2. SECTORIAL PRICE SHOCK PROPAGATION VIA INPUT-OUTPUT LINKAGES[1]

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Abstract

This paper presents an input-output framework, which also incorporates novel elements inspired by network literature along with Monte Carlo simulation techniques to analyse the propagation process of diverse sectorial cost shocks in the economy as well as to evaluate the risks associated to these sectorial inflationary pressures. In the static perspective over the impact of shocks on consumer inflation, the paper calculates sector specific first-round direct and cumulated sensitivities, showing evidence for the importance of indirect linkages within the economy. The sensitivity analysis also finds that a handful of economic sectors might exert particularly large influence on final consumer prices. Beside the static examination, the study introduces a network (or graph) representation of the input-output table that provides a flexible framework for analysing the diffusion phenomena of shocks in a dynamic manner. The price pressure indicators generated by the dynamic approach is able to explain a large share of the annual variation in Romania's headline and core inflation measures. Combining the diffusion model with Monte Carlo simulation techniques, the study shows that the magnitude of recent price shocks - determined mainly by global factors - corresponds to a fat tail event, with no any similar episode since the introduction (2005) of inflation targeting in Romania.

Keywords: inflation, input-output linkages, networks, shock diffusion, pass-through, composite indicators, risk evaluation, Monte Carlo simulation

JEL Classification: E31, E37, E52, D57, F41, L14

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1. Introduction

As of early 2022, inflation rates across advanced as well as a series of emerging and developing economies reach multi-decade highs, causing serious challenges for policy makers, professional forecasters and other economic actors. In addition, society's most vulnerable segments are particularly hit by the rising cost of living, after the price of basic consumer items, such as food and energy, rose sharply. The force by which inflation revived took many by surprise. Despite the tremendous efforts dedicated for preparing well-grounded inflation forecasts - supported also by advanced econometric models - the projections of central banks as well as professional forecasters undershot consumer price dynamics by a wide margin. The elevated level of recent inflation appears to be especially surprising, as the rebound had happened suddenly, with unexpectedly high and volatile price growth figures showing up after a decade-long era of persistently low and stable inflation. In the post-2008 business cycle, the worlds' most powerful central banks, but also several emerging market decision-makers, struggled to bring inflation to target on a sustained basis, despite highly accommodative monetary policy strategies. In the post-Covid recovery, however, this low inflation environment seems to have come to an end.

In order to gain a better understanding over the sudden shift in the inflationary environment and to extend the set of tools for analysing consumer price developments, I present an input-output framework - that also incorporates novel elements inspired by network literature - to monitor and to evaluate the risks coming from sectorial cost pressures. In addition, I provide an empirical application of the approach for the case of Romania.

The literature of analysing the impact of price shocks on inflation is particularly rich and diverse. Therefore, papers in this domain might be classified taking into account a wide range of characteristics. While acknowledging that a clear-cut distinction is hard to draw, I choose to highlight two main categories: approaches that rely primarily on statistical models and analysis that build on input-output linkages. As providing a truly complete review of the literature is difficult, at least, I focus on a narrow subset of researches, which are relevant for this study as well as might be also representative for a relatively broad area of different methods.

Among papers, that analyse the pass-through of shocks, many focus on individual rather than joint effects of certain inflationary factors, such as commodity prices. For instance, Furlong and Ingenito (1996) examined the empirical relationship between changes in commodity prices and inflation using bivariate and multivariate VARs combined with rolling regression methods. Their results showed that the link between the analysed data series has changed dramatically over time: during the 1970s and early 1980s, commodity price swings had been important and statistically robust leading indicators for overall inflation, but they have become rather poor precursors for inflation dynamics since the early 1980s. As global commodity prices had been surged in the period of 2006-2008, Hobijn (2008) examined the impact of these developments on inflation for various US personal consumption expenditure categories by calculating crops as well as oil and gas input shares from input-output accounts. His results suggested that the impacts were modest and concentrated in a narrow set of goods prices. Bukeviciute et al. (2009) investigated the transmission mechanisms along the food supply chain in EU member states applying various OLS regressions as well as error correction models (ECM). Nonetheless, when constructing weighted cost indices for the food and beverage industry of individual member states, the authors used input-output tables as well. Their study found that commodity price shocks were absorbed differently across EU members. European Central Bank's (2010a) Structural

Issues Report provided a conceptual framework for characterising first-round direct and indirect effects along with second-round impacts of energy prices on overall inflation. In order to estimate the associated sensitivities, the study applied a wide range of analytical methods, including the input-output framework, various structural VAR (SVAR) and large-scale macroeconomic models. Conflitti and Luciani (2017) estimated the pass-through of crude oil shocks into US and Euro Area consumer prices based on dynamic factor models (DFM) and VAR. Among others, they showed that the pass-through - via the common component of inflation - into core consumer price indicators is small, but non-negligible (i.e. statistically different from zero and long lasting).

Beside commodity prices, exchange rate and labour cost developments could also play a key role in inflation dynamics. In this regard, Osbat et al. (2021) studied the exchange rate pass-through (ERPT) on disaggregated import price data for the euro area. They employed VAR models with exogenous variables (frequently referred as VAR-X models) that helped explaining industry-specific heterogeneity of the ERPT. In contrast to the VAR method, Camatte et al. (2021) applied an “accounting” approach based on input-output tables for the global economy to calculate the elasticities of household consumption expenditures’ deflator relative to the exchange rate. They found a modest level of average elasticity at global level, yet important heterogeneity across countries. Unsurprisingly, small-open economies were much more exposed to exchange rate developments than their larger peers, the results pointed out. Murarașu and Stoian (2015) conducted a comprehensive analysis about the ERPT in Romania, a small-open economy and relatively new member of the EU. The study implemented a wide range of econometric methods, such as regressions with time-varying coefficients using the Kalman filter, ECM and VAR - including threshold VAR (TVAR) too. One of their interesting finding was related to the significant asymmetries with respect to the sign and size of the exchange rate movements. The study also presented evidence for the weakening of the ERPT over time. The channel between labour costs and consumer prices is another subject that has been generating particularly extensive interest from many researchers for decades. Among these studies, I choose to highlight a relatively recent paper of Bobeica et al. (2021). Employing various VAR models on US data, authors’ results showed a steadily declining response of inflation to labour cost shocks over time. Using the regime-switching specification of the VAR model, they also showed that, when inflation was above the sample average, the response of inflation to labour cost shocks were not only stronger, but more rapid as well. Nevertheless, the change of the inflation regime was not a sole driver of the declining pass-through from labour cost, the authors noted and, in this respect, they proposed additional important factors, such as sector specific trade openness and firm pricing power.

In contrast to the above papers, which focused primarily on the individual impact of inflationary factors - commodity prices, exchange rate and labour cost -, several studies did not stick to these categories rigorously, but tried to analyse the phenomena from a different perspective. For instance, Auer et al. (2019) attempted to infer the underlying cost shocks - i.e. a sort of reverse engineering - using a dataset that combines information on industrial producer prices (IPP) and exchange rates with international and domestic input-output linkages across sectors. Beside the evidence of high IPP synchronisation amplified by global input-output linkages, an interesting conclusion of their paper was that the structure of input-output relationships was such that the fat-tailed shocks did not average out. Thus, the IPP series inherited the fat tailed nature of the underlying shock process. These results were in line with the pioneering work of Acemoglu et al. (2017), which demonstrated how microeconomic idiosyncratic shocks might lead to significant aggregate fluctuations if a few sectors played a disproportionately important role as input suppliers. Frohm and Gunella (2021) came to similar conclusions: the presence of large hub sectors could cause economic disturbances to spread over more easily.

For a comprehensive collection of analysis that attempt to reveal the main drivers behind the era (2013-2019) of extra low inflation in the euro area, the study conducted by Koester et al. (2021) is worth noticing. The authors shed light on the role of interconnected factors, such as cyclical developments, less well-anchored longer-term inflation expectations, constraints due to the effective lower bound as well as disinflationary structural trends.

In addition to the above analysis, this paper also drew inspiration from the rapidly expanding network literature, with a particular focus on diffusion and learning phenomena (Section 2 provides a more detailed overview) as well as from studies related to stress testing (e.g. Virolainen, 2004) and composite indicators for inflationary pressures (e.g. Álvarez and Sánchez, 2018).

The rest of the paper is structured as follows: Section 2 identifies the sectors with potentially important influence on inflation dynamics, discusses the underlying structure of the Romanian economy and presents the static and dynamic perspective over the impact of sectorial cost shocks on consumer prices. In addition, the final part of Section 2 provide technical details with respect to the evaluation method of inflationary risks. Section 3 discusses the main findings and Section 4 concludes.

2. Data and Methodology

2.1 Selecting Sectors with Potentially Important Influence over Consumer Price Developments

This section aims to identify a relatively small sub-set of sectors, which might have important effects on the overall price dynamics in the economy. In order to do so, the paper analyses a broad range of price data from the period of 2005 to 2019. The selection of this time interval can be explained by practical challenges related to the availability and quality of data, as well as fundamental factors. Among the latter, it is important to note that the chosen period excludes the early transition phase of Romania from a centrally planned economy to that of a free market-based system - a structural transformation that played a key role in inflation developments. In addition, the National Bank of Romania introduced its inflation-targeting regime in 2005 and, in the same year, the treaty that arranged the accession of Romania to the European Union was also signed[3]. These developments could have caused a structural change in the price-setting process of economic agents. Moreover, the selected period ends before the outburst of the global COVID-19 crisis, thus, capturing price fluctuations associated with "normal" business cycle conditions.

The first group of analysed datasets covers industrial producer price indices (IPP)[4] for domestic market. In the identification procedure of sectors, several criterions are kept in sight, such as favouring industries, which locates close to upstream rather than downstream segments of the production value chain. Another principle is to advocate sectors, whose IPP are driven primarily by external factors - i.e. showing signs of co-movements with global

[3] With date of accession set to 1 January 2007.

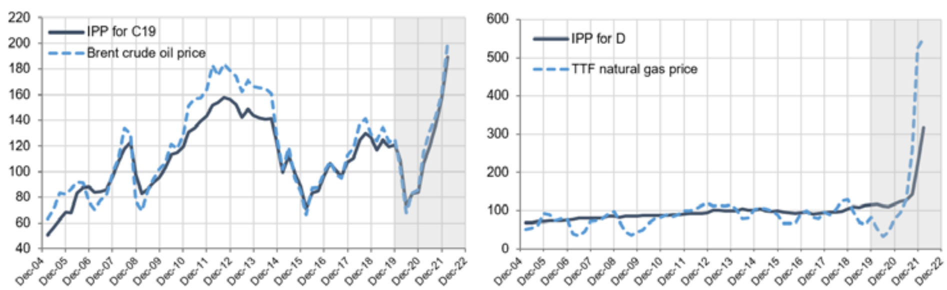
[4] For a detailed description of the raw data series, please see the notes provided by NIS's Tempo Online database under matrix code PPI1030.

commodity prices - and are hardly influenced by domestic monetary or other regulatory authorities. Furthermore, proper candidate sectors are expected to register relatively high level of price variability and they should be representative and large enough to create considerable price fluctuations at aggregate level.

On the back of these principles, three data series are selected, namely: the industrial producer price index for manufacturing of coke and refined petroleum products (NACE code: C19), electricity, gas, steam and air conditioning supply (D35 or simply D) as well as manufacturing of basic metals (C24). The IPP of the selected sectors show well above average volatility (Table A1 from the Supplementary Appendix), with C19, C24 and D, ranking 1st, 2nd and 6th by their variance among industrial branches. Another option could be to utilise the producer price index for the mining and quarrying sector (B, ranked 3rd). Nevertheless, in the case of Romania, the majority state-owned companies play an important role in this sub-sector, with a de-facto monopole in coal and lignite extraction. Therefore, the related IPP index may be less representative from the perspective of market-based price formation dynamics. In the case of basic pharmaceutical products and pharmaceutical preparations (C21, ranked 4th) and manufacturing of tobacco products (C12, ranked 5th) the situation is quite similar, as government policies related to taxes and subsidies have crucial contribution to the final price of these goods. Moreover, in comparison to the selected industrial branches, B, C21 and C12 are rather small measured by their size (total supply) that indicates modest influence on the economy. In addition, the selected sectors can explain a quite large share of the headline IPP's quarterly variation[5], while following the general evolution of global energy and metal commodity markets (Figure 1, Panel A and Panel B) as well. In terms of upstreamness - besides the common association of energy and metal producers with upstream characteristics -, Section 3 of the paper provide evidence that all of the three selected sectors may exert important influence over consumer prices via indirect linkages.

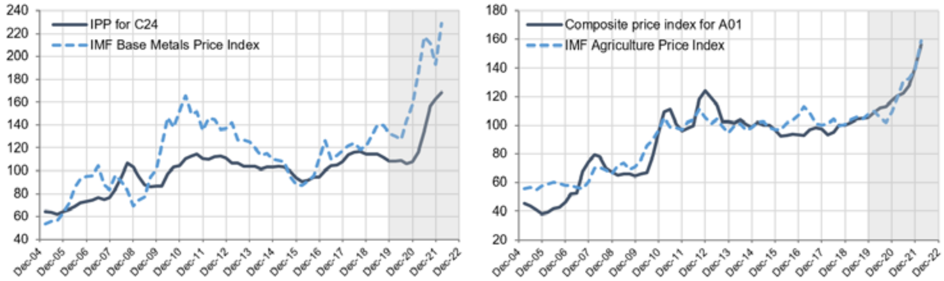
Figure 1. Sectorial Price Indices (2015 av. = 100)

Panel A

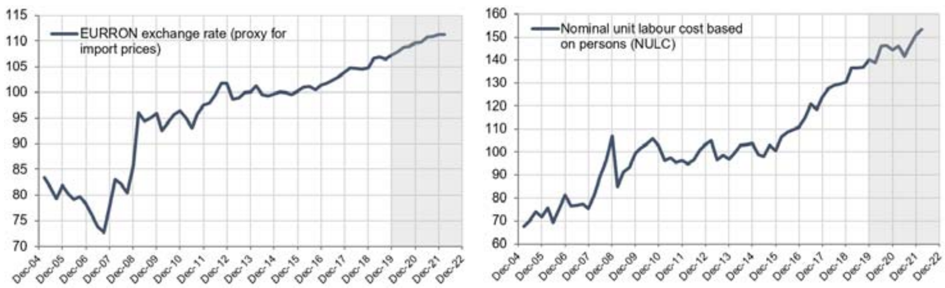


[5] *Running a simple ordinary least squares (OLS) estimation between the quarterly growth rates of the headline IPP and the selected sub-indices - IPP for C19, C24 and D along with a constant - yields 0.77 R-squared statistic with all independent variables being significant at 1% level.*

Panel B



Panel C



Notes: IMF commodity price indicators are converted from USD to RON; all data series are tested and, if necessary, adjusted for seasonality using JDemetra+; structural breaks in NULC data is corrected in JDemetra+ using LS-type (level shift) dummy variables.
Sources: NIS, Refinitiv, IMF, NBR, Eurostat, author's calculation.

After the selection of key data series from industry, the list of indicators is extended to ensure a broader coverage by adding specific indicators for agriculture[6], import prices and labour costs. In the case of agriculture, a composite index is constructed using the average selling price of main products set by agricultural producers at farm gate[7] (Figure 1, right-hand-side of Panel B). The specific weight for each product is derived using data from the consumer basket[8] (according to Table A2 from the Supplementary Appendix). One may think to use the GDP deflator of agriculture as an alternative and easier-to-implement option. Nevertheless, this approach would suffer from several drawbacks. First of all, gross value added (GVA) deflators contain information for the price developments of sectorial final production along with intermediate consumption that may result in divergent signals. Furthermore, the indicator associated to agriculture is subject of significant data revisions

[6] *More specifically, crop and animal production, hunting and related service activities (NACE code: A01)*

[7] *For a detailed description of the raw data series, please see the notes provided by NIS's Tempo Online database under matrix code PPA102C.*

[8] *For technical information about the compilation of Romanian consumer basket and inflation data, please see NIS's methodological explanations. Available at: <https://insse.ro/cms/files/statistici/comunicate/ipc/a22/methodological_explanations_04.pdf> [Accessed May 2022].*

and shows little evidence of co-movement with consumer food prices. Therefore, the author chooses the former (constructing a specific composite index) approach.

In order to approximate the evolution of import prices, the paper utilise the EURRON exchange rate as a proxy (Figure 1, left-hand-side of Panel C) instead of imports' deflator, as the latter may echo global commodity price evolution as well. In this manner, the "double counting" of commodity price related effects is avoided. Finally, the analysis includes nominal unit labour costs (NULC) to capture the price pressure experienced by producers from the direction of labour market (Figure 1, right-hand-side of Panel C). When monitoring inflationary risks, shocks coming from labour costs should be kept in sight due to their relevance in the price-setting behaviour of economic agents.

2.2 Transmission of Sectorial Price Shocks into Consumer Prices via Input-Output Linkages

2.2.1 The Structure of the Economy

Having set up the final list of sectors with potentially important impact on consumer prices, I turn to the presentation of the transmission mechanism of shocks. In order to establish a bridge between (primarily) cost-push inflationary shocks and final consumer prices, the study uses input-output linkages. To be more specific, the analysis builds on the supply and uses table (SUT)[9] to capture the structural features of the production chain - the backbone of the propagation channel.

According to the European System of Accounts (ESA 2010), SUT tables are matrices describing the structure of the costs of production, the income generated in the production process together with the flows of goods and services produced within the national economy as well as the rest of the world. In mathematical form, the input-output table A, is a symmetric matrix with elements A_{ij}, representing the amount of input i required for the production of output j. A key analytic strength of input-output matrices is that they enable the measurement of first-round direct as well as indirect impacts. For instance, a sharp increase in energy prices is expected to affect not only those industries that use energy intensively, but also those sectors that use the outputs of energy-intensive producers. In some conditions, such spillover effects might be highly relevant. Moreover, the SUT framework is able to capture the relationships between the production, expenditure and income side of the economy, providing a more comprehensive understanding of the indirect effects of diverse shocks.

An additional, but rarely exploited, feature of the input-output table is that it can be transformed into a network (or graph) representation that may provide further insight about the anatomy of the economy under review. In the network representation[10], each sector i corresponds to a node (or vertex), while the elements of the supply and use table can be seen as components of an adjacency matrix, where each element of A_{ij} denotes a directed and weighted link (or edge) from sector i to sector j. In order to make the network complete

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[9] For a detailed description of how Eurostat compiles and utilises supply and uses tables - and, in general, the input-output framework - see European System of Accounts (ESA 2010), Ch. 9. Available at: <https://ec.europa.eu/eurostat/esa2010/chapter/view/9/#h449> [Accessed March 2022].

[10] Barabási (2016, Ch. 2), Jackson (2008, Ch. 2) and Menczer et al. (2020, Ch. 1) provide technical overview about the network representation of diverse systems.

and more useful for analysis, we keep not only the producing sectors with NACE codes, but also entry- (e.g. labour contribution to production, imports) and terminal nodes (e.g. household consumption, exports) as well.

A visualisation of the network based on the SUT table for Romania is provided in Figure 2. To make the visualisation more transparent and easier to interpret, the study uses the OpenOrd layout as well as modularity algorithms[11] for identifying potential clusters. Based on the results of the algorithms four main partitions can be distinguished (marked by different colours on Figure 2), out of which, the two largest groups are particularly relevant from the perspective of consumer price-setting behaviour.

The first cluster (in purple on Figure 2) is formed in the vicinity of households' final consumption expenditures (CH - a terminal node, characterised exclusively by inward linkages).

This cluster is dominated by sectors associated primarily with the domestic market, e.g. food industry as well as a wide range of private services. Suppliers from the group serve domestic household needs via strong direct ties[12] and through important indirect linkages[13]. In addition, the cluster includes capital share K[14] as, from the perspective of revenue generation and business orientation of Romanian companies, domestic consumption is more relevant than export markets.

The second largest division (marked by green on Figure 2) is associated mainly with industrial good producers that are well integrated into global value chains, suggested by their proximity to exports (EX) and imports (IM), the two dominating nodes of the cluster. In line with expectations, manufacturing of motor vehicles, trailers and semi-trailers (C29), Romania's flagship exporting sector, is part of this partition. Beside a wide range of industries from manufacturing, a few representatives of the tertiary sector are also included here, which may need a short explanation. For instance, land transport and transport via pipelines (H49) plays an important role not only in the domestic distribution of imported goods, but Romanian companies from this sector are engaged in sizable foreign operations too[15]. Another interesting case is that of computer programming, consultancy, and information service activities (J62_63). IT firms report well above average profitability that explains the sector's proximity to node K (capital share). However, they dispose also a significant portion of their output directly to foreign users as well as to Romanian exporters.

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[11] *During the visualisation and partitioning exercise, the author tested several alternative algorithms and set-ups. However, those competing alternatives provided less straightforward cuts with economically difficult to explain outputs. Therefore, the results of the alternative approaches are not presented in the paper. For more information about the algorithms, see Blondel et al. (2008), Lambiotte et al. (2009) and Martin et al. (2011).*

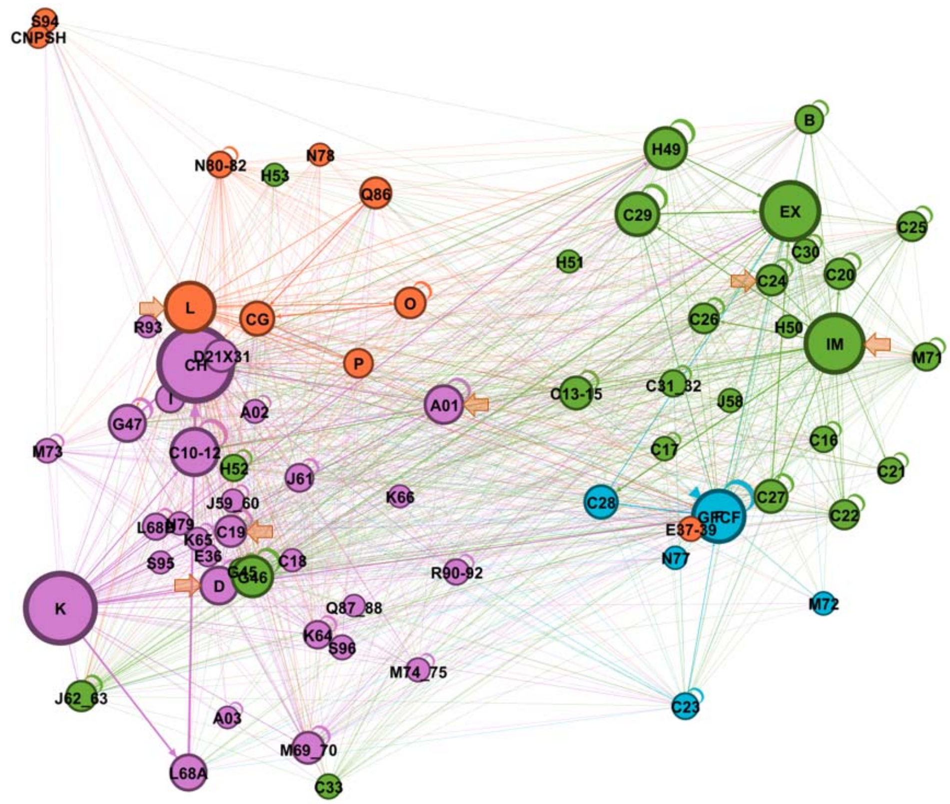
[12] *For instance, manufacture of food, beverages and tobacco products (C10-12), retail trade, except of motor vehicles and motorcycles (G47), accommodation and food service activities (I).*

[13] *Highlighting only a few: crop and animal production, hunting and related service activities (A01 - the key supplier of food industry), telecommunications (J61, a sector which provides services for households as well as for companies that, ultimately, can produce for the domestic market too), advertising and market research (M73 - businesses from this segment usually cooperate with other companies, but the final aim of those collaborations is to reach final consumers).*

[14] *A node with only outward linkages, approximated by value added excluding compensation of employees.*

[15] *The associated revenues are registered under the line of export of services.*

Figure 2. Romania's Economic Network Derived from the Supply and Use Table (2015)



Note: The visualisation of SUT table is performed using Gephi; colours represent clusters identified by searching algorithms; sectors' size is proportional with their corresponding weighted degree (maximum of either in- or out degree); CH = final consumption expenditure by households, CG = final consumption expenditure by government, CNPSH = final consumption expenditure by non-profit organisations serving households, GFCF = gross fixed capital formation, EX = exports of goods and services, IM = imports of goods and services, D21X31 = taxes less subsidies on products, L = labour share (compensation of employees), K = capital share (value added excluding compensation of employees), other sectorial names correspond with their NACE codes (Table A3 from the Supplementary Appendix); the orange arrows mark the position of sectors (C19, C24, D, A01, IM and L) selected in Section 2.1; links with low weight are not shown.
Sources: Eurostat, NIS, author's compilation

The third, rather small and concentrated cluster (marked by blue on Figure 2) is related to the value chains of investments, with gross fixed capital formation (GFCF - another terminal node) being the largest. GFCF's surroundings are composed of NACE codes, including construction (F) and manufacture of other non-metallic mineral products (C23 - the primary supplier of construction materials), manufacture of machinery and equipment (C28 - a sector related to investments into equipment), rental and leasing activities (N77 - an important intermediary for financing investment needs), as well as scientific research and development (M72 - associated with R&D type investments).

The fourth and last partition stem mainly from domains related to the public sector, including the endpoint node of final consumption expenditure by government (CG), human health activities (Q86), public administration and defence, compulsory social security (O) as well as education (P). It is important to note, that the algorithm classified labour's contribution to production (L - measured as compensation of employees) as a constituent of the last cluster, after the labour share of income in public services is particularly high compared to sectors dominated by private actors.

2.2.2 Static Perspective

Having introduced the structural features of SUT data, I turn to the description of the transmission mechanism. In this regard, the study implements two approaches: the first presents a static perspective over the measurement of direct and indirect effects, while the second part of the analysis introduces dynamism into the analysis. For the evaluation of the first order direct effects, the study utilises A^* matrix, a transformed version of the original A supply and use table (that is compiled in absolute values rather than as weights), where ${A^*}_{ij}$ is the percentage share of sector i in the total market size of j, as follows:

$$ {A^*}_{ij} = \frac{A_{ij}}{k_j} \quad (1) $$

The market size k_j corresponds to the total supply and/or total use of sector j. More technically, k_j is the weighted (maximum of either in- or out) degree of node j. The column of A^* associated with households' consumption expenditures is the vector, which contains the calculated sensitivities related to the direct effects of sectorial cost shocks. It is worth noting that this approach is rather a proxy for the shocks' impact on the consumer price index (CPI) as the structure of households' consumption utilised in SUT (national account compilation) may differ from the specific weights applied for the CPI consumer basket[16]. In the case of Romania, the latter is favoured for monetary policy purposes. Nevertheless, sensitivities ${A^*}_{ij}$ can still provide interesting and relevant insight for policy analysis.

In order to quantify the second order indirect impacts as well, the study employs Leontief inverse matrix that is calculated according to equation 2:

$$ L_{leon} = (I_n - A^*)^{-1} \quad (2) $$

where I_n is an $(n \times n)$ identity matrix, with n corresponding to the number of nodes in the network. The column of the L_{leon} matrix associated with households' consumption expenditures contains the coefficients related to the cumulated impact, when assuming full pass-through of cost shocks along the value chain. Thus, the indirect effects can be derived as the differences between the coefficients of the direct and cumulated sensitivities. The results of the static perspective on the impact of inflationary shocks are presented in Section 3.

[16] *For further details see the NIS's methodological explanations on CPI indices. Available at: <https://insse.ro/cms/files/statistici/comunicate/ipc/a22/methodological_explanations_04.pdf> [Accessed May 2022].*

2.2.3 Dynamic Perspective

The static evaluation of direct and indirect effects can provide helpful information about the underlying inflationary risks coming from sectorial shocks, but tell little about the characteristics of the propagation process. Therefore, I also implement a dynamic approach that aims to fill the gap between the estimated direct and cumulated effects, providing deeper insight into the propagation channels as well as shedding some light on the potential timeline of transmission. Moreover, the dynamic evaluation facilitates the monitoring of risks in real time, as new shocks can be fed into the network, whenever updated information suggests so.

In the dynamic perspective, shocks propagate via the economy similarly to other diffusion and learning phenomena - such as diseases, ideas, information and influence - discussed in network literature[17]. In this setup, a node of the system can infect - *i.e.* transmit the cost shock to - its successors. In our particular case, the influence of sector i on sector j is expressed by equation 3:

$$S^{j}_{t+1|S^{i}_{t}} = A^{*}{}_{ij} * S^{i}_{t} \tag{3}$$

where S^{i}_{t} represents the price increase operated by sector i at quarter t.

A stylised overview of the transmission mechanism through which sectorial price shocks influence overall inflation may be useful to summarise the key characteristics of diverse propagation processes. In this regard, I distinguish between first-round direct and indirect effects as well as second-round impacts of different shocks[18]. Table 1 provides an analogy to how these categories can correspond to diverse spreading processes on a simplified network.

Let suppose a directed network with only five nodes and seven weighted links, as presented in Table 1 (columns associated with first-round effects). This system is composed of three producers, out of which two (P1 and P2) are rather commodity-like upstream sectors and the remaining downstream node (P3) provides more complex goods and/or services to consumers (CH). Meanwhile, L represents labour input in the production process reflecting NULC developments. The level of consumer price inflation can be measured at node CH.

Also suppose that (Table 1, column associated with direct first-round effects), at time $t = 0$, a relatively mild shock S^{P1}_{0} hits P1 - e.g. a modest increase of crude oil price. With two directed links, P1 may influence consumer prices at node CH as well as the producer price of P3. At $t = 1$, the impact of the initial shock can be measured on overall inflation - e.g. the almost immediate impact of higher crude quotation on the fuel component of the consumer basket -, applying equation 3: $S^{CH}_{1|S^{P1}_{0}} = A^{*}{}_{P1,CH} * S^{P1}_{0}$. At the same time, another mild shock S^{P2}_{1} appears in P2. Nevertheless, P2 has a very limited role in the economy, represented by a link with low weight pointing from P2 to P3. As a result, the influence of P2 on P3, $S^{P3}_{2|S^{P2}_{1}} = A^{*}{}_{P2,P3} * S^{P2}_{1}$ might be small. In a linear threshold diffusion model with threshold set to θ_i, node i remains inactive (absorbs rather than transmits the initial price shock), if $S^{i}_{t} < \theta_i$. This may be the case, if P3 is able to offset the impact of additional costs using its operating

[17] *For an in-depth review of spreading phenomena please see Barabási (2016, Ch. 10), Jackson (2008, Ch. 7 and Ch. 8) and Menczer et al. (2020, Ch. 7).*

[18] *For a similar categorisation, please see European Central Bank (2004, 2010a and 2010b) and Lane (2022).*

margin or raising the output prices of P3 is not feasible, as changing prices could also imply relatively important costs etc. As a result, at time $t = 2$ already, both sectorial price shocks are faded out, while consumer inflation returns to its initial level. That is to say, mild and heterogeneous sectorial shocks have only limited and transitory effects on headline inflation via the non-core items of the consumer basket.

In a second scenario, however (Table 1, column associated with direct and indirect first-round effects), a severe and simultaneous shock might be assumed, with important price increases (S_0^{P1} and S_0^{P2}) registered by P1 and P2 at time $t = 0$. Similar to the previous example, the direct and almost immediate effect of P1 on CH can be measured at $t = 1$. Nonetheless, due to the sizable and synchronised nature of the shock, $S_{1|S_0^{P1},S_0^{P2}}^{P3} = A^*{}_{P1,P3} * S_0^{P1} + A^*{}_{P2,P3} * S_0^{P2}$ and $S_{1|S_0^{P1},S_0^{P2}}^{P3} \geq \theta_{P3}$, P3 becomes active and increases its output price. At time $t = 2$, this action translates into higher consumer inflation, driven by the rising core component of the inflation indicator. With other words, consumers can also perceive the indirect effects of the initial sectorial shock. Such a pass-through process is similar to the information cascade phenomena discussed in the network literature. Nonetheless, the propagation of the shock stops at $t = 3$. From the perspective of monetary policy, this second scenario is more challenging yet, with a credible central bank, shocks are expected to die out, while inflation is set to remain relatively stable and low in longer time horizon.

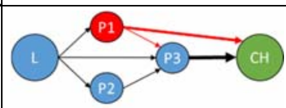
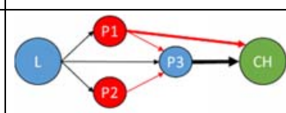
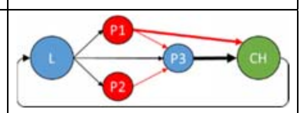
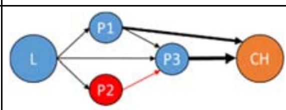
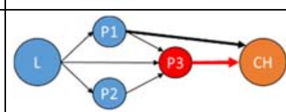
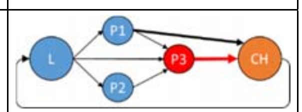
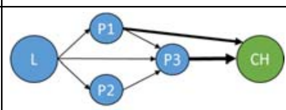
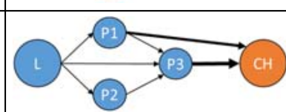
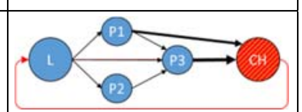
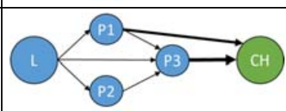
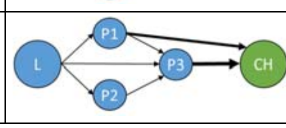
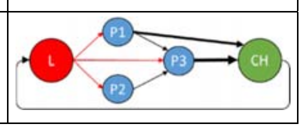
In the final setup (Table 1, column associated with first- and second round effects), a new weighted link is added to the network - from CH to L with weight proportional to the sensitivity of wages to inflation, i.e. wage Phillips curve -, in order to incorporate spiralling second-round effects. The spiral refers to the possibility that, in addition to the direct and indirect impacts, high inflation could influence wages-setting behaviour, if employees attempt to re-establish their real purchasing power to pre-shock levels via wage negotiations (or, automatically, by wage-indexation practices). Technically, in this special case, the propagation of the shock doesn't stop at $t = 3$, as CH doesn't only observe, but it can pass on the price pressure to its successor as well, if $S_{2|S_1^{P3}}^{CH} \geq \theta_{CH}$. As a result, CH may exert influence over L, possibly, triggering the so-called price-wage spiral. Primarily, this extended network could be proper for an economy, in which inflation expectations become loosely anchored - i.e. central bank credibility is damaged.

Incorporating second-round effects into the system is expected to imply important consequences regardin the characteristics of the spreading phenomena. Concerning the intersectoral network of the US economy, Acemoglu et al. (2012) point out that a power law distribution of degrees appears to be a good approximation to the empirical data. In other words, the structure of the US economy seems to show scale-free properties. Similarly, Frohm and Gunella (2021) provide evidence regarding the presence of hub sectors - nodes with a number of links that greatly exceeds the average degree of nodes in the network - in global value chains. In a scale-free network, diseases, information flow as well as, in our case, sector-specific shocks can propagate more easily due to the presence of hubs (or super-spreaders; Barabási, 2016, Ch. 10). Adding a strong tie between two particularly important hubs (CH and L) of the network is set to enhance the spreading phenomena. This means that, in contrast to the first two stylised examples, sector-specific shocks may trigger long-lasting inflationary pressures, as a relatively large share of nodes are active - increase their output prices - at any point in time. With simultaneous and more frequent sectorial price increases, CPI inflation also accelerates, while individual consumer basket components start to show significantly higher correlation: a regime shift unfolds and inflation becomes entrenched.

The characteristics of shock diffusion in the presence of hubs seem to be analogous with evidence found by the literature aiming to reveal the specific features of inflation dynamics. For instance, Bank for International Settlements (2022) and Borio et al. (2021) point out that *"the transmission of disaggregated sectoral price changes to other sectors, measured by the share of the total variance that these account for, is much higher and more pervasive in high-inflation regimes"*, while *"once inflation is tamed, idiosyncratic relative price changes rather than price co-movements explain much of the change in the overall price index"*.

In the empirical implementation of the dynamic model, the paper aims to reveal the threats coming from first-round direct and indirect effects of shocks. Therefore, the network doesn't incorporate the feedback loop associated to long-lasting second-round effects, which would require very careful calibration. As the study, primarily, aims to measure the inflationary risks rather than to provide fine-tuned point forecasts, the threshold θ_i is set to 0 for $i \in n$, while the condition for activation corresponds to $S^i \neq \theta_i$. That is to say, all positive and negative price shocks are transmitted to successor nodes regardless of their magnitude. It is worth mentioning that the model uses quarterly synchronous updates for node states and self-loops ($j = i$, when the analysed sector is also its own supplier) are allowed in the network. This specific diffusion model relates very closely to DeGroot's (1974) social learning process.

Table 1. Stylised Price Shock Propagation

Time	**First-round effects**		**First- and Second-round effects**
	Direct	*Direct and Indirect*	*Spiral (wage reaction on)*
t = 0			
t = 1			
t = 2			
t = 3			

Source: Author's compilation

An analogy can also be drawn with a classic vector autoregressive (VAR) approach of form $S_{t+1} = A^{*T} * S_t + \gamma_t$, where S_t is a time-varying $(n \times 1)$ vector capturing the states of nodes with the elements of the error vector γ_t set to 0. Nevertheless, the study favours the former network framework, as the assumptions of quarterly synchronous updates as well as full pass-through can be relaxed. For instance, certain sectors may update their prices at higher (or lower) frequencies compared to their neighbours as well as nodes may also absorb a significant portion of the cost shocks depending on their operating margin and/or productivity trends - i.e. sticky prices. The relaxation of these, rather strong, assumptions open up new perspectives for further research not discussed in the study.

2.3 Inflationary Risk Evaluation using Monte Carlo Simulation

In order to get better understanding over the potential risks coming from sectorial cost shocks and to provide a clearer evaluation of price pressures relative to their historical levels, I extend the analysis by implementing a Monte Carlo (MC) simulation. Within the MC framework, the simulation is conducted as follows: first, a $(r \times 1)$ vector of random shocks[19] S_t^{subset} is generated with mean and variance-covariance structure matching those of the quarterly growth rates of selected series in Section 2.1, according to equation 4:

$$S_t^{subset} - \mu^{subset} = L_{chol} * R_t \qquad (4)$$

where μ^{subset} is the $(r \times 1)$ vector that contains the mean growth rates of the selected series, R_t is a $(r \times 1)$ vector of pseudo random numbers with $N(0,1)$ distribution and L_{chol} is the $(r \times r)$ lower triangular matrix obtained by the Cholesky decomposition of variance-covariance matrix Ω^{subset}.

Having the innovations generated in line with the desired mean and variance-covariance structure, the propagation of the cost shocks follows the diffusion mechanism presented in equation 3. In order to obtain a smoothed distribution of potential effects on consumer prices, the simulation procedure is repeated 10 000 times[20].

3. Results

In this section, first, I present the results on the static evaluation of inflationary shocks (Figure 3, left-hand-side). In this regard, an interesting conclusion might be that the impact of indirect connections (or network effects) over consumer prices is sizeable. The sensitivities derived from Leontief inverse matrix L_{leon} suggest that indirect connections may be responsible for roughly two-thirds of the variation in inflation[21].

Another compelling observation is that a limited number of nodes exert disproportionally strong influence on consumer prices, with the top 10 sectors registering around two-thirds out of the total cumulated impact on headline inflation (Figure 3, left-hand-side). Out of these particularly important nodes, capital- (K) and labour shares (L) - i.e. company mark-ups and nominal unit labour costs - are less surprising. K's sensitivity coefficient is 0.47 meaning that, in a (theoretical) scenario where all entrepreneurs of the economy decide simultaneously to require 10% higher compensation for their capital, final consumer prices would experience 4.7 percentage-points increase. In the case of a similar 10% rise of labour costs, the impact

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[19] In our case, with price indices for sectors A01, C19, C24, D, L and IM, r is set to 6.

[20] The implementation of the Monte Carlo exercise is performed using NetworkX, a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks. For further information please visit NetworkX's homepage. Available at: <https://networkx.org/> [Accessed November 2021].

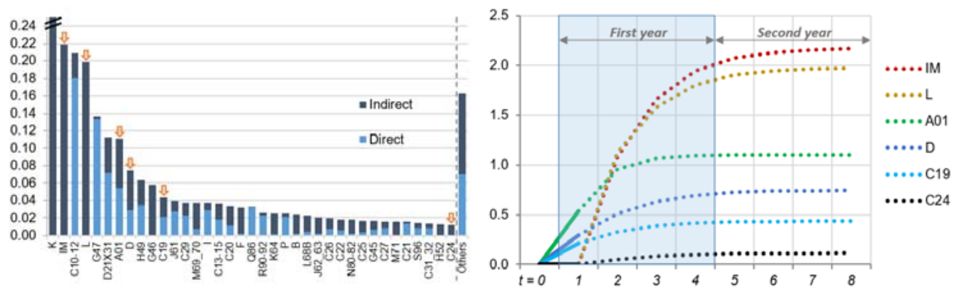
[21] Off-course, in the presence of sticky prices and partial pass-through of sectorial shocks the ratio is set to be lower but still sizeable. Nevertheless, when a multitude of significant cost shocks hit the economy - and demand remains relatively healthy -, companies may lean (or even be forced) to pass through a higher portion of extra costs in order to maintain their business continuity. These underline the importance of monitoring indirect linkages, when inflationary risks are evaluated.

on inflation would be less than half, around 2.0 percentage-points. At this result, it is worth mentioning that, in the case of Romania, the borderline between capital- and labour share is not a clear cut, as mixed income[22] makes up a significant portion of aggregate income, while the study treats mixed income as part of K. This approach enables the analysis to focus more on the evaluation of cost-type shocks (for instance, a compulsory minimum wage hike, which instantly raise compensation of employees, but not mixed income). The results also indicate that, in a small and open economy, import prices - and, implicitly, the evolution of the exchange-rate - could have substantial influence on consumer prices, with a 10% shock lifting CPI indicator about 2.2 percentage-points higher. Unsurprisingly, food industry (C10-12) and retail trade (G47) are ranked among top nodes with sensitivity coefficients dominated by direct effects, as these sectors are positioned closely to consumers along the value chain. Nonetheless, the case of agriculture[23] as well as the energy sector composed from NACE codes D and C19 - with sensitivity coefficients of 0.11, 0.08 and 0.04 - seem to be less straightforward. All three coefficients unfold a relatively balanced mix of proportions between direct and indirect components. In the case of A01, the value chain has a quite simple structure, with a particularly strong indirect linkage to consumers via food industry (C10-12). In the case of energy sector, however, the composition of the chain is rather finely wired, with several important paths toward consumers. This relative complexity could have consequences on how energy shocks propagate via the system.

Figure 3. Static Sensitivities and Dynamic Responses to Sectorial Shocks

Static direct and indirect sensitivities of consumer prices to sectorial shocks

Cumulative response of consumer prices to a 10% shock in selected sectors (%)



Notes: In Figure 3 (left-hand-side), the orange arrows mark sectors selected in Section 2.1; only sectors with cumulative sensitivity over 0.01 are showed; the sector of imputed rents of owner-occupied dwellings (L68A) not shown as, in the case of Romania, it has little relevance in CPI calculation (and, accordingly, in policy decision-making process). On Figure 3 (right-hand-side), the continuous (dotted) line indicate the first-round direct (indirect) effects of price shocks, assuming full pass-through and synchronous quarterly update of nodes; in the model's setup, IM (import prices) and L (nominal unit labour costs) exert only indirect effects over consumer prices.

Sources: Eurostat, NIS, author's calculation

Figure 3 (right-hand-side) shows the cumulative response of headline inflation to individual 10% shocks originated in selected sectors using the dynamic approach. Assuming quarterly time-steps and full pass-through, the results suggest that the bulk of the shocks are

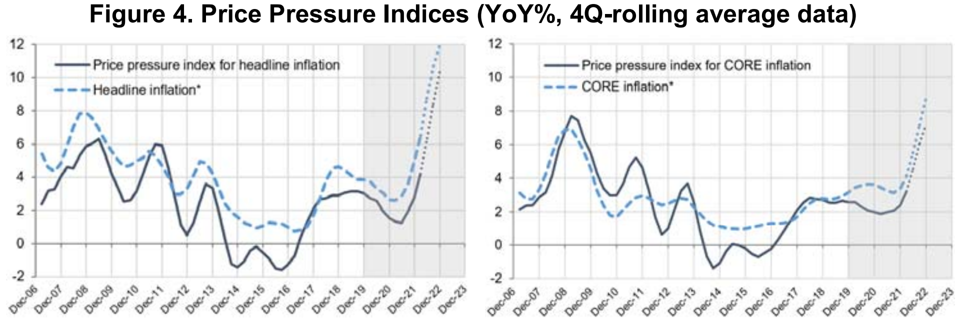
[22] *Joint remuneration of capital and labour in unincorporated enterprises.*
[23] *More precisely, NACE code: A01.*

transmitted to households within cca. one year. Owing to the simple setup of the model coupled with other unincorporated factors (price rigidities, stock accumulation, longer-term business contracts etc.) intra-year results are indicative, at best. Accordingly, any interpretation related to the short-term pass-through should be particularly cautious. Nonetheless, for illustrative purposes, some differences in the shape of individual pass-through may be worth mentioning: agriculture (A01) related shocks tend to exhaust their largest portion of influence on CPI in two- to three quarters, while higher energy prices feed into headline inflation a bit slower, in three- to four quarters. The mass impact of higher labour costs and import prices has appear up to four- to five quarters as, in the network, these nodes have no direct link to consumption expenditures (CH). Because of the sectors' relatively small size, innovations in the manufacturing of basic metals (C24) show limited effect on consumer prices, however, they tend to be quite persistent (the bulk of the impact appears in five quarters).

It is important to recall that the above analysis doesn't take into account any feedback loop from higher consumer prices to labour compensation (i.e. price-wage spiral). As noted in Section 2.2, this assumption can be relaxed by setting a link from households' consumption (CH) to labour compensation (L) proportional with the sensitivity of wages to inflation (i.e. wage Phillips curve). This additional link in the network would result in longer-lasting inflationary pressures[24].

Having discussed the sensitivity coefficients calculated based on the input-output matrix together with the particularities of the transmission of shocks suggested by the dynamic approach, I turn to the presentation of the practical experiments, when the dynamic model is applied on factual economic data. Introducing the historical shocks - originated from the six selected sectors - into the network, inflationary pressures indicated by the model seem to explain a large share of the annual variation in the headline as well as CORE consumer price indices (Figure 4).

Figure 4. Price Pressure Indices (YoY%, 4Q-rolling average data)



*Note: dotted lines mark model projections for price pressure indices as well as NBR forecasts for headline and CORE2 adjusted inflation measures (NBR forecasts taken from May 2022 Inflation Report); *data excludes the VAT first round effect.*

Sources: Eurostat, NIS, NBR, author's calculation

In both cases, correlation coefficients point to rather high values (above 0.8). The approach captures quite well the rising price pressure experienced up until the Great Financial Crisis

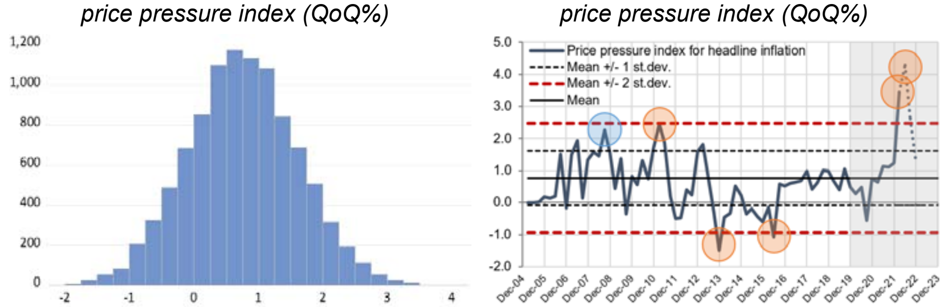
[24] The results of this additional exercise is not presented in the paper.

in 2008, the resurgence of inflation in the period of 2010-2011 driven by the global economic recovery, a short-lived revival in 2013 as well as the era of extra-low inflation in 2014-2016, characterised by the subdued level of global commodity prices. In addition, the model provided correct signals regarding 2017's shift in CPI dynamics, mild pressures in 2020 and early 2021, as well as the abrupt revival of inflationary risks starting from mid-2021. Besides headline inflation, the study also analyses a proxy indicator for CORE2 adjusted inflation that includes only a subset of sectors in order to match more closely the composition of the NBR's preferred underlying inflation measure (for more details please see Table A3 in the Supplemetary Appendix). Despite the longer value chains and more complex interactions between sectors, the proxy index is able to reproduce the general trends of CORE inflation (Figure 4, right-hand-side). One exception could be the year of 2020, when the model indicated easing price pressures but, in fact, underlying inflation climbed slightly higher. Nonetheless, in this period, prices showed unusual evolutions amid stringent mobility restrictions and sudden shifts in consumer preferences driven by the COVID-19 pandemic.

In the last part of Section 3, the outcome of Monte Carlo simulation is discussed. Figure 5 (left-hand-side) shows the distribution of the quarter-on-quarter (QoQ) growth paces of the cost pressure index for headline inflation after running the simulation 10 000 times. The Monte Carlo exercise yields 0.75 mean and 0.85 standard deviation, which values can be used to evaluate the severity of sectorial cost shocks. Figure 5 (right-hand-side) presents the QoQ index after running the dynamic model with factual historical data along with the threshold levels obtained in the Monte Carlo simulation. In the pre-COVID era, there were three quarters or around 5% of cases, when the index laid outside the usual mean +/- 2 standard deviations range and, once, the index got very close to the upper limit.

Figure 5. Risk Evaluation of Inflationary Pressures

Unconditional distribution of the sectorial price pressure index (QoQ%) | *Factual historical data for the sectorial price pressure index (QoQ%)*



Note: Coloured bubbles mark the quarters when the index comes close to (blue) or exceeds (orange) the mean +/- 2 standard deviations limits; dotted line marks model projection for the price pressure index using information up to Q1 2022.

Sources: Eurostat, NIS, author's calculation

During the pandemic, two main periods could be distinguished, at least. According to the model, in the early stage of the crisis, inflationary risks were low. However, the situation changed significantly at the end of 2020, with the index pointing to rising inflationary risks. Moreover, the turn-of-the-year - from 2021 to 2022 - can be characterised by an explosion-like event, with cost shocks reaching their highest level since 2005, when inflation targeting was introduced. The magnitude of the shock seen in early 2022 is unprecedented, exceeding the upper two standard deviation threshold by a wide margin.

Figure 5 (right-hand-side) also shows a one-year ahead projection (dotted line) using factual data up until Q1 2022. According to the model - that assumes no further cost shocks beyond Q1 2022 for the six key sectors of the economy - inflationary pressures are expected to reach a new all-time high before starting to fade gradually in the second half of 2022.

4. Conclusions

After calculating sector specific first-round direct and cumulated sensitivities using input-output linkages and the Leontief inverse matrix, the study points out that cost shocks might lead to sizeable impact on final consumer prices via indirect relations between sectors. Moreover, in a naïve static framework - that assumes full pass-through of price shocks -, indirect effects clearly outweigh direct impacts. The sensitivity analysis also presents that a handful of economic sectors could exert particularly large influence on final consumer prices.

Beyond the static examination of the supply and use data, the study introduces a network (or graph) representation of the input-output table that opens up new perspectives and possibilities for the in-depth research of intersectorial economic structures as well as processes. The network representation provides a particularly flexible framework for analysing diverse diffusion phenomena of price shocks in a dynamic manner. In a stylised context, the paper also presents how the classic categorisation of first-round direct and indirect effects together with the second-round impacts of sectorial shocks on overall consumer inflation relates to different propagation processes on a network.

When applying a dynamic diffusion model on factual data, the paper finds that the bulk of the impact coming from cost shocks - originated in specific key sectors of the economy - is expected to feed through to consumers in a one-year horizon, while the decay rate of shocks is dependent on the specific structure of input-output linkages. The results also show that the price pressure indicator generated by the model is able to explain a large share of the annual variation in Romania’s headline and core inflation measures, providing tentative signs regarding inflationary turning points too. In addition, the findings suggest that, in a small open economy like Romania, sectorial price shocks - triggered mainly by global factors - can play a particularly important role in the evolution of domestic consumer prices. The relaxation of rather strong assumptions used in the propagation model points to enticing research directions.

In the final part of the study, I run a Monte Carlo simulation that identifies specific threshold levels to evaluate the severity of pressures coming from sectorial price shocks. Using the results of the Monte Carlo simulation, I show that the magnitude of sectorial cost shocks experienced in early 2022 corresponds to an extreme - fat tail - event, with no any similar episode since the introduction of inflation targeting[25] in Romania.

References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A. and Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. *Econometrica*, 80(5), pp.1977-2016. https://doi.org/10.3982/ECTA9623.

[25] *Despite the methodological differences, this conclusion is similar to that of NBR (2022).*

Acemoglu, D., Ozdaglar, A. and Tahbaz-Salehi, A., 2017. Microeconomic origins of macroeconomic tail risks. *American Economic Review*, 107(1), pp.54-108. https://doi.org/10.1257/aer.20151086.

Álvarez, L.J. and Sánchez, I., 2018. Composite indicators of inflationary pressures. Banco de Espana, *Economic Bulletin* 4/2018, Analytical Articles.

Auer, R.A., Levchenko, A.A. and Sauré, P., 2019. International inflation spillovers through input linkages. *Review of Economics and Statistics*, 101(3), pp. 507-521. https://doi.org/10.1162/rest_a_00781.

Bank for International Settlements (BIS), 2022. Inflation: a look under the hood. *Annual Economic Report*, Ch. II.

Barabási, A.L., 2016. Network science, *Cambridge University Press*.

Blondel, V.D., Guillaume, J.L., Lambiotte, R. and Lefebvre, E., 2008. Fast unfolding of communities in large networks, *Journal of statistical mechanics: theory and experiment*, 2008(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008.

Bobeica, E., Ciccarelli, M. and Vansteenkiste, I., 2021. The changing link between labor cost and price inflation in the United States. *European Central Bank, Working Paper Series*, No 2583. https://doi.org/10.2866/32827

Borio, C., Disyatat, P., Xia, D. and Zakrajšek, E., 2021. Monetary policy, relative prices and inflation control: flexibility born out of success. Bank for International Settlements (BIS), *Quarterly Review*, September 2021.

Borio, C., Disyatat, P., Xia, D. and Zakrajšek, E., 2022. Looking under the Hood: The Two Faces of Inflation, *VoxEU*.org, 25. Available at: <https://voxeu.org/article/looking-under-hood-two-faces-inflation> [Accessed April 2022].

Bukeviciute, L., Dierx, A. and Ilzkovitz, F., 2009. The functioning of the food supply chain and its effect on food prices in the European Union. Office for infrastructures and logistics of the European Communities, *Occasional Papers* (47).

Camatte, H., Daudin, G., Faubert, V., Lalliard, A. and Rifflart, C., 2021. Estimating the elasticity of consumer prices to the exchange rate: an ac https://doi.org/10.2866/67917 counting approach. European Central Bank, *Working Paper Series*, No 2610.

Carstens, A., 2022. The return of inflation. Speech at the International Center for Monetary and Banking Studies, Geneva, 5 April. Available at: < https://www.bis.org/speeches/sp220405.htm> [Accessed April 2022].

Conflitti, C. and Luciani, M., 2017. Oil Price Pass-Through into Core Inflation. Bank of Italy, *Occasional Papers* (405). https://doi.org/10.2139/ssrn.3082191.

DeGroot, M.H., 1974. Reaching a consensus. *Journal of the American Statistical association*, 69(345), pp. 118-121. https://doi.org/10.1080/01621459.1974.10480137.

Dietrich, A., Eiglsperger, M., Mehrhoff, J. and Wieland, E., 2021. Chain linking over December and methodological changes in the HICP: view from a central bank perspective. European Central Bank (ECB), *Statistics Papers Series*, No. 40. https://doi.org/10.2866/910251.

European Central Bank (ECB), 2004. Recent oil price developments and their impact on euro area prices. *Monthly Bulletin* (July 2004), Box 3.

European Central Bank (ECB), 2010a. The impact of energy prices on inflation. *Structural Issues Report*, Ch. 3.

European Central Bank (ECB), 2010b. Oil prices - their determinants and impact on euro area inflation and the macroeconomy. *Monthly Bulletin* (August 2010), Articles.

Eurostat, 2013. European system of accounts. ESA 2010. *Publications Office of the European Union*. Available at: <https://ec.europa.eu/eurostat/documents/3859598/5925693/KS-02-13-269-EN.PDF/44cd9d01-bc64-40e5-bd40-d17df0c69334> [Accessed March 2022]. https://doi.org/10.2785/16644.

Frohm, E. and Gunnella, V., 2021. Spillovers in global production networks. *Review of International Economics*, 29(3), pp. 663-680. https://doi.org/10.1111/roie.12526.

Furlong, F. and Ingenito, R., 1996. Commodity prices and inflation. *Economic Review*, Federal Reserve Bank of San Francisco, pp. 27-47.

Hobijn, B., 2008. Commodity price movements and PCE inflation. *Current Issues in Economics and Finance*. Federal Reserve Bank of New York, 14(8).

Jackson, M.O., 2008. Social and economic networks. *Princeton University Press*. https://doi.org/10.2307/j.ctvcm4gh1.

Koester, G., Lis, E., Nickel, C., Osbat, C. and Smets, F., 2021. Understanding low inflation in the euro area from 2013 to 2019: cyclical and structural drivers. European Central Bank (ECB), *Occasional Papers*, No 80. https://doi.org/10.2866/869984.

Lambiotte, R., Delvenne, J.C., and Barahona, M., 2009. Laplacian dynamics and multiscale modular structure in networks. Available at: < https://arxiv.org/abs/0812.1770> [Accessed April 2022]. https://doi.org/10.48550/arXiv.0812.1770.

Lane, P.R., 2022. Inflation in the near-term and the medium-term. Opening remarks at MNI Market News Webcast. Available at: <https://www.ecb.europa.eu/press/key/date/2022/html/ecb.sp220217_1~592ac6ec12.en.html> [Accessed February 2022].

Martin, S., Brown, W.M., Klavans, R. and Boyack, K.W., 2011. OpenOrd: an open-source toolbox for large graph layout. *Visualization and Data Analysis*, 7868, pp.45-55. SPIE. https://doi.org/10.1117/12.871402.

Menczer, F., Fortunato, S. and Davis, C. A., 2020. *A first course in network science*. Cambridge University Press. https://doi.org/10.1017/9781108653947.

Miller, R.E. and Blair, P.D., 2009. *Input-output analysis: foundations and extensions*. Cambridge University Press. https://doi.org/10.1017/CBO9780511626982.

Muraraşu, B. and Stoian, A., 2015. On the exchange rate pass-through in Romania. *National Bank of Romania (NBR), Occasional Papers*, No 18.

National Bank of Romania (NBR), 2022. Harta termică a presiunilor inflaționiste din economie. *Annual Report* for 2021, Ch. 3, Box 3.

Osbat, C., Sun, Y. and Wagner, M., 2021. Sectoral exchange rate pass-through in the euro area. European Central Bank (ECB), *Working Paper Series*, No 2634. https://doi.org/10.2866/102470.

Virolainen, K., 2004. Macro stress testing with a macroeconomic credit risk model for Finland. Bank of Finland, *Research Discussion Paper*, (18). https://doi.org/10.2139/ssrn.622682.