An Empirical Inquiry into the Distributional Consequences of Energy Price Shocks

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Abstract

We estimate how energy shocks affect the functional distribution of income. Using structural vector autoregressions identified with an external instrument, we find that an increase in oil prices leads to a substantial and long-lasting decline in the wage share. Real aggregate wage income is significantly impacted, with a considerable part of this decline stemming from distributive dynamics. We also investigate possible asymmetries in the response to oil supply shocks, finding that the wage share is more sensitive to negative shocks than to positive ones. This suggests that wage earners lose from oil price hikes more than they benefit from declines.

Keywords: Oil shocks; Income distribution; proxy-SVAR; Asymmetries.
JEL classification: C32; E25; E31; E32; Q43.

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1 Introduction

The macroeconomic literature on energy shocks has predominantly dealt with inflation and output, paying less attention to distributional impacts. Energy crises, however, often produce uneven effects due to a variety of factors. For instance, energy costs disproportionately burden low-income households, who are also the most vulnerable to recessions that follow economic shocks. Moreover, different income sources may adjust differently to energy shocks, with direct repercussions on inequality. Thus, while distributional effects are likely, their magnitude is not yet fully understood. This paper helps address this gap by estimating the impact of oil supply news shocks on functional income distribution, a key channel through which energy shocks shape distributional outcomes.

The main intuition is straightforward: input prices are inherently distributional variables in a functional sense, particularly for inputs that are difficult to substitute, such as energy. This implies that when energy prices rise, a larger share of national income is redirected to the energy sector, reducing the share of aggregate income available to workers and final goods producers. How this loss is distributed between workers and firms determines shifts in the functional income distribution (Wildauer et al., 2023). Our main contribution is to provide the first quantitative estimation of this distributive channel, showing that this effect has sizeable welfare implications. To do so, we need a source of exogenous variation in at least one energy price, which we obtain by using the oil supply news shock instrument proposed by Känzig (2021). This instrument supplies a reliable source of exogenous variation in the real oil price and accounts for much of its historical fluctuations, which makes it especially suitable for the research question at hand.

We conduct our analysis using quarterly U.S. data, finding that a 10% innovation in the oil price leads to a statistically significant and long-lasting decline in the wage share, with a fall of approximately 0.001 on impact. This occurs alongside a decrease in nominal Gross Domestic Income (GDI). We then use these estimates to calculate the aggregate wage loss resulting from a hypothetical 10% oil price increase occurring in 2019Q1. On impact, we find that the real aggregate wage loss amounts to \$36.5bn, measured in 2019Q1 dollars. A quantitatively relevant figure, leading to a cumulative \$669.6bn aggregate wage loss over twelve quarters. The most interesting result, however, is that the wage share decline explains a relevant part of this wage loss, 60% on impact and 50% cumulative. This result underscores that focusing only on the aggregate output response overlooks important welfare effects that are unevenly distributed across individuals. In particular, the shock negatively impacts individuals who depend primarily on labour income, beyond the aggregate output loss.

To complement this analysis, we study a variety of other distributional variables. Our companion results can be summarised as follows: we estimate a positive profit share response to the shock which offset the decline in the wage share. On top of that, the percentage of aggregate profits distributed as dividends reduces in the aftermath of the shock. As a result, the share of dividend income in GDI decreases on impact, although the drop turns out to be extremely short-lived. In contrast, interest income tends to rise, likely reflecting the monetary policy reaction to the shock, which favours financial income through high interest rates.

Another set of results shed light on possible asymmetries in the response to oil shocks. In particular, we study differences in the distributional impact of rising (negative) versus decreasing (positive) oil price shocks. We find that the wage share is more responsive to an oil price increase compared to a decrease, meaning that wages bear the brunt of negative shocks while benefitting comparatively little from positive ones. This result echoes asymmetries in the pass-through rate of energy shocks, which our estimates confirm. Specifically, the Consumer Price Index (CPI) reacts more strongly to oil price increases than to decreases, which likely explains the asymmetry found in the wage share response. One can indeed rationalise the two observations as follows: when the oil price rises, firms readily revise prices upwards, securing a larger share of aggregate income before wages can respond. Conversely, oil price falls do not prompt firms to lower prices as aggressively, resulting in higher profit margins rather than a strong increase in the wage share.

Our estimations are obtained using a set of structural vector autoregressive (SVAR) models. In particular, we rely on the proxy-SVAR methodology (Mertens and Ravn, 2013; Stock and Watson, 2012). Proxy-SVAR is a partial identification approach that exploits external instruments to identify the impact matrix, needed to estimate the impulse response functions (IRFs) of the model. It requires a relevant and exogenous variable, which is correlated with the structural shock to be identified and uncorrelated with the shocks that are not of interest. The approach is similar to an instrumental variable (IV) regression, but the instrumented variable is the (unobserved) shock of interest. As already mentioned, we use the oil supply news instrument developed by Känzig (2021), which exploits surprises around the Organization of the Petroleum Exporting Countries (OPEC) announcements (henceforth the surprise series) in a high-frequency fashion.

Our choice of identification strategy is based on two reasons. First of all, as pointed out by Herwartz et al. (2022), proxy-SVARs combine the strength of both theoretical- and data-driven approaches to identification since they allow identifying structural shocks by exploiting meaningful external information. This is particularly true in our case, where the dynamic of the energy market is mainly dictated by the behaviour of OPEC (Känzig, 2021). Second, as we are interested only in the identification of a subset of structural shocks (i.e. the oil price shock) regardless of the others, proxy-SVAR is one of the most natural ways to achieve partial identification. Having said that, our main results are robust to several specifications, including identification through heteroscedasticity, and local projections.

To study sign asymmetries, we use the nonlinear proxy-SVAR framework developed by Debortoli et al. (2020) and Forni et al. (2023, 2024). The procedure follows three steps: (i) we detect the oil price shock through the proxy-SVAR; (ii) we estimate an exogenous vector autoregression (VARX) embodying a set of endogenous variables of interest together with the identified shock and a nonlinear transformation of it as exogenous variables; (iii) we obtain the asymmetric IRFs by summing the coefficients of the exogenous variables.

The rest of the paper is organised as follows. In Section 2 we place our contribution into the relevant literature. In Section 3, we propose a simple theoretical framework to rationalise the relationship between energy price shocks, functional income distribution and inflation. In Section 4, we introduce the econometric framework and describe our approach to identification and estimation. In Section 5, we present our main results: the distributive impacts of the energy shock and the relative asymmetries. Section 6 concludes.

2 Contribution to the literature

We contribute primarily to the empirical literature on energy and the economy (Kilian, 2008a), with a specific focus on the macroeconomic impacts of energy shocks. Empirical research has consistently shown that negative oil shocks are typically followed by periods of stagflation (Hamilton, 1983; Kilian, 2008b; Känzig, 2021), while recent research has found similar outcomes for gas (Alessandri and Gazzani, 2023) and carbon price (Känzig, 2023) shocks. Moreover, this general claim has been complemented by several further observations, such as that the macroeconomic impacts of oil shocks have lessened over time (Blanchard and Gali, 2007; Baumeister and Peersman, 2013) and that oil demand and supply shocks have distinct impacts, with only the latter causing recessions (Kilian, 2009; Baumeister and Hamilton, 2019).

Empirical evidence on the distributional effects of energy shocks is relatively scarce instead. However, studies using SVARs identified with external (high-frequency) instruments suggest that carbon price shocks (Känzig, 2023) and oil supply shocks (Drossidis et al., 2024) unevenly reverberate across the personal income distribution, with low-income households experiencing larger income losses. In a similar vein, Kröger et al. (2023) document that gas shocks disproportionally hit low-income households due to the larger share of energy expenditures in their consumption baskets. A growing body of theoretical research has explored the reasons behind this regressive effect (Del Canto et al., 2023), identifying three main channels: (i) low-income households inability to save, which hampers their ability to smooth consumption during the shock and diversify income sources (Bobasu et al., 2024); (ii) the compression of the labour income share, which disproportionately affects those at the lower end of the income distribution (Ciola et al., 2023; Wildauer et al., 2023; Ciambezi et al., 2024; Fierro et al., 2024; Kremer et al., 2024); and (iii) stabilisation policies implemented in response to energy shocks, which often carry significant distributional consequences (Turco et al., 2023).

We contribute to the energy-macro literature by showing that the distributional impact of energy shocks is both statistically significant and quantitatively substantial. Specifically, we provide quantitative estimates of the wage share response to energy shocks, a key aspect highlighted in theoretical research but previously lacking empirical estimation. Furthermore, we decompose aggregate wage losses into recessive and distributional components, showing that the wage share adjustment accounts for a relevant part of the decline in the real value of aggregate wages. Our analysis also reveals asymmetries in pass-through rates, which have direct distributional consequences: oil price increases lead to larger CPI responses than oil price decreases, resulting in greater wage share sensitivity to negative energy shocks vis-à-vis positive ones.

We also contribute to the empirical literature on inequality and macroeconomics. Since the recognition that inequality has been rising in most economies for decades (Alvaredo et al., 2013), virtually all subfields of macroeconomics have been reinterpreted through the lenses of income and wealth distribution, to cite a few: saving and consumption behaviour (Mian et al., 2020; Dynan et al., 2004), monetary policy (Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017), and fiscal policy (Heathcote et al., 2010). Our work adds to this body of research by highlighting the importance of cost-push shocks, particularly energy price shocks, as a relevant area of inquiry. We also show that the functional income distribution is a key, though often overlooked, aspect of this issue (see Bhaduri and Marglin, 1990; Stockhammer et al., 2009; Onaran and Galanis, 2014, for notable exceptions).

Finally, we touch upon the literature on market power in both goods (Autor et al., 2020) and labour markets (Manning, 2013), as well as the literature on conflict inflation (Rowthorn, 1977). While we do not empirically examine these factors, we discuss from a theoretical standpoint how they intersect to shape the distributional impact of energy price hikes. We indeed propose a simple model where energy price shocks trigger a distributional conflict between wages and profits, which ultimately influences the price dynamics. Additionally, we discuss how the distribution of power in the goods and labour markets shapes the adjustment in income distribution and the resulting inflationary pressures that follow an energy price hike.

3 Insights from a simple theoretical framework

In this section, we examine the relationship between energy price shocks, functional income distribution, and inflation from a theoretical perspective. We use a simple, static framework in which the only assumption is on the production function, while all results follow directly from accounting identities. More specifically, we consider an economy where labour and energy are the only factors of production and final good prices are set as markups over unit cost. Our focus lies in the short run, defined as the unit of time where the factors of production are perfectly complementary and the input-output ratios remain constant. Thus, we can assume a Leontief production function, taking the form:

$$Y = \min\Big(\gamma^l L, \gamma^e E\Big), \tag{1}$$

where Y is output, L is labour and E is energy; γ^L and γ^E are the productivities of labour and energy respectively, which, in a Leontief production function, also determine the efficient output-input ratios. Given the production function (1), we can express the price equation as:

$$P = \Bigg(1 + \mu\Bigg)\Bigg(\frac{w}{\gamma^l} + \frac{p_e}{\gamma^e}\Bigg), \tag{2}$$

where P is the price, μ is the markup, w is the nominal wage rate, and p_e is the energy price; $\frac{w}{\gamma^l}$ is the unit labour cost $\big(uc_l\big)$, $\frac{p_e}{\gamma^e}$ is the unit energy cost $\big(uc_e\big)$, and the sum $uc_l + uc_e$ determines the unit cost of production $\big(uc\big)$.

Using the production function (1) and the price equation (2), we can compute the wage share $\big(\theta\big)$ and the final good sector profit share $\big(\pi\big)$ of nominal GDI (i.e. $P \cdot Y$):[1]

$$\pi = \frac{\mu}{1+\mu}; \qquad \theta = \frac{\Gamma^l}{1+\mu}, \tag{3}$$

where Γ^l is the share of labour costs in total production costs, defined as uc_l/uc.

The income shares in Equation (3) are intuitive: higher markups are associated with larger profit shares, while the wage share decreases as markups rise and increases with a higher proportion of labour costs in overall production costs. Simply put, when firms raise markups, they capture a larger portion of aggregate income, reducing the share accruing to labour (and the energy sector). Γ^l represents the share of total production costs attributable to labour, which depends on the labour intensity relative to other inputs (i.e. the ratio γ^e/γ^l) and on the level of wages relative to other input prices (i.e. the ratio w/p_e). The higher Γ^l, the larger the share of wages in aggregate income, as a greater portion of production costs is tied directly to labour.

As we are interested in the response of prices, wage share, and profit share to energy price hikes, we can use Equations (2) and (3) to compute the elasticities of the final good price (ϵ_p), labour share (ϵ_θ), and profit share (ϵ_π) with respect to the energy price. This, however, requires making assumptions about the response of markups and wages to energy price shocks. In other words, we need the signs of the partial derivatives $\partial\mu/\partial p_e$ and $\partial w/\partial p_e$. The response of markups and wages to a cost-push shock reflects an

[1]The derivations for Equations (3)–(6) discussed in this section are provided in Appendix A.

underlying conflict over the distribution of aggregate income. Indeed, when energy prices rise, the total income available to be shared between workers and final goods producers decreases. The question of who bears the loss depends on their respective abilities to adjust wages and markups. Essentially, this is a matter of power in the labour and goods markets: if firms have limited power in the goods market, the shock is absorbed by markups, while if workers have limited power in the labour market, the shock is absorbed by real wages. Let us refer to the case in which firms have complete power in the goods market as *monopoly*, and to the case in which firms have complete power in the labour market as *monopsony*. In the case of monopoly, markups are shock-insensitive, i.e. the pass-through is perfect, while in the absence of monopoly, the markups decrease when the energy price increases so that only part of the shock is passed through prices. In the case of monopsony, (nominal) wages are shock-insensitive, while in the absence of monopsony, workers obtain higher (nominal) wages when the energy price increases. Based on this distinction, we can think of three scenarios:[2]

- A *monopoly-monopsony* scenario, where $\partial\mu/\partial p_e = 0$ and $\partial w/\partial p_e = 0$, that is, the shock is fully passed through to the final good price, and workers do not adjust wages.

- A *monopoly* scenario, where $\partial\mu/\partial p_e = 0$ and $\partial w/\partial p_e > 0$, that is, again we have perfect pass-through, but workers respond by obtaining higher wages.

- A *monopsony* scenario, where $\partial\mu/\partial p_e < 0$ and $\partial w/\partial p_e = 0$, that is, the pass-through is not perfect, but workers are unable to obtain higher wages.

To keep our framework as simple as possible, we must make a few further assumptions: (i) we focus solely on the immediate impact of the shock, disregarding any second-round effects that could potentially lead to wage-price spirals; (ii) we treat the energy sector as a passive agent, assuming a one-time increase in energy prices without modelling any behavioural responses to firms' or workers' reactions; (iii) we focus exclusively on energy price increases because in any given scenario the sign of $\partial\mu/\partial p_e$ and $\partial w/\partial p_e$ behaves asymmetrically depending on whether energy prices rise or fall (see Section 5.5 for an empirical exploration of asymmetric wage share responses to energy shocks).

[2]Note that this approach draws from the post-Keynesian literature on conflict inflation (e.g., Rowthorn, 1977, 2024; Setterfield, 2007; Lavoie, 2024), though it does not strictly adhere to it. For full consistency with this literature, one would assume that firms and workers have aspirational targets for profit and wage shares, respectively, with wages and markups adjusting to meet these targets. Here, we take a simplified approach where wages and markups respond endogenously to the energy price shock –yet this response can still be viewed as an attempt by each group to preserve its income share. Furthermore, the capacity to adjust markups and wages is influenced by market power, an insight also drawn from the conflict inflation literature. While our model cannot capture price-wage spirals, it still provides a reasonable representation of inflationary dynamics based on conflict over the distribution of aggregate income and market power.

In the *monopoly-monopsony* scenario the responses of the final good price, wage share, and profit share are given by:

$$\epsilon_\pi = 0; \quad \epsilon_\theta = -\Gamma^e; \quad \epsilon_p = \Gamma^e. \tag{4}$$

Perfect pass-through implies that the energy price shock does not impact the profits share. In addition, if wages remain unchanged, prices increase by a factor equal to Γ^e, which represents the energy contribution to production costs $\big(uc_e/uc\big)$. The factor Γ^e is also equal to the percentage drop in the wage share. Intuitively, an energy price increase of 1% results in a percentage reduction of the non-energy income share equal to Γ^e, which in the *monopoly-monopsony* scenario, is entirely passed on prices with wages being unresponsive. It follows that the wage share must absorb this entire loss.

In the *monopoly* scenario, the profits share is again fixed, but as wages respond to increases in the energy price, we obtain stronger inflationary pressures and a less pronounced fall in the wage share:

$$\epsilon_\pi = 0; \quad \epsilon_\theta = -(1-\epsilon_w)\Gamma^e; \quad \epsilon_p = \Gamma^e + \epsilon_w\Gamma^l, \tag{5}$$

where $\epsilon_w \equiv \frac{\partial w}{\partial p_e}\frac{p_e}{w} > 0$ represents the wages elasticity to the energy price. As in the *monopoly-monopsony* scenario, the decline in the wage share is tied to Γ^e. However, in this case, the nominal wage response to the shock mitigates the loss in the wage share. If the wage increase perfectly matches the energy price increase (i.e. $\epsilon_w = 1$), the wage share becomes shock insensitive. Moreover, the extent of the wage adjustment directly influences the price response, as any wage increase is fully passed onto prices. Therefore, in the *monopoly* scenario, the decline in the labour share is partially offset by the level of workers' bargaining power in the labour market, i.e. the level of ϵ_w. However, this generates a trade-off, as a strong wage adjustment necessarily results in high inflation.

In the *monopsony* scenario, nominal wages do not adjust, but, unlike in the *monopoly-monopsony* scenario, firms are not able to fully pass through the energy price increase onto prices:

$$\epsilon_\pi = \frac{\epsilon_\mu}{1+\mu}; \quad \epsilon_\theta = -\big(\epsilon_\mu\pi + \Gamma^e\big); \quad \epsilon_p = \epsilon_\mu\pi + \Gamma^e, \tag{6}$$

where $\epsilon_\mu \equiv \frac{\partial \mu}{\partial p_e}\frac{p_e}{\mu} < 0$ represent the markup elasticity to the energy price. In this scenario, the income loss from the energy price shock is distributed between profits and wages, resulting in lower inflation compared to the *monopoly-monopsony* scenario. The decline in the profit share is proportional to both the markup response and the pre-shock markup level. This dependency arises from the way the price equation (2) is structured, specifically because $\big(1+\mu\big)$ multiplies the unit cost. The wage share decrease is again tied to Γ^e, but it is contained due to the partial markup absorption of the shock. Moreover, the partial pass-through results in weaker inflationary pressures relative to the *monopoly-*

monopsony scenario.

Intuitively, when the shock is at least partially absorbed by markups, its propagation through the economy is softened, resulting in weaker inflationary pressures. Note that the *monopsony* scenario can also be interpreted as one where prices remain relatively stable after the shock, reducing pressure to raise wages. The result is a more balanced distribution of losses between wages and profits and a more stable price dynamics.

This section aims to further justify our focus on empirically estimating the response of the wage share and other (functional) distributive variables to energy shocks. Although our empirical framework does not allow us to directly determine which of the outlined scenarios best captures the economic context underlying the selected oil shocks, these theoretical insights help to interpret our main empirical findings and rationalise the asymmetries observed in the wage share response to oil shocks.

4 Methodology

In this section, we provide the econometric framework and we describe our approach to identification and estimation.

Since we want to test the distributive nature of energy prices, we make use of the institutional characteristics of OPEC, and the insights derived from high-frequency data, to detect a shock in expectations regarding oil supply. To do that, we exploit the series of high-frequency surprises around OPEC announcements of Känzig (2021).

Similarly to the literature concerning high-frequency identification of monetary policy shocks (see, e.g., Gürkaynak et al., 2005; Nakamura and Steinsson, 2018), we do not directly include the surprise series in our SVAR model, rather we adopt a proxy-SVAR by using the surprise series as an external instrument for the oil price shock.[3] In this manner, we can identify a structural oil supply news shock.

4.1 The econometric framework

We consider a set of K endogenous variables $y_{kt} = (y_{1t}, \dots, y_{Kt})'$, with $t = 1, \dots, T$, which can be represented using a structural vector autoregressive (SVAR) model of the form:

$$\mathbf{\Gamma}_0 \mathbf{y}_t = \boldsymbol{\mu}_0 + \mathbf{\Gamma}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{\Gamma}_P \mathbf{y}_{t-P} + \boldsymbol{\varepsilon}_t, \tag{7}$$

where $p = 1, \dots, P$ is the lag order, $\mathbf{\Gamma}_0$ and $\mathbf{\Gamma}_p$ are $(K \times K)$ matrices denoting the contemporaneous and lagged coefficients, respectively, and $\boldsymbol{\varepsilon}_t$ is a $(K \times 1)$ vector of structural shocks with diagonal covariance matrix $\mathbf{\Sigma}_{\boldsymbol{\varepsilon}}$, hence we assume that $\boldsymbol{\varepsilon}_t$ are uncorrelated.

[3] We recall that an external instrument is a variable that exhibits correlation with the specific shock of interest while featuring no correlation with other unrelated shocks. We refer to Section 4.2 for more details.

We rewrite the model in Equation (7) in reduced-form that is more convenient for estimation:

$$\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_P\mathbf{y}_{t-P} + \mathbf{u}_t, \tag{8}$$

where $\boldsymbol{\mu} = \mathbf{B}\boldsymbol{\mu}_0$, $\mathbf{B} = \boldsymbol{\Gamma}_0^{-1}$ is the $(K \times K)$ matrix of contemporaneous impacts, $\mathbf{A}_p = \mathbf{B}\boldsymbol{\Gamma}_p$ and

$$\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t \tag{9}$$

is the $(K \times 1)$ vector of reduced-form innovations. The covariance matrix of $\mathbf{u}_t$ is

$$\boldsymbol{\Sigma}_{\mathbf{u}} = \mathbf{B}\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}\mathbf{B}'. \tag{10}$$

We indicate with ε_{1t} the structural shock we want to recover, i.e. the energy price shock. This implies that we will identify the first column of $\mathbf{B}$, which we will call $\boldsymbol{\gamma}_1$.

Since we want to compute the structural impulse response functions, we must represent $\mathbf{y}_t$ as a moving-average (MA) process. If $\mathbf{B}$ is invertible and if the process $\mathbf{y}_t$ is stable, i.e. $\det\left(\mathbf{I}_K - \mathbf{A}_1 z - \cdots - \mathbf{A}_p z^p\right) \forall z \in \mathbb{C}, |z| \leq 1$, then $\mathbf{y}_t$ admits a Wold moving-average representation:

$$\mathbf{y}_t = \boldsymbol{\varphi} + \sum_{\ell=0}^{\infty} \boldsymbol{\Phi}_\ell \mathbf{u}_{t-\ell}, \tag{11}$$

where $\boldsymbol{\varphi} = \mathbf{A}(1)^{-1}\boldsymbol{\mu}$, $\mathbf{A}(1) = \left(\mathbf{I}_K - \sum_{p=1}^{P} \mathbf{A}_p\right)$, $\boldsymbol{\Phi}_0 = \mathbf{I}_K$ and $\boldsymbol{\Phi}_\ell = \sum_{d=1}^{\ell} \boldsymbol{\Phi}_{\ell-d}\mathbf{A}_d$ for $\ell = 1, 2, \ldots$ with $\mathbf{A}_d = 0$ if $d > P$. We can also write Equation (11) as follows:

$$\mathbf{y}_t = \boldsymbol{\varphi} + \sum_{\ell=0}^{\infty} \boldsymbol{\Psi}_\ell \boldsymbol{\varepsilon}_{t-\ell}, \tag{12}$$

where $\boldsymbol{\Psi}_0 = \mathbf{B}$, and $\boldsymbol{\Psi}_\ell = \boldsymbol{\Phi}_\ell \mathbf{B}$. The entries of the matrices $\boldsymbol{\Psi}_\ell$, for $\ell = 1 \ldots H$, are the impulse response functions, i.e. $\psi_{jk,\ell} = \frac{\partial y_{jt+\ell}}{\partial \varepsilon_{k,t}}$ where $\psi_{jk,\ell}$ is the (j,k) entry of $\boldsymbol{\Psi}_\ell$.

Invertibility assumption not only allows to obtain the MA representation of the process but also ensures that the VAR collects all the information to identify the structural shocks (see, e.g., Nakamura and Steinsson, 2018, for a discussion). More general conditions on invertibility are discussed in Miranda-Agrippino and Ricco (2023), among others. The authors demonstrate that identification can be achieved if the shock of interest is invertible — a condition known as partial invertibility — and if the instrument satisfies a "limited lead-lag exogeneity condition", which ensures that the VAR innovations and the proxy correlate only via the contemporaneous structural shock of interest. In Section 5.2 we exploit the invertibility test of Forni et al. (2022) to control for informational sufficiency.

4.2 Identification strategy

As mentioned above, the identification strategy is based on external instruments. We define with z_t, for $t = 1, \ldots, T$, the selected instrument, i.e. the oil supply surprise series. To be valid, z_t must satisfies the following assumptions:

$$\mathbb{E}\left[z_t \varepsilon_{1t}\right] = \alpha, \tag{13}$$

$$\mathbb{E}\left[z_t \boldsymbol{\varepsilon}_{2:K,t}\right] = \mathbf{0}, \tag{14}$$

where ε_{1t} is the oil supply news shock, $\boldsymbol{\varepsilon}_{2:K,t}$ is a $((K-1) \times 1)$ vector containing the other shocks, Equation (13) represents the relevance requirement and Equation (14) is the exogeneity condition. If the assumptions in Equations (13)–(14) are fulfilled, then we can identify $\boldsymbol{\gamma}_1$ up to sign and scale:

$$\widetilde{\boldsymbol{\gamma}}_{2:K,1} \equiv \frac{\boldsymbol{\gamma}_{2:K}}{\gamma_{1,1}} = \frac{\mathbb{E}\left[z_t \mathbf{u}_{2:K,t}\right]}{\mathbb{E}\left[z_t u_{1t}\right]}, \tag{15}$$

where $\boldsymbol{\gamma}_{2:K}$ are the $2, \ldots, K$ columns of $\mathbf{B}$ and $\mathbb{E}\left[z_t u_{1t}\right] \neq 0$. Equation (15) is obtained by writing

$$\mathbb{E}\left[z_t \mathbf{u}_t\right] = \mathbf{B}\mathbb{E}\left[z_t \boldsymbol{\varepsilon}_t\right] = \begin{pmatrix} \boldsymbol{\gamma}_1 & \mathbf{B}_{2:K} \end{pmatrix} \begin{pmatrix} \mathbb{E}\left[z_t \varepsilon_{1t}\right] \\ \mathbb{E}\left[z_t \boldsymbol{\varepsilon}_{2:K,t}\right] \end{pmatrix} = \boldsymbol{\gamma}_1 \alpha, \tag{16}$$

where $\boldsymbol{\gamma}_1$ is of dimension $(K \times 1)$ and $\mathbf{B}_{2:K}$ is of dimension $(K \times (K-1))$, partitioning Equation (16)

$$\mathbb{E}\left[z_t \mathbf{u}_t\right] = \begin{pmatrix} \mathbb{E}\left[z_t u_{1t}\right] \\ \mathbb{E}\left[z_t \mathbf{u}_{2:K,t}\right] \end{pmatrix} = \begin{pmatrix} \gamma_{1,1}\alpha \\ \boldsymbol{\gamma}_{2:K,1}\alpha \end{pmatrix} \tag{17}$$

and combining Equations (16) and (17). Finally, we have the following structural impact vector:

$$\boldsymbol{\gamma}_1 = \begin{pmatrix} \gamma_{1,1} \\ \widetilde{\boldsymbol{\gamma}}_{2:K,1}\gamma_{1,1} \end{pmatrix}. \tag{18}$$

The scale of $\gamma_{1,1}$ is adjusted by applying a normalisation. According to Stock and Watson (2016), two normalisations are possible: (i) the unit standard deviation normalisation, which is obtained by fixing $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} = \mathbf{I}_K$ or, in other words, by imposing unit variance to each shock; (ii) the unit effect normalisation, which sets the scale of the k-th shock such that an incremental change of one unit in ε_{kt} reflects a simultaneous variation of magnitude x in a particular observed variable y_{kt}. This means that, by fixing $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} = \operatorname{diag}\left(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_K}\right)$ and $\gamma_{1,1} = x$, we can write the structural impact vector as follows:

$$\boldsymbol{\gamma}_1 = \begin{pmatrix} x \\ \widetilde{\boldsymbol{\gamma}}_{2:K,1}x \end{pmatrix}. \tag{19}$$

To aid in the interpretation of the results, we follow Känzig (2021) and we normalise ε_{1t} such that the shock corresponds to a 10% increase in the oil price.

4.3 Empirical specification

We specify 12 different proxy-SVAR models to test the impacts on income distribution over different dimensions. Each SVAR model includes the main macroeconomic variables, i.e. gross domestic income/industrial production, consumer price index and oil price plus a variable peculiar to the dimension we want to analyse. For instance, to study the impacts on oil production, we consider oil price, world oil production, world oil inventories, world industrial production, industrial production index and consumer price index; to study the impacts on the functional distribution of income we consider oil price, gross domestic income, consumer price index and labour share. The detailed description of the variables included in the analysis is shown in Table 1, while in the first column of Table 3 we report all the SVAR specifications.

The surprise series used to instrument the energy price shock is defined as follows:

$$z^h_{t,d} = F^h_{t,d} - F^h_{t,d-1}, \tag{20}$$

where d and t is the day and month of the announcement, respectively, and $F^h_{t,d}$ is the (log) settlement price of the h-months ahead oil futures contract. The proxy z_t is then obtained by aggregating $z^h_{t,d}$ to a monthly/quarterly series.

The instrument must respect the assumptions devised in Equations (13) and (14). These conditions have been empirically tested by Känzig (2021), who finds no evidence of correlation between the surprise series and other shock measures present in the literature (e.g., oil price, oil supply, global demand, productivity, fiscal policy, etc.). It must be noticed that, in principle, instrument exogeneity is inherently untestable, since the proxy should be plausible exogenous with respect to all potentially relevant "unobservable" confounders. A way to control for this condition has been proposed by Schlaak et al. (2023), who provide a hypothesis test by combining the information coming from the instrument with identification through heteroscedasticity in an augmented SVAR (AC-SVAR) model. In Appendix C.2 we use their procedure to check whether the instrument respects the relevance and exogeneity conditions. The results of the test confirm that these conditions are met.

To carry out the estimation exercise, we must verify that the data are stationary, at least in differences. To check for stationarity, we perform an Augmented Dickey-Fueller (ADF) test in differences. The results of the ADF test are presented in Table 2. For all the features included in the analysis we reject the null hypothesis of non-stationarity. Although the variables are difference-stationary, we estimate VARs in log-levels to avoid loss of information. This is a common practice in time series econometrics

Table 1: Data summary.

Variable	Description	Source	Sample	Computation	Transf.
		Aggregate variables			
Instr	WTI crude oil futures hh-month contract (settlement price)	Känzig's webpage	1983Q1-2019Q4		$\sum_{m=1}^{4} \text{Instr}_m$
	WTI crude oil futures hh-month contract (settlement price)	Känzig's webpage	1983M1-2019M12		
P_t^{oil}	WTI spot crude oil price deflated by U.S. CPI	FRED (WTISPLC)	1983Q1-2019Q4		$100 \times \log$
	WTI spot crude oil price deflated by U.S. CPI	FRED (WTISPLC)	1983M1-2019M12		$100 \times \log$
Y_t	U.S. gross domestic income	FRED (GDPC1)	1983Q1-2019Q4		$100 \times \log$
	U.S. industrial production index	FRED (INDPRO)	1983M1-2019M12		$100 \times \log$
P_t	U.S. CPI for all urban consumers	FRED (CPIAUCSL)	1983Q1-2019Q4		$100 \times \log$
	U.S. CPI for all urban consumers	FRED (CPIAUCSL)	1983M1-2019M12		$100 \times \log$
W_t^{oil}	World oil production	Känzig's webpage	1983M4-2017M12		$100 \times \log$
Y_t^{world}	World industrial production	Känzig's webpage	1983M4-2017M12		$100 \times \log$
W_t^{inv}	World oil inventories	Känzig's webpage	1983M4-2017M12		$100 \times \log$
		Distributional variables: shares of GDI			
ℓ_t	Labour share	BEA (NIPA 1.10)	1983Q1-2019Q4	$\frac{\textit{Compensation of employees}}{\textit{GDI}}$	
pr_t^{bt}	Profits share before taxes	BEA (NIPA 1.10)	1983Q1-2019Q4	$\frac{\textit{Profits before tax}}{\textit{GDI}}$	
pr_t^{at}	Profits share after taxes	BEA (NIPA 1.10)	1983Q1-2019Q4	$\frac{\textit{Profits after tax}}{\textit{GDI}}$	
d_t	Dividends share	BEA (NIPA 1.10)	1983Q1-2019Q4	$\frac{\textit{Net dividends}}{\textit{GDI}}$	
pr_t^{ret}	Retained profits share	BEA (NIPA 1.10)	1983Q1-2019Q4	$\frac{\textit{Undistributed corporate profits}}{\textit{GDI}}$	
		Distributional variables: shares of aggregate personal income			
ℓ_t^{priv}	Private labour share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Compensation of employees(PS)}}{\textit{Personal income}}$	
$n\ell_t$	Non-labour share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Personal income receipts on assets}}{\textit{Personal income}}$	
ℓ_t^{gov}	Government labour share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Compensation of employees(GOV)}}{\textit{Personal income}}$	
i_t^{sh}	Interests share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Personal interest income}}{\textit{Personal income}}$	
b_t	Social benefits share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Government social benefits to persons}}{\textit{Personal income}}$	
d_t^{pi}	Dividends share	BEA (NIPA 2.6)	1983M1-2019M12	$\frac{\textit{Personal dividend income}}{\textit{Personal income}}$	

Table 2: Results of the ADF test in differences.

Variable	Sample	Test statistic	p-value
Aggregate variables			
P_t^{oil}	1983M1-2019M12	-8.0215	0.01
	1983Q1-2019Q4	-5.9057	0.01
Y_t	1983M1-2019M12	-5.2669	0.01
	1983Q1-2019Q4	-4.1382	0.01
P_t	1983M1-2019M12	-7.3199	0.01
	1983Q1-2019Q4	-4.1584	0.01
W_t^{oil}	1983M1-2017M12	-9.1684	0.01
Y_t^{world}	1983M1-2017M12	-5.6820	0.01
W_t^{inv}	1983M1-2017M12	-6.2890	0.01
Distributional variables: shares of GDI			
ℓ_t	1983Q1-2019Q4	-4.4626	0.01
pr_t^{bt}	1983Q1-2019Q4	-4.3331	0.01
pr_t^{at}	1983Q1-2019Q4	-4.6307	0.01
d_t	1983Q1-2019Q4	-6.2096	0.01
pr_t^{ret}	1983Q1-2019Q4	-5.4486	0.01
Distributional variables: shares of aggregate personal income			
ℓ_t^{priv}	1983M1-2019M12	-8.4405	0.01
$n\ell_t$	1983M1-2019M12	-5.7126	0.01
ℓ_t^{gov}	1983M1-2019M12	-5.0063	0.01
i_t^{sh}	1983M1-2019M12	-6.0725	0.01
b_t	1983M1-2019M12	-7.8931	0.01
d_t^{pi}	1983M1-2019M12	-6.5021	0.01

as VAR coefficients are still consistently estimated even in the presence of unit roots and cointegration (see Sims et al., 1990; Kilian and Lütkepohl, 2017, Sec. 3.2.3).

For quarterly data, we use $P = 4$ lags, while for monthly data we use $P = 12$ lags. Since the oil surprise series is available starting from 1983, we estimate our models considering the time window 1983-2019. In particular, for quarterly SVARs, we use 148 observations from 1983Q1 to 2019Q4, while for monthly SVARs we employ 444 observations from 1983M1 to 2019M12 (see Table 1 and Table 3 for details). We decide to exclude the last three years from our sample (i.e. 2020, 2021 and 2022) to avoid the effects of the COVID-19 shock. This allows us to exclude extreme observations for which a full recovery may not have occurred yet (see Lenza and Primiceri, 2022).

5 Results

5.1 Testing the instrument

The fact that the proxy is correlated with the shock to be identified but uncorrelated with the others, could not be a sufficient condition. Indeed, the instrument may be only weakly correlated with the structural shock.

Therefore, as a preliminary step, we must test the strength of the external instrument. Following Montiel Olea et al. (2021), this can be done using a F-test in the first-stage regression of the oil price VAR residuals on the surprise series. If the F-statistics is greater than 10, then the instrument is strong. In Table 3 we report the results of the first-stage regression, i.e. the coefficient, the F-statistic, the R^2, the adjusted R^2, the number of observations in the sample and the frequency of the observations for the 12 SVAR specifications.

Table 3: Results of the first-stage regression.

SVAR	Coeff.	F-statistic	R^2	Adj.-R^2	N. obs.	Frequency
$\{P_t^{\text{oil}}, W_t^{\text{oil}}, W_t^{\text{inv}}, Y_t^{\text{world}}, Y_t, P_t\}$	1.0488	19.07	4.507	4.27	417	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{bt}}\}$	1.7345	10.9	7.081	6.432	148	Quarterly
$\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{at}}\}$	1.7637	11.21	7.272	6.623	148	Quarterly
$\{P_t^{\text{oil}}, Y_t, P_t, \ell_t\}$	1.650	9.725	6.367	5.713	148	Quarterly
$\{P_t^{\text{oil}}, Y_t, P_t, d_t\}$	1.7729	11.47	7.427	6.78	148	Quarterly
$\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{ret}}\}$	1.8465	12.63	8.113	7.47	148	Quarterly
$\{P_t^{\text{oil}}, Y_t, P_t, \ell_t^{\text{priv}}\}$	10.4649	620.5	59.01	58.92	444	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, n\ell_t\}$	10.7122	679.7	61.2	61.11	444	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, d_t^{\text{pi}}\}$	10.7358	685.9	61.41	61.32	444	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, \ell_t^{\text{gov}}\}$	10.5282	649.6	60.48	60.39	444	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, i_t^{\text{sh}}\}$	10.6209	670.3	60.68	60.77	444	Monthly
$\{P_t^{\text{oil}}, Y_t, P_t, b_t\}$	10.1729	583.1	57.5	57.4	444	Monthly

In all cases, the F-statistic is at least close to or greater than 10. Hence, we can conclude that the instrument is strong.

5.2 Testing for informational sufficiency

We now apply the invertibility test of Forni et al. (2022) to verify if the informational sufficiency hypothesis holds. To do that, we first regress the instrument on the current value and the first H leads of the estimated Wold residuals $\widehat{\mathbf{u}}_t$:

$$z_t = \sum_{\ell=0}^{H} \boldsymbol{\lambda}' \widehat{\mathbf{u}}_{t+\ell} + \eta_t. \tag{21}$$

Then, we use a F-test to check whether the regressors in Equation (21) are statistically significant. In particular, the null hypothesis is $\mathsf{H}_0 : \boldsymbol{\lambda}_0 = \boldsymbol{\lambda}_1 = \cdots = \boldsymbol{\lambda}_H = 0$, while the alternative is that at least one coefficient is different from 0.

For our purposes, we estimate the regression (21) using ($4 \leq H \leq 12$) leads and the residuals of the VAR $\{P_t^{\text{oil}}, Y_t, P_t, \ell_t\}$. The p-values for each regression including the current value and up to H leads of the Wold residuals are reported in Table 4.

Table 4: Results of the invertibility test.

	Number of leads								
	$H=4$	$H=5$	$H=6$	$H=7$	$H=8$	$H=9$	$H=10$	$H=11$	$H=12$
p-value	0.9003	0.9469	0.7142	0.8827	0.9451	0.6469	0.7409	0.4434	0.4112

For all the leads H, the p-values are above the confidence levels (1%, 5% and 10%). Therefore, we cannot reject the hypothesis of invertibility.

5.3 The effects on macroeconomic variables

We now introduce our first results. In line with Känzig (2021), we start by discussing the effects of the identified oil supply shock on real oil price, world oil production, world oil inventories, world industrial production, domestic industrial production index and consumer price index. For the sake of comparison, we choose the same frequency and sample size adopted by Känzig (2021). The IRFs of the shock, normalised in such a way that ε_{1t} corresponds to a 10% increase in the oil price, are depicted in Figure 1. The solid black lines are the average responses, the dark grey shaded area corresponds to the 68% confidence interval, while the light grey shaded area corresponds to the 90% confidence interval. The confidence bands are obtained using 2000 bootstrap replications. As suggested by Jentsch and Lunsford (2022) and Angelini et al. (2024), among others, we rely on residual-based moving block bootstrap (MBB). In fact, when only one instrument is used to identify a single shock, as in our case, the MBB allows us to obtain confidence intervals for normalised impulse responses that are valid regardless of proxy strength (see Jentsch and Lunsford, 2022).

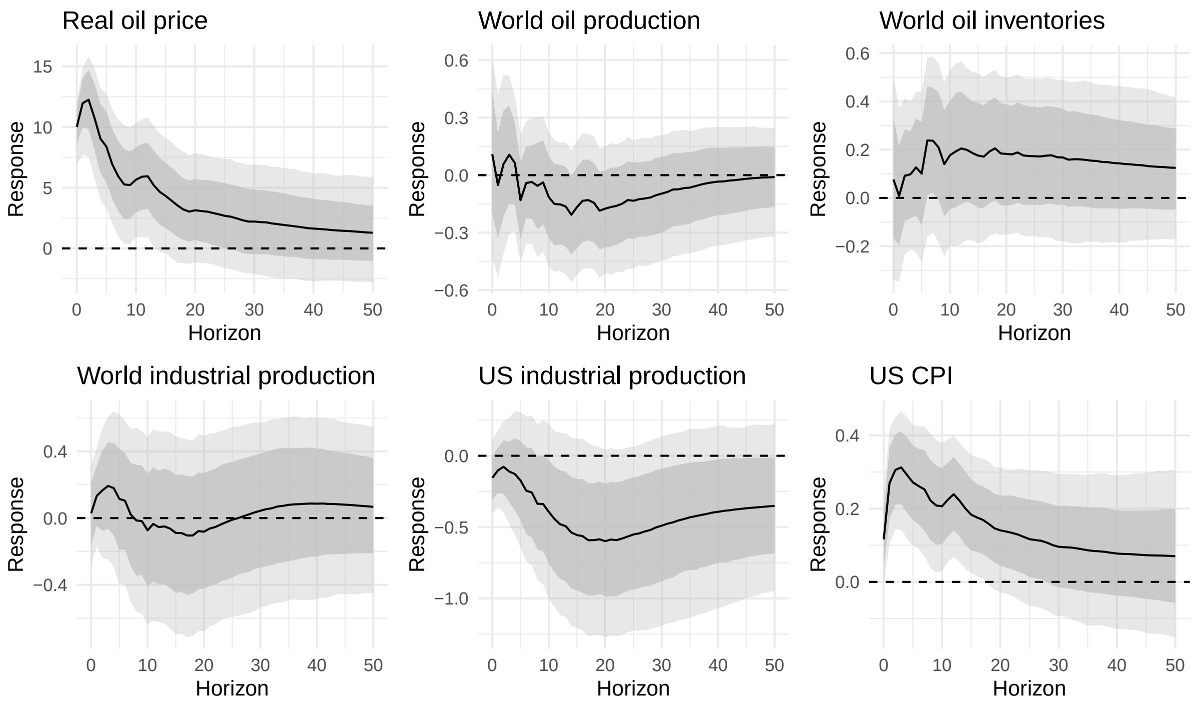

Figure 1: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: 68% and 90% confidence interval respectively (confidence bands are obtained using 2000 bootstrap replications). Real oil price $\equiv P_t^{\text{oil}}$, World oil production $\equiv W_t^{\text{oil}}$; World oil inventories $\equiv W_t^{\text{inv}}$; World industrial production $\equiv Y_t^{\text{world}}$; U.S. industrial production $\equiv Y_t$; Consumer price index $\equiv P_t$. For the variables description we refer to Table 1.

The results are in line with the findings of Känzig (2021). A negative oil supply news shock leads to an increase in oil prices and has the expected macroeconomic effects: quantitatively moderate stagflation measured by a durable, although modest, drop in domestic industrial production and an increase in the consumer price index. Domestic industrial production declines by approximately 0.15% on impact, with the decrease continuing to reach 0.5% after 15 months, where it then stabilises. The consumer price index increases on impact by approximately 0.2% and after six months starts falling towards its pre-shock level. The subsequent decline in CPI results from the dissipation of the shock, as the oil price returns to pre-shock levels. This effect is likely reinforced by monetary policy responses and the recessionary impact, which feedback into the CPI through a Phillips curve-type of relationship.

Global variables also align with the findings of Känzig (2021): (i) world oil inventories increase, indicating a precautionary accumulation of oil in response to the negative supply news shock; (ii) world industrial production remains relatively unaffected, likely because oil price increases positively impact oil-producing countries while negatively affecting oil-consuming countries, resulting in a net effect close to zero; (iii) world oil production decreases due to the direct impact of the negative supply shock.[4]

[4]For a thorough comparison see Figure A.27 in the Online Appendix of Känzig (2021).

5.4 The redistributive effects of the energy shock

We now evaluate the effects of an oil supply shock leading to rising oil prices, on the functional distribution of income — that is, the shares of different income sources of GDI — as well as the distribution of aggregate personal income across different income sources.

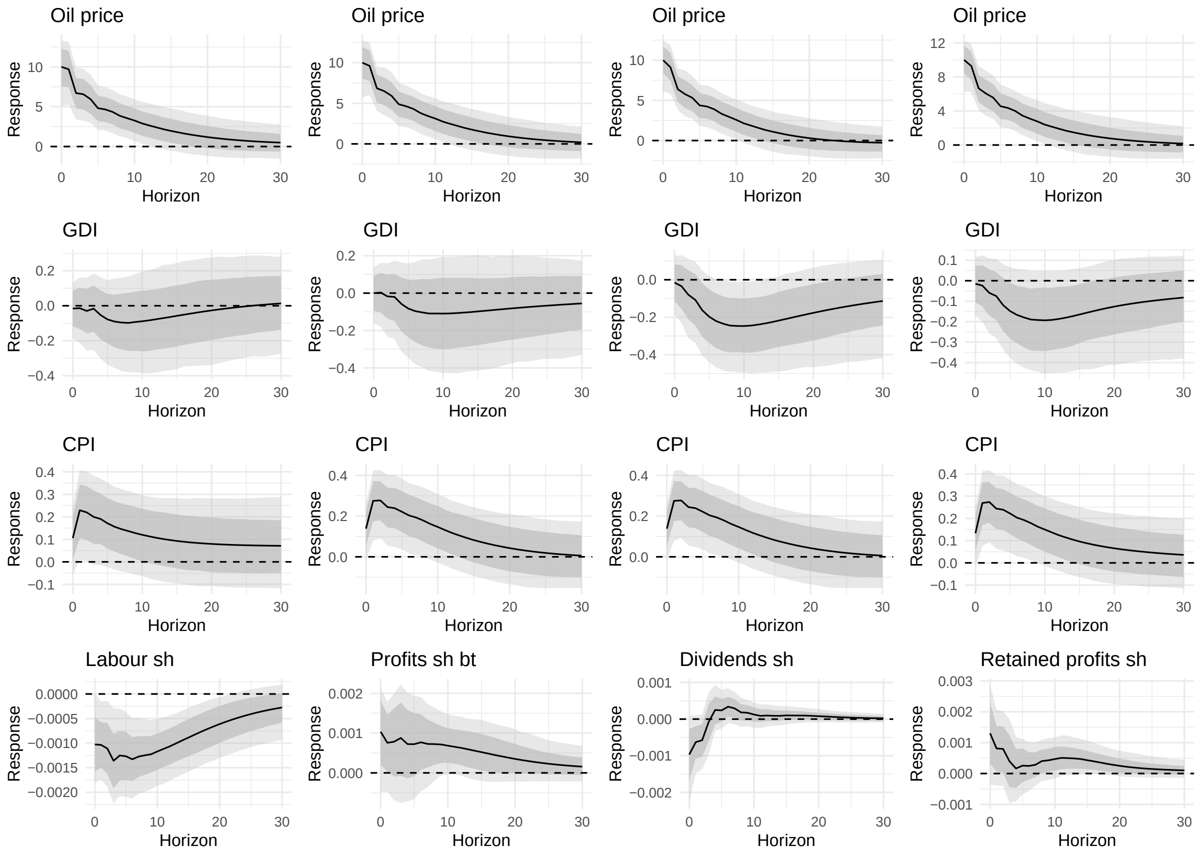

Figure 2: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: 68% and 90% confidence interval respectively (confidence bands are obtained using 2000 bootstrap replications). *First column*: $\{P_t^{\text{oil}}, Y_t, P_t, \ell_t\}$; *Second column*: $\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{bt}}\}$; *Third column*: $\{P_t^{\text{oil}}, Y_t, P_t, d_t\}$; *Fourth column*: $\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{ret}}\}$. For the variables description we refer to Table 1.

5.4.1 Energy shock effects on functional income distribution

Figure 2 shows a long-lasting and statistically significant fall in the labour share following a 10% innovation in the price of oil. The labour share decreases by 0.001 on impact, remaining at such a level for up to 15 quarters after the shock and recovering to the pre-shock level only after 30 periods. At first glance, a 0.001 decrease may seem negligible, but a closer look highlights its quantitative importance. For instance, one could consider that the labour share of GDI was around 0.578 in 1980 and declined to 0.533 by the end of 2019 — a long-term drop of 0.045 over nearly three decades. Therefore, our on-impact estimate represents about 2.28% of that long-term decline, making it a notable contribution when assessed from a historical perspective (see Table 5).

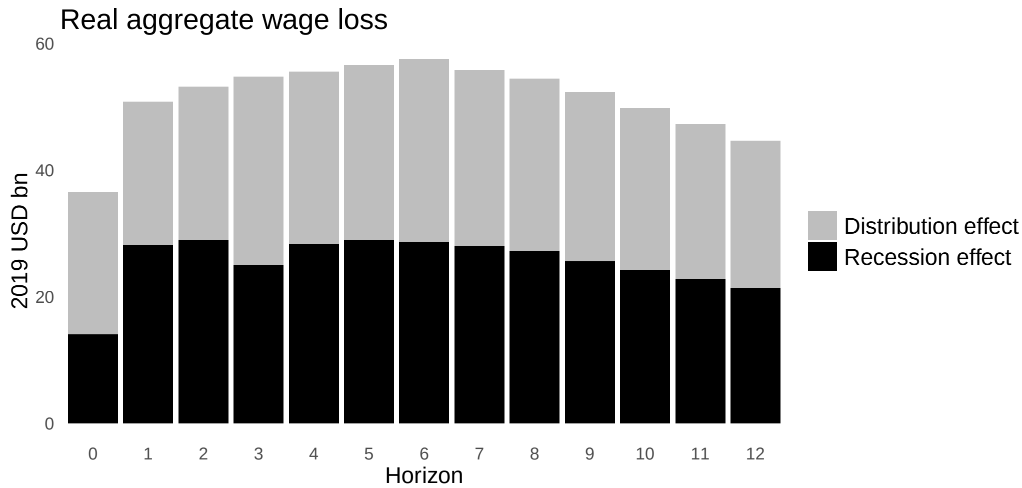

Figure 3: The vertical bars represent the real aggregate wage loss resulting from a 10% increase in oil prices, as implied by the estimated IRFs shown in the first column of Figure 2. The x-axis shows the periods following the shock, with "0" indicating the wage loss on impact. We assume the shock occurs in 2019, so the monetary loss is expressed in 2019 billion dollars. Detailed calculations for the wage loss and its breakdown between redistribution and recession effects are reported in Table 5 and Appendix B.

Another way to gauge the significance of a 0.001 drop in the wage share is by estimating its monetary impact on aggregate wages. Following an energy price shock, aggregate wages decline due to a distribution and a recession effect. If we consider 2019Q1 as our base quarter and account for both recession and distribution effects, on impact we estimate a reduction in the real value of aggregate wages of approximately \$36.5bn. While over 12 quarters after the shock, the estimated wage loss amounts to \$668.6bn, as measured in 2019Q1 dollars. When we abstract from the recession effect, i.e. we assume the real GDI to be constant at its 2019 value, we estimate an aggregate wage loss on impact equal to \$22.4bn and a cumulative wage loss over 12 quarters after the shock of \$337.7bn. This indicates that the wage loss due to the distribution effect is significant in absolute terms and — more importantly — accounts for a relevant part of the real aggregate wage loss. Specifically, it explains 50% of the loss on impact and 60% of the cumulative loss over 12 quarters (see Figure 3 and Table 5).[5]

The decline in the labour share is nearly entirely offset by an increase in the profit share. However, this does not necessarily imply that firms have passed much of the shock onto workers, as the profit share variable used here does not distinguish between energy and non-energy profits. The significant drop in the wage share, coupled with the strong CPI increase, might however raise this question, which we address more thoroughly in Section 5.5, where we examine asymmetries in the wage share and CPI responses. Notably, despite the increase in the profit share, the share of dividends in national income

[5]Detailed calculations are presented in Appendix B.

Table 5: Quantifying the labour share response to a 10% increase in the energy price.

Measure	Value
Impact shock relative to secular trend	2.28%
Distributive effect	
Aggregate labour income loss on impact	\$22.4bn
Cumulative aggregate labour income loss	\$337.736bn
Distributive + recessionary effect	
Aggregate labour income loss on impact	\$36.468bn
Cumulative aggregate labour income loss	\$668.601bn

Notes: (i) "Impact shock relative to secular trend" refers to the ratio between the estimated wages share drop on impact and the observed wage share decline during the sample under consideration. (ii) Losses are expressed in 2019Q1 dollars. (iii) For detailed calculations underlying the values reported in the table, please refer to Appendix B.

initially falls. This is explained by firms distributing fewer dividends in response to the shock, as indicated by the rise in retained profits as a share of GDI. Nevertheless, the dividend share recovers, much faster than the labour share, returning to its pre-shock level within five quarters.

5.4.2 Energy shock effects on the distribution of personal income across different income sources

In this section, we present the redistributive effects across various sources of personal income. Unlike the previous section, where variables were expressed as shares of GDI, here all variables are defined as shares of aggregate personal income. Due to data availability, all results are based on monthly frequency data instead of quarterly data (see Table 1).

Figure 4 illustrates that following a 10% rise in oil prices, the share of aggregate personal income allocated to private sector workers declines significantly. In contrast, the income share for public sector workers does not experience a statistically significant drop on impact, and if anything, it even tends to increase in the following periods. This difference may be attributed to fewer layoffs in the public sector and/or the absence of wage cuts for public employees during the shock. This underscores an additional distributional effect, as the majority of wage losses documented earlier primarily affect private sector workers, who are more vulnerable to the shock. Additionally, the share of personal income derived from social benefits rises. This increase is likely attributable to automatic stabilisers and temporary policy measures aimed at alleviating the impact of the shock on households. Together with the growing income share of public workers, this response is consistent with the notion that public expenditures should be counter-cyclical and thus expansive in the face of negative shocks.

In the aftermath of the shock, the share of income derived from sources other than labour income rises. As noted in the previous section, dividends are unlikely to contribute to this trend, and indeed we estimate a temporary decrease in the dividends share of aggregate personal income. In contrast, we observe a statistically significant and durable increase in the share of interest income. This shift is likely driven by the monetary tightening that typically follows an inflationary shock, resulting in higher interest rates and, consequently, increased financial revenues.

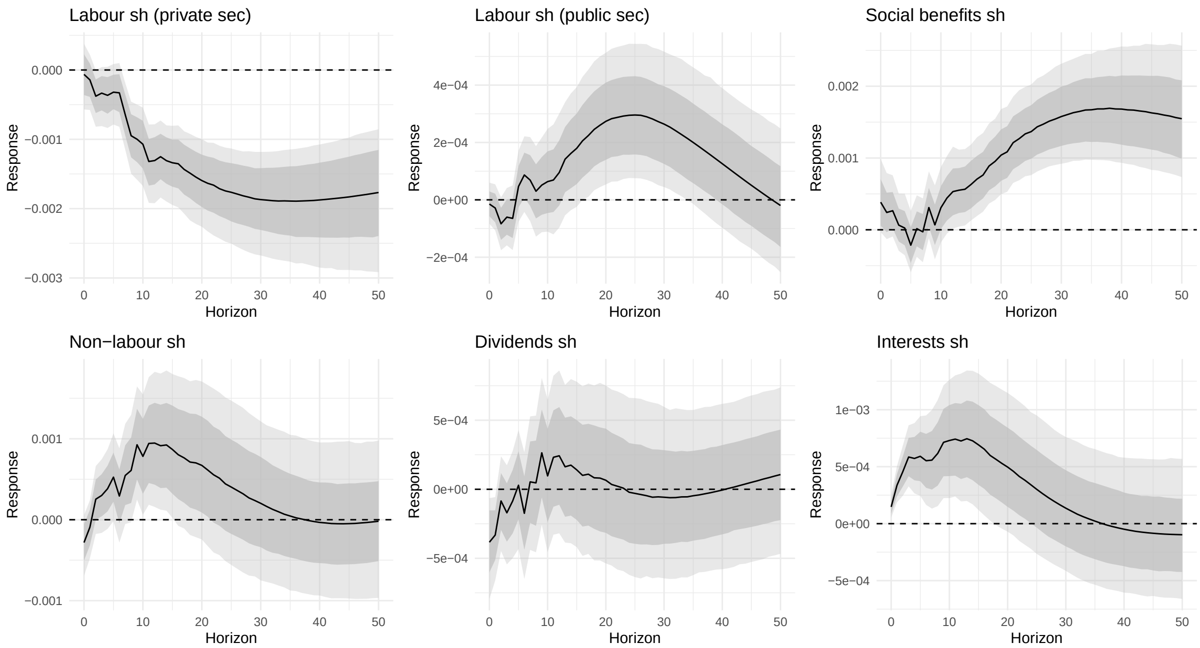

Figure 4: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: 68% and 90% confidence interval respectively (confidence bands are obtained using 2000 bootstrap replications). Labour sh (private sec) $\equiv \ell_t^{\text{priv}}$; Labour sh (public sec) $\equiv \ell_t^{gov}$; Social benefits sh $\equiv b_t$; Non-labour sh $\equiv n\ell_t$; Dividends sh $\equiv d_t$; Interests sh $\equiv i_t^{sh}$. For the variables description we refer to Table 1.

5.5 Disentangling the effect of positive and negative oil supply shocks

We now investigate whether negative and positive oil shocks have asymmetric impacts on the distributional variables. Our main focus concerns the labour income share.[6]

To estimate the effects of a positive (negative) shock, we decide to exploit a nonlinear proxy-SVAR in the same vein as Debortoli et al. (2020); Forni et al. (2023, 2024).[7] The procedure involves two main steps: (i) the identification of the shock of interest using the surprise series of Känzig (2021), (ii) the utilisation of the identified shock, together

[6] In Appendix C.4, we discuss the asymmetric effects on other distributional variables such as the share of income (before and after taxes) due to profits, the share of income due to dividends and the share of income due to retained profits.

[7] Although other approaches are possible, i.e. the method proposed by Gonçalves et al. (2021) that includes nonlinear regressors in a linear structural dynamic model to obtain nonlinear impulse responses, we rely on Debortoli et al. (2020) as we deal with proxy-SVARs.

with a nonlinear transformation of it, as exogenous variables in a SVARX embodying the endogenous variables of interest to obtain the asymmetric IRFs. Below, we outline the key passages for estimation:

1. Starting from the reduced-form model in Equation (8), we estimate the reduced-form residuals $\widehat{\mathbf{u}}_t$ through OLS;

2. We exploit the linear projection $z_t = \boldsymbol{\lambda}'\widehat{\mathbf{u}}_t + \eta_t$, where z_t is the proxy used for identification, to estimate $\widehat{\boldsymbol{\lambda}}'$ and identify the (normalised) structural shock as follows:

$$\widehat{\varepsilon}_{1t} = \frac{\widehat{\boldsymbol{\lambda}}'\widehat{\mathbf{u}}_t}{\sqrt{\widehat{\boldsymbol{\lambda}}'\widehat{\boldsymbol{\Sigma}}_{\mathbf{u}}\widehat{\boldsymbol{\lambda}}}}, \tag{22}$$

   where $\widehat{\boldsymbol{\Sigma}}_{\mathbf{u}} = \frac{1}{T-KP-1}\sum_{t=1}^{T}\widehat{\mathbf{u}}_t\widehat{\mathbf{u}}_t'$ is the estimated covariance matrix of $\mathbf{u}_t$;

3. We estimate a VARX model including a set of endogenous variables of interest and simultaneously $\widehat{\varepsilon}_{1t}$ and $g\left(\widehat{\varepsilon}_{1t}\right)$ as exogenous variables, where $g\left(\cdot\right)$ is a nonlinear function of the structural shock (see below);

4. We compute the asymmetric IRFs by summing the coefficients of $\widehat{\varepsilon}_{1t}$ and $g\left(\widehat{\varepsilon}_{1t}\right)$.

In particular, to account for positive shocks, i.e. an expected decrease of the oil price, we use the following nonlinear function:

$$g^{+}\left(\widehat{\varepsilon}_{1t}\right) = \begin{cases} \widehat{\varepsilon}_{1t}, & \text{if} \quad \widehat{\varepsilon}_{1t} > 0 \\ 0, & \text{if} \quad \widehat{\varepsilon}_{1t} \leq 0, \end{cases} \tag{23}$$

while to account for negative shocks, i.e. an expected increase of the oil price, we use the following transformation:

$$g^{-}\left(\widehat{\varepsilon}_{1t}\right) = \begin{cases} \widehat{\varepsilon}_{1t}, & \text{if} \quad \widehat{\varepsilon}_{1t} < 0 \\ 0, & \text{if} \quad \widehat{\varepsilon}_{1t} \geq 0. \end{cases} \tag{24}$$

Figure 5 shows the nonlinear transformations of the shocks used to estimate the asymmetric effects of an oil supply news shock. The red line refers to the expected increases in oil prices due to OPEC announcements, while the blue line concerns the expected decreases in oil prices.

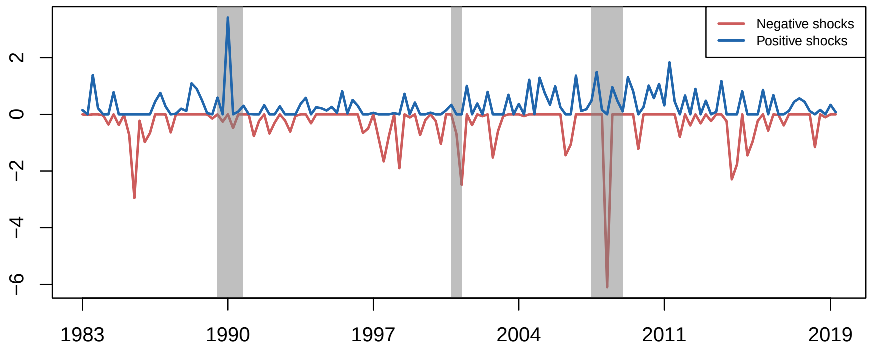

Figure 5: Transformed shocks used to identify negative (red) and positive (blue) shocks. Shaded areas represent episodes of economic recession as defined by NBER.

These specifications are in line with the reasoning of Mork (1989), who concludes that increases in oil prices account for more than decreases, which is also our conclusion (see below). As noted in Gonçalves et al. (2021), this idea has been applied by many authors to study the effects of asymmetric pass-through of oil shocks to gasoline prices (Venditti, 2013), the asymmetric effects of exogenous tax changes (Hussain and Malik, 2016) and the asymmetric effects of financial market disruptions (Barnichon et al., 2022).

This choice has been the subject of discussion in the literature (see, e.g., Hamilton, 2003, 2011 and Kilian and Vigfusson, 2011, 2017). The main point of Kilian and Vigfusson (2011) is that the intrinsic misspecification of censored oil price VAR models leads to biased estimates. To overcome this issue, they propose to estimate an encompassing model in which the first equation is the same as a standard linear oil VAR, but the others include both the linear and nonlinear transformation of the oil price. The structural IRFs are then obtained through Monte Carlo integration since the model has nonlinear variables and the responses depend on the state of the system at the time of the shock (Kilian and Lütkepohl, 2017). The method of Debortoli et al. (2020); Forni et al. (2023, 2024) is in line with the approach of Kilian and Vigfusson (2011) as they consider both the linear and nonlinear part of the shock. For this reason, we adopt the former since they directly treat the case of proxy-SVARs and allow for a simpler representation of the IRFs without recurring to Monte Carlo integration.

Finally, it is worth noting that, in the realm of proxy-SVAR studies, it is not uncommon to encounter variables truncated to zero. This censoring often arises when researchers put forward proxies stemming from infrequent or irregularly timed events (see, e.g., the instrument proposed by Mertens and Ravn, 2013).[8]

[8] We are aware that censoring at zero may provide biased estimates. Luckily, recent contributions tackle this drawback (see Jentsch and Lunsford, 2022; Angelini et al., 2024). In particular, the bootstrap

The asymmetric IRFs for oil price innovation normalised 10% are shown in Figure 6. To improve comparability between the negative and positive shocks, we normalise the IRFs by taking the absolute value of the oil price response. In other words, all the IRFs for the positive oil supply shock shown in Figure 6 are mirrored versions of the original IRFs.

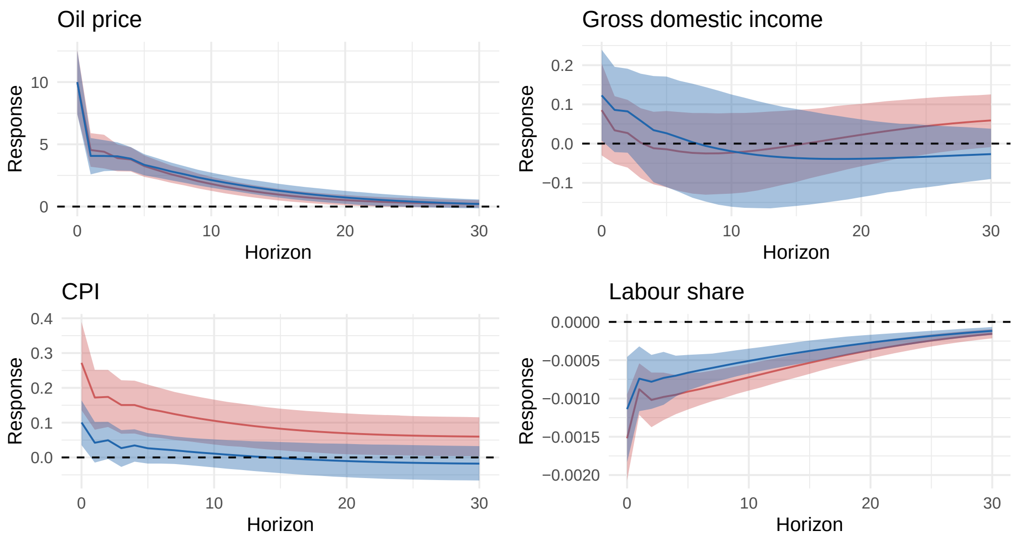

Figure 6: *Solid red line*: Asymmetric IRFs for oil price innovation normalised to 10% (negative shocks). *Red shaded areas*: 68% confidence interval. *Solid blue line*: Asymmetric IRFs for oil price innovation normalised to 10% (positive shocks). *Blue shaded areas*: 68% confidence interval. All confidence bands are obtained using 2000 bootstrap replications. Oil price $\equiv P_t^{\text{oil}}$ (instrumented); Gross domestic income $\equiv Y_t$; CPI $\equiv P_t$; Labour share $\equiv \ell_t$.

Although the normalisation factors used to obtain a 10% change in the oil price are different for the case of positive and negative shocks, we do not observe any asymmetry in the dynamic response of the oil price. While this is an interesting result in itself, it also implies that the responses of other variables of interest, both on impact and dynamically, are not affected by differing oil price reactions to positive versus negative supply shocks.

On impact, the estimated CPI response is stronger for negative shocks than for positive ones. However, the dynamic response is similar, with the IRFs returning to their pre-shock values in a parallel fashion. We can interpret the response on impact as the pass-through rate and therefore we can conclude that the pass-through rate is asymmetric, with negative shocks being transmitted onto prices to a larger extent than positive ones. The symmetric post-shock decline in CPI suggests that wage-price spirals are not a significant inflationary force correlated to oil price movements. Indeed, in the case of a negative oil price shock (i.e. an oil price increase), a wage-price spiral would cause wages to rise, further fuelling inflation beyond the initial shock. This would result in a greater CPI sensitivity beyond impact for negative oil shocks compared to positive ones. However,

procedure proposed by Jentsch and Lunsford (2022), which we use, remain asymptotically valid under the assumption that the truncation process is stationary and α-mixing.

the IRFs show the opposite: the asymmetry in CPI response occurs only on impact, while the longer-term dynamics are nearly identical. This indicates that the after-shock CPI's behaviour is mainly driven by the gradual reversal of the oil price shock, rather than wage-related inflationary pressures.

In Section 3 we argued that the general price response to oil shocks is tied to the adjustment of the functional income distribution. Our empirical findings support this interpretation. Indeed on impact, we detect an asymmetry in the labour share response to oil shocks, which closely resembles the asymmetric response of CPI. This suggests that since negative shocks are passed onto prices to a larger extent, the loss for workers — reflected in the wage share decline — is larger than the gain experienced during positive shocks. However, it is worth noting that, unlike the CPI, the wage-share response remains asymmetric even after the initial shock. In the case of a negative shock, the wage share recovers more quickly, with negative and positive shocks converging to similar values around 20-25 periods after the initial shock. We conclude that the asymmetric pass-through accounts for the asymmetry in the wage response on impact. However, the subsequent adjustments in the wage share are likely driven by additional factors that our current framework is unable to capture.

These findings are compliant with the theoretical discussion of Section 3. First of all, the asymmetric pass-through rate strongly suggests that non-energy firms hold considerable power in the good market. Additionally, the lack of wage-price spirals, as seen in the symmetric post-shock CPI dynamics, indicates that nominal wages fail to keep pace with the shock and the initial CPI increase. This, in turn, implies that workers lack sufficient bargaining power in the labour market to drive a wage adjustment in response to the shock. In the theoretical framework of Section 3, this setting corresponds to the *monopoly-monopsony* scenario, which, consistently with our empirical findings, predicts sustained inflation and wage share decline in the aftermath of a negative energy shock.

Although a positive energy shock appears to foster an expansionary effect on the U.S. economy in the short term, it is followed by a long-lasting decline. This effect is probably amplified by the nonlinear term $g(\cdot)$, which plays a crucial role in detecting sign asymmetries (see, e.g., Forni et al., 2023 for similar results). However, we do not find a statistically significant overall response of GDI to an oil price shock, nor do we observe a statistical difference between negative and positive responses.

6 Conclusions

We provide novel estimates of the distributive effects of energy shocks, presenting the first quantitative evidence of the adjustments in the wage share and other functional distributive variables. We use U.S. data and obtain estimates from a series of proxy-SVAR models identified with the oil supply news shock proposed by Känzig (2021).

Results confirm the well-known empirical finding that an oil supply shock is generally associated with a period of slow economic activity and sustained inflation. Our novel contribution is the estimation of a quantitively significant and durable decline in the labour share. We also document a substantial decline in real aggregate labour income, largely driven by redistributive dynamics.

Different sources of personal income are found to respond differently to the shock. In summary: (i) the share of labour income for private-sector workers declines significantly, while public-sector workers appear to be better protected from the shock; (ii) although the profit share of GDI increases, firms tend to distribute less profits, leading to a temporary decline in the share of aggregate personal income accruing to dividends; (iii) the share of interest income in personal income shows a marked increase, likely driven by the monetary policy response to energy shocks, which raises interest rates and, consequently, financial incomes.

We also identify asymmetries in the response to oil supply shocks, with stronger pass-through rates for negative shocks than for positive ones. This asymmetry has direct distributional consequences: a strong pass-through rate makes the wage share more sensitive to oil price changes, leading to a sharper decline in the wage share for negative shocks than the corresponding increase for positive shocks. Additionally, examining these asymmetries offers insights into the relevance of price-wage spirals following oil supply shocks. Despite the stronger pass-through for negative shocks, we find no evidence of price-wage spirals, suggesting that wages do not keep pace with CPI in the wake of the shock. We argue that this outcome is consistent with a scenario where workers have weak bargaining power in the labour market, while firms exert some monopoly-like power in the goods market.

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Appendix

A Some derivations for the theoretical framework

In this section, we detail the derivation of the theoretical accounting framework discussed in Section 3.

A.1 Income shares

A.1.1 Wage share

$$\theta = \frac{\big(Y/\gamma^l\big)w}{PY} = \frac{w/\gamma^l}{\big(1+\mu\big)\Big(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\Big)} = \frac{1}{\big(1+\mu\big)\big(1+uc_e/uc_l\big)} = \frac{\Gamma^l}{1+\mu}$$

A.1.2 Profit share (excluding energy)

$$\pi = \frac{PY-\big(Y/\gamma^l\big)w-\big(Y/\gamma^e\big)p_e}{PY} = 1-\frac{w/\gamma^l+p_e/\gamma^e}{P} = 1-\frac{w/\gamma^l+p_e/\gamma^e}{\big(1+\mu\big)\big(w/\gamma^l+p_e/\gamma^e\big)} = \frac{\mu}{1+\mu}$$

A.1.3 Energy profit share

$$\eta = \frac{\big(Y/\gamma^e\big)p_e}{PY} = \frac{p_e/\gamma^e}{\big(1+\mu\big)\Big(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\Big)} = \frac{1}{\big(1+\mu\big)\big(1+uc_l/uc_e\big)} = \frac{\Gamma^e}{1+\mu}$$

A.2 Elasticities with respect to the energy price

A.2.1 Monopoly-monopsony scenario

In the *monopoly-monopsony* scenario we have $\frac{\partial \mu}{\partial p_e} = \frac{\partial w}{\partial p_e} = 0$.

Wage share We first calculate the derivative of θ with respect to p_e:

$$\frac{\partial \theta}{\partial p_e} = -\frac{\frac{w}{\gamma^l\gamma^e}}{\big(1+\mu\big)\Big(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\Big)^2}.$$

The elasticity ϵ_θ can be compute as:

$$\begin{aligned}\epsilon_\theta \equiv \frac{\partial \theta}{\partial p_e}\frac{p_e}{\theta} &= -\frac{\frac{w}{\gamma^l\gamma^e}}{\big(1+\mu\big)\Big(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\Big)^2}\cdot p_e \cdot \frac{\big(1+\mu\big)\Big(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\Big)}{w/\gamma^l} \\ &= -\frac{p_e/\gamma^e}{w/\gamma^l+p_e/\gamma^e} = -\frac{uc_e}{uc} = -\Gamma^e.\end{aligned}$$

Price We first calculate the derivative of P with respect to p_e:

$$\frac{\partial P}{\partial p_e} = \frac{1+\mu}{\gamma^e}.$$

The elasticity ϵ_p can be compute as:

$$\epsilon_p \equiv \frac{\partial P}{\partial p_e}\frac{p_e}{P} = \frac{1+\mu}{\gamma^e}\frac{p_e}{(1+\mu)uc} = \frac{uc_e}{uc} = \Gamma^e.$$

A.2.2 Monopoly scenario

In the *monopoly* scenario we have $\frac{\partial \mu}{\partial p_e} = 0$ and $\frac{\partial w}{\partial p_e} > 0$.

Wage share We first calculate the derivative of θ with respect to p_e:

$$\frac{\partial \theta}{\partial p_e} = -\frac{\frac{\gamma^l}{w\gamma^e} - \frac{\partial w}{\partial p_e}\frac{p_e\gamma^l}{w^2\gamma^e}}{(1+\mu)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)^2} = -\frac{(1-\epsilon_w)\frac{\gamma^l}{w\gamma^e}}{(1+\mu)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)^2}.$$

The elasticity ϵ_θ can be compute as:

$$\begin{aligned}
\epsilon_\theta \equiv \frac{\partial \theta}{\partial p_e}\frac{p_e}{\theta} &= -\frac{(1-\epsilon_w)\frac{\gamma^l}{w\gamma^e}}{(1+\mu)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)^2} \cdot p_e \cdot (1+\mu)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right) \\
&= -\frac{(1-\epsilon_w)\frac{p_e}{\gamma^e}\frac{\gamma^l}{w}}{1+\frac{p_e}{\gamma^e}\frac{\gamma^l}{w}} = -\frac{(1+\epsilon_w)uc_e/uc_l}{1+uc_e/uc_l} = -(1-\epsilon_w)\frac{uc_e}{uc_l+uc_e} \\
&= -(1-\epsilon_w)\Gamma^e.
\end{aligned}$$

Price We first calculate the derivative of P with respect to p_e:

$$\frac{\partial P}{\partial p_e} = (1+\mu)\left(\frac{1}{\gamma^e} + \frac{\partial w}{\partial p_e}\frac{1}{\gamma^l}\right).$$

The elasticity ϵ_p can be compute as:

$$\begin{aligned}
\epsilon_p \equiv \frac{\partial P}{\partial p_e}\frac{p_e}{P} &= (1+\mu)\left(\frac{1}{\gamma^e} + \frac{\partial w}{\partial p_e}\frac{1}{\gamma^l}\right)\frac{p_e}{(1+\mu)uc} \\
&= \frac{uc_e}{uc} + \frac{\partial w}{\partial p_e}\frac{p_e}{w}\frac{uc_l}{uc} \\
&= \Gamma^e + \epsilon_w\Gamma^l.
\end{aligned}$$

A.2.3 Monopsony scenario

In the *monopsony* scenario we have $\frac{\partial \mu}{\partial p_e} < 0$ and $\frac{\partial w}{\partial p_e} = 0$.

Profit share We first calculate the derivative of π with respect to p_e:

$$\frac{\partial \pi}{\partial p_e} = \frac{\frac{\partial \mu}{\partial p_e}\left(1+\mu\right) - \frac{\partial \mu}{\partial p_e}\mu}{\left(1+\mu\right)^2} = \frac{\partial \mu/\partial p_e}{\left(1+\mu\right)^2}.$$

The elasticity ϵ_π can be compute as:

$$\begin{aligned}\epsilon_\pi &= \frac{\partial \pi}{\partial p_e}\frac{p_e}{\pi} = \frac{\partial \mu/\partial p_e}{\left(1+\mu\right)^2} \cdot p_e \cdot \frac{1+\mu}{\mu} \\ &= \frac{\partial \mu}{\partial p_e}\frac{p_e}{\mu}\frac{1}{1+\mu} = \frac{\epsilon_\mu}{1+\mu}.\end{aligned}$$

Wage share We first calculate the derivative of θ with respect to p_e:

$$\frac{\partial \theta}{\partial p_e} = -\frac{\frac{\partial \mu}{\partial p_e}\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right) + \frac{\gamma^l}{w\gamma^e}\left(1+\mu\right)}{\left(1+\mu\right)^2\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)^2}.$$

The elasticity ϵ_θ can be compute as:

$$\begin{aligned}\epsilon_\theta \equiv \frac{\partial \theta}{\partial p_e}\frac{p_e}{\theta} &= -\frac{\frac{\partial \mu}{\partial p_e}\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right) + \frac{\gamma^l}{w\gamma^e}\left(1+\mu\right)}{\left(1+\mu\right)^2\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)^2} \cdot p_e \cdot \left(1+\mu\right)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right) \\ &= -\frac{\frac{\partial \mu}{\partial p_e}\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right) + \frac{\gamma^l}{w\gamma^e}\left(1+\mu\right)}{\left(1+\mu\right)\left(1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\right)} \cdot p_e = -\left(\frac{\partial \mu}{\partial p_e}p_e\frac{1}{1+\mu} + \frac{p_e}{w}\frac{\gamma^l}{\gamma^e}\frac{1}{1+\frac{p_e}{w}\frac{\gamma^l}{\gamma^e}}\right) \\ &= -\left(\frac{\partial \mu}{\partial p_e}\frac{p_e}{\mu}\frac{\mu}{1+\mu} + \frac{uc_e/uc_l}{1+uc_e/uc_l}\right) = -\left(\epsilon_\mu \pi + uc_e/uc\right) \\ &= -\left(\epsilon_\mu \pi + \Gamma^e\right).\end{aligned}$$

Price We first calculate the derivative of P with respect to p_e:

$$\frac{\partial P}{\partial p_e} = \frac{\partial \mu}{\partial p_e}\left(\frac{w}{\gamma^l} + \frac{p_e}{\gamma^e}\right) + \frac{1+\mu}{\gamma^e}.$$

The elasticity ϵ_p can be computed as:

$$
\begin{aligned}
\epsilon_p &\equiv \frac{\partial P}{\partial p_e}\frac{p_e}{P} = \left[\frac{\partial \mu}{\partial p_e}\left(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\right)+\frac{1+\mu}{\gamma^e}\right]\cdot p_e \cdot \frac{1}{\left(1+\mu\right)\left(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\right)} \\
&= \frac{\partial \mu}{\partial p_e} p_e \frac{1}{1+\mu} + \frac{p_e}{\gamma^e}\frac{1}{\left(\frac{w}{\gamma^l}+\frac{p_e}{\gamma^e}\right)} = \frac{\partial \mu}{\partial p_e}\frac{p_e}{\mu}\frac{\mu}{1+\mu} + \frac{uc_e}{uc} \\
&= \epsilon_\mu \pi + \Gamma^e.
\end{aligned}
$$

B Disentangling redistribution and recession effects in aggregate wage loss

In Section 5.4.1, we discussed the reduction in the real value of aggregate wages resulting from a hypothetical oil supply shock occurring in 2019Q1. Here, we describe how to disentangle the distribution effect contribution to the total aggregate wage decline.

Let us call $\mathbf{\Psi}_h^i$ the response of a generic variable i to an oil supply shock at the time horizon h. The $\mathbf{\Psi}_h^i$'s are the IRFs presented in Section 5.4.1; to refer to the effect on impact, we will use $h = 0$, and we will focus on three variables: wage share, GDI, and CPI, indexed as ℓ, Y, and P, respectively.

To isolate the distributive effect on impact, we need a counterfactual where no recession occurred amid the shock, thus we assume that the GDI remain at its 2019Q1 level $\left(Y_{2019Q1}\right)$, irrespectively of the shock. We can then calculate the implicit level of aggregate wages as:

$$
\widetilde{W}_0^{distr} = \underbrace{\left(1+\mathbf{\Psi}_0^\ell\right)\ell_{2019Q1}}_{\text{Distribution effect}} \cdot Y_{2019Q1}, \tag{25}
$$

where ℓ_{2019Q1} is the wage share in 2019Q1. Note that $\widetilde{W}_0^{distr}$ is expressed in 2019 U.S. dollars, and since all other quantities will also be in 2019 U.S. dollars, it can be interpreted as being in real terms.

We can also calculate the level of aggregate wages resulting from an oil supply shock, accounting for both distributional and recessionary effects. This can be done by multiplying Y_{2019Q1} in Equation (25) by the GDI variation due to the shock. However, since GDI is a nominal variable, this approach would mix price changes with real output changes. Hence, to isolate the recessionary contribution, we need to remove the CPI fluctuations induced by the shock. We can therefore write the real value of aggregate wages following the shock as:

$$\widetilde{W}_0^{total} = \underbrace{\left(1+\mathbf{\Psi}_0^{\ell}\right)\ell_{2019Q1}}_{\text{Distribution effect}} \cdot \underbrace{\underbrace{Y_{2019Q1}\left(1+\frac{\mathbf{\Psi}_0^{Y}}{100}\right)}_{\text{GDI response}} \cdot \underbrace{\left(1+\frac{\mathbf{\Psi}_0^{P}}{100}\right)^{-1}}_{\text{Price adjustment}}}_{\text{Recession effect}}. \tag{26}$$

To calculate the real value of GDI resulting from the shock, we divide the GDI response by the CPI level implied by the shock $\left(\widetilde{P}_0\right)$ and then multiply by the actual CPI level in 2019Q1 $\left(P_{2019Q1}\right)$, thereby expressing the result in 2019 U.S. dollars. However, note that by definition:

$$\widetilde{P}_0 = \left(1+\frac{\mathbf{\Psi}_0^{P}}{100}\right)P_{2019Q1} \Longleftrightarrow \frac{P_{2019Q1}}{\widetilde{P}_0} = \left(1+\frac{\mathbf{\Psi}_0^{P}}{100}\right)^{-1},$$

so we can use $\left(1+\frac{\mathbf{\Psi}_0^{P}}{100}\right)^{-1}$ directly as the price adjustment factor in Equation 26.

The aggregate wage loss on impact due to the distributive effect is therefore defined as $\widetilde{L}_0^{distr} = |\widetilde{W}_0^{distr} - W_{2019Q1}|$, where W_{2019Q1} is the actual level of total wages in 2019Q1 calculated as $\ell_{2019Q1} \cdot Y_{2019Q1}$. The total aggregate wage loss is instead given by $\widetilde{L}_0^{total} = |\widetilde{W}_0^{total} - W_{2019Q1}|$. The distributive effect contribution to the total loss in aggregate income is finally given by $\frac{\widetilde{L}_0^{distr}}{\widetilde{L}_0^{total}}$.

All cumulative effects reported in Section 5.4.1 can easily be obtained by calculating the desired variable in each relevant time horizon h and sum over the computed values. For example, the cumulative aggregate wage loss attributable to the distribution effect is computed as: $\sum_{h=0}^{12} \widetilde{L}_h^{distr}$.

C Robustness checks

In this section, we provide some robustness checks. In particular: (i) in Section C.1, we compare the IRFs estimated through the proxy-SVAR with the ones obtained using heteroscedasticity-based identification; (ii) by combining identification by changes in volatility and the external instrument, in Section C.2 we verify whether the proxy used for identification respects the relevance and exogeneity conditions; (iii) in Section C.3, we compare the IRFs estimated through the proxy-SVAR with the ones obtained using local projections; (iv) in Section C.4, we investigate the asymmetric effects of an oil shock on further distributional variables.

C.1 Identification through heteroscedasticity

Identification by changes in volatility (Rigobon, 2003; Rigobon and Sack, 2004) exploits shifts in the covariance matrix of a time series to identify the structural shocks. Formally, since the shifts in the covariance matrix happen at some specific breakpoints, we have the following representation of the covariance matrix:

$$\mathbb{E}\left(\mathbf{u}_t\mathbf{u}_t'\right) = \mathbf{\Sigma}_t = \mathbf{\Sigma}_{\mathbf{u}}\left(m\right), \tag{27}$$

with $t = 1, \ldots, T$ and $m = 1, \ldots, M$, where M is the volatility regime. The structural break(s) provoking changes in variance can be identified using external information (when available) or through statistical tools. For our purposes, we identify one structural break in 2008Q1 and apply a multivariate Chow test. The results of the multivariate Chow test are reported in Table 6. The null hypothesis of no breaks at a particular time point is

Table 6: Test statistics, 95% critical values and p-values of the multivariate Chow test.

Break-point test	
Test statistic	570.1
95% critical value	555.3
p-value	0.0000

rejected, therefore we conclude that the structural break is correctly identified.

Since we detect one structural break, Equation (27) becomes:

$$\mathbb{E}\left(\mathbf{u}_t\mathbf{u}_t'\right) = \begin{cases} \mathbf{\Sigma}_1, & \text{for} \quad t = 1, \ldots, \mathcal{T}_B - 1 \\ \mathbf{\Sigma}_2, & \text{for} \quad t = \mathcal{T}_B, \ldots, T, \end{cases} \tag{28}$$

where $\mathcal{T}_B \in \{1, \ldots, T\}$ is the time point of the structural break and $\mathbf{\Sigma}_1 \neq \mathbf{\Sigma}_2$.

Since we assume that the impact matrix $\mathbf{B}$ is constant, the covariance matrices can be decomposed as $\mathbf{\Sigma}_m = \mathbf{B}\mathbf{\Lambda}_m\mathbf{B}'$. Therefore, for each regime we have:

$$\mathbf{\Sigma}_1 = \mathbf{B}\mathbf{\Lambda}_1\mathbf{B}' \qquad \mathbf{\Sigma}_2 = \mathbf{B}\mathbf{\Lambda}_2\mathbf{B}', \tag{29}$$

where $\mathbf{\Lambda}_m = \operatorname{diag}\left(\lambda_{1m}, \ldots, \lambda_{Km}\right)$ with $\lambda_{ij} > 0$ and $i, j = 1, \ldots, K$. The elements λ_{ij} represent the variances of the structural shocks in regime two, while in the first regime, the shocks are normalised in such a way to have unitary variance (i.e. $\mathbf{\Lambda}_1 = \mathbf{I}_K$). If all elements of $\mathbf{\Lambda}_2$ are distinct, the structural shocks are uniquely identified. Assuming that the reduced-form residuals are Gaussian, the matrices $\mathbf{B}$ and $\mathbf{\Lambda}_2$ can be estimated by maximising the following log-likelihood function:

$$\begin{aligned} \ell = & \frac{KT}{2}\log 2\pi - \frac{\mathcal{T}_B - 1}{2}\left[\log\det\left(\mathbf{B}\mathbf{B}'\right) + \operatorname{tr}\left(\widehat{\mathbf{\Sigma}}_1\left(\mathbf{B}\mathbf{B}'\right)^{-1}\right)\right] \\ & - \frac{T - \mathcal{T}_B + 1}{2}\left[\log\det\left(\mathbf{B}\mathbf{\Lambda}_2\mathbf{B}'\right) + \operatorname{tr}\left(\widehat{\mathbf{\Sigma}}_2\left(\mathbf{B}\mathbf{\Lambda}_2\mathbf{B}'\right)^{-1}\right)\right]. \end{aligned} \tag{30}$$

Finally, $\widehat{\mathbf{\Sigma}}_1$ and $\widehat{\mathbf{\Sigma}}_2$ are estimated from $\widehat{\mathbf{u}}_t$ as follows:

$$\widehat{\mathbf{\Sigma}}_1 = \frac{1}{\mathcal{T}_B - 1} \sum_{t=1}^{\mathcal{T}_B - 1} \widehat{\mathbf{u}}_t \widehat{\mathbf{u}}_t' \qquad \widehat{\mathbf{\Sigma}}_2 = \frac{1}{T - \mathcal{T}_B + 1} \sum_{t=\mathcal{T}_B}^{T} \widehat{\mathbf{u}}_t \widehat{\mathbf{u}}_t'. \tag{31}$$

The comparison between IRFs based on proxy-SVAR and heteroscedasticity IRFs is shown in Figures 7 and 8. The black solid lines represent the proxy-based IRFs for oil price innovation normalised to 10% (the dark grey and light grey shaded areas are 68% and 90% confidence intervals respectively). The orange solid lines represent the heteroscedasticity-based IRFs for oil price innovation normalised to 10% (the dotted orange bands and dashed orange bands are 68% and 90% confidence intervals respectively).

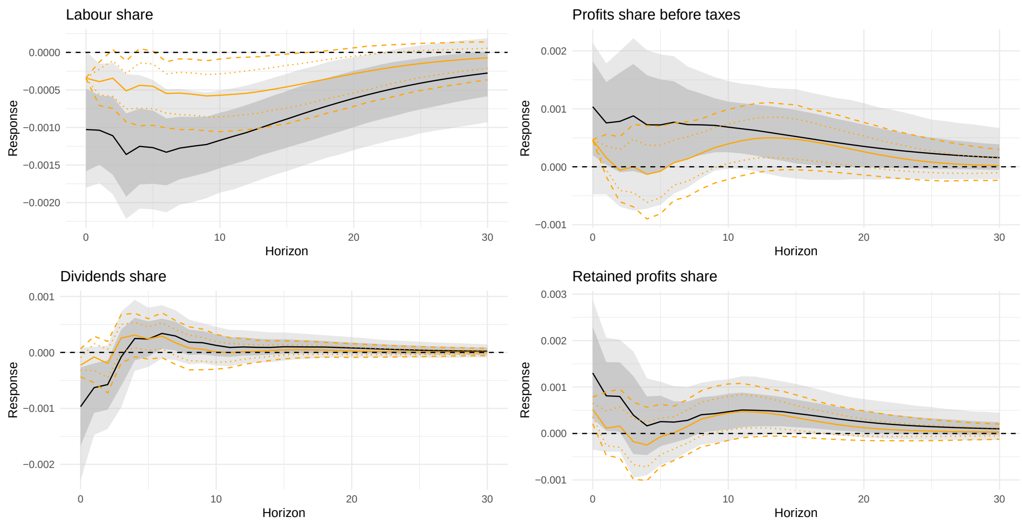

Figure 7: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: proxy-SVAR IRFs 68% and 90% confidence intervals, respectively. *Dotted orange and dashed orange lines*: heteroscedasticity-based IRFs 68% and 90% confidence intervals, respectively. Confidence bands are obtained using 2000 bootstrap replications. Labour share $\equiv \ell_t$; Profits share before taxes $\equiv pr_t^{\text{bt}}$; Dividends share $\equiv d_t$; Retained profits share $\equiv pr_t^{\text{ret}}$. For the variables description we refer to Table 1.

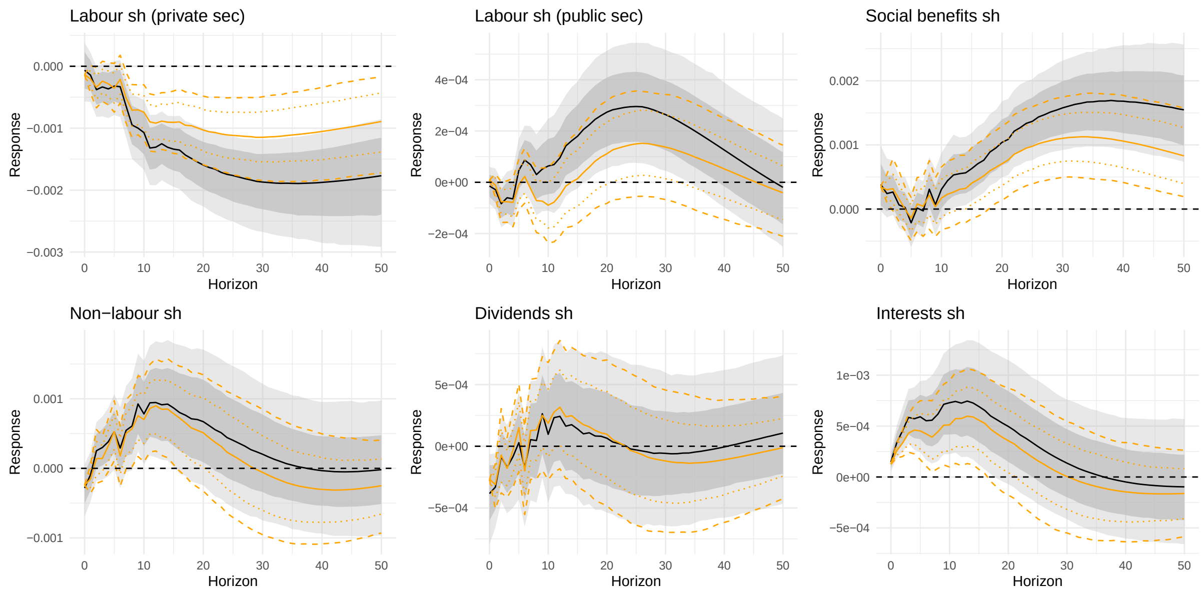

Figure 8: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: proxy-SVAR IRFs 68% and 90% confidence intervals, respectively. *Dotted orange and dashed orange lines*: heteroscedasticity-based IRFs 68% and 90% confidence intervals, respectively. Confidence bands are obtained using 2000 bootstrap replications. Labour sh (private sec) $\equiv \ell_t^{\text{priv}}$; Labour sh (public sec) $\equiv \ell_t^{\text{gov}}$; Social benefits sh $\equiv b_t$; Non-labour sh $\equiv n\ell_t$; Dividends sh $\equiv d_t^{\text{pi}}$; Interests sh $\equiv i_t^{\text{sh}}$. For the variables description we refer to Table 1.

The heteroscedasticity-based IRFs yield results that are qualitatively similar to those obtained using external instrument-based identification. The main finding remains robust: an oil supply shock leads to a redistribution from wages to profits on impact. To be fair, the results of the heteroscedasticity-based IRFs are less pronounced: the decline in the wage share is smaller and the increase in the profit share is less pronounced. Additionally, under the heteroscedasticity-based approach, the drop in the dividend share of GDI is negligible and statistically insignificant, along with the corresponding increase in the retained profit share of GDI. However, proxy-SVAR IRFs and heteroscedasticity-based IRFs are not statistically different.

We also assess the robustness of the results for the shares of aggregate personal income (Figure 8). In this case, the IRFs are similar on impact, both qualitatively and quantitatively. However, some variables revert to their pre-shock levels more quickly when the IRFs are derived using the heteroscedasticity-based identification method, with this effect being particularly evident for the private sector labour share.

C.2 Testing instrument validity

In the same vein of Schlaak et al. (2023), we combine the information coming from the instrument with identification through heteroscedasticity in an AC-SVAR (see, e.g., Angelini and Fanelli, 2019; Arias et al., 2021; Giacomini et al., 2022) to test instrument validity. In the following, without loss of generality, we order the structural shock of interest first.

Let us introduce the AC-SVAR model by first rewriting Equation (8) as follows:

$$\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{A}\mathbf{x}_t + \mathbf{u}_t, \tag{32}$$

where $\mathbf{y}_t$ is the $(K \times 1)$ vector of endogenous variables, $\mathbf{x}_t \coloneqq \left(\mathbf{x}'_{t-1}, \ldots, \mathbf{x}'_{t-P}\right)'$ is the $(KP \times 1)$ vector of lagged variables, $\mathbf{A} \coloneqq (\mathbf{A}_1, \ldots, \mathbf{A}_P)$ is the $(K \times KP)$ matrix of autoregressive coefficients. The instrument has a linear data generating process of the form:

$$z_t = \boldsymbol{\alpha}\boldsymbol{\varepsilon}_t + \eta\omega_t, \tag{33}$$

where $\boldsymbol{\varepsilon}_t$ is the $(K \times 1)$-vector of structural shocks, $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_K)$ is a $(1 \times K)$-vector of coefficients, ω_t is a normalised measurement error term orthogonal to $\boldsymbol{\varepsilon}_t$ and η is a coefficient that scales the effect of the noise.

Now, by combining Equation (32) and Equation (33), we obtain the following augmented VAR:

$$\mathbf{w}_t = \boldsymbol{\delta} + \boldsymbol{\zeta}\mathbf{x}_t + \boldsymbol{\xi}_t, \tag{34}$$

where $\boldsymbol{\delta}$ is the $((K+1) \times 1)$-vector of constants, $\mathbf{w}_t = (\mathbf{y}'_t, z_t)'$ is a vector of dimension $((K+1) \times 1)$, $\boldsymbol{\zeta}$ is the matrix containing the autoregressive components and $\boldsymbol{\xi}_t$ is a $((K+1) \times 1)$ vector of serially uncorrelated residuals. The relation between $\boldsymbol{\xi}_t$ and the structural innovations $\boldsymbol{\nu}_t$ is the following:

$$\begin{aligned} \boldsymbol{\xi}_t =& \mathbf{G}\boldsymbol{\nu}_t \\ =& \begin{bmatrix} \mathbf{B}_{(K\times K)} & \mathbf{0}_{(K\times 1)} \\ \boldsymbol{\alpha}_{(1\times K)} & \eta \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \omega_t \end{bmatrix}. \end{aligned} \tag{35}$$

Identification by changes in volatility allows to identify the matrix $\mathbf{G}$ only locally, which means that is identified up to sign and column permutation if the model respects the following conditions (Lanne et al., 2010): (i) $\mathbf{G}$ is constant; (ii) $\boldsymbol{\nu}_t$ are orthogonal; (iii) $\lambda_{im} = \lambda_{jm}$ for $i, j \in \{1, \ldots, K+1\}$ with $i \neq j$, $\exists m \in \{2, \ldots, M\}$, which means that there are sufficiently many and distinct changes in the variances of $\boldsymbol{\nu}_t$. Conditions (i) and (ii) are common in the proxy-SVAR literature (Stock and Watson, 2012; Mertens and Ravn, 2013) and, in general, in the SVAR analysis. Condition (iii) can be verified by comparing the estimated variances λ_{jm}, with $j = 1, \ldots, K+1$.

To test for exogeneity, we impose zero-restrictions on the vector $\boldsymbol{\alpha}$, i.e. $\boldsymbol{\alpha} = (\alpha_1, 0, \ldots, 0)$, we estimate the matrix

$$\widetilde{\mathbf{G}} = \begin{bmatrix} \boldsymbol{\gamma}_1 & \mathbf{B}_{2:K} & \mathbf{0}_{(K\times 1)} \\ \alpha_1 & \mathbf{0}_{(1\times(K-1))} & \eta \end{bmatrix},$$

where $\boldsymbol{\gamma}_1$ is the $(K \times 1)$-vector of coefficients of interest, $\mathbf{B}_{2:K}$ is the $(K \times (K-1))$-

matrix of coefficients that are not of interest and α_1 is the relevance parameter, through heteroscedasticity and we compute the likelihood of the restricted model. Then, we estimate the unrestricted model, i.e. $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_K)$, and we compare the likelihood of the latter with the one of the restricted model using a likelihood ratio test (LR-test). Formally, we perform the following test:

$$\begin{aligned} \mathsf{H}_0 :& \alpha_2 = \cdots = \alpha_K = 0, \\ \mathsf{H}_1 :& \exists j \in \{2, \ldots, K\} \quad \text{s.t.} \quad \alpha_j \neq 0. \end{aligned}$$

If we reject H_0, then the instrument is endogenous.

To test for relevance we impose the restriction $\alpha_1 = 0$, we estimate the matrix $\widetilde{\mathbf{G}}$ and we compute the likelihood of the restricted model. Then, we estimate the model with α_1 unrestricted and we compare the likelihood of the latter with the one of the restricted model. Under both H_0 and H_1, $\alpha_2 = \cdots = \alpha_K = 0$. In this case, we have the following test:

$$\begin{aligned} \mathsf{H}_0 :& \alpha_1 = 0, \\ \mathsf{H}_1 :& \alpha_1 \neq 0. \end{aligned}$$

If we reject the null, then the instrument is relevant. If the proxy is both relevant and exogenous, then the instrument is valid.

The results of the tests for different VAR specifications are reported in Table 7. The

Table 7: Testing relevance and exogeneity conditions.

		Exogeneity			Relevance		
SVAR	Sample	LR-statistic	DoF	p-value	LR-statistic	DoF	p-value
$\{P_t^{\text{oil}}, Y_t, P_t, \ell_t\}$	1983Q1-2019Q4	0.6602	3	0.8825	12.7501	1	0.0004
$\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{bt}}\}$	1983Q1-2019Q4	0.2179	3	0.9746	14.5801	1	0.0001
$\{P_t^{\text{oil}}, Y_t, P_t, d_t\}$	1983Q1-2019Q4	0.5322	3	0.9118	10.8241	1	0.001
$\{P_t^{\text{oil}}, Y_t, P_t, pr_t^{\text{ret}}\}$	1983Q1-2019Q4	1.6735	3	0.6428	12.8461	1	0.0003

Notes: The table shows the LR-statistic, the number of restrictions (DoF) and the p-value for the tests of proxy exogeneity ($\mathsf{H}_0 : \alpha_2 = \cdots = \alpha_K = 0$, $\mathsf{H}_1 : \boldsymbol{\alpha}$ unrestricted) and proxy relevance ($\mathsf{H}_0 : \alpha_1 = 0$, $\mathsf{H}_1 : \alpha_1 \neq 0$).

LR-statistics for the exogeneity test are small and their p-values are way above the significance levels. Therefore, we cannot reject the null hypothesis of exogeneity and the instrument can be considered exogenous. For what concerns the relevance test, we reject the null hypothesis that the instrument is unrelated to all structural shocks at the 1% significance level. Therefore, it can be considered relevant. Since the proxy is both exogenous and relevant, we can conclude that it is valid.

C.3 Local projections

In the same spirit of Känzig (2021) and Ramey and Zubairy (2018), among others, we compute the IRFs for oil price innovation using local projections (Jordà, 2005) to investigate whether the dynamic implied by the VAR structure is too restrictive. Therefore, we run a set of regressions of the type:

$$y_{k,t+\ell} = \beta_0^k + \psi_\ell^k \widehat{\varepsilon}_{1t} + \boldsymbol{\beta}_\ell^{k,\prime} \mathbf{x}_{t-1} + \xi_{k,t,\ell}, \tag{36}$$

where $y_{k,t+\ell}$, for $k = 1, \ldots, K$, $t = 1, \ldots, T$ and $\ell = 1, \ldots, H$, is the outcome variable of interest, $\widehat{\varepsilon}_{1t}$ is the structural shock identified through the proxy-SVAR, $\mathbf{x}_{t-1}$ is a vector of controls, i.e. one lag of the outcome variables of interest to tackle the issue of non-stationarity, and $\xi_{k,t,\ell}$ is a (serially uncorrelated) error term. Finally, ψ_ℓ^k is the impulse response to the oil shock of variable k at horizon ℓ.

The comparison between IRFs based on proxy-SVAR and local projections IRFs is shown in Figures 9 and 10. The black solid lines represent the proxy-based IRFs for oil price innovation normalised to 10% (the dark grey and light grey shaded areas are 68% and 90% confidence intervals respectively). The orange solid lines represent the local projections-based IRFs for oil price innovation normalised to 10% (the dotted orange bands and dashed orange bands are 68% and 90% confidence intervals respectively).

Figure 9: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: proxy-SVAR IRFs 68% and 90% confidence intervals, respectively. *Dotted orange and dashed orange lines*: Local projections IRFs 68% and 90% confidence intervals, respectively. Confidence bands are obtained using 2000 bootstrap replications. Labour share $\equiv \ell_t$; Profits share before taxes $\equiv pr_t^{\mathrm{bt}}$; Dividends share $\equiv d_t$; Retained profits share $\equiv pr_t^{\mathrm{ret}}$. For the variables description we refer to Table 1.

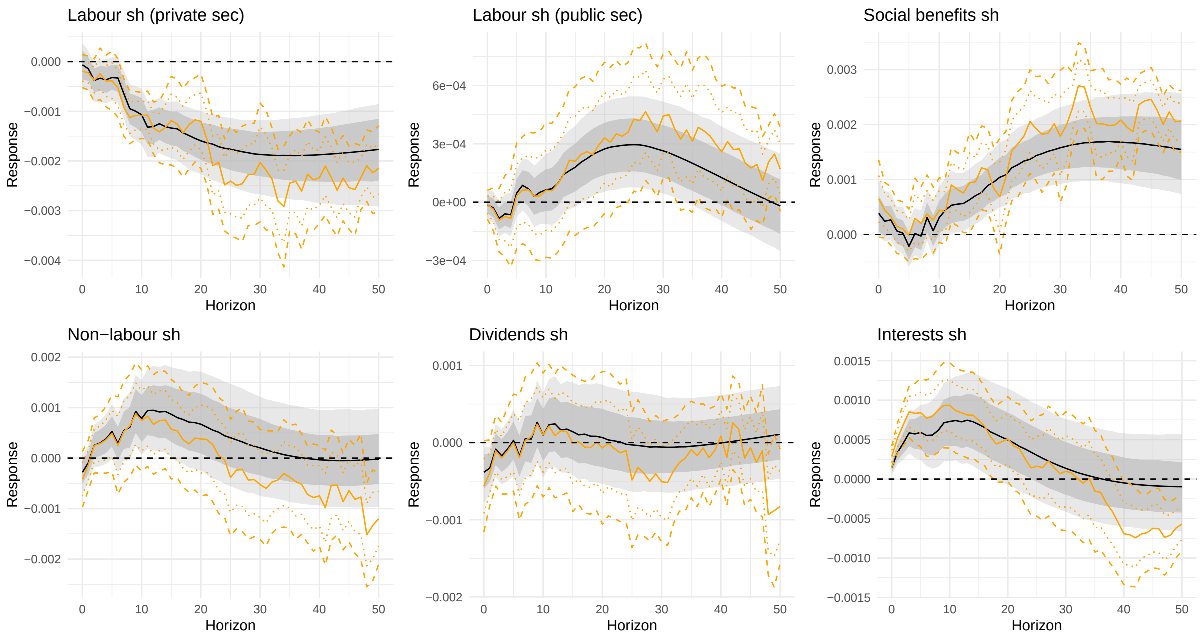

Figure 10: *Solid line*: IRFs for oil price innovation normalised to 10%. *Dark grey and light grey shaded areas*: proxy-SVAR IRFs 68% and 90% confidence intervals, respectively. *Dotted orange and dashed orange lines*: Local projections IRFs 68% and 90% confidence intervals, respectively. Confidence bands are obtained using 2000 bootstrap replications. Labour sh (private sec) $\equiv \ell_t^{\text{priv}}$; Labour sh (public sec) $\equiv \ell_t^{\text{gov}}$; Social benefits sh $\equiv b_t$; Non-labour sh $\equiv n\ell_t$; Dividends sh $\equiv d_t^{\text{pi}}$; Interests sh $\equiv i_t^{\text{sh}}$. For the variables description we refer to Table 1.

In this case, since we include the structural shock identified through the proxy-SVAR directly in the local projection, the IRFs from the local projection estimation closely match those from the proxy-SVAR, for both distributional variables measured as shares of GDI and shares of aggregate personal income. This similarity holds true both on impact and in the periods following the shock.

C.4 Other asymmetric effects

In this section, we further investigate the asymmetric effects of positive and negative oil shocks on some distributional variables, i.e. profits share before taxes, profits share after taxes, dividends share and retained profits share. The asymmetric IRFs for oil price innovation normalised to 10% are shown in Figure 11.

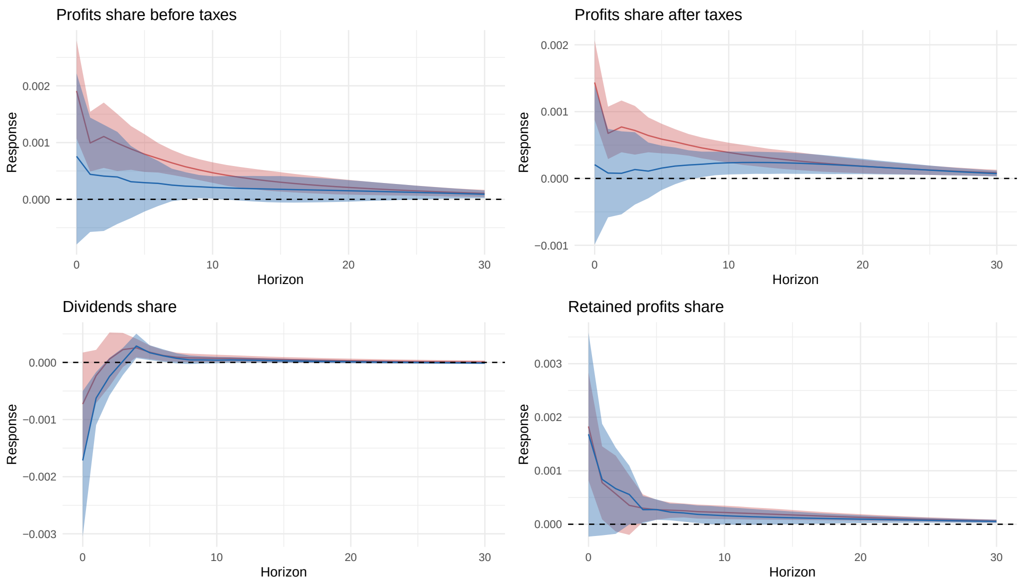

Figure 11: *Solid red line*: Asymmetric IRFs for oil price innovation normalised to 10% (negative shocks). *Light red shaded areas*: 68% confidence interval. *Solid blue line*: Asymmetric IRFs for oil price innovation normalised to 10% (positive shocks). *Light blue shaded areas*: 68% confidence interval. All confidence bands are obtained using 2000 bootstrap replications. Profits share before taxes $\equiv pr_t^{\text{bt}}$; Profits share after taxes $\equiv pr_t^{\text{at}}$; Dividends share $\equiv d_t$; Retained profits share $\equiv pr_t^{\text{ret}}$.

The asymmetry in the profit share reflects the previously discussed asymmetry in the wage share: following a negative oil supply shock, the profit share increases significantly, as firms attempt to maintain profit margins and volume by passing on much of the shock. In contrast, for a positive oil supply shock, the pass-through is considerably lower, and the decline in the profit share is not statistically significant. Finally, we do not observe any asymmetry in the retained profit share of GDI, making any asymmetry in the dividend share of GDI a direct consequence of the asymmetry in the profit share estimates.