For England! On its economic outlook in the face of changing trading costs

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Abstract

This paper examines the relationship between trade costs and trade for the United Kingdom, in order to inquire about its economic outlook after its 31 January 2020 withdrawal from the European Union. By using a recently developed implicit trade cost measure and temporally disaggregated data from OECD's 2020 edition of the Structural Analysis database into a quarterly frequency, we deploy an autoregressive distributed lag model for import and export estimations with three other countries: France, The Netherlands and Italy. From a Keynesian perspective, output is determined by aggregate demand so that changes in any of the component demand functions should translate onto the real economy. Two such component demand functions of aggregate demand are export and import. The relationships between trade costs, export and import are therefore are therefore theoretically significant in determining the future output of the UK. We apply a Mundell-Fleming framework where a decrease in net export in the medium-term perspective causes a contraction of the real economy. We investigate the relationship between trade costs, export and import by establishing an empirical model with the implicit trade cost measure. Within the temporal perspective of 1989-2017, we find empirical support for several cointegrated relationships between the trade cost measure, export and import, which all suggest negative relationships between trade costs and trade.

Dedication

To my family.

Acknowledgements

I wish to thank my supervisor Ragnar Nymoen for his support throughout the writing of this paper. Specifically, his genuine passion for econometrics has been a true source of inspiration. It is quite impossible not to be intrigued after discussing dynamic modelling with him. His enthusiasm throughout the writing of this paper has provided invaluable incitement. Thank you.

Data files in the format *.bn7* from OxMetrics and *.R* from RStudio containing all estimations are available upon request.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

In June 2016 a historic referendum was held in the United Kingdom, where the people of Britain voted marginally in favor of leaving the European Union. A four year long process ensued and on 31 January 2020 it was settled that the UK would depart from the EU. The 51.89% majority vote of the public referendum (Matti & Zhou, 2017) meant that the 47 year long membership came to an end as the UK became the first nation to ever leave the EU. During a transition period it remained as a part of the European Union Customs Union and the European Single Market, but as of 31 December 2020 23:00 GMT also the transition period came to an end. This means that the United Kingdom can no longer in any official capacity be considered a member state of the European Union.

From the perspective of economics, the exit from the single market of the EU is a significant trade theoretical event. It means that the UK regains a sovereign trade policy, such that it is free to negotiate bilateral trade agreements with other countries. As of 28 December 2020, the prioritized free trade agreements that the UK government were pursuing were mainly with Australia, New Zealand and the United States (International Trade, 2020). Out of these three countries, the EU has free trade agreements with none. So while the Brexit deal did not explicitly introduce any tariffs or taxes for trade (International Trade, 2021), it is not unreasonable to question the degree to which the two entities will stay integrated in terms of trade in the long-run.

Given that the UK is still geographically located in very close proximity to the EU, it is however highly probable that the majority of UK's trade will be conducted with the EU within the foreseeable future. As we will see in chapter 2, one of the most empirically successful models in economics has been claimed to be the gravity model, which in accordance with its name predicts that entities in close proximity to a larger extent are expected to partake in bilateral trade. Nonetheless, the aforementioned independence in trade policies may cause the UK and the EU trade markets to become less integrated.

While not necessarily manifesting as direct implementation of tariffs, the potential divergence in trade policies could prompt indirect trade costs to be incurred. For example, bureaucratic red tape and other border measures related to tolls and customs have been shown to deter trade (Wilson et al., 2003).

In order to capture these indirect costs of trade which can be difficult to measure empirically, we will use the recently developed indirect trade cost measure by Novy (2013). This will be outlined in chapter 2. The purpose of this paper will be to investigate the empirical relationships between trade costs and trade, which within a macroeconomic theoretical framework can be shown to have effects on the total production of the economy. We will use empirical econometric modeling in order to better understand these relationships and see if the theoretical effects are supported by data. Thus chapter 3 introduces the macroeconomic framework, followed by chapter 4 which presents the data set. The results from the empirical econometric modeling are presented in chapter 5 and lastly, we conclude this paper in chapter 6.

Chapter 2

Trade costs

In this chapter we turn to the operationalization of the concept of trade costs and how they can be measured. We give an exposition of the theory behind the indirect trade cost measure developed by Novy (2013), which is based on the work of Anderson and Van Wincoop (2003, 2004) and ultimately the gravity model.

2.1 On the measurement of trade costs

The measurement of trade costs is notoriously difficult. This is mainly due to poor data availability but also in part due to its fleeting definition. While being an increasingly important part of trade theory, their definition and measurement remain in their infancy as Sourdin and Pomfret (2012) succinctly puts it. Trade costs can theoretically be seen as all potential impediments hindering or otherwise limiting the free flow of a good or a service between two countries. This would thus include everything from tolls, customs, bureaucratic red tape and other border measures to freight and shipping costs. Naturally this is a non-exhaustive list of what constitutes as trade costs, but it draws upon the historically recent field of trade facilitation. Numerous studies have tried to capture the relation between trade flows and trade facilitation (Moïsé & Sorescu, 2013; Wilson et al., 2003, 2005). Since trade facilitation measures are introduced to encourage trade between countries it often focuses on direct measures of trade costs. These are however often subjected to partial or incomplete sets of data. In the cases where data is available, it tends to rely upon other fragmented or unavailable data in order to be useful, as expressed by Anderson and Van Wincoop (2004). For our purposes the main drawback of direct measures of trade costs is that they only capture a few aspects of trade. These commonly include costs for transportation and insurance and other policy related barriers such as tariff and non-tariff measures. They fail however in encompassing costs related to bureaucratic red tape for which sets of data are simply not available (Chen & Novy, 2012).

Given the difficulties of capturing trade costs with direct measures, there has in tandem been research made on indirect measures of trade costs, circumventing primarily the issue of data availability. Chen and Novy (2012) presents a literature review on both the measuring of trade costs thus far, as well as a comparison between direct and indirect measures. Their focus lies on non-tariff related measures and they argue that insights are available from both methods, but each measure with its own potential drawbacks. For direct trade cost measures intended for empirical analysis, more precise measures of standards and regulations are needed, while for indirect trade cost measures future research needs to examine their robustness.

Thus for our purpose of estimating the potential impact of trade costs on trade and subsequently aggregated demand, the indirect approach seems more promising. In steering clear from measures based on individual product standards and technical regulations, an indirect trade cost measure allows us to more appropriately capture the full extent of the potential costs incurred by the UK leaving the EU. With this approach the trade cost measure should rightly be thought of as an upper bound estimation. This is because the indirect approach of measuring simply infers the costs from observed trade flow data and compares them to a hypothetical benchmark scenario absent from frictions in trade. Furthermore, the use of an indirect trade cost measure allows us to explore the recently developed microfounded trade cost measure due to Novy (2013).

2.2 The gravity equation model

The origin of many indirect trade cost measures has long been the gravity equation. With its acclaimed empirical success (Kalirajan, 1999; Khadaroo & Seetanah, 2008; Poot et al., 2016; Van Bergeijk & Brakman, 2010; Westerlund & Wilhelmsson, 2011; Yotov et al., 2016) it has both been described as one of the most (Anderson & Van Wincoop, 2003) and the most empirically successful models in economics (Anderson, 2011). Thus there is good reason to continue with the development of this framework. In its most basic essence it relates bilateral trade flows with distance and the economic dimensions of the countries involved, as proposed in the original article by Isard (1954). While being empirically successful in explaining bilateral trade flows, the original and subsequent formulations were for many years unable to find firm theoretical foundations. They offered little explanation as to why there was evidence from the US-Canada border of inter-province trade being 22 times larger than the international trade (McCallum, 1995)[1], or what is also known as one of six major puzzle's in international economics (Obstfeld & Rogoff, 2000). Furthermore, if the difference in magnitudes of trade were solely due to frictions associated with national borders, the illustrated home bias effect would not persist within US states as opposed to between US states, which were the findings of Wolf (2000). Based on this motivation, Anderson and Van Wincoop (2003) claims to have solved the McCallum border puzzle[2] [3]. With the development of a theoretical gravity equation they are able to more reasonably explain the reduction in trade due to the US-Canada border to be about 44% and around 30% attributable to border effects for other industrialized countries.

2.3 A gravity model with bilateral trade costs

The initial assumptions by Anderson and Van Wincoop (2003) are a multiple country setting with individual optimizing consumers. A single differentiated good is endowed to each country and the preferences of the consumers are characterized by a love of variety. This puts us in an Armington world where trade is motivated by inherent differences between goods, not productivity differences as in a Ricardian world. In addition, the preferences of the consumers are identical for all countries and are captured by constant elasticity of substitution utility. The gravity equation developed by Anderson and Van Wincoop (2003) with trade costs is presented below,

$$x_{ij} = \frac{y_i y_j}{y^W} \left(\frac{t_{ij}}{\Pi_i P_j} \right)^{1-\sigma}, \tag{2.1}$$

where x_{ij} denotes nominal exports from country i to country j; y_i is nominal income of country i; y^W is world income defined as $y^W \equiv \sum_j y_j$. If we were to only pay attention to these variables and substitute y^W for a variable D_{ij} for distance between the countries and multiply this fraction by a constant G, this would yield the original gravity equation by Isard (1954). In addition Andersson and Van Wincoop incorporates trade costs by multiplying with the last fraction where t_{ij} is a gross bilateral trade cost factor (one plus the tariff equivalent); $\sigma > 1$ is the elasticity of substitution across goods; Π_i and P_j are price indices for country i and j respectively.

[1] Also using the gravity model framework Nitsch (2000) later on estimated intranational trade (in all essence similar to inter-province trade) to be ten times higher than international trade, averaged across EU countries.

[2] A study by Straathof et al. (2008) later on estimated the US-Canada border effect proposed by Anderson and Van Wincoop (2003) to be half as large, using the same data and assumptions.

[3] Balistreri and Hillberry (2007) argues that the border puzzle is not solved, as the results of Anderson and Van Wincoop (2003) relies too heavily on trade costs being symmetric and their treatment of the US intranational data.

In this formulation, the bilateral trade flows x_{ij} decrease with an increase in the bilateral trade cost factor t_{ij}. The relation has to be compensated for however with the two price indices Π_i and P_j which Anderson and Van Wincoop (2003) call *multilateral resistance* variables. They should be interpreted as the average cost of trading with all other trading partners. Π_i denotes the *outward* multilateral resistance variable, while P_j denotes the *inward* multilateral resistance variable. Thus we notice that the bilateral trade flows increase with both of these multilateral resistance variables, which might seem counter-intuitive. Their reasoning however is that as the multilateral resistance to trade increases, this creates a streamlined effect for the bilateral trading partner. In other words, when resistance in trading with all other nations is high, it forces trade into a channel where it can occur: the bilateral trade flow x_{ij}.

The main drawback of the trade cost measure in Anderson and Van Wincoop (2003) is that since both multilateral resistance variables are unobserved, the bilateral trade cost factor t_{ij} has to be estimated as a trade cost function. This introduces an element of uncertainty that should be nontrivial for all empirical purposes. As Novy (2013, p. 5) rightly points out, the trade cost function might be misspecified, its functional form might be incorrect and it might omit important trade cost determinants such as tariffs.

2.3.1 The Novy (2013) measure: gravity redux

Through the insight that not only *international* trade, but also *intranational* trade is affected by bilateral trade barriers, Novy (2013) is able to arrive at an *analytical* solution to the trade cost measure by Anderson and Van Wincoop (2003). In comparison with Anderson and Van Wincoop (2003) it does not require estimation of a trade cost function and it allows trade costs to be asymmetric. For completeness, a brief summary of Novy's work is presented in the following.

As mentioned above, the variables for multilateral resistance, Π_i and P_j in equation (2.1), are unobserved. Since the bilateral trade cost factor t_{ij} is also unknown, only by conditioning on a number of additional assumptions are Anderson and Van Wincoop (2003) able to find an implicit solution for the multilateral resistances. One of the assumptions is that the bilateral trade cost factor is symmetric. With $t_{ij} = t_{ji}$, this implies that the variables for inward and outward multilateral resistance are equal ($\Pi_i = P_i$). This abstraction is not necessary by incorporating intranational trade into the gravity equation, where intranational trade is a country's trade with itself, x_{ii}. To clarify, one way of measuring this (which will be explained later) is by simply calculating $y_i - x_i$, where y_i is national income and x_i is total exports. The remainder is then a nations trade with itself, the amount of intranational trade. By using the concept of intranational trade and the Anderson and Van Wincoop (2003) measure from equation (2.1), Novy (2013) solves for a country i's multilateral resistances:

$$\Pi_i P_i = \left(\frac{x_{ii}/y_i}{y_i/y^W}\right)^{\frac{1}{\sigma-1}} t_{ii}. \tag{2.2}$$

Having obtained an explicit expression for the multilateral resistance variables for a country i, he calculates a bidirectional gravity equation by multiplying equation (2.1) with the corresponding bilateral trade flow from the opposite direction, x_{ji}:

$$x_{ij}x_{ji} = \left(\frac{y_i y_j}{y^W}\right)^2 \left(\frac{t_{ij}t_{ji}}{\Pi_i P_i \Pi_j P_j}\right)^{1-\sigma}. \tag{2.3}$$

With the use of equation (2.2), substituted into equation (2.3) and rearrangement, he obtains:

$$\frac{t_{ij}t_{ji}}{t_{ii}t_{jj}} = \left(\frac{x_{ii}x_{jj}}{x_{ij}x_{ji}}\right)^{\frac{1}{\sigma-1}}. \tag{2.4}$$

Finally, Novy takes the geometric mean of the barriers in both directions. This is motivated by the allowance of the bilateral trade flows to be asymmetric ($t_{ij} \neq t_{ji}$) and that the intranational trade costs are allowed to differ ($t_{ii} \neq t_{jj}$). He defines the resulting trade cost measure τ_{ij} as:

$$\tau_{ij} \equiv \left(\frac{t_{ij}t_{ji}}{t_{ii}t_{jj}}\right)^{\frac{1}{2}} - 1 = \left(\frac{x_{ii}x_{jj}}{x_{ij}x_{ji}}\right)^{\frac{1}{2(\sigma-1)}} - 1, \tag{2.5}$$

where minus one is used to obtain a tariff equivalent measure, and τ_{ij} represents the bilateral trade costs ($t_{ij}t_{ji}$) relative to domestic trade costs ($t_{ii}t_{jj}$). As Novy (2013, p. 6) puts it, the measure therefore does not impose frictionless domestic trade and captures what makes international trade more costly over and above domestic trade. In the next section, we outline a macroeconomic framework, where the trade cost measure can be put into context.

Chapter 3

A Macroeconomic framework

As a conceptual framework we use the Mundell-Flemming model (Fleming, 1962; Mundell, 1963). The model defines export and import as them main channels whereby trade costs can affect GDP. There are two countries, home and foreign, where foreign represents the rest of the world. We introduce a minimalist view of the framework and adapt it to our purposes of analysing the goods market.

3.1 A Keynesian perspective

The Mundell-Fleming framework belongs to the Keynesian school of thought where production is determined by aggregated demand. It further presumes predetermined prices and that home and foreign goods are imperfect substitutes. From a trade theoretical perspective, this means we are still in the Armington world. These are traditional Keynesian assumptions and they imply that the productive capacity of the economy is allowed to be disequilibrated from aggregate demand (Rødseth, 2000). In studying the open economy we also have to make an assumption about the relative impact of our economy in relation to the rest of the world. Given that our country of interest is the United Kingdom, a reasonable assumptions is that of the small open economy and it is thus unable to affect the world market interest rate.

In the Mundell-Fleming framework trade, in form of exports and imports, enters the model through the IS curve. The IS curve can be characterized as the aggregate demand function of the economy. It shows the combinations of Y and i that are compatible with equilibrium in the goods market, where i is the nominal interest rate and Y is home production. We can define the real interest rate as:

$$\rho = i - p_e, \tag{3.1}$$

where p_e represents expected inflation. This formulation is in line with the above assumption of predetermined prices and suggests an underlying assumption of nominal wage rigidity. Without delving deeper into price forming mechanisms we assume for simplicity that p_e is exogenous. This gives us the following formulation of the IS curve:

$$Y = C(Y, \rho) + I(\rho) + G + X(R, Y, Y_*). \tag{3.2}$$

C is consumption, depending on production Y and the real interest rate ρ; I is private investment; G is consumption and investment by the government; X is net exports, depending on the real exchange rate R, home production Y, and foreign production Y_*. The Mundell-Fleming framework also consists of a LM curve, describing the combinations of Y and i that are compatible with equilibrium in the money market. Due to the IS curve fully describing our interest in the goods market, we will make a standard assumption about the LM curve being a continuous and monotonously increasing function of i and Y. It will thus remain in the background of the Mundell-Fleming model we present.

With the theoretical model given by (3.1) and (3.2), Y and ρ are endogenous variables, while G and p_e are exogenous. In addition, since Y_* is given from the foreign economy, it is also exogenous. For simplicity, we assume that the real exchange rate, R, is a predetermined variable in the theoretical model. Thus the nominal variable i remains. For the UK, the nominal interest rate is set by the central bank and it therefore follows that i is set exogenously (Bank of England, 2021).

3.1.1 A real demand shock

An for our purposes important component demand function expressed in equation (3.2) is net exports. This is where trade enters into our IS equation as the difference between export and import. If we incorporate trade costs, denoted by τ, we can express the component demand function for net export as $X(R, Y, Y_*, \tau)$. Given the assumptions above, we can analyse the theoretical effect when the economy is subjected to an exogenous shock. One particular type of exogenous shock is a real demand shock to a component demand function that constitutes the IS curve. A real demand shock to such a function would, ceteris paribus, cause the IS curve to shift as a result of changing the equilibrium conditions in the goods market (Rødseth, 2000). With the interest rate set exogenously by the central bank, this exogenous shift necessarily manifests itself in the real economy by a change in aggregate demand, Y.

Turning to trade costs, they can be modeled exactly as such an exogenous shock to the IS curve. An increase in trade costs can be treated as a negative real demand shock. The net export component demand function, $X(R, Y, Y_*, \tau)$, is then hit by an exogenous reduction in foreign import demand, i.e. home's export supply. This would cause an inward shift of the IS curve and lead to a real contraction in domestic aggregate demand, Y.

3.1.2 A real effect with ambiguous consequences

That was in a simple theoretical model. In the real world however, the economy is more complex. First, the above result relies on exports being more affected by an increase in trade costs than imports, such that the net effect is negative, in order for the real contraction to occur. Second, there may be various automatic stabilizers in place to dampen the fluctuations in Y. Their effectiveness in stabilizing output can be questioned however. McKay and Reis (2016) use a new Keynesian model with nominal rigidities and find with US data that the stabilization of aggregate demand has a negligible effect on the dynamics of the business cycle. On the contrary, Dolls et al. (2012), finds a demand stabilization of up to 30% with EU data, but with large amount of heterogeneity both within the EU and compared to the US. Third, what has been implicitly assumed so far has been a Laissez-faire policy with little or no interventionism. The Bank of England however does not only use the interest rate as policy instrument. As is increasingly more common in the era of zero bank rates, its monetary policy also consists of digital open market operations in the form of quantitative easing (Bank of England, 2021). This would also serve to counter a decrease in aggregate demand and stabilize the IS curve.

Given this exposé of the Mundell-Fleming framework, there is theoretical support of the predicted effect of a negative real demand shock translating onto the real economy. However when incorporating elements from more complex models of the real world economy the effect might be mitigated by automatic stabilizers and active monetary policy. Furthermore, it is uncertain if the increase in trade costs affect imports and exports jointly or separately and to what degree. Hence, although the theoretical effect of an increase in trade costs could cause aggregate demand to fall, the empirical effect is uncertain. In order to quantify the medium-term effects an empirical model must be established, which will be done in chapter 5. In the next chapter, we first present how we have constructed time series for trade costs, using data for the UK economy and for three foreign economies: France, Italy and The Netherlands.

Chapter 4

The data set

All data is quarterly, except for the Structural Analysis Database (hereafter STAN) which is annual, but will be temporally disaggregated to the quarterly frequency (see appendix B). The sample period is 1989Q1-2017Q4. The data set consists of two subsets, one for the trade cost measures and one for the UK economy.

4.1 The trade cost measure

The data for the trade cost measure consists of two parts, the *intranational* trade data and the *bilateral* trade flow data. This is the numerator and denominator of equation (2.5) respectively. The trade flow data is taken from the IMF Direction of Trade Statistics (DOTS) and is denominated in US dollars. It presents the value of merchandise exports and imports disaggregated according to each country's primary trading partner (IMF, 2021). Since imports are reported on a cost, insurance and freight (CIF) basis and exports are reported on a free on board (FOB) basis, only export values have been used in the calculation of the bilateral trade flows. Since country A's imports from country B theoretically are country B's exports to country A, the trade flows could also have been calculated using the import and export data reported for a single country A, in relation to a country B. While preserving national reporting standards for import and export data, the confounding of CIF and FOB values was estimated to be more severe, which is why only export data was used. It would also have been a possibility to calculate a CIF/FOB ratio and adjust nationally reported values, but the downside of distorting the data was also in this case seen as greater than the potential benefit.

4.1.1 Intranational trade

Since intranational trade is a concept rather than a readily available variable, this measure has to be constructed. There are two main potential avenues used in the literature and the first one is to base the measure on GDP. The famous article by McCallum (1995) uses a gravity based regression model to infer the intranational trade flows with GDP as a regressor[1]. This approach was continued by Helliwell (1996, 1997, 2000), McCallum and Helliwell (1995), and Nitsch (2000). As shown by Helliwell, Schembri, et al. (2005) however, the use of GDP data tends to overstate the phenomenon of intranational trade. This is mainly due to the fact that GDP includes services. Services are not present in the IMF DOTS bilateral trade volumes, which only incorporates goods data. In fact, bilateral trade data for services seems to be parsimoniously scarce, if available at all. A natural explanation is of course that trade in services historically might not have constituted a large part of bilateral trade. With the advent of internet and globalization however, there is reason to believe that international trade in services has increased. In any case, the absence of services in the bilateral trade flows inflates the calculation of intranational trade. Moreover, a second problem with the use of GDP data is that it measures value added. Since exports are reported as merchandise value, the numerator and denominator in equation (2.5) will be measured in vitally different units. As an example, the GDP of the UK in 2017 was reported as $2,068,757$ millions GBP, while the value of their production as reported by the STAN archives was $3,564,472$ millions GBP, both reported as nominal values and including services. With a difference of approximately 70% this would serve as a counteracting agent and diminish the calculation of intranational trade. The net effect when using GDP (value added) together with bilateral trade flow data (total value) seems to be an undue inflation of intranational trade (Helliwell, Schembri, et al., 2005)[2].

The second approach is therefore to use the STAN archives database. The output of production data in the STAN database is defined as the value of goods and services (including knowledge capital products) produced in a year, whether sold or stocked (OECD, 2020). Moreover, with data on total services the STAN database facilitates the extraction of the total value (not value added) of goods produced. This allows for both intranational and bilateral trade to be measured in a collective unit. The approach was used by Wei (1996) and later by Novy (2013) and we therefore follow their method of calculating intranational trade as $y_i - x_i$, due to market clearing, where y_i is total income and x_i is total exports, both in nominal terms. Total exports are defined for country i as, $x_i \equiv \sum_{j \neq i} x_{ij}$, where x_{ij} are bilateral exports from country i to country j.

[1] McCallum looks at the border effect of US-Canada trade with states and provinces as data nodes. The terminology used by McCallum is therefore interstate trade, which is equivalent to the Anderson and Van Wincoop (2003) and Novy (2013) measure of intranational trade.

[2] Novy (2013) shows that with the use of his trade cost measure (equation (2.5)) the overstated effect when using GDP instead of STAN data corresponds to a drop from 97 and 35 percent to 61 and 24 percent for $\sigma = 5$ and $\sigma = 10$ respectively.

4.1.2 The elasticity of substitution

The final component of the trade cost measure is the exponent of the fraction of intranational and international trade, σ. This parameter represents the elasticity of substitution across goods. Since we assume an Armington world, where trade is motivated by love of variety, setting a high value of σ implies a high substitutability between home and foreign goods. Conversely by setting a low value of σ we would imply that the goods produced in the different countries are inherently very different. In the exposition of the trade cost measure however, Novy (2013) shows that his measure also can be derived from both a Ricardian and a Heterogeneous Firms model perspective. In these settings the equivalent parameters are ϑ and γ respectively. In the Heterogeneous Firms framework, γ is the shape parameter of the Pareto distribution, from which the productivity level of firms are drawn. In a Ricardian framework, ϑ also specifies the differences in productivity, but modeled with a Fréchet distribution instead (Novy, 2013).

As Novy (2013) points out, this implies that when setting the parameter value of σ, consideration should also be taken of the potential values of the Fréchet distribution parameter, ϑ, and the Pareto distribution parameter, γ. In a Ricardian framework, Eaton and Kortum (2002) estimates ϑ to be in the range of 3.6 to 12.9, depending on estimation methods and data used. Their 2SLS estimations yields values for ϑ of 3.6 and 12.9 for wage and price data respectively. In a more naive method-of-moments estimation they estimate ϑ to be 8.28. As for the pareto parameter, it is usually obtained by fitting a regression to the Pareto distribution and calculating the slope coefficient $\gamma/\sigma - 1$. This is done by Chaney (2008), Eaton et al. (2011), and Helpman et al. (2004) who obtain slope coefficient values of 2, 1.5 and 1 respectively. This lends some support to σ in fact being proportionally smaller than γ. Corcos et al. (2012) directly estimates γ and obtains estimates ranging from 1 to 3 depending on industry. For direct estimations of σ, Anderson and Van Wincoop (2003) initially uses a value of 5, then later (Anderson & Van Wincoop, 2004) probes further into possible values for σ and finds a possible range of 5 to 10. In sensitivity analyses however, Anderson and Van Wincoop (2003) finds that the elasticity of substitution plays a very small role for their results, which turn out close to unchanged for different elasticities[3]. This is in line with the sensitivity analysis of Novy (2013), who also finds the overall results not being sensitive. We therefore follow Anderson and Van Wincoop (2004) and Novy (2013) in setting $\sigma = 8$.

[3]In section 5, table 6, they analyse the sensitivity of the impact of borders on trade and the McCallum border parameter for elasticities of 5 and 10. They find that while having no impact on the nonlinear estimator itself, the different values somewhat affects the equilibrium values of when no border is present. Moreover, although not reported, they find that the insensitivity remains even for elasticities of 2 and 20.

4.1.3 Bilateral trading partners

The trade cost measure requires a bilateral trading partner to be specified. In selecting a potential trading partner for the UK, there were mainly two criteria that needed to be met. First, data needed to be available. While the IMF DOTS database offers bilateral trade data for most European countries from 1970 onward, the production and services data from the STAN database is much more restrictive. Although offered in at least five different editions and revisions[4], these are not easily aggregated to a complete time series, due to successive changes in estimation methods and reporting standards (OECD, 2020). The value of maintaining the empirical integrity of the data was thus seen as more important than extending the time series and potentially introduce unnecessary bias into the trade cost measure due to measurement errors.

Thus for the UK the STAN database has annual data points as far back as 1970, but since we need to subtract total services to calculate intranational trade, total services also has to be available. For the UK they are reported from 1989 to 2017, which motivates the entire temporal time frame. Thus any potential trading partner also has to match this time frame, both in total production and in total services. This directly excluded a number of otherwise interesting potential trading partners such as Ireland, Belgium, Germany, Spain and Switzerland who all qualify as being in the top ten seen to percentage share of total UK exports (Pritchard, 2020). Second, due to the scope and limitations of this thesis, not all countries for which there was data available could be included. Thus the chosen countries had to be relevant enough in terms of percentage share of UK exports. Following these criteria three countries emerged as potential trading partners. These were France, The Netherlands and Italy. We collected data and constructed the trade cost measure for all three countries.

Figure 4.1 shows the calculated trade cost measures with France, Italy and The Netherlands as bilateral trading partners. There is clear seasonal variation in the data, most notably for France and Italy, this will be accounted for in chapter 5 when specifying the model equations. At a first glance, the trade cost measure appears to report unseemly high values, since the interpretation is a tariff equivalent. Remembering however that the trade cost measure is an implicit measure of trade costs, it encapsulates all costs associated with trade in the goods market. An observation that can be made is that there

[4]In terms of total production for the UK, STAN 2005 ed. covers 1970-2003, SNA93 ISIC Rev. 3 and 4 covers 1970-2007, SNA08 ISIC Rev. 4 covers 1970-2016 and finally STAN 2020 ed. covers 1970-2017. The data availability issue however stems from that common for all 5 editions is that total services is only available from 1989 onward.

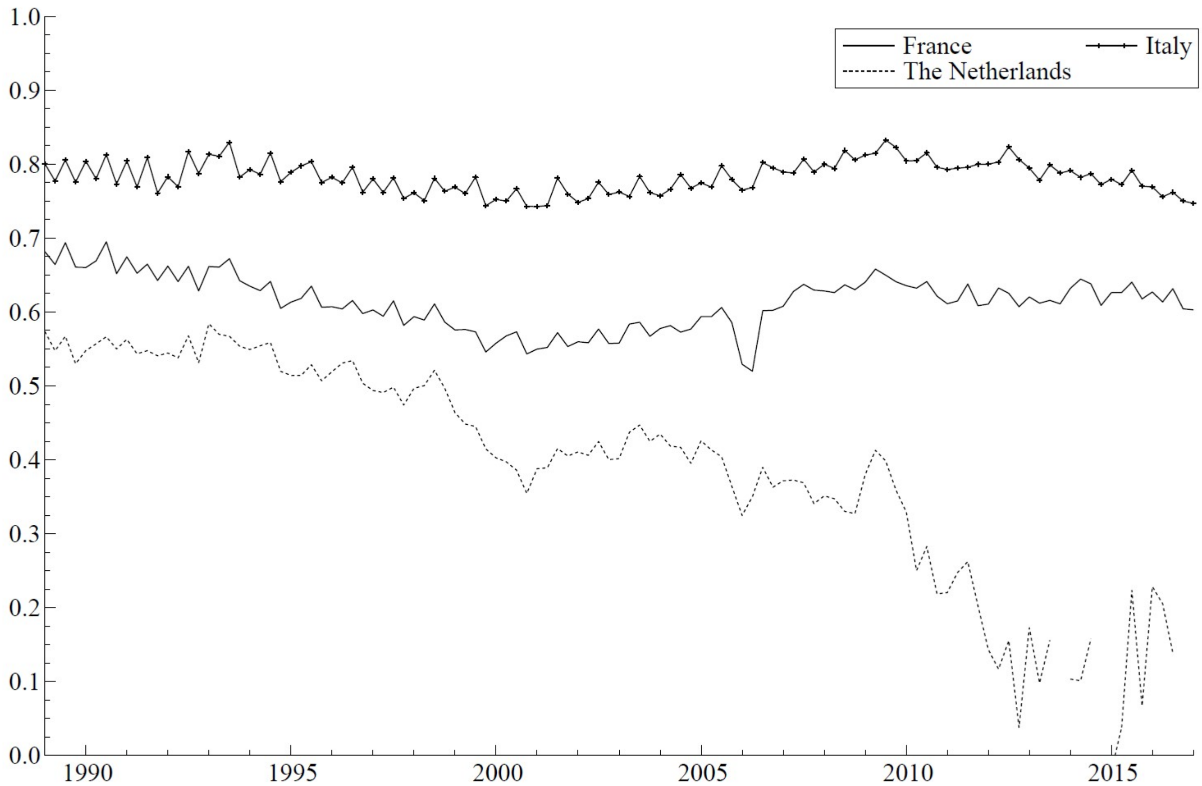


Figure 4.1: The trade cost measure with France, Italy and The Netherlands from 1989Q1 - 2017Q4, expressed as a tariff equivalent.

seems to be an ordering based on geographical distance, such that Italy which is the furthest from the UK has the highest bilateral trade costs. Another observation that can be made is that in 2017 the trade cost measure differs approximately 40 percentage points for bilateral trade with France compared to trade with The Netherlands. At the same time the total amount of bilateral trade with each of the two countries in 2017 only differed approximately 5% (Pritchard, 2020). Seen together, these two observations suggest that the deciding factor of bilateral trade costs is not the amount of bilateral trade, but one or several other factors. The observation also lends some support for geographical distance having a significant impact on bilateral trade costs. Another deciding factor might be that countries with a high trade-to-GDP ratio in general have lower trade costs. By calculating the preferable trade-to-production ratio (since both factors are measured in the common unit total value, not value added) using the STAN database, the ratio for France in 2017 was 0.92 while for The Netherlands 2.29 (IMF, 2021; OECD, 2020).

As can be seen in figure 4.1 the high trade-to-production ratio for The Netherlands causes some problems when calculating Novy's trade cost measure. Specifically, the calculation of intranational trade becomes negative for countries which have a high value of exports in relation to their total value of production. A negative value for intranational trade means that the fraction in equation (2.5) becomes negative for all positive values of production, which means the root is not defined. This is an inherent weakness of the trade cost measure developed by Novy (2013), in that it is less robust to countries with high trade-to-production ratios. In order to secure efficient estimations in the empirical modeling in chapter 5, we therefore limit the number of observations to 90 for The Netherlands, which confines its temporal perspective to 1989Q1 - 2011Q4.

As a last remark on the data for the trade cost measure, the issue of currency denomination needs to be addressed. For the four countries that are the UK, France, The Netherlands and Italy the IMF DOTS database reports the bilateral trade data in US dollars such that for our purposes there is no conversion needed. As for the STAN data however, it is reported in national currency. Given the temporal time frame of 1989-2017, this might introduce some confusion in terms of currency conversion for the bilateral trading partners France, The Netherlands and Italy, who all switched to euro on 1 Jan 1999. For all three countries, the STAN database reports their data in euro. Since both France and The Netherlands had their national currencies pegged to the European Currency Unit (hereafter ECU) via the European Exchange Rate Mechanism (hereafter ERM) during the whole duration of 1989 until their euro accession in 1999, their data should be free from measurement errors. Italy however, while having their lira also pegged to the ECU via ERM from 1979 onward, withdrew from ERM in September 1992 as a result of the exchange rate crisis (Preda, 2017).

Since the application of euro currency to the STAN database is done in the standard way of using the exchange rates at the date of accession[5], this will to a lesser extent take into account any exchange rate fluctuations for Italy in the period of 1992 to 1999, since they were outside the ERM. This might introduce some measurement errors in the data for Italy. Moreover, since the euro currency was not introduced until 1999 and we want to express all monetary values in US dollars, theoretical exchange rates estimated by the ECB had to be used[6]. While well founded theoretical estimations are used by the ECB, this historical euro currency estimation might also introduce some amount of measurement error in the data for all countries.

[5]The fixed exchange rates were in terms of national currency per euro equal to 1,936 lira, 6,55 franc and 2,20 gilder (ECB, 2021)

[6]The theoretical historical exchange rates uses a basket of currencies of the founding euro area members. The weights are based on the share of each euro area country in the total manufacturing trade of the euro area vis-à-vis non-euro area countries(Schmitz et al., 2013).

4.2 Data for the UK economy

With a few exceptions, all data for the UK is collected from the quarterly national accounts data set from the office for national statistics (hereafter ONS), the official statistical authority of the UK. It is collected and expressed in seasonally adjusted, real terms of its national currency GBP with 2018 as reference year. The exceptions are interest rate, exchange rate and consumer price indices (hereafter CPI), which due to availability issues had to be found from other sources specified in section 4.2.2.

4.2.1 Quarterly national accounts data

The production of the UK economy, Y, will be represented by GDP, as is practice in the growth literature (Acemoglu, 2012; Aghion & Howitt, 1990; Barro, 1991; Barro et al., 2003; Solow, 1956; Vollrath & Jones, 2013). Although Kohli (2004) finds that improvements in terms of trade (specifically, a decrease in import prices) can be misinterpreted as a GDP inflationary effect when using the standard GDP deflator, we abstract from any unconventional deflations of GDP and proceed with a chained volume measure with an implied deflator. The remaining variables in this data set are also deflated as chained volume measures. Investment is represented by gross fixed capital formation; total exports and total imports concerns goods and services.

4.2.2 Other data sources

The first "other data" source is the OECD, from which the CPI measures were collected. CPI was needed for calculating the real interest rate and the real exchange rate. The second source of other data was the Bank of England, from which the nominal interest rate and the nominal exchange rate were collected. Since we are interested in medium-term dynamics, the short interest rate is used and it is represented as the immediate interbank rate (not to be confused with the bank rate) in per cent per annum. The nominal exchange rate is expressed as the average spot exchange rate. Any exchange rates expressed will throughout this paper be denoted as domestic currency per foreign currency. An appreciation thus corresponds to the value of domestic currency, GBP, increasing in relation to the foreign currency, EUR. This implies that an appreciation corresponds to the real exchange rate, R, decreasing and vice versa for a depreciation.

Chapter 5

Single equation modelling of the empirical relationship between trade costs and UK exports and imports

Having presented the data we now turn to the empirical modeling. While the relationship between trade costs and the GDP of UK is of ultimate interest, the conceptual framework in chapter 3 showed that export and import can be the main channels through which trade costs affect aggregate demand. This was illustrated with the component demand function of net export, which is export minus import. This chapter will therefore be an empirical investigation of the relationship between trade costs and trade, as represented by export and import. We first outline an autoregressive model framework which we will use throughout this chapter. We then analyze export and import separately when estimated with the trade cost measure. We conclude the chapter with instrumental variable estimations for both export and import. With reference to table A.1 in the appendix, all variables have been tested for unit roots and are under the null hypothesis believed to be $I(1)$ processes at a 1% level of significance. All variables have been log-transformed, except for ρ due to negative real interest rates. This facilitates an elasticity interpretation of marginal effects. Log-transformed variables are denoted by lower-case letters, such that for example log of exports (Z^*) is z^*. Variables which have been transformed into first differences are denoted by the difference operator (Δ).

5.1 Autoregressive model equations for exports and imports

The modeling of export and import will apply the Autoregressive Distributed Lag model framework (referred to as ADL models hereafter). One advantage with ADL modeling that we will make use of is its reparameterization into Equilibrium Correction Model (hereafter ECM) form. This will allow us to investigate and study potential cointegrating relationships and the speeds of adjustment back to equilibrium. While the same type of model equation is used for both export and import, the set of control variables is different for export and import. The specified regression models contains one predetermined variable and three regressors. The autoregressive variable is predetermined in the sense that it is assumed to be uncorrelated with future disturbances, but not past ones. Initially *weak exogeneity* is assumed for the explanatory variables. This means we will achieve efficient parameter estimation by conditioning on them. Lastly, the error terms are assumed to be white noise processes and satisfy the Gauss-Markov assumptions.

Under the given assumptions the OLS estimator is BLUE[1]. In addition, the OLS estimator will be a consistent estimator, where the consistency property only holds as long as the error terms are not autocorrelated. Given that our model equations are of the ADL type however, all $I(1)$ variables in our model equations will in addition need to be cointegrated for the OLS estimator to be consistent. The OLS estimator is also subjected to finite sample bias, but given the sample sizes of 90-114 observations the samples should be large enough to make estimation, testing and interpretation of results meaningful. Thus the conditional ADL model equation is given by:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \sum_{j=1}^{3} \sum_{i=0}^{1} \beta_{ji} x_{j(t-i)} + \epsilon_t, \tag{5.1}$$

where the disturbances are assumed to satisfy:

$$E(\epsilon_t \mid x_{j(t)}, x_{j(t-1)}, y_{(t-1)}) = 0, \quad j = 1, 2, 3. \tag{5.2}$$

Out of the three regressors, the trade cost measure will be one, together with two other control variables.

Before proceeding to the empirical estimations for the export and import functions, the issue of misspecification needs to be addressed. In order to discern any signs of the

[1]The Best Linear Unbiased Estimator is best in the sense that it is the asymptotically most efficient and thus minimizes the sum of squared residuals.

assumptions we have made thus far about the estimator and the error terms being violated, a series of standard diagnostic tests will be used. These are in the following sections provided at the end of each table. First, a joint significance test is reported to check the null hypothesis of the coefficient of determination being equal to zero. Second, the perhaps most important AR 1-5 test is the F-form test for residual autocorrelation suggested by Harvey (1990). The "ARCH", "Hetero" and "Hetero-X" tests are diagnostic tests for heteroscedasticity. "ARCH" is the test by Engle (1982) for autoregressive conditional heteroscedasticity (hereafter ARCH); "Hetero" is the test by White (1980) when using squared residuals; "Hetero-X" is also the test by White (1980) using cross-products in addition to squares and is only reported when there are a large number of observations in relation to the number of variables in the regression. "Normality" tests the skewness and kurtosis of the residuals as suggested by Doornik and Hansen (1994). Finally, "RESET" is the test by Ramsey (1969) for functional form misspecification.

Regarding the RESET test, its importance when using dynamic model equations can be put into question. Specifically, when reparametrizing models (which we will do to a large extent, see section 5.2.1) the RESET test can give different results despite the fact that no intrinsic change has been made. It will therefore remain comparatively in the background throughout this chapter. We next proceed with the empirical estimations for the export function.

5.2 The export function and trade costs

The control variables used for estimating exports are the real exchange rate, denoted by r, and foreign GDP, denoted by y^*. The standard theoretical assumption is that a depreciation in GBP (measured as an increase in r) affects exports positively. A positive coefficient is also to be expected for foreign GDP which increases demand for home's exports.

Table 5.1 reports six model equations, (1)-(6), two where foreign is represented by France, two where foreign is represented by The Netherlands and two where foreign is represented by Italy. Each column reports a model equation of the form

$$\Delta z_t^* = \phi_0 + \phi_1 \Delta z_{t-1}^* + \beta_{10}\Delta\tau_t^m + \beta_{11}\Delta\tau_{t-1}^m + \beta_{20}\Delta y_t^m + \beta_{21}\Delta y_{t-1}^m + \beta_{30}\Delta r_t + \beta_{31}\Delta r_{t-1} + \epsilon_t, \tag{5.3}$$

as implied by the model equation (5.1). z_t^* is UK exports in GBP; $\tau_t^m \in [0,1]\ \forall t$ is the trade cost measure where foreign is represented by $m \in \{France,\ The\,Netherlands,\ Italy\}$,

	Dependent Variable: Δz_t^*					
	m = *France*		m = *The Ne.*		m = *Italy*	
(x_t)	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{z}^*_{t-1}$	-0.29^{***}	-0.25^{**}	-0.04	-0.01	-0.21^{**}	-0.23^{**}
	(0.10)	(0.10)	(0.08)	(0.10)	(0.10)	(0.11)
$\Delta\hat{\tau}^m_t$	-0.65^{***}	-0.66^{***}	-0.17^{**}	-0.17^{**}	-0.69^{**}	-0.82^{**}
	(0.11)	(0.11)	(0.07)	(0.08)	(0.29)	(0.31)
$\Delta\hat{\tau}^m_{t-1}$	-0.25^{***}	-0.19^{**}	-0.10	-0.09	-0.53^{**}	-0.54^{**}
	(0.08)	(0.08)	(0.07)	(0.09)	(0.23)	(0.23)
$\Delta\hat{y}^m_t$	1.33^{**}	1.50^{***}	1.40^{***}	1.39^{***}	-0.46^{**}	0.55
	(0.62)	(0.61)	(0.45)	(0.47)	(0.44)	(0.47)
$\Delta\hat{y}^m_{t-1}$	0.58	0.64	-0.62	-0.63	0.75^{**}	0.62
	(0.47)	(0.44)	(0.55)	(0.61)	(0.33)	(0.40)
$\Delta\hat{r}^m_t$	0.03	0.06	0.17	0.17	0.07	0.10
	(0.09)	(0.08)	(0.12)	(0.11)	(0.10)	(0.09)
$\Delta\hat{r}^m_{t-1}$	-0.06	-0.12	-0.17^{*}	-0.17^{*}	-0.12	-0.19^{*}
	(0.08)	(0.09)	(0.09)	(0.10)	(0.08)	(0.10)
$\hat{z}^*_{t-1}$		-0.12		-0.06		-0.04
		(0.05)		(0.09)		(0.02)
$\hat{\tau}_{t-1}$		-0.13		0.00		-0.19
		(0.05)		(0.03)		(0.12)
$\hat{y}^m_{t-1}$		0.27		0.09		0.18
		(0.12)		(0.16)		(0.08)
$\hat{r}_{t-1}$		0.06		0.00		0.08
		(0.02)		(0.02)		(0.03)
ESTIMATION METHOD	OLS	OLS	OLS	OLS	OLS	OLS
OBSERVATIONS	114	114	90	90	114	114
$\overline{R}^2$	0.45	0.47	0.31	0.30	0.18	0.20
JOINT SIGNIF. TEST, $F =$	10.3^{**}	8.24^{**}	4.95^{**}	3.78^{**}	3.53^{**}	3.06^{**}
AR 1-5 TEST, $F =$	0.95	0.70	0.68	0.60	0.57	0.84
ARCH 1-4 TEST, $F =$	1.50	1.15	1.45	1.77	5.21^{**}	5.15^{**}
NORMALITY TEST, $\chi^2 =$	5.12	6.06^{*}	7.98^{*}	6.61^{*}	28.4^{**}	24.9^{**}
HETERO. TEST, $F =$	2.12^{*}	1.80^{*}	0.76	2.48^{**}	0.64	0.84
HETERO-X TEST, $F =$	1.67^{*}	1.28	2.53^{**}		1.38	2.41^{**}
RESET TEST, $F =$	2.23	2.93	0.68	1.11	0.76	0.24

Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Variables in first differences are tested against the critical values of student's t-distribution. Variables in levels are tested against the critical values of the ADF distribution, where for four $I(1)$ variables and a constant term 10% = 3.44; 5% = 3.76; 1% = 4.36. Seasonal variables and constant not reported. Estimated robust standard errors are reported in parenthesis below the coefficients. Standard misspecification tests are reported at the end of the table.

Table 5.1: Estimated export functions with trade costs.

expressed as a tariff equivalent; y_t^m is GDP for foreign country m; r_t is the real exchange rate between GBP and EUR expressed as GBP/EUR.

The first columns for each trading partner, (1), (3) and (5), are model equations estimated in direct accordance with equation (5.3). We see that the estimated coefficient for the trade cost measure, $\Delta\tau_t$, is statistically significant with all three countries at a 5% level of significance. The column labelled France contains coefficients that are significant at a 1% level of significance for both $\Delta\tau_t$ and $\Delta\tau_{t-1}$. Of considerable importance is also that the coefficients for $\Delta\tau_t$ and its first lag are estimated with the expected sign with all three countries, suggesting that an increase in trade costs has a negative impact on exports.

The model equations with France and Italy as 'foreign', (1) and (5), both show estimated elasticities of approximately 0.65 for contemporary marginal effects. This means that a 1% increase in the first differences of the trade cost measure would imply a 0.65% decrease in the first differences of exports. The adjusted coefficient of determination is in the range 0.18-0.45, which is considered reasonable in order to make the estimations relevant. Additional support for the explanatory power of the regressors is given by the F-test of joint significance, which rejects the null hypothesis of all regression coefficients being zero for all model equations. Most importantly however, all the model equations show no signs of residual autocorrelation. Specifically for dynamic model equations and time series data, autocorrelation often poses a looming threat to internal validity (see Keele and Kelly (2006) for an interesting analysis of the coefficient bias using Monte Carlo simulations). Since Harvey's F-form test for residual autocorrelation (Harvey, 1990) is insignificant for all the estimated model equations (shown as AR 1-5 test), this lends support to the coefficient estimator being consistent[2].

There are however some indications that our equations do not represent a close approximation to the true underlying data generating process (hereafter DGP). With all countries there is evidence of some form of heteroscedasticity, which compromises the estimated standard errors, although arguments can be made that the use of robust standard errors remedies this to some extent. The signs of the disturbances not adhering to the normal distribution are less concerning. Their estimation will be biased to some degree but also consistent and therefore approximately correct when estimated in large samples. The ARCH test with Italy is perhaps the most problematic since it suggests there might be an element of time dependence for the variance of the disturbances. Overall, the misspecification tests entail that the statistical significance of the coefficients should be interpreted with some care.

Keeping in mind that all level variables are assumed to be $I(1)$ processes, the model equations in (1), (3) and (5) can only be used to assess short-run effects and not dynamic multipliers or potential long-run relationships. We therefore turn to columns (2), (4) and (6) in table 5.1, which are models of the ADL type in equation (5.3) with additional lags of all regressors in levels (not first differences). There are many positive results from these ECM models. First, they suggest that there might be a cointegrated relationship, which will be discussed shortly, allowing us to study the relationship between trade costs and the

[2] The case of residual autocorrelation is not straight forward to resolve as illustrated by Mizon (1995) who shows that many potential corrections have limited effectiveness.

export function (in levels). The indication of this is the estimated coefficient of z^*_{t-1} which is negative and therefore might act as error correcting. Second, the coefficients for trade costs are estimated with the expected sign for all countries, both in first differences and in levels. Third, the misspecification seems to be less of a problem with most countries.

The issue of heteroscedasticity is reduced with France and traded for a slightly higher F-statistic with regards to non-normality, which is deemed a feasible improvement. The estimation with The Netherlands is in all essence similar, but exhibit minor amelioration with regards to normality. The estimation in column (6) with Italy show no signs of improvement however, since when estimated with squares and cross-products of the original regressors, the squared error terms exhibit signs of heteroscedasticity which was not present in (5). What will be of ultimate interest however, is the adjustment coefficient and its stability. We therefore now turn to the ECM interpretation of the model equations with lagged level variables included.

5.2.1 Testing for cointegration and estimation of long-term relationships

As mentioned above, the ADL model equation (5.1) can reparametrized into ECM form. For clarity of exposition we present the general ECM model equation with only one regressor. The interpretation is the same as with more regressors and the extension is straight forward. The reparameterization is done by subtracting y_{t-1} on both sides of equation (5.1) and adding and subtracting the product of the lagged regressor with its coefficient, $\beta_0 x_{t-1}$, on the RHS. The result is the ECM model equation below.

$$\Delta y_t = \phi_0 + \beta_0 \Delta x_t + (\phi_1 - 1)\left(y_{t-1} - \frac{(\beta_0 + \beta_1)}{(1-\phi_1)} x_{t-1}\right) + \epsilon_t \tag{5.4}$$

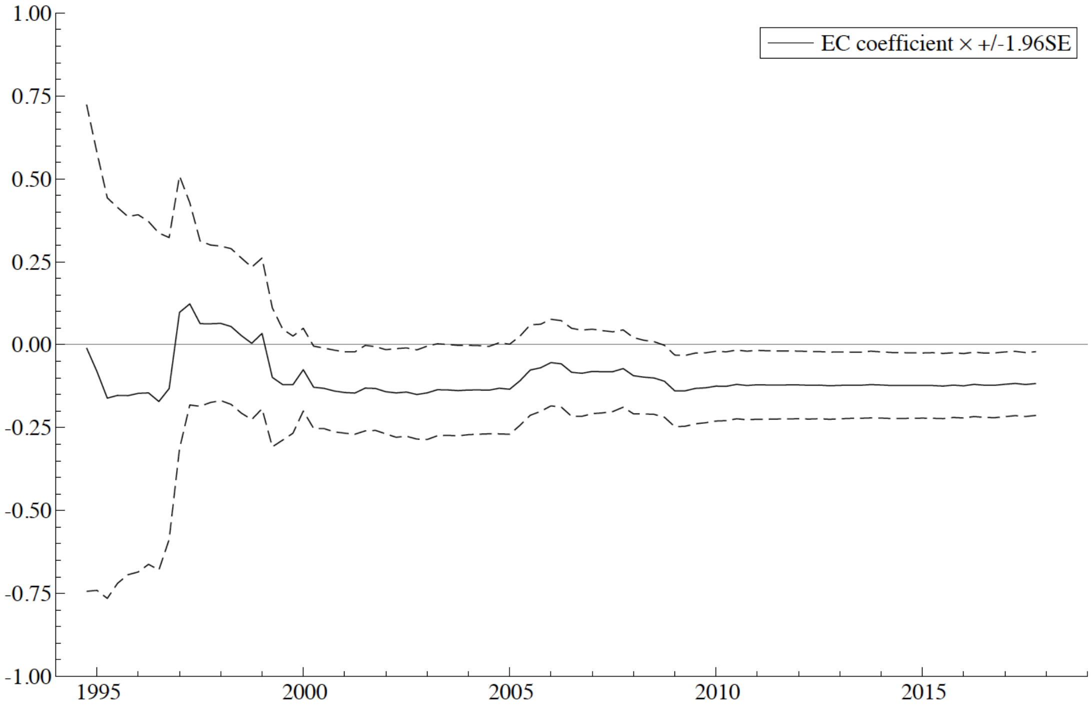
Expressed in this way, an economic interpretation would be that the data on Δy_t in general represents deviations from a *steady state*. These deviations can then in part be explained by the expression inside the parenthesis. The condition for this to be the case is that there exists a linear combination of y_t and x_t which is $I(0)$. If it does, y_t and x_t are assumed to share the same stochastic trend. The ECM test for cointegration thus relies upon the coefficient of this linear combination, $\phi_1 - 1$, being significantly different from 0. It is aptly called the equilibrium correction (hereafter EC) coefficient and is tested against the augmented Dickey-Fuller distribution (hereafter ADF), as described by Ericsson and MacKinnon (2002).

The ECM test is preferred over the Engle-Granger test for cointegration because it has been shown to have higher power (Kremers et al., 1992). This means the rejection frequencies of the null hypothesis of no cointegration when it is wrong, are increased (or similarly, a reduction in type-II error probability). Interestingly enough the t-values are estimated to be 2 and 2.4 for Italy and France respectively. While this does not formally qualify as a rejection of the null hypothesis of no cointegration being present, the estimated adjustment coefficient is numerically quite high when France's GDP is used which in itself is in support of a long-run relationship. The critical values according to table 3 in the article by Ericsson and MacKinnon (2002), with four $I(1)$ variables and a constant term, are 3.44 and 3.76 for a 10% and 5% level of significance respectively. Thus some weak support is being lent for the existence of a linear combination working as an equilibrium correcting variable. As previously established, the null hypothesis of no cointegration stipulates that the EC coefficient, $(\phi_1 - 1)$, cannot be significantly different from 0. Continuing this argument, $(\phi_1 - 1)$ should also not be significantly different from 0 as the sample size increases. On the contrary the EC coefficient should approach 0 as $t \longrightarrow \infty$. Thus in order to further investigate the possibility of a cointegrating relationship, we can examine the estimated parameter stability.

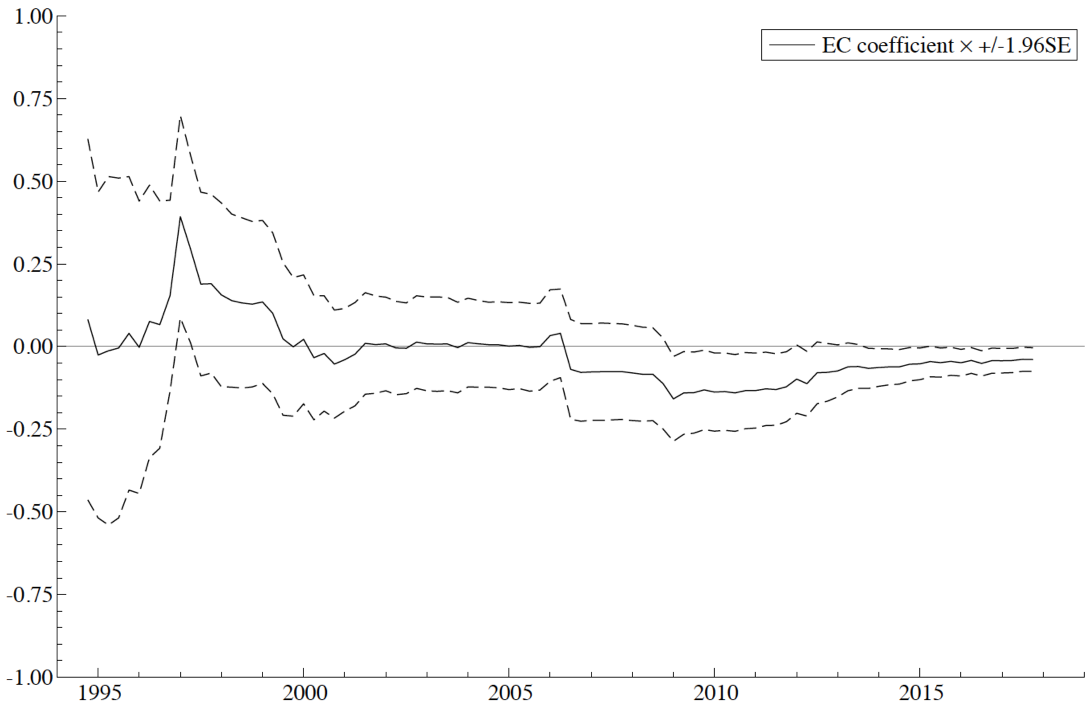
Figure 5.1 shows recursive estimations of the EC coefficient, the coefficient of z^*_{t-1}, for different sample lengths. Since the estimated export model equations with 'foreign' represented by The Netherlands show no evidence of cointegration, we focus on Italy and France. Figure 5.1 lends informal support for the existence of a cointegrating relationship with both countries. With France, figure 5.1a shows clear signs of parameter stability. With Italy there is a tendency for parameter stability as well, although the estimated adjustment coefficient is smaller in absolute value. This means that the support for equilibrium correction is stronger when estimated with France not only due to recursive stability, but also due to the larger estimated magnitude of the EC coefficient which signifies a higher speed of adjustment to the new potential equilibrium (or equivalently, steady state).

Under the assumption of cointegrating relationships it is possible to examine the long-term effects. Returning to equation (5.4), we can calculate the expected values. Given that the variables are $I(1)$ processes and that the error term is white noise they both have an expected value of zero. The long-term effects for trade costs on exports can thus be calculated as

$$z^*_t = \frac{\phi_0}{(\phi_1 - 1)} + \frac{\beta_0 + \beta_1}{(\phi_1 - 1)}\tau^m_t + \frac{\beta_2 + \beta_3}{(\phi_1 - 1)}y^m_t + \frac{\beta_4 + \beta_5}{(\phi_1 - 1)}r_t, \tag{5.5}$$



(a) France



(b) Italy

Figure 5.1: Recursive estimations of the equilibrium correcting coefficient, the coefficient of z_{t-1}^*

where additional coefficients have been added in form of $\beta_2, \beta_3, \beta_4$ and β_5 to extend equation (5.4) to multiple regressors. The long-term effect of trade costs on export when estimated with France as 'foreign' yields

$$z_t^* = \left(\frac{0.10}{0.12}\right) + \left(\frac{-0.13}{0.12}\right)\tau_t^{fr} + \left(\frac{0.27}{0.12}\right)y_t^{fr} + \left(\frac{0.06}{0.12}\right)r_t \tag{5.6}$$

$$z_t^* = (0.83) - (1.08)\tau_t^{fr} + (2.25)y_t^{fr} + (0.50)r_t, \tag{5.7}$$

and with Italy as foreign,

$$z_t^* = \left(\frac{-0.40}{0.04}\right) + \left(\frac{-0.19}{0.04}\right)\tau_t^{it} + \left(\frac{0.18}{0.04}\right)y_t^{it} + \left(\frac{0.08}{0.04}\right)r_t \tag{5.8}$$

$$z_t^* = -(10.0) - (4.75)\tau_t^{it} + (4.50)y_t^{it} + (2.00)r_t. \tag{5.9}$$

When the foreign economy is represented by France the long-term effect on export after several periods of dynamic adjustment ends up being -1.08% for every 1% increase in trade costs. When foreign is represented by Italy the long-term effect is -4.75% for every 1% increase in trade costs. The sizeable discrepancy can largely be explained by the smaller EC coefficient with Italy, since the cointegration coefficients for trade costs both are estimated to be of similar size (-0.13 and -0.19). The smaller EC coefficient implies that equilibrium correction is slower and therefore ultimately the long-term impact ends up being larger. On the contrary however, the long-term impact relies on a cointegrated relationship which in turn is reliant upon the EC coefficient being large enough to be statistically significant. So while estimations with Italy show large potential long-run effects, the existence of the long-run relationship itself is more uncertain.

In summary, there is some support for a long-term negative effect on exports by increased trade costs when modeled with both countries. An important aspect however is that these estimations only represent parts of the export market for the UK. This means that we cannot expect a cointegrated relationship between export and trade costs in general, unless the export markets themselves are cointegrated. Formulated analogously, the export markets y_t^m, $m \in \{France, The\,Netherlands, Italy\}$, will have to be cointegrated in order to make broader inferences about the long-term relationship between UK export and trade costs.

5.2.2 Tests of weak and strong exogeneity

In the beginning of this chapter (section 5.1) it was stipulated that weak exogeneity was assumed for all regressors, in order to achieve efficient estimations. This can be tested formally with the Durbin-Wu-Hausman (hereafter DWH) test for endogeneity (Durbin, 1954; Hausman, 1978; Wu, 1973). The concept of weak exogeneity is most easily defined from a system model perspective, where the marginal model equation can be abstracted from without any loss of information when estimating the conditional model equation. From a single equation model perspective we can interpret this as when conditioning upon our variable of interest, the trade cost measure, no information is being foregone by not considering the process where the variable is being generated (Nymoen, 2019). Table 5.2 below shows the estimation results for the DWH tests of weak exogeneity with France and Italy.

The first two columns with each country, columns (1)-(2) and (5)-(6), represent two marginal model equations for the trade cost measure, where 'foreign' is France and Italy respectively. The first set of marginal models, (1) and (5), are limited to first order dynamics and are given by

$$\Delta\tau_t^m = \Delta z_{t-1}^* + \Delta\tau_{t-1}^m + \Delta y_{t-1}^m + \Delta r_{t-1} + \Delta z_{t-1} + \Delta\rho_{t-1} + \Delta i_{t-1} + \epsilon_t, \tag{5.10}$$

where new variables are z_{t-1}, which is total UK import; ρ_{t-1}, which is the real interest rate for the UK and i_{t-1} which is total investment for the UK. Since these variables are not included in the conditional model equations for z_{t-1}^*, it is implied that their exclusion represents a valid restriction of the conditional model. The second set of marginal models, (2) and (6), adds second order dynamics in order to test robustness. Columns (3)-(4) and (7)-(8) represent the same type of ECM model equations as in table 5.1, but since the suspected endogenous variable is being conditioned we will in the context of exogeneity refer to them as conditional model equations. In (3)-(4) and (7)-(8) the residuals from each of the two marginal model equations have therefore been added to the conditional models. $\epsilon_t^{marginal(1,5)}$ are the residuals from the marginal models (1) and (5). $\epsilon_t^{marginal(2,6)}$ are the residuals from the marginal models (2) and (6). According to the DWH test a regressor is exhibiting weak exogeneity if the residuals from its marginal model equation do not have explanatory power in the conditional model equation where it is being estimated.

With regards to misspecification, the marginal models with first order dynamics in table 5.2 appear to be subjected to mild forms of residual autocorrelation. In addition there are signs of the residuals exhibiting heteroscedasticity and non-normality (only with France as foreign). This is compromising both for the white noise assumption and for the DWH test, since it relies specifically on the marginal model equation's residuals. Since residual autocorrelation is one of the more acute forms of misspecification (particularly for the DWH test), second order dynamics was added for some of the variables. For France, the second order dynamics of $\Delta\rho$ induced other technical problems and was therefore left out. While this restriction might generate omitted variable bias, depending on the correlation with the other regressors (particularly investment), not excluding it was deemed to be more detrimental for the model. This indicates that there might be issues with robustness for the marginal model equations.

Overall however, the inclusion of second order dynamics in the second set of marginal model equations generated the expected result. Residual autocorrelation in (2) and (6) diminished and can no longer be shown to be significant. With France as 'foreign', some heteroscedasticity and non-normality remains which should be kept in mind when evaluating the test statistic. With Italy as 'foreign' however, the marginal model (6) appears to be well specified and the misspecification tests give us no direct reason to mistrust the residuals. When tested in the conditional model equations neither the residuals from the first set of marginal models, nor the residuals from the second set of marginal models can be shown to be statistically significant at a 10% level of significance. According to the DWH test, this lends support to the assumption that the trade cost measure can be regarded as weakly exogenous. With France as 'foreign' the estimated coefficient for $\epsilon_t^{marginal(2,6)}$ in (4) is quite large. The weak exogeneity result should therefore not be treated as particularly robust. The conditional model with Italy as foreign is as mentioned before subjected to heteroscedasticity which to some extent undermines the reliability of the DWH test result. This is observable in the relatively large estimated standard error of 0.56 in (8), which with an improved specification could make the residuals significant given their also relatively large coefficient of 0.49.

Given that the trade cost measure contains production data, it is not unreasonable to question the direction of causality when estimated with export, which to some extent is expected to be correlated with production. Of further interest is therefore the concept of *strong exogeneity*, meaning the absence of Granger causality, or more specifically that τ_t^m is not Granger caused by z_t^*. This is tested by including the lag of export, Δz_{t-1}^*, in the marginal models for trade costs, (1), (2), (5) and (6). Judging from the marginal models with second order dynamics, (2) and (6), Δz_{t-1}^* is not significant when estimated with France as 'foreign'. This is support for τ_t^m exhibiting strong exogeneity in the conditional models (or similarly the ECM model equations in table 5.1). With Italy as foreign however the null hypothesis is rejected at a 5% level of significance, which should be seen as a quite reliable test statistic given the absence of misspecification. With France as foreign the estimated coefficient of -0.04 is low. Although there are reasons for not relying too much on inference due to heteroscedasticity and non-normality in the estimated standard errors with France as foreign, they would have to be reduced from 0.11 to approximately 0.02 in order to reject the null hypothesis of no strong exogeneity.

	m = France				*m = Italy*			
	Dependent Variable:				*Dependent Variable:*			
	$\Delta\tau_t^m$		Δz_t^*		$\Delta\tau_t^m$		Δz_t^*	
(x_t)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\hat{z}^*_{t-1}$	-0.01	-0.04	-0.28^{***}	-0.27^{**}	-0.06	-0.09^{**}	-0.26^{**}	-0.25^{**}
	(0.10)	(0.11)	(0.11)	(0.10)	(0.04)	(0.04)	(0.11)	(0.11)
$\Delta\hat{\tau}^m_{t-1}$	-0.16^{**}	-0.15^{*}	-0.27^{**}	-0.24^{**}	-0.44^{***}	-0.37^{***}	-0.81^{**}	-0.73^{*}
	(0.08)	(0.08)	(0.10)	(0.09)	(0.11)	(0.10)	(0.35)	(0.39)
$\Delta\hat{y}^m_{t-1}$	0.13	-0.39	0.49	0.49	0.02	-0.08	0.52	0.53
	(0.63)	(0.63)	(0.45)	(0.46)	(0.24)	(0.25)	(0.42)	(0.46)
$\Delta\hat{r}_{t-1}$	0.06	0.07	-0.08	-0.09	0.01	-0.02	-0.18^{*}	-0.18^{*}
	(0.06)	(0.06)	(0.09)	(0.09)	(0.04)	(0.04)	(0.10)	(0.10)
$\Delta\hat{z}_{t-1}$	-0.18	-0.14			-0.03	-0.02		
	(0.14)	(0.14)			(0.07)	(0.06)		
$\Delta\hat{\rho}_{t-1}$	-0.56^{*}	-0.66^{**}			-0.64	-0.63^{***}		
	(0.32)	(0.30)			(0.21)	(0.19)		
$\Delta\hat{i}_{t-1}$	0.08	0.04			0.03	-0.01		
	(0.06)	(0.07)			(0.04)	(0.04)		
$\Delta\hat{z}_{t-2}$		0.13				0.13^{***}		
		(0.16)				(0.04)		
$\Delta\hat{y}^m_{t-2}$		0.53				-0.02		
		(0.52)				(0.17)		
$\Delta\hat{r}_{t-2}$		-0.06				0.04		
		(0.04)				(0.04)		
$\Delta\hat{i}_{t-2}$		0.05				0.02		
		(0.07)				(0.03)		
$\Delta\hat{\rho}_{t-2}$						0.39^{**}		
						(0.19)		
$\Delta\hat{\tau}^m_t$			-1.28^{***}	-1.07^{***}			-1.33^{**}	-1.20^{*}
			(0.39)	(0.26)			(0.56)	(0.64)
$\Delta\hat{y}^m_t$			1.41^{**}	1.41^{**}			0.53	0.56
			(0.66)	(0.66)			(0.48)	(0.47)
$\Delta\hat{r}_t$			0.06	0.06			0.10	0.09
			(0.08)	(0.08)			(0.09)	(0.09)
$\hat{z}^*_{t-1}$			-0.12	-0.11			-0.04	-0.04
			(0.05)	(0.05)			(0.02)	(0.02)
$\hat{\tau}^m_{t-1}$			-0.13	-0.14			-0.18	-0.20
			(0.05)	(0.06)			(0.13)	(0.12)
$\hat{y}^m_{t-1}$			0.27	0.25			0.18	0.18
			(0.11)	(0.11)			(0.08)	(0.08)
$\hat{r}_{t-1}$			0.06	0.05			0.08	0.09
			(0.02)	(0.02)			(0.03)	(0.03)
$\hat{\epsilon}_t^{marginal(1,5)}$			0.65				0.58	
			(0.40)				(0.51)	
$\hat{\epsilon}_t^{marginal(2,6)}$				0.43				0.49
				(0.26)				(0.56)
ESTIMATION METHOD	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
OBSERVATIONS	111	111	111	111	111	111	111	111
$\overline{R}^2$	0.44	0.44	0.48	0.48	0.78	0.80	0.20	0.20
JOINT SIGNIF. TEST, $F =$	9.76^{**}	7.37^{**}	8.03^{**}	7.91^{**}	40.3^{**}	30.0^{**}	2.88^{**}	2.90^{**}
AR 1-5 TEST, $F =$	2.45^{*}	1.85	0.62	0.66	2.83^{*}	1.12	0.82	0.78
ARCH 1-4 TEST, $F =$	7.85^{**}	9.84^{**}	0.66	0.93	0.39	0.70	5.11^{**}	4.88^{**}
NORMALITY TEST, $\chi^2 =$	120^{**}	111^{**}	5.89	6.25^{*}	0.39	0.48	24.6^{**}	20.8^{**}
HETERO. TEST, $F =$	0.38	1.75^{*}	2.46^{**}	2.07^{**}	0.71	0.81	0.91	0.94
HETERO-X TEST, $F =$	0.33	1.06	1.79	1.99^{*}	1.89^{**}	1.05	2.96^{**}	2.72^{**}
RESET TEST, $F =$	0.28	3.07	2.68	2.78	1.10	0.05	1.69	0.21

Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Variables in first differences are tested against the critical values of student's t-distribution. Variables in levels are tested against the critical values of the ADF distribution, where for four $I(1)$ variables and a constant term 10% = 3.44; 5% = 3.76; 1% = 4.36. Seasonal variables and constant not reported. Estimated robust standard errors are reported in parenthesis below the coefficients. Standard misspecification tests are reported at the end of the table.

Table 5.2: DWH tests for exogeneity, export functions

5.3 The import function and trade costs

The estimations of the import function are in many ways mirroring the estimations of the export function. In the control variable set, foreign GDP has thus been swapped for home GDP and the real exchange rate remains as the second control variable. The coefficient for the real exchange rate is however expected to be of opposite sign compared to exports and affect imports negatively, such that a real depreciation (measured as an increase in r_t) would imply a decrease in imports. A positive coefficient is to be expected of home GDP which increases home demand for imports.

Table 5.3 reports six model equations, (1)-(6), two with France as foreign, two with The Netherlands as foreign and two with Italy as foreign. Each column reports a model equation of the form

$$\Delta z_t = \phi_0 + \phi_1 \Delta z_{t-1} + \beta_{10} \Delta \tau_t^m + \beta_{11} \Delta \tau_{t-1}^m + \beta_{20} \Delta y_t + \beta_{21} \Delta y_{t-1} + \beta_{30} \Delta r_t + \beta_{31} \Delta r_{t-1} + \epsilon_t, \tag{5.11}$$

which is in all essence similar to equation (5.3), but with z_t representing UK imports and y_t representing GDP of the UK. The first columns with each country, (1), (3) and (5), are model equations estimated in accordance with equation (5.11). Also for the import function the trade cost measure is statistically significant for all countries at a 1% or 5% level of significance. Notably, the coefficients are still estimated to be of the expected sign, such that an increase in trade costs affects import negatively. When modeled with France and Italy the estimated elasticities are again moderately high. A 1% increase in the first difference of trade costs implies a 0.57% and 0.39% decrease respectively in the first difference of imports as contemporary marginal effects. An interesting observation is therefore that the contemporary marginal effects appear to be similarly distributed in absolute magnitude between each representation of 'foreign' for the import function as they were for the export function. Under the assumption that the marginal effects are to a larger extent governed by the bilateral trading partner than the type of trade (import or export), this consistency in marginal effects lends some support the external validity of the model equations.

With regards to internal validity, the first order dynamic model equations for import show similar specification results when compared to the first order dynamic model equations for export in table 5.1. While there appears to be some evidence of heteroscedasticity and issues with normality, all model equations still show no sign of residual autocorrelation. The values for the estimated coefficients of the trade cost measure are also for the

	Dependent Variable: Δz_t					
	m = *France*		m = *The Ne.*		m = *Italy*	
(x_t)	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{z}_{t-1}$	−0.22**	−0.10	−0.04	0.18	−0.07	0.03
	(0.10)	(0.12)	(0.08)	(0.11)	(0.07)	(0.09)
$\Delta\hat{\tau}^m_t$	−0.57***	−0.54***	−0.12**	−0.10**	−0.39**	−0.44**
	(0.14)	(0.08)	(0.05)	(0.04)	(0.18)	(0.18)
$\Delta\hat{\tau}^m_{t-1}$	−0.26**	−0.20	−0.08	−0.05	−0.28	−0.36**
	(0.10)	(0.10)	(0.07)	(0.06)	(0.17)	(0.17)
$\Delta\hat{y}_t$	1.16***	1.25***	1.39***	1.80***	1.15***	1.42***
	(0.30)	(0.32)	(0.40)	(0.45)	(0.28)	(0.34)
$\Delta\hat{y}_{t-1}$	0.76*	0.36	0.31	−0.08	0.73*	0.40
	(0.39)	(0.44)	(0.50)	(0.53)	(0.41)	(0.48)
$\Delta\hat{r}^m_t$	−0.04	−0.04	−0.04	−0.08	−0.01	−0.01
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
$\Delta\hat{r}^m_{t-1}$	0.00	0.00	0.02	0.06	−0.05	−0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)
$\hat{z}_{t-1}$		−0.28**		−0.39		−0.23
		(0.07)		(0.12)		(0.10)
$\hat{\tau}_{t-1}$		−0.13		−0.01		−0.05
		(0.05)		(0.02)		(0.10)
$\hat{y}_{t-1}$		0.54**		0.76		0.45
		(0.13)		(0.25)		(0.19)
$\hat{r}_{t-1}$		−0.01		−0.06		−0.03
		(0.02)		(0.03)		(0.02)
ESTIMATION METHOD	OLS	OLS	OLS	OLS	OLS	OLS
OBSERVATIONS	114	114	90	90	114	114
$\overline{R}^2$	0.46	0.50	0.29	0.39	0.23	0.29
JOINT SIGNIF. TEST, $F =$	8.24**	9.21**	6.20**	6.07**	5.92**	4.23**
AR 1-5 TEST, $F =$	1.84	1.98	1.55	0.53	1.27	0.66
ARCH 1-4 TEST, $F =$	1.06	0.28	3.14*	3.24*	3.21*	5.70**
NORMALITY TEST, $\chi^2 =$	0.53	3.13	51.3**	27.8**	52.6**	41.1**
HETERO. TEST, $F =$	3.02**	1.43	0.67	2.15**	0.63	2.04**
HETERO-X TEST, $F =$	1.64*	1.41	2.79**	N/A	1.42	1.94*
RESET TEST, $F =$	11.3**	6.53**	1.85	5.27**	0.56	5.61**

Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Variables in first differences are tested against the critical values of student's t-distribution. Variables in levels are tested against the critical values of the ADF distribution, where for four $I(1)$ variables and a constant term 10% = 3.44; 5% = 3.76; 1% = 4.36. Seasonal variables and constant not reported. Estimated robust standard errors are reported in parenthesis below the coefficients. Standard misspecification tests are reported at the end of the table.

Table 5.3: Estimated import functions with trade costs

import function numerically high, which lends some support of trade costs also affecting imports negatively.

Columns (2), (4) and (6) are model equations also based on equation (5.11), but with additional lags in levels in order to test for a cointegrating relationship with the ECM test. With regards to specification the second model equation is less likely to fit the underlying DGP when estimated with Italy. Issues with heteroscedasticity become more prevalent according to White's test, when estimated with cross-products and when conditioned on time. With The Netherlands however the result is more ambiguous. While the RESET test indicate that the functional form may be subject to improvement, the more important

AR 1-5 test shows a refined test statistic and normality is improved. Foremost with regards to misspecification, it must be highlighted that neither the model equations with second order dynamics exhibit signs of residual autocorrelation, which lends support for the estimated coefficients.

Subject to these remarks, the ECM model equations for import also exhibit numerically quite high estimates of the adjustment coefficient. Given the relatively low estimated standard errors, its t-value when estimated with France and The Netherlands is 4 and 3.25 respectively. When measured against the critical values of the ADF distribution for four $I(1)$ variables and a constant term (Ericsson & MacKinnon, 2002), the null hypothesis of no cointegration (as specified by the ECM test) can be rejected at a 5% level of significance with France. Moreover, the ECM model equation with France show less signs of misspecification when compared to (1). Most notably the null hypotheses of homoscedastic error terms can no longer be rejected for any of the tests for heteroscedasticity. Overall the estimated standard errors for the import function should also be interpreted with some caution, most notably when estimated with the Netherlands and with Italy, where the assumption of homoscedastic disturbances cannot be shown to hold. Since the null hypothesis of no cointegration cannot be rejected with France and The Netherlands, where the issues with residual misspecification are smallest, we next focus on these model equations.

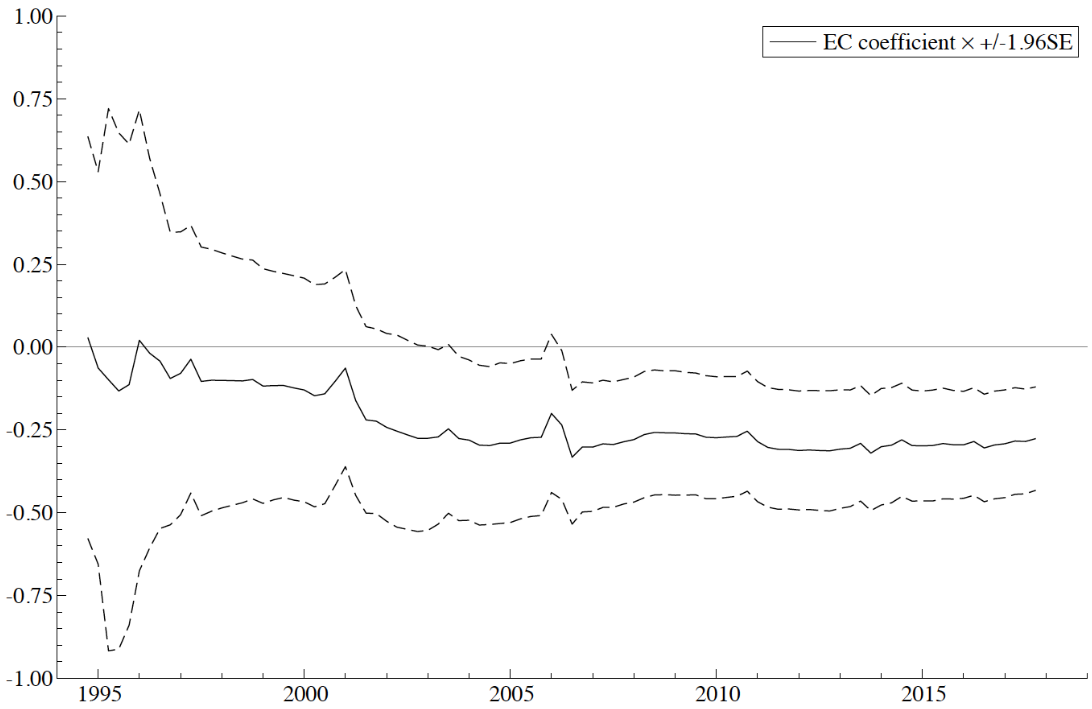
5.3.1 Testing for cointegration and estimation of long-term relationships

Figure 5.2 shows recursive estimations of the EC coefficient from the ECM model equations in (2) and (4) in table 5.3, with France and The Netherlands represented as foreign. As with the recursive estimation with France in figure 5.1a, the estimated adjustment coefficient in the import function also show rather clear signs of recursive stability, which is consistent with cointegration. When estimated with The Netherlands the EC coefficient also appear to tend towards a negative sign but is less recursively stable.

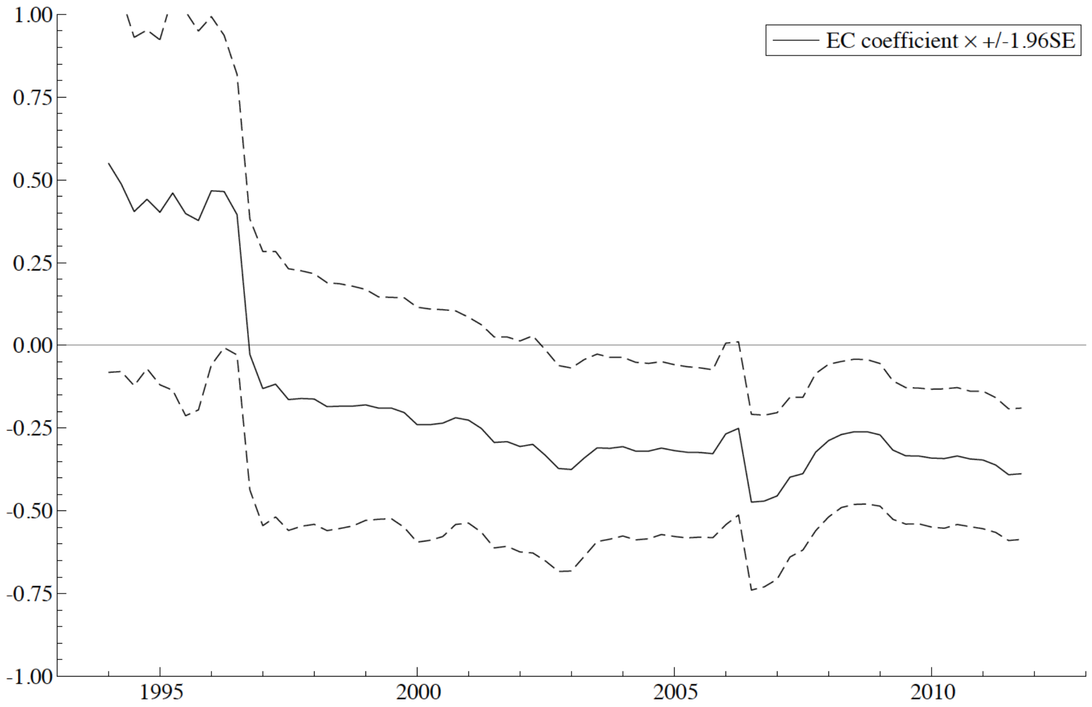
Under the assumption of cointegrating relationships we can again examine the long-term effects. When estimated with France as foreign, the long-term relationship between trade costs and the import function is given by

$$z_t^* = \left(\frac{-3.82}{0.28}\right) + \left(\frac{-0.13}{0.28}\right)\tau_t^{fr} + \left(\frac{0.13}{0.28}\right)y_t^{fr} + \left(\frac{-0.01}{0.28}\right)r_t \tag{5.12}$$

$$z_t^* = (13.6) - (0.46)\tau_t^{fr} + (0.46)y_t^{fr} - (0.04)r_t, \tag{5.13}$$



(a) France



(b) The Netherlands

Figure 5.2: Recursive estimations of the equilibrium correcting coefficient, the coefficient of z_{t-1}

and with The Netherlands as foreign it is given by

$$z_t^* = \left(\frac{-5.36}{0.39}\right) + \left(\frac{-0.01}{0.39}\right)\tau_t^{ne} + \left(\frac{0.76}{0.39}\right)y_t^{ne} + \left(\frac{-0.01}{0.39}\right)r_t \tag{5.14}$$

$$z_t^* = -(13.7) - (0.03)\tau_t^{ne} + (1.95)y_t^{ne} - (0.03)r_t. \tag{5.15}$$

With France the long-term effect on import, again after several periods of dynamic adjustment, ends up being -0.46% for every 1% increase in trade costs. When foreign is represented by The Netherlands the long-term effect is estimated to be -0.03% for every 1% increase in trade costs. The estimated adjustment coefficient for the import function is notably more than twice the size than that of the export function when estimated with France (0.28 compared to 0.12). While this lends support for faster equilibrium correction than for exports, this also means that the long-term impact of trade costs is smaller (0.46 compared to 1.08). When estimated with The Netherlands the equilibrium correction is quite large, 0.39, but the coefficient for trade costs specifically is almost insignificant. In summary, while both estimations show support for long-term relationships, the estimated long-term negative effect on imports associated with increased trade costs is most and perhaps only supported when modeled with France. Analogously with export, cointegrated relationships between UK import and trade costs are not expected to hold in general unless the import markets are cointegrated. As before, that is the imports markets y_t^m, $m \in \{France,\ The\,Netherlands,\ Italy\}$, will have to be cointegrated in order to make broader inferences about the long-term relationship between UK import and trade costs.

5.3.2 Tests of weak and strong exogeneity

With regards to exogeneity of the trade cost measure, when it is estimated in the above ECM model equations for import, we investigate the matter with the same approach as with the export function. Table 5.4 below report the DWH test results with France and The Netherlands, since these countries show evidence of cointegrated relationships with UK imports. This means that the marginal model equations (1) and (2) in table 5.4 are the same marginal models (1) and (2) reported in table 5.2, but their residuals are tested in different conditional model equations. The conditional model equations (3), (4), (7) and (8) are of the ECM type of model equations that we have explained before. $\epsilon_t^{marginal(1,5)}$ again represent the residuals from the marginal equations (1) and (5) and $\epsilon_t^{marginal(2,6)}$ similarly represent the residuals from the marginal equations (2) and (6).

The marginal model equations with The Netherlands, (5) and (6), show reasonable estimation results. Compared with both France and Italy (for comparison with Italy see table 5.2) they are not subjected to the same issue of residual autocorrelation, not even with first order dynamics solely. This is very positive for the DWH test. The conditional model equations for import, (7) and (8), do however compromise the DWH test results to some degree. Nevertheless, across the board none of the tested residuals are significant in any of the conditional models.

With misspecification in mind, table 5.4 show some support for weak exogeneity, most notably with France in (4) where the residuals have an estimated coefficient of 0.01. In fact, the residuals from the marginal models with second order dynamics show low coefficients also with The Netherlands. That these residuals show lower estimated coefficients is consistent with the results from the DWH test for exports in table 5.2. It is a positive result since the marginal models with second order dynamics in general also appear to better represent the underlying DGP, both for imports and for exports. Thus in total, the DWH test has not been able to reject the null hypothesis of weak exogeneity in any of the conditional models (export and import). With second order dynamics, the estimations in table 5.4 pass the DWH test for strong exogeneity, since $\Delta\hat{z}_{t-1}$ is not significant in either (2) or (6). While the estimated coefficient with France in (2) is relatively low, the coefficient with The Netherlands in (6) is numerically much higher, which challenges the robustness of the strong exogeneity result. It should be noted however that when estimated with France as 'foreign', there is some support for trade costs not being Granger caused by neither export nor import.

	m = *France*				m = *The Netherlands*			
	Dependent Variable:				*Dependent Variable:*			
	$\Delta\tau_t^m$		Δz_t		$\Delta\tau_t^m$		Δz_t	
(x_t)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\hat{y}_{t-1}$			0.22	−0.23			−0.24	−0.23
			(0.43)	(0.43)			(0.52)	(0.53)
$\Delta\hat{z}_{t-1}$	−0.18	−0.14	−0.03	−0.06	−0.63*	−0.61	0.18*	0.18*
	(0.14)	(0.14)	(0.12)	(0.12)	(0.35)	(0.37)	(0.10)	(0.10)
$\Delta\hat{\tau}_{t-1}^m$	−0.16**	−0.15*	−0.13	−0.16	−0.03	0.00	−0.04	−0.05
	(0.08)	(0.08)	(0.11)	(0.10)	(0.15)	(0.16)	(0.06)	(0.06)
$\Delta\hat{r}_{t-1}$	0.06	0.07	−0.02	−0.01	0.34*	0.41**	−0.02	0.00
	(0.06)	(0.06)	(0.05)	(0.05)	(0.18)	(0.19)	(0.09)	(0.08)
$\Delta\hat{z}_{t-1}^*$	−0.01	−0.04			0.64**	0.65*		
	(0.10)	(0.11)			(0.27)	(0.33)		
$\Delta\hat{y}_{t-1}^m$	0.13	−0.39			0.00	0.12		
	(0.63)	(0.63)			1.20	(1.21)		
$\Delta\hat{\rho}_{t-1}$	−0.56*	−0.66**			−0.06	−0.53		
	(0.32)	(0.30)			(0.76)	(0.84)		
$\Delta\hat{i}_{t-1}$	0.08	0.04			−0.37	−0.30		
	(0.06)	(0.07)			(0.31)	(0.26)		
$\Delta\hat{z}_{t-2}$		0.13				−0.05		
		(0.16)				(0.26)		
$\Delta\hat{y}_{t-2}^m$		0.53				−0.28		
		(0.52)				(0.89)		
$\Delta\hat{r}_{t-2}$		−0.06				−0.31		
		(0.04)				(0.25)		
$\Delta\hat{i}_{t-2}$		0.05				0.16		
		(0.07)				(0.30)		
$\Delta\hat{\rho}_{t-2}$						−1.15		
						(0.71)		
$\Delta\hat{\tau}_t^m$			−0.42	−0.56**			−0.04	−0.09
			(0.30)	(0.27)			(0.13)	(0.10)
$\Delta\hat{y}_t$			1.29***	1.28***			1.90***	1.88***
			(0.32)	(0.32)			(0.45)	(0.46)
$\Delta\hat{r}_t$			−0.04	0.04			−0.04	−0.04
			(0.06)	(0.06)			(0.08)	(0.08)
$\hat{z}_{t-1}$			−0.29**	−0.29**			−0.35	−0.36
			(0.07)	(0.07)			(0.13)	(0.13)
$\hat{\tau}_{t-1}^m$			−0.16	−0.16			−0.01	−0.01
			(0.05)	(0.05)			(0.02)	(0.02)
$\hat{y}_{t-1}$			0.57***	0.57***			0.70	0.71
			(0.13)	(0.13)			(0.26)	(0.26)
$\hat{r}_{t-1}$			0.00	0.00			−0.06	−0.06
			(0.02)	(0.02)			(0.03)	(0.03)
$\hat{\epsilon}_t^{marginal(1,5)}$			−0.14				−0.08	
			(0.32)				(0.12)	
$\hat{\epsilon}_t^{marginal(2,6)}$				0.01				−0.04
				(0.26)				(0.10)
ESTIMATION METHOD	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
OBSERVATIONS	111	111	111	111	90	90	90	90
$\overline{R}^2$	0.44	0.44	0.52	0.51	0.29	0.28	0.40	0.40
JOINT SIGNIF. TEST, $F =$	9.76**	7.37**	8.93**	8.91**	4.67**	3.25**	4.92**	4.89**
AR 1-5 TEST, $F =$	2.45*	1.85	1.01	0.90	1.49	1.52	1.40	1.28
ARCH 1-4 TEST, $F =$	7.85**	9.84**	0.14	0.14	4.02**	6.17**	3.12*	2.96*
NORMALITY TEST, $\chi^2 =$	120**	111**	3.13	2.89	18.6**	15.0**	29.4**	28.2**
HETERO. TEST, $F =$	0.38	1.75*	1.43	1.44	1.04	0.99	2.12**	2.03*
HETERO-X TEST, $F =$	0.33	1.06	1.51	1.36	1.40	N/A	N/A	N/A
RESET TEST, $F =$	0.28	3.07	6.11**	6.34**	1.96	3.02	6.09**	6.24**

Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Variables in first differences are tested against the critical values of student's t-distribution. Variables in levels are tested against the critical values of the ADF distribution, where for four $I(1)$ variables and a constant term 10% = 3.44; 5% = 3.76; 1% = 4.36. Seasonal variables and constant not reported. Estimated robust standard errors are reported in parenthesis below the coefficients. Standard misspecification tests are reported at the end of the table.

Table 5.4: DWH tests for exogeneity, import functions

5.4 IV estimations for the export and import functions

To conclude the single equation estimations, we include instrumental variable (hereafter IV) estimations for both export and import equations. This is motivated by the results from the DWH tests and from a more abstract perspective. Since the aggregate demand function outlined in chapter 3 has export and import as constituent parts, they are inherently correlated with aggregate demand. We also saw in chapter 3 that within the Mundell-Flemming framework and the Keynesian perspective, aggregate demand determines total production. Intuitively therefore, it is not unreasonable to think that since the trade cost measure contains production data it is endogenous and correlated with both export and import. To investigate these latter relationships was therefore largely the purpose of the DWH tests in sections 5.2.2 and 5.3.2.

The DWH tests for export and import were unable to reject the null hypothesis of the trade cost measure exhibiting weak exogeneity unabridged with all tested foreign countries. This result does as mentioned however come with the forbearance of misspecification. The model equations with France as foreign (both for export and import) demonstrated the most reliable DWH test results, specifically when the marginal model equations incorporated second order dynamics. In terms of strong exogeneity, only export estimations with Italy as foreign were able to reject the null in the better specified second order dynamical model equations. Heteroscedasticity was however prevalent in most of the model equations and with no country were both the marginal and the conditional model equation free from any form of misspecification. On this basis we turn to IV estimation. Since both the OLS and the IV estimator are consistent estimators in the absence of autocorrelated error terms, it will be interesting to compare the two.

We use the generalized instrumental variable estimator (GIVE), or equivalently two-stage least squares (2SLS) estimation. As with all IV estimators, this introduces unknown small sample bias for the estimated coefficients. The bias will be particularly sensitive to weak instruments with an instrument relevance close to zero. On the contrary however, if the instruments are valid and reasonably strong, the IV estimator is consistent in the particular cases where OLS is inconsistent due to simultaneity or variable measurement errors. The 2SLS estimator will also be the most efficient estimator in the case that the structural model equations should be overidentified[3]. Table 5.5 below reports six IV model equations, three for export and three for import, with each foreign country. The model equations are the same type of ECM model equations we have studied throughout this chapter (see table 5.1 and 5.3) but with instruments for the suspected endogenous trade cost measure, τ_t^m. For the IV model equations for export, (1), (2) and (3), the variables used as instruments are Δz_{t-1}, Δi_{t-1}, Δi_{t-2} and Δr_{t-2}. For the IV model equations for import, (4), (5) and (6), the variables used as instruments are Δz^*_{t-1}, Δz^*_{t-2}, Δi_{t-1} and $\Delta \rho_{t-1}$.

Judging from table 5.5 estimations with France as foreign show the most reliable results. Most importantly, none of the IV model equations show any signs of autocorrelation and Sargan's specification test (see Sargan (1958, 1988)) cannot reject the null of the overidentifying restrictions being valid. This means that at least $n-1$ of the n used instruments can be considered to fulfill the instrument exogeneity criteria[4]. With regards to the instrument relevance criteria we know from the marginal model equations in the DWH tests in tables 5.2 and 5.4 that most of the instrumental variables used can be shown to exhibit instrument relevance[5]. If we study the estimated coefficient values for the IV trade cost measure in table 5.5 and compare them to the estimated coefficient values in the ECM model equations in tables 5.1 and 5.3, we see that in all cases but one the IV model equations report in absolute values much higher estimated coefficients. For example, the export function with France reports an almost twice as high estimated coefficient (-1.04 compared to -0.66), and the export function with Italy reports a coefficient over six times higher with IV estimation (-5.44 compared to -0.82). The absolute difference between IV estimations and OLS estimations is significantly smaller for the trade cost coefficients of the import function. With France and Italy as foreign the coefficients move from -0.54 to -0.64 and from -0.44 to -0.61 respectively. This is interesting because it suggests that the estimated negative relationship of trade costs with both export and import in sections 5.2 and 5.3 is not overstated.

[3] Efficient here means having the lowest variance, which in our applications will be an asymptotic property.

[4] If $Z_{1t}, Z_{2t}, ..., Z_{nt}$ are n instrumental variables and ϵ_t is the error term from the second-stage 2SLS regression, the instrument exogeneity criteria is considered to be fulfilled if $Cov(Z_{nt}, \epsilon_t) = 0, \forall n$.

[5] This is defined as at least one of the instruments $Z_{1t}, Z_{2t}, ..., Z_{nt}$ having a nonzero coefficient in the first-stage 2SLS regression.

	Dependent Variable: Δz_t^*			*Dependent Variable:* Δz_t		
	m = *Fr.*	m = *Ne.*	m = *It.*	m = *Fr.*	m = *Ne.*	m = *It.*
(x_t)	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{\tau}_t^{m(IV)}$	-1.04^{***}	-0.18	-5.44	-0.64	-0.02	-0.61
	(0.37)	(0.15)	(4.24)	(0.47)	(0.12)	(0.45)
$\Delta\hat{\tau}_{t-1}^{m(IV)}$	-0.23^{*}	-0.10	-2.58	-0.21^{*}	-0.04	-0.44^{*}
	(0.12)	(0.06)	(1.92)	(0.12)	(0.05)	(0.25)
$\Delta\hat{z}_{t-1}^*$	-0.28^{***}	-0.01	-0.57			
	(0.11)	(0.12)	(0.38)			
$\Delta\hat{y}_t^m$	1.08	1.36^{**}	-0.54			
	(1.68)	(0.61)	(1.43)			
$\Delta\hat{y}_{t-1}^m$	0.69	-0.65	-0.72			
	(0.55)	(0.51)	(1.57)			
$\Delta\hat{r}_t$	0.06	0.17^{*}	0.34	-0.04	-0.07	0.00
	(0.08)	(0.10)	(0.30)	(0.06)	(0.09)	(0.08)
$\Delta\hat{r}_{t-1}$	-0.10	-0.16	-0.38	0.01	-0.01	-0.02
	(0.08)	(0.11)	(0.28)	(0.06)	(0.09)	(0.07)
$\Delta\hat{z}_{t-1}$				-0.13	0.19	0.00
				(0.17)	(0.13)	(0.13)
$\Delta\hat{y}_t$				1.19^{**}	1.79^{***}	1.39^{***}
				(0.47)	(0.51)	(0.46)
$\Delta\hat{y}_{t-1}$				0.37	0.13	0.39
				(0.41)	(0.60)	(0.48)
$\hat{\tau}_{t-1}$	-0.20	0.00	-1.50	-0.15	-0.01	-0.09
	(0.10)	(0.03)	(1.27)	(0.08)	(0.02)	(0.17)
$\hat{z}_{t-1}^*$	-0.12	-0.06	-0.13			
	(0.05)	(0.10)	(0.09)			
$\hat{y}_{t-1}^m$	0.28	0.08	0.62			
	(0.13)	(0.22)	(0.46)			
$\hat{r}_{t-1}$	0.08	0.00	0.32	0.00	-0.06	0.02
	(0.04)	(0.04)	(0.24)	(0.03)	(0.03)	(0.04)
$\hat{z}_{t-1}$				-0.26	-0.43	-0.20
				(0.11)	(0.13)	(0.10)
$\hat{y}_{t-1}$				0.51	0.85	0.39
				(0.21)	(0.27)	(0.20)
Estimation method	IV	IV	IV	IV	IV	IV
Observations	114	90	114	114	90	114
Specification test, $\chi^2 =$	3.86	5.66	0.24	2.26	1.54	1.79
Joint signif. test, $\chi^2 =$	54.3^{**}	42.0^{**}	6.04	79.1^{**}	58.8^{**}	54.5^{**}
AR 1-5 test, $F =$	1.16	0.64	0.46	1.93	1.20	0.63
ARCH 1-4 test, $F =$	1.15	1.57	0.59	0.38	2.75^{*}	5.89^{**}
Normality test, $\chi^2 =$	5.52	5.82^{*}	2.13	5.68	35.3^{**}	32.2^{**}
Hetero. test, $F =$	1.61	2.46^{**}	1.30	0.80	2.05^{*}	2.01^{**}
Hetero-X test, $F =$	1.28	N/A	2.11^{**}	1.19	N/A	1.99^{*}

Note.– $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$. Variables in first differences are tested against the critical values of student's t-distribution. Variables in levels are tested against the critical values of the ADF distribution, where for four $I(1)$ variables and a constant term 10% = 3.44; 5% = 3.76; 1% = 4.36. Seasonal variables and constant not reported. Estimated robust standard errors are reported in parenthesis below the coefficients. Standard misspecification tests are reported at the end of the table.

Table 5.5: Instrumental variable estimations of import and export functions with trade costs

Chapter 6

Conclusion

Increased trade costs has been topical in the analysis and debate about the economic consequences of Brexit. The measurement of trade costs are however far from trivial. One contribution of the thesis has been to operationalize the concept of trade costs using time series data for the UK and three trading partners: France, The Netherlands and Italy. Theoretically, we extended the implicit trade cost measure developed by Novy (2013) to a macroeconomic setting. The new edition of the STAN database (OECD, 2020) was a valuable resource for the data construction, which allowed trade costs to be better measured than the use of GDP data would have allowed. Since the STAN database only provides time series data with an annual frequency, we used the method of temporal disaggregation to construct time series with a quarterly frequency.

Using the new trade cost measure and macroeconomic time series the UK economy, we estimated econometric models for exports and imports. All model equations for export and import showed negative coefficients for the trade cost measure. Moreover, we found empirical support for cointegrated relationships. This suggests that there can be negative long-term effects on both export and import from increased costs of trade. One of the main issues with time series data is usually autocorrelation of the residuals. This was however only manifested in very few of the model equations. In these cases, the extension to second order dynamics improved the estimations.

Overall, estimations with France as the foreign country provided the most internally valid results. Since the model equations with regard to misspecification however proved to be somewhat sensitive to the country specified as 'foreign', their robustness can be questioned. In order to provide more reliable results about the exogeneity of the trade cost measure, improving the marginal model equations is suggested as further research. Their improvement can lend additional support in resolving the direction of causality between trade costs and trade, specifically when an implicit measure is used.

In summary, this thesis has presented empirical results for the relationship between trade costs and trade, which within the framework of a standard theoretical model will have an effect on the GDP of the UK. These results are based on econometric modeling. If we interpret the results from the most reliable estimations with France, we see that export appears to be more sensitive to changes in trade costs than import. The estimated long-term elasticities with France were -0.46% for import and -1.08% for export. Therefore, if Brexit leads to increased costs of trade between the UK and the EU, the results presented in this thesis suggest that the effect on export will be dominant. This further implies that the net export effect will be negative. From a Keynesian perspective this will decrease aggregate demand and ultimately cause a contraction of the real economy of the UK.

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Appendix A

Additional tables and statistics

A.1 Unit root testing

Table A.1 below shows the results from the ADF test. All tested variables have been log-transformed, except for ρ due to the real interest rate taking on negative values. Column (1) contains t-values for the variables when tested in levels. Column (2) contains the t-values for the variables when tested in first differences. The superscripts fr, ne, it denote France, The Netherlands and Italy respectively.

(x_t)	(1) t-ADF	(2) t-ADF
y_t	-0.61	-4.68***
i_t	0.20	-6.10***
c_t	-0.91	-4.79***
z^*	-1.56	-6.04***
z	-0.86	-7.82***
ρ	-1.28	-4.25***
r	-2.22	-5.03***
τ^{fr}	-1.86	-5.61***
τ^{ne}	0.34	-12.01***
τ^{it}	-1.02	-4.81***
y^{fr}	-0.77	-4.21***
y^{ne}	-1.86	-4.74***
y^{it}	-1.81	-4.88***
OBSERVATIONS	114	114

Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, according to the critical values for the ADF distribution when unit roots are tested with a constant, where 10% = 2.57; 5% = 2.86; 1% = 3.43. Lag length for differences: 3.

Table A.1: ADF test results

Appendix B

Temporal disaggregation

In this appendix we present the chosen method for temporal disaggregation and its results. Specifically, we show how the yearly production data from the STAN archives was disaggregated into a quarterly frequency. We first go into methodological detail in section B.1, which outlines the Litterman (1983) approach to temporal disaggregation, then move on to an exposition of the disaggregated data in section B.2.

B.1 The Litterman approach

To some extent the methodology developed by Litterman (1983) was a response to other proposed regression-based methods of temporally disaggregating series of data, most notably by Chow and Lin (1971) and Fernandez (1981). The core idea of the regression-based methods of disaggregation is to only transfer the variability that is significant in explaining the low-frequency series, $\boldsymbol{y}_l$ (in our case the annual STAN data). This is done by the aid of one or more indicator variables, which we call the high-frequency series. As will be described below, the three different methods outlined makes different assumptions about the underlying DGP. While we in chapter 5 found empirical support for several cointegrated relationships, we know little about how the STAN production data relates to other variables. The Chow and Lin (1971) method of disaggregation assumes that the underlying DGP consists of stationary or cointegrated series, while the methods proposed by Litterman (1983) and Fernandez (1981) allows for non-stationarity in the data. We next follow Sax and Steiner (2013) in the exposition of the applied methodology of temporal disaggregation, the difference between the three mentioned approaches and how the relevant variation in the high-frequency indicator variables can be transferred onto the low-frequency series.

An initial step is to use the Generalized Least Squares (GLS) estimator to regress the low-frequency series on the *annualized* high-frequency indicator series, such that the GLS estimator $\hat{\boldsymbol{\beta}}$ is given by,

$$\hat{\boldsymbol{\beta}}(\boldsymbol{\Sigma}) = \left[\boldsymbol{X}'\boldsymbol{C}'(\boldsymbol{C\Sigma C}')^{-1}\boldsymbol{CX}\right]^{-1}\boldsymbol{X}'\boldsymbol{C}'(\boldsymbol{C\Sigma C}')^{-1}\boldsymbol{y}_l, \tag{B.1}$$

where $\boldsymbol{\Sigma}$ is a given variance-covariance matrix; $\boldsymbol{X}$ is a $n \times m$ matrix which contains the m number of indicator series; $\boldsymbol{C}$ is a conversion matrix which annualizes the high-frequency (quarterly) indicator series, such that the annualized versions of the quarterly series can be expressed as $\boldsymbol{CX}$; $\boldsymbol{y}_l$ is a vector of the low-frequency (annual) series.

Let $\boldsymbol{y}$ denote the disaggregated high-frequency series (in contrast to $\boldsymbol{y_l}$, the low-frequency series). By assuming that the relationship between the low-frequency series ($\boldsymbol{y_l}$ and $\boldsymbol{CX}$) in the GLS regression above also holds for the high-frequency series ($\boldsymbol{y}$ and $\boldsymbol{X}$), a preliminary disaggregated high-frequency series can be calculated as the fitted values of the GLS regression,

$$\boldsymbol{p} = \hat{\boldsymbol{\beta}}\boldsymbol{X}, \tag{B.2}$$

where $\boldsymbol{p}$ is the preliminary high-frequency disaggregated series of $\boldsymbol{y}_l$. The series $\boldsymbol{p}$ is preliminary in the sense that the difference between the annualized version of $\boldsymbol{p}$ and the true annual series, $\boldsymbol{y}_l$ must be accounted for. Let this difference be defined as the low-frequency residual,

$$\boldsymbol{u}_l \equiv \boldsymbol{y}_l - \boldsymbol{Cp}, \tag{B.3}$$

where again the matrix $\boldsymbol{C}$ converts the high-frequency series into a low-frequency series, or analogously, $\boldsymbol{C}$ annualizes $\boldsymbol{p}$. The residual $\boldsymbol{u}_l$ then needs to be distributed across the preliminary series estimated in equation (B.2). We can then calculate the final disaggregated series as,

$$\hat{\boldsymbol{y}} = \boldsymbol{p} + \boldsymbol{D}\boldsymbol{u}_l, \tag{B.4}$$

where $\hat{\boldsymbol{y}}$ is the final temporally disaggregated series and $\boldsymbol{D}$ is a $n \times n_l$ distribution matrix, where n is the number of high-frequency observations and n_l is the number of low-frequency observations. The distribution matrix given by,

$$\boldsymbol{D} = \boldsymbol{\Sigma C}'(\boldsymbol{C\Sigma C}')^{-1}. \tag{B.5}$$

The methodology presented so far is a general approach when using indicator variables and is therefore shared by Chow and Lin (1971), Fernandez (1981), and Litterman (1983). The principal methodological difference lies in the treatment and assumptions about the variance-covariance matrix $\mathbf{\Sigma}$. Specifically, the assumptions about the residuals from the GLS regression in equation (B.2) determine how $\mathbf{\Sigma}$ is estimated. Without going into further detail on how each approach estimates the different variance-covariance matrices, we note that all three methods estimates the variance-covariance matrix as a function of the Markov parameter ρ, such that $\mathbf{\Sigma}(\rho)$. Let the vector of the high-frequency residuals from equation (B.2) be denoted by $\boldsymbol{u}$ (not to be confused with the low-frequency residuals $\boldsymbol{u}_l$). Chow and Lin (1971) assumes that the residuals in $\boldsymbol{u}$ follow a stationary first order Markov process,

$$u_t = \rho u_{t-1} + v_t, \tag{B.6}$$

where $|\rho| < 1$ and v_t is assumed to be a white noise process, denoted as: $v_t \sim WN(0, \sigma_v^2)$, where σ_v^2 denotes the finite variance of v_t. As argued by Litterman (1983) however, the Chow and Lin (1971) specification of the residuals fails to take into account non-stationarity and residual autocorrelation, as is frequently observed with time series data. To take non-stationarity into account, Fernandez (1981) proposed that u_t should instead be modeled as a random walk,

$$u_t = u_{t-1} + v_t, \tag{B.7}$$

where again $v_t \sim WN(0, \sigma_v^2)$. While to a larger extent accounting for non-stationarity when compared to Chow and Lin (1971) modelling, this model specification of the error process does introduce a filter that removes autocorrelation, but only when the model is correct (Litterman, 1983, p. 170). The proposed remedy for this by Litterman is therefore not to impose the restriction of $v_t \sim WN(0, \sigma_v^2)$, but rather specify v_t as a first order Markov process. This means the error process is modeled by combining the random walk specification of u_t from Fernandez (1981) and combining it with a first order Markov process. We thus have the following specification of the error process,

$$u_t = u_{t-1} + v_t, \tag{B.8}$$

where v_t is given by,

$$v_t = \rho v_{t-1} + \epsilon_t, \tag{B.9}$$

with the initial condition $u_0 = v_0 = 0$ and $\epsilon_t \sim WN(0, \sigma_\epsilon^2)$. By going back to vector notation, we can denote v_t as $\boldsymbol{v} \sim N(\mathbf{0}, \mathbf{\Sigma})$, where N is the normal distribution and

$\boldsymbol{\Sigma}$ as before is the variance-covariance matrix. We see that according to the Litterman specification of the error process, it is in all essence an Autoregressive Integrated Moving Average (ARIMA) model, with the moving average set to zero, or expressed differently, $\boldsymbol{u}$ can be described as an ARIMA(1,1,0) process[1].

B.1.1 The 'tempdisagg' package in R

When disaggregating the STAN data the programming language R was used. Specifically, we used the 'tempdisagg' package in R. We noted in the above section that while we will not go into detail on how the variance-covariance matrix $\boldsymbol{\Sigma}$ is estimated, we know it is a function of the autoregressive parameter, so that $\boldsymbol{\Sigma}(\rho)$. The 'tempdisagg' package offers two main alternatives for the estimation of ρ. As outlined by Sax and Steiner (2013), these are either the minimization of the weighted residual sum of squares (WLS) or the maximization of a GLS likelihood function. Since according to Sax and Steiner (2013) the WLS estimator is sensitive to the specification of $\boldsymbol{\Sigma}$, we use the maximum likelihood approach.

The 'tempdisagg' package estimates the autoregressive parameter by maximizing the likelihood of the GLS-regression,

$$L(\boldsymbol{\rho}, \boldsymbol{\sigma}_{\epsilon}^2, \boldsymbol{\beta}) = \frac{exp\left[-\frac{1}{2}\boldsymbol{u}_l\boldsymbol{'}(\boldsymbol{C\Sigma C'})^{-1}\boldsymbol{u}_l\right]}{(2\pi)^{\frac{n_l}{2}} \cdot [det(\boldsymbol{C\Sigma C'})]^{\frac{1}{2}}}, \tag{B.10}$$

where most expressions have been explained thus far. Suitably, the $\boldsymbol{\beta}$ is the same GLS estimator, $\hat{\boldsymbol{\beta}}$, from equation (B.1) and $\boldsymbol{u}_l$ is the low-frequency residual defined in equation (B.3). The variable in the exponent for the mathematical constant π is n_l, which we know from before is the number of low-frequency observations defining the distribution matrix $\boldsymbol{D}$ in equations (B.4) and (B.5).

B.2 The temporally disaggregated data

We now move on to presenting the disaggregation results. In performing the disaggregations a few parameters had to be set. The method on how to estimate the Markov parameter is the maximization of the likelihood function in equation (B.10) as mentioned above. In addition, we decided that the low-frequency values $\boldsymbol{y}_l$ should be interpreted as sums of the high-frequency values, which arguably is the most feasible option for time series data. As for the Markov parameter, none of the estimations required for it to be

[1]This can be shown algebraically by substituting equation (B.9) into equation (B.8).

truncated to 0, which the 'tempdisagg' package offers an option for. The main purpose of this is to avoid negative values of ρ by automatically setting it to 0 when negative values are detected. As is shown in table B.1, this was not necessary for any of the estimations. As for the indicator variables, we chose two. The first is an industrial production index from the *main economic indicators* database from OECD (2021). The index consists of output data from industrial establishments and covers sectors such as manufacturing, mining, gas and electricity, which are thought to contain variation similar to what can be expected of the STAN production data. The second indicator variable is the export data expressed in total value from IMF (2021), which is also thought to share variance with the STAN data, given that a relatively large share of the goods market are exports. The results from the low-frequency GLS estimations according to equation (B.1) are reported in table B.1 below.

	Dependent Variable: $Y_t^{m(STAN)}$			
	m = *UK*	m = *France*	m = *The Ne.*	m = *Italy*
(x_t)	(1)	(2)	(3)	(4)
$\hat{Y}_t^{m(INDEX)}$	1474**	2249***	248.4	2055***
	(416.0)	(308.7)	(225.1)	(294.2)
$\hat{Z}_t^{*m(IMF)}$	0.395***	0.351**	0.273***	0.627***
	(0.101)	(0.099)	(0.057)	(0.164)
ESTIMATION METHOD	GLS	GLS	GLS	GLS
OBSERVATIONS	29	29	29	29
$\overline{R}^2$	0.74	0.89	0.66	0.88
MARKOV PARAMETER (ρ)	0.82	0.78	0.37	0.58

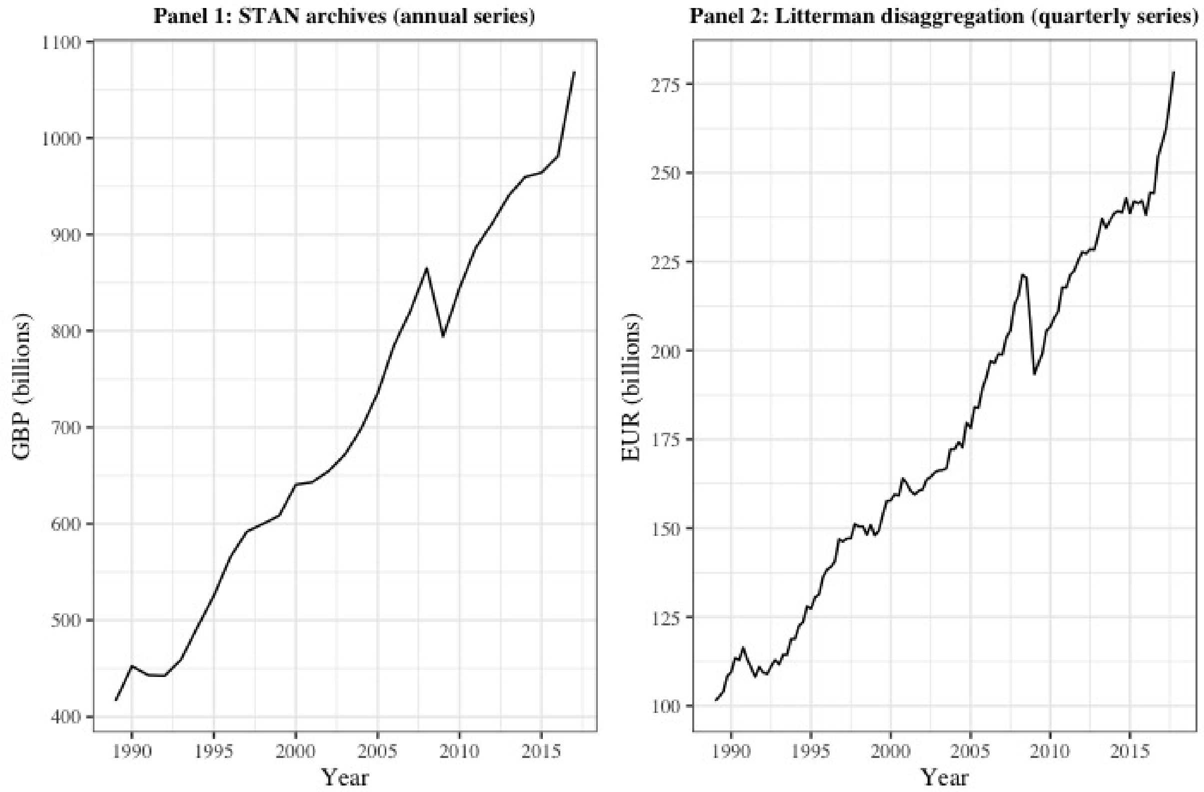
Note.– $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Variables are tested against the critical values of student's t-distribution. Constant not reported. Estimated standard errors are reported in parenthesis below the coefficients.

Table B.1: Estimations of low-frequency series

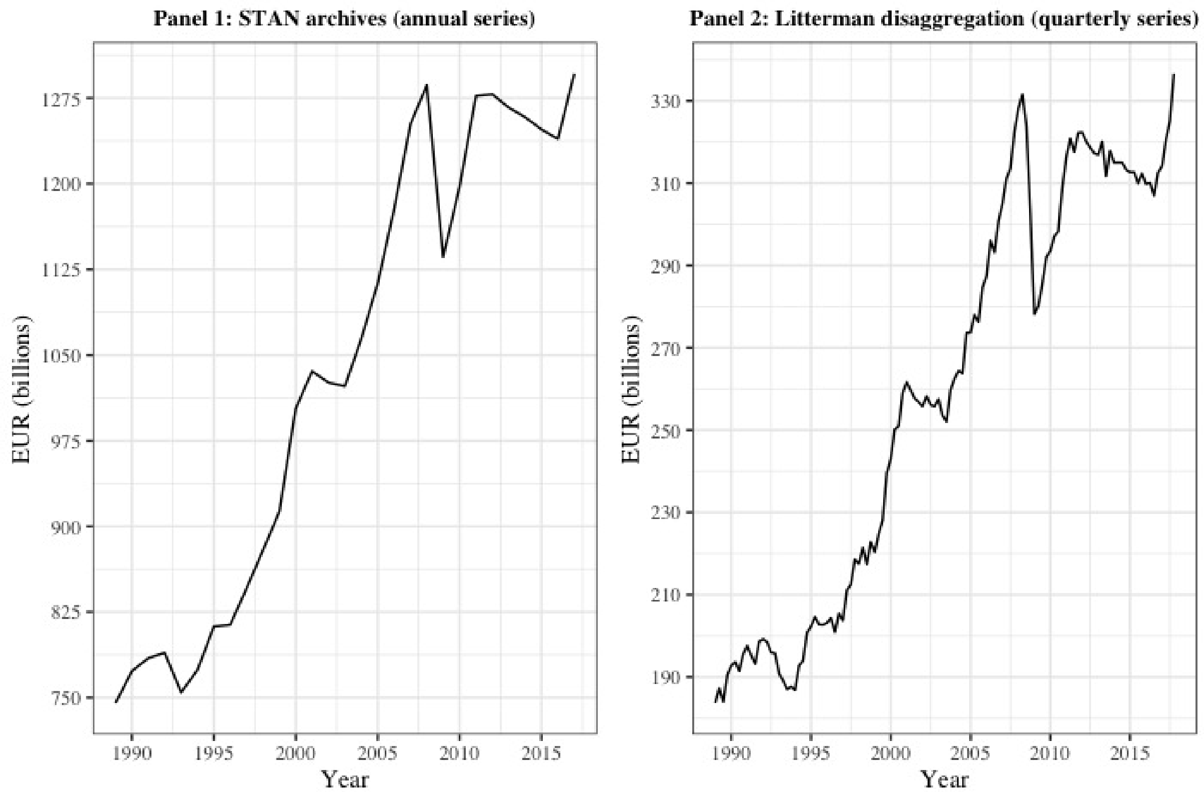
$Y_t^{m(STAN)}$ is the low-frequency annual STAN production data; $Y_t^{m(INDEX)}$ is the high-frequency annualized OECD production index for country m; $Z_t^{*m(IMF)}$ is the high-frequency annualized total value of total export data from IMF for country m. The superscripts *STAN, INDEX* and *IMF* are used so that the variables are not confused with the production and export variables for the gross value added data in chapter 5.

Studying table B.1 we immediately notice the huge estimated coefficients of $Y_t^{m(INDEX)}$. While they may appear odd, these coefficients are to be expected since $Y_t^{m(INDEX)}$ is an *index* series, meaning that the dependent variable is several orders of magnitude larger than the index series. While for purposes of disaggregation the numerical values of the estimated coefficients are not too important, other than in their relation to their estimated standard errors, what is more important is that all estimations show the expected signs. Moreover, almost all annualized high-frequency variables are highly statistically significant. This means their variance to a larger extent will be transferred onto $Y_t^{m(STAN)}$. The perhaps most important test statistic for disaggregation is the adjusted coefficient of determination, since it shows to what extent the annualized high-frequency variables are able to explain the low-frequency variable. If this value is low, little of the variation will be transferred. Table B.1 shows very satisfactory results for most countries, given the high estimated coefficients of determination and the significance of the chosen indicator series. It should be noted that although the Markov parameter is presented in table B.1 for exposition purposes, it is as mentioned before estimated from equation (B.10). Lastly, it is a positive result that all estimated Markov parameters are estimated to be $0 < \rho < 1$, since negative values of ρ can yield undesirable side-effects (Sax & Steiner, 2013, p. 86).

Figures B.1 and B.2 below shows a comparison of the original low-frequency annual series and the temporally disaggregated high-frequency quarterly data using the approach suggested by Litterman (1983) for UK, France, The Netherlands and Italy. With reference to section B.1, this means that 'panel 1' shows $\boldsymbol{y}_l$ and 'panel 2' shows $\hat{\boldsymbol{y}}$. All panels cover the temporal perspective of 1989Q1 to 2017Q4.

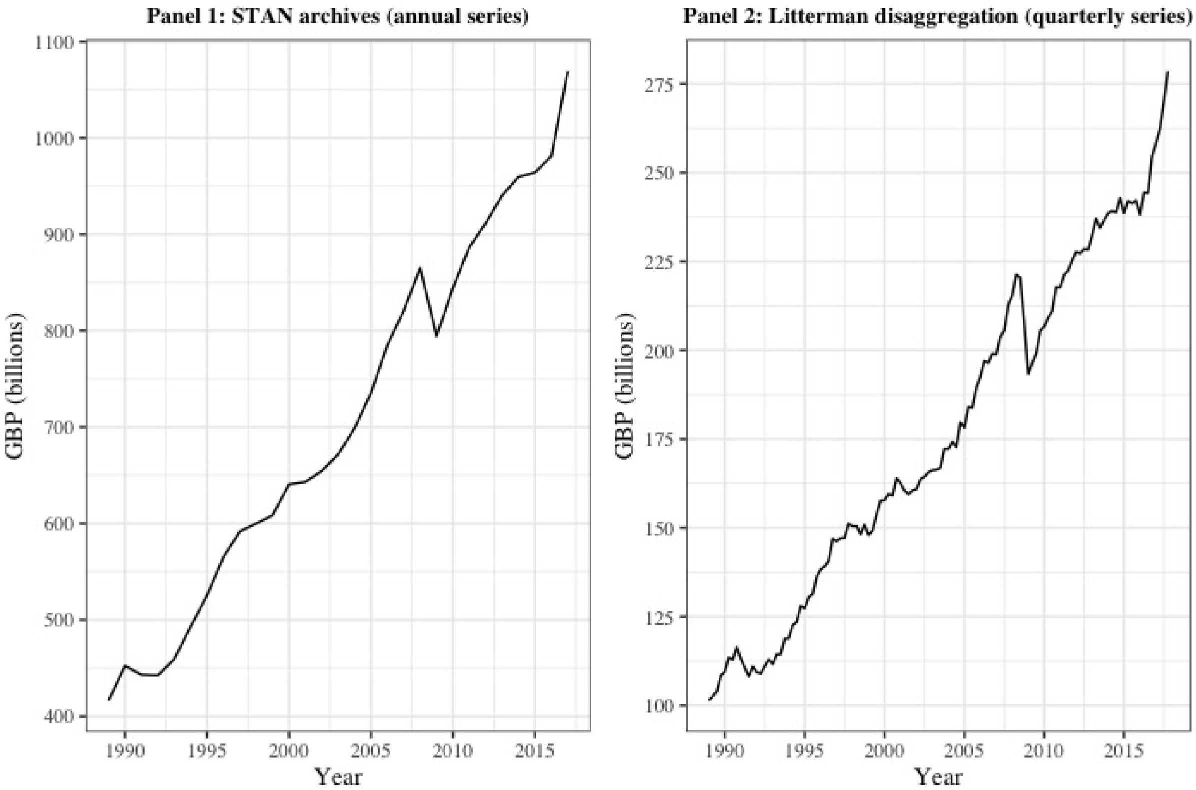


(a) The United Kingdom

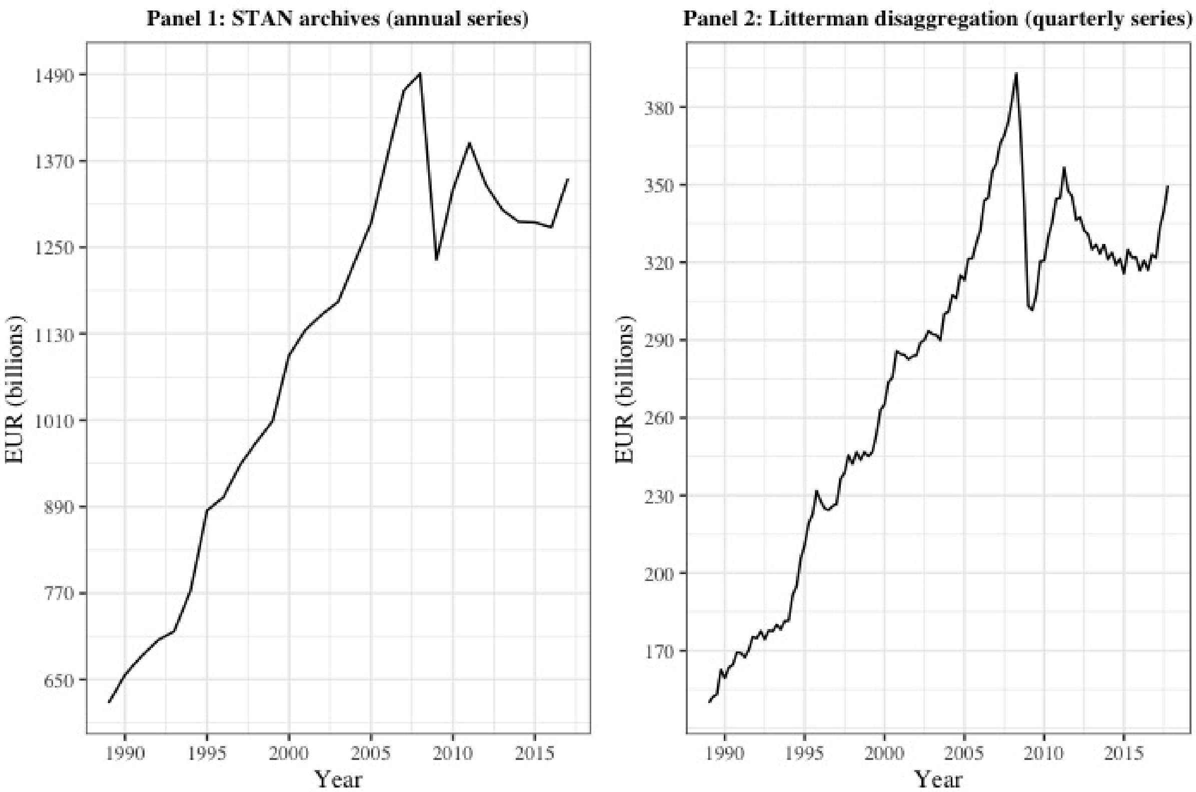


(b) France

Figure B.1: Temporal disaggregations of the STAN archive annual data from 1989-2017 for the UK and France, using the Litterman approach with two indicator series.



(a) The Nehterlands



(b) Italy

Figure B.2: Temporal disaggregations of the STAN archive annual data from 1989-2017 for The Netherlands and Italy, using the Litterman approach with two indicator series.