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The relationship between shipping freight rates and inflation in the Euro Area

Nektarios A. Michail, * Konstantinos D. Melas, ** and Lena Cleanthous***

Abstract

Consumer inflation across the globe has rebounded during 2021, also as a result of supply side disruptions, one of which is the increase in freight costs. To elaborate on the relationship between inflation and shipping costs, we employ a Vector Error Correction Model (VECM) and use disaggregated monthly data from January 2009 to August 2021, using both constant tax and the standard price indices. Following a shock in freight rates, the most hard-hit sectors appear to be garments and major household appliances, items that have traditionally been manufactured outside the euro area. In addition, using a threshold regression methodology we show that when freight rates rise more than $1,300-$1,500 per day, the sensitivity of inflation to freight changes increases.

Keywords: inflation, shipping, freight rates, supply shock

JEL Classification: E31, R4

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The relationship between shipping freight rates and inflation in the Euro Area

1. Introduction

Consumer inflation across the globe has rebounded much faster than expected, following the decline in 2020 triggered by the COVID19 pandemic. In fact, by April 2021, global price levels had risen above pre-pandemic levels. The increase is considered to have been the outcome of both supply and demand pressures, following the unprecedented 2020 situation.

On the demand side, lockdowns and restrictive measures implemented across the globe since the outbreak of the pandemic have led to pent-up demand and shifts in consumption patterns towards durable goods instead of services, with this mostly taking place via a move to online orders. In addition, increased government spending further strengthened demand for goods. On the supply side, the increase in energy prices in 2021 following their collapse in 2020 led to a double-digit increase in energy inflation. At the same time, the increase in online orders, coupled with supply chain disruptions because of the pandemic-induced limitations, led to port congestion and a subsequent increase in global container shipping freight rates, with transport costs rising to record highs. This rise was further exacerbated by limited airfreight capacity as international flight volumes plunged due to travel restrictions and flight cancellations.

The ongoing problems associated with freight costs relate with ports than the ships themselves. About 350 containerships capable of carrying almost 2.4m Twenty-Foot Equivalent Units (TEUs) are waiting off ports globally, a problem more pronounced in Asia, as Chinese ports (Yantian, Ningbo-Zhoushan) faced partial shutdowns. As recent data shows, the congestion has been getting worse, with idle capacity reaching 4.6% of the global fleet, up from 3.5% in July 2021.

The reason that ocean-going freight rates are considered of prime importance is due to the fact that approximately 85% of the world trade is taking place through the world's sea routes (UNCTAD, 2021). This underlines the crucial role of the maritime industry for economic growth, with Kilian (2009) showing that the transportation of dry cargo acts a leading indicator for world economy. Likewise, other have shown the importance of container cargo that it is transported through the ocean routes. Michail et al., (2021)have shown that an increase by 1% in the containers that are transported through a country's ports increase its real GDP by 0.2%. In a similar context, Angelopoulos et al., (2021)provide evidence that the Australian GDP is highly correlated with the economic activity of the country's ports.

Interestingly, the opposite also holds, as countries that do not have access to sea routes are negatively affected by the transportation of cost of containers (Pham and Sim, 2020). Most recently, Carriere-Swallow et al., (2022), provide strong evidence between the relationship of shipping freight rates and inflation both for developed and developing economies. Based on this, we examine how an exogenous disruption in the shipping part of the supply chain will affect the economy. While some research has been conducted on the growth-shipping realm (Mańkowska et al., 2021; March et al., 2021; Michail and Melas, 2020; Xu et al., 2021), the current paper enhances the existing bibliography by examining the relationship between shipping costs and inflation in the Eurozone.

To provide further insights to this area, we empirically examine how an increase in freight rates can potentially affect inflation, using disaggregated monthly EU data from January 2009 to August 2021 for the Non- Energy Industrial Goods (NEIGs, thereafter) as they are provided by the …… database. Our results, using both constant tax and the standard price indices, suggest that, in accordance with the previous studies on the issue, the impact of freight rates on inflation is relatively mild, with a maximum impact of 0.35% after a 10% freight cost shock. However, we note that, after controlling for the 2021 effect on freight rates, the impact decreases significantly, with the inclusion of 2021 at times offering an almost 50% rise in the impact. This implies the presence of potential non-linearities in the relationship, and raises the question of whether prices could be affected differently if the increases continue.

Policy-wise, our results bare serious implications for the effect that supply chain disruptions have on the EU economy. Given the fact that there are two main NEIGs that have been pushing inflation in higher rates (i.e. Garments and home appliances), after the coronavirus pandemic, the EU should act so minimize how much it release to outside manufacturers for the latter goods. Having in mind the fact that, while this research is written further disruptions may happen in the global trade given the Russia – Ukranian war, EU should focus its manufacturing policies to become as self sufficient as possible in the above mentioned NEIGs so to avoid future problems of very high inflation.

Following this introduction, the remainder of this paper is organized as follows: section 2 provides a review of the literature on the issue, section 3 describes the methodology and the data used, section 4 discusses the empirical results obtained, and section 5 concludes on the findings.

2. Literature Review

The recent disruptions in supply chains (coronavirus, the closure of Suez canal , the Russian – Ukrainian war), have led to a surge in shipping costs and ultimately raises the question to what extent these are passed on to the rest of the pricing chain.

Input cost pressures affect the early stages of the production and distribution chain and indeed have led to marked increases in import and producer prices for intermediate goods in the euro area. In particular, they have pushed up producer prices in the manufacturing sector, in which intermediate goods have a large weight, with the latter reflecting price increases observed for, especially, basic metals, chemicals and chemical products, machinery and equipment, and cars. The majority of the goods mentioned above, fall in the Non-Energy Industrial Goods (NEIG) category, with imports of final goods accounting for around 12% of the HICP NEIG basket (Koester et al., 2021).

It is worth mentioning here that, historically, NEIG inflation has been relatively subdued in the euro area, averaging 0.6% from 1999 to 2019, with a limited contribution to the total HICP inflation, despite having a weight of around 25% in total inflation. However, in the first eight months of 2021, the contribution of NEIG inflation to total inflation almost quadrupled to 0.27% compared with an average contribution of 0.07% since 2014. This increase has, to a large extent, been driven by inflation in the furniture and household goods categories, one that has been heavily hurt by the supply chain disruptions described above.

Inevitably, the surge in inflation to a 10-year-high is a source of concern to policymakers and is expected to play a significant role in future policy meetings. A key question that needs to be answered is whether the rise in NEIG inflation reflects increased shipping and other input costs, and whether this is a temporary phenomenon.

The existing literature on the topic is minimal, with the first research item being Herriford et al., (2015), who show that a 15% increase in shipping costs leads to a 0.10% increase in core inflation after a year. In Europe, Koester et al., (2021), using a simple reduced-form regression analysis, show that the pass-through to consumer prices usually takes more than one year. Furthermore, Attinasi et al., (2021) estimates that a 50% annual increase in the Harpex index (a variable that represents the containers costs and it is derived by the Harper Index of Harper Petersen & Co. Ltd.) could raise annual PCE inflation by up to 0.25 percentage points one year later. The small size of this effect is explained by the fact that international shipping costs make up only a relatively small share of the final cost of manufacturing output (N. A. Michail and Melas, 2021). Finally, the recent working paper of Carriere-Swallow et al., (2022) provide strong evidence between the existence of a positive relationship between shipping costs and the global inflation rates. In their study, the reveal that on average, a one-standard-increase in global shipping costs, increases domestic headline inflation by 0.15 percent. A very recent study of Carriere-Swallow et al., (2022) is using data since 1992 and examines both advanced and emerging economies. Compared to already existing bibliography, our paper comes to fill in the gap in the literature by providing further insights for the reaction that EU countries suffer specifically from increased freight rates and try to provide solutions so that the Union can alleviate inflation problems in the future.

3. Data and Methods

The main, direct, effect of a supply-side shock to freight rates is expected to be passed on to the economy via imported goods. This, as elaborated in the previous section, is expected to take place via an increase in the categories that contain the most import content, i.e. Non-Energy Industrial Goods (NEIG). Given the large number of sub-categories under the NEIG (37), we propose the use of the major categories under it, namely those whose weight is close to, or more than, 10, using the 2021 weights.[1] To put this in perspective, a weight of 10 implies a 1% effect on the overall HICP.

As Table 1 below indicates, this analysis yielded a total of 9 categories. These nine categories account for approximately 61% of the whole NEIG weight, with the remaining 28 categories amounting to the remaining 39%. It should be noted here that category CP0321 does not have a long enough series of observations, as the first observation starts in 2016M12. To this end, we exclude this category from the estimation. Despite the exclusion, the eight remaining sub-categories account for 57% of the total NEIG weight, hence amounting to around 15% of the overall HICP.

Table 1: Category Weights in NEIG Inflation

COICOP/GEO	Weight
CP0312 - Garments	38.54
CP0321 - Shoes and other footwear	10.52
CP0511 - Furniture and furnishings	20.34
CP0531_0532 - Major household appliances whether electric or not and small electric household appliances	9.98
CP0561 - Non-durable household goods	10.05
CP0611 - Pharmaceutical products	12.45
CP0612_0613 - Other medical products, therapeutic appliances and equipment	8.65
CP0711 - Motor cars	35.81
CP1212_1213 - Electrical appliances for personal care; other appliances, articles and products for personal care	17.54
IGD_NNRG - Non-energy industrial goods	269.07
Share of top 9 in total NEIG	60.9%
Share excluding CP0321	57.0%

To examine the relationship between vessel freight rates and inflation, we propose the use of a Vector Error Correction specification, as per the seminal work of Johansen and Juselius (1990), defined as:

$$\Delta M_{j,t} = \alpha_{1,0} + \sum_{i=1}^{p} \beta_{1,i,j} \Delta M_{j,t-i} + \sum_{k=1}^{K-1} \sum_{i=1}^{p} \gamma_{k,i,j} \Delta \boldsymbol{W}_{t-i} + \delta_j \left(M_{t-1} - \theta_{1,j} \boldsymbol{W}_{t-1} - \theta_{0,j} \right) + \varepsilon_{j,t} \qquad (1)$$

where the total number of variables is K, $M_{j,t}$ is the natural logarithm of variable j, and $\boldsymbol{W}_t$ is a $(K-1 \times N)$ matrix that contains all variables included in the estimation, other than variable j. Δ is the first difference operator, while. $\beta_{i,i,j}$ and $\gamma_{k,i,j}$ refer to the own

[1] Robustness checks using average weights over time did not change the selected categories.

and other variable coefficient values in the estimations, with j again signifying that the coefficient refers to the equation identified with variable j, while k refers to the specific variable within matrix $\boldsymbol{W}_t$. $\varepsilon_{j,t}$ refer to the error processes in each equation.

The long-run relationship between the two variables is found within the brackets of equation (1) with δ_j determining the speed of adjustment to the long-run equilibrium. The long run, as per Johansen and Juselius (1990), refers to the equilibrium relationship between the variables, i.e. the one that exists in the absence of any external shocks to the system of equations in the estimation model. Similarly, short run refers to the fluctuations that take place and allow for deviations from the equilibrium value. As such, it should be noted that the terms "long run" and "short run" do not refer to any predetermined time period, but rather an equilibrium relationship.

Table 2: Unit Root Tests

	ADF Test		PP Test	
Variables	Levels	First Differences	Levels	First Differences
CP0312	-0.13	-17.68***	-1.91	-54.92***
CP0511	-0.86	-2.42*	-0.78	-15.34***
CP0531_2	-1.80	-14.91***	-1.69	-15.06***
CP0561	-1.22	-3.91***	-1.43	-12.80***
CP0611	-1.98	-16.68***	-1.99	-16.59***
CP0612_3	-3.71*	-15.58***	-4.03**	-15.58***
CP0711	1.77	-15.83***	1.51	-16.06***
CP1212_13	-1.63	-3.93**	-2.46	-13.98***
Freight Rates	-0.69	-9.55***	-0.78	-7.85***
Oil Price	-2.45	-8.89***	-2.46	-8.20***

*,**,*** denote significance at the 10%, 5%, and 1% level. The coding of variables stands for: *CP0312-Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.*

To empirically examine whether a long-run relationship exists between the set of variables employed in the estimation, we need to first test for the existence of a cointegrating relationship. In other words, there needs to be an empirical justification for the use of the term in brackets. However, before we are able to perform the Johansen test for cointegration we first need to establish that both variables are I(1), i.e. they follow a unit root process (for more details see Hendry & Juselius, 2000, 2001). Table 1 presents the results from such an estimation. To avoid over-burdening the text, we only provide estimates for the main sub-categories. The unit root results for the constant tax and 5-digit COICOP categories are available upon request.

In Table 2, we test for the presence of a unit root using both the Augmented Dickey-Fuller test (Dickey and Fuller, 1981; Mackinnon, 1996) and the Philips and Perron (1988) tests at the levels and the first differences. The main difference between the two tests is that the first uses a parametric approach based on the residuals while the second is nonparametric. The results suggest that there is evidence of a unit root in all the tested variables given that neither test rejects the unit root hypothesis. The fact that the series are I(1) is confirmed in the lower panel of Table 1 as the null of a unit root is rejected in the first differences of the variables. As such, given that both variables follow a unit root process, we can proceed with the estimation of a cointegrating relationship.

With regards to the data range employed, the main COICOP categories observed in Table 1 range from 2009M01 to 2021M08. To account for potential taxation changes, such as the VAT reduction in Germany from July to December 2020, we also employ data for Constant Tax HICP, which range from 2012M12 to 2021M08. This allows us to control for any domestic economy issues that could blur the relationship between freight rates and inflation. Finally, we also delve into a more disaggregated approach, as we go to the 5-digit category breakdown for a more detailed impact. Data for these categories range from 2016M12 to 2021M08. All inflation data were obtained by Eurostat while freight rates for the Europe-China route are from Clarksons Shipping Intelligence. Oil prices were obtained by the European Central Bank's Statistical Data Warehouse (SDW); to avoid any potential exchange rate issues, we have transformed US Dollar prices to Euro prices, using the exchange rate also obtained by SDW. All inflation series were seasonally adjusted prior to the estimation.

To ensure comparability of the results, all VECMs use one lag and one cointegrating equation. The impulse responses were created using a Choleski decomposition, with oil prices ordered first, with freight rates coming second and the inflation variables following. This allows the exogenous supply shocks to be insensitive to changes in inflation, while as oil is employed as fuel in vessels, freight rates are expected to be contemporaneously affected by changes in oil prices. The empirical estimates can be found in the following section.

4. Results

4.1. VECM Estimation

This section presents the responses of the inflation categories to a shock in freight rates. The impulse responses are also complemented by a bootstrapped confidence interval, as per Hall (2013, 1986). Following Bernanke et al., (2005) a 68% confidence interval is presented. Figure 1 indicates that categories CP0511, CP0531_2, CP0711, and CP1212_13 are the categories that we observe a positive relationship between them and freight rates. The highest response to a shock in freight rates comes from the major household appliances category (CP0531_2), where a one standard deviation shock in freight rates implies a long-run 0.1% increase the category. Following this, furniture and furnishing (CP0511) is the category with the second largest response, standing at approximately 0.06%. In the other two categories, motor cars (CP0711) and electrical appliances for personal care (CP1212_13), the response is smaller, at around 0.04% and 0.025% respectively. In the remaining categories, the effects range from zero to negative, depending on the category's dependence on imports.

However, the responses hide an important issue, namely that the majority of the impact is actually the outcome of 2021's freight rate increases. In Figure 2, the estimates suggest that, when the 2021 impact is eliminated via a dummy variable (2021M01 to 2021M08), the results suggest that the CP0531_2 effect drops to 0.05%, and the CP0511, CP0711, and CP1212_13 ones are effectively zero. As such, given that a single year has that much of an effect, it implies that the impact of large freight increases is non-linear. This also suggests that if freight rates continue to increase, the sensitivity of inflation to such changes may become even larger. The non-linearity issue is further addressed in section 4.

To account for any potential taxation changes that could impact the inflation series, Figure 3 presents the estimates using the constant tax HICP. In this case, it appears that three categories remain positive to changes in freight rates, household appliances (CP0531_2), furniture and furnishing (CP0511), and motor cars (CP07110). In addition, one new category, garments (CP0312), is now significant. The exclusion of taxation appears to have had an impact on electrical appliances for personal care (CP1212_13), which now appears not to be significantly affected by changes in freight rates. The estimates are now the largest for garments, at 0.25%, whereas for furniture and furnishings the effect stands at 0.07%. Household appliances report a slightly larger effect at 0.08%, while the smallest effect comes from motor cars, at 0.05%.

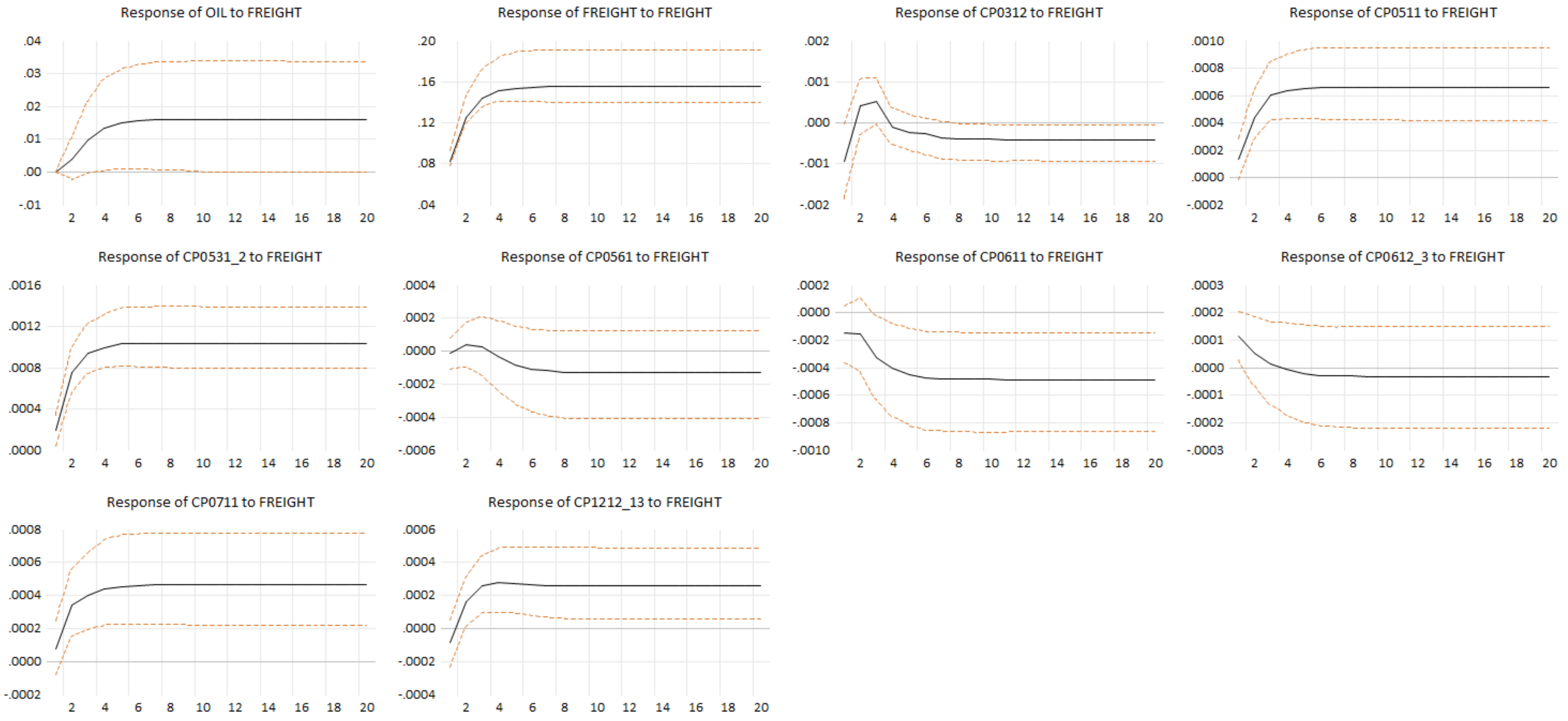
A similar story to Figure 2 also appears for Figure 4. The use of a dummy variable for 2021 reduces the impact of freight rates on furniture and furnishings to zero, with a similar effect observed for motor cars. For household appliances (CP0531_2), the effect is now reduced to 0.05% from 0.08%, while for garments (CP0312) the effect is reduced by a lesser extent, to 0.20% from 0.25%. Nonetheless, the same non-linear relationship appears to hold, as the majority of the overall impact appears to have been created in 2021.

It should be noted that the long-run shock in freight rates depicted in Figures 3 and 4 is much smaller than the one in Figures 1 and 2. While in the first two Figures the effect stood at approximately 14% following the fourth period, in the last two, the long run impact stands at around 1%. This implies that the magnitude of the shock should be more pronounced in the constant tax case, further underlining the importance of freight costs in these inflation categories.

Finally, Figure 5 presents the estimates from an even more disaggregated level. In particular, for the sub-categories for which a significant positive response has been reported, we obtain further disaggregation, by obtaining the 5-digit sub-sub-categories. However, given the small data range of these, as data exist only from 2016M12 onwards, and the large number of categories, we have only selected those for which a more than 2% upwards movement in the index was observed. In particular, we have used categories CP05311 - Refrigerators, freezers and fridge-freezers, CP05313 – Cookers, CP05314 - Heaters, air conditioners, CP05319 - Other major household appliances, CP05322 - Coffee machines, tea-makers and similar appliances, CP05324 - Toasters and grills, and CP12131 - Non-electrical appliances. Figure 5 presents the responses of the above categories to a shock in freight rates.

As Figure 5 suggests, the largest impact comes from other major household appliances (CP05322) at 0.25%, followed by heaters and air conditioners (CP05314), and toasters and grills (CP05324) at 0.20%. Other categories such as refrigerators, freezers and fridge-freezers (CP05311), and coffee machines, tea-makers and similar appliances (CP05322) have a smaller reaction, while cookers (CP05313) and non-electrical appliances (CP12131) do not report a significant response.

Figure 1: Impulse Responses to a shock in freight rates



The figure shows the response of the variables to a shock in freight rates. Dashed lines show the 68% bootstrapped confidence interval. The coding of variables stands for: *CP0312- Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.*

Figure 2: Impulse Responses to a shock in freight rates (with 2021 Dummy)

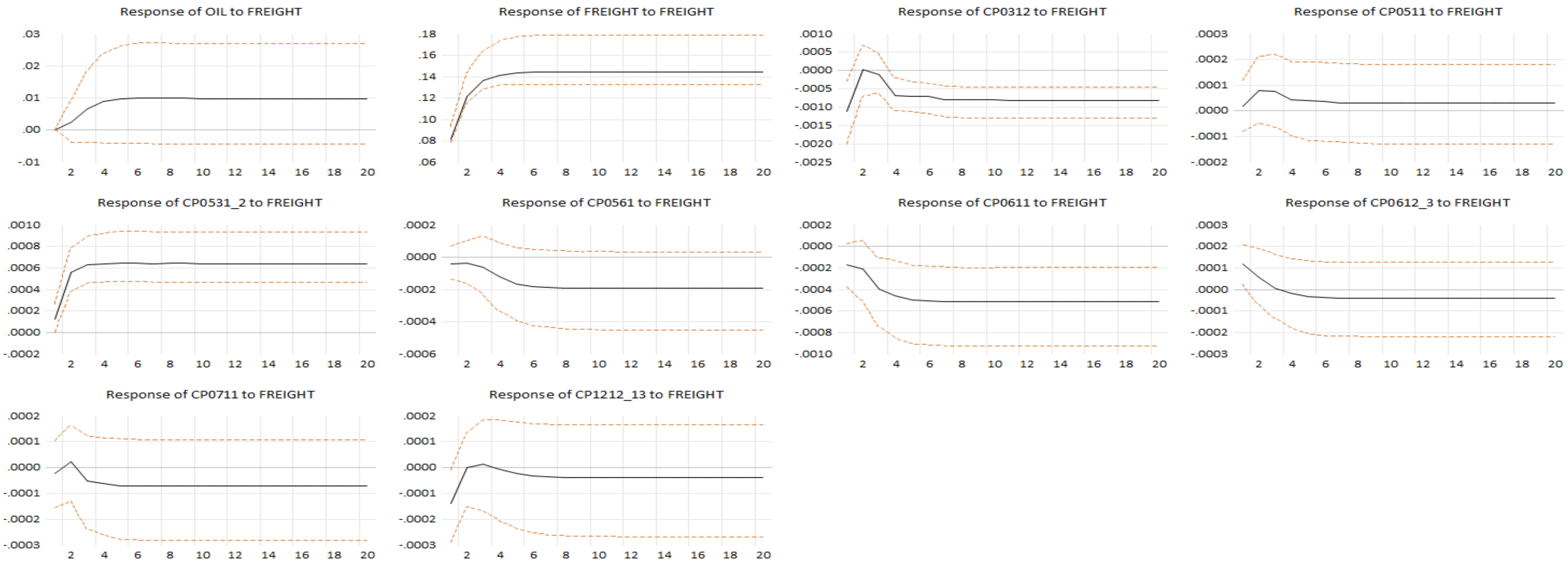


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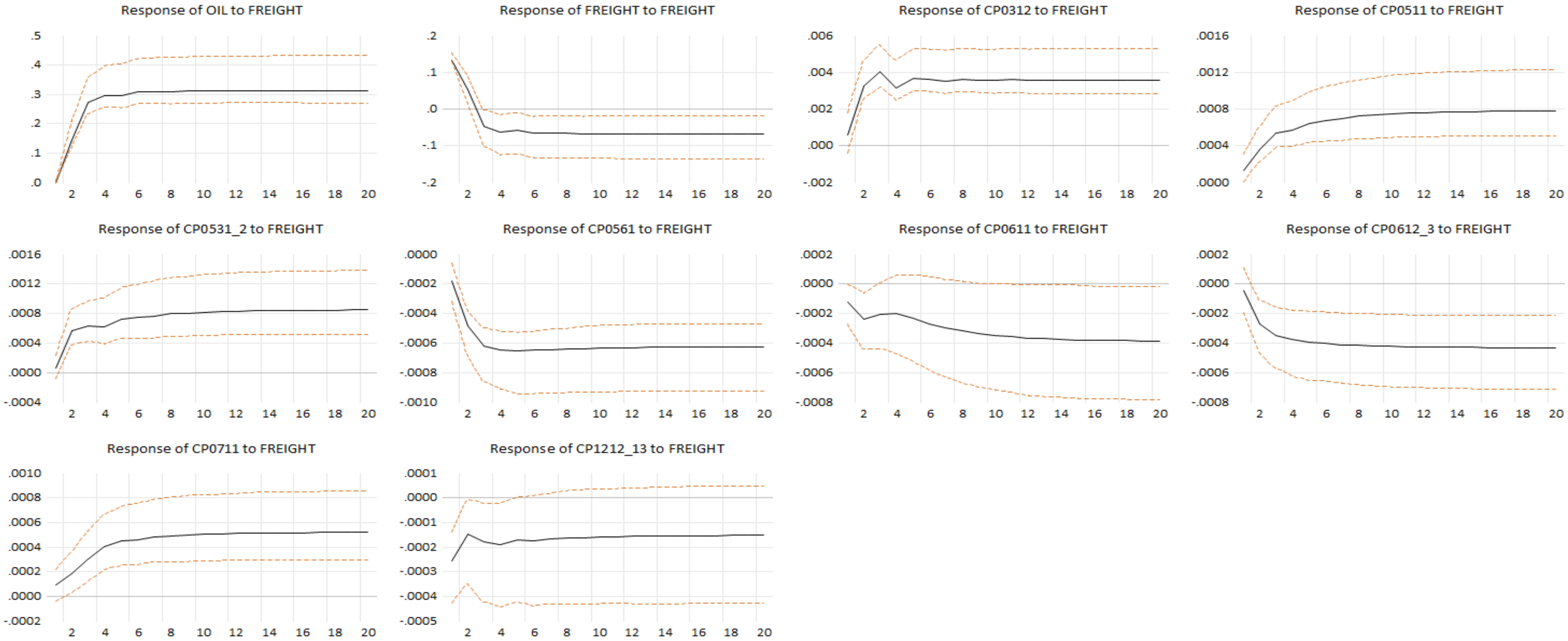
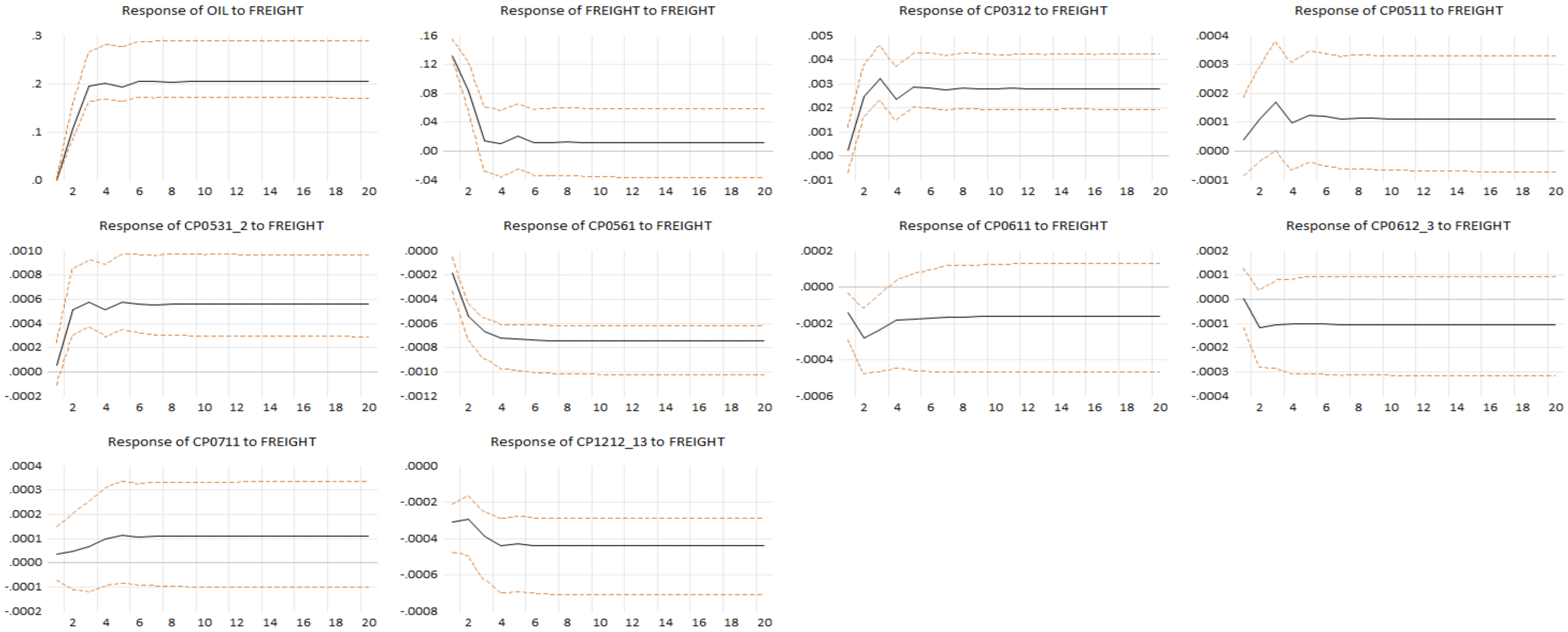
Figure 3: Impulse Responses to a shock in freight rates (HICP Constant Taxes)



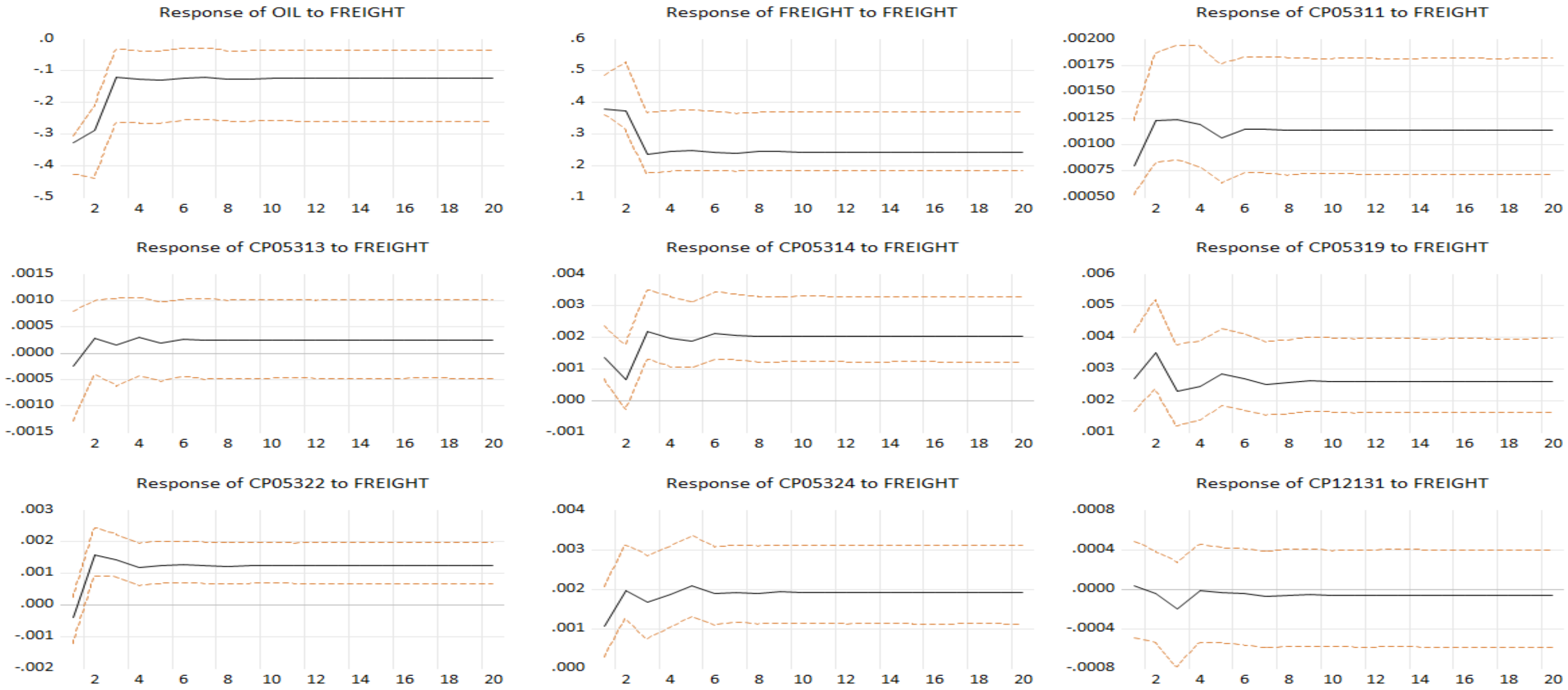
The figure shows the response of the variables to a shock in freight rates. Dashed lines show the 68% bootstrapped confidence interval. The coding of variables stands for: *CP0312- Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.*

Figure 4: Impulse Responses to a shock in freight rates (HICP Constant Taxes, 2021 Dummy)



The figure shows the response of the variables to a shock in freight rates. Dashed lines show the 68% bootstrapped confidence interval. The coding of variables stands for: *CP0312- Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.*

Figure 5: Impulse Responses to a shock in freight rates (5-Digit COICOP)



The figure shows the response of the variables to a shock in freight rates. Dashed lines show the 68% bootstrapped confidence interval. The coding of variables stands for: CP0312- Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.

Overall, the results from the above five figures suggest that freight rates have a significant positive impact on the sub-categories of Non-Energy Industrial Goods (NEIG). Following a shock in freight rates, the most hard-hit sectors appear to be garments and major household appliances, items that have traditionally been manufactured outside the euro area. The magnitude of our results is broadly in line with those of Herriford et al., (2015), even though it appears that the majority of the impact is driven by the large increase in freight rates over 2021. When controlling for this year, the effect is greatly reduced, and becomes insignificant in some categories. As such, this underlines the non-linearity of the relationship, and also implies that in the case of further freight rate increases the inflation impact would become even more pronounced.

4.2. Non-Linear Estimates

4.2.1. Threshold Regression

Most studies, across any stream of the literature are usually based on regression-based models. However, the usual regression model requires the assumption parameter constancy across the sample for the estimates to precise, effectively ruling out the possibility of structural change in a variable. To address this, a realm of the literature has focused at the development of methodologies which extend the usual regression model to allow for structural change to have an impact on the estimates (see Hansen (2001) and Perron (2006) for an overview).

In order to identify structural breaks, following in the tradition of Chow (1960), Quandt (1960), Andrews (1993), and Andrews and Ploberger (1994), a test has been developed by Bai (1997) and Bai and Perron (1998; 2003a). In this specification, the breakpoints do not have to be known or specified in advance, even though the possibility exists that the researcher can impose a priori known break dates. More formally, starting from the linear regression model with T periods and m potential breaks (and thus m+1 regimes), the regression model of Bai and Perron (2003a) becomes:

$$y_t = Z_t' \delta_j + W_t' \beta + \epsilon_t \tag{8}$$

where $j = 0,1,2 \dots m$ refers to the number of regimes. Here, regressors are divided into two groups, W and Z, where W refers to the variables whose coefficients remain constant across regimes and Z to the variables that have regime-specific coefficients. Concerning timing, the break date is specified to be the first date of the subsequent regime.

If the δ_j's in equation (1) are found to be equal across regimes, then no structural break exists. To test the null of no breaks, i.e., that $\delta_0 = \delta_1 = \delta_2 = \cdots \delta_{l+1}$, against the alternative of l breaks, an F-statistic is employed. The general form of the Bai-Perron test is:

$$F(\hat{\delta}) = \frac{1}{T}\left(\frac{T - (1 + l)q - p}{kq}\right)(R\hat{\delta})'\left(RV(\hat{\delta})R'\right)^{-1}R\hat{\delta} \tag{9}$$

where $\hat{\delta}$ is the optimal l-break estimate of δ. $(R\delta)' = (\delta_0' - \delta_1', \dots, \delta_1' - \delta_{l+1}')$ is the difference between regimes, and $V(\hat{\delta})$ is an estimate of the variance-covariance matrix of $\hat{\delta}$ which may be robust to serial correlation and heteroscedasticity. In general, the form of $V(\hat{\delta})$ depends on assumptions regarding the data distribution and the errors across the regimes (see Bai and Perron, 2003a, for more). To avoid the issue of having to know the number and dates of the breaks, the null of no structural change is compared to an upper-bound maximum level of breaks, denoted as m*. Effectively, m* defines the maximum number of regimes allowed in the specification. Bai and Perron (2003b) provide critical values for the above tests (see also Yao, 1988).

To use the test, the first step is, as per equation (8), to estimate a standard multiple linear regression model with T observations and m potential thresholds. Then, Bai and Perron (2003a) suppose that there is an observable threshold variable q_t with strictly increasing threshold values $\gamma_1 < \gamma_2 < \gamma_3 \ldots < \gamma_m$ such that we are in regime j if and only if $\gamma_j \leq q_t < \gamma_{j+1}$. Thus, we are in regime j if the value of the threshold variable is at least the same as the j-th threshold value, but smaller than the j+1-th threshold value.

To combine the individual regime specifications, an indicator function is employed, such that:

$$y_t = \sum_{j=0}^{m} 1_j(q_t, \gamma) \cdot Z_t' \delta_j + W_t' \beta + \epsilon_t \tag{10}$$

where $1_j(f)$ is the indicator function that distinguishes the regimes. In this case, the threshold variable q_t and the regressors Z_t and W_t will determine the type (regime-wise) of the threshold specification. To get the δ_j, β, and γ from equation (12), a nonlinear least squares approach is followed, defining the sum-of-squares objective function as:

$$S(\delta, \beta, \gamma) = \sum_{t=1}^{T} \left(y_t - W_t' \beta - \sum_{j=0}^{m} 1_j(q_t, \gamma) \cdot Z_t' \delta_j \right)^2 \tag{11}$$

In this case, the standard minimization approach is employed to reach the coefficient estimates. Interpretation is straightforward, since for within every given γ (i.e., threshold value and hence regime) the minimization of equation (13) is a simple least squares problem, within the sub-sample of the regime. Intuitively, the process for detecting more than one breaks is a sequential application of breakpoint tests, as per Bai (1997), with the procedure being repeated until all sub-samples do not reject the null hypothesis, or until the maximum number of breakpoints, i.e., m*, is reached. In what follows, we have applied this threshold regression approach to evaluate the non-linearity of the relationship between freight rates and inflation.

4.2.2. Threshold Regression Estimates

Table 3 presents the estimates from a non-linear threshold regression estimation. In particular, the methodology shows, starting from an agnostic view on the number and location of structural breaks, how the relationship between the variables changes when a certain threshold is exceeded. In all cases, the first lag of freight rates is used as the threshold variable.

In order to illustrate how the results from this methodology should be interpreted, in the Garments (CP0312) category, we observe that no significant relationship exists between freight rates and the said category when freight rates are below 7,04 (approximately $1.100). On the other hand, a small negative relationship appears to be present when freight rates between 7.04 and 7.27, i.e. between $1,100 and $1,500 per day. This unusual result is likely driven by the particular sub-sample used and does not necessarily imply the presence of a negative relationship between the two variables. The greatest impact stands when prices rise above the $1,500 mark, where a 1% increase in freight rates implies a 0.032% increase in the Garments category.

Table 3: Threshold Regression Estimates (Constant Tax HICP)

	CP0312	**CP0511**	**CP0531_2**	**CP0561**	**CP0611**	**CP0612_3**	**CP0711**	**CP1212_13**
Regime 1								
Freight Rates	0.001	-0.001	-0.001	0.001	0.001*	0.003***	0.000	0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Oil Prices	0.005	-0.001	-0.002**	-0.000	-0.001*	-0.002***	0.001***	0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Regime 2								
Threshold	*7.04*	*7.27*	*7.12*			*7.14*		
Freight Rates	-0.02**	0.009***	0.008***			-0.005***		
	(0.006)	(0.002)	(0.002)			(0.002)		
Oil Prices	0.016***	-0.001***	-0.001***			0.001*		
	(0.005)	(0.000)	(0.000)			(0.000)		
Regime 3								
Threshold	*7.27*							
Freight Rates	0.032***							
	(0.005)							
Oil Prices	-0.007***							
	(0.001)							
Non-Threshold								
AR(1)	0.003	0.685***	0.837***	0.897***	0.866***	0.648***	0.839***	0.922***
	(0.05)	(0.067)	(0.040)	(0.044)	(0.049)	(0.063)	(0.056)	(0.046)
D2020m07	0.076***	0.010***	0.011***	0.000	-0.002	0.006***	0.004**	0.001
	(0.005)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
D2021m07	-0.063***	-0.005***	-0.014***	0.002	0.001	-0.004**	-0.001	-0.001
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.003	0.002***	-0.002***	0.000	0.001**	0.002***	0.002***	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observations	92	92	92	92	92	92	92	92
Durbin-Watson	1.29	2.16	1.67	2.08	1.85	1.63	2.03	2.07

*,**,*** denote significance at the 10%, 5%, and 1% level respectively. Threshold variable is the first lag of the freight rate. All variables are in annual growth rates. Regime 1 includes all the variables below the Regime 2 threshold value. The coding of variables stands for: *CP0312- Garments, CP0511 - Furniture and furnishings, CP0531_2 - Major household appliances whether electric or not and small electric household appliances, CP0561 - Non-durable household goods, CP0611 - Pharmaceutical products, CP0612_3 - Other medical products, therapeutic appliances and equipment, CP0711 - Motor cars, CP1212_13 - Electrical appliances for personal care; other appliances, articles and products for personal care.*

As we can observe, the $1,500 level is also significant for the furniture and furnishings category, after which a 1% increase implies an approximately 0.01% increase in inflation. Regarding the major household appliances (CP0531-0532) and the electrical appliances (CP1212-1213) categories, the threshold value stands at around $1.250 per day. However, it appears that the positive relationship holds only for the major household appliances category, while no significant relationship appears to exist for electrical appliances. Finally, it appears that in other medical products (CP0612_0613), a negative relationship holds after the threshold.

As the application of the non-linear relationship suggests, the relationship between freight rates and inflation tends to be more pronounced as freight rates increase. In the overall NEIG category (not reported here but available upon request), we also find that this relationship holds when freight rates exceed $1,500 per day, with the impact standing at 0.01% per 1% increase. As such, an average 100% increase in freight rates would imply a 1% increase in NEIG inflation

5. Conclusions

In the current paper, we have examined the relationship between the consumer inflation in the EU states which has rebounded much faster than expected, following the decline in 2020 triggered by the COVID19 pandemic. Especially, during the period of the curfews in the EU zone, consumers shifted towards durable goods instead of services, with this mostly taking place via a move to online orders (Hall et al., 2021; Sheth, 2020). This fact, coupled with supply chain disruptions because of the pandemic-induced limitations, led to port congestion and a subsequent increase in global container shipping freight rates, with transport costs rising to record highs. As a result, because of the increase in freight costs, the Non-Energy Industrial Goods (NEIG) inflation contribution to total inflation, in the first eight months of 2021, almost quadrupled to 0.27%, compared with an average contribution of 0.07% since 2014.

To elaborate on the relationship between inflation and shipping costs, we employ a Vector Error Correction Model (VECM) and use disaggregated monthly data from January 2009 to August 2021, using both constant tax and the standard price indices. The results suggest that freight rates have a significant positive impact on the sub-categories of Non-Energy Industrial Goods (NEIG). Following a shock in freight rates, the most hard-hit sectors appear to be garments and major household appliances, items that have traditionally been manufactured outside the euro area. The findings are also supported by the application of a non-linear methodology, namely threshold regression, which suggests that the relationship between freight rates and inflation tends to become positive once the former rise above the $1,200-$1,500 levels, depending on the category.

From a policy perspective, the European Union has not been adequately prepared for such an event, The lack of self-sufficiency when it comes to NEIGs, have further increased the inflation in the area. The latter can act as a good indicator on the new approach that the EU should focus its attention in the near future. More precisely, an adequate self-sufficiency when it comes to NEIGs is demanded, so as to alleviate problems that have to do with supply chain disruptions.

Business-wise, the results extracted from our study imply that while just-in-time practices in warehousing are widely used these days (Ibrahim et al., 2015), a disruption in supply chain can have a domino effect in consumption, something that is more evident for goods such as garments and home appliances. From a business perspective, companies could potentially enhance their optimization methods when it comes to minimum stock something that could prove useful in the presence of a structural shock (Golan et al., 2020; Queiroz et al., 2020). Nonetheless, the lack of an optimized way to alleviate such shocks, at least in the supply side, could further imply additional costs for the firms (i.e. financing, lack of potential raw material suppliers, increased after sales service costs), which may prevent both shareholders and stakeholders to further invest in the companies that operate primarily in Europe.

Finally, we should highlight the fact that our paper, focus only on NEIGs and it does not take into account any energy disruptions or volatility in the prices that are rising. Recent research concerning the disruptions of energy either due to supply chain operational problems due to the recent curfews (Yu et al., 2021) or the more recent war (Deng et al., 2022; N. Michail and Melas, 2021) have not been addressed in the current paper and will be a fruitful area for future research.

References

Andrews, D.W.K., 1993. Tests for Parameter Instability and Structural Change With Unknown Change Point. Econometrica 61, 821–856. https://doi.org/10.2307/2951764

Andrews, D.W.K., Ploberger, W., 1994. Optimal Tests when a Nuisance Parameter is Present Only Under the Alternative. Econometrica 62, 1383–1414. https://doi.org/10.2307/2951753

Angelopoulos, J., Vitsounis, T., Paflioti, P., Chlomoudis, C., Tsmourgelis, I., 2021. Reflecting economic activity through ports: The case of Australia. Maritime Transport Research 2, 100021. https://doi.org/10.1016/J.MARTRA.2021.100021

Attinasi, M.G., Bobasu, A., Gerinovics, R., 2021. What is driving the recent surge in shipping costs? Economic Bulletin Boxes 3.

Bai, J., 1997. Estimating Multiple Breaks One at a Time. Econometric Theory 13, 315–352. https://doi.org/10.1017/S0266466600005831

Bai, J., Perron, P., 2003a. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18, 1–22. https://doi.org/10.1002/jae.659

Bai, J., Perron, P., 2003b. Critical values for multiple structural change tests. The Econometrics Journal 6, 72–78. https://doi.org/10.1111/1368-423X.00102

Bai, J., Perron, P., 1998. Estimating and Testing Linear Models with Multiple Structural Changes. Econometrica 66, 47–78. https://doi.org/10.2307/2998540

Bernanke, B.S., Boivin, J., Eliasz, P., 2005. Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. The Quarterly Journal of Economics 120, 387–422. https://doi.org/10.1162/0033553053327452

Carriere-Swallow, Y., Deb, P., Furceri, D., Jiménez, D. and O.J.D., 2022. Shipping Costs and Inflation (No. WP/22/61).

Chow, G.C., 1960. Tests of Equality Between Sets of Coefficients in Two Linear Regressions. Econometrica 28, 591–605. https://doi.org/10.2307/1910133

Deng, M., Leippold, M., Wagner, A.F., Wang, Q., 2022. Stock Prices and the Russia-Ukraine War: Sanctions, Energy and ESG. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4080181

Dickey, D.A., Fuller, W.A., 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root Author. Econometrica 49, 1057–1072.

Golan, M.S., Jernegan, L.H., Linkov, I., 2020. Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic. Environment Systems and Decisions 2020 40:2 40, 222–243. https://doi.org/10.1007/S10669-020-09777-W

Hall, M.C., Prayag, G., Fieger, P., Dyason, D., 2021. Beyond panic buying: consumption displacement and COVID-19. Journal of Service Management 32, 113–128. https://doi.org/10.1108/JOSM-05-2020-0151/FULL/PDF

Hall, P., 2013. The bootstrap and Edgeworth expansion. . Springer Science & Business Media.

Hall, P., 1986. On the Bootstrap and Confidence Intervals on JSTOR. The Annals of Statistics 14, 1431–1452.

Hansen, B.E., 2001. The New Econometrics of Structural Change: Dating Breaks in U.S. Labor Productivity. Journal of Economic Perspectives 15, 117–128. https://doi.org/10.1257/jep.15.4.117

Hendry, D.F., Juselius, K., 2001. Explaining Cointegration Analysis : Part II. The Energy Journal 21, 75–120. https://doi.org/10.2307/41322908

Hendry, D.F., Juselius, K., 2000. Explaining Cointegration Analysis: Part I. The Energy Journal 21, 1–42. https://doi.org/01956574

Herriford, T., Johnson, E.M., Sly, N., Smith, A.L., 2015. How Does A Rise in International Shipping Costs Affect U.S. Inflation? The Macro Bulletin - Macroeconomic research from the Federal Bank of Kansas City 1–3.

Ibrahim, H.W., Zailani, S., Tan, K.C., 2015. A content analysis of global supply chain research. Benchmarking 22, 1429–1462. https://doi.org/10.1108/BIJ-04-2013-0038/FULL/PDF

Johansen, S., Juselius, K., 1990. Maximum Likelihood Estimation and Inference on Cointegration — With Applications To the Demand for Money. Oxford Bulletin of Economics and Statistics 52, 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x

Kilian, L., 2009. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. American Economic Review 99, 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Koester, G., Rubene, I., Gonçalves, E., Nordeman, J., 2021. Recent developments in pipeline pressures for non-energy industrial goods inflation in the euro area, Economic Bulletin Boxes. European Central Bank.

Mackinnon, J.G., 1996. Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics 11, 601–618. https://doi.org/10.1002/(SICI)1099-1255(199611)11:6<601::AID-JAE417>3.0.CO;2-T

Mańkowska, M., Pluciński, M., Kotowska, I., Filina-Dawidowicz, L., 2021. Seaports during the COVID-19 Pandemic: The Terminal Operators' Tactical Responses to Disruptions in Maritime Supply Chains. Energies 2021, Vol. 14, Page 4339 14, 4339. https://doi.org/10.3390/EN14144339

March, D., Metcalfe, K., Tintoré, J., Godley, B.J., 2021. Tracking the global reduction of marine traffic during the COVID-19 pandemic. Nature Communications 2021 12:1 12, 1–12. https://doi.org/10.1038/s41467-021-22423-6

Michail, N., Melas, K., 2021. Geopolitical risk and the LNG-LPG trade. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3933751

Michail, N.A., Melas, K.D., 2021. Covid-19 and the energy trade: Evidence from tanker trade routes. The Asian Journal of Shipping and Logistics 1–30. https://doi.org/10.1016/j.ajsl.2021.12.001

Michail, N.A., Melas, K.D., 2020. Shipping markets in turmoil: An analysis of the Covid-19 outbreak and its implications. Transportation Research Interdisciplinary Perspectives 7, 100178. https://doi.org/10.1016/j.trip.2020.100178

Michail, N.A., Melas, K.D., Batzilis, D., 2021. Container shipping trade and real GDP growth: A panel vector autoregressive approach. Economics Bulletin 41, 304–315. https://doi.org/10.2139/ssrn.3724480

Perron, P., 2006. Dealing with Structural Breaks, in: Palgrave Handbook of Econometrics. pp. 278–352.

Pham, N.T.A., Sim, N., 2020. Shipping cost and development of the landlocked developing countries: Panel evidence from the common correlated effects approach. World Economy 43, 892–920. https://doi.org/10.1111/twec.12871

Philips, P.C.B., Perron, P., 1988. Testing for a Unit Root in Time Series Regression. Biometrika Trust 75, 335–346. https://doi.org/10.1093/poq/nf1045

Quandt, R.E., 1960. Tests of the Hypothesis That a Linear Regression System Obeys Two Separate Regimes. J Am Stat Assoc 55, 324–330. https://doi.org/10.1080/01621459.1960.10482067

Queiroz, M.M., Ivanov, D., Dolgui, A., Fosso Wamba, S., 2020. Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of Operations Research 2020 1–38. https://doi.org/10.1007/S10479-020-03685-7

Sheth, J., 2020. Impact of Covid-19 on consumer behavior: Will the old habits return or die? Journal of Business Research 117, 280–283. https://doi.org/10.1016/J.JBUSRES.2020.05.059

UNCTAD, 2021. Review of Maritime Transport. New York.

Xu, L., Shi, J., Chen, J., Li, L., 2021. Estimating the effect of COVID-19 epidemic on shipping trade: An empirical analysis using panel data. Marine Policy 133, 104768. https://doi.org/10.1016/J.MARPOL.2021.104768

Yao, Y.-C., 1988. Estimating the number of change-points via Schwarz' criterion. Statistics & Probability Letters 6, 181–189. https://doi.org/10.1016/0167-7152(88)90118-6

Yu, Z., Razzaq, A., Rehman, A., Shah, A., Jameel, K., Mor, R.S., 2021. Disruption in global supply chain and socio-economic shocks: a lesson from COVID-19 for sustainable production and consumption. Operations Management Research. https://doi.org/10.1007/s12063-021-00179-y