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The Transmission of Supply Shocks in Different Inflation Regimes

Abstract

We show that the impact of supply and monetary policy shocks 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 upstream supply shocks using instrumental variables based on data 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 (State 2) compared to phases of more stable consumer price growth (State 1). Similarly, monetary policy shocks are more effective in State 2. 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 invest in price flexibility. This model predicts that stricter inflation targeting reduces price flexibility and, consequently, the pass-through of all shocks to inflation, beyond the standard channel that affects demand.

JEL-Codes: E310, E520, E320.

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

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1 Introduction

Policymakers have, particularly during times of rising inflation, voiced the suspicion that the inflation process 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 action. Specifically, current inflation projections hinge on assumptions regarding the speed and extent to which changes in producer prices are transmitted to consumer prices. These considerations are especially important when central banks aim to contain price pressures generated by supply shocks. Similarly, the optimal timing of interest-rate changes designed to achieve the goal of price stability relies on estimates of lags in the transmission of monetary policy.[2]

We investigate this issue empirically by analyzing whether and when inflation dynamics undergo 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 estimate state-dependent causal effects of a shock to producer prices—provided by the producer price index (PPI) stage-of-processing system of the Bureau of Labor Statistics—on downstream price growth. That is, we estimate how supply shocks to the crude material PPI affect intermediate and finished goods PPIs as well as consumer prices in a dynamic way. We also investigate shocks at intermediate stages and their subsequent transmission. We rely on PPI data as we are interested in relatively broad-based shocks to input prices. Given that, e.g., crude materials display a much larger variance compared to consumer prices, PPI price processes are more noisy. We, therefore, use movements in the respective PPI series that exceed normal fluctuations in input prices and move prices and industrial production at the same production stage in different directions as instruments for supply shocks.

Our results show that in periods of high inflation volatility, downstream prices, including the consumer price index (CPI), react much stronger to cost shocks in the initial and several following months. In this regime, prices are arguably more flexible and, hence,

[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 recent 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.

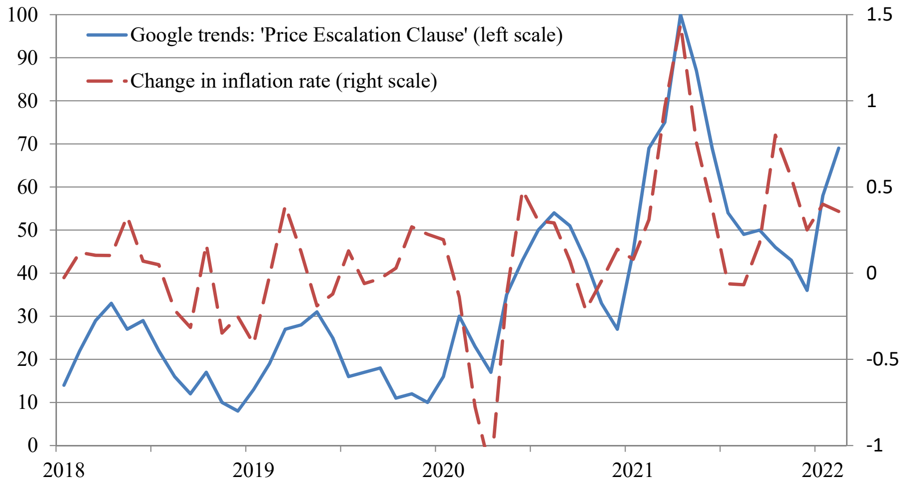

Figure 1: Index for Google searches of 'Price escalation clause' (left axis) and monthly change in annualized s.a. CPI inflation rate in percentage points (right scale).

react more promptly to shocks. We validate our results for general supply shocks by estimating the responses to 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]

Additionally, we investigate the effects of monetary policy shocks in the two inflation regimes. In the high-volatility regime, CPI responds more promptly to such shocks, particularly in the short run. In contrast, we hardly find an effect on monthly CPI inflation in the low-volatility regime. We infer that, given the more direct pass-through of cost changes to consumer prices and the heightened effectiveness of monetary policy during periods of high volatility, the economy is likely to revert to the low-volatility regime if central banks monitor producer prices closely and respond decisively and swiftly during times of increasing volatility.

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. Specifically, we assess the impact of exogenously conditioning regimes on other potentially influential variables, such as the level of CPI inflation, the volatility in Crude PPI inflation, or the size of the shocks. None of these separations generates a state dependency that comes close to the one generated by inflation volatility.[5]

Our findings may be grounded in a faster pricing behavior of firms when facing larger price volatility in their sales markets. This explanation is supported by anecdotal evidence from the recent 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

[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]In the case of separating by the volatility of Crude PPI, there is a slight state-dependency for shocks to Intermediate PPI, which is in line with our theoretical explanation in Section 5.

contracts between seller and buyer, these clauses automatically adjust sales prices based on changes in the seller's input costs.[6] That is, widespread use of these clauses implies 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 speak in favor of models in which price setters opt for more price flexibility in the face of volatile competitor prices. We, therefore, propose a model based on Devereux (2006) in which price setters can invest in the flexibility of their prices.[7] 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 increases the incentive to invest in price flexibility, explaining our finding of a more substantial pass-through of cost and monetary policy shocks during periods of volatile inflation. The model further predicts that inflation targeting by central banks 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. For example, monetary policy that is more accommodating in the face of supply shocks tends to increase price flexibility. We also investigate the implications of the most important alternative explanation. Menu-cost models, as developed by, e.g., Golosov and Lucas (2007), would predict the shape of CPI responses to depend strongly on the shock size, something that we do not find in our data for cost-push shocks. Furthermore, standard Calvo price setting would not predict any state dependency at all.

Despite the important implications, surprisingly little research has focused on the pass-through of shocks to consumer prices in different inflation regimes. 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

[6]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, such as Mack (1946), who describes different variations and provides advice for buyers facing escalation clauses.

[7]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. Alternatively, but in a very similar spirit, observation costs in a menu cost model as in Álvarez et al. (2018) would also give rise to the prediction 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).

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%. Hall (2023) argues that menu-cost models imply lower price rigidities if inflation is volatile, while Ascari and Haber (2022) estimate more substantial price effects of monetary shocks, as identified by Romer and Romer (2004), in high-inflation regimes and for large shocks. Our approach differs from the above studies in that we study the effects of well-identified supply shocks 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.[8] In addition, we analyze the impact of monetary policy shocks in the different regimes.

We also contribute to the literature on the general pass-through of cost shocks, but indirectly, given our focus on its regime dependence.[9] A large part of this literature centers on the exchange-rate pass-through (see, e.g., Bonadio et al., 2019; Álvarez et al., 2017; Enders et al., 2018; Campa and Goldberg, 2005; International Monetary Fund, 2006; Taylor, 2000; Auer and Schoenle, 2016). 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 essential element in our explanation of the role of CPI inflation volatility in price setting (see above).[10] 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 competitor's 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.

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 4. Section 5 develops the model, and Section 6 concludes.

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

[9] 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.

[10] Elsayed et al. (2023) divide supply shocks into transportation cost shocks and shocks to input material. They find different effects of both shocks on consumer prices.

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 $m = \{1, 2\}$ states, just like the variance of the residual term $e_{m,t}$.[11] 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.[12] 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 $1 - H_t$.

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:

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

[11] Since we are using monthly data, we also estimated an MS-AR including four lags plus the 12^{th} lag and did not observe significant differences in the timing of the resulting regimes.

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

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

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 local projection 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.

The sample we use to estimate our baseline model (4) for the United States is in monthly frequency and spans from January 1972 to December 2021.[13] For the response y_t in the baseline model, we use log differences of US CPI. The endogenous variable x_t represents log differences of one of the three producer price indices of the Bureau of Labor Statistics' stage-of-processing (SOP) system: Crude materials (referred to as *Crude PPI*); intermediate materials, supplies, and components (*Intermediate PPI*); and finished goods (*Finished PPI*). We also use industrial production SOP data for crude goods, primary and semi-finished goods, as well as finished goods (IP^i). For a robustness exercise and the identification of monetary policy shocks, we employ overall industrial production (IP). The set of controls W_t includes $n = 8$ lags of the response y_t, the instrument Z_t (see below), the corresponding IP growth (ΔIP^i_t), CPI growth (ΔCPI_t), if not equal to y_t, and the PPI growth of the previous and the subsequent stage of the SOP system (that is, Δ*Intermediate PPI* in case x_t equals Δ*Crude PPI*, etc.). 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

[13]In a robustness check that uses an alternative identification scheme, we extend the sample forward to October 1948, see Appendix D.

are often due to rare and unforeseen events, are correlated with the exogenous shocks that we wish to identify.[14] 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).[15] To ensure that demand shocks are not the cause of the observed outliers, we only consider those outliers for which the industrial-production index IP^i of the same stage of production does not move contemporaneously in the same direction as the respective PPI data.[16]

We therefore construct the outlier-based instrument Z_t in the following way:

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

Z_t takes the value of 1 when there is a positive outlier in the PPI series and no positive movement in the corresponding IP series in period t. We denote the different stages of production by the index i. In case of a negative outlier and no negative change in the corresponding IP series, $Z_t = -1$, and $Z_t = 0$ if there is no anomaly detected. 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 8 lags of Z_t, y_t, stage-specific industrial production growth (ΔIP_t^i), and the PPI growth of the previous and the next stage of the SOP system (i.e., for a shock to Δ*Intermediate PPI* we control for Δ*Crude PPI* and Δ*Finished PPI*), summarized in W_t, as controls in regressions (2), (3), and (4). 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, which would fail the third LP-IV condition. By including lags of the corresponding IP series as a monthly proxy for activity, we correct for any correlation between Z_t and earlier developments. Controlling for lags of ΔCPI_t as well as the previous and the next stage PPI rules out the possibility that the instrument Z_t is correlated with a shock to consumer prices or the producer prices of neighboring stages. This, in addition to the restriction on ΔIP^i, 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.

[14] 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.

[15] 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: $E[\eta_{t+i}Z_t] = 0, \forall i \neq 0$.

[16] We equate *Crude PPI* with the Crude IP, *Intermediate PPI* with the Primary and Semi-finished IP (referred to as *Intermediate IP*), and *Finished PPI* with the finished IP.

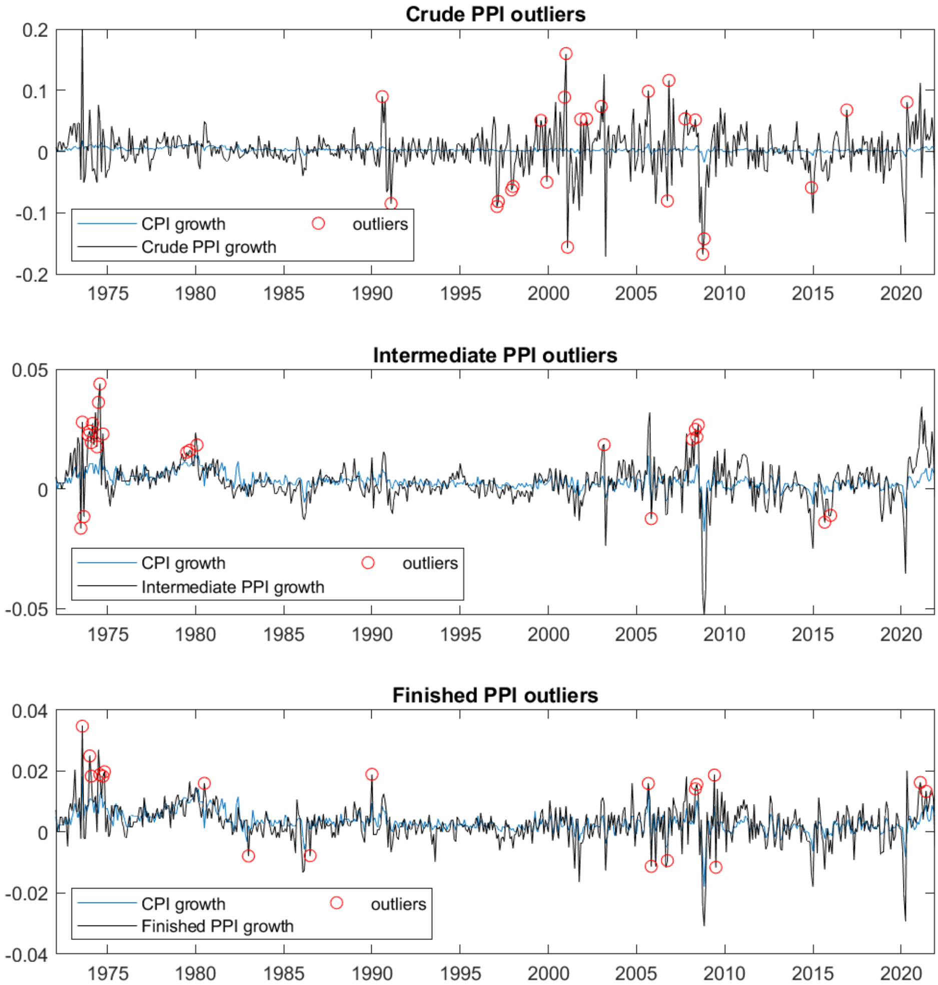

Figure 2: Panels show the outliers in monthly growth rates (black) of the Crude, Intermediate, and Finished PPI series, respectively, against monthly CPI growth (blue). Dots mark the outliers generated with the iForest algorithm that survive the restriction described in equation (5).

We detect outliers in the producer price indices using the isolation forest algorithm (iForest) proposed by Liu et al. (2012).[17] 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 72 outliers.[18] Figure 2 shows the three PPI series and the detected outliers at which the corresponding IP index does not co-move. The outliers coincide with periods when there were prominent events on the supply side that led to volatile and elevated inflation, like the oil price crisis in the 1970s, turmoil

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

[18]We choose 0.06 as lower values result in too few shocks and consequently weak instruments. Higher values might classify price movements not connected to supply shocks as such. We, therefore, prefer this rather conservative value but also run a robustness check with a value of 0.1, see below.

during the financial crisis, or the pick-up in inflation due to severe supply constraints after lifting the COVID-19 lockdowns of 2020.

The next section presents our empirical results. In Section 4, we will conduct robustness checks regarding alternative regime definitions, based on either the level of inflation or the volatility of the Crude PPI. We also implement alternative identification schemes by using overall industrial production data instead of the series for the individual stages of processing (to prolong the sample), by restricting additional price movements instead of industrial production, identifying more outliers, by controlling for exchange-rate movements and contemporaneous industrial production, and by using start dates after the onset of the great moderation. Alternatively, we also rely on oil-supply shocks as identified by Baumeister and Hamilton (2019) to measure supply shocks. In all cases, results are similar to our baseline estimates.

3 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. Next, we turn to the individual stages of processing. We also investigate the differences between positive vs. negative shocks and explore the effects of monetary policy shocks in the different regimes.

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 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 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.[19]

In Table 1, upper panel, we report descriptive statistics of the two states of inflation. 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

[19] Using European micro data from 11 countries over the period 2005-19, Gautier et al. (2022) 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.

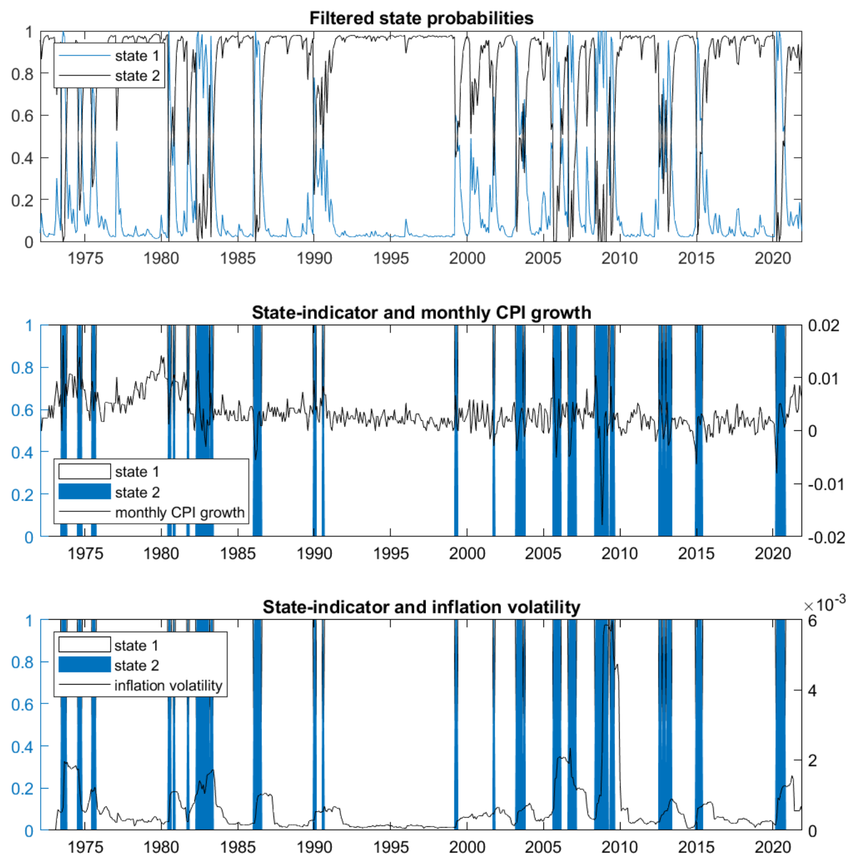

Figure 3: Top panel: filtered state probabilities estimated from model (1); middle panel: monthly growth of CPI; bottom panel: inflation volatility, each against the state-indicator H_t. Inflation volatility is calculated as the variance of monthly CPI growth over a rolling window of 12 months.

in State 1 and more than double (0.56) in State 2. This higher volatility is only to a 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 the fact that not the overall level of inflation but rather its volatility and sudden changes characterize 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:

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

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
Mean size outliers intermediate	0.02	0.02
Mean size outliers finished	0.01	0.01
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: Upper panel: characteristics of the two states. all statistics in percent. Lower panel: regression of filtered state probabilities on exogenous volatility indicator and its lags, maximizing R^2.

The contemporaneous indicator and the first four lags are significant at the 5% level.[20] 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 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. 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.

[20] 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.

3.2 Effects of supply shocks on CPI and IP

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. Here and in the following we estimate Regression (4) by setting y_t equal to the changes in the respective PPIs 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 which is associated with higher volatility in monthly CPI growth—CPI reacts more quickly and more strongly, compared to State 1. That is, we find clear evidence for state dependency of the CPI response to supply shocks. Next, we calculate the effect of a shock to Crude PPI on industrial production of crude goods. The right panel of Figure 4 depicts the results. As discussed in Section 2.3, to identify supply shocks we restricted industrial production of crude goods to fall in the period of a contractionary shock to Crude PPI. In State 2, this effect extends to a longer period and is much stronger compared to State 1.

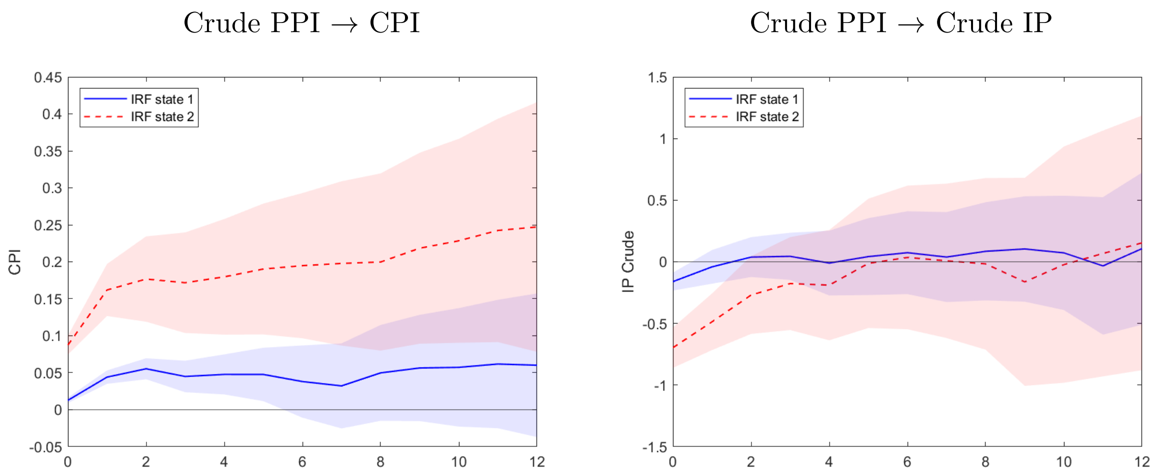

Figure 4: Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude PPI (left) and corresponding industrial production response (right). Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

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).[21]

We also investigate the responses of the CPI to shocks to Intermediate and Finished PPIs and the reactions of the corresponding IP series. On impact, the responses of all stages of processing PPIs in states 1 and 2 are significantly different from each other, with a stronger response in State 2. Differences are, however, weaker in comparison to the effects of shocks to Crude PPI. The size of the effect of a producer price shock is larger, the closer the respective stage of processing is to the CPI, i.e., for more downstream

[21] 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 8 lags of y_t in the local projection regressions.

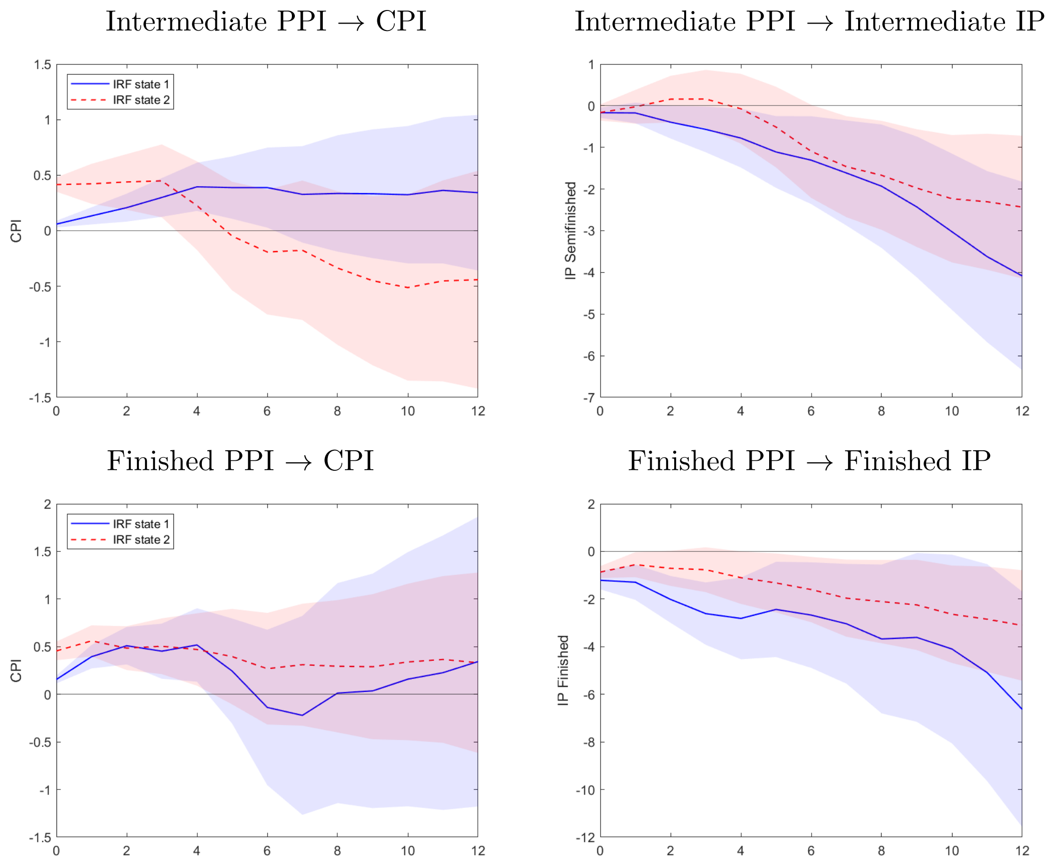

Figure 5: Left: impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Intermediate (upper row) and Finished PPI (lower row) and corresponding industrial production responses (right). Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

prices. This is to be expected, given that further cost components are added at each stage. Regarding the responses of the corresponding industrial production series, differences are much smaller for shocks to Intermediate and Finished PPIs than for Crude PPI. Yet, in both cases, the corresponding industrial production falls in the medium run.

In Appendix B we check several econometric issues, among them potentially weak instruments.[22] Furthermore, Figure C-1 in Appendix C demonstrates that the different CPI responses in the two regimes are not due to a systematically different reaction of monetary policy across regimes.[23]

The main conclusion that emerges from our empirical results is that during a high-inflation-volatility regime, the transmission of producer price shocks to consumer prices is stronger and quicker than during times of more tranquil inflation. This state dependency is the largest and the most persistent for shocks to Crude PPI and decreases for shocks to PPIs of downstream stages of processing.

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

[23]Specifically, monetary policy reacts stronger to a shock to Crude PPI in State 2 than in State 1, in line with the larger CPI response. It reacts similarly for shocks to Intermediate PPI; only in the case of Finished PPI shocks do we see a stronger reaction of monetary policy in State 2 after three months. Here, however, the differences in the CPI response are the smallest.

3.3 Effects between stages of processing

Next, we analyze the effect of a producer price shock on its downstream price index in the stages of processing system, namely the effect of a shock to Crude PPI on Intermediate and Finished PPI and the effect of Intermediate on Finished PPI. Therefore, we set the response variable y_t in (4) equal to Intermediate (upper left panel of Figure 6) or Finished PPI (upper middle and right panels). The independent variable x_t is then either Crude (upper left and middle panels) or Intermediate PPI (upper right panel). We leave the rest of model (4) unchanged, also the instruments follow the same rule as in the analysis for Figure 4.

In all three cases we can see a significantly differing response between states 1 and 2 on impact. This difference is most pronounced and most persistent for a shock to Crude PPI. Again, the weak instrument test by Lewis and Mertens (2022) leads to a rejection of the weak instrument hypothesis in all three cases (see right panel of Figure B-1 in Appendix B).

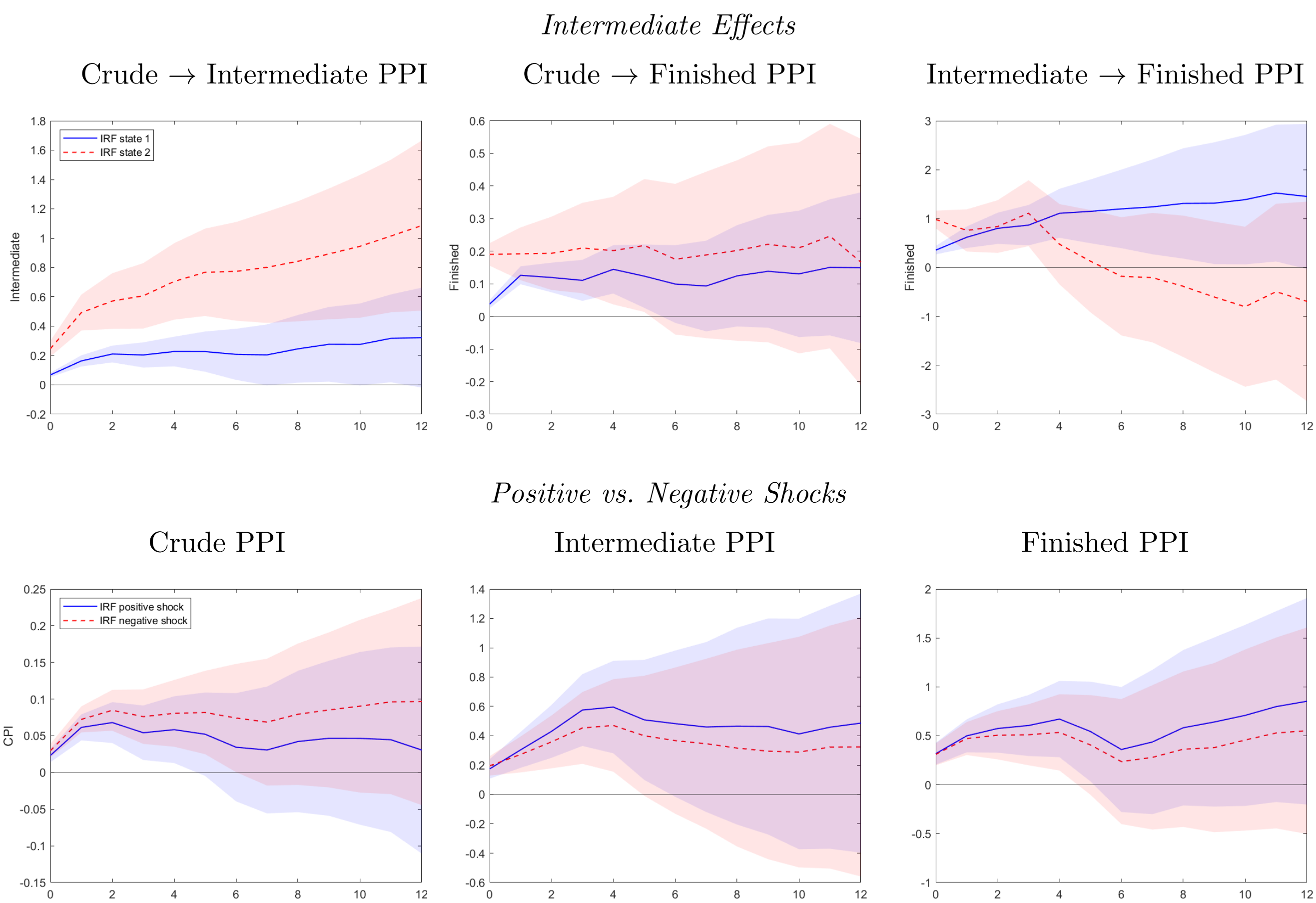

Figure 6: Top row: impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of Intermediate and Finished PPIs to a shock to Crude PPI and Finished PPI to a shock to Intermediate PPI. Bottom row: Impulse responses of CPI to positive (solid blue lines) and negative (dashed red lines, responses flipped) shocks to Crude, Intermediate, or Finished PPIs. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

3.4 Positive vs. negative shocks

The bottom row of Figure 6 reports CPI responses to positive (red dashed lines) or negative (solid blue lines) shocks to Crude, Intermediate, and Finished PPI. The reactions to negative shocks are multiplied by -1 for a better comparison across shock signs. 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.

3.5 Effects of a monetary policy shock

Next, we estimate the state-dependent effect of a contractionary monetary policy shock on monthly CPI. Departing from the IV approach, we directly regress monthly CPI growth (y_t) in the following way on the monetary policy shock series ($shock_t$) that Jarociński and Karadi (2020) construct by combining high-frequency information and sign restrictions:

$$y_{t+h} = \mu_h + H_t \left(\beta_h^1 shock_t + \sum_{l=1}^{n} \delta_{l,1} W_{t-l} \right) + (1 - H_t) \left(\beta_h^2 shock_t + \sum_{l=1}^{n} \delta_{l,2} W_{t-l} \right) + u_{t+h}. \tag{7}$$

The set of controls W_t now contains 8 lags of y_t, ΔIP_t, and the US narrow real effective exchange rate index (EER) provided by the Bank for International Settlements. Coefficients β_h^1 and β_h^2 denote the impulse responses at horizon h in states 1 and 2 respectively. The sample length for Model (7) spans from 1990M1 to 2019M6 due to the availability of Jarociński and Karadi (2020)'s monetary policy shock series.

Effect of a contractionary monetary policy shock on CPI

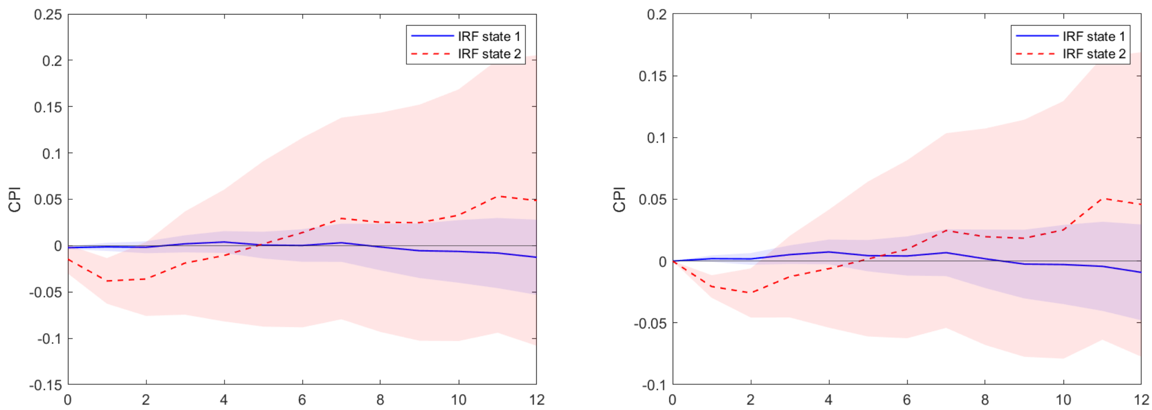

Figure 7: Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a one-standard-deviation contractionary monetary policy shock by Jarociński and Karadi (2020). Left: baseline controls, right: controls with IP_t & CPI_t. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

Figure 7 shows the resulting IRFs of Model (7). As visible in the left panel, the effect of a monetary policy shock of one standard deviation on the CPI differs across states 1 and 2. On impact, the effect in State 2 is negative, falls further, and increases slowly in the subsequent periods. That is, an initial fall in inflation is followed by positive rates. In State 1, however, the effect of a monetary policy shock is insignificant. Both results do not change if we include contemporaneous values of the overall industrial production index and the CPI as controls (right panel).[24] We interpret our findings such that, in the short run, monetary policy is more effective in changing inflation in the high-volatility regime, likely due to the stronger responsiveness of prices prevailing in this state.

4 Robustness

In this section we explore the robustness of our results, first with regard to alternative regime definition and second concerning alternative identification assumptions and regression setups.

4.1 Alternative regime definitions

As stated in Section 2.1, the regimes are determined by inflation volatility and not by, e.g., the level of inflation itself. To 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, but investigate whether alternative regime definitions also result in state-dependent transmissions of supply shocks. To this end, we split regimes such that we are in State 1 whenever an exogenously chosen variable is below its average value and in State 2 if it is above the average.

We first 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, as this exogenous variable. The upper row of Figure 8 shows the results. State 1 corresponds to a below-average inflation volatility. 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 figures 4 and 5. Supply shocks to intermediate PPIs are transmitted more quickly and strongly to consumer prices if the current change in CPI inflation is above average. Importantly, this is not the case for several other candidate variables. To generate the middle row of Figure 8, we use the *level* of CPI inflation as the external variable, again separating regimes below (blue solid lines) and above (red dashed lines) its average. No clear state dependency is visible. In particular, while the impact response of CPI inflation after a shock to Crude PPI is slightly higher than in State 2, it is below State 1 in the following periods. Reactions to Intermediate and Finished PPI shocks also do not display a clear pattern. Similarly,

[24]We explore both possibilities, as it is debatable whether the CPI and/or IP can react contemporaneously to monetary policy shocks. We conduct the same robustness for our baseline specification in the next section.

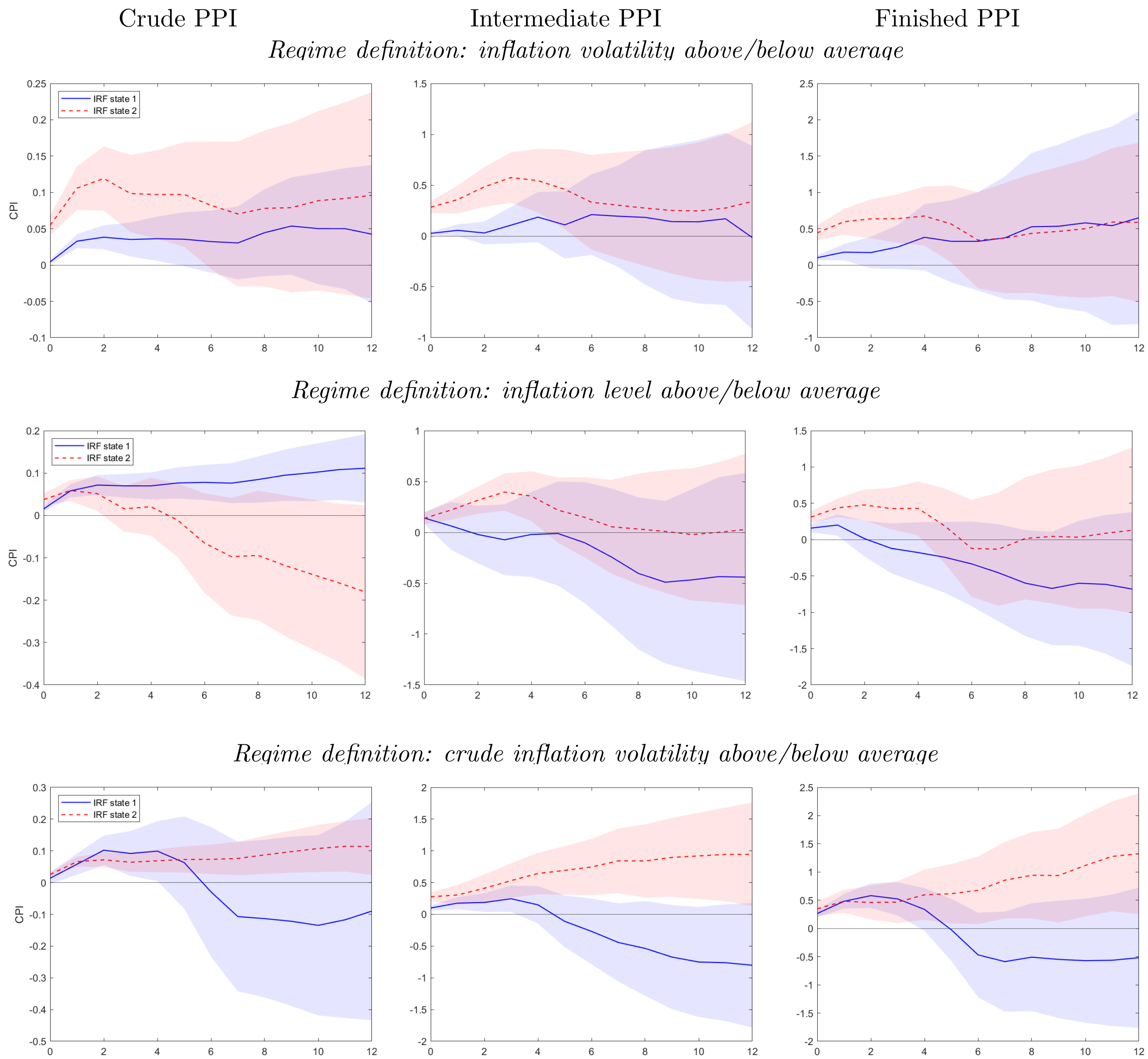

Figure 8: Alternative regime definitions. Impulse responses in Regime 1 (low state, solid blue lines) and Regime 2 (high state, dashed red lines) of CPI to a shock to Crude, Intermediate, or Finished PPIs. Top: State 1/2 if absolute change in CPI inflation is below/above average. Middle: level of CPI inflation below/above average. Bottom: absolute change in Crude inflation below/above average. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

a mostly state-independent picture emerges once we let regimes depend on the volatility of Crude PPI, see the lower row of Figure 8. However, here the response in State 2 is significantly above that of State 1 in the case of shocks to Intermediate PPI during most of the periods. This hints towards a somewhat higher price flexibility in case of larger volatility of input prices, a result we revisit when discussing theoretical explanations in Section 5.

4.2 Alternative shock identifications and setups

We now turn to alternative identification schemes for identifying supply shocks. First, we exchange our identified shocks with a series of supply shocks that are well established in the literature, i.e., oil-supply shocks. Specifically, 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 2.1. The left panel of Figure 9 shows the results. In the right panel we include the contemporaneous value of the exchange rate as a control.[25] As 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.

Effect of an oil price shock on monthly CPI inflation

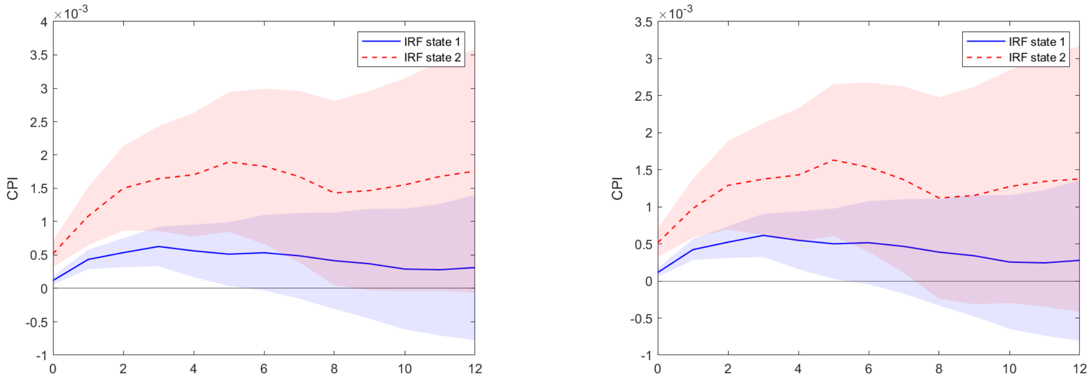

Figure 9: Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a contractionary oil price shock by Baumeister and Hamilton (2019). Left: baseline controls, right: controls with EER_t. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

Second, we extend the sample forward to October 1948. Because the industrial production data for the different stages of production is available only since 1972, we replace these series with data for overall industrial production. We accordingly modify the restriction that supply shocks are not allowed to move PPIs and industrial production in the same direction such that it refers to overall industrial production. Results are shown in Figure 10 and are similar to the baseline estimates. Note, however, that the oil price was regulated in the US before 1974, such that this important part of raw materials did account for much fewer shocks compared to later periods.

Given the drawback that the overall industrial-production data does not directly correspond to the PPI price data in this specification, we, third, implement alternative identification schemes in Appendix D. Specifically, we keep the long sample but do not impose assumptions on industrial production movements. We rather restrict changes in

[25] We thereby focus on the direct effects of the oil price shock that do not work via the contemporaneous exchange rate response.

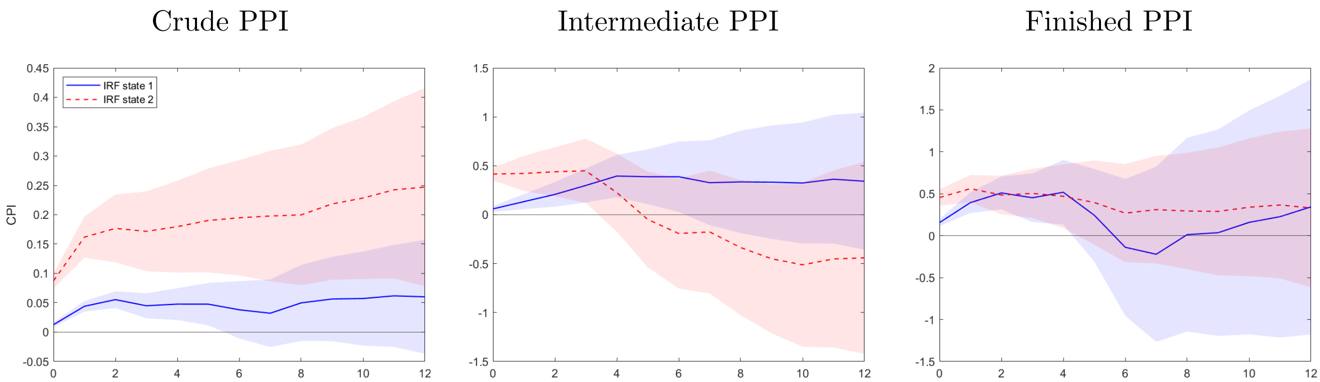

Figure 10: Sample starting in 1948: impulse responses in Regimes 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude, Intermediate, or Finished PPIs. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

downstream prices preceding supply shocks. That is, we identify those outliers as supply shocks that move PPI prices more than a certain factor compared to earlier downstream prices. In this way, we sort out demand shocks that work their way up the supply chain. Again, the results turn out to be similar to our baseline estimates, visible in the first three rows of Figure D-1 in Appendix D.

Fourth, we check for robustness regarding the number of identified outliers. As discussed in Section 2.3, we allow for 8% of observations to be outliers. Increasing this number by a quarter to 10% yields the bottom row in Figure D-1 in Appendix D. Results change only slightly compared to the baselines.

Last, we test different specifications of the local projections in Appendix E. In particular, we include contemporaneous values of industrial production and the exchange rate as controls, demonstrating again that our results are not driven by demand shocks or by a simultaneous effect of the exchange rate on prices of several stages of production. We also consider starting dates after the great moderation.

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 builds on the model of Devereux (2006), who suggests that firms can invest in price flexibility. Using related intuitions, observation costs as in Álvarez et al. (2018) or models of rational inattention (Mackowiak and Wiederholt, 2009) can also account for our evidence. Yet, Devereux's mechanism is much simpler while leading to very similar conclusions. Before sketching the model in Section 5.2 and deriving some policy implications, however, we first explore the most prominent alternative explanation, a standard menu-cost model.[26]

[26] Calvo-pricing with a fixed Calvo parameter would predict a constant pass-through of costs to inflation and is therefore clearly not able to replicate our empirical findings. Our preferred theory could, however, be used to determine the determinants of a time-varying Calvo parameter.

5.1 Models based on menu costs

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 always have a relatively larger impact on consumer prices compared to smaller ones, see Ascari and Haber (2022).

To test this prediction in our data, Figure 11 shows the reaction to small versus large shocks. We pursue two alternative strategies. In the top row, we follow the approach of Ascari and Haber (2022) and include the term $|\hat{x}_t| \cdot \hat{x}_t$ in Model (3), additional to the existing terms. That 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 merely interested in the effect of the shock size as an alternative explanation for our results. The effects of input-price shocks on 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 lead to a larger pass-through compared to smaller shocks.[27] In the lower row of Figure 11, we conduct a similar exercise.

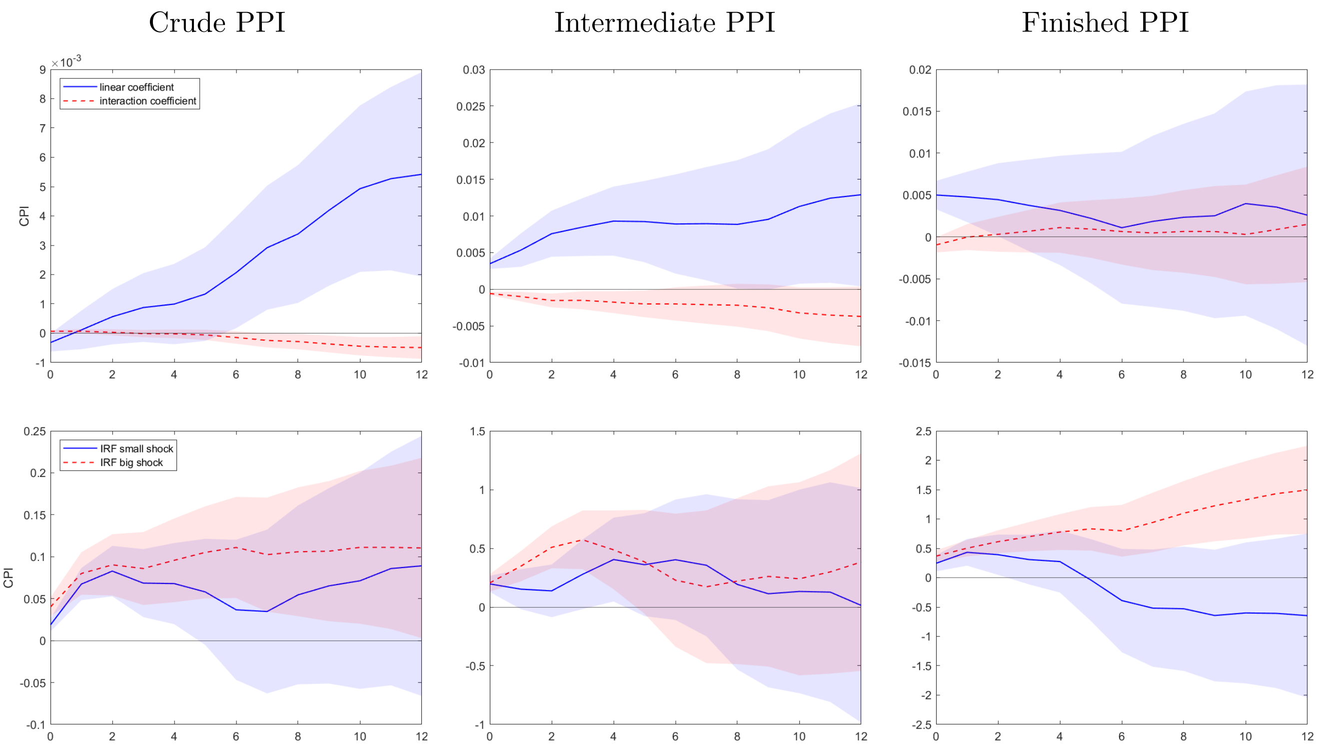

Figure 11: Effects of large vs. small shocks. Impulse responses of CPI to a shock to Crude, Intermediate, or Finished PPIs. Top row: specification including linear (solid blue lines) and interaction term $|\hat{x}_t| \cdot \hat{x}_t$ (red dashed lines). Bottom row: shock sizes below (solid blue lines) or above (dashed red lines) average. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

[27]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, which might be quite different depending on the size of the shock.

Specifically, we separate the outliers, as identified in Section 3.1, 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. In the following section, we therefore explore a different class of models that can replicate our empirical findings, in contrast to menu-cost models.

5.2 A model of endogenous price flexibility

We now sketch our preferred theory, which builds on Devereux (2006). We deviate from the original model 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 the larger deviations in Section 5.2.2 and list the corresponding calculations in Appendix F. Model predictions are derived in Section 5.2.3.

5.2.1 Setup

Consider firm i that produces according to

$$Y_t = (I_i - D_i \Phi(i))^{\alpha},$$

where $I_i = R_i^{\beta} L_i^{1-\beta}$ represents firm i's usage of a combined input factor consisting of raw material R_i and employment L_i.[28] $\Phi(i)$ 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_i 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 only be possible to negotiate if price discounts are granted to clients and/or require 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, $\Phi(i)$ would then be a shortcut to costs arising from a closer observation of the market. 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 larger supply shocks transmit to consumer

[28] We are mainly interested in the short-term decisions of firms, leaving out capital by fixing it at unity.

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 in Section 5.1.

The firm maximizes profits subject to a standard demand function

$$Y_i = \left(\frac{P_i}{P}\right)^{-\varepsilon} Y,$$

where P_i is the output price of firm i, P denotes the overall price level, and $\varepsilon > 1$ is the price elasticity. Y represents total demand in the economy. The price C for one unit of the input factor I_i consists of wages W, which are set in advance and are therefore fixed, and the price of the raw material C_R. The latter is stochastic, so are Y and P, seen from the firm's perspective. As usual, minimized costs for one unit of I_t are then

$$C = \frac{C_R^{\beta} W^{1-\beta}}{\beta^{\beta}(1-\beta)^{(1-\beta)}}. \tag{8}$$

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

$$E\Gamma\left[P_i\left(\frac{P_i}{P}\right)^{-\lambda} Y - W\left(\left(\frac{P_i}{P}\right)Y\right)^{\frac{1}{\alpha}} - CD_i\Phi(i)\right],$$

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 $\Phi(i)$, it can adjust its price after observing C, 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

$$P_i^1 = \delta\left[C^{\alpha}(\hat{Y})^{1-\alpha}\right]^{\omega}, \tag{9}$$

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 set their price in advance do this according to

$$P_i^0 = \delta\frac{E\left[\Gamma C(\hat{Y})^{\frac{1}{\alpha}}\right]^{\alpha\omega}}{E\left[\Gamma\hat{Y}\right]^{\alpha\omega}}. \tag{10}$$

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

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

where $V^1(\Theta)$ are profits for $D_i = 1$ and $V^0(\Theta)$ for $D_i = 0$. 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 $D_i = 1$ and $D_i = 0$ is higher than the discounted costs of investing in price flexibility, i.e., if $V^1(\Theta) - V^0(\Theta) \geq \Phi(i) E\,\Gamma\, C$, or

$$\Delta(\Theta) = \frac{V^1(\Theta) - V^0(\Theta)}{E\,\Gamma\, C} \geq \Phi(i). \tag{11}$$

$\Delta(\Theta)$ 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:

$$\Delta(\Theta) \approx \frac{\Omega\alpha}{2} Var\left(\ln C + \frac{1-\alpha}{\alpha}\ln \hat{Y}\right) = \frac{\Omega\alpha}{2}\left[\sigma_c^2 + \left(\frac{1-\alpha}{\alpha}\right)^2 \sigma_{\hat{y}}^2 + 2\frac{1-\alpha}{\alpha}\sigma_{c,\hat{y}}\right] > 0, \tag{12}$$

where lower-case letters stand for percentage deviations from the stochastic steady state, such as $c = \ln C - E \ln C$. Furthermore, $\Omega = [V(\exp(E\ln\Theta))/\exp(E(\ln\Gamma + \ln C))]\varepsilon(\varepsilon - 1)\omega^2 > 0$, where $V(\exp(E\ln\Theta))$ are profits evaluated at the mean $E\ln\Theta$ and $\sigma_c^2, \sigma_{\hat{y}}^2, \sigma_{c,\hat{y}} > 0$ are the variances of input costs and market demand, as well as their covariance. Given expression (8), the cost variance σ_c^2 depends on the variance of (the log of) raw material costs in the following way: $\sigma_c^2 = \beta^2\sigma_{c_R}$. Equations (11) and (12) deliver an important insight regarding 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.

5.2.2 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 $i = 0$ has the lowest costs $\Phi(0) = 0$ and that with $i = 1$ the highest. We also assume that the resulting $\Phi(i)$ is uniformly distributed and differentiable. Denote the index of the firm that is indifferent to whether to invest in price flexibility as z, that is z is the measure of firms that do invest. The resulting value of z is determined by the following conditions

$$\Delta(\Theta) = \Phi(z), \quad 0 \leq z < 1, \tag{13}$$
$$\Delta(\Theta) > \Phi(1), \quad z = 1. \tag{14}$$

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

$$P = \left[z(P^1)^{1-\varepsilon} + (1-z)(P^0)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{15}$$

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

$$YP = \frac{M}{\chi}, \tag{16}$$

where χ features i.i.d. shocks to velocity and has an expected value of unity.[29] We refer to these shocks as the demand shock from now on. Inserting equation (16) into the optimal

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

prices of firms (9) and (10), while observing that all firms that can adjust set the same prices, results in

$$P^1 = \delta \left[C^\alpha P^{(1-\alpha)(\varepsilon-1)} (M\nu/\chi)^{1-\alpha}\right]^\omega \tag{17}$$

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

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

$$\frac{M}{M_{-1}} = \left(\frac{P}{P_{-1}}\right)^\phi \nu, \tag{19}$$

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., $\phi \leq 1$. 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.[30] Theoretically, ν could also be linked to demand shocks. Given the focus in policy circles on lower reactions to inflation in case of supply shocks, we focus on a correlation with this kind of shock.[31]

To derive the expression for equation (12) in general equilibrium, we use the linearized price index (17) together with the linearized versions of equations (15) and (19), see Appendix F. This yields

$$p = \frac{\varphi(z)\omega}{\Delta}\left[\alpha c + (1-\alpha)(\hat{\nu} - \hat{\chi})\right], \tag{20}$$

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 (20) we derive—again in the appendix—the variance of $\ln C + \frac{1-\alpha}{\alpha}\ln\hat{Y}$ and use this in equation (12) to arrive at equations (13) and (14) in general equilibrium as

$$\frac{\Omega\alpha}{2\Delta^2}\left[\sigma_c^2 + \left(\frac{1-\alpha}{\alpha}\right)^2(\sigma_{\hat{\chi}}^2 + \sigma_{\hat{\nu}}^2) + 2\frac{1-\alpha}{\alpha}\sigma_{c,\hat{\nu}}\right] = \Phi(z) \qquad 0 \leq z < 1 \tag{21}$$

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

with

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

Hence, $\Delta = [1-\phi(1-\alpha)]/[\alpha+\varepsilon(1-\alpha)]$ for $z = 1$ in (22). The covariance $\sigma_{c,\hat{\nu}}$ corresponds to $\phi_C\sigma_c^2$, see footnote 30.

[30] The functional form would be $\nu = (C/C_{-1})^{\phi_C}\tilde{\nu}$, with $\tilde{\nu}$ being 'pure' monetary policy shocks.

[31] 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)

5.2.3 Model predictions

Equations (21) and (22) 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., $z < 1$).[32] We first assert the relation between 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 (20) 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 (21).[33]

Proposition 1 (Effects of shock volatilities) *Higher volatility of the shocks to the costs of raw materials (σ_c^2), demand ($\sigma_{\hat{\chi}}^2$), and/or the money supply ($\sigma_{\hat{\nu}}^2$, 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 $\sigma_c^2, \sigma_{\hat{\chi}}^2$ and/or monetary policy variables ($\sigma_{\hat{\nu}}^2, \sigma_{c,\hat{\nu}}$, 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 a price adjustment after observing shock realizations more valuable (Proposition 1). This effect also works via inflation volatility, which can be influenced by monetary policy: If the prices of competitors are fluctuating strongly, it pays off to invest in the ability to change prices after observing the resulting demand. In such a situation, more firms decide to invest in price flexibility, which increases the response of inflation to shocks. This is in line with our empirical result: an increase in inflation volatility leads to a larger pass-through of cost and monetary policy shocks to inflation (Corollary 1).[34]

Equation (20) implies a larger shock pass-through not only if more firms have invested in price flexibility (a higher z) but also if monetary policy is less aggressive in fighting inflation (a higher ϕ, which lowers Δ). Put differently, the inflation response depends

[32] 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.

[33] Proofs for the propositions and the corollary are given in Appendix F.

[34] The influence of the variance of the costs of raw materials also aligns well with our finding in Figure 8 that, for shocks to the Intermediate PPI, inflation tends to react stronger if the volatility of Crude PPI is higher.

on how many firms are able to adjust their price after observing the shocks and by how much they adjust. The direct effect of monetary policy, via a changing Δ, is standard in the literature. A lower value of ϕ (raising Δ) corresponds to stricter inflation targeting. Specifically, letting ϕ approach minus infinity fixes the price level at its previous level. However, the impact of ϕ on the variances of the price level and demand changes the incentives of firms to invest in price flexibility, which entails an indirect influence of monetary policy. The role of price flexibility, via $\varphi(z)$, is new in this model. Regarding this indirect effect of monetary policy, we can derive the following result.

Proposition 2 (Effects of monetary policy) *Stricter inflation targeting (a lower 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 $Cov(c, \hat{\nu})$) increases price flexibility (z) and thereby the pass-through of all shocks to inflation.*

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.[35] 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 counteracting the price response, monetary policy can reduce this incentive. Naturally, lower volatility achieved by reducing monetary policy shocks has the same effect. 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. Given that we basically consider a one-period model, we do not capture this notion here. Second, we are only interested in the connection between shocks and inflation. That is, we do not conduct a proper welfare analysis, which would require a household sector and a carefully modeled tradeoff between distortions generated by price rigidities and the costs of investments in price flexibility.

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

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

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, Intermediate, and Finished PPI series as instruments.

We find that the impulse responses of 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. Monetary policy shocks also have a regime-dependent effect on consumer prices.

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. On the upside, we find monetary policy to be more effective in the high-volatility regime, at least in the short run. To achieve their goal of price stability, central banks may leverage this effectiveness to transition back to a regime with lower 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 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 that are used for personal consumption or which businesses use as capital investment. Government purchases and exports are excluded from the SOP system.

Seasonally adjusted data on the stages of processing industrial production indices were retrieved from the Federal Reserve Board (FRB). The indices are classified into crude processing, primary & semifinished processing, and finished processing, and are available since 1972, or 1967 in the case of Crude IP.

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.

B Econometric checks

The instrumental variable we use 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 PPI_t (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.

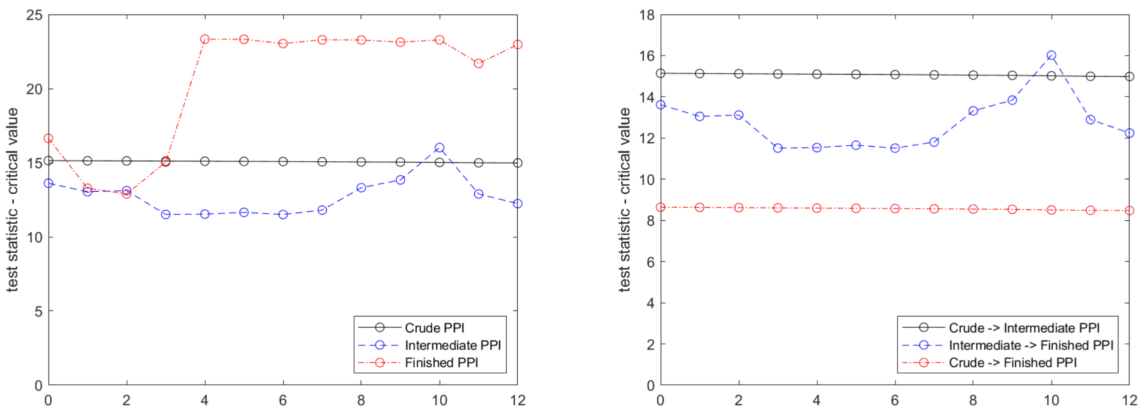

Figure B-1: Left panel: Results of the Lewis and Mertens (2022)-test for weak instruments: difference of the test statistic and the critical value for baseline results (figures 4 and 5). Right panel: same statistics between stages of processing (Figure 6).

In recent work, Gonçalves et al. (2022) derive conditions for which the state-dependent local projection (LP) estimands $\beta^1_{LPIV,h}$ and $\beta^2_{LPIV,h}$ recover the population impulse responses. Specifically, if a shock affects the response variable y_t, it might 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. The required independence might not be clearly given in our case as the MS-AR we use to estimate the filtered state probabilities consists of monthly CPI growth. Nonetheless, we assume that a one-time unit shock will not induce an alternation of the states as the regimes we estimate exhibit a relatively high persistence of 33 months in State 1 and almost 8 months in State 2. Furthermore, we have shown with Regression (6) that not only the contemporaneous level of inflation volatility but also its first four lags are highly relevant for the likelihood of switching to the high volatility regime. This means that inflation volatility needs to remain elevated for a few months to switch regimes, which is unlikely to be induced by a one-time shock to inflation.

C Reactions of shadow rate

Figure C-1 shows the response of the shadow rate, the updated series from Krippner (2013), to shocks to Crude, Intermediate, and Finished PPI. As visible, the monetary policy reaction is not responsible for the observed state dependency of CPI responses. Monetary policy reacts stronger to shocks to Crude PPI in State 2 than in State 1 and similarly for shocks to Intermediate PPI. In the case of Finished PPI shocks, we indeed find a weaker reaction of monetary policy in State 2 after three months. Yet, the differences in the CPI response are the smallest at this point.

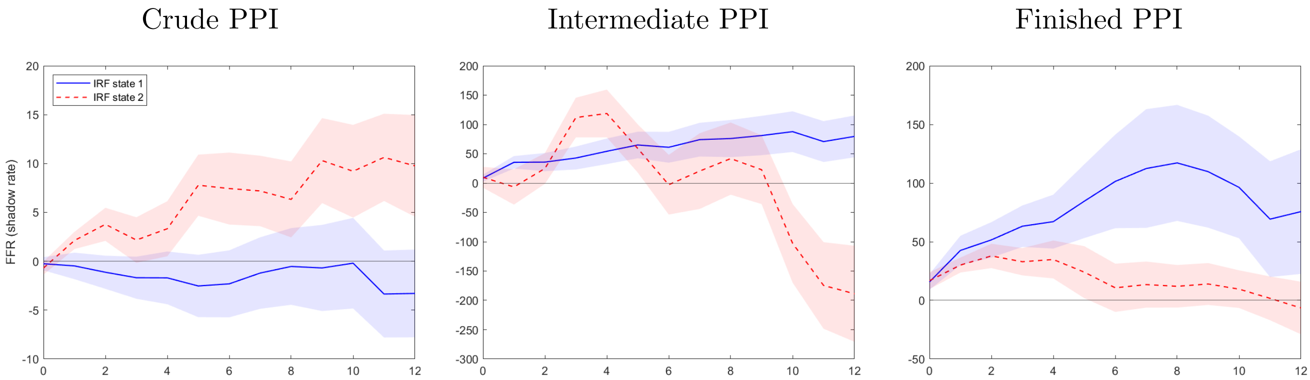

Figure C-1: Impulse responses of shadow rate in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) to shocks to Crude, Intermediate, or Finished PPIs. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

D Alternative identification scheme

As alternative identification strategies for the long sample starting in 1948, due to the unavailability of industrial production data for individual stages of production, we replace the restrictions on IP movements with three different restrictions on price movements. These restrictions rule out that movements in consumer prices were first triggered by an increase in demand. Specifically, if there is an outlier in the respective PPI in period t, then, in order to be counted as a supply shock, the following alternative restrictions have to be fulfilled.

i) ΔCPI_{t-1} divided by its sample standard deviation must be smaller than 50% of ΔPPI_t divided by its sample standard deviation

ii) ΔCPI_{t-1} divided by its regime-dependent sample standard deviation must be smaller than 50% of ΔPPI_t divided by its regime-dependent sample standard deviation

iii) ΔCPI_{t-2} must be smaller than the sample standard deviation of ΔCPI.

The first three rows of Figure D-1 show the resulting impulse response functions of restrictions i-iii. In all three cases, we can see a state dependency in the impulse responses with a larger effect of a producer price shock in State 2.

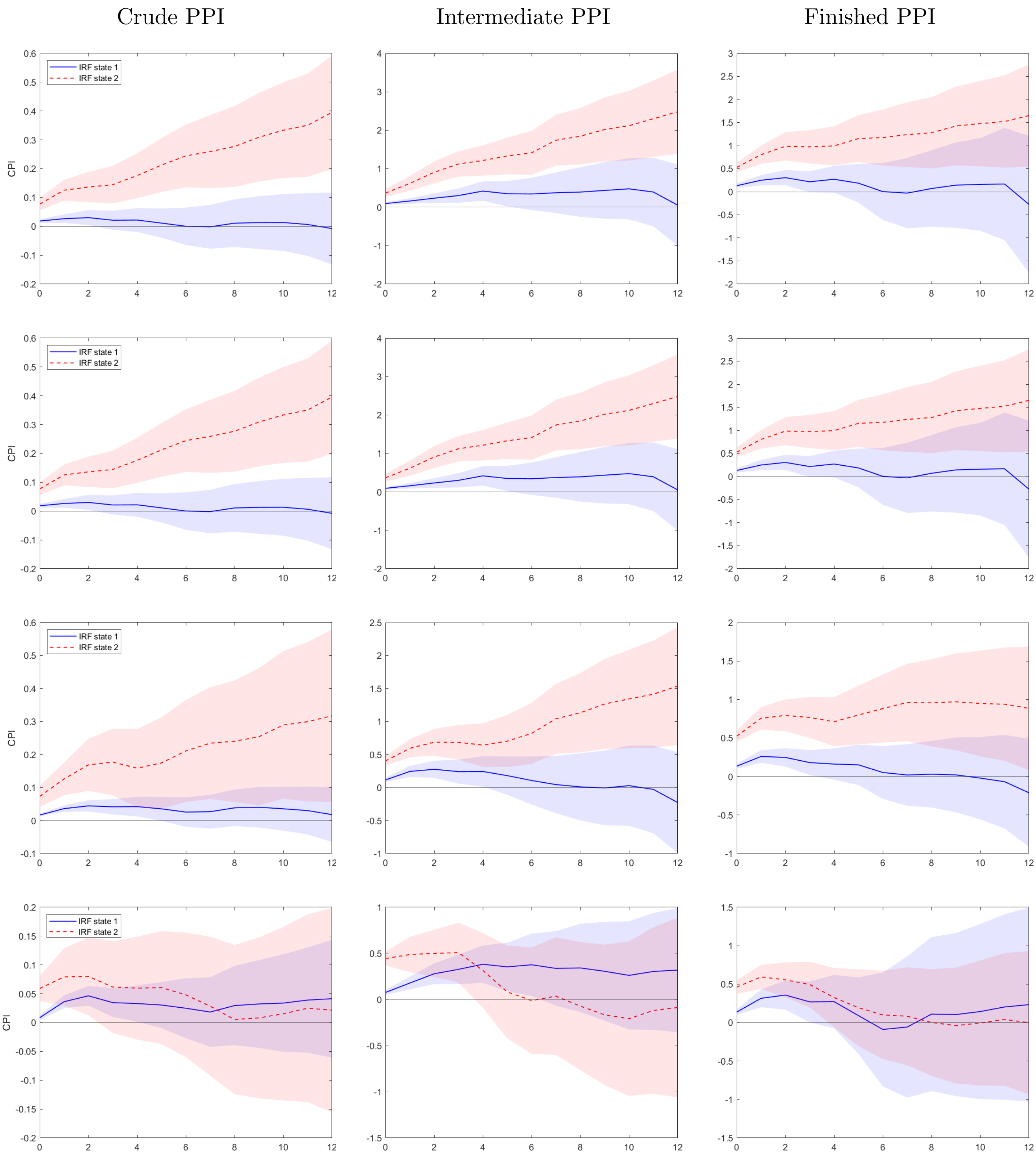

Figure D-1: Alternative identifications. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude, Intermediate, or Finished PPIs. Top three rows: restrictions i-iii, as described in the text. Bottom row: allowing for 10% outliers. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

To further check the robustness of our results, we also increase the number of admitted outliers by a quarter from 8% to 10%. The bottom row of Figure D-1 plots the responses, which are similar to the baseline results.

E Alternative local projection specifications

In the baseline specification of the local projections we only include lagged values in the set of control variables. In the case of industrial production, we alternatively also control for its contemporaneous value. The resulting IRFs of this specification are shown in the top row of Figure E-1 and do not differ very much from the baseline results.

A possible concern is that the impulse responses we estimate are driven by exchange rate movements as the CPI also includes imports, while PPI is measured excluding im- and exports. To address this issue, we include the contemporaneous value and eight lags of the US narrow real effective exchange rate index (EER) provided by the Bank for International Settlements as control variables. We show the resulting IRFs in the second row of Figure E-1. The results are, again, very similar to the baseline responses.

In a last robustness check, we estimate the baseline local projections with a start date after the onset of the great moderation. We consider the following sample lengths: 1984M1 - 2021M12 (third row of Figure E-1) and 1987M1 - 2021M12 (bottom row of Figure E-1). To ensure that we have enough shocks in each sample, the reactions to shocks in the Finished PPI were estimated while setting the fraction of outliers to 10% in this case (see Appendix D). Despite some small differences between the resulting IRFs, the overall picture we get is very similar to the baseline.

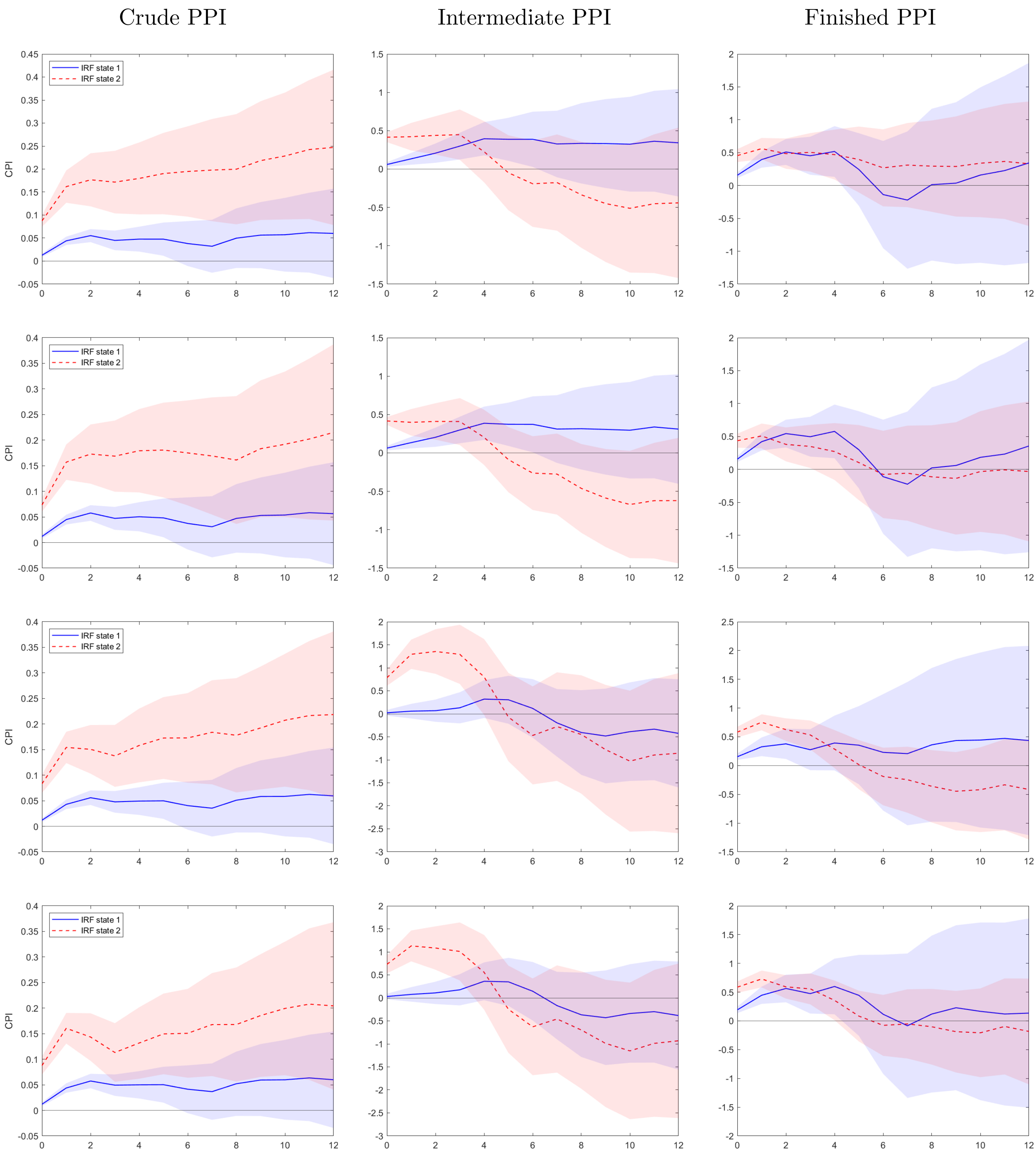

Figure E-1: Alternative specifications. Impulse responses in Regime 1 (low volatility, solid blue lines) and Regime 2 (high volatility, dashed red lines) of CPI to a shock to Crude, Intermediate, or Finished PPIs. First row: contemporaneous value of IP included as a control. Second row: contemporaneous value and eight lags of EER included as controls. Third row: 1984M1 to 2021M12 Bottom row: 1987M1 to 2021M12. Horizontal axes denote months. Shaded areas represent 68% confidence intervals.

F Model derivations and proofs

Derivation of equation (20)**.** 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 (17) of flexible firms p^1 is

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

such that (20) results.

Derivation of equations (21) **and** (22)**.** Given the expression (20) for the price index, we obtain $\hat{y}$ as

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

We therefore get the following

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

The resulting variance is then

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

which can be used in equation (12), together with equation (11), to derive conditions (21) and (22).

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 (21) 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: one unique equilibrium at $0 < z < 1$, one unique equilibrium at $z = 1$, or 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 (21)) is higher than the costs $\Phi(z)$. We therefore disregard the intermediate equilibrium in the case of three equilibria. If we are already at a corner solution, z can obviously not rise any further. Since the left-hand-side of inequality (21), for any given value of z, is increasing in $\sigma_c^2, \sigma_{\hat{\chi}}$, 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 (20) is

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

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 (20) 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):

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

where the first derivative determines the sign of $\partial\Delta(\Theta)/\partial\phi$ and $\Delta(\Theta)$ is the left-hand-side of inequality (21). Proposition 2 follows directly from these derivatives. ■