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Decomposing the Rate of Inflation: Price-Setting and Monetary Policy

Lilian Muchimba^{a*}, Mimoza Shabani^b, Alexis Stenfors^c and Jan Toporowski^d

Abstract

The paper adopts a TVP-VAR methodology to investigate the dynamics of inflation components for three countries: the UK, the US and Japan from 1993 to 2023. We deconstruct the CPI into components to examine the actual price changes that make up the CPI and the degree to which changes in those prices influence each other. By doing so, we uncover the connectedness and spillovers between domestic inflation components. We find that whilst connectedness of price changes has been moderate over the last three decades it has increased significantly since the CPI started to soar in late 2021, suggesting the existence of a spillover effect among price-setting firms in the economy. Furthermore, our empirical evidence shows that the transmission mechanism across domestic CPI components varies significantly across countries and over time. From a monetary policy perspective, the findings suggest that a signalling process among consumer market producers complements the signalling by central banks in relation to inflation. Lastly, the cross-country variations over time imply that “no size fits all”, thus emphasizing the importance of domestic spillovers.

JEL Classifications: C81, E31, E52, D43

Keywords: Consumer Prices, Dynamic Connectedness, Inflation, Monetary policy, Signalling, TVP-VAR.

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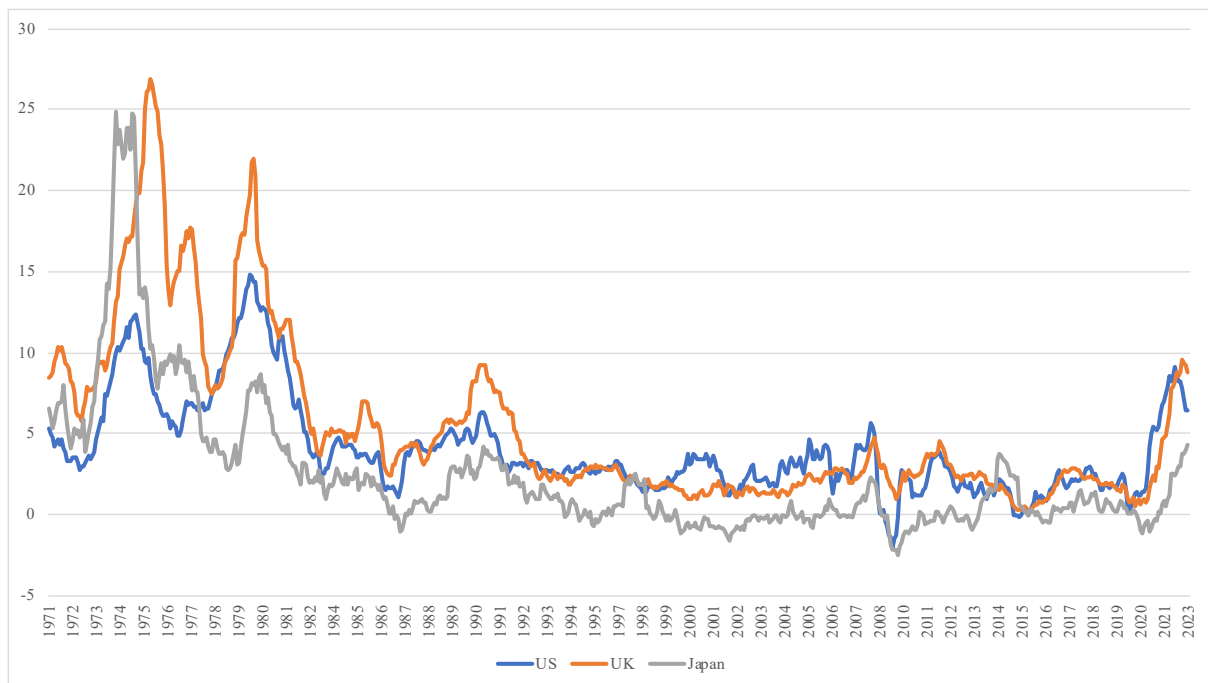
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*The conclusions and recommendations contained in this does not represent the official position of the Board and Staff of the Bank of Zambia but entirely those of the author.

1. Introduction

After more than three decades of low and stable price increases, inflation returned with a vengeance in late 2021 (see Figure 1). Much of the debate about the surge in inflation is attributed to the unforeseen economic events associated with the Covid-19 pandemic and the war in Ukraine. However, a common argument provided by both policymakers and academics alike was that inflation would be transitory (Ball et al., 2022). This gave ground to central banks not immediately responding to the rise in inflation.

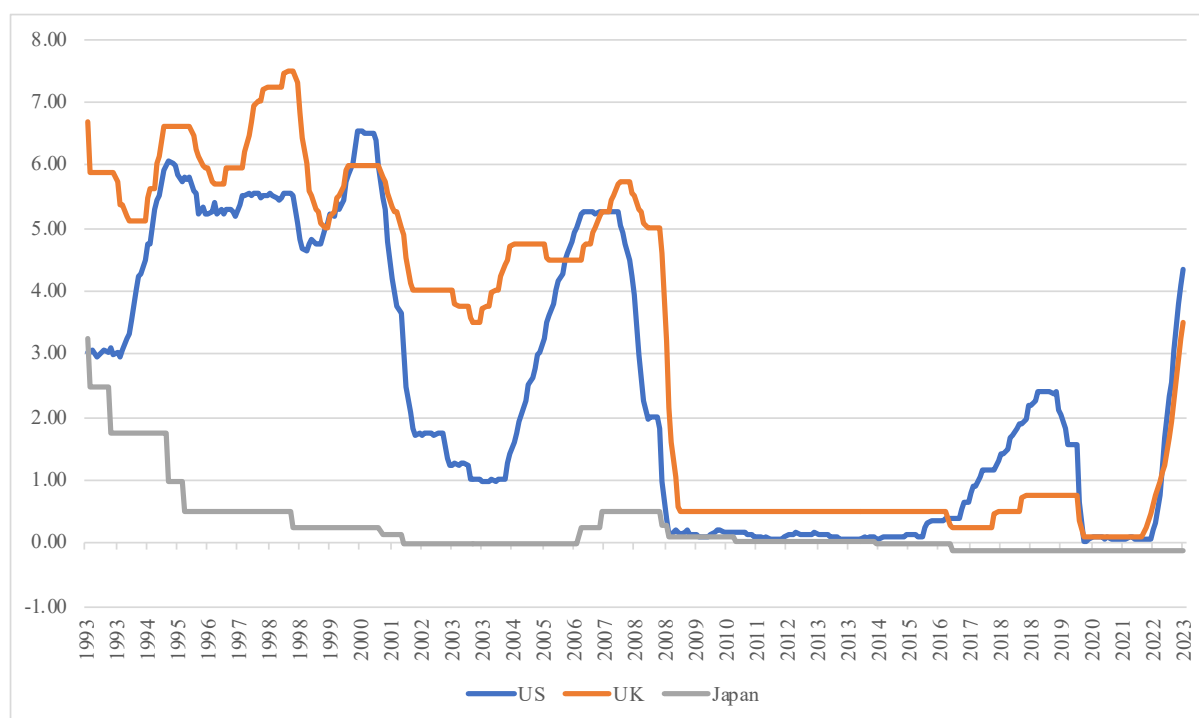
Figure 1: CPI, January 1971 – January 2023 (monthly)



Source: OECD

This turned out not to be the case, and numerous central banks made a U-turn when realising that the strong inflationary pressures might be long-lasting. At the time of writing, Japan stands out as the only advanced economy not to have raised its short-term policy rate (see Figure 2).

Figure 2: Central bank policy rate, January 1993 – January 2023 (monthly)



Sources: BIS, Bank of England, FRED

The failure to predict the sudden and substantial rise in inflation and the persistently high inflation despite successive rate hikes poses the question of whether other factors determine the price formation mechanism.

In our paper, we explore the processes of inflation by looking at the different components making up the consumer price index (CPI). More specifically, we decompose the index into different components representing different sectors of the economy. We then apply a TVP-VAR methodology to examine the connectedness and spillovers between the domestic inflation components to examine the actual price changes that make up the CPI and the degree to which price changes influence each other. We run the model on three major economies (US, UK and Japan) using monthly data from 1993 to 2023 to allow for a cross-country comparison.

We find that the connectedness of price changes has been moderate, ranging between 15%-45, over the last three decades. Importantly, the increases in connectedness are most notable since the CPI started to soar in late 2021, suggesting that inflation components have started to affect each other more. This could be interpreted as firms setting prices, taking cues from how firms in other sectors of the economy are behaving – creating a kind of spillover effect. We also find that the overall total connectedness has been remarkably stable throughout the period. The

implication here is that different sectors of the economy do not react to their price changes by the monetary policy interest rate changes. If so, connectedness would have shown spikes around and after changes in monetary policy. Thirdly, our empirical evidence shows that the transmission mechanism across domestic CPI components varies significantly across countries and over time.

From a monetary policy perspective, the findings suggest that a signalling process among consumer market producers complements signalling by central banks with regard to inflation. Thus, to understand the processes of inflation, the attention should shift from the CPI as an index to each component and how they affect each other. Lastly, the cross-country variations over time imply that “no size fits all”, therefore highlighting the importance of domestic spillovers.

Our paper contributes to the literature on the sources of inflation by analyzing how price changes of the components of inflation influence each other. The originality of our research stems mainly from three aspects. First, we focus on domestic spillovers of the components of the inflation price indices for three distinct countries (the US, the UK and Japan.) Second, we examine the process by which inflation happens which can explain how prices in different markets rise more or less simultaneously. Third, we employ a novel approach to model the degree of connections of price changes, which to the best of our knowledge has not been used by other studies on sources of inflation.

This paper is organized as follows. Section 2 provides a short overview of the related literature on the topic. Section 3 outlines the methodology and describes the data. Section 5 provides the empirical results. Section 6 concludes.

2. Short overview of the literature

Inflation has always been regarded as a macroeconomic phenomenon. Studies of inflation, therefore, concentrate on the effects on economic growth, exchange rates, monetary and financial stability or on the distributional consequences of inflation (Camera and Chien, 2014; Albanesi, 2007). Other inflation studies have examined the causes of inflation in wages and additional costs, inflationary expectations, fiscal balances, monetary aggregates, interest rates, and exchange rates (IMF, 2023; Parkin, 2008). In the latest bout of inflation, there has been

some discussion as to how far price inflation is the outcome of pressure to expand profit margins, as opposed to the old ‘cost-push’ inflation (Nikiforos and Grothe, 2023).

The backbone of any underlying analysis of the drivers of inflation in the conventional view is the notion that monetary policy can control inflation. Eickmeier and Hofmann (2022) analyse the US demand and supply conditions over 50 years, including the inflation surge in mid-2021, and argue that central banks could potentially reduce inflation by tightening monetary policy. The analysis is based on disentangling demand and supply factors and assessing their role in inflation dynamics. Using a structural factor model, the study imposes sign restrictions on factor loading, which are based on the premise that changes in the supply move inflation and economic activity in the opposite direction, whereas demand changes result in both variables moving in the same direction. The results suggest that the recent 2021 inflation has been driven by a combination of strong demand conditions and tight supply conditions, with demand playing a slightly more significant role quantitatively than supply. Furthermore, the study also assesses the dynamic impact of monetary policy using a vector autoregressive model. The results suggest that a tightening of monetary policy leads to a contraction of both demand and supply.

Similarly, Shapiro (2022) uses data from the personal consumption expenditure (PCE) basket of goods and services in the US and divides categories into demand and supply-driven groups. The methodology aims to capture the evolving impact of supply- and demand-driven factors on monthly inflation changes. In doing so, the expected sign for both prices and quantities are the same where shifts in demand are identified and in the opposite direction in the case of shifts in supply. The results imply that supply factors are responsible for more than half of the surge in PCE inflation, with demand playing a lesser role, explaining a third of the recent rise in inflation.

Bernanke and Blanchard (2023) point to the sectoral mismatches between supply and demand conditions as the initial cause of the sources of the US pandemic-era inflation. They employ a dynamic model of prices, wages, and short and long-run inflation expectations considering labour market tightness, energy and food price shocks, and sectoral shortages. They argue that the current inflation that began in 2021 is the result of shocks in the economy to prices given wages. These shocks to prices include increases in commodity prices, reflecting the strong aggregate demand supported by monetary and fiscal policy, and sectorial price spikes, resulting from shifts in the level and composition of the sectoral composition of demand and supply

constraints. However, they suggest that whilst they find that a tight labour market has not been the main source of the pandemic-era inflation, the effect of labour-market shocks on inflation is more long-lasting. Their decomposition of inflation into its sources analysis suggests that product-market shocks, which were initially the primary drivers of inflation, would have largely subsided over time, even without the implementation of policy. However, if the tight market labour conditions persist, they would likely not dissipate without policy action.

In the academic literature, as well as in policy reports and the popular press, inflation is proxied by the Consumer Price Index (CPI) – made up of a basket of goods and services that reflect the consumption pattern of the average citizen. The items and the weights of the components change over time. To people not employed by the Office for National Statistics, the Bureau of Labor Statistics or equivalent institutions elsewhere, the inclusion and weights of the components are of limited interest and importance. That is not to say that the CPI only can be conceptualised in one way. On the contrary, countless versions of the CPI often express country-specific variants of inflation that are adjusted for tax changes, energy prices, volatile items, housing costs, mortgage rates, etc. – such as CPI-trim, CPI-median and CPI-common (Canada); CPI-ATE and CPIXE (Norway); CPIF (Sweden); CPIH (UK) to name just a few. Certain items, such as energy prices and housing, are crucial and tend to generate attention independently, given their significant weight or impact on distribution and economic activity. Nonetheless, the detailed nuances of the index as a whole are rarely the focus of the debate. In practice, therefore, some version of the “core CPI” tends to be considered the most suitable measure of inflation because it seeks to strip out or mitigate the impact of volatile components to distinguish the “true” inflation from transient noise (Anand et al., 2015; Arora et al., 2013).

Since the 1990s, the ruling policy doctrine for dealing with inflation has been the setting of the short-term rate of interest by independent central banks, with a view to achieving a target rate of inflation (proxied by a CPI version) over a time horizon of around two years (Goodhart, 1999; Ortiz Martínez, 2008). Inflation targeting has, therefore, increased the attention of policymakers and market participants to the precise level and definition of the CPI – at the expense of the price developments of items and components making up the index. In a system where inflation is fundamentally seen as a monetary phenomenon, the detailed mechanics underpinning the relation between CPI components are of relatively little relevance. Instead, the ultimate authority rests with the central bank and its monetary policy.

3. Data and Methodology

In our paper, we explore the processes of inflation using a methodology that has not, to our knowledge, been used in this context before. This is done by breaking down the actual rate of inflation into the components of the CPI indices. This allows us to examine the actual price changes that make up the rate of inflation and the degree to which those price changes influence each other.

We use monthly inflation data from January 1993 to January 2023 for the UK, Japan and the US. The data is sourced from the Office for National Statistics, Official Statistics of Japan and the Bureau of Labor Statistics. In our study, we go deeper than inflation (CPI) and variants, including/excluding food and energy. Instead, for the granularity, we use 12, 12 and 9 inflation components for the UK, Japan and the US, respectively (see Table 1).

Table 1: Inflation components

UK		Japan		US	
Short name	Official description	Short name	Official description	Short name	Official description
Food	Food and non-alcoholic beverages	Food	Food (Including beverages)	Food	Food and beverages
Alcohol	Alcoholic beverages & tobacco	Alcohol	Alcoholic beverages		
Clothes	Clothing & footwear	Clothes	Clothes & footwear	Clothes	Apparel
Housing	Housing, water, electricity, gas & other fuels	Housing	Housing		
Household	Furniture, household equipment & maintenance	Household	Furniture & household utensils	Household	Housing
Health	Health	Health	Medical care	Health	Medical care
Transport	Transport	Transport	Private transportation	Transport	Transportation
Communication	Communication	Communication	Communication	Communication	Communication
Recreation	Recreation & culture	Recreation	Culture & recreation	Recreation	Recreation
Education	Education	Education	Education	Education	Education
Restaurants	Restaurants & hotels	Restaurants	Meals outside the home		
Misc	Miscellaneous goods & services	Misc	Miscellaneous	Misc	Other goods and services

Sources: Office for National Statistics, Official Statistics of Japan and the Bureau of Labor Statistics.

By doing so, we put forward another possibility that has not been considered previously in the literature, namely that business managers setting prices are more likely to set them in accordance with changes in prices in other lines of business. This is measured by the connectedness of changes in prices of particular goods and services in consumer price indices with previous changes in prices of other goods and services. Since we are dealing here with finished goods and services, the analysis excludes cost-push pressures because finished goods

do not enter as costs into each other's price-setting calculations, as they would in the input-output analysis. Emulating the price-setting of other businesses provides a more objective basis for price-setting than relying on subjective expectations. Such prices are also the prices of actual market transactions rather than indices that are subject to index number distortions and have no actual market value, except in the market for inflation-linked securities, which, of course, do not enter into any consumer price index.

A comparison with financial markets may serve to illustrate this process further. The CPI and the S&P 500 index are made up of prices of goods/services and stocks in different sectors. The indices do not capture available consumer prices or stock prices but have nonetheless evolved into conventional ways for economic agents to express "inflation" and "the stock market" and have, therefore, become crucial indicators. When the S&P 500 goes up and down, it does not mean that all 500 stock prices rise or fall in tandem. However, following important events (such as an unexpected monetary policy announcement) or during episodes of stress and uncertainty, they are more likely to track each other. This is not an automatic process. Rather, the buying and selling by traders and investors determines the price changes of a specific stock, which, in turn, influences the expectations of probable price changes of other stocks. Prices of stocks with the same sector (e.g. energy) or related sectors (e.g. energy and airline industry) tend to track each other more. The CPI is also made up of hundreds of items (consumer goods and services). Similarly, consumer prices do not rise or fall automatically. The prices are set by firms operating in different sectors – competing with each other, independent of each other, or collaborating with each other. Like stocks, prices of items (e.g. tomatoes) within the same CPI component (e.g. food) are likely to track each other more closely than prices across components (e.g. food and restaurants). Nonetheless, firms operating in the restaurant business are not only glancing at prices set by competing restaurants. They are also dependent on price developments of components that matter to them. In sum, the CPI and S&P500 can be seen as networks containing components representing different sectors of the economy.

A widely used framework to trace and evaluate spillovers in a predetermined financial or economic network is the connectedness approach proposed by Diebold and Yilmaz (2009, 2012, 2014). This study applies the model developed by Antonakakis et al. (2018), which was founded on Diebold and Yilmaz (2009, 2012, 2014) and is based on the vector autoregressive model (VAR). It is superior to the VAR model as it offers both static and dynamic analysis of a network of variables. Further, as noted by Chatziantoniou et al. (2020), unlike other models, the results are not affected by the size of the rolling window, and any existing outliers do not

affect the outcomes. Additionally, the model does not exclude observations when moving across windows.

Connectedness and spillover investigations using TVP-VAR methods have been applied to numerous financial markets, such as stock markets indices (Diebold and Yılmaz, 2009), commodities (Balcilar et al., 2021), FX spot rates (Antonakakis et al., 2020), interest rates swaps (Chatziantoniou et al., 2021; Stenfors et al., 2022a), government bond yields (Stenfors et al., 2022b) and cross-currency basis swaps (Chatziantoniou et al., 2020). Empirical studies on macroeconomic variables, including inflation and unemployment across countries (see, for instance, Pham and Sala, 2021), have also been conducted. Antonakakis et al. (2019) employ TVP-VAR to examine the transmission of international monetary policy spillovers for four developing economies, namely the Euro Area, Japan, the UK and the US. They focus on distinguishing whether monetary policy spillovers differ during episodes of normal times and unconventional monetary policy.

Most studies that have considered spillovers of inflation focus on the synchronized movements of international inflation rates and find that global factors do indeed have an impact on the domestic inflation of countries (see, for example, Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012). Baurle et al. (2021) examine the shock dependence in international inflation spillovers for Switzerland using consumer price index quarterly data from 1992 to 2011.

They employ a structural factor model and find that approximately half of the Swiss price variations are driven by foreign shocks, with domestic shocks accounting for only 20%.

We depart from these studies and focus on domestic spillovers. More specifically, we decompose the CPI index into components representing different sectors of the economy. As far as we are aware, no previous studies have investigated the role of individual components that make up a macroeconomic variable.

Specifically, our study uses this model (TVP-VAR) model to measure the extent and dynamic connectedness of selected CPI components for three major countries, namely the United Kingdom, Japan and the United States. This model uses variance decompositions, which facilitate the aggregation of spillover effects across the CPI components into a single spillover measure. The study estimates the following TVP-VAR model suggested by the Bayesian Information Criteria (BIC) for each country's CPI aggregated major components:

$$Z_t = B_t Z_{t-1} + u_t \quad u_t \sim N(0, S_t) \quad (1)$$

$$vec(B_t) = vec(B_{t-1}) + v_t \quad v_t \sim N(0, R_t) \quad (2)$$

Z_t , Z_{t-1} and u_t are $k \times 1$ dimensional vectors and represent all CPI components in t , $t-1$, and the respective error term, for each country. B_t and S_t are $k \times k$ dimensional matrices, $vec(B_t)$ and v_t are $k^2 \times 1$ dimensional vectors and R_t is a $k^2 \times k^2$ dimensional matrix. The H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) are calculated in line with Koop et al. (1996) and Pesaran and Shin (1998). Significantly, the calculated GFEVD is invariant to the order of variables as opposed to the orthogonalized forecast error variance decomposition (Diebold and Yilmaz, 2009). The representation is based on Wold representation theorem. Consequently, the estimated TVP-VAR model is transformed into a TVP-VMA process:

$$z_t = \sum_{i=1}^p B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \quad (3)$$

The (scaled) GFEVD normalises the unscaled GFEVD, $\phi_{ij,t}^g(H)$ so that each row sums to 1. Therefore, $\widetilde{\phi}_{ij,t}^g(H)$ below characterises the influence on variable i 's forecast error variance from variable j , also called pairwise directional connectedness from j to i .

$$\phi_{ij,t}^g(H) = \frac{S_{ii,j}^{-1} \sum_{t=1}^{H-1} (i' A_t S_t i_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (i A_t S_t A_t' i_i)} \quad (4)$$

$$\widetilde{\phi}_{ij,t}^g(H) = \frac{\phi_{ij,t}^g(H)}{\sum_{j=1}^k \phi_{ij,t}^g(H)} \quad (5)$$

Where $\sum_{j=1}^k \tilde{\phi}_{ij,t}^g(H) = 1$, $\sum_{j=1}^k \tilde{\phi}_{ij,t}^g(H) = k$ and i is the selection vector with unity on the i^{th} position and zero, otherwise. Then the GFEVD is computed as per Diebold and Yilmaz (2012, 2014) which allows us to calculate the following connectedness measures:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H) \quad (6)$$

$\tilde{\phi}_{ij,t}^g$ is the impact of the shock of j on i . The $TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H)$ is also called the total directional connectedness. It denotes the combined effect on other variables arising from a shock on variable j .

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H) \quad (7)$$

$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H)$ also called the total directional connectedness from others is the combined impact of a shock on all the other variables on variable j . The following net total connectedness index shows which variable is a net transmitter or receiver:

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (8)$$

If $NET_{jt} > 0$, then the variable is a net transmitter of shocks, and if $NET_{jt} < 0$, then the variable in question is the net receiver of shocks.

$$TCI_t = k^{-1} \sum_{j=1}^k TO_{jt} \equiv k^{-1} \sum_{j=1}^k FROM_{jt} \quad (9)$$

TCI_t (Total connectedness index) represents total forecast error variance in one CPI component explained by the shocks of all the other variables. The range for the TCI is 0% - 100%. If TCI = 100%, this implies that, on average, all variables in the system of variables (network) explain

100% of the variation of given variable. In the context of our study, a high TCI indicates that a shock (or ‘signal’) in one CPI component is very likely to be transmitted to all other variables in the network. On the other hand, a TCI of 0% means that the CPI components are independent of each other and are not affected by shocks (alternatively: ‘signals’) of all other variables in the network. The metrics used for this study are the TCI and the Net Total Connectedness Index.

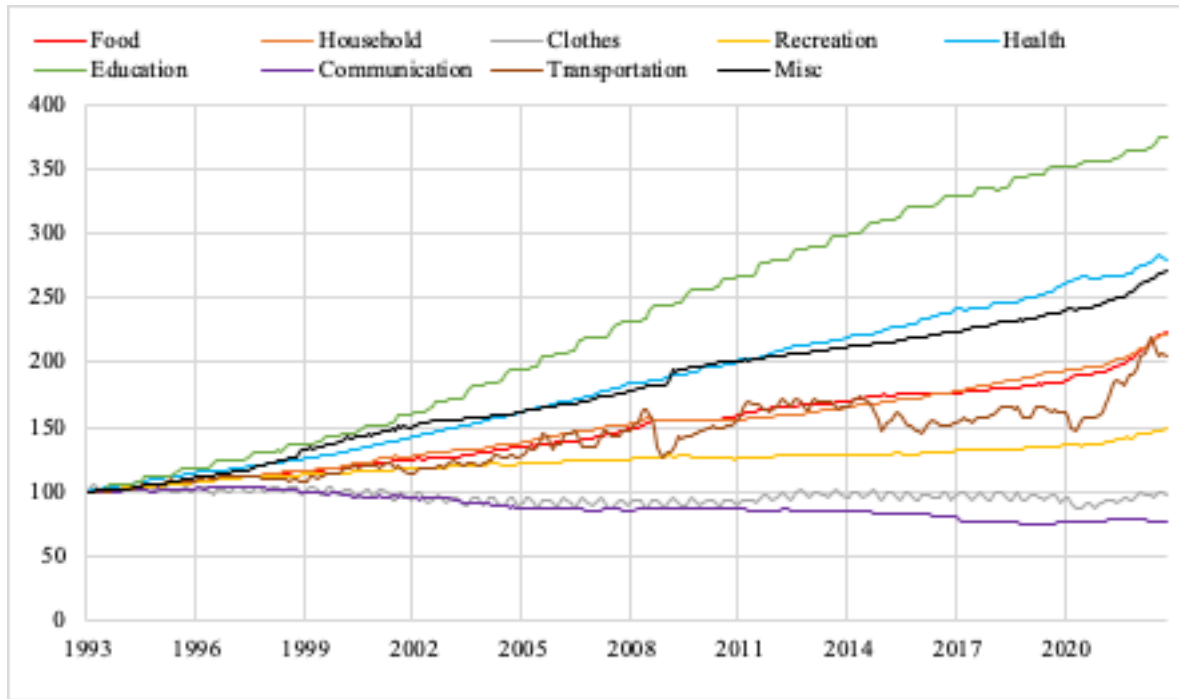
4. Empirical Results

4.1. United States

4.1.1. Summary Statistics (US)

Figure 3 below shows the US CPI index for 9 major components namely, Food, Household, Clothes, Recreation, Health, Education, Communication, Transportation, and miscellaneous items (Misc). To allow for comparisons with other countries, the CPI components are indexed to 1993.

Figure 3: CPI, major components (US)



Source: U.S. Bureau of Labour Statistics and authors' calculations Notes: The CPI uses 1993 as the base year (1993=100).

Table 2 below shows the summary statistics for the 1-month (M) percentage changes of the CPI components. The Elliot, Rothenberg, and Stock (ERS) shows that all series (1M percentage changes) are stationary in their levels at 5% level of significance (Elliot et al., 2016). Further, the skewness and kurtosis show evidence of non-normality and of serial autocorrelation (D'Agostino, 1970; Anscombe and Glynn, 1983; Jarque and Bera, 1980), therefore the study proceeds to estimate the TVP-VAR model as an appropriate model of the study.

As a robustness check, we also run the model using 12-month percentage changes, given that CPI typically is expressed as y/y. The results are, however, similar. If anything, the connectedness indices, as reported and elaborated on below, are somewhat lower. This suggests that monthly changes, despite being subject to more seasonal fluctuations, are more suitable for the study at hand – similarly to how higher observation frequency often is preferred when investigating connectedness and spillovers in financial markets.

Table 2: Summary Statistics (US)

CPI Component	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(10)	Q2(10)	Obs.
Food	0.2250	0.0750	0.866***	1.623***	84.031***	-4.493***	139.133***	184.400***	358
Household	0.2230	0.0720	0.417***	0.390	12.633***	-5.146***	78.059***	38.640***	358
Clothes	0.0140	4.5480	0.090	-0.967***	14.418***	-2.383**	602.554***	98.547***	358
Recreation	0.1110	0.0660	0.184	0.547*	6.472**	-3.173***	19.296***	44.249***	358
Health	0.2870	0.0530	0.244*	1.011***	18.801***	-7.665***	40.853***	23.498***	358

Education	0.3710	0.3200	2.142***	3.962***	507.871***	-6.341***	123.589***	67.653***	358
Communication	-0.068	0.1840	-0.899***	12.901***	2530.907***	-5.653***	9.373*	1.605	358
Transport	0.2130	2.4860	-0.887***	5.586***	512.360***	-8.749***	106.253***	70.004***	358
Misc	0.2810	0.2170	2.750***	16.459***	4492.375***	-7.188***	16.359***	31.124***	358

Source: U.S. Bureau of Labour Statistics and authors' calculations. Notes: obs = number of observations. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Skewness and Ex. Kurtosis are measured in line with D'Agostino (1970) and Anscombe and Glynn (1983). JB = Jarque Bera is the test for Normality (Jarque and Bera, 1980). ERS = the Elliot, Rothenberg and Stock (ERS) unit root tests for stationarity (Elliot et al. 1996). The Q(20) and Q2(20) represent the weighted Ljung-Box statistics for serial correlation in the series (Fisher and Gallagher, 2012), respectively.

4.1.2. Static Connectedness Measures (US)

Table 3 below presents the static connectedness measures of the US inflation components. The TCI measures the degree of the connectedness of variables in a network. The TCI is the total forecast error variance in one inflation component explained by the shocks of all the other variables. The range for the TCI is [0%, 100%]. A TCI of 0% means that the variables in question are unrelated and thus independent of each other. This implies that a variable in the system does not react to shocks of all other variables in the network. On the other hand, a value of 100% means that the network of variables is highly interconnected. A measure of or close to 100% implies that a shock in one variable will spill over to other variables in the network. From an inflation perspective, a high TCI is a possible indication that price increases/decreases in one sector are likely to spill over to others. In other words, a high TCI indicates that a component is susceptible/vulnerable to changes across each variable that makes up the index. The TCI of 21.00 (Corrected TCI) and 18.67 (TCI) shows that the percentage of variation of a variable attributable to all other variables in the network is lower compared to studies on networks in financial markets.

Decomposing the TCI into "TO" and "FROM" measures, the "TO" index measures the extent of transmission of shocks from each component to the entire network. On the other hand, the "FROM" measures the shocks on an aggregate basis that each component receives from the entire system of variables. However, the "TO" and "FROM" measures do not show which

component is a net transmitter or absorber of shocks. The “NET” indicator provides this information. The NET shows which variable is a transmitter or receiver of shocks (signals) on a net basis in the network. Food (FO), Household (HH), Clothes (CL), Education (ED) and Transport (TR) are net transmitters of shocks, while the Recreation (RC), Health (HE), Communication (CO) and Misc (MI) sectors are net receivers of shocks in the network. The diagonal elements show the shocks within the sectors. While the TCI is low, there is high connectedness within each sector (i.e. CPI component), with values exceeding 60.

Table 3: Average Connectedness Measures (US)

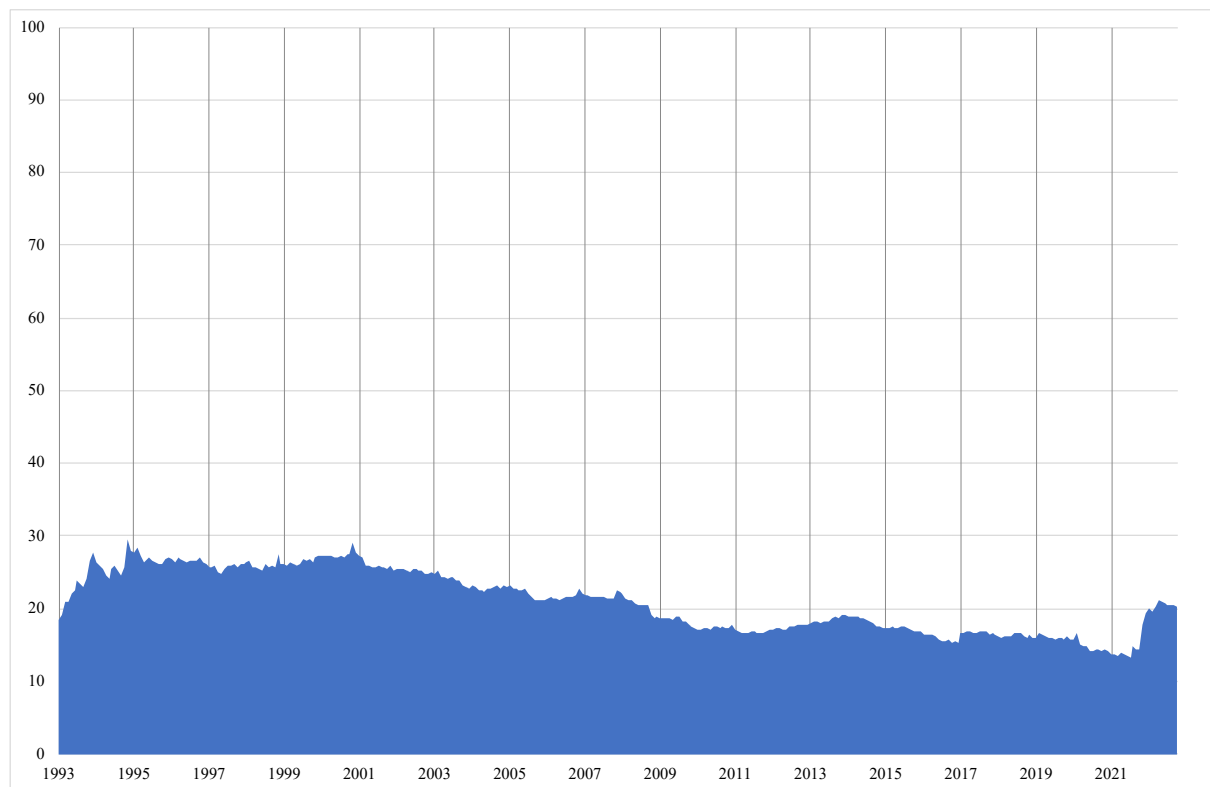
	FO	HH	CL	RC	HE	ED	CO	TR	MI	FROM
FO	81.78	3.49	3.64	3.61	4.01	0.67	0.64	1.15	1.02	18.22
HH	5.55	71.32	9.5	1.28	6.29	3.91	0.52	0.78	0.85	28.68
CL	3.53	9.49	75.96	0.74	2.29	5.7	0.35	0.71	1.22	24.04
RC	5.76	1.61	1.88	79.45	5.72	1.25	0.93	2.26	1.14	20.55
HE	6.85	8.51	9.07	5.03	63.28	1.83	0.85	3.54	1.05	36.72
ED	0.38	1.57	0.24	3.37	1.97	88.23	0.55	2.59	1.1	11.77
CO	2.32	1.09	1.01	1.34	1.03	0.7	91.08	0.65	0.78	8.92
TR	0.85	2.14	1.63	0.79	1.14	0.83	1.24	90.25	1.13	9.75
MI	0.74	0.98	1.09	1.6	0.65	1.59	1.45	1.28	90.61	9.39
TO	25.99	28.89	28.05	17.76	23.1	16.48	6.52	12.97	8.29	168.04
Inc.Own	107.77	100.21	104.01	97.21	86.38	104.71	97.6	103.21	98.9	cTCI/TCI
NET	7.77	0.21	4.01	-2.79	-13.62	4.71	-2.4	3.21	-1.1	21.00/18.67
NPT	4	5	6	3	3	5	2	5	3	

Source: U.S. Bureau of Labour Statistics and authors’ calculations. Notes: NPT (net pairwise transmission) measures the average contribution of transmission of each variable in the bidirectional relationships with other variables, in the entire period. The CPI components shown in the table are the following: Food (FO), Household (HH), Clothes (CL), Recreation (RC), Health (HE), Education (ED), Communication (CO), Transport (TR) and Misc (MI).

4.1.3. Dynamic Connectedness Measures (US)

The static connectedness measures presented above provide a starting point for an analysis. However, they do not show the evolution of the interrelations among variables over time. Figure 4 below shows the evolution of the connectedness of US inflation components since 1993. Notable from Figure 4 is that the TCI index has ranged between 10% and 30% during the last 30 years. Strikingly, however, the level of connectedness has shown a gradual decline over time. Consistent with documented literature (see, for instance, Chatziantoniou et al., 2020; Stenfors et al., 2022b), connectedness is highly event-dependent and tends to soar during periods of high volatility, financial market stress and economic uncertainty. Interestingly, the US TCI index has not been subject to any significant spikes.

Figure 4: Dynamic Total Connectedness (US)



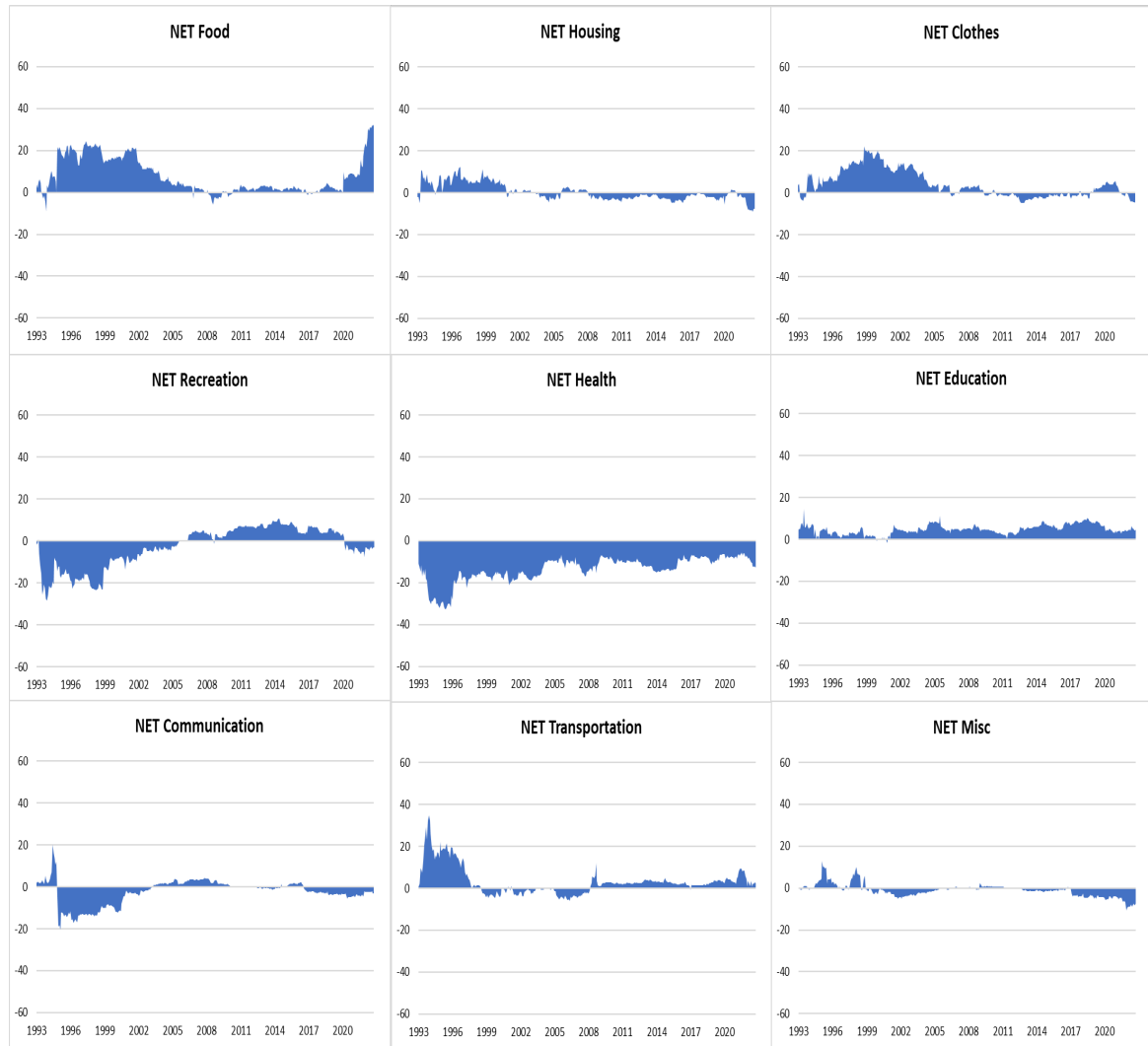
Notes: Dynamic Total Connectedness. Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

4.1.4. Net Total Directional Connectedness (US)

In addition to the evolution of the TCI (average aggregate connectedness) over time, Figure 5 below shows the time-varying characteristics of each variable in the network. A value greater than zero is an indication that the variable is a net transmitter of shocks (signals) in the network. On the other hand, a value below zero indicates that a variable is a net receiver of shocks in the network. Notable is that the transmission of shocks varies over time, with the Food, Education and Transportation being the predominant transmitters of shocks in the network over time. The

Health and Misc components and Housing assume a unique role as predominant receivers of shocks most of the time (since 1999). Recreation, Clothes, and Communication assume mixed roles.

Figure 5: Net Total Directional Connectedness (US)

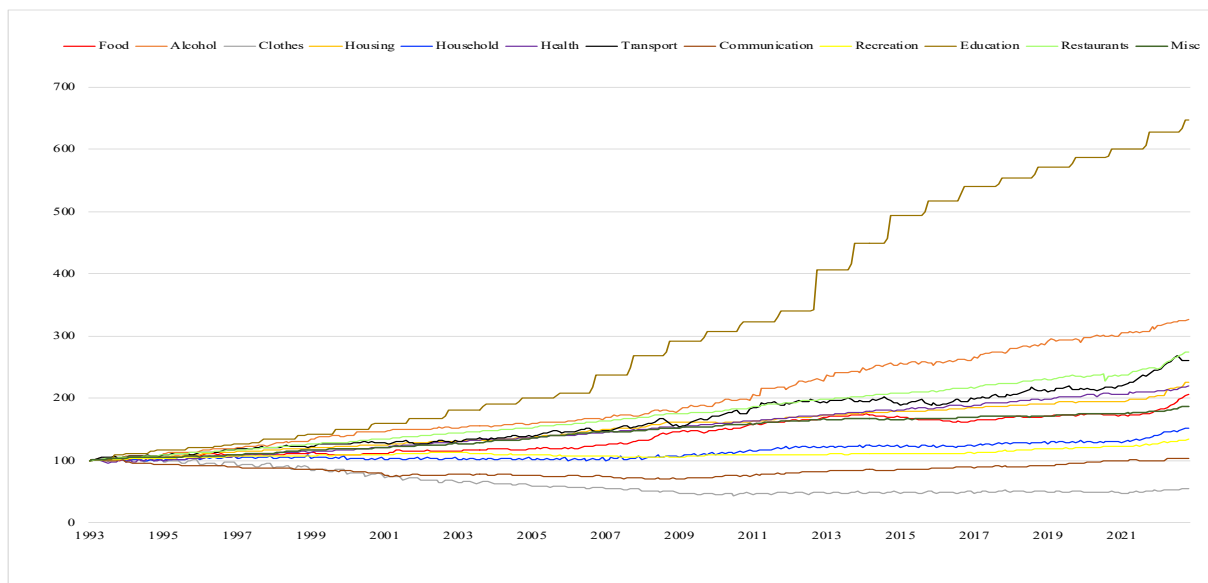


4.2. United Kingdom

4.2.1. Summary Statistics (UK)

Figure 6 below shows the CPI index for 12 major components namely, Food, Alcohol, Household, Clothes, Housing, Recreation, Health, Education, Communication, Restaurants, Transportation and miscellaneous items (Misc). To allow for comparisons with other countries, the CPI components are indexed to 1993.

Figure 6: CPI, major components (UK)



Source: Office for National Statistics and authors' calculations Notes: The CPI uses 1993 as the base year (1993=100).

Table 4 below shows the summary statistics for the 1-month (M) percentage changes of the CPI components for the United Kingdom. The Elliot, Rothenberg, and Stock (ERS) shows that

all series (1M percentage changes) are stationary in their levels 5% level of significance and the skewness and kurtosis tests show evidence of non-normality and of serial autocorrelation.

Table 4: Summary Statistics (UK)

	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(10)	Q2(10)
Food	0.2040	0.4350	0.289**	0.668**	11.644***	-2.560**	34.428***	72.492***
Alcohol	0.3360	0.7900	1.854***	5.593***	671.716***	-9.295***	34.730***	22.735***
Clothes	-0.1350	6.0850	-0.829***	0.844***	51.626***	-8.266***	227.578***	123.312***
Housing	0.2290	0.1810	6.019***	55.993***	48928.504***	-4.093***	24.241***	28.292***
Household	0.1290	2.2070	-1.003***	1.053***	76.560***	-5.667***	385.741***	25.764***
Health	0.2240	0.7400	0.495***	14.202***	3023.158***	-8.036***	122.983***	331.332***
Transport	0.2740	1.1150	-0.453***	0.686**	19.251***	-5.571***	37.893***	24.296***
Communication	0.0090	0.5000	0.041	5.308***	420.372***	-4.830***	14.944***	3.035
Recreation	0.0810	0.1470	0.189	1.426***	32.478***	-3.982***	22.698***	33.769***
Education	0.5360	2.8290	5.746***	47.081***	35035.351***	-10.280***	18.133***	0.751
Restaurants	0.2830	0.1780	-3.305***	55.980***	47397.271***	-6.934***	39.110***	47.128***
Misc	0.1770	0.1030	0.0220	1.585***	37.513***	-3.074***	11.540**	25.083***

Source: Office for National Statistics and authors' calculations. Notes: obs = number of observations. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Skewness and Ex. Kurtosis are measured in line with D'Agostino (1970) and Anscombe and Glynn (1983). JB = Jarque Bera is the test for Normality (Jarque and Bera, 1980). ERS = the Elliot, Rothenberg and Stock (ERS) unit root tests for stationarity (Elliot et al. 1996). The Q(20) and Q2(20) represent the weighted Ljung-Box statistics for serial correlation in the series (Fisher and Gallagher, 2012), respectively.

4.2.2. Static Connectedness Measures (UK)

Table 5 below shows the average connectedness measures for the significant CPI components for the United Kingdom. Similar to the United States CPI components, the Clothes (CL), Education (ED), and Transport (TR) CPI components are net transmitters of shocks in the network. Contrary to the US, however, the static analysis shows that Alcohol (AL), Housing (HO), Health (HE) and Restaurants (RS, though not a separate US component) are net transmitters of shocks. On the other hand, the net receivers of shocks are Food (FO), Household (HH), Communication (CO), Recreation (RC) and other miscellaneous (Misc., MI) components. The diagonal elements also show higher connectedness within sector connectedness than across components, with values exceeding 58.47.

Table 5: Average Connectedness Measures (UK)

	FO	AL	CL	HO	HH	HE	TR	CO	RC	ED	RS	MI	FROM
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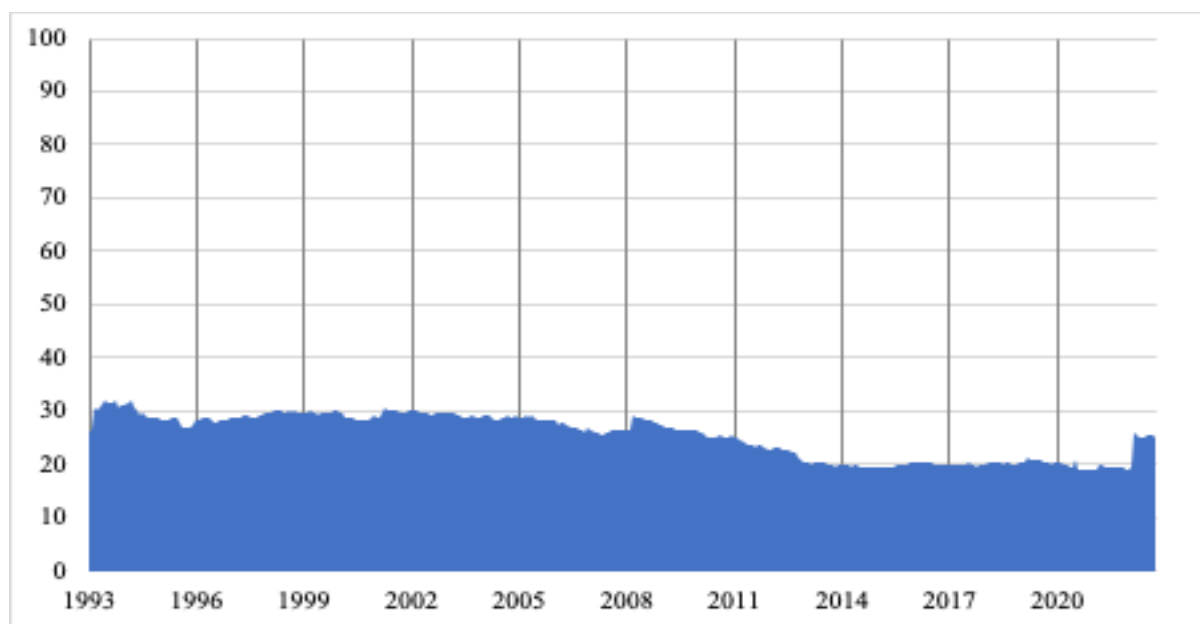
FO	77.62	1.93	1.6	6.33	2.35	0.54	1.47	1.29	1.73	1.17	2.74	1.23	22.38
AL	1.22	73.05	5.03	2.15	5.37	1.67	2.28	0.8	0.39	2	5.2	0.83	26.95
CL	0.62	4.36	60.69	4.37	17.95	0.3	0.99	2.8s	0.94	4.02	1.76	1.19	39.31
HO	0.7	3.17	2.6	77.47	1.97	0.99	1.92	2.19	3.36	0.27	3.23	2.13	22.53
HH	1.16	4.38	19.41	1.51	58.47	2.04	0.69	1.25	1.37	2.35	5.03	2.34	41.53
HE	0.65	2.53	0.3	1.58	0.95	87.17	0.68	2.03	0.8	0.77	1.13	1.4	12.83
TR	0.82	1.14	2	1.7	1.73	3.9	82.15	0.55	1.71	1.32	1.49	1.5	17.85
CO	1.13	1.35	4.69	2.04	2.41	1.9	0.79	82.44	0.7	0.66	0.87	1.01	17.56
RC	0.36	0.84	0.82	4.31	2.23	2.15	4.79	1.34	77.33	1.97	1.83	2.04	22.67
ED	0.59	2.83	2.52	0.34	1.09	0.81	3.74	0.81	1.16	85.14	0.55	0.41	14.86
RS	0.83	5.95	1.51	4.09	2.53	1.99	1.15	0.59	1.48	1.28	77.71	0.89	22.29
MI	0.89	1.1	4.08	2.76	2.21	1.09	2.61	1.15	1.08	0.77	1.73	80.53	19.47
TO	8.96	29.6	44.56	31.19	40.81	17.4	21.11	14.79	14.7	16.57	25.57	14.96	280.22
Inc.Own	86.58	102.65	105.25	108.66	99.28	104.57	103.26	97.23	92.04	101.71	103.28	95.49	cTCI / TCI
NET	-13.42	2.65	5.25	8.66	-0.72	4.57	3.26	-2.77	-7.96	1.71	3.28	-4.51	25.47 / 23.35
NPT	1	8	7	7	6	5	7	6	2	6	7	4	

Source: Office for National Statistics and authors' calculations. Notes: NPT (net pairwise transmission) measures the average contribution of transmission of each variable in the bidirectional relationships with other variables, in the entire period. The CPI components shown in the table are the following: Food (FO), Alcohol (AL), Clothes (CL), Housing (HO), Household (HH), Recreation (RC), Health (HE), Education (ED), Communication (CO) Transport (TR), Restaurants (RS) and Misc (MI).

4.2.3. Dynamic Connectedness Measures (UK)

Further to the static connectedness measures above, Figure 7 below shows the developments of the interconnectedness of the major CPI components in the UK over time. Similar to the US, interconnectedness is low (below 35) compared to 100 (an indication that the 100 per cent variation of the variable would be attributable to all other variables in the network). Further, the connectedness is time-varying, showing a gradual decline to values close to 25 beyond 2016.

Figure 7: Dynamic Total Connectedness (UK)

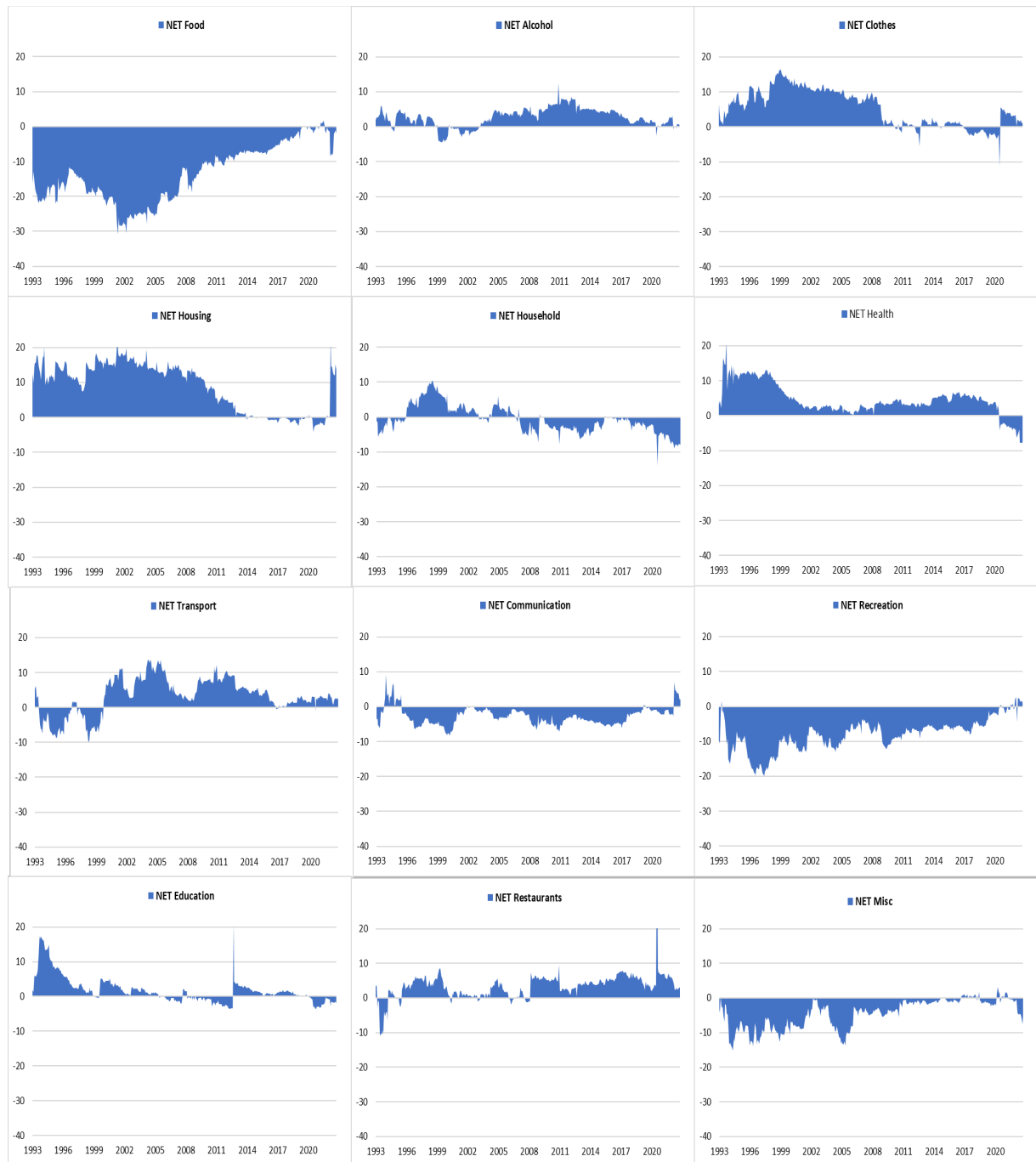


Notes: Dynamic Total Connectedness. Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

4.2.4. Net Total Directional Connectedness (UK)

Further to the evolution of the TCI (average aggregate connectedness) over time, Figure 8 below shows the time-varying characteristics of each variable in the network overtime. Similar to the US findings presented above, the transmission of shocks varies over time. Notably, Food, Household, Communication, Recreation and Misc assume a unique role of being net receivers of shocks most of the period. On the other hand, the CPI components, namely, Alcohol, Clothes, Health, Housing, Restaurants, Education and Transport are predominant transmitters of shocks in the network.

Figure 8: Net Total Directional Connectedness (UK)

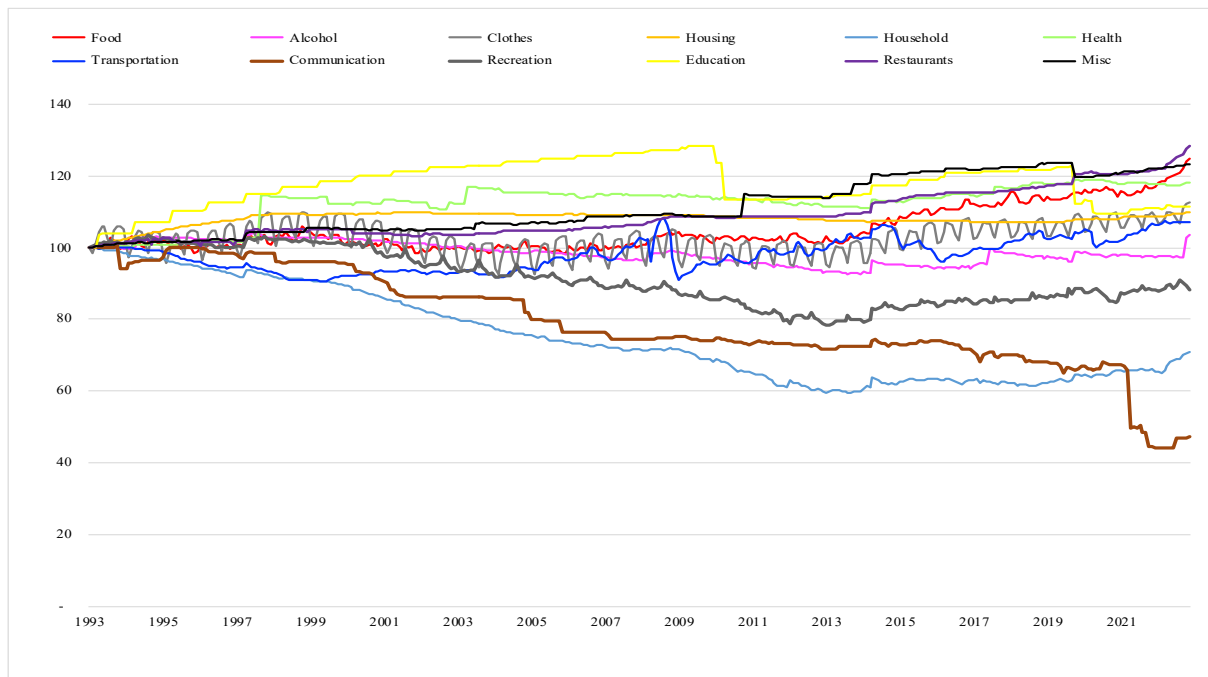


4.3. Japan

4.3.1. Summary Statistics (Japan)

Figure 9 below shows the Japanese CPI for 12 major components namely, Food, Alcohol, Household, Clothes, Housing, Recreation, Health, Education, Communication, Restaurants, Transportation and miscellaneous components (Misc). To allow for comparisons with other countries, the CPI components are indexed to 1993.

Figure 9: CPI, major components (Japan)



Source: Statistics Bureau of Japan Notes: The CPI is based on 1993=100.

Table 6 below shows the summary statistics for the 1-month (M) percentage changes of the CPI components. The Elliot, Rothenberg, and Stock (ERS) shows that all series (1M percentage changes) but Housing are non-stationary in their levels at 5% level of significance (Elliot et al., 2016). To avoid spurious results, the series are transformed by differencing and become stationary when differenced once at 5% level of significance and the skewness and kurtosis show evidence of non-normality and of serial autocorrelation.

Table 6: Summary Statistics (Japan)

CPI Component	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(10)	Q2(10)
Food	-0.001	1.111	0.15	0.109	1.44	-5.44***	92.86***	19.60***
Alcohol	-0.002	0.614	-0.26**	21.19***	6683.63***	-9.45***	95.48***	83.31***
Clothes	-0.006	14.503	-0.54***	-0.29	18.52***	-2.93***	210.86***	65.84***
Housing	0	0.015	-0.34***	3.79***	219.77***	-12.98***	105.39***	59.49***
Household	-0.002	0.527	0.08	14.92***	3309.79***	-14.36***	101.05***	85.95***
Health	0	1.008	0.01	93.14***	129044.03***	-15.19***	87.82***	88.24***
Transportation	0	1.189	-4.09***	58.99***	52754.83***	-12.67***	72.57***	36.02***
Communication	-0.003	4.927	-1.06***	71.73***	76606.27***	-17.20**	142.42***	88.62***
Recreation	0.005	1.728	0.73***	1.48***	63.86***	-12.45***	167.26***	36.15***
Education	0	1.216	0.05	38.69***	22266.39***	-8.98***	92.46***	87.75***
Restaurants	-0.001	0.221	-1.03***	14.64***	3250.73***	-13.53***	120.26***	79.03***
Misc	0	0.376	0.02	50.27***	37590.39***	-15.81***	84.98***	87.08***

Source: Statistics Bureau of Japan and author's calculations. Notes: obs = number of observations. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Skewness and Ex. Kurtosis are measured in line with D'Agostino (1970) and Anscombe and Glynn (1983). JB = Jarque Bera is the test for Normality (Jarque and Bera, 1980). ERS = Elliot, Rothenberg and Stock (ERS) unit root tests for stationarity (Elliot et al. 1996). The Q(20) and Q2(20) represent the weighted Ljung-Box statistics for serial correlation in the series (Fisher and Gallagher, 2012), respectively.

4.3.2. Static Connectedness Measures (Japan)

Table 7 below shows the average connectedness measures for the major CPI components in Japan. The static analysis shows that the common transmitter of shocks in the network across all countries (United States, United Kingdom, and Japan) is the Education CPI component. Like in the UK, Health and Restaurants are net transmitters of shocks in the network. On the other hand, Food, Alcohol, Clothes, Housing, Transportation and Communication are net receivers of shocks. Similar to the US and the UK, the diagonal elements also show higher connectedness within sectors (CPI components) than across components, with values exceeding approximately 50.

Table 7: Average Connectedness Measures (Japan)

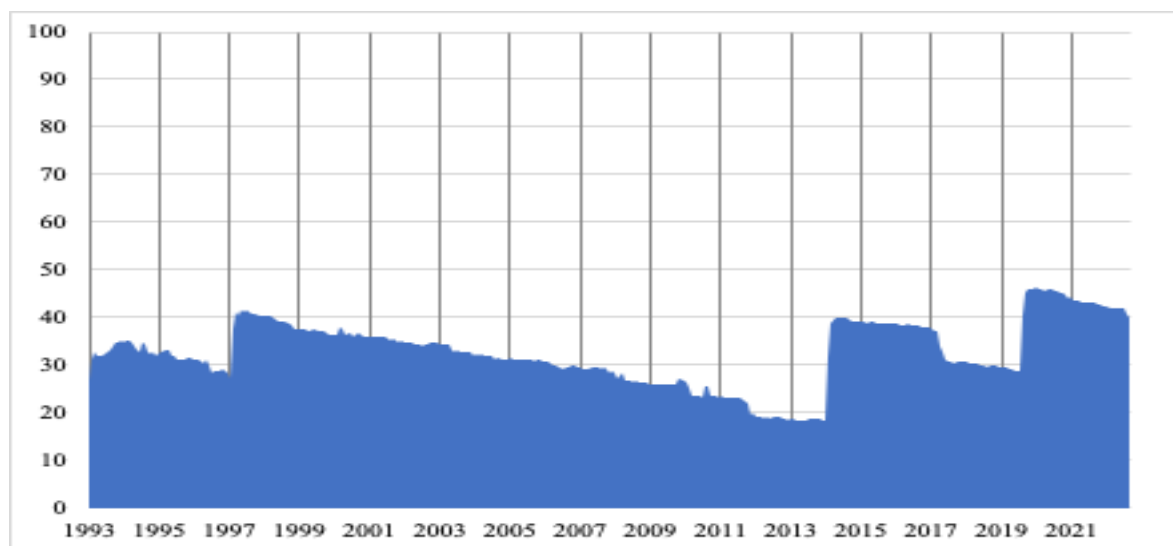
	FO	AL	CL	HO	HH	HE	TR	CO	RC	ED	RS	MI	FROM
FO	73.77	2.8	1.39	1.27	6.45	1.01	1.16	0.99	3	1.39	4.71	2.06	26.23
AL	2.33	56.39	0.35	2.01	13.45	3.56	2.27	0.92	3.22	5.89	6.1	3.51	43.61
CL	6.16	0.57	68.7	1.46	1.04	1.47	0.32	2.25	12.68	3.49	0.67	1.17	31.3
HO	1.04	2.24	0.52	74.32	1.94	1.39	3.08	0.68	1.31	3.8	7.17	2.53	25.68
HH	3.85	11.83	0.35	1.26	49.59	1.47	3.33	1.01	4.39	4.25	8.33	10.34	50.41
HE	0.47	1.67	1.57	1.26	3.13	84.28	0.19	0.2	0.63	1.44	4.54	0.63	15.72
TR	0.29	2.91	0.11	1.74	5.66	0.19	80.96	0.47	1.04	2.23	1.35	3.05	19.04
CO	0.67	0.55	2.19	0.88	1.33	0.48	0.2	90.53	0.76	1.12	0.91	0.38	9.47
RC	2.3	4.35	8.34	1.31	7.54	0.61	0.91	0.61	68.23	1.28	2.42	2.1	31.77
ED	1.69	3.35	0.9	2.88	7.84	2.08	1.27	0.89	1.28	69.72	5.43	2.68	30.28
RS	4.85	5.35	0.29	3.25	9.46	4.2	1.13	0.42	1.7	4.12	57.34	7.91	42.66
MI	1.82	5.28	0.77	1.82	10.53	0.61	1.89	0.19	1.48	2.66	8.03	64.93	35.07
TO	25.47	40.91	16.77	19.14	68.35	17.07	15.74	8.62	31.48	31.69	49.66	36.35	361.25
Inc.Own	99.23	97.3	85.47	93.46	117.94	101.35	96.7	99.15	99.71	101.41	107	101.28	cTCI / TCI
NET	-0.77	-2.7	-14.53	-6.54	17.94	1.35	-3.3	-0.85	-0.29	1.41	7	1.28	32.84 / 30.10
NPT	3	6	1	3	11	5	4	4	6	6	9	8	

Source: Statistics Bureau of Japan and author's calculations. Notes: NPT (net pairwise transmission) measures the average contribution of transmission of each variable in the bidirectional relationships with other variables, in the entire period. The CPI components shown in the table are the following: Food (FO), Alcohol (AL), Clothes (CL), Housing (HO), Household (HH), Recreation (RC), Health (HE), Education (ED), Communication (CO) Transport (TR), Restaurants (RS) and Misc (MI).

4.3.3. Dynamic Connectedness Measures (Japan)

Further to the static connectedness measures above, Figure 10 below shows the developments of the interconnectedness of the major Japanese CPI components over time. Similar to the US, interconnectedness is low (below 50) compared to 100 (an indication that the 100 per cent variation of the variable would be attributable to all other variables in the network). The notable difference with other countries is that, while the TCI is still moderate, it is higher in certain periods when Japan experienced peaks close to 40 (1997, 2014, 2019) compared to the trend observed over time in the case of the US and the UK, discussed above.

Figure 10: Dynamic Total Connectedness (Japan)

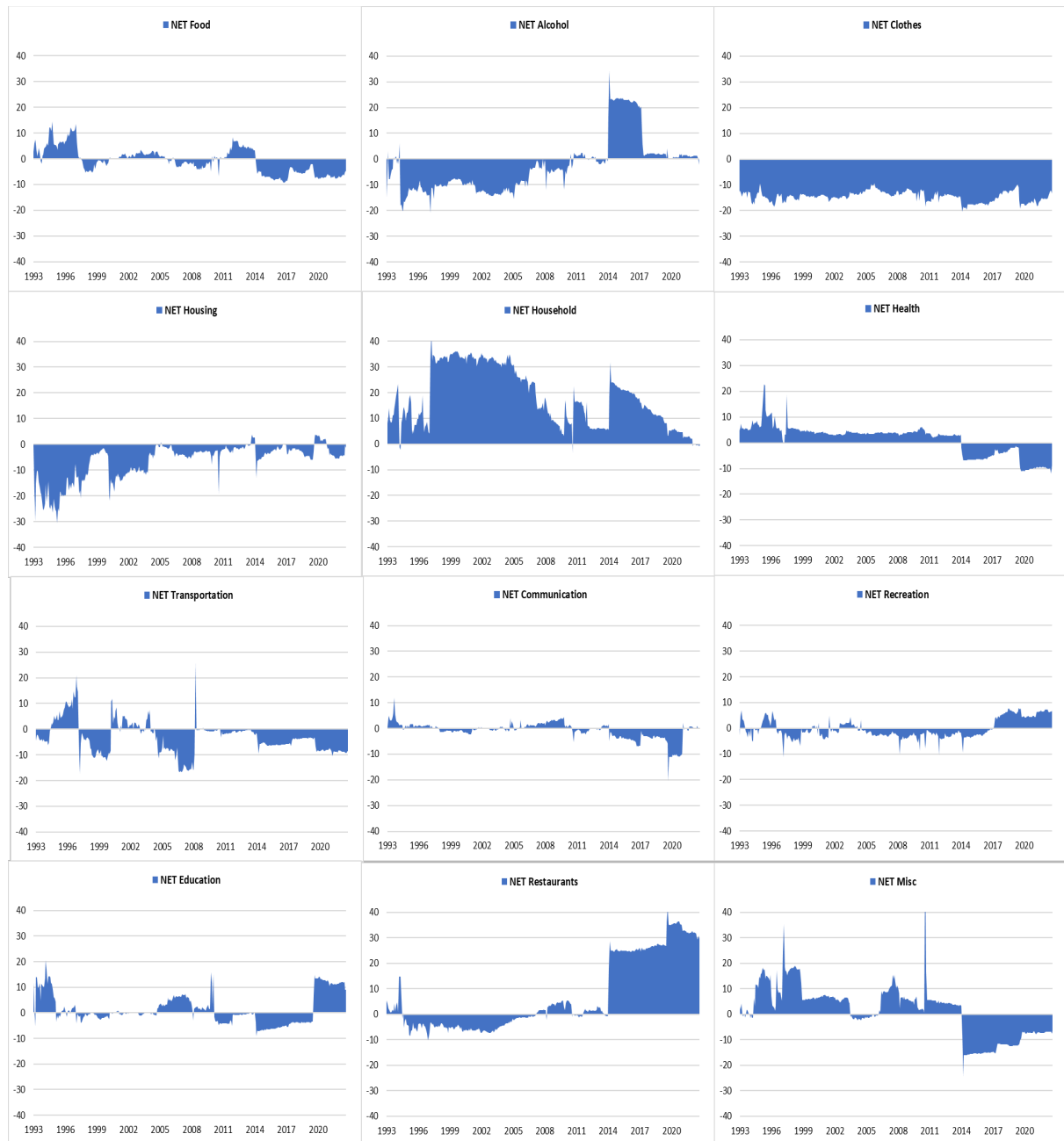


Notes: Dynamic Total Connectedness. Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

5.3.4 Net Total Directional Connectedness (Japan)

Further to the evolution of the TCI (average aggregate connectedness) over time, Figure 11 below shows the time-varying characteristics of each CPI component over time. Similar to the US and UK findings presented above, the transmission of shocks varies over time. Notably, Clothes, Transportation, Housing and Recreation assume a unique role of net receivers of shocks in the network for most of the period. On the other hand, the predominant transmitters of shocks are Household and Health. Food, Alcohol, Restaurants, Education, Communication and Misc assume mixed roles in the network over time.

Figure 11: Net Total Directional Connectedness (Japan)



5. Concluding Discussion

In this paper, we have used a TVP-VAR methodology to investigate the dynamics of inflation components for the UK, the US and Japan from 1993 to 2023. Our methodology deconstructs the CPI into components, allowing the examination of the actual price changes that make up the CPI and the degree to which changes in those prices influence each other. By doing so, we uncover the connectedness and spillovers between domestic inflation components, which, as far as we are aware, has not been done before.

We document three key findings. First, the total connectedness index has been moderate (15%-45%). During the last three decades, the connectedness has gradually decreased in the US and the UK. Increases in connectedness are notable during specific episodes, such as the VAT increases in Japan in 2014 and 2019, but more generally, since the CPI started to soar from late 2021 onwards in the US and the UK. During these episodes, inflation components have started to affect each other more. This could be interpreted as firms setting prices, taking cues from how firms in other sectors of the economy are behaving – creating a kind of spillover effect. Second, overall, the TCI has been remarkably stable throughout the period. In contrast to studies on financial markets, no spikes are reported in the immediate aftermath of substantial volatility, uncertainty in the financial system or monetary policy shocks. This is inconsistent with the notion that different sectors of the economy react to monetary policy tightening [easing] by lowering [raising] prices. Third, the transmission mechanism across domestic CPI components varies significantly across countries and over time. These empirical results are very different from studies on networks in financial markets. It appears as if connectedness between inflation components within the *same country* is lower than, say, connectedness among exchange rates or government bonds and stock markets of *different countries*.

The findings have implications both for monetary and financial policy. From a monetary policy perspective, the findings suggest that signalling by central banks with regard to inflation (see, for instance, Melosi, 2016) is complemented by a kind of signalling process among consumer market producers. Thus, to understand the processes of inflation, attention needs to be paid to each component and how they affect each other. Regardless of the headline CPI, a sharply higher inflation connectedness can be seen as an indicator that firms in numerous sectors have begun to take cues from each other in their price-setting behaviour. The distributional effects

are likely to be highest among strongly connected sectors, which may have important implications for fiscal policy. The findings also imply that the weighting and exclusion of CPI components may be practical for policy, but it also serves to mask hidden underlying phenomena that are crucial to grasping the micro-foundations of price-setting behaviour in the economy. Finally, it is notable that the variations across countries and over time imply that “no size fits all”. A more integrated global economic and financial system has undoubtedly resulted in an increase in the speed and magnitude of inflation spillovers between countries. However, domestic spillovers remain important.

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