The Transmission of Supply Shocks in Different Inflation Regimes*

Sarah Arndt† Zeno Enders‡

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Abstract

We show that the impact of supply on consumer prices is state-dependent. First, we let the data determine two inflation regimes and find that they are characterized by high and low inflation volatility. We then identify supply shocks using instrumental variables based on outliers in the producer price series. Such shocks exhibit a more substantial and more persistent effect on downstream prices during periods of elevated inflation volatility compared to phases of more stable consumer price growth. Exogenously differentiating regimes by the level of inflation or the shock size does not reveal state dependency. The evidence supports a model in which producers optimally invest in price flexibility. This model predicts that stricter inflation targeting lowers inflation volatility in two ways: it reduces price flexibility and, consequently, the pass-through of all shocks to inflation on top of the standard channel that affects demand.

Keywords: Inflation regimes, supply shocks, monetary policy, cost pass-through, producer prices

JEL-Codes: E31, E52, E32

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†Heidelberg University

‡Heidelberg University, CESifo, and HEiKA - Heidelberg Karlsruhe Strategic Partnership, Heidelberg University, Karlsruhe Institute of Technology (KIT)

1 Introduction

Policymakers have, particularly during times of rising inflation, voiced the suspicion that the reaction of inflation to external shocks is not stable over time but depends on the level or volatility of inflation itself.[1] Such changing dynamics would be particularly significant for central banking, impacting inflation forecasts and the expected outcomes of monetary policy actions. Specifically, inflation projections often hinge on assumptions regarding the speed and extent to which changes in producer prices are transmitted to consumer prices. These considerations are crucial when central banks aim to contain price pressures generated by supply shocks.[2] Relying on theory for this question is difficult, as alternative models of nominal rigidities, such as menu costs or Calvo pricing, yield different predictions for the pass-through of supply shocks to consumer prices. Consequently, identifying changing inflation dynamics also informs us about the validity of certain model assumptions.

We investigate this issue empirically by analyzing whether and when inflation dynamics undergo general changes. Using US data, we uncover two regimes by estimating a Markov-switching process based on inflation dynamics. Crucially, we do not restrict the regimes to depend on some exogenous indicator, such as an inflation threshold, but let the inflation process itself endogenously determine them. It turns out that inflation volatility (quick changes in inflation rates) plays a more significant role in determining the regimes than its level. More precisely, if annualized monthly inflation changes by more than 5.2 pp. (as in April, May, and July 2022), the economy is likely to be in a high volatility regime.[3]

In a second step, we investigate state-dependent causal effects of a shock to producer prices—provided by the the Bureau of Labor Statistics—on downstream price growth. Starting in 1948, we estimate how supply shocks to the crude material PPI dynamically affect consumer prices. We also investigate the effects on intermediate stages of the production process. We rely on PPI data as we are interested in more broadly defined supply shocks instead of price movements of a single input factor, which generalizes the results. Given that, e.g., crude materials display a much larger variance compared to consumer prices, PPI price processes are noisier. We, therefore, use movements in the crude-material PPI series that exceed normal fluctuations in input prices and move material prices and production in different directions as instruments for supply shocks.

[1] Philip Lane, Member of the Executive Board of the ECB, writes on November 25, 2022: "Our corporate contacts started [towards the end of 2021] expressing more concern about the persistence of input cost pressures, raising their price expectations for 2022 (also in view of rising energy prices). [...] Since the beginning of this year, many contacts also told us that prices would be increased more frequently." (Lane, 2022) More frequent price changes would alter the nature of the inflation process profoundly, as regards, e.g., the strength and speed of cost pass-through to inflation.

[2] See Sinn (2021) for an early warning of the 2021/22 surge in inflation based on rising producer prices and the implications for monetary policy.

[3] Here and the following, we use the words state and regime interchangeably.

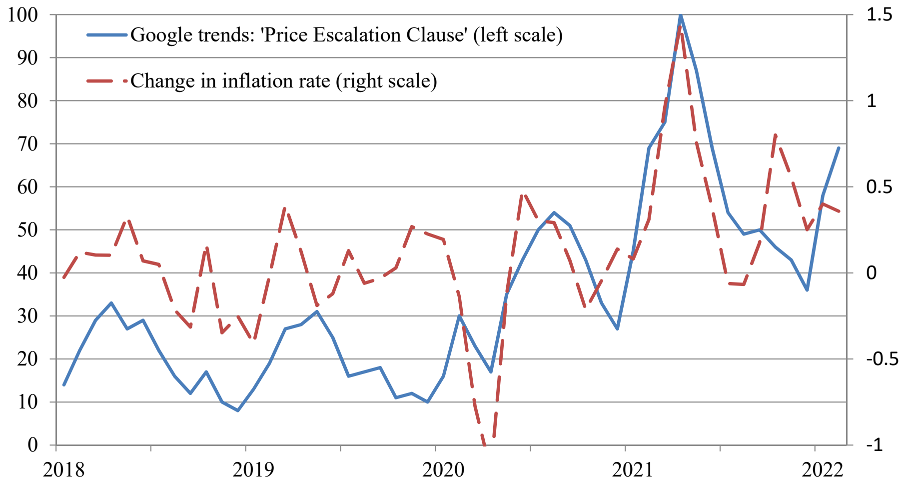

Figure 1: Escalation clauses. Index for Google searches of 'Price escalation clause' (left axis) and monthly change in annualized s.a. CPI inflation rate in percentage points (right scale).

Our results show that in periods of high inflation volatility, downstream prices, including the consumer price index (CPI), react much more strongly to cost shocks on impact and in subsequent months. In this regime, prices are arguably more flexible and, hence, react more promptly to shocks. We validate our results for general supply shocks by estimating the responses to a specific one, i.e., oil-supply shocks as identified by Baumeister and Hamilton (2019). Again, the CPI exhibits a swifter and more pronounced reaction in the high-volatility state.[4]

To emphasize the critical role of inflation volatility in determining regimes, we explore whether similar state dependencies emerge when departing from the endogenous determination of regimes via the Markov-switching model. Our long sample—879 months—allows us to disentangle periods of large shocks, high inflation, and high inflation volatility. These episodes are correlated, but not identical and are of different natures. Specifically, we repeat our analysis but condition regimes exogenously on the level of CPI inflation or the size of the shocks. Both separations fail to generate a state dependency that comes close to the one induced by inflation volatility.

Our findings can be explained by firms' quicker price adjustments when facing higher price volatility in their sales markets. This explanation is supported by anecdotal evidence from the 2021/22 surge in inflation. Figure 1 depicts Google searches for the term 'Price escalation clause' alongside the change in the CPI inflation rate. If agreed upon in contracts between seller and buyer, these clauses automatically adjust sales prices based on changes in the seller's input costs.[5] That is, widespread use of these clauses implies

[4]Our findings square well with the observation in Borio et al. (2021) that 'salient,' i.e., large and positive, sectoral price movements displayed a lower pass-through to core PCE inflation during the great moderation, compared to previous periods.

[5]The use of price escalation clauses is not just a recent phenomenon in the US; articles dating back to the 1940s already mention these clauses. For example, Mack (1946) describes different variations and provides advice for buyers facing escalation clauses.

a much faster price reaction to upstream cost changes, significantly altering inflation dynamics. Interest in this kind of clause is, as visible in the figure, correlated to the *change* in the inflation rate, peaking in the spring of 2021. This coincided with a swift global rise in input prices due to several factors, among them strained global supply chains. Survey evidence corroborates this observation, as 34% of sampled German firms in the Bundesbank Online Panel reported using price escalation clauses from 2021 onward, compared to only 17% before 2021.

Regarding economic theory, our results, therefore, speak in favor of models in which prices react quicker to shocks in the face of higher inflation volatility. We propose a model based on Devereux (2006) in which price setters can invest in the flexibility of their prices.[6] The crucial difference to other models of state-dependent pricing, such as menu-cost models, is the assumption that firms have an influence on price-setting costs if, in anticipation, they take adequate measures, such as using price-escalation clauses in new contracts. In the presence of strategic complementarities in price setting, the payoff of being able to react quickly to new developments is higher in times of elevated inflation volatility. This increased incentive to invest in price flexibility explains our finding of a more substantial pass-through of cost shocks during periods of volatile inflation. The model predicts a 'double dividend' to inflation targeting in terms of reducing inflation volatility, as it leads to a lower pass-through of shocks to inflation through the traditional direct channel of altering demand, but also indirectly via reducing optimal price flexibility.[7] In contrast, monetary policy that is more accommodating in the face of supply shocks tends to increase price flexibility.

In a dynamic extension of the model, we follow Kimura and Kurozumi (2010) and allow firms to choose an optimal price-setting frequency, based on overall volatility and price-setting costs. The predicted inflation responses to supply shocks in high and low-volatility regimes are reasonably close to our empirical findings. In line with the predictions of the analytical model, we find that stricter inflation targeting dampens the inflation response to cost-push shocks via an endogenous reduction of the price-setting frequency, on top of the standard demand channel. This effect is particularly strong for the high-volatility case. We also compare our empirical results to predictions of prominent alternative pricing models. In menu-cost models, as developed by, e.g., Golosov and Lucas (2007), the shape of CPI responses depends strongly on the shock size, which we do not find in our data for cost-push shocks. Furthermore, standard Calvo price setting would not predict any state dependency at all.

[6] We build our theoretical explanation on Devereux (2006) since his model setup captures the essential determinants for a firm's decision to invest in price flexibility in the most parsimonious way. Moreover, it represents a straightforward implementation of price-escalation clauses in a theoretical framework. Alternatively, but in a very similar spirit, observation costs in a menu cost model as in Álvarez et al. (2018) would also predict that higher volatility leads to more frequent price reviews and, hence, a higher cost pass-through. Rational-inattention models work in a similar way (Mackowiak and Wiederholt, 2009).

[7] See also Kimura and Kurozumi (2010) as well as Paciello and Wiederholt (2014) for a related theoretical mechanism in a context of rational inattention.

Despite the important implications, surprisingly little research has focused on the pass-through of shocks to consumer prices in different inflation regimes until recently. Given the policy relevance of this question, most existing research was conducted in policy institutions. By using Granger-Causality tests, Weinhagen (2002, 2016) demonstrates that upstream changes in prices explain price changes at each stage of production in the BLS PPI data, while more downstream price changes do not Granger-cause price changes. Bobeica et al. (2020, 2021) concentrate on the pass-through of labor costs to output prices, considering two regimes that depend on whether the level and volatility of inflation are above or below their historical means. Their findings, based on a Cholesky decomposition to identify labor cost shocks, indicate a quicker and more substantial pass-through in the high-inflation regime. Similarly, the Bank for International Settlements (2022) investigates the pass-through of relative price changes, oil price shocks, and exchange-rate movements into consumer prices, finding them to be dampened in periods of inflation below 5% (see also Borio et al., 2021, 2023). De Santis and Tornese (2023) find a stronger transmission of energy supply shocks on consumer prices in high-inflation regimes, too, while Ascari and Haber (2022) estimate more substantial price effects of monetary policy shocks, as identified by Romer and Romer (2004), in high-inflation regimes and for large shocks. Using micro data, Vavra (2014) shows that price changes become more dispersed during recessions and that this dispersion is high when more products are changing prices. Our model aligns with these observations, as recessions typically feature higher volatility and higher volatility increases the share of firms that are able to change prices.[8]

Our approach differs from the above studies in that we analyze the effects of general supply shocks, derived by a novel identification scheme, on prices in later stages of production. Importantly, when identifying different inflation regimes, we do not impose a threshold of inflation or its volatility but let the inflation process itself determine the regimes. By doing so, we uncover the significance of inflation volatility in determining the regimes, a factor that has not been considered so far.[9] Using a very long time series allows us to disentangle the effects of high inflation vs. high inflation volatility. This is not an easy task, as, e.g., inflation surges are generally not one-time spikes but lead to a prolonged period of inflation movements, see Blanco et al. (2025). Our sample, however, features periods of high volatility during times of higher and lower inflation levels. Moreover, in our sample, some large shocks trigger high-volatility phases, others do not.

[8]Berger and Vavra (2019) also find evidence for time-varying responsiveness of prices to shocks. Vavra (2014) favors a theoretical explanation based on a menu-cost model featuring shocks to the volatility of idiosyncratic firm productivity, see also Hall (2023). Higher volatility reduces the effect of aggregate demand shocks on output in this context. As described above, our empirical results for supply shocks do not support menu-costs models.

[9]In fact, the empirical literature on state-dependent inflation dynamics typically focuses on the effect of the level of inflation without separating it from the impact of its volatility (see, e.g., Álvarez et al., 2019).

We also contribute to the literature on the general pass-through of cost shocks.[10] A large part of this literature centers on the exchange-rate pass-through (see, e.g., Taylor, 2000; Campa and Goldberg, 2005; International Monetary Fund, 2006; Auer and Schoenle, 2016; Álvarez et al., 2017; Enders et al., 2018; Bonadio et al., 2019). A recurrent finding is a falling exchange-rate pass-through over time until recently, in line with our result that lower inflation volatility is associated with less frequent price adjustments. Amiti et al. (2019) and Muehlegger and Sweeney (2022) consider cost shocks more broadly and find strong strategic complementarities in price setting, an important element in our explanation of the role of CPI inflation volatility in price setting.[11]

The remainder of this paper is organized as follows. Section 2 outlines our methodology, including shock identification. Section 3 presents the results, with robustness checks discussed in Section 3.5. Section 5 develops the model, and Section 6 concludes.

2 Methodology

2.1 A Markov-switching model to detect inflation regimes

We detect inflation regimes by employing a Markov-switching autoregressive model (MS-AR) based on log differences of US CPI data. This type of model was introduced by Hamilton (1989). The basic modeling idea is that there are different states s_t of the AR model characterized by regime-specific model coefficients and error variances. A discrete first-order Markov process governs the transition between these states. In our setting, we restrict the model to have two states. The Markov process can then be described by the following transition matrix:

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}, \quad \text{where} \quad p_{i,j} = Pr(s_{t+1} = j | s_t = i),$$

where inflation dynamics are allowed to differ across states 1 and 2:

$$\Delta CPI_t = \begin{cases} \nu_1 + A_{1,1}\Delta CPI_{t-1} + \cdots + A_{1,4}\Delta CPI_{t-4} + e_{1,t}, & \text{if} \quad s_t = 1 \\ \nu_2 + A_{2,1}\Delta CPI_{t-1} + \cdots + A_{2,4}\Delta CPI_{t-4} + e_{2,t}, & \text{if} \quad s_t = 2. \end{cases} \tag{1}$$

We explain ΔCPI_t (seasonally adjusted CPI data in monthly log differences) by an intercept ν_m and autoregressive terms of four lags, which all switch between $m = \{1, 2\}$

[10] Our paper is also related to studies on the price-setting behavior of firms. Given the vast number of significant contributions in this field, we cannot even give a partial overview of this literature here and thus focus on the most directly related studies.

[11] In a similar vein, using surveys, Blinder et al. (1998) and Fabiani et al. (2005) find that firms hesitate to change prices due to the fear of losing customers to competitors. The importance of competitors' prices is further underlined by Dedola et al. (2022), who, employing micro data, ascertain that the pass-through of import cost shocks is lower for larger firms than for smaller ones, suggesting a role for strategic complementarities. Similarly, Gödl-Hanisch and Menkhoff (2023), also using micro data, show that the pass-through of individual cost shocks undershoots that of aggregate shocks by 40%, likely an effect of strategic complementarity. Moreover, they find a more pronounced pass-through for firms that are uncertain about their future business situation, aligning with our result of a higher pass-through in volatile times.

states, just like the variance of the residual term $e_{m,t}$.[12] We choose a rather small number of regimes and lags to keep the model as parsimonious as possible and thus to increase the reliability of the estimates. In this way we also reduce computational cost significantly.

We estimate the model parameters and the hidden Markov chain with the expectation maximization (EM) algorithm.[13] We then obtain the filtered state probabilities $Pr(State_t)$, which we use for constructing the state indicator H_t (Chauvet and Hamilton, 2006). When the filtered probability of being in State 2 is greater than 0.5 in period t, H_t is assigned the value of 1, and 0 otherwise. Correspondingly, the indicator for being in State 1 is $1 - H_t$.[14]

2.2 State-dependent local projections

We follow the local projection instrumental variable (LP-IV) approach of Stock and Watson (2018) to construct the impulse responses. This method consists of a first-stage regression (2) in which the endogenous variable x_t is regressed on the instrument Z_t, and a second stage (3) that regresses the response variable y_t on the fitted values of the first stage, $\hat{x}_t$, and a set of (lagged) control variables W_t:

$$x_t = \mu_1 + \beta_1 Z_t + \sum_{l=1}^{n} \delta_{1,l} W_{t-l} + \epsilon_t \tag{2}$$

$$y_{t+h} = \mu_{2,h} + \beta_{LPIV,h} \hat{x}_t + \sum_{l=1}^{n} \delta_{2,l} W_{t-l} + u_{t+h}. \tag{3}$$

The coefficients $\hat{\beta}_{LPIV,h}$ then represent the impulse responses at each projection horizon h. $\hat{\mu}_1$ and $\hat{\mu}_2$ denote the intercepts, ϵ_t and u_t the error terms.

Adding to this core model, we interact the fitted values $\hat{x}_t$ and the controls W_t with a state indicator H_t taking the value 0 in State 1, and 1 in State 2. Modifying the second-stage equation (3) in this way allows us to estimate state-dependent impulse response functions (IRFs):

$$\begin{aligned} y_{t+h} =& \mu_{2,h} + (1 - H_t)(\beta^1_{LPIV,h} \hat{x}_t + \sum_{l=1}^{n} \delta^1_{2,l} W_{t-l}) \\ &+ H_t(\beta^2_{LPIV,h} \hat{x}_t + \sum_{l=1}^{n} \delta^2_{2,l} W_{t-l}) + u_{t+h}. \end{aligned} \tag{4}$$

The coefficients $\hat{\beta}^1_{LPIV,h}$ and $\hat{\beta}^2_{LPIV,h}$ form the impulse responses at horizon h in states 1 and 2 respectively. Estimation of equation (4) is done via ordinary least squares regression for each projection horizon h separately.

[12] Since we use monthly data, we also estimated an MS-AR including four lags plus the 12^{th} lag. We did not observe significant differences in the timing of the resulting regimes. The identified regimes are generally not sensitive to the lag length.

[13] For further explanation of the EM algorithm, see Hamilton (1990).

[14] Our main results remain unchanged if we assign periods to State 2 if the filtered probability is above 0.4 or 0.7, where in the latter case we have to reduce the number of lags to 8, as we would otherwise end up with too few outliers in State 2, see below.

The sample we use to estimate our baseline model (4) for the United States is in monthly frequency and spans from October 1948 to December 2021. The endogenous variable x_t is the log difference of the crude materials producer price index (referred to as Crude PPI) of the Bureau of Labor Statistics' stage-of-processing (SOP) system. For the response y_t in the baseline model, we use log differences of the US CPI. In alternative setups, we also employ the SOP-PPI data for intermediate materials, supplies, and components (Intermediate PPI), and finished goods (Finished PPI) or the industrial production SOP data for crude goods (Crude IP) as dependent variables. Appendix A provides more details on the PPI and IP data.

2.3 Shock identification

To identify the causal effect of a producer price shock on consumer price inflation, we identify the effects of unexpected and unusual price movements, filtering out smaller ups and downs over time. Given the relatively high frequency of our data set (monthly), this approach makes us more confident that we identify actual shocks. To do so, we introduce a new identification approach and argue that outliers in time series data, which are often due to rare and unforeseen events, are correlated with the exogenous shocks that we wish to identify.[15] Specifically, we instrument producer prices with a variable based on data outliers in the respective PPI series and assume that outliers in the PPI series are correlated with structural producer price shocks but uncorrelated with other shocks. The outlier-based instrument, hence, satisfies the LP-IV relevance and contemporaneous exogeneity condition of Stock and Watson (2018).[16]

To ensure that demand shocks are not the cause of the observed outliers, we only consider those outliers for which the materials industrial-production index IP^M from the board of governors does not move contemporaneously in the same direction as the Crude PPI.[17] That is, we construct the outlier-based instrument Z_t in the following way:

$$Z_t = \begin{cases} 1, & outlier > 0 \quad \& \quad \Delta IP^M < 0 \\ -1, & outlier < 0 \quad \& \quad \Delta IP^M \geq 0 \\ 0, & else. \end{cases} \tag{5}$$

Z_t takes the value of 1 when there is a positive outlier in the PPI series and no positive movement in the IP series in period t. In case of a negative outlier and no negative change in the corresponding IP series, $Z_t = -1$, and $Z_t = 0$ if no anomaly is detected.

[15] Li et al. (2022) also follow a data-driven approach for shock identification as they identify shocks of Bitcoin and crude oil returns via the empirical quantiles of the two series. Kapetanios and Tzavalis (2010) show that well-known oil price shock events coincide with periods in which they find an outlier in their oil price data.

[16] Those are: i) Z_t must be relevant, i.e., the shock of interest $\eta_{j,t}$ must be correlated with the instrument: $E[\eta_{j,t} Z_t] \neq 0$, ii) Z_t must be contemporaneously exogenous to all other shocks $\eta_{-j,t}$: $E[\eta_{-j,t} Z_t] = 0$ and iii), Z_t must be exogenous to all shocks at all leads and lags: $E[\eta_{t+i} Z_t] = 0, \forall i \neq 0$.

[17] We use this IP index as it corresponds closely to the Crude PPI and is available for our whole sample, starting in 1948.

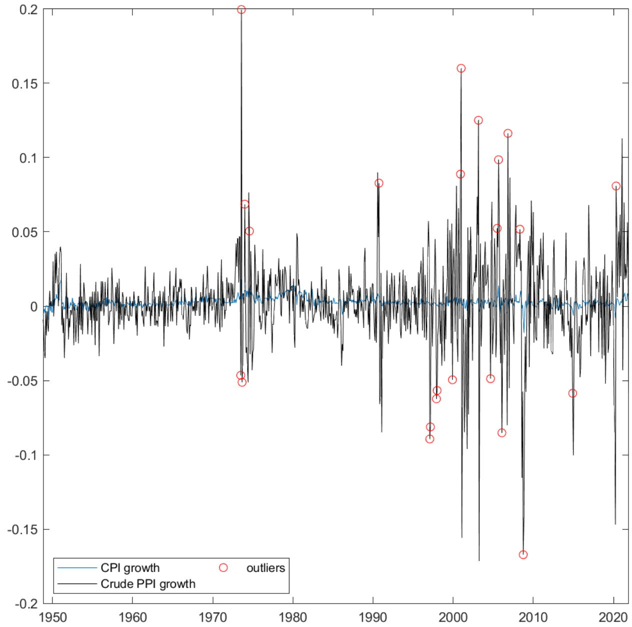

Figure 2: Crude PPI growth and outliers. Monthly growth rates (black) of the Crude PPI series, respectively, against monthly CPI growth (blue). Red circles mark the outliers generated with the iForest algorithm that survive the restriction described in equation (5).

To ensure that Z_t satisfies the third LP-IV condition (exogeneity to all shocks at all leads and lags), we follow Stock and Watson (2018) and include 12 lags of Z_t, y_t, $\Delta \log IP_t^M$, and the growth of the log of the Intermediate PPI, summarized in W_t, as controls in regressions (2) and (4). Furthermore, we include lags of Z_t as controls to correct for a possible correlation between the instrument and past values of the shock of interest. By including lags of the materials IP series as a monthly proxy for activity, we correct for any correlation between Z_t and earlier developments.[18] Controlling for lags of CPI and Intermediate PPI growth rules out the possibility that the instrument Z_t is correlated with a shock to consumer prices or the producer prices of the previous stage. This, in addition to the restriction on ΔIP^M, further ensures that the dynamic effect we measure is not driven by a previous hike in demand leading to an increase in downstream prices first, followed by increasing upstream prices thereafter.

We detect outliers in the producer price indices using the isolation forest algorithm (iForest) proposed by Liu et al. (2012).[19] Instead of first defining normal instances in the data, the iForest directly detects anomalies through two quantitative properties: i) anomalies are the minority, and ii) they have attribute values different from those of normal instances. When setting the proportion of outliers in the PPI series (transformed to log differences) to 0.08, the iForest algorithm detects 71 outliers.[20] Figure 2 shows the Crude

[18]If Crude IP is the dependent variable, we correspondingly control for Crude IP.

[19]Specifically, we use the implementation in the Scikit-learn Python package by Pedregosa et al. (2011). For further explanations of the algorithm, see Liu et al. (2012).

[20]We choose 0.08 as lower values result in too few shocks and consequently weak instruments. Higher values might identify price movements that are not connected to clear supply shocks. We, therefore,

PPI series and the detected outliers at which the materials IP index does not move in the same direction. The outliers coincide with periods when there were prominent events on the supply side that led to large movements in Crude PPI inflation. Visible are the oil-price shock in 1973, which led to a spike in crude-material prices with a subsequent adjustment and re-escalation, the tensions surrounding the gulf war in 1990, the Asian crisis in 1997—which caused a decline of Asian commodities demand (exogenous to the US) and an appreciation of the dollar—OPEC production cuts in early 2001, supply adjustments and a dollar appreciation following the financial crisis in 2008, and supply chain disruptions in 2021.

These shocks occur in phases of low and high inflation volatility. That is, a single outlier does not necessarily move the economy to a high-volatility regime, which might happen for a series of large and/or more frequent smaller shocks. For example, as shown below, turbulent oil prices in the 1970s induced switches to a high-volatility regime, while the Asian crisis did not.

3 Empirical results

We now turn to the results of the baseline specification. We first describe the differences in the identified regimes, then the effects of shocks to producer prices on consumer prices and industrial production in these regimes. In sections 3.3.-3.5 we conduct robustness checks regarding alternative state-dependencies, based on either the level of inflation or the size of the shock. Alternatively, we rely on oil-supply shocks as identified by Baumeister and Hamilton (2019) to measure supply shocks. We also check whether the sign of the shock makes a difference, change the starting date, check the responses of the interest rate and other stages of production, and control for the exchange rate. The conclusion remains the same: it is the prevailing volatility that has a significant impact on the transmission of supply shocks.

3.1 Identified regimes

Figure 3 shows the filtered state probabilities, estimated with the methodology described in Section 2.1, and the resulting state indicator H_t in comparison with monthly growth rates of CPI and inflation volatility. We measure inflation volatility by the variance of monthly CPI growth over a rolling window of 12 months. As is visible, the inflation regime is in State 2 whenever there are sudden swings in monthly CPI growth and generally increased volatility. Specifically, the correlation between the state indicator and a

prefer this rather conservative value. In any case, we also obtain state-dependent responses of inflation to shocks to Crude PPI for values of, e.g., 0.04 or 0.16.

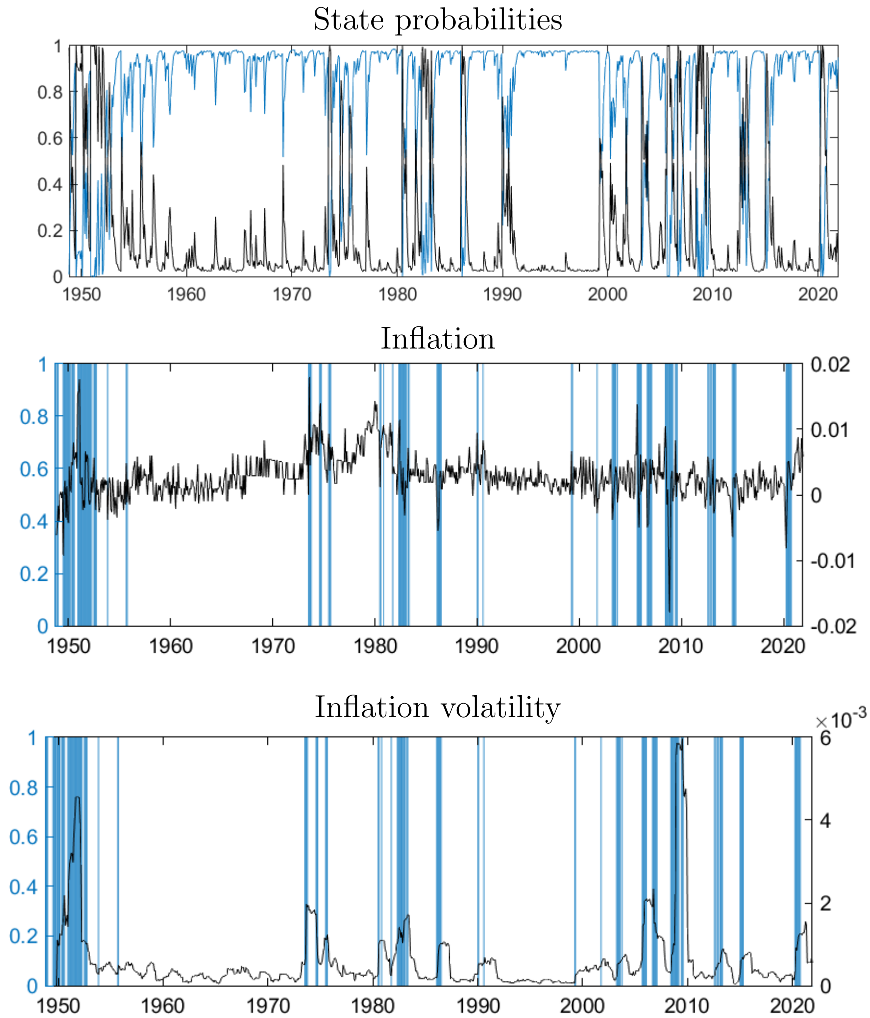

Figure 3: Identified regimes. Top panel: filtered state probabilities estimated from model (1); blue line: State 1, black line: State 2. Middle panel: monthly growth of CPI (black line); white areas: State 1, blue areas: State 2. Bottom panel: inflation volatility (black lines, variance of monthly CPI growth over a rolling window of 12 months); white areas: State 1, blue areas: State 2.

volatility indicator variable vol_t—which takes the value 1 if the absolute change in the CPI is above its average and zero otherwise—is 30% and significant.[21]

In the upper panel of Table 1, we report descriptive statistics for the inflation regimes. The states are relatively persistent: The probability of staying in State 1 when being in the same state (i.e., p_{11}) is 0.97, and 0.87 for State 2 (p_{22}). This translates to an average state duration of 33 periods for State 1 and 7.7 periods for State 2. Comparing the standard deviation of monthly inflation within each state we find an average of 0.27 in State 1 and more than double (0.56) in State 2. This higher volatility is only to a

[21] Using European micro data from 11 countries over the period 2005-19, Gautier et al. (2024) find an increased frequency of price setting at the end of the 2000s in the period during and after the financial crisis, in line with our theoretical interpretation of more flexible prices in State 2. Similarly, Dedola et al. (2023), making use of the same micro data, argue that recent evidence suggests that the return of higher and more volatile inflation seems to be associated with higher frequencies of price changes. Furthermore, Galeone and Gros (2023) find core inflation behavior to have shifted in the 2022/23 period as regards it magnitude, its rate of change, and its stickiness, as well as its responsiveness to energy prices.

Parameters	State 1	State 2
Probability to stay in regime	0.97	0.87
Avg. state duration in months	33	7.7
Std. dev. of monthly Δ CPI in %	0.27	0.56
Mean size outliers crude	0.06	0.07
CPI autocorrelation lag 1	0.75	0.48
CPI autocorrelation lag 2	0.65	0.21
Mean of monthly Δ CPI in %	0.34	0.24

Variables	β	p-value	Variables	β	p-value
constant	-0.30	0.00	vol_{t-5}	0.02	0.36
vol_t	0.46	0.00	vol_{t-6}	0.02	0.37
vol_{t-1}	0.30	0.00	vol_{t-7}	0.05	0.04
vol_{t-2}	0.13	0.00	vol_{t-8}	0.03	0.14
vol_{t-3}	0.12	0.00	vol_{t-9}	0.03	0.24
vol_{t-4}	0.08	0.00	vol_{t-10}	0.00	0.94
R^2	0.69		$Adj.\ R^2$	0.68	
Obs.	589				

Table 1: Regime characteristics and determinants. Upper panel: characteristics of the two regimes. All statistics in percent. Lower panel: regression of filtered state probabilities on exogenous volatility indicator and its lags, maximizing R^2.

very low degree driven by larger outliers in the SOP PPI data, as we find similar values for their mean values at the different stages of production across regimes. Instead, the regime-dependent autocorrelation of monthly CPI growth seems to contribute more to the state differences. We calculate this autocorrelation up to two lags, considering only those regime realizations that consist of at least three consecutive periods. In State 1, we find a value of 0.75 for the first lag and 0.65 for the second, in contrast to 0.48 and 0.21 for lag one and two in State 2. Interestingly, the overall mean of monthly CPI growth is 0.34% in State 1 and only 0.24% in State 2. This highlights that not the overall level of inflation but rather its volatility characterizes the different inflation regimes.

We further demonstrate the regime dependence on inflation volatility by regressing the Markov filtered state probabilities $Pr(State_t)$ on the volatility indicator vol_t in the following way:

$$Pr(State_t) = c + \sum_{i=0}^{t=10} vol_{t-i}. \tag{6}$$

The contemporaneous indicator and the first four lags are significant at the 5% level.[22] Alternatively, we define the volatility indicator variable vol such that the R^2 of the mentioned regression is maximized, reaching 0.69, and find a threshold for the absolute value of the monthly change in CPI growth of 0.43 pp., or 5.28 pp. in annualized terms. That

[22]That is, observing a higher-than-average absolute change in the CPI increases the likelihood to be in State 2, resulting from the Markov-switching model, by 17 pp. If, additionally, the last four monthly absolute changes were also above average, the likelihood is 46 pp. higher.

is, the optimized indicator variable takes the value of 1 if the absolute change in monthly inflation is above this threshold and zero otherwise. This value corresponds to approximately the 90th percentile of our sample; it was reached in, e.g., April 2022 (change in monthly inflation: -0.6 pp.), May 2022 (0.5 pp.), and July 2022 (-1.22 pp.). The correlation between the Markov state probabilities and this indicator is 0.65 and significant. The lower panel of Table 1 reports the resulting coefficients from repeating regression (6) with the optimized threshold. If the current monthly absolute change in CPI growth is above 0.43 pp., the likelihood of being in State 2 increases by 46 pp. (significant at the 1% level), ceteris paribus. The first four lags are also significant at the 1% level with decreasing coefficients.

Results are very similar if we include the contemporaneous values of the monthly VIX index, the growth rate of industrial production, and trend inflation (obtained by HP-filtering monthly inflation rates): the contemporaneous value and the first four lags of the volatility remain significant at the 1% level, while the adjusted R^2 increases to 0.71. The optimal threshold for the indicator is still 0.43 pp. of the change in CPI growth and the correlation of the Markov state probabilities with the indicator remains at 0.65. To sum up, if annualized monthly inflation changes by more than 5.2 pp., the inflation regime is likely to switch to State 2. Furthermore, the longer inflation is volatile, the higher the likelihood of reaching State 2.

3.2 Effects of supply shocks in different volatility regimes

The left panel of Figure 4 shows the state-dependent responses of monthly CPI to a unit shock to Crude PPI over a horizon of 12 months. We estimate regression (4) by setting y_t equal to the changes in the CPI and report the cumulated responses. They are significantly different from each other in states 1 and 2 over almost the whole horizon considered. Specifically, in State 2—the one associated with higher volatility in monthly CPI growth—CPI reacts faster and stronger, compared to State 1. That is, we find clear evidence for state dependency of the CPI response to supply shocks, where the transmission of producer price shocks to consumer prices is stronger and quicker during a high-inflation-volatility regime than during times of more tranquil inflation.[23] The shaded areas represent 68% confidence bands. We construct them with Eicker-Huber-White (EHW) heteroskedasticity-robust standard errors as suggested by Montiel Olea and Plagborg-Møller (2021).[24]

In Appendix B we check several econometric issues, among them potentially weak instruments.[25] Furthermore, the left panel of Figure C-1 in Appendix C demonstrates

[23] Inflation remains mostly higher in State 2 up to a horizon of 23 months and falls thereafter.

[24] They show that when augmenting the local projection with lags of the response variable, EHW standard errors produce favorable results without the need to further correct for serial correlation in the regression residuals. In line with this argument, we include 12 lags of y_t in the local projection regressions.

[25] Using the test of Lewis and Mertens (2022), we show that none of our instruments is weak, see the left panel of Figure B-1.

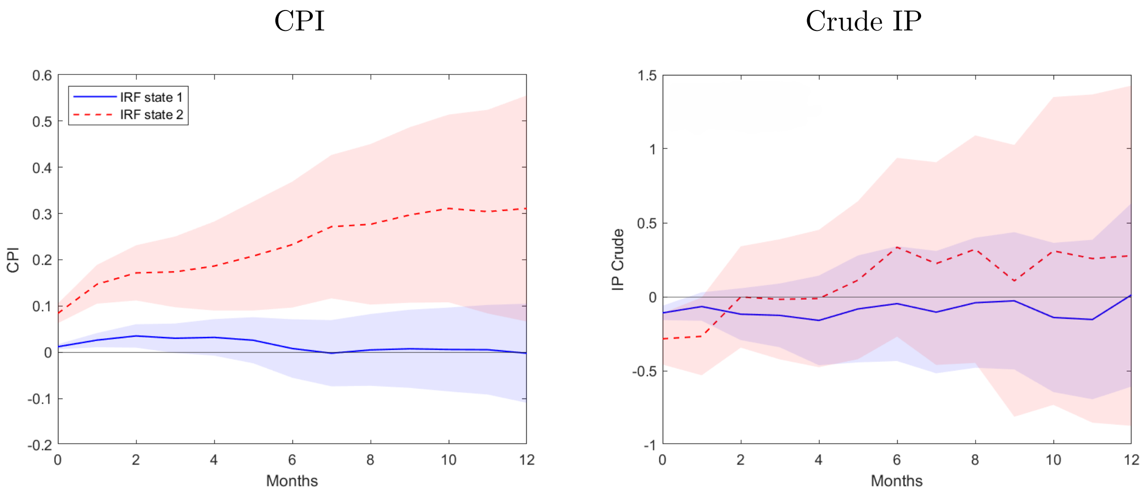

Figure 4: Baseline results. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude PPI (left) and corresponding industrial production response (right). Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

that the different CPI responses in the two regimes are not due to a more expansionary monetary policy reaction in State 2.[26] Lastly, the right panel of Figure C-1 shows that the exchange rate appreciates more in the high-volatility regime, such that regime differences are not due to an exchange-rate depreciation that raises PPIs and the CPI alike.

We also calculate the effect of a shock to Crude PPI on industrial production of crude goods.[27] The right panel of Figure 4 depicts the results. As discussed in Section 2.3, to identify supply shocks we restrict industrial production to decrease in the period of a contractionary PPI shock. In the high-volatility regime, this effect is somewhat more pronounced, but the difference between regimes is much smaller compared to the CPI response and statistically not different from each other throughout.

3.3 Alternative regimes: inflation level and shock size

As stated in Section 2.1, the Markov-switching model indicated to separate regimes by their inflation volatility and not by the level of inflation itself. To further demonstrate that it is this dependency that causes impulse responses to differ across regimes, we no longer consider regimes as they were found by our Markov-switching model. Instead, we investigate whether alternative regime definitions based on the inflation level or the shock size also result in a state-dependent transmission of supply shocks. To this end, we split regimes such that we are in State 1 whenever inflation is below its average value and in State 2 if it is above the average. The left panel of Figure 5 shows the results for regimes below (blue solid lines) and above (red dashed lines) the average inflation level. No clear state dependency is visible. In particular, while the impact response of CPI inflation after

[26] Specifically, monetary policy reacts more strongly to a shock to Crude PPI in State 2 than in State 1, in line with the larger CPI response.

[27] Given the availability of the Crude IP series, we move the starting date to January 1967.

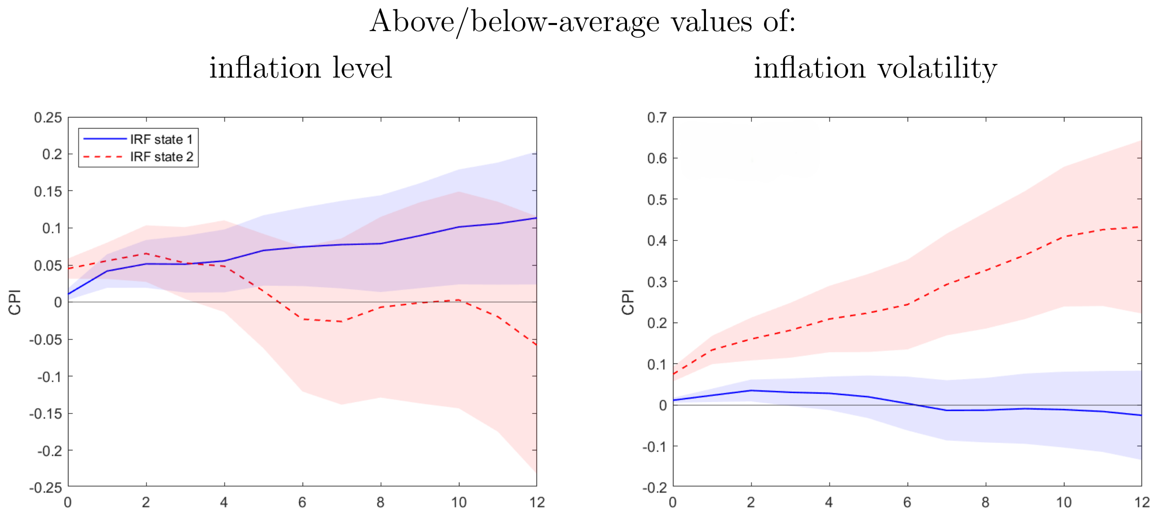

Figure 5: Inflation level vs. volatility. Impulse responses in Regime 1 (low state, solid blue lines) and Regime 2 (high state, dashed red lines) of CPI to a shock to Crude PPI. Left: State 1/2 if level CPI inflation is below/above average. Right: inflation volatility, calculated as in Figure 3, below/above average. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

a shock to Crude PPI is slightly higher than in State 2, it is below State 1 in the following periods. To corroborate this finding, we redo the same analysis for different cut-offs of the inflation level for defining states 1 and 2. Comparing the reactions to supply shocks in states where inflation is above or below its 65th, 70th, 80th, or 90th percentile shows very similar responses.[28]

We then verify that this approach yields state-dependent effects similar to our baseline results when we use inflation volatility, i.e., the change in CPI inflation, to exogenously separate regimes (rather than endogenously, as in our baseline). The right panel of Figure 5 shows the results. State 1 corresponds to a below-average inflation volatility, defined as in Figure 3. Blue solid lines depict the respective responses, while red dashed lines show the responses in State 2 (inflation volatility above its average). The state dependency is indeed similar to our baseline Figure 4, if not stronger. Supply shocks to Crude PPI are transmitted more quickly and strongly to consumer prices if inflation volatility is above average.

Next, we turn to the effects of the shock size. In standard menu cost models without observation costs (such as Golosov and Lucas 2007), price-setting behavior depends on the size of contemporaneous shocks. A central result is that large input-price shocks have a relatively larger impact on consumer prices compared to smaller ones, see Ascari and Haber (2022). Given that periods of higher inflation volatility could be correlated to the average shock size in these periods, we check whether this correlation can explain the above findings. Figure 6 shows the reaction to small versus large shocks. We pursue two alternative strategies. In the left panel, we follow the approach of Ascari and Haber (2022) and include the term $|\hat{x}_t| \cdot \hat{x}_t$ in Model (3), in addition to the existing terms. That

[28] Results are available upon request.

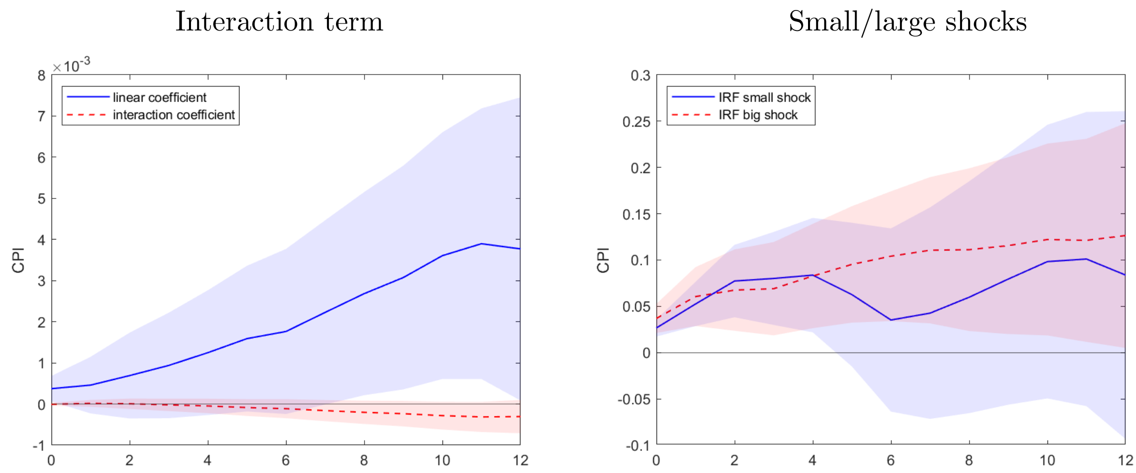

Figure 6: Effects of large vs. small shocks. Impulse responses of CPI to a shock to Crude PPI. Left: specification including linear (solid blue lines) and interaction term $|\hat{x}_t| \cdot \hat{x}_t$ (red dashed lines). Right: shock sizes below (solid blue lines) or above (dashed red lines) average. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

is, we measure the effect of the squared shock but conserve the sign of the shock. We do this independently of the regimes, as we are here interested in the effect of the shock size as an alternative explanation for our results. The effects of input-price shocks on the CPI via this interaction term and the linear coefficient are plotted by red dashed and blue solid lines, respectively. The interaction term is either insignificant or even negative, showing that large supply shocks do not automatically lead to a larger pass-through compared to smaller shocks.[29] If, however, several larger shocks (or a series of smaller shocks) result in higher CPI volatility, the shock transmission is profoundly altered, see above.

In the right panel of Figure 6, we conduct a similar exercise. Specifically, we separate the outliers, as identified in Section 2.3, depending on whether they are larger or smaller than the average. As in the previous exercise, we do not find a significant difference between the effects of relatively large vs. small shocks. That is, the influence of inflation volatility on the effect of supply shocks cannot be explained by the differential effects of the shock size.

3.4 Alternative shocks: oil price shocks

We now turn to an alternative scheme for identifying supply shocks. Specifically, we exchange our identified shocks with oil-supply shocks, i.e., a series of supply shocks that are well established in the literature. We use the oil-supply shocks from Baumeister and Hamilton (2019), which range from February 1975 to December 2022. We again investigate possible differences in the CPI response in the two regimes identified in Section 3.1. The

[29] Given that Ascari and Haber (2022) consider the effects of monetary policy shocks instead of supply shocks, our results do not contradict their findings. For example, the effects of monetary policy decisions depend to a large degree on central bank communication and media coverage, influencing expectations, which might work quite differently depending on the size of the shock.

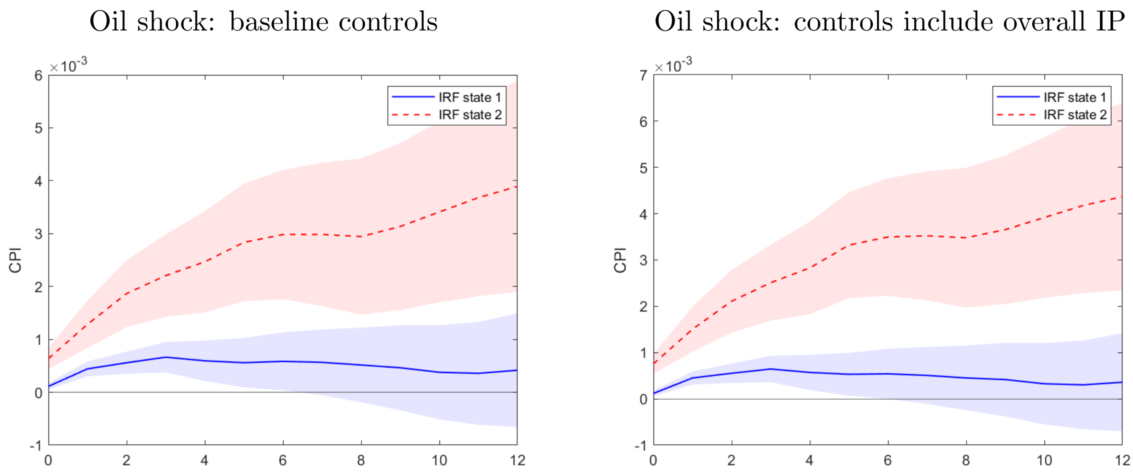

Figure 7: Effects of oil price shocks. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a contractionary oil price shock by Baumeister and Hamilton (2019). Left: baseline controls; right: controls with lags of overall IP. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

left panel of Figure 7 shows the results. In the right panel we include lags of overall industrial production as a control, another way to exclude demand shocks as the source of the responses. As is visible, the effects are similar to our more broad-based supply shocks of the baseline specification. Specifically, the effects of a supply shock are stronger on impact and thereafter in the high-volatility State 2.

3.5 Further Robustness

In this section we explore the robustness of our results with regard to the sign of the shock, different samples, regression setups, and identification schemes.

First, we analyze potential asymmetries between positive and negative shocks. We first create an instrument containing only the positive outliers and then a second one with only negative outliers. We estimate both directions of the shock at the same time to avoid potential biases by truncated variables (Garzon and Hierro, 2021):

$$y_{t+h} = \mu + \beta_h^+ \hat{x}_t^+ + \beta_h^- \hat{x}_t^- + \sum_{l=1}^{n} \delta_{2S,l,1}^T W_{t-l} + u_{t+h}. \quad (7)$$

In Model (7), $\hat{\beta}_h^+$ and $\hat{\beta}_h^-$ denote the positive and negative impulse responses, respectively. $\hat{x}_t^+$ and $\hat{x}_t^-$ are the fitted values from a regression of the dependent variable x_t (Crude PPI) on the positive or negative instrument and lagged controls W_t, which are the same as employed in Model (4). The left panel of Figure 8 reports the resulting CPI responses to positive (solid blue lines) or negative (red dashed lines, positive values for ease of comparison) shocks to Crude PPI. The point estimates are fairly similar and confidence intervals overlap at all horizons. That is, the direction of the shock hardly changes the shape of the responses. An uneven distribution of positive versus negative shocks is, therefore, not responsible for the documented state dependency.

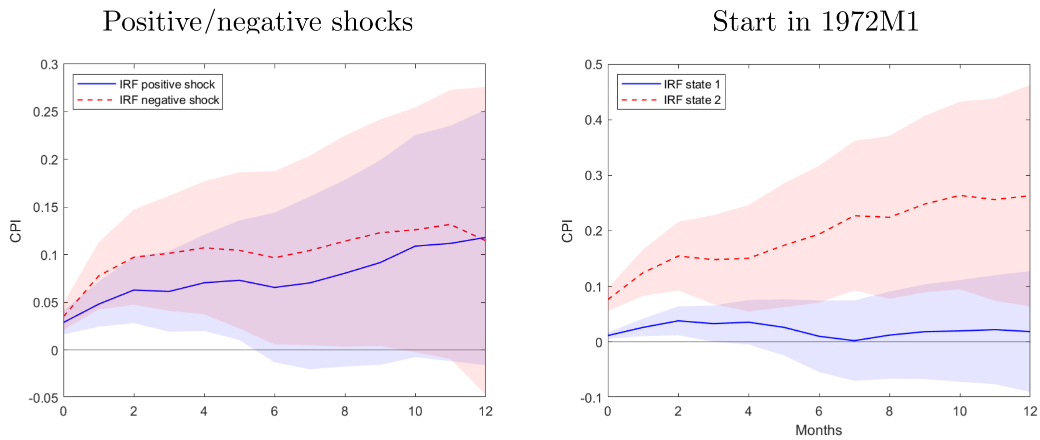

Figure 8: Robustness I. Left: Impulse responses to positive (solid blue lines) and negative (dashed red lines, positive values) of CPI to a shock to Crude PPI. Right: Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude PPI, starting in 1972M1. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

Second, we move the sample start to 1972, after the peg of the dollar to gold was cut and towards the end of regulated oil prices in the US. Results are shown in the right panel of Figure 8 and are similar to the baseline estimates. Third, we change the lag length to 8 lags. Figure 9 shows the cases for a starting date in 1948M10 (left panel) and 1972M10 (right panel). Again, results do not change much.

Fourth, we test different specifications of the local projections to further demonstrate that we do not pick up demand shocks in our analysis. In particular, we include the contemporaneous value of IP^M (in addition to its lags) in the regression. The left panel of Figure 10 displays the results, which are similar to the baseline. The right panel of Figure 10 depicts the case in which we do not only restrict IP^M to have the opposite sign

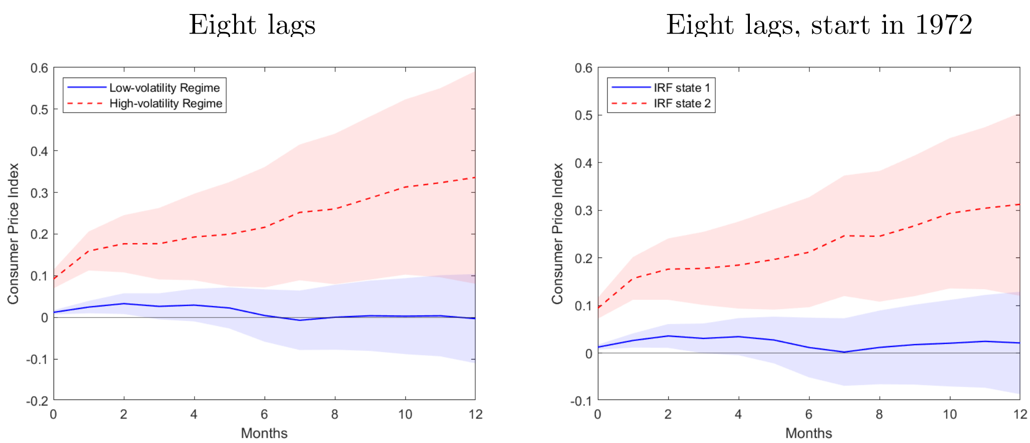

Figure 9: Robustness II. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude PPI. Left: 8 lags, start in 1948M10. Right: 8 lags, start in 1972M1. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

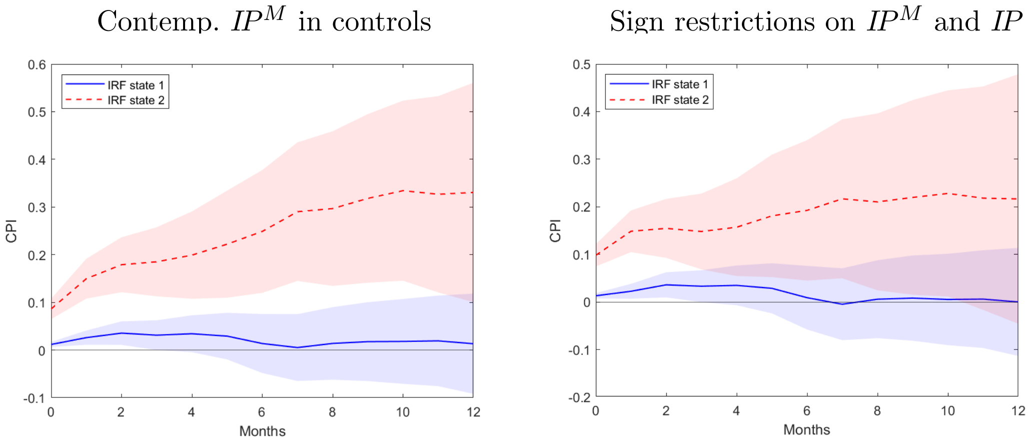

Figure 10: Robustness III. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude PPI. Left: contemporaneous value of IP^M included in controls. Right: sign restrictions on IP^M and overall IP employed. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

as Crude PPI, but both IP^M and overall industrial production.[30] Again, results change only mildly.

Lastly, we explore the possibility that the identified regimes depend on the dependent variable. Specifically, as shown by Gonçalves et al. (2024), if a shock affects the response variable y_t, it could also alter the state indicator H_t, if this depends on y_t. This might affect the state-dependent LP estimands and thus generate a bias in the impulse response. Nonetheless, in our baseline we assume that a one-time unit shock will not induce an alternation of the states as the regimes we estimate a relatively high persistence of 33 months in State 1 and almost 8 months in State 2.[31] In a robustness check, we follow Ramey and Zubairy (2018) and Cloyne et al. (2023) by lagging the indicator variable in regression (4). Results remain similar to our baseline. We also regress the state indicator variable on the contemporaneous and three lags of the fitted values of equation (2). None of the coefficients turns out to be significant.[32]

4 Effects on intermediate stages of processing

Next, we analyze the effect of a producer price shock on the prices of products located downstream in the stages of processing system. That is, we check how a shock to Crude PPI impacts Intermediate and Finished PPI by setting the response variable y_t in (4) equal to Intermediate (left panel of Figure 11) or Finished PPI (right panel). Note that neither PPI includes imports. We add the corresponding industrial production data in

[30] We also include overall IP in the controls in this specification.

[31] Furthermore, given that lags of inflation volatility are important in determining the volatility regime (see above), a one-time shock is not likely to induce a regime switch.

[32] All results are available upon request.

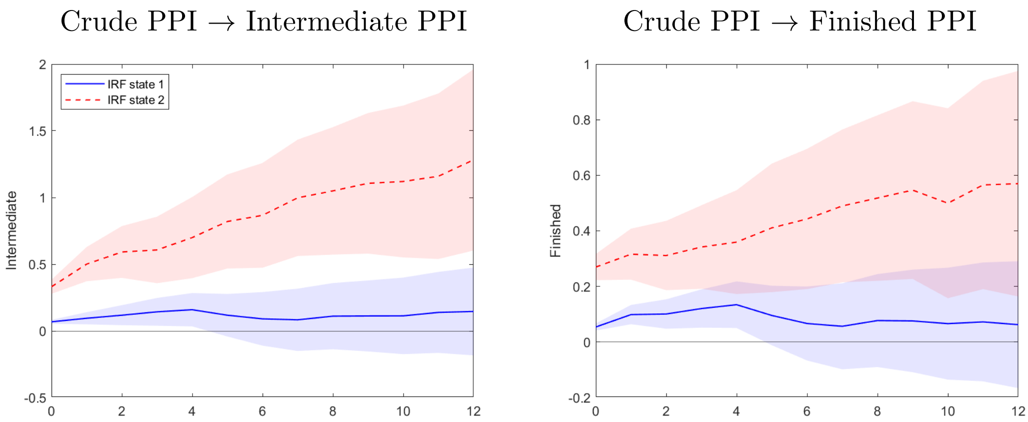

Figure 11: Effects of shocks to Crude PPI on intermediate stages. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of Intermediate PPI (left panel) and Finished PPI (right panel) to a shock to Crude PPI. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

the controls, which moves, due to data availability, the starting date to 1972M1.[33] We leave the rest of Model (4) unchanged.

We again see a significantly differing response between states 1 and 2 on impact and in the following periods. The observation is quantitatively larger for Intermediate PPI than for Finished PPI, where, in turn, the effect is larger than for the CPI. This effect is as expected since at each stage of processing further inputs, such as labor, are added to the input materials.

5 Implications for theory

We now turn to potential theoretical explanations for our empirical finding of a stronger and quicker transmission of input prices to consumer prices in times of high inflation volatility. Our preferred theory assumes that firms are able to invest in price flexibility. In Section 5.1, we first rely on the mechanism developed by Devereux (2006) in a one-period model to derive analytical results. Observation costs as in Álvarez et al. (2018) or models of rational inattention (Mackowiak and Wiederholt, 2009) could also account for our evidence. The main intuition is the same across these models: depending on current observations, firms change their future price-setting behavior. Yet, Devereux's mechanism is much simpler while leading to very similar conclusions. It can also be seen as a direct implementation of price escalation clauses into a standard pricing model. Our version is kept deliberately simple since we aim to derive analytical results and to develop an intuition that could be used in several larger models.[34] We then move on to derive quantitative predictions in an infinite-period version, relying on the mechanism

[33] We equate the industrial production index for primary & semifinished processing with Intermediate PPI and that of finished processing with Finished PPI.

[34] See Khalil and Lewis (2024) for a quantitative version of the model in Devereux (2006) that includes endogenous entry and exit of firms.

proposed by Kimura and Kurozumi (2010) and others. Here, firms invest in price flexibility by choosing the probability of being able to set prices in future periods, where higher flexibility is associated with larger costs.

We discard explanations based on menu costs or Calvo pricing with a fixed Calvo parameter for the following reasons. In standard menu cost models without observation costs (such as Golosov and Lucas 2007), price-setting behavior depends on the size of contemporaneous shocks. A central result is that large input-price shocks have a larger impact on consumer prices than smaller ones, see Ascari and Haber (2022). This prediction can be tested in our data, see Figure 6 for the reaction to small versus large shocks. As discussed in Section 3.3, we do not find a significant difference between the effects of large and small shocks.

Calvo pricing with a fixed Calvo parameter, on the other hand, would predict a constant impact of cost changes on inflation and is, therefore, clearly unable to replicate a state-dependent pass-through. In the following sections, we, therefore, explore a different class of models that can replicate our empirical findings.

5.1 Analytical model

We now sketch our preferred theory in a one-period model. We deviate from the original model in Devereux (2006) by introducing raw input material and a reaction function for the central bank—the model then features demand, supply, and monetary policy shocks—as well as simplifying the model by reducing it to a closed-economy setup and assuming pre-set wages. The following description of the model setup largely follows Devereux (2006), where more detailed derivations can be found. We introduce more significant changes to the original model in Section 5.1.2 and list the corresponding calculations in Appendix D. Model predictions are derived in Section 5.1.3.

5.1.1 Setup

Households maximize a utility function

$$U_t = \sum_{t=0}^{\infty} \log C_t - \frac{L_t^{1+\zeta}}{1+\zeta},$$

subject to the budget constraint $C_t P_t + B_t = (1+i_t)B_{t-1} + W_t L_t + C_{R,t} R_t + \Pi_t$, with $L_t = \int_0^1 L_{j,t}$; C_t is consumption, $L_{j,t}$ is hours worked at firm j, R_t is the aggregate input of raw materials, $C_{R,t}$ their price, Π_t are profits or losses (including price setting costs) from firms, and B_t are nominal bonds that pay $1 + i_t$ in period $t + 1$.[35] W_t is the wage, which is equal for all firms. Consumption bundles are composed of infinitely many varieties of

[35] As we model a closed economy, we assume that raw materials are available with unlimited supply at an fixed price $C_{R,t} = C_{RR,t} W_t$, where the relative price $C_{RR,t}$ of raw material to labor is exogenously given.

goods:

$$C_t = \left(\int_0^1 C_{j,t}^{(\varepsilon-1)/\varepsilon} dj \right)^{\varepsilon/(\varepsilon-1)},$$

where $\varepsilon > 1$ is the elasticity of substitution between differentiated goods and market clearing implies $Y_{j,t} = C_{j,t} \forall j, t$. The aggregate price index is then

$$P_t = \left(\int_0^1 P_{j,t}^{1-\varepsilon} dj \right)^{\frac{1}{1-\varepsilon}}.$$

This setup gives rise to a standard demand function

$$Y_{j,t} = \left(\frac{P_{j,t}}{P_t} \right)^{-\varepsilon} Y,$$

with $P_{j,t}$ as the output price of firm j and P_t denotes the overall price level. Y_t represents total demand in the economy. As we will consider only one period in this version of the model, we drop time indexes in the remainder of this section.

Now consider firm j that produces according to

$$Y_j = (I_j - D_j \Phi(j))^{\alpha}, \tag{8}$$

where $I_j = R_j^{\gamma} L_j^{1-\gamma}$ represents firm j's usage of a combined input factor consisting of raw material R_j and employment L_j.[36] $\Phi(j)$ is a firm-specific cost of price flexibility. The parameter $0 < \alpha < 1$ measures the degree of decreasing returns to scale. The indicator variable D_j equals one if the firm chooses to have ex-post flexible prices in the period under consideration and zero if it decides to forego the opportunity of setting prices after observing this period's shock realizations. In our context, we interpret this cost as, e.g., using price-escalation clauses, which might require price discounts to clients and/or additional legal advice. Similarly, preserving price flexibility by using contracts that cover only short periods instead of fixing prices for longer may cause costs, such as lower negotiable output prices and more frequent contracting costs.

A related, but more complex, mechanism relies on 'observation costs,' proposed by Álvarez et al. (2018). In our model, $\Phi(j)$ would then be a shortcut to costs arising from a closer market observation. These costs would induce firms to monitor economic developments more thoroughly in times of higher volatility, while the model of Devereux (2006) relies on higher investments in price flexibility. Both models predict that current observed volatility raises the responsiveness of prices to future shocks, which will be crucial for accounting for our findings. That is, even large supply shocks transmit to consumer prices only to a low degree if they happen in tranquil times. This prediction differentiates these models from other approaches, such as menu cost models without observation costs, discussed above.

The price MC for one unit of the input factor I consists of the wage W, which is set in advance and is therefore fixed in this one-period model, and of the price of the

[36] We fix capital by fixing it at unity, as we are mainly interested in the short-term decisions of firms.

raw material C_R. The latter is stochastic, and so are Y and P, as seen from the firm's perspective. As usual, minimized costs for one unit of I are then

$$MC = \frac{C_R^{\gamma} W^{1-\gamma}}{\gamma^{\gamma}(1-\gamma)^{(1-\gamma)}}. \tag{9}$$

We refer to unexpected movements in the costs of raw materials as supply shocks. Expected discounted profits of the firm are

$$E\Gamma \left[P_j \left(\frac{P_j}{P} \right)^{-\varepsilon} Y - MC \left(\left(\frac{P_j}{P} \right) Y \right)^{\frac{1}{\alpha}} - MC D_j \Phi(j) \right],$$

where E is the expectational operator and $\Gamma = 1/(PY)$ is the stochastic discount factor of the firm, corresponding to the marginal utility of one dollar of a hypothetical household with log utility. If the firm chooses to pay the (known, idiosyncratic) costs $\Phi(j)$, it can adjust its price after observing MC, Y, and P; otherwise, it sets its price based on expectations regarding these variables. The optimal price for firms that have chosen to invest in price flexibility is

$$P_j^1 = \delta \left[MC^{\alpha} (\hat{Y})^{1-\alpha} \right]^{\omega}, \tag{10}$$

where $\delta = \{\varepsilon/[\alpha(\varepsilon-1)]\}^{\alpha\omega}$ and $\omega = 1/[\alpha + \varepsilon(1-\alpha)]$. Furthermore, $\hat{Y} = P^{\varepsilon} Y$ is the part of a firm's demand that is independent of its price. Firms that chose to set their price in advance do this according to

$$P_j^0 = \delta \frac{E\left[\Gamma MC (\hat{Y})^{\frac{1}{\alpha}} \right]^{\alpha\omega}}{E\left[\Gamma \hat{Y} \right]^{\alpha\omega}}. \tag{11}$$

Expected profits under optimal price setting then depend on the choice to invest in price flexibility in the following way

$$\begin{aligned} V^1(\Theta) &= \Psi E\Gamma (MC^{\alpha(1-\varepsilon)} \hat{Y})^{\omega} \\ V^0(\Theta) &= \Psi (E\Gamma MC \hat{Y}^{1/\alpha})^{(1-\varepsilon)\alpha\omega} (E\Gamma \hat{Y})^{\varepsilon\omega}, \end{aligned}$$

where $V^1(\Theta)$ are profits for $D_j = 1$ and $V^0(\Theta)$ for $D_j = 0$. The parameter Ψ equals $\delta^{1-\varepsilon} - \delta^{-(\varepsilon/\alpha)}$ and $\Theta = \{C, Y, P\}$. The firm chooses ex-post price flexibility whenever the difference in expected profits for $D_j = 1$ and $D_j = 0$ is higher than the discounted costs of investing in price flexibility, i.e., if $V^1(\Theta) - V^0(\Theta) \geq \Phi(j) E\,\Gamma\, MC$, or

$$\Delta(\Theta) = \frac{V^1(\Theta) - V^0(\Theta)}{E\,\Gamma\, MC} \geq \Phi(j). \tag{12}$$

$\Delta(\Theta)$ is the discounted gain from investing in price flexibility, normalized by the cost of the combined input factor. This equation can be solved by taking a second-order approximation around the mean value $E \ln \Theta$, see Devereux (2006) for details:

$$\Delta(\Theta) \approx \frac{\Omega\alpha}{2} Var\left(\ln MC + \frac{1-\alpha}{\alpha} \ln \hat{Y} \right) = \frac{\Omega\alpha}{2} \left[\sigma_{mc}^2 + \left(\frac{1-\alpha}{\alpha} \right)^2 \sigma_{\hat{y}}^2 + 2\frac{1-\alpha}{\alpha} \sigma_{mc,\hat{y}} \right] > 0, \tag{13}$$

where lower-case letters stand for percentage deviations from the stochastic steady state, such as $mc = \ln MC - E\ln MC$. Furthermore, $\Omega = [V(\exp(E\ln\Theta))/\exp(E(\ln\Gamma + \ln MC))]\varepsilon(\varepsilon-1)\omega^2 > 0$, where $V(\exp(E\ln\Theta))$ are profits evaluated at the mean $E\ln\Theta$ and $\sigma_c^2, \sigma_{\hat{y}}^2, \sigma_{mc,\hat{y}} > 0$ are the variances of input costs and market demand, as well as their covariance. Given expression (9), the cost variance σ_{mc}^2 depends on the variance of (the log of) raw material costs in the following way: $\sigma_{mc}^2 = \gamma^2\sigma_{c_R}^2$. Equations (12) and (13) deliver an important insight in line with our empirical findings: higher volatility $\sigma_{\hat{y}}^2$ of market demand $\hat{Y} = P^\varepsilon Y$, which itself depends on price volatility, increases the incentives for firms to invest in price flexibility.

5.1.2 Closing the model

We now close the model, leading to several differences to Devereux (2006). Assume that there is a unit mass of firms. We then rank firms according to their cost of investing in price flexibility. The firm with the index $j = 0$ has the lowest costs $\Phi(0) = 0$ and the one with $j = 1$ the highest. We also assume that $\Phi(j)$ is uniformly distributed and differentiable. Denote the index of the firm that is indifferent to whether to invest in price flexibility or not as z. That is, z is the measure of firms that do invest. The resulting value of z is determined by the following conditions

$$\Delta(\Theta) = \Phi(z), \quad 0 \leq z < 1, \tag{14}$$
$$\Delta(\Theta) > \Phi(1), \quad z = 1. \tag{15}$$

The overall price index for a given value of z is then

$$P = \left[z(P^1)^{1-\varepsilon} + (1-z)(P^0)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{16}$$

Nominal demand is determined by the money supply in the following way

$$YP = \frac{M}{\chi}, \tag{17}$$

where χ features i.i.d. shocks to velocity and has an expected value of unity.[37] We refer to these shocks as the demand shock from now on. Inserting equation (17) into the optimal prices of firms (10) and (11), while observing that all firms that can adjust set the same prices, results in

$$P^1 = \delta\left[MC^\alpha P^{(1-\alpha)(\varepsilon-1)}(M\nu/\chi)^{1-\alpha}\right]^\omega \tag{18}$$
$$P^0 = \delta\frac{E\left[\Gamma MC\left(P^{\varepsilon-1}(M\nu/\chi)^{1-\alpha}\right)^{\frac{1}{\alpha}}\right]^{\alpha\omega}}{E\left[P^{\varepsilon-1}\right]^{\alpha\omega}}. \tag{19}$$

The central bank sets the change in the nominal money supply based on current inflation:

$$\frac{M}{M_{-1}} = \left(\frac{P}{P_{-1}}\right)^{-\phi}\nu, \tag{20}$$

[37] These shocks can be derived from shocks to households' preference for holding money, see Devereux (2006).

where we normalize the previous period's values of the money stock and the price level to unity $M_{-1} = P_{-1} = 1$. We assume that the central bank does not react to higher inflation by increasing the money supply overproportionally, i.e., $\phi \geq -1$. Stricter inflation targeting corresponds to a higher value of ϕ. The variable ν with an expected value of unity may stand for monetary policy shocks, but also for systematic deviations from a rule that focuses on inflation only. In particular, we allow for a positive correlation between ν and the supply shock, which represents a monetary policy strategy that is relatively more accommodating in case of supply shocks.[38] Theoretically, ν could also be linked to demand shocks. Given the debate in some policy circles surrounding lower reactions to inflation in case of supply shocks, we focus on a correlation with this kind of shock.[39]

To derive the expression for equation (13) in general equilibrium, we use the linearized price index (18) together with the linearized versions of equations (16) and (20), see Appendix D. This yields

$$p = \frac{\varphi(z)\omega}{\Delta} \left[\alpha mc + (1-\alpha)(\hat{\nu} - \hat{\chi})\right], \tag{21}$$

with

$$\Delta = 1 - \varphi(z)\omega(1-\alpha)(\varepsilon - \phi - 1),$$

where $\hat{\chi} = \ln \chi - E \ln \chi$ and $\hat{\nu} = \ln \nu - E \ln \nu$. The parameter $\varphi(z)$ is given in the appendix and follows $\varphi(0) = 0, \varphi(1) = 1, \varphi'(z) > 0, \varphi''(z) > 0$. Using equation (21) we derive—again in the appendix—the variance of $\ln MC + \frac{1-\alpha}{\alpha} \ln \hat{Y}$ and use this in equation (13) to arrive at equations (14) and (15) in general equilibrium as

$$\frac{\Omega\alpha}{2\Delta^2}\left[\sigma_{mc}^2 + \left(\frac{1-\alpha}{\alpha}\right)^2 (\sigma_{\hat{\chi}}^2 + \sigma_{\hat{\nu}}^2) + 2\frac{1-\alpha}{\alpha}\sigma_{mc,\hat{\nu}}\right] = \Phi(z) \qquad 0 \leq z < 1 \tag{22}$$

$$\frac{\Omega\alpha}{2\Delta^2}\left[\sigma_{mc}^2 + \left(\frac{1-\alpha}{\alpha}\right)^2 (\sigma_{\hat{\chi}}^2 + \sigma_{\hat{\nu}}^2) + 2\frac{1-\alpha}{\alpha}\sigma_{mc,\hat{\nu}}\right] > \Phi(1) \qquad z = 1, \tag{23}$$

The covariance $\sigma_{mc,\hat{\nu}}$ corresponds to $-\phi_{mc}\sigma_{mc}$, see footnote 38.

5.1.3 Model predictions

Equations (22) and (23) then determine the equilibrium value of z, depending on the variances and covariances of the three shocks. As shown in the appendix, there can be one or three equilibria. However, in case of multiple equilibria, one is unstable. In the following, we focus on the description of the stable equilibrium in which the economy is not already at full price flexibility (i.e., $z < 1$).[40] We first assert the relation between

[38] The functional form would be $\nu = (MC/MC_{-1})^{-\phi_{mc}}\tilde{\nu}$, with $\tilde{\nu}$ being 'pure' monetary policy shocks.

[39] See, e.g., Fabio Panetta, member of the executive board of the ECB, who stated: "Bad inflation reflects negative supply shocks that raise prices and depress economic activity, which monetary policy should look through." (Panetta, 2022)

[40] If all firms have already invested in price flexibility, changes in parameter values can reduce price flexibility but can obviously not increase it any further.

price flexibility and the pass-through of shocks to inflation. Given that the derivative of the term $\varphi(z)\omega/\Delta$ in the expression for the price index (21) with respect to z is positive, we directly obtain the following lemma.

Lemma 1 (Effect of price flexibility) *A higher price flexibility (a higher z) translates into a larger pass-through of shocks to inflation.*

The following proposition then follows from equation (22).[41]

Proposition 1 (Effects of shock volatilities) *Higher volatility of the shocks to the costs of raw materials ($\sigma^2_{c_R}$), demand ($\sigma^2_{\hat{\chi}}$), and/or the money supply ($\sigma^2_{\hat{\nu}}$, for a given covariance with input costs) raises price flexibility (z) and hence the pass-through of shocks to inflation.*

We also obtain the following corollary, which is linked to our empirical findings.

Corollary 1 (Relation to inflation volatility) *Any change in the shock volatilities $\sigma^2_{c_R}, \sigma^2_{\hat{\chi}}$ and/or monetary policy variables ($\sigma^2_{\hat{\nu}}, \sigma_{mc,\hat{\nu}}$, and ϕ) that increases inflation volatility raises price flexibility and hence the pass-through of all shocks to inflation.*

Intuitively, higher variances of costs and/or demand make the possibility of a price adjustment after observing shock realizations more valuable (Proposition 1). This effect also works via the level of inflation volatility: If the prices of competitors are fluctuating strongly, it pays off to invest in the ability to change prices after observing the resulting demand. Higher price flexibility, in turn, increases the response of inflation to shocks. This aligns with our empirical result: higher inflation volatility leads to a larger pass-through of cost shocks to inflation (Corollary 1).

Technically, equation (21) implies a larger shock pass-through if more firms have invested in price flexibility (how many firms are able to adjust their price after observing the shocks) and if monetary policy is less aggressive in fighting inflation (by how much do the adjusters adjust). The latter, direct effect of monetary policy on demand is standard in the literature. In particular, a higher value of ϕ raises Δ and corresponds to stricter inflation targeting. In the extreme, ϕ approaches infinity, which fixes the price level at its previous level. Additionally, the impact of ϕ on the variances of the price level and hence demand changes the firms' incentives to invest in price flexibility (see above), which entails an indirect influence of monetary policy via $\varphi(z)$. Regarding the effects of monetary policy, we can derive the following result.

Proposition 2 (Effects of monetary policy) *Stricter inflation targeting (a higher ϕ) reduces the response of inflation to all shocks in two ways: directly by reacting to the change in inflation and indirectly by reducing price flexibility. In contrast, an accommodating monetary policy stance towards supply shocks (raising $Cov(mc, \hat{\nu})$) increases price flexibility (z) and thereby the pass-through of all shocks to inflation.*

[41] Proofs for the propositions and the corollary are given in Appendix D.

Regarding the last part of the proposition, note that contractionary supply shocks increase costs and the general price level simultaneously. Seen from the perspective of an individual firm under strategic complementarity in pricing, both developments create an incentive to raise prices.[42] Similar reasoning applies to expansionary demand shocks, which increase demand and the price level. Firms are thus more likely to invest in price flexibility if the correlation of shocks with the price level is high. By dampening the price response, monetary policy can reduce this incentive.[43] A more accommodating policy, overall or just in case of supply shocks, counteracts this reasoning and leads—ceteris paribus—to a higher price flexibility and therefore a higher pass-through of shocks to inflation.

Despite this clear result, two caveats are in order. First, one argument for a muted monetary policy reaction to supply shocks is their transitory nature in combination with lags in the transmission of policy actions. Given that we consider a quite stylized model, we do not capture this notion here. Second, we are only interested in the connection between shocks and inflation and, hence, do not conduct a proper welfare analysis.

5.2 Dynamic model

To obtain quantitative predictions beyond those of the analytical one-period version above, we now move on to a numerical simulation of the infinite-period version. Here, we follow Kimura and Kurozumi (2010), which is based on concepts from Devereux and Yetman (2002), and let firms choose their individual degree of price flexibility (their Calvo parameter θ_j) once, given the parameters and shock variances. That is, they can set the probability of being able to adjust prices. As above, they pay the costs Φ whenever firms get the opportunity to do so, such that higher flexibility entails larger costs.

Specifically, we introduce the above structure of raw material inputs to production into the New Keynesian framework of Kimura and Kurozumi (2010) and use the resulting model to analyze different inflation regimes. Thus, we retain the setup of the analytical model in Section 5.1 but assume an infinite planning horizon and allow the wage to be set in each period. For simplicity, we assume constant returns to scale, $\alpha = 1$, and constant costs of being able to adjust prices, $\Phi(j) = \Phi$.[44] Furthermore, for ease of notation, we define this cost, expressed in prices of the aggregate output good, as $F_t \equiv \Phi MC_t/P_t$.

The firm's profit maximization is equivalent to minimizing its loss in profit from not being able to reset its price. Up to second order, this loss is proportional to (see Walsh, 2003)

$$\mathcal{L}_t(\theta_t, \theta) = F_t + \min_{p_{j,t}} E_t \sum_{k=0}^{\infty} (\beta\theta_j)^k (p_{j,t} - p^*_{j,t+k})^2 + \beta(1-\theta_j) \sum_{k+1}^{\infty} (\beta\theta_j)^{k-1} E_t \mathcal{L}_{t+k}(\theta_j, \theta),$$

[42] Strategic complementarity is the standard case in this kind of model and is given by assuming $\alpha < 1$.

[43] Naturally, lower volatility achieved by reducing monetary policy shocks has the same effect.

[44] That is, fluctuations in aggregate demand affect costs via the wage rather than through decreasing returns to scale, with similar implications.

where lower-case letters refer to variables linearized around the flexible-price steady-state, β is the firms' discount factor, and $p^*_{j,t}$ is the price the firm would set if no nominal rigidities were present, which is $p^*_{j,t} = mc_t = \gamma c_{R,t} + (1-\gamma)w_t$. The wage is determined from households' optimization problem and is given by

$$w_t - p_t = \sigma c_t + \zeta l_t = \xi y_t + \zeta \gamma c_{RR,t},$$

where $c_{RR,t}$ is the relative price of raw materials to labor $c_{R,t} - w_t$ and $\xi = \sigma + \zeta/[1+(1-\theta)\Phi/Y)]$, with Y denoting output in steady state.[45] The desired price is therefore equal to

$$p^*_{j,t} = p_t + \gamma c_{RR,t} + w_t = p_t + \xi x_t, \tag{24}$$

with x_t as the output gap. The optimal price that results from this minimization is

$$p^0_{j,t} = (1-\beta\theta_j)E_t \sum_{k=0}^{\infty} (\beta\theta_j)^k p^*_{j,t+k} = (1-\beta\theta_j)E_t \sum_{k+0}^{\infty} (\beta\theta_j)^k (p_t + \xi x_{t+k}). \tag{25}$$

Following Kimura and Kurozumi (2010), we assume that the firm chooses its individual Calvo parameter θ_j to minimize the unconditional expected loss in profit due to rigid prices, which is

$$E\mathcal{L}_t(\theta_j, \theta) = \frac{1-\beta\theta_j}{1-\beta} \left[F + E \sum_{k=0}^{\infty} (\beta\theta_j)^k (p^0_{j,t} - p^*_{j,t+k})^2 \right],$$

where E is the unconditional expectations operator and F the unconditional expectation of F_t. That is, firms may decide for higher price flexibility (a lower θ_j) if they reckon that it pays off to be able to respond quickly to changing conditions. This is associated with higher costs, as they have to pay the price-setting costs F more often in this case. The first-order condition is then, using (24) and (25),

$$F + \sum_{k=0}^{\infty} (\beta\theta_j)^{k-1} [(k+1)\beta\theta_j - k] V \left[\sum_{h=1}^{k} \pi_{t+h} + \xi x_t - \tilde{\mathcal{L}}_t(\theta_j, \theta) \right] = 0, \tag{26}$$

where V is the unconditional variance and

$$\tilde{\mathcal{L}}_t(\theta_j, \theta) = \sum_{h=1}^{\infty} (\beta\theta_j)^h E_t \pi_{t+h} + \gamma(1-\beta\theta_j) \sum_{h=0}^{\infty} (\beta\theta_j)^h E_t x_{t+h}.$$

We reach an equilibrium if the optimal $\theta_j = \theta$ for each firm j, which yields the standard New Keynesian Phillips Curve

$$\pi_t = \beta E_t \pi_{t+1} + \frac{\gamma(1-\theta)(1-\theta\beta)}{\theta} x_t.$$

On the demand side, household optimization results in the dynamic IS equation

$$x_t = E_t x_{t+1} - (i_t - E_t \pi_{t+1} - r^*_t)/\sigma,$$

[45] This expression is derived from the linearization of aggregate labor demand, given the production function (8), in which D_j equals unity if firm j can set its price and $\alpha = 1$.

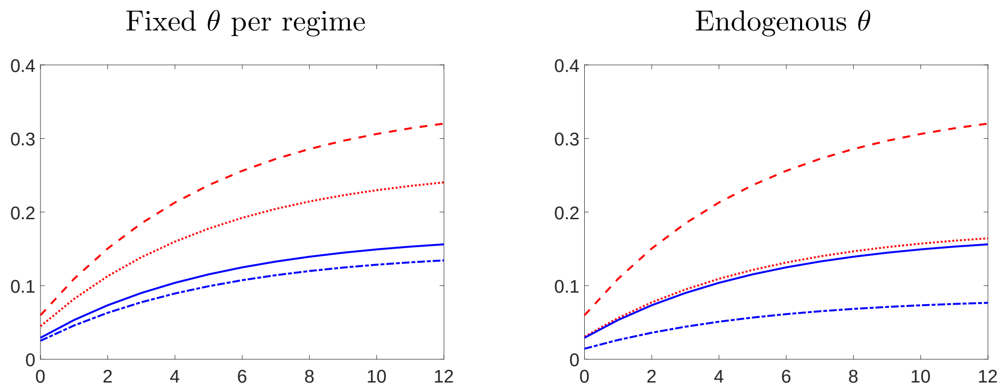

Figure 12: Theoretical responses with counterfactuals. Both panels: Impulse responses in Regime 1 (low volatility, blue solid lines) and Regime 2 (high volatility, red dashed lines) of CPI to a unit shock to the price of crude material $c_{R,t}$. Left: Responses in Regime 1 (blue dashed-dotted line) and Regime 2 (red dotted line) for stricter inflation targeting with unchanged, regime-specific price-setting frequency. Right: Responses in Regime 1 (blue dashed-dotted line) and Regime 2 (red dotted line) for stricter inflation targeting with endogenous, regime-specific price-setting frequency. Horizontal axes denote months.

where r_t^* is the natural rate of interest, which is given by

$$r_t^n = -\frac{\sigma\gamma(1+\zeta)}{\xi} E_t \Delta c_{RR,t+1}.$$

Lastly, we assume a Taylor rule for the interest-rate decisions of the central bank

$$i_t = \phi_\pi \pi_t + \phi_x x_t.$$

To obtain a numerical solution, we search for a θ that, once the model is solved for this value and the equilibrium paths are inserted into (26), fulfills this equation for $\theta_j = \theta$.

5.2.1 Calibration and model predictions

The calibration of the model equals that of Kimura and Kurozumi (2010), where applicable. That is, we set $\beta = 0.99, \sigma = 1.86, \zeta = 1, \phi_\pi = 1.5, \phi_y = 0.5$ (on an annual basis), and $\rho^n = 0.83$, assuming an AR(1) process for $c_{RR,t}$ and hence r_t^n. Instead of employing their assumed variance of the natural-rate shock across both volatility regimes, however, we set this variance differently in each regime. In particular, we choose values such that the model generates the observed standard deviation of CPI inflation in each regime (0.27% and 0.56%, respectively). The resulting standard deviation of innovations to r_t^n is 0.2% in the low-volatility regime and 0.4% in the high-volatility regime. We then simulate a shock to the real price of raw materials that raises the nominal costs of raw materials by 1%, as in our empirical estimations.

Figure 12 displays the response of CPI inflation after such a shock in the two regimes. The blue solid line in both panels represents the low-volatility scenario with a resulting Calvo-parameter of 0.7, while the red dashed line shows the high-volatility case with an endogenous Calvo-parameter of 0.53. Considering the stylized nature of the—three-equation New Keynesian—model, we deem the fit to the corresponding responses in Figure 4 as a success. In particular and in line with Proposition 1, we obtain a higher inflation on impact and in the following periods in the high-volatility regime, induced by the higher share of price-adjusting firms. We also conduct two hypothetical scenarios in which the central bank adheres to stricter inflation targeting by increasing its reaction coefficient ϕ from 1.5 to 2. The left panel of Figure 12 shows the responses if we leave the Calvo-parameter unchanged for each regime, i.e., at 0.7 and 0.53, respectively. We thereby isolate the traditional monetary-policy channel that reduces inflation by dampening demand.

While the stronger reaction already achieves a lower inflation response to the cost-push shock for given values of θ, the effect is magnified once we allow for an endogenous re-adjustment of the price-setting frequency, as also discussed by Kimura and Kurozumi (2010). The right panel displays the corresponding responses that result from optimally chosen Calvo-parameters, based on the shock variances in both regimes (which are unchanged) and the new value for ϕ. Specifically, we obtain values of $\theta = 0.79$ in the low-volatility regime and $\theta = 0.67$ in the high-volatility regime. By comparing both panels, we find that the dampening of the inflation response is particularly successful in the high-volatility regime. In particular, the response in the high-volatility regime for $\phi = 2$ is similar to that in the low-volatility regime for $\phi = 1.5$. In short, stricter inflation targeting pays off double in terms of reducing inflation fluctuations, as predicted by Proposition 2.

6 Conclusion

We examine the impact of producer price shocks on consumer price inflation in the United States, taking into account different inflation regimes. Employing a Markov-switching model, we identify two distinct regimes and use the filtered state probabilities to construct a regime indicator. It turns out that the regimes are characterized by different inflation volatilities. We then interact a local projections model with the indicator and estimate responses with Stock and Watson (2018)'s LP-IV approach, using data outliers in the Crude PPI series as instruments.

We find that the impulse responses of the CPI following a producer price shock are indeed regime-dependent. If a producer price shock occurs during the high volatility regime, the increase in consumer prices is more pronounced on impact and takes longer to decay than in times of stable and low inflation. This distinction is not observable when considering different levels of inflation or shock sizes.

The main policy implication we draw from our results for inflation-targeting central banks is that they should pay close attention to the current and potential future inflation regimes when assessing the impact of current developments. If these developments lead to high CPI volatility, the economy may transition to a regime where cost shocks are passed on to consumer prices more rapidly and to a larger extent. This could result in persistently higher CPI inflation volatility. Put differently, a stricter monetary policy stabilizes inflation not only directly, but also indirectly by reducing price flexibility.

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Appendix

A Data description

Seasonally adjusted data on the CPI and the three producer price indices were obtained from the US Bureau of Labor Statistics (BLS). Until 2014, the BLS used the stage of processing (SOP) aggregation system to report producer prices. Afterward, the BLS switched to the Final Demand-Intermediate Demand (FD-ID) system. Table A-1 reports the SOP and the corresponding FD-ID codes as well as the respective variable names.

The BLS defines crude materials as unprocessed goods and intermediate materials as processed goods that businesses purchase as inputs for their production. Products included in the Crude PPI enter the market for the first time and will undergo processing when purchased. Intermediate materials are already processed to some degree but need further processing before becoming a finished good. Finished goods comprise commodities used for personal consumption or that businesses use as capital investment. Government purchases and exports are excluded from the SOP system.

SOP Code	Title	FD-ID Code	Title
SOP1000	Crude materials	ID62	Unprocessed goods for intermediate demand
SOP2000	Intermediate materials, supplies and components	ID61	Processed goods for intermediate demand
SOP3000	Finished goods	FD49207	Finished goods

Table A-1: Variable description of Crude (SOP1000), Intermediate (SOP2000), and Finished (SOP3000) PPI. More information available on https://www.bls.gov/ppi/fd-id/ppi-stage-of-processing-to-final-demand-intermediate-demand-aggregation-system-index-concordance-table.htm.

Seasonally adjusted data on the stages of processing industrial production indices and overall industrial production were retrieved from the Federal Reserve Board (FRB). The indices are classified into raw materials, primary & semifinished processing, and finished processing, and are available since 1972, or 1947 in the case of IP Materials.

B Econometric checks

Our instrumental variable consists of few non-zero data points and can thus be characterized as a *sparse instrument*. Giacomini et al. (2022) argue that sparse instruments, often constructed from narrative restrictions, are likely to be weak instruments. We test the relevance of our IV by applying the robust test for weak instruments with multiple endogenous regressors proposed by Lewis and Mertens (2022). We interact the instrument and Crude PPI (our endogenous regressor) with the state indicator H_t and use the same set of controls as in our respective local projection specifications. Following Lewis and Mertens (2022), the test rejects weak instruments if the test statistic lies above the critical value. For our baseline specification, this is the case at all horizons and for all three stages of processing PPIs, as can be seen in Figure B-1.

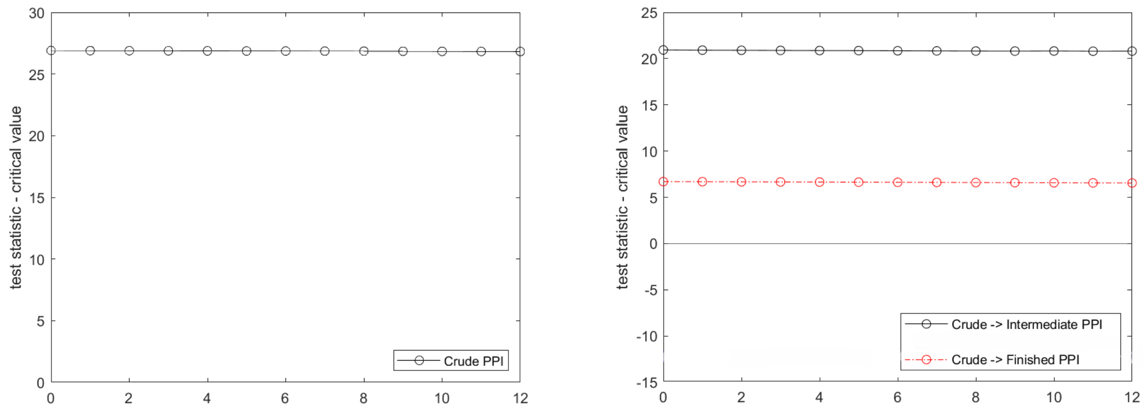

Figure B-1: Left panel: Results of the Lewis and Mertens (2022)-test for weak instruments: difference of test statistic and critical value for baseline results (Figure 4). Right panel: same statistic between stages of processing (Figure 11). Horizontal axes denote months.

C Alternative channels

The left panel of Figure C-1 shows the response of the shadow rate—the updated series from Krippner (2013)—to shocks to Crude PPI. As visible, the monetary policy reaction is not responsible for the observed state dependency of CPI responses. Monetary policy reacts more to shocks to Crude PPI in State 2 than in State 1, in line with the stronger inflation response. That is, if anything, monetary policy dampens the further course of inflation.

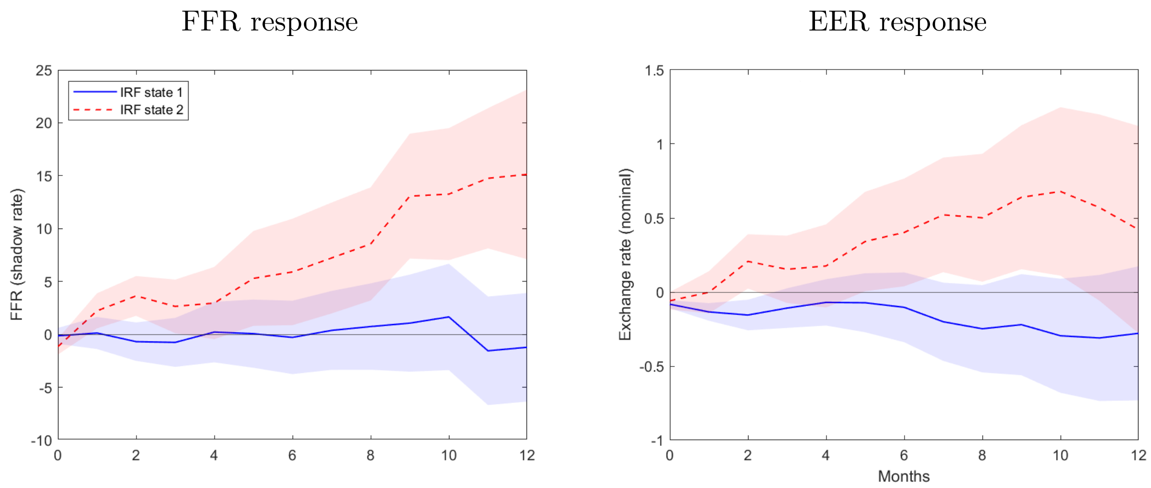

Figure C-1: Impulse responses of shadow rate (left panel) and nominal effective exchange rate (right panel, higher values correspond to an appreciation) in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) to shocks to PPI. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

The right panel shows the response of the nominal broad effective exchange rate (EER), provided by the BIS. We reduced the lag number to 8 since the exchange rate is only available from 1994 onward. The exchange rate appreciates more in the high-volatility regime, in line with the stronger interest-rate response. That is, the stronger inflation reaction in the high-volatility regime cannot be explained by a depreciation that leads to rising PPIs at all stages of production and the CPI. Similarly, the responses of the Intermediate PPI and the Finished PPI in Figure 11, which exclude imports, further demonstrate that our results are not driven by the exchange-rate response.

D Model derivations and proofs

Derivation of equation (21)**.** The linearized price index is, see Devereux (2006),

$$p = \varphi(z)p^1,$$

with

$$\varphi(z) = \frac{z\exp(E\ln P^1(1-\varepsilon))}{z\exp(E\ln P^1(1-\varepsilon)) + (1-z)\exp(E\ln P^0(1-\varepsilon))}.$$

The linearized price (18) of flexible firms p^1 reads as

$$p^1 = \alpha\omega mc + (1-\alpha)(\varepsilon-\phi-1)\omega p + (1-\alpha)\omega(\hat{\nu}-\hat{\chi})$$

such that (21) results.

Derivation of equations (22) **and** (23). Given the expression (21) for the price index, we obtain $\hat{y}$ as

$$\begin{aligned}\hat{y} &= \frac{(\varepsilon-\phi-1)\varphi(z)\omega}{\Delta}\left[\alpha mc+(1-\alpha)(\hat{\nu}-\hat{\chi})\right]+\hat{\nu}-\hat{\chi} \\ &= \frac{(\varepsilon-\phi-1)\varphi(z)\omega\alpha}{\Delta}mc+\frac{1}{\Delta}\left(\hat{\nu}-\hat{\chi}\right).\end{aligned}$$

We therefore get the following

$$mc+\frac{1-\alpha}{\alpha}\hat{y}=\frac{1}{\Delta}\left[mc+\frac{1-\alpha}{\alpha}\left(\hat{\nu}-\hat{\chi}\right)\right].$$

The resulting variance is then

$$Var\left(mc+\frac{1-\alpha}{\alpha}\hat{y}\right)=\frac{1}{\Delta^2}\left[\sigma^2_{mc}+\left(\frac{1-\alpha}{\alpha}\right)^2(\sigma^2_{\hat{\nu}}+\sigma^2_{\hat{\chi}})+2\frac{1-\alpha}{\alpha}\sigma_{mc,\hat{\nu}}\right],$$

which can be used in equation (13), together with equation (12), to derive conditions (22) and (23).

Proof of Proposition 1. Note that

$$\begin{aligned}\Delta &= \frac{\alpha+\varepsilon(1-\alpha)-\varphi(z)(1-\alpha)(\varepsilon-\phi-1)}{\alpha+\varepsilon(1-\alpha)} \\ &= \frac{\alpha-\varphi(z)(1-\alpha)(\phi-1)+\varepsilon(1-\alpha)(1-\varphi(z))}{\alpha+\varepsilon(1-\alpha)}>0,\end{aligned}$$

which holds since $\phi<1$. Furthermore, $\Delta=1$ at $z=0$, such that the left-hand-side of inequality (22) is positive at $z=0$. At this point, the right-hand-side $\Phi(0)=0$ (there is a firm that has zero costs of investing in price flexibility). Moreover, $\Phi'(z)>0$. The sign of the slope of the left-hand-side is determined by

$$\frac{\partial\Delta^{-2}}{\partial z}=2\Delta^{-3}\omega(1-\alpha)(\varepsilon-\phi-1)\varphi'(z).$$

This expression is positive if $\phi>1-\varepsilon$ and vice versa. A positive slope corresponds to strategic complementarity in the choice of flexibility: the more firms choose to invest in price flexibility, the more it pays off for an individual firm to also do so. A negative slope corresponds to strategic substitutability in the choice of flexibility, see Devereux (2006). We hence get a unique equilibrium value for z if $\phi\leq 1-\varepsilon$. Note that the second derivative of Δ^{-2} with respect to z can only be negative if the first derivative is also negative. For $\phi>1-\varepsilon$, we have therefore three possibilities: a) one unique equilibrium at $0<z<1$, b) one unique equilibrium at $z=1$, or c) three equilibria, one for a low value of $0<z<1$, one at an intermediate value of $0<z<1$, and one at $z=1$. All considered equilibria are stable—except for the intermediate one in the case of three equilibria—as for lower z the benefit of investing in price flexibility (left-hand-side of inequality (22)) is higher than the costs $\Phi(z)$. We therefore disregard the intermediate equilibrium in the case of three equilibria. If we are already at the corner solution, z can obviously not rise any further. Since the left-hand-side of inequality (22), for any given value of z, is increasing in $\sigma_{mc}^2, \sigma_{\hat{\chi}}$, and $\sigma_{\hat{\nu}}^2$, and its slope is, for interior solutions, larger than that of the right-hand-side, Proposition 1 obtains. ■

Proof of Corollary 1. The volatility of the price level (21) is

$$\begin{aligned}\sigma_p^2 &= \left(\frac{\varphi(z)\omega}{\Delta}\right)^2 \left[\alpha^2\sigma_{mc}^2 + (1-\alpha)^2(\sigma_{\hat{\nu}}^2 + \sigma\hat{\chi}^2) + \alpha(1-\alpha)\sigma_{mc,\hat{\nu}}\right] \\ &= \frac{2\alpha(\varphi(z)\omega)^2}{\Omega}\Delta(\Theta).\end{aligned}$$

The corollary directly follows from this. ■

Proof of Proposition 2. The direct effect of a changing ϕ is visible when taking the derivative with respect to ϕ of the term in the price index (21) that multiplies all shocks:

$$\frac{\partial\varphi^2(z)\omega\Delta^{-1}}{\partial\phi} = \varphi(z)\omega\Delta^{-2}\omega(1-\alpha) > 0.$$

Reducing ϕ (stricter inflation targeting) hence decreases the effect of shocks on inflation for a given value of z. The indirect effect of changing ϕ on z depends on the following derivatives (remember that $\Delta > 0$ from the proof of Proposition 1):

$$\begin{aligned}\frac{\partial\Delta^{-2}}{\partial\phi} &= 2\Delta^{-3}\varphi(z)\omega(1-\alpha) \geq 0 \\ \frac{\partial\Delta(\Theta)}{\partial\sigma_{mc,\hat{\nu}}} &= \frac{\Omega(1-\alpha)}{\Delta^2} > 0,\end{aligned}$$

where the first derivative determines the sign of $\partial\Delta(\Theta)/\partial\phi$ and $\Delta(\Theta)$ is the left-hand-side of inequality (22). Proposition 2 follows directly from these derivatives. ■