Department for International Trade

Analysis

Analysis of trends in industrial sectoral demand

Rapid Evidence Assessment - Final Research Report

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This is a report of research carried out by Economic Insight, on behalf of the Department for International Trade.

Research Contractor: Economic Insight

Contents

1. Executive summary

Economic Insight has been commissioned by the Department for International Trade (DIT) to undertake a rapid evidence assessment (REA) that is intended to support both trade policy and promotion activities. Specifically, the objective of this REA is to help inform a roadmap for the data analysis required to forecast import demand across: (i) all sectors; (ii) all markets; and (iii) over time, on a consistent basis, to support DIT identify sources of greatest export opportunity. In light of our findings, we recommend that DIT employ a two- step approach to forecasting import demand. By this we mean that, it may be most effective to: (i) first identify a set of key opportunities at a higher level of (product and market) aggregation, before (ii) then going on to conduct forecasts at a more granular level, honing into a more limited number of key opportunities.

1.1 Objectives and research questions

Economic Insight has been commissioned by the Department for International Trade (DIT) to undertake a rapid evidence assessment (REA) that is intended to support both trade policy and promotion activities. Specifically, the objective of this REA is to help inform DIT's roadmap for the data analysis required to forecast import demand across: (i) all sectors; (ii) all markets; and (iii) over time, on a consistent basis. Such data analysis will allow DIT to more effectively identify priority UK export opportunities, both supporting the development of effective trade agreements, and focusing trade promotion resources.

In order to arrive at this data analysis roadmap, and to identify the appropriate forecasting methodologies to achieve DIT's aims, this REA sets about answering the following key research questions (RQ):

1. RQ1: What research is there into drivers of consumption and how patterns of import demand at the sector level shift in response to long-term changing economic and demographic conditions?

- How does a country's stage of development influence their import demand at sector level?

- How does a country's stage of development influence their positioning in global value chains, for example is a country's contribution of low-level extractive inputs or high-level services dependent on its level of development?

- How does the value of individual goods/services in a GVC change as a country becomes more developed?

2. RQ2: What previous qualitative research has there been into forward looks for sectoral import demand? What quantitative methodologies have been used to inform these forward looks and what are the strengths and weaknesses of these?

- What data exists that can be used to inform trends in import demand (for example patents, demographics, household consumption)?

- What new data may be required to inform regular production of future global sectoral import demand insights?

3. RQ3: How does the feasibility of identifying future changes at different granularities (for example for goods, can it be conducted at a granular product level)?

- How does feasibility change with different geographies? How does this compare across low/middle/high income countries? Give examples.

- How does the feasibility of identifying emerging goods and services import demand compare? Give examples.

- How does the feasibility change with different time horizons? Give examples.

4. RQ4: How do a set of identified methodologies score against each other in terms of simplicity, time horizon, accuracy, granularity and feasibility for replication?

To answer these questions, we gathered a wealth of evidence to first understand the key drivers of consumption and import demand, and in particular, to understand how these drivers vary by sector and market, and also according to a country's stage of development. As such, the first part of our work focused on answering RQ1.

Once this had been done, we looked to understand both (i) the macroeconomic forecasting methodologies that are **available** to be applied to import demand; and (ii) which of these methodologies has in fact been **used in practice**. In doing so, we assessed the relative advantages and disadvantages of applying these methodologies to forecasting import demand at varying levels of sector and market granularity. Importantly, where forecasting methodologies are built on modelling the drivers of consumption and import demand, we used the findings in relation to RQ1 to inform feasibility assessments. Due to the strong links between the research questions, we worked concurrently on RQ2, RQ3 and RQ4.

In this section of the report, we summarise our approach to gathering the evidence used within this REA, before detailing out our key findings across the research questions. Following this, we set out recommendations for DIT.

1.2 Research methodology

Our approach to gathering evidence for the REA was composed of three main search steps:

- Our first step involved developing a search strategy for gathering evidence. In doing so, we identified and agreed appropriate search terms based on the key research questions specified by DIT. These search terms were then used to identify potential sources to review.
- Following this, we applied a list of inclusion and exclusion criteria to the studies

identified to determine which of these would be downloaded for further review.

- Finally, we conducted an in-depth review of the literature (i.e. reviewing the entire article), and used our findings to answer the four key research questions.

The resulting body of evidence was comprised of 208 studies. The nature of these are summarised in the table overleaf.

Table 1: Summary of evidence base

	Evidence on drivers of import demand and consumption patterns	Evidence on methodologies to generate import forecasts	Supplementary literature regarding macroeconomic forecasting methodologies	Total
Academic	92	20	18	130
Grey	46	9	0	55
Commercial	13	10	0	23
Total	151	39	18	208

Source: Economic Insight Ltd

As shown, the vast majority of the evidence relates to academic literature, with more limited grey and commercial examples available. In addition, a significant body of evidence is available regarding the drivers of import demand and consumption patterns, whereas more limited studies of methodologies being applied to forecast import demand were found.

1.3 Findings on RQ1

In answering the first research question, we identified drivers affecting consumption and import demand at both the aggregate and more granular sector levels. By this we mean, we looked carefully at the drivers that affect both the **level of aggregate imports of an economy**, and the drivers that determine the **particular mix of imports within this.** When looking at the mix of imports, we analysed this at the sector level.

We found that there is a general consensus that key factors affecting the economy-wide level of imports are income, relative prices, and trade liberalisation. On the other hand, evidence shows that the mix of imports of an economy is determined predominantly by a country’s stage of development. This is also the key influence dictating the position of that country in global value chains (GVCs). In particular, we found that:

- At low levels of development, countries tend to focus their economies on supplying primary products, such as agriculture, mining and fossil fuel extraction. As a result, domestic ability to satisfy demand for manufactured goods and services is low. However, domestic demand for these products is limited due to low levels of per capita income, and as such, the requirement for imports to satisfy this demand is also low.

- Following this, developing countries traditionally experience a period of industrialisation as production shifts to the manufacturing sector. As a result, demand for primary products and manufacturing goods as inputs into the manufacturing process increases, and so imports of both of these tend to increase at this stage of development. In addition, rising per capita income levels lead to increased demand for imports of manufactured goods and services.

- As countries develop further, they tend to focus their economies on the supply of services. As a result, demand for both primary and secondary goods rises, as the ability of the country to meet demand for these domestically falls. In addition to this, as per capita incomes grows, so too does demand for (i) agricultural products (due to increased preferences for more varied diets and fresh produce); (ii) manufactured goods; and (iii) services.

However, our evidence has found that **historical patterns of development are changing** – that is, developing countries are no longer conforming to the historical transformation process outlined above. Countries are now moving from manufacturing to services at a much lower level of per capita income than has been historically observed. In addition, many countries are moving directly to services production without transitioning through the manufacturing stage. These findings imply that **historic trends may be becoming less informative for estimating future import demand, and that the nature of the relationships between import demand patterns and its drivers can, and is, changing**.

1.4 Findings on RQ2, RQ3 and RQ4

After examining the factors driving import demand, we then considered both: (i) what methodologies **have been used** to generate previous forecasts of import demand; and (ii) what macroeconomic forecasting methodologies **available** to generate forward looks of import demand, before evaluating these methodologies.

The table overleaf summarises where we found evidence of methods being employed to forecast import demand at different levels of product and geographical granularity. A tick indicates that we have found evidence of this method at the specified level of granularity.

Table 2: Summary of evidence

Granularity of application / Methods		Global			Region			Country		
		Aggregate imports	Sector imports	Product imports	Aggregate imports	Sector imports	Product imports	Aggregate imports	Sector imports	Product imports
Qualitative	Expert opinion							✓		
	Historical analogy method									✓
	Horizon scanning		✓							
	Scenario building		✓			✓	✓		✓	✓
Quantitative	Naïve forecast									
	Historic trend (univariate) models							✓	✓	
	Causal (multivariate) models							✓	✓	✓
Composite models								✓		✓
Off-the-shelf		✓			✓			✓	✓	✓

Source: Economic Insight Ltd
Note: For details about each of these methodologies, please see Chapter 5.

As can be seen, the granularity at which the forecasts of import demand have been applied varies across methodologies and there are a number of gaps in the literature. In particular, we have found evidence of the expert opinion, historical analogy, and horizon scanning approaches only being employed at one level of granularity, and have found no evidence of naïve forecasting approaches being used to forecast import demand. On the other hand, scenario building, historic trend and causal models have been applied at more than one level of aggregation.

Having understood where these methodologies have previously been employed in to forecast import demand, we supplemented this evidence with a broader literature review to both: (i) gain a fuller understanding of the relative advantages and disadvantages of using these methodologies; and (ii) to understand, in cases where these methods have not been applied to forecasting import demand, whether they could be used to do so.

In doing this, we looked to evaluate the methodologies against the criteria set out in the table below:

Table 3: Methodology assessment criteria

<table>
<tr><th colspan="2">Criteria</th><th>Definition</th></tr>
<tr><td rowspan="2">Accuracy</td><td>Predictive power</td><td>How accurate the methodology is at forecasting import demand
– that is, how likely it is that the forecasted levels will equal actual future levels.</td></tr>
<tr><td>Precision</td><td>Whether forecasts are (i) precise, numerical forecasts; or (ii) more ‘high-level’ forecasts, such as ranges.</td></tr>
<tr><td rowspan="2">Simplicity</td><td>Complexity</td><td>How difficult implementing the methodology would be.</td></tr>
<tr><td>Resource requirements</td><td>What internal and external resourcing would be required for DIT to implement the method.</td></tr>
<tr><td colspan="2">Data requirements</td><td>What data is required to implement the method.</td></tr>
<tr><td colspan="2">Time horizon</td><td>Whether the method can be used for longer time horizons, or only relatively short ones.</td></tr>
</table>

Source: Economic Insight Ltd

Based on this, by understanding the relative strengths and weaknesses of the methodologies, we assessed the feasibility of applying these methodologies to forecast import demand across levels of granularity.

The table overleaf summarises our assessment of the methodologies, against the aforementioned criteria and in terms of the level of granularity at which they feasible. As shown, we found that the feasibility of applying these methods to different levels of aggregation varies.

Table 4: Methodology assessment (1)

Criteria		Accuracy		Simplicity		Data requirements	Time horizon	Feasibility for replication
		Predictive power	Precision	Complexity	Resource requirements			
Qualitative methodologies	Expert opinion							Aggregate x country, for a set of countries
	Historical analogy							Sector x country
	Horizon scanning							Sector x region / sector x global
	Scenario building							Country x sector, for a set of countries
Quantitative methodologies	Naïve forecasting							Country x product
	Historic trend							Country x product
	Causal model							Aggregate x country; and a smaller set of country x product

Source: Economic Insight Ltd

Table 5: Methodology assessment (2)

		Accuracy		Simplicity		Data requirements	Time horizon	Feasibility for replication
		Predictive power	Precision	Complexity	Resource requirements			
Other methodologies	Composite							Range of granularity levels
	Off the shelf							Aggregate x country, with some sector / product level country forecasts available

Source: Economic Insight Ltd

As summarised in the table, the qualitative methods, despite generally having lower data requirements than the quantitative methods, are more resource intensive, in terms of the time and cost of using these methods to generate forecasts. The quantitative methods score well against the predictive power and accuracy criteria, and can be designed at varying levels of complexity.
We understand that analyst teams within DIT are well placed to implement these methodologies.

There is evidence to suggest that composite methods, which generate forecasts using combinations of qualitative and/or quantitative methodologies, are more accurate than forecasts generated by one method alone. However, in terms of the resourcing and data requirements, as well as complexity, these models are generally more difficult to assess, since these particular characteristics are dependent upon precisely which individual methodologies they comprise.

Off-the-shelf products, by which we mean import demand forecasts that are readily available to purchase, have by nature minimal resourcing (though, of course, would need to be paid for) and data requirements for the organisation looking to use these forecasts. Often, these products provide precise forecasts, with a wide coverage. However, the accuracy of these methods is difficult to assess, as in most cases the particular methodology underpinning the forecast is not detailed.

Importantly, our research indicates that it may not be desirable to use the vast majority of available forecasting methods to generate forward looks for import demand at the country by product level. This is due to both: (i) the large amounts of data that many of the methods, and particularly the quantitative methods, would require, and; (ii) the extensive time and monetary resources that many of the methods, and particularly the qualitative methods, would use to generate import demand forecasts.

1.5 Conclusions and recommendations

We understand that DIT is most interested in forecasting import demand at the product by country level of granularity. However, as noted above, our research has found that it would not be feasible to use the majority of forecasting methodologies to generate forward looks of import demand for every product in every country, due to the large resourcing requirements.

Given this, we recommend a two-step approach to forecasting import demand at the country by product level of granularity. By this we mean, it may be most effective to: (i) first identify a set of key opportunities at a higher level of (product and market) aggregation, before (ii) then going on to conduct forecasts at a more granular level, honing into a more limited number of key opportunities.

The **first step** is to identify key opportunities at a more feasible, higher level of aggregation, and there are two ways of going about this.

1. The first approach would be to forecast import demand at **an economy-wide level for each country**, in order to identify the set of countries that present the greatest opportunity for UK exports.

- Here, we consider that the most appropriate methodologies would be either **historic trend or causal models**. This is because they are both less resource intensive than qualitative methods, meaning that practically, implementing the method across all countries would be feasible, and the methodologies also allow for the generation of long-term forecasts.

- In particular, **historic trend methods** apply regression techniques to historical import data, without the introduction of any additional variables. **Causal methods**, on the other hand, look to model the relationship between the dependent variable and its drivers.

- Of these methodologies, we recommend that DIT employ a **gravity model**. This model is a particular type of causal model that would allow DIT to forecast the strength of the trade relationships between the UK and its trading partners specifically. As such, it is particularly advantageous in that the **import demand opportunity for the UK specifically** would be considered, as opposed to understanding the level of import demand of a country more broadly, without considering the potential for the UK to satisfy this demand. A further advantage of this model is that it is based upon the set of drivers identified as being the most important during the first phase of our work, specifically: (i) income (GDP) of the country pairs; (ii) relative prices; (iii) the geographical distance between country pairs; and, in some cases, (iv) trade liberalisation is also built into the models.

- **Off-the-shelf products** are another option for DIT in this case, which benefit from very low resourcing requirements. However, their predictive power is ambiguous, and typically, off- the-shelf products available only forecast imports one to two years ahead.

2. A second approach would be to forecast import demand at the sector or product level globally, or by region, in order to identify the particular set of sectors or product markets that present the greatest opportunity for UK exports.

- In this case, we favour forward-looking methodologies, including **horizon scanning and scenario building**, over methods examining historic trends, because import demand for services (an important export market for the UK) is expected to grow most rapidly in developing countries, where changes in import demand are becoming less predictable.
- In particular, we recommend using **horizon scanning** to forecast imports at this level of aggregation, as it provides more precise forecasts and is less complex than scenario building.
- The horizon scanning methodology focuses on identifying future threats and opportunities, whereas scenario building looks to identify a range of potential future outcomes, based on plausible developments in an underlying set of drivers.

Once key country or product level opportunities have been identified, the **next step** is to forecast imports at a more granular product by country level – that is either (i) forecast sector or product level import demand for a more limited set of countries; or (ii) forecast import demand for a more limited range of sectors or products at the country level. When conducting forecasts of import demand at the product by country level of aggregation, distinct approaches would need to be taken for countries at different stages of development. In particular:

1. Our research has shown that changes affecting developing countries are becoming less predictable, because they are no longer following historical patterns of development. This implies that historic trends are becoming less informative for estimating future import demand in these countries, and so forward-looking methods should be favoured.

- In this case, **horizon scanning** or **scenario building** approaches can be used, however, both are relatively resource intensive.
- Given this, we recommend employing **a composite model**, that triangulates evidence from implementing a number of differing forecasting methodologies. That is, DIT could employ a causal model and ask for expert opinion to help build it or stress-test it, to gain a better understanding of future changes.

2. On the other hand, developed countries have much more stable economies, and so methodologies examining historic trends should be favoured.

- In particular, we recommend DIT employ either (i) **historic trend** methodologies; or (ii) **naïve forecasting** approaches that use past actuals to forecast the future, as these are both less complex and resource and data intensive than other methodologies focusing on historical patterns. However, we recognise that there no examples of naïve forecasting in the literature. There are several plausible explanations for this, including that they are less accurate than other approaches.

- Another option would be to consult **off-the-shelf products**, however, the predictive power of these is unknown.

2. Introduction

Economic Insight has been commissioned by the Department for International Trade to undertake a rapid evidence assessment that is intended to support both trade policy and promotion activities. Specifically, the objective of this REA is to help inform a roadmap for the data analysis required to forecast import demand across: (i) all sectors; (ii) all markets; and (iii) over time, on a consistent basis. This analysis will allow DIT to more effectively identify priority UK export opportunities, both supporting the development of effective trade agreements, and focusing trade promotion resources.

In order to arrive at this data analysis roadmap, and to identify the appropriate forecasting methodologies to achieve DIT's aims, this REA sets about answering the following key research questions:

1. RQ1: What research is there into drivers of consumption and how patterns of import demand at the sector level shift in response to long-term changing economic and demographic conditions?

- How does a country's stage of development influence their import demand at sector level?

- How does a country's stage of development influence their positioning in global value chains, for example is a country's contribution of low-level extractive inputs or high-level services dependent on its level of development?

- How does the value of individual goods/services in a GVC change as a country becomes more developed?

2. RQ2: What previous qualitative research has there been into forward looks for sectoral import demand? What quantitative methodologies have been used to inform these forward looks and what are the strengths and weaknesses of these?

- What data exists that can be used to inform trends in import demand (for example patents, demographics, household consumption)?

- What new data may be required to inform regular production of future global sectoral import demand insights?

3. RQ3: How does the feasibility of identifying future changes at different granularities (for example for goods, can it be conducted at a granular product level)?

- How does feasibility change with different geographies? How does this compare across low/middle/high income countries? Give examples.

- How does the feasibility of identifying emerging goods and services import demand compare? Give examples.

- How does the feasibility change with different time horizons? Give examples.

4. RQ4: How do a set of identified methodologies score against each other in terms of simplicity, time horizon, accuracy, granularity and feasibility for replication? This report looks to answer each of these questions, and is structured as follows:

  - **Chapter 1: Evidence Gathering Approach**. We begin by setting out the framework for gathering evidence required to answer the research questions, before assessing the strength of the body of evidence obtained by using this framework.

  - **Chapter 2: Evidence on the drivers of consumption and import demand**. In this chapter, we use the evidence gathered to understand the key drivers of consumption and import demand, and in particular, we look to understand how these drivers vary by sector and market, and also according to a country's stage of development. As such, this chapter focuses on answering RQ1.

  - **Chapter 3: Methodologies for forecasting import demand**. In this chapter, we look to understand both (i) the macroeconomic forecasting methodologies that are available to be applied to import demand; and (ii) which of these methodologies has in fact been used in practice. In doing so, we assess the relative advantages and disadvantages of applying these methodologies to forecasting import demand at varying levels of sector and market granularity. Importantly, where forecasting methodologies are built on modelling the drivers of consumption and import demand, we use the findings set out in the previous chapter to inform feasibility assessments. Due to the strong links between the research questions, this chapter analyses evidence pertaining to both RQ2, RQ3 and RQ4.

  - **Chapter 4: Conclusions and recommendations**. Using the evidence analysed during the previous chapters, we put forward our conclusions and recommendations regarding the particular methodologies that are most appropriate to achieve DIT's aims.

3. Evidence gathering approach

In this chapter, we set out our approach to gathering evidence for this REA, before detailing the resultant body of evidence that has informed the answers to the four key research questions. Our approach to gathering evidence comprised three key stages, and was designed to ensure that only sources meeting the academic standards for publication, or produced by well-regarded institutions, were used within this REA. As a result of this approach, a total of 208 sources have been used to inform this REA.

Our overarching evidence gathering methodology is comprised of the following three key stages:

- **Step 1** – We first developed a search strategy, that included identifying and agreeing appropriate search terms, and using these search terms to identify potential sources of evidence through an agreed set of databases
.
- **Step 2** – We then reviewed these potential sources against specified inclusion / exclusion criteria, before filtering out those to be excluded. Our inclusion and exclusion criteria were designed to result in a body of evidence comprising only relevant sources that: (i) in the case of academic works, meet the academic standards for publication; and (ii) in the case of commercial and grey literature, have been published by well-regarded institutions.

- **Step 3** – Our final step was to conduct an in-depth review of the studies identified for inclusion, before using this evidence to answer the specified research questions.
In the following pages, we set out each of these steps in turn, detailing the process decisions taken at each of these stages, as well as the evidence we have relied on to answer the research questions (discussed in the subsequent chapters).

3.1 Our search strategy

The strategy adopted to search for evidence to answer the set of research questions specified by DIT has been to identify and agree on consistent search criteria, before using these criteria to search through databases and download the available papers of relevance.

Firstly, we compiled lists of key words and synonyms for use within our search. These are specified in the table overleaf.

Table 6: Keywords and synonyms by categories and sub-categories

Categories and sub-categories		Key words and synonyms
Import demand and consumption		import demand; imports; import demand function; consumption
Methodologies	**General**	methods; methodologies; techniques; estimation
	Quantitative	quantitative methods; quantitative methodologies; quantitative techniques
	Qualitative	qualitative methods; qualitative methodologies; qualitative techniques
	Specific (based on our prior knowledge of forecasting methods)	historic trend impact analysis; horizon scanning; econometric; Delphi method; gravity model; scenario planning; cross impact analysis; progression curves; agent-based modelling; dynamic structural model
Forecast		forecast; forecasting; forward look; forward looks; forward-looking; future; predict; prediction; predicting; trends
Sector	**Aggregated**	sector; industry
	Primary	primary goods; primary sector; extraction; primary industry; agriculture; fishing; mining; farming; water
	Secondary	secondary goods; secondary sector; manufacturing; manufacturing sector; manufacturing industry; manufacturing industries; production sector; production industry; construction; construction sector; construction industry
	Tertiary	tertiary sector; tertiary goods; tertiary industry; services; service sector; services sector; services industry; service industries; retail; retail services; transport; accommodation; food services; information and communication; financial services; insurance; banking; professional services; administrative services; public administration; defence; health services; education; entertainment services
Stage of development		less developed; underdeveloped; developing; emergent; developed; advanced; industrialised; industrialised; global value chain
Market		market; nation; country; economy
Timeline		short-term; medium-term; long-term; shorter-term; longer-term; short run; long-run

Source: Economic Insight Ltd

As shown in this table, we included key words that allowed us to search for both (i) drivers of consumption and import demand; and (ii) instances whereby import demand is forecast. Words were included that allowed us to home in on differing levels of sector and market aggregation that are of interest to DIT, and ensured that we searched for evidence pertaining to all sectors (in particular, we included words that would allow us to search across sectors to the 4-digit SIC code level).

As can be seen, our key words focused on identifying literature that would answer RQ1 and RQ2. This was because, upon gathering and analysing evidence on the methodologies used to forecast import demand, as well as evidence on the drivers that might be required as inputs to conduct these methodologies, we would have the necessary information to critically appraise these methodologies for use to achieve DIT's aims, and therefore to answer RQ3 and RQ4.

In addition, we included key words for those methodologies that were **expected** to be seen within the research, based upon our prior knowledge of macroeconomic forecasting methods. This approach was taken to ensure that, not only were we able to identify evidence of particular forecasting methodologies that **have been employed specifically to generating import demand forecasts**, we were also able to understand where particular methodologies **have not been used, but that are available to generate forecasts of import demand**. In other words, this better enabled us to understand gaps in the evidence. This approach also enabled us to gain a deeper understanding of the relative advantages and disadvantages of the different types of forecasting methodologies.

Using the key words outlined we created search strings, appropriate for the relevant databases. A sample of the search strings we used include:

- "drivers of import demand"
- "patterns of import demand"
- "consumption drivers" AND "mining"
- "import demand" AND "estimation techniques" OR "forecasting methodologies" OR "forecasting methods"
- "sector" AND "import demand" AND "estimation techniques" OR "forecasting methodologies" OR "forecasting methods"
- "import demand" AND "developing countries" AND "estimation techniques" OR "forecasting methodologies" OR "forecasting methods"
- "import demand" AND "Delphi" AND "forecasting methodologies" OR "forecasting methods" OR "forecasts"

  The full list of search strings used is included in the research catalogue, appended to this document.

3.2 Databases for review

We have primarily consulted both Google and Google Scholar databases. This allows access to a wide range of academic, grey, and commercial literature, that is both publicly accessible, and that is only accessible via a paywall.

Firstly, when conducting our search of the specified databases and organisations, the returns were set to be ordered according to relevance, in order to ensure that the evidence gathered for further review is effective at the research questions. We searched specifically for academic, grey and commercial literature, defined as follows:

- **Academic literature** includes journal articles and other works meeting the standards for publication by academic publishing houses, such as Oxford University Press, Taylor & Francis and Reed-Elsevier for example.

- **Grey literature** includes literature not published by a commercial publishing house, but produced by a well-regarded institution. For instance, this can include the literature produced by government departments and multinational organisations, such as the Organisation for Economic Cooperation and Development (OECD). To ensure that we accessed key sources of grey literature, we searched a number of such organisations specifically. These included the OECD, World Bank, the International Monetary Fund (IMF), the Bank of England, and the European Central Bank (ECB).

- **Commercial literature** includes literature that is once again, not published by a publishing house, but is produced and distributed by well-regarded commercial institutions, including macro-forecasters, consultancies and financial institutions. To ensure our search method captured key available commercial evidence, we conducted specific searches of a number of organisations, including Capital Economics and Oxford Economics.

Secondly, we then applied a list of inclusion and exclusion criteria to the studies returned during our database search, to identify which of the papers would be downloaded for further review. The inclusion and exclusion criteria differed for RQ1 and RQ2, subjecting the nature of the questions. In particular, when gathering evidence for RQ1, we employed the inclusion and exclusion criteria detailed in the table below. In applying the inclusion and exclusion criteria, we sought to balance the trade-off between unduly narrowing or broadening our search.

Table 7: Inclusion and exclusion criteria for RQ1

Criteria type	Detail
Inclusion	Must relate to import demand and/or consumption patterns.
	Must specify / discuss the drivers of, or factors affecting, import demand and/or consumption patterns.
	Written in English.
Exclusion	Student paper, dissertation, unpublished work, working paper, fails to meet the definition of academic, grey, or commercial literature as defined above.
	States information only regarding changes in import demand and/or consumption patterns, with no explanation of reasons for these changes.

Source: Economic Insight Ltd

The inclusion and exclusion criteria employed when looking to answer RQ2 is detailed in the table overleaf.

Table 8: Inclusion and exclusion criteria for RQ2

Criteria type	Detail
Inclusion	Must relate specifically to import demand
	Primary study specifying a methodology for forecasting import demand, or a methodology of backward looking that allows for the identification of long-term trends
	Secondary study that critically reviews methodologies for forecasting import demand
	Written in English
Exclusion	Published prior to 2000
	Student paper, dissertation, unpublished work, working paper, fails to meet the definition of academic, grey, or commercial literature as defined above
	Deals only with forecasting demand / consumption, unrelated to imports specifically

Source: Economic Insight Ltd

Key differences in this criteria between the different stages of research include:

- **The date of publication of the papers**. For those papers specifying methodologies used to generate forecasts for import demand, we limited inclusion to only those papers published since 2000. This was because, forecasts generated more recently are expected to have built on the research conducted before them, and therefore, focusing on more recent papers will allow us to better understand best practice. In contrast, the publication date of papers identifying drivers of import demand and consumption changes was not limited, with a view to understand if and how import patterns, and the underlying drivers, have changed over time.

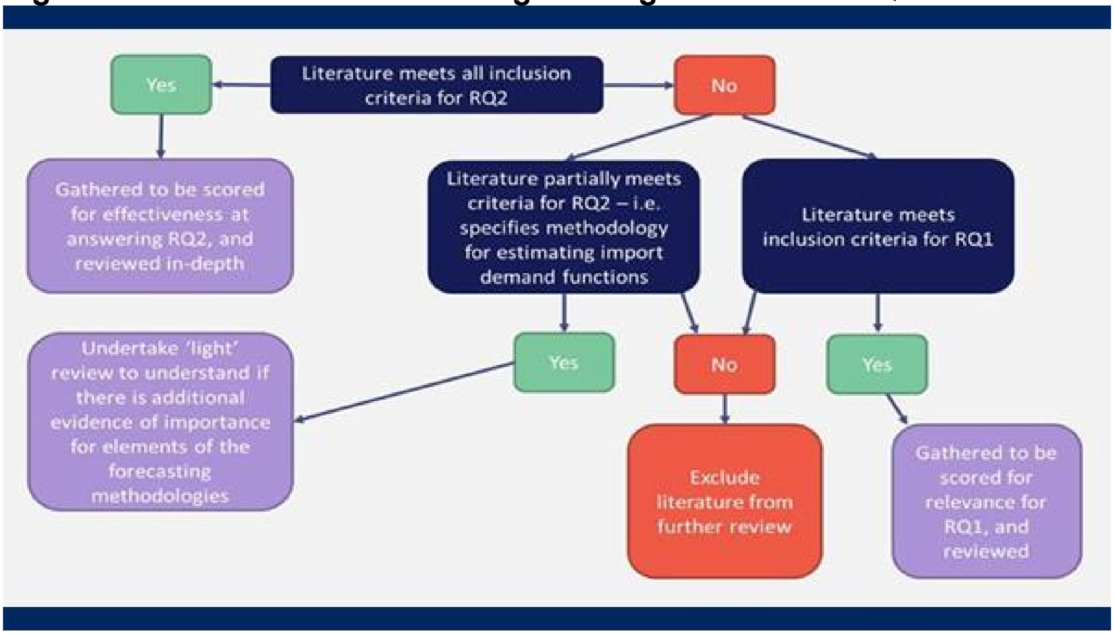
- **The inclusion of consumption patterns at RQ1**. At RQ1, understanding factors driving domestic consumption patterns is important in order to gain a holistic understanding of why a country's imports change. As such, it was important during this stage that the work not omit papers considering drivers of consumption patterns. However, at RQ2, it was important to refine our search, and hone in on methodologies forecasting import demand specifically. This is because, consumption forecasts would not detail whether a country is able to meet consumption changes domestically, or whether these consumption changes would result in changes to the trade balance.

Thirdly, once we reached the point in our review of database returns where no further papers are of relevance (i.e. they fail our inclusion criteria), we entered an alternative search string.

Fourthly, when conducting our evidence gathering at RQ2, our search returned numerous papers that did not specify a methodology for **forecasting import demand**, but that did however construct import demand functions. These papers therefore are not informative in relation to RQ2, however, provide valuable information about the factors that are considered to drive import demand. As such, we looked to ensure that, where we identified papers that failed the inclusion criteria for RQ2, but that were both relevant for RQ1 and had not been identified previously, we continued to gather this evidence.

In the figure below we detail the decision framework that was applied in order to control for this.

Figure 1: Decision framework for gathering evidence at RQ2



Source: Economic Insight Ltd

3.3 Supplementary literature

In addition to the evidence gathering as specified above, where necessary, we looked to supplement the evidence base with further literature reviews. Specifically, we conducted an additional literature review regarding macroeconomic forecasting methodologies more broadly.

In doing so, we looked to identify details regarding key steps required to implement the well- established set of macroeconomic forecasting methodologies, alongside any critical appraisal of these methodologies. The rationale behind this additional search was to both: (i) understand the macroeconomic forecasting methodologies that could potentially be applied to forecasting import demand; and (ii) enable the identification of gaps in their use. Further, additional evidence regarding the advantages and disadvantages of these methodologies more broadly, better enabled us to critically appraise each of these techniques for DIT's purposes, and therefore answer RQ3 and RQ4.

3.4 Resultant body of evidence

Completion of the evidence gathering process led to a total of 208 sources being reviewed to answer the research questions in this REA.

The table overleaf specifies the nature of this body of evidence.

Table 9: Summary of evidence base

Type of literature	Evidence on drivers of import demand and consumption patterns	Evidence on methodologies to generate import forecasts	Supplementary literature regarding macroeconomic forecasting methodologies	Total
Academic	92	20	18	130
Grey	46	9	0	55
Commercial	13	10	0	23
Total	151	39	18	208

Source: Economic Insight Ltd

As shown, a significant body of evidence is available regarding the drivers of consumption and import demand patterns. A total of 151 papers were used to understand the drivers of import demand and consumption. All of these papers were publicly available. Due to the body of evidence available regarding the drivers of consumption and import demand patterns specifically, we did not deem it necessary to access papers subject to a paywall.

On the other hand, regarding the evidence relating to research forecasts of import demand, the body of evidence was far more limited. Specifically, we reviewed a total of 39 papers detailing the methodologies and results of import demand forecasts. This body of evidence is a mix of both publicly available literature, as well as literature subject to a paywall.

The supplementary literature review of academic papers detailing macroeconomic forecasting methodologies comprised a total of 18 academic papers.

4. Evidence on the drivers of consumption and import demand

In this chapter, we have set out the evidence we have found regarding the key drivers of consumption and import demand. We have found that income (GDP), relative prices, trade liberalisation and geographical factors are key drivers of aggregate imports, while the stage of development of a country has been found to be the strongest influence over the level of sector specific imports. However, the evidence also suggests that previously observed historical development patterns are changing. These findings imply that historic trends may be becoming less informative for estimating future import demand, and that the nature of the relationships between import demand patterns and its drivers can, and is, changing.

4.1 Introduction and summary

In this chapter, we set out the evidence provided by the assessed literature pertaining to RQ1:

- What research is there into drivers of consumption and how patterns of import demand at the sector level shift in response to long-term changing economic and demographic conditions?
- How does a country's stage of development influence their import demand at sector level?
- How does a country's stage of development influence their positioning in global value chains, for example is a country's contribution of low-level extractive inputs or high-level services dependent on its level of development?
- How does the value of individual goods/services in a GVC change as a country becomes more developed?

We have found that there is a wealth of research into the drivers of consumption and import demand patterns, and in answering the above questions, we have reviewed evidence from a total of 151 sources. The majority of our evidence is gathered from academic papers, though we have also gathered evidence from both grey literature and commercial sources. The evidence is split as follows: (i) 92 academic papers; (ii) 46 sources of grey literature; and (iii) 13 commercial sources. A significant proportion of the evidence reviewed assesses consumption and import demand patterns at an aggregated level, with a more limited body of literature available pertaining to the sectoral, or more granular product level.

When conducting research into the drivers of consumption patterns and import demand, we have been conscious to carefully consider the relative importance of the drivers identified. Throughout this section, we detail those drivers that have been cited in the literature to have a **significant effect** on import patterns. As a result, all drivers considered in this chapter have been shown to be key to understanding import and consumption patterns.

Indeed, most of the literature suggests that several drivers simultaneously affect import demand. The immediate implication is that approaches to forecasting import demand that rely on a single driver (or a subset of them) for example examining whether a country's GDP is forecast to rise or fall, may result in inaccurate forecasts as changes in the other drivers may reinforce or offset its effect. In short, the effects of all potential drivers should be considered in the round, where possible.

In looking to home in on the **relative importance between these key factors**, we have not looked to compare their specific elasticities with respect to imports. This is because, due to differences in estimation approaches and the use of case studies across levels of aggregation, elasticities from different evidence sources are not directly comparable[1].

Rather than extracting elasticities (which measures the percentage change in the level of import demand that is caused or correlated with a 1 percentage change in an individual driver), we present the number of times a particular driver has been cited within the literature to have a significant impact on import and consumption patterns in the research, as we consider this to be a more informative way of assessing the relative importance of different categories of drivers.

To identify which categories of drivers are most important, we employed the following grading system:

- **Green**: over 10 pieces of evidence cite a driver in this category as significant.
- **Orange**: between 5 and 10 pieces of evidence cite a driver in this category as significant.
- **Red**: less than 5 pieces of evidence cite a driver in this category as significant.

In quantitative evidence (representing the majority of the evidence), 'significant' means statistically significant. The table overleaf summarises our findings of the relative importance of the categories of drivers at the aggregate and sector levels.

Table 10: Summary of evidence for RQ1

Sector	Macroeconomic factors	Stage of development	Social development	Demographic factors	Input availability and relative prices	Political factors	Dependency on other sectors	Technological change	Other
Aggregate	Green	Orange	Red	Red	Green	Orange	Red	Red	Green
Primary	Green	Green	Orange	Green	Green	Green	Orange	Orange	Orange
Secondary	Green	Green	Orange	Orange	Orange	Red	Orange	Red	Red
Tertiary	Green	Green	Green	Green	Orange	Green	Red	Green	Red

Source: Economic Insight Ltd

[1] Often, this will result from the use of differing functional forms in the calculation of elasticities. As such, further computation would be required in order to be able to compare elasticities on a like- for like basis.

We have looked carefully at drivers determining the overall **level of aggregate imports** in an economy, and those drivers that determine the particular **mix of imports** (at the sector level). As such, in the table above, the first row summarises the drivers of the level of aggregate imports, while the remaining rows summarise the drivers that are important in determining the mix of primary, secondary and tertiary imports within this.

We found that, at the **aggregate level**, there is broad consensus that key factors affecting economy-wide import demand are **income** (GDP) and **relative prices**. In addition, **trade liberalisation** is also specified as a key determinant of aggregate import levels.

The evidence shows that a country's stage of development is the key influence dictating both the position of that country in GVCs, and the **particular mix of imports demanded** as a result. A country's stage of development refers to the extent to which it's economy has moved from undertaking mostly primary economic activities – such as agriculture – to a highly diversified and sophisticated mix of economic activities, including secondary and tertiary activities. The stage of development could be viewed as another macroeconomic factor, but we have separately identified it in view of its importance in the literature as a driver of import demand.

Specifically:

- **At low levels of development**, countries tend to take advantage of the natural resources available to them, focusing on the extraction and supply of primary products (such as agriculture, mining, and the extraction of fossil fuels). As a result, the ability to satisfy any demand for manufactured goods and services domestically is low. However, low per capita income limits the demand for these goods, and as such, the requirement for imports to satisfy this demand is also low.

- **Developing countries** typically experience a period of industrialisation, with domestic supply moving from primary products to the production of manufactured goods. This means that: (i) the country's ability to self-sustain with respect to primary goods weakens; and (ii) the country experiences an increase in demand for these primary goods as inputs into the manufacturing process. As such, imports of primary goods tends to increase at this stage of development. Additionally, as per capita incomes (and therefore standards of living) increase, domestic consumers' demand for manufactured goods and services also rises. This leads to increases in import demand of these goods too.

- **At higher levels of development**, countries tend to move into the supply of services. As a result, demand for both primary and secondary goods rises, as the ability of the country to meet demand for these domestically falls. Further, as per capita incomes grows, so too does the demand for agricultural products (due to increased preferences for more varied diets and fresh produce), manufactured goods, and services. Therefore, even though they are the highest exporters of services, developed countries also tend to have the highest import demand for services.

The evidence gathered also shows that the ratio of domestic value-added to gross value of exports generally declines as a country develops. Specifically, as developing countries move from exporting primary products at low stages of development to importing these products, research has shown that the ratio of domestic value-added tends to fall.

Despite these findings, our research has shown that these historic trends may be becoming less informative in relation to estimating future import demand, as the rapid pace of development is now resulting in countries moving along GVCs in different ways. Specifically, countries are now moving from manufacturing to services at a much lower level of per capita income than has been historically observed. In addition, many countries are moving directly to services production without transitioning through the manufacturing stage. This implies that the nature of the relationships between import demand patterns and its drivers can, and is, changing.

This might have implications on: (i) the findings in this chapter; and (ii) the most appropriate methodologies for forecasting import demand. We discuss this further in considering the methodologies in the next chapter.

4.2 Structure of this chapter

This chapter is structured as follows:

- First, in section 4.3, we set out our findings relating to consumption and import demand patterns at an economy-wide level. Here, we detail those factors identified as having a key influence on aggregate consumption and import demand, and discuss their relative importance.

- Having done so, we discuss the findings relating to the particular mix of imports in sections 4.4- 4.6. Since our research has shown that a country's stage of development is the main driver of import demand across sectors, as well as the relevance of this to a country's positioning in global value chains, we set out the drivers of consumption and import demand at the primary, secondary and tertiary sector level. Where the evidence we collected allowed us to, we have included discussion at more granular levels of aggregation, for instance, at industry or product specific levels. However, where we have not included discussion at a more granular level, we cannot categorise this as a gap in the evidence base. This is because we did not direct our search at this level.

- Throughout this discussion, we also consider how a country's stage of development influences their positioning in global value chains, and provide our conclusions on this in section 4.7.

4.3 Drivers of consumption and import demand at an aggregate level

In this section, we set out the findings of our research relating to the drivers found to significantly affect **economy-wide import demand patterns**. The table overleaf summarises our findings.

Table 11: Summary of evidence at an aggregate level (1)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Macroeconomic factors	48	Aggregated GDP / income	19
		Disaggregated measures of GDP (C + I + G + NX)	10
		Exchange rate	13
		Stage of the business cycle	1
		Global economic conditions	2
		External macroeconomic shocks	1
		Country debt burden	1
		Unemployment rate	1
Stage of development	5	Household / per capita income and wealth	5
Social development	0		0
Demographic factors	2	Population	2
Input availability and relative prices	21	Relative prices	21
Political factors	9	Trade liberalisation	8
		Political circumstances	1
Dependency on other sectors	0		0
Technological change	1	Technology	1

Source: Economic Insight Ltd

Table 12: Summary of evidence at an aggregate level (2)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Other	17	Historical dynamics of the country	1
		Historical connections	2
		Geographical distance	7
		Common language	4
		Colonized	1
		Landlocked	2
Case study countries	EU member countries, Euro area, Sub-Saharan African countries (panel of 28), Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Bulgaria, Romania, Croatia, Turkey, Euro arena, South Africa, Sri Lanka, India, China, Pakistan, Bangladesh, Brunei, US, Australia, Japan, Brazil, Bolivia, Chile, Germany, Spain, UK, Ghana, South Africa, Zambia, Cambodia, Nigeria, East Africa, Indonesia, Philippines, Saudi Arabia, Tanzania, Bahrain.		

Source: Economic Insight Ltd

4.3.1 Income and relative prices

As shown in the previous table, a significant proportion of the evidence reviewed specified two key factors affecting consumption and import demand patterns. These are: (i) **income**; and (ii) **relative prices**. This is unsurprising, since a traditional import demand function models import demand as a function of only relative prices and income.

This simple import demand function specification is based on the theory that, as an economy's income (GDP) rises, consumption, by definition, increases. To satisfy this increase in consumption, the level of imports too will rise[2].

In relation to relative prices, economic theory also suggests that as relative prices (i.e. the price of imported goods compared to their domestic counterparts) rise, imports will decline, as imported goods are substituted in favour of the cheaper domestic alternatives. Relative prices can change both as a result of exchange rate fluctuations, but also as a result of relative changes to production efficiency domestically compared to overseas.

[2] This is unless the market in question can increase domestic production to meet this rise in consumption. As a result, the factors affecting consumption are often one and the same as those affecting import demand, **unless** they also affect the production patterns of an economy.

Studies modelling import demand using only income and relative prices as explanatory variables include: Marwat (2015)[3]; Tsionas and Christopoulos (2004)[4]; Chilpili (2013)[5]; Omoke (2010)[6]; and Gumede (2000)[7]. Certain papers also model this simple relationship, but look to disaggregate income into its components parts (private consumption expenditure, government consumption expenditure, investment, and net exports), in order to investigate whether certain aspects of an economy's income have a greater influence over import demand than others. Such papers include: Xu (2002)[8]; Reininger (2008)[9]; Yin and Hamori (2011)[10]; Muhammad and Zafar (2016)[11]; Onwuka and Zoral (2009)[12]; and Hor et al. (2018)[13].

In line with the theory, Marwat (2015) found that a 1% increase in relative prices will reduce Pakistan's economy-wide imports by up to 3.2%, while a 1% increase in GDP will boost imports by 0.93%, over the time period 1982-2011. Similarly, Tsionas and Christopoulos (2004) modelled import demand for France, Italy, the Netherlands, the UK and US over the period 1960-1999 using this function; and in all cases found a significant positive relationship between income and imports, and a significant negative relationship between relative prices and imports. Chilpili (2013) also used this simple function to model import demand in Zambia, and consistent with economic theory and existing evidence, income was found to have a strong positive influence on imports, while in the long-run prices showed a negative relationship with imports. Importantly, Chilpili found that in the shorter run, the relationship between import demand and exchange rate volatility was comparatively inelastic, likely being due to firms being unable to respond immediately to any price changes.

Yin and Hamori (2011) also find a positive relationship between income and import demand, and a negative relationship between price and import demand in China. They note that import demand is significantly more responsive to changes in income than price. Supporting this, Gumede (2000) also found that demand for imports is much more responsive to income than to relative prices in South Africa.

Turning to understanding the influence of the individual components of income, Onwuka and Zoral (2009) explore the relationship of imports with relative prices, income overall, and the foreign direct investment component of income. In line with expectation, they find that the most significant determinants of imports growth in Turkey are income overall, and relative and domestic prices. They find that the foreign direct investment component of income has an insignificant effect. Hor et al. (2018) find that the key component of income affecting import demand in Cambodia

[3] 'Estimated import demand function for Pakistan: a disaggregated analysis'. Marwat (2015).
[4] 'International evidence on import demand'. Tsionas and Christopoulos (2004)
[5] 'Exchange rate volatility and trade flows in Zambia.' Chipili (2013).
[6] 'Error correction, co-integration and import demand function for Nigeria'. Omoke (2010).
[7] 'Import performance and import demand functions for South Africa' Gumede (2000).
[8] 'The dynamic-optimizing approach to import demand: A structural model.' Xinpeng (2002).
[9] 'Factors Driving Import Demand in Selected Central, Eastern and Southeastern European Countries' Reininger (2008).
[10] 'Estimating the import demand function in the autoregressive distributed lag framework: the case of China.' Fengbao and Hamori (2011).
[11] 'Determinants of Imports Demand Functions of Pakistan: An ARDL Bound Testing Approach' Muhammad and Zafar (2016).
[12] 'Foreign direct investment and import growth in Turkey'. Onwuka and Zoral (2009).
[13] 'An Empirical Analysis of Cambodia's Import Demand Function.' Hor et al (2018).

is in fact export demand. The findings of Reininger (2008) support this, showing that the elasticity of imports with respect to exports is highly significant and large in selected central and eastern European countries, suggesting a strong-import export link. It is likely that this is a result of these countries being strong manufacturers, and thus increasing exports require an increase in imports of inputs into the manufacturing process. As such, the strength of the different components of income is likely to be affected by the particular position on the global value chain of the economy in question. This relationship is discussed in greater detail in the following sections.

4.3.2 Trade liberalisation and political factors

As shown in the summary table set out previously, the evidence shows that there are a number of additional factors found to drive aggregate import levels. In particular, many studies examine and confirm a statistically significant and positive relationship between trade liberalisation and import demand, including Emran and Shilpi (2010)[14]; Kassim (2015)[15]; Zakaria (2014)[16]; Rahman (2010)[17]; and Gaalya et al. (2017)[18].

While studying the effect of trade liberalisation on import and export growth in Sub-Saharan Africa, Kassim (2015) finds that the nature of the relationship between imports and trade liberalisation differs between the short- and long-run. It was found that in the year of increased liberalisation, import growth in fact falls due to an expectation of future lower prices, before rising significantly in subsequent years.

Kassim (2015) and Zakaria (2014) also explore the effect of trade liberalisation on international trade more broadly, and find that the positive relationship of liberalisation with an economy's imports is twice as strong as that with exports. As such, not only has trade liberalisation been found to drive an economy's imports, but it has also been found to worsen an economy's trade balance.

Further, both Emran and Shilpi (2010) and Kassim (2015), find that the traditional formulation of the import demand function (comprising only income and relative prices), that does not control for the level trade liberalisation, strongly biases downwards the strength of the relationship between relative prices and import demand. In other words, they expect the true relationship between relative prices and import demand to be in fact stronger than much of the existing literature suggests. As such, this might explain the substantial differences in the relative elasticities of price and income with respect to import demand found by both Yin and Hamori (2011) and Gumede (2000) detailed previously.

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[14] 'Estimating an import demand function in developing countries: A structural econometric approach with applications to India and Sri Lanka' Emran and Shilpi (2010).
[15] 'The impact of trade liberalization on export growth and import growth in Sub-Saharan Africa.' Kassim (2015).
[16] 'Effects of trade liberalization on exports, imports and trade balance in Pakistan: A time series analysis' Zakaria (2014).
[17] 'Exploring Australia's global trade potential: a gravity approach with panel data' Rahman (2010).
[18] 'Trade Openness and Disaggregated Import Demand in East African Countries'. Glaava et al (2017).

4.3.3 Geographical factors

Geographical factors have also shown to be of high importance across the literature reviewed. Specifically, the importance of geography has predominantly been discussed in relation to the strength of bilateral trade relationships between country pairs[19]. As such, geographical factors are particularly important to consider when looking to understand the trade potential between one economy and its trading partners.

Despite being a strong driver of the **level of imports between economies**, geographical factors also drive import demand more generally, due to affecting the ease at which economies are able to engage in international trade. For instance, it has been shown by Josheki and Fotov (2013)[20] that being **landlocked** is a significant impediment to international trade. Similar findings are set out by Kareem et al (2016). [21]

4.4 Drivers of import demand in the primary sector

While above we set out the key factors affecting aggregate imports, there is also evidence showing that certain factors affect the particular mix of imports demanded. Here, we consider the factors affecting the relative level of primary sector imports.

The primary sector includes the extraction of natural resources and the cultivation of raw materials. Imports in this sector include: (i) minerals, such as coal and gas; (ii) agricultural products; and (iii) water.

The tables overleaf summarise the key drivers of demand for primary imports. The tables show that while there is significant overlap between the drivers cited in the literature at the aggregated and sector levels, there are some differences, especially in terms of the specific sub-drivers. It is not clear from the literature whether these differences are caused by different authors making different choices about how best to measure the drivers of interest, or whether certain sub-drivers are more relevant to some sectors than to others, or a combination of both factors.

[19] The method used to examine this relationship is typically the gravity model, which is discussed in detail in the next chapter of this report.
[20] 'Gravity modeling: International trade and R&D.' Josheki and Fotov (2013).
[21] 'Fitting the Gravity Model when Zero Trade Flows are Frequent: a Comparison of Estimation Techniques using Africa's Trade Data.' Kareem, Fatima Olanike, Inmaculada Martinez-Zarzoso, and Bernhard Brümmer. (2016).

Table 13: Summary of evidence in the primary sector (1)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Macroeconomic factors	11	GDP growth rate	4
		Inflation	2
		Exchange rates	1
		Economic growth	4
Stage of development	18	Household / per capita income and wealth	10
		Infrastructure	3
		Changes to economic structure	1
		Stage of development	1
		Industrialisation	2
		Rising living standards	1
Social development	9	Urbanisation	5
		Consumer attitudes and trends	3
		Education	1
Demographic factors	13	Age	2
		Population size	2
		Population growth	8
		Average household size	1
Input availability and relative prices	10	Relative prices	6
		Domestic prices	1
		Domestic resource supply	3

Source: Economic Insight Ltd

Table 14: Summary of evidence in the primary sector (2)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Political factors	17	Trade liberalisation	3
		Trade agreements	2
		Environmental standards and practices	2
		Government priorities / policies	9
		Regulations	2
Dependency on other sectors	8	Domestic demand for land use not related to food production	1
		Share of resource intensive industries in an economy	1
		Fracking revolution	1
		Demand for food and electricity production	1
		Management of interdependencies with other sectors	1
		Sectoral energy intensities	1
		Growth of industrial sector	1
		Downstream commercial interest in phasing out fossil fuels	1
Technological change	7	Technological change	4
		Capital-labour ratio	1
		Productivity	2
Other	9	Climate change	4
		Environmental awareness	1
		Geographical distance	2
		Seasonal weather	2
Case study countries	Global trends, UK (Scotland), China, US, India, Brazil, Chile, New Zealand, EU.		

Source: Economic Insight Ltd

As shown, the evidence suggests that the **stage of development** is the most important factor driving consumption and import patterns of primary sector products. **Political and regulatory factors, along with demographic factors**, are also identified as key drivers.
Pertaining to the stage of development, evidence shows that the demand for imports of extractive primary inputs, and in particular fossil fuels such as coal and gas, follows an inverted U shape over the course of a country's development. Specifically, **low income or less developed countries have historically relied on exporting primary products during the early stages of development of their development, and hence have low import demand for these products**.

However, as a country develops, production traditionally shifts away from the extraction of primary materials, to manufacturing. The effect of this is twofold. Firstly, domestic supply of primary materials falls, relative to GDP. Secondly, increasing manufacturing activity causes domestic demand for these materials to rise, as they are inputs into the manufacturing process. As a result, **import demand for primary products (in the form of extractive inputs) rises for developing countries, or countries going through a period of industrialisation**.[22] [23] [24] [25]

As countries become increasingly developed, historic trends indicate that they shift towards a service economy, and the reliance on the manufacturing sector declines. As a result, demand for imports of primary extractive inputs also declines. In support of this, Wårell and Olsson predict that the high levels of steel use currently observed in China and India will decline as they develop further. Robert et al (2016) also predict that, as China moves from manufacturing exports to services, their import demand for commodities will decline.[26]

The exception to this trend is demand for imports of agricultural products and water. Import demand for these primary products instead follows an increasing trend over the course of a country's development. Less developed countries traditionally have low import demand for agricultural products, due to low levels of income and because agriculture is typically their dominant export sector, and so they are self-sufficient. Indeed, in Kenya, agriculture accounts for 70% of the workforce, and around 25% of GDP each year.[27] As countries develop further, and per capita income levels grow, demand for fresh produce increases, with agricultural imports rising in response.

Overleaf, we run through key industry and product specific findings.

[22] 'Why Coal Will Keep Burnin'. BCG Henderson Institute (2018).
[23] 'Gas 2019: Analysis and Forecast to 2024' IEA (2019).
[24] 'Trends and Development in the Intensity of Steel Use: An Econometric Analysis' Warell and Olsoon (2009).
[25] 'Determinants of Sectoral Import in Manufacturing Industry: A Panel Data Analysis' Colak et al (2014).
[26] 'China's Evolving Demand for Commodities' Roberts et al (2016).
[27] 'Kenya – Agriculture' US Government (2019), available here: https://www.export.gov/article?id=Kenya-Agriculture.

4.4.1 Coal

A number of studies have found that demand for coal also depends on **government policies** and the **growth of green energy**.[28] [29]For instance, IEEFA (2019) suggests that the erosion of the coal market is due to a decline in renewable energy costs; rising corporate interest in green energy; and increased concern regarding climate change. Similarly, BCG Henderson Institute (2018) finds that coal consumption depends on regulations such as the clean air incentive policies introduced by China and OECD countries. Their report also states that coal consumption depends on the **level of industrialisation**. This is unsurprising, as developing countries with economies focused on secondary products will have higher demand for primary inputs like coal.

4.4.1 Gas

Similarly, the International Energy Agency (2019) has found that the main driver of demand for gas is **industrial usage**.[30] Interestingly, China is predicted to account for more than 40% of global gas demand growth by 2024 and to become a net importer of natural gas. This is mostly due to policies aimed at improving air quality. Indeed, the Oxford Institute of Energy Studies (2015) found that drivers of gas demand in China included **environmental awareness** and **government policies and priorities**.[31]

4.4.3 Water

A number of papers have found **population growth** to be an important driver of demand for water. [32][33][34] Indeed, UN Water (2018) states that population growth has a positive impact on water demand, and notes that over half of population growth expected between 2017 and 2050 is due to occur in Africa.[35] The report also highlights that water demand is a function of **global demand for agricultural and electricity production**, which are both water intensive industries and are expected to increase by 60% and 80% respectively by 2025. **Economic development** also has a positive impact on water demand – that is, less developed countries will have lower water demand.[36][37] Finally, **climate change** has been found to be an important driver of water demand, as drier regions have higher water demand for example.[38][39]

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[28] 'Why Coal Will Keep Burning' BCG Henderson Institute (2018).
[29] 'Coal Outlook 2019 Domestic Market Decline Continues' IEEFA (2019). 30
[30] 'Gas 2019: Analysis and Forecast to 2024' IEA (2019).
[31] 'Natural gas in China: a regional analysis' The Oxford Institute for Energy Studies (2015).
[32] 'Nature-based solutions for water' UN Water (2018).
[33] 'Scotland National Needs Assessment (NNA)- Demand Drivers' ITRC (2019).
[34] 'Water Scarcity and Future Challenges for Food Production' Mancosu et al. (2015
[35] Ibid.
[36] Ibid.
[37] Ibid.
[38] 'Water consumption patterns as a basis for water demand modelling' Avni et al (2015).
[39] 'Water Scarcity and Future Challenges for Food Production' Mancosu et al. (2015).

4.4.4 Agriculture

Per capita income is a key driver of demand for agricultural products. Huang et al (2009) found that rising incomes in China has led to changing consumption patterns and increased demand for meats, fish and fruit.[40] Similarly, Cook (1999) found that rising income levels change consumer diets towards diets richer in animal protein, fruit and veg.[41] The author also found that advances in **technology**, such as improved shipping ability, increases demand for fresh produce.

Popp et al (2010)[42] and Alexander et al (2015)[43] both found that **population growth** increases demand for agricultural products. On the other hand, Huang et al (2009) found that population growth was a relatively weak factor in explaining consumption pattern changes in China.
Interestingly, the UN (2011) found that population growth was one of the reasons Africa has become a net importer of food and agricultural products since the mid-1970s.[44] Other reasons included: (i) **weak institutions and poor infrastructure**; (ii) **low and stagnating agricultural productivity**; and (iii) **policy distortions**. The report found that import levels vary across the countries according to countries' level of income.

A number of papers have found **trade liberalisation** to be an important driver of agricultural demand and imports.[45] [46] The Food Climate Research Network (2015)[47] and Wood (2008)48[48] both found that **urbanisation** is another key driver of agricultural demand, as it exacerbates the effects of rising per capita income. Urbanisation also reduces the proportion of people living in rural areas, leading to a shortage of agricultural workers, and increases agricultural land conversion, resulting in constraints on supply.

4.5 Drivers of import demand in the secondary sector

This section outlines the key drivers of import demand and consumption in the secondary sector.[49]

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[40] 'China's Agriculture: Drivers of Changes and Implications to China and the Rests of the World' Huang et al (2009)
[41] 'An Overview of Key Food Industry Drivers: Implication for the Fresh Produce Industry' Cook (1999).
[42] 'Food consumption, diet shifts and associated non-CO2 greenhouse gases from agricultural production' A et al (2010).
[43] 'Drivers for global agricultural land use change: the nexus of diet, population, yield and bioenergy' Alexander et al (2015).
[44] 'Drivers for global agricultural land use change: the nexus of diet, population, yield and bioenergy' UN (2011).
[45] 'China's Agriculture: Drivers of Changes and Implications to China and the Rests of the World' Huang et al (2009).
[46] 'An Overview of Key Food Industry Drivers: Implication for the Fresh Produce Industry' Cook (1999).
[47] 'Overview of changes and drivers in China's food system' Food Climate Research Network (2015).
[48] 'Drivers of change in global agriculture' Wood (2008).
[49] From our conversations with DIT, we understand that automotive, engineering and aerospace industries are 'priorities' for the Department. However, in conducting our research into drivers of consumption and import demand in the secondary sector, we have not found any evidence relating to these industries when employing the search terms outlined in Section 3.

The secondary sector uses primary products to create finished goods, or products used in the assembly of other goods. In other words, it is concerned with manufacturing and construction activities.

The tables overleaf summarise the key drivers of secondary sector imports.

Table 15: Summary of evidence in the secondary sector (1)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Macroeconomic factors	15	Domestic demand	1
		Export demand	1
		Real exchange rates	3
		Consumer spending	1
		Interest rates	3
		Business confidence	1
		Rate of growth of new businesses	1
		Economic growth	3
		Macroeconomic factors	1
Stage of development	15	Household / per capita income and wealth	5
		Income	4
		Industrial production	1
		Economic development	3
		Changing labour market structure	1
		Living standards	1
Social development	8	Immigration rates	2
		Urbanisation	4
		Consumer attitudes and trends	1
		Level of education	1

Source: Economic Insight Ltd

Table 16: Summary of evidence in the secondary sector (2)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Demographic factors	9	Demographic trends	1
		Population growth	3
		Age	2
		Average household size	1
		Ethnic diversity	1
		Number of households	1
Input availability and relative prices	9	Relative prices	3
		Material costs	1
		Resource depletion	1
		Wage inflation	1
		Prices of commodities (oil and gas)	1
		Energy supply	1
		House prices	1
Political factors	4	Government policies related to construction / infrastructure	2
		Government legislation	1
		Trade liberalisation	1
Dependency on other sectors	6	Domestic manufacturing sector performance	3
		Home price index	1
		Retailing (such as food industry marketing or transnational corporations)	2
Technological change	3	Technological progress affecting production capacity	1
		Digital revolution / BIM / big data	2

Source: Economic Insight Ltd

Table 17: Summary of evidence in the secondary sector (3)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Other	3	Total energy production	1
		Climate change	2
Case study countries	Global trends, developing countries, China, Africa, Ghana, US, Spain, Asia, Turkey		

Source: Economic Insight Ltd

As shown, the evidence we have found suggests that, once again, **a country's stage of development** is of key importance in explaining secondary sector import demand and consumption patterns. In addition, **macroeconomic factors** are also shown to be important.

Pertaining to a country's stage of development, the evidence shows that **less developed countries will have lower demand for secondary products due to their low levels of income per capita**, which is a key driver of manufactured goods.

As countries develop and shift production to the manufacturing sector, their demand for importing secondary products follows two opposing paths:

- On one hand, **import demand for manufactured products decreases since these are produced domestically**. Indeed, Godbout and Langcake (2013) support this, and showed that as domestic firms improve production capacity – that is, develop their secondary sector – countries import less manufactured goods. However, since less developed countries already have low import demand for manufactured goods, this effect is likely to be small.

- On the other hand, **import demand for manufactured products are likely to increase as countries develop, due to rising incomes**. Developing countries in the manufacturing stage of development will also demand more imports of secondary products because these are often also used as inputs into the production process of other manufactured goods. Indeed, Colak et al (2014) found that motor vehicles, electrical machinery and textiles all had high elasticities of import demand with respect to industrial production in Turkey.[50]

Finally, **as countries continue to develop and expand their service sector, demand for importing manufactured goods will increase again, due to incomes rising further and because these products are no longer produced domestically**.

The rest of this section discusses our findings in more detail.

[50] 'Determinants of Sectoral Import in Manufacturing Industry: A Panel Data Analysis' Colak et al (2014).

4.5.1 Manufacturing

Evidence suggests that the key driver of consumption and import patterns in the manufacturing industry is **per capita income** (a measure of economic development).[51][52] [53] As income levels rise, consumer demand shifts from basic needs such as food, to more sophisticated manufactured products. This is known as Engel's law – that is, the share of a household's budget allocated to necessities declines as income grows.[54] Indeed, Brookings (2018) hypothesised that recent rising incomes in Africa would lead to rapid growth in demand for manufactured products, and in particular, noted that analysts predict the largest increase will be in the processed food and beverages industry.[55]

Godbout and Langcake (2013) examined drivers of imports of manufactured goods in China between 2001 and 2011, and explored the relative importance of domestic demand and export demand in driving imports of manufactured goods.[56] The authors found that, while both domestic demand and export demand have a positive relationship with imports of manufactured goods, **the effect of domestic demand is stronger than that of export demand**. Specifically, they found that a 1% rise in China's aggregate exports leads to a 0.35% increase in imports of manufactured goods, whereas a 1% increase in domestic demand leads to a 0.55% increase in imports of manufactured goods. Additionally, they showed that as domestic firms improve **production capacity**, they become less reliant on imports of manufactured goods, as they are produced domestically.

4.5.2 Electricity generation

Electricity is derived from primary energy sources and so is considered part of the secondary sector. Perez-Garcia and Moral-Carcedo (2016) show that **GDP growth** is the main driver of demand for electricity in Spain.[57] The authors find that **relative prices** of electricity, **population size** and **prevalence of durable goods** that need to be powered by electricity are also important. The International Energy Agency (2018) found that rising demand for air conditioners and electric fans occurred due to **climate change, economic growth** and **population growth**, as well as **rising incomes and living standards**.[58]

4.5.3 Construction

Turning to the construction sector, Li (2014) examined how **demographic** and **economic factors** affect housing demand in US and China.[59] The author found that in both countries, demographic factors had a greater impact than economic factors.

[51] 'Industrial Development Report' UN (2018).
[52] 'The potential of manufacturing and industrialization in Africa.' Brookings (2018).
[53] 'Manufactured goods consumption, relative prices and productivity.' UN (2018).
[54] 'Industrial Development Report' UN (2018).
[55] 'The potential of manufacturing and industrialization in Africa.' Brookings (2018).
[56] 'Demand for Manufacturing Imports in China' Godbout and Langcake (2013).
[57] 'Analysis and long term forecasting of electricity demand trough a decomposition model: A case study for Spain' Perez-Garcia and Moral-Carcedo (2016).
[58] 'The Future of Cooling - Opportunities for energy-efficient air conditioning' IEA (2018).
[59] 'Demographics, Markets, and the Future of Housing Demand' Li (2014).

Specifically, they found that a 1% increase in the size of the working age population leads to a 2.7% increase in house prices, whereas a 1% increase in GDP growth only leads to a 0.9% increase in house prices. The importance of demographic factors for real estate demand is confirmed by Dicks (1988)[60] and Green and Lee (2016)[61].

The drivers of consumption and import patterns in the construction sector have also been studied by a number of other sources, including Gao et al (2019)[62]; Turner and Townsend (2018)[63]; Ofori (2012)[64]; BPIE (2016)[65]; and IBIS World (2019)[66]. These papers have found the following additional factors to be important:

- **Income per capita**;
- **Social development factors**, such as immigration rates and urbanisation. As an economy develops and becomes increasingly urbanised, demand for construction increases;
- **Input costs**, including labour costs;
- **Government policies** related to infrastructure and construction;
- **Technological factors**; and
- **Climate change**.

4.5.4 Food manufacturing

Demand for manufactured foods is driven by **per capita income, changing labour market structure** and increasing **urbanisation** according to Baker and Friel (2016).[67] Ultra-processed foods are increasingly being demanded in developing countries, such as middle-income countries in Asia, and are already in high demand in the developed world. Kearney (2010) notes that when per capita income increased in China after economic reform, high-fat food consumption increased.[68] This is also confirmed by Brooks et al (2009) who find that imports of ‘consumer ready foods’ are influenced by income and **education** levels.[69]

4.6 Drivers of import demand in the tertiary sector

[60] ‘The demographics of housing demand; household formations and the growth of owner-occupation.’ Dicks (1988).
[61] ‘Age, demographics, and the demand for housing, revisited’ Green and Lee (2016).
[62] ‘Evolution of the Construction Industry in China from the Perspectives of the Driving and Driven Ability’ Gao et al (2019).
[63] ‘International construction market survey’ Turner and Townsend (2018).
[64] Developing the Construction Industry in Ghana: the case for a central agency’ Ofori (2012).
[65] ‘Driving transformational change in the construction value chain’ BPIE (2016).
[66] Available here: https://www.ibisworld.com/industry-insider/analyst-insights/key-construction- drivers-part-4-industrial-construction-trends/
[67] ‘Food systems transformations, ultra-processed food markets and the nutrition transition in Asia’ Baker and Friel (2016).
[68] ‘Food consumption trends and drivers’ Kearney (2010).
[69] ‘Globalization and Evolving Preferences Drive U.S. Food- Import Growth’ Brooks et al (2009).

In this section, we turn to the key drivers of imports and consumption in the tertiary sector. This sector provides services to customers, and encompasses a wide range of industries including (i) retail; (ii) education; (iii) financial and professional services; (iv) health care; (v) insurance activities;
(vi) arts and entertainment; (vii) tourism; (viii) food services; (ix) defence; and (x) transport.

Drivers of imports in the tertiary sector are much more varied than in the primary and secondary sectors, which is unsurprising due to the varied nature of the industries it covers. As shown in the table overleaf, our evidence suggests that **social development, macroeconomic, and demographic factors**, as well as a country's **stage of development**, are the most important drivers of consumption and imports in this sector.

Table 18: Summary of evidence in the tertiary sector (1)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Macroeconomic factors	24	GDP growth rate	7
		Exchange rates	1
		Fiscal revenues	1
		Public debt	1
		Export debts	1
		Structural shifts	1
		Employment	1
		Job stability	1
		Strength of the housing market	1
		Inflation	4
		Interest rates	3
		Globalisation	3
Stage of development	17	Per capita income	8
		Per capita expenditure	1
		Income	3
		Less physically demanding work	1
		Disposable income	3
		Infrastructure and network capacity	2

Source: Economic Insight Ltd

Table 19: Summary of evidence in the tertiary sector (2)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Social development	29	Consumer preferences	2
		Urbanisation	3
		Development	1
		Psychological costs	1
		Car ownership	2
		Education	9
		Lifestyle / cultural changes	3
		Shorter working hours	1
		Changing risk aversion	1
		Religion	4
		Health	1
		Access to internet	1
Demographic factors	21	Proportion of female working population	1
		Population growth	5
		Age	12
		Household size	1
		Dependency ratio	1
		Gender	1
Input availability and relative prices	8	Fuel prices	2
		Price of service	5
		Tuition fees	1

Source: Economic Insight Ltd

Table 20: Summary of evidence in the tertiary sector (3)

Drivers	Number of times cited as significant	Sub-drivers	Number of times cited as significant
Political factors	19	Trade policy liberalisation	2
		Regulation	1
		Trade openness	1
		Institutional factors	4
		Regulation and policy interventions	1
		Government spending on social security	1
		Level of public finances	1
		Democracy	2
		Internal and external conflict	2
		Arms race	1
		Neighbours' and rivals' military spending	2
		Trade barriers	1
Dependency on other sectors	3	Availability of credit	1
		Industrial activity	1
		Merchandise and trade levels	1
Technological change	12	Technological progress	3
		Technology	7
		Travel facilitators	1
		Digital technology	1
Other	2	Quality of service	1
		Public health insurance	1
Case study countries	Global trends, UK, EU, US, India, China, Europe, Tunisia, Turkey, Greece, developing countries, Singapore, ASEAN, Australia, Austria, Italy		

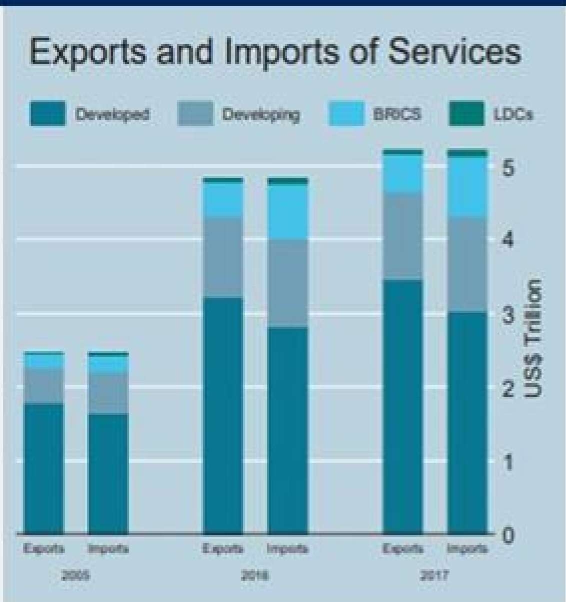
Source: Economic Insight Ltd

As for both the primary and secondary sectors, the **stage of development** of a country (as measured by per capita income) is also a key driver of import demand for the tertiary sector. Indeed, under- or less-developed countries have very low import demand for services.[70]

As countries develop and production shifts to the manufacturing sector, incomes rise and spending on non-essential items such as services increases. Indeed, rising per capita incomes has been shown to lead to: (i) increased demand for retail in India[71]; (ii) an increase in eating out in China[72]; and (iii) the growth of creative services in developing countries more generally[73].
Additionally, developing countries have high demand for shipping due to the nature of their economies. Nevertheless, import demand for services in developing countries can also vary. For instance, life insurance consumption in developing countries is low due to cultural and religious regions. [74]

As countries develop further, historical trends suggest that production shifts away from manufacturing and expands into services. Despite predominantly exporting services, developed countries also account for the majority of import demand for services, as shown below.

Figure 2: Exports and imports of services according to level of development



Source: ‘Key Statistics and Trends in International Trade’ UNCTAD (2018).

[70] ‘Key Statistics and Trends in International Trade’ UNCTAD (2018).
[71] ‘Indian Retail Industry - Structure & Prospects’ Care Ratings (2017).
[72] ‘Overview of changes and drivers in China’s food system’ Food Climate Research Network (2015).
[73] ‘’Why is the creative economy growing so strongly?’ Hajkowicz (2015).
[74] ‘Life insurance markets in developing countries’ Outreville (1996).

The evidence also suggests that **social development** and **demographic factors** are key drivers of the demand for tertiary imports. The rest of the section discusses these drivers in more detail for individual industries.[75]

4.6.1 Retail

A number of studies have examined consumption drivers and import patterns in the retail industry.[76][77] CARE Ratings (2017) examined the drivers of retail demand in India and found that **population growth, urbanisation, rising incomes** and **ease of availability of credit** all had important effects on retail demand.[78] Specifically, the study found that an increase in the earning age population and especially high spending appetite of under 25 year olds in tandem with increased use of credit cards resulted in a growth rate in the retail industry of 12% per annum.

4.6.2 Education

Chadee and Naidoo (2008) looked to understand drivers of demand for higher education from students from seven Asian countries studying in the UK and the US.[79] The authors found that in four of the seven countries, import demand for higher education depends on the **degree of access to domestic higher education** – that is, as domestic access increases, import demand decreases for China, India, South Korea and Thailand. The **exchange rate** between the two countries and **per capita income** in the domestic country are also found to be important drivers of demand, as well as **tuition fees**, which is in line with findings by Hopkins (1974).[80]

Pertaining to education more generally, Freeman (1974) found that demand depends on five categories: (i) societal demand; (ii) sectoral shifts; (iii) substitutability between educated labour and other inputs; (iv) individual decision-making; and (v) the level of public finances.[81]

4.6.3 Financial and professional services

Technology is a key driver of the consumption of professional services.[82] Brentani and Regot (1996) suggest that this is because technology increases the demand for external services to help understand changes.[83] The ACCA (2018) predicts that key drivers of regional consumption in Singapore, China and ASEAN will be the growth

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[75] We understand from our conversations with DIT that they are particularly interested in FinTech, asset management and the services side of construction industry. However, our research has not found any evidence relating to these industries when employing the search terms outlined in Section 3
[76] 'Demand Drivers Are Shifting the Industrial Development Pipeline' Newmark Knight Frank (2018).
[77] 'New retail reinvigorates China's imports' Deloitte Insights (2018).
[78] 'Indian Retail Industry - Structure & Prospects' Care Ratings (2017).
[79] 'Higher Educational Services Exports: Sources of Growth of Asian Students in US and UK' Chadee and Naidoo (2008).
[80] 'Higher Education Enrolment Demand' Hopkins (1974).
[81] 'Demand for education' Handbook of Labor Economics; Volume 1, Pages 357-386; Freeman (1986).
[82] '2019 Banking Industry Outlook' Deloitte (2019).
[83] 'Developing New Business-to-Business Professional Services: What Factors Impact Performance?' Brentani and Regot (1996).

of e-commerce, as well as the digital economy.[84] The report also notes that **globalisation** increases demand for external advice. Similarly, the Bank of England (2010) found that globalisation and financial innovation have increased demand for banking services.[85]

Poterba (2004) found that **demographic factors** also impact demand for financial services, notably the share of different ages of the population.[86] The paper showed that demand for financial investments is highest when households are aged between 30 and 50.

4.6.4 Healthcare

A number of papers have found that **household income** is a key driver of demand for healthcare – as income rises, demand for healthcare increases.[87] [88]Jack (2000) found that low income households are more price-elastic than higher income ones.[89] The author also noted that **prices** and **demographic factors** influence the demand for medical care, which was also found by Grossman (1972).[90]

The **relative price** of domestic healthcare services and those abroad has also been found to influence demand for imports of healthcare by Herman (2009) and Horowitz et al (2007).[91] [92] Lautier (2008) also found that **quality** of the service and **trade barriers** influence import demand.[93] The author noted that although developing countries have a cost advantage over developed countries for similar quality health care services, trade barriers seem to dampen demand for imports of health services from developing countries.

4.6.5 Insurance activities

Hussels et al (2005) found that the most important drivers of insurance demand are **political and legal factors** – that is, political stability and stable legal systems increase insurance demand.[94] This was in line with a number of other papers, including Browne et al (2000)[95], Browne and Kim (1993)[96] and Elango and Jones (2011)[97]. Hussels et al also found that **household income** is positively related to insurance demand and that **religion** also plays a key role, since some Muslim countries have beliefs against insurance. Outreville (1996) similarly noted that demand for life insurance is low in many developing countries due to cultural and

[84] 'Market demand for professional business and advisory services' ACCA (2018).
[85] 'Evolution of the UK banking system' Bank of England (2010).
[86] 'The Impact of Population Aging on Financial Markets' Poterba (2004).
[87] "The Demand for Health Care Services" Jack (2000).
[88] 'On the Concept of Health Capital and the Demand for Health' Grossman (1972).
[89] Ibid.
[90] Ibid.
[91] 'Medical Tourism: Globalization of the Healthcare Marketplace' Horowitz, Rosensweig, and Jones (2007).
[92] 'Assessing international trade in healthcare services' Herman (2009).
[93] 'Export of health services from developing countries: The case of Tunisia' Lautier (2008).
[94] 'Simulating the demand for insurance' Hussels et al (2005).
[95] 'International property-liability insurance consumption' Browne et al (2000).
[96] 'An International Analysis of Life Insurance Demand' Browne and Kim (1993).
[97] 'Drivers of insurance demand in emerging markets' Elango and Jones (2011). '

religious reasons.[98]

Hussels et al's findings are in line with Beck and Webb (2003), who found that development levels, religion and institutional factors are important drivers of insurance.[99] The authors also showed that surprisingly, education, life expectancy, the dependency ratio and social security did not play a role in insurance demand. Beck and Webb note that life insurance consumption is low in developing countries, while more developed, higher income countries with better developed institutions have higher life insurance consumption.

4.6.6 Arts and entertainment

Demographic factors are the most important drivers of arts and entertainment consumption. The University of Wisconsin-Madison (2011) found that education increases demand for arts and entertainment, and that middle-aged people had the highest consumption.[100] They also found that an individual's **income** increases demand for arts and entertainment, however, Seaman (2006) showed that education is a stronger driver than income.[101] The latter paper also found that '**lifestyles'**, such as sexual orientation, gender and socialization impact demand. Finally, Hajkowicz (2015) showed that increased **access to internet and rising household incomes** explained the rapid growth of creative services in developing countries.[102]

4.6.7 Tourism

Per capita income is the main driver of demand for tourism.[103] Divisekera (2010) found that the level of tourism is highly sensitive to incomes, but less to prices. Demand for accommodation is the most sensitive to incomes, with an income elasticity of 1.33, whereas income elasticities for the other commodities, such as food, transport and shopping were close to 1. Deloitte also noted that an individual's income drives travel in the US in its 2019 US Travel and Hospitality Outlook.[104]

Bernini and Cracolici (2015) show that the level of **education** is another key driver of tourism.[105] More educated individuals are more likely to attain a higher level of income, and so can spend more on non-essential items such as tourism. Interestingly, the authors also find that age has a negative effect on the desire to travel, but a positive effect on tourism expenditure. Moller et al (2007) suggest that ageing population is likely to drive demand for longer-term and off-season tourism from Austria.[106]

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98 'Life insurance markets in developing countries' Outreville (1996).
99 'Economic, demographic and institutional determinants of life insurance consumption across countries' Beck and Webb (2003).
100 'Evaluating Arts and Entertainment Opportunities' University of Wisconsin-Madison (2011).
101 'Empirical Studies of Demand for the Performing Arts' Seaman (2006).
102 "Why is the creative economy growing so strongly?" Hajkowicz (2015).
103 "Economics of tourist's consumption behaviour" Divisekera (2010).
104 "2019 US Travel and Hospitality Outlook" Deloitte (2019).
105 "Demographic change, tourism expenditure and life cycle behaviour" Bernini and Cracolici (2015).
106 The changing travel behaviour of Austria's ageing population and its impact on tourism' Moller et al (2007).

Changing working environments have been found to drive tourism. Dwyer et al (2003)[107] found that increasing stress-free working environments encouraged tourism, while Martin and Mason (1987)[108] found that shorter working hours and less physically demanding work increased demand for tourism. Both papers also found the demographic factors such as education and ageing population also affect demand.

4.6.8 Food services

The most important driver of food service consumption is **per capita income**.[109]The Food Climate Research Network (2015) found that rising incomes in China lead to increasing numbers of consumers eating out.[110] Stewart et al (2004) found that single person households and households with multiple adults but no children tend to spend more on restaurants per capita.[111]

Cultural changes also affect demand for food service activities. Vuong (2016) found that culture drives demand for eating out in restaurants.[112]Interestingly, the paper found that recently consumers prefer cheaper mid-tier restaurants over more fashionable options. We note that this example is more relevant for consumption demand than import demand.

4.6.9 Defence

Defence spending has been found to depend on **macroeconomic factors and political factors**.[113] Waszkiewicz (2016) looked at factors influencing military spending in Turkey and Greece, which both have higher military spend that the NATO average, and found that national security concerns explain spending levels in Turkey, while economic factors are the main driver of defence spending in Greece. Dunne and Freeman (2003) examined whether determinants of military spending changed after the cold war but found little evidence of change.[114] The paper showed that military spending both before and after the cold war depended on: (i) **neighbouring countries' military spend**; (ii) **internal and external conflict**; (iii) **the level of democracy**; and (iv) **demographic factors**. Leuprecht (2016) also found that demographic factors are an important driver of military spending.[115] As the proportion of the population aged 15 to 64 declines, defence spending decreases. The paper hypothesises that this is because ageing populations tend to be less predisposed to conflict.

[107] 'Trends Underpinning Tourism to 2020: An analysis of key drivers for change' Dwyer et al (2003).
[108] 'Social trends and tourism' Martin and Mason (1987).
[109] 'The Demand for Food Away from Home' Stewart et al (2004).
[110] 'Overview of changes and drivers in China's food system' Food Climate Research Network (2015).
[111] 'The Demand for Food Away from Home' Stewart et al (2004).
[112] 'Good Taste: Foodie Culture Drives Restaurant Demand' Vuong (2019).
[113] 'Drivers of Greek and Turkish Defense Spending' Waszkiewicz (2016).
[114] 'The Demand for Military Spending in Developing Countries' Dunne and Freeman (2003).
[115] 'Scanning the Consequences of Demographic Change for the Emerging Security Landscape' Leuprecht (2016).

4.6.10 Transport

Interreg Central Europe (2018) found that demand for transport is influenced by external factors, such as **infrastructure** and **regulation**, as well as **demographic factors** such as education and age.[116] The report found that income and car ownership were also important drivers of demand, which was confirmed by the Commission on Travel Demand (2018).[117] The latter also noted that **urbanisation** and ICT **innovations** also drive travel demand.

According to UNCTAD (2017), shipping demand is driven by range of factors including: (i) **GDP growth**; (ii) **industrial activity**; and (iii) **structural shifts**, such as the slowing down of globalisation and supply chain fragmentation.[118]The report notes that demand for shipping is important in developing countries, as they have high levels of industrial activity since production is focused in the secondary sector. Developing countries import large quantities of primary and other secondary products, which are then exported as manufactured goods, therefore they have a high demand for shipping. UNCTAD (2017) find developed countries only account for 35% of world shipping, whereas developing countries account for 59% of exports and 64% of imports.

4.7 Countries' stage of development

As discussed throughout this chapter, the evidence suggests that the stage of development of a country is a key determinant of the mix of imports demanded, but also their position in global value chains. More than two-thirds of world trade occurs through global value chains, in which production crosses at least one border, and typically many borders, before final assembly.[119]

In this section, we discuss (i) the 'premature deindustrialisation' observed recently in developing countries; (ii) the value-added to goods and services at different stages of development; and (iii) the 'smile curve'.

4.7.1 Premature industrialisation of developing countries

Traditionally, as countries develop, they move from exporting primary products to manufactured goods, and then to services. However, existing research suggests that developing countries today do not conform to this historical transformation process. Countries are now experiencing 'premature deindustrialisation' or non-industrialisation – that is, they are moving from manufacturing to services at much lower level of per capita income than was observed historically during the industrialisation of today's advanced economies.

Many countries appear to be transitioning directly to services, with little or no

[116] 'New Demand Patterns for Public Transport Due to Demographic Change' Interreg Central Europe (2018).
[117] 'All Change? The future of travel demand and the implications for policy and planning' Commission on Travel Demand (2018).
[118] 'Development in International Seaborne Trade' UNCTAD (2017).
[119] 'Global Value Chain Report' WTO (2019).

development of their manufacturing sector, such as Sri Lanka and India.[120] Indeed, manufacturing in India has performed poorly while its service sector is relatively strong. Amirapu and Subramanian (2016) found that Indian states were starting to deindustrialise before manufacturing had reached 20% of output, or even 15% in some cases.[121]

Case study example: Offshore Services Global Value Chain
Information and communication technology developments have facilitated the separation of the production and consumption of services. The offshore services industry includes a range of skilled activities now being carried out in developing countries, which were previously only performed in developed countries. Lower segments of the global value chain require low-cost labour with basic education. In the Philippines, call centre wages are among the lowest in the world. Higher segments of the value chain require an educated workforce. For instance, Chile's entry into high-value engineering services for mining was due to the availability of a large number of well-educated engineers.

Source: 'The Offshore Services Global Value Chain' Fernandez-Stark et al. (2011).

Haraguchi et al. (2017) explore the reasons for low levels of industrialisation recently observed in developing countries. They find that declining manufacturing employment in many developing countries is due to a shift of manufacturing activities to a small number of populous countries such as China, resulting in manufacturing activities being concentrated in specific developing countries.[122]

Case study example: Apparel Global Value Chain
Low-income countries account for three-quarters of world clothing exports. Developing countries typically enter into the lowest segments of the value chain due to advantages such as low labour costs and favourable trade agreements. Low-cost countries such as China and Bangladesh are emerging as leading in the lower-value segments of the global value chain. Due to this, smaller countries like Sri Lanka and Turkey are being forced to upgrade into higher-value segments, which rely on high-quality human capital such as branding and design.

Source: 'The Apparel Global Value Chain' Fernandez-Stark et al. (2011).

One possible implication of this phenomenon is that developing countries could demand **fewer primary product imports**, as these will not be required as part of the manufacturing process. On the other hand, a premature shift to services could mean that per capita income will rise more rapidly than if countries had remained in an industrialisation phase. In this case, **demand for secondary and tertiary imports would also increase prematurely**.

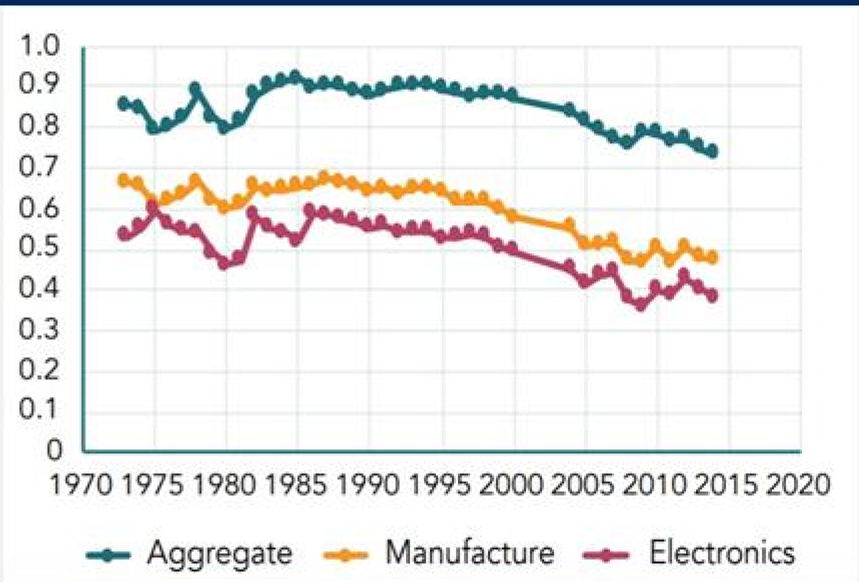
[120] The services powerhouse: Increasingly vital to world economic growth' Deloitte (2018).
[121] 'Manufacturing or Services? An Indian Illustration of a Development Dilemma' Amirapu and Subramanian (2016).
[122] 'The Importance of Manufacturing in Economic Development: Has This Changed?' Haraguchi et al. (2017).

4.7.2 Value-added over the course of a country's development

Evidence shows that the ratio of domestic value-added to gross value of exports generally declines as a country develops. As developing countries move from exporting primary products at low stages of development to importing these products, research has shown that the ratio of domestic value-added tends to fall. For example, China, Mexico and Vietnam all initially exported primary products and observed a reduction in their value-added ratio when they expanded their manufacturing sectors and increased imports of primary products.[123]

Domestic value-added can be seen to follow a non-linear trend over time in early industrialised Asian economies. The figure below depicts domestic value-added in Japanese exports over time. The ratio fell in the 1950s as Japan expanded its manufacturing sector and began importing high- value inputs, but then rose in the 1980s as the country became a capable producer of a wide range of manufactured intermediates and parts. However, since the 1990s, there has been a steady decline in the ratio.

Figure 3: Domestic value-added in Japanese exports



Source: "Global Value Chain Report" WTO (2019).

China also experienced a sharp drop in its domestic value-added ratio when it moved from exporting primary products to manufacturing. However, the ratio has been rising over the past decade due to technological advances in the country, which is similar to what happened to Japan in the 1980s. However, if the trend in China continues to follow that of previously developed Asian countries such as Japan, the World Trade Organisation (WTO) predicts that this ratio will start to decline.[124]

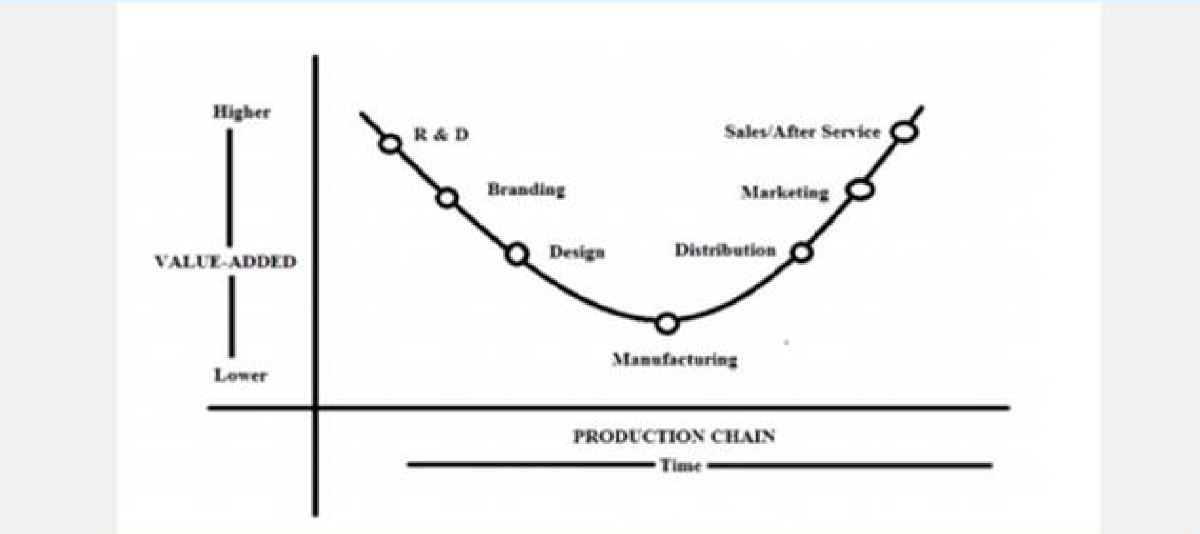
[123] 'Global Value Chain Report' WTO (2019).
[124] 'Global Value Chain Report' WTO (2019).

This implies that the value-added of imported goods will also vary over the course of a country's development. Developing countries will import high-value added primary products and low-value manufactured goods as inputs into the production process of their own manufactured goods. On the other hand, developed countries will mostly import low-value manufactured goods and services.

4.7.3 The smile curve

The value-added to a product has also been found to vary depending on whether a country operates at the high or lower end of the global value chain, which is known as the 'smile curve'. This concept was first proposed in relation to the personal computer industry by Shih, the founder of Acer. As can be seen in the figure below, activities at either end of the chain, such as research and development on one hand, and sales on the other, create higher value than the middle part.

Figure 4: The smile curve



Source: Mudambi (2006).

Activities at either end of the chain are mainly performed in developed countries, whereas the middle part – manufacturing – is typically performed in developing countries. One example of this was the production chain of a Nokia N95. Although the phone was mostly made in Asia, notably in China, more than half the value-added was found to be in Europe.[125]

Since the 2000s, most of the manufacturing activities in the ICT sector have shifted to developing countries, particularly in China and East Asia, while advanced economies have focused on elements such as design, development and marketing.[126] Despite this shift in production, most of the value-added has remained in developed countries, as higher value is created at the upstream and downstream

[125] 'Global value chains in a changing world' WTO (2013).
[126] 'The distribution of value added among firms and countries: The case of the ICT manufacturing sector' ILO (2017).

levels – the ‘smile curve’. Indeed, despite the number of jobs in this sector China almost tripling in the past decades, China only increased its share of total value-added from 5.5% in 2000 to 15.4% in 2011. The US and Western Europe still attract 22.7% and 14% respectively of the total value-added in the sector, because they are importing low-value manufactured goods.

These findings imply that countries importing services will have high value-added imports. These will be primarily developed, high income countries, as discussed previously. On the other hand, countries importing manufactured goods will be importing low value-added goods. Manufactured goods will be imported by (i) developing countries as inputs to the manufacturing process, or due to rising incomes; and (ii) developed economies.

4.8 Conclusion

Evidence suggests that a country’s stage of development is the most important driver of import demand across sectors. Indeed, we found that:

- In less developed countries, domestic demand for imported goods and services is limited as a result of low levels of per capita incomes.

- Following this, developing countries traditionally experience a period of industrialisation as production shifts to the manufacturing sector. As a result, the country’s ability to self-sustain with respect to primary goods weakens and demand for these products as inputs into the manufacturing process increases. Thus, imports of primary goods tend to increase at this stage of development. Additionally, as per capita income levels rise, domestic demand for manufactured goods and services also increases, leading to higher import demand of these products too.

- Finally, as countries develop further, income per capita levels grow, and so too does demand for (i) agricultural products (due to increased preferences for more varied diets and fresh produce); (ii) manufactured goods; and (iii) services.

  However, our evidence has found that these historical development patterns are changing. Developing countries are now moving from manufacturing to services at much lower levels of per capita income than has been historically observed, or are not developing a manufacturing sector at all and shifting directly to services. These findings imply that historic trends may be becoming less informative for estimating future import demand, and that the nature of the relationships between import demand patterns and its drivers can, and is, changing.

5. Methodologies for forecasting import demand

In this chapter, we set out both: (i) the categories of qualitative and quantitative forecasting methodologies available for macroeconomic forecasting; and (ii) where these methodologies have been applied to forecast import demand. As well as this, we assess the relative advantages and disadvantages of each methodology against a set of criteria, before evaluating the feasibility of applying this methodology across different levels of granularity. In doing so, our research has found that the feasibility of applying forecasting methodologies at different levels of sector and market granularities varies.

Having considered the evidence regarding the factors that influence import demand, in this chapter we consider the methodologies available to generate forward looks for import demand. In particular, we look to answer the following REA questions:

- RQ2: What previous qualitative research has there been into forward looks for sectoral import demand? What quantitative methodologies have been used to inform these forward looks and what are the strengths and weaknesses of these?
    - What data exists that can be used to inform trends in import demand (for example patents, demographics, household consumption)?
    - What new data may be required to inform regular production of future global sectoral import demand insights?
- RQ3: How does the feasibility of identifying future changes at different granularities (for example for goods, can it be conducted at a granular product level)?
    - How does feasibility change with different geographies? How does this compare across low/middle/high income countries? Give examples.
    - How does the feasibility of identifying emerging goods and services import demand compare? Give examples.
    - How does the feasibility change with different time horizons? Give examples.
- RQ4: How do a set of identified methodologies score against each other in terms of simplicity, time horizon, accuracy, granularity and feasibility for replication?

Our approach to answering these questions comprised a number of steps. In order to both direct our search for evidence, and allow us to understand where gaps in the evidence lie, we first began by conducting a literature review directed at gaining a comprehensive understanding of the broad set of macroeconomic forecasting techniques. Upon doing so, we looked to understand if, and how, these methodologies have been applied to generate forward looks for import demand specifically.

Importantly, this approach has allowed us to: (i) understand where potentially suitable forecasting methodologies have not been applied to import demand (i.e. where gaps in the evidence base lie); and (ii) gain a broader understanding of the advantages and disadvantages of each of these methodologies, in order to further support our assessment of them for DIT's purposes.

This chapter is structured as follows. First, we summarise the key categories of qualitative and quantitative methodologies used for conducting macroeconomic forecasts, before setting out the evidence we have found regarding the application of these methodologies to forecasting import demand specifically.

Following this, for each methodology, we:

- Set out a description of the methodology, and detail the key steps required to implement it;
- Describe where the method has been applied to forecast import demand; and
- Assess the relative advantages and disadvantages of the methodology against the criteria set out in the table below.

Table 21: Methodology assessment criteria

Criteria		Definition
Accuracy	Predictive power	How accurate the methodology is at forecasting import demand – that is, how likely it is that the forecasted levels will equal actual future levels. This is often based on comparing 'within sample forecasts' to the actuals.
	Precision	Whether forecasts are (i) precise, numerical forecasts; or (ii) more 'high-level' forecasts, such as ranges.
Simplicity	Complexity	How difficult implementing the methodology would be.
	Resource requirements	What internal and external resourcing would be required for DIT to implement the method.
Data requirements		What data is required to implement the method.
Time horizon		Whether the method can be used for longer- or shorter-term forward looks.

Source: Economic Insight Ltd

Finally, by gaining an understanding of the relative strengths and weaknesses of each method in terms of this criteria, we assess the feasibility of applying these methodologies more broadly across different levels of granularity. In particular, we consider the following granularities:

- Market (geographical). That is, whether imports are forecasted at the global level; regional level; or individual country level.

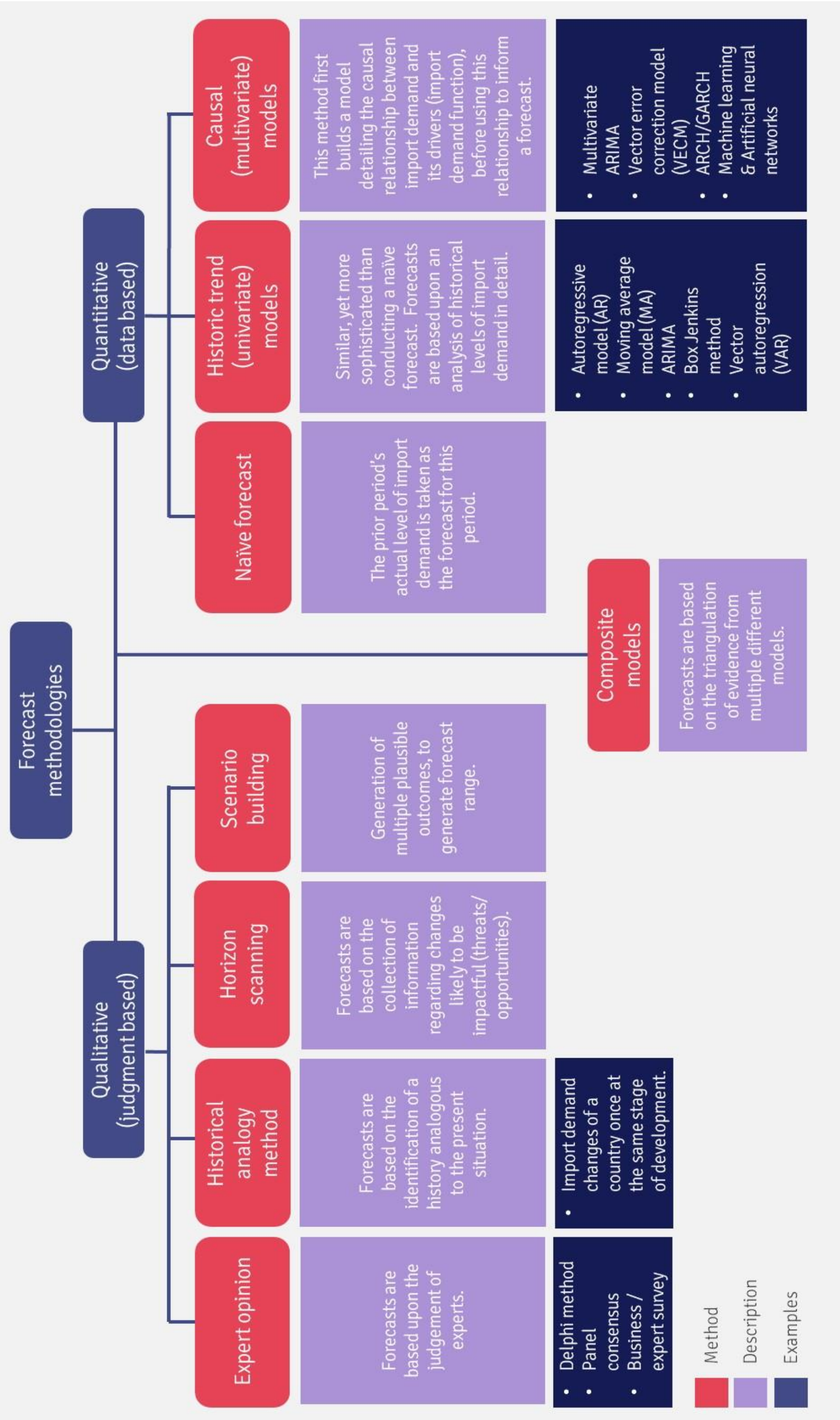
- Product. That is, whether aggregate; sector (primary/secondary/tertiary); or product (for example, the Harmonised System product) level imports are forecasted.

5.1 Overview of macroeconomic forecasting methodologies

Broadly, macroeconomic forecasts can be categorised as either quantitative (data based), or qualitative (judgment based). Composite models triangulate evidence generated through conducting forecasts using a number of differing methodologies. The methodologies contributing to the composite model may be solely quantitative, qualitative, or combine methodologies from each of these categories.

In the figure overleaf, we present an infographic setting out the key categories of macroeconomic forecasting methodologies, before detailing each in turn.

Figure 5: Summary of forecasting methodologies



Source: Economic Insight Ltd.

In the table below, we set out a summary of where methods have been employed to forecast import demand at different levels of product and geographical granularity. A tick indicates that we have found evidence that the method has been applied to forecast imports at the specified level of granularity.

Table 22: Summary of evidence

Granularity of application / Methods		Global			Region			Country		
		Aggregate imports	Sector imports	Product imports	Aggregate imports	Sector imports	Product imports	Aggregate imports	Sector imports	Product imports
Qualitative	Expert opinion							✓		
	Historical analogy method									✓
	Horizon scanning		✓							
	Scenario building		✓			✓	✓		✓	✓
Quantitative	Naïve forecast									
	Historic trend (univariate) models							✓	✓	
	Causal (multivariate) models							✓	✓	✓
Composite models								✓		✓
Off-the-shelf		✓			✓			✓	✓	✓

Source: Economic Insight Ltd.

As can be seen, the level of granularity at which the forecasts of import demand have been conducted varies across methodologies.

Specifically, in relation to qualitative methodologies, we have found:

- multiple examples of the expert opinion methodologies being applied to forecast country- specific aggregate imports, but we have not found this method applied at any other levels of granularity;
- evidence that the historical analogy method has been used to forecast product level imports (of electronic parts) at a country-specific level (for China)[127];
- evidence that horizon scanning has been used to understand how global consumption of products aggregated at the sector level are expected to change, and therefore, the impact this is expected to have on trade and overall import levels of these goods globally;
- evidence of the use of scenario building to both: (i) forecast future global demand for energy; and (ii) generate forward looks for how this will affect both the sector level energy imports, and product level oil and gas imports, of both regions and specific countries.

  In contrast, we have found the following in relation to quantitative methodologies:

- evidence that historic trend, or univariate, models have been concentrated on providing country-specific forecasts at both the aggregate level and the sector specific level;
- evidence of causal models being used to forecast country-specific imports at all levels of product aggregation – that is, aggregate; sector; and product imports;
- no evidence of naïve forecasting models being used to forecast imports.

Broadly, the organisations generating these forecasts can be categorised as follows: (i) macroeconomic forecasters and public organisations; (ii) government bodies; (iii) consultancies; (iv) financial services firms; (v) market researchers; and (vi) academics.

Overall, we have identified and reviewed evidence of 39 forecasts of import demand specifically. As shown in the table overleaf, we have found evidence from a wide range of forecasters, with many academic examples available.

[127] For further detail, see page 48.

Table 23: Source of forecasts

Forecaster	Number of forecasts reviewed
Macroeconomic forecasters and public organisations	7
Government bodies	2
Consultancies	4
Financial services firms	4
Market researchers	2
Academics	20
Total	39

Source: Economic Insight Ltd

We have also reviewed 18 academic papers as part of our literature review of the set of macroeconomic forecasting techniques.

In the following section, we detail each forecasting methodology in turn.

5.2 Qualitative methods

The defining characteristic of qualitative forecasting methodologies is that they are based predominantly on judgment, as opposed to an analysis of historical data. Generally, qualitative methodologies are employed to generate forecasts where there is a lack of data available to inform the forecast.[128]

However, this is not to say that qualitative methodologies are necessarily inferior to quantitative methods, or that they are not at all informed with reference to measurable information. Often, the judgment of experts informing the forecast is based upon a strong experience and knowledge of past trends, and the driving forces of the particular variable subject of the forecast.

Further, expert insight into likely future changes, and why and how past patterns may change going forward, may be more informative in the case of changing global landscapes, than generating forward looks based on historical data alone. Despite this, qualitative forecasting techniques are subjective by nature, and therefore are at risk of errors due to behavioural biases.[129]

[128] 'Perception-Based Functions in Qualitative Forecasting'; Batyrshin and Sheremetov; Perception-based Data Mining and Decision Making in Economics and Finance (2007); pages 119- 134.
[129] 'Analysing inaccurate judgemental sales forecasts'; A. Kerkkanen, & J. Huiskonen; European Journal of Industrial Engineering, Vol. 1, No.4 (2007); page 355.

The set of qualitative macroeconomic forecasting methodologies can be broadly divided into four approaches. These are: (i) expert opinion; (ii) historical analogy; (iii) horizon scanning; and (iv) scenario building. In this section, we detail the key characteristics of each of these approaches.

5.2.1 Expert opinion

This method generates a forecast by gathering the opinion(s) of expert(s) regarding the expected future outcome. Obtaining expert opinion is perhaps the simplest of the four qualitative approaches. However, within this, there are a number of ways in which these opinions can be obtained and analysed to arrive at the forecast, which vary in complexity. Namely, forecasts can be derived from gathering expert opinion via: (i) surveys; (ii) panel consensus; or (iii) though implementing the Delphi method. Each particular approach is discussed in detail below.

5.2.1.1 Surveys

5.2.1.1.1 Description

The simplest way of gathering expert opinion to inform a forecast is through the use of surveys.

There are multiple examples of the use of surveys in macroeconomic forecasting. For instance, the Business Confidence Index looks to provide a view “of future developments based upon opinion surveys on developments in production, orders and stocks of finished goods in the industry sector”.[130] In turn, this index, along with a variety of other indicators calculated using business and consumer opinion surveys (such as the industrial confidence indicator, or construction confidence indicator), are used to inform wider forecasts, and in particular, to predict “turning points in economic activity”.[131]

5.2.1.1.2 Use for forecasting import demand

There is evidence that surveys have been used as a method to predict future import demand changes. Specifically, the Turkish Ministry of Trade compile Export and Import Expectation Indices on a quarterly basis. These indices are constructed using “assessments of Turkish leading foreign trade firms, regarding recent and current situations along with their future expectations”.[132]

The Import Expectation index combines expert expectations regarding the level of Turkey’s aggregate imports, as well as import unit prices, over the upcoming 3-month period. An index value of 100 indicates a stable outlook, a value of more than

[130] ‘Business confidence index (BCI)’; OECD (2019); available here: https://www.oecd-ilibrary.org/economics/business-confidence-index-bci/indicator/english_3092dc4f-en
[131] Ibid.
[132] Available here: https://www.trade.gov.tr/announcements/foreign-trade-expectation-survey-of- 4th-quarter-of-2019

100 indicates a positive outlook, while a value of below 100 indicates a negative outlook.

5.2.1.1.3 Advantages and disadvantages

The data required to implement this methodology is the primary data collected through conducting the survey itself. As such, a clear advantage of this method is that it is therefore not limited in application to forecast import demand across geographies, and at different levels of product aggregation. By modifying the respondent list and questions asked, this method can be adapted to generate import demand forecasts across these differing levels of granularity. Specifically, questions could be modified to understand future expectations regarding the key drivers of import demand, specific to the sector or industry level in question (as identified in chapter 2 of this report).

This may: (i) lead experts to consider the full range of key drivers when generating their forward looks (thereby generating better forecasts); and (ii) also provide DIT with a better understanding of the reasons underpinning these expert views.

An additional advantage of this method is that it results in forecasts informed by the aggregate knowledge of a large number of experts.

Despite this, implementing this methodology across markets and sectors would incur high resourcing cost, in terms of requiring extensive data collection and analysis functions, while the design and implementation of the surveys also incur time and monetary cost. As such, this method is better suited to a more limited application.

Further, as the examples of application detailed above illustrate, this method tends to be used to produce forecasts in the form of indices, used to indicate short- to medium-term future changes, as opposed to generating specific numerical forecasts. Despite there being no particular barriers to using this method to generate numerical forecasts, the lack of evidence that this is done (both in relation to import demand specifically, but also more broadly) could be an indication that this methodology does not lend itself to a high degree of forecasting accuracy.

5.2.1.2 Panel consensus

5.2.1.2.1 Description

Panel consensus refers to aggregating the view of a panel of experts.[133] The way in which these views is aggregated can differ, in that the consensus method can be implemented by either (i) calculating the mean of the individual panellists' forward looks, or alternatively; (ii) through facilitating a collaborative and creative discussion between the group of panellists, until the panellists reach an agreed view.

133 'The Evolution of Consensus in Macreconomic Forecasting'; Gregory, A.W.; Yetman, J. A.; International Journal of Forecasting (2004); pages 461-473.

5.2.1.2.2 Use for forecasting import demand

Pertaining specifically to forecasting import demand, we have found evidence that the panel consensus method is employed by FocusEconomics[134] and Consensus Economics[135].

FocusEconomics generates five-year annual forecasts, and one-year quarterly forecasts for aggregate imports on a country by country basis. To generate these forecasts, FocusEconomics averages the existing forecasts a panel of leading forecasters. For instance, a sample report published in 2018 forecasting the imports of China averaged the forecasts (where these were available) across a panel of 48 organisations[136] It is unclear whether this panel is adapted according to the country subject to the forecast. The particular methodologies used by these panellists to arrive at their individual forecasts is not specified, but it is expected that there will be differences between the panellists.

Consensus Economics generates two- to four-year forecasts of aggregate imports for over 100 countries. The consensus method is implemented by aggregating the predictions of the “world’s leading forecasters”.[137] The particular panellists contributing to the forecast are not detailed, and as such, it is difficult to assess the reliability and accuracy of the information underlying this consensus view.

5.2.1.2.3 Advantages and disadvantages

Both of approaches to implementing the panel consensus method have relative advantages and disadvantages.

The approach to panel consensus that involves calculating the mean value of individual experts’ forecasts is simple to implement, requiring no primary data collection and analysis. Further, the individual forecasts undertaken by the panellists might be informed by a variety of both quantitative and qualitative forecasting methodologies. As such, the overall mean forecast can be underpinned by vast amounts of data and sophisticated analysis.

However, ensuring that each of these individual forecasts are directly comparable to one another might be complex; as it is essential that the forecasts relate to the same time horizon, and precisely the same independent variable. Additionally, by having to

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[134] Available here: https://focusanalytics.focus-economics.com/

[135] Available here: https://www.consensuseconomics.com/what-are-consensus-forecasts/

[136] The particular participants in this panel were: Allianz, ANZ, AXA IM, Bank of China (HK), Bank of East Asia, BBVA Research, Berenberg, BNP Paribus, Capital Economics, China First Capital, CICC, Citigroup Global Mkts, Coface, Commerzbank, Credit Suisse, Daiwa, Danske Bank, DBS Bank, DekaBank, DIW Berlin, EIU, Euromonitor Int., Fitch Ratings, Fitch Solutions, Frontier Strategy Group, Goldman Sachs, Hang Seng Bank, HSBC, ING, JP Morgan, KBC, Kiel Institute, Lloyds Bank, Macroeconomic Policy Institute, Mizuho Securities, Moody’s Analytics, Nomura, NORD/LB, Nordea, Oxford Economics, S-Bank, Scotiabank, Shanghai Commercial Bank, Société Générale, Standard Chartered, UBS, Unicredit, United Overseas Bank.

[137] Available here: https://www.consensuseconomics.com/what-are-consensus-forecasts/

rely on previously conducted forecasts, this method is limited in its application to forecast import demand across product and geographical granularities to only those levels of aggregation for which there already exists multiple comparable forecasts. Further, it is important to ensure the reliability and credibility of each of these forecasts before including them to generate an average.

On the other hand, the approach to panel consensus that involves facilitating a discussion between experts gives the opportunity for the experts to review and refine their own opinions, based upon evidence presented by other panellists that they may not have previously considered. Therefore, the resulting forecast may represent a more holistic view of a broader set of available evidence.
As well as this, the ability to apply this particular method of panel consensus to forecasting import demand across product and geographical markets is not limited by data availability constraints, as the panel of experts can be selected specifically to generate forecasts across any level of aggregation.

Primary data collection and analysis is also not required, unlike the survey method, with only the resulting consensus forecast produced by the expert panel requiring collection.

Despite this clear advantage, this type of panel consensus is complex to implement, incurring time and cost in selecting the appropriate panel of experts suited to the particular forecast to be generated, and facilitating the discussion between them, and similarly to the survey technique. This method is therefore better suited to generating a more limited number of in-depth forecasts. It is also important to note that the outcome of group discussions can be negatively affected by biases, and peer influence, which would affect the reliability of the forecast.

5.2.1.3 The Delphi method

5.2.1.3.1 Description

Similar to the panel consensus method, the Delphi method looks to derive a forecast from arriving at a consensus of opinion across a panel of experts. However, in this case, the key difference to the panel consensus method is that the experts are anonymous to one another, and the opinions are gathered through running iterative surveys. As such, this method combines elements of both the survey and panel consensus methodologies listed above.

By anonymising the experts, the Delphi method looks to address one of the key criticisms of panel consensus forecasting, in that “its structure is intended to allow access to the positive attributes of interacting groups (such as knowledge from a variety of sources and creative synthesis), while pre- empting the negative aspects that often lead to suboptimal group performance (attributable to social, personal, and political conflicts)”,[138] thereby, reducing bias and the risk of peer influence.[139]

[138] ‘Expert Opinions in Forecasting: The Role of the Delphi Technique.’ Rowe, G; Wright, G; International Series in Operations Research and Management Science (2001).
[139] ‘The Delphi method: A qualitative means to a better future.’ Bourgeois, J.; Pugmire, L.; Stevenson, K.; Swanson, N.; Swanson, B.; (2006); URL:

Rowe and Wright (2001)[140] set out the main steps required to implement the methodology, as follows. A questionnaire is typically split across a number of rounds, and distributed to between 10-18 experts. Following the initial questionnaire, comprised of a low number of open-ended questions, each subsequent round presents the respondents with the other experts' answers from the prior round, along with a new set of questions designed in light of these answers.
Respondents are able to review and refine their responses to previous questions during each new round. This iterative process continues until a consensus amongst the experts is reached. This consensus is then taken as the forecast.

5.2.1.3.2 Use for forecasting import demand

Our research has not identified any examples of the Delphi method being used to forecast import demand.

5.2.1.3.3 Advantages and disadvantages

Advantages of this method include its ability to be tailored to forecast import demand across any level of product and geographical aggregation as, similarly to the other qualitative methods set out, experts can be selected to suit the particular forecast to be generated, and questions can be modified to understand future expectations regarding drivers specific to the imports in question.
Additionally, Delphi groups have been shown to result in forecasts of greater accuracy than by consulting individual experts, panel groups or statistical groups.[141]

On the other hand, this method entails certain disadvantages, namely; (i) significant time and monetary cost in selecting the panels of anonymous experts appropriate for each forecast; (ii) the time and monetary cost involved in designing and implementing the iterative surveys; and (iii) the collection and analysis of the primary data produced at each round of these surveys.

Despite our research having not identified examples of the Delphi method being applied to forecast import demand, in light of the above, there are no direct limitations of this method being applicable to generating import demand forecasts. However, due to the complexity and resource requirements of this method, it is best suited to generating a limited number of in-depth forecasts.

5.2.1.4 Evaluation of feasibility for replication

Based on the advantages and disadvantages set out above, the table overleaf summarises our overall evaluation of the expert opinion method for forecasting import demand.

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http://www.freequality.org/documents/knowledge/Delphimethod. pdf
[140] 'Expert Opinions in Forecasting: The Role of the Delphi Technique.' Rowe, G; Wright, G; International Series in Operations Research and Management Science (2001).
[141] Ibid.

Table 24: Expert opinion methodology assessment

Criteria		Expert opinion
Accuracy	Predictive power	Likely to vary from case to case. - Delphi method is likely to have the highest predictive power, since it combines elements of the survey and panel approaches.
	Precision	- Can be used to give more precise, numerical forecasts in some circumstances, for example when very sector specific expertise is required.
Simplicity	Complexity	- Implementing a survey or gathering expert opinion is relatively straightforward.
	Resource requirements	- Relatively high resource requirements. For instance, the survey method requires primary data collection. - Additionally, relevant experts need to be identified and consulted, which we understand would be difficult based on our conversations with DIT.
Data requirements		- No set data requirements, and can be implemented with very little data.
Time horizon		- This methodology can be employed to forecast to any time horizon. However, forecasts will most likely be valid up to 5 – 10 years ahead, depending on (i) the expertise of individuals consulted; and (ii) the stability of the market and industry in question.
Feasibility for replication		- This method is most suited to the **aggregate x country level**, for a set of countries.

Source: Economic Insight Ltd

The expert opinion methodology is not feasible for forecasting imports at the country by product level, due to the relatively high resource requirements of this approach. Indeed, if DIT were to employ the panel method, the Department would need facilitate a discussion between a panel of experts for each product in each country, which appears unfeasible. A similar issue would arise when carrying out surveys and Delphi methods.

For this reason, expert opinions are most suited to forecasting imports at the aggregate x country level of granularity, which is in line with our findings in the literature. Nevertheless, this is unlikely to be feasible to implement for every country due to high resourcing requirements.

5.2.2 Historical analogy method

5.2.2.1 Description

A historical analogy forecast bases forward looks on outcomes of closely comparable situations in the past. As such, the key to implementing this methodology is to identify a historical occurrence that is homogenous with respect to the key drivers of the feature being forecast.

As noted by Goldfarb et al., “if the two [occurrences] are similar enough in these essential features, then one extrapolates from a feature of interest that is known for one of the entities to that same unobserved feature of the other”.[142] Importantly, Goldfarb et al. also noted that it is unlikely that the two occurrences will be exactly homogenous with respect to these features, and as such, judgment must be employed to modify the forecast to take account of the differing factors.[143]

5.2.2.2 Use for forecasting import demand

Relating specifically to forecasts of import demand, we have found evidence that this methodology has been employed by the World Trade Organisation (WTO). For instance, in its ‘Global Value Chain Development Report 2019’,[144] the WTO noted that at the start of its economic reform, China was focused on importing electronic parts produced in other countries to then assemble and export. As the economy developed and technological advances occurred, China began importing less of these parts, instead producing them domestically.

The WTO went on to state that this is analogous to what happened in Japan and South Korea in the 1980s and 1990s, and on this basis, suggest that China may continue to follow the same path as these countries. In other words, it is therefore expected that imports of these components will begin to rise again in the future, as labour-intensive production is off-shored to lower-wage countries.

5.2.2.3 Advantages and disadvantages

Advantages of this method in relation to forecasting import demand are that there are no set data requirements affecting its ability to be implemented. However, the more data that is available, the better able the forecaster is to both: (i) identify analogous occurrences; and (ii) ensure the homogeneity of the key drivers of import demand between these occurrences. In turn, this is expected to bolster the accuracy of the forecast. However, it should be noted that, even with relatively limited data one still might be able to draw useful analogous comparisons.

[142] ‘‘Methodological issues in forecasting: Insights from the egregious business forecast errors of late 1930.’ Goldfarb, R.; Stekler, H.; David, J.; Journal of Economic Methodology. (2005) pages 517-542.
[143] Ibid.
[144] ‘Global Value Chain Development Report 2019: Technological innovation, supply chain trade, and workers in a globalized world.’ World Trade Organisation (2019). Available here: documents.worldbank.org/curated/en/384161555079173489/pdf/Global-Value-Chain- Development-Report-2019-Technological-Innovation-Supply-Chain-Trade-and-Workers-in-a- Globalized-World.pdf

Similarly to other qualitative methods, this technique does not lend itself to being applied to generate a vast number of forecasts because it would require identifying and investigating a suitable analogy for every forecast.

Additional disadvantages of this method are that its accuracy is likely to be less predictable, and vary significantly from case to case. No two economies will be entirely homogenous in respect to all of the key drivers of import demand, and the accuracy of this method is contingent on being able to identify the key drivers of import demand in the first place, as discussed in the previous chapter. Further, it may be the case that few analogous instances can be found to generate forecasts for import demand across the board – i.e. across all countries and product markets.

5.2.2.4 Evaluation of feasibility for replication

The table below sets out our evaluation of the historical analogy method against each criterion.

Table 25: Historical analogy methodology assessment

Criteria		Historical analogy
Accuracy	Predictive power	- Predictive power will vary from case to case, depending on the level of similarly with the analogy.
	Precision	- Generally used to give 'high-level' forecasts rather than precise forecasts.
Simplicity	Complexity	- Low complexity, so long as an appropriate historical analogy is available.
	Resource requirements	- This method requires expert opinion, which would need to be outsourced. - Based on our conversations with DIT, we understand that this would be difficult, and so resourcing requirements are high.
Data requirements		- No set data requirements, and can be implemented with data on historic trade, which is widely available.
Time horizon		- This methodology can be employed to forecast at any time horizon, however, will typically only be valid 5 – 10 years ahead.
Feasibility for replication		- This method is most suited to the **sector x country** level.

Source: Economic Insight Ltd

The historical analogy methodology is most suited to forecasting import demand at **sector by country level**. This is because the method generally relies on stage of development to make cross country comparisons, as the WTO does when applying this method to import demand in China. However, due to recent global trends, such as the premature de-industrialisation of developing countries, historical analogies may provide less reliable forecasts than in the past.

It is also unlikely that this method will be feasible for implementation in each country at the sector level, as historical analogies may not be available. This also explains why the historical analogy methodology is not feasible for forecasting at country x product level of granularity. That is, it is implausible that analogous comparators could be identified at this level across all countries and product markets and so it may only be possible to carry this out in a subset of priority products and/or countries. In addition to this, it is unlikely to have a high predictive power at the product level compared to the sector or aggregate level, and would have relatively high resource requirements to implement for each country and each product.

5.2.3 Horizon scanning

5.2.3.1 Description

Horizon scanning describes a systematic way of detecting future changes. As such, the focus is on identifying future threats and opportunities which may result in developments away from current trends.

As noted by the OECD, horizon scanning is often implemented through conducting desk research, and consulting a wide variety of sources, including, but not limited to: “the Internet, government ministries and agencies, non-governmental organisations, international organisations and companies, research communities, and on-line and off-line databases and journals.” [145] Experts, who are familiar with past trends and also with greatest knowledge of up-and-coming issues and opportunities are also used to help inform horizon scanning.

5.2.3.2 Use for forecasting import demand

Pertaining specifically to forecasting import demand, we have found evidence that the Agriculture and Horticulture Board use horizon scanning to forecast trade of agricultural products for the UK.[146]

In this case, horizon scanning is used to generate trade forecasts for the upcoming year, across the dairy, pork, beef, lamb, cereals, oilseeds, and potatoes markets. As expected, due to the nature of the methodology, specific ‘figures’ for imports and exports are not forecast. Instead, more qualitative statements are made regarding the likely state of the world over the coming 12 months, with a focus on the expected level of international competitiveness of the UK in these markets.

As such, key factors that may influence UK trade in these markets, and in particular

[145] Available here: https://www.oecd.org/site/schoolingfortomorrowknowledgebase/futuresthinking/overviewofmethodologies.htm

[146] Horizon Forecast: Agri-market outlook.’ Agriculture and Horticulture Development Board, (2018). Available here: https://ahdb.org.uk/knowledge-library/forecast-agri-market-outlook

exports, over the coming year are discussed. For instance, there is focus on changing consumer trends and lifestyles (including the growth in obesity motivating an increasing interest in health, and modern lifestyles reducing the prevalence of home cooking)[147] and a discussion of how these trends are expected to affect trade in the near future.

5.2.3.3 Advantages and disadvantages

Generally, horizon scanning is not used to generate specific numerical forecasts, but instead, to give indication of the likely ‘direction of travel’ of the variable in question, and an indication of the scale of impact of any potential changes. Specifically, “the aim of horizon scanning is not to predict what will happen but to gather signals of change that, taken together, provide insights into future development”.[148]As such, this methodology is not suited to providing very precise forecasts.

The approach and data used to generate each different horizon scan is tailored specifically to the horizon scan in question. Therefore, it is not limited in its ability to be applied to generate forward looks for import demand across the different levels of product and geographical aggregation.
However, because of this, the method is very resource intensive, particularly if horizon scans are to be used to generate forecasts of import demand across multiple geographies and levels of product aggregation. It would therefore not be feasible to implement across all markets and sectors, and like other qualitative methodologies, is better suited to a very the generation of a limited number of in-depth forecasts.

5.2.3.4 Evaluation of feasibility for replication

In the table overleaf, we set out our assessment of the horizon scanning methodology.

Horizon scanning is not feasible to implement at the country x product level, as this would increase the (i) complexity; (ii) resource requirements; and (iii) data requirements of the methodology.
Moreover, the predictive power of horizon scanning at this level of granularity will be particularly low, as it is unlikely that many useful insights can be found for such a detailed level.

Therefore, in our opinion, this methodology is most suitable for generating forecasts of imports at the sector x region, or at the sector x global level, as less internal resourcing would be required and fewer sources and experts would need to be consulted.

[147] Ibid.
[148] ‘Horizon Scanning Toolkit; Smarter Regulation of Waste in Europe’; Cranfield University and Waverley Consultants (2018). Available here: https://www.sepa.org.uk/media/367059/lsw-b4- horizon-scanning-toolkit-v10.pdf

Table 26: Horizon scanning methodology assessment

Criteria		Horizon scanning
Accuracy	Predictive power	- Considers risks and opportunities so likely to be more accurate than the historical analogy method.
	Precision	- Generally used to give 'high-level' forecasts rather than precise forecasts.
Simplicity	Complexity	- Medium complexity, according to number of sources and experts consulted.
	Resource requirements	Medium resourcing requirements. - Requires expert opinion, however this could be undertaken internally by DIT. - Desk-based research could also be undertaken within DIT. Relatively, time consuming.
Data requirements		- No set data requirements, however, data requirements can be large if lots of resources are consulted.
Time horizon		- Generally long time horizons.
Feasibility for replication		- This method is most feasible at the (i) sector x region; and (ii) sector x global level.

Source: Economic Insight Ltd

5.2.4 Scenario building

5.2.4.1 Description

Scenario building looks to identify a range of potential future outcomes, based upon generating a set of plausible developments in the underlying set of drivers. As such, this method does not look to produce a singular precise forecast, but a range based upon potential future 'states of the world'.

As noted by Coates (2000), "the fundamental principle [of scenario building] is that one wants to identify the themes that illustrate the most significant kinds of potential future developments. Each theme is generally clustered around on or two primary variables dominating a future situation".[149]

Therefore, to implement this methodology, it is important to first identify the variables

[149] 'Scenario Planning.' Coates, J.F.; Technological Forecasting and Social Change; (2000) pages 115-123.

that are expected to have the greatest influence over the forecast, before hypothesising how these might change over the course of time. The evidence set out in the first chapter of this report provides detail of the key variables at differing levels of aggregation, and as such this research may assist completion of this first stage of implementation. Upon agreeing the key variables, logic models are then built to understand how these underlying changes are expected to affect the variable subject to the forecast.

5.2.4.4 Use for forecasting import demand

We have found evidence of the method being applied to generate import demand forecasts out to 2040. Specifically, BP's Energy Outlook[150] uses scenario building as part of their technique to understand plausible changes in global, regional and country-specific consumption patterns for energy, with discussion regarding the effect this will have on trade and import patterns over this time horizon.

Within this report, BP 'considers a range of scenarios to explore different aspects of the energy transition. The scenarios have some common features, such as ongoing economic growth and a shift towards a lower carbon fuel mix, but differ in terms of policy, technology or behavioural assumptions'[151]

In particular, the 'Evolving transition (ET)' scenario, "assumes that government policies, technology and social preferences continue to evolve in a manner and speed seen over the recent past"[152], while the 'less globalisation' scenario considers a case in which trade disputes increase and have a persistent impact on the energy system'[153]. Differences in outcomes between these scenarios are expected to be concentrated on those regions with greatest exposure to international trade, and more specifically, BP expects China's imports of oil and gas to be 12% and 40% lower respectively, compared to the ET scenario.[154]

5.2.4.3 Advantages and disadvantages

This methodology is resource intensive, requiring expert input to arrive at the set of plausible developments in the underlying indicators, and then to generate the range of forward looks. Similarly to other qualitative methodologies, there are no set data requirements to be met in order to do this, and it is likely that each scenario building exercise will draw on different data, specific to the forecast in question. However, in many cases, the data that is used within each scenario building exercise will be extensive, and due to the resource intensive nature of this methodology, even at the aggregate import level of granularity, this method would be rendered infeasible on a country by country basis.

[150] 'BP's Energy Outlook: 2019 Edition.' Available here: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy- economics/energy-outlook/bp-energy-outlook-2019.pdf
[151] Ibid. page 13.
[152] Ibid. page 13.
[153] Ibid. page 73.
[154] Ibid. page 75.

Often, scenario building looks to generate longer-term forecasts than the other qualitative methodologies. For instance, BP employs this method to forecast import demand until 2040.

5.2.4.4 Evaluation of feasibility for replication

The table overleaf summarises our evaluation of this methodology against the set of criteria.

It is unlikely to be feasible to employ scenario building to forecast imports on a country x product level, due to the (i) complexity; (ii) resourcing requirements; and (iii) data requirements of the methodology. Indeed, DIT would need to generate forecasts for the range of underlying indicators for each product and in each country, in order to forecast imports. Therefore, this method is more feasible for generating country x sector level forecasts, as BP has done, for a subset of countries.

Table 27: Scenario building methodology assessment

Criteria		**Horizon scanning**
Accuracy	Predictive power	- Likely to have higher predictive power than the other qualitative methods since it considers the underlying drivers. - Additionally, it provides a range, rather than a point estimate, and so will be more accurate.
	Precision	- This will vary case by case. However, typically this method builds a range of potential scenarios rather than precise forecasts.
Simplicity	Complexity	More complicated than other qualitative methods. - Need to generate forecasts of underlying indicators, before estimating a range of forward looks.
	Resource requirements	Medium resourcing requirements. - Requires expert opinion, however this could be undertaken internally by DIT.
Data requirements		- Higher data requirements than the other qualitative methods, as it examines underlying indicators, as well as imports.
Time horizon		- Generally long time horizons.
Feasibility for replication		- This method is most feasible at the country x sector level, for a set of countries.

Source: Economic Insight Ltd

5.3 Quantitative methodologies

Quantitative methodologies are based on the analysis of data to forecast forward, and can broadly be separated into structural and non-structural models of forecasting.[155][156] Structural forecasting first looks to build a model of the interactions between drivers and the independent variable subject of the forecast. In other words, these are causal models that look to understand the relationships between the independent variable (in this case, import demand) and its drivers. By understanding these relationships, future changes in these drivers can be modelled, and as such, this will allow forecasters to examine how these changes will drive future import demand.

Non-structural models, on the other hand, do not look to understand the interplay between the independent variable and its drivers. Instead, these models rely largely on historical trends and using past data regarding the variable in question to generate forward looks, as is the case in the World Trade's Outlook Indicator.[157] As such, these models are often simpler to implement and understand. Non-structural models can include naïve forecasts, and historic trend models.

The rest of this section describes three quantitative methods of forecasting, and outlines where we have found evidence of this method being used to forecast imports.

At the outset, we note the following important finding by Emran (2010) "estimates of the price elasticity also display wide variance across studies and estimation techniques"[158]. The variation in elasticities observed in the literature has two immediate potential implications for forecasting.

- First, where there is variation within the same country, sector and time period, it suggests that relying on a single forecasting model or approach may be prone to error and it is advisable to draw on several models or approaches. This strategy will help identify the extent to which different forecasting models give rise to materially different forecasts. If they do, it is advisable to use the average forecast from all the models and/or use the range of forecasts emerging from the models, so that decisions are not unduly influenced by a single forecasting model.

- Second, where there is variation between countries, sectors and time periods this points to using / developing forecasting models for each country/sector combination, rather than relying on a single model or approach to cover them all. It may also point to using up-to-date / periodically updating forecasting models to reflect the latest data and, where relevant, any changes in a country's stage of development. Put another way, this type of variation suggests that 'one size does

[155] 'The past, present, and future of macroeconomic forecasting.' Diebold, F. X.; Journal of Economic Perspectives 12.2 (1998): pages175-192.
[156] 'A comprehensive evaluation of macroeconomic forecasting methods.' Carriero, A.; Galvao, A.B.; Kapetanios, G.; International Journal of Forecasting 35.4 (2019): pages 1226-1239
[157] Available here: https://www.wto.org/english/res_e/statis_e/wtoi_e.htm
[158] 'Estimating an import demand function in developing countries: A structural econometric approach with applications to India and Sri Lanka' Emran and Shilpi (2010).

not fit all'.

5.3.1 Naïve forecasts

5.3.1.1 Description

Naïve forecasting methods use past actuals to forecast the future. Under this approach, forecasts can be set equal to the most recently observed value, or to the average of values observed in the past.

5.3.1.2 Use for forecasting import demand

Our research has identified no examples of naïve forecasting being used to forecast import demand. The specific reasons for this are not clear from the literature, though it could be that the approach is not of academic interest and/or is inaccurate. The absence of it from the literature does not necessarily mean it is not a sensible method to consider in some circumstances, discussed below.

5.3.1.3 Advantages and disadvantages

These methods are a simple and cost-effective way of forecasting, as they are easy to implement and have low data requirements. Naïve forecasting only requires recent import demand data, which is available to the product level of granularity, across countries globally. Specifically, the United Nations Comtrade and Centre Trade Map databases hold data regarding country level imports at a product level (using the Harmonised System classification), meaning that this forecasting methodology is feasible at the product by country level of granularity.

Despite this, since this method does not account for any changes, naïve forecasting is typically only used as a comparison for more sophisticated methods.[159] For economies undergoing rapid change, particularly in respect to known key drivers of import demand, this method may prove less accurate. For more stable economies whose import demand does not vary period to period, this method may be more useful. Additionally, naïve forecasting will be less accurate for longer time horizons, as more change can be expected, especially for developing countries.

5.3.1.4 Evaluation of feasibility for replication

The table below sets out our evaluation of the naïve forecasting methods for predicting import demand against each criterion.

[159] 'Using Naïve Forecasts to Assess Limits to Forecast Accuracy and the Quality of Fit of Forecasts to Time Series Data' Goodwin (2014). Available at SSRN: http://dx.doi.org/10.2139/ssrn.2515072

Table 28: Naïve forecasting methodology assessment

Criteria		Naïve forecasting
Accuracy	Predictive power	- High predictive power for developed over short time-horizons and stable economies. - Less accurate for developing countries, since it does not account for changes. Lower predictive power for longer time horizons.
	Precision	- Provides precise, numerical forecasts.
Simplicity	Complexity	- Very simple to implement.
	Resource requirements	- Relatively low resourcing requirements. Requires simple analysis of pre-existing data.
Data requirements		- Relatively limited data requirements, as only import demand of the most recent period is required. Data available to implement at any level of granularity.
Time horizon		- Typically used to generate relatively short-term forecasts.
Feasibility for replication		- This method is feasible to generate **country x product** import demand forecasts.

Source: Economic Insight Ltd

Naïve forecasting methods are simple to implement and have relatively low data requirements, therefore they can be used to generate country by product forecasts of import demand. However, it is important to bear in mind that these methodologies will have lower predictive power for rapidly changing developing countries, as opposed to more stable, developed countries, especially for longer-term forecasts.

5.3.2 Historic trend (univariate) models

5.3.2.1 Description

Historical trend models, or univariate models, are more advanced than naïve forecasts and apply regression techniques to historical data, but do not introduce any additional variables. The three most commonly used univariate time-series models are outlined below.

- **Autoregressive (AR) models**. Observed values depend on (i) a weighted linear combination of past values; and (ii) a random shock term.

- **Moving average (MA) models**. Observed values depend on a weighted linear sum of current and past random error terms, which are independent in each period.

- **Autoregressive integrated moving average (ARIMA) models**. These models are combinations of the above processes, and so are composed of (i) lagged values of the dependent variable (the autoregressive component); and (ii) lagged values of the random shock terms (the moving average component).

The choice of univariate model will depend on the characteristics of the data. Box Jenkins is an approach to identifying, fitting and checking ARIMA models. The key stages are as follows: (i) model identification and selection: ensuring stationarity of the variables, identifying seasonality, and determining the appropriate order for the lag / moving average components; (ii) estimation of parameter values: this is mainly done using maximum likelihood as MA processes cannot be estimated by ordinary least-squares (OLS); and (iii) diagnostic checking: to ensure the residuals are modelled adequately.[160]

5.3.2.2 Use for forecasting import demand

Univariate models are often used in academic papers seeking to forecast imports. For instance, Milad et al. (2014) employ the Box Jenkins approach to forecast imports of machinery, transport and crude materials in Malaysia, over the time period 2011-2013. [161]

Keck et al. (2010) employ both an ARIMA model and autoregressive distributed lag model (ARDL), a type of ARIMA model, to forecast demand for imports across 25 advanced OECD countries.[162] The authors find that the ARDL model performs particularly well when forecasting two-quarters ahead of time.

Kargbo (2007) also used an ARIMA model in their analysis to forecast agricultural imports in South Africa. The author's analysis was shown to be robust in explaining the behaviour of agricultural trade flows, when measured for accuracy against the mean absolute error (MAE), mean absolute percent error (MAPE) and root mean square error (RMSE). Other measures of accuracy involve comparing a within-sample forecast to actuals. The ARIMA model used is shown to outperform others included in their analysis, which include vector autoregression (VAR) and vector error correction (VECM) models.[163]

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[160] The Box Jenkins Method' NCSS. Available here: https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/The_Box-Jenkins_Method.pdf
[161] 'Modelling and forecasting the volumes of Malaysia's import' Milad et al; Int. Conf. Glob. Trends Acad. Res. Bali, Indonesia Global Illuminators, Kuala Lumpur, Malaysia (2014).
[162] 'Forecasting international trade' Keck et al; OECD Journal: Journal of Business Cycle Measurement and Analysis 2009.2 (2010): 157-176.
[163] 'Forecasting agricultural exports and imports in South Africa' Kargbo; Applied Economics 39.16 (2007): 2069-2084.

5.3.2.3 Advantages and disadvantages

To run univariate regressions, forecasters only require historical import demand data. As discussed in the previous section, this implies that this method can be used at varying levels of granularity and for countries with different levels of development. However, univariate models will require past data from a longer time period than naïve forecasts (typically for the country of interest), which only use recent data. The World Integrated Trade Solution (WITS) database holds historic annual import data at a product level, by country, from 1988 onwards. However, this data is not complete in all cases, and for many countries the data is not available for the entirety of this period. Despite this, it is expected that this methodology is feasible at the country x product level of granularity, for a significant proportion of countries globally. A further advantage of univariate models is that they can also forecast for any time horizon.

Univariate models can vary in complexity, and evidence shows that simpler time-series models perform better than more advanced ARIMA models.[164] Mondal et al (2014) evaluate the accuracy of ARIMA models in predicting future stock prices in different sectors, and with varying spans of previous data.[165] The authors find that ARIMA models perform well overall, and are most accurate for the fast moving consumer goods sector. They also found that the accuracy for different spans of historical data varies between sectors. The implication is that the statistical performance (including forecasting) of ARIMA models should be evaluated on a case-by-case basis after they are developed before strong conclusions are reached about whether any individual ARIMA model is suitable for forecasting future levels of import demand.

5.3.2.4 Evaluation of feasibility for replication

The table overleaf describes our evaluation of the historic trend method against the set of criteria.

[164] 'Accuracy of Forecasting: An Empirical Investigation' Makridakis and Hibon; Journal of the Royal Statistical Society. Series A (General) Vol. 142, No. 2 (1979); p.97-145.

[165] 'Study of Effectiveness of Time Series Modeling in Forecasting Stock Prices' Mondal et al; International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol.4, No.2 (2014).

Table 29: Historic trend methodology assessment

Criteria		Historic trend
Accuracy	Predictive power	- Evidence suggests these methods have high predictive power. - This method may become less accurate as a result of historic trends changing, or if there are significant changes in the underlying drivers of import demand. - Given this, historic trend approaches may be less appropriate for forecasting import demand in developing countries.
	Precision	- Provides precise, numerical forecasts.
Simplicity	Complexity	- More advanced than naïve forecasting methods and can vary in complexity.
	Resource requirements	- Relatively low resourcing requirements, as requires simple econometric analysis of pre-existing data.
Data requirements		- Higher data requirements than naïve methods, as a longer time period of historical import demand data is required. However, this data is available for a large proportion of countries. Data available to implement at any level of granularity.
Time horizon		- Used to generate longer forecasts.
Feasibility for replication		- This method is feasible to generate **country x product** import demand forecasts.

Source: Economic Insight Ltd

Due to relatively low data and resourcing requirements, this method is feasible for forecasting imports at the **country x product** level of granularity. That is, since historical import data is the only input required, historic trend methods can be used to forecast imports at the product level in any country for relatively long time horizons, so long as the data is available.

5.3.3 Causal models

Causal models seek to model the relationship between the dependent variable and its drivers, and as such, are often more complex with higher data requirements than univariate models. There are broadly three categories of causal models: (i) econometric regression models; (ii) gravity models; and (iii) machine learning. In this section, we run through these categories in turn.

5.3.3.1 Regression models

5.3.3.1 Description

There are a number of different types of regression models, which range in complexity from simple linear regression models to more complex models, such as error correction models. When choosing between different types of models, choices need to be made, which will depend on characteristics of the dataset, as well as economic theory. If the choices made are incorrect,
regression results will be misleading and incorrect conclusions could be drawn. The most important are the choices relating to whether to include or exclude potential drivers of import demand from the regression model – these are typically informed by economic theory and existing evidence.

5.3.3.1.2 Use for forecasting import demand

Econometric regression approaches are used widely across different types of forecasters, including:

- **Academics**. Simionescu and Bilan (2013) specified a linear regression model in logs to forecast aggregate imports for Romania, over the period 2011 to 2013.[166] However, the authors found that this method overestimated import demand for 2011-12, indicating that this was a result of the model not taking into account shocks in the economy. Shao et al. (2014) also assessed the use of multiple linear regressions in forecasting demand for imports of crude oil in Taiwan.[167]

- **Consultancies**. Oxford Economics employ a 'global economic model' to forecast imports.[168] Forecasts are carried out at the economy level for 200 countries, as well as at the product level for 33 countries, for a 35-year time horizon. Hackett Associates, a maritime consultancy firm, use six econometric models to forecast trade volumes at 16 major container ports in North America.[169]

- **Financial services firms**. Moody's use a structural economic model to forecast imports at the country level for over 70 countries.[170] Deloitte forecast US imports six years ahead using Oxford Economics' causal model. [171]

- **Macroeconomic researchers**. The Economist Intelligence Unit use a macroeconomic model to predict imports for 61 countries.[172] Kiel Institute also use macroeconomic models to forecast imports at the country and regional level

[166] 'Econometric forecasting of imports and exports indexes in Romania' Simionescu and Bilan; Bulletin of the Transilvania University of Brasov. Economic Sciences. Series V 6.2 (2013).
[167] 'Hybrid soft computing schemes for the prediction of import demand of crude oil in Taiwan' Shao et al; Mathematical Problems in Engineering (2014).
[168] Available here: https://www.oxfordeconomics.com/global-trade-flows
[169] Available here: https://www.hackettassociatesllc.com/
[170] Available here: https://www.moodysanalytics.com/product-list/global-economic-data-forecasts
[171] 'United States Economic Forecast' Deloitte (2018). Available here: https://www2.deloitte.com/content/dam/insights/us/articles/4488_USEF-Q4-2018/DI_USEF_2018_Q4.pdf
[172] Available here: https://www.eiu.com/handlers/publicdownload.ashx?mode=m&fi=data-section/market-indicators-_-forecasts.pdf

for Germany, China, UK, Japan and the US, as well as the Euro area.[173] DIW Berlin forecast imports in Germany using causal models.[174]

5.3.3.1.3 Advantages and disadvantages

As is the case for univariate models, causal regression models allow forecasts of imports for any time horizon, as long as forward-looking and/or historical data on the key drivers is available.
Indeed, causal regressions require more data than univariate models, because they model the relationship between the dependent variable (in this case, imports) and a range of independent variables, and so also require historical / forward-looking data for these variables as well.

Data availability is therefore dependent upon the particular variables intended to be incorporated into the model. For instance, generating a forecast of aggregate imports from the start-point of a traditional import demand function, that incorporates relative prices and income as the only exogenous variables, is expected to be feasible on a country x aggregate import level basis. This is because data availability regarding these variables is high, with income (GDP) data across countries being available from the World Development Indicator database of the World Bank, and exchange rate and price indices data available from the International Financial Statistics database of the IMF.

As additional variables look to be added, data availability is likely to become scarcer. Further, at increasingly granular levels of product aggregation, historical data for the key independent variables one would like to include in the regression may not be available for all countries, especially in developing countries. As such, feasibility is dependent upon the complexity of the structural model intended to be built, and the number of exogenous variables to be included.

Causal regression techniques have been used extensively in macroeconomic forecasting, due to the rationale that, if changes in the underlying drivers of a variable can be modelled and understood, the forecaster will be better placed to evidence why and how the independent variable subject to the forecast is expected to change. This is therefore often expected to generate more robust forecasts. However, in some instances these models have been found to be less accurate than other forecasting approaches. For instance, Goh found that multiple linear regression models were the least accurate method of forecasting construction demand in Singapore.[175] Nikolopoulos et al (2007) also found that multiple linear regressions were less accurate than a variety of different methods, including machine learning.[176]

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[173] Available here: https://www.ifw-kiel.de/institute/research-consulting-units/macroeconomic- policy-under-market-imperfections/forecasting-and-business-cycle-analysis/
[174] Available here: https://www.diw.de/en/diw_01.c.617047.en/forecasting_and_economic_policy_department.html
[175] 'Forecasting residential construction demand in Singapore: a comparative study of the accuracy of time series, regression and artificial neural network techniques' Goh; Engineering, Construction and Architectural Management, Vol. 5 No. 3 (1998); p.261-275.
[176] 'Forecasting with cue information: A comparison of multiple regression with alternative forecasting approaches' Nikolopoulos et al; European Journal of Operational Research 180(1):354- 368 (2007).

5.3.3.2 Gravity model

5.3.3.2.1 Description

A well-established causal model for use in understanding international trade is the gravity model, which is a specific type of regression model. This model builds on the traditional import demand function, modelling the relative incomes of trading partners, and relative prices, but with the addition of the **geographical distance between the partners**. The introduction of this distance variable is a **proxy for transportation costs**, which is noted as an important determinant of trading decisions.[177]

5.3.3.2.2 Use for forecasting import demand

Khan and Hossain (2010)[178] and Alam et al. (2009)[179] both conduct a panel analysis using the gravity model to explore the trade relationships of Bangladesh. In both cases, a significant negative coefficient is found for the distance variable, indicating that Bangladesh indeed imports relatively more from its neighbouring countries.

When exploring Australia's global trade potential with its 57 trading partners (that make up over 90% of its total trade), using data over 1972-2006, Rahman also finds that geographical distance between economies is a significant determinant of the strength of their trade relationship.
Specifically, the study finds that for every 1% increase in the distance between trading pairs, bilateral trade falls by 2.05%.

Papazoglou (2007) also used a gravity model to forecast export and import potential between Greece and other EU countries at the aggregate level.[180]

5.3.3.2.2 Advantages and disadvantages

See the advantages and disadvantages listed under ‘regression analysis’ set out above.

5.3.3.3 Machine learning

5.3.3.1 Description

Machine learning is a diverse field with numerous classes of model, which vary in complexity. Many of the model classes work in different ways, with different objective functions, and therefore some will be more suited to individual forecasting tasks than others. For example, Artificial Neural Networks (ANN) is a machine learning algorithm that seeks to process information in a similar way to the human brain and

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[177] ‘Model of Bilateral Trade Balance: Extensions and Empirical Tests’ Khan and Hossain (2010).
[178] 178 Ibid.
[179] ‘Import inflows of Bangladesh: the gravity model approach’ Alam et al (2009).
[180] ‘Greece’s potential trade flows: a gravity model approach’ Papzoglou (2007).

has been used to forecast GDP growth.[181]

5.3.3.3.2 Use for forecasting import demand

This methodology was employed by Shao et al (2014) to forecast the imports of crude oil in Taiwan over 2001-2010.[182] The forecasts were compared to the actual values of imports of crude oil over this time. It was found that the forecasts were more efficient when applying a double stage forecasting approach – i.e. by selecting the variables to be used by conducting a multiple linear regression, before then going on to applying the machine learning techniques.

5.3.3.3.3 Advantages and disadvantages

The main aim of machine learning is prediction of outcomes, in contrast to econometrics which often looks to establish unbiased relationships between variables of interest. As a result, machine learning can be more accurate than regression models for tasks such as prediction and forecasting. Indeed, Goh (1998) found that ANN perform better than univariate and multiple regression models when forecasting construction demand in Singapore.[183]

Machine learning is also much more flexible than regression techniques. For instance, ANN do not require a particular model form to be specified, whereas regression models such as ARIMA models assume a linear correlation structure and so do not capture non-linear patterns.[184]

While univariate and causal regression models involve potentially incorrect choices about data and model characteristics, machine learning approaches automate these choices, and so remove human judgment and assumptions.[185] Indeed, Hall (2018) found that machine learning models perform better than autoregressive models and consensus forecasting, when forecasting the unemployment rate, especially for shorter time horizons. [186]

5.3.3.4 Evaluation of feasibility for replication

Based on the advantages and disadvantages of the three causal methods outlined above, in the table overleaf, we set out our evaluation of this methodology.

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[181] 'Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models' Gonzalez; Working Papers-Department of Finance Canada (2000).
[182] 'Hybrid soft computing schemes for the prediction of import demand of crude oil in Taiwan' Shao et al; Mathematical Problems in Engineering (2014).
[183] 'Forecasting residential construction demand in Singapore: a comparative study of the accuracy of time series, regression and artificial neural network techniques' Goh; Engineering, Construction and Architectural Management, Vol. 5 No. 3 (1998); p.261-275.
[184] 'Time series forecasting using a hybrid ARIMA and neural network mode' Zhang; Neurocomputing (2003).
[185] 'Machine Learning Approaches to Macroeconomic Forecasting' Hall; Economic Review, Federal Reserve Bank of Kansas City, issue Q IV (2018); p.63-81.
[186] Ibid.

Table 30: Causal model assessment

Criteria		Causal model
Accuracy	Predictive power	- May be more accurate than historic trend models, as the drivers of import demand are built into the model. - However, this assumes the nature of the future relationship between import demand and its drivers follows past patterns.
	Precision	- Provides precise, numerical forecasts.
Simplicity	Complexity	- Medium to high complexity, depending upon the number of drivers intended to be incorporated in the model.
	Resource requirements	- Medium resourcing requirements, as requires econometric analysis of pre-existing data.
Data requirements		- Highest data requirements of all the methods, however, the extent of these requirements is highly dependent upon the complexity of the model to be generated. - Specifically, traditional import demand function requires only historical and/or forward-looking data on relative prices, income and import demand. Adding other factors, such as trade liberalisation, stage of development, geographical factors, and other drivers of high importance necessarily increases the data requirements of this method. - Data availability varies by country and so feasibility depends on country / sectors of interest.
Time horizon		- Used to generate longer forecasts.
Feasibility for replication		- This method is most feasible to generate (i) **country x aggregate** import demand forecasts; and (ii) a smaller set of **country x product** forecasts.

Source: Economic Insight Ltd

The increased complexity and resourcing requirements of causal models mean that to generate the complete set of country by products forecasts will be a significant task. Therefore, this method is expected to be better suited to conduct a smaller number of in-depth looks, or country looks on a more aggregated product level.

Ultimately, the feasibility of this method hinges on the number of drivers intended to be included. More specifically, models including greater numbers of drivers will be less feasible for developing countries, as data availability in these countries will be more limited than for developed nations.

5.4 Composite models

5.4.1 Description

Composite models generate forecasts by triangulating evidence collected through implementing a number of differing forecasting methodologies. These models can therefore be, and often are, a hybrid of both qualitative and quantitative methods.

5.4.2 Use for forecasting import demand

Trading Economics looks to produces aggregate import forecasts for each country. The coverage of these forecasts is extensive, with Trading Economics looking to generate forward looks for every country. However, there are instances whereby forecasts are not generated (the reason for which is not specified), and in these instances only historic trends are published. Where forecasts are available, the following time horizons are covered: (i) one-quarter ahead; (ii) one year ahead and (iii) two years ahead. While Trading Economics notes that the forecasts are generated according to their global macroeconomic models, analysts' expectations as well as econometric models, the specific methodologies underpinning the macroeconomic and econometric models used are not detailed.[187]
The OECD also produces country level aggregate import forecasts. These forecasts cover a total of 35 countries, comprised predominantly of developed economies, but also includes some developing countries, such as South Africa and China. The forecasts generated look one year ahead. Once again, although the specific methodologies underpinning the forecasts are not specified, the OECD does note that it uses a "combination of model-based analyses and expert judgment"[188] techniques, and therefore, this can be classified as a composite model.
Shao et al (2014)[189] used a number of alternative causal econometric models to forecast Taiwan's import demand for crude oil, namely: (i) multiple linear regression; (ii) support vector regression; (iii) artificial neural networks, and; (iv) extreme learning machine methodologies.

5.4.3 Advantages and disadvantages

The complexity of composite models can vary significantly, based upon the type and number of methodologies used to arrive at the composite forecast. Similarly, the accuracy of these models is also contingent upon the accuracy of those individual methodologies making up the composite model.

However, it has been found that generating forecasts using a number of differing

[187] UK example available here: https://tradingeconomics.com/united-kingdom/imports
[188] Available here: https://data.oecd.org/trade/trade-in-goods-and-services-forecast.htm
[189] 'Hybrid soft computing schemes for the prediction of import demand of crude oil in Taiwan' Shao et al; Mathematical Problems in Engineering (2014).

methodologies, and aggregating these results can produce more accurate predictions. For instance, Zhang (2003) found evidence that a combination of causal methodologies generated forecasts of increased accuracy as opposed to each methodology individually. Specifically, it was found that a hybrid model combining both ARIMA econometric models, and an artificial neural network machine learning model took advantage of their unique strengths. This led to results that indicated “that the combined model can be an effective way to improve forecasting accuracy achieved by either of the models used separately”.[190]

This has also been found when applying composite models specifically to import demand forecasts. For example, Shao et al (2014) showed that hybrid models comprised of a multiple linear regression model and one other quantitative method outperformed the models taken individually in their predictive power and accuracy.[191]

5.4.4 Evaluation of feasibility for replication

In the table below, we set out our evaluation of composite methods against each criterion.

Table 31: Composite methodology assessment

Criteria		Composite
Accuracy	Predictive power	- Composite models have been found to have higher predictive power than individual methodologies.
	Precision	- Can be used to generate precise, numerical forecasts.
Simplicity	Complexity	- Varies according to (i) whether existing research is used or ‘new’ research is created; and (ii) the type and number of methods employed.
	Resource requirements	- Varies according to the type and number of methods employed.
Data requirements		- Varies according to the type and number of methods employed.
Time horizon		- Can be used to generate longer forecasts.
Feasibility for replication		- Feasible at a **range of granularity levels**, depending on the type of methods employed.

Source: Economic Insight Ltd

Since composite models are based on a combination of a range of other forecasting

[190] ‘Time series forecasting using a hybrid ARIMA and neural network model’ Zhang; Neurocomputing (2003).
[191] Ibid.

methods, they are feasible at a number of different levels of granularity. The most appropriate granularity level will vary according to the type of methods included. For instance, if naïve forecasting and expert opinion methodologies are used to estimate a composite forecast, a country x product level would be most feasible.

5.5 Off-the-shelf forecasts

We have found a number of instances whereby financial services firms, consultancies and macroeconomic forecasters conduct import forecasts, but do not publish their research methodologies. This is because, in these instances, the forecasts are 'off-the-shelf' products to be purchased. As a result, there have been instances where we have found evidence of import forecasts being generated, but have been unable to establish the precise methodologies that have been used.

Despite therefore being unable to learn from, and critically appraise, the specific methodologies used in these cases, **the forecasts generated are directly obtainable for use by DIT, and therefore, would be the simplest way of arriving at a set of import forecasts**. The table below summarises the off-the-shelf products we have found.

Table 32: Off-the-shelf products

Company	Market level	Product level	Coverage	Time horizon
Moody's Analytics	Country	Aggregate	Wide range of countries	30 years ahead
JP Morgan	Country	Aggregate	Unknown	Unknown
Goldman Sachs	Country	Aggregate	Unknown	Unknown
Oxford Economics	Country	Aggregate; product	Wide range of countries and products	25 years ahead
Capital Economics	Country	Aggregate	Wide range of countries	2 years ahead
EIU	Regional; country	Aggregate	Wide range of countries and regions	5 years ahead
OECD	Country	Aggregate	Mostly developed countries	1 year ahead
OBR	Global	Aggregate	Unknown	3 years ahead
IMF	Country	Aggregate, sector	Unknown	5 years ahead

Source: Economic Insight Ltd

5.5.1 Financial services firms

Financial services firms operate in the finance industry, and include (i) banking and investment firms; (ii) insurance companies; (iii) accountancy firms; and (iv) other firms offering financial and investment services. These firms typically provide forecasts of a wide range of variables for their clients.

Moody's Analytics offer aggregate, country level forecasts imports for over 70 countries, ranging from developing countries to more advanced economies, for a 30-year time horizon.[192] These forecasts are estimated using a "structural economic model" and are updated on a monthly basis.

Many financial services firms also publish economic outlook reports, which can include country level import forecasts. These reports can be published on a regular basis, such as JP Morgan's year 'Global Market Outlook', or on an ad-hoc basis, as is done by Goldman Sachs for example.[193] [194] However, in these reports, imports are often only forecast at a high-level, such as the economy or regional level, and typically only include a couple of countries or regions.
Moreover, these reports do not always include import forecasts, and so are not expected to be particularly useful for DIT.

5.5.2 Economic consultancies

Economic consultancies apply economic theory and analysis to a wide range of issues, including forecasting.

Oxford Economics provide forecasts of imports for over 200 countries at the economy level, and for 33 countries at the product level. Forecasts are available for a varied set of countries, ranging from low income countries such as Indonesia to developed countries like the US.[195] At the product level, forecasts are offered for a wide range of sectors, such as food and live animals; chemicals and related products; and manufactured goods. Forecasts are available until 2035, and are updated quarterly at the economy level, and twice a year at the product level. Oxford Economics' predictions are estimated through their 'Global Economic Model', for which details of precisely how this model is estimated are unspecified.

Capital Economics also offer economy level forecast imports for over 40 countries, ranging from developed to developing countries, over a time horizon of two years ahead.[196] However, it is also unclear which methodology specifically is used to estimate these forecasts.

5.5.3 Macroeconomic research organisations

192 Available here: https://www.moodysanalytics.com/product-list/global-economic-data-forecasts
193 Available here: https://www.goldmansachs.com/insights/topics/economic-outlooks.html
194 Available here: https://www.jpmorgan.com/global/research/global-market-outlook-2019
195 Available here: https://www.oxfordeconomics.com/global-trade-flows
196 Available here: https://www.capitaleconomics.com/forecasts/our-key-forecasts/

Macroeconomic research organisations analyse and provide insight into macroeconomic trends.

The Economist Intelligence Unit (EIU) offers country level forecasts for over 60 countries and 11 regions, covering a wide range of development levels.[197] Forecasts are updated on a monthly basis and based on an unspecified macroeconomic model, with a 5-year time horizon.

The OECD also provide 1-year import forecasts at the economy level, based on "a combination of model-based analyses and expert judgement".[198] These forecasts are available for 35 countries, which are mostly developed economies, with some developing countries such as South Africa and China.

The Office for Budget Responsibility (OBR) produces UK export demand forecasts, by looking to establish import growth of the UK's trading partners. This is done by producing a world trade forecast, and then reweighting this according to the proportion of UK exports accounted for by each global region. This, combined with assumptions regarding the proportion of trade across these markets that is expected to be satisfied by UK exporters over future periods, jointly determines UK export forecasts.[199] The OBR publishes the forecast for overall UK export growth in its 'Economic and fiscal outlook' updates.[200] However, forecast export growth is not broken down by region. We expect the specific methodologies involved in producing these forecasts to be causal in nature, as the OBR states that the forecasts are adjusted on the basis of expected changes in certain drivers of trade, such as exchange rate movements and policy changes (including the decision of the UK to leave the EU).[201]

The IMF generates import forecasts across varying levels of granularity, over a time horizon of up to 5 years forward. The methodology used to generate these forecasts is a 'bottom-up' approach, in that, country teams within the IMF generate forecasts for economy-wide import demand for each individual country. These country-specific forecasts are then aggregated to produce trade volume forecasts for 'advanced economies' and 'emerging market and developing economies', before being aggregated further to generate forward looks of world trade volumes. The process of generating these forecasts at each level of granularity is iterative, in that, results of the aggregated forecasts are used to feed back into, and refine, the individual country forecasts.

5.5.4 Feasibility for replication

The table overleaf sets out our assessment of the off-the-shelf methodologies of forecasting import demand against criterion.

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197 Available here: https://www.eiu.com/handlers/publicdownload.ashx?mode=m&fi=data-section/market-indicators-_-forecasts.pdf
198 Available here: https://data.oecd.org/trade/trade-in-goods-and-services-forecast.htm
199 Available here: https://obr.uk/forecasts-in-depth/the-economy-forecast/world-economy-and-drivers-of-uk-exports/
200 Available here: https://cdn.obr.uk/EFO_October-2018.pdf
201 Ibid.

Table 33: Off-the-shelf methodology assessment

Criteria		Off-the-shelf
Accuracy	Predictive power	- We are unable to assess the predictive power of these methods.
	Precision	- Provide precise, numerical forecasts.
Simplicity	Complexity	- Low complexity to implement.
	Resource requirements	- No resource requirements.
Data requirements		- No data requirements.
Time horizon		- Time horizon varies between products, but typically ranges from 1 to 30 years.
Feasibility for replication		- Most off-the-shelf forecasts are available at the **country x aggregate imports level**, though product or sector level forecasts are available for some countries.

Source: Economic Insight Ltd

Off-the-shelf forecasts are simple to implement and have no data requirements. However, we are unable to assess their predictive power, as the methods underlying these forecasts are not publicly available. The off-the-shelf products we have found forecast imports between one and thirty years ahead, and are often only available at the country by aggregate import level of granularity.
However, in some cases, product or sector level forecasts are available in individual countries.

5.6 Conclusions

After considering the methods against a set of key criteria, we found that the feasibility of applying these methods to different levels of aggregation varies. In particular, our research has found that it would not be feasible to use the vast majority of these forecasting methods to generate forward looks for import demand at the country by product level – that is, at the level of granularity most useful for DIT's purposes. This is due to both: (i) the **large amounts of data** that many of the methods, and in particular the quantitative methods, would require; and (ii) the **extensive time and monetary resources** that many of the methods, and particularly the qualitative methods, would require to generate import forecasts.

6. Conclusions and Recommendations

In this chapter, we put forward our conclusions and recommendations regarding the most appropriate methodologies for DIT to generate forecasts of import demand at the country by product level, based on the evidence set out in Chapter 4 and Chapter 5. In light of our findings that it would not be feasible to apply most methodologies this level of granularity, we recommend that DIT employ a two-step approach to forecasting import demand. By this we mean that, it may be most effective to: (i) first identify a set of key opportunities at a higher level of (product and market) aggregation, before (ii) then going on to conduct forecasts at a more granular level, honing into a more limited number of key opportunities.

The overarching objective of this research is to help inform the development of an approach to forecasting import demand by sector and market, in order to enable DIT decision makers to make better informed decisions about potential future trade. In particular, DIT would like to understand the feasibility of conducting import demand forecasts at the country by product level of granularity.

This report therefore looks to provide DIT with an understanding of potential methodologies that could be used to effectively forecast import demand, at differing levels of granularity, achieving global coverage. In this section, we set out our conclusions and recommendations, in terms of the most feasible options available to DIT to arrive at a set of import demand forecasts.

Table 34: Methodology assessment (1)

Criteria		Accuracy		Simplicity		Data requirements	Time horizon	Feasibility for replication
		Predictive power	Precision	Complexity	Resource requirements			
Qualitative methodologies	Expert opinion							Aggregate x country, for a set of countries
	Historical analogy							Sector x country
	Horizon scanning							Sector x region / sector x global
	Scenario building							Country x sector, for a set of countries
Quantitative methodologies	Naïve forecasting							Country x product
	Historic trend							Country x product
	Causal model							Aggregate x country; and a smaller set of country x product

Source: Economic Insight Ltd.

Table 35: Methodology assessment (2)

		Accuracy		Simplicity		Data requirements	Time horizon	Feasibility for replication
		Predictive power	Precision	Complexity	Resource requirements			
Other methodologies	Composite							Range of granularity levels
	Off the shelf							Aggregate x country, with some sector / product level country forecasts available

Source: Economic Insight Ltd

As shown in the summary tables above, after considering the methods against a set of key criteria, the feasibility of applying these methods to different levels of aggregation varies.

Importantly, our research indicates that it would not be feasible to use the vast majority of available forecasting methods to generate forward looks for import demand at the country level, for every product – in other words, at the level of granularity most useful for DIT's purposes. This is due to both: (i) the **vast amounts of data** that many of the methods, and particularly the quantitative methods, would require, and; (ii) the **extensive time and monetary resources** that many of the methods, and particularly the qualitative methods, would use in order to generate the forecast.

In light of these findings, a more pragmatic approach to generating import demand forecasts may take the form of an iterative forecasting process, which takes advantage of the relative benefits of the available methods at each stage. By this we mean, it may be most effective to: (i) first identify a set of key opportunities at a higher level of (product and market) aggregation, before (ii) then going on to conduct forecasts at a more granular level, honing into this more limited number of key opportunities.

There are two ways one could go about this:

- Begin by identifying the UK's **key country markets**, before generating forecasts of import demand at a sector/product level for this limited set of countries specifically. This would allow forecasters to gain an understanding of the particular mix of imports these key countries are expected to demand.

- Begin by identifying the UK's **key sector or product markets**, before generating forecasts of import demand at a country level for this limited set of product markets specifically. This would allow forecasters to gain an understanding of the particular countries driving the particular sector or product based opportunities.

In this section, we detail each of these approaches in turn, before turning to how to forecast imports at a more granular level once key opportunities have been identified. Finally, we discuss some important considerations relating to the global economy.

6.1 Identifying key country markets

This approach would begin by forecasting import demand at an economy-wide level for each country, in order to identify the set of countries that present the greatest opportunity for UK exports.

Quantitative methodologies are less resource intensive than qualitative approaches, and so it is more feasible to generate economy level forecasts of import demand for every country using these methods than the latter approaches. Historic trend and causal models will be more appropriate quantitative methodologies, because naïve forecasts have low predictive power when countries are undergoing rapid change and are typically only used for shorter-term forecasts, whereas both of the more advanced quantitative methods can be used for long-term forecasts and have high predictive power.

Therefore, we have identified the following methodologies as being most suitable for forecasting import demand at the aggregate by country level of granularity:

- Historic (univariate forecasting);
- Causal models; and
- Off-the-shelf.

In particular, we recommend DIT employ a gravity model to identify the most appropriate trading parties **for the UK specifically**. This type of causal model includes a more limited number of independent variables – that is, gravity models typically include relative incomes, relative prices and geographical distance – resulting in lower complexity, data and resourcing requirements.

As a result, this model advantageous given the level of resourcing required to implement it. However, we consider that the key advantage of this model for DIT's purposes is that it does not just identify key export opportunities in terms of the sources of the largest overall level of import demand. Instead, the model looks to identify those sources of greatest import demand, that, given the connections to the UK, the UK has greatest potential to fulfil.

Off-the-shelf products are another option for obtaining forecasts of import demand at the aggregate level for each country. However, these products typically only forecast imports one to two years ahead, and their predictive power is often unknown.

6.2 Identifying key product markets

Another approach would be to identify key product or sector markets, as opposed to key countries. This approach would begin by forecasting import demand at the sector or product level globally, or by region, in order to identify the particular set of sectors or product markets that present the greatest opportunity for UK exports.

Services represent an important export market for the UK, and import demand for this sector is expected to grow most rapidly in developing countries due to rising per capita income levels.
Given that changes in these countries are becoming less predictable, methodologies that examine historical patterns, such as quantitative methods, may not be appropriate, and so forward-looking methods should be favoured. Taking this into consideration, we have identified the following methodologies as most suitable for forecasting future sector / product demand on a global / regional scale:

- Horizon scanning; and
- Scenario building.

Here, **horizon scanning** may be more appropriate than scenario building for two reasons. Firstly, horizon scanning provides more precise forecasts as compared to scenario building, which builds a range of potential scenarios, and so would be more useful for identifying opportunities. Secondly, this methodology is less complex than scenario building, as the latter requires forward looks of underlying indicators to be generated before forecasting import demand, whereas horizon scanning only involves desk-based research and/or expert consultation.

6.3 Forecasting import demand at a granular level

Once key opportunities have been identified, a wider range of methodologies would then become feasible for use in forecasting import demand, for either:

- Forecasting sector and/or product import demand for a more limited range of countries; or
- Forecasting country-specific demand for a more limited range of sectors or products.

When conducting import demand forecasts at a product by country level of aggregation, our research has identified that there are a number of key considerations that have implications for how to conduct these forecasts.

Specifically, our research has shown that historic trends may be becoming less informative in relation to estimating future import demand, as the rapid pace of development is now resulting in countries moving along GVCs in different ways. Specifically, countries are now moving from manufacturing to services at a much lower level of per capita income than has been historically observed. In addition, many countries are moving directly to services production without transitioning through the manufacturing stage. This implies that the nature of the relationships between import demand patterns and its drivers can, and is, changing. As such, it might become more important to consider: (i) how the drivers of import demand are changing; (ii) how the relationship between these drivers and import demand is changing; and therefore (iii) what implications this has on future import demand.

These findings have important implications for forecasting import demand in developing countries. Indeed, they indicate that forward-looking approaches will be better suited than methods examining historical trends in this case because changes affecting developing countries are becoming less predictable. Since scenario building and horizon scanning methodologies are relatively resource intensive, one option would be to employ a **composite model** to forecast import demand in developing countries – that is, one could employ causal models and ask for expert opinion on movements of individual drivers, to gain a better understanding of future changes.

On the other hand, developed countries have more stable economies and have finishing transitioning, and so methodologies examining historical patterns will be more telling. Given the relative complexity, resourcing and data requirements of causal methods, we expect that less advanced methodologies such as **naïve forecasting or historic trend** models will be most suitable. One could also consult off-the-shelf products to gain an understanding of future import demand in developed countries, however, as discussed, the accuracy of these is unknown.

6.4 Key considerations for the global economy

Over the past century, globalisation has been the key driver of changing patterns of consumption and demand. The reduction of trade barriers, alongside innovations reducing both transportation time and cost have led to the explosion of world trade. Indeed, economies across the world and across different stages of development participate in GVCs, which account for two-thirds of world trade.

More recently, however, **technology** is driving consumer demand. The rise of the digital economy and big data have led to globalisation playing a lesser role in consumption patterns. For instance, McKinsey found that digital flows – that is, data and information sharing – now have a larger effect on GDP growth than global trade in goods.[202]

In view of this, it is important to 'step back' from more granular country by product forecasts of import demand, and consider the key changes affecting economies on a global scale.
Technological advances may prompt the development of entirely new industries or substantial change in existing industries, presenting key opportunities which may be missed if global trends are not considered.

[202] 'Digital globalization: the new era of global flows' McKinsey (2016).

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