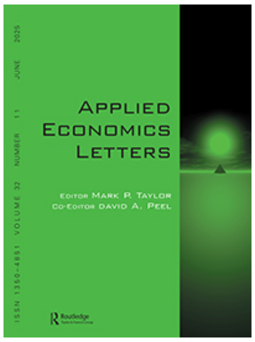

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What are price mark-up shocks?

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ABSTRACT

Using US data, we show that a large share of the variation in price mark-up shocks estimated from standard Dynamic Stochastic General Equilibrium (DSGE) models can be explained by energy and commodity price dynamics. We identify robust drivers of the price mark-up in the US and find that around 30% of the variation in their changes can be explained by variation in energy, metal and import prices. The explanatory power increases to over 60% if short-term fluctuations in price mark-ups are smoothed.

KEYWORDS
Price mark-up shocks; dynamic stochastic general equilibrium models

JEL CLASSIFICATION
E13; E31; E32

I. Introduction

In standard New Keynesian dynamic stochastic general equilibrium (DSGE) models (see Ireland 2004; Smets and Wouters 2007, for instance), inflation dynamics are described by the New Keynesian Phillips Curve. This functional relationship which takes the form

$$\pi_t = \kappa mc_t + \iota\pi_{t-1} + \beta\mathbb{E}_t[\pi_{t+1}], \quad (1)$$

where π_t and mc_t denote respectively inflation and the marginal costs of production at time t, κ, ι, β are model parameters and $\mathbb{E}_t[\cdot]$ is the expectation operator conditional on information up to period t. Common specifications of such models feature labour and capital as the sole inputs of production. Consequently, marginal costs mc_t are a weighted average of wages (w_t) and the rental rate of capital (r_t),

$$mc_t = (1-\alpha)w_t + \alpha r_t, \quad (2)$$

with $\alpha \in (0,1)$. Additionally, in estimated models where inflation is included among the observable covariates, it is common to include a stochastic shock in the Phillips Curve given by Equation (1). The full Phillips Curve is therefore given by

$$\pi_t = \kappa((1-\alpha)w_t + \alpha r_t) + \iota\pi_{t-1} + \beta\mathbb{E}_t[\pi_{t+1}] + \varepsilon_t^p, \quad (3)$$

where the shock ε_t^p captures variation in inflation which is not attributable to an (expected) rise in wages or capital input costs.

The importance of ε_t^p to explain observed inflation dynamics is large. In their seminal contribution Smets and Wouters (2007), find that ε_t^p is the main determinant of inflation in the short run. Several interpretations for the nature of such shocks can be found in the literature. Smets and Wouters (2007) interpret it as a shock to the market power of producers (a *price mark-up shock*) whereas Christiano, Trabandt, and Walentin (2011) describe it as a shock to taxes on production (a *cost-push shock*). The effects of such shocks on inflation have been found to depend on the price-setting behaviour of firms (Khan 2005). The empirical estimates of the responses of price mark-ups to macroeconomic shocks are often found to be inconsistent with standard DSGE models (Born and Pfeifer 2021).

Some contributions in the literature assess the role of energy price shocks in DSGE models by including oil as an input in the production function and explicitly modelling the oil sector (see Lee and Song 2011; Presno and Prestipino 2024, for example). Such a generalization of the model setting leads to a specification of inflation dynamics which incorporates oil price changes as an

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additional driving force of headline inflation. Empirically, global supply chain disruptions and commodity price shocks have been shown to be an important driver of inflation rates in developed economies, in particular in recent times (see Diaz, Cunado, and de Gracia 2024, for example).

In the context of such theoretical uncertainty about the nature of price mark-up shocks in DSGE models, in this paper we show that the changes in price mark-up shocks implied by the model in Smets and Wouters (2007) are well explained by changes in commodity prices, especially energy. In particular, we identify robust drivers of price mark-up shocks in the US using model averaging methods and find that around 30% of the variation in their changes can be explained by variation in energy, metal and import prices. The explanatory power increases to over 60% if short-term fluctuations in price mark-up shocks are smoothed using a rolling average.

The paper is structured as follows. In section II, we briefly present the model framework used (which corresponds to that in Smets and Wouters 2007) and the estimation results. Section III presents the results of the statistical analysis linking price mark-up shock estimates to commodity prices and section IV concludes.

II. The model

We employ the Smets-Wouters model to estimate the price mark-up shock (Smets and Wouters 2007). The model is estimated using Bayesian methods on seven macroeconomic time series of the US economy, sourced from the FRED database[1] GDP, consumption, investment, real wages, hours worked, inflation and the interest rate, for quarterly data ranging from 1957:Q1 to 2007:Q4, with the first 10 years of the sample used to formulate priors about latent states, so the effective sample period starts in 1967:Q1. The data are sourced from the Federal Reserve Economic Database. GDP is expressed in billions of Chained 2017 Dollars, real consumption is measured by real personal consumption expenditures, real investment by real gross private domestic investment and real wages by the real hourly compensation in the nonfarm business sector. Inflation is measured by the implicit GDP price deflator, the interest rate is the Federal Funds Rate and hours worked are measured by average weekly hours in the nonfarm business sector multiplied by the employment level, as in Smets and Wouters (2007). We follow Smets and Wouters (2007) and express real variables per capita by dividing by the total population over 16 years of age, use growth rates for GDP, consumption, investment and wages and we remove a log-linear trend from our measure of aggregate hours worked.

The estimation is performed using 250,000 draws of a Random Walk Metropolis-Hastings algorithm, where the first 100,000 are discarded as burn-ins. The parameter estimates are displayed in Table 1 and compared with the original estimates from Smets and Wouters (2007) (SW), which were obtained for data ranging until 2004. We present the mean, 5th and 95th percentile of the posterior distribution for each estimated parameter. The estimates are largely in line with those reported in the original paper.

We apply the Kalman smoother to the state space representation of the linearized model to estimate the historical trajectory of the price mark-up shock and we employ the median estimate in the subsequent empirical analysis.

III. Predictors of price mark-up shocks

In order to assess empirically the predictors of the estimated price mark-up shocks, we estimate linear models where the variation in the mark-up shock is potentially explained by variation in the price of metals, energy, food, housing, vehicles, electricity and oil, as well as the interest rate, the tax rate and import prices. We entertain models where the price mark-up shock is expressed in (a) quarter-on-quarter percent changes, or (b) relative log-level to the GDP deflator (approximated by taking the difference between the percent change of the respective price index and inflation and forming the cumulative sum). In addition, we estimate models where the variables are smoothed using a 4-quarter moving average, to eliminate short-term volatility.

[1]All data are obtained from fred.stlouisfed.orgfred.stlouisfed.org.:

Table 1. Posterior distribution of the parameters in the model based on data ranging from 1957:Q1 to 2007:Q4 compared to Smets and Wouters (2007) (SW).

		Mean		5%		95%	
		Update	SW	Update	SW	Update	SW
ϕ_K	Capital adjustment cost	3.93	5.74	2.81	3.97	5.25	7.42
σ_c	Intertemporal eos	1.29	1.38	1.07	1.16	1.54	1.59
h	Habit formation	0.54	0.71	0.43	0.64	0.66	0.78
ξ_w	Calvo wages	0.57	0.70	0.44	0.60	0.68	0.81
σ_L	Inverse Frisch elasticity	2.25	1.83	1.10	0.91	3.40	2.78
ξ_p	Calvo prices	0.65	0.66	0.55	0.56	0.74	0.74
ι_w	Wage indexation	0.57	0.58	0.34	0.38	0.79	0.78
ι_p	Price indexation	0.56	0.24	0.40	0.10	0.72	0.38
ψ	Capital utilization adjustment cost	0.56	0.54	0.39	0.36	0.74	0.72
Φ	Fixed cost of production	1.59	1.60	1.46	1.48	1.75	1.73
r_π	Taylor rule inflation coefficient	1.76	2.04	1.49	1.74	2.04	2.33
ρ	Interest rate indexation	0.80	0.81	0.75	0.77	0.84	0.85
r_y	Taylor rule output gap coefficient	0.21	0.08	0.15	0.05	0.28	0.12
r_{dy}	Taylor rule output growth coefficient	0.26	0.22	0.20	0.18	0.33	0.27
$100(1-\beta^{-1})$	Discount factor	0.23	0.16	0.06	0.07	0.48	0.26
α	Capital share	0.15	0.19	0.13	0.16	0.16	0.21
σ_a	St. dev. productivity shock	0.46	0.45	0.42	0.41	0.51	0.50
σ_b	St. dev. financial shock	0.53	0.23	0.32	0.19	0.89	0.27
σ_g	St. dev. govt. spending shock	0.32	0.53	0.29	0.48	0.35	0.58
σ_I	St. dev. investment efficiency shock	1.79	0.45	1.51	0.37	2.08	0.53
σ_r	St. dev. monetary policy shock	0.24	0.24	0.22	0.22	0.27	0.27
σ_p	St. dev. price mark-up shock	0.05	0.14	0.03	0.11	0.07	0.16
σ_w	St. dev. wage mark-up shock	0.17	0.24	0.12	0.20	0.23	0.28
ρ_a	Persistence productivity shock	0.96	0.95	0.94	0.94	0.98	0.97
ρ_b	Persistence financial shock	0.78	0.22	0.64	0.07	0.88	0.36
ρ_g	Persistence govt. spending shock	0.94	0.97	0.91	0.96	0.97	0.99
ρ_I	Persistence investment efficiency shock	0.25	0.71	0.12	0.61	0.39	0.80
ρ_r	Persistence monetary policy shock	0.12	0.15	0.03	0.04	0.25	0.24
ρ_p	Persistence price mark-up shock	0.92	0.89	0.81	0.80	0.99	0.96
ρ_w	Persistence wage mark-up shock	0.92	0.96	0.87	0.94	0.95	0.99
μ_p	MA coef. price mark-up shock	0.59	0.69	0.43	0.54	0.75	0.85
μ_w	MA coef. wage mark-up shock	0.42	0.84	0.28	0.75	0.55	0.93
ρ_{ga}	Productivity effect on govt. spending	0.22	0.52	0.13	0.37	0.31	0.66

Metals prices are measured by the corresponding Producer Price Index. Energy, food, housing, vehicles and electricity prices are measured by the corresponding Consumer Price Index for urban consumers in U.S. cities. The oil price is measured by West Texas Intermediate spot price. The interest rate is the Federal Funds rate. Tax rates are measured by taxes less subsidies on production and imports as a share of GDP. Import prices are measured by the implicit price deflator for imports of goods and services.[2]

We perform Bayesian Model Averaging (BMA, see Steel 2020, for a review) on the class of linear regression models linking the price mark-up shock with all possible combinations of the explanatory variables used, in order to address specification uncertainty. Bayesian approaches to model uncertainty have been known to perform particularly well as variable selection techniques when compared to alternative methods, such as Lasso or ridge regressions (see Bainter et al. 2023; Porwal and Raftery 2022, for example). We present the estimation results of the corresponding *median probability models* (Barbieri et al. 2021; Barbieri, Berger, and Universita Roma Tre 2004). The median probability model is the single specification with covariates corresponding to the controls which achieve more than 0.5 posterior inclusion probability in the BMA exercise. We employ a g-prior on the parameters of the individual models (Fernandez, Ley, and Steel 2001) and a beta-binomial hyperprior on model size (Ley and Steel 2009) to obtain the posterior model probabilities and thus the posterior inclusion probabilities of the individual covariates.[3]

[2]The data are sourced from the FRED database and their series IDs can be found in Table A1.

[3]In order to ensure the robustness of our results, we also performed our empirical analysis making use of Lasso regressions. Although the selected variables partly differ from those included in the median model, the qualitative insights of the specifications estimated using Lasso are similar.

Table 2. Median probability models for the price mark-up.

	change (%)	relative price	change (%) smoothed	relative price smoothed
Energy price	0.010***		0.008***	0.068***
	(0.001)		(0.002)	(0.021)
Import price	−0.012***		−0.020***	
	(0.003)		(0.003)	
Metals price	0.007***	0.161***	0.010***	0.173***
	(0.002)	(0.037)	(0.003)	(0.026)
Electricity price	0.008***		0.013***	−0.143***
	(0.003)		(0.003)	(0.035)
Food price		0.470***		0.422***
		(0.057)		(0.048)
Tax rate			0.010***	0.012***
			(0.004)	(0.003)
Oil price			0.002**	
			(0.001)	
Intercept	−0.009*	− 0.025***	− 0.014***	− 0.048***
	(0.005)	(0.005)	(0.004)	(0.006)
Observations	163	163	160	160
R^2	0.288	0.353	0.445	0.654
Adjusted R^2	0.270	0.345	0.424	0.643

Standard errors in parenthesis, $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The estimates from the median probability models are presented in Table 2 for the different transformations of the variables. The variables employed can explain between 29% and 65% of the variation in the dynamics of price mark-up shocks, depending on the particular measure used. Price mark-up shocks correlates positively with changes in energy and food prices, as well as with the price of commodities such as metals and oil.

IV. Conclusions

We show that a large part of the variation of price mark-up shock estimates obtained from standard DSGE models can be explained making use of energy and commodity price dynamics. The results of the analysis imply that modelling energy markets within DSGE specifications appears central to the understanding of price mark-up shock dynamics (see Batten and Millard 2024, for example)

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Al the data used in the paper are available from the authors upon request.

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Appendix: Data sources

Table A1. Explanatory variables in the model averaging exercise.

Indicator	Series Name	Series ID
Metals price	Producer Price Index by Commodity: Metals and Metal Products	WPU10
Energy price	Consumer Price Index for All Urban Consumers: Energy in U.S. City Average	CPIENGSL
Food price	Consumer Price Index for all Urban Consumers: Food in U.S. City Average	CPIUFDSL
Housing price	Consumer Price Index for All Urban Consumers: Housing in U.S. City Average	CPIHOSSL
Vehicle price	Consumer Price Index for All Urban Consumers: New Vehicles in U.S. City Average	CUSR0000SETA01
Electricity price	Consumer Price Index for All Urban Consumers: Electricity in U.S. City Average	CUSR0000SEHF01
Oil price	Spot Crude Oil Price: West Texas Intermediate	WTISPLC
Interest rate	Federal Funds Effective Rate	FEDFUNDS
Tax rate	Taxes on production and imports less subsidies	W254RC1Q0275BEA
Import price	Imports of goods and services (implicit price deflator)	A021RD3Q086SBEA