Research Article

Corey J. M. Williams*

Unraveling Producer Price Inflation Pass-Through: Quantification, Structural Breaks, and Causal Direction

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Abstract: Producer price inflation has long been considered a leading indicator for consumer price inflation. However, the evidence supporting the cost-push theory of inflation over extended periods is inconclusive and lacks direct quantification. To address this gap, we employ structural break and causality tests, regression analysis, and local projection impulse-response functions. Our analysis allows us to precisely identify instances when producer prices lead consumer prices and quantify short-run and long-run pass-through rates. We find relatively robust evidence of a producer price pass-through rate between 8 and 12%. However, there are significant periods where unidirectional pass-through does not hold. Local projections reveal that producer price pass-through is small but persistent in states where producer prices lead consumer prices, and larger but shorter-lived in states where there is no causal directionality. Our findings enhance the understanding of producer price pass-through to consumer inflation, providing valuable insights for policymakers and market participants interested in accurately forecasting and managing inflationary pressures.

Keywords: pass-through, inflation, producer prices

JEL Codes: E31, D2, C33

1 Introduction

United States inflation has reached its highest level in decades. By the end of June 2022, a 40 year inflation high was recorded at 8.93%. Popular media and academics have pointed toward distortions in global supply chains and shortages in key commodities as primary sources of this recent bout. This rhetoric is grounded in the longstanding theory that producer prices both cause and lead consumer prices.[1] As such, producer prices are traditionally thought of as a leading indicator for future consumer prices. Stemming from this train of thought, if producer prices are increasing, one would expect some amount of pass-through to consumer prices. This assumption has established a precedent for using producer prices as a predictor for consumer price inflation. Although forecasters, policymakers, firms, and consumers all have a vested interest in understanding the direction that prices are moving, inflation remains difficult to forecast (Blomberg & Harris, 1995; Dorestani & Arjomand, 2006; Sidaoui et al., 2009).[2]

Beyond these stylized facts, however, debate over the long-run relationship between consumer and producer prices is ongoing. While some studies find mixed evidence of a long-run relationship between consumer and producer prices, as in the case of Blomberg and Harris (1995), others find the long-run relationship both evident and imperative for sound policymaking (Dorestani & Arjomand, 2006). Despite the prevailing sentiment, and existing empirical evidence that producer prices lead consumer prices over long sample periods in the United States, there are competing views of inflation pass-through such as the derived-demand view of producer price inflation – more widely known as demand-pull inflation. This competing view postulates that at times "too much money is chasing too few goods." This view, while contradictory to the production view theory of pass-through (cost-push), has supporting empirical evidence as well (Barth & Bennett, 1975; Mehra, 1991) and raises several empirical questions with regard to analyzing producer

* **Corresponding author: Corey J. M. Williams,** Department of Economics, 225 DHC, Shippensburg University, Shippensburg, PA 17257, United States, e-mail: corey.james.mount.williams@gmail.com

1 This is known as the *production view* theory of pass-through. It is worth noting that the production view theory of pass-through is rooted in the historically strong correlation between consumer prices and lagged producer prices; currently, $\mathrm{cor}(\log(\mathcal{P}_t^{\mathcal{C}}), \log(\mathcal{P}_{t1}^{\mathcal{P}})) = 0.99$.

2 As discussed in Stock and Watson (2007), multivariate inflation forecasting models seldom outperform a time-varying univariate model of inflation.

price inflation pass-through over the long-run. In an era of globally integrated supply chains wherein producer prices can partially express some degree of supply chain strain, the welfare implications of policies geared toward stabilizing producer price inflation are becoming more important now than ever (Wei & Xie, 2020). Thus, understanding ***when*** and ***by what magnitude*** producer prices lead consumer prices is imperative for sound policymaking and inflation forecasting.

We attempt to address these concerns through an extensive subsample analysis of producer price inflation using structural breaks and causality testing to differentiate periods where producer prices lead consumer prices from periods where they do not. Building off our structural break and causality tests, we attempt to quantify pass-through coefficients in both the short-run and the long-run through the estimation of several augmented Phillips curves within an error-correction framework. Finally, we leverage local projection impulse-response functions (IRFs) to forecast the impact of producer price inflation shocks on consumer prices under two different regimes: one where producer prices lead consumer prices unidirectionally and one where there is no causal direction between producer or consumer prices. From these exercises, we offer four main contributions to the literature on producer price pass-through:

1. We show through causality tests that producer prices *mostly*, but not *always*, lead consumer prices.
2. We quantify producer price inflation pass-through to be between 7 and 12% over the extent of time that data are available.
3. We affirm the fact that there is a long-run relationship (cointegration) between consumer and producer prices; however, in states of disequilibrium, estimated adjustment speeds (error correction) of producer price inflation to the consumer price level (CPL) are statistically zero.
4. We show that consumer price inflation responses to producer price inflation shocks are highly dependent on whether the economy is in a state where producer prices lead consumer prices or an alternative regime where the production view theory does not hold.

These findings are most informative to audiences with a vested interest in forecasting inflation. By extension, our first main result serves to caution policymakers and forecasters who rely on using producer prices as a leading indicator for future consumer prices. This practice is **not** always reliable, particularly during periods where the production view theory of inflation fails to hold.

Our second main result informs policymakers and macroeconometricians as to the rate of pass-through from producer to consumer prices. Given that the average rate of inflation is roughly 3.6% over our full sample, this result implies that a minimum of 25 basis points worth of producer price inflation passes-through to consumer prices.

Our third result sheds new light on those interested in long-run inflation dynamics and informs relevant audiences that while producer prices and consumer prices are cointegrated, neither acts as a vehicle for reverting short-run deviations in inflation back to the steady-state price level. In essence, factors driving error correction from the short run to the long run are not identified by producer prices at the very least.

Our fourth result is complementary to our first three and serves to highlight the asymmetries in consumer price inflation responses to producer price inflation shocks depending on the likelihood of the production view theory of pass-through holding. Most relevant to today as supply chain shocks permeate the world economy, policymakers would be misinformed to reign in producer price inflation in hopes of also lowering future consumer prices if we are in a state where producer prices fail to lead consumer prices.

2 A Brief Literature Overview

Broadly speaking, the pass-through literature focuses on oil prices, producer prices, and exchange rates with exchange rate pass-through dominating the bulk of the literature. For our study, we focus on producer price pass-through considering the Coronavirus disease (COVID-19) pandemic and persistent shocks to global supply chains that followed. Early research on post-pandemic pass-through shows that exposure to global supply chain bottlenecks plays a modest role in producer price inflation pass-through (Santacreu & LaBelle, 2022). With this in mind, we survey a series of key articles in the producer price pass-through literature, but borrow some methodologies employed in the exchange rate and oil price pass-through literature.

Clark (1995) provided the groundwork for investigating producer price level (PPI) pass-through by attempting to address the degree to which producer prices lead consumer prices and aggregates quarterly one-step-ahead rolling forecasts of US consumer price index (CPI) inflation and averaged them to generate the equivalent yearly forecasts. With forecasts generated from a series of vector autoregression (VAR) models, Clark (1995) used the mean absolute error (MAE) criterion to evaluate forecast quality. His results illustrated that multivariate forecasting models including PPI inflation tend to generate lower forecast errors over long samples regardless of whether one is forecasting core inflation or core goods inflation but produce mixed evidence over small sample periods in both cases.

While Clark (1995) investigated the predictive content of a VAR with PPI inflation, a more contemporary approach would be that of Akcay (2011) who compared causality and the direction of causality associated with CPI and PPI inflation for a handful of European nations. The author used monthly data from August 1995 through December 2007 to construct VAR models for each country. The author then used Toda and Yamamoto's (1995) causality tests to assess the direction of causality associated with the price indices of interest in each country. Causal direction results are mixed but are generally supportive of the production view theory of pass-through, which posits that producer prices unidirectionally lead consumer prices.

In a similar vein, Ghazali et al. (2008) motivated their investigation of inflation pass-through using data from a less developed nation where the traditional view of the relationship between the production chain and consumer goods markets might differ when compared to developed countries. Using monthly Malaysian data from January 1986 through April 2007, the authors constructed bivariate vector error correction (VEC) models leveraging an existing long-run stochastic trend shared between PPI and CPI. Following similar approaches in the literature, the authors used both Granger's (1969) causality tests and Toda and Yamamoto's (1995) causality tests to address the presence and direction of causality between CPI and PPI in Malaysia. Their findings tend to fall in line with the production view theory wherein Malaysian PPI inflation leads CPI inflation.

On a related note, Topuz et al.'s (2018) studied the direction of causality associated with PPI and CPI indices for the United Kingdom and Turkey. Their underlying goal is not only to examine the direction of causality alone, but the dominance of one causal direction versus the other. The authors used a bivariate VAR model to generate IRFs, performed a variance decomposition exercise, and conducted Granger's (1969) causality tests. Overall, the results of Topuz et al. (2018) support a strong link between CPI inflation and PPI inflation with the production view theory dominating the causal direction associated with most of the results.

More recent studies such as Jiménez-Rodríguez and Morales-Zumaquero (2022) looked at a broader definition of pass-through across the valuable chain, which includes, but is not limited to, producer prices. Notwithstanding this caveat, Jiménez-Rodríguez and Morales-Zumaquero (2022) showed that there is partial pass-through from commodity prices to producer prices and that world producer price pass-through is led by a mix of developing and advanced nations. These results in a way reaffirm the cross-country studies of Ghazali et al. (2008) and Topuz et al. (2018).

Overall, the common practices within the producer price pass-through literature are testing for the causal direction of producer prices and examining cross-country heterogeneity in pass-through from developed versus emerging economies. While these studies are valuable contributions to the literature in and of themselves, they often lack direct quantification of pass-through and refrain from subsample analysis wherein the production view theory of pass-through could fail to hold.

3 Data and Descriptive Statistics

For our analysis, we focus on four variables from the United States: the consumer price level (CPL), the PPI, real gross domestic product (GDP), and the M2 money supply. Data on the CPI, and the PPI are obtained from the Bureau of Labor Statistics (BLS). Data on real GDP (RGDP) is retrieved from the Bureau of Economic Analysis. Data on the M2 money supply level are sourced from the Federal Reserve Board of Governors. As highlighted in our empirical analysis, it is necessary to use both the log levels of our data and stationary transformations of our data to estimate pass-through and properly construct our econometric models. Figure 1 shows our data in their natural units (log levels) as well as in their stationary states (achieved through converting the levels of data to annual growth rates or through linear detrending).

We see that the natural units of our variables of interest trend positively over time, as expected. We note that the scales of the level of producer and consumer prices are identical reflecting the classic production view theory of producer prices leading consumer prices. We do note that the level of producer prices is more rigid and, at times, lumpy relative to the CPL. Visual evidence of incongruence between producer and consumer prices become clearer when looking at their respective growth rates. The relative volatility of producer price inflation over time is much grander in scale compared to consumer price inflation. We note that the years since COVID-19 tend to exhibit the most extreme observations for almost all transformed series in one way or another. Furthermore, it looks like visual comovement between producer and consumer price inflation is close in correspondence and correlation early on in our sample, but later sample periods tend to reflect a decoupling between producer and consumer price inflation, indicating that the degree to which producer prices lead consumer prices may have diminished in recent decades.

In Table 1, we provide detailed descriptive statistics on all data series in their natural units and in their

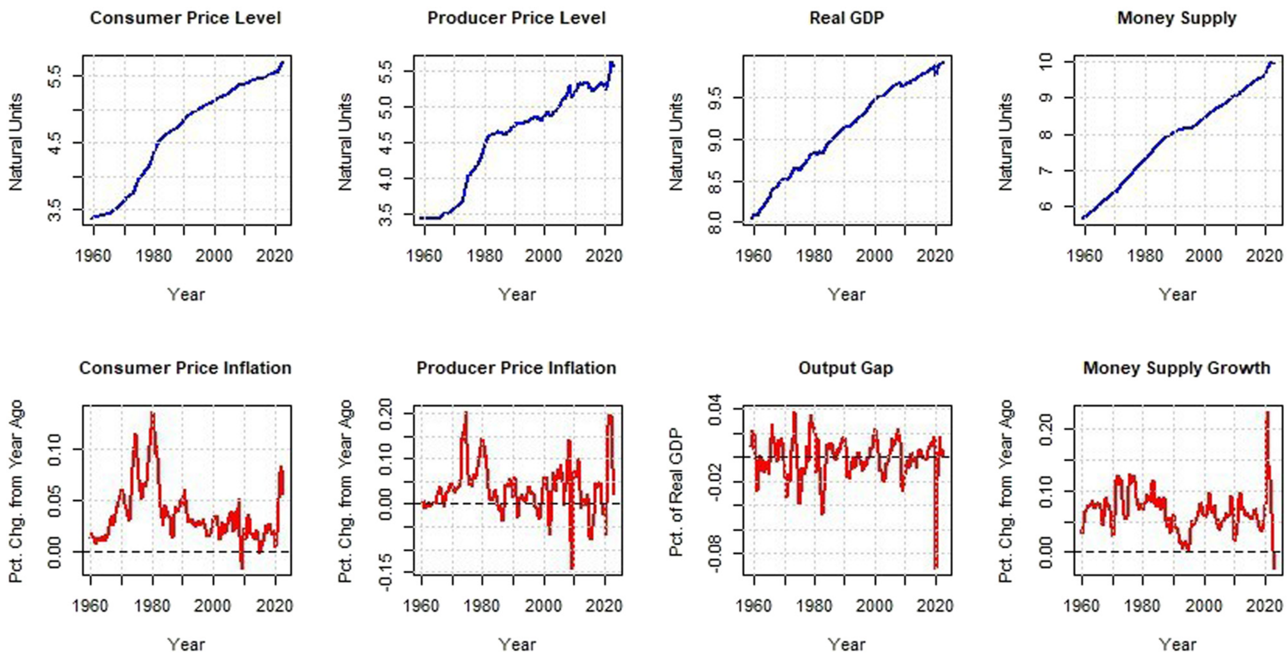

Figure 1: Data in log levels (natural units) and transformed data.

Table 1: Descriptive statistics

Variable notation			Levels				Transformed			
Series name	**Levels**	**Transformed**	**Mean**	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Consumer prices	$\log(\mathcal{P}^{\mathcal{C}}_t)$	$\pi^{\mathcal{C}}_t$	4.66	0.75	3.37	5.71	0.04	0.03	−0.02	0.13
Producer prices	$\log(\mathcal{P}^{\mathcal{P}}_t)$	$\pi^{\mathcal{P}}_t$	4.56	0.66	3.45	5.61	0.03	0.05	−0.14	0.20
Real GDP	$\log(\mathcal{Y}_t)$	$\tilde{\mathcal{Y}}_t$	9.11	0.54	8.05	9.92	0.00	0.02	−0.09	0.04
M2 money supply	$\log(\mathcal{M}_t)$	$\pi^{\mathcal{M}}_t$	7.89	1.22	5.66	9.98	0.07	0.03	−0.03	0.23

transformed stationary states along with variable notation that will be used throughout our analysis. All data collected are in quarterly buckets and range from 1959:Q1 through 2023:Q1.

From a data construction standpoint, our inflation rates for producer and consumer prices, as well as the money supply growth rate, are derived by taking the ratio of the logs of each variable contemporaneously to the lag of itself from four quarters (1 year) ago such that for any variable $\log(x_t)$, its corresponding inflation rate can be expressed as $\pi_t^X = \left(\frac{\log(x_t)}{\log(x_{t-4})}\right)$. Furthermore, our conversion of RGDP to the output gap ($\widetilde{\mathcal{Y}}_t$) is achieved by taking the difference of its linear trend – which derived using the Hodrick and Prescott (1997) filter (HP filter) – from its log level, $\log(\mathcal{Y}_t)$.[3]

We note that the key differences between producer price inflation ($\pi_t^{\mathcal{C}}$) and consumer price inflation ($\pi_t^{\mathcal{P}}$) lie in their extremes and volatility despite their central moments (the mean) being relatively similar over the full sample. We note that the standard deviation for producer price inflation is 2% higher than that for consumer price inflation with considerably more extreme minimum and maximum values. With our data in mind, we turn toward our empirical analysis and econometric models.

3 Our smoothing parameter for linear detrending is set to $\lambda = 1{,}600$. We also acknowledge the critiques of the HP filter outlined by Hamilton (2018). While Hamilton (2018) raised valuable concerns over the use of the HP filter, we believe it is appropriate for our econometric analysis given that our variables of interest are largely consumer and producer prices. Furthermore, our main results are not economically different when using alterative measures of the output gap such as the Congressional Budget Office (CBO) output gap estimates. Auxiliary models using the CBO output gap are available upon request.

4 Empirical Analysis

Our empirical methodology is multi-step by design. First, we identify structural breaks in both producer and consumer price inflation; second, using our estimated break dates for consumer price inflation, we test for the causal direction of producer prices on consumer prices, and vice versa, to identify subsample regimes where producer prices lead consumer prices; third, we quantify producer price pass-through over our full sample and subsample regimes using an error-correction framework; finally, we estimate the state-dependent local projection IRFs through a dummy variable approach that identifies the probability of being in a state where producer prices lead consumer prices versus a state where the production view theory of pass-through does not hold.

4.1 Structural Breaks

While we are interested in quantifying by how much producer prices lead consumer prices over our full sample, the potential for the presence of structural changes in consumer price inflation necessitates consideration for subsample analysis. Rather than impose beliefs *a priori* as to when and how many structural breaks might be present in consumer or producer price inflation, we test for structural breaks formally by leveraging the methodology described in Bai and Perron (2003), which tests endogenously for the number of structural breaks in each time series as well as the break dates themselves. This methodology begins with a simple ordinary least-squares regression of our outcome variable of interest against a constant term (drift term) and a linear time trend (T_t). Equation array (4.1) describes these statistical models:

$$\begin{aligned} \pi_t^{\mathcal{C}} &= A_{\mathcal{C}} + \tau T_t + u_t^{\mathcal{C}}, \\ \pi_t^{\mathcal{P}} &= A_{\mathcal{P}} + \tau T_t + u_t^{\mathcal{P}}. \end{aligned} \tag{4.1}$$

Beyond the standard statistical models for estimating structural breaks, we can test for structural breaks on similar models that capture both the production view and derived-demand theories of inflation pass-through. Equation array (4.2) describes these competing views:

$$\begin{aligned} \pi_t^{\mathcal{C}} &= A_{\mathcal{CP}} + \pi_{t-1}^{\mathcal{P}} + \tau T_t + u_t^{\mathcal{CP}}, \\ \pi_t^{\mathcal{P}} &= A_{\mathcal{PC}} + \pi_{t-1}^{\mathcal{C}} + \tau T_t + u_t^{\mathcal{PC}}. \end{aligned} \tag{4.2}$$

In theory, if producer (consumer) prices lead consumer (producer) prices, then the lag dynamics of producer (consumer) prices may contain information relevant for estimating subsequent structural breaks as well. Table 2 reports the estimated break dates with 95% confidence intervals for each equation described within arrays (4.1) and (4.2).

We observe that, in the case of equation array (4.1), there is not much difference in both the number of breaks and break dates themselves between consumer and producer price inflation. It is worth noting that the mean of each estimated break date for producer price inflation tends to precede slightly or coincide with consumer price inflation but exhibits wider confidence intervals. From equation array (4.2), we observe twice as many estimated breaks compared to equation array (4.1) with both producer and consumer price inflation rates breaking coincidentally as well. The disparities reflected in Table 2 underscore the sensitivity of estimated producer and consumer price inflation structural breaks to model specification. The natural question that arises from this is if these breaks also correspond to deviations or confirmations of producer prices leading consumer prices. To address this question, we need to implement an alternative strategy, one that entails testing for cointegration and causal direction.

4.2 Cointegration and Causal Direction

An important stylized fact about the relationship between producer and consumer prices is that they are cointegrated

Table 2: Structural break test results

Model	Est.	CPI breaks			PPI breaks		
	Breaks	Lower	Mean	Upper	Lower	Mean	Upper
(4.1)	(1)	(1981:Q3)	1981:Q4	(1982:Q3)	(1981:Q2)	1981:Q3	(1982:Q3)
	(2)	(2012:Q2)	2013:Q4	(2014:Q1)	(2008:Q4)	2013:Q4	(2014:Q1)
(4.2)	(1)	(1969:Q3)	1971:Q3	(1971:Q4)	(1971:Q4)	1972:Q2	(1972:Q3)
	(2)	(1982:Q2)	1982:Q3	(1983:Q1)	(1982:Q2)	1982:Q3	(1983:Q2)
	(3)	(1991:Q4)	1992:Q1	(1993:Q2)	(1991:Q4)	1992:Q2	(1992:Q4)
	(4)	(2007:Q3)	2009:Q4	(2010:Q1)	(2007:Q4)	2009:Q4	(2010:Q1)

with one another over their full samples. However, given the multitude of breaks present across each series, and ambiguity over whether the production view theory dominates the derived demand theory of pass-through, it is possible that cointegration and causal direction of producer and consumer price inflation is heterogeneous across various subsamples. Again, refraining from assumptions on breaks in consumer price inflation, we let our results from Table 2 guide our choice of subsample analysis for cointegration and causal direction testing. Specifically, we identify the following regimes to conduct cointegration tests and causality tests: **1)** 1960:Q1–1971:Q4, **2)** 1972:Q1–1982:Q3, **3)** 1982:Q4–1992:Q1, **4)** 1992:Q2–2009:Q4, and **5)** 2010:Q1–2023:Q1.

While we could test for both cointegration and causal direction separately from one another, advances in the cointegration literature make testing for both simultaneously possible via Toda and Yamamoto's (1995) causality testing. The Toda–Yamamoto (TY) causality test considers a VAR model in levels with a maximum, r_{Max}, cointegrating relationships, and ρ optimum lags as prescribed by the akaike information criterion (AIC) criteria. An augmented VARX($\rho + r_{\text{Max}}$) is then estimated where the VARX (vector autogressive model with exogenous variables) is constructed with the optimum lag length of ρ plus additional lag lengths equal to r_{Max} treated as exogenous regressors. From a performance standpoint, because the VARX is constructed with the endogenous variables in their levels, rather than their first differences, the test is strictly more efficient than Granger's (1969) causality tests by treating each variable as seemingly unrelated to one another. Furthermore, strictly in a bivariate VARX, the statistical evidence of causal direction (unidirectional or bidirectional) in the TY framework also confirms evidence of cointegration simultaneously.[4] Equation (4.3) describes the general form of our bivariate VARX model estimated over our established subsamples:

$$Z_t = \alpha + \sum_{i=1}^{\rho} \Gamma_i Z_{t-i} + \Theta X_{t-r_{\text{Max}}} + \tau T_t + \varepsilon_t, \tag{4.3}$$

where $Z_t = [\log(\mathcal{P}_t^C), \log(\mathcal{P}_t^P)]^T$ describes our vector of endogenous variables; Γ_i describes the coefficient vector of our lagged endogenous variables from $i = 1$ to $i = \rho$ lags, where ρ is the maximum number of lags prescribed by the AIC criteria; and Θ describes the coefficient vector associated with our exogenous variables. The full sample and subsample results of our TY causality tests are exhibited in Table 3.

Over the full sample, we see results not unlike other pieces in the literature that show bidirectional or mixed evidence of producer price pass-through (Akcay, 2011; Clark, 1995; Topuz et al., 2018). However, we note considerable heterogeneity over our identified subsamples. Prior to the Productivity Slowdown in our earliest regime (1960:Q1–1971:Q4), we find that producer prices lead consumer prices unidirectionally at an incredibly strong level of statistical significance (<1%). By comparison, during our second regime, which includes the Productivity Slowdown through the end of the Great Inflation Era (1972:Q1–1982:Q3), we still see producer prices lead consumer prices unidirectionally, but at a weaker statistical level (5%). In our third regime, which starts at the end of the Great Inflation and continues through the beginning of the New Economy Boom (1982:Q4–1992:Q1), we find no evidence of causality in any direction – the same is true for our final regime that starts after the Financial Crisis recovery through the present day (2010:Q1–l2023:Q1). Finally, our fourth regime (1992:Q2–2009:Q4), which encompasses both the New Economy Boom and Financial Crisis once more shows evidence of unidirectional cost-push pass-through.

Simply put, while producer prices lead consumer prices *most* of the time, there are significant subsamples – including the present day – where the production view theory of producer price pass-through fails to hold. The evidence put forth from Table 3 gives us a sense of **when** producer prices lead consumer prices but does not tell us the magnitude of pass-through itself. To quantify pass-through, we turn toward an error-correction framework, which is commonly leveraged in the oil price and exchange rate pass-through literature.[5]

4.3 Error-Correction Model

We use a two-step error-correction framework to map short-run variation in lagged producer price inflation to the long-run CPL. The basic framework follows the work of Engle and Granger (1987) and consists of two stages. The first stage is a long-run model from which the vector of residuals post-estimation is obtained, $\hat{\varepsilon}_t$, and tested for a unit root. Assuming $\hat{\varepsilon}_t$ is integrated at an order of one, or $\sim I(0)$, then a second-stage model is estimated using lagged differences (or growth rates) of the regressors and a lagged error-correction term (ECT_t), which is our lagged residual vector from our long-run model. Following Chen (2009), we estimated an augmented long-run Phillips curve and short-run Phillips within an error-correction framework. The augmented long-run Phillips curve is described by the

4 One caveat to this is that failing to confirm causality or causal direction does not imply that there are $r = 0$ cointegrating relationships.

5 See Chen (2009) and De Gregoria et al. (2007).

Table 3: TY causality test results

Sample length	$\rho + r_{\text{Max}}$	Null hypothesis	*F*-Stat	*P*-value	Causality
1959:Q1–2023:Q1	6 + 1 = 7	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	3.98	0.001	$\log(\mathcal{P}_t^{\mathcal{P}}) \longleftrightarrow \log(\mathcal{P}_t^{C})$
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	2.26	0.037	
1960:Q1–1971:Q4	12 + 1 = 13	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	3.64	0.009	$\log(\mathcal{P}_t^{\mathcal{P}}) \longrightarrow \log(\mathcal{P}_t^{C})$
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	1.85	0.125	
1972:Q1–1982:Q3	12 + 1 = 13	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	3.98	0.050	$\log(\mathcal{P}_t^{\mathcal{P}}) \longrightarrow \log(\mathcal{P}_t^{C})$
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	2.65	0.120	
1982:Q4–1992:Q1	11 + 1 = 12	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	4.75	0.187	*No Causality*
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	2.38	0.333	
1992:Q2–2009:Q4	2 + 1 = 3	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	6.26	0.003	$\log(\mathcal{P}_t^{\mathcal{P}}) \longrightarrow \log(\mathcal{P}_t^{C})$
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	2.15	0.121	
2010:Q1–2023:Q1	9 + 1 = 10	$\log(\mathcal{P}_t^{\mathcal{P}})$Does Not Cause $\log(\mathcal{P}_t^{C})$	1.06	0.427	*No Causality*
		$\log(\mathcal{P}_t^{C})$Does Not Cause $\log(\mathcal{P}_t^{\mathcal{P}})$	1.85	0.110	

following equation:

$$\log(\mathcal{P}_t^{C}) = \beta_0 + \beta_{\mathcal{Y}} \log(\mathcal{Y}_t) + \beta_{\mathcal{P}} \log(\mathcal{P}_t^{\mathcal{P}}) + \epsilon_t, \quad (4.4)$$

where $\beta_{\mathcal{P}}$ describes the long-run pass-through (LRPT) of producer prices to consumer prices. While some may object to a "long-run" model of the price level augmented with producer prices as being relatively *ad hoc*, we believe this adequately captures the production view theory of inflation pass-through. For example, if producer prices lead consumer prices in logs, we have $\log(\mathcal{P}_t^{C}) = \log(\mathcal{P}_{t-1}^{\mathcal{P}})$. Under the assumption that both producer and consumer prices are cointegrated, in steady state, there is a linear contemporaneous combination of producer and consumer prices that is stationary such that $\log(\mathcal{P}_t^{C}) - \beta_{\mathcal{P}}\log(\mathcal{P}_t^{\mathcal{P}}) = \epsilon_t \sim I(0)$, where $\beta_{\mathcal{P}}$ has the same meaning as before. In a sense, this formulation when mapped to equation (4.4) describes a long-run representation of the Phillips curve considerate of the production view theory of inflation pass-through. With our long-run model defined, we also identify a corresponding augmented short-run Phillips curve described by the following equation:

$$\pi_t^{C} = \alpha_0 + \sum_{i=1}^{4} \omega_i \pi_{t-i}^{C} + \gamma \tilde{\mathcal{Y}}_{t-1} + \sum_{i=1}^{4} \theta_i \pi_{t-i}^{\text{PPI}} + \psi \hat{\epsilon}_{t-1} + \varepsilon_t. \quad (4.5)$$

Chen (2009) defined partial short-run pass-through (PSRPT) as the θ_1 coefficient associated with the first lag of producer price inflation. Additionally, Chen (2009) showed via inversion of the short-run Phillips curve that short-run pass-through (SRPT) can be constructed using the point estimates associated with LRPT ($\beta_{\mathcal{P}}$), PSRPT (θ_1), and the lagged error-correction term (ψ). Formally, we denote SRPT as ξ and define its numerical construction by the following equation:

$$\xi = \theta_1 + (\psi \cdot \beta_{\mathcal{P}}). \quad (4.6)$$

Another convenience afforded by the two-step error-correction framework beyond its functional form flexibility is its ability to allow for "time-varying" estimation. As shown in Chen (2009), we can define dummy variables corresponding to specific regimes or temporal breaks in consumer price inflation. This allows us to directly extend our analysis and discussion of Tables 2 and 3 by quantifying heterogeneity in SRPT, specifically in the second stage of our model. To achieve this, we define regime specific dummies, D_{rt}, described by the following equation array:

$$D_{rt} = \begin{cases} D_{1t} \coloneqq 1 & \text{from} \quad 1959:\text{Q1–1971}:\text{Q4}, \\ D_{2t} \coloneqq 1 & \text{from} \quad 1972:\text{Q1–1982}:\text{Q3}, \\ D_{3t} \coloneqq 1 & \text{from} \quad 1992:\text{Q2–2009}:\text{Q4}. \end{cases} \quad (4.7)$$

To formally incorporate the regime-specific dummies from equation array (4.7), we rewrite equation (4.5) as the following equation:

$$\begin{aligned} \pi_t^{C} = \alpha_0 &+ \sum_{i=1}^{4} \omega_i \pi_{t-i}^{C} + \gamma \tilde{\mathcal{Y}}_{t-1} + \sum_{i=1}^{4} \theta_i \pi_{t-i}^{\text{PPI}} \\ &+ \sum_{r=1}^{3}\sum_{i=1}^{4} \delta_{ri}(\pi_{t-i}^{\text{PPI}} \cdot D_{rt-i}) + \psi \hat{\epsilon}_{t-1} + \varepsilon_t. \end{aligned} \quad (4.8)$$

In a sense, our short-run model now contains deterministic linear splines in accordance with our established breaks. Thus, we can estimate "time-varying" SRPT over regimes where producer prices unidirectionally cause consumer prices.[6] In a similar vein, we can use our point estimates from our long-run model (which is unchanged,

6 The interpretation of these results will be relative to periods where producer prices do not lead consumer prices.

Table 4: ADF test results

Variable		Test statistic		Critical values		
Levels	**Transformed**	**Levels**	**Transformed**	**1% C.V.**	**5% C.V.**	**10% C.V.**
$\log(\mathcal{P}_t^{\mathcal{C}})$	$\pi_t^{\mathcal{C}}$	−1.62	−3.13	−3.44	−2.87	−2.57
$\log(\mathcal{P}_t^{\mathcal{P}})$	$\pi_t^{\mathcal{P}}$	−2.59	−5.71	−3.44	−2.87	−2.57
$\log(\mathcal{Y}_t)$	$\tilde{\mathcal{Y}}_t$	−0.83	−6.37	−3.44	−2.87	−2.57
$\log(\mathcal{M}_t)$	$\pi_t^{\mathcal{M}}$	−1.30	−4.83	−3.44	−2.87	−2.57

as it captures a time-invariant long-run steady state) and equation (4.8) to arrive at regime-specific SRPT coefficients as described by the following equation:

$$\zeta_r = \theta_1 + (\psi \cdot \beta_{\mathcal{P}}) + \delta_{r1}. \tag{4.9}$$

4.3.1 Pre-estimation Considerations

As is the norm in all error-correction models, there are some specific assumptions that must be satisfied. The first assumption is that our data are $\sim I(1)$ or stationary when differenced or detrended. The second assumption is that there is cointegration between our outcome variable of interest and at least one of regressors (Granger, 1969; Johansen, 1995). Given that this is a two-stage error-correction model, it is not the norm to formally test for cointegration like one would using the Johansen's (1995) test (although one could); rather, it is the norm to conduct a unit root test on the error-correction term generated from the first-stage estimator (Granger, 1969). If $\hat{\epsilon}_t \sim I(0)$, then we can proceed to estimate a short-run model leveraging that it is our error-correction term. To discern whether our data are $\sim I(1)$, consider the following statistical model described by the following equation:

$$\log(x_t) = D_{\mathbb{0}} + D_{\mathbb{1}} \log(x_{t-1}) + D_2 \Delta \log(x_{t-1}) + e_t. \tag{4.10}$$

Of interest to us is the autoregressive coefficient $D_{\mathbb{1}}$, which we will test the hypothesis $D_{\mathbb{1}} = 0$ under the null hypothesis that $D_{\mathbb{1}} = 1$. Failing to reject the null hypothesis at moderate statistical confidence using the augmented Dickey-Fuller (ADF) test statistic tells us that our datum of interest, $\log(x_t)$, is nonstationary in its levels. Table on reports these results for the logs of the CPL, PPL, real GDP, and the M2 money supply aggregate.[7] The results of our ADF tests are described in Table 4.

Our ADF test results for our variables of interest in their levels are largely unsurprising, as most test as nonstationary at strong levels of confidence except for $\log(\mathcal{P}_t^{\mathcal{P}})$, which seems to fail to reject the null hypothesis at a level around 10%. However, 10% is not so strong as to rule out the possibility that $\log(\mathcal{P}_t^{\mathcal{P}})$ is $\sim I(1)$. In fact, at a level of significance that is smaller than 1%, we overwhelmingly reject the null hypothesis that producer price inflation, $\pi_t^{\mathcal{P}}$, is nonstationary or contains a unit root. For all other variables of interest, their transformed states also strongly reject the null hypothesis of containing a unit root. These results more than satisfy the first assumption necessary for pursuing an econometric strategy using an error-correction framework.

Notwithstanding our results from Table 4, we acknowledge that there are many limitations to ADF unit root testing. Despite being the staple for empirical unit root testing in macro data, it can suffer from bias due to sample size limitations and struggles with finite sample performance, as well as performance at lower levels of data frequency; furthermore, research in the unit root testing literature stresses the issues that can arise from near-unit roots, and the difficult in distinguishing between a "true" unit root versus a near, but still stationary, characteristic root (Cochrane, 1991; Campbell & Perron, 1991; Cunningham, 1993). To remedy this, we consider applying an alternative unit root test to our data: the KPSS trend-stationary test. KPSS test results affirm that our results from Table 4 are robust and can be found in Appendix A.

7 The inclusion of M2 acts as a potential control for monetary policy to satisfy the concerns of Caporale et al. (2002), who highlighted that the omission of monetary policy when estimating pass-through can heavily bias the magnitude and significance of estimated pass-through coefficients. We also acknowledge that while we could use the nominal interest rate as our control for monetary policy, it likely tests as $\sim I(0)$ in its levels, particularly during periods where the economy is at zero lower bound (ZLB). M2, on the other hand, visually trends positively over time and is much more likely to be $\sim I(1)$, making it more compatible with the assumptions of our two-step framework.

Table 5: Error-correction model results

	Dependent variable: $\pi_t^{\mathscr{C}}$							
Equation	**(4.5)**		**(4.5)**		**(4.8)**		**(4.8)**	
Coefficient	**Estimate**	**Std. error**	**Estimate**	**Std. error**	**Estimate**	**Std. error**	**Estimate**	**Std. error**
α_0	0.002**	(0.001)	−0.001	(0.002)	0.003***	(0.001)	0.001	(0.001)
ω_1	0.99***	(0.10)	0.99***	(0.09)	0.83***	(0.13)	0.84***	(0.11)
ω_2	0.07	(0.17)	0.10	(0.16)	0.04	(0.21)	0.05	(0.16)
ω_3	0.13	(0.15)	0.14	(0.14)	0.19	(0.15)	0.21	(0.15)
ω_4	−0.22*	(0.11)	−0.28**	(0.10)	−0.18*	(0.09)	−0.22*	(0.09)
γ	0.07.	(0.04)	0.10**	(0.03)	0.09.	(0.05)	0.11**	(0.03)
θ_1	0.09**	(0.03)	0.08**	(0.03)	0.11*	(0.04)	0.09*	(0.04)
θ_2	−0.14**	(0.05)	−0.13**	(0.05)	−0.08	(0.06)	−0.07	(0.06)
θ_3	0.01	(0.04)	0.00	(0.04)	0.0001	(0.05)	−0.01	(0.06)
θ_4	0.02	(0.03)	0.03	(0.03)	−0.02	(0.03)	0.00	(0.04)
ψ	−0.01.	(0.01)	−0.002	(0.01)	0.001	(0.01)	0.01	(0.01)
δ_{11}					0.14	(0.09)	0.14	(0.12)
δ_{12}					−0.12	(0.12)	−0.12	(0.18)
δ_{13}					0.002	(0.08)	0.03	(0.06)
δ_{14}					−0.002	(0.07)	−0.03	(0.12)
δ_{21}					0.14*	(0.07)	0.13*	(0.06)
δ_{22}					−0.09	(0.08)	−0.09	(0.10)
δ_{23}					0.007	(0.07)	0.02	(0.10)
δ_{24}					0.002	(0.05)	−0.01	(0.06)
δ_{31}					−0.04	(0.04)	−0.02	(0.04)
δ_{32}					−0.03	(0.05)	−0.04	(0.06)
δ_{33}					−0.03	(0.03)	−0.04	(0.06)
δ_{34}					0.05	(0.04)	0.05	(0.04)
$\beta_{\mathscr{P}}$	0.77***		0.78***		0.77***		0.78***	
ADF Stat.	−2.19**		−2.68***		−2.19**		−2.68***	
ξ	0.08		0.08		0.11		0.12	
ζ_1	—		—		0.25		0.001	
ζ_2	—		—		0.25		0.01	
ζ_3	—		—		0.06		0.14	
Controls?	No		Yes		No		Yes	
N	249		249		249		249	
Adj. R^2	0.94		0.95		0.95		0.95	

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $p < 0.10$.

4.3.2 Estimation Results

Table 5 reports our error-correction model results and pass-through coefficient estimates. We report results for both equations (4.5) and (4.8) with and without controls. Controls include a linear time trend (T_t) as well as the money supply level ($\log(\mathcal{M}_t)$) in our long-run model and money supply growth ($\pi_t^{\mathcal{M}}$) in our short-run model. Additionally, we report our long-run rate of producer price pass-through, $\beta_{\mathcal{P}}$, along with the ADF test statistic associated with our error-correction term generated from our long-run model. Finally, an additional consideration we take to protect against autocorrelation and heteroscedasticity is the employment of Newey and West's (1987) standard errors.

We observe that PSRPT, θ_1, hovers between 9 and 11% with a fair degree of statistical confidence. Over the full sample, PSRPT implies that a percentage point increase in producer price inflation leads to a 9% increase in consumer price inflation. Furthermore, SRPT hovers between 8 and 12% going off the point estimates alone. While analytically like PSRPT, SRPT carries a slightly different meaning: if producer price inflation increases by one percentage point, then we would an 8% increase in the CPL. Effectively, SRPT maps the transition of producer price inflation to the CPL, while PSRPT maps the marginal impact of producer inflation to consumer price inflation. While our results from Table 5 suggest a modest rate of pass-through between both PSRPT and SRPT, the statistical significance and magnitude of our error-correction term bring into question the reliability of elasticity-based estimates of PSRPT and SRPT.

With regard to the time-varying specification of our short-run Phillips curve, we see that the regime-specific SRPT estimates are wide-ranging and highly sensitive to the inclusion of controls. However, our SRPT estimates, ξ, across all equations are robust despite our long-run and short-run controls. There is no doubt that producer prices do not always lead consumer prices, but tend to most of the time, discrete estimates of regime-specific pass-through coefficients, ζ_r, are not informative nor robust. To account for variation in pass-through direction, we need a more flexible framework to nonlinearly incorporate the regime-switching nature of producer prices leading to consumer prices.

4.3.3 Robustness to Oil Prices

While our choice of controls within equations (4.5) and (4.8) are consistent with the literature, and acknowledge the importance of the monetary authority's ability to influence macroeconomic conditions, and subsequently the price level (Caporale et al., 2002), we admit there are likely other controls that are worth exploring that *could* impact the price level, namely, oil price inflation, and the USD-Euro exchange rate. These potential controls have their own distinct pass-through literatures and likely contain information that could confound the true effect of producer price inflation pass-through. To explore this, consider the error-correction framework described by the following equations:

$$\begin{aligned}\log(\mathcal{P}_t^C) = \beta_0 + \beta_{\mathcal{Y}} \log(\mathcal{Y}_t) + \beta_{\mathcal{P}} \log(\mathcal{P}_t^{\mathcal{P}}) \\ + \beta_{\mathcal{M}} \log(\mathcal{M}_t) + \beta_{\mathcal{O}} \log(\mathcal{O}_t) + \tau\mathcal{T} + \epsilon_t,\end{aligned} \tag{4.11}$$

$$\begin{aligned}\pi_t^C = \alpha_0 + \sum_{i=1}^{4} \omega_i \pi_{t-i}^C + \gamma \widetilde{\mathcal{Y}}_{t-1} + \sum_{i=1}^{4} \theta_i \pi_{t-i}^{\mathrm{PPI}} + \mu \pi_{t-1}^{\mathrm{MNY}} \\ + \lambda \pi_{t-1}^{\mathrm{OIL}} + \psi \hat{e}_{t-1} + \varepsilon_t.\end{aligned} \tag{4.12}$$

Note that we can also specify equation (4.11) to include discrete variation in pass-through across time analogous to equation (4.8). Equation (4.13) captures this while simultaneously controlling for oil price inflation:

$$\begin{aligned}\pi_t^C = \alpha_0 + \sum_{i=1}^{4} \omega_i \pi_{t-i}^C + \gamma \widetilde{\mathcal{Y}}_{t-1} + \sum_{i=1}^{4} \theta_i \pi_{t-i}^{\mathrm{PPI}} \\ + \sum_{r=1}^{3} \sum_{i=1}^{4} \delta_{ri} (\pi_{t-i}^{\mathrm{PPI}} \cdot D_{rt-i}) + \\ \mu \pi_{t-1}^{\mathrm{MNY}} + \lambda \pi_{t-1}^{\mathrm{OIL}} + \psi \hat{e}_{t-1} + \varepsilon_t.\end{aligned} \tag{4.13}$$

Herein, we consider the possibility that long-run PPI pass-through, as well as short-run PPI pass-through can be confounded by oil prices, which has a historically strong influence on consumer price inflation in the US (Chen, 2009; Conflitti & Luciani, 2019; De Gregorio et al., 2007). The long-run relationship between consumer prices, $\log(\mathcal{P}_t^C)$, and oil prices, $\log(\mathcal{O}_t)$ is captured by the $\beta_{\mathcal{O}}$ coefficient. In our short-run model, lagged oil price inflation pass-through, π_{t-1}^{OIL}, is controlled for and captured by the λ term.[8]

For our study, oil prices are West Texas instruments spot crude oil prices retrieved from the Reserve Bank of St. Louis. Data go back as far as 1946:Q1, which is consistent with the window of time we conduct our study over. We stress that while it would be optimal to control for exchange rates, data on the USD-Euro spot exchange rate only go back as far as 1999; furthermore, data on the currency conversion between the USD and Euro only go as far back as 1979. As a result, and consequently, the length of exchange rate data available, and the window of time associated with our study is largely incompatible.[9] Estimation results for equations (4.12) and (4.13) are provided in Table 6.

We note that controlling for oil prices and oil price inflation does not seem to alter SRPT nor PSRTP significantly. This is not too surprising when one considers that the producer price index for the United States can be thought of in the aggregate as the weighted sum of the largest commodity-specific producer price indices. Referring to the BLS page on the composition of United States PPI, one would note that the WPU05 component of PPI is defined as "fuel and related products and power," which contains information on the prices producers pay for coal, gas fuels, electric power, gasoline, and refined petroleum among other commodities. As a result, it is likely that the aggregate producer price index is indirectly capturing *some* variation in oil prices on its own.[10]

We also take note that accounting for discrete variation in pass-through via our ζ_r terms is once more not informative for understanding variation in pass-through across different eras in US history. We can, however, obtain a better idea of "smoother" variation in pass-through using a rolling

8 Time series characteristics of oil prices, including ADF tests for stationarity, can be found in Appendix B.

9 Because of these incompatibilities, it is often common to see exchange rate pass-through work in isolation of other pass-through studies such as the works of Gagnon and Ihrig (2004) and Gopinath et al. (2010).

10 It should be noted that disaggregated PPI weights available from the BLS are only available as far back as the early 2000s. As a result, disaggregation of PPI down to its weighted components and subsequent disaggregated pass-through rates are exercises best left for future research.

Table 6: Error-correction model results (additional controls)

	Dependent variable: $\pi_t^{\mathscr{C}}$			
Equation	**(4.12)**		**(4.13)**	
Coefficient	**Estimate**	**Std. error**	**Estimate**	**Std. error**
α_0	−0.001	(0.001)	0.001	(0.001)
ω_1	0.99***	(0.09)	0.84***	(0.13)
ω_2	0.10	(0.16)	0.05	(0.20)
ω_3	0.14	(0.14)	0.20	(0.15)
ω_4	−0.28**	(0.11)	−0.23*	(0.10)
γ	0.09**	(0.03)	0.11*	(0.05)
θ_1	0.09**	(0.03)	0.09*	(0.04)
θ_2	−0.14**	(0.05)	−0.07	(0.06)
θ_3	0.001	(0.04)	−0.01	(0.05)
θ_4	0.03	(0.03)	−0.002	(0.03)
ψ	−0.01	(0.01)	0.01	(0.02)
δ_{11}			0.14	(0.09)
δ_{12}			−0.12	(0.12)
δ_{13}			0.03	(0.08)
δ_{14}			−0.03	(0.07)
δ_{21}			0.13*	(0.06)
δ_{22}			−0.09	(0.08)
δ_{23}			0.01	(0.07)
δ_{24}			−0.01	(0.05)
δ_{31}			−0.02	(0.04)
δ_{32}			−0.04	(0.06)
δ_{33}			−0.04	(0.03)
δ_{34}			0.05	0.04
$\beta_{\mathscr{P}}$	1.32***		1.32***	
ADF Stat.	−4.52***		−4.52***	
ξ	0.07		0.10	
ζ_1	—		0.24	
ζ_2	—		0.24	
ζ_3	—		0.07	
Controls?	Yes		Yes	
N	249		249	
Adj. R^2	0.95		0.95	

regression framework like that of Chen (2009). Consider a rolling configuration of equation (4.13) with windows equal to 40 quarters, or 10 years. If we roll equation (4.13) and refit our model's coefficients accordingly, we can plot estimates for θ_1 – our partial short-run pass-through rate – over time. Figure 2 illustrates our rolling regression estimates of θ_1.

Note that the shaded orange bars in Figure 2 represent the regimes we discretely accounted for in Tables 5 and 6. We note that the mean PSRPT rate from our rolling regression is around 0.13, which is slightly larger compared to our estimation results. Most striking, during regimes where producer prices lead consumer prices (highlighted by the shaded orange bars in Figure 2), we see that inflation pass-through is, on average, more stable, and lower by

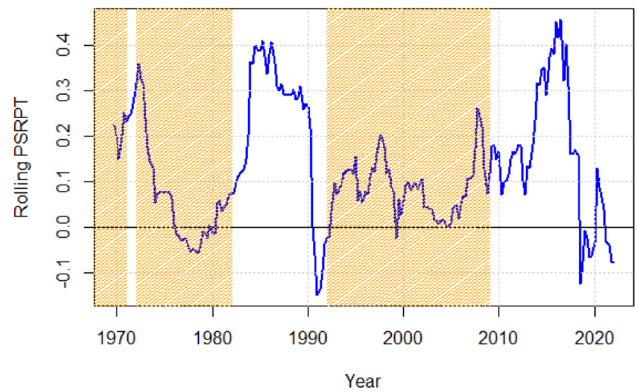

Figure 2: Rolling PSRPT.

comparison to states where there is no causal direction, or relationship present. An implication of this finding is that pass-through almost follows a regime-switching process. There are some states where producer prices lead consumer prices, and some states where they do not. As such, discrete estimation of pass-through over subsamples may not be as efficient or informative. Furthermore, while most pass-through studies (producer prices, oil, and exchange rates) leverage error-correction frameworks to quantity pass-through (oil, and exchange rate pass-through, in particular) by capitalizing on the cointegration between producer and consumer prices, the adjustment speeds from short-run to long-run, as captured by our ψ terms, are relatively weak and insignificant in most cases. Because of this, most SRPT and PSRPT rates are not numerically different from one another over our full sample. These findings motivate a more flexible framework that can account for the regime-switching nature of the production view theory of producer price inflation pass-through and rely less on the cointegrating relationships traditionally leveraged in error-correction frameworks.

4.4 Local Projection IRFs

An alternative approach for estimating pass-through is through the construction of IRFs. In essence, shocks – unit or standard deviations – also capture the pass-through of producer prices to consumer prices, or *vice versa*. An issue with traditional IRF projections, particularly in this setting, is that producer prices are not always leading consumer prices. In essence, there is a probability that we are in a state where the production view theory holds and a state where it does not; thus, we must account for regime-switching in producer prices for correctly identifying pass-through from our shocks.[11] Thankfully, Jordà (2005) provided a flexible framework for circumventing these issues. We first identify two regimes as described by the following equation:

$$z_t = \begin{cases} 1, & \text{if} \log(\mathcal{P}_t^{\mathcal{P}}) \longrightarrow \log(\mathcal{P}_t^{C}) \\ 0, & \text{if otherwise.} \end{cases}, \tag{4.14}$$

Conveniently, we have already identified these regimes via our structural break tests and TY causality tests reported in Tables 2 and 3, respectively. Formally, our local projection model takes on the following general form described by the following equation:

$$\begin{aligned} \mathcal{Z}_{t+h} = \alpha^h + \beta_{1,R_1}^h(\mathcal{Z}_{t1}\cdot(1 - F(\mathcal{Z}_{t1}))) \\ + \cdots + \beta_{\rho,R_1}^h(\mathcal{Z}_{t\rho}\cdot(1 - F(\mathcal{Z}_{t1}))) \\ + \beta_{1,R_2}^h(\mathcal{Z}_{t1}\cdot F(\mathcal{Z}_{t1})) + \cdots + \beta_{\rho,R_2}^h(\mathcal{Z}_{t\rho}\cdot F(\mathcal{Z}_{t1})) + u_{t+h}^h, \end{aligned} \tag{4.15}$$

where $\mathcal{Z}_t = [\pi_t^C, \tilde{\mathcal{Y}}_t, \pi_t^P]^T$ describes our vector of endogenous variables carrying their same meanings as in equation (4.6), h describes our forecast horizon, ρ describes our lag length as selected by the AIC criteria, and β_{i,R_j} describes our lagged coefficient vectors corresponding to lag i and regimes $j \in \{1,2\}$.[12] Furthermore, our state probabilities are computed via a logistic function that follows the form of equation (4.16):

$$F(z_t) = \frac{\exp^{-\gamma z_t}}{(1 + \exp^{(-\gamma z_t)})}, \tag{4.16}$$

where $\gamma > 0$ describes our time-invariant scaling factor.[13] With our model definitions in mind, we can compute state-dependent nonlinear IRFs described by the following equation:

$$\hat{\text{IRF}}^{R_j}(t, h, d_i) = \hat{\beta}_{i,R_j} d_i, \text{ from } \quad h = 0, \cdots, H - 1, \tag{4.17}$$

where R_j captures our states such that $j \in \{1,2\}$, h captures our forecast horizon, and d_i is a matrix of our shocks.[14] Figure 3 illustrates the responses of our endogenous variables to standard deviation shocks under each regime along with shaded 90% confidence intervals.

11 Note that similar regime-switching models have been employed in pass-through literatures outside producer price pass-through, such as Baharumshah et al. (2017).

12 Our lag length is $\rho = 9$ selected via the AIC criteria with a maximum lag length considered at $\bar{\rho} = 12$.

13 Given that our data are at quarterly frequencies, we set $\gamma = 3$.

14 Following Jordà (2005), d_i is obtained from a state-independent structural VAR (SVAR) following a form like equation (4.15). This is done automatically using the "lpirfs" package in the statistical software, R (see Adämmer, 2019 for details and documentation).

Panel **A** expresses responses under regime R_1 wherein producer prices lead consumer prices, while Panel **B** expresses responses under regime R_2 wherein producer prices do not lead consumer prices. We observe that in the state where producer prices lead consumer prices, CPI inflation responds slowly to standard deviation shocks PPI inflation peaking after around eight fiscal quarters ahead. We note that such shocks may seem modest with a mean response around 0.5% but persist up until 12 quarters ahead. An implication herein is that a single shock from producer price inflation is somewhat slow to permeate itself across consumer price inflation but can have a dramatic cumulative effect given the length of the shock's persistence. Interestingly, we also note that producer price inflation responds contemporaneously to a standard deviation shock from consumer price inflation at a rate of around 1.25%, but such a shock is short-lived with producer price inflation reverting to statistical zero after only four quarters.

These two findings alone shed interesting light on the dynamics between both consumer and producer price inflation. The shocks confirm that derived-demand inflation during states where producer prices unidirectionally lead consumer prices exerts an immediate, but transitory response from producer prices. On the other hand, producer price inflation shocks take time to disseminate but are rigid and slow to revert to statistical zero.

Turning toward our regime where producer prices do not lead consumer prices, or vice versa, we see dramatically different responses from standard deviation shocks. We observe that producer price inflation shocks do not affect CPI inflation contemporaneously but after some time, can lead to small levels of deflation that persist for six quarters or so before jumping to modest levels of positive pass-through around a mean response of 2% persisting for eight quarters or so. On the other hand, producer price inflation responds significantly, albeit at a very weak rate, to a standard deviation shock from consumer price inflation; however, this effect lasts for a little less than two fiscal quarters before reverting and lingering around zero for the remainder of the projection horizon.

Panels **(a)** and **(b)** taken together reflect that knowledge of *which* state the economy is in is imperative – not only for forecasting and quantifying the impacts of producer price inflation shocks themselves, but also for timing policy responses to stabilize inflation over long periods. In states where producer prices lead consumer prices, our local projections suggest that policy responses to stabilize producer prices and minimize pass-through should be enacted early and executed over a long horizon (between 10 and 12 fiscal quarters). On the other end of the spectrum, in states where the production view theory of pass-through

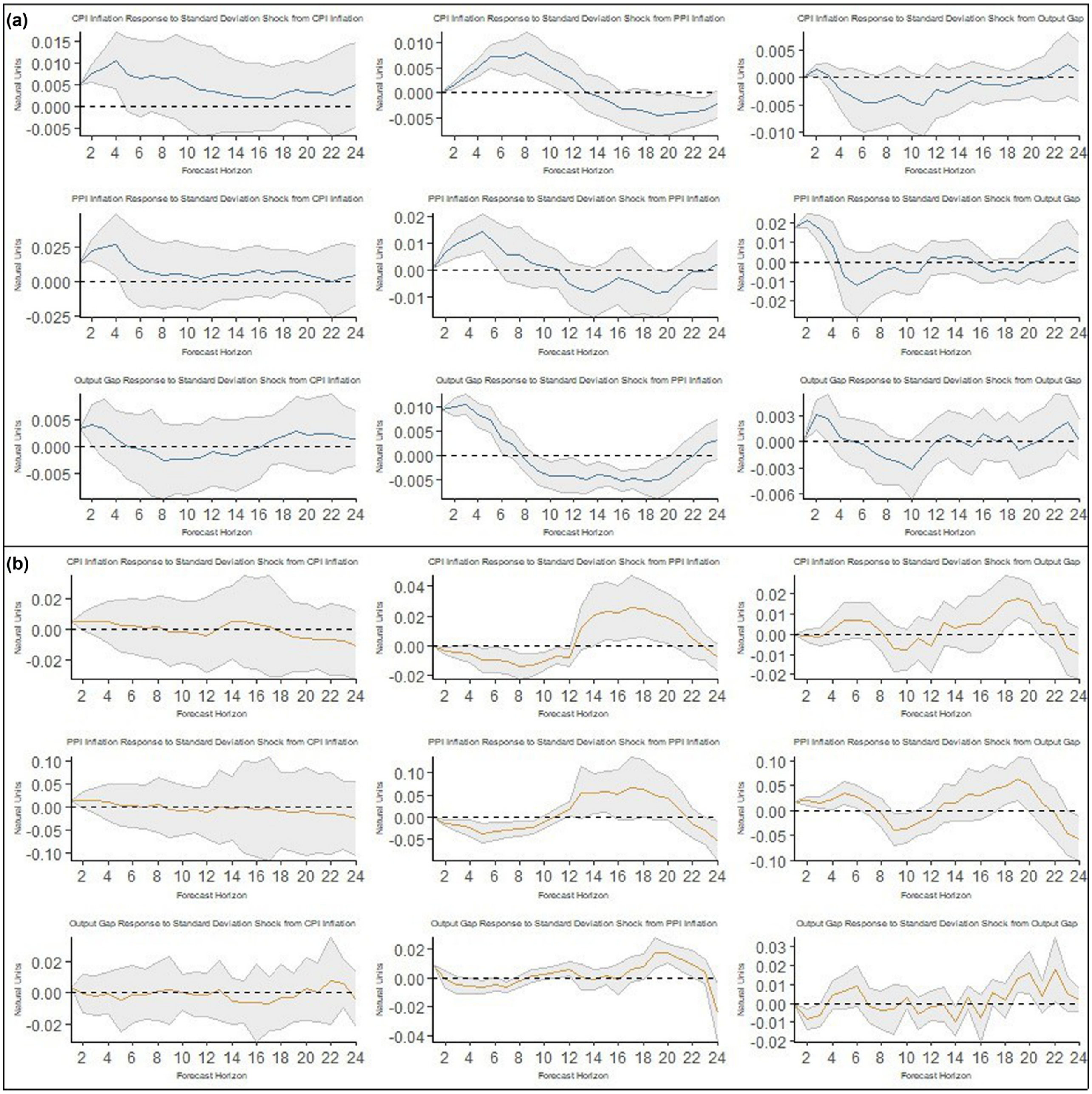

Figure 3: Panel (a): Local projection responses to shocks when PPI leads CPI. Panel (b): Local projection responses to shocks when PPI does not lead CPI.

does not hold, policy responses to stabilize producer prices would likely be minimal in effect and could be quite costly from a practical standpoint.

5 Conclusion and Policy Implications

Producer price inflation has long been heralded as a strong leading indicator for consumer price inflation. Empirical evidence over long samples tends to support the so-called production view theory of cost-push inflation dominating the "derived demand" theory of demand-pull inflation. These stylized facts notwithstanding, the dynamics of inflation are exceedingly intricate, complex, and notoriously difficult to forecast.[15] In a world of globally integrated value chains, and given how vested policymakers, firms,

15 See Stock and Watson (2007) for exposition on the difficulties of inflation forecasting.

and households are in understanding the direction of the general price level, scrupulous analysis of the determinants and leading indicators of consumer price inflation is more essential now than perhaps ever before in recent memory.

Within this study, we contribute to the literature on pass-through, specifically through the lens of producer price inflation, and find that producer prices over long samples do, indeed, lead consumer prices, consistent with the literature. We specifically estimate the short-run pass-through of producer price inflation to the CPL to be around 8%. In practical terms, given that the average rate of inflation is roughly 3.6% over our full sample, this implies that 29 basis points worth of producer price inflation pass-through to consumer prices.

When looking at pass-through over subsample breaks in consumer price inflation, we find that there are states where producer prices fail to serve as an adequate leading indicator for consumer prices. When evaluating pass-through in a regime-switching framework, in states where producer prices unidirectionally lead consumer prices, we find responses of consumer price inflation to producer price inflation shocks to be sluggish and small in magnitude at roughly 50 basis points, but persistent for long periods leading to a larger cumulative effect. On the other end of the spectrum, in states where producer prices have no causal relationship with consumer prices, consumer prices tend to express higher mean rates of pass-through at around 2% but revert to zero very quickly.

From a practical standpoint, one approach policymakers can take to minimize final goods price volatility is through the stabilization of producer commodity prices (Schmitz et al., 1981). Based on our analysis, such an approach may be hindered in effectiveness or misinformed altogether if the economy is in a state where producer prices do not lead consumer prices. Second, given that the pass-through of producer to consumer prices in the aggregate is small, such policy pursuits may be more costly to pursue than the small gains in disinflation that could in theory be achieved. These points notwithstanding, PSRPT *can* be informative for policymakers interested in managing transitory episodes of inflation driven by supply shocks. It is also worth stressing that policies aimed at achieving *long-run* inflation stability likely do not stand to gain considerably from actions aimed to first stabilize producer prices, as evident by weak error-correction rates.

Overall, producer prices still have the potential to serve as an important leading indicator for consumer prices, but only if policymakers and practitioners are confident in whether we are in a state where the production view theory of pass-through holds. Failing to account for the regime-switching nature of producer prices can lead to erroneous or inconsistent measures of pass-through and can misinform policy actions seeking to stabilize producer prices and minimize its impact on economic welfare.

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Appendix A Alternative Unit Root Test Results

The KPSS test has a null hypothesis (H_0) that a given time series is trend stationary and an alternative hypothesis (H_a) that the data contain a unit root. Note that a rejection of our null hypothesis is sufficient analogue to our ADF tests presented in Table 4.

Table A1: KPSS test results

Variable	Test statistic	Critical values		
		1% C.V.	5% C.V.	10% C.V.
$\log(\mathcal{P}_t^C)$	0.974	0.347	0.146	0.216
$\log(\mathcal{P}_t^P)$	0.761	0.347	0.146	0.216
$\log(\mathcal{Y}_t)$	0.775	0.347	0.146	0.216
$\log(\mathcal{M}_t)$	0.814	0.347	0.146	0.216
$\log(\mathcal{O}_t)$	0.352	0.347	0.146	0.216

Appendix B Time Series Characteristics of Oil prices

Figure A1, Tables A2 and A3

Table A2: Descriptive statistics for oil prices

Data	Mean	Std. dev.	Min.	Max
$\log(O_t)$	2.94	1.15	1.07	4.82
π_t^{OIL}	0.05	0.30	−0.82	1.04

Table A3: ADF test results (oil)

Variable		Test statistic		Critical values		
Levels	Transformed	Levels	Transformed	1% C.V.	5% C.V.	10% C.V.
$\log(O_t)$	π_t^{OIL}	−1.40	−7.70	−3.44	−2.87	−2.57

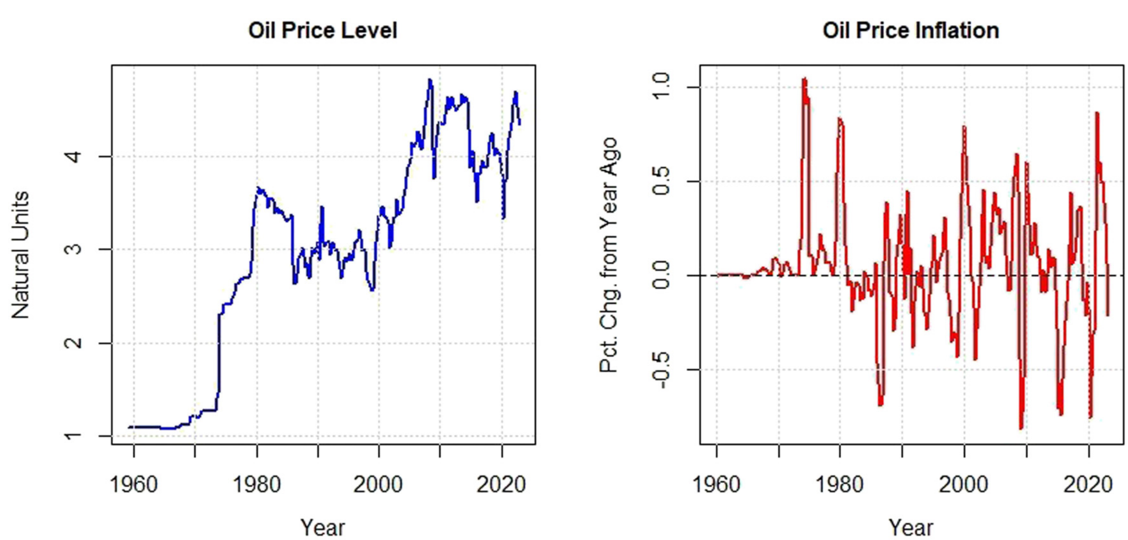

Figure A1: Oil price level and inflation time series.