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Commodity prices and global economic activity☆

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ABSTRACT

Commodity prices provide useful information about current and future global economic activity. First, we show that overall commodity prices indeed tend to comove with economic activity. Second, we try to extract the global demand factor(s) using many commodity prices. While commodity prices reflect both demand and supply factors, by relying on a wide variety of commodity prices, supply shocks can be filtered out as they tend to be commodity-specific idiosyncratic shocks except for widespread supply disruptions confined to a few historical periods. In this paper, we then show that factors extracted from commodity prices movement contain useful information to nowcast and forecast global GDP and industrial production.

1. Introduction

What do commodity prices tell us about economic activity? This paper 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.[1]

There are at least two major reasons why commodity prices are useful indicators of global economic activity. First, even in a world where services take the spotlight, commodities still represent about 17% of global trade and are fundamental inputs into production.[2] A change in global economic activity, by affecting the consumption of inputs into production, will therefore be reflected in the global demand for commodities (Barsky and Kilian, 2004; Alquist et al., 2020). Second, some commodities are storable, so, like those of financial assets, their prices reflect both current and expected future demand and supply conditions. Since many commodities are regularly traded in liquid and deep markets, their price 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 are in fact prominent confounding influences[3] or even reasons 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 part identifies commodity price cycles and provides insights into the cyclical synchronization between commodity prices and economic activity. The second part exploits co-movements 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. Of course, this assumption has a limitation in the case of rare disasters (including wars) where various commodities suffer from supply disruptions as supply factors cannot be abstracted away using a large number of commodities.

This paper is related to a large body of literature on the co-movement

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

[2] Industrial commodities (metals and raw agricultural materials) are crucial inputs for the manufacturing sector. Energy commodities, by being crucial to the transport and petrochemical sectors and to power generation, indirectly affect the entire global productive system. Finally, food and beverages commodities, usually affected by income, underpin the food chain.

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

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in commodity prices. Existing studies differ according to the group of commodities that are investigated and the empirical methodology that are used, they generated consistent views: common factors extracted from a panel of commodity prices not only reflect some central characteristics of commodity prices, but are also strongly related to measures of economic activity (e.g., Byrne et al. 2013; West and Wong, 2014; Yin and Han, 2015; Alquist et al., 2020; Delle Chiaie et al., 2022). In the context of the oil market, there have been comprehensive analyses of oil prices and the co-movement of oil with other commodities. For example, Baffes (2007) estimated the pass-through of oil price changes to a wide range of commodities; Barsky and Kilian (2004), Kilian (2009), and Alquist et al. (2013) evidenced that non-fuel industrial commodity price movements reflect global demand that affects all industrial commodities. Our work is also related to a much smaller literature on forecasting using commodity prices. These papers include those that use common factors to forecast commodities prices themselves (e.g., West and Wong, 2014; Delle Chiaie et al., 2022), inflation (Gospodinov and Ng, 2013), and exchange rate (Chen et al., 2014).

This paper complements existing literature in three ways. Firstly, it contributes to the empirical evidence on the cyclical properties of commodity prices and the synchronization between commodities and economic activity in the past few decades. Secondly, to the best of our knowledge, this paper is the first to nowcast and forecast global GDP and industrial production using a bulk of high frequency commodity prices. We show that factor(s) from commodity prices can statistically improve nowcast and out-of-sample forecast results compared to a benchmark AR (p) process. Lastly, our nowcasting/forecasting exercise gives policymakers and practitioners a parsimonious framework to get a timely estimate of global economic activity.

In the following sections, we first analyze a few commodities and utilize the co-movement to nowcast and forecast the global economic activity. We also conduct some robustness checks before conclude.

2. Cyclicality and co-movements of commodity prices

This section identifies commodity price cycles and looks, across a broad set of commodity prices, at those 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).[4] 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.[5] The same procedure is also applied to de-trended global industrial production (IP) and GDP.[6,7] (Fig. 1 presents four examples.).

Most commodities show asymmetric phases characterized by longer and dull contractions punctuated by sharp expansions (Table 1).[8] Energy commodities stand out for having 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 in line with a long-standing 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 et al. 2002).

While supply shocks, especially when inventory stocks or spare production capacity are low, tend to create spikes in prices, a vast literature has also stressed the role of demand factors (Barsky and Kilian, 2004; Alquist et al., 2020 among many). It is therefore useful to calculate the synchronization of phases (or technically, *concordance*) between commodity prices and economic activity.[9]

With few exceptions, agricultural prices, especially food prices, are on average only modestly in sync with economic activity (Fig. 2). Bellwethers of global IP are mostly base metals (such as zinc, copper, and tin) and to a lesser extent energy and fertilizers. Propane shows the highest sync with global IP, but its time series and the one 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 in 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 a relatively high synchronization with global IP while in general food and beverages, relatively to other commodities, are more synchronized to global GDP rather than IP, as income rather than production plays a more relevant role in their demand (an example is arabica coffee).[10]

Periods of sizeable movements in economic activity (booms or busts) should increase co-movement, and therefore synchronization among all commodities. Most commodities, not only bellwethers, should move in sync with global IP or GDP. Accordingly, it is useful to derive a metric

[4] Drawing 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) is required to be at least 12 months in length. (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 dataset.)

[5] All commodity price series are monthly averages of prices from the IMF's Primary Commodity Price System; all prices are denominated in USD and divided by US consumer price inflation. Prices are not prefiltered since 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) argued that commodity prices have a downward tendency while, more recently, Jacks (2019) and Stuermer (2018) found a modest upward trend. Results are mostly unchanged if a linear trend is removed.

[6] Global IP and GDP are from IMF internal database; both are PPP weighted, based on a sample of 39 countries (17 advanced economies and 22 emerging countries).

[7] An HP filter with a very low lambda is used to extract a stable trend from global IP and GDP. Quarterly GDP data have been interpolated monthly. Although the dating algorithm can handle non-stationarity, some statistics that compare stationary and non-stationary series (for example, concordance) can be misleading.

[8] Table A1 in the Appendix shows cyclical properties for each individual commodity price series.

[9] Technically, the synchronization metric used is the *concordance*, which calculates the share of time two series 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.

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

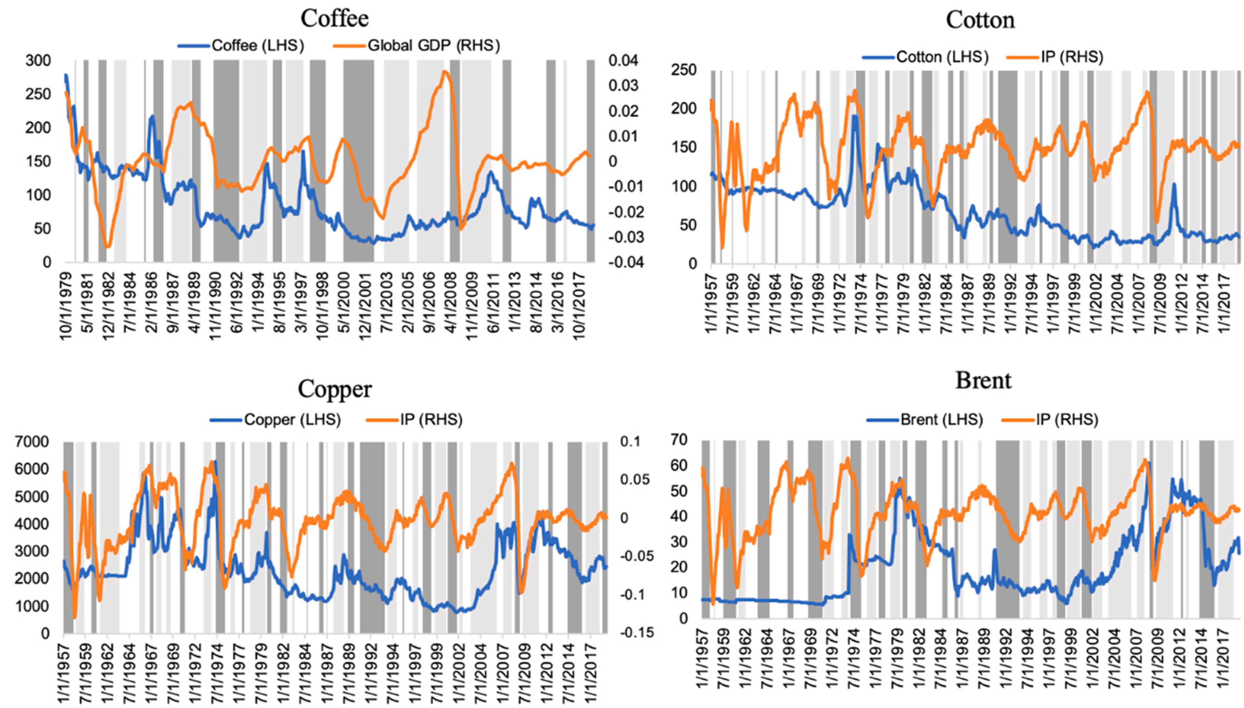

Fig. 1. Commodity cycles and economic activity. *Sources*: IMF, Primary Commodity Price System; Organization for Economic Co-operation and Development (OECD); and IMF staff calculations. Note: Peaks and troughs identified using the Harding and Pagan (2002)'s business-cycle dating procedure. IP is global industrial production, spliced back using OECD IP(1975–1979) 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 asynchronized movements.

Table 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.

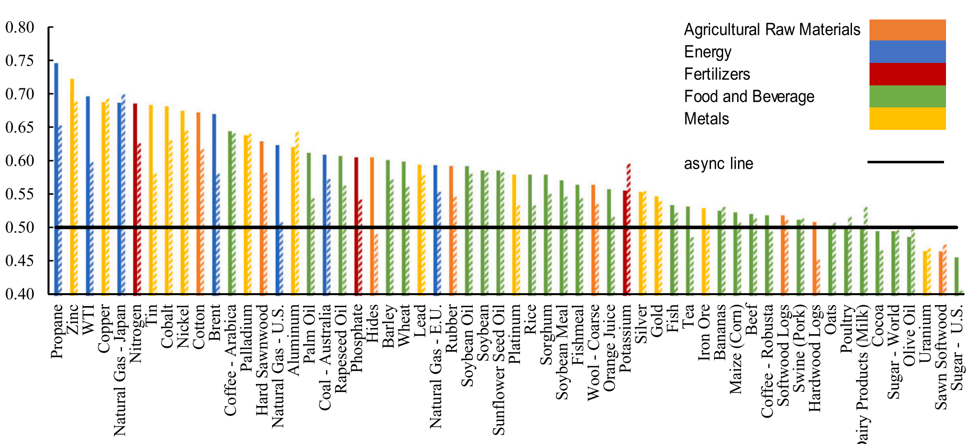

Fig. 2. Synchronization with economic activity. *Sources*: IMF, Primary Commodity Price System; Organization for Economic Co-operation and Development (OECD); and IMF staff calculations. *Note*: Bars represent the synchronization of a given commodity with de-trended IP (blocked bars) and GDP (patterned 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 (2002)'s procedure. Concordance calculates the share of time two series are in the same phase, a concordance above 0.5 denotes a positive synchronization.

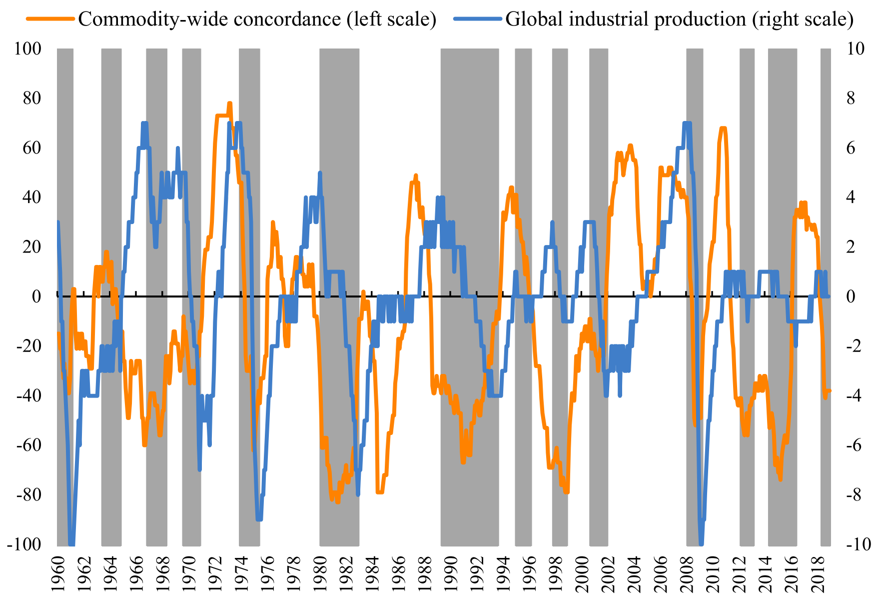

Fig. 3. Commodity-wide synchronization(percent). *Sources*: IMF, Primary Commodity Price System; Organization for Economic Co-operation and Development (OECD); and IMF staff calculations. *Notes*: Global industrial production (IP) is spliced back using OECD IP (1975–1979) and US IP (<1975). Shading represents contractions in the IP variable. Commodity-wide concordance is the share of commodities in expansion (contraction).

that calculates the share of commodities that are in the expansion (contraction) phase—that is, a commodity-wide concordance.[11] 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 commodity-specific demand factors, are driving commodity prices in a given period.

Fig. 3 shows that commodity-wide concordance anticipates turning points of economic activity since 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 global business cycle using commodity prices.

3. 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 et al., 2022).[12] Since supply and commodity-specific demand shocks make commodity prices diverge, estimating those latent factors that induce commodity prices to comove should help construct a proxy for global economic activity.[13][14] Following this logic, the higher the number of commodities used, the better the global demand factors are identified. In practice, however, it might be recommendable 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] A caveat: in rare instances, global shocks to the supply of commodities can increase the co-movement of commodity prices. The recent war in Ukraine is a case in point since both Russia and Ukraine are major commodity exporters. To avoid the issue, the econometric analysis stops before the start of the war (and the pandemic which also induced a dislocation of demand patterns that was extremely unusual). Another common factor that could affect all variables at the same time is the interest rate. Controlling for interest rates, however, does not substantially change results. In part because higher real rates are often associated with above-trend economic growth while it is the surprising component of monetary policy that would independently affect commodity prices—however, the role of monetary policy shocks in explaining the business cycle is modest, especially in the recent period (Gertler and Karadi, 2015, among many). Robustness checks in the next section provide more details on this.

The first two extracted factors explain about 20% of the variance of

[11] A value of 1 (−1) means all commodities prices are expanding (contracting) simultaneously, perfect synchronization, while a value of 0 implies that half commodity prices are in the same phase, lowest synchronization.

[12] The approach in Delle Chiaie et al. (2022) that allows for group specific factors gave slightly inferior results.

[13] The idea that global demand induces comovement in commodity prices is clearly not novel. For example, Barsky and Kilian (2004) interpreted the strong comovement of the real price of oil and a real price index of industrial raw materials and metals in the early 1970 s 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 et al., 2020; Delle Chiaie et al., 2022, among others).

[14] Interestingly, Pindyck and Rotemberg (1990) noted 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 heteroskedastic) factor that affects all prices at the same time (Alquist et al., 2020).

[15] To estimate the latent factors the log-differences of prices (divided by the US CPI) have been z-scored. It is less relevant for the estimation whether to use log-detrended or log-differences (Kilian and Zhou, 2018).

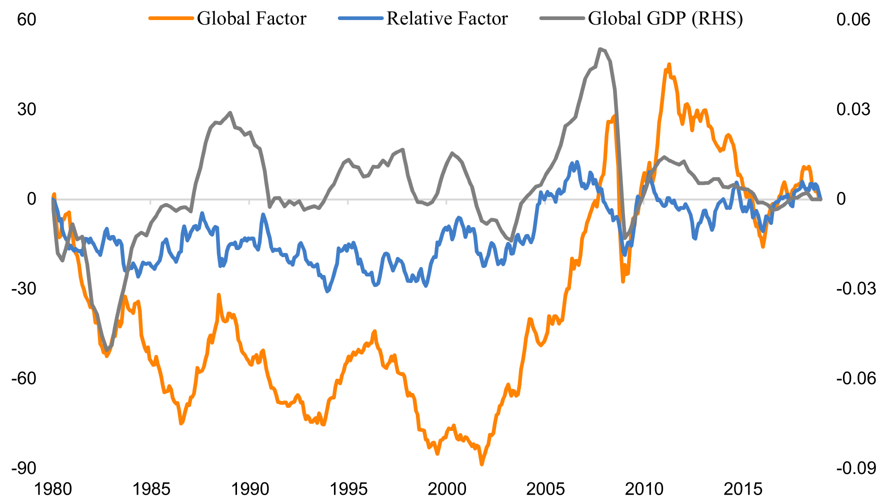

Fig. 4. Latent factors and economic activity. *Sources*: IMF, Primary Commodity Price System; and IMF staff calculations. *Note*: First and second principal components are cumulated; log difference in global GDP is de-meaned and cumulated.

commodity price monthly changes. The relevance of the other remaining factors drops off quickly and is not statistically related to economic activity.[16] Fig. 4 plots the first and second latent factors extracted jointly with (de-meaned) global GDP growth, cumulated over time. Even though the first and second factor are contemporaneously orthogonal by construction, when cumulated they show a positive correlation, 0.67. The first factor is a *global factor*, while the second represents a negative demand shift for agricultural products relative to energy and metals, it 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 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 relation between the global factor with global GDP is visually quite striking (Fig. 4), but the relative-price factor also seems to move with GDP during some sharp downturns (by leading them) and subsequent recoveries.[19]

Since the first release of global IP lags by 2 months and the one of GDP lags by a quarter and are often substantially revised, it is useful to test whether latent factors can help nowcast global activity. To do so, global IP and GDP are regressed on latent factors and one-period of its own lag. Whether the introduction of the latent factor statistically improves the nowcast estimate of economic activity indicator (IP or GDP) is tested and the results compared to a benchmark AR(p) process (following Stock and Watson, 2002). Different specifications have been tried: where both the global and relative factors are introduced together (specification 1); where only the global factor is used (specification 2); where the sample is split into agriculture and non-agriculture commodities and the respective first factors are used (specification 3). All specifications can include own lags optimally chosen.

Table 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.

The results, shown in Table 2, indicate that for IP, at monthly frequency, introducing the global factor and the relative-price factor increases the ability to nowcast IP relative to the benchmark AR(p) process—where the number of lags, p, are determined optimally. Since monthly IP growth is quite volatile, the nowcasting gives modest improvements. More striking is its ability to nowcast GDP (Table 3). The improvement in the root mean square error (RMSE) relative to the AR(p) benchmark is already 10% just with the global factor from one month of commodity price information. The improvement increases to 15% when the quarter is completed. The R-squared is also high at about 0.5.[20] Interestingly, commodity prices are mostly informative in periods of high economic volatility, when the AR(p) process fails the most (Fig. 5). Results are similar when using the two first factors extracted from the agricultural and nonagricultural group taken separately.

Since factor lags are also significant, whether commodity prices also help predict global activity can be tested. Forecast evaluations are based on the out-of-sample forecasts performance. Given data for industrial production, GDP, and estimated principal components, each specification is first estimated using the sample period 1980–1998 and then

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

[17] This can be seen by inspecting the factor loadings, available upon request.

[18] A regression of the global (relative-price) factor on the first factors extracted from the agriculture and non-agriculture samples separately yields an R-square of 0.99 (0.88).

[19] The (negative of the) first factor in levels mimics movements in the US dollar real effective exchange rate (REER), this is not a surprise given that the dollar is the numeraire 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, non-commodity currencies are excluded because, as 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 has not altered the results.

[20] Regression results are available in the Appendix. It is also worth noting that predictability declines when using global GDP (IP) at market exchange rates probably because of the greater relevance of services in AEs.

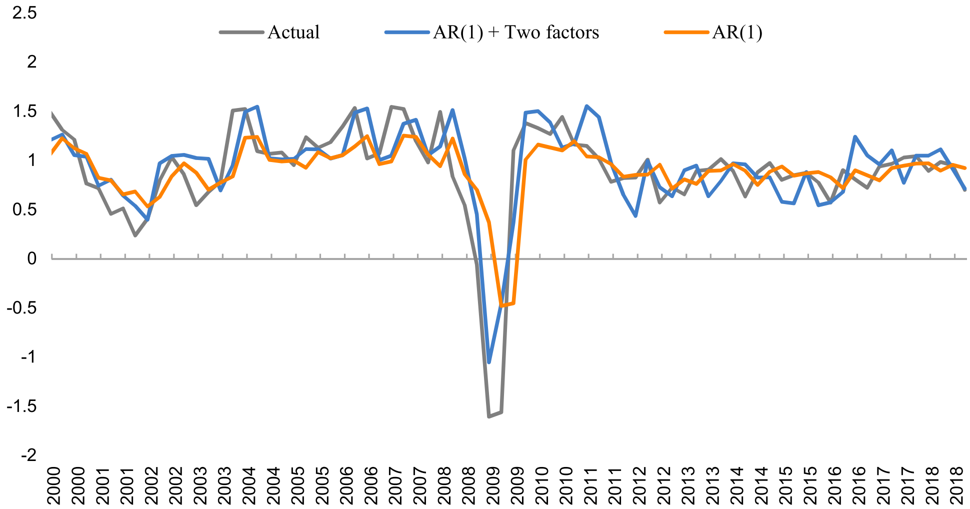

Fig. 5. Global real GDP growth nowcast: actual vs. fitted value (percent, quarter-over-quarter. *Sources*: IMF, Primary Commodity Price System; and IMF staff calculations. *Notes*: Two factors = first two principal components.

Table 3
Global GDP nowcast.

	Metric	Benchmark	Specification 1	Specification 2	Specification 3
One Month Information	RMSE	0.42%	0.37%	0.37%	0.37%
	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:Q4. 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.

Table 4
Forecasting global industrial production and GDP.

		Metric	Benchmark	Specification 1	Specification 2	Specification 3
IP	Month	RMSFE	0.55%	0.50%	0.49%	0.50%
		Ratio	1	0.92	0.90	0.92
GDP	One Month Information	RMSFE	0.51%	0.50%	0.51%	0.51%
		Ratio	1	0.99	1.00	1.00
	Two Months Information	RMSFE	0.51%	0.48%	0.48%	0.48%
		Ratio	1	0.95	0.95	0.95
	Quarter Information	RMSFE	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. RMSFE = root mean squared forecast error. Ratio = relative RMSFE, RMSFE divided by benchmark RMSFE.

Table 5
Global industrial production nowcast – with additional variables.

	AR (p)	Commodity	Interest rate	Stock	Commodity + Interest rate	Commodity + Stock	Commodity + Interest rate + Stock
RMSE	0.55%	0.53%	0.57%	0.57%	0.52%	0.53%	0.52%
Ratio	1	0.97	1.05	1.04	0.96	0.97	0.95

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Sample period = January 1980 to December 2018. AR(p) = autoregressive process with the optimal lag based on Bayesian information criterion; Commodity = first two principal components; Interest rate = T-bill monthly changes; Stock = MSCI global equity index monthly returns. 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.

Table 6
Global GDP nowcast – with additional variables.

	Metric	AR (p)	Commodity	Interest rate	Stock	Commodity + Interest rate	Commodity + Stock	Commodity + Interest rate + Stock
One Month Information	RMSE	0.42%	0.37%	0.42%	0.37%	0.38%	0.35%	0.35%
	Ratio	1	0.90	1.00	0.89	0.90	0.84	0.84
Two Months Information	RMSE	0.42%	0.36%	0.40%	0.38%	0.35%	0.35%	0.34%
	Ratio	1	0.87	0.97	0.91	0.85	0.84	0.81
Quarter Information	RMSE	0.42%	0.36%	0.37%	0.41%	0.33%	0.36%	0.33%
	Ratio	1	0.86	0.90	0.98	0.80	0.86	0.78

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Sample period = 1980:Q1 to 2018:Q4. AR(p) = autoregressive process with the optimal lag based on Bayesian information criterion; Commodity = first principal component; Interest rate = T-bill quarterly changes; Stock = MSCI global equity index quarterly returns. 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.

recursively re-estimated to forecast over 2000–2018.[21] For each period, the model forecasts for next period 1-month-ahead IP and 3-month-ahead GDP growth.[22] The forecast performance is based on the root mean squared forecast error (RMSFE).

Results (Table 4) show that all specifications improve the one-month-ahead global IP forecast (relative to the benchmark) with specification (1), that uses both the global and relative factors, coming out first and improving the forecast by 10%. The 1-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 while 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% relative to the benchmark.

4. Robustness checks

4.1. Control variables

In this section, we check the robustness of the nowcasting and forecasting power of latent factors extracted from commodity prices. To do so, we use the best forecast specifications from previous section and add interest rate and stock returns as control variables. We source data on U.S. 1 year T-bill yield and MSCI global equity index from Datastream.

Upon the inclusion of control variables, for global IP nowcast, the coefficients for latent factors extracted from commodity prices remain stable; for global GDP nowcast, the estimated coefficient of latent factors is slightly smaller, but still contained within the 95% confidence interval of the estimates without control variables and remain highly statistically significant (Tables A4 and A5 in the Appendix).

In Tables 5 and 6, we examine whether adding additional variables into the nowcast model can help improve the nowcast performance or not. We also compare the nowcasting power of each single variable. For global IP, commodity price information is the best single nowcast predictor. Adding interest rate and stock information to the model can only slightly increase the nowcast performance. For global GDP, overall, commodity price information is the best nowcast predictor, except for stock prices which perform marginally better than the commodity prices when only one month's information is available. Considering that stock market is relatively forward-looking and contains information about future, it's not surprising that it outperforms at the beginning of a quarter. In contrast to IP nowcast, both interest rate and stock contain additional helpful nowcast information for GDP. Adding both variables to nowcast model can make the improvement relative to AR(p) benchmark increase from 14% to 22% when the quarter is completed.

Table 7 shows the out-of-sample forecast performance comparison. As in previous section, the forecast performance is based on the root mean squared forecast error (RMFSE). For global IP, the forecast results are mostly consistent with the nowcast results: commodity price information is the best single predictor. Adding interest rate and stock to the model can only give modest forecast improvement. For global GDP, although the forecasting power of stock outperforms commodity along

[21] Each model is reestimated with the addition of new data (recursive scheme). Models using principal components are fixed lag length, but the optimal lag length of AR model is chosen each time using Bayesian Information Criteria (BIC) or Akaike Information Criteria.

[22] After running forecast through entire periods, several forecast performance measures are calculated. They 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 upon request.

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

Table 7
Forecasting global industrial production and GDP – with additional variables.

	Metric	AR (p)	Commodity	Interest Rate	Stock	Commodity + Interest rate	Commodity + Stock	Commodity + Interest Rate + Stock
IP								
Month	RMSFE	0.55%	0.49%	0.55%	0.54%	0.49%	0.48%	0.48%
	Ratio	1	0.90	1.00	0.99	0.89	0.89	0.88
GDP								
One Month Information	RMSFE	0.51%	0.50%	0.51%	0.43%	0.50%	0.44%	0.44%
	Ratio	1	0.99	1.01	0.86	0.99	0.87	0.87
Two Months Information	RMSFE	0.51%	0.48%	0.49%	0.44%	0.47%	0.43%	0.42%
	Ratio	1	0.95	0.98	0.87	0.93	0.86	0.84
Quarter Information	RMSFE	0.51%	0.46%	0.49%	0.44%	0.45%	0.41%	0.40%
	Ratio	1	0.91	0.98	0.88	0.90	0.82	0.79

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: AR(p) = autoregressive process with the optimal lag based on Bayesian information criterion; Commodity = first two principal components for IP, first principal component for GDP; Interest rate = T-bill changes; Stock = MSCI global equity index returns. 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. RMSFE = root mean squared forecast error. Ratio = relative RMSFE, RMSFE divided by benchmark RMSFE.

the entire quarter, the improvements of "Commodity + Stock" column compared to "Stock" column indicate that commodity prices contain additional information that is helpful for the forecast.

4.2. Subsample analysis

For model evaluation over a long-time span, it is usually crucial to consider time variation in parameters. For our global IP and GDP models, Chow tests indicate a potential structural break around 2008 global financial crisis (GFC). Therefore, in this section, we split our sample into pre-GFC and post-GFC and discuss subsample results (Tables A6 and A7 in Appendix).

For global IP, subsample regressions show that the statistical change in parameters across two subsamples is dominated by the change in the autoregressive process: the coefficient of the autoregressive process switches from significantly negative to significantly positive in the post-GFC subsample, which is consistent with the fact that the post-GFC sample is relatively short, and lack of recession or high volatile times. Focusing on the coefficient of factors extracted from commodity prices, the first factor plays a key role in both sub-samples. Compared to the pre-GFC sample, the coefficient of the lag of first factor becomes larger and more significant while the contemporaneous first factor becomes less important. In terms of model performance, post-GFC subsample's RMSE (0.45%) is lower than that of pre-GFC sample (0.53%). For global GDP, the commodity information plays a more important role in the post-GFC subsample. Model performance also improves in the recent subsample, with RMSE decreases from 0.37% to 0.32% (full quarter information).

Considering the sample length, we choose not to conduct out-of-sample forecasts (recursive regressions) over subsamples. Instead, we take a closer look to the evolutions of coefficients estimated in out-of-sample forecasts using full sample in previous section (Figs A1 and A2 in Appendix). Overall, the evolutions of coefficients overtime are in line with what we find from in-sample regressions for pre-GFC and post-GFC. For GDP, there is one interesting finding: though coefficients for latent factors jump during GFC, they gradually go back to pre-GFC levels in the years after.

5. Conclusion

There is a wealth of information embedded in commodity prices that can be extremely useful for taking the pulse of global economic activity. Once cleaned of idiosyncratic factors, major movements in prices of base metals and, to some extent, energy and agricultural products can provide insights about the state of the global economy, especially when economic activity takes place in a period of high fluctuations—when the need for forecasting and nowcasting is most compelling. Future research can expand to see the predictability across different characteristic of countries, or inclusion of monetary policy shocks. These extensions will deepen the understanding of the linkage between commodity markets and macroeconomy.

Appendix A

See Tables A1–A7 and Figs. A1 and A2 here.

Table A1
statistical properties of real commodity prices.

Commodity	Start Date	End Date	Average amplitude of contraction	Average amplitude of expansion	Average duration of contraction	Average duration of expansion	# of contractions	# of expansions	Average sharpness of contraction	Average sharpness of expansion
ALL INDEX										
ENERGY										
Coal										
Coal, Australia	1979m1	2018m11	-0.71	0.68	-36.75	26.71	7	8	-0.02	0.03
Coal, South Africa	1990m1	2018m11	-0.76	0.78	-45.40	24.40	5	5	-0.02	0.03
Crude Oil										
Brent	1957m1	2018m11	-0.79	0.85	-41.40	30.09	11	10	-0.02	0.03
Dubai Fateh	1957m1	2018m11	-0.86	0.94	-46.89	32.30	10	9	-0.02	0.03
WTI	1957m1	2018m11	-0.73	0.77	-44.70	29.80	10	10	-0.02	0.03
Natural Gas										
Natural Gas, E.U.	1985m1	2018m11	-0.80	0.89	-56.75	36.40	5	4	-0.02	0.02
Natural Gas, Japan	1992m1	2018m11	-0.62	0.61	-29.20	29.83	6	5	-0.02	0.02
Natural Gas, U.S.	1991m1	2018m11	-1.07	1.05	-26.67	25.29	7	6	-0.04	0.04
Propane	1992m7	2018m11	-1.30	1.24	-48.33	43.50	4	3	-0.03	0.03
NON-ENERGY										
Agriculture										
Agricultural Raw Materials										
Cotton	1957m1	2018m11	-0.61	0.51	-28.36	24.86	14	14	-0.02	0.02
Hides	1957m1	2018m11	-0.76	0.76	-40.73	29.70	10	11	-0.02	0.03
Rubber	1957m1	2018m11	-0.94	0.82	-41.10	37.11	9	10	-0.02	0.02
Timber										
Hardwood										
Hardwood Logs	1980m1	2018m11	-0.62	0.61	-36.43	30.57	7	7	-0.02	0.02
Hard Sawnwood	1980m1	2018m11	-0.50	0.51	-32.86	34.14	7	7	-0.02	0.01
Softwood										
Softwood Logs	1975m1	2018m11	-0.57	0.44	-40.00	35.57	7	7	-0.01	0.01
Sawn Softwood	1975m1	2018m11	-0.44	0.33	-35.38	30.75	8	8	-0.01	0.01
Wool + Yarn										
Wool, Coarse	1957m1	2018m11	-0.65	0.61	-35.33	29.18	11	12	-0.02	0.02
Wool, Fine	1957m1	2018m11	-0.70	0.64	-31.64	23.23	13	14	-0.02	0.03
Beverages										
Coffee										
Coffee, Arabica	1957m1	2018m11	-0.75	0.66	-34.08	28.00	12	12	-0.02	0.02
Coffee, Robusta	1957m1	2018m11	-0.93	0.79	-40.90	37.33	9	10	-0.02	0.02
Cocoa	1957m1	2018m11	-0.80	0.73	-37.45	30.27	11	11	-0.02	0.02
Tea	1957m1	2018m11	-0.66	0.55	-35.25	24.77	13	12	-0.02	0.02
Food										
Cereals										
Barley	1975m1	2018m11	-0.84	0.65	-38.25	27.88	8	8	-0.02	0.02
Maize (Corn)	1957m1	2018m11	-0.66	0.56	-43.60	28.09	11	10	-0.01	0.02
Oats	1959m7	2018m11	-0.72	0.65	-42.60	28.90	10	10	-0.02	0.02
Rice	1957m1	2018m11	-0.76	0.71	-44.30	30.20	10	10	-0.02	0.02
Sorghum	1962m1	2018m11	-0.80	0.76	-70.67	43.50	6	6	-0.01	0.02
Wheat	1957m1	2018m11	-0.68	0.56	-35.58	26.50	12	12	-0.02	0.02
Meat										
Beef	1957m1	2018m11	-0.49	0.45	-47.10	30.44	9	10	-0.01	0.01
Lamb	1980m1	2018m11	-0.53	0.35	-32.63	29.71	7	8	-0.01	0.01
Poultry	1980m1	2018m11	-0.21	0.26	-20.00	47.00	7	7	-0.01	0.01
Swine (Pork)	1980m1	2018m11	-0.97	0.78	-30.44	21.67	9	9	-0.03	0.04
Seafood										
Shrimp	1957m1	2018m11	-0.47	0.40	-27.57	27.62	13	14	-0.01	0.01
Fish	1979m1	2018m11	-0.79	0.56	-44.43	24.29	7	7	-0.01	0.02
Sugar										
Sugar, U.S.	1957m1	2018m11	-0.60	0.54	-42.30	29.27	11	10	-0.01	0.02
Sugar, World	1957m1	2018m11	-1.47	1.44	-43.44	39.33	9	9	-0.03	0.04
Vegetable Oil Index										

(*continued on next page*)

Table A1 (*continued*)

Commodity	Start Date	End Date	Average amplitude of contraction	Average amplitude of expansion	Average duration of contraction	Average duration of expansion	# of contractions	# of expansions	Average sharpness of contraction	Average sharpness of expansion
Olive Oil	1978m9	2018m11	-0.56	0.49	-36.14	38.67	6	7	-0.01	0.01
Palm Oil	1957m1	2018m11	-0.75	0.65	-28.36	24.86	14	14	-0.02	0.03
Rapeseed Oil	1980m1	2018m11	-0.69	0.54	-28.88	29.75	8	8	-0.02	0.02
Soybean	1957m1	2018m11	-0.76	0.63	-45.00	29.50	10	10	-0.01	0.02
Soybean Oil	1957m1	2018m11	-0.79	0.66	-41.36	26.36	11	11	-0.02	0.03
Soybean Meal	1957m1	2018m11	-0.70	0.62	-34.50	27.58	12	12	-0.02	0.02
Sunflower Seed Oil	1960m1	2018m11	-1.00	0.89	-62.57	38.71	7	7	-0.01	0.02
Other Food										
Bananas	1975m1	2018m11	-0.73	0.72	-35.38	35.14	7	8	-0.02	0.02
Citrus Fruit + Orange Juice	1967 m2	2018m11	-0.70	0.64	-26.54	23.25	12	13	-0.02	0.03
Dairy Products (Milk)	1993m7	2018m11	-0.67	0.54	-33.00	18.17	6	6	-0.02	0.03
Fishmeal	1957m1	2018m11	-0.66	0.58	-26.92	30.38	13	13	-0.02	0.02
Groundnuts + Tree Nuts	1980m1	2018m11	-0.71	0.61	-39.29	27.71	7	7	-0.02	0.02
Legumes (Chickpea)	2005m10	2018m11	-0.75	0.93	-18.00	35.33	3	3	-0.05	0.03
Non-Citrus Fruit (Apple)	1998m1	2018m11	-0.49	0.52	-17.40	41.50	4	5	-0.03	0.01
Vegetables (Tomato)	1998m1	2018m11	-0.64	0.68	-45.75	17.50	4	4	-0.01	0.04
Fertilizers										
Nitrogen	1977 m2	2018m11	-0.88	0.76	-40.57	27.50	8	7	-0.02	0.03
Phosphate	1977 m2	2018m11	-0.68	0.63	-36.63	23.44	9	8	-0.02	0.03
Potassium	1960m1	2018m11	-0.57	0.60	-50.38	38.25	8	8	-0.01	0.02
Metals										
Base Metals										
Aluminum	1957m1	2018m11	-0.59	0.48	-39.09	28.64	11	11	-0.01	0.02
Cobalt	1981m1	2018m11	-0.93	1.05	-24.89	25.89	9	9	-0.04	0.04
Copper	1957m1	2018m11	-0.81	0.79	-45.89	36.89	9	9	-0.02	0.02
Iron Ore	1975m1	2018m11	-0.47	0.57	-47.43	24.63	8	7	-0.01	0.02
Lead	1957m1	2018m11	-0.83	0.83	-41.00	26.73	11	11	-0.02	0.03
Molybdenum	2010m5	2018m11	-1.36	0.82	-32.50	40.00	1	2	-0.03	0.02
Nickel	1957m1	2018m11	-0.91	0.83	-40.10	34.40	10	10	-0.02	0.02
Tin	1957m1	2018m11	-0.58	0.55	-38.45	29.27	11	11	-0.01	0.02
Uranium	1980m1	2018m11	-0.95	0.86	-55.80	31.67	6	5	-0.02	0.03
Zinc	1957m1	2018m11	-0.68	0.69	-31.85	25.46	13	13	-0.02	0.03
Precious Metals										
Gold	1964m1	2018m11	-0.63	0.77	-51.57	42.86	7	7	-0.01	0.02
Silver	1968m1	2018m11	-0.78	0.78	-31.00	33.67	9	10	-0.03	0.02
Palladium	1987m1	2018m11	-0.93	1.40	-47.50	48.75	4	4	-0.03	0.03
Platinum	1976m1	2018m11	-0.66	0.71	-46.00	32.50	6	7	-0.02	0.02

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

Note: This table shows cyclical properties for each individual commodity price series. Peaks and troughs are determined according to the Harding and Pagan (2002) algorithm. 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. Window and minimum phase and minimum cycle length set at 3, 12 and 24 months respectively.

Table A2
Global industrial production nowcast.

	(1) Benchmark	(2) Specification 1	(3) Specification 2	(4) Specification 3
IP monthly log changes (one month lag)	0.0459	0.0316	0.0180	0.0234
	(1.00)	(0.71)	(0.41)	(0.52)
IP monthly log changes (two months lag)	0.2824 ***			
	(6.43)			
IP monthly log changes (three months lag)	0.1790 ***			
	(3.91)			
First principal component		0.0003 **	0.0003 **	
		(2.62)	(2.81)	
(one month lag)		0.0007 ***	0.0006 ***	
		(6.53)	(6.46)	
Second principal component			0.0005 ***	
			(4.27)	
First principal component of agricultural group				-0.0001
				(−1.14)
(one month lag)				0.0004 **
				(2.98)
First principal component of nonagricultural group				0.0006 ***
				(4.45)
(one month lag)				0.0006 ***
				(4.41)
Constant	0.0013 ***	0.0025 ***	0.0026 ***	0.0026 ***
	(4.27)	(9.16)	(9.46)	(9.33)
Observations	465	466	466	466
R^2	0.13	0.15	0.18	0.17

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Global industrial production (IP) growth regressed on its own lags and principal components of commodity prices. See Section 3 for details. Sample period = January 1980 to December 2018. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A3
Global GDP nowcast.

	Panel 1: 1 month information				Panel 2: 2 months information				Panel 3: Quarter information			
	(1) Benchmark	(2) Specification 1	(3) Specification 2	(4) Specification 3	(1) Benchmark	(2) Specification 1	(3) Specification 2	(4) Specification 3	(1) Benchmark	(2) Specification 1	(3) Specification 2	(4) Specification 3
Lag of GDP growth	0.5489 ***	0.4158 ***	0.4003 ***	0.4101 ***	0.5489 ***	0.4249 ***	0.4055 ***	0.4151 ***	0.5489 ***	0.4358 ***	0.4201 ***	0.4291 ***
	(8.13)	(6.44)	(6.14)	(6.32)	(8.13)	(6.9)	(6.63)	(6.81)	(8.13)	(7.23)	(7.1)	(7.25)
First principal component		0.0006 ***	0.0006 ***			0.0007 ***	0.0007 ***			0.0007 ***	0.0007 ***	
		(6.07)	(6.15)			(6.98)	(7.13)			(7.3)	(7.47)	
Second principal component			0.0002				0.0004 *				0.0005 **	
			(1.49)				(2.38)				(2.86)	
First principal components of agricultural group				0.0003 *				0.0003				0.0002
				(2.3)				(1.87)				(1.48)
First principal components of nonagricultural group				0.0006 ***				0.0008 ***				0.0009 ***
				(3.94)				(5.11)				(5.52)
Constant	0.0040 ***	0.0052 ***	0.0054 ***	0.0053 ***	0.0040 ***	0.0052 ***	0.0053 ***	0.0052 ***	0.0040 ***	0.0051 ***	0.0052 ***	0.0051 ***
	(5.86)	(8.04)	(8.2)	(8.09)	(5.86)	(8.28)	(8.62)	(8.51)	(5.86)	(8.27)	(8.66)	(8.53)
Observations	155	155	155	155	155	155	155	155	155	155	155	155
R^2	0.3	0.43	0.44	0.43	0.3	0.46	0.48	0.48	0.3	0.48	0.5	0.5

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Global GDP growth regressed on its own lag and principal components of commodity prices. See Section 3 for details. Sample period = 1980:Q1 to 2018:Q4. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A4
Global industrial production nowcast with control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
IP monthly log changes (one month lag)	0.0180	0.1043 *	0.1334 **	-0.0201	0.0233	-0.0166
	(0.41)	(2.26)	(2.96)	(−0.45)	(0.53)	(−0.38)
First principal component	0.0003 **			0.0003 **	0.0002 *	0.0003 **
	(2.81)			(3.3)	(2.29)	(2.7)
(one month lag)	0.0006 ***			0.0006 ***	0.0006 ***	0.0006 ***
	(6.46)			(6.14)	(6.18)	(5.79)
Second principal component	0.0005 ***			0.0005 ***	0.0005 ***	0.0005 ***
	(4.27)			(4.35)	(3.97)	(3.99)
T-bill monthly changes		0.0017 **		0.0013 *		0.0013 **
		(3.16)		(2.58)		(2.69)
(one month lag)		0.0011 *		0.0014 **		0.0016 **
		(2.02)		(2.87)		(3.18)
Global MSCI monthly log changes (one month lag)			0.0283 ***		0.0136 *	0.0168 **
			(4.57)		(2.24)	(2.8)
Constant	0.0026 ***	0.0024 ***	0.0020 ***	0.0027 ***	0.0025 ***	0.0026 ***
	(9.46)	(8.19)	(6.97)	(10.11)	(8.87)	(9.51)
Observations	466	466	467	466	466	466
R^2	0.18	0.05	0.06	0.21	0.19	0.22

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Column 1 is the same as Column 3 of Table A2 – regressing global industrial production (IP) growth on one-period of its own lag and principal components of commodity prices. Columns 4–6 add additional variables (interest rate changes and stock returns). Columns 2–3 test the individual nowcasting power of interest rate changes and stock returns. See Section 4 for details. Sample period = January 1980 to December 2018. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A5
Global GDP nowcast (quarter information) with control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Lag of GDP growth	0.4358 ***	0.5235 ***	0.5250 ***	0.4336 ***	0.4425 ***	0.4405 ***
	(7.23)	(8.6)	(8.49)	(7.78)	(7.61)	(8.27)
First principal component	0.0007 ***			0.0006 ***	0.0006 ***	0.0005 ***
	(7.3)			(6.5)	(5.67)	(4.84)
T-bill quarterly changes		0.0018 ***		0.0014 ***		0.0015 ***
		(6.08)		(5.18)		(5.5)
Global MSCI quarterly return (one quarter lag)			0.0217 ***		0.0135 ***	0.0138 ***
			(5.58)		(3.52)	(3.95)
Constant	0.0051 ***	0.0044 ***	0.0037 ***	0.0052 ***	0.0047 ***	0.0048 ***
	(8.27)	(7.09)	(5.91)	(9.18)	(7.8)	(8.75)
Observations	155	155	155	155	155	155
R^2	0.48	0.43	0.41	0.55	0.51	0.59

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Column 1 is the same as Column 2 of Table A3, Panel 3 – regressing global GDP growth on one-period of its own lag and first principal component of commodity prices using full quarter's information. Columns 4–6 add additional variables (interest rate changes and stock returns). Columns 2–3 test the individual nowcasting power of interest rate changes and stock returns. See Section 4 for details. Sample period = 1980:Q1 to 2018:Q4. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A6
Global industrial production nowcast – subsample.

	1980:M1 – 2008:M9	2008:M10 – 2018:M12
IP monthly log changes (one month lag)	-0.1649 **	0.4110 ***
	(−3.14)	(6.04)
First principal component	0.0004 **	0.0001
	(3.09)	(0.41)
(one month lag)	0.0005 ***	0.0007 ***
	(3.75)	(5.32)
Second principal component	0.0005 ***	0.0004
	(3.64)	(1.8)
Constant	0.0031 ***	0.0015 ***
	(9.86)	(3.4)
Observations	343	123
R^2	0.11	0.53

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Regress global industrial production (IP) growth on one-period of its own lag and principal components of commodity prices (Column 3 of Table A2) using subsamples (before and after 2008 global financial crisis). See Section 4 for details. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table A7
Global GDP nowcast (quarter information) – subsample.

	1980:Q1 – 2008:Q3	2008:Q4 – 2018:Q4
Lag of GDP growth	0.3985 ***	0.4942 ***
	(4.89)	(5.66)
First principal component	0.0007 ***	0.0008 ***
	(4.33)	(6.44)
Constant	0.0055 ***	0.0044 ***
	(6.59)	(5.09)
Observations	114	41
R^2	0.34	0.69

Sources: IMF, Primary Commodity Price System; and IMF staff calculations.
Note: Regress global GDP growth on one-period of its own lag and first principal component of commodity prices (Column 2 of Table A3, Panel 3) using subsamples (before and after 2008 global financial crisis). See Section 4 for details. t statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

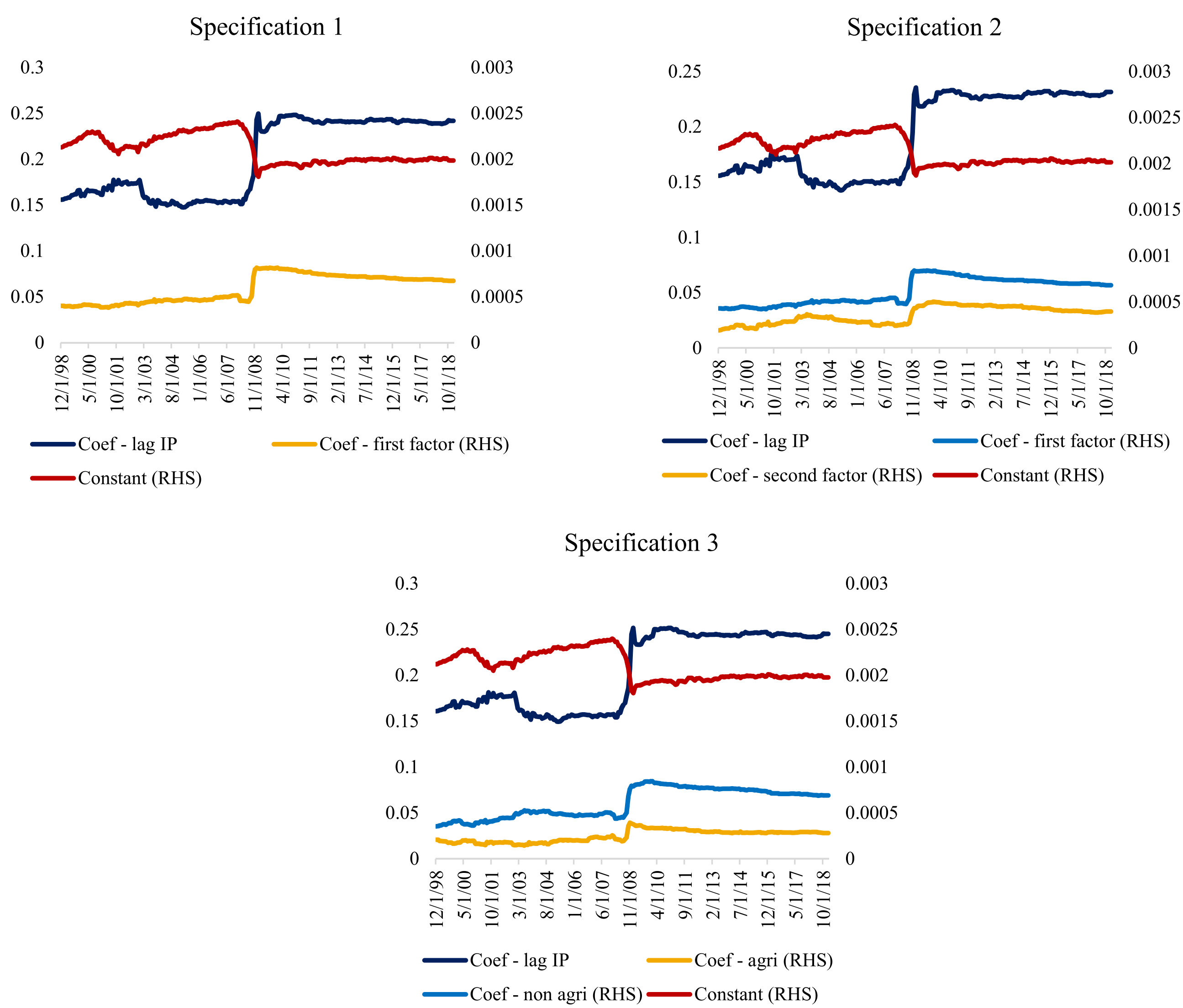

Fig. A1. Regression coefficients for Global Industrial Production Forecast. Note: This panel shows the estimated coefficients from global industrial production (IP) out-of-sample forecasts using different model specifications. Each specification is first estimated using the sample period 1980–1998 and then recursively re-estimated to forecast over 2000–2018. First factor = first principal component; Second factor = second principal components; Agri = first principal component of agricultural commodities; Non agri = first principal component nonagricultural commodities. See Section 3 for details. Date on x-axis represents the end of expanding estimation window.

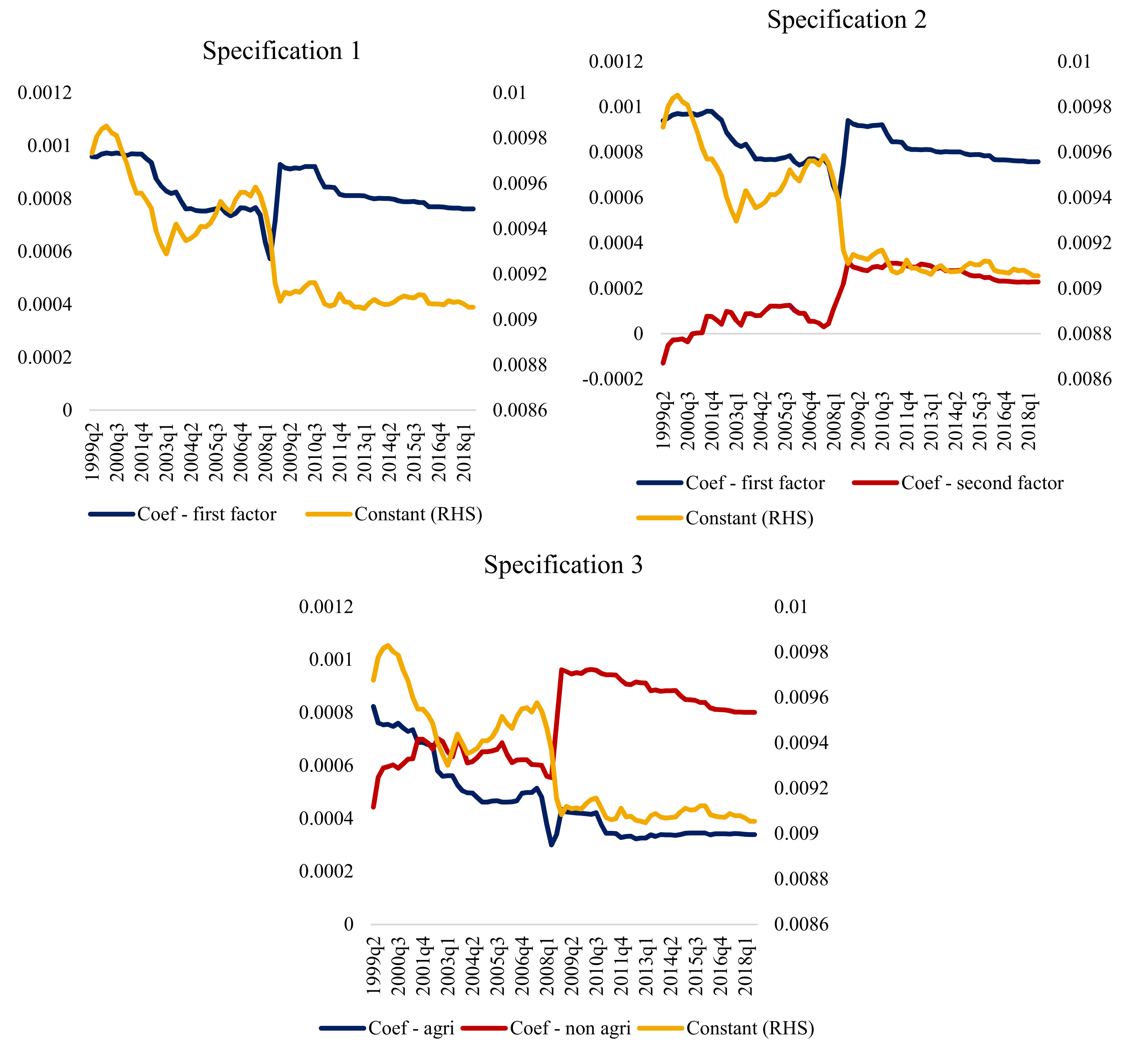

Fig. A2. Regression coefficients for Global GDP Forecast (Quarter Information). Note: This panel shows the estimated coefficients from global GDP out-of-sample forecasts using different model specifications. Each specification is first estimated using the sample period 1980–1998 and then recursively re-estimated to forecast over 2000–2018. First factor = first principal component; Second factor = second principal components; Agri = first principal component of agricultural commodities; Non agri = first principal component nonagricultural commodities. See Section 3 for details. Date on x-axis represents the end of expanding estimation window.

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