

Special Feature: Commodity Market Developments and Forecasts

Energy prices have decreased since the release of the October 2018 World Economic Outlook (WEO), mostly driven by lower oil prices. After surging to their highest point since 2014 because of concerns over US sanctions against Iran, oil prices fell to their lowest point since the second half of 2017 following record US oil production growth, the prospects for weaker global economic growth, and temporary waivers for imports of Iranian oil. In response to falling prices, oil exporters agreed to cut production, providing some price support. While a growth slowdown in China and trade tensions put downward pressure on metal prices in 2018, metal prices recovered on fiscal stimulus in China, improved global market sentiment, and supply disruptions in some metal markets. Prices of agricultural goods have increased somewhat as news of weaker global income growth and excess supply conditions in some grain markets were more than offset by a recovery of world sugar prices and excess demand for animal protein sources. This special feature also includes an in-depth analysis of the relationship between commodity prices and economic activity.

The IMF's Primary Commodity Price Index declined by 6.9 percent between August 2018 and February 2019, the reference periods for the October 2018 and current WEO, respectively (Figure 1.SF.1, panel 1). Amid high volatility, energy prices drove that decline, falling sharply by 17.0 percent, while base metal prices increased as trade tensions and weaker economic activity in China were more than offset by supply disruptions. Food prices increased by 1.9 percent as exceptional yields in some grain markets were more than offset by higher prices for meat and a rebound in sugar prices. Oil prices increased to more than \$80 a barrel in early October, attaining their highest level since November 2014 as US sanctions against oil imports from Iran loomed.¹ In the last months of 2018, however, oil prices declined sharply thanks to record production growth in the United States and the issuance of waivers for most of the countries that import oil from Iran. In response to that slump, Organization of the Petroleum Exporting

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¹Oil price in this document refers to the IMF average petroleum spot price, which is based on UK Brent, Dubai, and West Texas Intermediate, equally weighted, unless specified otherwise.

Countries (OPEC) and non-OPEC oil exporters agreed to cut production. Coal prices decreased as China's economy grew at its slowest pace since 1990, while natural gas prices fluctuated widely, driven by changing weather conditions, especially in North America.

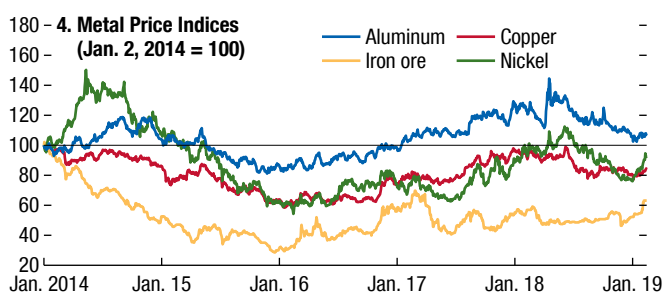
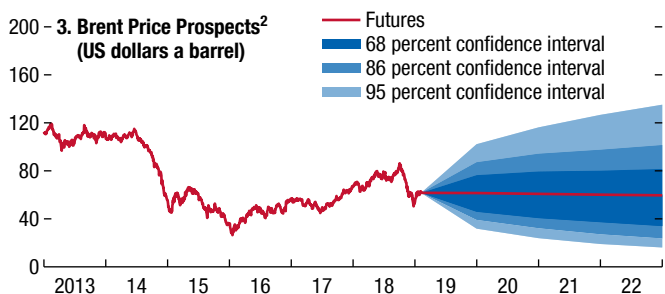
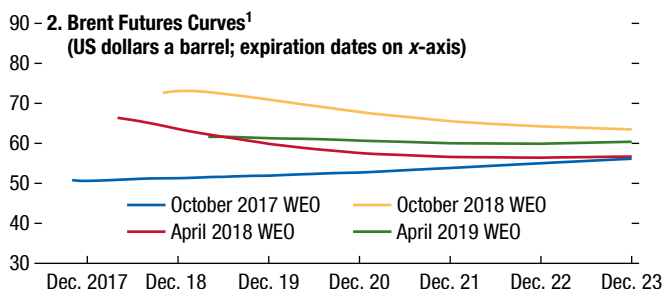
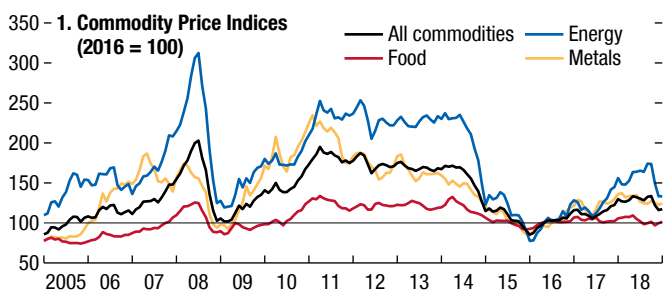
Oil Price Roller Coaster

In early October, oil prices surpassed \$80, their highest level since November 2014, ahead of US sanctions against Iran's oil sector that took effect in November. However, the US administration issued waivers that allowed several major importing countries to continue importing crude oil from Iran. In addition, US crude oil production averaged 10.9 million barrels a day (mbd) in 2018, an increase of 1.6 mbd over the previous year (exceeding expectations by 0.3 mbd since the October WEO) and the largest growth in its history.² Canada, Iraq, Russia, and Saudi Arabia also produced at high levels. As a result, oil prices fell sharply between early October and the end of November. On December 7, 2018, OPEC and non-OPEC (including Russia) countries agreed to cut their crude oil production by 0.8 mbd and 0.4 mbd, respectively, from their October 2018 level, starting in January 2019 for an initial six-month period. Oil producers' cuts, coupled with unplanned outages supported oil prices, which rebounded to above \$60 in February. Natural gas spot prices declined sharply in response to ample supply following a volatile start of the winter because of changing weather conditions; long-term natural gas contract prices declined in tandem with medium-term oil price futures. Coal prices have decreased, prompted by lower Chinese economic activity as well as lower oil prices.

As of February, oil futures contracts indicated that Brent prices will stay at about \$60 for the next five years. (Figure 1.SF.1, panel 2). Baseline assumptions, also based on futures prices, suggest average annual prices of \$59.2 a barrel in 2019—a decrease of 13.4 percent from the 2018 average—and \$59.0 a barrel in 2020 for the IMF's average petroleum spot prices. On the demand side, lower oil prices are offsetting underlying oil demand from weaker global economic growth—the International Energy Agency expects oil demand

²In September 2018, the Energy Information Agency expected an increase in US oil production of 1.3 mbd.

Figure 1.SF.1. Commodity Market Developments



Sources: Bloomberg Finance L.P.; IMF, Primary Commodity Price System; Thomson Reuters Datastream; and IMF staff estimates.

Note: WEO = *World Economic Outlook*.

¹WEO futures prices are baseline assumptions for each WEO and are derived from future prices. October 2018 WEO prices are based on February 7, 2019, closing.

²Derived from prices of futures options on February 7, 2019.

to grow by 1.3 mbd and 1.4 mbd in 2018 and 2019, respectively, a 0.1 mbd downward revision for both years (relative to the October WEO). On the supply side, since the beginning of 2019, mandatory production cuts by Canada and the supply cuts by OPEC and non-OPEC countries, including involuntary outages in Venezuela, are gradually slowing oil output growth.

Although risks are balanced, substantial uncertainty around the baseline oil price projections remains because of high policy uncertainty (Figure 1.SF.1, panel 3). Upside risks to prices in the short term include geopolitical events in Middle East, civil unrest in Venezuela, a tougher US stance against Iran and Venezuela, and slower-than-expected US production growth. Downside risks include stronger-than-expected US production and noncompliance among OPEC and non-OPEC countries. Trade tensions and other risks to global growth can also further affect global activity and its prospects, in turn reducing oil demand.

Metal Prices Rebounded

Metal prices increased 7.6 percent between August 2018 and February 2019. By the end of 2018, the IMF annual base metals price index had reached its lowest point in 16 months due to weakening growth, notably in China, and global trade tensions. However, metal prices rebounded since then, driven by the expectation of fiscal stimulus in China and improved global market sentiment—coupled with a sharp increase in iron ore prices due to the Brumadinho dam disaster (Brazil).

Iron ore prices increased 28.8 percent between August 2018 and February 2019 amid supply disruptions from the world’s top iron ore miners, including a derailment of a BHP iron ore train on November 5, a fire at a Rio Tinto’s export terminal on January 10, and the collapse of Brumadinho dam at Vale SA’s mine on January 25. The dam collapse will have ramifications for the industry, which could experience a prolonged halt of operations at some iron ore mines and a slowdown of new projects. (Figure 1.SF.1, panel 4). Copper prices increased 4.1 percent on US–China trade optimism and market deficit for both concentrate and refined copper. Aluminum fell 9.2 percent, following the lifting of US sanctions on the giant Russian aluminum producer Rusal and improved prospects for removal of the production embargo by the Brazilian Federal government on Hydro’s Alunorte (the world’s largest alumina refinery) in the second half of 2019. Nickel, a key

input for stainless steel and batteries in electric vehicles, dropped 5.4 percent between August and February 2019 on stronger-than-expected production from Indonesia and the Philippines. Zinc, which is used mainly to galvanize steel, increased 7.8 percent from August to February 2019 on persistent supply tightness, partly due to the ongoing environmental clampdown in China, the world's largest producer of zinc. Cobalt saw the deepest fall in prices of all metals during the reference period, declining by 49.3 percent due to rising supply from the Democratic Republic of the Congo.

The IMF annual base metal price index is projected to increase by 2.4 percent in 2019 (relative to its average in 2018) and decrease by 2.2 percent per year in 2020. Upside risks to the outlook are higher-than-expected metals demand from China and supply shortages as a result of more stringent environmental regulations in major metal-producing countries. Downside risks stem from a faster moderation in global economic growth and a further slowdown of the Chinese economy (the biggest world metal consumer).

Food Prices Increased Slightly

Trade tensions, weak emerging market currencies, and exceptionally strong US grain yields constituted the primary drags on global food prices in the first three quarters of 2018. Since then, prices have been less volatile. The IMF's food and beverage price index has increased slightly, by 1.9 percent, as news of weaker global economic activity and excess supply in markets, such as those for wheat and cotton, was outweighed by excess demand for animal protein sources and a recovery of world sugar prices from multiyear lows.

Wheat prices decreased by 15.8 percent between August 2018 and February 2019 as a competitive Russian ruble supported Russian exports. Absent news on harvests from major producing countries and in anticipation of lower trade tensions, a reversal of yields to the mean, and normalization of US dollar strength, prices of corn and soybeans have slowly moved up, increasing by 4.4 percent and 5.6 percent, respectively, between August 2018 and February 2019.

Poultry prices increased, by 3.9 percent, because of strong consumer demand. World sugar prices jumped by 23.7 percent, in part due to expectations of lower output in 2019 from top producers Brazil and India. Following weaker-than-expected demand and given ample stocks in China, the price of cotton declined by 14.2 percent between August 2018 and February 2019, even as hot weather took a toll on global cotton crops.

Food prices are projected to decrease by 2.9 percent a year in 2019 and then increase by 2.1 percent in 2020. Weather disruptions are an upside risk to the forecast. On February 14, 2019, the US National Oceanic and Atmospheric Administration announced that weak El Niño climate conditions have taken effect and are expected to continue into spring, which could have local impacts on crops. A resolution of the trade conflict between the United States—the world's largest food exporter—and China is another source of upside potential for prices.

Commodity Prices and Economic Activity

Introduction

What do commodity prices tell us about economic activity? This special feature analyzes the bountiful and rich information embedded in the prices of the many commodities traded in major commodity markets around the world and shows how this information is useful to nowcast or even forecast global economic activity.³

There are at least two major reasons commodity prices are useful indicators of global economic activity. First, even in a world where services take the spotlight, commodities still represent about 17 percent of global trade and are fundamental production inputs.⁴ A change in global economic activity will therefore be reflected in the global demand for commodities (Barsky and Kilian 2004; Alquist, Bhattarai, and Coibion forthcoming). Second, commodities are storable, so, like those of financial assets, their prices reflect both current and expected *future* demand and supply conditions. Given that many commodities are regularly traded in liquid and deep markets, their prices can swiftly move in response to changes in market tightness, including news and changes in sentiment about global economic conditions.

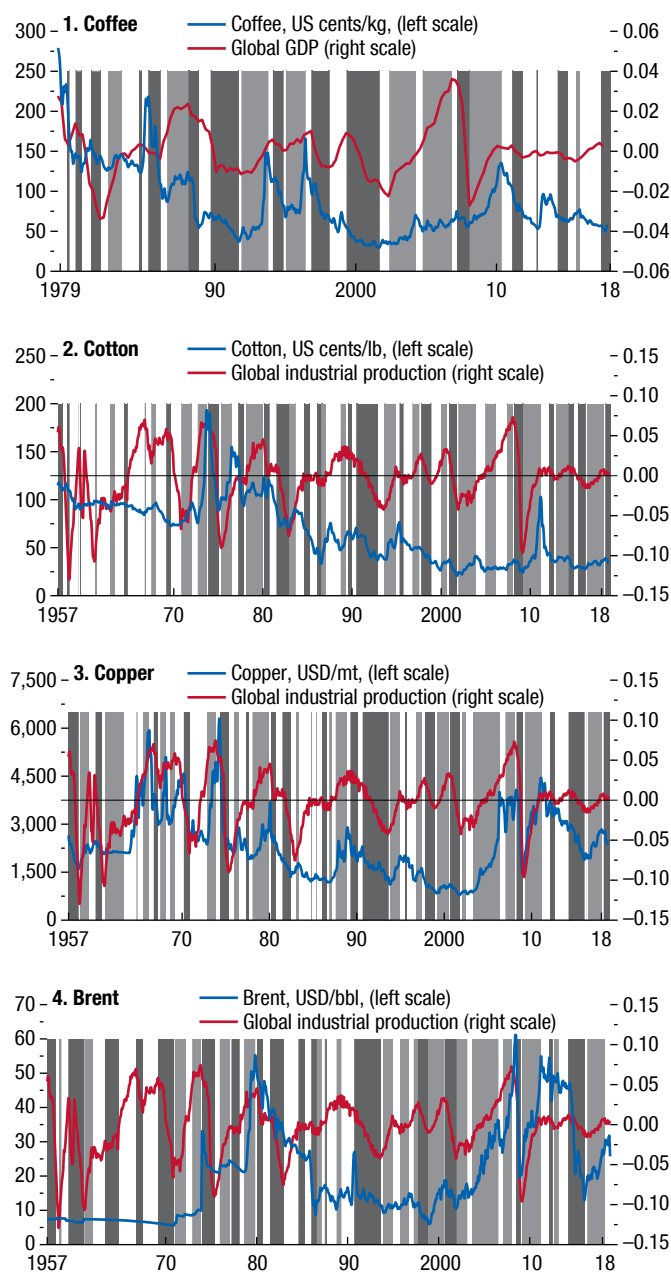
In practice, it is not easy to infer economic activity from commodity prices. The presence of commodity supply shocks and commodity-specific demand factors is, in fact, a prominent confounding influence⁵ and

³Nowcasting is a statistical model that exploits real-time data to provide a timely estimate of major economic activity indicators (such as GDP) that are usually released by statistical agencies with a delay.

⁴Industrial commodities (metals and raw agricultural materials) are essential inputs for the manufacturing sector. Energy commodities, because they are crucial to the transportation and petrochemical sectors and to power generation, indirectly affect the entire global production system. And food and beverage commodities, usually affected by income, underpin the food chain.

⁵For example, extreme weather conditions can substantially affect crop output and demand for natural gas.

Figure 1.SF.2. Commodity Cycles and Economic Activity



Sources: IMF, Primary Commodity Price System; Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.

Note: Peaks and troughs are identified using the Harding and Pagan's (2002) business cycle dating procedure. Global industrial production (IP) is spliced back using OECD IP (1975/79) and US IP (<1975). Dark (light) shaded areas represent synchronized contractions (expansions) in both economic activity and the selected commodity price. White shaded areas represent asynchronous movements. bbl = barrel; kg = kilogram; lb = pound; mt = metric ton; USD = US dollar.

even perhaps a reason for reverse causality—especially in the case of oil—potentially introducing an element of countercyclicality (Hamilton 1996, 2003). To tackle this problem, the analysis is split into two parts. The first identifies commodity price cycles and provides insights into the cyclical synchronization between commodity prices and economic activity. The second part exploits comovement among commodity prices to isolate global demand factors from other confounding influences and then tests whether the extracted global factors have nowcasting and predictive power for economic activity.

Cyclicality and Comovement of Commodity Prices

This section identifies commodity price cycles and looks, across a broad set of commodity prices, at commodities with the highest pair-wise synchronization with economic activity (that is, *bellwethers*). It also derives a commodity-market-wide synchronization measure.

The methodology to identify periods of *contraction* and *expansion* follows the business-cycle-dating procedure of Harding and Pagan (2002).⁶ This procedure is applied to an unbalanced panel, starting in 1957, of 57 (real) commodity price series that fall into four broad categories: energy, metals, food and beverages, and raw agricultural materials.⁷ The same procedure is also applied to detrended global industrial production and GDP.⁸ (Figure 1.SF.2 presents four examples.)

⁶Drawing on Cashin, McDermott, and Scott (2002), the Harding and Pagan (2002) methodology is used to identify peaks and troughs in the time path of real commodity prices. A candidate turning point is identified as a local maximum or minimum if the price in that month is either greater or less than the price in the two months before and the two months after. The sequence of resulting candidate turning points is then required to alternate between peaks and troughs. Furthermore, each phase defined by the turning points (expansion or contraction) must be at least 12 months long. (This commodity-price-cycle-dating algorithm is an adaptation of the business-cycle-dating algorithm set out by Bry and Boschan (1971) and later popularized by Harding and Pagan (2002). An advantage of using a Bry and Boschan-type algorithm to date commodity price cycles is that it provides a tractable means of applying an objective cycle-dating rule to a large data set.)

⁷All commodity price series are monthly averages of prices from the IMF's Primary Commodity Price System and are denominated in US dollars and divided by US consumer price inflation. Prices are not prefiltered, given that most commodities do not show a clear trend. The academic literature still debates whether commodity prices, in general, have a trend. Grilli and Yang (1988) argues that commodity prices have a downward tendency; more recently, Jacks (2013) and Stuermer (2018) found a modest upward trend. Results are mostly unchanged if a linear trend is removed.

⁸A Hodrick-Prescott filter with a very low lambda is used to extract a stable trend from global industrial production and GDP. Quarterly GDP data have been interpolated monthly. Although the dating algorithm can handle nonstationarity, some statistics that

Table 1.SF.1. Commodity Price Cycle Descriptive Statistics

	Duration (Months)		Amplitude (Log difference, percent)		Sharpness (Log difference, percent)	
	Expansion	Contraction	Expansion	Contraction	Expansion	Contraction
Energy	20	24	64.72	62.81	3.37	3.01
Base Metals	18	24	55.19	57.98	3.05	2.41
Food and Beverages	16	20	45.25	49.60	2.80	2.33
Agricultural Raw Materials	18	22	43.27	46.70	2.46	2.00

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.

Note: Price cycles are identified using the Harding and Pagan (2002) methodology. Duration measures the average length (in months) of a price phase (expansion or contraction). Amplitude measures the average price change (in percentage terms) from trough to peak in case of an expansion, and from peak to trough in case of a contraction. Sharpness measures the average price increase per month (in percentage terms) experienced during an expansion, and the average price decline during a contraction. All statistics are calculated by averaging over all commodities in a particular group.

Most commodities show asymmetric phases characterized by longer and dull contractions punctuated by sharp expansions (Table 1.SF.1).⁹ Energy commodities stand out because they have the longest and sharpest phases; a full energy cycle tends to last slightly less than four years. Overall, however, the characterization of cycles is quite similar across commodity groups and appears to be in line with a long-standing body of literature that highlights the interaction of commodity supply shocks with storage demand as an important driver of commodity price movements (Deaton and Laroque 1992; Cashin, McDermott, and Scott 2002).

Supply shocks, especially when inventory stocks or spare production capacity is low, tend to cause spikes in prices, but a large array of literature also stresses the role of demand factors (Barsky and Kilian 2004; Alquist, Bhattacharai, and Coibion forthcoming—among many). It is therefore interesting to calculate the synchronization of phases (or technically, *concordance*) between commodity prices and economic activity.¹⁰

With few exceptions, agricultural prices, especially food prices, are, on average, only modestly in sync with economic activity (Figure 1.SF.3). Bellwethers of global industrial production are mostly base metals (such as zinc, copper, and tin) and, to a lesser extent, energy and fertilizers. Propane shows the highest synchronization with global industrial production, but its time series and the time series for natural gas

start only in 1992 and hence are shorter than for most other commodities—suggesting a possible increase in synchronization between commodities and economic activity over the past few decades, which is also consistent with the findings of the factor analysis in the next section. Interestingly, some raw agricultural materials, such as cotton, have relatively high synchronization with global industrial production while, in general, food and beverages, relative to other commodities, are more synchronized to global GDP than to industrial production. This is because income, rather than production, plays a more relevant role in their demand (an example is arabica coffee).¹¹

Periods of sizable movement in economic activity (booms or busts) should increase comovement, and therefore synchronization, among all commodities. Most commodities, not only bellwethers, should move in sync with global industrial production or GDP. Accordingly, it is useful to derive a metric that calculates the share of commodities that are in the expansion (contraction) phase—that is, a commodity-wide concordance.¹² This metric should be related to global economic activity, with turning points (periods of maximum or minimum synchronization among commodity prices) falling within expansionary or contractionary phases of global activity. The commodity-wide concordance should, thus, be indicative of how much global demand factors, relative to supply or

compare stationary and nonstationary series (for example, concordance) can be misleading.

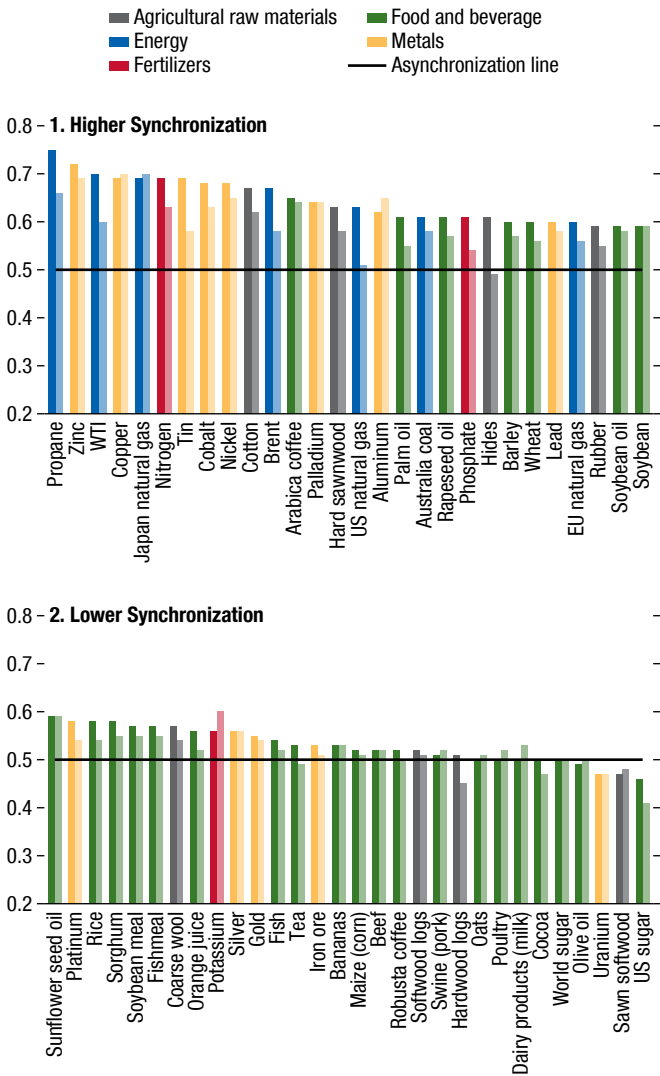
⁹Online Annex 1.SF.1 (available at www.imf/en/Publications/WEO) shows cyclical properties for each individual commodity price series and tests different sets of parameters for the dating algorithm that impose longer minimum durations for phases and cycles.

¹⁰Technically, the synchronization metric used is the *concordance*, which calculates the share of time two series that are in the same phase (Harding and Pagan 2002). Concordance is bounded between 0 and 1; two independent random walks have a concordance of 0.5.

¹¹As expected, the metals that are less in sync with economic activity are precious metals, such as gold and silver, and those that have not always been freely traded in spot markets, such as iron ore (before 2009), because both buyers and suppliers seek long-term security in a market with little output growth. Uranium is not freely traded because of its unique applications and geopolitical sensitivity.

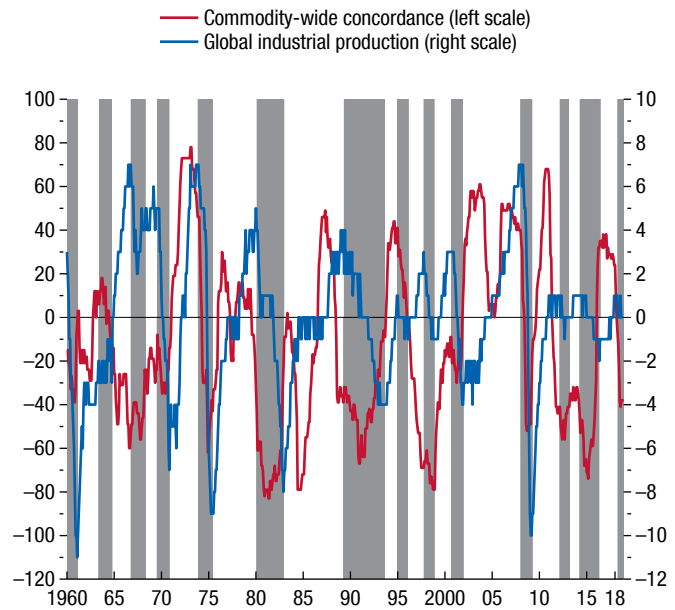
¹²A value of 1 (–1) means that all commodity prices are expanding (contracting) simultaneously—perfect synchronization—while a value of 0 implies that half of commodity prices are in the same phase, lowest synchronization.

Figure 1.SF.3. Synchronization with Economic Activity



Sources: IMF, Primary Commodity Price System; Organisation for Economic Co-operation and Development; and IMF staff calculations.
 Note: Bars represent the synchronization of a given commodity with de-trended global industrial production (IP) (darker bars) and GDP (lighter bars). Synchronization is defined as the concordance between the price cycle of a given commodity and the business cycle (de-trended GDP or IP) where phases of expansions and contractions are identified using Harding and Pagan's (2002) procedure. Concordance calculates the share of time two series are in the same phase; a concordance above 0.5 denotes a positive synchronization. WTI = West Texas Intermediate.

Figure 1.SF.4. Commodity-Wide Synchronization (Percent)



Sources: IMF, Primary Commodity Price System; Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.
 Note: Global industrial production (IP) is spliced back using OECD IP (1975–79) and US IP (<1975). Shading represents contractions in the IP variable. Commodity-wide concordance is the share of commodities in expansion (contraction).

commodity-specific demand factors, are driving commodity prices in a given period.

Figure 1.SF.4 shows that commodity-wide concordance anticipates turning points of economic activity, given that it typically peaks (or troughs) when activity is expanding (or contracting) most. This is a promising result, highlighting the presence of common latent factor(s) related to global activity that drive commodity prices. The next section will try to exploit this insight to nowcast and forecast movements in the global business cycle using commodity prices.

Do Commodity Prices Help Nowcast and Forecast Global Economic Activity?

To isolate movements in commodity prices that are driven by global economic activity, a factor model is estimated at monthly frequency using principal components (Stock and Watson 2002; West and Wong 2014; Delle Chiaie, Ferrara, and Giannone 2018).¹³

¹³The approach in Delle Chiaie, Ferrara, and Giannone (2018) that allows for group-specific factors gives slightly inferior results.

Given that supply- and commodity-specific demand shocks make commodity prices diverge, estimating latent factors that cause commodity prices to comove should help construct a proxy for global economic activity.¹⁴ Following this logic, the higher the number of commodities used, the better the identification of global demand factors. In practice, however, it may be preferable to exclude commodities, such as gold and silver, that behave more like financial assets or those that are too closely related, such as soybean meal and soybean oil (Kilian and Zhou 2018).¹⁵

The first two extracted factors explain about 20 percent of the variance in commodity price monthly changes. The relevance of the remaining factors drops off quickly and is not statistically related to economic activity.¹⁶ Figure 1.SF.5 plots the first and second latent factors extracted jointly with (demeaned) global GDP growth, cumulated over time. Even though the first and second factors are contemporaneously orthogonal by construction, when cumulated, they show a positive correlation, 0.67. The first factor is a *global factor*; the second represents a negative demand shift for agricultural products relative to energy and metals and is therefore a *relative-price factor*.¹⁷ Given that the relative-price factor helps account for movements in agricultural prices, first factors are extracted by first splitting the sample into agricultural and nonagricultural (energy and metals) commodities. Interestingly, the global factor and the relative-price factor are very

¹⁴The idea that global demand causes comovement in commodity prices is clearly not novel. For example, Barsky and Kilian (2004) interprets the strong comovement of the real price of oil and a real price index of industrial raw materials and metals in the early 1970s as evidence of a common demand component in both prices. More generally, a large body of literature is based on a range of different models and data that finds most of the fluctuations in (especially industrial) commodity prices are driven by shifts in aggregate demand (see, for example, Barsky and Kilian 2004; Kilian 2009; Nakov and Pescatori 2010; Kilian and Murphy 2014; Alquist, Bhattarai, and Coibion forthcoming; and Delle Chiaie, Ferrara, and Giannone 2018, among others).

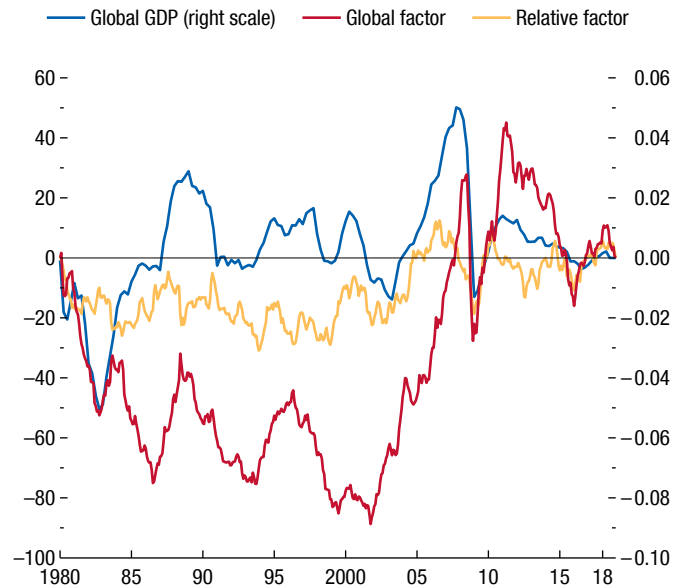
¹⁴Interestingly, Pindyck and Rotemberg (1990) notes how seemingly uncorrelated commodities (whose cross-price elasticities of demand and supply are close to zero) show excess comovement, which suggests the presence of a latent global (possibly heteroscedastic) factor that affects all prices at the same time.

¹⁵To estimate the latent factors, the log differences of prices (divided by the US consumer price index) have been z-scored. The use of log-detrended or log differences is less relevant for the estimation (Kilian and Zhou 2018).

¹⁶This is in line with Stock and Watson (2002). That study uses a different set of indicators to show that the first two factors are the most informative and have the highest predictive content.

¹⁷This can be seen by inspecting the factor loadings, available on request.

Figure 1.SF.5. Latent Factors and Economic Activity



Sources: IMF, Primary Commodity Price System; and IMF staff calculations. Note: First and second principal components are cumulated; log difference in global GDP is de-measured and cumulated.

well approximated by a linear combination of the two first factors of the split subsamples.¹⁸ The relative-price factor, however, has a negative sign on the first factor of the agriculture subsample. The relationship between the global factor and global GDP is visually quite striking (Figure 1.SF.5), but the relative-price factor also seems to move with GDP during some sharp downturns (by leading them) and subsequent recoveries.¹⁹

Because the first release of global industrial production lags by two months and that of GDP lags by one quarter, they are often substantially revised, so it is useful to test whether latent factors can help nowcast global activity. To do so, global industrial production and GDP are regressed on their own lagged value

¹⁸A regression of the global (relative-price) factor on the first factors extracted from the agriculture and nonagriculture samples separately yields an *R*-squared of 0.99 (0.88).

¹⁹The (negative of the) first factor in levels mimics movements in the US dollar real effective exchange rate (REER), which is not a surprise, given that the dollar is the numerator for all commodity prices in the sample. This association is, however, much weaker at higher frequencies, such as monthly changes, and weakens further when, to construct the REER, noncommodity currencies are excluded because, as is well known, they move inversely with the price of the commodity exported (Chen and Rogoff 2003). Introducing the US dollar REER into the nowcasting and forecasting exercise does not alter the results.

Table 1.SF.2. Global Industrial Production Nowcast

	Benchmark	Specification 1	Specification 2	Specification 3
RMSE	0.55%	0.54%	0.53%	0.54%
Ratio	1	0.99	0.97	0.98

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.

Note: Sample period = January 1980 to December 2018. Benchmark = autoregressive process with the optimal lag based on Bayesian information criterion; Specification 1 = first principal component; Specification 2 = first two principal components; Specification 3 = first principal components of agricultural and nonagricultural commodities. Optimal lag of independent variables added based on Bayesian information criterion for all specifications. RMSE = root mean square error; Ratio = relative RMSE, RMSE divided by benchmark RMSE.

and latent factors and on one period of their own lag. Whether the introduction of the latent factors statistically improves the nowcast estimate of the economic activity indicator (industrial production or GDP) is tested, and the results are compared with a *benchmark* autoregressive (AR)(p) process (following Stock and Watson 2002). Varying specifications are tried: only the global factor is used (specification 1); the global and relative factors are introduced together (specification 2); the sample is split into agricultural and nonagricultural commodities and the respective first factors are used (specification 3). All specifications can include their own lags, optimally chosen.

Results shown in Table 1.SF.2 indicate that for industrial production, at monthly frequency, introducing the global factor and the relative-price factor increases the ability to nowcast industrial production relative to the benchmark AR(p) process—in which the number of lags, p , is determined optimally. Because monthly industrial production growth is quite volatile, nowcasting yields modest improvements. More striking is its ability to nowcast GDP (Table 1.SF.3). The improvement in the root mean square error relative to the AR(p) benchmark is already 10 percent with only the global factor from one month of commodity price information. The improvement increases to 15 percent when the quar-

ter is completed. The R -squared is also high, at about 0.48.²⁰ Interestingly, commodity prices are mostly informative during periods of high economic volatility, when the AR(p) process fails the most (Figure 1.SF.6). Results are similar when using the two first factors extracted from the agricultural and nonagricultural group taken separately.

Factor lags are also significant, so it is possible to test whether commodity prices also help predict global activity. Forecast evaluations are based on the out-of-sample forecast performance. Given data for industrial production, GDP, and estimated principal components, each specification is first estimated using the sample period 1980–98 and then recursively reestimated to forecast for 2000–18.²¹ For each period, the model forecasts for next period's one-month-ahead and three-month-ahead industrial

²⁰Regression results are available upon request. It is also worth noting that predictability declines when using global GDP (industrial production) at market exchange rates, probably because of the greater relevance of services in advanced economies.

²¹Each model is reestimated with the addition of new data (recursive scheme). Models using principal components have a fixed lag length, but the optimal lag length of the AR model is chosen each time, using Bayesian information criteria or Akaike information criteria.

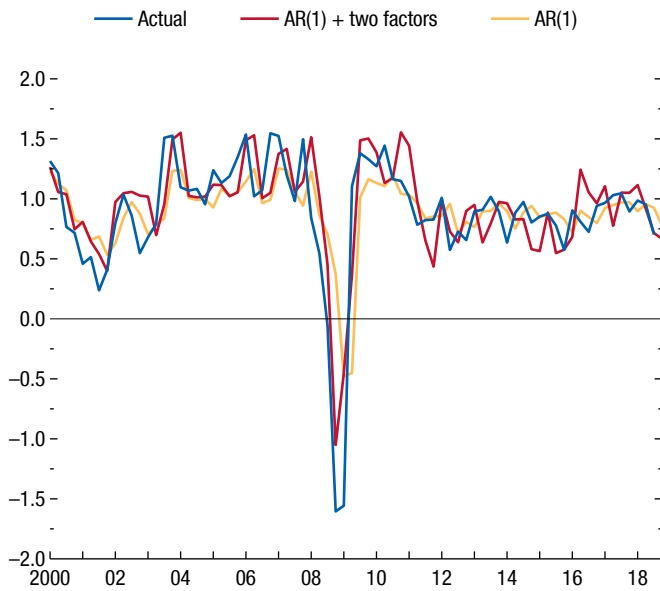
Table 1.SF.3. Global GDP Nowcast

	Metric	Benchmark	Specification 1	Specification 2	Specification 3
One Month Information	RMSE	0.42%	0.38%	0.37%	0.38%
	Ratio	1	0.90	0.90	0.90
Two Months Information	RMSE	0.42%	0.36%	0.36%	0.36%
	Ratio	1	0.87	0.86	0.86
Quarter Information	RMSE	0.42%	0.36%	0.35%	0.35%
	Ratio	1	0.86	0.84	0.85

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.

Note: Sample period = 1980:Q1 to 2018:Q3. Benchmark = autoregressive process with the optimal lag based on Bayesian information criterion; Specification 1 = first principal component; Specification 2 = first two principal components; Specification 3 = first principal components of agricultural and nonagricultural commodities. One-period lagged dependent variable is added in all specifications. Information is available one, two, or three months into the quarter. RMSE = root mean square error; Ratio = relative RMSE, RMSE divided by benchmark RMSE.

Figure 1.SF.6. Global Real GDP Growth Nowcast: Actual versus Fitted Value
(Percent, quarter-over-quarter)



Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: AR = autoregressive process; two factors = first two principal components.
Regressions are based on quarterly data from 1980:Q1 to 2018:Q3.

production growth.²² The forecast performance is based on the root mean squared forecast error.

²²After running the forecast through entire periods, several forecast performance measures are calculated. These include the root mean squared prediction errors between model forecasts and actual growth, mean absolute prediction errors, bias (mean prediction error), and efficiency (the correlation between prediction error and prediction). Results are available on request.

Results in Table 1.SF.4 show that all specifications improve the one-month-ahead global industrial production forecast (relative to the benchmark): specification (2), which uses both the global and relative factors, does best and improves the forecast by 10 percent.

The one-quarter-ahead GDP forecast is also improved, but only as price information in the quarter becomes available.²³ In practice, global GDP data may not be available in the next two quarters. For example, in May, first-quarter world GDP is not available, whereas data for April commodity prices are. This timeliness is why commodity prices are useful to forecast GDP growth for the next quarter. As months pass, the forecasting performance improves because commodity price movements more accurately reflect the current quarter. When the full quarter is available, the root mean squared forecast error of the next-quarter GDP is improved by almost 10 percent relative to the benchmark.

In conclusion, there is a wealth of information embedded in commodity prices that can be very useful for taking the pulse of global economic activity. Once idiosyncratic factors are eliminated, major movements in prices of base metals, and, to some extent, energy and agricultural products, can tell us a lot about the state of the global economy, especially when economic activity takes place during significant fluctuations—when the need for forecasting and nowcasting is most compelling.

²³The specification is tested when price data for the first, both first and second, and all three month(s) of the quarter are available.

Table 1.SF.4. Forecasting Global Industrial Production and GDP

		Metric	Benchmark	Specification 1	Specification 2	Specification 3
IP	Month	RMSE	0.55%	0.50%	0.49%	0.50%
		Ratio	1	0.92	0.90	0.92
GDP	One Month Information	RMSE	0.51%	0.50%	0.51%	0.51%
		Ratio	1	0.99	1.00	1.00
	Two Months Information	RMSE	0.51%	0.48%	0.48%	0.48%
		Ratio	1	0.95	0.95	0.95
	Quarter Information	RMSE	0.51%	0.46%	0.46%	0.46%
		Ratio	1	0.91	0.91	0.90

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.

Note: Benchmark = autoregressive process with the optimal lag based on Bayesian information criterion; Specification 1 = first principal component; Specification 2 = first two principal components; Specification 3 = first principal components of agricultural and nonagricultural commodities. One-period lagged dependent variable is added in all specifications for IP. Information is available one, two, or three months into the quarter. IP = industrial production; RMSE = root mean square error; Ratio = relative RMSE, RMSE divided by benchmark RMSE.