedy impact of a 10% reduction in the costs of the treated firm in each post-initiation quarter. The second variant had a trade remedy impact that began small but grew as the post-initiation period progressed. In particular, the trade remedy impact began with a 1% reduction in costs in the first initiation quarter, then grew quarterly by 1% increments until reaching 10% where it remained until the end of the sample.[121]
- First, the results are presented for all scenarios with 10 firms and there is an assessment of the relative performances of the SCM and BCI and how this is affected by greater volatility in the data and a time-varying trade remedy. Then, there is a discussion on how increasing the number of comparator firms from 10 to 30 alters these collective findings.

[121] The TRA has communicated that while it does time for the impact of the trade remedy to feed through to firm-level costs, the impact of the trade remedy often begins gradually but then grows very quickly soon after. The reality of how firms' costs may be impacted by the trade remedy lays somewhere between the two specifications.

Analysis with 10 comparator firms

Baseline

8.115 The baseline case investigates the impact of the trade remedy with 10 firms assuming the effect of the trade remedy was constant over time (i.e. the reduction in costs are a one-off change that persist for the rest of the sample) and the underlying volatility in the data was relatively low. The results from estimating the SCM and BCI on this data are summarised in the tables below. Table 21 shows the estimated impact of the trade remedy using the SCM with the full and trimmed samples, and Table 22 shows the corresponding results using the BCI. The reported results are the true and estimated aggregate impact of the trade remedy in the entire post-initiation period and the average proportional impact of the trade remedy. The final income shows the statistical significance of the average impact in the post-initiation period. The performance of the models will be judged on how well they estimate causal impacts that are similar to the true impacts and how precisely they can estimate causal impacts (i.e. whether the p-value indicates that causal impacts are statistically different from 0).

Table 22: SCM results with constant trade remedy impact and low volatility (10 comparators)

Outcome	True Aggregated Impact	Estimated Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-91	-10.0	-9.15	0.455
Costs (trimmed sample)	-100	-181	-10.0	-16.68	0.833
Demand	3,927	3,642	23.5	21.36	0.364
Demand (trimmed sample)	3,927	5,369	23.5	35.04	0.667
Profit	13,320	11,829	11.1	9.74	0.545
Profit (trimmed sample)	13,320	20,071	11.1	17.73	0.667
Revenue	146,516	124,909	11.1	9.31	0.545
Revenue (trimmed sample)	146,516	220,775	11.1	17.73	0.667

Notes: The results in the table show the impacts estimated by the SCM for a specification with 10 comparator firms and low data volatility. Low data volatility refers to when the random noise in the cost and sales data is relatively low. The trimmed sample is a sample where unsuitable comparators are removed. The impact of the trade remedy is assumed to be a constant reduction in costs that commences on the initiation date and remains for the entire post-initiation period. The aggregate impact shows the sum of the true and estimated quarterly impacts for each quarter in the post-initiation period. The average impact shows the average true and estimated quarterly impact of the trade remedy as a proportion of the predicted imports. The p-value of the average impact shows the statistical significance of the average impact. Statistically significant average impacts have values that are less than 0.05.
Source: GT Analysis.

Table 23: BCI results with constant trade remedy impact and low volatility (10 comparators)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-149	-10.0	-14.16	0.0640
Costs (trimmed sample)	-100	-111	-10.0	-10.95	0.0002
Demand	3,927	3,978	23.5	23.89	0.0568
Demand (trimmed sample)	3,927	4,071	23.5	24.57	0.0002

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Profit	13,320	11,877	11.1	9.79	0.0167
Profit (trimmed sample)	13,320	13,476	11.1	11.26	0.0002
Revenue	146,516	130,647	11.1	9.79	0.0163
Revenue (trimmed sample)	146,516	148,234	11.1	11.26	0.0002

Notes: The results in the table show the impacts estimated by the BCI for a specification with 10 comparator firms and low data volatility. Low data volatility refers to when the random noise in the cost and sales data is relatively low. The trimmed sample is a sample where unsuitable comparators are removed. The impact of the trade remedy is assumed to be a constant reduction in costs that commences on the initiation date and remains for the entire post-initiation period. The aggregate impact shows the sum of the true and estimated quarterly impacts for each quarter in the post-initiation period. The average impact shows the average true and estimated quarterly impact of the trade remedy as a proportion of the predicted imports. The p-value of the average impact shows the statistical significance of the average impact. Statistically significant average impacts have values that are less than 0.05.
Source: GT Analysis.

8.116 The results yield the following insights. The best performing BCI model outperforms the best performing SCM model for almost all outcomes as the BCI estimates are closer to the true impact than the SCM estimates. The SCM with the full sample predicts the true impact of the trade remedy on costs quite well but performs notably worse than the BCI with the remaining outcomes. The superior performance of the BCI may be due to its ability to estimate the relationship between the treated firm and the comparator firms with better precision and, thus, predict counterfactual outcomes with greater accuracy. This is underscored by the finding that the BCI estimates causal impacts with more statistical precision than the SCM. All but one of the average impacts estimated by the BCI are statistically significant at the 5% significance level, with the only exception being with respect to demand with the full sample. Conversely, none of the impacts estimated by the SCM are statistically significant. This finding also points to the SCM's need for a large set of comparators to undertake causal estimation with precision.

8.117 Finally, trimming the sample of unsuitable comparator firms generally improves the BCI's estimates of the true impact (notably, the estimated average impact for demand is not statistically different from 0 for this result). This illustrates the bias that unsuitable comparators introduce to the estimation and highlights the importance of identifying and removing poor comparators from the sample before undertaking causal estimation. Conversely, trimming the sample of unsuitable comparators arguably worsens the performance of the SCM. This may trace back to the SCM's need for a large set of comparators to undertake precise estimation of causal impacts and the arbitrage between bias and precision that emerges when undertaking causal inference. The SCM with the full sample may be able to estimate causal impacts with more precision than when using the trimmed sample, despite the full sample generating biased estimates due to unsuitable comparators. The reduction in bias from trimming the sample may be outweighed by the resulting increase in imprecision that stems from having fewer comparators, resulting in causal estimates that are further away from the true impact.[122]

High volatility in the data

8.118 The results from undertaking the analysis with greater volatility in the data are shown in Appendix 3: Model outputs for illustrative Case Study 3: TD0004 and TS0005 Biodiesel from the USA and Canada. This adjustment yielded similar insights to those above, however the key findings are more exaggerated. Firstly, the superiority of the BCI over the SCM in terms of performance is more pronounced. The SCM significantly underestimates or overestimates the true impact while the BCI's with the trimmed sample estimates remain roughly in line with the truth. Secondly, trimming the sample improves the estimation power of the BCI to an even greater extent while the SCM performance deteriorates notably regardless of which sample is used. These findings

[122] The specific impact that trimming the sample had on the performance of these methodologies is local to this particular dataset and will differ in other contexts. Generally speaking, it is always recommended to remove unsuitable comparators from the sample when they have been identified as leaving them in the sample will likely cause bias the causal estimates.

emphasise the importance of selecting an appropriate and a suitable set of comparators when the underlying data is noisy.

Time-varying trade remedy impact

8.119 The analysis was repeated to allow the impact of the trade remedy to vary with time; beginning small and growing over time until reaching a satiation point of a 10% reduction in the costs of the treated firm. The results are shown in the Appendix 3: Model outputs for illustrative Case Study 3: TD0004 and TS0005 Biodiesel from the USA and Canada, and they remain largely unchanged from the above. The BCI generally outperforms the SCM in terms of estimating the true impact of the trade remedy for most outcomes, and completely outperforms the SCM in terms of statistical precision for all outcomes. Trimming the sample also improves the performance of the BCI. Both findings are exacerbated when the data is volatile; the SCM's performance further deteriorates while the BCI with the trimmed sample continues to predict the true impact with accuracy and precision. These results illustrate that selecting the correct methodology and specification becomes even more important for causal estimation when the impact of the trade remedy can be small and varies over time.

Analysis with 30 comparator firms

8.120 The baseline case for the analysis with 30 firms investigates the impact of the trade remedy assuming the effect of the trade remedy was constant over time and the underlying volatility in the data was relatively low. The results from estimating the SCM and BCI on this data are summarised in the tables below. Table 24 shows the estimated impact of the trade remedy using the SCM with the full and trimmed samples, and Table 25 shows the corresponding results using the BCI.

Table 24: SCM results with constant trade remedy impact and low volatility (30 comparators)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-89	-56	-10.0	-6.49	0.452
Costs (trimmed sample)	-89	-47	-10.0	-5.44	0.667
Demand	13,927	6,882	23.5	10.45	0.161
Demand (trimmed sample)	13,927	7,199	23.5	10.87	0.667
Profit	42,120	-10,424	11.1	-2.40	0.968
Profit (trimmed sample)	42,120	-43,111	11.1	-9.29	0.833
Revenue	463,320	-114,445	11.1	-2.39	0.968
Revenue (trimmed sample)	463,320	-474,391	11.1	-9.30	0.833

Notes: The results in the table show the impacts estimated by the SCM for a specification with 30 comparator firms and low data volatility. Low data volatility refers to when the random noise in the cost and sales data is relatively low. The trimmed sample is a sample where unsuitable comparators are removed. The impact of the trade remedy is assumed to be a constant reduction in costs that commences on the initiation date and remains for the entire post-initiation period. The aggregate impact shows the sum of the true and estimated quarterly impacts for each quarter in the post-initiation period. The average impact shows the average true and estimated quarterly impact of the trade remedy as a proportion of the predicted imports. The p-value of the average impact shows the statistical significance of the average impact. Statistically significant average impacts have values that are less than 0.05.
Source: GT Analysis.

Table 25: BCI results with constant trade remedy impact and low volatility (30 comparators)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-89	-70	-10.0	-7.95	0.0614
Costs (trimmed sample)	-89	-79	-10.0	-8.91	0.0002
Demand	13,927	4,421	23.5	6.39	0.2692
Demand (trimmed sample)	13,927	12,520	23.5	20.58	0.0189
Profit	42,120	-20,663	11.1	-4.68	0.4457
Profit (trimmed sample)	42,120	42,974	11.1	11.37	0.0425
Revenue	463,320	-227,295	11.1	-4.68	0.4447
Revenue (trimmed sample)	463,320	472,717	11.1	11.37	0.0421

Notes: The results in the table show the impacts estimated by the BCI for a specification with 30 comparator firms and low data volatility. Low data volatility refers to when the random noise in the cost and sales data is relatively low. The trimmed sample is a sample where unsuitable comparators are removed. The impact of the trade remedy is assumed to be a constant reduction in costs that commences on the initiation date and remains for the entire post-initiation period. The aggregate impact shows the sum of the true and estimated quarterly impacts for each quarter in the post-initiation period. The average impact shows the average true and estimated quarterly impact of the trade remedy as a proportion of the predicted imports. The p-value of the average impact shows the statistical significance of the average impact. Statistically significant average impacts have values that are less than 0.05.
Source: GT Analysis.

8.121 Increasing the number of comparator firms makes the difference in the performance across methodologies and across samples starker. The trade remedy impact estimated using BCI with the trimmed sample remains very close to the true impact and is statistically significant for all outcomes. This specification now outperforms all SCM specifications and the BCI with the full sample for all outcomes. However, the performance of the SCM deteriorates greatly; the estimated impact of the trade remedy on revenues and profit is estimated so imprecisely that it is now negative whereas the true effects for these outcomes are positive. Furthermore, the impacts estimated by the BCI with the full sample deviate notably from the true impact (being negative for revenue and profit) and are statistically insignificant for all outcomes.

8.122 It must be noted that the specific way in which the results varied with the number of comparators and the nature of the sample is highly specific to this context and will likely materialise in different ways as the underlying data changes. This particularly applies to the number of comparators; what truly matters for the performance of these methodologies is how well the comparators predict the outcomes of the treated unit and that the comparators are not influenced by spillovers. The quantity of comparators is somewhat less important than their 'quality' in these respects.[123]

8.123 The results for the remaining specifications are shown in the Appendix 3: Model outputs for illustrative Case Study 3: TD0004 and TS0005 Biodiesel from the USA and Canada and can be summarised as follows. When the underlying data is volatile, the BCI with the trimmed sample outperforms all the SCM specifications and the BCI with the full sample, although its estimates are slightly worsened by greater noise in the data. The remaining specifications report impacts that diverge greatly from the true impacts and are statistically insignificant.

8.124 When the impact of the trade remedy varies over time, the BCI with the trimmed sample outperforms all the SCM specifications and the BCI with the full sample, although its estimates are slightly worsened by the fact that the trade remedy impact is smaller and more difficult to detect. The estimated impacts are still comparable to the true impact, although the estimated impacts on revenue and profit are not statistically significant when the data has low volatility. These results

[123] However, conditional on a set of comparators having equal predictive power and not being contaminated by spillovers, increasing the number of comparators will improve the precision with which the SCM is estimated. This is because the number of comparators determines the number of placebo effects that are estimated, and this is directly related to the statistical significance of the average estimated impact.

are somewhat unchanged when the underlying data is more volatile. The BCI with the trimmed sample is the best performer, with the impacts on revenue and profit now being statistically significant. However, the accuracy of the estimated impacts slightly declines relative to when the data was less volatile. Nevertheless, the estimates from the BCI with the trimmed sample remain comparably robust even with noisy data as the other specifications report estimates that are both highly dissimilar to the true impacts and are not statistically different from 0.

Conclusion

8.125 This case study focused on a trade remedy investigation that changed the scope of an existing measure in a context with an abundance of data in terms of the number of time periods. It illustrates how both the tabular format and the decision tree format of the methodology selection framework can be applied to select the appropriate models for estimating causal impact of the trade remedy. The SCM and BCI methodologies are applied to synthetic firm-level under varying scenarios. The scenarios investigated included: (i) low versus high data volatility; (ii) a constant trade remedy impact versus a time-varying trade remedy impact; (iii) 10 comparator firms versus 30 comparator firms; and (iv) a sample consisting of some unsuitable comparators (full sample) versus a sample consisting of no unsuitable comparators (trimmed sample).

8.126 The best performing model in terms of both accuracy and precision across the board was the BCI, and that a trimmed sample with no unsuitable comparators yielded the best results. This finding was robust to all the modifications made to the underlying data. This result is likely due to the ability of the BCI to generate more precise estimates of causal impacts despite the underlying data is noisy or the true impact of the trade remedy being small and time-varying.

8.127 This case study also underscored the importance of removing unsuitable comparators from the sample before undertaking causal analysis. Keeping unsuitable comparators in the sample generates bias that may cause models that are highly robust to noise (i.e. the BCI) to perform poorly, especially as the data becomes noisier, the number of comparators changes and as the impact of the trade remedy becomes more complex.

Illustrative Case Study 4: TS0023 Stainless Steel Bars and Rods from India

8.128 This case study aims to illustrate use of methodologies that can be used when there are few valid comparators or only a few time periods but can still deliver results that are relatively simple and easy to interpret causally.

8.129 This section is structured as follows:

- An introduction of the context surrounding the trade remedy under investigation;
- Identification of key dates for econometric purposes;
- Illustration of the methodology used;
- Results and discussion of results;[124] and
- The implications of results.

8.130 This case study is a transition review of a countervailing measure previously initiated by the EU on 19 April 2010, and imposed on 19 April 2011.[125] This investigation was initiated following a complaint lodged on 15 February 2010 by the European Federation of Iron and Steel Industries (Eurofer) on behalf of producers representing a major proportion (in this case more than 25%) of total EU production of Stainless Steel Bars and Rods.[126]

8.131 The transition review was initiated following Notice under regulation 98 of the Trade Remedies Regulations 2019 on 21 June 2022,[127] and the countervailing measure was revoked following withdrawal of interest by the UK industry, which was confirmed in a final recommendation published on 15 June 2023.[128]

8.132 This case study focusses on Stainless Steel Bars and Rods, not further worked than cold-formed or cold-finished, other than bars and rods of circular cross-section of a diameter of 80mm or more originating in India. The commodity codes impacted, and duty rates no longer in place are reported in the Appendix 4: Illustrative Case Study 4: TS0023 Stainless Steel Bars and Rods from India.

Key dates

8.133 To conduct econometric analysis for this case study, key dates must be identified. These key dates are aimed at identifying the pre- and post- event dates. In this case study, the pre-trade remedy data spanned the time period when the original trade remedy was in place. The post-event data includes dates after the UK's transition review began, on 21 June 2022. The relevant investigations are chosen as dates to avoid any anticipation effects, as causal interpretations can be heavily influenced by anticipation.

8.134 Hence, the key dates for this case study are:

- Earliest possible start date: The date of EU policy initiation, 15 February 2010. This date is the date of the initiation of the policy, and the earliest possible date for any analysis; and
- Date of intervention: The date of initiation of the transition review that resulted in removal of the trade remedy. In this case study this corresponds to 21 June 2022.

Synthetic data construction

- It is assumed that annual data is available for the variable of interest. The outcome of interest is sales revenue;

[124] Results are outlined for three scenarios, to illustrate possible issues with diff-in-diff analysis.
[125] Notice of initiation of an anti-subsidy proceeding concerning imports of certain stainless steel bars originating in India (europa.eu)
[126] https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2011:108:0003:0010:EN:PDF
[127] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)
[128] TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

- There is data available only for two years before, and one year after intervention;[129]
- There is one treated firm and one comparator firm;
- The revocation of the countervailing measure reduces the sales revenue of the treated firm by £10,500; and
- There is a small amount of random noise in the data. This assumption will be relaxed later in the analysis.

8.135 The methodology for this case study is split into two sections. The methodology for data construction is included in the Appendix 4: Illustrative Case Study 4: TS0023 Stainless Steel Bars and Rods from India. The following section outlines an estimation strategy for the methodologies.

Methodology selection

8.136 This case study has a context of limited data with a few time periods. While comparators are present, the number of comparators is limited to one. The framework is used to determine a suitable approach for causal analysis; beginning with the tabular framework and then applying the decision tree framework thereafter.

8.137 The first step is to establish the set of feasible approached based on the criteria in Table 12. The data contains both pre- and post-initiation data, the trade remedy investigation did result in imposed duties changing and there is a single valid comparator. However, there are only a few time periods in the data. This means that, among the quasi-experimental methodologies, the diff-in-diff is feasible and the event study is partially feasible. The next step is applying the suitability criteria in Table 13. The data is not noisy, there is only one comparator and causal interpretation is important. This leads to the conclusion that the diff-in-diff is the most suitable causal approach among the causal approaches that are feasible in this case.

8.138 Applying the decision tree framework in Figure 7:

- The trade remedy investigation did result in imposed duties changing. Follow “yes” to the next node;
- Data before and after the initiation is observed. Follow “yes” to the next node.
- There are some commodities that are affected by the trade remedy and others that are not. Follow “yes” to the next node;
- The data is observed for a few time periods. Follow “no” to the next node; and
- This leads to the conclusion that diff-in-diff may be the most appropriate approach. The caveats of this approach are that the parallel trends assumption holds, and that there are no spillovers or anticipation effects.

8.139 The preference of the diff-in-diff over the event study stems from the constructed data violating two conditions that must be satisfied for event studies to be suitable for causal analysis. Firstly, event studies generally require several pre-initiation periods to train the model. Secondly, event studies generally require several comparators to credibly predict the unobserved counterfactual. The nature of the data in this case study breaches these requirements and, therefore, makes event studies less suited than the diff-in-diff.

8.140 The analysis focusses on estimations for one firm, and then expands to explain options for estimating impacts for multiple firms.

8.141 The following section explains the relevant model and the results of:

- Diff-in-diff estimation when the parallel trends assumption holds; and
- Diff-in-diff estimation when the parallel trends assumption does not hold

[129] Due to the lack of time periods, the date of intervention is assumed to be the day after the second annual data point. In this case, this is 01/01/2023. This allows for identification of difference in differences. As a consequence of this, the analysis will capture some changes that had occurred prior to the intervention.

Difference-in-differences (diff-in-diff)

8.142 The data used in this section assumes one comparator firm, and one treated firm. The

"treatment" corresponds to exposure to the revocation of the countervailing measure. Hence, the "treated" firm corresponds to a firm that was initially exposed to the countervailing measure prior to its is likewise exposed to the impact of the measure's revocation following the trade remedy investigation.

8.143 Initial assumptions for the parallel-trend compliant analysis for constructing the data include:

- The trend in the comparator firm's outcomes (i.e. sales) over time is parallel to the corresponding trend of the treated firm;
- The untreated firm has higher sales than the treated firm; and
- There is little noise present.

8.144 The model to be estimated for this approach is a simple diff-in-diff estimator, as follows:

$$\boldsymbol{Sales_{i,t} = \beta_0 + \beta_1 Treated_i + \beta_2 After_t + \beta_3 (Treated_i * After_t) + \epsilon_{i,t}} \quad (3)$$

Where $Sales_{i,t}$ is the sales for firm *i* at time *t*, $Treated_i$ is a binary variable that equals 1 if the firm i is in the treatment group (in-scope of the trade remedy) and zero otherwise, $After_t$ is a binary variable that is equal to 1 if the observation is post-initiation of the treatment,[130] and zero otherwise. $Treated_i * After_t$ is the interaction of $Treated_i$ and $After_t$, taking a value of 1 if the observation is post-initiation of the treatment and in the treated group (in-scope), and zero otherwise. $\boldsymbol{\epsilon_{i,t}}$ is the error term. β_0 , β_1, β_2 and β_3 (β_3 is sometimes referred to as the diff-in-diff estimator) are parameters to be estimated.[131]

8.145 The definition of treatment differs somewhat from the Case Study 1. In Case Study 1, treatment was binary; a commodity that was within scope of the trade remedy and thus affected by the trade remedy was treated whereas commodities that were out of scope were untreated. In this case, treatment is aligned with a firm's exposure to the trade remedy and is based on the goods it imports. Therefore, treatment is more of a continuum as it relates to treated firms. Untreated firms are those that do not import the targeted commodity at all, whereas treated firms can vary in terms of treatment exposure due to varying intensities at which they import the targeted commodity. For instance, importers with cost bases that have a high proportion of the targeted commodity are more impacted by the trade remedy than importers with cost bases that only have a small fraction of the target commodity. In the first instance, treatment will use a binary variable that equals 1 if the firm reports a positive amount of imports of the targeted commodity and 0 otherwise (i.e. no imports of the targeted commodity).

8.146 Whilst inclusion of controls is necessary for estimation of true data, synthetic data can be constructed in a way that allows for identification of impacts without the inclusion of controls. In practice, it is necessary to include controls if those controls improve the likelihood of the parallel trends assumptions being satisfied. Typical factors that are controlled for include seasonality, market trends, industry specific factors, and firm-specific controls such as firm size, firm age and industry.

8.147 This methodology remains the same for the estimations whereby the data does not have a parallel trend. The difference for the non-parallel trend estimation is in the underlying data, where the comparator does not exhibit a parallel trend prior to treatment. If the parallel assumption trend does not hold, then results of a diff-in-diff estimation will be biased.

8.148 For all estimations, the interpretation of any summary statistics is not indicative. The data in this case study has been constructed for illustrative purposes and may not represent the level of accuracy of real-data estimations.

[130] The treatment here is removal of the trade remedy.
[131] For more noisy data, the use of logged sales may be more appropriate. Consideration of the functional form of estimations should be conducted on an individual estimation basis.

Key assumptions

8.149 The following assumptions are necessary for the analysis:

- It is assumed that the pre-treatment period corresponds to the years preceding the trade remedy investigation date, and the post-treatment period corresponds to the period coinciding with this date. This assumption reduces the possibility of anticipation impacts being omitted;
- It is assumed that there is one comparator, and this comparator has a parallel trend;[132] and
- There is some random noise incorporated into the data.

Results

Parallel trend diff-in-diff

8.150 The analysis uses the baseline assumptions regarding the data. The results from estimating the diff-in-diff in equation (3) are shown in the table below. As stated in the data construction subsection, the synthetic data has been constructed to simulate a drop in sales of £10,500 following the revocation of the countervailing measures; which to a 22% reduction in sales revenue in the simulated data.[133]

Table 26: Estimation results for diff-in-diff with the parallel trend

	Sales
(Intercept)	50.76***
	(0.2598)
Treated	-2.0495**
	(0.3674)
After	0.9115
	(0.00942)
Treated x After	-10.4661***
	(0.6364)
R-squared	0.9975
Adj R-squared	0.9937
F-statistic	265.2***
Residual standard error	0.3674

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

8.151 The results of this regression are as expected as the coefficient of interest (i.e. the coefficient associated with "Treated x After") estimates that the trade remedy reduced total sales by £10,466; essentially identical to the true impact of a £10,500 reduction. The statistical significance of the estimates is signified by the number of star symbols (i.e. *) beside the coefficient estimates. According to the key in the notes of the table, one or more stars signifies that the coefficient estimate is statistically significant at the 5* significance level, with more stars indicating more precise estimates. The effect of the trade remedy is statistically significant at the 5% significance level. This is the "ideal" diff-in-diff estimation, whereby there is a parallel trends for the comparator firm and little noise. Additionally, the F-statistic indicates the model parameters are jointly

[132] In practise, it may be difficult to identify a single comparator with a parallel trends. However, this can be aided by selecting a comparator from a similar industry to the treated firm, and with similar firm-level characteristics as the treated firm, such as firm size and sales. If there are several comparators available, consideration of matching should be taken. This is further discussed later in the chapter.

[133] For the baseline scenario, the random noise component is normally distributed with a mean of zero and standard deviation of 100.

statistically different from 0 (this is driven by a statistically significant trade remedy impacts), and the adjusted R squared indicates good fit of the model.[134]

Table 27: Log diff-in-diff estimation with parallel trends

	Log Sales
(Intercept)	3.93***
	(0.005)
Treated	-0.041**
	(0.0074)
After	0.018
	(0.0091)
Treated x After	-0.236 ***
	(0.013)
R-squared	0.998
Adj R-squared	0.995
F-statistic	326***
Residual standard error	0.0074

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

8.152 There are two characteristics of the data and/or comparators are altered with the remaining analysis additional volatility in the underlying data and failure of the parallel trends assumption. These alterations serve to illustrate limitations that may arise occur with diff-in-diff estimators, and recommendations for how they can be addressed are discussed.

8.153 The same estimation is run with sales in log form. The estimation is illustrated in Table 27. This illustrates a similar estimated impact to those in Table 26 of a fall in sales of 21.0%.

The role of volatility

8.154 The performance of the diff-in-diff estimator is expected to reduce as the level of underlying volatility/noise in the outcome increases. This is particularly likely to be the case when a small number of observations, as it will be difficult to separate noise from the underlying trend. A high number of data points make it easier for the diff-in-diff estimator to identify a trend, even if the data contains noise. The underlying volatility in the data was increased to investigate how this would impact the ability of the diff-in-diff to estimate the causal impact of the trade remedy.[135] The results of this estimation are illustrated in Table 28.

[134] The R-squared and adjusted R-squared vary from 0 to 1; 0 represents that the model explains no variation in sales while 1 represents a near perfect fit between modelled sales and true sales. It must be noted that the R-squared and adjusted R-squared are extraordinarily high (i.e. essentially equal to 1) relative to what would be expected with real data (i.e. less than 0.8-0.9 in most cases). However, model diagnostics such as the R-squared are essentially meaningless in this case because the parallel trends were artificially designed to hold.

[135] For the high volatility scenario, the random noise component is normally distributed with a mean of zero and standard deviation of 500. This is five times greater than the volatility in the baseline scenario.

Table 28: Estimation results for diff-in-diff with the parallel trend and noise

	Sales
(Intercept)	50.9446***
	(0.4891)
Treated	-2.3956**
	(0.6917)
After	0.7353
	(0.8471)
Treated x After	-10.6277**
	(1.1980)
R-squared	0.992
Adj R-squared	0.98
F-statistic	82.56**
Residual standard error	1.246

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

8.155 As expected, the performance of the diff-in-diff declines when the data displays more volatility. The estimated trade remedy impact is -£10,628, which overestimates the true trade remedy impact of £10,500. However, it must be noted that estimated trade remedy impact is still somewhat comparable to the true impact. Furthermore, the trade remedy impact is statistically different from 0. Hence, while noisier data will diminish the diff-in-diff's ability to estimate causal impacts, it may still perform reasonably well if the level of volatility is not too great.

8.156 This estimation is repeated for logged sales, and the results are reported below. The trade remedy is estimated to reduce sales by 24.7%, which is lower than the true impact of a 21.8% reduction. The logged form of this estimation may partially mitigate for the some of the noise because log transformations reduce the impact of extreme values on estimation performance. Therefore, the functional form of the diff-in-diff specification should be considered when noise is present.

Table 29: Log diff-in-diff estimation for parallel trend and noise

	Log Sales
(Intercept)	3.934***
	(0.0175)
Treated	-0.056
	(0.02472)
After	0.0142
	(0.0302)
Treated x After	-0.247**
	(0.0428)
R-squared	0.981
Adj R-squared	0.954
F-statistic	35.36*
Residual standard error	0.0247

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

8.157 Due to the adverse impact of noise on the performance of the diff-in-diff, it may be possible to incorporate Bayesian methods into diff-in-diff estimation. This adjustment may mitigate the negative repercussions of noise, but it would require more data in order to be feasible.[136] For example, if there are multiple comparators available with more frequent time periods, BCI or SCM can be used, as illustrated in case study 1.

8.158 Generally speaking, it can be difficult to minimise data volatility and noise when the dataset is small. Further steps that can be taken to mitigate this include careful consideration of what data is collected from firms. For example, historic sales figures from previous years may contain less noise that projected sales in upcoming years because sales projections contain an inherent amount of uncertainty.

8.159 However, no noise is not essential for estimations of diff-in-diff; the results showed that estimated will not be considerably inaccurate when noise present, so long as the level of noise is small relative to the magnitude of the underlying trend. If noise is larger than the underlying trend, then ascertaining the trend can be difficult and this can cause diff-in-diff estimations to be poor.

The role of the parallel trends assumption

8.160 The following section uses data that is constructed with the following characteristics:

- A pre- trade remedy difference in trend for the treated and comparator firms;
- It is assumed that the treatment date is the date in the set of observations prior to the trade remedy being removed;[137]
- A small amount of random noise;[138] and
- A post- trade remedy shift in trend for the treated firm.

8.161 The impact for this estimation is the same as for the Parallel trends analysis, a reduction in sales of £10,500 following the trade remedy removal. The results of the estimation for the diff-in-diff analysis with non-parallel trends are reported in Table 30 below.

Table 30: Estimation results for diff-in-diff with non-parallel trends

	Sales
(Intercept)	50.079 ***
	(1.386)
Treated	-5.519
	(1.960)
After	5.961
	(2.401)
Treated x After	-15.589**
	(3.395)
R-squared	0.9711
Adj R-squared	0.9266
F-statistic	22.36*
Residual standard error	1.960

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

[136] Incorporating Bayesian econometrics into diff-in-diff methodologies is possible, see: Normington, J.P., Lock, E.F., Murray, T.A. and Carlin, C.S., 2022. Bayesian variable selection in hierarchical difference-in-differences models. *Statistical methods in medical research*, *31*(1), pp.169-183. for further information.

[137] It is likely that this would have an impact on ability to interpret the results causally. However, trend analysis and other quantitative analysis, or simplifying assumptions can be used to estimate the impact.

[138] This case study was constructed with a small amount of noise to allow for direct comparison when the trends are not parallel.

8.162 The estimated diff-in-diff estimator indicates that a firm exposed to the revocation of a trade remedy measure experiences an estimated £15,589 drop in sales revenue. This is more than 50% larger than the actual synthetic drop of £10,500. The estimated trade remedy impact is biased due to capturing some of the differences between the trends of the treated and comparator units.

8.163 The same analysis is run in log form and results are shown below. The trade remedy is estimated to reduce sales of approximately 26.9% which, again, overestimates the true trade remedy impact due to the failure of the parallel trends assumption.

Table 31: Diff-in-diff logged analysis with non-parallel trends

	Log Sales
(Intercept)	4.026 ***
	(0.025)
Treated	-0.103*
	(0.035)
After	0.102
	(0.04)
Treated x After	-0.313**
	(0.061)
R-squared	0.976
Adj R-squared	0.9409
F-statistic	27.54*
Residual standard error	0.03498

*Notes: Significance codes: p<0.001***; p<0.01**; p<0.05*.*

Standard errors are reported in parentheses. Coefficient estimates refer to units in 000's.

GT Analysis.

8.164 In this scenario, finding an alternative comparator is necessary to successfully use the diff-in-diff methodology. This illustrates the need for not only a comparator, but an appropriate comparator unit when conducting diff-in-diff estimations.

8.165 In practice, comparator units are difficult to identify, especially in the context of trade remedies. This is because comparator units should be sufficiently similar in terms of sales, sector and size of firms, but not themselves be impacted by the trade remedy directly or indirectly through spillovers. In addition, the comparator must not be impacted by any remedies or trade remedy investigations external to the trade remedy in question.[139]

8.166 In some cases, an appropriate comparator may not exist. In these cases, the framework may be consulted for alternative methodologies that do not need a comparator or control group; such as before-during-after analysis, aggregate analysis and interrupted time series.

Testing for parallel trends

8.167 The parallel trends assumption is critical for diff-in-diff to yield causal estimates. Therefore, it is important to verify whether this assumption is likely to be satisfied in the data before undertaking causal analysis. This point is discussed after the analysis and results because, in this instance, the

[139] The problem of identifying comparator firms that were not impacted by the trade remedy indirectly becomes more difficult if the commodities impacted by the trade remedy have wide reaching implications on the production of an economy in general. Suppose a commodity targeted by a trade remedy is an instrumental part of production for several aspects of the economy (e.g. natural gas). Even if a firm is not directly impacted by the trade remedy through immediate consumption of the targeted commodity, or indirectly through substitution or complementary effects, it may still be exposed to the trade remedy if upstream or downstream firms in its supply chain are directly impacted by a trade remedy. There may be, in some sense, no perfectly valid control group as many firms would be impacted by the trade remedy in some way. This is, of course, an extreme case but it does highlight that careful consideration must be made when defining a control group. In such a scenario, ex-post counterfactual analysis may be infeasible and other alternative would need to be considered.

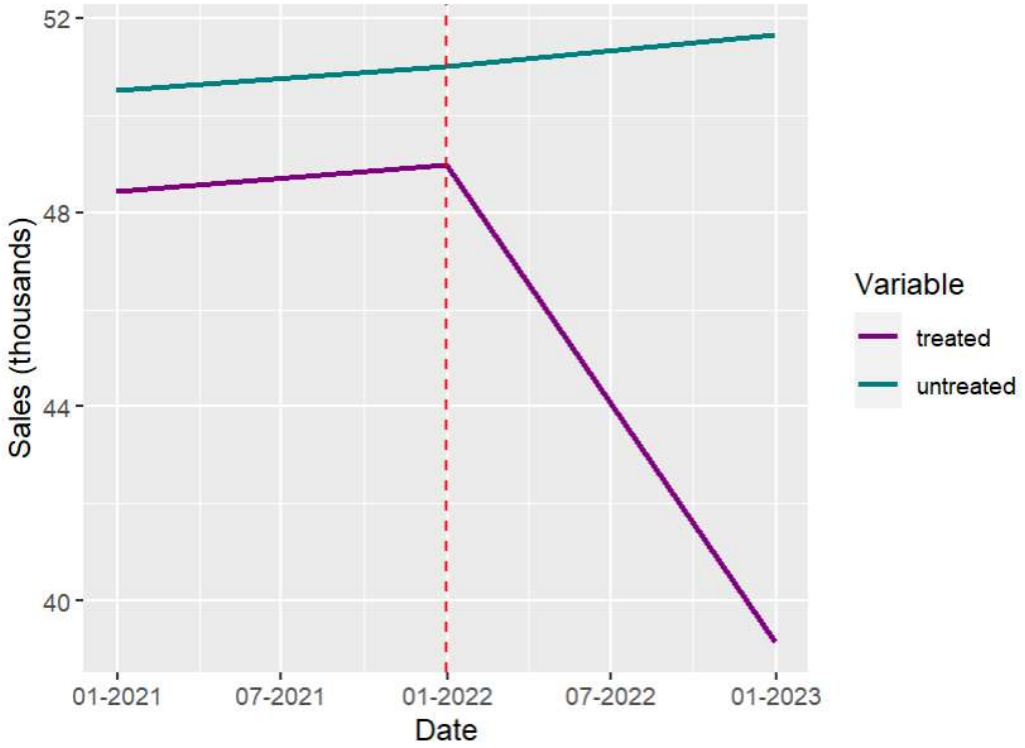
validity of the parallel trends assumption was predetermined and did not need to be verified. However, in other cases this assumption must be verified before undertaking analysis.

8.168 In principle, it is not possible to determine with certainty if a parallel trend in the outcomes of the treated and control units would have persisted into the post-initiation period had the trade remedy not taken place. However, it is possible to determine whether these units shared an identical trend in the pre-initiation period. The intuition is that the existence of parallel trends in the pre-initiation period (otherwise known as pre-trends) makes it more likely that parallel trends would have existed in the post-initiation period in absence of the trade remedy.

8.169 Pre-trends in the pre-initiation period are not a guarantee of parallel trends in the post-initiation period under the unobserved counterfactual; however, pre-trends do provide evidence that the parallel trends assumption may be satisfied. Likewise, the absence of pre-trends makes existence of parallel trends unlikely; if the treated and control units had different trends in the pre-initiation period, there is little reason to believe that they would have had parallel trends in the post-initiation period under the unobserved counterfactual.

8.170 There are informal and formal tests for pre-trends. The informal test for pre-trends is visual inspection of the trends for the treated and control units in the pre-initiation period; if the trends are similar then it is evidence of pre-trends and, thus, parallel trends. The plot of sales over time assuming the parallel trends assumption is satisfied is shown below.

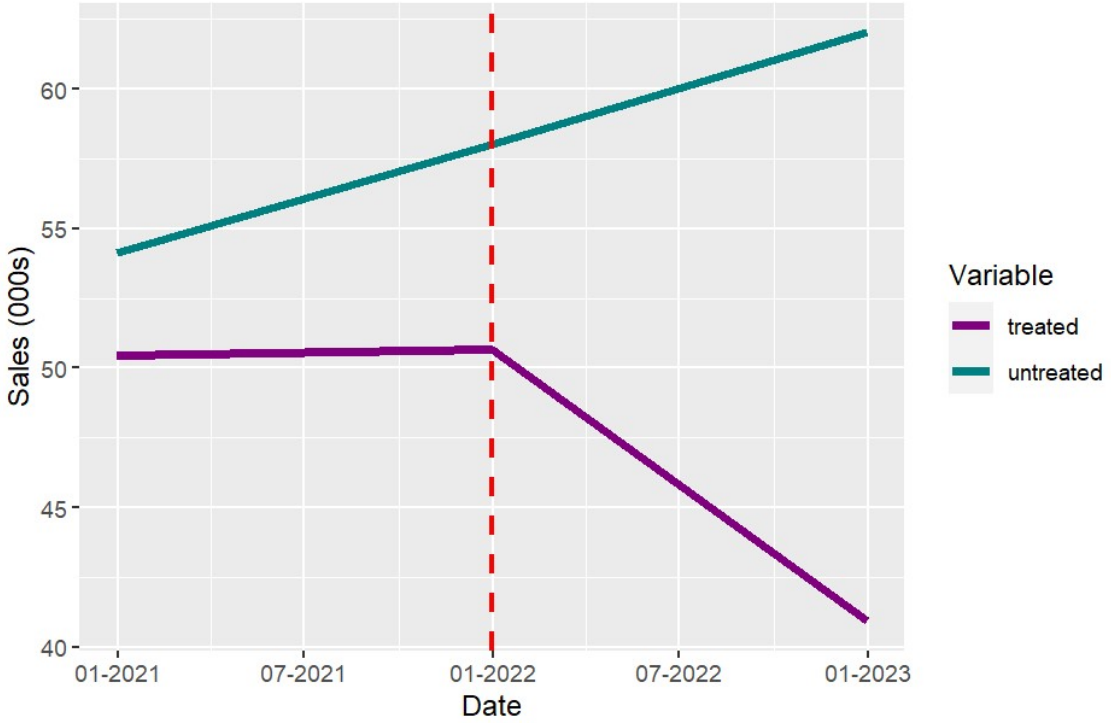
Figure 18: Plot of pre-trends assuming parallel trends assumption is satisfied



Source: GT analysis.

8.171 The figure above shows the sales for the treated and untreated firms over time assuming that the parallel trends assumption is satisfied. The red dashed line signifies the date that the trade remedy investigation is initiated and, therefore, the commencement of the trade remedy impacts. Visual inspection of the pre-initiation sales suggests that the treated and untreated firms have similar trends, which suggests pre-trends and gives validity to the parallel trends assumption. This can be juxtaposed with the figure below which illustrates the case where the parallel trends assumption is violated.

Figure 19: Plot of pre-trends assuming parallel trends assumption is violated



Source: GT analysis.

8.172 The figure above shows the sales for the treated and untreated firms over time assuming that the parallel trends assumption is violated. The red dashed line signifies the date that the trade remedy investigation is initiated and, therefore, the commencement of the trade remedy impacts. Visual inspection of the pre-initiation sales suggests that the treated and untreated firms have highly dissimilar trends, which casts doubt on the validity of pre-trends and the parallel trends assumption. Causal estimates from the diff-in-diff in this scenario, without any further details about the nature of the underlying data, should be treated with caution.

8.173 It is also possible to formally test for pre-trends with a statistical diagnostic test. This is done by testing for any statistically significant differences between the trends of treated and control units in the pre-initiation period. Econometrically, this is identical to estimating a diff-in-diff but only for the pre-initiation period.[140] As there is no treatment in the pre-initiation period, any statistically significant differences between the trends of the treated and control units would be driven by underlying differences that would also likely invalidate the parallel trends assumption.

Multiple Treated firms

8.174 Trade remedies are seldom applied to only one firm; in reality, multiple firms in the same industry may be exposed to the trade remedy. In the context of Diff-in-diff, this would require data from multiple comparator firms. Estimating diff-in-diff for multiple treated and control firms may increase the likelihood of bias as it is less likely that the parallel trends assumption is satisfied. This is because treated and control firms may possess highly different characteristics (e.g. costs, sector of operation and input mixes) and this heterogeneity may result in different firms having incomparable trends. This may be mitigated by incorporating diff-in-diff with propensity score matching. This methodology involves matching treated firms with control firms that possess highly similar pre-remedy characteristics. A diff-in-diff is then undertaken for the matched treated and

[140] In this case, as there are two years prior to the initiation of the trade remedy investigation, this would be equivalent to treating the second year as the 'treated' period and running a diff-in-diff between the treated and control firms. In cases where the number of pre-initiation years is greater than two, it would be possible to estimate a separate diff-in-diff for every pre-initiation year barring one and testing the joint significance of each diff-in-diff estimate using an F-test. If the F-statistic from the test exceeds the specified threshold, then the diff-in-diff estimates are jointly significant, and the null hypothesis of pre-trends would be rejected. This would, therefore, cast doubt on the validity of the parallel trends assumption.

control firms, and this can be used to estimate the average impact of the trade remedy on the treated units. The incorporation of matching methods increases the likelihood of the parallel trends assumption being satisfied due similar firms are compared to one another.[141]

Alternatives to diff-in-diff

8.1 Whilst mitigations can be taken to identify close matches for the basis of comparison including propensity score matching, if the parallel trends assumption still does not hold, alternative methodologies should be considered.

8.2 Alternatives include before-during-after analysis, theoretical modelling and interrupted time series. However, causal interpretation of alternative methodologies is more difficult with limited data.

8.3 If causal interpretation is necessary, obtaining data with a greater number of temporal observations could make other ex-post causal approaches feasible, including event studies, BCI and SCM.

Conclusion

8.4 There are a number of factors that can influence the magnitude and accuracy of a diff-in-diff estimation. Most importantly, robust causal interpretation requires that the underlying assumptions of diff-in-diff are tested and validated. The conditions that must be met for causal interpretation are:

- No spillovers: the comparator chosen must not be treated. In the context of trade remedies, this means that:
  1. the goods that are impacted by the trade remedy must not form part of the upstream or downstream industry of the comparator firm; and
  2. there must be no circumvention of the imposed trade remedy measure;[142]
- The comparator units must not be impacted by any unobserved shocks that would not have also impacted the treated unit in absence of the trade remedy; [143]
- There must not be significant noise such that the underlying trend is unidentifiable;
- The comparator must have a parallel trend prior to treatment; and
- There must be at least three time observations; two periods before the initiation of a trade remedy investigation and one period after. [144]

8.5 When these assumptions hold, it is possible to identify a causal impact of a trade remedy with a diff-in-diff. This approach can be particularly powerful even when the amount of data available for estimation is minimal in terms of time periods and comparators. However, these conditions can be difficult to achieve, and care must be taken to verify that they are satisfied.

[141] This methodology estimates the probability of being in the treated group based on observed variables. Treated firms are then matched with control firms based on how similar their scores are, and diff-in-diff is performed on these matched firms. This is also discussed in Chapter 3.
[142] In practice, analysis of possible circumventions should accompany the diff-in-diff estimations.
[143] Notable shocks that should be considered include economy-wide shocks such as the financial crisis, Brexit and COVID-19.
[144] Ideally, the initiation date of the trade remedy investigation should be align with the dates observed in the data. For example, if the initiation date is on 10 October 2021, the data should be sufficiently granular to allow the pre-initiation and post-initiation periods to be separated by this date. Ideally, there should be no overlap between the pre- and post-initiation periods in the data. However, as is the case here, the data be insufficiently granular to allow this (i.e. the data is at the annual level, but the initiation date happened in the middle of the year). In such cases, the data must assume that the treatment began earlier than it did in reality. In particular, the period in the data defined as the post-initiation period would contain dates that were in the pre-initiation period in reality. However, this may understate the true impact of the trade remedy because the post-initiation differences in trend (i.e. the impact of the trade remedy) would also partially consist of the pre-initiation pre-trends. This would attenuate the remedy impact toward zero assuming pre-trends hold.

9. Key lessons and recommendations

9.1 This chapter discusses the key lessons and recommendations that can be drawn from the case studies and the wider report. It covers high level lessons but also drills through into more localised micro-findings that were uncovered from the specific applications in the case study. It delivers a suite of practical advice and proposals intended to equip the TRA with the tools to undertake robust causal analysis of trade remedies in the present. It also provides guidance on how the TRA can develop a long-term view with respect to its data collection practises that will optimally place it to carry out causal analysis in future. In particular, this chapter covers:

- Application of the methodology framework: the caveats and considerations that the TRA should make when applying the framework. In particular, that the framework should not be read prescriptively but as guidance that serves as a starting point for causal analysis;
- Data collection considerations: this includes recommendations for how the TRA can enhance its data collection capabilities in order to make the most robust causal methodologies more suitable; and
- Practical considerations for causal analysis: this includes the key lessons learnt from carrying out causal analysis in the case studies and recommendations for future investigations carried out by the TRA.

Application of the methodology framework

9.2 The key aim of this report was to develop a framework for methodology selection that the TRA can use to select suitable approaches for the causal analysis of trade remedies in a way that is tailored to the various contexts that the TRA are likely to encounter. The methodology selection framework was developed with this aim in mind. The framework delivers a mapping between a comprehensive and diverse menu of methodologies and a given set of circumstances and constraints that the TRA may face at a given point in time. This mapping yields a strategic pairing between a situation and one or more methodologies; where the paired methodologies are capable of estimating causal impacts of trade remedies in that situation. This framework delivers the TRA with more than just a toolkit for causal analysis; it provides the TRA with a guide for selecting the right tools for the right task.

9.3 The case studies illustrated how this framework can be applied to four distinct contexts where the nature of the prevailing outcome and the unobserved counterfactual are unique. Each case study was unique in terms of the context of the trade remedy that was applied, the nature of the counterfactual problem implied by the trade remedy and the data that was available for analysis. For each case, the methodologies employed were guided by the framework. When comparing the outcomes of multiple methodologies, the one that was identified as the most suitable by the framework ultimately delivered the best outcomes. The high-level take-away is that the framework can be relied upon to choose causal approaches, from a suite of feasible methodologies, that are tailored to the nuances of the context. However, the framework should not be read prescriptively; the framework and its proposed methodologies should not be followed blindly and judgement is necessary. Further, the framework should not be interpreted as proposing a particular method be used with certainty and exclusivity. The framework is intended to serve as general guidance for the contexts and constraints that make some methodologies more suitable and others less so. In practice, it would be ideal to apply all of them and use the findings of each method to triangulate the most credible answer. This can be done by implementing multiple methodologies, where feasible, and thereafter:

- Assessing the degree of similarity in their findings;
- Identifying potential factors that determine diverging results, should divergences arise;
- Evaluating the importance of each finding based on the merits and limitations of each approach in light of the context;
- Being transparent with any assumptions that have been made due to limited evidence;
- Being transparent with all shortcomings in the methodologies considered and caveat results accordingly; and
- Coming to a reasonable and well-balanced conclusion.

9.4 The fourth point on assumptions is particularly important when the TRA is led by the framework to use approaches that are less capable of producing causal estimates but are the most suitable due to time and complexity constraints. The framework has been endowed with the flexibility of proposing approaches that the TRA can use to deliver expedient results when there is a shortage of time, data or expertise. However, these approaches tend to be less able to produce causal findings when compared to more robust yet resource intensive alternatives. The TRA must ensure that all results are caveated appropriately when endeavouring to use the framework to deliver results at pace. The case studies, particularly Case Study 1 and Case Study 3, illustrate that different methodologies can yield vastly different results, and that methodologies that are less suitable for causal analysis in a given context can produce estimates that diverge from reality. Furthermore, in cases where the TRA relies of purely theoretical approaches they should view the findings of these approaches as illustrative rather than precise and causal.

9.5 In all, the framework is a very useful tool for identifying suitable methodologies for causal analysis. However, leaping from the selected methodologies to correctly inferring the causal the causal impact of trade remedies from them must take a measured and balanced approach. This approach must consult multiple methodologies and sources of evidence where possible, appraise the findings of the methodologies in consideration of their strengths and weaknesses, be transparent about any assumptions that must be made where evidence is limited, caveat all results appropriately in light of methodological shortcomings, and come to a balanced, evidence-based conclusion.

Data collection considerations

9.6 The importance of data in the causal analysis of trade remedies cannot be stressed greatly enough. The nature and abundance of the data that is available will determine which methodologies are feasible and most suitable to the context. Situations may arise when methodologies that would be most capable of delivering causal estimates will be infeasible due to data constraints, and the TRA may be limited to alternatives that produce less reliable and robust results. This outcome may be mitigated by the TRA intentionally positioning itself to have access to the best possible data when assessing trade remedies in future.

9.7 It is understood that the TRA faces many data constraints that can be inflexible in the short-term, particularly with respect to firm-level data. The TRA's database of firm-level information has historically depended upon the voluntary data contributions of domestic producers, domestic importers, firms in the wider domestic supply chain and overseas exporter. This has led to occasions where the sample has been quite limited in terms of respondents, especially with respect to domestic importers and other companies in the domestic supply chain. Furthermore, the TRA explained that their data collection scheme for each investigation only collects annual firm-level data for the four years leading up to the initiation of the trade remedy investigation and supplements all post- trade remedy information using data sources such as Companies House and Dun and Bradstreet. Consequently, the TRA may encounter data that comprises of few time periods and few firms when undertaking its investigations. This heavily limits the methodologies that the TRA can feasibly apply when investigating trade remedies; data-hungry approaches such as the SCM and BCI would likely be unworkable.

9.8 The following recommendations are put forward for the TRA to consider in light of existing data constraints:

- Collect more granular data or for longer time periods: increasing the number of time periods that can be assessed will create opportunities for the TRA to implement a greater number of robust approaches for causal inference. This can be done either by collecting data at a higher frequency (e.g. at the monthly or quarterly level) or by incorporating a greater number of pre-trade remedy years into the sample. Increasing the granularity and length of the data would make data demands for participating firms more onerous and may further disincentivise the already limited number of respondents. The key issue here is that firm participation is on a voluntary basis. However, to the extent that it is possible, TRA may be able to elicit participating firms to cooperate with greater data demands by stressing the importance of data in coming to sound determinations;
- Encouraging firms to participate: Whilst compelling firms to participate may not be possible, strong encouragement of participation could lead to better insights from the data. There may be a particularly strong argument for this in scenarios where the trade remedy in under review is likely to have widespread and significant effects on UK industry and the wider economy. In such cases, making correct deductions about the impact of a trade remedy can have large economic ramifications on the UK and it would behove the TRA to give make the best approaches feasible by having ample data; and
- Make the most of what is available: despite data for individual investigations being limited, the TRA has collected data from multiple firms operating in a wide range of industries across all the investigations it has ever undertaken. If the TRA were able to harmonise all the data that has been collected from previous investigations into a single database, it may be able to leverage this information in future investigations. This may allow the TRA to increase the number of time periods and comparators contained in future data samples by appending relevant information from prior investigations. In theory, this could expand the data available to the TRA in the long-term without jeopardizing the participation of its questionnaires' respondents in the short-term.[145]

[145] The TRA will need to ensure that it adheres to any data storage and utilisation terms within the data provision agreements it made with respondents from past investigations.

Practical considerations for causal analysis

9.9 The framework provides the TRA with guidance for how to select feasible and suitable methodological approaches for the causal assessment of trade remedies, subject to various contexts and constraints. However, there are many considerations that the TRA must bear in mind when practically undertaking causal analysis with these approaches in order to meaningfully interpret their findings. These considerations include many of the key lessons gleaned from the case studies within this report but also go beyond them. They include:

- The unit of treatment and unit of analysis: in general, assessing the impact of a trade remedy with data requires conceptual overlap between the data and the trade remedy in question. The extent to which the data diverges from the truth will be the extent to which the estimated impacts diverge from true impacts. A key area where divergence may occur is with respect to the unit of treatment. If the unit of the treatment being assessed differs from the unit impacted by the trade remedy, it is imperative to understand these divergences and how they may impact the analysis. Mitigations can be made thereafter, or caveats should mitigations fail;
- Pre-initiation effects: effects of a trade remedy that materialise prior to the initiation of the trade remedy investigation may be indicative of factors that must be accounted for in causal analysis. The source of these effects must be identified in order to inform the appropriate steps to be taken thereafter. Should these pre-initiation effects be a result of anticipation effects, whereby producers or importers of the affected commodities pre-empt the trade remedy and adjust their behaviour accordingly, the evaluation should consider these effects as part of the aggregate impact of the trade remedy. Should these pre-initiation effects be indicative of other factors unrelated to the trade remedy, they must be separated from the impact of the trade remedy. Failing this, the aggregate of the pre-initiation effects and the trade remedy effects may be reported and caveated accordingly;
- Spillover effects: these may arise when commodities that are out of scope of a trade remedy are impacted due to substitution effects, complementary effects or other effects connected to the trade remedy. Failing to account for spillover effects may result in the estimated impact of the trade remedy being heavily biased. Therefore, spillover effects must be mitigated to the greatest extent possible. This can be done by identifying and removing comparators affected by the trade remedy from the sample;
- Volatility matters: The underlying volatility of the data has implications for the performance of the many of the methodologies considered within this report. Numerous ways were proposed and executed to mitigate the amount of noise in the data. This included taking log or inverse hyperbolic sine transformations of key variables of interest, aggregating the data so that it is less granular and limiting the sample to only consist of periods where the data appears to be more stable; and
- Sample selection: as previously mentioned, the TRA gathers its data for domestic producers, domestic importers, overseas exporters and firms in the wider domestic supply chain through questionnaires that are submitted on a voluntary basis. This means that firms that participate in the trade remedies investigations opt in, and often because they have something to gain from doing so. Their submissions can contribute to evidence that is used to inform policy that has the potential to improve their business prospects. This creates sample selection issues whereby the sample is not representative of the general market. In its most extreme form this can lead to samples containing no firms that are unlikely to be impacted by the trade remedy, as they have little incentive to participate and supplying data can be time-consuming and costly. Such a sample would not be appropriate for ex-post counterfactual analysis because there are no comparators for the firms that are affected by the trade remedy. Alternatively, if there are some unaffected firms, then causal analysis may need to account for sample selection when reporting causal estimates. In particular, the estimates from the sample may not be indicative of the impact of the trade remedy on average but may only be generalisable to firms that have the incentive to participate in trade remedy investigations. If the impact of the trade remedy is likely to vary across firms, then sample estimates can diverge greatly from the average trade remedy impact. This can be overcome by implementing approaches

that are robust to sample selection (these are beyond the scope of this report) or caveating the findings and resulting conclusions appropriately.[146]

Closing remarks

9.10 Assessing the causal impact of trade remedies on trade and economic performance is a crucial aspect of the work carried out by the TRA. The key aim of this report is to provide the TRA with a framework that aids the selection of suitable approaches in assessing the causal impact of trade remedies. This report also illustrates how the framework can be effectively used to carry out causal analysis in four distinct case studies that are generalisable to work that the TRA will undertake in future.

9.11 The key takeaways from this report are that the framework can be used as an effective tool for causal analysis, but that its methodology recommendations should not be treated prescriptively or with exclusivity. This report proposes that the framework be used as a guide and that, where possible, a plethora of approaches be used proportionately in order to triangulate the most accurate and credible answer. Furthermore, this report identifies the hurdles that must be overcome when implementing causal analysis in practice and recommends actionable solutions where possible. Finally, this report puts for some suggestions for ways in which the TRA can maximise and expand on the available data such that robust causal analysis can be more feasible.

[146] A prominent approach used in the sample selection literature is a 'Heckitt' sample selection model. This model separately models the probability of a unit participating in the sample and the outcome of interest (e.g. separately modelling the probability a firm participating in the investigation and the impact of the remedy on firm costs, revenues, etc.). The idea is that modelling the sample selection explicitly allows the evaluator to control for the resulting bias that sample selection has on the estimated impact of the remedy. For more details on the theory and implementation of this approach, please refer to Puhani, Patrick. "The Heckman correction for sample selection and its critique." *Journal of economic surveys* 14, no. 1 (2000): 53-68. For practical implementation of this approach in R, please refer to Toomet, O. and Henningsen, A., 2008. Sample selection models in R: Package sample Selection. *Journal of statistical software*, *27*, pp.1-23.

10. Appendix

Appendix 1: Illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC

Commodities investigated in illustrative Case Study 1: Aluminium Extrusions from the PRC

Table 32: Plot of pre-trends assuming parallel trends assumption is violated

8-digit commodity code	8-digit commodity code description	10-digit commodity code within 8-digit commodity code	Is the 10-digit commodity code within the trade remedy's scope?
76041010	Bars, rods and profiles, of non-alloy aluminium	7604101011	in scope
		7604101090	in scope
76041090	Profiles of non-alloy aluminium, n.e.s.	7604109011	in scope
		7604109019	in scope
		7604109025	in scope
		7604109029	in scope
		7604109080	in scope
		7604109089	in scope
76042100	Hollow profiles of aluminium alloys, n.e.s.	7604210010	in scope
		7604210090	in scope
76042910	Bars and rods of aluminium alloys	7604291010	in scope
		7604291030	in scope
		7604291040	in scope
		7604291090	in scope
76042990	Solid profiles, of aluminium alloys, n.e.s.	7604299010	in scope
		7604299020	in scope
		7604299090	in scope
76081000	Tubes and pipes of non-alloy aluminium (excl. hollow profiles)	7608100011	in scope
		7608100019	in scope
		7608100020	in scope
		7608100080	in scope
		7608100089	in scope
76082081		7608208110	in scope

8-digit commodity code	8-digit commodity code description	10-digit commodity code within 8-digit commodity code	Is the 10-digit commodity code within the trade remedy's scope?
	Tubes and pipes of aluminium alloys, not further worked than extruded (excl. hollow profiles)	7608208120	out of scope
		7608208190	in scope
76082089	Tubes and pipes of aluminium alloys (excl. such products welded or not further worked than extruded, and hollow profiles)	7608208910	in scope
		7608208920	in scope
		7608208930	in scope
		7608208940	out of scope
		7608208990	in scope
76109090	Structures and parts of structures, of aluminium, n.e.s., and plates, rods, profiles, tubes and the like, prepared for use in structures, of aluminium, n.e.s. (excl. prefabricated buildings of heading 9406, doors and windows and their frames and thresholds for doors, bridges and bridge-sections, towers and lattice masts)	7610909010	in scope
		7610909091	out of scope
		7610909092	out of scope
		7610909095	out of scope

Source: GT Analysis

Data adjustments in illustrative Case Study 1: AD0012 Aluminium Extrusions from the PRC

10.1 The first adjustment was to identify any non-affected commodities for which the evidence suggests that they were impacted by the trade remedy. This is because a key assumption in all the methodologies applied is that the unaffected commodities were not impacted by the treatment in any way. Violation of this assumption would bias the estimated impact of the trade remedy because the unaffected commodities would no longer be good proxies for affected commodity in absence of the trade remedy. There are at least three key reasons why some commodities may fail to satisfy this assumption in this general setting:

- The non-targeted commodity is a substitute for the targeted commodity: this means that an increase in the price of the targeted commodity due to the trade remedy will result in an increase in the imports of the non-targeted commodity because the two goods are used interchangeably. For example, an increase in the price of butter would increase demand for margarine as the two goods are substitutes.
- The non-targeted commodity is a complement of the targeted commodity: this means that an increase in the price of the targeted commodity due to the trade remedy will result in a reduction in the imports of the non-targeted commodity because the two goods are used in alongside one another. For example, an increase in the price of tennis rackets would reduce demand for tennis balls as the two goods are complements.
- The non-targeted commodity was impacted by another policy that occurred in tandem with or soon after the trade remedy.

10.2 The identification of non-target commodities that were affected by the trade remedy and their exclusion from the analysis is essential for the validity of the analysis. Therefore, it is proposed that a rigorous approach that balances quantitative and qualitative evidence should be taken by the TRA to identify and exclude such commodities where possible. Ideally, the TRA would assess the suitability of each non-targeted commodity as a suitable comparator for a targeted commodity on a case-by-case basis. The following steps are proposed:

- Identify all non-target commodities that share the same HS chapter as the target commodity;
- All non-target commodities that are known to have been targeted by other remedies that occurred simultaneously with or soon after the main trade remedy in question should be removed from the analysis. It is understood that the TRA has information on which commodities have been targeted by remedies at a given point in time. Therefore, it is proposed that the TRA use any existing database to exclude any non-target commodities that have been targeted by a separate trade remedy within the estimation period that they are using to assess an impact of a particular trade remedy;
- Assess the conceptual similarity of each non-target commodity with the target commodity by reviewing the similarity of the in the same classification. Commodities that are likely to be strong substitutes or complements should be identified and their removal from the sample should be considered. There may be difficulties in establishing substitutability or complementary of commodities from a conceptual basis alone. Therefore, quantitative measures are proposed that may be used alongside this in latter steps. Any commodities that appear to be highly unrelated to the targeted commodity should also be identified for further scrutiny in the following steps;
- Convert the weight of imports from kilograms to the inverse hyperbolic sine of weight in kilograms.[147] The analysis will be conducted on this transformation of imports. For each non-target commodity, calculate the average imports in the a given number years prior to the initiation of the trade remedy investigation and the average imports reported after the initiation

[147] This is to reduce the impact of extreme values on the calculated average. This transformation generally deals with outliers in reported exports while still allowing observations with 0 imports to be retained. The logarithmic transformation is the more commonly used method for this, but it treats observations with 0 imports as missing and removes them from the dataset. This creates issues with non-random attrition and panel imbalance that are better avoided. Therefore, this method was not chosen.

of the trade remedy investigation. Take the difference between the average imports before and after the trade remedy and calculate this difference both in levels and as a percentage;

- Identify the commodities that appear in the top 5% and bottom 5% of the proportionate change in imports and consider removing these commodities from the sample. Commodities that were identified as conceptual substitutes or complements in step 3 should especially be treated with suspicion.

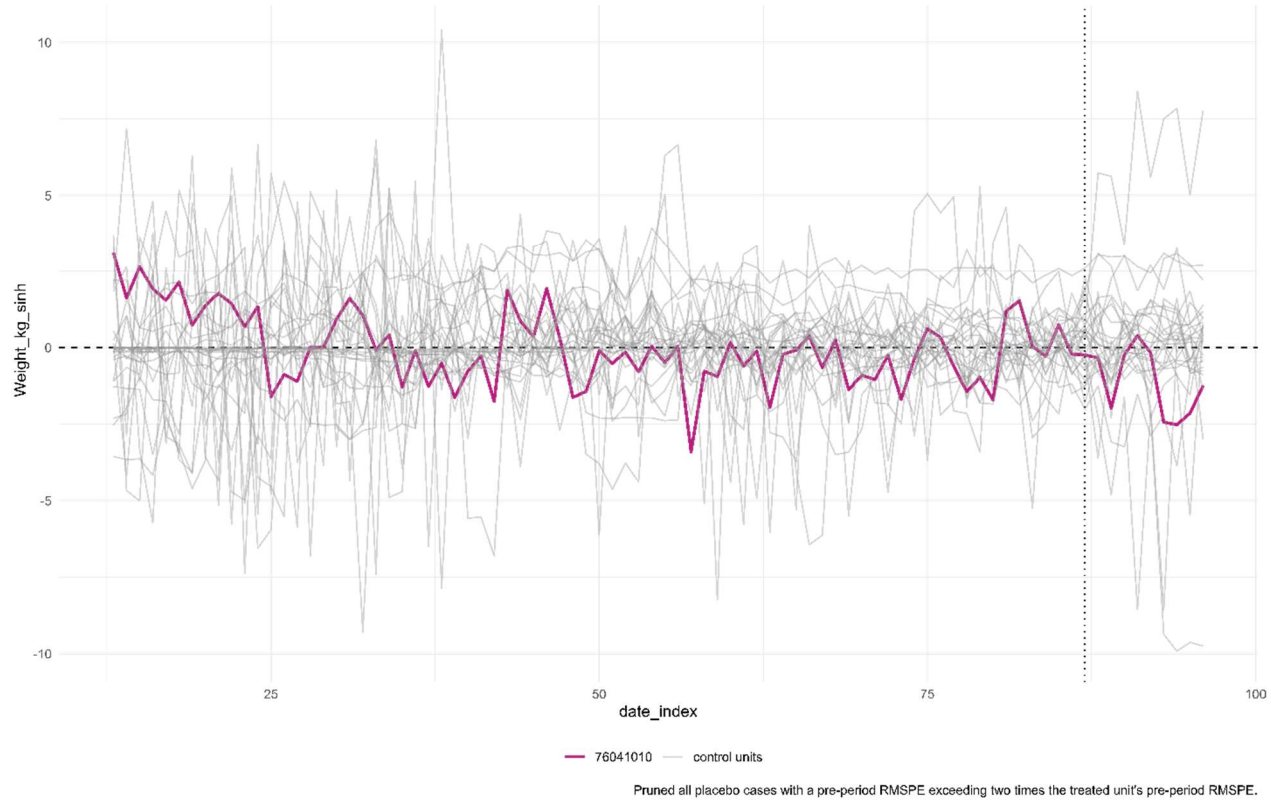
10.3 Step 1 is very easy to apply in any context because it is binary in nature. The degree to which findings from steps 3, 5 and 6 can be used to definitively draw conclusions about whether a non-targeted commodity should be removed from the analysis is more nuanced and will vary with the situation.

10.4 When conducting the analysis for the Case Study 1, the identification of non-targeted commodities that should be excluded from the analysis was quite apparent because they displayed highly dissimilar behaviour to other non-targeted commodities when checks were carried out. Due to time constraints, it was not possible to implement all the proposed checks. However, steps 5 and 6 were carried out, and these checks alone allowed for the identification of some commodities that can be reasonably excluded from the analysis.

10.5 The full sample consisted of 54 non-targeted commodities. The first step was to calculate the percentage change in average imports for each commodity in the three years prior to the initiation of trade remedy investigation relative to all post-initiation years. Four commodities had a missing value for the proportionate change because they reported no imports in the three years prior to the initiation of trade remedy investigation but reported a notable increase in imports post-initiation. These commodities were removed from the analysis. Thereafter, the commodities that fell into the top and bottom 5% of the proportionate change were identified. These commodities displayed much more drastic changes than the other commodities. Therefore, they were removed from the analysis. This resulted in an additional six non-target commodities being dropped in total, 10 being excluded in total thus far.

10.6 The SCM was carried out for each target commodity using the remaining 44 commodities as the comparators. The variables that were used to generate the synthetic control weights were the entire history of pre-initiation imports, as outlined in the methodology. The plots of the placebos were visually inspected and the reported effects for non-target commodities were reviewed. Two commodities had atypically large effects post-initiation. This is illustrated in the plot below, which shows the treatment effect and corresponding placebo effect using a SCM for commodity 76041010.

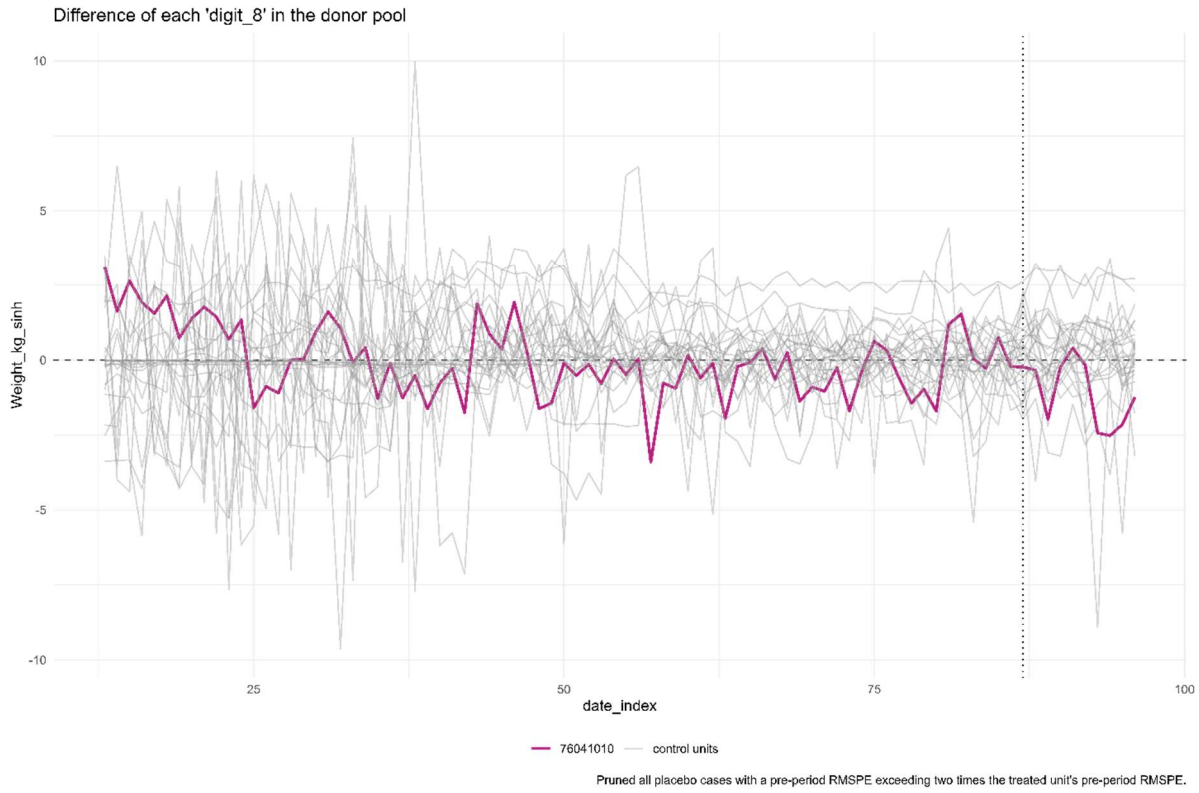
Figure 20: Placebo plot for commodity 76041010 without removing outliers



Notes: The plot above displays the results from running the SCM for commodity 76041010. The y-axis is the reported treatment effect in terms of the inverse hyperbolic sine of total imported weight in kilograms and the x-axis shows time in quarters. The purple line in the reported impact for the commodity 76041010 in a given quarter, while the grey lines are the reported affects for each of the non-target commodities used as comparators.
Source: GT Analysis using tidysynth.R package in R.

10.7 The darker, thicker line shows the difference between reported imports for commodity 76041010 and the estimated imports for the SCM in each quarter. This corresponds to the impact of the trade remedy in each quarter. The black dashed line signifies the initiation date for the trade remedy investigation. This purple line would be expected to be close to 0 in the periods prior to the initiation date because the trade remedy has been imposed yet. If the trade remedy had the expected impact on imports for targeted commodity, the purple line would be expected to go down after the initiation date. The plots for non-targeted commodities would be expected to be close to 0 for the entire period because they were never impacted by the trade remedy. However, there are two placebos that display abnormal post-initiation impacts: one displays the largest post-initiation increase while the other displays the largest post-initiation decrease. Such changes would not be expected if the commodity was not impacted by the trade remedy in some way, so these commodities should be removed from the sample. The result from removing the outliers is displayed in the figure below. The remaining placebos seem to be relatively unaffected by the trade remedy and are likely to be better comparators for the target commodity.

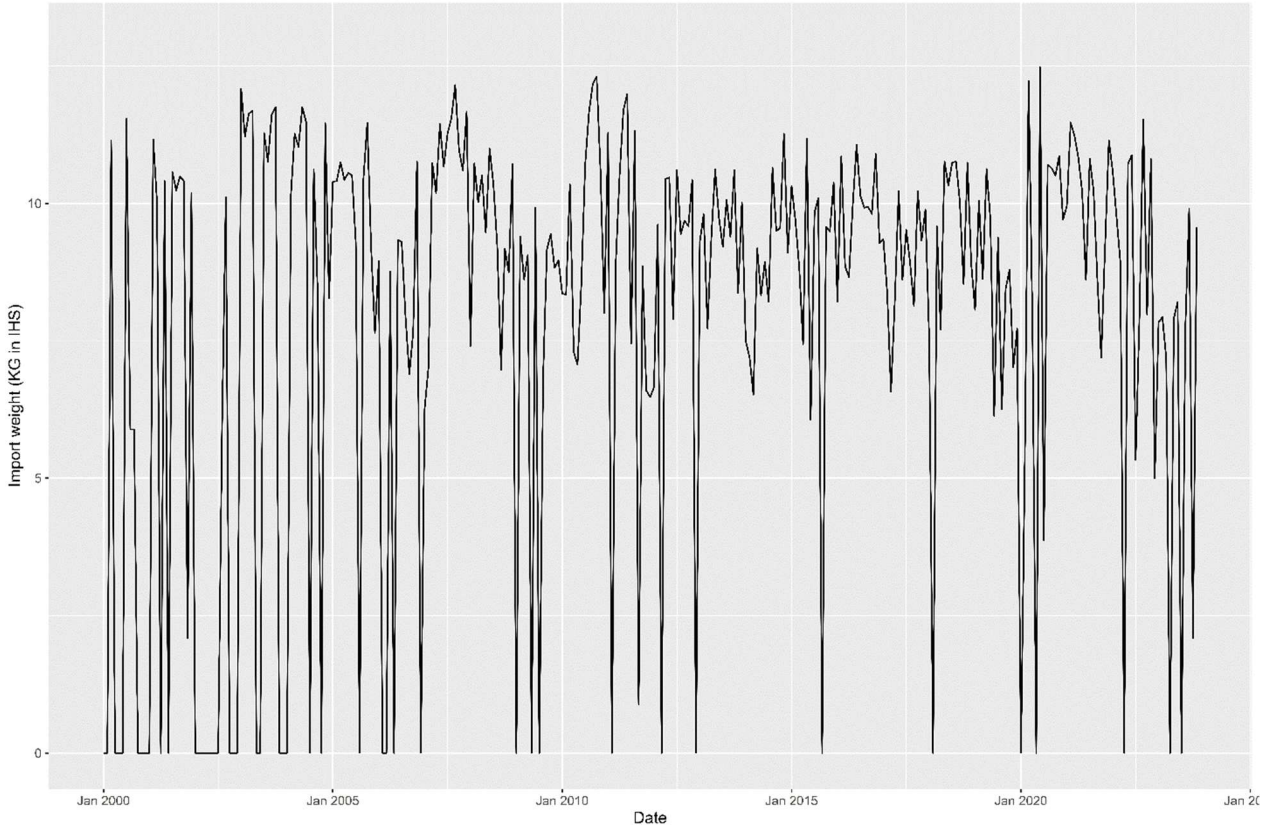
Figure 21: Placebo plot for commodity 76041010 after removing outliers



Notes: The plot above displays the results from running the SCM for commodity 76041010 after dropping the commodities deemed to be outliers on the basis of the placebo plot.
Source: GT Analysis using tidysynth.R package in R.

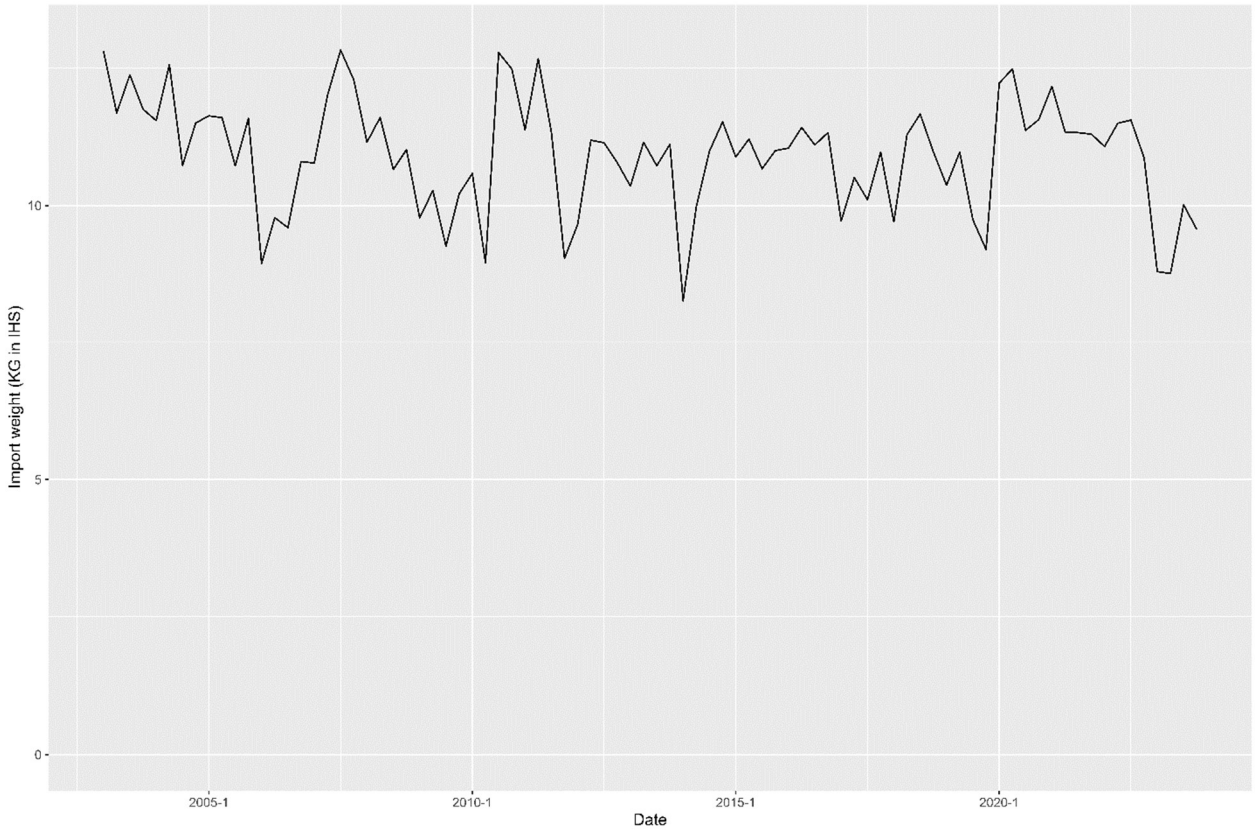
10.8 After removing the outliers, the final adjustments made were to aggregate the data from the monthly-level to the quarterly-level, and to trim the earlier months of each dataset. These adjustments were to deal with high level of volatility displayed in the monthly data for several commodities, especially for earlier parts of the sample where some months had no reported imports. Without these adjustments, the data displayed extreme fluctuations in imports that would introduce more noise to the data. This noise would in turn reduce the ability of any of the models to accurately predict the unobserved counterfactual. Therefore, adjustments were taken to minimise the noise in the data and increase the prediction power of the models. This resulted in having datasets of varying lengths for each affected commodity. The results from aggregation and trimming the sample for commodity 76041010 are shown in the figures below. It can be observed that the monthly data with the full sample is quite noisy, while the quarterly data with a trimmed sample is more stable. This concludes the data cleaning procedure.

Figure 22: Monthly imports with untrimmed sample for commodity 76041010



Source: GT Analysis using tidysynth.R package in R.

Figure 23: Quarterly imports with trimmed sample for commodity 76041010



Source: GT Analysis using tidysynth.R package in R.

10.9 The final adjustment converted the units of imports from weight in kilograms to the inverse hyperbolic sine of import weight in kilograms. This was to deal with outliers in a similar way to taking a log transformation while retaining observations with 0 reported imports. This approach diverges from that taken in the Swedish Board of Trade report, where this study looks at impacts as a percentage of the imports observed in the quarter prior to the event of interest. However, this approach is not suitable for this case study because this variable is significantly more volatile than the inverse hyperbolic sine of import volumes. All the estimated impacts reported in the final results were transformed into kilotons to improve the interpretability of the findings.

10.10 A caution to bear in mind when transforming imports using the inverse of the hyperbolic sine is that this transformation brings large values and small values of the untransformed variable (import volumes in kilograms in this case) closer together. This tendency becomes more extreme for larger values of the import volumes. The table below illustrates this by considering a hypothetical example of import volumes over time.

Table 33: Illustration table of inverse hyperbolic sine

Commodity	Period	Weight (KG)	Weight (IHS of KG)	Growth of weight in KG	Growth of weight in IHS of KG
A	1	10,000	9.903488	-	-
A	2	20,000	10.59663	10,000	0.693147
B	1	100,000	12.20607	-	-
B	2	110,000	12.30138	10,000	0.095310

Commodity	Period	Weight (KG)	Weight (IHS of KG)	Growth of weight in KG	Growth of weight in IHS of KG
C	1	1,000,000	14.50866	-	-
C	2	1,010,000	14.51861	10,000	0.009950

Notes: IHS stands for inverse hyperbolic sine

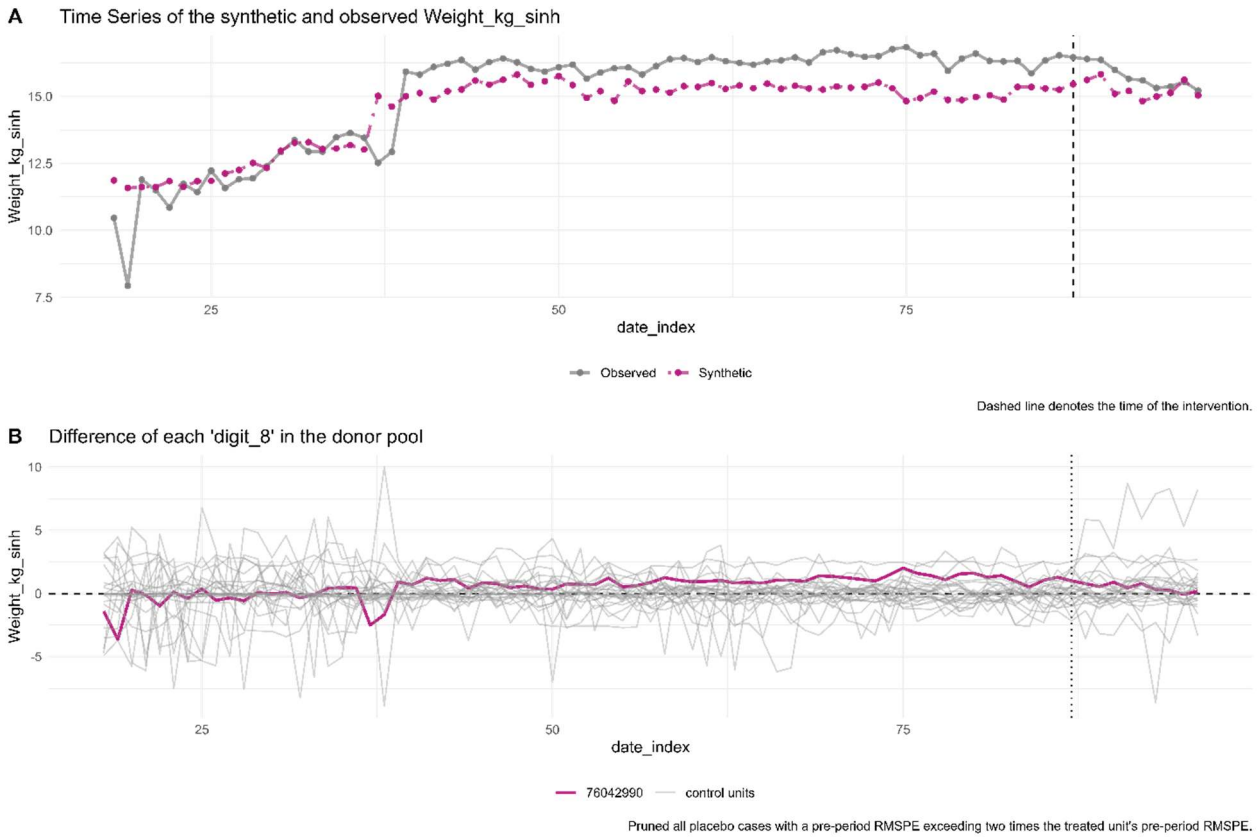
Sources: GT Analysis.

10.11 The table above shows the evolution if imports across two time periods for commodities A, B and C. The weight of the imports in both periods is shown in both kilograms and the inverse hyperbolic sine of imports. The change in imports over time is also shown for both measures of imports. The change in imports is identical for all three commodities and is equal to 10,000kgs. However, the change in imports with respect to the inverse hyperbolic sine of import weight becomes smaller as the base import weight grows, despite the change in terms of kilograms remaining identical. This shows that the inverse hyperbolic sine, for a given distance between two values, reduces the difference between two values as the size of the values themselves grow.

10.12 This principle is important to bear in mind when converting between imports in kilograms and imports in terms of their inverse hyperbolic sine as there can be visual discrepancies in the relative magnitudes of imports over time when transitioning from one measure to the other. The implications of this on the analysis and the interpretation of the results is covered when discussing the case studies in the main report.

Model outputs for illustrative Case Study 1: Commodity 76042990

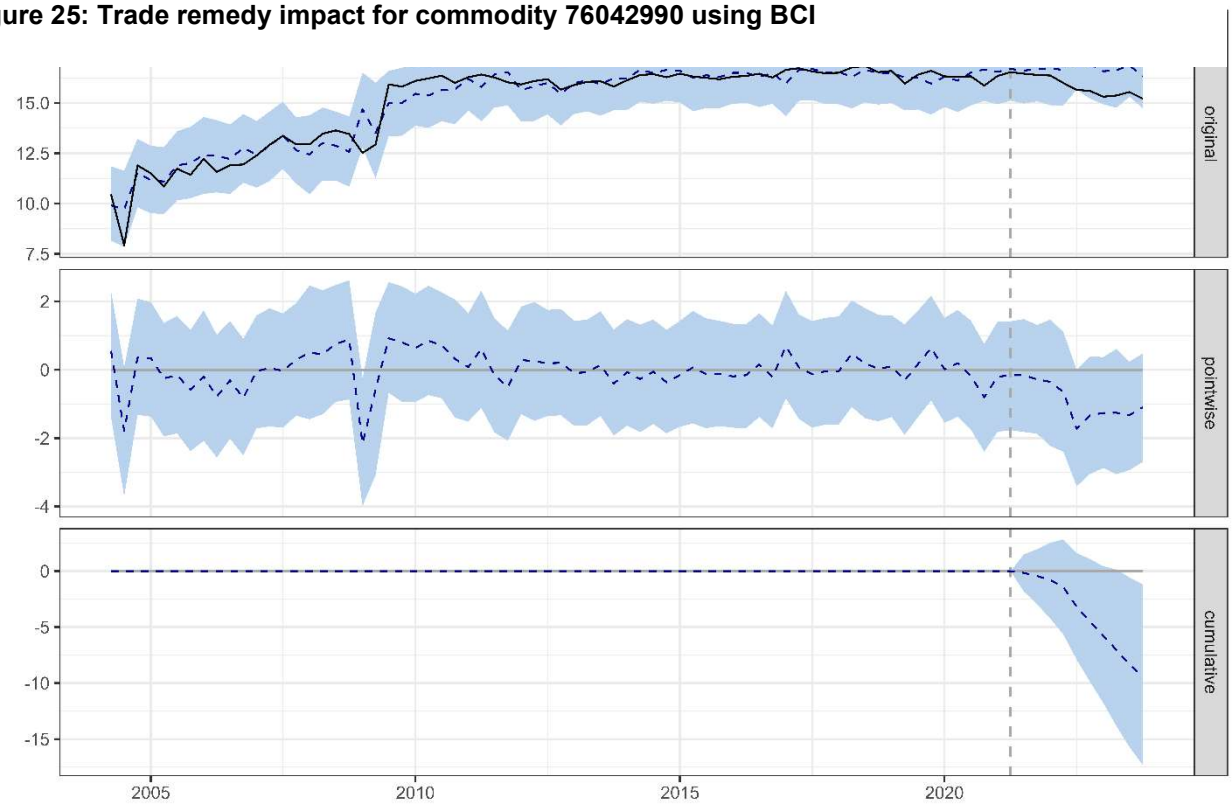
Figure 24: Trade remedy impact for commodity 76042990 using SCM



Notes: Panel A shows the predicted and observed imports of commodity over time using the SCM. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the time periods denominated by an index. The initiation date is signified by the black vertical dashed line close to the end of the time series. Panel B shows the difference between the observed and predicted imports for commodity 76042990 over time. The y-axis corresponds to the difference between the two plots shown in Panel A and also represents the effect of the trade remedy in each period. The pink line represents the targeted commodity and the grey lines correspond to the placebo treatment effects of each comparator commodity used to generate the predicted imports.
Source: GT Analysis using tidysynth.R package in R.

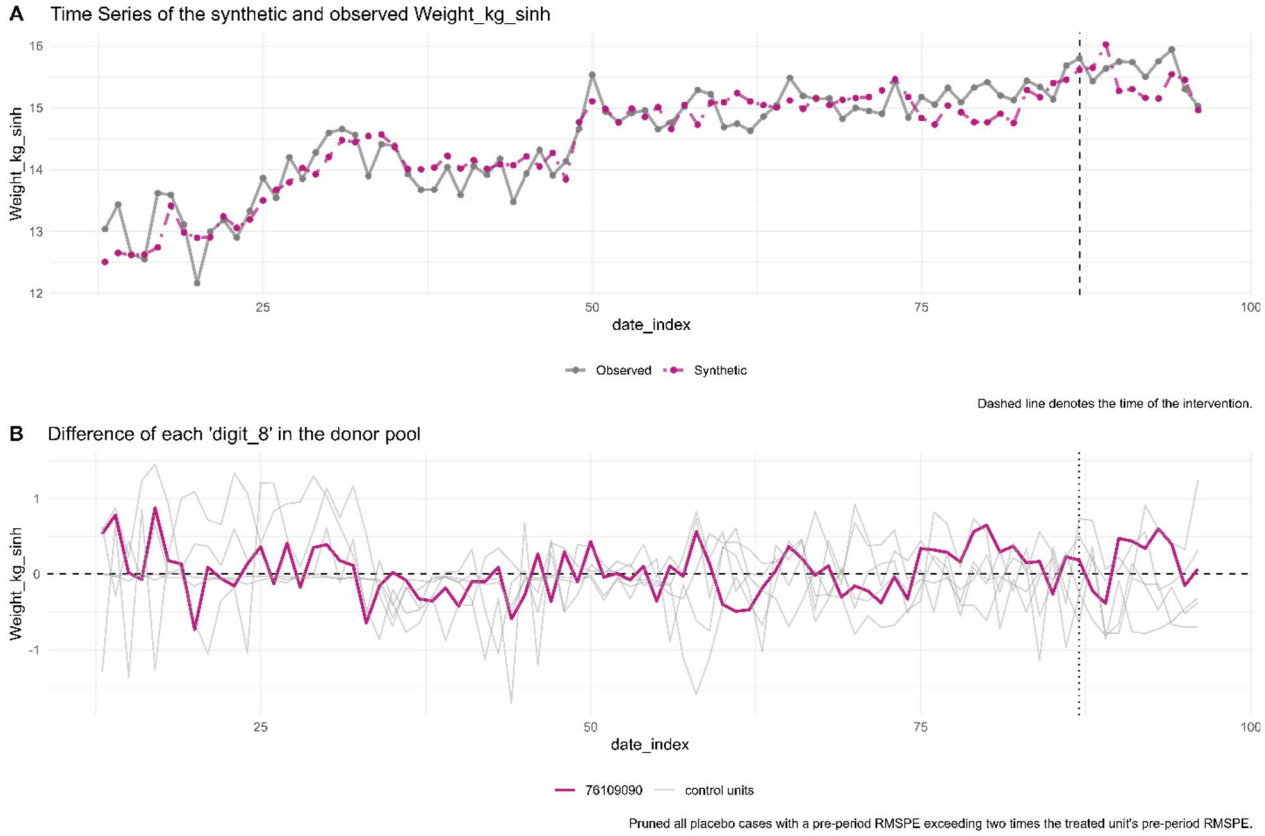
Model outputs for illustrative Case Study 1, with and without post-initiation spikes

Figure 25: Trade remedy impact for commodity 76042990 using BCI



Notes: The first panel from the top shows the predicted (dashed line) and observed (solid line) imports of commodity 76042990 over time using the BCI. The light blue shading represents the 95% confidence interval around the predicted imports. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the date. The initiation date is signified by the grey vertical dashed line close to the end of the time series. The second panel the difference between the observed and predicted imports for commodity 76042990 over time. The light blue shading represents that 95% confidence interval around the estimated treatment effect. The y-axis corresponds to the difference between the two plots shown in the first panel and also represents the effect of the trade remedy in each period. The third panel represents the accumulated treatment effect: it is the sum of the treatment effect from the initiation date going forwards. The y-axis shows the accumulated treatment effect in terms of the inverse hyperbolic sine of import volumes. The light blue shading represents that 95% confidence interval around the estimated accumulated treatment effect.
Source: GT Analysis using CausalImpact.R package in R.

Figure 26: Trade remedy impact for commodity 76109090 using SCM



Notes: Panel A shows the predicted and observed imports of commodity over time using the SCM. The y-axis shows the inverse hyperbolic sine of import volumes while the x-axis shows the time periods denominated by an index. The initiation date is signified by the black vertical dashed line close to the end of the time series. Panel B shows the difference between the observed and predicted imports for commodity 76109090 over time. The y-axis corresponds to the difference between the two plots shown in Panel A and also represents the effect of the trade remedy in each period. The pink line represents the targeted commodity and the grey lines correspond to the placebo treatment effects of each comparator commodity used to generate the predicted imports.
Source: GT Analysis using tidysynth.R package in R.

10.13 The final adjustment converted the units of imports from weight in kilograms to the inverse hyperbolic sine of imports of weight in kilograms. This was to deal with outliers in a similar way to taking a log transformation while retaining observations with 0 reported imports.

Appendix 2: Derivations for illustrative Case Study 2: TD0014 Heavy Plate from the PRC

The model

10.14 The model here is a simple Cournot model in which firms compete on quantity (specifically, they choose how much of the commodity to supply to the domestic market taking as given the amount supplied by the other firm). The products of the foreign and domestic firms are assumed to be identical, and there is no cooperation between firms.

10.15 Suppose there are two firms: a domestic firm i and a foreign firm j (i.e. a foreign firm that is exporting to the UK market). They compete in the domestic marketplace by deciding how much of the good to supply to the market, x_i and x_j respectively. The profit of the domestic firm can be written as:

$$\pi_i = x_i . p(x_i + x_j) - c_i(x_i) \tag{4}$$

where $p(.)$ is the inverse demand function and $c_i(.)$ is the domestic firm's cost function.

10.16 The domestic firm chooses x_i to maximise profit. This means setting the first derivative of (4) with respect to x_i equal to zero (using the product rule):

$$\pi_i' = p(x_i + x_j) + x_i . p'(x_i + x_j) - c_i'(x_i) = 0 \tag{5}$$

10.17 Note that $c_i'(x_i)$ is simply firm i's marginal cost. Rearranging this, and dividing by $p(x_i + x_j)$ yields:

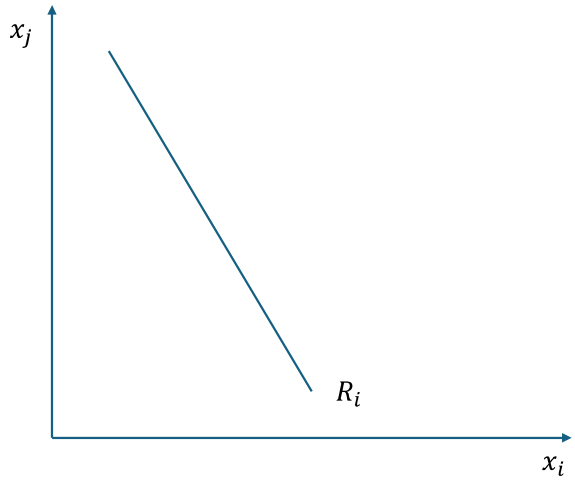
$$-\left(\frac{p(x_i + x_j) - c_i'(x_i)}{p(x_i + x_j)}\right) = x_i . \frac{p'(x_i + x_j)}{p(x_i + x_j)} \tag{6}$$

10.18 Multiplying and dividing by $(x_i + x_j)$ yields:

$$\left(\frac{p(x_i + x_j) - c_i'(x_i)}{p(x_i + x_j)}\right) = \frac{x_i}{x_i + x_j} . - \frac{p'(x_i + x_j).(x_i + x_j)}{p(x_i + x_j)} \tag{7}$$

10.19 Equation (7) represents the 'best response' function of firm i: it tells the profit maximising level of output of the domestic firm x_i as a function of the quantity supplied by the foreign firm x_j. The best response function slopes downwards, as seen in the below. This means that, if the foreign firm supplies more to the domestic market, the domestic firm's profit maximising response is to reduce its supply (essentially to help uphold prices in the domestic market).

Figure 27: Domestic firm's best response function



Source: GT Analysis.

10.20 Note that $\frac{p(x_i+x_j)-c_i'(x_i)}{p(x_i+x_j)}$ is just the price cost margin (denoted by pcm_i), $\frac{x_i}{x_i+x_j}$ is simply the market share of the domestic firm (s_i), and $-\frac{p'(x_i+x_j).(x_i+x_j)}{p(x_i+x_j)}$ is the inverse of the elasticity of demand (denoted ϵ). Hence, the price cost margin can be written as:

$$pcm_i = \frac{s_i}{\epsilon} \tag{8}$$

10.21 Turning to the foreign firm, suppose that an ad-valorem (i.e. percentage) tariff of t is imposed by the domestic country on the foreign firm's goods sold in that market. Firm j's profit function is then:

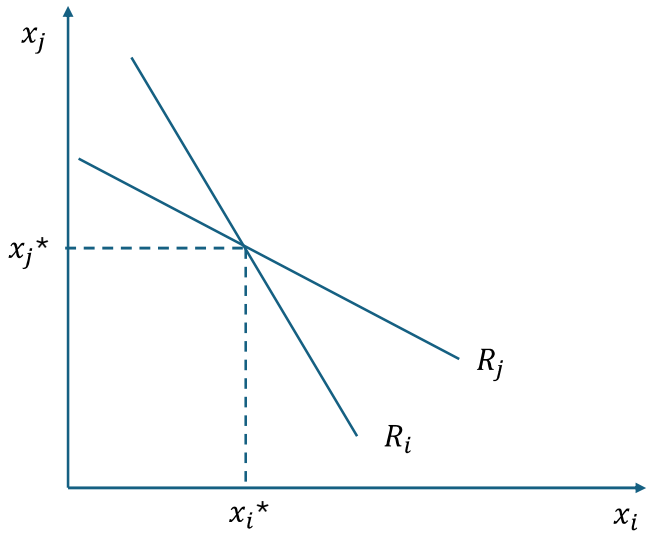
$$\pi_j = x_j.p(x_i + x_j) - c_j(x_j) - tx_j \tag{9}$$

10.22 Following the same process as above, the foreign firm's best response function can be written as:

$$\frac{p(x_i + x_j) - c_j'(x_j) - tx_j}{p(x_i + x_j)} = \frac{x_j}{x_i + x_j}.\frac{p'(x_i + x_j).(x_i + x_j)}{p(x_i + x_j)} = \frac{s_j}{\epsilon} \tag{10}$$

10.23 The domestic market is in equilibrium when both firms are maximising profits given the output supplied by the other (i.e. when they are both on their best response function). The point at which the best response functions cross is the equilibrium in this market, see diagram below (note that, in principle, there could be more than one equilibrium depending on the precise nature of demand and the behaviour of firms' costs).

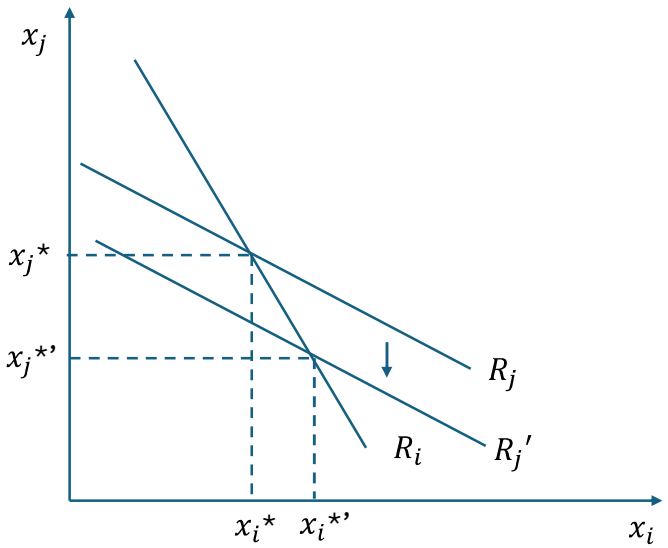
Figure 28: Market equilibrium



Source: GT Analysis.

10.24 It is then possible to use the model to explore the impact of trade policy. Suppose that country i introduces an import tariff (or increases an existing tariff). This means that all else equal it is less profitable for the foreign firm to supply the domestic market. Firm j's reaction function R_j shifts downward. The new equilibrium involves the domestic firm producing more output, at the expense of the foreign firm. This means that the domestic firm's market share s_i increases. From condition (5), it is clear that this results in an increase in the domestic firm's price-cost margin. Since both the quantity supplied by the domestic firm and its margin on each unit increase, firm i's total profits rise.

Figure 29: Impact of an import tariff



Source: GT Analysis.

Putting it into practice

10.25 This section shows how the model could be used to give an indication of the impact of introducing an import tariff (or retaining one). To simplify matters for the purposes of this illustration, the two firms' marginal costs (the costs of producing an additional unit) are assumed to be constant at c_i

and c_j. Then, by substituting (10) into (7) and noting that $s_i = 1 - s_j$, the domestic firm's market share can be expresses as a function of price, the firms' marginal costs and the import tariff:

$$s_i = \frac{p - c_i}{2p - c_i - c_j - t} \tag{11}$$

10.26 This equation is intuitive. Note that t appears in the denominator with a negative sign, meaning that a higher tariff increases the domestic market share (as seen above). Note also that if the import tariff is zero ($t = 0$) and the firms have the same marginal cost $c_i = c_j$ the market share becomes $s_i = 0.5$ or 50%: since the firms have the same marginal costs in the domestic market and no tariff is applied, the market is split equally between the two firms.

Appendix 3: Model outputs for illustrative Case Study 3: TD0004 and TS0005 Biodiesel from the USA and Canada

10 comparator firms

Table 34: SCM results with constant trade remedy impact and high volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-94	-10.0	-9.43	0.273
Costs (trimmed sample)	-100	-184	-10.0	-16.93	0.833
Demand	3,952	2,764	23.5	15.28	0.455
Demand (trimmed sample)	3,952	5,467	23.5	35.61	0.500
Profit	13,377	3,985	11.1	3.07	0.636
Profit (trimmed sample)	13,377	20,523	11.1	18.12	0.500
Revenue	147,151	53,143	11.1	3.74	0.636
Revenue (trimmed sample)	147,151	225,750	11.1	18.12	0.500

Source: GT Analysis.

Table 35: BCI results with constant trade remedy impact and high volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-84	-10.0	-8.57	0.1180
Costs (trimmed sample)	-100	-110	-10.0	-10.83	0.0002
Demand	3,952	3,427	23.5	19.73	0.0006
Demand (trimmed sample)	3,952	4,041	23.5	24.16	0.0002
Profit	13,377	10,327	11.1	8.37	0.0002
Profit (trimmed sample)	13,377	12,963	11.1	10.76	0.0002
Revenue	147,151	113,594	11.1	8.37	0.0002
Revenue (trimmed sample)	147151	142593	11.1	10.76	0.0002

Source: GT Analysis.

Table 36: SCM results with varying trade remedy effect and low volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-69	-63	-6.79	-6.22	0.0909
Costs (trimmed sample)	-69	-150	-6.79	-13.66	0.8330
Demand	2,537	2,291	15.50	13.71	0.0909
Demand (trimmed sample)	2,537	3,979	15.50	26.16	0.6670
Profit	8,793	7,343	7.40	6.09	0.2730
Profit (trimmed sample)	8,793	15,544	7.40	13.77	0.6670
Revenue	96,725	76,969	7.40	5.78	0.1820
Revenue (trimmed sample)	96,725	170,984	7.40	13.77	0.6670

Source: GT Analysis.

Table 37: BCI results with varying trade remedy effect and low volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-69	-111	-6.79	-10.4	0.069
Costs (trimmed sample)	-69	-80	-6.79	-7.74	0.0004
Demand	2,537	2,775	15.5	17.31	0.0668
Demand (trimmed sample)	2,537	2,681	15.5	16.57	0.0002
Profit	8,793	8,323	7.4	6.98	0.0152
Profit (trimmed sample)	8,793	8,949	7.4	7.55	0.0002
Revenue	96,725	91,553	7.4	6.98	0.0146
Revenue (trimmed sample)	96,725	98,443	7.4	7.55	0.0002

Source: GT Analysis.

Table 38: SCM results with varying trade remedy effect and high volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-69	-66	-6.79	-6.56	0.182
Costs (trimmed sample)	-69	-153	-6.79	-13.93	0.500
Demand	2,553	1,602	15.50	9.07	0.273
Demand (trimmed sample)	2,553	4,068	15.50	26.68	0.500
Profit	8,834	1,614	7.40	1.26	0.727

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Profit (trimmed sample)	8,834	15,980	7.40	14.14	0.500
Revenue	97,178	24,487	7.40	1.75	0.727
Revenue (trimmed sample)	97,178	175,776	7.40	14.14	0.500

Source: GT Analysis.

Table 39: BCI results with varying trade remedy effect and high volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-69	-61	-6.79	-6.11	0.1142
Costs (trimmed sample)	-69	-78	-6.79	-7.64	0.0002
Demand	2,553	2,154	15.50	12.70	0.0016
Demand (trimmed sample)	2,553	2,642	15.50	16.18	0.0002
Profit	8,834	6,260	7.40	5.14	0.0010
Profit (trimmed sample)	8,834	8,420	7.40	7.07	0.0002
Revenue	97,178	68,855	7.40	5.14	0.0008
Revenue (trimmed sample)	97,178	92,620	7.40	7.07	0.0002

Source: GT Analysis.

30 comparator firms

Table 40: SCM results with constant trade remedy impact and high volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-89	-34	-10.0	-4.09	0.548
Costs (trimmed sample)	-89	-48	-10.0	-5.51	0.667
Demand	13,983	5,252	23.5	7.71	0.677
Demand (trimmed sample)	13,983	7,608	23.5	11.51	0.500
Profit	42,248	-9,151	11.1	-2.10	0.903
Profit (trimmed sample)	42,248	-41,022	11.1	-8.85	0.667
Revenue	464,727	-100,807	11.1	-2.10	0.935
Revenue (trimmed sample)	464,727	-451,343	11.1	-8.85	0.667

Source: GT Analysis.

Table 41: BCI results with constant trade remedy impact and high volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-89	-69	-10.0	-7.88	0.0622
Costs (trimmed sample)	-89	-81	-10.0	-9.19	0.0002
Demand	13,983	5,778	23.5	8.50	0.2215
Demand (trimmed sample)	13,983	14,482	23.5	24.50	0.0018
Profit	42,248	-17,762	11.1	-3.98	0.4690
Profit (trimmed sample)	42,248	46,940	11.1	12.54	0.0058
Revenue	464,727	-195,387	11.1	-3.98	0.4706
Revenue (trimmed sample)	464,727	516,336	11.1	12.54	0.0067

Source: GT Analysis.

Table 42: SCM results with varying trade remedy effect and low volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-61	-39	-6.79	-4.43	0.323
Costs (trimmed sample)	-61	-19	-6.79	-2.17	0.667
Demand	9,043	4,964	15.50	7.85	0.452
Demand (trimmed sample)	9,043	2,316	15.50	3.65	0.667
Profit	27,778	-12,099	7.40	-2.89	0.935
Profit (trimmed sample)	27,778	-57,453	7.40	-12.36	0.500
Revenue	305,557	-132,830	7.40	-2.88	0.903
Revenue (trimmed sample)	305,557	-632,154	7.40	-12.37	0.500

Source: GT Analysis.

Table 43: BCI results with varying trade remedy effect and low volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-61	-44	-6.79	-5.02	0.0600
Costs (trimmed sample)	-61	-50	-6.79	-5.67	0.0010
Demand	9,043	2,614	15.50	3.94	0.2626
Demand (trimmed sample)	9,043	7,636	15.50	12.74	0.0359
Profit	27,778	-10,073	7.40	-2.39	0.4421
Profit (trimmed sample)	27,778	28,632	7.40	7.66	0.0931

Revenue	305,557	-110,804	7.40	-2.39	0.4413
Revenue (trimmed sample)	305,557	314,954	7.40	7.66	0.0973

Source: GT Analysis.

Table 44: SCM results with varying trade remedy effect and high volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-61	-25	-6.79	-2.89	0.484
Costs (trimmed sample)	-61	-19	-6.79	-2.24	0.667
Demand	9,064	3,688	15.50	5.65	0.645
Demand (trimmed sample)	9,064	2,689	15.50	4.24	0.667
Profit	27,831	-10,802	7.40	-2.58	0.871
Profit (trimmed sample)	27,831	-55,439	7.40	-11.94	0.500
Revenue	306,140	-118,985	7.40	-2.58	0.903
Revenue (trimmed sample)	306,140	-609,931	7.40	-11.94	0.500

Source: GT Analysis.

Table 45: BCI results with varying trade remedy effect and high volatility (30 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-61	-44	-6.79	-5.04	0.0640
Costs (trimmed sample)	-61	-53	-6.79	-5.97	0.0004
Demand	9,064	4,060	15.50	6.26	0.2043
Demand (trimmed sample)	9,064	9,563	15.50	16.46	0.0060
Profit	27,831	-10,489	7.40	-2.49	0.4853
Profit (trimmed sample)	27,831	32,523	7.40	8.81	0.0443
Revenue	306,140	-115,381	7.40	-2.49	0.4930
Revenue (trimmed sample)	306,140	357,749	7.40	8.81	0.0439

Source: GT Analysis.

Duty amount by type of goods

10.27 The final duties for FAME products is indicated in the tables below. FAME is subdivided into Category 1 goods and Category 2 goods. Category 1 goods include biodiesel, pure or blend, with a greater than 20% biodiesel content. Category 2 goods refer to biodiesel, blend, with less than 20% biodiesel content.

Table 46: Final Anti-dumping duty for Category 1 goods

Country or territory	Overseas exporter	Duty amount GBP (£) per tonne net	Additional TAP code
Canada	All overseas exporters[148]	144.11	B999
United States	Archer Daniels Midland Company, Decatur	57.41	A933
	Cargill Inc., Wayzata	Nil	A934
	Green Earth Fuels of Houston LLC, Houston	59.08	A935
	Imperium Renewables, Inc., Seattle	64.02	A936
	Peter Cremer North America LP, Cincinnati	165.70	A937
	World Energy Alternatives LLC, Boston	69.30	A939
	Overseas exporters otherwise specified	96.74	
	All other overseas exporters (residual amount)	144.11	A999
	Overseas exporters otherwise specified	144.11	

Source: TD0004 Final determination: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Table 47: Final Anti-dumping duty for Category 2 goods

Country	Overseas exporter	Duty amount GBP (£) per tonne net	Additional TAP code
United States	Archer Daniels Midland Company	57.41	A933
	Cargill Inc. Wayzata	Nil	A934
	Green Earth Fuels of Houston LLC, Houston	59.10	A935
	Imperium Renewables Inc., Seattle.	64.02	A936
	Peter Cremer North America LP, Cincinnati	165.70	A937
	World Energy Alternatives LLC, Boston	69.21	A939
	Overseas exporters otherwise specified	96.74	
	All other overseas exporters	114.11	A999
	Overseas exporters specified	114.11	

[148] Except BIOX Corporation, Oakville, Ontario; DSM Nutritional Products Canada Inc., Dartmouth, Nova Scotia; and Rothsay Biodiesel, Guelph, Ontario.

Source: TD0004 Final determination: TRA Investigations - Trade Remedies Service - GOV.UK (trade-remedies.service.gov.uk)

Appendix 4: Illustrative Case Study 4: TS0023 Stainless Steel Bars and Rods from India

10.28 The commodity codes impacted are as follows:[149]

- 7222202100
- 7222202900
- 7222203100
- 7222203900
- 7222208100
- 7222208900.

Table 48 illustrates the duty rates for goods that were in place before transition review.

Table 48: Duty rates in place before transition review

Exporter	Countervailing duty rate *(ad valorem)*
Viraj Profiles Limited, Palghar, Maharashtra and Mumbai, Maharashtra	Nil
Venus Wire Industries Pvt. Ltd, Mumbai	3.3%
Sieves Manufacturer India Pvt. Ltd, Mumbai	3.3%
Precision Metals, Mumbai	3.3%
Hindustan Inox Ltd, Mumbai	3.3%
Chandan Steel Ltd, Mumbai	3.4%
Ambica Steel Ltd	4.0%
Bhansali Bright Bars Pvt. Ltd	4.0%
Chase Bright Steel Ltd	4.0%
D. H. Exports Pvt. Ltd	4.0%
Factor Steels Ltd	4.0%
Global Smelters Ltd	4.0%
Indian Steel Works Ltd	4.0%
Jyoti Steel Industries Ltd	4.0%
Laxcon Steels Ltd	4.0%
Meltroll Engineering Pvt. Ltd	4.0%
Mukand Ltd	4.0%
Nevatia Steel & Alloys Pvt. Ltd	4.0%
Panchmahal Steel Ltd	4.0%
Raajratna Metal Industries Ltd	4.0%
Rimjhim Ispat Ltd	4.0%

[149] https://www.trade-remedies.service.gov.uk/public/case/Ts0023/

Exporter	Countervailing duty rate *(ad valorem)*
Sindia Steels Ltd	4.0%
SKM Steels Ltd	4.0%
Parekh Bright Bars Pvt. Ltd	4.0%
Shah Alloys Ltd	4.0%
All other overseas exporters (residual amount)	4.0%

Source: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017R1141

Data construction

10.28 Due to the sensitive nature of firm specific data, the TRA has been unable to share data for this case study. Instead, synthetic data is constructed for the purpose of this case study.

10.29 The synthetic data is constructed in R, and is created with the following properties:[150]

- Assuming annual frequency of data between 31 December 2021 and 31 December 2023;[151]
- Data is assumed for the treatment group, and a limited number of untreated units;
- A linear trend is assumed for the both the treatment group and the untreated group. This is accompanied by a break in trend after the treatment; and
- There is assumed to be some random noise[152] present in the data.

10.30 These assumptions were constructed with the aim of identifying the minimum viable data set for diff-in-diff analysis.

10.31 The data used for each methodology in this section is modified slightly such that it illustrates the differences between each estimation. The specific assumptions used are illustrated in each of the relevant sections.

[150] This case study data set is constructed with the aim to emulate as close as possible to TRA's data restrictions from data collection.
[151] This was chosen to be the minimum viable data set for difference-in-differences estimation. Data from comparator units may be acquired from annual accounts.
[152] Random noise is in this case, generated by a computer, with a mean of zero, and a standard deviation varying for each estimation. This is created to encapsulate irregular and unpredictable fluctuations that obscure the underlying signal or trend in the data. Random noise lacks any discernible pattern or meaningful structure.

Appendix 5: Bank of assumptions

10.32 The econometric methods outlined in Chapter 3 require key assumptions to be met in order for them to yield causal insights. This subsection below provides a detailed description of the various assumptions that underpin these methodologies, followed by a correspondence that lists the underlying assumptions associated with each methodology. The underlying assumptions that are assigned to each methodology are for the purposes of this report. They are not to be thought of as exhaustive, but rather as the key assumptions that must generally hold for causal inference to be valid.

Assumption description

10.33 Ignorability assumption: this assumption states that all factors and events that would bias the estimated impact of the trade remedy on a particular outcome have been explicitly accounted for within the methodology. This often involves the evaluator incorporating (or believing that they have incorporated) measures of all such factors within their specification of the methodology. This means that implementation of and exposure to the trade remedy is essentially random and that causal impacts can be estimated using the methodology. This assumption is often unrealistic because it is highly unrealistic that any specification will account for all such factors in practice. This assumption is also untestable because all factors that must be accounted for are often not known or observed.

10.34 Constant trend: trend analysis and uninterrupted time series rely on the general assumption that outcomes for the impacted unit would have evolved in the same way as they had in the past if the trade remedy had never been applied. This means that the observed outcome of the treated unit in the post-trade remedy period, had the trade remedy not been applied, would have been equal to the extrapolated pre- trade remedy trend.

10.35 Parallel trends assumption: the evolution in the outcomes of the impacted unit would have been identical to the evolution in the outcomes of the comparator unit had the trade remedy not been applied. This means that the difference in outcomes between the impacted unit and comparator unit pre-remedy would be same as the corresponding difference post- trade remedy if the trade remedy was not implemented. This assumption can be investigated by testing for pre-trends; this involves testing for parallel trends between the treated and comparator units in the pre- trade remedy period. The idea being that these parallel trends would have persisted into the post- trade remedy period if the trade remedy had not been applied.

10.36 Availability of a comparator group: the SCM aggregates commodities that were not impacted by the trade remedy to create a proxy for the target commodity in absence of the trade remedy. Therefore, it must be the case that the data contains some commodities that were in no way impacted by the trade remedy in question. Furthermore, these comparator commodities must not be influenced by alternative measures that are comparable with the trade remedy in question, especially if the target commodity would not have been affected by those alternative measures in absence of the trade remedy. Finally, this assumption implies that the comparator commodities must be somewhat comparable to the target commodity prior to initiation of trade remedy investigation. Comparator commodities that experience shocks that are not shared with the target commodity may be poor proxies for the target commodity. All commodities that are deemed to be poor comparators based on the above criteria should be dropped from the sample.

10.37 Convex hull assumption: formally, this assumption requires that the comparator commodities can be weighted and aggregated into a single synthetic commodity that closely matches the pre- trade remedy imports of the treated commodity. Less formally, the assumption is that the comparator commodities in the post- trade remedy period are very similar to the target commodity in the prior to the trade remedy. The implication of this assumption is that this weighted sum of the comparator commodities in the post- trade remedy period will be a good proxy for what the imports of the target commodity would have been in absence of the trade remedy. This assumption may be violated if the pre- trade remedy outcomes of the target commodity are extreme compared to the outcomes of the comparator commodities.

10.38 No anticipation effects: anticipation effects refer to effects of the trade remedy that arise prior to the initiation of trade remedy investigation date because economic agents are forward-looking and adapt their behaviour in anticipation of a trade remedy before trade remedy investigation has been initiated.

10.39 No spillover effects: these effects refer to the inadvertent impacts that a trade remedy may have on non-target commodities. The main spillovers that are discussed in detail include substitution and complementary effects. Substitution effects occur when the trade remedy impacts import volumes of non-targeted commodity because the non-targeted commodity is a substitute for the targeted commodity. For example, a trade remedy that increases the cost of importing butter may, all else constant, result in greater margarine imports because margarine is a substitute for butter. Complementary effects occur when the trade remedy impacts the imports of a non-targeted commodity because the non-targeted commodity is a complement of the targeted commodity. For example, a trade remedy that reduces the cost of importing tennis rackets may, all else constant, result in greater tennis ball imports because these two products are used together.

10.40 Stability in the relationship between the target commodity and comparator commodities between the pre-initiation and post-initiation periods: the weights used to generate the synthetic commodity are estimated using data prior to the initiation date. However, the objective of the SCM is to estimate counterfactual imports in absence of the trade remedy in the post-initiation period. Therefore, the estimated relationship between the target commodity and the comparator commodities in the pre-initiation period must hold in the post-initiation period in order for SCM to generate causal estimates. If the relationship between the target commodity and comparator commodities modelled by the SCM changes in the post-initiation period, then the synthetic commodity may no longer reflect the counterfactual imports of the target commodity in absence of the trade remedy and the SCM's estimated impacts would be biased.

10.41 Sufficiently long time-horizon in the pre-initiation and post-initiation data: the validity of the SCM depends on how well the synthetic commodity can track the pre-initiation imports of the target commodity. Estimating a credible set of comparator weights that allow the synthetic commodity to do this requires a suitably long time-horizon in the pre-initiation period. A short pre-initiation period may not give the model enough a sufficiently long data panel to estimate these weights accurately and may lead to biased results.[153] A sufficiently long post-initiation period is required to allow the full effect of the trade remedy to measured; this is particularly important for trade remedies that only have impacts after a considerable period of time.[154]

10.42 Low volatility in the outcome relative to the size of the treatment impact: if the outcome variable is highly volatile, especially due to factors that are unique to the target commodity and are not shared with the comparator commodities, then SCM would struggle to detect a causal impact. This may be true even when the impact of the intervention is particularly large.

Methodology-assumption correspondence

10.43 Difference-in-differences: Parallel trends assumption; no anticipation effects; no spillover effects; low volatility in the outcome variable

10.44 Synthetic Control Method: convex hull assumption; no anticipation effects; no spillover effects; stable relationship pre- and post-initiation; sufficiently long pre- and post-initiation data; low volatility in the outcome variable.

10.45 Event Studies: no anticipation effects; no spillover effects; stable relationship pre- and post-initiation; sufficiently long pre- and post-initiation data; low volatility in the outcome variable.

10.46 Bayesian Econometrics: no anticipation effects; no spillover effects; stable relationship pre- and post-initiation; sufficiently long pre- and post-initiation data

10.47 Gravity models: ignorability assumption, no anticipation effects, no spillover effects

[153] Abadie et al (2010) show that the bias of an SCM converges to 0 as the number of pre-initiation periods used to train the model increases. The exception to this rule is when the data experiences large and notable structural breaks. In such instances, long pre-initiation periods may lead to the peer weights being misspecified due to the unstable nature of the data.
[154] Generally speaking, there are no rules of thumb that define a credible guideline for what number of periods are sufficient.

10.48 Before-during-after analysis: ignorability assumption, no anticipation effects, no spillover effects, low volatility in the outcome variable

10.49 Trend analysis/Interrupted time-series: constant trend; no anticipation effects, no spillover effects, low volatility in the outcome variable.

Appendix 6: Interpretation of estimated impacts

10.1 This appendix provides an interpretation of the results reported in Case Study 1 and Case Study 3.

Case Study 1

Table 49: Estimated effect for each commodity using synthetic control method (SCM)

Commodity	Aggregated treatment effect (Kilotons)	Average impact (%)	P-value for Average Impact
76041090	-13.54	-89.5	0.023
76081000	-0.46	-49.5	0.023
76082089	-1.54	-79.9	0.023
76042910	-4.09	-86.5	0.045
76082081	-0.94	-68.0	0.114
76042100	-1.69	-36.8	0.136
76041010	-0.41	-44.4	0.250
76109090	5.47	26.2	0.295
76042990	22.78	93.4	0.750

10.2 Each interpretation is given for commodity 76041090. 'Aggregated treated effect (kilotons)' shows that trade remedy is predicted to reduce the total volume of imports over the entire post initiation period (i.e. Q2 2021 – Q4 2023) by 13.54 kilotons. 'Average impact (%)' reports the trade remedy caused imports to be 89.5% lower than what they would have been in the absence of the trade remedy on average for the post-initiation period. 'P-value for Average Impact' reports that the average impact of the trade remedy had a p-value that corresponds to 0.023. As this value is less than 0.05, it can be concluded that the average impact is statistically significant at the 5% significance level.

Case Study 3

Table 50: SCM results with constant trade remedy impact and high volatility (10 comparator firms)

Outcome	True Aggregated Impact	Aggregated Impact	True Average Impact (%)	Average Impact (%)	P-value for Average Impact
Costs	-100	-94	-10.0	-9.43	0.273
Costs (trimmed sample)	-100	-184	-10.0	-16.93	0.833
Demand	3,952	2,764	23.5	15.28	0.455

Demand (trimmed sample)	3,952	5,467	23.5	35.61	0.500
Profit	13,377	3,985	11.1	3.07	0.636
Profit (trimmed sample)	13,377	20,523	11.1	18.12	0.500
Revenue	147,151	53,143	11.1	3.74	0.636
Revenue (trimmed sample)	147,151	225,750	11.1	18.12	0.500

10.3 The 'Outcome' column indicates the outcome of interest under investigation. The '(trimmed sample)' specification for each outcome indicates that the sample was trimmed of all unsuitable comparators when undertaking the analysis. Each interpretation is given for the 'Costs' outcome with untrimmed sample. 'True Aggregated Impact' reports that true impact of the trade remedy specified within the synthetic data reduced the total costs of the synthetic firm over the entire post initiation period by £100,000.[155] 'Aggregated Impact' reports that the impact of the trade remedy estimated by the SCM is predicted to reduce the total costs of the synthetic firm over the entire post initiation period by £94,000. 'True Average Impact (%)' reports that the true impact of the remedy specified within the synthetic data caused imports to be 10% lower than what they would have been in the absence of the trade remedy on average for each quarter in the post-initiation period. 'Average Impact (%)' reports that the trade remedy was predicted to cause imports to be 9.4% lower than what they would have been in the absence of the trade remedy on average for each quarter in the post-initiation period. 'P-value for Average Impact' reports that the average impact of the trade remedy had a p-value that corresponds to 0.273. As this value is greater than 0.05, it can be concluded that the average impact is statistically insignificant at the 5% significance level.

[155] Recall that Case Study 3 was undertaken using synthetic data where the impact of the remedy was specified by the evaluator. This result is not indicative of the remedy that materialised in reality and is for illustrative purposes only.

11. Glossary

Table 51: A table to explain econometric terminology used throughout this report.

Term	Meaning
Anticipation effect(s)	This refers to economic agents pre-empting a trade remedy before it is imposed; particularly if a trade remedy investigation or a date for a trade remedy decision is announced. This can cause economic agents to change their behaviour in anticipation of the trade remedy's imposition (e.g. increased pricing or change in strategy) despite the trade remedy not being officially imposed.
Bayes Theorem	Bayes theorem describes how to update the probability of an event based on new evidence.
Bayesian Inference	This is a statistical method that uses Bayes theorem to update the probability of a hypothesis as new evidence or data becomes available. It uses prior knowledge, in the form of a prior distribution, to estimate posterior probabilities. These distributions are updated using Bayes theorem, to estimate parameters of the model.
Empirical Bayes Approach	An approach where the prior distribution is estimated from the data itself, rather than being specified beforehand. This approach leads to shrinkage towards the mean than stated priors, and reduces the variance of estimates.
Treatment Group	A group that is impacted by the intervention of interest. With application to trade remedies, this refers to commodities or firms that are impacted by an imposed trade remedy. Treated commodities are those that are within the trade remedy's scope, and treated firms are those that are exposed to the trade remedy by virtue of a commodity targeted by a trade remedy being a part of its production process.
Control Group	A group that is used as a base for comparison. For example, in the case of a trade remedy measure, a firm not impacted by the trade remedy measure could be considered a control group. The control group should be sufficiently similar to the treated group.
Counterfactual	The unobserved scenario that is used to calculate the causal impact.
Goodness-of-fit	How closely the model fits the data, and the extent to which a model is able to explain variations in the data.
In-sample Estimation	A technique used to identify the accuracy of a model based on using part of the data that the model was created from to evaluate the performance of the model.
Noise	Unwanted or irrelevant signals or disturbances that exist in data, that may interfere with understanding an underlying trend or distribution.
Parallel Trends Assumption	The assumption that prior to implementation of trade remedy, the trend of a comparator firm must be parallel to that of a treated firm for diff-in-diff estimations to be interpreted as causal.
Prior	A probability distribution that illustrates a researcher's belief of the value of unknown parameters of a model before observing the data. This can be constructed from a researcher's own beliefs, existing literature or the data.
Reverse Causality	A situation where the direction of causality between two variables is mistakenly inferred or reversed.
Structural Break	A shift in trend, or a significant change that leads to a breakdown of relationships between variables over time. This can be due to shifts in consumer preferences, or worldwide impacts, such as COVID-19 pandemic.

Term	Meaning
Natural Experiment	This occurs when naturally occurring phenomena (e.g. how a trade remedy is implemented) can be exploited to replicate a laboratory setting; whereby assignment to treatment is 'as good as random'. Random assignment of treatment is essential in overcoming the identification problem; it necessarily means that the control group is a good proxy for the unobserved counterfactual and the treatment effect can be identified by comparing the outcomes of the treatment and the control groups.
Ex-post Counterfactual analysis	This refers to any approach that estimates the causal impact of an intervention or trade remedy after the fact, hence 'ex-post' This necessarily implies that the trade remedy has been imposed, that the imposed trade remedy led to a change in imposed duties, and that outcomes before and after the imposition of a trade remedy are observed and available to the evaluator. The idea of counterfactual implies that these approaches endeavour to estimate the impact of the trade remedy by estimating the unobserved counterfactual outcomes that would have occurred in absence of the trade remedy. Not all ex-post counterfactual approaches predict the unobserved counterfactual effectively.
Inverse Hyperbolic Sine	This is a transformation that can be applied to non-negative real number. In simple terms, this is a transformation that brings numbers that are very far apart much closer together and is to reduce the impact of extreme values on the calculated average. This transformation generally deals with outliers in reported exports while still allowing observations with 0 values to be retained.
Cournot Oligopoly Model	This is a theoretical formulation of strategic interactions between profit-maximising firms competing for a limited market. The objective of firms in this formulation is to maximise their profits by setting production quantities that allow this while also accounting for the quantities set by their competitors.
Pre-Initiation Effects	This refers to any notably differences that emerge between the treatment and control group prior to the initiation date of a trade remedy investigation. It is a catch-all term that includes anticipation effects but also factors unrelated to the trade remedy in question that may be driving differences between the treated unit and the control units.
Fixed Effects	This refers to time invariant characteristics that are specific to the unit of analysis within econometric analysis. For instance, in an econometric specification where the unit of observation is a firm, firm-level fixed effects account for all firm-specific characteristics that are fixed over time (e.g. the year a firm was founded)
Chilling Effects	(Not quite sure about this, TRA used this term so I'm unsure about where it fits)
Spillover Effects	This occurs when the control unit is inadvertently impacted by the treatment (i.e. the trade remedy). In the case of trade remedies, spillovers are most likely to occur through substitution effects or complementary effects.
Placebo Effects	These are treatment effects that are estimated despite the treatment never actually occurring. With application to the synthetic control method, placebo effects refer to the estimated impact of treatment for control units. These impacts should, in principle, be close to zero because the control units are not impacted by the treatment. The placebo effects are intended to display impacts arising purely due to statistical uncertainty.
Ignorability assumption	This assumption states that all factors and events that would bias the estimated impact of the trade remedy on a particular outcome have been explicitly accounted for within the methodology. This often involves the evaluator incorporating (or believing that they have incorporated) measures of all such factors within their specification of the methodology. This means that implementation of and exposure to the trade remedy is essentially random and that causal impacts can be estimated using the methodology. This assumption is often unrealistic because it is highly unrealistic that any specification will account for all such factors in practice. This assumption is also untestable because all factors that must be accounted for are often not known or observed.

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