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# Effects of Commodity Price Shocks on Inflation: A Cross-Country Analysis

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## Abstract

Since the 2000s, large fluctuations in commodity prices have become a concern among policymakers regarding price stability. This paper investigates the effects of commodity price shocks on headline inflation with a monthly panel consisting of 144 countries. We find that the effects of commodity price shocks on inflation virtually disappear within about one year after the shock. While the effect on the level of consumer prices varies across countries, this transitory effect is fairly robust, suggesting a low risk of a persistent second-round effect on inflation. Employing the smooth transition autoregressive models that use past inflation as the transition variable, we also explore the possibility that the effect of commodity price shocks could be persistent, depending on inflation regimes. In this specification, commodity price shocks may not have transitory effects when a country's currency is pegged to the U.S. dollar. However, the effect remains transitory in countries with exchange-rate flexibility.

**Keywords**

Commodity prices, inflation, pass-through, local projections, smooth transition autoregressive models

**JEL Classification**

E31, E37, Q43

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# Effects of Commodity Price Shocks on Inflation: A Cross-Country Analysis*

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Since the 2000s, large fluctuations in commodity prices have become a concern among policymakers regarding price stability. This paper investigates the effects of commodity price shocks on headline inflation with a monthly panel consisting of 144 countries. We find that the effects of commodity price shocks on inflation virtually disappear within about one year after the shock. While the effect on the level of consumer prices varies across countries, this transitory effect is fairly robust, suggesting a low risk of a persistent second-round effect on inflation. Employing the smooth transition autoregressive models that use past inflation as the transition variable, we also explore the possibility that the effect of commodity price shocks could be persistent, depending on inflation regimes. In this specification, commodity price shocks may not have transitory effects when a country's currency is pegged to the U.S. dollar. However, the effect remains transitory in countries with exchange-rate flexibility.

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# 1 Introduction

Fluctuations in commodity prices since the early 2000s have renewed policymakers' attention to their effects on inflation. One of the concerns for policymakers is how commodity price shocks could spill over into prices of goods and services other than commodities. Commodity price shocks affect consumer prices through changes in the commodity price themselves (the first-round effect), but the first-round effect may transmit to prices of goods and services other than commodities through effects on production costs or price setting of firms (the second-round effect). If the second-round effect on inflation persists for long periods (e.g., more than a year), it would raise the issue of how monetary policy should respond to the commodity price shocks. For example, Janet Yellen, then Vice Chair of the Federal Reserve, argued that commodity price shocks have only modest and transitory effects on U.S. inflation and that fluctuations in commodity prices during the 2000s did not "warrant any substantial shift in the stance of monetary policy."[1] By contrast, Mario Draghi, the President of the European Central Bank, expressed a concern that fluctuations in commodity markets may have a "lasting impact on the outlook for prices."[2]

This paper investigates the effects of commodity price shocks on inflation by estimating impulse responses (IRs). Using the cross-country Consumer Price Indexes (CPIs), we ask whether fluctuations in commodity prices have a persistent or transitory effect on the headline inflation.[3] Typically, the first-round effect is considered to be short-lived. Thus, if commodity price shocks have only a weak and transitory second-round effect, the response of headline inflation would be only modest and transitory. In this case, as Yellen argued regarding U.S. inflation, further monetary policy responses to changes in commodity prices may not be required. However, if commodity price shocks have a strong and persistent second-round effect, the response of headline inflation would be large and persistent, creating concerns for central bankers. To study how the effect of commodity price shocks evolves over time, we estimate IRs rather than the commodity price pass-through to inflation.[4]

[1] Janet Yellen at Economic Club of New York, "Commodity Prices, the Economic Outlook, and Monetary Policy," April 11, 2011.

[2] Mario Draghi, at ECB press conference - introductory statement, September 3, 2015.

[3] Some central banks pay close attention to a "core" measure of inflation that excludes food and energy prices. However, the central banks in most countries monitor the headline measure due to the large expenditure shares on food and energy. Hence, our analysis throughout the paper relies on the headline CPI for all countries. See also De Gregorio (2012) for the reason why most central banks focus on headline inflation in their policymaking.

[4] Many previous studies on the effect of commodity prices focused on the commodity price pass-through to in-

We find that the effects of commodity price shocks on the headline inflation are transitory. The benchmark estimation suggests that, on average, the headline CPI increases by 1.87 percent in 12 months in response to a 10 percent increase in commodity prices. However, changes in consumer prices in the subsequent year become substantially small, implying that commodity price shocks have only a transitory effect on inflation. We point out cross-country differences in IRs to commodity price shocks. For example, when the currency in a country is pegged to the U.S. dollar, the effect of commodity price shocks tends to be larger than otherwise. However, we show that the transitory effect on inflation is fairly robust, regardless of the magnitude of the effect. This suggests that risks of a persistent second-round effect are low.

In terms of methodology, we use panel local projections. The local projections developed by Jordà (2005) have some practical advantages, compared to the standard approach such as vector autoregressions (VAR). First, local projections can be made using the least squares of the single equation. Therefore, we can easily apply regressions to the cross-country panel and/or extend regressions with interaction terms. Second, local projections are relatively robust to misspecification. Because the direct estimation of IRs based on local projections does not constrain the shape of IR functions, we could mitigate biases arising from the misspecification such as the lag structure of regressions. Third, the nonlinearity of the estimation equation can be addressed with less computational burden than the standard nonlinear estimation. In this paper, we extend the model to the smooth transition autoregressive (STAR) model. As explained in Auerbach and Gorodnichenko (2013), estimating IRs using local nonlinear projections does not need to keep track of the transition variable's changes over time.

Our STAR model explores the possibility that responses of consumer prices depend on the lagged inflation rate in each economy. The dependence of price responses on inflation reflects Taylor's (2000) argument that higher inflation leads to more frequent price changes, resulting in the increased sensitivity of prices to shocks. Auerbach and Gorodnichenko (2013) use smooth transition models and focus on government multipliers varying between recessions and expansions. Instead of looking at recessions and expansions, we focus on the IRs varying between high- and

flation. For example, see Cecchetti and Moessner (2008), Chen (2009), Rigobon (2010), and Gelos and Ustyugova (2012), among others. Ferrucci, Jiménez-Rodríguez, and Onorante (2012) analyze the pass-through of international commodity prices to food price indexes in the euro area.

low-inflation regimes.[5]

The estimation results suggest that the IRs differ between the two regimes, when a country's currency is pegged to the U.S. dollar. In particular, when the country is experiencing high inflation relative to its average inflation, commodity price shocks tend to increase inflation substantially, and to decrease afterward. Under a low-inflation regime, the effect of commodity price shocks on inflation persists, although inflation *per se* is not substantially high. However, such differences are not observed when countries have exchange-rate flexibility. IRs in developed countries with exchange-rate flexibility exhibit very similar patterns, regardless of inflation regimes. Therefore, we conclude that, even if we allow for the dependence on inflation regimes, there would be a low risk of a persistent second-round effect, at least in countries with exchange-rate flexibility.

This paper is organized as follows. Section 2 formally describes our motivation and methodology. Section 3 shows the main results along with robustness analysis. Section 4 introduces nonlinearity to the estimation equation based on the STAR model. Section 5 concludes.

# 2 Motivation and Methodology

## 2.1 Motivation

To motivate our empirical analysis, we begin by discussing how effects of commodity price shocks on inflation could be persistent or transitory. Let $p_{j,t}$ be the logarithm of headline CPI in country $j$. We define $p_{j,t}$ by

$$p_{j,t} = \lambda_j p_{c,j,t} + (1 - \lambda_j) p_{g,j,t}, \tag{1}$$

where $p_{c,j,t}$ and $p_{g,j,t}$ denote the (log) commodity price index and the price index of goods (and services) other than commodities, respectively. All prices are denominated in the country's currency. Also, $\lambda_j$ is the share of commodities in the CPI.

Commodity price shocks affect $p_{j,t}$ through two transmission channels. First, a shock to $p_{c,j,t}$ via international commodity markets directly affects $p_{j,t}$. We call this direct effect the first-round effect. We consider this effect to be quickly transmitted to $p_{j,t}$. Second, $p_{c,j,t}$ affects $p_{j,t}$ through $p_{g,j,t}$. For example, the first-round effect on $p_{j,t}$ may affect wages or inflation expectations, changing

[5] The time-varying effects of commodity (oil) price shocks are also studied by Chen (2009), Clark and Terry (2010), Shioji and Uchino (2011), and Baumeister and Peersman (2013).

production costs or price setting of firms. In addition, production itself relies on commodities such as oil. We call this indirect effect through $p_{g,j,t}$ the second-round effect (see Cecchetti and Moessner 2008 and International Monetary Fund (IMF) 2008, 2011). This second-round effect is related to how price-setting firms respond to commodity price shocks.

To consider how the headline inflation evolves over time in response to commodity price shocks, we take the difference of (1) to obtain $\pi_{j,t} = \lambda_j \pi_{c,j,t} + (1 - \lambda_j)\pi_{g,j,t}$, where $\pi_{j,t}$, $\pi_{c,j,t}$, and $\pi_{g,j,t}$ are the headline, commodity price, and underlying inflation, respectively.

Responses of $\pi_{g,j,t}$ may be persistent to commodity price shocks. The standard sticky-price models predict the persistent response to a commodity price shock since, by assumption, firms slowly adjust prices to all shocks. In our context, slow responses of $p_{g,j,t}$ to a commodity price shock would generate a slow adjustment of $p_{j,t}$ to the new path after a commodity price shock.

Alternatively, responses of $\pi_{g,j,t}$ may be much less persistent to commodity price shocks than the sticky-price models predict. The rational-inattention models predict fast responses of prices, given a highly volatile commodity price shock (e.g., Maćkowiak and Wiederholt 2009 and Paciello 2012, among others). In their models, firms decide what shocks they should be attentive to. Firms pay much attention to volatile shocks because volatile shocks tend to generate a large loss of profits when prices are not adjusted. For example, Paciello (2012) shows that his model can explain fast responses of inflation to a technology shock and slow responses of inflation to a monetary policy shock, based on the difference in volatility of these shocks. In our context, a highly volatile commodity price shock would lead to a fast price adjustment of $p_{j,t}$ to the new path after a commodity price shock, because $p_{g,j,t}$ is quickly adjusted to the optimal level.

The magnitude of the price response to commodity price shocks would be important for exploring policy implications of commodity price shocks. For example, if the response of $\pi_{j,t}$ is large and persistent in a country, the central bank may have to accommodate the shock. However, the response could be small in another country, even though it is persistent. In this case, a policy response may not be required because the price instability is limited.

We thus explore differences in the magnitude of the effect of commodity price shocks. To facilitate our interpretations, note that the commodity prices are often denominated in the U.S. dollar. Under the law of one price in the commodity markets, we obtain $p_{c,j,t} = s_{j,t} + p_{c,t}$, where $s_{j,t}$ and $p_{c,t}$ denote the (log) nominal exchange rate vis-á-vis the U.S. and the (log) commodity price denominated in the U.S. dollar, respectively. Hence, the headline CPI becomes

$$p_{j,t} = \lambda_j (s_{j,t} + p_{c,t}) + (1 - \lambda_j) p_{g,j,t}. \tag{2}$$

According to the literature, we consider the following four factors that may affect IRs:

**Exchange-rate flexibility** De Gregorio, Landerretche, and Neilson (2007) and Rigobon (2010) find a stabilizing role of the exchange rate on consumer prices in response to commodity price shocks. Because commodity prices are denominated in the U.S. dollar, the pass-through of commodity prices to each country's CPI would be affected by variations in the flexible nominal exchange rate. Equation (2) shows that, if depreciations of the U.S. dollar (i.e., declines in $s_{j,t}$) take place with increases in commodity prices, *ceteris paribus*, an increase in $p_{c,t}$ is offset by a decline in $s_{j,t}$. Hence, responses of $p_{j,t}$ would be smaller than in countries with currencies pegged to the U.S. dollar. In this case, we interpret that the flexibility of the exchange rate vis-à-vis the U.S. is stabilizing consumer prices.

**Inflation targeting** Blanchard and Galí (2010) argue that an improvement in monetary policy has contributed to the decline in the oil price pass-through since the 1980s. A good monetary policy may stabilize inflation expectations and dampen the second-round effect. In our context, we have $\pi_{j,t} = \lambda_j(\Delta s_{j,t} + \pi_{c,t}) + (1 - \lambda_j)\pi_{g,j,t}$ from (2), where $\Delta s_{j,t}$ is the nominal exchange rate growth in country $j$ and $\pi_{c,t} = p_{c,t} - p_{c,t-1}$. If inflation expectations are well anchored by inflation targeting (IT), IT may dampen responses of $\pi_{j,t}$ to commodity price shocks through the stability of $\pi_{g,j,t}$.[6]

**Degree of economic development** Chen (2009) and Blanchard and Galí (2010) state that a higher oil intensity and/or higher share of food in the CPI basket would lead to a higher pass-through coefficient. This may also be the case for the general commodity. In our context, a higher $\lambda_j$ makes the first-round effect more dominant, leading to more sensitive responses of $p_{j,t}$.

In our empirical analysis, we proxy $\lambda_j$ by the degree of economic development. In this regard, IMF (2008, 2011) finds that the pass-through of commodity price shocks to CPIs is negatively related to the degree of economic development, due to higher energy intensity and food share of

[6]Levin, Natalucci, and Piger (2004) show evidence that IT stabilizes long-run inflation expectations.

the CPI in less developed countries (LDCs) than in developed countries (DCs).[7]

**Degree of trade openness** Chen (2009) empirically finds that the short-run oil price pass-through is lower in countries with a higher degree of trade openness. He argues that the increasing flow of inexpensive imports may weaken increases in oil prices because inexpensive imported goods are substituted for expensive domestic goods. In our context, it would be reflected in the weak responses of $p_{g,j,t}$. Thus, a higher degree of trade openness may dampen the responses of $p_{j,t}$.

We could also argue that price responses are more sensitive in countries with a higher degree of trade openness. In particular, $p_{g,j,t}$ may be more sensitive to commodity price shocks in countries that import more commodities, if the country's production highly depends on commodities. Likewise, increases in commodity prices may have more influence on $p_{g,j,t}$ in countries that export more commodities. This is because the improved terms of trade generated by higher commodity prices may lead to higher incomes in countries and this in turn may boost aggregate demand for goods. In both cases, a higher degree of trade openness may amplify the responses of $p_{j,t}$.

## 2.2 Methodology

### 2.2.1 Benchmark regressions

To introduce the benchmark regression, consider a panel AR($q$) process:

$$p_{j,t} - p_{j,t-1} = \alpha_j + \sum_{i=1}^{q} \beta_i (p_{j,t-i} - p_{j,t-i-1}) + \gamma u_{c,t} + u_{j,t}. \tag{3}$$

Here, we decompose shocks to inflation into the international commodity price shock $u_{c,t}(\sim\text{i.i.d.}(0, \sigma_c^2))$ and a linear combination of other shocks to inflation $u_{j,t}$. We assume that these shocks are serially uncorrelated and $u_{c,t}$ is orthogonal to $u_{j,t}$. For now, we leave the description of how unobservable $u_{c,t}$ is estimated to the subsequent section and assume that it is observable. The parameter $\alpha_j$ includes the country fixed effects, $\beta_i$ captures persistence of inflation, and $\gamma$ represents the sensitivity of inflation to $u_{c,t}$. Note that (3) can also be understood as an approximation of the general ARMA process.

[7] Another reason for taking this approach is that, if we construct the data of $\lambda_j$ for regressions, a number of countries need to be dropped from the sample.

The purpose of our analysis is to estimate IRs of CPIs and inflation to a commodity price shock. Rather than estimating the IRs from (3), we directly estimate IRs from the local projections:

$$p_{j,t+k} - p_{j,t-1} = \alpha_{j,k} + \sum_{i=1}^{q} \beta_{i,k}(p_{j,t-i} - p_{j,t-i-1}) + \gamma_k u_{c,t} + u_{j,t+k}^{k}, \quad \text{for } k = 0, 1, ..., K, \tag{4}$$

where $k$ denotes the forecast horizons.[8] Here, we estimate $\alpha_{j,k}$, $\beta_{i,k}$, and $\gamma_k$ for each horizon $k$ with $K+1$ separate regressions. In (4), shocks to inflation are again decomposed into $u_{c,t}$ and $u_{j,t+k}^{k}$, but the latter typically includes $u_{j,t+i}$ for $i = 0, 1, ..., k$ and $u_{c,t+i}$ for $i = 1, 2, ..., k$. This implies that $u_{j,t+k}^{k}$ follows the MA($k$) process. In the estimation, we set $K$ at 24 months and the maximum number of lags $q$ is determined by the Bayesian Information Criterion (BIC).

The IR of CPIs for the $k$-th period after a one percent increase in $u_{c,t}$ can be written as

$$IR(k) = \gamma_k, \text{ for } k = 0, 1, ..., K. \tag{5}$$

The coefficient $\gamma_k$ represents the response of $k$-period-ahead consumer prices to a current commodity price shock. Another interpretation of $\gamma_k$ is the cumulative IR of inflation over $k$ periods because $p_{j,t+k} - p_{j,t-1} = \sum_{i=0}^{k} \pi_{j,t+i}$. Note that, if we estimate IRs from (3), the estimated IR function is a nonlinear function of $\hat{\beta}_i$ and $\hat{\gamma}$, where the hatted parameters denote the estimates of coefficients. By contrast, the local projections directly estimate IRs and the estimated IRs do not depend on $\hat{\beta}_{i,k}$. Hence, the lagged inflation is introduced into (4) only to control for the inflation persistence rather than to estimate the IRs. This direct estimation of IRs can mitigate biases arising from misspecification of the stochastic process (see Jordà 2005 and Teulings and Zubanov 2014). While the local projections have advantages, they also have some limitations. Our approach may not perform better than the standard approach in terms of the mean squared forecast error. Marcellino, Stock, and Watson (2006) argue that, if the model is correctly specified, forecasts of the standard approach tend to be more efficient than direct forecasts of the local projections. Kilian and Kim (2011) also report that the confidence intervals of the IRs from local projections may be wider than the bootstrap VAR confidence interval, based on Monte Carlo simulations. Hence, there is a trade-off between bias and estimation variance.

[8] A similar specification was employed by Furceri and Zdzienicka (2012), who estimated the effects of debt crises on output with local projections.

We estimate (4) using the least squares dummy variable (LSDV) estimator with the Newey–West heteroskedasticity and autocorrelation consistent covariance matrix, because $u^k_{j,t+k}$ for $k > 0$ follows a moving average process. It is well known that the presence of lagged dependent variables in panel estimations may lead to severe bias when the serial correlation of the dependent variables is high and the time-series dimension of the data is short (Nickell 1981). Although the serial correlation of the dependent variables may be high, the sample period used for our estimation is not extremely short ($T = 95$) compared to the cross-sectional dimension ($N = 144$ or 120). We thus proceed with the LSDV estimator.

### 2.2.2 Regressions allowing for cross-country differences in IRs

In (5), we assume that the IRs are the same across all countries. When we relax this assumption, we augment (4) with interaction terms:

$$p_{j,t+k} - p_{j,t-1} = \tilde{\alpha}_{j,k} + \sum_{i=1}^{q} \beta_{i,k}(p_{j,t-i} - p_{j,t-i-1}) + \gamma_{j,k} u_{c,t} + u^k_{j,t+k}, \tag{6}$$

for $k = 0, 1, ..., K$. Here, $\gamma_{j,k}$ is the IR for country $j$ and is specified as

$$IR(k, j) = \gamma_{j,k} = \gamma_k + \gamma_{USD,k} D^{USD}_j + \gamma_{IT,k} D^{IT}_j + \gamma_{LDC,k} D^{LDC}_j + \gamma_{TO,k} D^{TO}_j, \tag{7}$$

where $D^g_j$ for $g = USD, IT, LDC, TO$ denotes the dummy variable and its coefficient measures the difference across country groups. The dummy variable corresponds to our discussion in the previous section and takes one or zero under the following conditions. For $g = USD$, $D^{USD}_j = 1$ if country $j$ pegs its currency to the U.S. dollar. Likewise, $D^{IT}_j = 1$ for IT countries, $D^{LDC}_j = 1$ if a country is grouped with the LDCs, and $D^{TO}_j = 1$ if country $j$ is categorized as a country with a high degree of trade openness. Note that, although we express these four dummy variables as being independent of $t$ for notational simplicity, these new dummy variables are in practice time-dependent.[9] We also replace $\alpha_{j,k}$ by $\tilde{\alpha}_{j,k}$ defined by $\tilde{\alpha}_{j,k} = \alpha_{j,k} + \alpha_{USD,k} D^{USD}_j + \alpha_{IT,k} D^{IT}_j + \alpha_{LDC,k} D^{LDC}_j + \alpha_{TO,k} D^{TO}_j$ to control for the direct effect of these dummy variables on inflation.

[9] For example, some countries move from an exchange-rate regime to another regime during the sample period; and some LDCs experiencing high economic growth become categorized into DCs during the sample period. Our estimation allows for this time dependence, because it is not only more precise than time-independent dummies but also allows us to avoid collinearity between country-specific fixed effects and the newly introduced dummy variables.

## 2.3 Estimating commodity price shocks

We can estimate the IRs of CPIs only when commodity price shocks $u_{c,t}$ are observable. To obtain a proxy of $u_{c,t}$, we take the commodity prices as given and assume that $u_{c,t}$ can be represented by the residuals in the following forecasting equation used by Chen, Rogoff, and Rossi (2010, hereafter CRR):

$$\pi_{c,t} = a + b\pi_{c,t-1} + c_{AUS}\Delta s_{AUS,t-1} + c_{CAN}\Delta s_{CAN,t-1} + c_{NZ}\Delta s_{NZ,t-1} + \varepsilon_{c,t}, \tag{8}$$

where $a$, $b$, and $c_j$ for $j = AUS, CAN, NZ$ are the parameters estimated and $\varepsilon_{c,t}$ is the error term. CRR show that the nominal exchange rate growth of resource-rich countries such as Australia (AUS), Canada (CAN), and New Zealand (NZ) has strong forecasting power for commodity price inflation $\pi_{c,t}$.[10] In (8), the lag length of explanatory variables is determined by the BIC, but our main results are robust to the lag length.

We assume that commodity price shocks $u_{c,t}$ can be represented by $\varepsilon_{c,t}$. We thus estimate $u_{c,t}$ using the residual of (8). While there might be some other important variables that are helpful in forecasting $\pi_{c,t}$, the literature suggests that finding such variables is not an easy task. Groen and Pesenti (2011) find that the factor-augmented regressions which replace $\Delta s_{j,t}$ with the principal components from the factor model often perform poorly compared to CRR's forecasting models.

The use of the residual $\hat{\varepsilon}_{c,t}$ leads to a generated regressor problem in our estimation. In this case, the usual standard error estimation for the coefficients in (4) is downward biased (Murphy and Topel 1985). To address this generated regressor problem, we use the heteroskedasticity-robust version of Murphy and Topel's (1985) standard error correction (see Hardin 2002).

## 2.4 Data

We construct a balanced panel for the headline CPIs taken from the International Financial Statistics (IFS) of the IMF from January 2000 to December 2010. Because the raw data of the CPIs are seasonally unadjusted, we use the X-12-ARIMA procedure to make a seasonal adjustment. We use

[10] CRR interpret their finding in terms of the difference in the informational content embodied in commodity prices and exchange rates. Commodity prices are sensitive to the global demand and supply; therefore, they are more likely to be inaccurate in terms of containing the market conditions in the future. In contrast, the exchange rate is very sensitive to future market conditions, including expectations on commodity markets. Because of the information difference, exchange rates can help to forecast commodity prices.

144 countries for the benchmark estimation.[11] The countries used in our analysis are summarized in Table 1.

Our analysis uses the data in the 2000s to address possible structural breaks in inflation rates. Rogoff (2003) argues that inflation in many countries was high until the 1990s but has become low and stable since the early 2000s. We perform Bai and Perron's (2003) structural break test for the average inflation rate across the sample countries in which the data are available from the 1990s and find a structural break in February 1994. When we use the world inflation rate published in the IFS, structural breaks are detected in July 1994 and October 1998. Hence, it is sensible to drop the data during the 1990s in the benchmark estimations.

To estimate aggregate commodity price shocks, we use the non-energy commodity price index published by the World Bank (WB) for the benchmark estimation. We also report the robustness checks to the choice of alternative commodity price indexes: the energy commodity price index of the WB; the All Commodity Price, Fuel Price, and Non-Fuel Price Indexes published by the IMF; and the spot index of the S&P Goldman Sachs Commodity Index (S&P GSCI).[12] We note that all of these indexes are denominated in the U.S. dollar. The estimation of commodity price shocks requires nominal exchange rate data. We take the data from Datastream.

As a preliminary analysis, Figure 1 plots the commodity price inflation and our forecasts from (8) in the upper panel and the residual $\hat{\varepsilon}_{c,t}$ in the lower panel. All series in the figure are expressed at an annual rate, and commodity price shocks are estimated based on the sample period from February 2001 to December 2008.[13] Both $\pi_{c,t}$ and $\hat{\varepsilon}_{c,t}$ are very volatile and show large declines during the global financial crisis (September and October 2008). We confirm that the nominal exchange rate growth in (8) Granger-causes commodity price inflation, consistent with CRR. In addition, the standard Ljung-Box statistics for $\hat{\varepsilon}_{c,t}$ for lags 1 to 12 are all insignificant at conventional significance

[11] The IFS has reported CPIs for 146 countries since January 2000. Of these countries, Australia, New Zealand, Papua New Guinea, Myanmar, and the Democratic Republic of Congo have missing values during the above sample period. In the first three countries, only the quarterly CPIs are available, so we linearly interpolate the quarterly CPIs. Myanmar has a single missing value in May 2003, which we fill the missing value by linear interpolation. We drop Angola and the Democratic Republic of Congo from the sample, because the former often experienced high inflation exceeding 100 percent during the 2000s and the latter has missing values from June 2009.

[12] Even though they are similar, the commodity baskets differ somewhat across these commodity price indexes. The commodity basket in the WB's index includes less information on trade of commodities in DCs than the IMF's index. As a result, the weight for agricultural raw materials is slightly higher in the WB's index than in the IMF's. The S&P GSCI has time-varying weights based on the world commodity productions for the most recent five years.

[13] This sample period is determined by the facts that we allow for 24 leads on the left-hand side of (4) and for the maximum lags of order 12 on the right-hand side. We use in-sample forecasts, because the standard error correction for generated regressors requires in-sample forecasts rather than out-of-sample forecasts.

levels, suggesting no serial correlation in $\hat{\varepsilon}_{c,t}$.

To allow for cross-country differences in IRs, we collect the cross-country information from the following data sources. For the exchange-rate regime, we rely on the *de facto* classification constructed by Ilzetzki, Reinhart, and Rogoff (2010).[14] The use of these data drops 15 countries from the sample.[15] We choose IT countries based on the definition of Roger (2009) and Hammond (2012). For $D_j^{LDC}$, we define the low- and middle-income economies in the WB's classification as LDCs. These data are missing in Anguilla, so we drop Anguilla. Finally, we construct $D_j^{TO}$ from the World Development Indicators (WDIs) of the WB. We take the data of the sum of imports and exports divided by GDP and split countries into country groups with a high or low degree of trade openness, based on the median of the data.[16] To use these data, we drop eight countries from the sample.[17] After all, the process of constructing the panel data with these control variables reduces the number of countries to 120. See panel (e) of Table 1 for countries dropped from the sample.

# 3 Results

## 3.1 Main results

### 3.1.1 Benchmark regressions

Figure 2 plots the estimated IRs of the CPIs to a 10 percent increase in a commodity price shock in period $t = 0$. Here, the estimated IRs are based on (4) and panel (a) of the figure refers to the results from the benchmark sample period. The IRs indicate that the CPIs increase by 1.87 percent (at an annual rate) in period 12 and the estimated responses after this period range from 1.80 to 2.13 percent. The 95 percent confidence intervals represented by the shaded area are narrow for all forecast horizons, suggesting that the IRs are estimated quite precisely.

[14]Ilzetzki, Reinhart, and Rogoff (2010) report 15 detailed classifications of exchange-rate regimes (e.g., hard peg, crawling peg, and managed floating, etc.), together with the reference currency for the peg. The data are monthly. In constructing $D_j^{USD}$, we define $D_j^{USD}$ as unity, if country $j$ adopts hard pegs to the U.S. dollar, crawling pegs to the U.S. dollar, or *de facto*, pre-announced or crawling bands around the U.S. dollar with $\pm$ 2 percent bands.

[15]Based on the data file from Ethan Ilzetzki's website, some countries have missing values for these data in 2000, 2001, or 2010. Due to missing values, we drop Cambodia, Macao, Ethiopia, Fiji, Rwanda, Samoa, São Tomé and Principé, Serbia, the Seychelles, the Solomon Islands, Syria, Tonga, Ukraine, Vanuatu, and Vietnam.

[16]Because the data of the sum of imports and exports divided by GDP are annual in the WDIs, we construct the dummy variable based on the single year's cross-country median. We confirm that the estimated IRs do not differ substantially, even if we replace the dummy with the sum of imports and exports divided by GDP.

[17]The eight countries are Côte d'Ivoire, Gabon, Guinea-Bissau, Guyana, Iran, Jamaica, Myanmar, and Suriname. They are dropped mainly because the data of the sum of imports and exports divided by GDP in recent years are not yet available in the WDIs.

The shape of the IRs suggests that the effects of commodity price shocks on inflation are transitory. Because the estimated IRs are defined for the price level, we can measure inflation responses using the slope of the IR function. In Figure 2, the slope is substantially steep during the first year after the shock but becomes nearly flat afterward. This implies that the effect of commodity price shocks on inflation virtually disappears in the second year after the shock. Therefore, the shape of the IRs suggests that the risk of a persistent second-round effect would be low at least in terms of the cross-country average.

To assess the shape of IRs, we introduce a simple measure. As long as inflation is stationary, the slope of the IR becomes zero in the long run. Hence, we measure the extent to which the slope of the IR deviates from zero during a year by the mean absolute deviations of $IR(k) - IR(k-1)$. We call this measure the *variability of inflation responses* (VIR). More specifically, the VIRs for the first and second year after commodity price shocks are defined by

$$VIR_1 = \hat{\sigma}_c \frac{1}{12} \sum_{k=1}^{12} |\hat{\gamma}_k - \hat{\gamma}_{k-1}|, \qquad VIR_2 = \hat{\sigma}_c \frac{1}{12} \sum_{k=13}^{24} |\hat{\gamma}_k - \hat{\gamma}_{k-1}|, \tag{9}$$

respectively. Here, $VIR_1$ quantifies the mean deviation of inflation responses for the first year after a one-standard-deviation commodity price shock. Similarly, $VIR_2$ quantifies that for the second year after the same shock. We multiply the mean absolute deviations by the standard deviation of an exogenous shock to allow for comparisons of the VIRs across different shocks.

In the benchmark estimations, $VIR_1$ is 0.53 percent but $VIR_2$ is only 0.13, a substantial reduction between two years. The reduction reflects the transitory effect of commodity price shocks on inflation. For comparison, we calculate the VIRs to a monetary policy shock, using the empirical results of Boivin, Giannoni, and Mihov (2009). Applying the factor-augmented VAR to a variety of the U.S. sectoral prices, they estimate the IRs to a monetary policy shock. They find that prices respond slowly to a monetary policy shock. We take their estimates of the IR of the deflator of personal consumption expenditure of all items and compute the VIRs according to (9). The resulting VIRs sharply contrast with our VIRs to a commodity price shock: $VIR_1 = 0.27$ and $VIR_2 = 0.33$, no reduction in the VIRs to a monetary policy shock.[18] This suggests that the

[18]Slow responses to monetary policy shocks are mostly observed in the U.S. data. To fully compare the VIRs, it would be more appropriate to identify monetary policy shocks of all countries and to compute VIRs.

price adjustment to commodity price shocks may be fast, in comparison to that to monetary policy shocks. In this sense, the rational-inattention model is consistent with the data.

A few remarks should be made on the benchmark estimation. First, the estimated IRs are basically unaffected even if we use the data from the 1990s. Given that the volatility of commodity prices might increase in the 2000s, our focus on the short sample may lead to biases in estimating IRs and the degree of persistence. We thus use the longer sample period from the 1990s.[19] Panel (b) of Figure 2 indicates that the estimated IRs are similar to panel (a), at least in point estimates, despite possible structural breaks in inflation during the 1990s. The resulting VIRs are also similar to the benchmark case: $VIR_1$ and $VIR_2$ are 0.39 and 0.09, respectively, implying the transitory effect of commodity price shocks.[20]

Second, one may wonder how our results differ in comparison to the standard approach. Note that our approach identifies shocks from (8) and then estimates IRs from (4), rather than identifying shocks via the multivariate system of equations as in VAR. In VAR, the estimated commodity price shocks vary, depending on numerous factors such as identifying assumptions, the number of variables, and countries included in the system. Hence, the IRs estimated from VARs are not directly comparable to those from our approach.

The method of Romer and Romer (2004) to estimate IRs is directly comparable to ours. Their narrative approach first identifies shocks and then estimates IRs from a separate equation with identified shocks. In our context, their approach is to run the following regression:

$$\pi_{j,t} = \alpha_j + \sum_{i=1}^{q} \beta_i \pi_{j,t-i} + \sum_{i=0}^{r} \gamma_i \hat{u}_{c,t-i} + \xi_{j,t}. \tag{10}$$

With a slight abuse of notations, $\alpha_j$, $\beta_i$, and $\gamma_i$ are parameters to be estimated. Unlike the local projection, (10) requires $\beta_i$ and $\gamma_i$ to compute IRs. However, the estimated IRs can vary, depending on specifications. For this reason, we set $q$ at 12 but $r = 6, 12$, or 18.[21]

Table 2 presents VIRs under three specifications for $r$ in (10) along with the results from local projections. Note that VIRs from Romer and Romer's method are not very robust across

[19] We select 105 countries due to the data availability.

[20] Our main result is also unaffected even if we drop countries where inflation is highly volatile. The estimated IRs and VIRs are reported in Appendix A of the paper. (The Appendix is available upon request.)

[21] Under (10), the BIC suggests $r = 5$, given $q = 12$. We take the slightly long lag length for commodity price shocks, because Romer and Romer (2004) typically allow for many lags for shocks.

specifications. However, the table also shows substantial reductions in VIR in all specifications, reconfirming the robustness of our benchmark results. Also note that $VIR_2$ in local projections is large relative to the standard approach. Hence, our local projections give us conservative estimates in evaluating the persistent effect of commodity price shocks on inflation.

#### 3.1.2 Regressions allowing for cross-country differences in IRs

We begin by mentioning how the IRs estimated from (6) are related to economic factors. Table 3 reports coefficients on the four dummy variables for each forecast horizon $k$, along with the Newey-West standard errors below the estimates. First, as shown in panel (a) of the table, $\hat{\gamma}_{USD,k}$ are all positive and statistically significant for $k = 1, 2, ..., 14$, 21, 23, and 24 at the five percent significance level. This suggests a stabilizing role for the exchange rate, consistent with the literature. The stabilizing role is confirmed particularly in the first year after a commodity price shock.

Second, $\hat{\gamma}_{IT,k}$ are shown in panel (b) of the same table and are negative for all forecast horizons. This suggests that IT may contribute to dampening price responses to a commodity price shock. However, they do not statistically differ from zero for all forecast horizons.

Third, $\hat{\gamma}_{LDC,k}$ are overall positive and increase as $k$ increases. Panel (c) indicates that some $\hat{\gamma}_{LDC,k}$ statistically differ from zero when forecast horizons are relatively long (for $k$ = 18, 19, and 21–24). This is consistent with the interpretation that price responses in LDCs tend to be large because the LDCs have high energy intensity and food shares in the CPI basket.

Finally, as indicated in panel (d) of Table 3, we do not find a significantly negative relationship between price responses and the degree of trade openness. When $\hat{\gamma}_{TO,k}$ is negative, it is neither statistically nor economically significant (see $\hat{\gamma}_{TO,k}$ for $k = 0, 1$, and 2). This is consistent with Gelos and Ustyugova (2012), who do not find a statistically significant relationship between the commodity price pass-through and the degree of trade openness.

We are now ready to discuss the IRs to confirm whether the effect of commodity price shocks remains transitory even after controlling for country-specific economic factors. We divide countries into four country groups, based on exchange-rate regimes and the degree of economic development. Given that $\hat{\gamma}_{j,k}^{IT}$ and $\hat{\gamma}_{j,k}^{TO}$ do not statistically differ from zero for all $k$, we consider four country groups: (a) developed countries with flexible exchange rates (DCs with FER); (b) less developed countries with flexible exchange rates (LDCs with FER); (c) developed countries with exchange rates pegged to the U.S. dollar (DCs with USD); and (d) less developed countries with exchange rates pegged to the U.S. dollar (LDCs with USD).

Figure 3 plots the IRs of the CPIs for the above four country groups to a 10 percent increase in commodity price shocks. To represent the IRs for each country group, we take the weighted average of the IRs using the share of IT countries and the share of countries with a high degree of trade openness. For instance, the IRs for LDCs with USD are represented as $\hat{\gamma}_k + \hat{\gamma}_{j,k}^{USD} + \omega_{IT}\hat{\gamma}_{j,k}^{IT} + \hat{\gamma}_{j,k}^{LDC} + \omega_{TO}\hat{\gamma}_{j,k}^{TO}$, where $\omega_{IT}$ (or $\omega_{TO}$) denotes the share of IT countries (or countries with a high degree of trade openness) in all the sample countries.[22]

Comparisons across the four panels reveal that, while the IR functions vary across the country groups, all panels of the figure overall suggest a transitory effect of commodity price shocks. Price increases in DCs with FER in panel (a) of Figure 3 are the smallest among the four country groups due to the stabilizing roles of the exchange rate and economic development. By contrast, the country group of LDCs with USD in panel (d) exhibits the largest price response in its peak response. The peak response in panel (d) is about twice as large as the peak response in panel (a). Nevertheless, the slopes of all IR functions are nearly flat during the second year after the shock, suggesting the low risk of a persistent second-round effect.

## 3.2 Robustness of the transitory effect of commodity price shocks

This subsection performs a variety of robustness checks. Our comparisons rely on the VIRs that are shown in Table 4. In the table, all VIRs are computed from the average IRs across country groups.

### 3.2.1 Specifications of forecasting equations

Let us consider alternative specifications for estimating commodity price shocks. First, CRR argue that the forecasting equation (8) can be extended with $\Delta s_{j,t}$ in Chile and South Africa, since they also have good forecasting performance. Hence, we add these countries' $\Delta s_{j,t}$ to (8) and reestimate IRs.[23] The first row of panel (a) of Table 4 indicates that the VIRs are similar in magnitude to the

[22]We set $\omega_{IT}$ at 0.18 from the time-series mean of the share for IT countries. On the other hand, $\omega_{TO}$ is 0.50 by construction, because we divided countries based on the median of the degree of trade openness.

[23]The p-value of the F-test for the null hypothesis that changes in the five countries' nominal exchange rates do not Granger-cause $\pi_{c,t}$ is 0.002. However, the p-value of the F-test for the null hypothesis that changes in the nominal exchange rates for Chile and South Africa do not Granger-cause $\pi_{c,t}$ is 0.367. Hence, the data support the original

benchmark estimation in the first row of Table 2.

Second, we could improve forecasts of $\pi_{c,t}$ by including the forward premium into (8). Let $f_{t+1,t}$ be the one-month-ahead forward price index of the commodities in period $t$. To construct the forward premium, $p_{c,t}$ and $f_{t+1,t}$ must be directly comparable in terms of weights of the basket. Unfortunately, however, $f_{t+1,t}$ is not available for the WB's and the IMF's commodity price indexes. Hence, we rely on the S&P GSCI, where $f_{t+1,t}$ is available. Given the forward premium calculated from the S&P GSCI and its forward price index, we reestimate the commodity price shock by

$$\pi_{c,t} = a+b\pi_{c,t-1}+c_{AUS}\Delta s_{AUS,t-1}+c_{CAN}\Delta s_{CAN,t-1}+c_{NZ}\Delta s_{NZ,t-1}+d_{FP}(f_{t,t-1}-p_{c,t-1})+\varepsilon_{c,t}, \quad (11)$$

where $\pi_{c,t}$ is redefined as the commodity price inflation based on the S&P GSCI and $d_{FP}$ is the parameter estimated. The second row of panel (a) in Table 4 reports VIRs based on (11). Again, the results remain essentially unaltered.

Finally, we depart from the forecasting equations of CRR. In the literature on oil price shocks, Kilian (2009) identifies the global demand shock specific to the crude oil market. He argues that the oil price increase after 2003 was driven mainly by the global demand shock. We take the oil demand shocks in Kilian (2009) from February 2001 to December 2007 and report the resulting VIRs in the last row of panel (a) of Table 4. Here, $VIR_1$ is somewhat small compared to those obtained from the forecasting equations of CRR. This small $VIR_1$ may be due to our departure from the forecasting equations of CRR, but it may also be due to the use of the energy commodity price index rather than the non-energy commodity price index. In fact, when we compute the IRs to the energy commodity price shocks (e.g., shocks to the WB's energy and the IMF's fuel price indexes), $VIR_1$ becomes small. Nevertheless, the VIR declines from $VIR_1$ to $VIR_2$, suggesting the robustness of the main results.

### 3.2.2 Distinction between net commodity importers and exporters

While the previous estimation separated countries based on the trade patterns for goods and services, the patterns of *commodity trade* may more directly affect price responses. In this regard, Chen, Turnovsky, and Zivot (2014) demonstrate that commodity prices have strong forecasting

forecasting equation in terms of the Granger causality.

power for inflation in heavy commodity exporters. Their finding may point to the importance of allowing for commodity trade patterns in understanding price responses.

We introduce the dummy variable for countries having a commodity trade surplus (net commodity exporters, for short) into (6). As in the previous section, the dummy variable is interacted with the commodity price shock.[24] Due to the data limitations of commodity trade, however, the number of countries is substantially reduced to only 84 countries.

Panel (b) of Table 4 reports the VIRs of net commodity importers and exporters.[25] Again, the effect of commodity price shocks is transitory: for the net commodity exporters, $VIR_1 = 0.31$ and $VIR_2 = 0.14$, and for the net commodity importers, $VIR_1 = 0.48$ and $VIR_2 = 0.15$. As we discuss in Appendix B, the price responses of net commodity exporters are, on average, smaller than those of net commodity importers. This may be because the second-round effect through the improved terms of trade in net commodity exporters is weak compared to the second-round effect through the cost of production in the net commodity importers.[26]

### 3.2.3 Alternative commodity price indexes

Panel (c) of Table 4 shows the VIRs when we replace the commodity price shocks with those obtained from alternative commodity price indexes. For comparison, the first-row reports the VIRs based on the non-energy commodity price index by the WB used for the previous results. The second row represents the VIRs based on the WB's energy index. Similar to the first row, the VIR decreases from 0.38 to 0.16, suggesting the transitory effect on inflation.[27] Similar patterns are observed for the IMF's commodity price indexes. The results are robust even when we use the

[24]We construct the dummy variable for the net commodity exporters by calculating each country's net commodity exports from the WDIs. The WDIs include the import and export data of agricultural raw materials, food, fuel, and ores and metals as a percentage of merchandise imports and exports. Using the quantity data of merchandise imports and exports, we compute the net exports of commodity for constructing the dummy variable.

[25]Appendix B of this paper provides the detailed results of this estimation.

[26]In this analysis, we face a trade-off between two sources of biases in estimates. The first source is the sample selection bias, because we use only countries in which the data of commodity trade are available. Indeed, we excluded many LDCs and the resulting average price responses are substantially lowered (e.g., 1.27 percent vs. 1.87 percent in terms of the weighted average of the price responses in period 12 to a 10 percent commodity price shock). The second source of bias is the omitted variable bias in the estimated IRs due to exclusion of the net commodity exporter dummy. Appendix B shows that the estimated coefficients on the interaction terms (i.e., $\hat{\gamma}_{USD,k}$, $\hat{\gamma}_{IT,k}$, $\hat{\gamma}_{LDC,k}$, and $\hat{\gamma}_{TO,k}$) remain essentially unaltered by the presence of the net commodity exporter dummy, both quantitatively and qualitatively. Hence, the first source would be more serious than the second source, justifying (7).

[27]We also check the robustness to using the agricultural commodity price index and the metal commodity price index of the WB, both of which are the WB's sub-index of non-energy commodity price index. Again, the VIR decreases similarly to the commodity price indexes in Table 4, particularly for the agricultural price index.

dummy variable for net commodity exporters.[28]

## 4 Evidence from the STAR model

So far, we have controlled for differences across country groups but not for cyclical factors. However, recent studies on the exchange rate pass-through demonstrate that the pass-through may depend on the inflation rate. For example, Taylor (2000) argues that inflation influences the pass-through since, as in the model of state-dependent pricing, inflation affects the frequency of price changes. Shintani, Terada-Hagiwara, and Yabu (2013) use a STAR model and find that the exchange rate pass-through depends on the past inflation rate in the U.S. economy. In this section, we use the logistic STAR model with the transition variable of each country's lagged inflation to see how IRs vary between high- and low-inflation regimes.

### 4.1 Estimation

We extend the linear model (6) to the STAR model discussed in Teräsvirta (1994). Let superscript $L$ and $H$ on $\gamma_{j,k}$ and $\beta_{i,k}$ be the coefficient on the low- and high-inflation regimes, respectively. Our estimation equation is

$$\begin{aligned} p_{j,t+k} - p_{j,t-1} = \tilde{\alpha}_{j,k} + F(z_{j,t-d}) &\left[ \sum_{i=1}^{q} \beta_{i,k}^{L} (p_{j,t-i} - p_{j,t-i-1}) + \gamma_{j,k}^{L} u_{c,t} \right] \\ + [1 - F(z_{j,t-d})] &\left[ \sum_{i=1}^{q} \beta_{i,k}^{H} (p_{j,t-i} - p_{j,t-i-1}) + \gamma_{j,k}^{H} u_{c,t} \right] + u_{j,t+k}^{k}, \end{aligned} \tag{12}$$

for each forecast horizon $k$. Here, $F(z_{j,t-d})$ is the transition function, and $z_{j,t-d}$ is the transition variable where $d$ denotes the delay parameter. The transition function is given by

$$F(z_{j,t-d}) = \frac{\exp(-\delta z_{j,t-d})}{1 + \exp(-\delta z_{j,t-d})}, \tag{13}$$

which implies that, as $z_{j,t-d} \to +\infty$, $F(z_{j,t-d}) \to 0$, meaning that the coefficients with superscript $H$ dominate the dynamics of the dependent variable. By contrast, as $z_{j,t-d} \to -\infty$, $F(z_{j,t-d}) \to 1$, implying that the coefficients with superscript $L$ are dominating. Likewise, if $\delta \to 0$, then $F(z_{j,t-d})$

[28] See Table B.2 in Appendix B.

converges to 1/2, which is effectively equivalent to the linear regressions (6), because parameters with superscript $H$ and $L$ can no longer be identified. For the transition variable $z_{j,t-d}$, we specify it as the standardized past inflation rate in country $j$: $z_{j,t-d} = (\pi_{j,t-d} - \bar{\pi}_j)/\hat{\sigma}_j$, where $\bar{\pi}_j$ and $\hat{\sigma}_j$ are the time-series average and the time-series standard deviations of country $j$'s inflation, respectively.

The IRs remain easy to compute: $IR(k,j,t) = F(z_{j,t-d})\gamma^L_{j,k} + [1 - F(z_{j,t-d})]\gamma^H_{j,k}$. In this specification, the past inflation rate affects the IRs, suggesting that inflation may affect firms' price setting as in the model of state-dependent pricing. We focus on $IR^L(k,j) = \gamma^L_{j,k}$ and $IR^H(k,j) = \gamma^H_{j,k}$ as extreme cases, since $IR(k,j,t)$ is the weighted sum of $\gamma^L_{j,k}$ and $\gamma^H_{j,k}$.

Our estimation strategy basically follows Auerbach and Gorodnichenko (2013), who estimate fiscal multipliers by a panel STAR model. Following them, we standardized the transition variable so that $z_{j,t-d}$ has zero mean and a unit variance. This standardization is somewhat restrictive because $F(\cdot)$ could include the location parameter. However, the standardization allows us to estimate (12) as a linear function if $\delta$ is fixed in (13). While Auerbach and Gorodnichenko (2013) parameterize $\delta$ at a single value in their analysis, we allow for more flexible parameterizations of $\delta$ by a grid search. In other words, we parameterize $\delta$ over a range of $\delta \in (0, \Delta)$ and run linear regressions for each grid constructed from an interval of $(0, \Delta)$. We then search for the best $\delta$ that minimizes the sum of squared residuals. We repeat this procedure for delay parameter $d$ for the range of $d \in \{1, 2, .., 12\}$ to choose a pair of $(\delta,\ d)$.[29]

## 4.2 Results from the STAR model

As a preliminary analysis, we performed a grid search of $(\delta, d)$. Overall, the chosen $\delta$ varies across $k$, ranging between 0.44 and 9.62.[30] By contrast, the chosen $d$ is stable: $d = 1$ for all $k$.

Two upper panels of Figure 4 plot IRs for (a) DCs with FER and (b) LDCs with FER and show that the effect of commodity price shocks is transitory under both the high- and low-inflation regimes. In both panels, the slopes of the IR function are modestly steep for the first year and become nearly flat afterward. The IRs are similar between the two regimes and not substantially

[29]We set the upper bound of $\delta$ at 10 because, when $\delta$ exceeds 10, even a small change in the standardized inflation rate generates $F(z_{t-d})$ that takes a value close to either zero or one. As a result, an upper bound larger than 10 does not change the estimation results. We set the upper bound of $d$ at 12 because the data are monthly.

[30]We choose $\delta$ to ensure that the resulting $\delta$ lies within the lower and upper bounds of $\delta$. When $q$ is small, $\delta$ tends to hit the upper bound of 10. To circumvent this, we select $q$ using the BIC for $6 \leq q \leq 12$. The resulting $\delta$s from $k = 0$ to 24 are 0.44, 1.54, 1.92, 2.84, 4.97, 5.47, 6.82, 6.38, 9.60, 9.62, 7.87, 8.20, 8.84, 7.15, 6.80, 6.20, 6.00, 6.30, 6.93, 8.24, 7.91, 8.43, and 9.20, respectively.

different from the case of the linear model in Figure 3. Hence, the risks of a persistent second-round effect would be low even under the two regimes.

By contrast, when we remove the effect of exchange rate variations on the price responses, the IRs differ substantially from the linear model. This is shown in lower panels of Figure 4: (c) DCs with USD and (d) LDCs with USD. The price responses under the high-inflation regime increase sharply until period 8 and decline somewhat afterward. However, those under the low-inflation regime slowly increase and continue to increase even in the second year. The IRs for the second year imply that the effect of commodity price shocks on inflation may not be transitory.

Table 5 computes the four country groups' VIRs under the linear model and the two inflation regimes. Comparisons across the three panels suggest that the effects of commodity price shock remain transitory in the country groups with FER but may be persistent in the country groups with the currencies pegged to the U.S. dollar. For DCs with FER, $VIR_2$ under the two regimes is similar in magnitude to $VIR_2$ in the linear model. This is also the case for LDCs with FER, although $VIR_2$ under the high-inflation regime is slightly larger than $VIR_2$ in the linear model. Turning to country groups with currencies pegged to the U.S. dollar, the VIRs contrast sharply with their linear model. $VIR_2$ in these country groups is higher than the linear model, confirming the shapes of the IRs presented in Figure 4.

We can test whether the price responses in a particular forecast horizon are statistically the same between the high- and low-inflation regimes. If we take an example of DCs with FER, the null hypothesis is that $\gamma_k^H + \omega_{IT}\gamma_{IT,k}^H + \omega_{TO}\gamma_{TO,k}^H = \gamma_k^L + \omega_{IT}\gamma_{IT,k}^L + \omega_{TO}\gamma_{TO,k}^L$. Similarly, if we test whether the price responses in LDCs with USD are the same across the two regimes, the null hypothesis is defined as $H_0$: $\gamma_k^H + \gamma_{USD,k}^H + \gamma_{LDC,k}^H + \omega_{IT}\gamma_{IT,k}^H + \omega_{TO}\gamma_{TO,k}^H = \gamma_k^L + \gamma_{USD,k}^L + \gamma_{LDC,k}^L + \omega_{IT}\gamma_{IT,k}^L + \omega_{TO}\gamma_{TO,k}^L$. Assuming that $\omega_{IT}$ and $\omega_{TO}$ are fixed, we test the null hypothesis using the Wald test for a single forecast horizon $k$.

Not surprisingly, as indicated in Table 6, we cannot reject the null hypothesis for countries with FER at the conventional significance level for any $k$. This suggests that the regime-dependent IRs may not be present in the DCs and LDCs with FER. For DCs with USD, we reject the null hypothesis in 11 forecast horizons at the 10 percent significance level (for $k = 0$ and $5 - 14$). For LDCs with USD, we reject the null hypothesis in 13 forecast horizons at the 10 percent significance level (for $k = 3 - 15$). Hence, at least during the first year after the shock, the IRs in the country group of DCs and LDCs with USD statistically differ between the two regimes.

## 5 Conclusion

Using local projections, we estimated the IRs of the CPIs to a commodity price shock and explored the implications for inflation. We found that the effect of commodity price shocks on inflation is transitory. This transitory effect is observed even when we control for exchange rate variations, adoption of IT, and degrees of economic development and trade openness. The result is also robust to changes in the method of identifying commodity price shocks, distinction between net commodity importers and exporters, and the use of other general commodity price indexes. Based on the STAR model that uses the past inflation rate as the transition variable, we found that commodity price shocks may have non-transitory effects on inflation in countries with exchange rates pegged to the U.S. dollar. Nevertheless, commodity price shocks continue to have transitory effects in the countries with exchange-rate flexibility.

Our study focused on CPIs. For a deeper understanding of the impact of commodity price shocks on economies as a whole, an investigation of the actual policy responses of central banks and the effects on the real economy and longer-term inflation expectations would be worthwhile. It is also important to identify demand and supply shocks in the commodity markets.

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Table 1: List of Countries

| Countries | | | |
|---|---|---|---|
| (a) Developed countries with flexible exchange rates (34 countries) | | | |
| Australia * | Estonia † | Italy | Slovak Rep. † |
| Austria † | Finland † | Japan | Slovenia † |
| Belgium † | France | Luxembourg † | South Korea *† |
| Canada * | Germany † | Malta † | Spain |
| Croatia † | Greece | Netherlands † | Sweden *† |
| Cyprus † | Hungary *† | New Zealand * | Switzerland † |
| Czech Rep. *† | Iceland *† | Norway * | United Kingdom * |
| Denmark † | Ireland † | Poland *† | |
| Equatorial Guinea † | Israel * | Portugal | |
| (b) Less developed countries with flexible exchange rates (34 countries) | | | |
| Armenia * | Chad | Mali | South Africa * |
| Benin | Colombia * | Mauritania † | Swaziland † |
| Botswana † | Congo, Rep. of † | Mexico * | Togo † |
| Brazil * | Indonesia * | Morocco | Tunisia † |
| Bulgaria † | Kenya | Mozambique | Turkey * |
| Burkina Faso | Latvia † | Niger | Uruguay |
| Cameroon | Lithuania † | Paraguay † | Zambia † |
| Cape Verde † | Macedonia | Romania *† | |
| Central African Rep. | Madagascar † | Senegal | |
| (c) Developed countries with exchange rates pegged to USD (9 countries) | | | |
| Aruba † | China, P. R.: Hong Kong † | Singapore † | |
| Bahamas † | Kuwait † | Trinidad and Tobago † | |
| Barbados † | Saudi Arabia † | United States | |
| (d) Less developed countries with exchange rates pegged to USD (43 countries) | | | |
| Albania *† | El Salvador | Malawi | Peru * |
| Algeria | Gambia | Malaysia † | Philippines * |
| Argentina | Georgia † | Mauritius † | Russia |
| Bangladesh | Ghana * | Moldova † | Sri Lanka |
| Bolivia | Grenada | Mongolia † | St. Kitts and Nevis |
| Burundi | Guatemala * | Nepal | St. Lucia † |
| Costa Rica † | Haiti | Nicaragua † | St. Vincent and Grens. † |
| Dominica † | Honduras † | Nigeria | Sudan |
| Dominican Rep. | India | Pakistan | Thailand *† |
| Ecuador | Jordan † | Panama † | Uganda |
| Egypt | Kazakhstan | Papua New Guinea † | |
| (e) Other countries (24 countries) | | | |
| Anguilla | Gabon | Rwanda | Suriname |
| Cambodia | Guinea-Bissau | Samoa | Syria |
| China, P. R.: Macao | Guyana | São Tomé and Principé | Tonga |
| Côte d'Ivoire | Iran | Serbia, Rep. of | Ukraine |
| Ethiopia | Jamaica | Seychelles | Vanuatu |
| Fiji | Myanmar | Solomon Islands | Vietnam |

Notes: List of countries used in the analysis. The number of countries is 144. The classification of countries from panels (a) to (d) is based on the information as of December 2010, together with the classification with $*$ and †. Countries with an asterisk (*) adopt inflation targeting. Countries with a dagger (†) have the ratio of the sum of imports and exports to the GDP higher than the median. Countries in panel (e) are included in the regression (4), but dropped in the regression (6), due to data limitations.

Table 2: Comparisons of estimation methods

| Estimation methods | $VIR_1$ | $VIR_2$ |
|---|---|---|
| Local projections | 0.531 | 0.134 |
| Romer and Romer's method | | |
| $q = 12$, $r = 6$ | 0.477 | 0.040 |
| $q = 12$, $r = 12$ | 0.555 | 0.049 |
| $q = 12$, $r = 18$ | 0.632 | 0.136 |

Notes: The table presents $VIR_1$ and $VIR_2$ under local projections and the standard approach by Romer and Romer's method. The VIRs are defined by (9). Romer and Romer's method uses (10) and specifies the lag length for the commodity price shock ($r$) is set to 6, 12, and 18.

Table 3: Estimates of $\gamma_{USD,k}$, $\gamma_{IT,k}$, $\gamma_{LDC,k}$, and $\gamma_{TO,k}$ based on the local linear projection with dummy variables

(a) Estimates of $\gamma_{USD,k}$

| $k=0$ | $k=1$ | $k=2$ | $k=3$ | $k=4$ | $k=5$ | $k=6$ | $k=7$ | $k=8$ | $k=9$ | $k=10$ | $k=11$ | $k=12$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.007 | 0.019 | 0.039 | 0.051 | 0.072 | 0.076 | 0.084 | 0.097 | 0.093 | 0.083 | 0.082 | 0.075 | 0.068 |
| (0.006) | (0.009) | (0.013) | (0.016) | (0.019) | (0.021) | (0.023) | (0.025) | (0.026) | (0.028) | (0.029) | (0.030) | (0.030) |
| $k=13$ | $k=14$ | $k=15$ | $k=16$ | $k=17$ | $k=18$ | $k=19$ | $k=20$ | $k=21$ | $k=22$ | $k=23$ | $k=24$ | |
| 0.069 | 0.067 | 0.061 | 0.061 | 0.063 | 0.065 | 0.065 | 0.066 | 0.072 | 0.070 | 0.079 | 0.086 | |
| (0.031) | (0.032) | (0.032) | (0.033) | (0.033) | (0.034) | (0.035) | (0.036) | (0.036) | (0.037) | (0.037) | (0.037) | |

(b) Estimates of $\gamma_{IT,k}$

| $k=0$ | $k=1$ | $k=2$ | $k=3$ | $k=4$ | $k=5$ | $k=6$ | $k=7$ | $k=8$ | $k=9$ | $k=10$ | $k=11$ | $k=12$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.000 | -0.007 | -0.008 | -0.006 | -0.009 | -0.022 | -0.030 | -0.034 | -0.040 | -0.041 | -0.041 | -0.041 | -0.046 |
| (0.005) | (0.007) | (0.011) | (0.014) | (0.016) | (0.018) | (0.021) | (0.023) | (0.025) | (0.026) | (0.028) | (0.028) | (0.029) |
| $k=13$ | $k=14$ | $k=15$ | $k=16$ | $k=17$ | $k=18$ | $k=19$ | $k=20$ | $k=21$ | $k=22$ | $k=23$ | $k=24$ | |
| -0.044 | -0.039 | -0.039 | -0.040 | -0.036 | -0.037 | -0.028 | -0.023 | -0.020 | -0.021 | -0.023 | -0.017 | |
| (0.029) | (0.030) | (0.030) | (0.031) | (0.031) | (0.031) | (0.032) | (0.032) | (0.032) | (0.033) | (0.033) | (0.033) | |

(c) Estimates of $\gamma_{LDC,k}$

| $k=0$ | $k=1$ | $k=2$ | $k=3$ | $k=4$ | $k=5$ | $k=6$ | $k=7$ | $k=8$ | $k=9$ | $k=10$ | $k=11$ | $k=12$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.001 | -0.001 | -0.002 | -0.004 | 0.001 | 0.013 | 0.015 | 0.013 | 0.022 | 0.030 | 0.037 | 0.037 | 0.047 |
| (0.005) | (0.008) | (0.011) | (0.014) | (0.016) | (0.017) | (0.019) | (0.021) | (0.021) | (0.022) | (0.022) | (0.023) | (0.023) |
| $k=13$ | $k=14$ | $k=15$ | $k=16$ | $k=17$ | $k=18$ | $k=19$ | $k=20$ | $k=21$ | $k=22$ | $k=23$ | $k=24$ | |
| 0.047 | 0.049 | 0.047 | 0.048 | 0.045 | 0.056 | 0.058 | 0.053 | 0.056 | 0.059 | 0.062 | 0.063 | |
| (0.024) | (0.025) | (0.025) | (0.026) | (0.026) | (0.026) | (0.026) | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) | |

(d) Estimates of $\gamma_{TO,k}$

| $k=0$ | $k=1$ | $k=2$ | $k=3$ | $k=4$ | $k=5$ | $k=6$ | $k=7$ | $k=8$ | $k=9$ | $k=10$ | $k=11$ | $k=12$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.003 | -0.003 | 0.000 | 0.006 | 0.011 | 0.015 | 0.015 | 0.018 | 0.029 | 0.036 | 0.034 | 0.034 | 0.041 |
| (0.005) | (0.008) | (0.011) | (0.014) | (0.016) | (0.018) | (0.021) | (0.023) | (0.024) | (0.026) | (0.027) | (0.028) | (0.029) |
| $k=13$ | $k=14$ | $k=15$ | $k=16$ | $k=17$ | $k=18$ | $k=19$ | $k=20$ | $k=21$ | $k=22$ | $k=23$ | $k=24$ | |
| 0.042 | 0.043 | 0.045 | 0.042 | 0.041 | 0.038 | 0.046 | 0.042 | 0.049 | 0.049 | 0.048 | 0.051 | |
| (0.029) | (0.030) | (0.030) | (0.031) | (0.031) | (0.032) | (0.033) | (0.033) | (0.034) | (0.034) | (0.035) | (0.035) | |

Notes: Estimated from (6). The numbers in parentheses are heteroskedasticity- and autocorrelation-consistent standard errors. Each of the dummy variables is defined as a variable that takes one (a) if a country's currency is pegged to the U.S. dollar and zero otherwise; (b) if a country adopts inflation targeting in its monetary policy and zero otherwise; (c) if a country is less developed and zero otherwise; and (d) if the degree of trade openness is above the median and zero otherwise.

Table 4: Variability of inflation responses: Differences across specifications

| Commodity price indexes | $VIR_1$ | $VIR_2$ |
|---|---|---|
| (a) Alternative forecasting equations | | |
| Five ERs | 0.467 | 0.116 |
| S&P GSCI | 0.448 | 0.170 |
| Demand shock by Kilian (2009) | 0.222 | 0.176 |
| (b) Commodity trade | | |
| Net commodity exporters | 0.305 | 0.143 |
| Net commodity importers | 0.479 | 0.150 |
| (c) Alternative commodity price indexes | | |
| WB (non-energy) | 0.490 | 0.131 |
| WB (energy) | 0.376 | 0.162 |
| IMF (all) | 0.422 | 0.130 |
| IMF (non-fuel) | 0.421 | 0.153 |
| IMF (fuel) | 0.372 | 0.160 |

Notes: The table presents $VIR_1$ and $VIR_2$ for several specifications. The VIRs are defined by (9). Panel (a) reports VIRs using alternative forecasting equations. "Five ERs" corresponds to the case where the nominal exchange rates of the Chilean peso and South African rand are newly included in (8) in estimating the commodity price shock. "S&P GSCI" refers to the case where commodity price shocks are estimated using (11). "Demand shock by Kilian (2009)" reports the VIRs when we replace the estimated commodity price shock by the global demand shock estimated by Kilian (2009). Panel (b) shows VIRs when we newly add the dummy variable for net commodity exporters as a new interaction term with commodity price shocks. Panel (c) reports VIRs using alternative commodity price indexes, where WB and IMF denote the data source of commodity price indexes. WB (non-energy) and WB (energy) mean that the VIRs are calculated using the WB's non-energy commodity price index and energy commodity price index, respectively. IMF (all), IMF (non-fuel), and IMF (fuel) refer to the case where the All Commodity Price Index, Non-Fuel Commodity Price Index, and Fuel Commodity Price Indexes are respectively used.

Table 5: Variability of inflation responses: Differences across country groups

| Country group | $VIR_1$ | $VIR_2$ |
|---|---|---|
| (a) Linear models with dummies | | |
| DCs with FER | 0.332 | 0.062 |
| LDCs with FER | 0.427 | 0.124 |
| DCs with USD | 0.614 | 0.138 |
| LDCs with USD | 0.644 | 0.198 |
| (b) STAR models: High-inflation regime | | |
| DCs with FER | 0.391 | 0.107 |
| LDCs with FER | 0.389 | 0.225 |
| DCs with USD | 1.105 | 0.200 |
| LDCs with USD | 0.914 | 0.285 |
| (c) STAR models: Low-inflation regime | | |
| DCs with FER | 0.269 | 0.105 |
| LDCs with FER | 0.536 | 0.129 |
| DCs with USD | 0.366 | 0.258 |
| LDCs with USD | 0.385 | 0.248 |

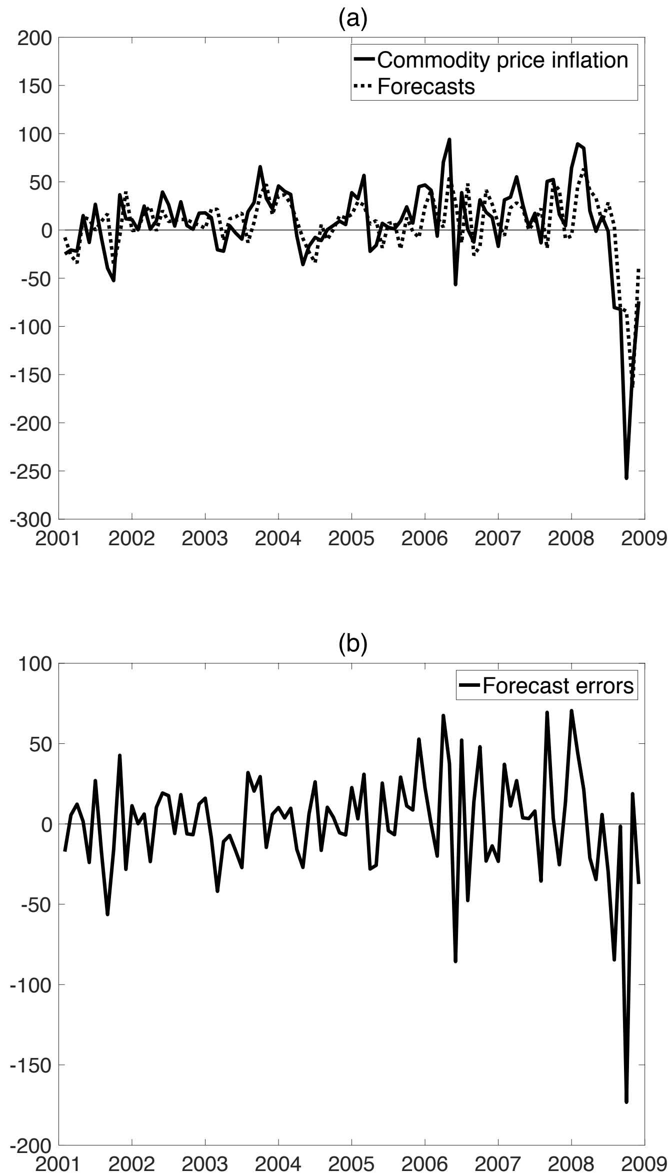
Notes: The commodity price index is the WB's non-energy commodity price index. The VIRs are defined by (9). DCs (LDCs) with FER stand for (less) developed countries with flexible exchange rates. DCs (LDCs) with USD refer to (less) developed countries with exchange rates pegged to the U.S. dollar.

Table 6: Tests for the equality of impulse responses between the high- and low-inflation regimes

| $k$ | DCs with FER | LDCs with FER | DCs with USD | LDCs with USD |
|---|---|---|---|---|
| 0 | 0.743 | 0.117 | 0.029 | 0.448 |
| 1 | 0.869 | 0.074 | 0.259 | 0.561 |
| 2 | 0.412 | 0.108 | 0.436 | 0.293 |
| 3 | 0.772 | 0.410 | 0.525 | 0.057 |
| 4 | 0.435 | 0.106 | 0.116 | 0.003 |
| 5 | 0.159 | 0.052 | 0.039 | 0.001 |
| 6 | 0.149 | 0.070 | 0.020 | 0.000 |
| 7 | 0.315 | 0.274 | 0.005 | 0.000 |
| 8 | 0.401 | 0.620 | 0.001 | 0.000 |
| 9 | 0.550 | 0.694 | 0.005 | 0.001 |
| 10 | 0.929 | 0.730 | 0.019 | 0.003 |
| 11 | 0.918 | 0.908 | 0.027 | 0.006 |
| 12 | 0.797 | 0.924 | 0.071 | 0.020 |
| 13 | 0.858 | 0.953 | 0.071 | 0.029 |
| 14 | 0.803 | 0.834 | 0.094 | 0.056 |
| 15 | 0.441 | 0.658 | 0.147 | 0.072 |
| 16 | 0.418 | 0.556 | 0.217 | 0.161 |
| 17 | 0.502 | 0.606 | 0.326 | 0.270 |
| 18 | 0.575 | 0.861 | 0.398 | 0.221 |
| 19 | 0.384 | 0.764 | 0.598 | 0.329 |
| 20 | 0.323 | 0.886 | 0.873 | 0.441 |
| 21 | 0.317 | 0.983 | 0.985 | 0.451 |
| 22 | 0.346 | 0.993 | 0.983 | 0.533 |
| 23 | 0.348 | 0.912 | 0.923 | 0.537 |
| 24 | 0.344 | 0.911 | 0.879 | 0.584 |

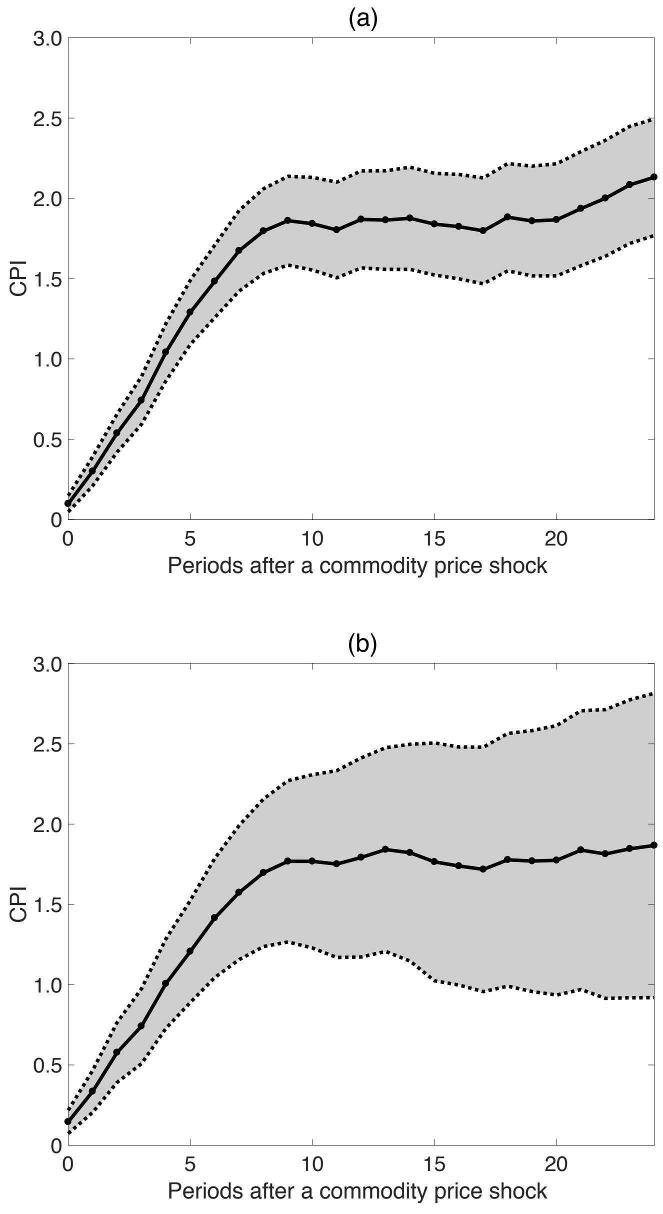
Notes: The p-values of the Wald tests whose null hypothesis is that country group's price response for forecast horizon $k$ does not differ between the high- and low-inflation regimes. The test statistics are defined for each forecast horizon $k$. See the footnote of Table 5 for abbreviations in the table.

Figure 1: Commodity price inflation and the estimated commodity price shocks



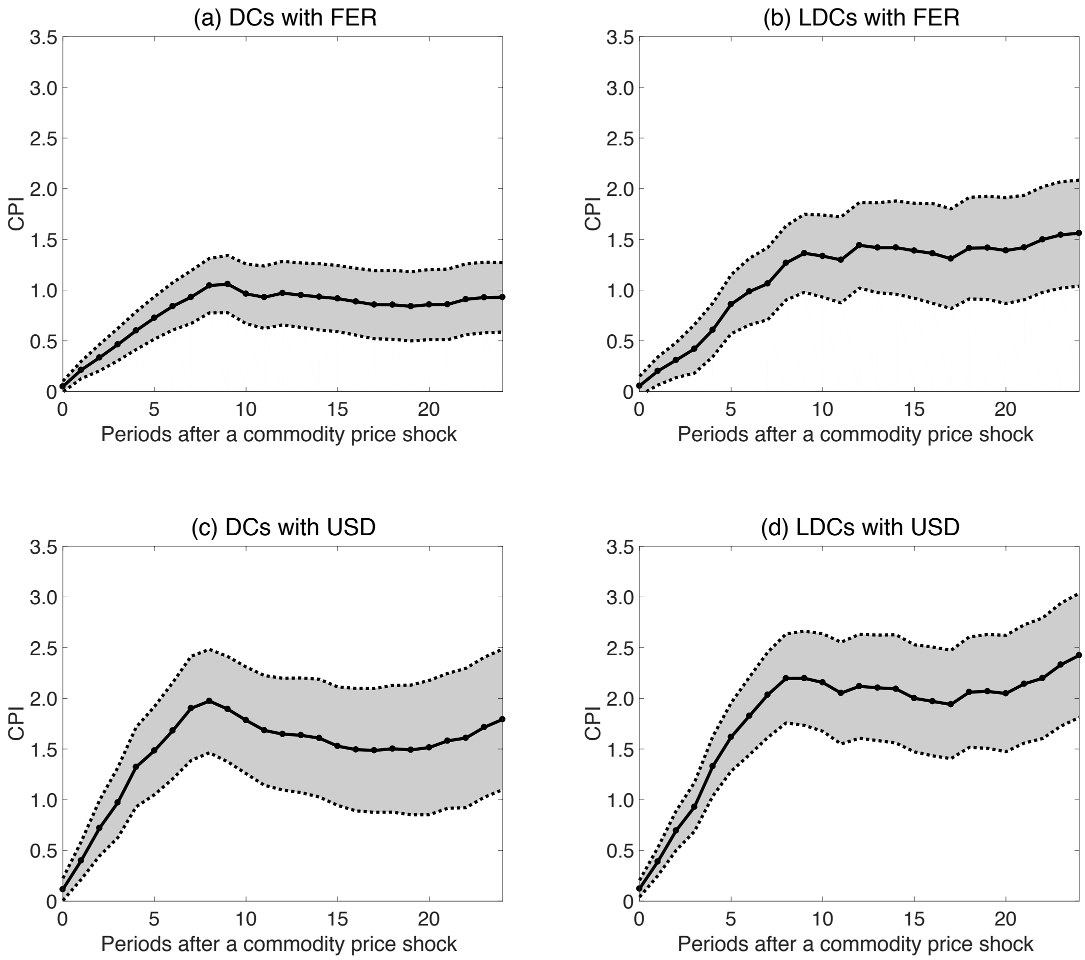

Notes: Panel (a) shows commodity price inflation and its forecasts based on (8). Panel (b) plots the residuals in (8).

Figure 2: Impulse responses of the CPI: Benchmark regressions



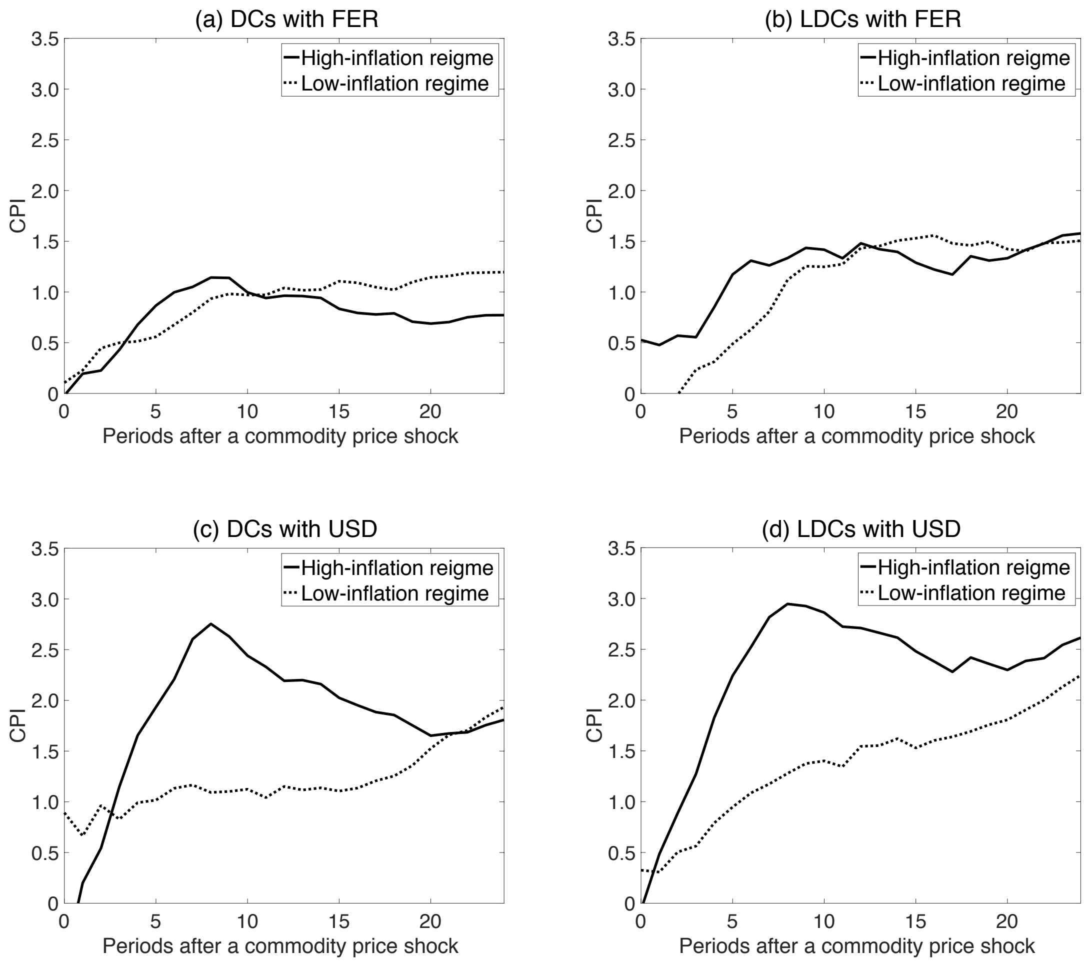

Notes: The panels plot impulse responses of the CPI to a 10 percent increase in commodity price shocks. The impulse responses are estimated from (4). The unit of the responses is percent. Panel (a) shows the CPI responses estimated from the benchmark regressions. Panel (b) shows those estimated from the longer sample period. The shaded areas represent the 95 percent confidence intervals.

Figure 3: Impulse responses of the CPI with interaction terms




Notes: The panels plot impulse responses of the CPI to a 10 percent increase in commodity price shocks. The impulse responses are estimated from (6). The unit of the responses is percent. Panels (a) and (b) show the responses of the CPI in developed countries with flexible exchange rates (DCs with FER) and less developed countries with flexible exchange rates (LDCs with FER), respectively. Panels (c) and (d) correspond to developed countries with exchange rates pegged to the U.S. dollar (DCs with USD) and less developed countries with exchange rates pegged to the U.S. dollar (LDCs with USD), respectively. The shaded areas represent the 95 percent confidence intervals.

Figure 4: Impulse responses of the CPI with interaction terms: High- and low-inflation regimes




Notes: The panels plot impulse responses of the CPI to a 10 percent increase in commodity price shocks under the high- and low-inflation regimes. The impulse responses are estimated from (12). See the footnote of Figure 3 for the other detail.