Shock Transmissions in Different Inflation Regimes*

—Preliminary and Incomplete—

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Abstract

We show that there is a regime-dependent effect of shocks to producer prices and monetary policy on consumer prices by estimating impulse responses via state-dependent local projections. We determine two inflation regimes with a Markov-switching autoregressive model and find that the regimes are characterized by different inflation volatility. We identify upstream supply shocks with an instrumental variable based on data outliers of the producer price series. Such shocks have a stronger and more persistent effect on downstream prices in a regime of elevated inflation volatility (state 2) than in periods of lower and more stable consumer price growth (state 1). At the same time, monetary policy shocks induce more inflation volatility in state 2, reinforcing the conclusion that transitions to this state should be prevented from the onset.

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1 Introduction

Policy makers have, in particular 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] These changing dynamics would be particularly important for central banking, as they would impact inflation forecasts and the expected effects of monetary policy actions. Specifically, current inflation projections crucially depend on the assumptions regarding how quickly and to which degree changes in producer prices are passed on to consumer prices. These considerations become apparent in situations in which central banks aim to contain price pressures generated by supply shocks. Similarly, the optimal timing of interest-changes designed to achieve the goal of price stability relies on estimates about lags in the transmission of monetary policy.

We take up this issue by empirically investigating whether and when inflation dynamics change. Specifically, using US data, we uncover two different regimes by estimating a Markov-Switching process based on inflation dynamics. Crucially, we do not restrict the regimes to be dependent on some exogenous inflation threshold but let them endogenously be determined by the inflation process itself. It turns out that inflation volatility (the presence of quick changes in inflation rates) seems to be more important in the determination of the regimes than its level. In a second step, we estimate state-dependent dynamic casual effects of a shock to producer prices—provided by the 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 the CPI in a dynamic way. We also investigate shocks to the intermediate stages. We identify supply shocks by using exceptional movements in the respective PPI series as instruments for the shocks. In doing so, we control for the endogenous reactions of upstream to downstream prices, such that our shock series does not capture demand shocks working their way up to previous stages of processing.

[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)

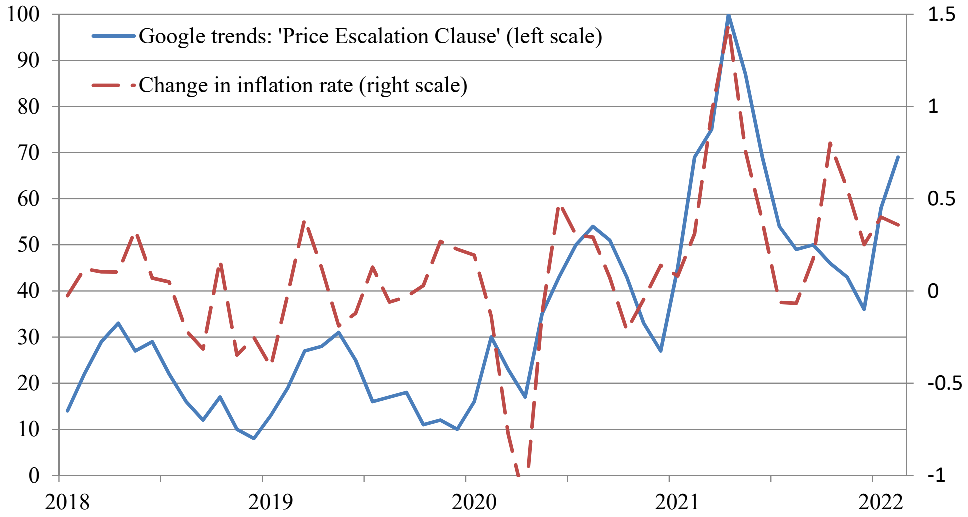

Figure 1: Index for google-searches for the term 'Price escalation clause' (left axis) and month-on-month change in annualized seasonally-adjusted CPI inflation rate in percentage points (right scale).

Our results show that in periods of high inflation volatility, downstream prices react much stronger in the initial and a number of following months. That is, in this regime, downstream prices are arguably more flexible and hence react quicker. This finding is in line with the anecdotal evidence regarding automatic adjustments discussed below. For shocks to the crude material PPI, we also find a higher long-run effect on the CPI. This confirms to the notion that in times of low inflation volatility firms allow margins to vary over time instead of passing changing costs quickly to customers, while in times of high inflation volatility the latter is preferred.

Lastly, we also investigate the effects of monetary policy shocks in the two inflation regimes. Again, CPI reacts much quicker to such shocks in the high-volatility state. However, a part of the initial reaction in the high-volatility regime is reversed later on. Hence, the medium-run effect is similar across regimes while monetary policy shocks seem to add to the inflation volatility if it is already high. This makes it more difficult to exit such a regime. Since cost changes are passed on more quickly and more strongly into consumer prices, monetary policy should prevent a transition to such a regime by counteracting phases of large price changes decisively and swiftly.

Our findings may be grounded in a different—faster and more decisive—price-setting behavior of firms when facing swiftly changing costs and/or observing larger price volatil-

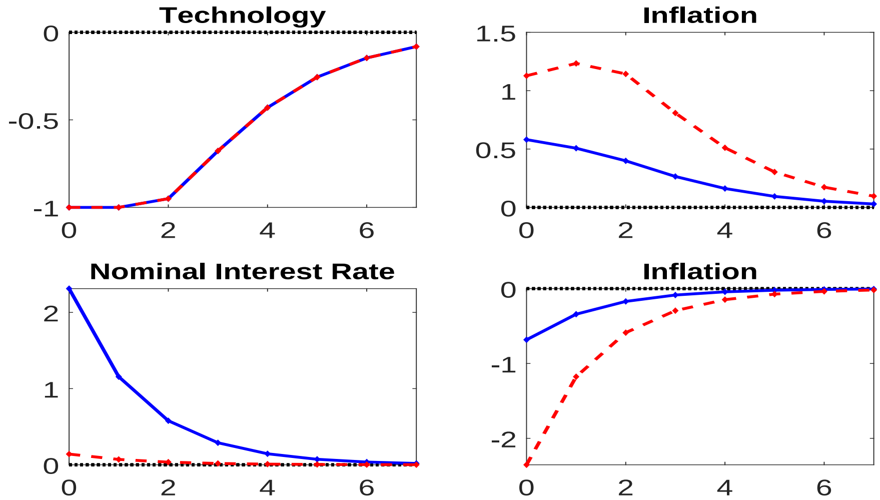

Figure 2: Theoretical reaction of inflation (right column) to an increase in production costs due to a reduction in technology (upper row), and to a contractionary monetary policy shock (lower row). The model is a standard three-equation New-Keynesian model with log utility, a discount factor of 0.99, a Frisch elasticity of unity, and a Taylor rule with an inflation coefficient of 1.5 and an output coefficient of 0.5. The Calvo parameter takes the value of 0.8 for the solid blue lines and 0.6 in case of the red dashed lines. The technology process was model to mimic the latest costs increases in a stylized way, i.e., a longer-lasting cost increase with a slow recovery afterwards.

ity in their sales markets. This line of explanation is supported by anecdotal evidence from the latest rise in inflation. Figure 1 depicts google searches for the term 'Price escalation clause', together with the change in the inflation rate. If agreed upon in contracts between seller and buyer, these clauses let sales prices rise automatically if the input costs of the seller rise (and vice versa for falling costs). That is, a widespread use of these clauses implies a much faster reaction of prices to upstream cost changes. As a result, inflation dynamics can change considerably with important implications for inflation projections and, potentially, for the way how monetary policy can stop the surge in inflation. As visible in the figure, interest in this kind of clauses seems to be linked to the change in the inflation rate, with an unseen peak in the spring of 2021. At this time, global input prices rose quickly due to several reasons, among them strained global supply chains. Similarly, 34% of sampled German Firms in the Bundesbank Online Panel reported that they use price escalation clauses after 2021, compared to only 17% before 2021.

On the theoretical side, it is well known that such quicker price reactions alter inflation dynamics even in the most basic New-Keynesian model. Figure 2 shows the reactions of inflation (right column) to an increase in costs due to a reduction of technology (upper row) and to a contractionary monetary policy shock (bottom row). The blue solid line depicts the situation when prices are, on average, changed every five quarters, while the red dashed line shows a scenario in which prices are changed every 2.5 quarters. As can been seen in the graph, the inflation response is much larger in absolute value in both cases.[2] That is, the most basic building block of New-Keynesian models predicts profound changes in inflation dynamics and shock transmission for different speeds of price adjustments.

Given the important implications, surprisingly little research has been done on the pass through of shocks to consumer prices in different inflation regimes. Due to the policy relevance of this question, most existing research was conducted in policy institutions. By using Granger-Causality tests, Weinhagen (2002, 2016) shows that price changes at each stage of production in the BLS PPI data are explained by upstream changes in prices, while downstream price changes do not Granger-cause price changes. Bobeica et al. (2020, 2021) focus on the pass-through of labor costs into output prices. In their analysis they consider two regimes, depending on whether the mean and volatility of inflation are above or below its historical mean. Using a Cholesky-decomposition to identify labor-cost shocks, they find that the mentioned pass-through is quicker and larger in the high-inflation regime. Similarly, the BIS (2022) investigates the pass-through of relative price changes, oil-price shocks, and exchange-rate movements into consumer prices and finds them to be dampened in periods of inflation below 5%.

Our approach differs from the above studies in that we study the effects of well-identified supply shocks on the prices in later stages of production. Importantly, when identifying different inflation regimes, we do not impose an ad-hoc threshold of inflation or its volatility but let the regimes be determined by the inflation process itself. In addition, we also analyze the effects of monetary policy shocks in the different regimes.

[2] As standard in these models, the strong negative inflation response reduces the reaction of the nominal interest rate to the contractionary monetary policy shock, as the low inflation rate exerts a negative pressure on the interest rate via the Taylor rule.

2 The model

2.1 State-dependent local projections

We follow the local projection instrumental variable (LP-IV) approach of Stock & Watson (2018) to construct the impulse responses. This method consists of a first-stage regression (1) in which the endogenous variable x_t is regressed on the instrument Z_t, and a second stage (2) 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.

$$x_t = \hat{\mu}_{FS} + \hat{\beta}_{FS} Z_t + \sum_{l=1}^{n} \hat{\delta}_{FS,l}^{T} W_{t-l} + \epsilon_t \tag{1}$$

$$y_{t,h} = \hat{\mu}_{2S,h} + \hat{\beta}_{LPIV,h} \hat{x}_t + \sum_{l=1}^{n} \hat{\delta}_{2S,l}^{T} W_{t-l} + u_t. \tag{2}$$

The coefficients $\hat{\beta}_{LPIV,h}$ then represent the impulse responses at each projection horizon h. $\hat{\mu}_{FS}$ and $\hat{\mu}_{2S}$ denote the intercepts, and ϵ_t and u_t the error terms. In this setting, Stock & Watson (2018) state three conditions on the instrument in order to uncover a causal effect: 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: $E[\eta_{t+i} Z_t] = 0, \forall i \neq 0$.

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

$$\begin{aligned} y_{t+h} =& \hat{\mu}_{2S,h} + H_t(\hat{\beta}_{LPIV,h}^{1} \hat{x}_t + \sum_{l=1}^{n} \hat{\delta}_{2S,l,1}^{T} W_{t-l}) \\ &+ (1 - H_t)(\hat{\beta}_{LPIV,h}^{2} \hat{x}_t + \sum_{l=1}^{n} \hat{\delta}_{2S,l,2}^{T} W_{t-l}) + u_{t+h}. \end{aligned} \tag{3}$$

The coefficients $\hat{\beta}_{LPIV,h}^{1}$ and $\hat{\beta}_{LPIV,h}^{2}$ form the impulse responses at horizon h in states 1 and 2 respectively. Estimation of equation (3) is done via ordinary least squares regression for each projection horizon h separately.

2.2 Data

The sample we use to estimate our baseline model (3) for the United States is in monthly frequency and spans from October 1948 to December 2021. For the response y_t we use log differences of US CPI. We set x_t to be 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 transform all price indices to log differences to achieve stationarity. The set of controls W_t includes $n = 8$ lags of the response y_t, the instrument Z_t, US industrial production growth (ΔIP_t), CPI growth (ΔCPI_t, if not equal to y_t), and the PPI growth of the subsequent stage of the SOP system. More details on the data set can be found in Appendix A.

2.3 A Markov-switching model to detect inflation regimes

We detect hidden inflation regimes by employing a Markov-switching autoregressive model (MS-AR) based on log differences of CPI data. This type of model was introduced by Hamilton (1989). The basic modelling idea is that there are different states s_t of the AR model impressed by regime-specific model coefficients and error terms. 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:

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

Equation (4) describes our set up in more detail:

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

ΔCPI_t (CPI data in monthly log differences) is explained by an intercept ν_m, autoregressive terms of four lags and a residual term $e_{m,t}$, which all switch between $m = \{1, 2\}$ states. We choose a rather small number of regimes and lags in order to keep the model as parsimonious as possible, to reduce computational costs and thus to increase the reliability of the estimates.

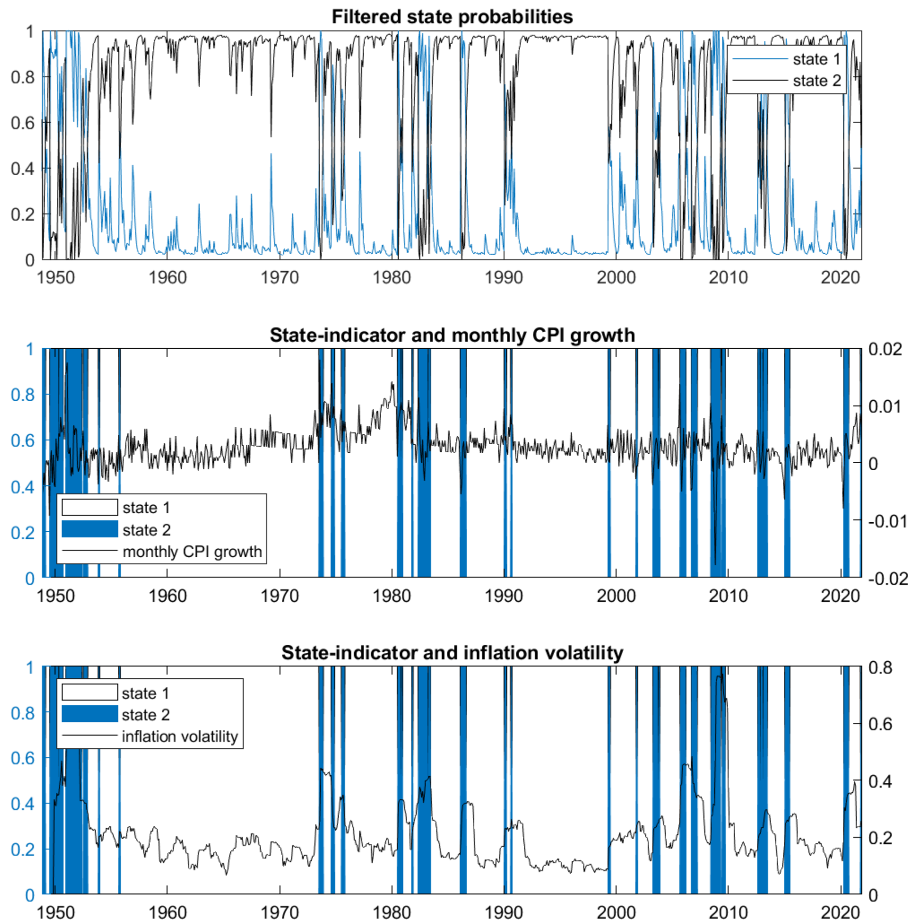

Figure 3: The top panel shows the filtered state probabilities estimated from model (4), the middle panel plots monthly growth of CPI and the bottom panel inflation volatility against the state-indicator H_t. Inflation volatility is calculated as the standard deviation of monthly CPI growth over a rolling window of 12 months.

Estimation of the model parameters and the hidden Markov chain is performed with the expectation maximization (EM) algorithm (for further explanation of the EM algorithm the reader is referred to Hamilton, 1990). We then obtain the filtered state probabilities (Chauvet & Hamilton, 2006) which we use for constructing the state-indicator H_t in (3). When in period t, the filtered probability of being in state 1 is greater than 0.5, H_t is assigned the value of 1 and 0 otherwise. The indicator for being in state 2 is then $1 - H_t$. The states we estimate are relatively persistent: The probability to stay in state 1 when being in state 1 (i.e., p_{11}) is 0.97 and respectively for state 2 (p_{22}), 0.87. This translates to an average state duration of 33 periods for regime 1 and 7.7 periods for regime 2.

Figure 3 shows the filtered state probabilities and the resulting state indicator in comparison with monthly growth rates of CPI and inflation volatility. We measure inflation volatility as the standard deviation of monthly CPI growth over a rolling window of 12 months. We can see that the inflation regime is in state 2 whenever there are sudden swings in monthly CPI growth and a generally increased volatility. Comparing the inflation volatility within each regime we find an average of 0.19 in state 1 and 0.37 in state 2. Further, we estimate the regime-dependent autocorrelation of monthly CPI growth of up to two lags by considering only those regime realizations that consist of at least three consecutive periods. In regime 1, we estimate an autocorrelation of 0.69 for the first lag and 0.62 for the second and in regime 2, 0.51 and 0.25 for lag one and two respectively. These estimates show that in state 1 is more persistent than state 2. Surprisingly, the overall mean of monthly CPI growth is 0.2% in state 2 and 0.3% in state 1. This highlights the fact that not the overall level of inflation but rather its volatility and sudden changes characterize the different inflation regimes we estimate.

3 Identification strategy

To identify the causal effect of a producer price shock on consumer price inflation, we instrument producer prices with a variable based on data outliers in the respective PPI series. 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 an exogenous shock in that time series[3]. Indeed, Kapetanios & Tzavalis (2010) show that well known oil price shock events coincide with periods in which they find an outlier in their oil price data.

Due to their unpredictability, we interpret rare data outliers as proxies for structural shock events, which Stock & Watson (2018) define as *"a primitive, unanticipated economic force, or driving impulse, that is unforecastable and uncorrelated with other shocks"*. Based on this definition, we assume that outliers in the PPI series are correlated with structural producer price shocks and uncorrelated with other shocks. Hence, we assume that the

[3]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.

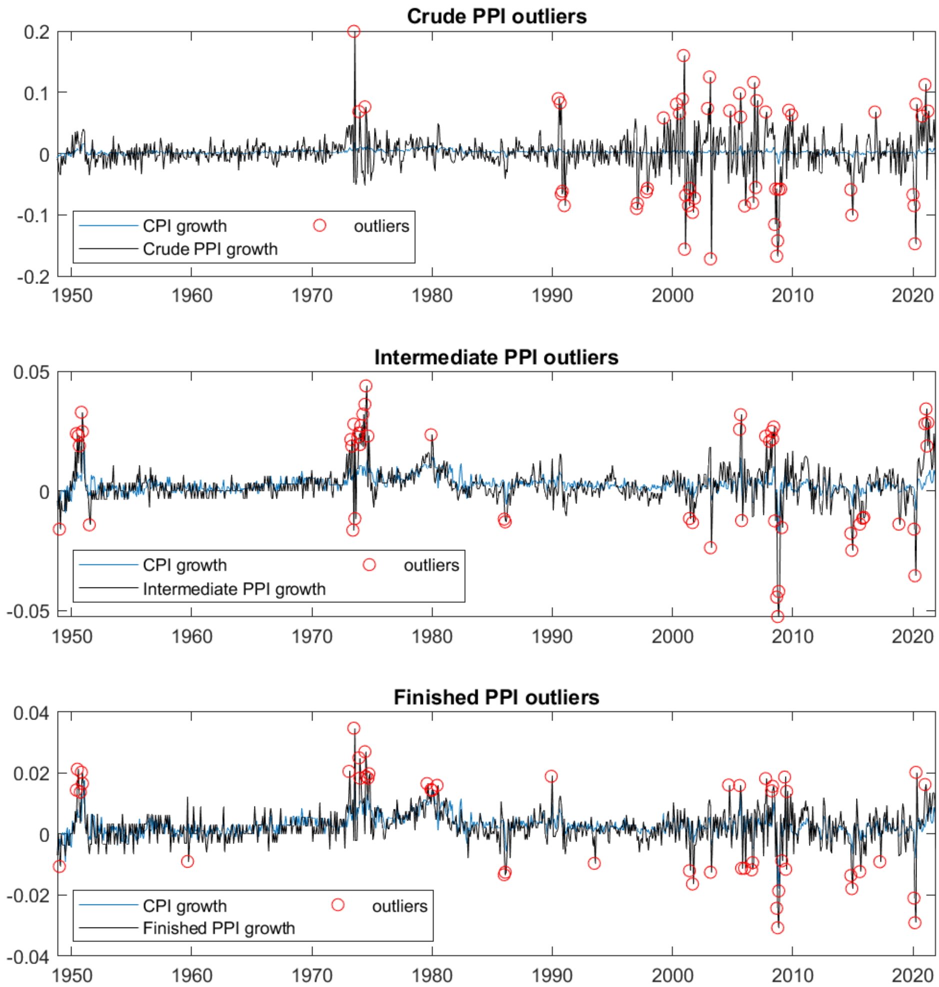

Figure 4: Each panel shows the outliers in the monthly growth rates of the Crude, Intermediate and Finished PPI series respectively (black) against monthly CPI growth (blue). The dots mark the outliers generated with the iForest.

outlier-based instrument satisfies the LP-IV relevance and contemporaneous exogeneity condition of Stock & Watson (2018). In our set up below, we make sure that demand shocks are not the ultimate cause of the observed outliers.

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

$$Z_t = \begin{cases} 1, & outlier > 0 \\ -1, & outlier < 0 \\ 0, & else. \end{cases}$$

Z_t takes the value of 1, when there is a positive outlier in the PPI series in period t, -1 when it is a negative outlier and 0 if there is no anomaly detected in t. To ensure that Z_t satisfies the third LP-IV condition (exogeneity to all shocks at all leads and lags), we follow Stock & Watson (2018) and include $n = 8$ lags of Z_t, y_t, industrial production growth (ΔIP_t), and the PPI growth of the next stage of the SOP system (i.e., for a shock in Crude PPI we control for Intermediate PPI), summarized in $W_t = \{Z_t, \Delta CPI_t, \Delta IP_t, \Delta PPI_t\}$, as controls in regressions (1) and (3). We include lags of Z_t as controls to correct for 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 industrial production as a proxy for GDP, we correct for any correlation between Z_t and a shock in GDP. Controlling for lags of ΔCPI_t and the next stage PPI rules out the possibility that the instrument Z_t is correlated with a shock in consumer prices or the following stage producer prices. This is important because we want to ensure 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. In Appendix C, we test alternative identification restrictions that restrict movements in downstream prices preceding identified supply shocks.

We detect outliers in the producer price indices using the isolation forest algorithm (iForest) proposed by Liu et al. (2012), which has been implemented in the Scikit-learn Python package by Pedregosa et al. (2011). Instead of first defining normal instances in the data, the iForest directly detects anomalies in the data through two quantitative properties: i) anomalies are the minority, and ii) they have attribute-values different from those of normal instances. For further explications the reader is referred to Liu et al. (2012). When setting the proportion of outliers in the PPI series (transformed to log differences) to 0.06, the iForest algorithm detects 54 outliers. Figure 4 shows the three PPI series and detected outliers over time. The outliers actually coincide with periods when there were prominent events in history that lead to volatile and elevated inflation, like the oil price crisis in the 1970s, turmoil during the financial crisis, or price falls due to a relaxation of supply-chain pressures after the COVID-19 lockdowns in 2020.

4 Results

4.1 Effects of producer price shocks on consumer prices

Figure 5 shows the state-dependent responses of monthly CPI growth to a unit shock in monthly growth rates of Crude, Intermediate and Finished PPI over a horizon of 12 months. On impact, the responses of all stages of processing PPIs in state 1 and 2 are significantly different from each other. The impact response of state two, the one which is associated with higher volatility in monthly CPI growth, always lays above the one of state 1. The effect of a shock in Crude dies out more slowly in state 2 than in state 1. When comparing the difference between state 1 and 2 across the three PPIs, we can see that for Crude PPI, the cumulative responses in state 1 and 2 are significantly different from each other over almost the whole horizon considered, while for Intermediate PPI and Finished PPI they start to overlap from period 1 and 2 onward. The size of the effect of a producer price shock are larger, the closer the respective stage of processing is to the CPI, i.e., for more downstream prices.

The dashed lines in Figure 5 represent 68% confidence bands. We construct them with Eicker-Huber-White (EHW) heteroskedasticity-robust standard errors as suggested by Montiel Olea & Plagborg-Møller (2021). Montiel Olea & Plagborg-Møller 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.

The instrumental variable we use consists only of a few data points unequal to zero and can thus be characterized as a *sparse instrument*. Giacomini et al. (2022) argue that these sparse instruments, often constructed from narrative restrictions, are likely to be weak instruments. We test the relevance of our IV applying the robust test for weak instruments with multiple endogenous regressors proposed by Lewis & Mertens (2022). We interact the instrument and PPI_t (our endogenous regressor) with the state indicator H_t and use 8 lags of CPI, IP and the IV as controls. Following Lewis & Mertens (2022), the test rejects weak instruments if the difference of the test statistic and the critical value is positive.

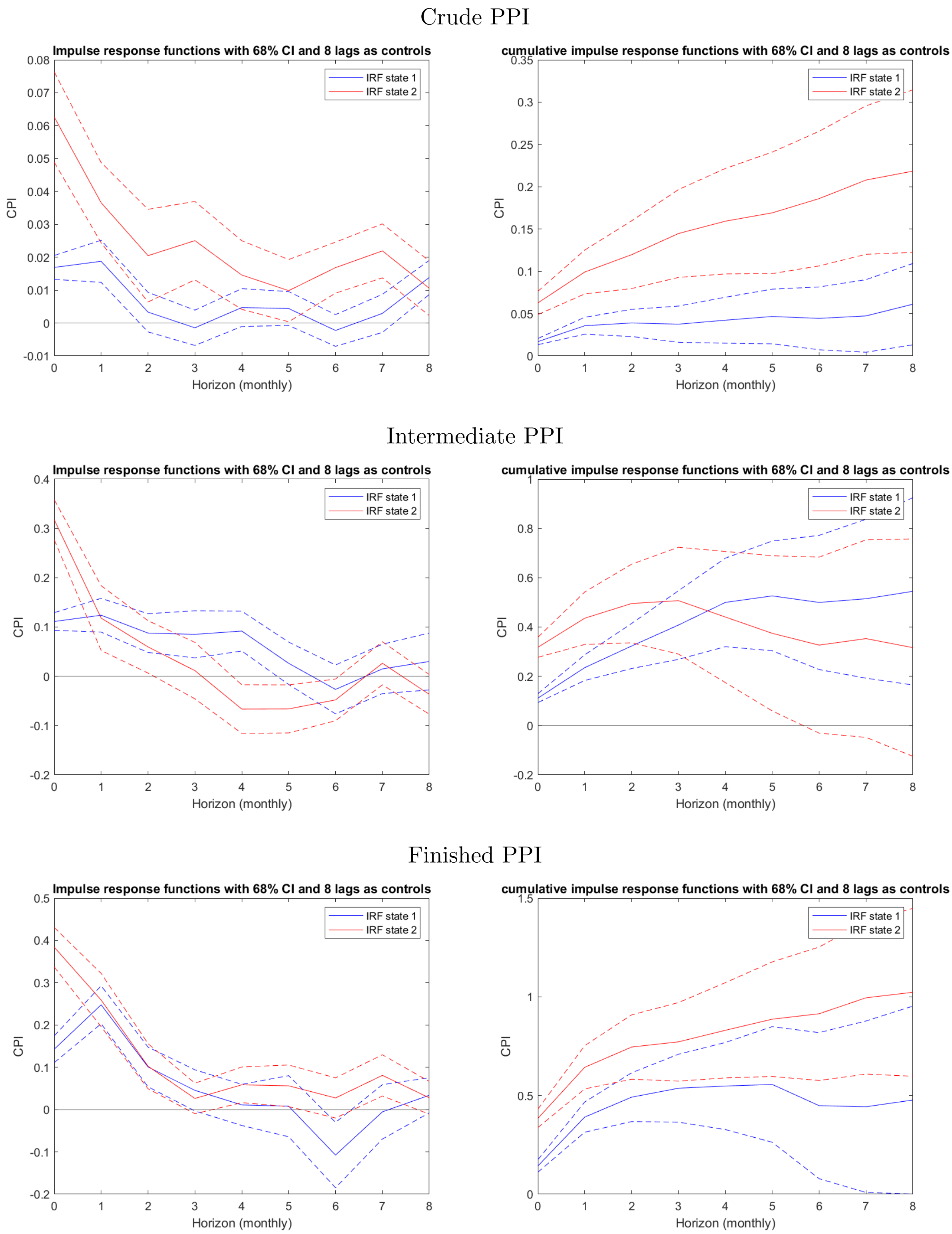

Figure 5: Impulse responses in regime 1 and 2 of a shock to Crude, Intermediate, or Finished PPIs on monthly CPI growth. The left hand side displays the IRFs in levels and on the right the cumulative IRfs are shown. Dashed lines represent 68% confidence intervals.

For our specification, this is the case at all horizons and for all three stages of processing PPIs, as can be seen in Figure 6. Hence, we reject the weak instrument hypothesis for the instruments based on Crude, Intermediate and Finished goods PPI respectively.

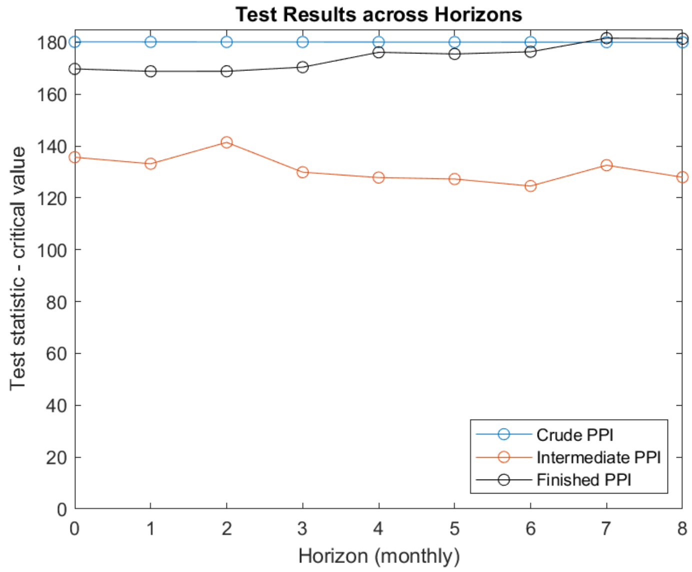

Figure 6: Results of the Lewis & Mertens (2022) test for weak instruments as the difference of the test statistic and the critical value. For all horizons and for all of the three PPI measures, this difference is positive and hence the weak instrument hypothesis can be rejected.

4.2 Effects between stages of processing

In a second step 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 in Crude PPI on Intermediate and Finished PPI and the effect of Intermediate on Finished PPI. Therefore, we set the response variable y_t in (3) equal to Intermediate (first row in Figure 7) or Finished PPI (last two rows) and x_t is then either Crude (first two rows) or Intermediate PPI (last row). We leave the rest of model (3) unchanged, also the instruments follow the same rule as in the analysis for Figure 5.

In all three cases we can see a significantly differing response between state 1 and 2 on impact. This difference is most pronounced and most persistent for a shock in Crude on Intermediate PPI. The effect of a shock in Crude PPI dies out more slowly in state 2 than in state 1. The response of downstream PPIs in state 2 in response to a shock in Crude PPI lays most of the time above those in state 1. In Figure 7, we show 68% confidence bands produced with EHW standard errors. Again, the weak instrument test by Lewis & Mertens (2022) leads to a rejection of the weak instrument hypothesis in all three cases (see Figure 11 in Appendix B).

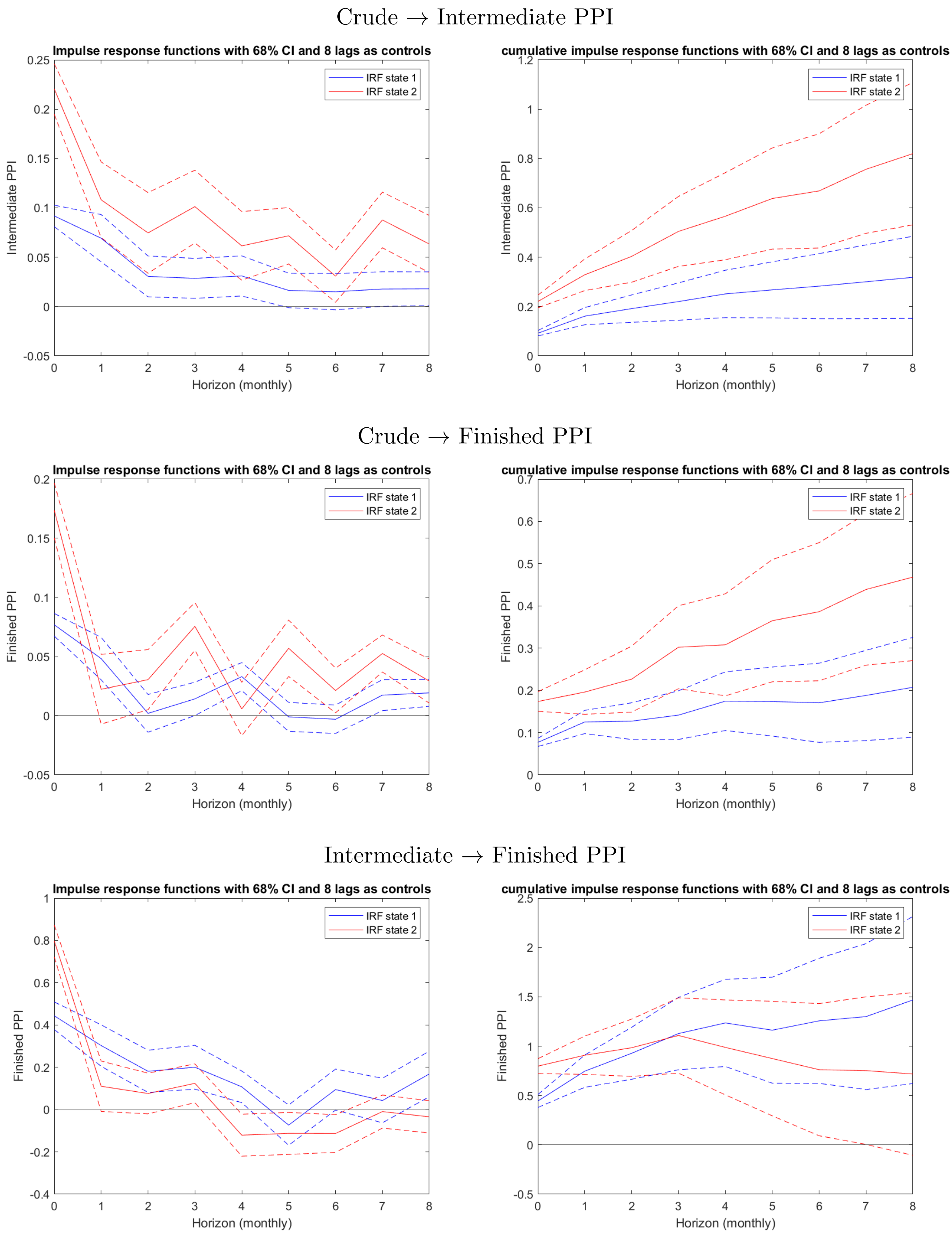

Figure 7: Impulse responses in regime 1 and 2 of a shock to Crude on Intermediate and Finished PPIs and of a shock in Intermediate on Finished PPI. The left hand side displays the IRFs in levels and on the right the cumulative IRfs are shown. Dashed lines represent 68% confidence intervals.

4.3 Effects of a monetary policy shock

In the third part of the analysis, we estimate the state-dependent effect of a monetary policy shock on monthly CPI growth. Departing from the IV approach, we directly regress monthly CPI growth (y_t) on the monetary policy shock series ($shock_t$) that Jarociński & Karadi (2020) construct combining high-frequency information and sign restrictions:

$$y_{t+h} = \hat{\mu}_h + H_t(\hat{\beta}_h^1 shock_t + \sum_{l=1}^{n} \hat{\delta}_{l,1}^T W_{t-l}) + (1 - H_t)(\hat{\beta}_h^2 shock_t + \sum_{l=1}^{n} \hat{\delta}_{l,2}^T W_{t-l}) + u_{t+h}. \quad (5)$$

The set of controls W_t now contains 8 lags of y_t, ΔIP_t, and the log differences of monthly West Texas Intermediate (WTI) crude oil price provided by the World Bank's commodity price database. Coefficients $\hat{\beta}_h^1$ and $\hat{\beta}_h^2$ denote the impulse responses at horizon h in states 1 and 2 respectively. The sample length for model (5) spans from 1990M2 to 2019M6 since Jarociński & Karadi (2020)'s monetary policy shock series is only available in this time span. Figure 8 shows the resulting IRFs of model (5). As we can see in the left panel, the effect of a monetary policy shock on monthly CPI growth differs across state 1 and 2. On impact, the effect in state 1 is negative and increases slowly in the subsequent periods. In state 2, the effect is negative until two months after impact, but then we can see a reversion of the effect and CPI growth gets significantly positive. Due to this initial 'overshooting', the cumulative responses are significantly different from each other until two month after impact but are similar some time after.

Effect of a monetary policy shock on monthly CPI inflation

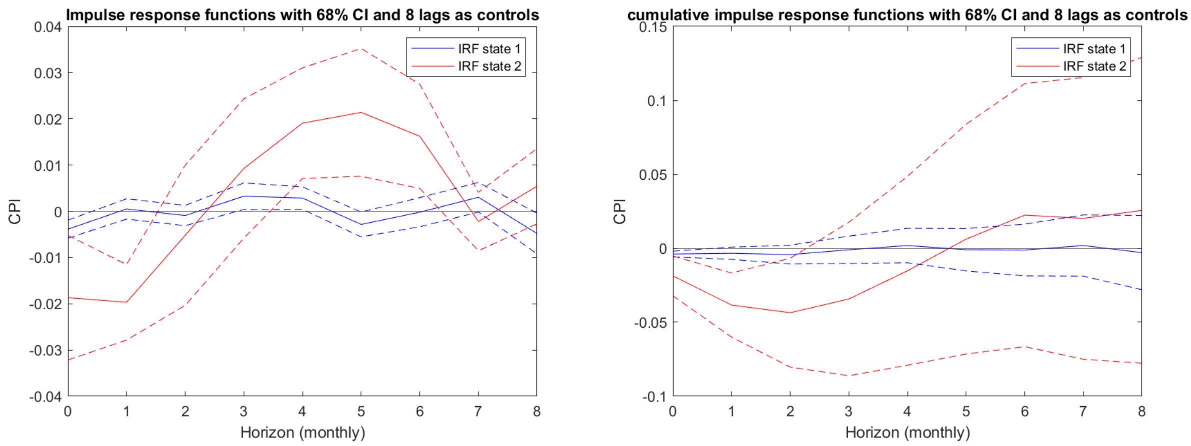

Figure 8: Impulse responses of monthly CPI growth in regime 1 and 2 induced by a monetary policy shock. The left hand side displays the IRFs in levels and on the right the cumulative IRfs are shown. Dashed lines represent 68% confidence intervals produced with EHW standard errors. To generate these IRFs we use the monetary policy shock series by Jarociński & Karadi (2020).

4.4 Positive vs. negative shocks

Lastly, we analyze potential regime-dependent 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

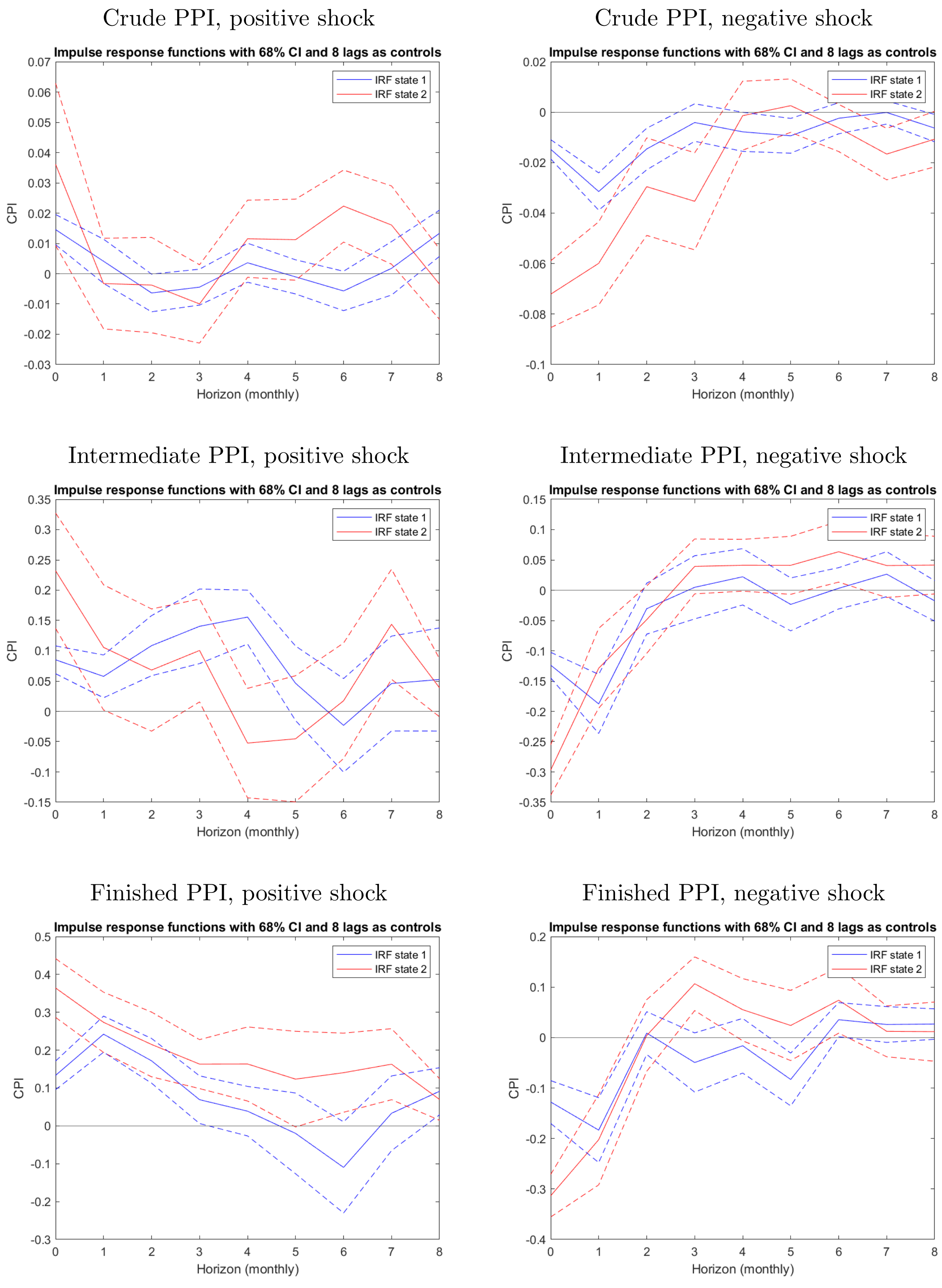

Figure 9: Resulting IRFs of a positive and negative shock in Crude, Intermediate, or Finished PPI on monthly CPI growth. The left hand side displays the IRFs in levels and on the right the cumulative IRfs are shown. Dashed lines represent 68% confidence intervals.

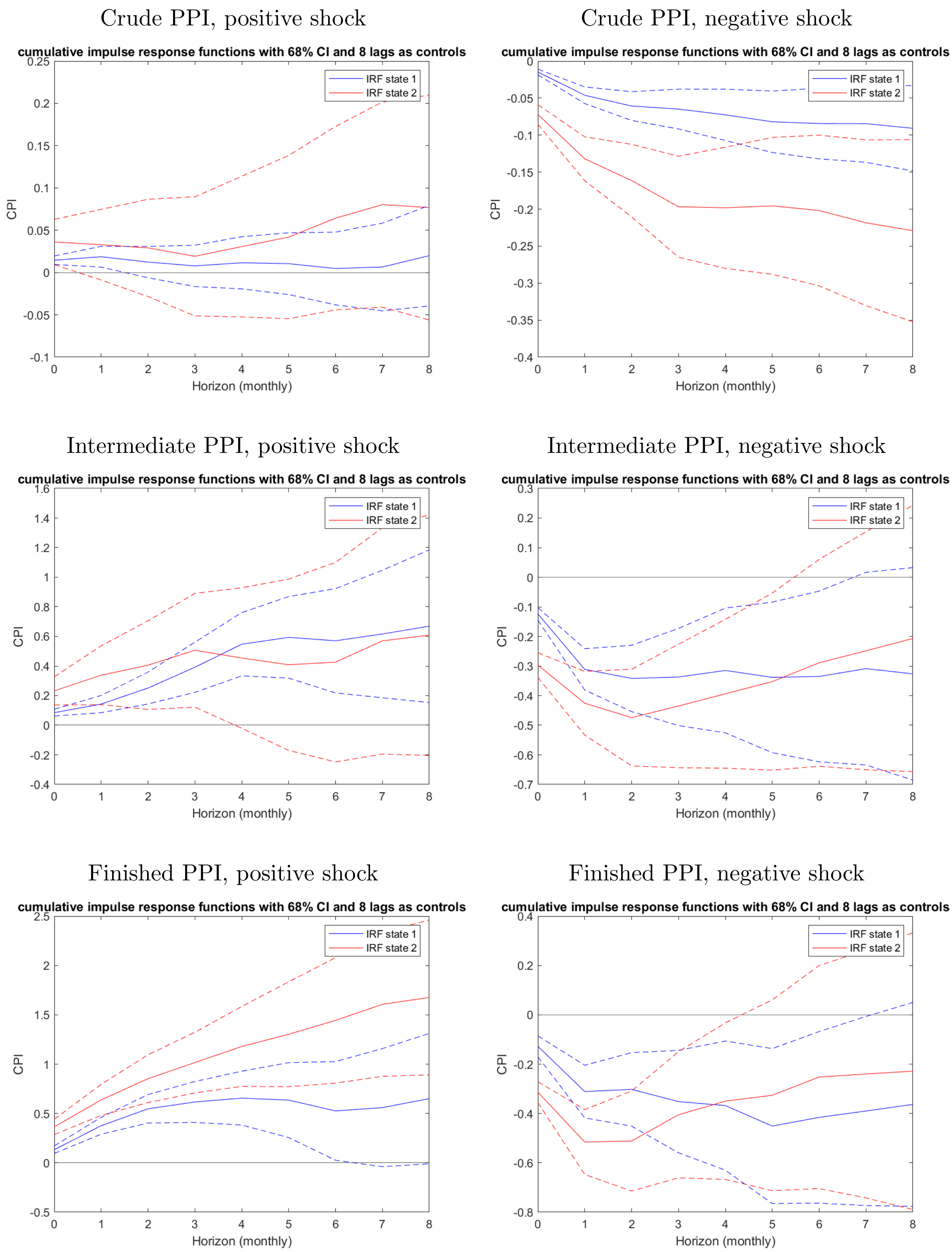

Figure 10: Resulting cumulative IRFs of a positive and negative shock in Crude, Intermediate, or Finished PPI on monthly CPI growth. The left hand side displays the IRFs in levels and on the right the cumulative IRfs are shown. Dashed lines represent 68% confidence intervals.

same time to avoid potential biases by truncated variables (Garzon & Hierro, 2021):

$$\begin{aligned} y_{t+h} =& \hat{\mu}_{2S,h} + H_t(\hat{\beta}^1_{LPIV,h,-}\hat{x}_{t,-} + \hat{\beta}^1_{LPIV,h,+}\hat{x}_{t,+} + \sum_{l=1}^{n} \hat{\delta}^T_{2S,l,1} W_{t-l}) \\ &+ (1-H_t)(\hat{\beta}^2_{LPIV,h,-}\hat{x}_{t,-} + \hat{\beta}^2_{LPIV,h,+}\hat{x}_{t,+} + \sum_{l=1}^{n} \hat{\delta}^T_{2S,l,2} W_{t-l}) + u_{t+h}. \end{aligned} \tag{6}$$

In model (6), $\hat{\beta}^1_{LPIV,h,+}$ and $\hat{\beta}^1_{LPIV,h,-}$ denote the positive and negative impulse responses in state 1, and $\hat{\beta}^2_{LPIV,h,+}$ and $\hat{\beta}^2_{LPIV,h,-}$ those of state 2 respectively. $\hat{x}_{t,+}$ and $\hat{x}_{t,-}$ are the fitted values from a regression of the dependent variable x_t on the positive or negative instrument and lagged controls W_t, which are the same as employed in model (3).

Figure 9 reports the resulting IRFs in levels and Figure 10 shows the cumulative responses. We distinguish two sorts of interaction effects here: The state-dependency between the two inflation regimes and an asymmetric effect of positive vs. negative shocks. For Crude PPI in state 2, the impact effect of a negative shock is stronger than its pendant of a positive shock. The same holds true for Intermediate PPI. The response of CPI growth to a negative shock in Finished PPI reaches the zero line the first time in the second month after impact, while this effect lasts longer for a positive shock. The reverse holds true for a shock in Crude PPI. Here, a negative shock seems to have a longer lasting effect. In the cumulative responses we can see that the state-dependency lasts longer when the economy is hit by a negative shock in producer prices.

5 Discussion of results and policy implications

The main picture that can be drawn from the results is that if the inflation regime is one of increased volatility, the transmission of producer price shocks on consumer prices is stronger and quicker than in a tranquil inflation regime. This state-dependency is largest and most persistent for shocks in Crude PPI and decreases downstream in the stages of processing. This result underpins the role of Crude PPI in driving the difference in regimes, supported by the observation of smaller regime differences in the transmission of a shock in Intermediate on Finished PPI growth. The larger state-dependency can be explained by a cumulation over the subsequent stages of production: if each stage reacts more strongly to cost changes in regime 2, these differences across regimes add up on their way downstream. The longer-lasting responses are likely due to lagging price changes at downstream production stages. This is visible in the effect of shocks to Crude PPI on Intermediate PPI in Figure 7.

Comparing the scale of the IRFs in Figure 5, we can see that a unit shock in Crude PPI induces the smallest response in CPI compared to shocks in Intermediate and Finished PPI. This can be explained by a) a mechanical effect, since more cost components are added at each stage, and b) the larger variability we observe in monthly Crude PPI growth compared to CPI and the other PPIs (see Figure 4). A 1 pp increase in Crude PPI growth then induces a smaller reaction in CPI than a 1pp increase in Intermediate and Finished PPI growth would do since firms prefer volatile margins over frequent price adjustments. At times when CPI inflation becomes more volatile, this preference shifts towards more frequent price adjustments. We can observe the same pattern in the effects between stages of processing in Figure 7 with the same reasoning behind.

In recent work, Gonçalves et al. (2022) derive conditions for which the state-dependent local projection (LP) estimands $\hat{\beta}^1_{LPIV,h}$ and $\hat{\beta}^2_{LPIV,h}$ recover the population impulse responses. According to Gonçalves et al. (2022), the state-indicator $\{H_t\}$ must be independent of the structural error of interest $\eta_{j,t}$ which holds when $\{H_t\}$ is a function of variables not contained in $\{y_t, x_t, W_t\}$ that are exogenous to the shock of interest. The idea is that if a shock occurs which affects the response variable y_t, this might alter the state-indicator H_t, if it is depending on y_t, and thus affect the state-dependent LP estimands, generating a bias in the impulse response. The independence of H_t and $\eta_{j,t}$ 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 relatively high persistence, albeit a potential bias cannot be excluded.

In case of a monetary policy shock, we again observe state-dependency in the impulse responses of monthly CPI growth. In state 2, a positive surprise in the 3-month Fed funds rate leads to an immediate decrease of CPI inflation which lasts for only one month after the impact period. The decrease is then followed by a significant increase of monthly inflation leading to several periods of positive growth after which the effect finally vanishes. This observation suggests that in times of high inflation volatility and therefore more flexible prices, initial price adjustments tend to 'overshoot', either because of misperceptions or because actual demand picks up after the early price reductions. In contrast, in state 1, after negative growth on impact, the reversion to positive growth in the medium term is less pronounced and of shorter duration than in state 2. As a result, an increase in the policy rates in state 2 is not more effective in bringing down inflation in the medium run than in state 1. In contrast, monetary policy shocks seem to add volatility to the inflation process in state 2.

The main policy implication we draw from our result is that central banks should pay close attention to the current and potential future inflation regime when assessing the impact of a producer price shock. If emerging large price increases are not been prevented, the economy may transition to a different regime in which cost shocks are passed on to consumer prices more quickly and more strongly. This can render CPI inflation persistently more volatile. Given that active monetary policy does not seem to be more effective in preventing inflation in the medium term in such a regime but rather adds to the inflation volatility, a transition to such a regime should be prevented at the onset. It may be difficult to escape this regime once it has come into existence.

6 Conclusion

In this paper we estimate regime-dependent IRFs of producer price shocks on consumer price inflation in the US. We identify a high volatility inflation regime with a Markov-switching model and use the filtered state probabilities to construct a regime indicator H_t. We interact a local projections model with the state indicator and estimate responses with Stock & Watson (2018)'s LP-IV approach. As instruments we use data outliers in the Crude, Intermediate and Finished PPI series respectively.

We find that the impulse responses in 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 on impact is stronger than in times of stable and low inflation, and it takes longer to decay. Also monetary policy shocks have a regime dependent effect on monthly CPI growth. Central banks should therefore closely monitor the current inflation regime and be aware of the different impact a producer shock might have in the respective regime.

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Appendix A: Data description

Data on CPI and the three producer price indices were obtained from the US Bureau of Labor Statistics (BLS) and are seasonally adjusted. Until 2014, the BLS used the stage-of-processing (SOP) aggregation system to report producer prices. After then, the BLS switched to the Final Demand-Intermediate Demand (FD-ID) system. Table 1 reports the SOP code and the corresponding FD-ID code and variable titles respectively.

The BLS defines crude materials as unprocessed goods and intermediate materials as processed goods which 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 for some degree but need further processing before becoming a finished good. Finished goods comprise commodities consumed as personal consumption or which businesses use as capital investment. Government purchases or exports are exported 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 1: Variable description of Crude (SOP1000), Intermediate (SOP2000) and Finished (SOP3000) PPI. More information available here: https://www.bls.gov/ppi/fd-id/ppi-stage-of-processing-to-final-demand-intermediate-demand-aggregation-system-index-concordance-table.htm

Appendix B: Weak instrument test results

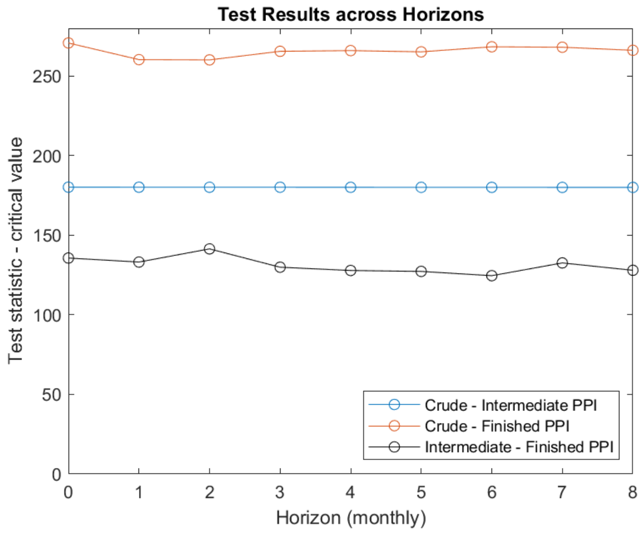


Figure 11: Results of the Lewis & Mertens (2022) test for weak instruments as the difference of the test statistic and the critical value. For all horizons across all three specifications (a shock in Crude on Intermediate (blue) and Finished PPIs (orange), and a shock in Intermediate on Finished PPI (black)), this difference is positive and hence the weak instrument hypothesis can be rejected.

Appendix C: Alternative identification scheme

As an alternative identification strategy we impose additional restrictions. These restrictions are supposed to rule out that movements in the consumer prices were first triggered by an increase in demand and hence in inflation. 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.

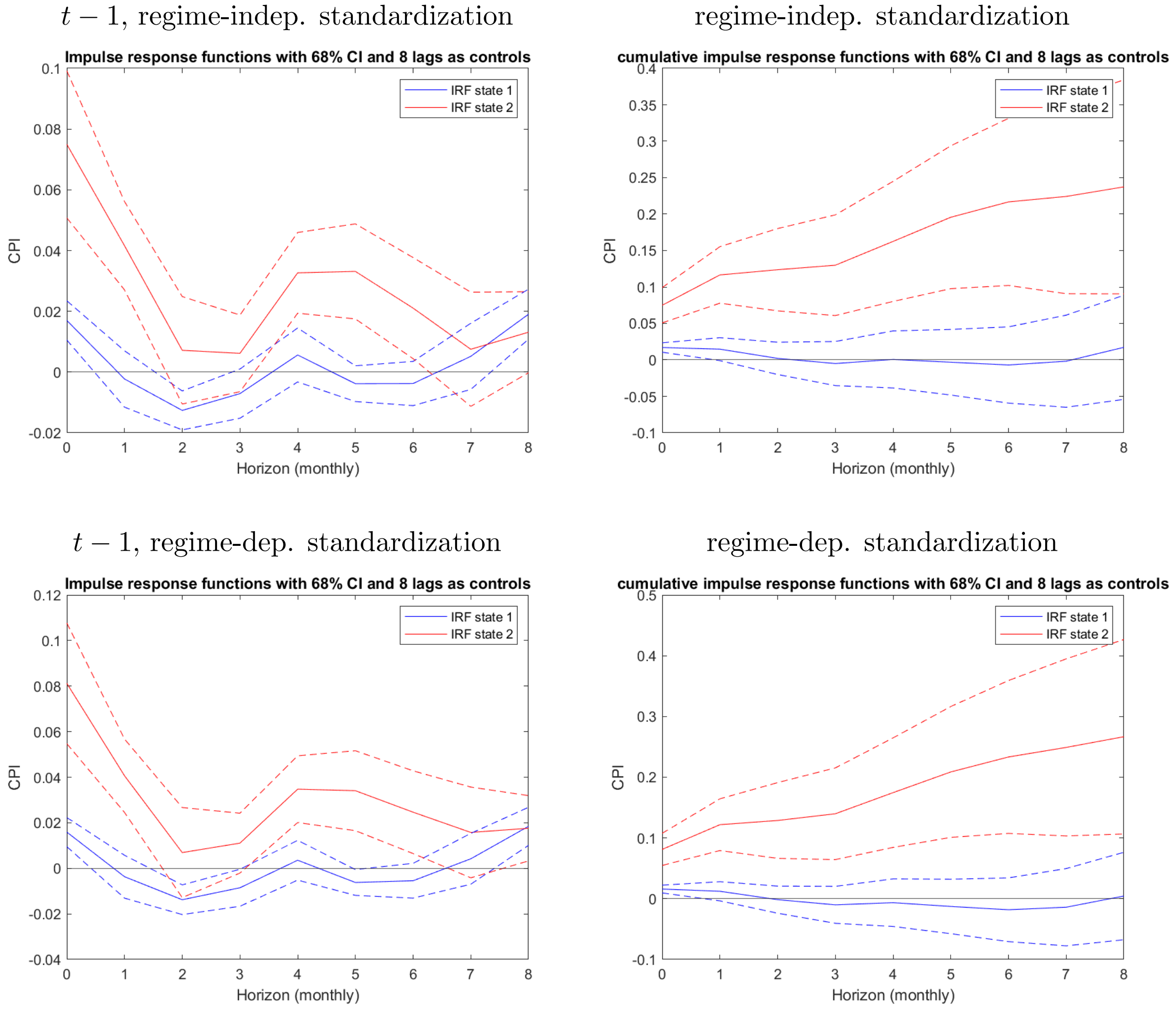
i) ΔCPI_{t-1} divided by its sample standard deviation must be smaller than 50% of PPI_t divided by its sample standard deviation

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

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

Figures 12 to 14 show the resulting impulse response functions of restrictions i) and ii) and Figure 15 shows the results of restriction 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.

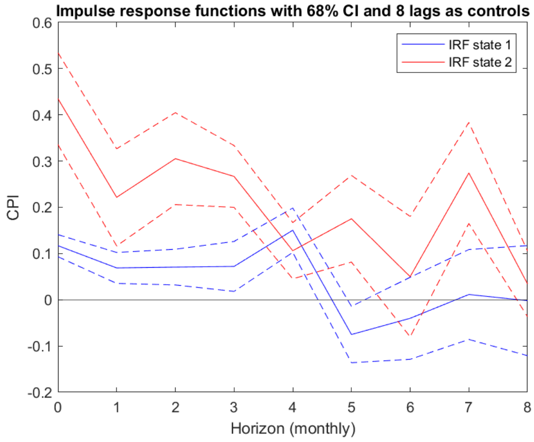
Figure 12: Crude PPI



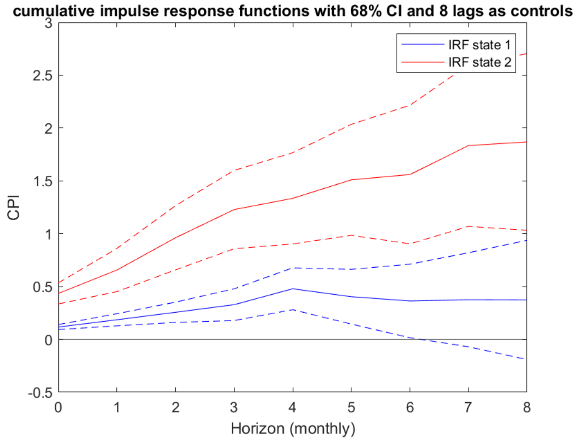
Note: regime dependent & regime independent standardization, restrictions i) and ii). The left column shows IRFs of a shock in Crude PPI on monthly CPI growth, on the right the cumulative responses.

Figure 13: Intermediate PPI

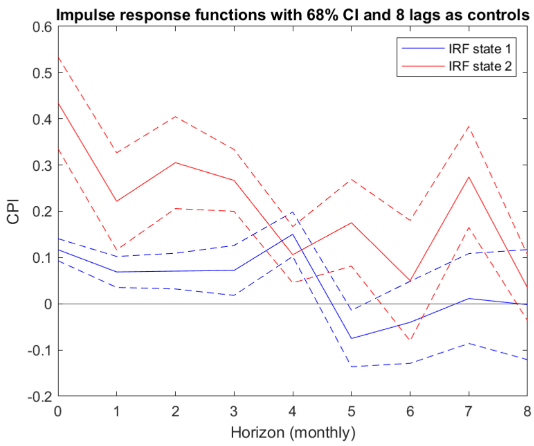
$t-1$, regime-indep. standardization



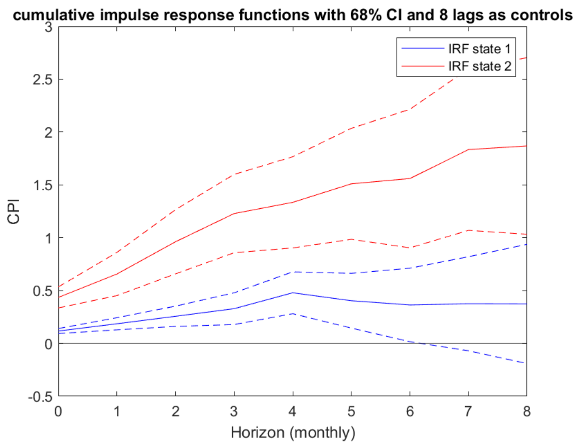
regime-indep. standardization



$t-1$, regime-dep. standardization



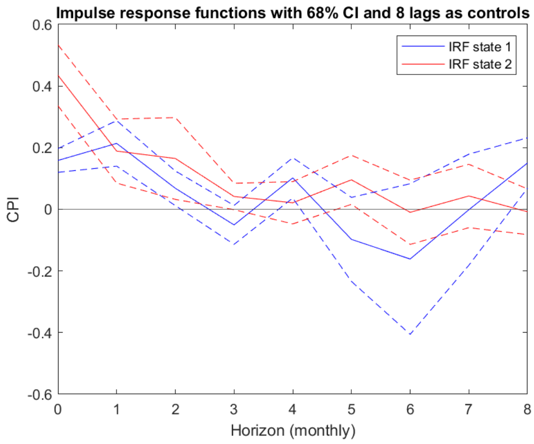
regime-dep. standardization



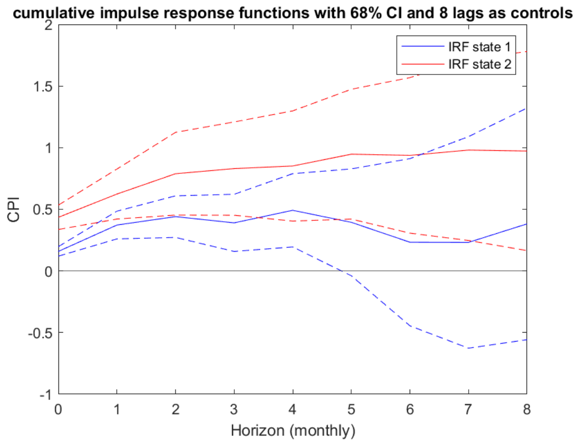
Note: regime dependent & regime independent standardization, restrictions i) and ii). The left column shows IRFs of a shock in Intermediate PPI on monthly CPI growth, on the right the cumulative responses.

Figure 14: Finished PPI

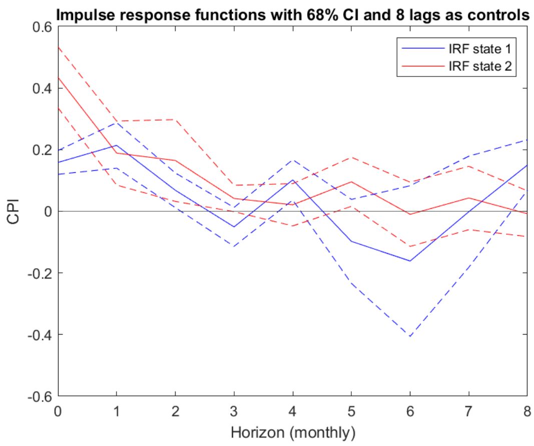
$t-1$, regime-indep. standardization



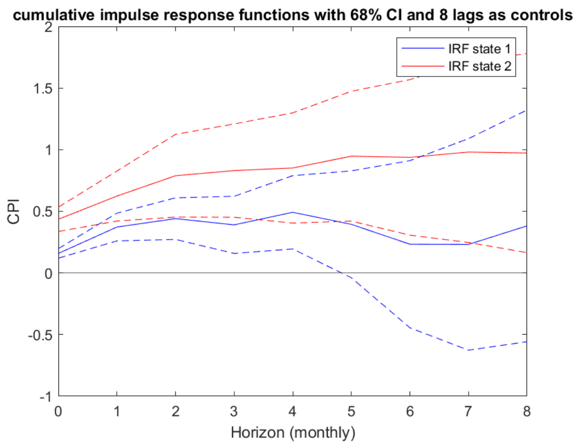
regime-indep. standardization



$t-1$, regime-dep. standardization



regime-dep. standardization



Note: regime dependent & regime independent standardization, restrictions i) and ii). The left column shows IRFs of a shock in Intermediate PPI on monthly CPI growth, on the right the cumulative responses.

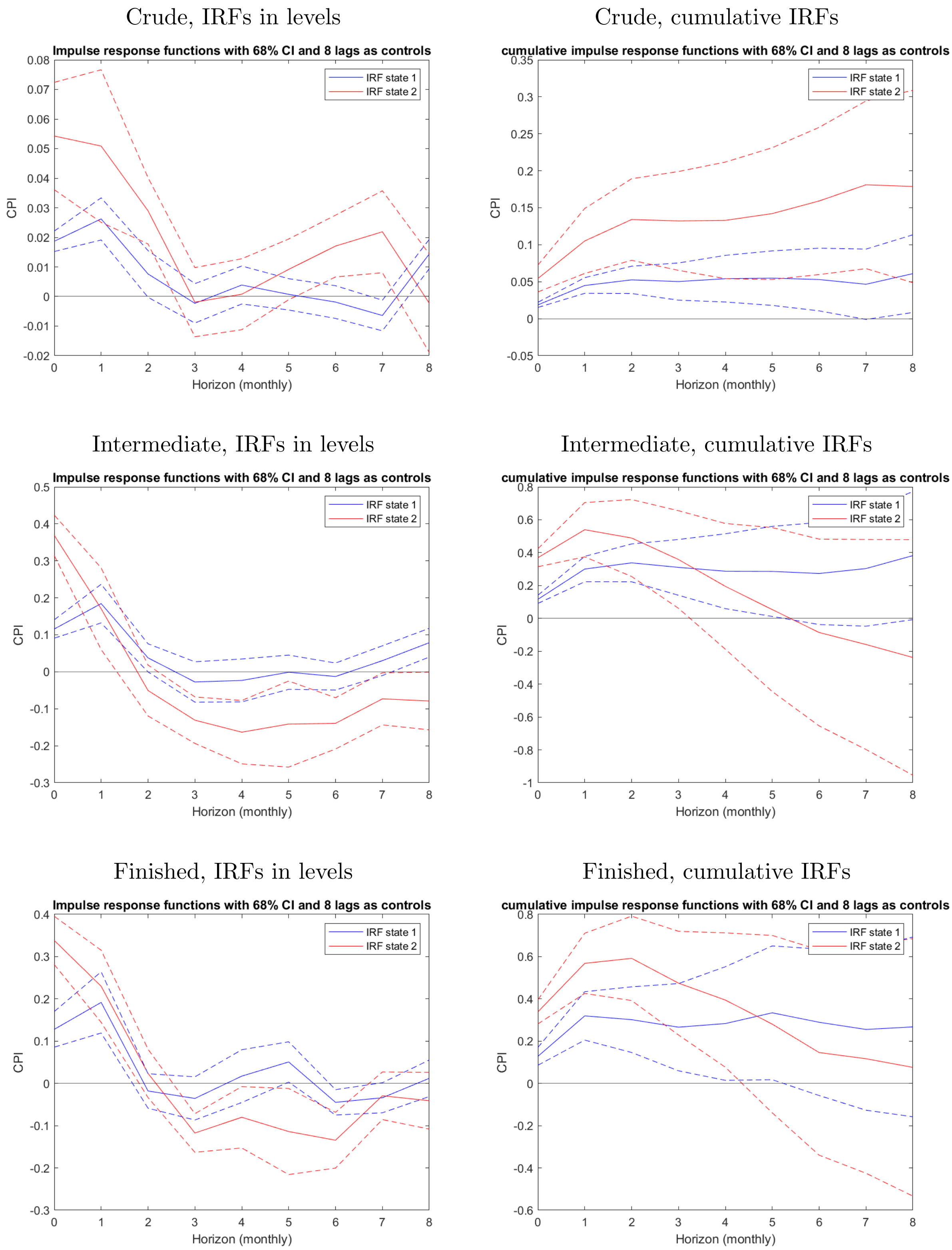


Figure 15: This figure shows the resulting IRFs of a shock in Crude, Intermediate or Finished PPI on monthly CPI growth when applying restriction iii). The left column shows the IRFs in levels and the right column displays the cumulative versions.