

# Inflation Dynamics in China: An Analysis of Latent Sectoral Risks to Overall Price Stability

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## Abstract

This paper analyses the asymmetric effects of supply shocks in different sectors on overall price levels in China. It employs a modified Leontief price model to identify the sectors which pose an asymmetrically large risk for monetary stability in China. The analysis is then extended to 42 different countries from the data set to draw comparisons. The study finds that sectoral inflation effects in China are asymmetrically distributed, with just seven sectors accounting for more than 50 percent of total simulated effects. This indicates a high latent risk for overall price stability in China originating from these systemically significant sectors. These sectors can be categorized into “agriculture and food”, “energy”, “basic consumption goods excluding agriculture and food”, and “basic production inputs excluding energy”. The results for China align with findings from other empirical studies on the US and the EU. However, the “agriculture and food” category is of particularly high importance in China compared to high-income economies. A more pronounced agri-food effect is also observed in other middle-income economies in the dataset.

**JEL codes:** C67, E31.

**Keywords:** inflation; China; input-output analysis; cost-push price formation.

## 1 Introduction

The phase of increased inflation since the Covid-19 pandemic has brought price increases and their causes into the focus of academic discourse. This period of inflation was characterised, among other things, by sectoral shocks on the supply side. These shocks were triggered by pandemic-related production restrictions and their effects on global supply chains, as well as supply contractions of certain products, in particular certain agricultural goods and fossil fuels due to the Russian war of aggression against Ukraine (see Guerrieri *et al.*, 2022; Blanchard and Bernanke, 2023; Setterfield, 2023).

It therefore makes sense to look at sectoral supply shocks and their impact on inflation. There are numerous theoretical contributions on this topic. Acemoglu *et al.* (2012) fundamentally analyse the relationship between idiosyncratic shocks to disaggregated sectors

and the fluctuation of aggregate macroeconomic variables. Ball and Mankiw (1995) analyse the effects of highly unevenly distributed changes in relative prices on aggregate inflation. Much has also been published on supply shocks in connection with the oil price shocks of the 1970s, both theoretical contributions (cf. e.g. Bruno and Sachs, 1985; Blinder, 1981; Rotemberg and Woodford, 1996) and empirical contributions (cf. e.g. Hooker, 2002; Blanchard and Galí, 2007; Nordhaus, 2007).

In addition to these theoretical contributions or empirical studies of oil price shocks, it seems relevant to identify which sectors (besides the oil sector) pose a particular risk of triggering inflation through supply shocks. Weber *et al.* (2022) investigate precisely this question for the United States of America (USA) using input-output data. They identify asymmetric effects of supply shocks in various sectors on the development of the US *consumer price index* (CPI). Ipsen *et al.* (2023) find similar effects in their analyses for the European Union. However, there is no comparable study for the People's Republic of China<sup>1</sup>. This study closes this research gap. It is thus embedded in the above-mentioned literature.

Specifically, I investigate whether there are sectors of the Chinese economy in which supply shocks have an asymmetrically strong impact on the Chinese CPI. Following Hockett and Omarova (2016, p. 1), I call these sectors "systemically significant".<sup>2</sup>

The structure of this paper is as follows: The methodology for determining the systemically significant sectors is presented in the following second chapter and the data used is presented in the third chapter. The empirical results are then presented and discussed in the fourth chapter. The fifth chapter contains a conclusion. Supplementary figures and tables can be found in the appendix.

## 2 Methodology

This paper utilises input-output analysis in the tradition of Wassily Leontief (cf. Leontief, 1951, 1986). Methodologically, it works with a modified Leontief price model according to Valadkhani and Mitchell (2002). This work is thus part of a young but growing

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<sup>1</sup> The Republic of China (Taiwan) is also part of the data set used in this paper. When the term China is used in the following, it refers to the People's Republic of China; the Republic of China is referred to as Taiwan in the following.

<sup>2</sup> Hockett and Omarova (2016) use both *systemically important* and *systemically significant* to describe particularly important prices and indices. Both terms appear to be used synonymously. As both Weber *et al.* (2022) and Ipsen *et al.* (2023) use the term *systemically significant*, I also use it.

literature that uses this modified Leontief price model to identify systemically significant sectors for the development of the consumer price index. Weber *et al.* (2022) were the first to apply this methodology to the USA and Ipsen *et al.* (2023) have presented an analysis for the EU. This paper now looks at the situation in China. This work builds on the work of the authors mentioned in this paragraph.

## 2.1 The classic Leontief pricing model

Input-output analysis understands the economy as a network of price-cost relationships (Weber *et al.*, 2022, p. 7). The output of one sector is the input of another sector or consumption of end consumers. With the help of input-output tables, this flow of goods and services (in the following I will only write of goods to simplify matters) through an economy can be traced (Leontief, 1951, p. 15).

An input-output model divides the economy into  $n$  sectors. It is assumed that each sector produces a homogeneous good. The  $n$  sectors can be shown in an input-output table in both the rows and the columns. Row  $i$  shows how the output of sector  $i$  is distributed among the sectors of the economy. Column  $j$  shows where sector  $j$  obtains the necessary inputs for its own output (Leontief, 1951, p. 18). An entry in the input-output table  $z_{ij}$  accordingly shows the monetary transaction value of the demand of sector  $j$  for inputs from sector  $i$  over a certain period - typically one year (Miller and Blair, 2022, p. 11).

This data is interesting for analysing price levels because expenditure for input goods is part of production costs. Therefore, it can influence the prices of output goods. The collective term  $V_j$  records the value added, which also has an impact on pricing as a cost factor. The term  $V_j$  includes, for example, wages, profits, indirect taxes and subsidies (see Valadkhani and Mitchell, 2002, p. 124).

Now let  $x_j$  be the total value of production of sector  $j$ . By dividing  $z_{ij}$  by  $x_j$  the so-called technical coefficient  $a_{ij}$  is obtained. This can be interpreted as the value of the goods from sector  $i$  that were necessary to produce goods worth one monetary unit (typically US dollars) in the observation period (Miller and Blair, 2022, p. 16). Formally written:

$$a_{ij} = \frac{z_{ij}}{x_j} \quad (1)$$

Now let  $P_j$  be the price index for sector  $j$ . The activities within a sector can then be captured in the following equation (cf. Ipsen *et al.*, 2023, p. 9):

$$x_j P_j = x_j a_{1j} P_1 + \dots + x_j a_{ij} P_i + \dots + x_j a_{nj} P_n + V_j \quad (2)$$

All  $n$  equations of the economy can be written in matrix notation as

$$\hat{X}P = \hat{X}A'P + V \quad (3)$$

(cf. Weber *et al.*, 2022, p. 8; Ipsen *et al.*, 2023, p. 9)<sup>3</sup>, where  $\hat{X}$  is a diagonal matrix with all  $x_j$  on the main diagonal,  $P$  a vector of price indices,  $A$  the matrix of technical coefficients and  $V$  is the vector of value added. If you now divide by  $\hat{X}$  you get

$$P = A'P + v \quad (4)$$

with  $v$  all  $\frac{V_j}{x_j}$  contains.

Subsequent rearrangement yields the classic Leontief price model with

$$P = (I - A')^{-1}v \quad (5)$$

with  $I$  being a  $n \times n$ -identity matrix (see Ipsen *et al.*, 2023, p. 9; Weber *et al.*, 2022, p. 8; Valadkhani and Mitchell, 2002, p. 124). Note that Weber *et al.* (2022) and Valadkhani and Mitchell (2002) still have a term for imports in their equation. Since Ipsen *et al.* (2023) and this paper use a global input-output system, the imports are endogenous variables of the model, which are captured via the technical coefficient matrix  $A$  and therefore do not require their own term. In the model all direct and indirect effects of changes in the exogenous variable(s) on the  $P$  vector can be calculated via the expression  $(I - A')^{-1}$ , the so-called transposed Leontief inverse. For a more detailed derivation of the equations (1) to (5) see Miller and Blair (2022, pp. 10-21, 44-48).

## 2.2 The modified Leontief pricing model

To simulate price shocks, one price index after another is set exogenous to the model. This is achieved by dividing the  $n$  linear equations from (4) into one equation for the exogenous sector and  $n - 1$  equations for the endogenous sectors. For the  $n - 1$  endogenous sectors, I obtain analogous to (4)

$$P_E = A'_{XE}P_X + A'_{EE}P_E + v_E \quad (6)$$

where  $P_X$  is the price index of the exogenous sector and  $P_E$  is the vector of the price indices of the endogenous sectors. Analogously, let  $v_E$  be the vector of the endogenous

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<sup>3</sup> In Ipsen *et al.* (2023, p. 9), the price index vector is missing on the right-hand side of equation (2). However, since it appears again in equation (3), it seems to belong there in their work as well.

elements of  $v$ . The technical coefficient matrix is divided into  $A_{XE}$ , the  $1 \times (n - 1)$ -row vector of the technical coefficients for the inputs from the exogenous sector to the endogenous sectors and  $A_{EE}$ , the  $(n - 1) \times (n - 1)$ -matrix of technical coefficients for the inputs of all endogenous sectors to all endogenous sectors (cf. Valadkhani and Mitchell, 2002, p. 125).

By rearranging I finally get

$$P_E = (I - A'_{EE})^{-1} A'_{XE} P_X + (I - A'_{EE})^{-1} v_E \quad (7)$$

with  $I$  a  $(n - 1) \times (n - 1)$  identity matrix (see Valadkhani and Mitchell, 2002, p. 125; Weber *et al.*, 2022, p. 10).

Because I am only interested in changes of  $P_E$  due to changes in  $P_X$  I can simplify to

$$\Delta P_E = (I - A'_{EE})^{-1} A'_{XE} \Delta P_X \quad (8)$$

(cf. Weber *et al.*, 2022, p. 11). This has the advantage that  $v_E$  no longer must be calculated.

To identify systemically significant prices, all sectors are now set exogenously one after the other and subjected to a simulated price shock by setting  $\Delta P_X \neq 0$ . Using equation (8) the effect of such a shock of  $P_X$  on all  $P_E$  can be calculated.

### 2.3 The synthetic consumer price index

The next step is to calculate the effects of these changed price indices on a synthetic CPI. For this purpose, the fact that input-output tables also contain information on the final consumption expenditure by households is utilised. The share that the final consumption of a sector has in the total consumption of households determines the weight of this sector in the synthetic CPI (see Valadkhani and Mitchell, 2002, p. 126; Weber *et al.*, 2022, p. 11; Ipsen *et al.*, 2023, pp. 11-12). Formally

$$c_i = \frac{C_i}{C_{tot}} \quad (9)$$

with  $C_i$  the household consumption expenditure on goods from sector  $i$ ,  $C_{tot}$  the total household consumption expenditure and  $c_i$  the share of consumption of sector  $i$  goods in  $C_{tot}$ .  $c_i$  can also be referred to as the CPI weight of sector  $i$ .<sup>4</sup>

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<sup>4</sup> In chapter 4, results are presented for various countries. For results from different countries, the  $c_i$  values are calculated individually for each country (see explanation in the Data section).

Three different effects on the synthetic CPI can now be distinguished: 1) the direct effect of the price shock  $\Delta P_X$  through its weight  $c_i$  in the synthetic CPI, 2.) the indirect effect, which is caused by the impact of the price shock  $\Delta P_X$  on all other prices in the production network and therefore on the CPI, and 3.) the total effect caused by the sum of 1.) and 2.). Formally one obtains

$$IP_{dir} = c_x \Delta P_X \quad (10)$$

$$IP_{ind} = \sum_{i \neq x} c_i \Delta P_i^E \quad (11)$$

$$IP_{tot} = \sum_{i \neq x} c_i \Delta P_i^E + c_x \Delta P_X \quad (12)$$

(cf. Weber *et al.*, 2022, p. 11; Ipsen *et al.*, 2023, p. 13).

These three effects are calculated for all  $n$  sectors and compared with each other. On this basis, statements are made about the systemic significance of different sectors.

## 2.4 The supply shocks

In addition to the model description, the supply shocks must also be defined. Following Weber *et al.* (2022, p. 7) and Ipsen *et al.* (2023, p. 11), I use the price volatility of the sectors as supply shocks. As in Ipsen *et al.* (2023, p. 11), I define sectoral price volatility as the standard deviation of the annual logarithmic price change:<sup>5</sup>

$$\Delta P_X = \sigma_x^{P_{t_0, t_1}} = \sqrt{\frac{1}{T} \sum_{t=t_0}^{t_1} (\Delta \ln P_t^x - \Delta \ln P_{t_0, t_1}^{\bar{x}})^2} \quad (13)$$

The longest possible period from the data is used to calculate the price shocks, in the case of this study the period from 2000 to 2014.

The use of sectoral price volatilities as shocks has the following advantage over the use of a uniform shock for all sectors: the structurally very different price volatility of different sectors can be considered and thus a better approximation of real shocks can be simulated (Ipsen *et al.*, 2023, p. 11; Weber *et al.*, 2022, p. 7).

Several specifications of the model are used in Weber *et al.* (2022, p. 12). In the basic specification, the standard deviations described in equation (13) are used as supply shocks. In a further specification in Weber *et al.* (2022), the empirical supply shocks from

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<sup>5</sup> Weber *et al.* (2022, p. 7) uses the annual percentage price change instead of the logarithmic price change.

the Covid-19 crisis years 2020 to 2022 are used. The empirical supply shocks from 2020 to 2022 were around three times as high as the standard deviations used in the basic specification (Weber *et al.*, 2022, p. 19). The data set used in this contribution does not have comparable data for recent years, but it is plausible to assume that the shocks used for this data set are also rather moderate and that higher shocks and thus stronger inflation effects are possible in extreme situations. In addition to the results in Weber *et al.* (2022), this is also plausible because the use of standard deviations as shocks means that it is precisely not the most extreme historical deviations or shocks that are used, but rather the somewhat more moderate standard deviations.

## 2.5 Systemically significant sectors

As described in the introduction, this paper aims to identify systemically significant sectors in the Chinese price structure. The definition of systemically significant sectors goes back to Hockett and Omarova (2016) and was adapted for inflation analysis by Weber *et al.* (2022).

Fundamentally, sectors that are systemically significant for the development of inflation are those sectors for which a change in the price index of those sectors has the greatest impact on the development of the CPI (cf. Weber *et al.*, 2022, pp. 1, 5-6). Weber *et al.* explicitly refer to three drivers of this significance: (i) the ubiquity of a sector's goods as input goods in the production of other goods, (ii) the weight of the sector in the CPI and (iii) the price volatility of the sector (cf. Weber *et al.*, 2022, pp. 5-7, 14).

The causal pathways of these drivers are briefly explained below:

(i) If a good  $i$  is needed as an input good in the production of other goods  $j$  then its price also influences the prices of all these other goods  $j$ . An increase in the price of the good  $i$  leads to higher input costs and thus higher production costs of the goods  $j$ . Companies will try to pass these higher production costs on to their customers<sup>6</sup>. In addition to end consumers, these customers can also be other companies whose production costs are now higher due to the price increases of goods  $j$  triggered by good  $i$ . This process is now iterated over many production chain steps and so a price increase of a good  $i$  can have a strong impact on the CPI if this good is very central for production. This driver is mainly responsible for the indirect effect from equation (11).

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<sup>6</sup> See the discussion of the model assumption on price pass-through below.

(ii) The weighting of a sector in the CPI – it could be referred to as the ubiquity in the consumption of end consumers - also determines the impact that price changes in this sector have on the CPI. Simply put, the price of luxury cars can triple, but if it barely features in the average basket of goods, it will hardly play a role in the development of the CPI. This also applies analogously to the first driver of the ubiquity of the good in production. The goods whose production costs are affected by the price of a good must have at least a certain cumulative weight in CPI in order for a significant effect to be observed. Driver (ii) thus drives especially the direct effect from equation (10).

(iii) The structural price volatility of a sector's goods also has a major impact on its significance. If a good has structurally higher price swings, then *ceteris paribus* higher effects on the CPI are observed due to these higher swings than for a good with smaller swings. This driver has an impact on both the direct and the indirect effect.

Drivers (ii) and (iii) can be measured directly via the calculated CPI weight  $c_i$  in equation (9) and the calculated price shocks  $\Delta P_X$  in equation (13). The ubiquity of a sector's goods in the production of other sectors' goods (driver (i)) can be approximated by the sector's forward linkages. Forward linkages are defined as the row sums of the Leontief inverses  $(I - A)^{-1}$  and indicate how much the production of good  $i$  would have to increase if the demand for all goods increased by one unit (cf. Weber *et al.*, 2022, p. 6). The greater the value, the more of good  $i$  is needed for the production of other goods. Unlike the measurements of drivers (ii) and (iii), however, the forward linkages are only an approximation of driver (i). After all, it is also conceivable that good  $i$  is needed very much to produce a very irrelevant good in terms of CPI weight. In this case, it could have high forward linkages, but still not really be central to the production of other central goods and therefore not have a large indirect effect. It is nevertheless a good enough approximation for the purposes of this paper. The three units of measurement will make it possible to understand in the results chapter by which of the three significance drivers the simulation results were driven.

Weber *et al.* (2022, p. 4) distinguish between latent and realised systemic significance of sectors. They describe the sectors that achieve systemic significance in the basic specification of the simulation with the historical price volatilities as latently significant. In their work, the research group also carries out the simulation with the realised price shocks during the Covid19 crisis years 2020 to 2022. The core result of the study is that from 2020 to 2022, the latently significant sectors were also systemically significant with the

actual price shocks (cf. Weber *et al.*, 2022), i.e. the latent significance became the so-called realised systemic significance from 2020 to 2022. Due to a lack of current price data, only the latent significance of sectors can be analysed in this paper. However, if the results of Weber *et al.* (2022) are applied to this study, the latently significant sectors identified in this study might have a high predictive power for the realised significance in the event of a crisis in China. Corresponding policy implications of the results are discussed in the conclusion. In the remainder of the paper, systemic significance always refers to latent systemic significance if not stated otherwise.

## 2.6 Gini coefficient of the inequality of simulated effects

The empirical results below show that there are sectors that have a much greater impact on the CPI than other sectors. Nevertheless, the exact boundary between systemically significant sectors and those that are not, is difficult to draw.<sup>7</sup>

This work does not resolve the limitation of sharp boundary setting between systemically significant sectors and non-significant sectors. However, I propose a new measure of the degree to which the simulated effects are distributed unequally across different sectors. This enables comparisons of these distributions between regions (in the case of this paper, states), which is a helpful extension of the existing literature. To the best of my knowledge, no such measure exists to date.

First, all sectors are sorted according to the size of their total simulated effect on the CPI (see equation (12)), starting with the sector with the largest effect size. The cumulative total effect can be calculated by adding up all the simulated effects for all sectors along this sequence up to any sector  $k$ . In formal terms, this can be written as

$$IP_k^{cum} = \sum_{i=1}^k IP_i^{tot} \quad (14)$$

This cumulative overall effect can be plotted graphically on the y-axis against the ranking of the sector on the x-axis. The axis values can both be normalised to the range 0 to 1 by dividing the sector ranking by the total number of sectors  $n$  and dividing the cumulative effect up to sector  $k$  by the cumulative effect of all sectors (i.e. the cumulative effect of sector  $i = n$ ) (see Figure 6 in Ipsen *et al.*, 2023, p. 21). I suggest adding a 45° line through

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<sup>7</sup> This also makes the term systemic significance somewhat misleading, as in statistics it is ultimately associated with a phenomenon for which a clear limit can be defined using the p-value. Systemically important prices, for example, would be a more appropriate term. However, due to the comparability with the work of Weber *et al.* (2022) and Ipsen *et al.* (2023), I also use the term systemic significance in this paper.

the origin to this graph. In this way, a kind of Lorenz curve is obtained (cf. Lorenz, 1905, p. 218), which illustrates how unequal the effects are distributed. The 45° line can be understood as a theoretical uniform distribution line; the actual distribution will always be a curvature above this uniform distribution line. The curvature indicates how unequal the simulated effects are distributed. I will use this Lorenz curve representation in the following. The area between the actual Lorenz curve and the 45° line can be used to calculate a Gini coefficient of the inequality of the simulated effects. The Gini coefficient is the area between the Lorenz curve and the 45° line divided by the area of the triangle above the Lorenz curve (see Dalton, 1920, pp. 353-354)<sup>8</sup>. The Gini coefficient takes values between 0 and 1, where 0 means an absolute uniform distribution of the effects across all sectors and 1 means a concentration of the complete effects on a single sector.

The cumulative effects should not be interpreted as the change in the CPI if all sectors that are added up for the cumulative effect were set exogenously in the model and then shocked at the same time. This would presumably result in interaction effects between the shocks that are not measured in the cumulative effect.

In addition, the Gini coefficient proposed here can change when the sector categorisation is changed. For example, if 55 of the 56 sectors in this data set were combined into one new very large sector, leaving one single second sector, the result would be highly unevenly distributed effects between these two new sectors and thus a very high Gini coefficient. Due to this limitation, the Gini coefficient proposed here should not be used as a perfect measure of effect inequality. The comparability between different studies with different data sources and thus different sectoral categorisations of the economy is therefore also not meaningful.

However, the Gini coefficient is helpful for the comparison of different countries in terms of their effect concentration on individual sectors in this study because all country data comes from the same data source and sector categorisation is therefore identical.

## 2.7 Discussion of critical modelling assumptions

The values of the technical coefficients  $a_{ij}$  from equation (1) are initially empirical findings of the prevailing production technology in the period used for the calculation in

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<sup>8</sup> If the axis values are normalised to 0 to 1 as described above, the area of the triangle above the 45° line will always be 0.5. The value of the Gini coefficient is obtained by doubling the area between the Lorenz curve and the 45° line.

relation to the prevailing price levels and demand for goods. However, the core element of input-output analysis is to keep all values  $a_{ij}$  constant, even in the event of changes within the model, in the case of this study changes in the price level. This implies some assumptions, namely (i) constant returns of scale (cf. Miller and Blair, 2022, p. 16, Valadkhani and Mitchell, 2002, p. 124), (ii) no substitution of input factors in production (cf. Miller and Blair, 2022, pp. 17-19, Valadkhani and Mitchell, 2002, p. 124, Ipsen *et al.*, 2023, p. 10), as well as (iii) complete price inelasticity of the quantities produced and thus of the demand for input goods (cf. Miller and Blair, 2022, p. 46, Weber *et al.*, 2022, p. 9), and (iv) model-exogenous constant demand from end consumers (cf. Valadkhani and Mitchell, 2002, p. 124).

The multiplication of the transposed Leontief inverse  $(I - A'_{EE})^{-1}$  with the price shock  $\Delta P_X$  in equation (8) also implies (v) a complete pass-through of cost increases along the production network (see Miller and Blair, 2022, p. 46, Ipsen *et al.*, 2023, p. 10). Finally, by removing the shocked sector's entries from the endogenous transposed Leontief inverse, it follows that (vi) no feedback effects from the simulated price increases of the endogenous sectors to the price index of the exogenous sector are possible (cf. Valadkhani and Mitchell, 2002, p. 125, Ipsen *et al.*, 2023, p. 10).

Assumptions (i) to (v) are very strong assumptions that are unrealistic in their absolute-ness. This has two consequences for the interpretation of the results. In the short term, it is much more plausible that assumptions (i), (ii) and (iii) are approximately correct. This is for example due to ongoing contracts and the time required for the conversion of production processes. The results should therefore be interpreted as short-term shock effects.

The remaining discrepancy between the assumptions and reality, even in the short term, presumably leads to the model overestimating effects. It is conceivable, for example, that it is not possible for sectors to pass on the full cost increases and that the CPI effect felt by end consumers is therefore lower than in the simulation (see Ipsen *et al.*, 2023, p. 10). In any case, the aim of this paper is not to make exact predictions along the lines of "price shocks of x lead to an exact inflation rate of y per cent". Rather, the aim is to develop a better understanding of which sectors pose high risks of triggering inflation. The simulation results will show very different effects across sectors. Even if some of the assumptions do not hold completely in reality and therefore no exact inflation forecasts can be made using this model, these distorting effects will not completely explain the strong

discrepancies in the sector results. The identification of systemically significant sectors should therefore still be meaningful.

## 2.8 Robustness check: Power series approximation of the transposed Leontief inverse

A weakness of static Leontief models such as the one used in this paper is the assumption that all adjustment effects occur immediately in response to shocks because the model does not recognise any dynamic adjustment processes. This is, of course, a simplifying assumption. A power series approximation to the Leontief inverse can be used as an indication of how far this simplifying assumption falls short of reality and to gain initial insights into possible round effects (see Ipsen *et al.*, 2023, p. 14). The Leontief inverse  $(I - A)^{-1}$  can be broken down into a power series of the technical coefficient matrix  $A$  such that

$$(I - A)^{-1} = I + A + A^2 + A^3 + \dots + A^\infty \quad (15)$$

(cf. equation (2.17) in Miller and Blair, 2022, p. 34, for the derivation cf. p. 33-34). The following applies analogously for the transposed Leontief inverse

$$(I - A')^{-1} = I + A' + A'^2 + A'^3 + \dots + A'^\infty \quad (16)$$

(see equation 13 in Ipsen *et al.*, 2023, p. 14). Now let  $A' = A'_{EE}$ . When equation (16) is plugged into equation (8) one obtains

$$\Delta P_E = (I + A'_{EE} + A_{EE}'^2 + A_{EE}'^3 + \dots + A_{EE}'^\infty) A'_{XE} \Delta P_X \quad (17)$$

If the calculation is performed up to the  $i$ -power of  $A'_{EE}$  the cumulative round effect is calculated up to the  $i$ -round.

If a large part of the total effect is achieved in a few rounds, it can be assumed that the interpretation of the model effects as the CPI effects in the short term is a reasonable interpretation. As described above, some modelling assumptions would then also be sufficiently plausible.

## 3 Data basis

The global input-output table of the *World Input-Output Database* (WIOD, see World Input-Output Database, 2021) serves as the data basis for this paper. I use the *World Input-*

*Output Table* (WIOT) from 2014 contained therein, as well as the price data from the *Socio-Economic Accounts* (SEA).<sup>9</sup>

The WIOT is a consolidation of the national input-output tables of 43 countries, including China, all EU28 countries (in 2014 still including the UK), the USA and numerous other countries, which together account for over 85 per cent of global *gross domestic product* (GDP). The remaining countries are modelled in a *rest of the world* (ROW) sector. The economies of all included countries and the ROW are modelled in 56 sectors each. These are linked to each other via international trade flows in order to obtain a WIOT (Timmer *et al.*, 2016, p. 17). This results in a WIOT with 2464 sectors. A detailed description of the WIOT compilation methodology can be found in Dietzenbacher *et al.* (2013, pp. 73-95). From the WIOT of 2014, I derive the required  $A_{EE}$  and  $A_{XE}$  matrices for the model. I also take the consumption data used for the CPI weights  $c_i$  from the WIOT. This data is available for all 43 states in the dataset. Using equation (9), synthetic CPIs and the effects of the 2464 sectors on these different CPIs can be calculated for all 43 states. This enables the comparisons between countries that can be seen in the results chapter.

The WIOD also contains price data for all modelled sectors in the SEA for the years 2000 to 2014. For a detailed description of the methodology and data sources of the SEA, see Gouma *et al.* (2018). I use the *producer price index* (PPI) data contained in the SEA to calculate the price shocks in the model. Like Ipsen *et al.* (2023, p. 15), I use the complete available price series from 2000 to 2014 to calculate the price volatility of the respective sectors and then use these as price shocks in the model in order to obtain a picture of price developments in the sectors that is as representative as possible. The SEA does not contain any price data for the ROW sectors, meaning that no price shocks can be implemented in the model for these sectors. Ipsen *et al.* (2023, p. 15) point out that the exclusion of the ROW sectors from the price shocks results in a slight distortion of the modelled CPI. However, the ROW sectors have a very low weight in the Chinese CPI, so that the direct effects on the CPI that are not modelled are probably negligible. And the forward linkages of the ROW sectors are also comparatively low, so that the omitted indirect effects should not cause any major distortion. In the calculation of the indirect effects of all sectors except the ROW sectors themselves, effects that are triggered in the ROW are also fully

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<sup>9</sup> Ipsen *et al.* (2023) also use data from the WIOD, so all dataset-related strengths and limitations also apply to this work.

mapped, as ROW is part of the producer network mapped in the WIOT and therefore these effects are also simulated (cf. Ipsen *et al.*, 2023, p. 15).

Using the WIOD makes it possible to model the propagation effects of price shocks in one sector through the entire global economy. This is an advantage over the use of national input-output tables, such as those used by Weber *et al.* (2022) for their calculations. As a result, they presumably underestimate the extent of the effects of a price shock on the CPI (cf. Ipsen *et al.*, 2023, p. 15).

However, the WIOD data also has some weaknesses that limit the contribution of this paper. The greatest weakness of the data lies in its limited time horizon. The most recent WIOD input-output table contains data from 2014, and the price data also only covers a period from 2000 to 2014. Unlike Weber *et al.* (2022), who use more recent data for the USA in their analysis, no direct statements can therefore be made about the recent past in this study. In the discussion of the results, however, I will address the transferability of the results to the present.

It should also be noted that the WIOD is a synthetic database that combines and harmonises data from various other primary databases and estimates missing data points (cf. Timmer *et al.*, 2015, 591, 596-597). This enables the global view that this paper (and the paper by Ipsen *et al.* (2023)) takes, but it necessarily results in certain estimation inaccuracies. However, the WIOD data are benchmarked against the national accounts of the data set countries, meaning that they are reliable estimates (see Dietzenbacher *et al.*, 2013, pp. 74, 79-82).

A more detailed discussion of the limitations of the WIOD can be found in Timmer *et al.* (2015, pp. 591-594). Despite its limitations, the WIOD is the best available data source for this work. It enables both the simulation of production chain effects along global, not just national, production chains and the comparison of effects among different countries within a standardised data set.

In addition to the WIOD, I use GPD data of the 43 WIOD countries. This GDP data comes from the *World Economic Outlook database* of the *International Monetary Fund* (IMF) in its publication from October 2023 (International Monetary Fund, 2023).

## 4 Results of the simulation

### 4.1 Results for China

Figure 1 illustrates and validates the three drivers of systemic significance identified in the methodology chapter (see pages 7-8). It depicts the 56 Chinese sectors in a scatter-plot<sup>10</sup>. On the x-axis, the forward linkages, as described in the chapter 2, are plotted as an approximation to driver (i), the ubiquity of inputs in the production of other goods. Price volatility is plotted on the y-axis to illustrate the significance driver (iii). The size of the plotted points represents the weight of the sector in the Chinese CPI and thus illustrates the significance driver (ii). The ten sectors with the largest simulated effect on the CPI are coloured red (for a closer look at these sectors, see Figure 2 and the associated discussion).

The expectation would be that points that are large, and to the north-east of the graph are coloured red. Especially a combination of the three effects should ensure a red colouring.

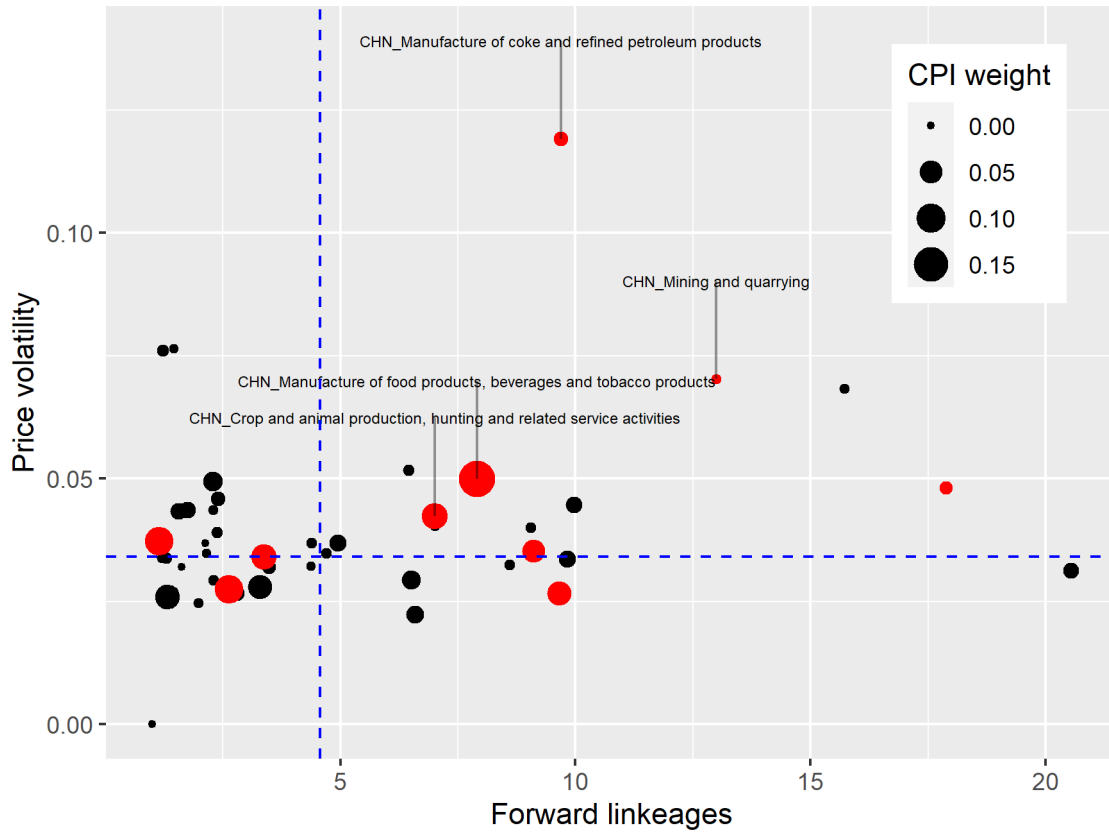
Seven of the ten red sectors lie to the right of the vertical average line for the forward links. In addition, seven sectors are above the horizontal average line for price volatility. Six red sectors have a CPI weight of over five per cent each. The two most important sectors (food processing and agricultural production) even combine an above-average level of all three significance drivers, while the sectors in third and fourth place (oil and mining) have strong price volatility and forward linkages. Figure 1 thus illustrates the relevance of the significance drivers described for the ten most important sectors.

At the same time, however, it can be observed that there are sectors with many forward linkages that are not among the top ten sectors, although one would expect them to be. This is presumably due to the effect that forward linkages only lead to large simulated CPI effects if the sectors influenced by the linkages have a high CPI weight, at least in the aggregate, or themselves influence sectors with a high CPI weight. Figure 1 therefore confirms that forward linkages are an imperfect measure of the driver of centrality in the production process.

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<sup>10</sup> The illustration of all 2464 sectors would be too confusing. As the sectors with the largest simulated effect are exclusively Chinese sectors, it seemed sensible to select the Chinese sectors for illustrative purposes.

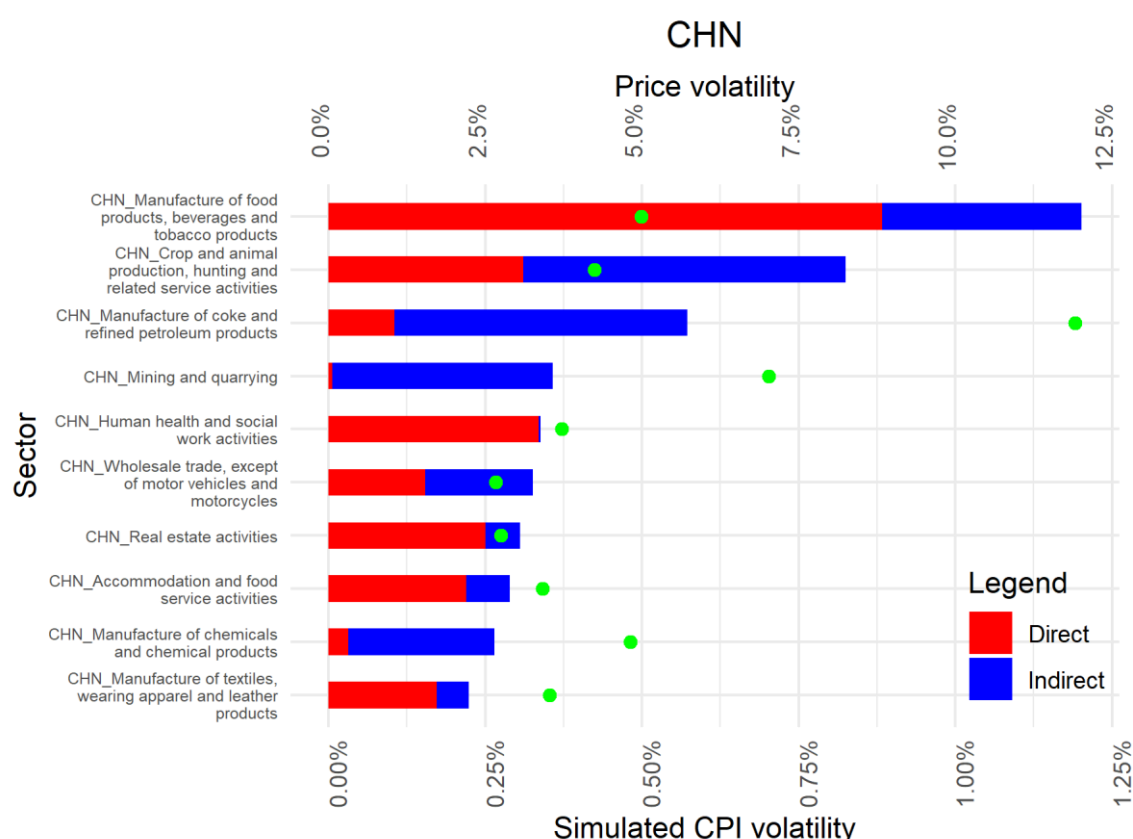
Figure 1: Forward linkages, price volatility & CPI weight



Notes: Illustration by the author based on Weber et al. (2022, p. 15). The ten sectors with the largest simulated effect are coloured red. The blue dashed lines show the average values of price volatility and forward linkages for China. The sizes of the dots indicate the CPI weight (see legend).

Figure 2 shows the results for the ten sectors with the greatest simulated impact on the Chinese CPI. The length of the bars indicates the overall effect. This is divided into the direct and indirect effect (see equations (10) and (11)). The direct effect can be understood as follows: End consumers consume goods from sector  $i$ . These have now become more expensive due to the supply shock, so end consumers feel a direct price increase. The indirect effect is to be understood as a measure of how the price effects spread through production chains and then affect end consumers. The price shock in the sector  $i$  results in an increase in production costs for all sectors that use the good from sector  $i$  for production. Under the modelling assumptions, these cost increases are now passed on in full, both to final consumers and to other sectors that use the affected goods as inputs. The indirect effect captures these far-reaching effects along the production chains.

Figure 2: Simulated CPI effects for China



Notes: Illustration by the author based on Weber *et al.* (2022, p. 13). The horizontal bars show the main results of the shock simulation of the ten sectors with the largest simulated effect on the CPI. CPI effect sizes are shown on the lower x-axis. The bars show the total effect and are divided into the direct effect and the indirect effect. The green dots represent the price shock used for the simulation (see calculation in equation (13)). The size of the shocks is shown on the upper x-axis.

For China, three of the most influential sectors have a particularly prominent impact on the CPI: Food processing<sup>11</sup>, agricultural production<sup>12</sup>, and the processed petroleum and coal sector<sup>13</sup>. These are followed by sectors that are important as input goods for the production in numerous other industries<sup>14</sup>, as well as some consumer goods sectors<sup>15</sup> and the wholesale trade sector. These Top 10 sectors are similar to the most important sectors in the USA in Weber *et al.* (2022, pp. 12-18). However, the order of the sectors is different, with food sectors playing a more pronounced role in China than in the USA. A detailed comparison of China with other countries can be found below.

<sup>11</sup> Manufacture of food products, beverages and tobacco products.

<sup>12</sup> Crop and animal production, hunting and related service activities.

<sup>13</sup> Manufacture of coke and refined petroleum products.

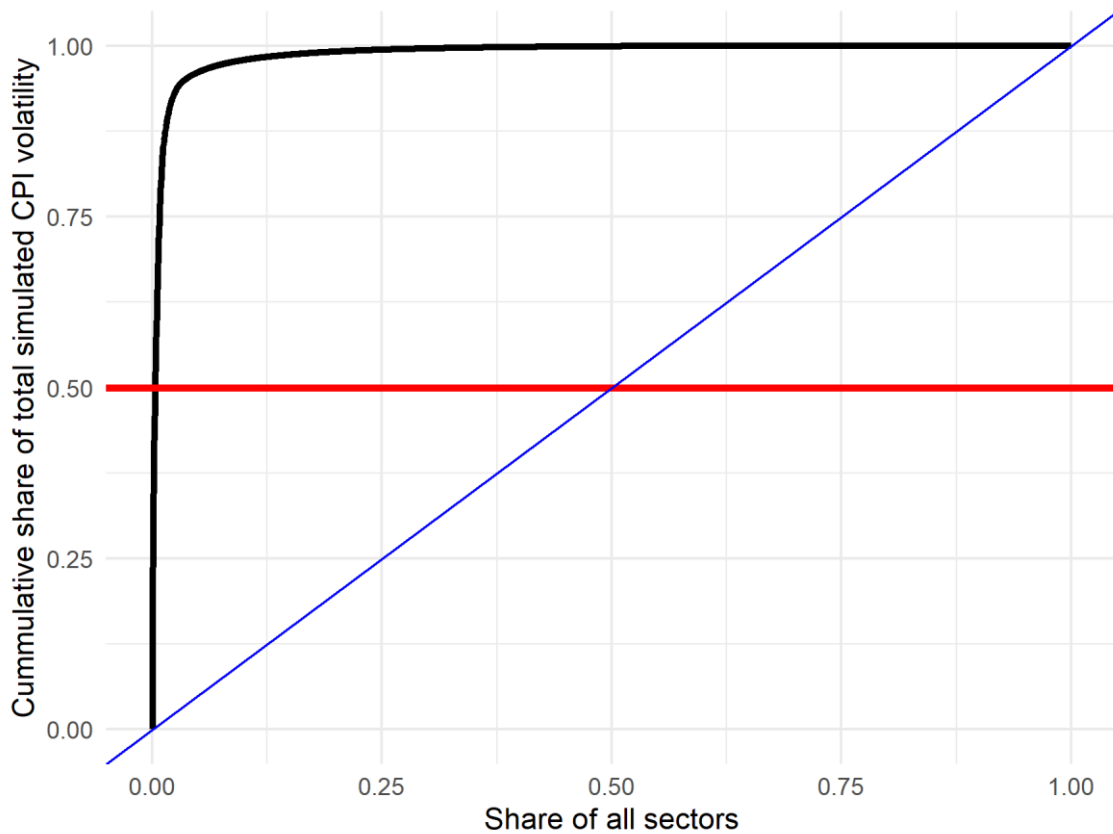
<sup>14</sup> Mining and quarrying and Manufacture of chemicals and chemical products.

<sup>15</sup> Human health and social work activities, real estate activities, accommodation and food service activities, Manufacture of textiles, wearing apparel and leather products.

The strong breaks in Figure 2 provide initial evidence in favour of the thesis of the existence of systemically significant sectors in the Chinese price structure. The Appendix contains Figure 8, an extension of Figure 2 up to the 100th sector. This figure also illustrates how strongly the effects vary across the sectors. In addition to the prominent importance of the first three sectors, it can also be seen here that the following sectors from Figure 2 also play an overriding role in the simulation results, albeit not as important as the first three sectors. In addition, Figure 8 also illustrates the problem of drawing boundaries. It is unclear up to what point a sector should be defined as systemically significant, and from what point it should no longer be. Drawing a clear boundary here would be somewhat arbitrary.

Further evidence must therefore be used to diagnose systemically significant sectors in the Chinese price structure. Figure 3 shows the Lorenz curve of the simulated effects described in the chapter 2 of this paper for the 2464 global sectors. The curve could hardly be clearer and shows a very uneven distribution of the effects across the various sectors. The corresponding Gini coefficient is 0.9777, i.e. very close to the maximum inequality value of 1. The first 9 sectors (approx. 0.4 per cent of all sectors) account for just over 50 per cent of the simulated effects. After approx. 1.8 per cent of all sectors, 90 per cent of the simulated effect is exceeded.

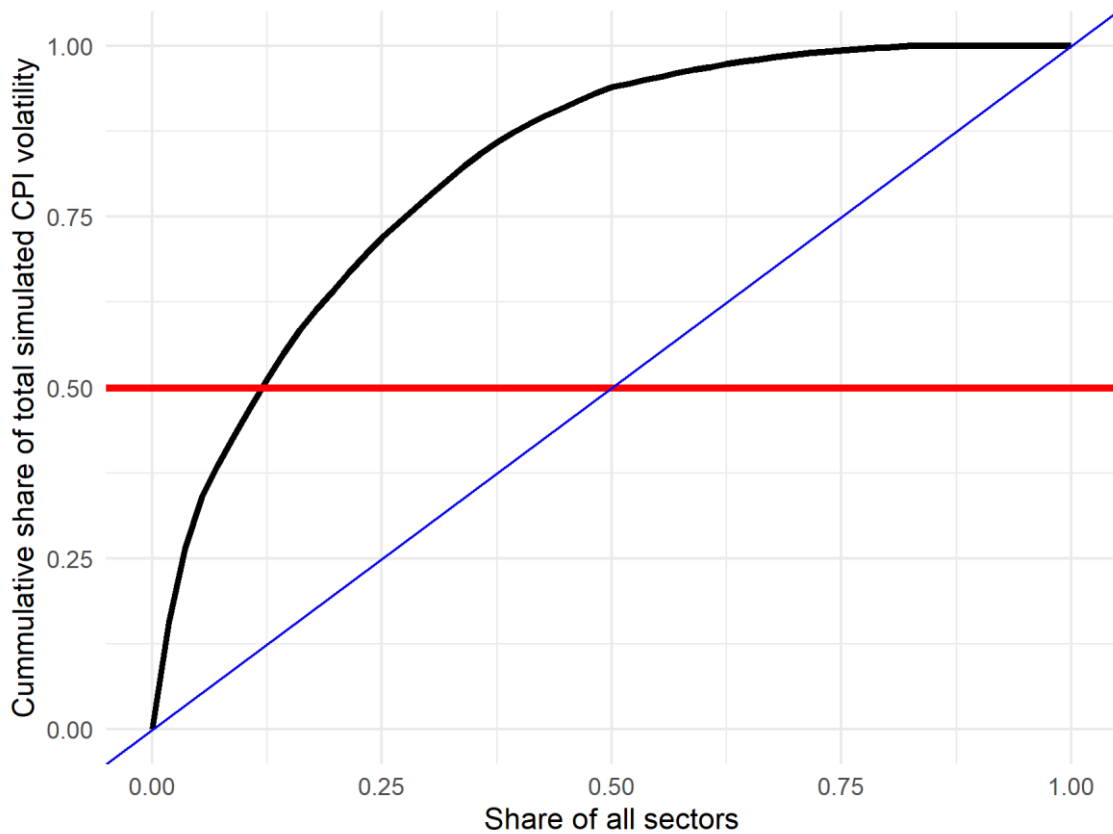
Figure 3: Lorenz curve of all sectors



*Notes: Illustration by the author. The blue line is the 45° line of the theoretical uniform distribution of the effects across all sectors. The black line is the actual Lorenz curve. The red line indicates that 50 per cent of the cumulative effect has been reached.*

It may be argued that it is to be expected that there are numerous sectors in the world that have hardly any weight in the Chinese CPI and hardly any input-output links to sectors relevant to the Chinese CPI and therefore have simulated effects close to zero. Firstly, it should be noted that the degree of concentration of the effects on a few sectors is nevertheless considerable, even in an international comparison (see Table 1, discussion below). In addition, the Lorenz curve for the 56 Chinese sectors in Figure 4 has a pronounced curvature that reflects an uneven distribution of the effects. The corresponding Gini coefficient of the 56 Chinese sectors is 0.6467. The first seven sectors (12.5 %) account for over 50 per cent of the simulated effects of all Chinese sectors, while the first 25 sectors (approx. 45 %) account for over 90 per cent of the effects. The uneven distribution is therefore less pronounced when comparing only the national sectors, but it is still clearly present. Figure 4 is therefore a further indication of the core hypothesis of this paper, namely that a few sectors drive a large part of the Chinese CPI effects. The simulation results therefore indicate that there are systemically significant sectors for inflation dynamics in China.

Figure 4: Lorenz curve of only the Chinese sectors



Notes: Illustration by the author. The blue line is the 45° line of the theoretical equal distribution of the effects across all sectors. The black line is the actual Lorenz curve. The red line indicates that 50 per cent of the cumulative effect has been reached.

## 4.2 Comparison with other countries

While the work of Weber *et al.* (2022) only analyses dynamics within the US economy without comparisons to other countries, my paper is able to compare dynamics in China with those in other countries. This allows statements to be made as to whether the observed Chinese dynamics are typical internationally or whether they are unique to China.

I will start with a comparison to four other countries in the data set. It seems reasonable to compare China with countries that a) have a similar GDP to China in 2014, and b) have a similar GDP per capita adjusted for purchasing power. Group a) is a meaningful comparison for effects that are presumably attributable to the absolute size of the economy, group b) is a meaningful comparison for effects that are presumably attributable to the level of prosperity of the population. In 2014, China is already the second largest economy in the world in terms of GDP, behind the USA and ahead of Japan. These two countries are used as comparison group a). At the same time, however, in 2014 China is one of the countries with the lowest purchasing power-adjusted GDP per capita in the data set

(41st out of 43), directly ahead of Indonesia and directly behind Brazil (see International Monetary Fund, 2023). These two countries are therefore used as comparison group b).

Firstly, it is striking that all four countries, just like China, have no foreign sectors in the ten largest sectors. The graphs of all countries in the appendix (see pp. 41 to 62) show that this is the rule not the exception. The only exceptions are some EU member states/member states of the *European Free Trade Association* (EFTA) as well as Mexico and Canada, which together with the USA form the countries of the *North American Free Trade Agreement* (NAFTA). The foreign sectors that have a significant influence on these countries are almost always sectors from the countries with which these countries are part of a close free trade agreement.<sup>16</sup> So, countries CPI seems to be predominantly effected by their own national sectors. However, this situation can be reversed through very close economic integration with other countries.

As far as the role of the food processing and agricultural production sectors is concerned, China clearly ranks among the poorest countries in the data set. The agri-food sectors play a particularly prominent role in these countries, including Indonesia and Brazil. This dynamic appears to be driven primarily by the comparatively high weighting of these sectors in the respective CPIs of the poorer countries. The richer people become, the smaller the proportion of their income they must spend on food. This relationship is illustrated graphically in the appendix with the data from this paper (see Figure 9 on page 40). This finding is somewhat trivial, but nevertheless relevant for the understanding of how results for the USA (see Weber *et al.*, 2022), for the EU (see Ipsen *et al.*, 2023) or for the countries in this paper can be transferred to other countries. It also allows to draw conclusions about how the Chinese results from this study can be transferred to contemporary China using data from 2014. Although China has experienced a significant increase in purchasing power-adjusted real GDP per capita in the last ten years (from 11,770 international dollars<sup>17</sup> to 18,127 int.-\$), it is still most comparable to the purchasing power level of Brazil in 2014 (16,384 int.-\$) (for all GDP values, see International Monetary Fund, 2023). The effect of the food sectors is therefore likely to be somewhat reduced in 2024, but still clearly present and more pronounced than in the USA or the EU countries, for example.

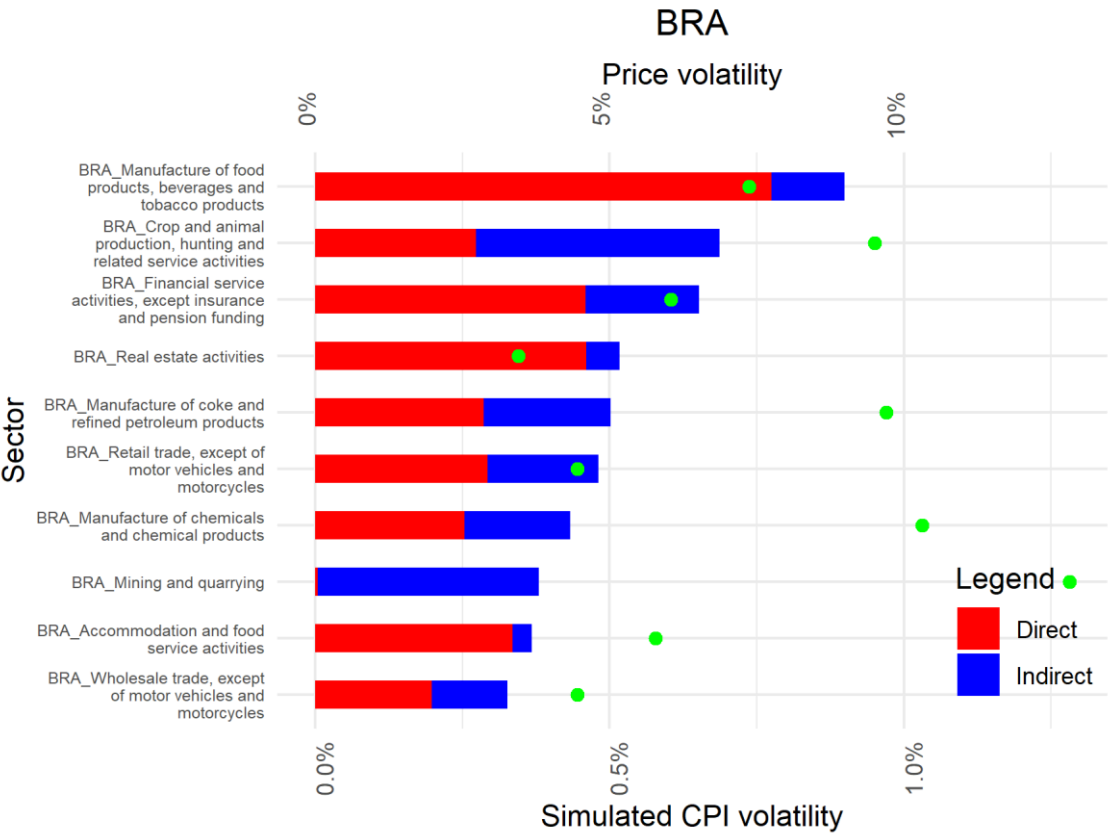
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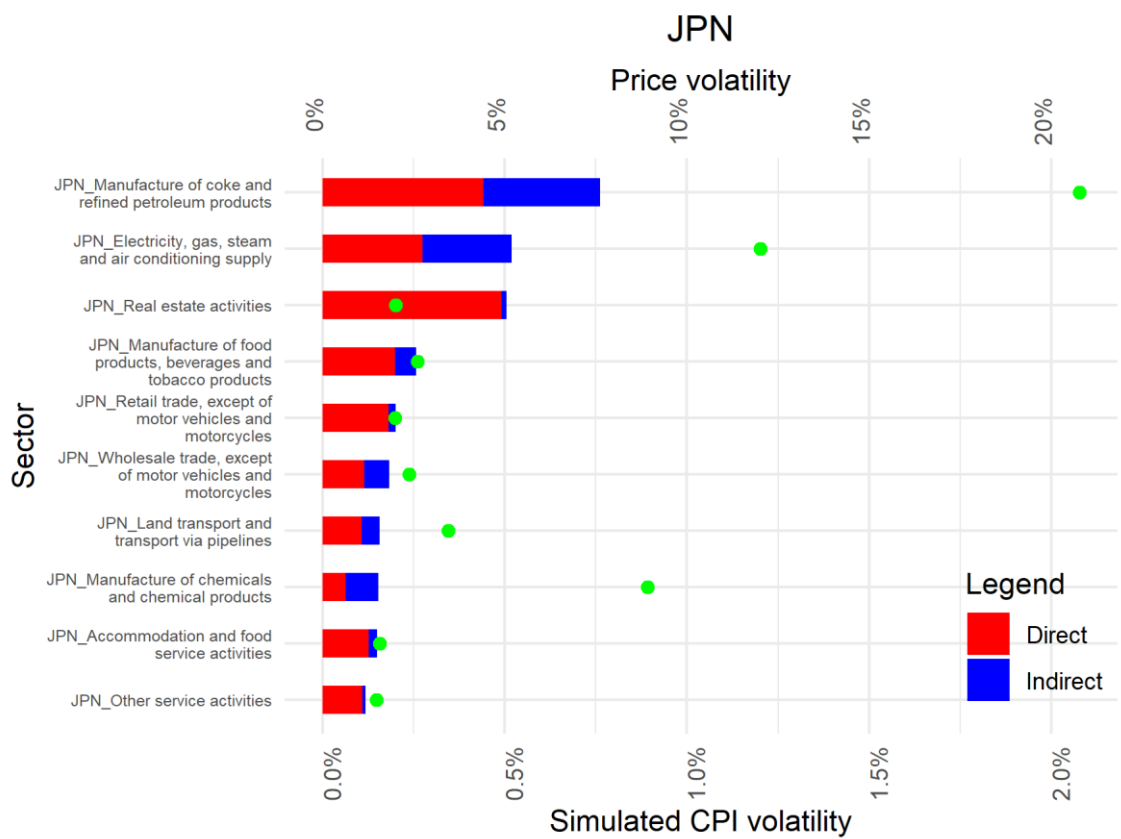
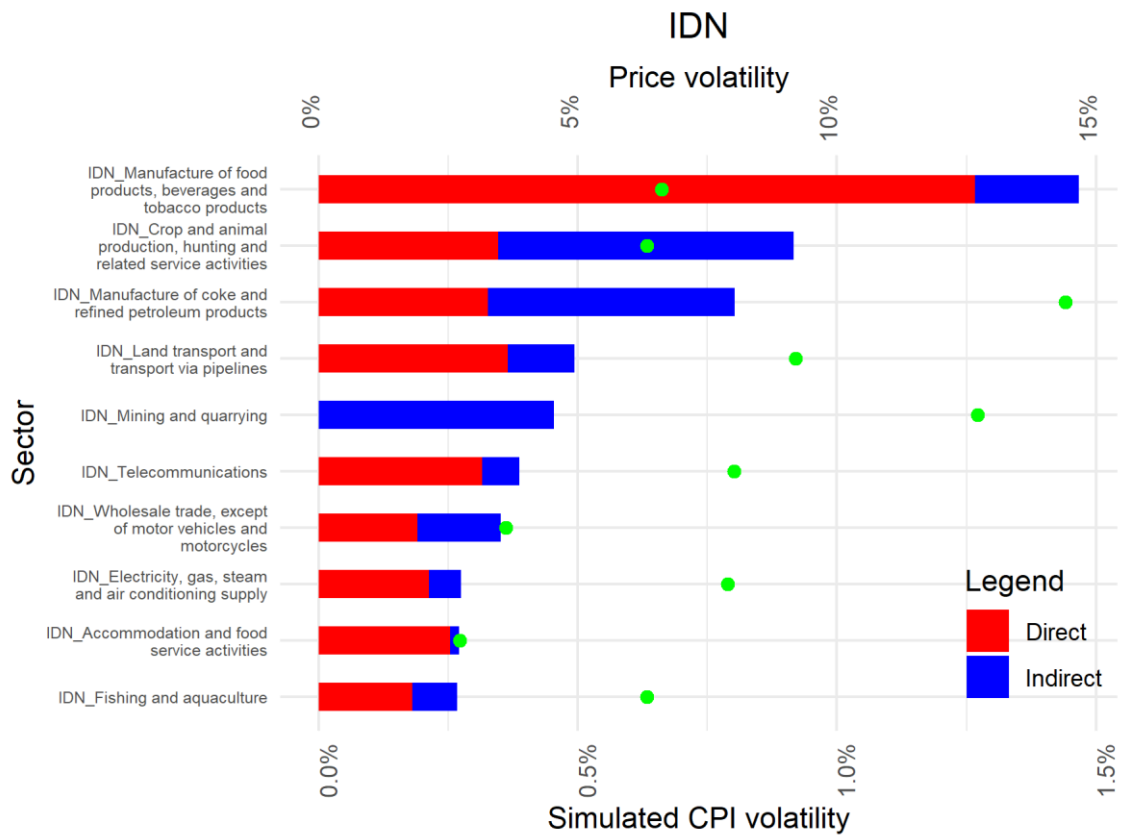
<sup>16</sup> The only exceptions to this are the energy commodity dependencies of European countries. Finland and Estonia have the Russian oil sector in their top 10 sectors, while Malta and the Netherlands have the US oil sector.

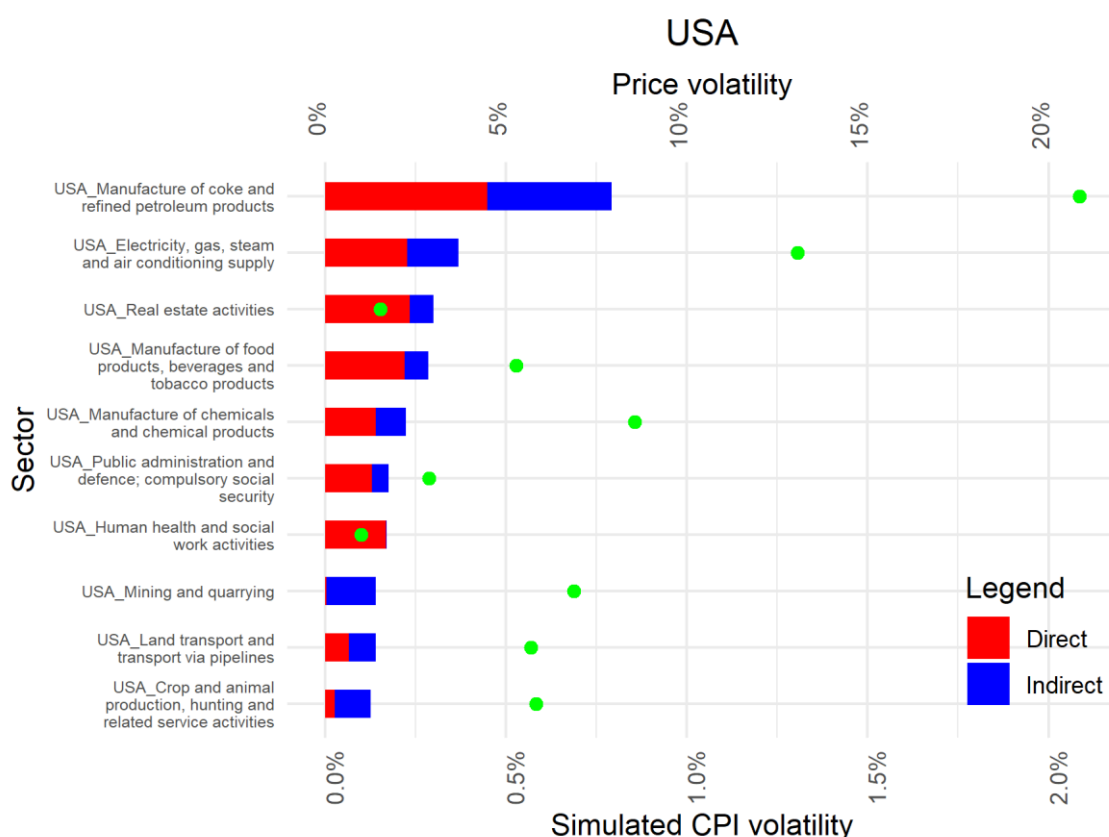
<sup>17</sup> The base year for the purchasing power adjustment in the data set is 2017 (see International Monetary Fund, 2017).

Compared to Japan and the USA, there are no trends that can be clearly attributed to the size of the economy in the same way that the dynamics of the food sectors in China, Indonesia and Brazil can be attributed to the purchasing power in these countries. Although there are similarities between the USA and Japan (e.g. the central role of the property sector and the electricity & gas sector), these are not reflected in China. Therefore, the effects do not appear to be due to the size of the economy, but rather due to the high purchasing power in Japan and the USA. This study therefore does not identify any characteristics that can be clearly attributed to the size of China's economy. This result is plausible insofar as the CPI is an index of purchasing power. It is therefore plausible that the purchasing power of a country's population is a more relevant explanatory factor than the size of the economy.

Figure 5: Simulated CPI effect Brazil, Indonesia, Japan, USA







Notes: Illustration by the author based on Weber et al. (2022, p. 13). Simulation results for the ten most influential sectors in Indonesia, Brazil, Japan and the USA. See Figure 2 for a detailed explanation of the figures.

The Gini coefficients of the 43 countries in the data set can be found in Table 1. The simulated effects for all 43 countries are more concentrated in a few sectors when all sectors of the data set are taken into account than when only the national sectors are considered. China is ranked 5th in the general Gini coefficient and 32nd in the Gini coefficient of the national sectors. This makes China one of the countries with one of the strongest concentrations of effects on a small number of sectors; the unequal distribution within the domestic sectors is therefore in the lowest third compared to other countries. However, the differences in the Gini coefficients, especially the general Gini coefficient, are not very large. Here, distortions in the results, caused for example by estimation errors when compiling the WIOD (cf. p. 15) or by violations of the modelling assumptions (cf. pp. 11 to 13), can easily change the values of the Gini coefficients. The exact ranking results should therefore be interpreted with the necessary caution. However, one finding is very robust: the simulated effects are unevenly distributed across the sectors in all countries, including China. Consequently, there appears to be a systemic significance of some sectors in all countries.

Table 1 : Gini coefficients of all 43 countries of the WIOD

State	Gini coefficient general	Gini coefficient national sectors	Gini coefficient rank general	Gini coefficient rank national
IDN	0,9792	0,6764	1	23
TUR	0,9790	0,7185	2	10
IND	0,9785	0,6995	3	17
BRA	0,9784	0,6163	4	40
CHN	0,9777	0,6467	5	32
MEX	0,9754	0,7765	6	6
RUS	0,9747	0,6938	7	18
ROU	0,9696	0,6439	8	33
JPN	0,9685	0,6799	9	22
IRL	0,9681	0,7754	10	7
TWN	0,9676	0,7013	11	15
KOR	0,9670	0,6011	12	42
USA	0,9662	0,6424	13	34
OFF	0,9613	0,6638	14	27
GBR	0,9590	0,6477	15	30
PRT	0,9532	0,8204	16	4
POL	0,9528	0,7171	17	11
CAN	0,9496	0,6517	18	29
ESP	0,9492	0,7014	19	14
FRA	0,9486	0,8301	20	2
BGR	0,9444	0,6105	21	41
LVA	0,9442	0,6677	22	26
NLD	0,9330	0,8686	23	1
LTU	0,9312	0,6998	24	16
HRV	0,9281	0,6552	25	28
CYP	0,9266	0,6846	26	21
GRC	0,9261	0,6716	27	25
ITA	0,9182	0,6318	28	37
NOR	0,9153	0,6215	29	39
SVK	0,9143	0,6468	30	31
HUN	0,9137	0,6912	31	20
LUX	0,9095	0,8274	32	3
BEL	0,9095	0,7823	33	5

DEU	0,9092	0,7130	34	12
EST	0,9078	0,7352	35	8
CHE	0,9037	0,7272	36	9
FIN	0,9022	0,6370	37	35
CZE	0,9021	0,6918	38	19
DNK	0,8946	0,7035	39	13
SVN	0,8943	0,5714	40	43
MLT	0,8928	0,6303	41	38
SWE	0,8887	0,6346	42	36
AUT	0,8859	0,6750	43	24

Notes: Illustration by the author. Gini coefficients of the effect distribution of the sectors of the model. An explanation of the country abbreviations can be found in the appendix.

### 4.3 Results of the robustness check

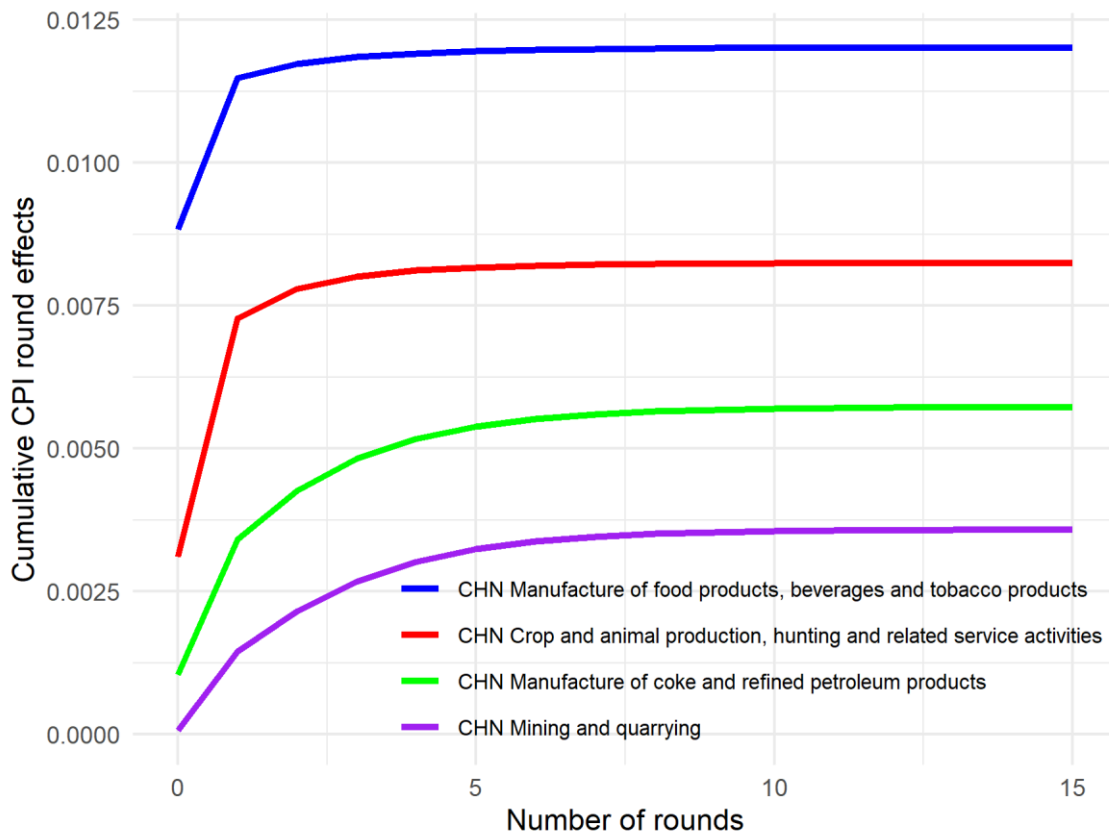
Figure 6 shows the results of the power series approximation from equation (17) for the first 15 rounds. A table with the numerical values of the power series approximation can be found in the appendix (see p. 38). The figure shows that the majority of the effects already occur in the first rounds. All four sectors reach at least 90 per cent of the total effect from the basic specification of the model after five rounds at the latest. This finding of rapid shock propagation strengthens the plausibility of the simulation results. It shows that it is plausible to assume that the effects of the simulation will occur in the short term, which strengthens the plausibility of the underlying modelling assumptions. Incidentally, this finding of rapid shock propagation replicates the result for the EU in Ipsen *et al.* (2023, pp. 24-26).

However, the speed of approaching the total effect from the basic specification is noticeably different for the four sectors shown. While the food processing sector (blue in Figure 6) already achieves more than 95 per cent of the total effect in the first round, the mining sector (purple) requires 7 rounds to do so.<sup>18</sup> It is striking that the speed at which the total effect is approached is significantly faster for sectors with a high proportion of direct effect and a low proportion of indirect effect (e.g. food processing) than for sectors with the opposite effect composition (e.g. mining). This finding is also plausible, as the direct effect has an immediate impact on the CPI, while the indirect effect can only unfold its

<sup>18</sup> For a detailed breakdown of the results of the four sectors, including the rounds required for over 90, 95 and 99 per cent, see Table 3 in the appendix.

impact via the effect on other prices (and in turn their effects on other prices). This shock propagation along the supply chains is necessarily slower than the direct effect on the CPI. For sectors with effects along very long production chains, a slower adjustment of the power series values to the values of the basic specification is to be expected. Conversely, a slow adjustment of the power series values to the values of the basic specification implies effects along longer production chains.

Figure 6: Power series approximation



Notes: Illustration by the author similar to Ipsen et al. (2023, p. 25). Result of the power series approximation as in equation (17) for the four sectors with the largest simulated effect on the Chinese CPI. The values at round 0 are the direct effects as in equation (10)

#### 4.4 Placement of the contribution in inflation theories

Finally, it should be noted that the calculations in this paper only include the size of the initial shock and the passing on of prices along the production chain. In response to this, a distributional conflict would now follow in the post-Keynesian sense, which would be accompanied by further price increase effects that are not taken into account in any form in this paper. In the New Keynesian sense, the calculated inflation triggers would now have resulted in a changed natural output level. The subsequent adjustment movements

from the resulting output gap back to a stable equilibrium are accompanied by further price adjustments, which are not taken into account in this paper. The calculated values should therefore not be understood as simulated values of the complete inflationary process triggered by the simulated supply shocks. The full inflation processes requires a more far-reaching simulation and is heavily dependent, for example, on the policy reactions of the central bank and/or the government. Instead, the calculated effect sizes provide information on which sectors are at risk of particularly high supply shocks, which could then trigger further inflationary processes. They thus sharpen the focus as to which sectors should be given special attention in the investigation of inflation processes in post-Keynesian modelling and in new-Keynesian modelling and in policy discussions.

## 5 Conclusion

In this study, systemically significant sectors were identified for China that pose a particularly high risk of triggering inflation. These sectors are especially two food sectors, as well as the oil and coal sectors. In addition, sectors of certain consumer goods, production inputs and the wholesale trade sector play an important role in inflation dynamics in China.

In an international comparison, the concentration of inflation effects on a few sectors is particularly pronounced in China, whereby the concentration of effects within the subgroup of national sectors is rather weak in an international comparison, although there is still a considerable unequal distribution.

These findings have relevant policy implications: In addition to the known inflation control tools available to the central bank, it would make sense to think about suitable new tools that can monitor nascent inflation triggers from systemically significant sectors in order to address them in a more targeted manner in the event of a crisis than the central bank's interest rate policy can. However, the precise development of such tools goes far beyond the scope of this paper. In particular, the social costs of interest rate policy would have to be compared with the social costs of sector-specific measures.

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## 7 Appendix: Supplementary figures and tables

Table 2: Country abbreviations

AUS	Australia
AUT	Austria
BEL	Belgium
BGR	Bulgaria
BRA	Brazil
CAN	Canada
CHE	Switzerland
CHN	China (People's Republic of)
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland
FRA	France
GBR	United Kingdom
GRC	Greece
HRV	Croatia
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ITA	Italy
JPN	Japan
KOR	South Korea
LTU	Lithuania
LUX	Luxembourg
LVA	Latvia
MEX	Mexico
MLT	Malta
NLD	The Netherlands
NOR	Norway
POL	Poland
PRT	Portugal
ROU	Romania
RUS	Russia
SVK	Slovakia
SVN	Slovenia
SWE	Sweden
TUR	Turkey
TWN	Taiwan (Republic of China)
USA	United States of America

ROW Rest of the world

Notes: Illustration by the author according to the Socio Economic Accounts of the World Input-Output Database (2021).

Table 3: Result of the power series approximation

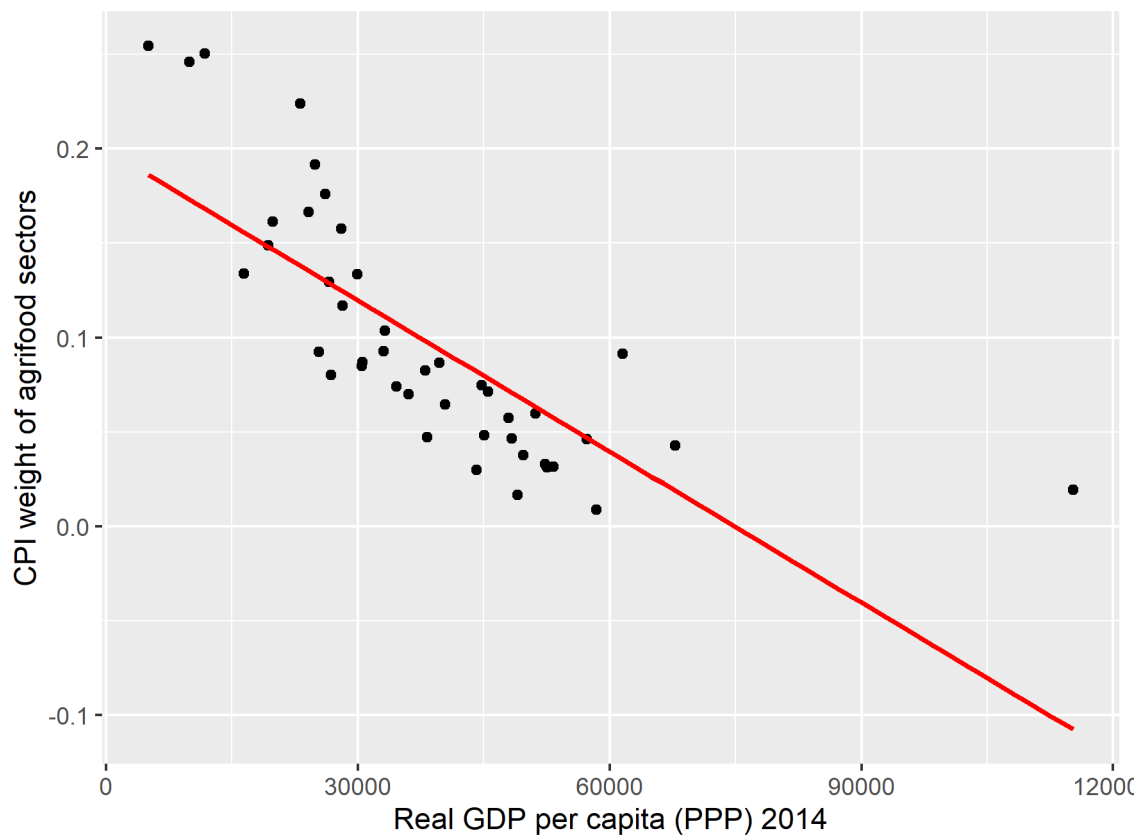
Rounds	CHN Manufacture of food products, beverages and tobacco products	CHN Crop and animal production, hunting and related service activities	CHN Manufacture of coke and refined petroleum products	CHN Mining and quarrying
Direct effect	0,0088	0,0031	0,0011	0,0001
1	0,0115**	0,0073	0,0034	0,0014
2	0,0117	0,0078*	0,0043	0,0022
3	0,0118	0,0080**	0,0048*	0,0027
4	0,0119***	0,0081	0,0052	0,0030
5	0,0120	0,0082***	0,0054	0,0032*
6	0,0120	0,0082	0,0055**	0,0034
7	0,0120	0,0082	0,0056	0,0035**
8	0,0120	0,0082	0,0056	0,0035
9	0,0120	0,0082	0,0057***	0,0035
10	0,0120	0,0082	0,0057	0,0036***
11	0,0120	0,0082	0,0057	0,0036
12	0,0120	0,0082	0,0057	0,0036
13	0,0120	0,0082	0,0057	0,0036
14	0,0120	0,0082	0,0057	0,0036
15	0,0120	0,0082	0,0057	0,0036

Notes: Illustration by the author. \*90 per cent of the simulated total effect is exceeded, \*\* 95 per cent, \*\*\* 99 per cent.

Notes: Illustration by the author based on Weber et al. (2022, p. 49). See Figure 2 for a detailed explanation of the figure.



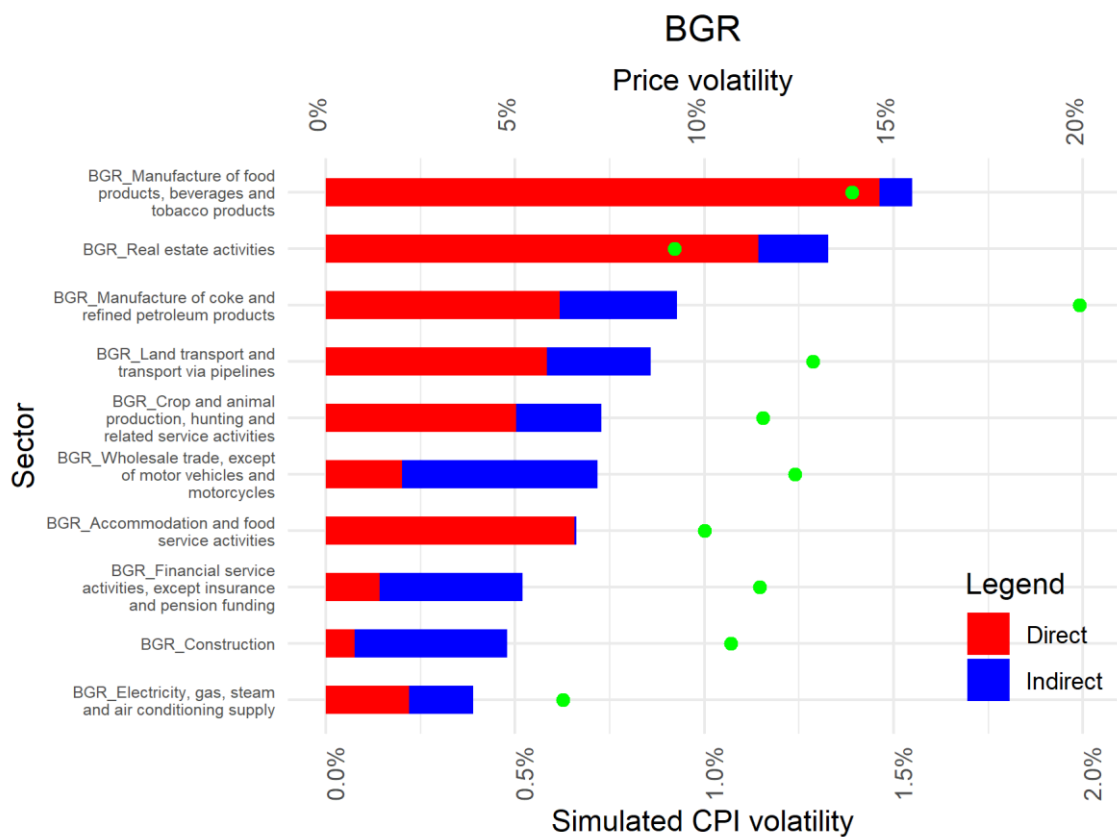
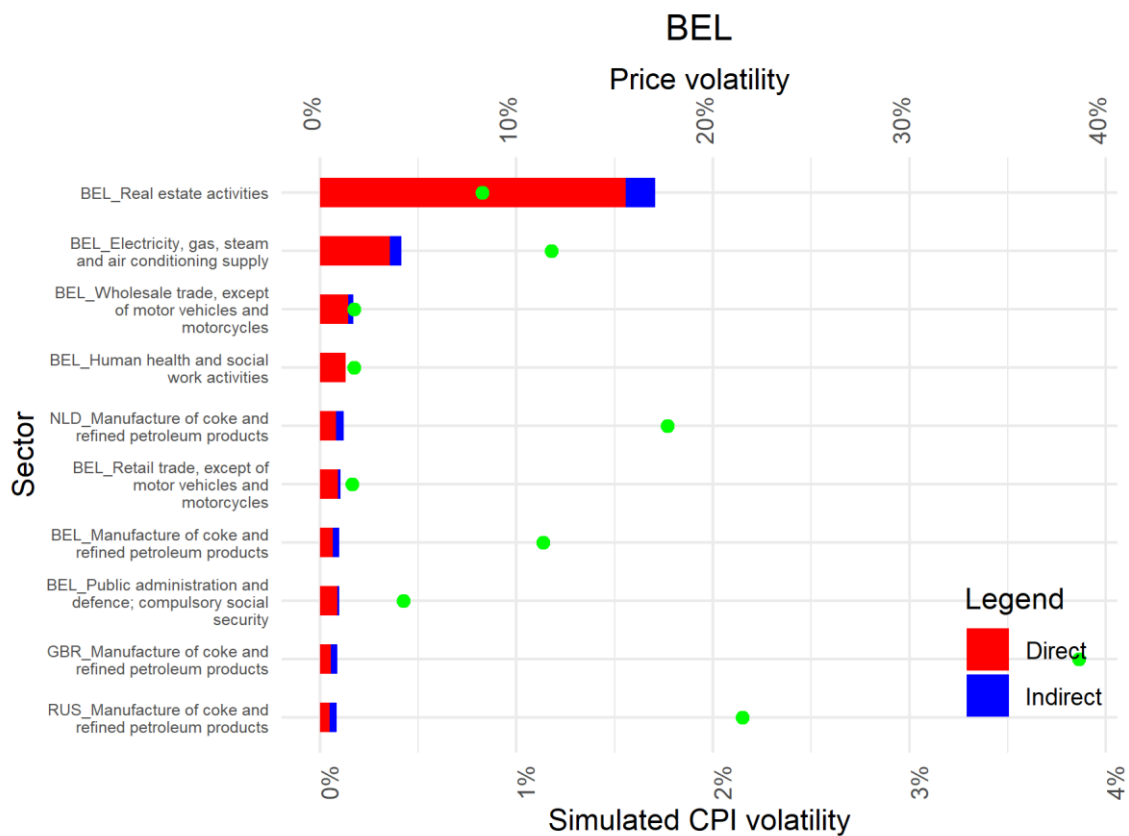
Figure 9: GDP per capita & agrifood sectors

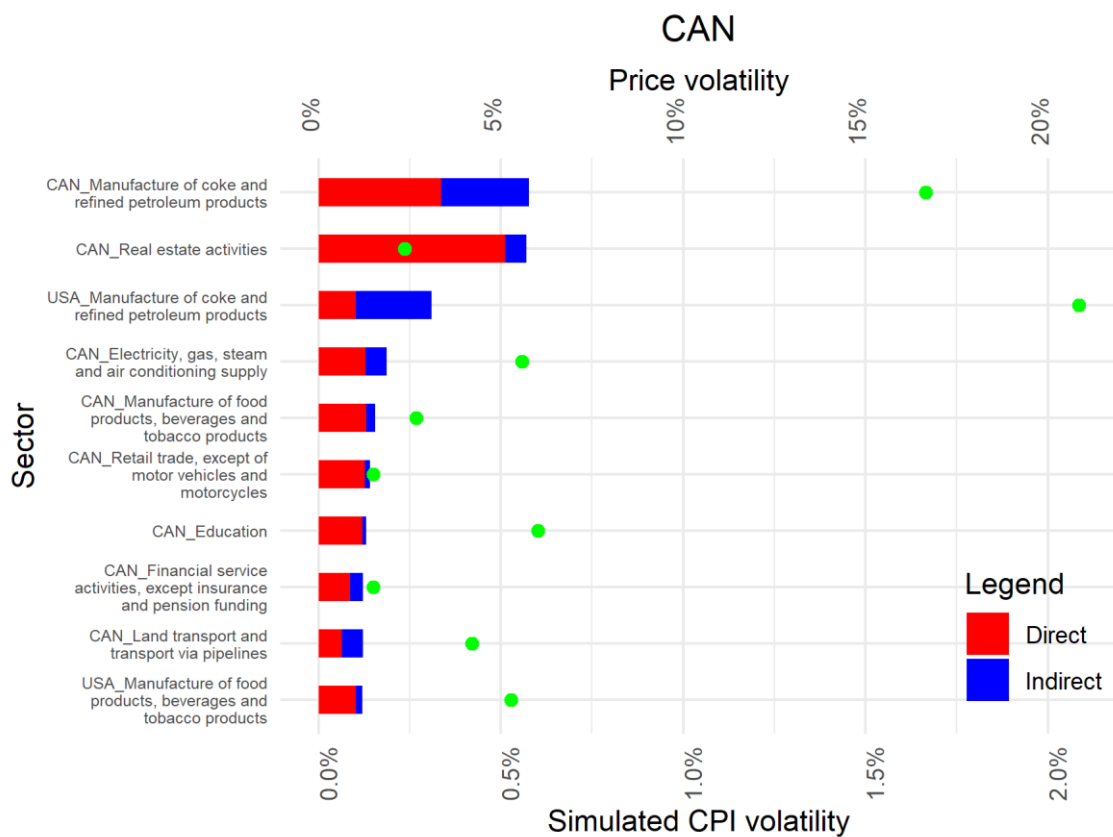
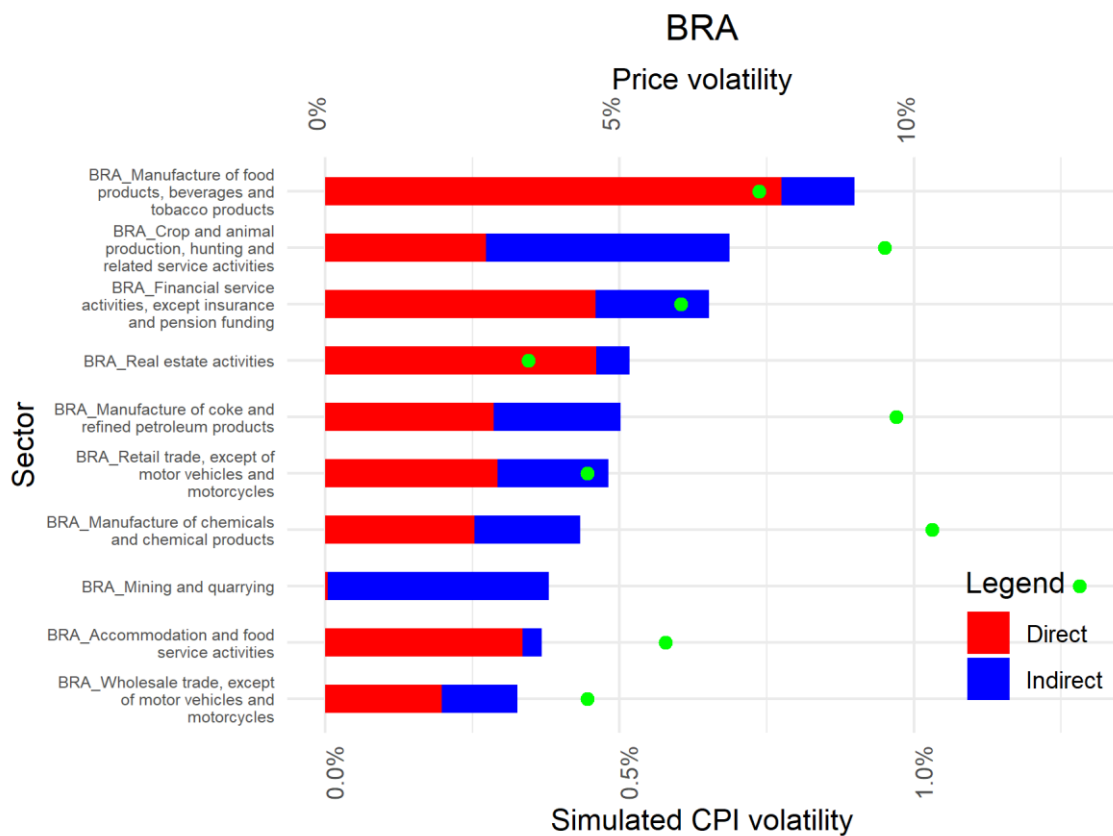


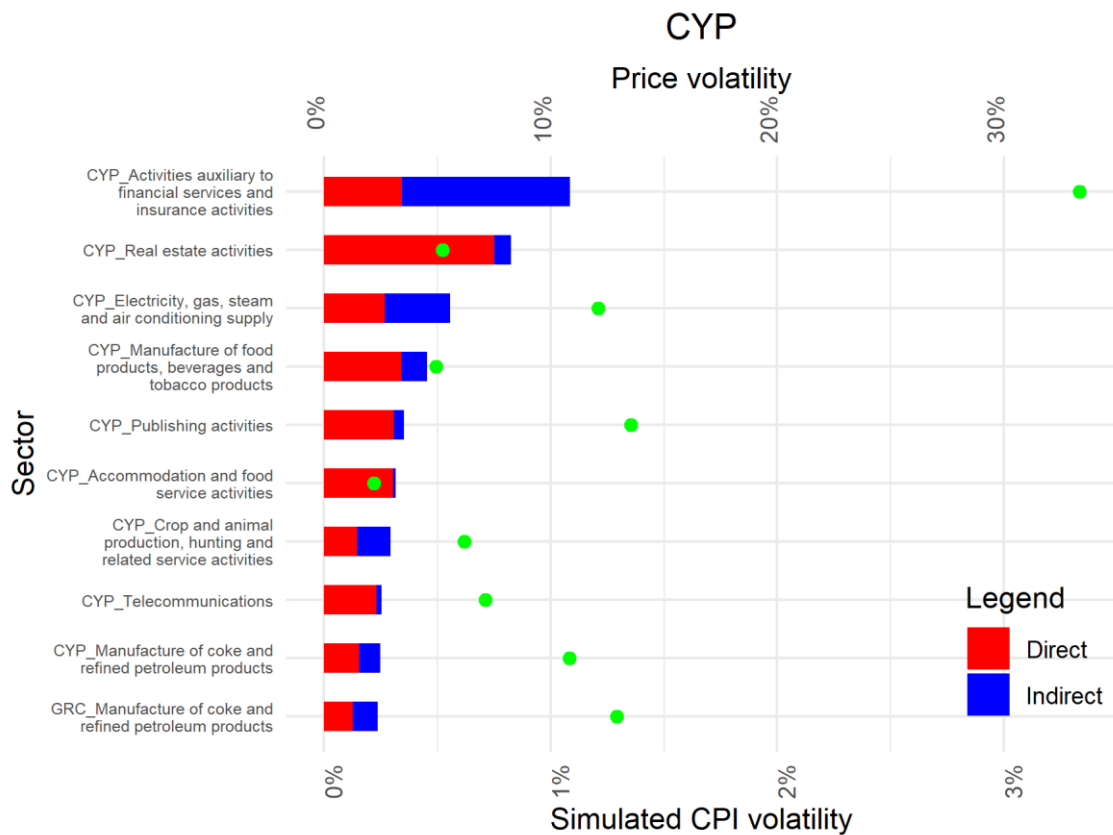
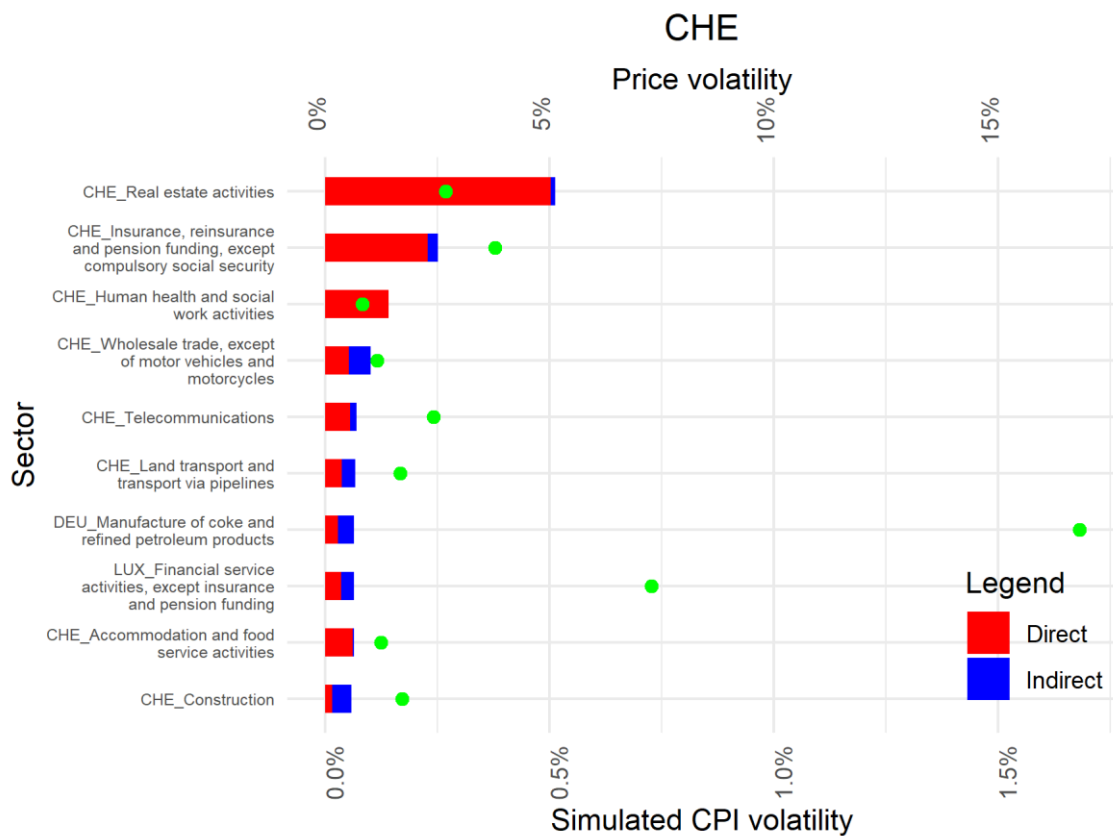
*Notes: Illustration by the author. Relationship of purchasing power-adjusted real GDP per capita in 2014 with the weights of the two national sectors "manufacture of food products, beverages and tobacco products" (food processing) and "crop and animal production, hunting and related service activities" (agricultural production). In the simple OLS regression of CPI weight of the two sectors on GDP per capita, GDP per capita is statistically significant at the 0.1% significance level. The graph and the regression analysis both imply a high correlation between the two variables.*

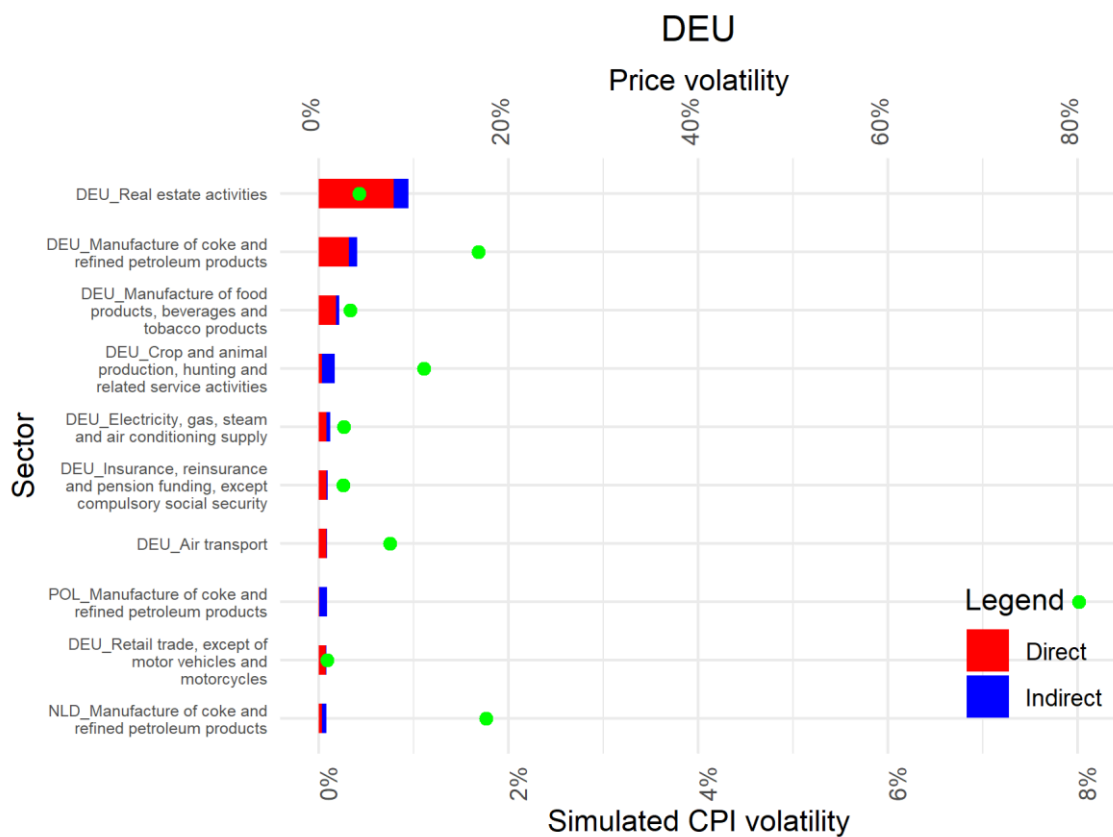
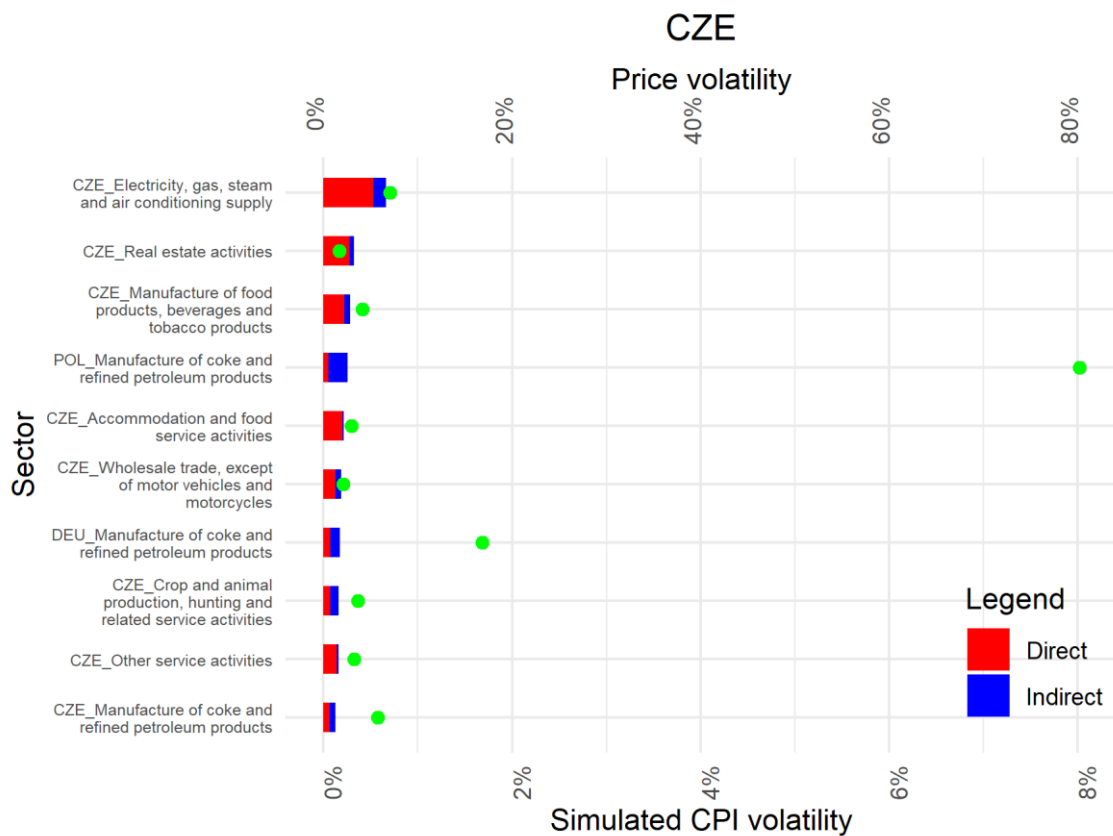
Figure 10: Simulated CPI effects of all 43 countries of the WIOD

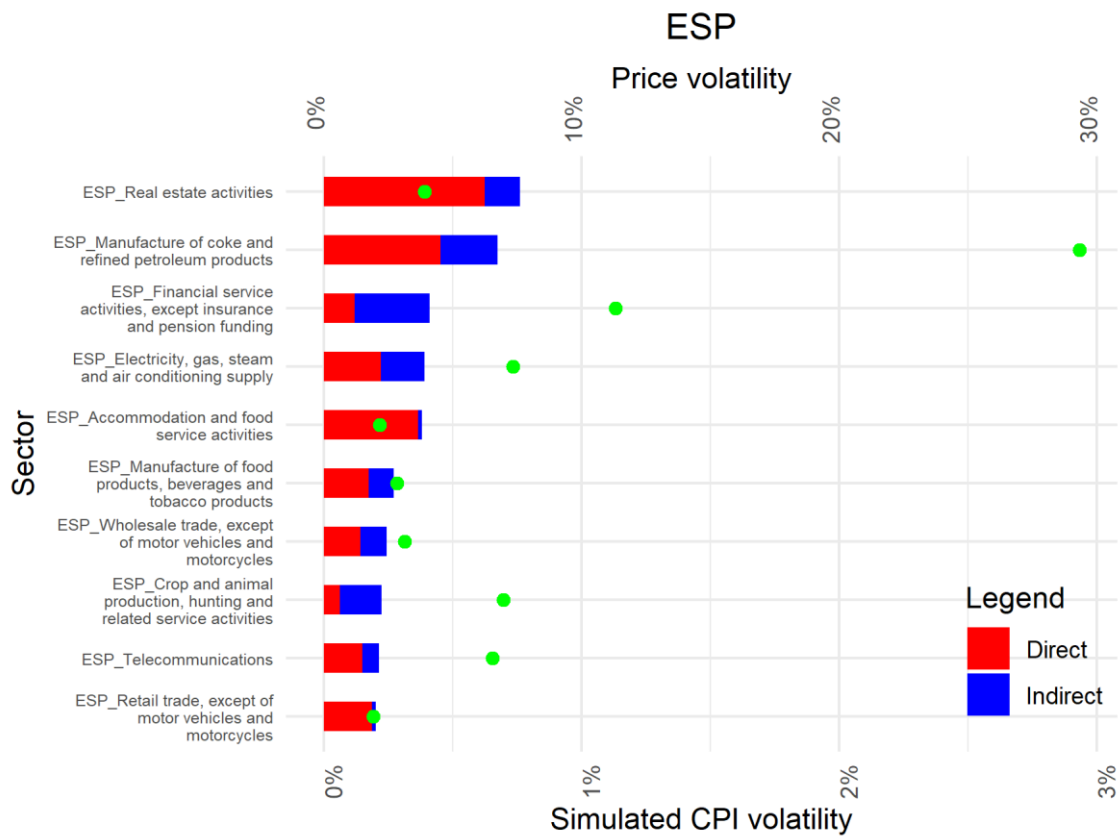
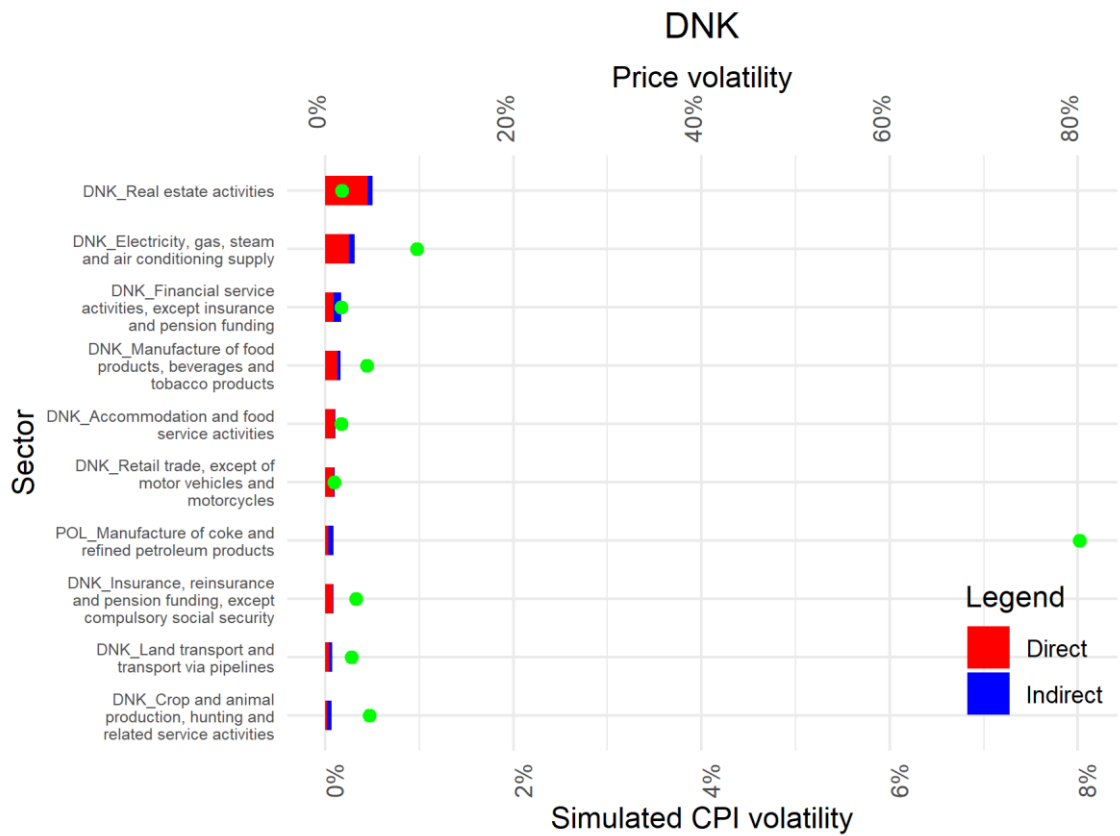


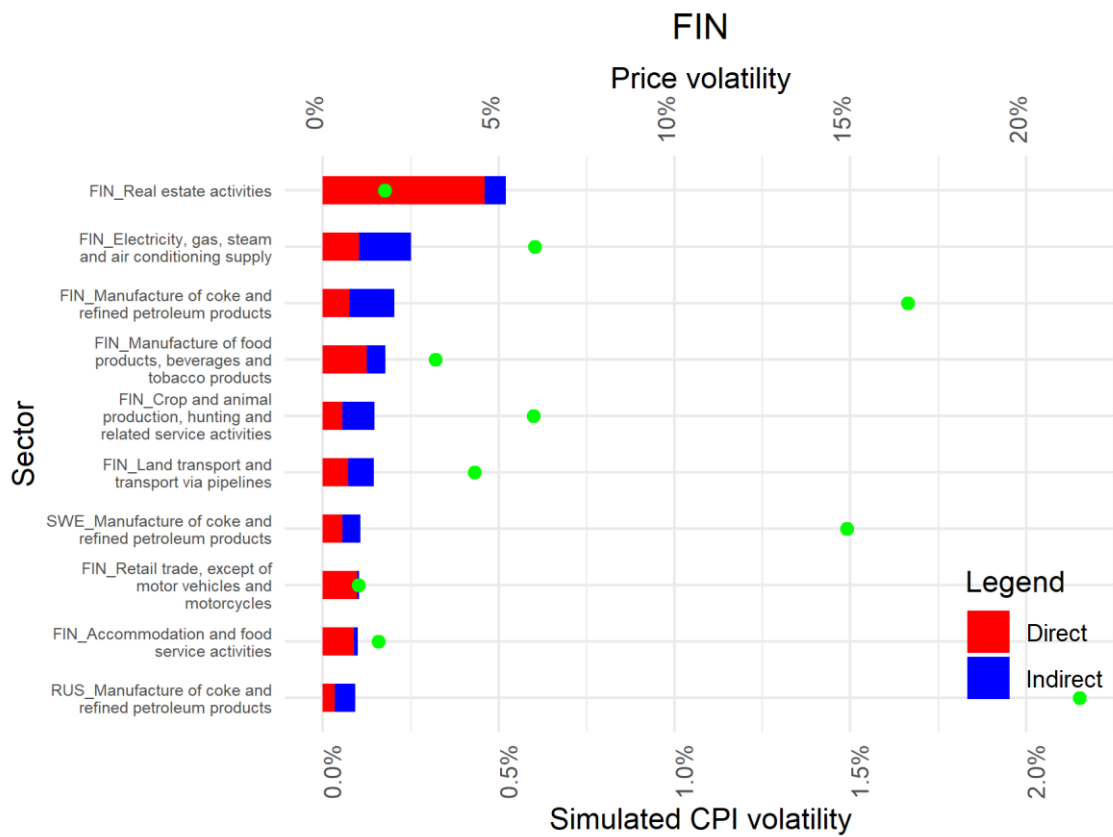
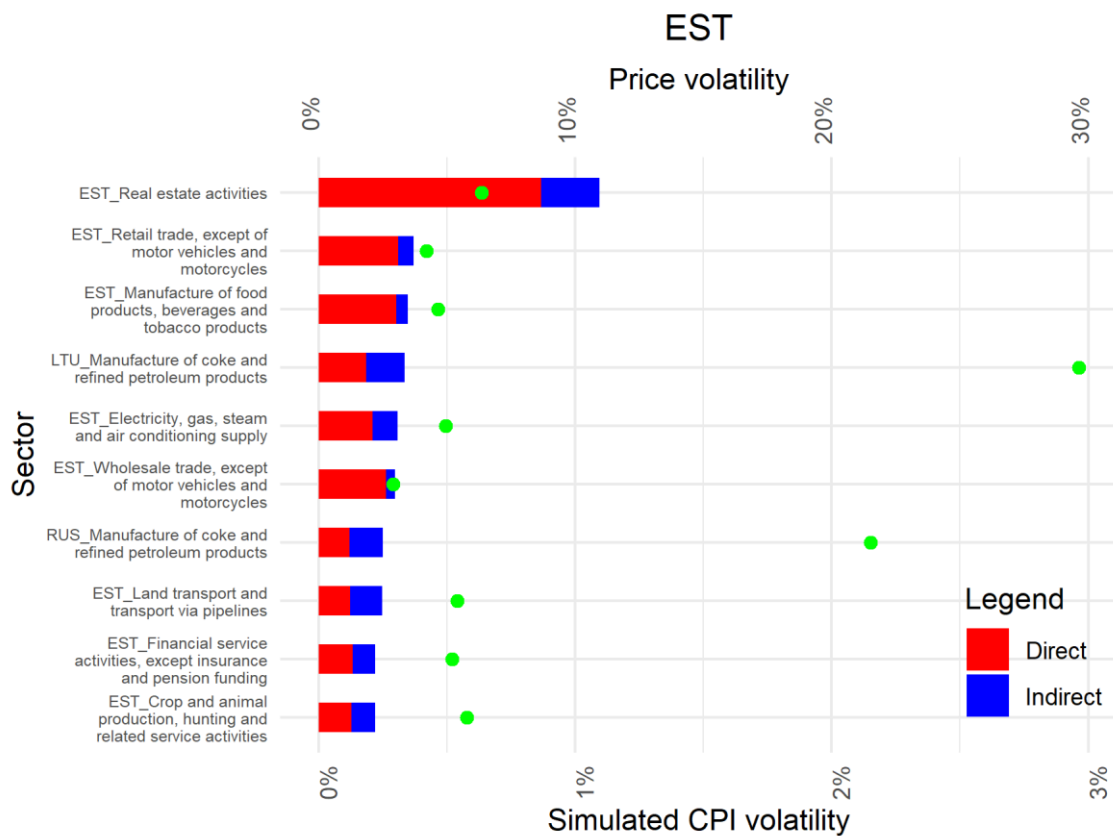


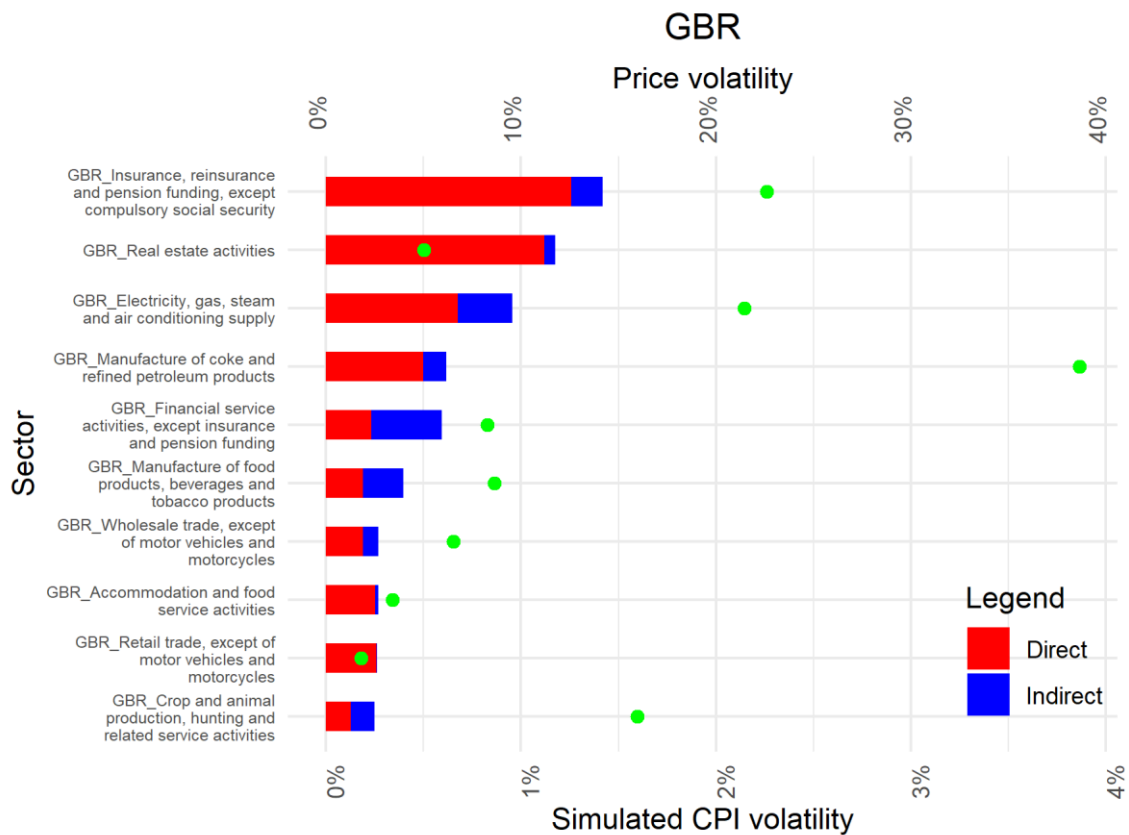
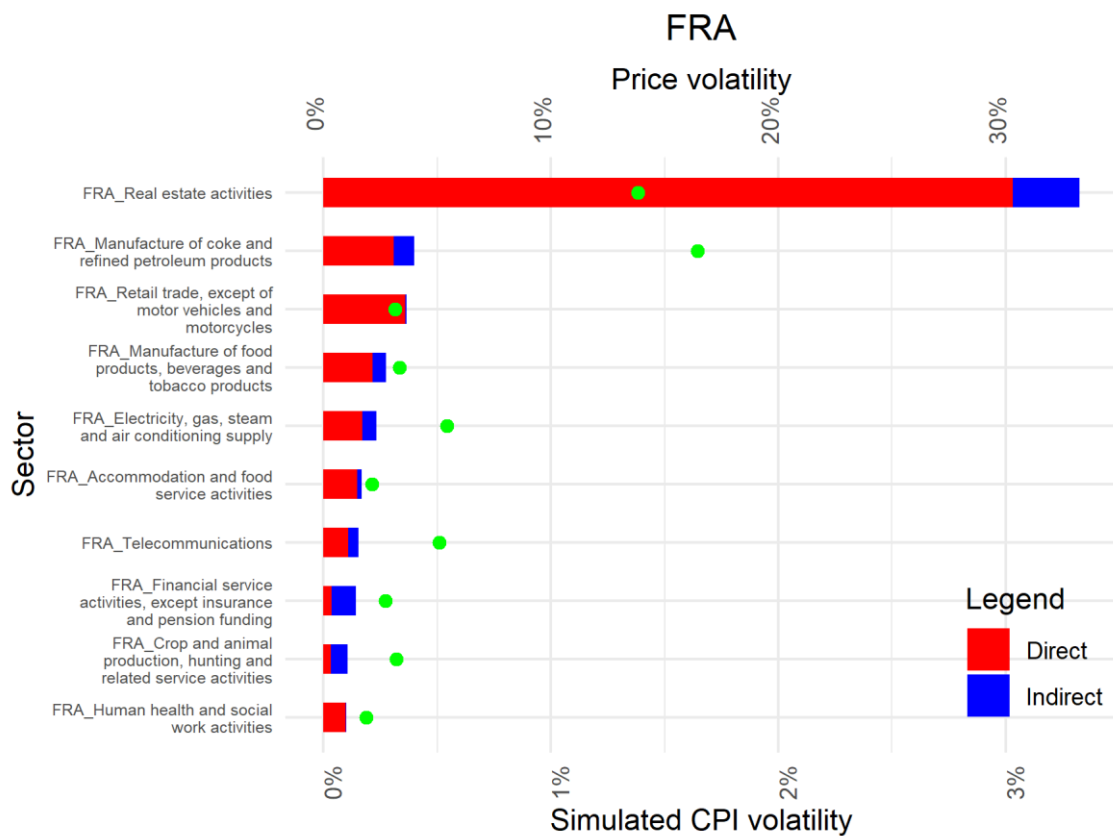


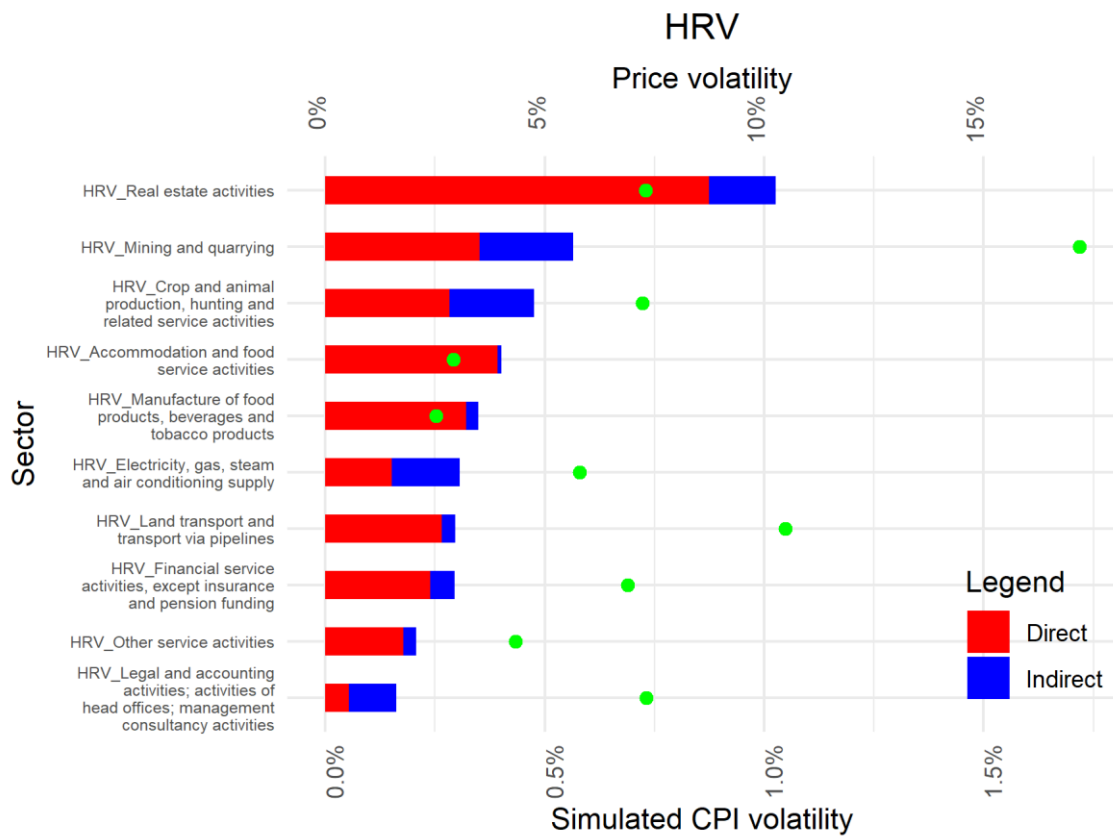
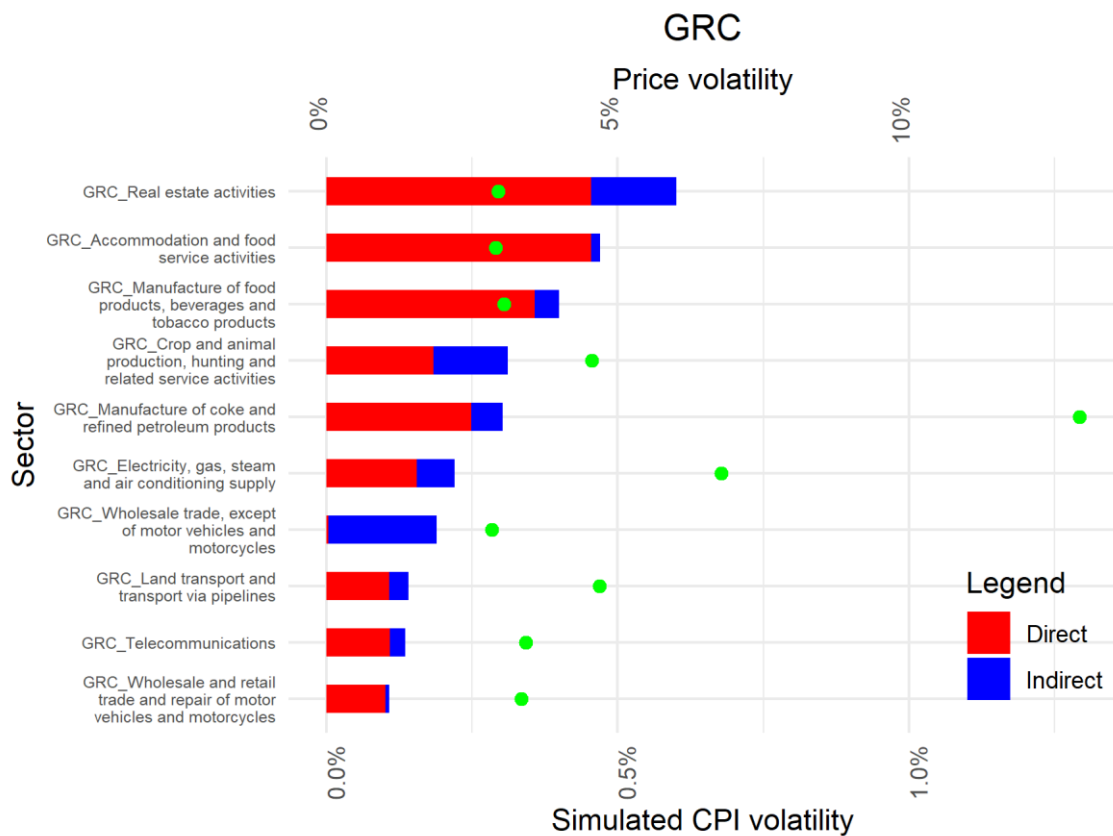


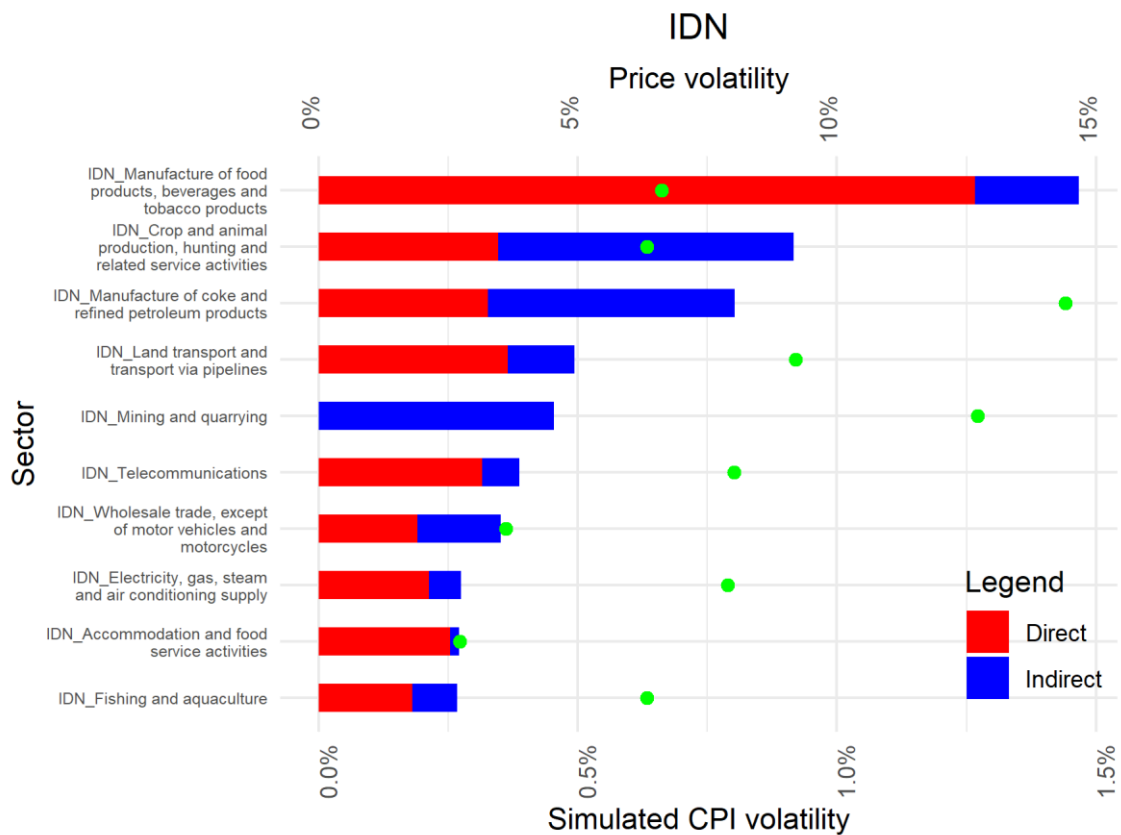
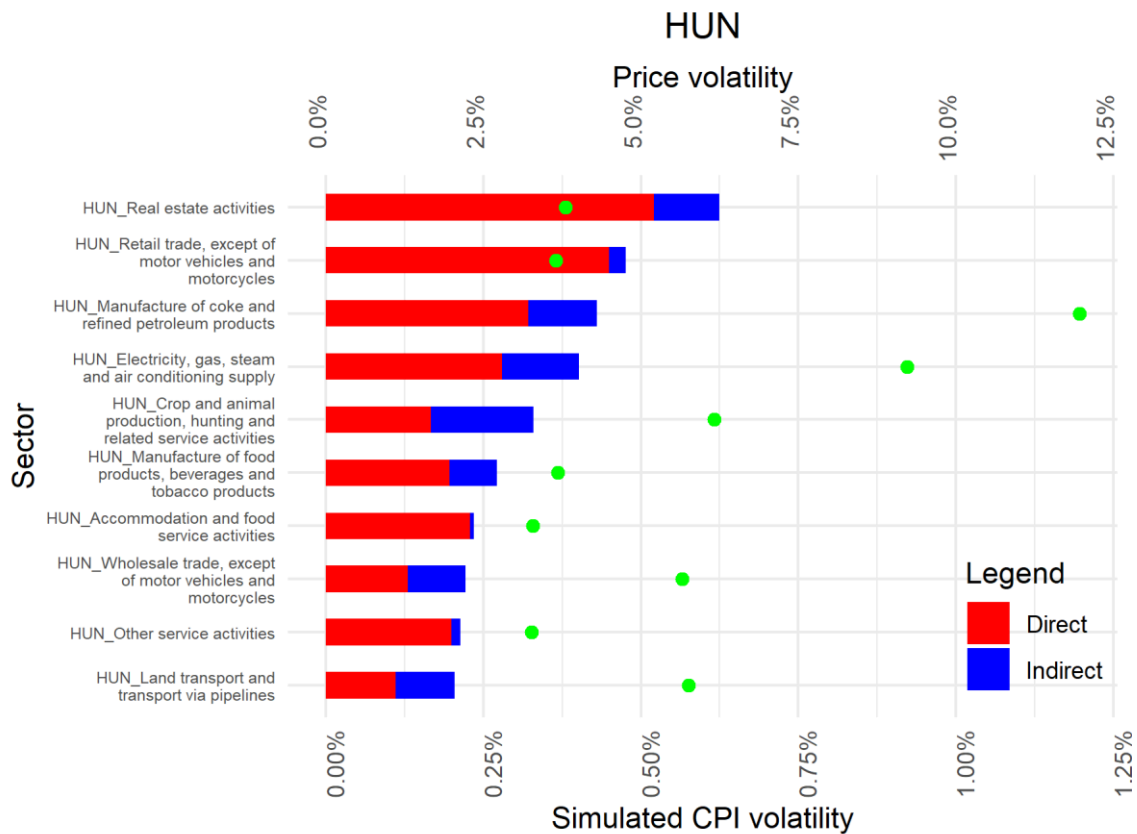


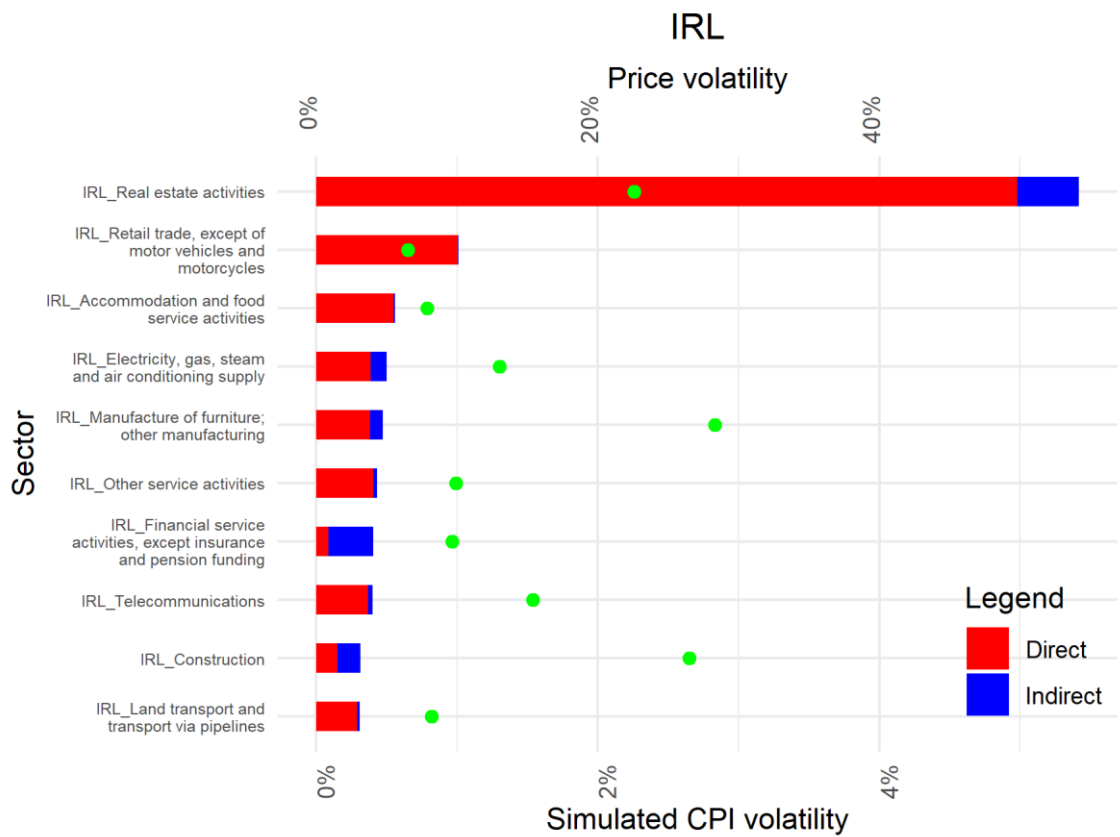
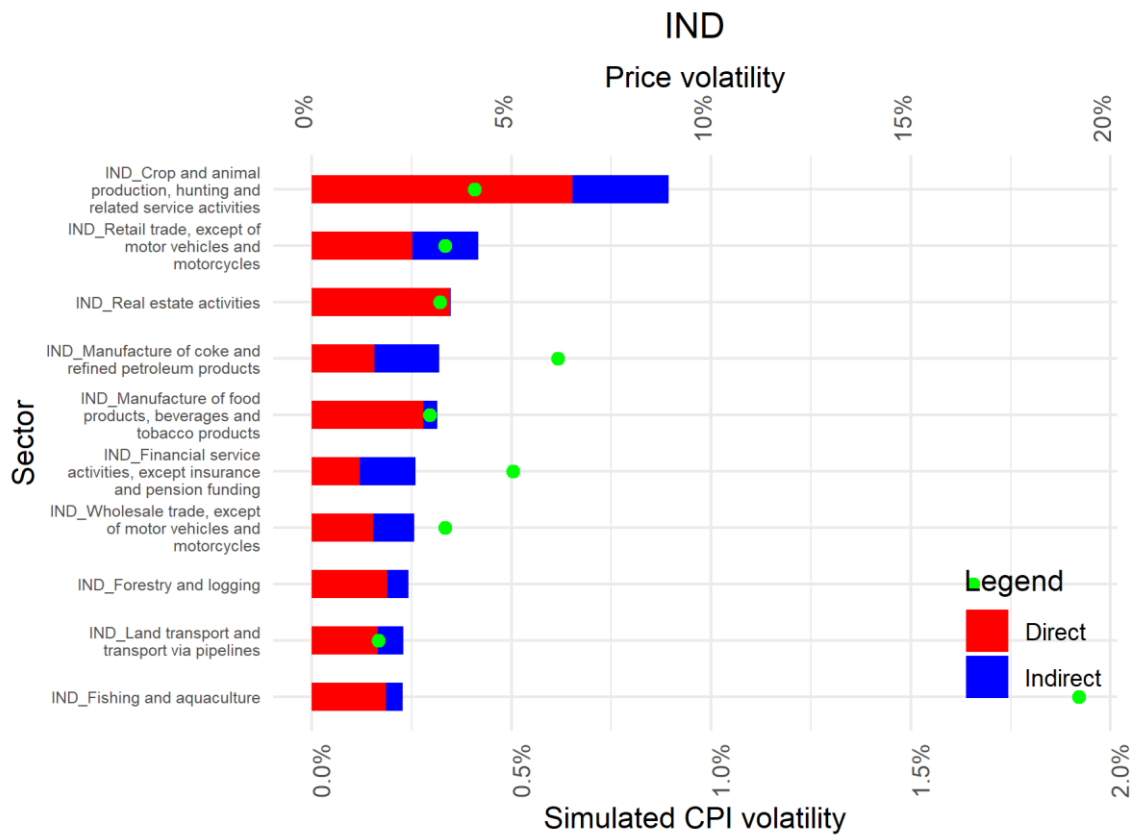


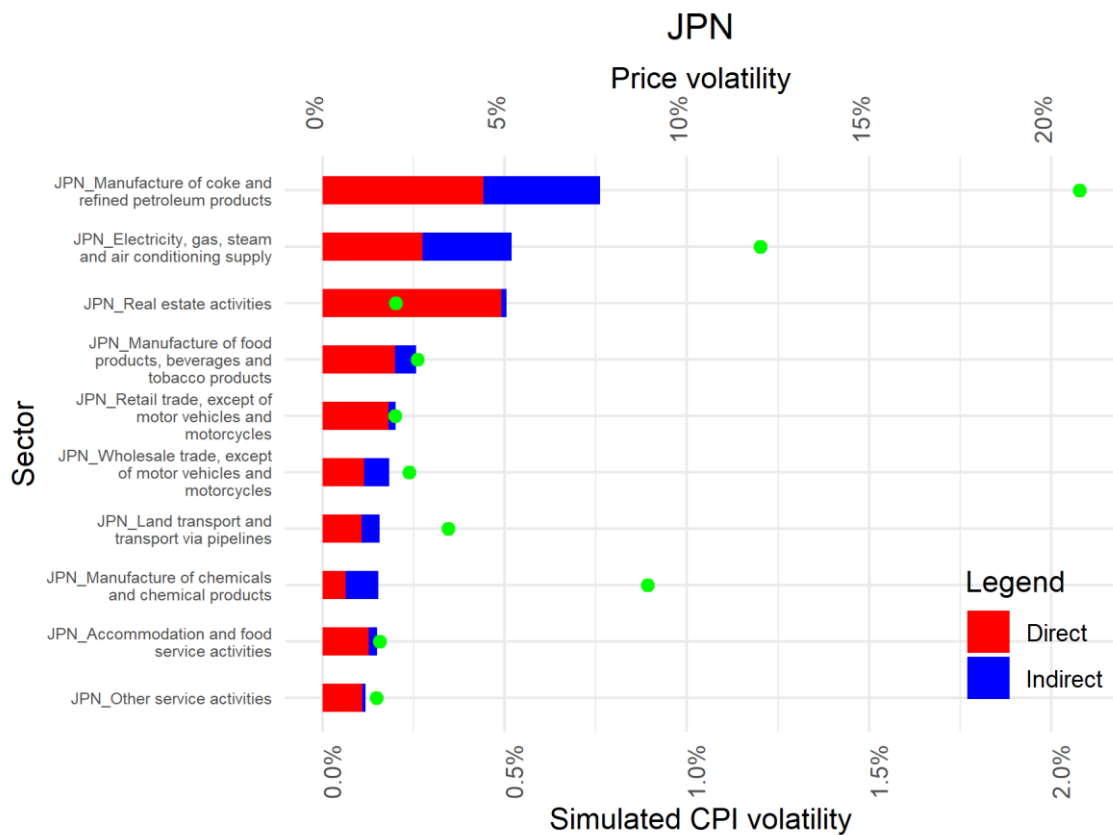
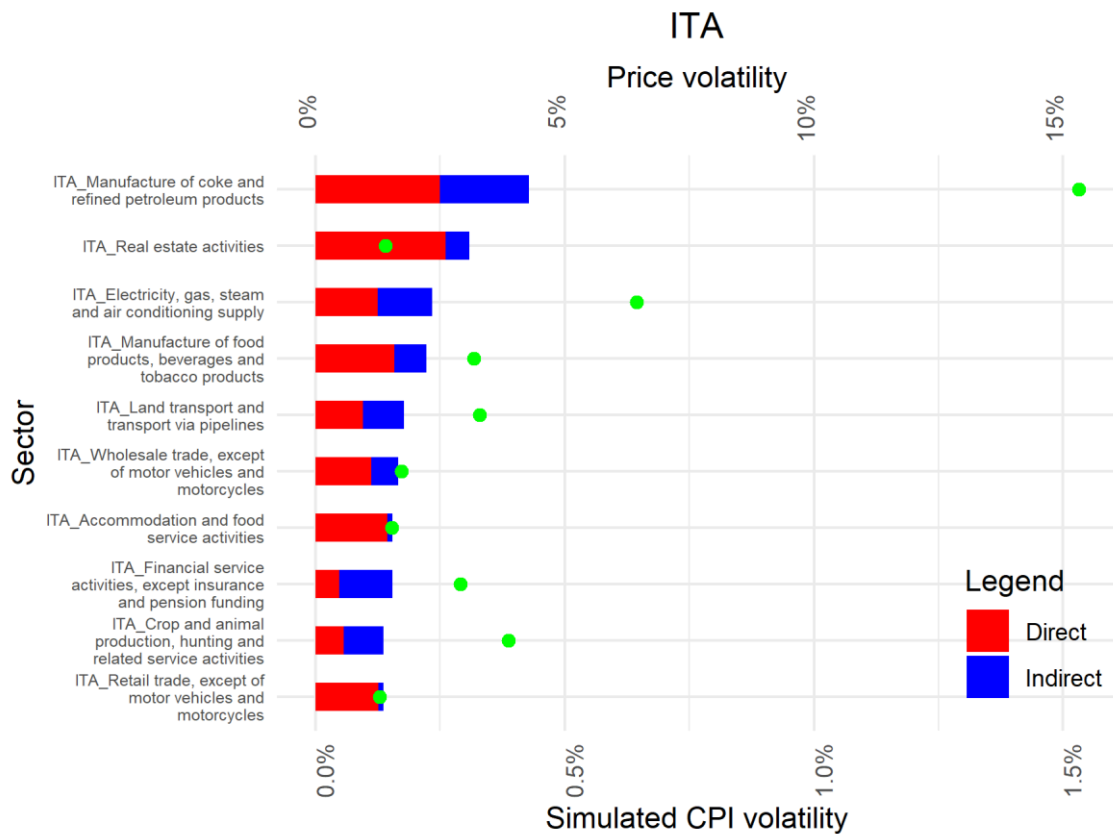


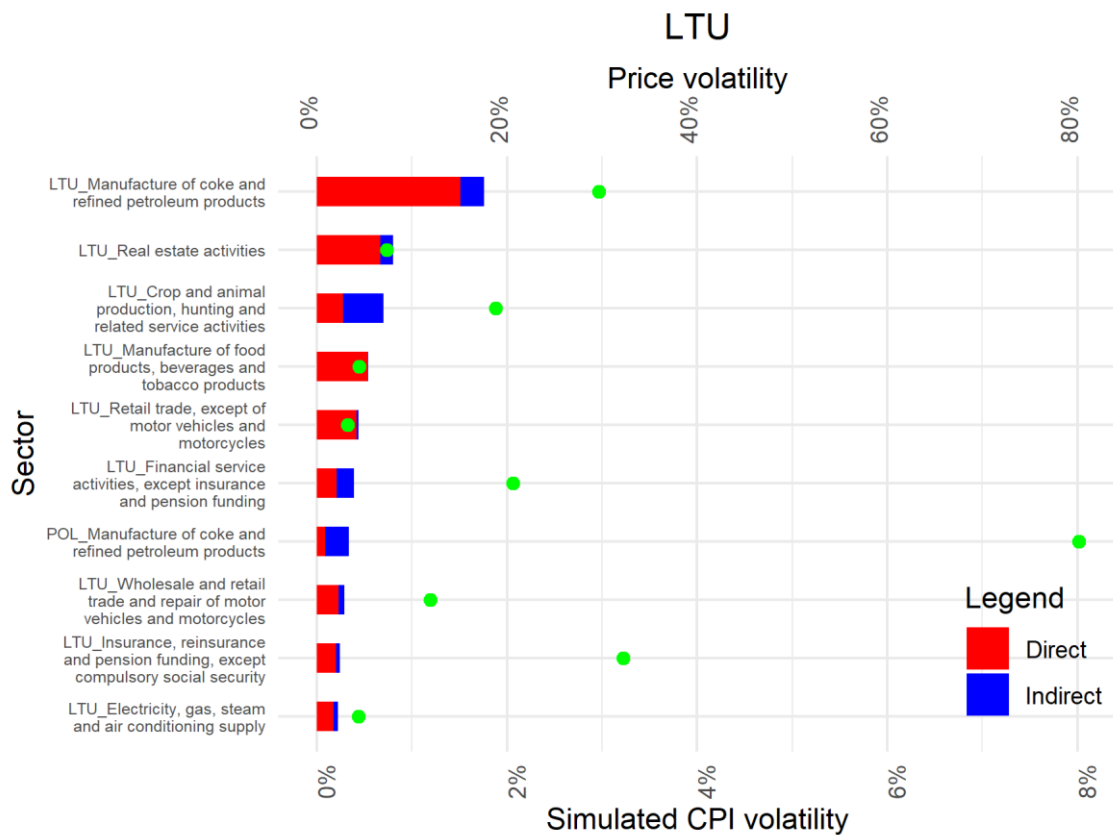
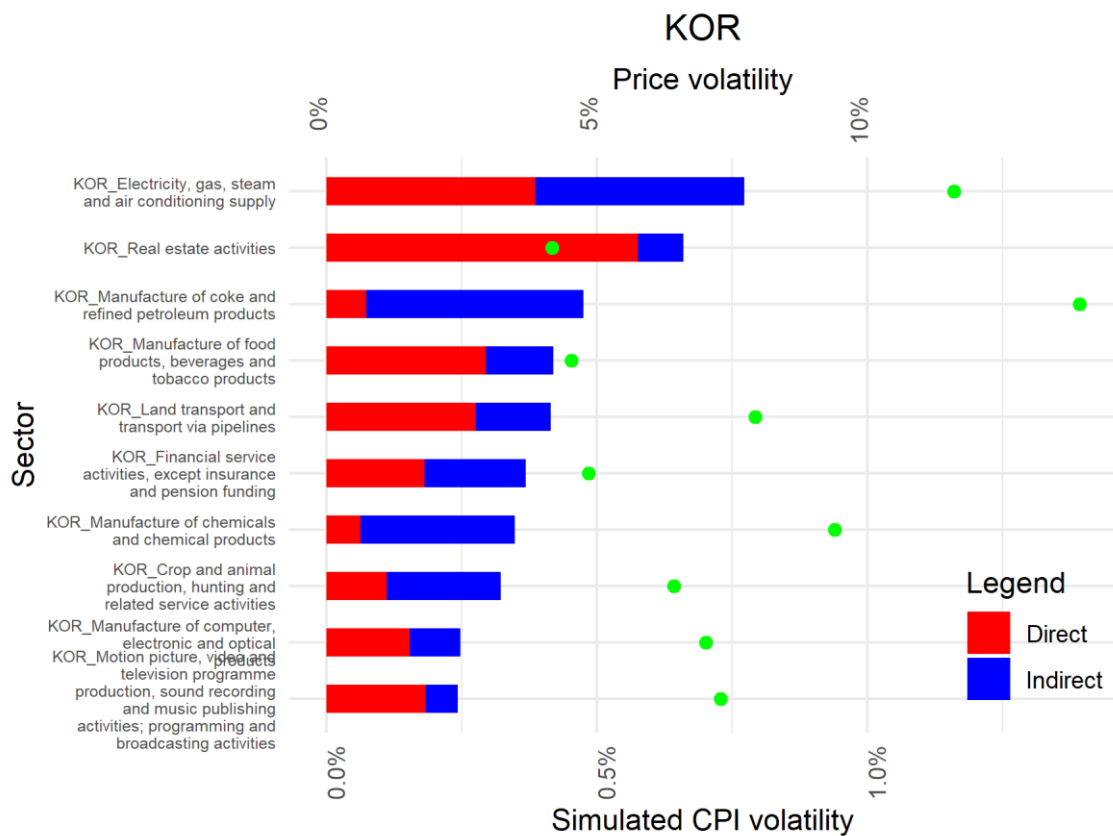


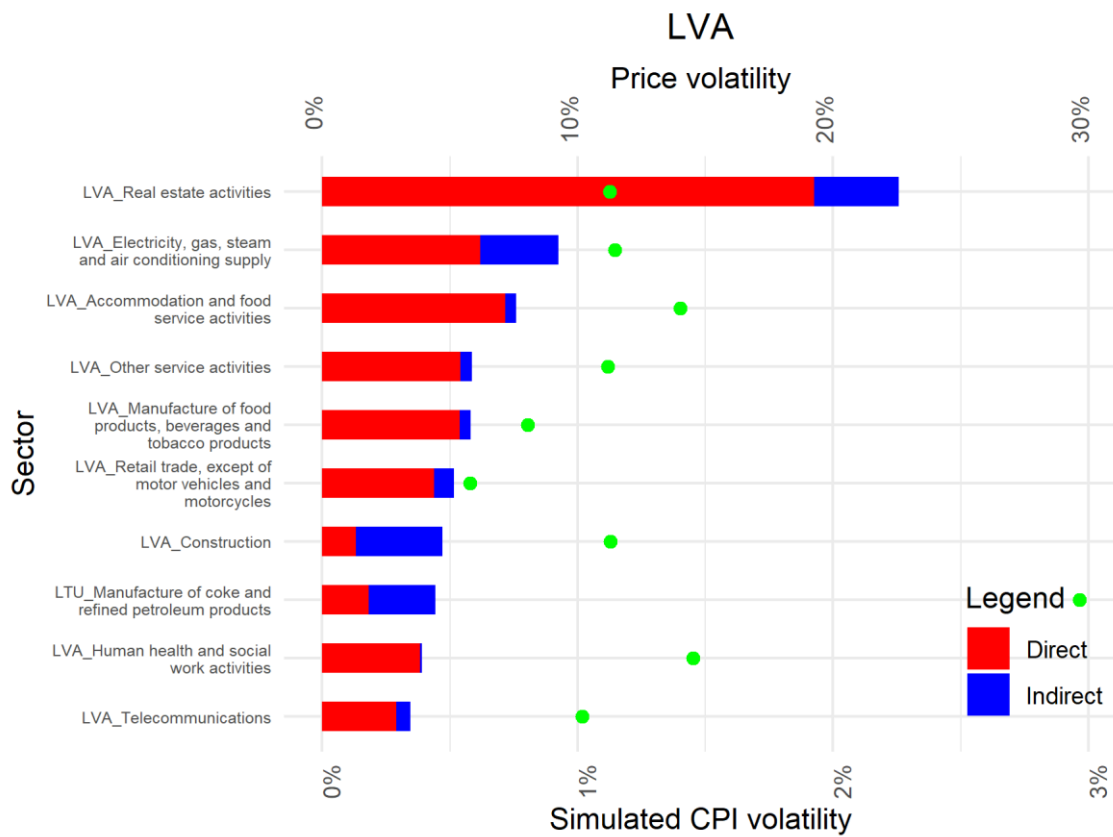
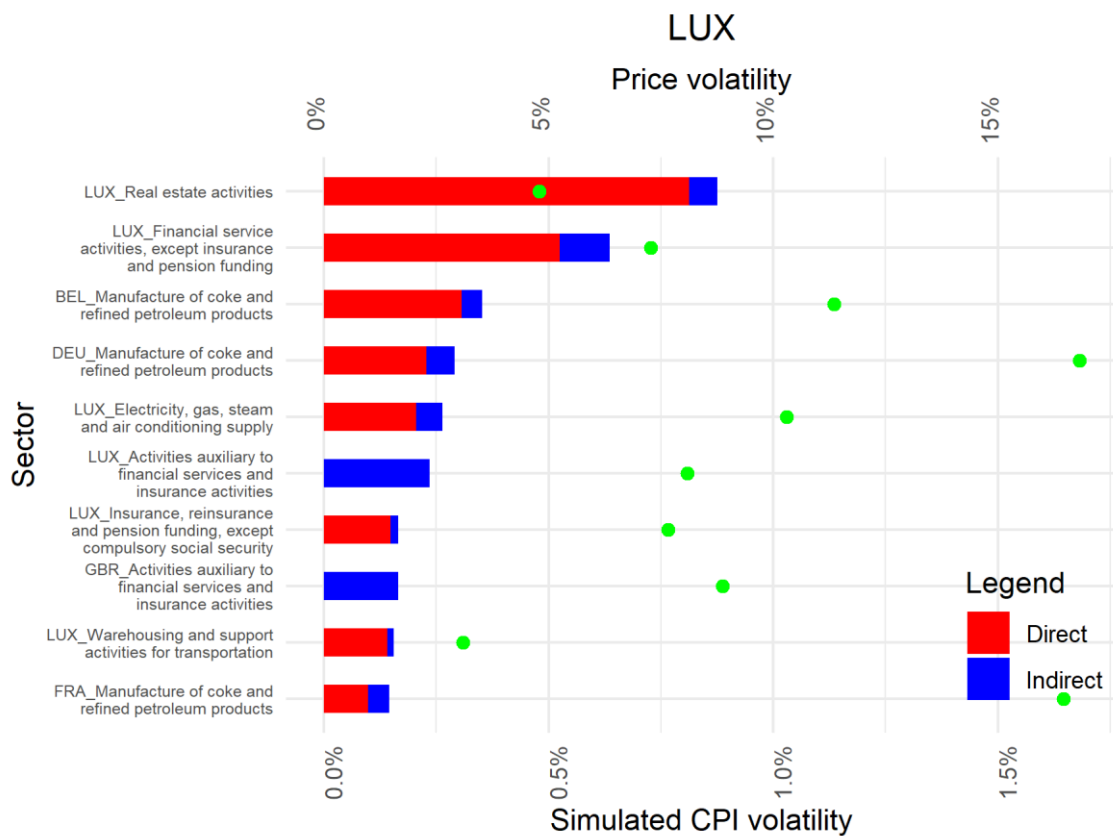


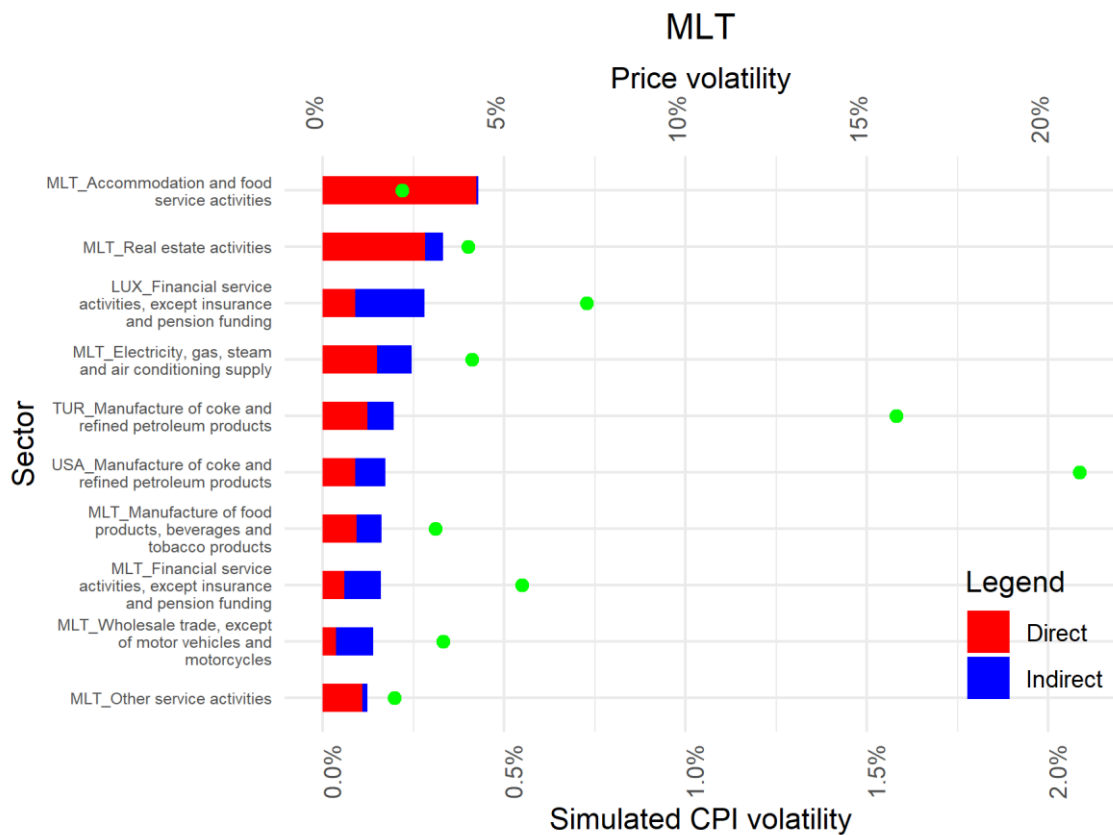
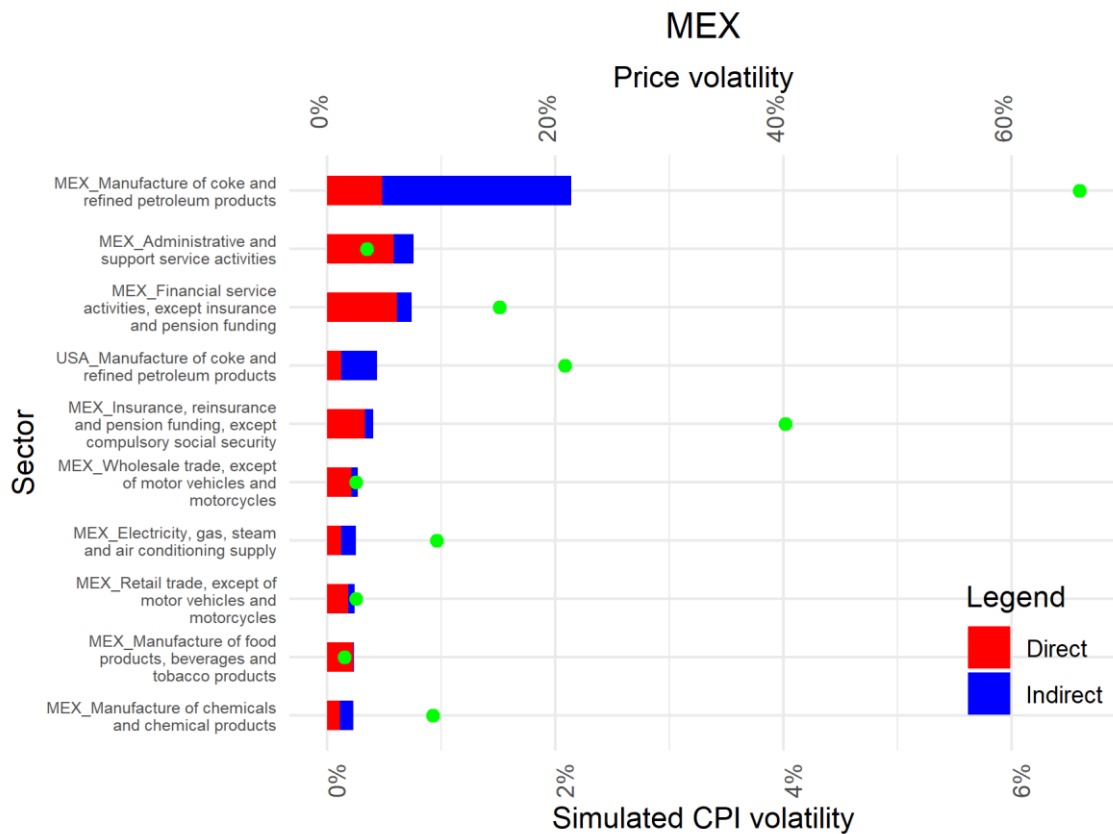


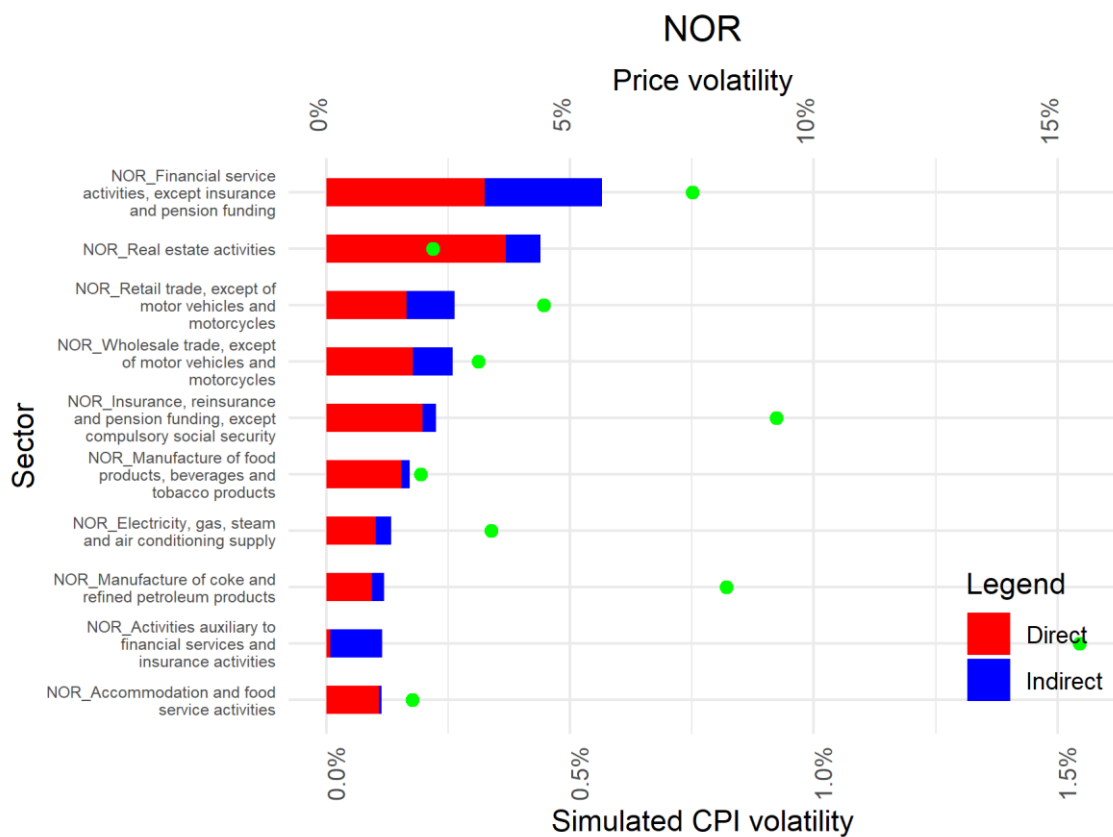
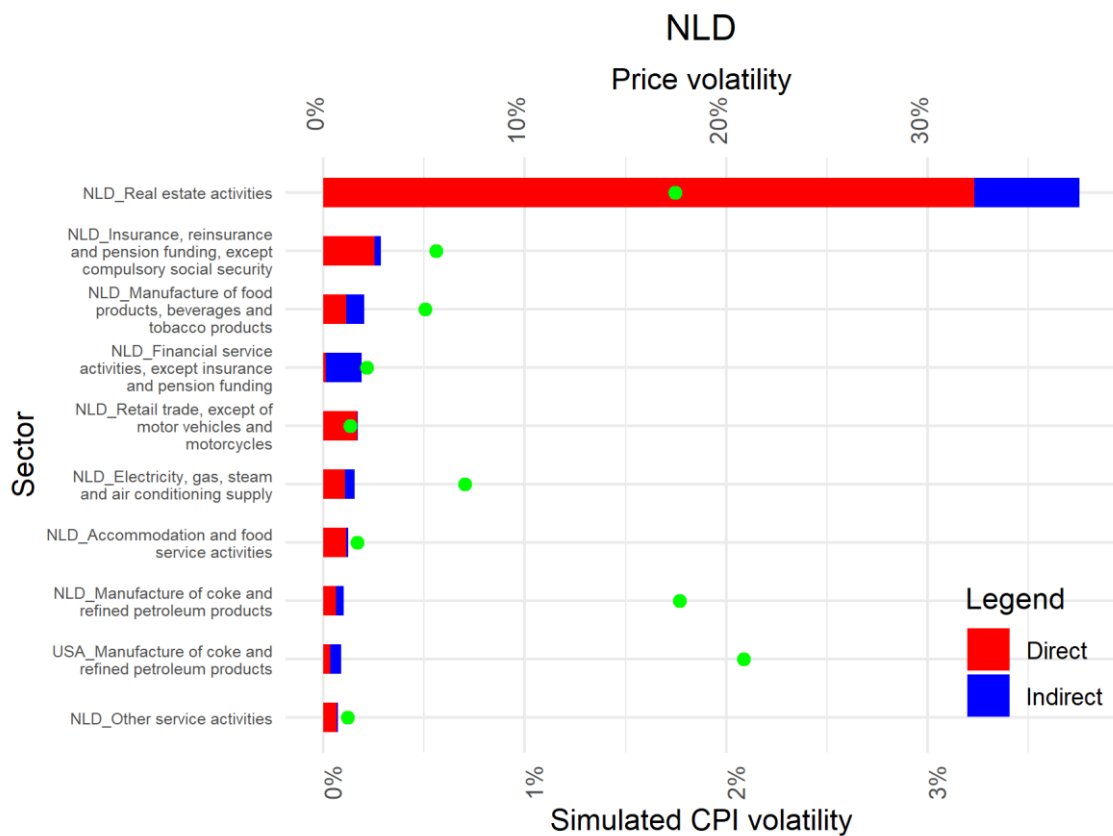


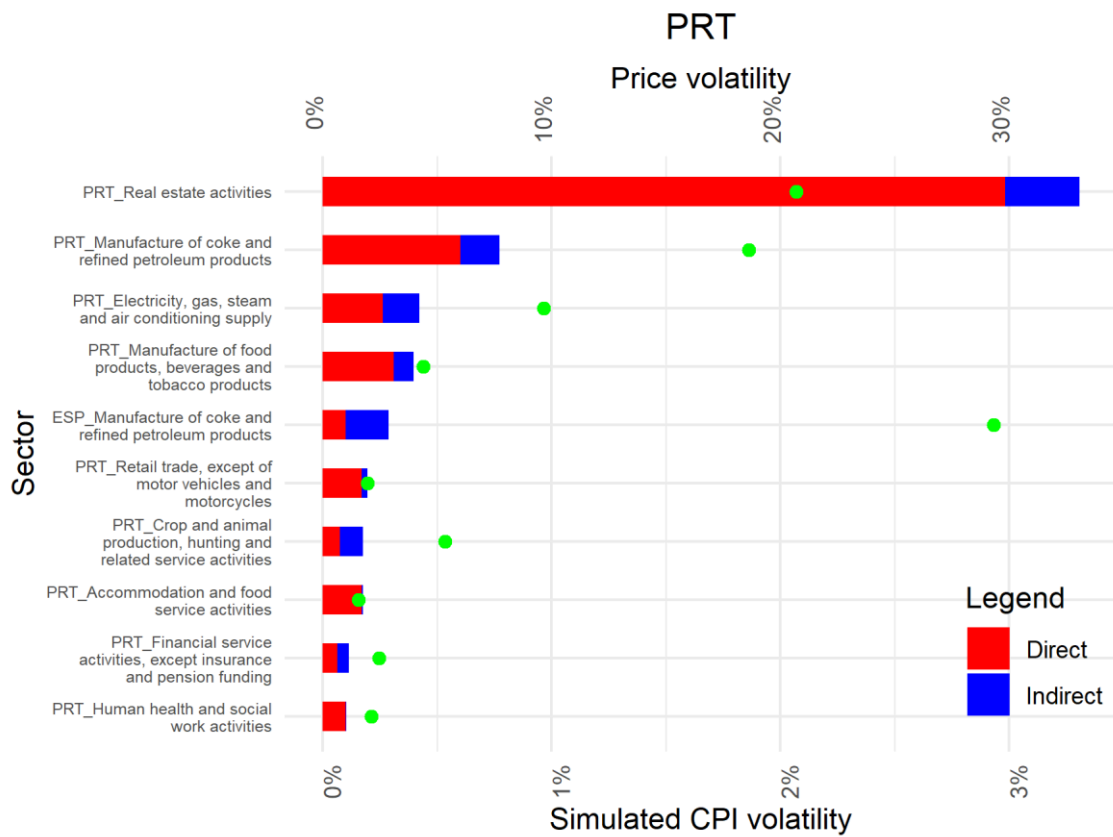
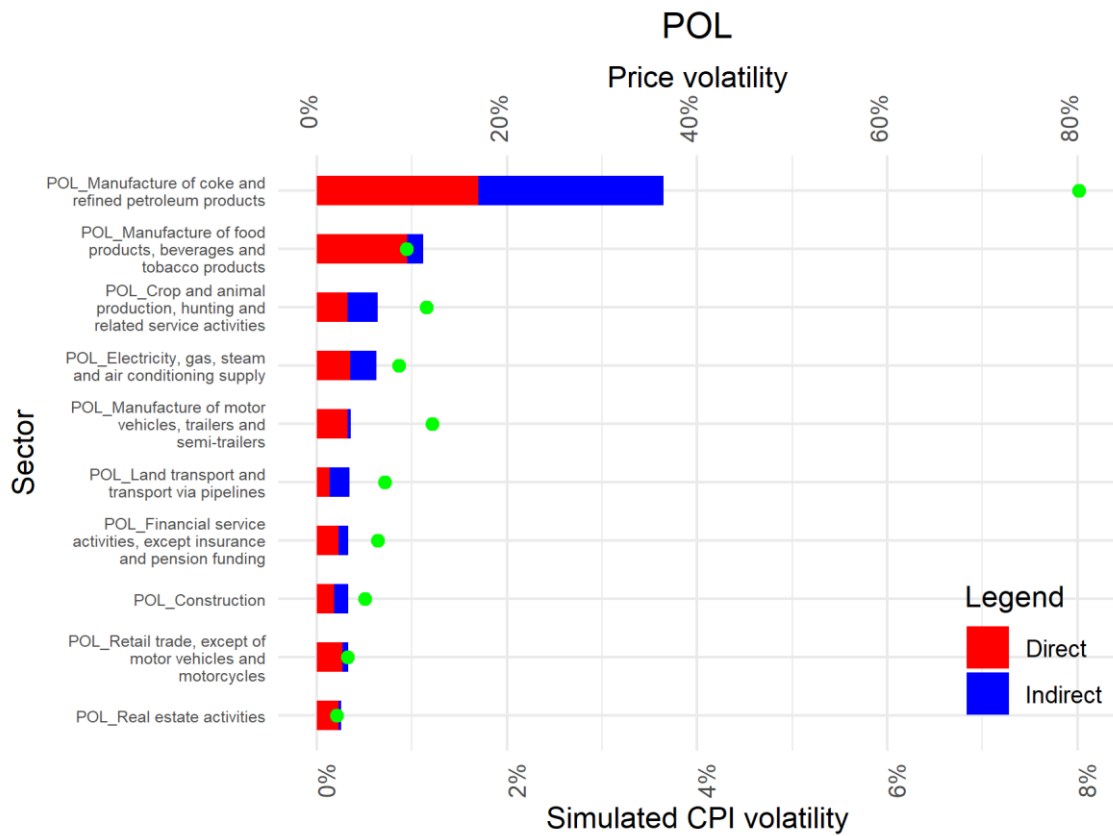


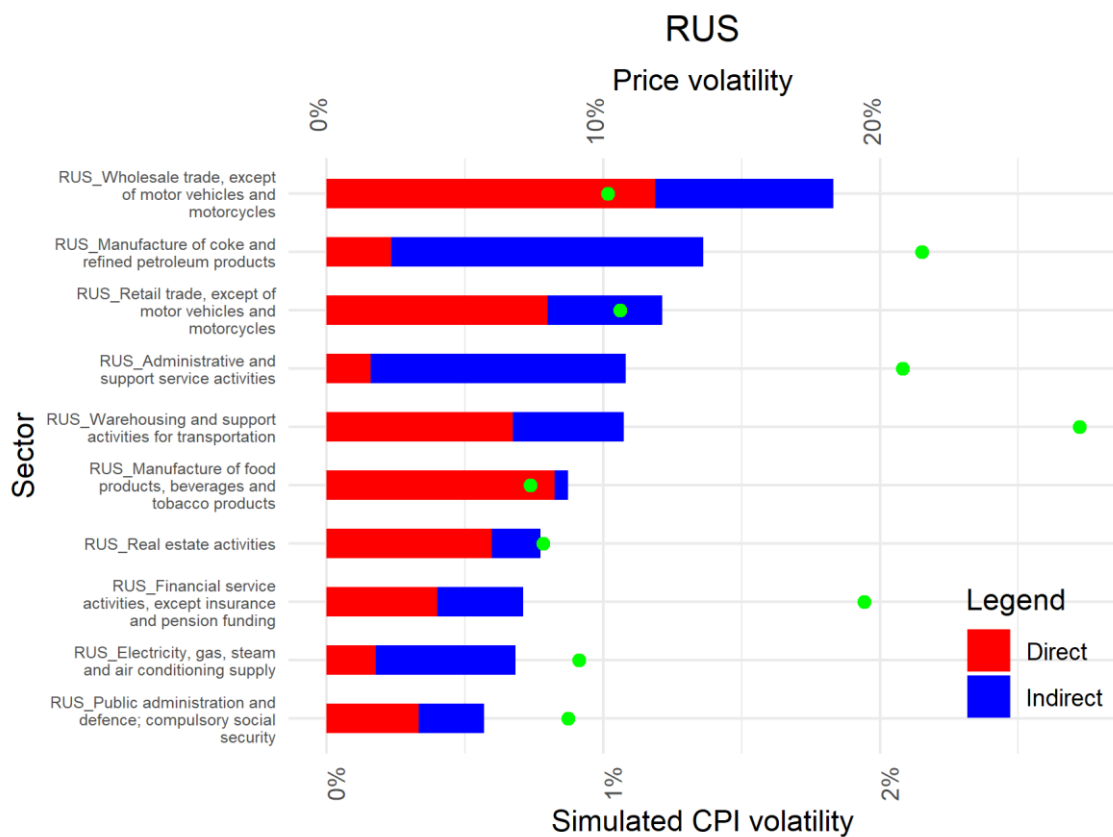
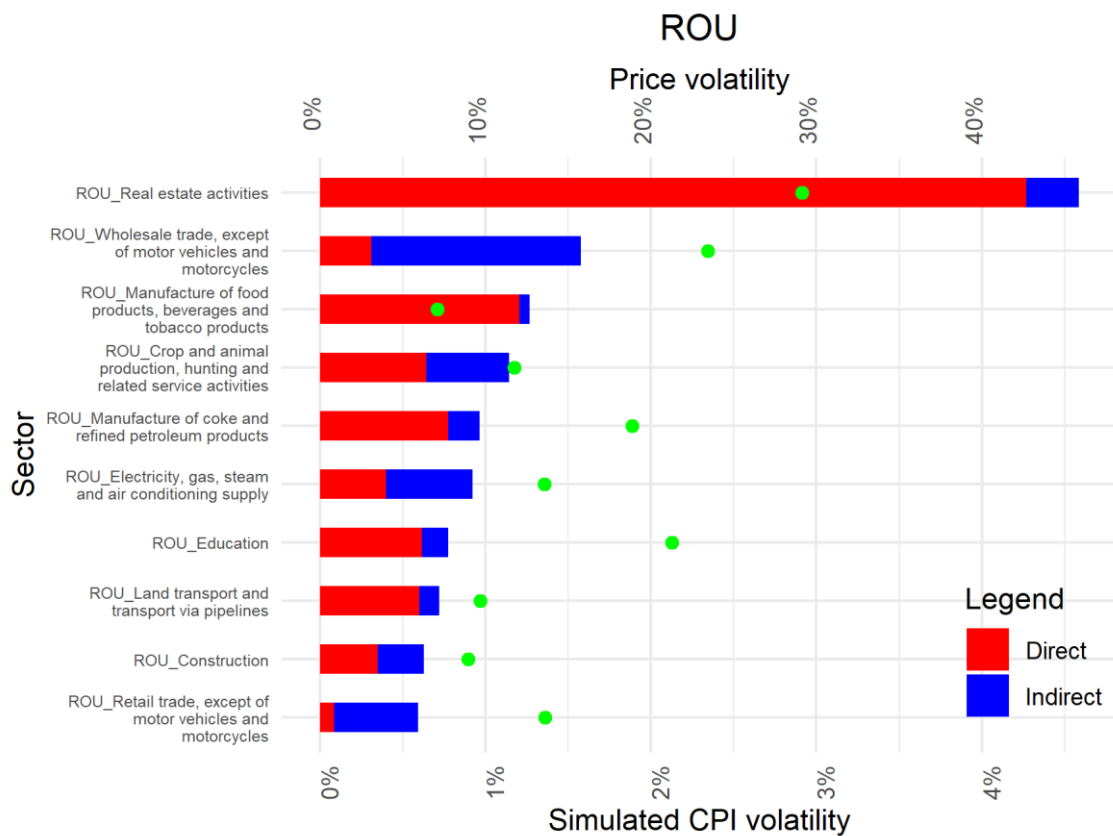


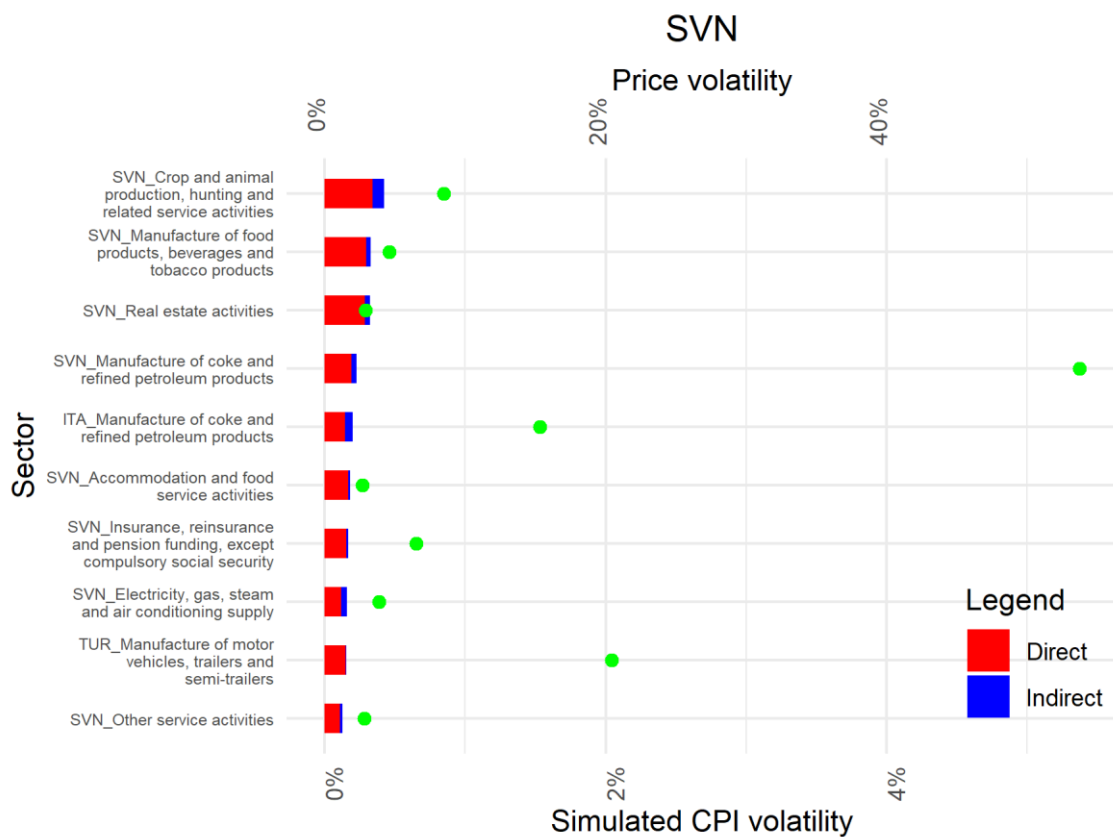
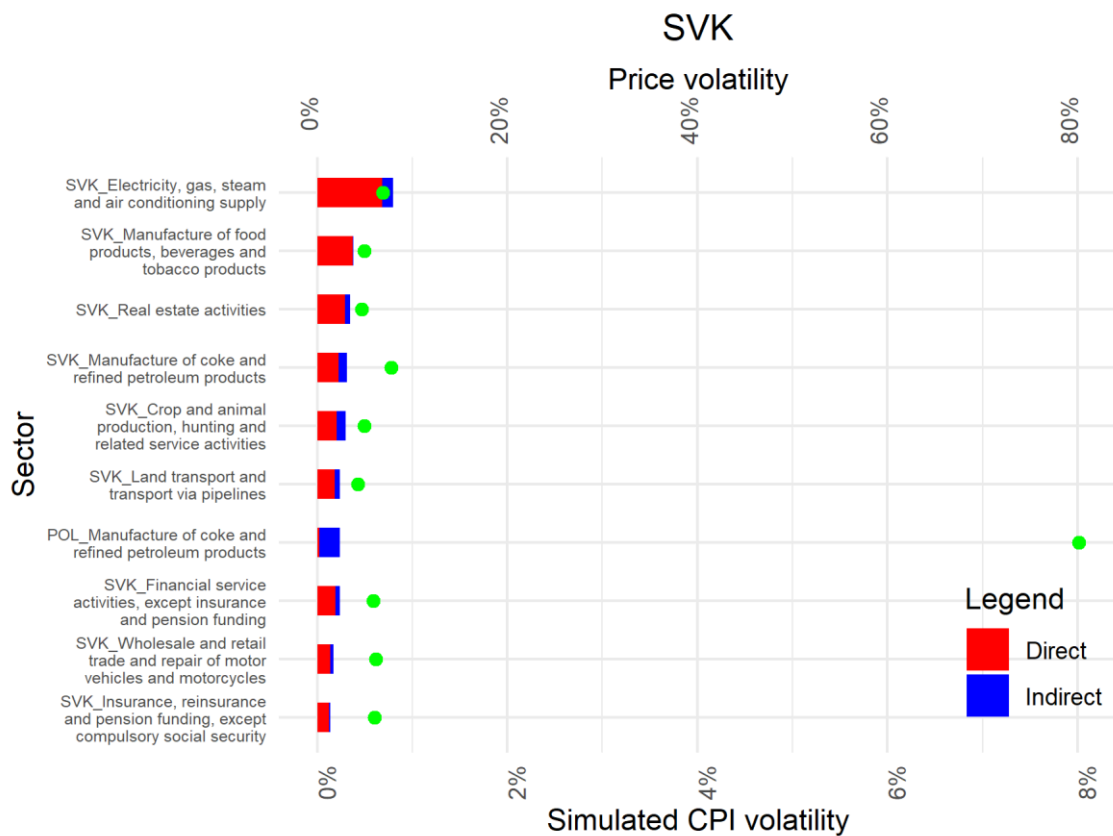


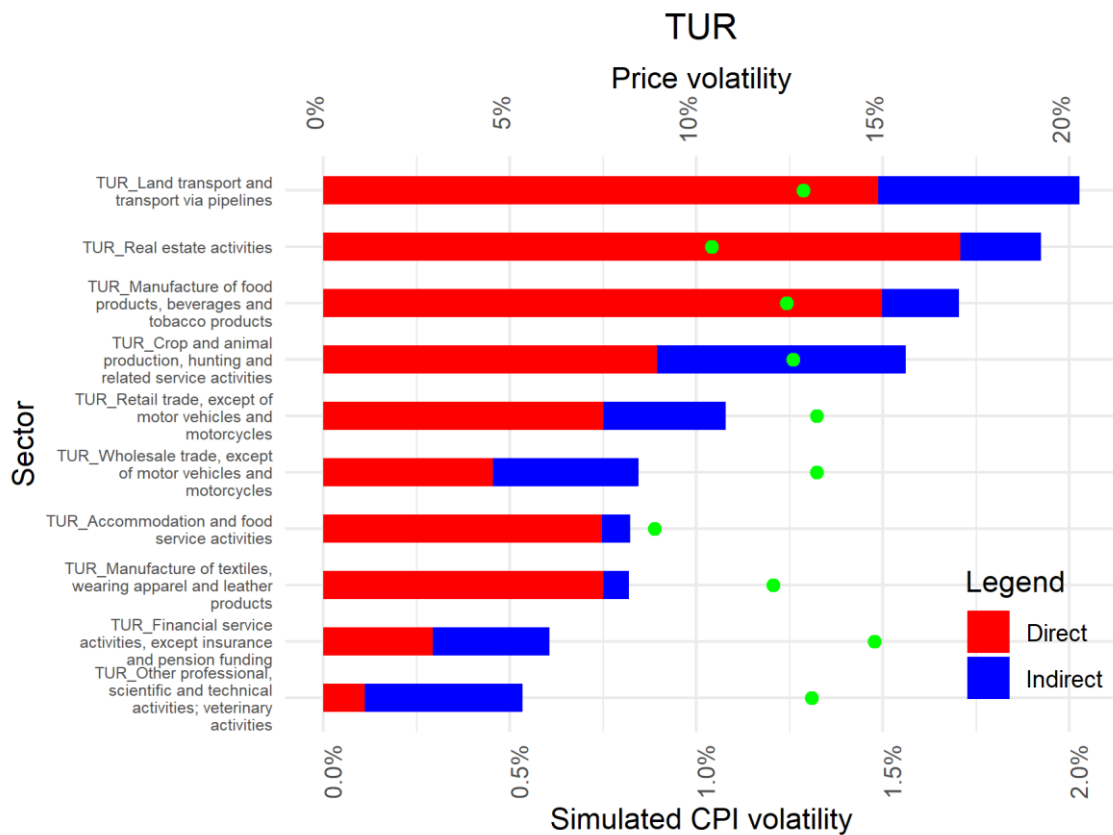
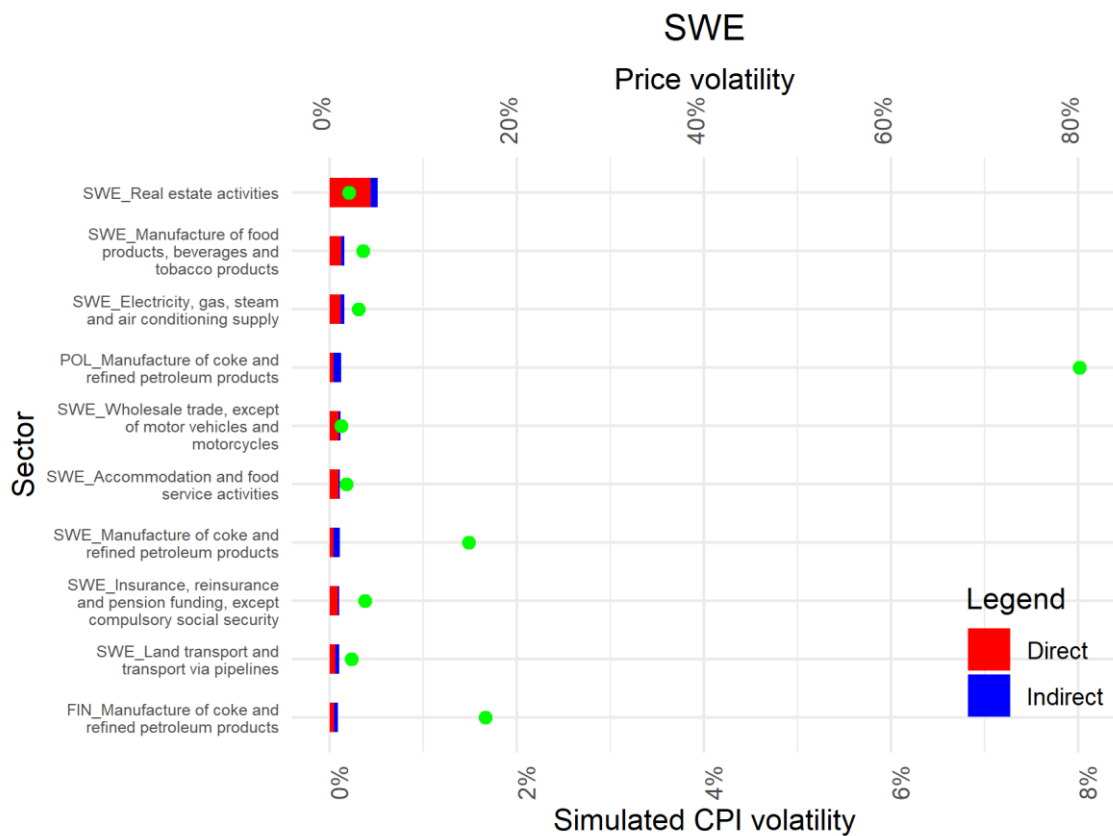


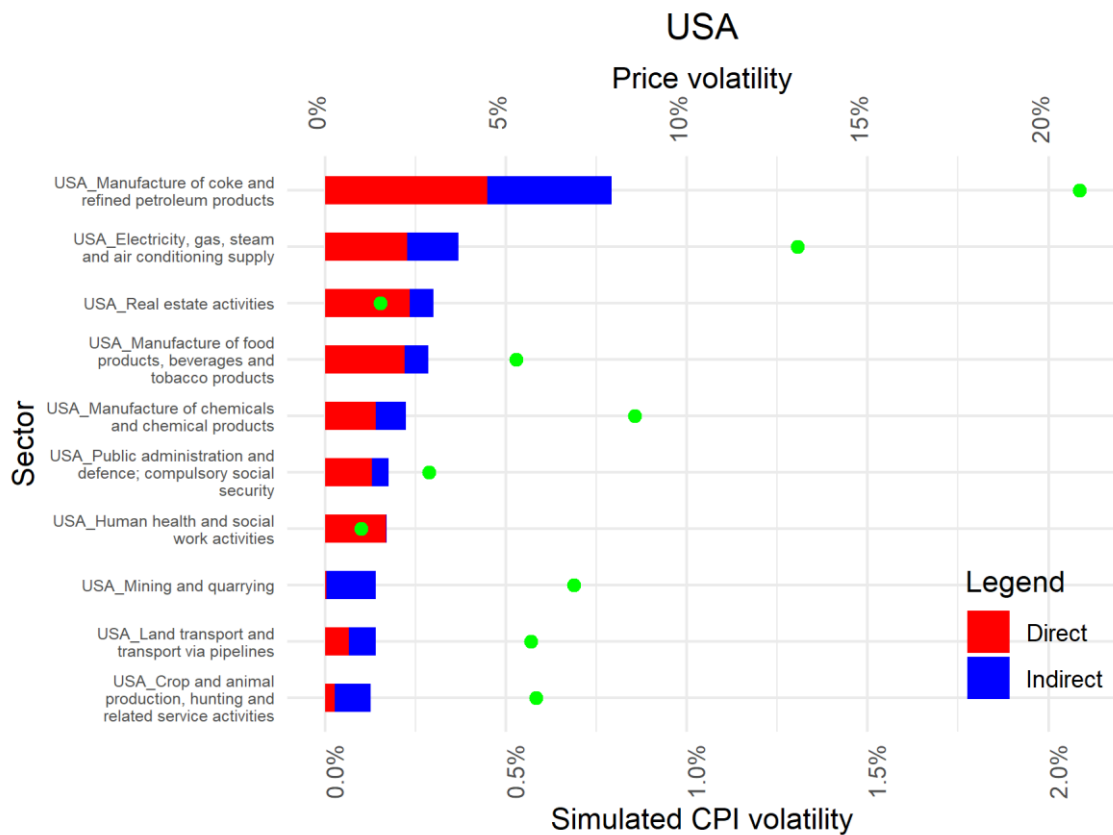
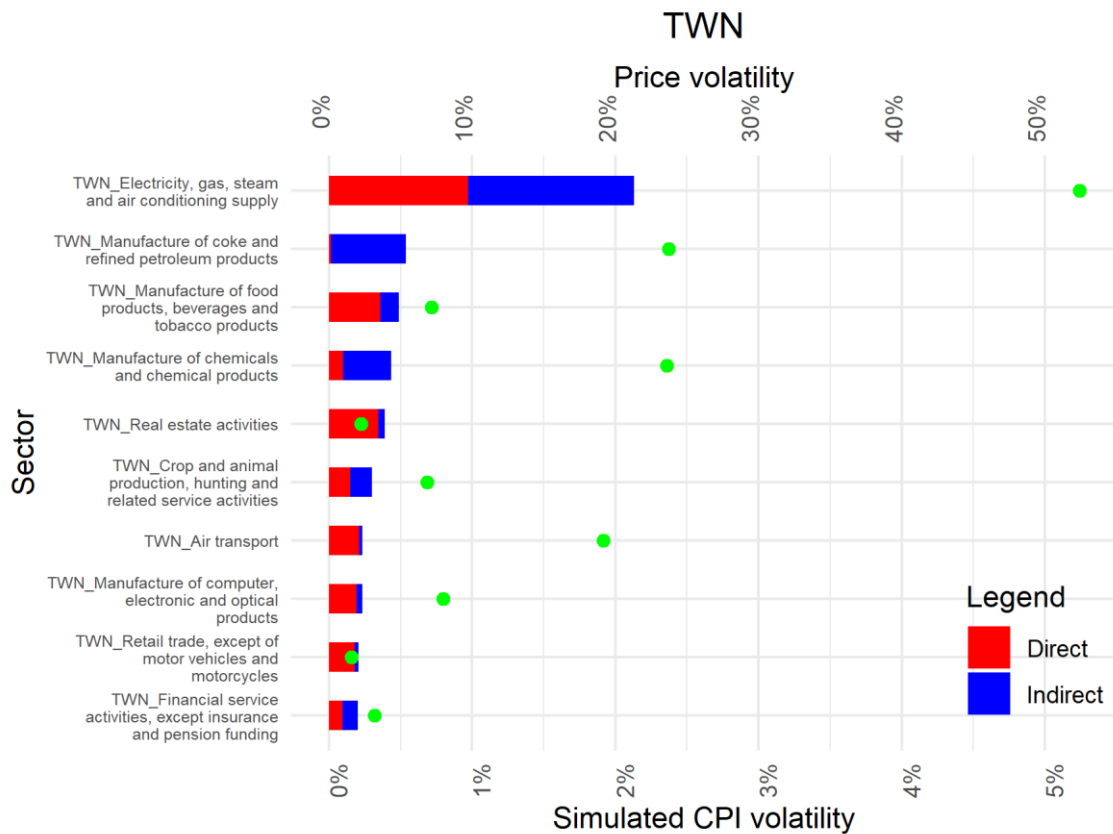












Notes: Illustration by the author based on Weber et al. (2022, p. 13). See Figure 2 for a detailed explanation of the figure.