10-2023

Measuring Persistent Global Economic Factors with Output, Commodity Price, and Commodity Currency Data

Arabinda Basistha

Richard Startz

Measuring Persistent Global Economic Factors with Output, Commodity Price, and Commodity Currency Data

by

Arabinda Basistha

(West Virginia University)

and

Richard Startz

(University of California, Santa Barbara)

Abstract

In this study we use monthly G7 industrial production data, commodity price index data, and commodity currency exchange rate data in a dynamic factor model to examine the global economic factors useful for commodity price prediction. We differentiate between the dynamic factors by specifying a persistent factor and a non-persistent factor, both as a single global factor using all data and as factors for each category of data. The in-sample predictive performances of the three persistent factors together are better than the non-persistent factors and the single global factors. Out-of-sample outcomes based on forecast combinations also support the presence of predictive information in the persistent factors for overall commodity prices and for most sub-categories of commodity price indexes relative to their means. The gains in forecast accuracy are heterogeneous; ranging from 5 to 7 percent in the 1 to 6 months horizon for the overall commodity prices to a high of around 20 percent for fertilizers in the 12 month horizon in the recent sample. We further show that the information in the persistent factors, especially in the commodity currency exchange rate based persistent factor, can be integrated with other global measures to further improve the predictive performances of the global measures.

Keywords: Dynamic factor model, industrial production, commodity price, commodity currency.

JEL Classification: C51, C53, F62, Q02.

Contact author: Arabinda Basistha, Department of Economics, John Chambers College of Business and Economics, West Virginia University, Morgantown, WV – 26506. Email:arbasistha@mail.wvu.edu. The authors would like to thank the two referees for their detailed comments and suggestions. The authors would also like to thank the participants in the 42nd International Symposium on Forecasting and the 29th International Conference in Computing in Economics and Finance for comments on earlier versions of the paper under different titles.

1. Introduction

Estimation of monthly global economic conditions is a key empirical challenge for understanding global economic dynamics, and for use in many global macroeconomic applications including prediction of commodity prices. Research studies focused on the estimation of global economic conditions have used different types of data sources and methods with heterogeneous outcomes. Data approaches to measurement of this dynamic and unobserved economic concept, usually specified as a single factor or index, can be broadly classified into three categories: output data based approach, price data based approach, and hybrid data approach using multiple sources of information. The methods range from using weighted indexes to aggregate the information to using principal components for estimating the static common components, and dynamic factor models for specifying explicit dynamics in the global economic activity[1]. Recent research by Baumeister and Guerin (2021) lists five global economic measures, and evaluates their predictive performance for forecasting world GDP growth. Among the five measures, the hybrid data based global factor proposed by the authors performs the best, and the other four measures show mixed success. Our aim in this study is to build on the multiple data based approach to estimate global factors that distinguishes between the persistence present in the data. We also examine the usefulness of multiple factor approach relative to a single factor approach, while distinguishing by the persistence present in the factors, for prediction of commodity prices.

In this study, we use a monthly dynamic factor model with disaggregated industrial production data, commodity price index data, and commodity currency exchange rate data to

[1] One of the most frequently used indicator in the output data based approach is the world industrial production index, as recently stressed by Hamilton (2019). In a similar vein, another recently proposed measure is world steel production by Ravazzolo and Vespignani (2020) as steel is a key input for many industrial products. Among the price data based measures, the first was a shipping cost based index proxying for global trade demand introduced by Kilian (2009), and later on refined in Kilian and Zhou (2018), Kilian (2019). Another price data based approach uses real commodity price common factor, initially proposed by West and Wong (2014) as a strong predictor of disaggregated commodity prices. This common commodity price approach was further developed in a dynamic factor model by Delle Chiaie et al. (2022) who show the common factor as closely linked global demand measures. Finally, in a hybrid approach with multiple data sources, a global economic condition based on the common factor of multiple indicators including the world industrial production and select commodity prices was proposed by Baumeister et al. (2020) for the energy markets. This overview is based on a selective list of current approaches discussed in detail in Baumeister and Guerin (2021).

estimate the global economic factors[2]. The data is disaggregated at the country level for industrial production and commodity currencies. The disaggregation is at the sectoral level for the commodity price index data. A dynamic factor model is particularly well equipped to extract the common features present in multiple sources of information with explicit dynamic specifications; a key condition of our estimation goal. Another advantage of the explicit dynamic specification of the unobserved factors in the model is that it allows us to decompose the common factors by their dynamics. Specific to our context, it allows us to specify a potentially non-persistent common factor by imposing zero serial correlation in its dynamics and, therefore, allows us to isolate a separate common factor with higher persistence. This common factor with higher persistence can be more informative with longer term information present in it after removal of the common non-persistent information. In absence of specifying the non-persistent factor, the common dynamic factor will present a weighted average of the common information with zero persistence and higher persistence.

We use the above advantage of the dynamic factor models to estimate the common persistent and non-persistent factors from all three categories of data. Moreover, we further estimate the common persistent and non-persistent factors for each of the three types of data. We examine the predictive information for commodity prices present in the persistent factors and the non-persistent factors from both approaches. Our estimated persistent global factor using all data from three categories show reasonable dynamics with moderately high persistence[3]. It captures the global crisis of 2008, the Asian crisis, and 9/11. The non-persistent global factor dynamics is less intuitive but does show an additional drop during the global crisis of 2008. The persistent factors from industrial production data and commodity price index data show high persistence and positive correlation with each other and with the persistent global factor. The persistent factor from the commodity currency exchange rate show dynamics with lower persistence and negative correlation with the persistent factors of industrial production, commodity prices and the persistent global factor. This is expected as a positive change in the exchange rates implies a

[2] In this study, to distinguish between our estimates and other measures, we will use the term 'global factor(s)' to denote our estimates. The alternative measures for comparison will be denoted as 'global economic measure(s)' or 'global economic activity' or 'global economic condition(s)' or 'global economic indicator(s)'.
[3] We use the terms persistent global factor and non-persistent global when we estimate these factors as common factors from all three categories of data.

depreciation. It should be noted that their mutual correlations are moderate in magnitudes showing presence of independent information in persistent factors of each category of data.

We evaluate our factors using predictive regressions for real commodity price returns using overall price indexes and various sub-categories of indexes. The in-sample predictive performances of the persistent global factor show higher average adjusted R^2s than the non-persistent global factor. However, when the persistent factors from the three categories are used together, the adjusted R^2 measures are usually higher than the persistent global factor showing additional usable information present in each category data. Our persistent factors perform well with respect to five additional measures of global activity. The non-persistent factors are not as informative. Out-of-sample outcomes based on forecast combinations also support the presence of predictive information in the persistent factors for overall commodity prices and for most sub-categories of commodity price indexes relative to their means. The gains in forecast accuracy are heterogeneous; ranging from 5 to 7 percent in the 1 to 6 months horizon for the overall commodity prices to a high of around 20 percent for fertilizers in the 12 month horizon, and the source of the gains is the more recent sample. We further show that the information in the persistent factors, especially in the commodity currency exchange rate based persistent factor, can be integrated with the world industrial production data and a common commodity price factor to further improve their predictive performances. Overall, our empirical evidence shows that the estimation of common persistent factors from multiple sources of information is useful and informative about the global commodity markets and can be flexibly used to further improve predictions in commodity prices. Our analysis highlights the roles of persistent common variation in the commodity currency data, and the necessary dynamic factor model adaptation to extract that variation, in improving the commodity prices forecasts.

Three features of our approach merit further discussion. The first issue is the use of multiple categories of data. One advantage of using this approach is due to data limitations present in a single category. In our case, the output data is limited in many countries when we aim to estimate a global factor. One can address this limitation by incorporating global price data. We augment our global model by using real commodity price indexes based on the evidence presented by Delle Chiaie et al. (2022) showing their strong promise as a global economic indicator. This addition helps us to address the issue of output data availability in other countries as commodity prices are typically global determined. However, an additional benefit of having multiple categories of disaggregated data is the ability to use each category of data flexibly in estimating and examining the common factors present in them, and incorporating that information with similar factors from other categories for predicting commodity prices. We also use this additional benefit to show the informational advantages of this multiple factor approach in our analysis.

The second issue is the use of information present in commodity currency exchange rate data. This selection is motivated by the Chen et al. (2010) study showing their predictive information for commodity prices, but with faster adjustment than commodity prices. This asset price nature of the commodity currency exchange rates opens up the possibility of inclusion of more information in the monthly setup beyond the common movement in commodity prices stressed by Delle Chiaie et al. (2022)[4]. The third issue is the use of the dynamic specification of the factors, and their interpretations in both single global factor and the multiple factors approaches. In the state-space model, we explicitly distinguish between two types of dynamics of the common factors. One common factor is allowed to have persistent dynamics whereas the other common factor is restricted to be serially uncorrelated. The presence of a common but serially uncorrelated factor can be due to multiple reasons; including global weather shocks, temporary geopolitical issues or asset market news in the commodity currency returns. This implies that the persistent global factor, although primarily statistical in nature, is likely related to the underlying global demand factor stressed by Delle Chiaie et al. (2022). We observe this in our results as the estimated persistent global factor is positively correlated with other measures of global demand. The persistent factors from each category of data can then be interpreted as informative about different dimensions of global demand, including their time dimension. We notice this feature in the fit of the predictive regressions where higher gains from the three persistent factors are in the 1 month and 12 month horizons.

[4] Commodity price comovements were also noted and analyzed in Bryne et al. (2013) and Yin and Han (2015). The predictive linkages between commodity prices and commodity currencies were further explored in Groen et al. (2011), and in Pincheira and Hardy (2021) for aluminum prices. Kwas et al. (2021) further analyze industrial metal price forecasting using factor approach with inclusion of exchange rate data.

In section 2, we present our main dynamic factor model, discuss the data and estimation details. We present our main estimates of the global factor, factors from each category of data, and compare with other measures in section 3. We evaluate the performance of our global factor and multiple factors estimates with in-sample predictive regressions analysis in section 4. We conduct our out-of- sample analysis in section 5. We briefly summarize and conclude in section 6.

2. The model, the data, and the estimation details

State-space models for estimating unobserved factors have a long history of applications, including estimating the business cycle features. Our core state-space model specified below closely follows the Stock and Watson (1989) approach of estimating US business cycles with dynamic factors. The approach of factor estimation, as outlined in Lawley and Maxwell (1962), to track an unobserved economic state was introduced in Geweke (1977), Sargent and Sims (1977). Maximum likelihood estimations of the models were further featured in Geweke and Singleton (1980) and Watson and Engle (1983)[5]. We use this approach to understand changes in global economic conditions using multiple categories of variables.

In the model below $y_{i,t}$ represents our observed signal variable i in the set of N variables about the global economy in month t. A dynamic factor analysis isolates the common variations in a set of $y_{i,t}$, with the possibility of multiple common factors, from the idiosyncratic variations in each signal variable. We focus on the common variation as our economic factor measure following the recent literature Delle Chiaie et al. (2022), Baumeister et al. (2020), and Baumeister and Guerin (2021). We further distinguish the common variation in $y_{i,t}$ between a persistent common factor and a non-persistent common factor. The aim is to classify the common information present in $y_{i,t}$ into two factors: one factor carrying longer term common information present in the data whereas the other factor capturing another kind of common information which is present only for the current period. Although our specifications of the factors are primarily statistical processes, the economic motivation for specifying the non-persistent common factor can follow from presence of global weather shocks, temporary geo-political turmoil or asset price news following Chen et al. (2010) where commodity currencies show asset price like behavior.

[5] A meta-analysis of dynamic factor models for predictive purposes was studied in Eickmeier and Ziegler (2008).

For our model specification, it is important to specify the non-persistent common factor simultaneously with the persistent factor so that the persistent factor can absorb the longer term common information in the data whereas the non-persistent factor is expected to capture the serially uncorrelated common information. In the absence of the non-persistent factor in the model, the common dynamic factor will represent a weighted average of the longer term common information and the non-persistent common information in the model. Our factor loadings are estimated which allows for the possibility of no non-persistent common factor in the data if the estimated factor loadings on the non-persistent factor are zero.

The common dynamic factors to be estimated are denoted as $f_{P,t}$, the persistent factor, and $f_{NP,t}$, the non-persistent factor. The idiosyncratic components of each observed signal $y_{i,t}$ are denoted as $z_{i,t}$. The measurement equations for the signal variables of the state-space model below are denoted as equation (1).

$$y_{i,t} = \lambda_{i,P} f_{P,t} + \lambda_{i,NP} f_{NP,t} + z_{i,t}, \quad i = 1, \dots, N. \tag{1}$$

In the above equation $\lambda_{i,P}$ represents the factor loadings of the persistent factor and $\lambda_{i,NP}$ represents the factor loadings of the non-persistent factor. We assume that the state variable, persistent factor, $f_{P,t}$ follows an autoregressive process in the state equation below:

$$\phi(L) f_{P,t} = v_{P,t} \tag{2}$$

where we standardize $v_{P,t} \sim N(0,1)$ as necessary normalization restriction. $\phi(L)$ represents the lag polynomial of the autoregressive process of the persistent factor, $f_{P,t}$. We restrict the next state variable, non-persistent factor, $f_{NP,t}$, to be serially uncorrelated in the state equation below:

$$f_{NP,t} = v_{NP,t} \tag{3}$$

where we standardize $v_{NP,t} \sim N(0,1)$ as necessary normalization restriction. We assume that $v_{P,t}$ and $v_{NP,t}$ are uncorrelated. We further assume that the idiosyncratic components of the observed signal variables, $z_{i,t}$, are serially and mutually uncorrelated. They are treated as the error components of the measurement equations and follow $z_{i,t} \sim N(0, \sigma_i^2)$. We estimate their variances.

In the above model, both the non-persistent factor and the idiosyncratic components exhibit zero serial correlation. The critical difference between the non-persistent factor and the idiosyncratic components is that the idiosyncratic components are restricted to be mutually uncorrelated across different data series whereas the non-persistent factor is allowed to have common information from different data series. In the special case where all non-persistent information in the data do not have any common information, our non-persistent factor is unidentified and its factor loadings are zero. The statistical motivation for our above model specification follows Doz et al. (2012) where an approximate factor model with weak autocorrelations and cross correlations can be consistently estimated by an exact factor model. This quasi-MLE approach builds on White (1980) and is useful in models with large number of variables. The estimation of the full state-space models based on equations (1) to (3) with all data, and its variations, were done using the maximum likelihood methods based on the Kalman filter as outlined in Kim and Nelson (1999). Our core interest is the estimation of the global factors$f_{P,t}$ and $f_{NP,t}$.

Our selection of the signal variables follow literature on global economic measure estimation with certain level of data disaggregation available in each category of data. The data on signal variables are classified into three categories: output, commodity prices, and commodity currency exchange rates. In output, industrial production data is available monthly for many countries and is a useful measure of global activity as the Hamilton (2019) results show. We use G7 countries as they are a substantial part of global economic activity and used in past literature (e.g. Glick and Rogoff (1995), Mitra and Sinclair (2012)) to analyze international economic issues. For commodity prices and global economy, the recent theoretical study by Alquist et al. (2020) provides the general equilibrium model of commodity price comovement and global economic activity. Our study is more closely linked to Della Chiaie et al (2022) showing a single commodity price common factor is empirically closely linked to other measures of the global economy. We use eight distinct sectoral commodity price indexes to capture their common movement. The selected sectors capture all major commodity types with approximately similar number of data series as the other two categories of signal variables. The selection of commodity currencies is driven by the Chen et al. (2010) study showing commodity driven exchange rates can capture information faster than commodity prices, and can serve as a predictor of commodity prices. This faster type of signal enables us to integrate more information in our monthly measures of global economic activity.

Our data is in monthly frequency, from January, 1992 to December, 2020. The timeframe is driven by the availability of commodity price index data. In output, our G7 industrial production data is obtained from OECD Main Economic Indicators. We compute the industrial production growth, annualized. The data on disaggregated commodity price indexes are obtained from IMF Primary Commodity Prices database, deflated by US CPI obtained from FRED database. We use the annualized monthly percentage changes. The commodity indexes used, based on the disaggregated level available from the IMF database, are Food and Beverage, Agricultural Raw Materials, Base Metals, Precious Metals, Fertilizer, Crude Oil, Natural Gas, and Coal. The commodity currencies are monthly returns of Australia, Canada, Chile, Norway, New Zealand, and South Africa currencies, all with respect to the US dollar, obtained from the FRED database. The selection of the currencies is based on Chen et al. (2010) with the addition of Norway. We use the sample from February, 1992 to December, 2019 for estimation of global factors. We standardized all the variables in the dynamic factor model by subtracting their mean and dividing by their standard deviation. The descriptive statistics and the sources of the unstandardized variables we use to estimate the factors are in Table 1.

We also compute 18 non-distinct commodity price index returns including all commodity price index return to represent the global commodity prices, and 54 disaggregated commodity price returns, for predictive evaluations based on the data obtained from IMF Primary Commodity Prices database. Finally, the data on five measures of global economic activity was obtained from Christiane Baumeister's website: https://sites.google.com/site/cjsbaumeister/datasets. The measures, as named in our tables of results, are World Industrial Production, World Steel Production, shipping cost based Kilian Index, Real Commodity Price Factor based on common factor of commodity prices, and Global Economic Condition based on common factor of multiple indicators including the world industrial production and select commodity prices as proposed by Baumeister et al. (2020).

3. Estimates of the persistent and non-persistent factors and their comparisons

We use a parsimonious autoregressive process of order one in our specification of the persistent factor, $f_{P,t}$. The specification is similar to Delle Chiaie et al. (2022) and the key persistence parameter is denoted as ϕ. We estimate the state-space model denoted by equations (1) – (3) four times: once using all 21 signal variables and one time individually for each three categories of data[6]. The parameter estimates of ϕ, the loading coefficients of the persistent factors, and the log likelihoods are reported in Table 2. We denote the model using all 21 variables as the global factors in the table. The models using output data, commodity price data, and commodity currency exchange rate data as each separate category are denoted as output factors, commodity factors, and currency factors respectively in the table. The estimates from the global factors show moderately high persistence of 0.77. The loadings from the persistent factor are all statistically significant with expected positive signs for output and commodity prices and expected negative signs for commodity currencies. To compare the magnitude of the loading coefficients, the weight on the US industrial production growth, denoted by $\lambda_{1,P}$, is the largest among output coefficients although the distribution of loadings is fairly balanced within the G7 countries. The largest loading among the commodity prices is on base metals, denoted by $\lambda_{10,P}$, and the largest loading among the currencies is on Australian Dollar denoted by $\lambda_{16,P}$. We also note that the lowest loading is on precious metals denoted by $\lambda_{11,P}$[7]. Among the loading coefficients (not reported due to space) of the non-persistent factor from the global factors 16 coefficients are statistically significant suggesting a fair amount of common non-persistent variation in the overall data[8].

The smoothed estimates of the persistent factor from global factors model, denoted as persistent global factor, are shown in the top panel of Figure 1. The smoothed estimates of the non-persistent factor from global factors model, denoted as non-persistent global factor, are shown in the bottom panel of Figure 1. We note that the persistent global factor captures the 2008 crisis pretty well, a feature that is present in other global measures. Moreover, the persistent global factor nicely captures the Asian crisis of 1997-1998, and 9/11 from late 2001, as persistent but less severe declines[9] in the global economy. The non-persistent global factor in the bottom

---

[6] We would like to thank an anonymous referee for this suggestion of allowing for more factors than one persistent factor and one non-persistent factor.

[7] We also experimented with dropping precious metals from our data as they are used as assets. The overall estimates do not change substantially but our predictive evaluations show a marginal decline in performance when precious metals are eliminated.

[8] In an earlier version of the paper, we estimated that the coefficient estimate of ϕ drops to 0.45 in absence of specifying the non-persistent factor suggesting a fair amount of common non-persistent movement in the overall data. There was also a large decline in the log-likelihood in that restricted model and a decline in predictive performance.

[9] https://www.eia.gov/finance/markets/crudeoil/spot_prices.php

panel shows a fluctuating pattern as is consistent with its dynamics of zero serial correlation. However it does capture a large fall during the 2008 global financial crisis as well suggesting a transitory component during that period.

In the next three columns of Table 2, we report the parameter estimates for output factors, commodity factors, and the currency factors. We note and compare a few parameters of interest with respect to the global factors estimates. First, we observe that the autoregressive coefficients are higher for the output and commodity factors than the currency factor suggesting a larger influence of these two categories in driving the persistence in the persistent global factor. Second, US is still highest persistent factor loading in the output factors, and Australian Dollar is still highest persistent factor loading in the currency factors. Third, the lowest loading in the commodity factors is still precious metals but the relative importance of the other loadings change a bit. The pattern of the persistent factor loadings in the global factors model is mostly present in the category specific persistent factors as well.

We denote the estimated persistent factors from the model with output factors, commodity factors, and currency factors as persistent output factor, persistent commodity factor, and persistent currency factor. We present them in Figure 2. The top panel shows persistent output factor, the middle panel shows persistent commodity factor, and the bottom panel shows persistent currency factor. In all panels we also show the persistent global factor for comparison. The persistent output factor and the persistent commodity factor show fairly persistent dynamics with positive comovement with the persistent global factor. The persistent currency factor show a fairly low persistence and negative comovement with the persistent global factor. The change in dynamics indicates the presence of independent information in this factor. All of them capture the 2008 global crisis.

In Table 3, we present the mutual correlations of our persistent global factor, persistent output factor, persistent commodity factor, persistent currency factor, non-persistent global factor with five other economic measures used in the literature. The other economic measures are world industrial production index used by Hamilton (2019), world steel production proposed by Ravazzolo and Vespignani (2020), the Kilian index based on Kilian (2009), Kilian and Zhou (2018), Kilian (2019), the real commodity price factor based on West and Wong (2014) and Delle Chiaie et al. (2022), and the global economic condition index developed in Baumeister et al.

(2020) and used in Baumeister and Guerin (2021)[10]. We note that the persistent global factor is positively correlated with all five economic measures. The positive correlation with the real commodity price factor used by Delle Chiaie et al. (2022) as a measure linked to the global demand is indicative that our persistent global factor is also linked to the global demand. Moreover, we note that our persistent global factor also show strong positive correlation with world industrial production used in Delle Chiaie et al. (2022) as a global demand measure and global economic conditions index. The second feature to note is that the correlations of our category specific persistent factors with the real commodity price factor are heterogeneous with persistent commodity factor and persistent currency factor showing stronger correlations. The persistent output factor shows higher correlations with the world industrial production and the global economic conditions index, both containing elements of global demand information. The third feature to note is that the mutual correlations between the persistent output factor, the persistent commodity factor, and the persistent currency factor are consistent with our expectations and moderate in their sizes suggesting presence of fair amount of independent information in each of them.

4. Predictive regression outcomes for commodity returns

We evaluate the information content of our two global factors, persistent global factor and non-persistent global factor, using a predictive regression analysis similar to Hamilton (2019). The parsimonious specification is useful to evaluate and compare the relative predictive information content across different measures of global economic activity. The predictive equation used is:

$$x_{q,t:t+h} = \alpha_{q,g,h} + \gamma_{q,g,h} f_{g,t} + u_{q,g,t+h} \tag{4}$$

where $x_{q,t:t+h}$ is the percentage change of real commodity price of commodity q over the horizon of h months. We use 18 real commodity price indexes for our primary evaluation with special attention to all commodity price index, all commodities price index excluding Gold, fuel (energy) price index, and crude oil price index over 1, 3, 6, and 12 month horizons[11]. We also use

[10] Please note that the specified indexes have been used in other important studies as well. We are using a selective list of references in this study. All five measures were used in Baumeister and Guerin (2021).
[11] The 18 commodity price indexes are all commodity price index, all commodities price index excluding Gold, non-fuel price index, food and beverage price index, food price index, beverage price index,

54 disaggregated commodities over 1, 3, 6 and 12 month horizons for additional analysis. The range of commodity indexes and disaggregated commodities used for this analysis is comparable to earlier studies like West and Wong (2014), Crespo Cuaresma et al. (2021), and Delle Chiaie (2022). The seven monthly global economic measures used individually as predictors are indexed by g, and denoted as $f_{g,t}$, for each commodity and horizon. The global economic measures used are our two global factors ($f_{P,t}$ and $f_{NP,t}$), world industrial production, world steel production, Kilian index, real commodity price factor, and global economic condition.

We evaluate the predictive performance of our category specific persistent and non-persistent factors and compare them with other global measures including our global factors in our next step. We extend equation (4) slightly to allow for multiple factor approach in the following equation:

$$x_{q,t:t+h} = \alpha_{q,P,h} + \sum_{k=1}^{3} \gamma_{q,k,P,h} f_{k,P,t} + u_{q,P,t+h} \tag{5}$$

Equation (5) allows for the three category specific persistent factors, denoted as $f_{k,P,t}$, where $k = 1,2,3$ show the persistent output factor, persistent commodity factor, and persistent currency factor. We label them as persistent three factors in Table 4 to Table 7. Similarly, to analyze the category specific non-persistent factors we use a comparable equation:

$$x_{q,t:t+h} = \alpha_{q,NP,h} + \sum_{k=1}^{3} \gamma_{q,k,NP,h} f_{k,NP,t} + u_{q,NP,t+h} \tag{6}$$

Equation (6) allows for the three category specific non-persistent factors, denoted as $f_{k,NP,t}$, where $k = 1,2,3$ show the non-persistent output factor, non-persistent commodity factor, and non-persistent currency factor. We label them as non-persistent three factors in Table 4 to Table 7. The structure in equations (5) and (6) preserves the all the information we used in estimating our global factors but relaxes the assumption of single global factor in them thereby examining the potential of additional cumulative information due to independent common variation present in each category.

---

industrial inputs price index, agriculture price index, agricultural raw materials index, all metals index, base metals price index, precious metals price index, all metals excluding Gold index, fertilizer index, fuel (energy) index, crude oil (petroleum) price index, natural gas price index, coal price index.

We compute the adjusted R^2s from predictive regressions using our two global factors, three category specific persistent factors together, three category specific non-persistent factors together, and five other global economic measures for each commodity and horizon. A higher adjusted R^2 in each regression indicates a better fit and more predictive information for each kind of economic measure(s) used at each horizon after adjusting the fit for multiple regressors[12]. We report the adjusted R^2s for our main variables (as returns): all commodity price index, all commodity price index excluding Gold, fuel (energy) price index, and crude oil (petroleum) price index. We report the average of adjusted R^2s for 16 commodity price index returns that excludes the two all commodity price indexes mentioned above, and for 54 disaggregated commodity returns. We report the adjusted R^2s and the average adjusted R^2s for each horizon and each economic measure(s) in Tables 4 to 7. We used the data till December 2020 for the commodity returns in this in-sample predictive analysis.

In Table 4, we report the adjusted R^2s for all economic measures for all commodity price indexes (top panel) and for all commodity price indexes excluding Gold (bottom panel). We note three patterns in our results present for both indexes. One, our persistent global factor has higher adjusted R^2s than non-persistent global factor suggesting that the persistent global factor is the more informative factor for commodity prices. This is true for all horizons. The non-persistent global factor is not very informative with mostly low adjusted R^2s. Two, the persistent three factors have higher adjusted R^2s than the persistent global factor at all horizons. The gains are larger at the 1 month horizon and at the 12 month horizon. This suggests that there is additional information present in the multiple factor approach for different time horizons. Similar to the previous result, our persistent three factors also show higher adjusted R^2s than the non-persistent three factors and non-persistent global factors. Three, in comparison with the other five economic measures, our persistent factors have higher adjusted R^2s suggesting presence of additional predictive information for the commodity markets. Among the five measures, the real commodity price measure performs well as given by higher adjusted R^2s. This supports the West and Wong (2014) and Delle Chiaie et al. (2022) studies. The world industrial production index is another strong measure for the commodity markets as shown in Hamilton (2019). Overall, we show that

[12] One can use mean squared error ratios as well for similar information. We chose adjusted R^2 because of ease of comparison as well as to show comparable regression fits with multiple predictors.

our persistent factors have predictive information about the commodity markets with persistent three factors performing well with additional flexibility in modeling.

In Table 5, we report the adjusted R^2s for all economic measures for real fuel (energy) price index (top panel) and for real crude oil (petroleum) price index (bottom panel). The pattern of results from both indexes are very similar to our results in Table 4. The persistent factors, both persistent global factor and persistent three factors, perform well relative to all other measures at all horizons. The gains from the persistent three factors over the persistent global factor is usually high at the 12 month horizon only suggesting that the energy sector was partly driving the gains at the 12 month horizon in Table 4. The non-persistent factors are less informative. The real commodity price factor performs well among other measures. The outcomes of the energy sectors mostly corroborates our previous results on overall commodity prices while highlighting a source of predictive information gain at the 12 month horizon.

In Table 6, we report the average adjusted R^2s for 16 non-distinct real commodity index returns but not including the two all commodity indexes reported in Table 4. The purpose is to examine if our results are robust beyond the specific overall indexes used in Table 4. The pattern of results are very similar to those presented in Table 4. We note the strong performances of our persistent factors with the persistent three factors showing the highest average adjusted R^2s at all horizons. The higher gains are still at the 1 month and the 12 months horizons. We further analyze disaggregated commodity data in Table 7 where we report the average adjusted R^2s for 54 disaggregated real commodity returns. The result show a similar pattern with the persistent three factors providing the highest average adjusted R^2s at all horizons. The gains are higher at the 1 month and at the 12 months horizon. However, we do note that there is heterogeneity in the predictive performances of the persistent factors. The real commodity price factor also performs well among other measures but shows heterogeneity in its predictive performance. The fairly large variation in the predictive performance for disaggregated commodity returns was noted by West and Wong (2014). Overall, the predictive regression evidence indicates that the persistent three factors approach can provide additional predictive information for the commodity markets that can be used with the currently available measures.

5. Out-of-sample evidence based on forecast combinations

We continue with our predictive analysis with out-of-sample evidence using the persistent three factors as our main economic measures based on the results in Section 4 and the flexibility in applications the three persistent factors individually offer. Matching the in-sample results and the out-of-sample outcomes is a difficult issue in applied time series analysis. The issue of relatively weaker outcomes of the out-of-sample results was noted in studies by Inoue and Kilian (2005) and Costantini and Kunst (2021). Both studies discuss how in-sample outcomes may accurately reflect the information in the data generating process but show weaker out-of-sample evidence. A big challenge in our context is the presence of potential instability in forecasting commodity prices as noted by Chen et. al (2010). To address a similar issue in asset prices, where in-sample predictability did not translate to supportive out-of-sample evidence as noted by Welch and Goyal (2008), Rapach, Strauss, and Zhou (2010) took a forecast combination approach in the presence of instability and multiple predictive regressors. We follow their approach in using the forecast combinations of persistent three factors. The forecasts are based on recursively estimating each of the three persistent factors k, denoted as $f_{k,P,t}$. We then use each of factors individually in forming forecasts of commodity return q at horizon h, denoted as $\hat{x}_{q,k,t:t+h}$, using a recursively estimated linear regression as stated below:

$$\hat{x}_{q,k,t:t+h} = \hat{\alpha}_{q,k.P,h|t} + \hat{\gamma}_{q,k,P,h|t} f_{k,P,t|t} \tag{7}$$

We then combine the forecasts of commodity return q at horizon h from the three persistent factors using time-varying weights $w_{q,k,t}$ to form the combined forecast of commodity return q at horizon h and denote it as $\hat{x}_{c,q,t:t+h}$:

$$\hat{x}_{c,q,t:t+h} = \sum_{k=1}^{3} w_{q,k,t} \hat{x}_{q,k,t:t+h} \tag{8}$$

In constructing the weights of the forecast combinations, we follow the widely used inverse squared error approach as applied recently by Ravazzolo and Vespignani (2020) in the global economic measures context and also used by Rapach, Strauss, and Zhou (2010). The approach was originally proposed by Bates and Granger (1969) to allow for relatively more accurate forecasts to have higher weights. In this approach, the weights are constructed using the average of cumulative forecast error squared from each forecasting regressions till time t , denoted as $\hat{\sigma}^2_{q,k,t}$, and using their inverse as the numerator weight for each forecast while the sum of the inverses as the denominator as stated below:

$$w_{q,k,t} = (\hat{\sigma}^2_{q,k,t})^{-1} / \sum_{k=1}^{3}\{(\hat{\sigma}^2_{q,k,t})^{-1}\} \tag{9}$$

Following Ravazzolo and Vespignani (2020), we use equal weights to construct the first forecast combination.

The initial window of estimation is the first half of our sample ending in January, 2006, such that we allow the predictive regressions of all horizons to use our persistent factors from three categories till January, 2006. This allows us to use 168 datapoints out of total 335. Accordingly, our first forecast for the one month horizon is March, 2006, the first forecast for the three month horizon is July, 2006, and we follow that pattern for 6 and 12 months. After that, we follow an expanding window estimation till our usable final sample of December, 2019 for the persistent factors. Our forecasts from the equation below are compared with a constant growth benchmark (denoted as mean) as in Rapach, Strauss, and Zhou (2010) to examine the presence of combined predictive information in the factors. Later, we also compare with our persistent global factor, and check whether our factors can combined with world industrial production or real commodity price factor to improve their forecasting performance. The use of multiple comparisons to better understand the forecasting performance was also suggested in Marcellino (2008).

We follow the Diebold and Mariano (1995) and West (1996) approach for comparing equal forecast accuracy using regression models[13]. Specifically, in our nested model comparison with respect to the mean that usually requires non-standard distributions for inference as noted by Clark and McCracken (2001), we use the Clark and West (2007) MSPE-adjusted tests for equal accuracy in nested models that allows us to use standard normal distribution for inference. For each commodity, we compute the MSPE-adjusted t-statistic for four horizons. However, for the infrequent case of negative long-run variance for longer horizons[14], we use a Bartlett Kernel to compute the MSPE-adjusted t-statistic. Harvey, Leybourne, and Whitehouse (2017) used this

[13] The evaluation presents an additional challenge as our main predictor is a generated regressor. However, a recent study by Goncalves, McCracken and Perron (2017) show that size and power of forecast accuracy tests perform well in finite samples with estimated factors even in nested models.

[14] We have three cases in the post 2010 sample at the 12 month horizon. None of them are statistically significant.

approach to compute and analyze the modified Diebold-Mariano statistic with fairly strong statistical performance.

Our first set of results for the 18 commodity indexes are reported in Table 8. We first note that the t-statistics are statistically significant at least at the 10 percent for one-sided tests, as suggested by Ashley et al. (1980), for both all commodity price indexes and all commodities excluding Gold for upto 6 months horizon. This suggests that our persistent factors do have predictive information for the overall commodity prices. In the sectoral analysis of other indexes, we note good predictive performances for agricultural raw materials, fertilizers, fuel (energy), natural gas, and coal. There is heterogeneity in predictive performances with food, beverage, and precious metals not performing well. The forecasts at the 12 months horizon do not show strong performance with only four out 18 cases being statistically significant. The results are better at the shorter horizons but mostly a mixed performance with substantial heterogeneity.

In Table 9, we use a more recent sample for forecast evaluation starting from 2010. The sample selection was driven by usability due more recent data and for exploring the possibility of how much instability is influencing our outcomes in Table 8. Accordingly, our first forecast for 1 month horizon is for January, 2010 with the rest following a similar pattern as previously discussed. The MSPE-adjusted t-statistics show much better results than in Table 8, especially at the longer horizon of 12 months. Both all commodity price index and all commodities excluding Gold are statistically significant at all four horizons with higher values. Other indexes that are statistically significant in for horizons are industrial inputs, base metals, fertilizer, fuel (energy), natural gas, and coal. Some others like agricultural raw materials and crude oil are statistically significant for three out of four horizons. For 12 months horizon, twelve out 18 indexes are statistically significant, a large improvement from only four in Table 8. We also note that food, beverage, and precious metals continue to show poor predictability, a pattern that will continue in our further analysis. The stronger results in the industrial inputs, base metals, energy, and energy related commodities provide support that our persistent factors are capturing different dimensions of global demand rather than weather shocks which influence food and beverage.

In Figures 3 to 6 we show the cumulative forecast error squared differentials of our combined forecasts from persistent factors with respect to the mean of the given commodity index for our results in Table 9, for all four horizons. We present three indexes for illustrative purposes.

The top panels show the differentials from the all commodity price index, the middle panels show the differentials from the fertilizer index, and lower panels show the differentials from the fuel (energy) index. A decline in the lines imply an improvement in the forecasting accuracy. We note that for both all commodity price index and fuel (energy) index, there is a sharp decline from 2014, for all four horizons. This empirical evidence illustrates the issue of instability in our out-of-sample evidence. It also shows that the gains are in recent sample, and not otherwise, making them more usable. We further note that the forecast accuracy gain in the fertilizer index is more gradual but still starts around 2011-12 and not before. We report the MSPE ratios for 18 commodities with respect to their means for the post 2010 sample in Table 10. The numbers less than one show an improvement in the forecast accuracy. The out-of-sample accuracy gains for all commodity price index are around 7 percent at the 1 month horizon to around 4 percent at the 12 month horizon. The fertilizer index usually show higher gains of upto 20 percent. Please note that all 18 commodity indexes have MSPE ratios less than one at the one month horizon and 14 out of 18 indexes have MSPE ratios less than one at the 12 months horizon.

In Table 11 we present the disaggregated analysis of 54 commodity prices using forecast combinations of our persistent three factors with respect to their historical mean for the post 2010 sample. The analysis sheds light on how our persistent factors are performing for each commodity. The structure of the analysis is similar to the analysis in Table 10 with a more detailed view. The MSPE ratios reveal a similar pattern of outcomes as we noted with indexes. The food, beverage, precious metals do not perform well while energy, fertilizers, base metals, agricultural metals perform well. We note the less than one MSPE ratios for two kinds of coal, three kinds of crude oil, Aluminum, Cobalt, Iron ore, Zinc, Urea, Diammonium Phosphate, and few others for all four horizons. In the one month horizon 42 out of 54 commodities show MSPE ratios less than one, in the three months horizon we note 43 out 54 commodities with less than one MSPE ratios, in the six months horizon, we have 40 out of 54 commodities with than one MSPE ratios, and in the 12 months horizon, we have 33 out of 54 commodities showing less than one MSPE ratios. In sum, our disaggregated results corroborate our results with the indexes with additional details on the specific commodities involved.

We next analyze the performance of our persistent factors with respect to other potential predictors using similar set of information and examine whether the persistent factors can be used to improve forecasts. The out-of-sample evidence starts in March, 2006, as reported in Table 8, since we are often using similar type of information for comparison and not examining the predictive information relative to mean. We first compare our forecasting performance from forecast combinations of three persistent factors to the forecasts from our persistent global factor. Both use the same data but the persistent global factor do impose the assumption of a single persistent factor in all three categories of data. This single factor approach is also more consistent with other measures of global economic activity. We construct the forecasts based on the following direct forecasting approach using the recursively estimated persistent global factor, denoted by $f_{g,P,t|t}$, similar to the model we used for all monthly global measures, including the persistent global factor, in equation (4):

$$\hat{x}_{q,g,t:t+h} = \hat{\alpha}_{q,g,P,h|t} + \hat{\gamma}_{q,g,P,h|t} f_{g,P,t|t} \tag{10}$$

The MSPE ratios are reported in Table 12. The numbers less than one imply improvements in the forecast accuracy in forecast combination from the three persistent factors. The numbers are mostly less than one, with some interesting changes. The all commodities price index shows less than one value for all four horizons with around 10 percent gain in accuracy in the shorter horizons. The gains are heterogeneous but do show the overall pattern that forecast combinations of three persistent factors provide better forecasting outcomes than a single persistent global factor. The exceptions are in natural gas, coal, and 6-12 months horizons of fertilizers. The numbers in those cases suggest that a single persistent global factor could be a valid assumption in the dynamic factor modeling. Overall, the MSPE gains with respect to the single persistent global factor showed that while gains in accuracy from the flexibility of the persistent three factors are mostly present, there could be commodity and horizon specific exceptions to that pattern.

Our next goal is to examine whether the persistent three factors could be integrated with other measures of global economic activity to improve their composite forecasting accuracy. In other words, we examine whether any of our persistent factors can provide additional predictive information that can be used to improve forecasting ability of the available measures. We use world industrial production index and real commodity price factor for as our candidates for global economic activities. The choice is based on two reasons: they perform well in our in-sample predictive analysis, and their easy availability of usable data for comparable out-of-sample analysis. The data availability in the disaggregated form is especially helpful the for real commodity price factor to perform a recursive estimation of the factor. The past literature on commodity prices, e.g. Hamilton (2019), West and Wong (2014) and Delle Chiaie et al. (2022), also connects these two indicators with the overall commodity markets. A further advantage of these two global indicators is that each of them fit nicely to one of the categories of we used in our persistent factors. Our approach is to use forecast combinations of each global indicator and two other persistent factors that are not in the category of the global indicator, one at a time, and examine whether the forecast combination helps improve the forecast accuracy relative to just using the global indicator. A nice feature is it allows us to show the sources of potential gain by the category of data.

We use the world industrial production index data as we used in our previous analysis. We construct the recursively estimated real commodity price factor by using the first principal component of 54 disaggregated real commodity prices that we used. This static factor approach based on principal components was proposed by West and Wong (2014) and is consistent with the findings of single global commodity price factor in Delle Chiaie et al. (2022). Please note that both indicators contain more data than we have used in that category. The world industrial production index uses all OECD countries plus six non-member countries. The 54 disaggregated commodity prices use more information than the eight sectoral indexes we used in estimating our persistent commodity factor. In the following forecasting regression we use the global indicators, $f_{g,t|t}$, one at a time to construct the commodity q, horizon h, specific forecasts, $\hat{x}_{q,g,t:t+h}$:

$$\hat{x}_{q,g,t:t+h} = \hat{\alpha}_{q,g,h|t} + \hat{\gamma}_{q,g,h|t} f_{g,t|t} \tag{11}$$

We then estimate the combined forecasts, $\hat{x}_{c,q,t:t+h}$ from equation (11) and a category-specific persistent factor from equation (7) using time-varying weighted average:

$$\hat{x}_{c,q,t:t+h} = w_{q,k,t}\hat{x}_{q,k,t:t+h} + w_{q,g,t}\hat{x}_{q,g,t:t+h} \tag{12}$$

The weights are constructed, as in the previous analysis, using the average of cumulative forecast error squared from each forecasting regressions, equations (7) and (11), till time t and using their inverse as the numerator weight for each forecast while the sum of the inverses as the denominator as stated below:

$$w_{q,k,t} = (\hat{\sigma}^2_{q,k,t})^{-1}/\{(\hat{\sigma}^2_{q,k,t})^{-1} + \{(\hat{\sigma}^2_{q,g,t})^{-1}\} \quad (13)$$

and $$w_{q,g,t} = (\hat{\sigma}^2_{q,g,t})^{-1}/\{(\hat{\sigma}^2_{q,k,t})^{-1} + \{(\hat{\sigma}^2_{q,g,t})^{-1}\} \quad (14)$$

Specifically, if we are using world industrial production as the global economic indicator, we then use the persistent commodity factor and the persistent currency factor, one at time, to form the combined forecasts. Similarly, we use the persistent output factor and the persistent currency factor, one at time, with the forecasts from real commodity price factor.

In Table 13, we report the MSPE ratios of the combined forecasts using world industrial production index with persistent commodity factor, and persistent currency factor, from post 2010 sample. The MSPE numbers less than one indicate a gain in forecast accuracy relative to forecast using equation (11) with world industrial production index. We report 10 selected commodity indexes due to space considerations and avoid reporting the food and beverage related indexes and precious metals as we find from our previous analysis that our factors are not very informative about them. In the top panel, the outcomes from forecast combinations of the world industrial production and the persistent commodity factors are reported. In the bottom panel, we report the MSPE ratios from using the world industrial production and the persistent currency factor. The MSPE ratios reveal that the persistent currency factor is the more informative factor in this case. The MSPE ratios for the persistent currency factor show numbers less than one for all four horizons for all commodity price index, all commodities excluding Gold, agricultural raw materials index, fuel index, crude oil index and coal index. The numbers are also less than one for all indexes reported in the shorter run till three months and in nine out ten indexes at the six months horizon. The size of the gains are heterogeneous with an average of 5 percent for all commodity price index. The numbers for persistent commodity factor are less favorable. This is not very surprising as we saw in our previous results that there is a fairly strong comovement between the commodity prices and industrial production.

In Table 14, we report the MSPE ratios of the combined forecasts using real commodity price factor from 54 commodity prices with persistent output factor, and persistent currency factor, from post 2010 sample. The MSPE numbers less than one indicate a gain in forecast accuracy relative to forecast using equation (11) with real commodity price factor. We report the same 10 selected commodity indexes as in Table 13. In the top panel, the outcomes from forecast combinations of the commodity price factor and the persistent output factors are reported. In the bottom panel, we report the MSPE ratios from using the real commodity factor and the persistent currency factor. Overall, the MSPE ratios reveal that the additional predictive information is coming from the persistent currency factor at the longer horizon of 12 months. They show numbers less than one for 12 months horizons for all 10 selected indexes suggesting that currency exchange rates and commodity prices carry information about different horizons of commodity prices. We also closely examined the individual squared forecast errors for all commodity price index (not reported). At the one month, three months, and six months horizons for all commodity prices, 48-49 percent squared forecast errors are lower in the forecasts that include commodity currency information with real commodity price factor relative to using just real commodity price factor. Among them, approximately 33 to 38 percent of squared forecast errors are more than 10 percent lower in the forecasts that include commodity currency information with real commodity prices relative to using just real commodity price factor. These numbers highlight the possibility of out-of-sample gains at all horizons in a fairly large portion of the sample considered for the analysis when using the persistent currency factor. The numbers for persistent output factor are less favorable as we saw in our Table 13 results too. While the results confirm that real commodity price factors are robust predictors of commodity prices, as initially proposed by West and Wong (2014), we show that our persistent currency factor can bring in additional predictive information to improve the forecasts at different horizons depending on the global indicator.

6. Summary and conclusion

In this study we use monthly G7 industrial production data, commodity price index data, and commodity currency exchange rate data in a dynamic factor model to examine the global economic factors useful for commodity price prediction. We differentiate between the dynamic factors by specifying a persistent factor and a non-persistent factor, both as a single global factor using all data and as factors for each category of data. The in-sample predictive performances of the persistent three factors framework are better than the non-persistent factors and the single global factors. Out-of-sample outcomes based on forecast combinations also support the presence of predictive information in the persistent factors for overall commodity prices and for most sub-categories of commodity price indexes relative to their means. Our results are stronger for commodities sectors like base metals, energy, and fertilizers, while the results are weaker for food, beverage, and precious metals. The gains in forecast accuracy are heterogeneous; ranging from 5 to 7 percent in the 1 to 6 months horizon for the all commodity price index to a high of around 20 percent for fertilizers index in the 12 month horizon in the recent sample. We further show that the information in the persistent factors, especially in the commodity currency exchange rate based persistent factor, can be integrated with other global measures to further improve the predictive performances of the global measures.

Overall, we conclude that our persistent factors approach with multiple categories of data, especially commodity currency data, contributed to inclusion of additional relevant information for predicting commodity prices. Our dynamic factor approach can be easily adapted to include more sources of information, possibly at different frequencies, to estimate other economic measures where persistence can make a difference in the outcomes. Further research can also adapt the hybrid approach to estimate global economic factors with output, commodity price, and commodity currency data with other kinds of data, while differentiating between persistent and non-persistent factors, to analyze other global economic issues.

References:

Alquist, R., Bhattarai, S. and Coibion, O. 2020. Commodity-price Comovement and Global Economic Activity. *Journal of Monetary Economics*, 112 (C), 41-56.

Ashley, R., Granger, C.W.J., and Schmalensee, R. 1980. Advertising and aggregate consumption: an analysis of causality. *Econometrica*, 48, 1149–1168.

Bates, J. M., and Granger, C. W. 1969. The Combination of Forecasts. *Journal of the Operational Research Society*, 20 (4), 451–468.

Baumeister, C., Korobilis, D. and Lee, T. K. 2020. Energy Markets and Global Economic Conditions. *The Review of Economics and Statistics*, doi: https://doi.org/10.1162/rest_a_00977.

Baumeister, C., and Guérin, P. 2021. A comparison of monthly global indicators for forecasting growth. *International Journal of Forecasting*, 37 (3), 1276-1295.

Byrne, J., Fazio, G. and Fiess, N. 2013. Primary commodity prices: Co-movements, common factors and fundamentals. *Journal of Development Economics*, 101, 16-26.

Clark, T. E., and McCracken, M.W. 2001. Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics*, 105, 85–110.

Clark, T. E., and West, Kenneth D. 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138 (1), 291-311,

Costantini, M., and Kunst, R. M. 2021. On using predictive-ability tests in the selection of time-series prediction models: A Monte Carlo evaluation. *International Journal of Forecasting*, 37 (2), 445-460.

Chen, Y-C., Rogoff, K. S. and Rossi, B. 2010. Can Exchange Rates Forecast Commodity Prices?. *The Quarterly Journal of Economics*, 125(3), 1145-1194.

Crespo C., J., Hlouskova, J., and Obersteiner, M. 2021. Agricultural commodity price dynamics and their determinants: A comprehensive econometric approach. *Journal of Forecasting*, 40 (7), 1245– 1273

Delle Chiaie, S., Ferrara, L. and Giannone, D. 2022. Common Factors of Commodity Prices. *Journal of Applied Econometrics*, 37 (3), 461-476.

Diebold, F.X., and Mariano, R.S. 1995. Comparing predictive accuracy. *Journal of Business and Economics Statistics*, 13, 253-263.

Doz, C., Giannone, D., and Reichlin, L. 2012. A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models. *The Review of Economics and Statistics*, 94 (4), 1014–1024.

Eickmeier, S., and Ziegler, C. 2008. How successful are dynamic factor models at forecasting output and inflation? A meta-analytic approach. *Journal of Forecasting*, 27, 237-265.

Geweke, J. F. 1977. The Dynamic Factor Analysis of Economic Time Series Models. D. Aigner and A. Goldberger (Eds.), *Latent Variables in Socioeconomic Models*, Amsterdam: North-Holland, 365-383.

Geweke, J. F., and Singleton, K. J. 1980. Maximum Likelihood Confirmatory Factor Analysis of Economic Time Series. *International Economic Review*, 22, 37-54.

Glick, R., and Rogoff, K. S. 1995. Global versus country-specific productivity shocks and the current account. *Journal of Monetary Economics*, 35 (1), 159-192.

Gonçalves, S., McCracken, M. W. and Perron, B. (2017). Tests of equal accuracy for nested models with estimated factors, *Journal of Econometrics*, 198 (2), 231-252.

Groen J. J. J., and Pesenti, P. A. 2011. Commodity Prices, Commodity Currencies, and Global Economic Developments. NBER Chapters, in: *Commodity Prices and Markets*, National Bureau of Economic Research, 15-42.

Hamilton, J. D. 2019. Measuring Global Economic Activity. *Journal of Applied Econometrics*; 1–11.

Harvey, D., Leybourne, S. and Whitehouse, E. 2017. Forecast evaluation tests and negative long-run variance estimates in small samples. *International Journal of Forecasting*, 33 (4), 833-847.

Inoue, A., and Kilian, L. 2005. In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use? *Econometric Reviews*, 23 (4), 371-402.

Kilian, L. 2009. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, 99(3), 1053-1069.

Kilian, L., and Zhou, X. 2018. Modeling fluctuations in the global demand for commodities. *Journal of International Money and Finance*, 88 (C), 54-78.

Kilian, L. 2019. Measuring global real economic activity: Do recent critiques hold up to scrutiny?. *Economics Letters*, 178(C), 106-110.

Kim, C-J., and Nelson, C. R. 1999. State-Space Models with Regime Switching. *MIT Press*, Cambridge, MA.

Kwas, M., Paccagnini, A., and Rubaszek, M. 2021. Common factors and the dynamics of industrial metal prices. A forecasting perspective. *Resources Policy*, 74 (C), number S0301420721003299.

Lawley, D. N, and Maxwell, A. E. 1962. Factor Analysis as a Statistical Method. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 12 (3), 209-229.

Marcellino, M. (2008). A Linear Benchmark for Forecasting GDP Growth and Inflation?. *Journal of Forecasting*, 27 (4), 304-340.

Mitra, S., and Sinclair, T. M. 2012. Output Fluctuations in the G-7: An Unobserved Components Approach. *Macroeconomic Dynamics*, 16 (3), 396-422.

Pincheira, P., and Hardy, N.. 2021. Forecasting aluminum prices with commodity currencies. *Resources Policy*, 73 (C), number S0301420721000829.

Rapach, D. E., Strauss, J. K., and Zhou, G. 2010. Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. *The Review of Financial Studies*, 23 (2), 821-862.

Ravazzolo, F., and Vespignani, J. 2020. World steel production: A new monthly indicator of global real economic activity. *Canadian Journal of Economics*, 53: 743-766.

Sargent, T. J., and Sims, C. 1977. Business Cycle Modelling without Pretending to Have Too Much A-Priori Economic Theory. Christopher Sims (Ed.), *New Methods in Business Cycle Research*, Minneapolis: Federal Reserve Bank of Minneapolis.

Stock, J., and Watson, M. 1989. New Indexes of Coincident and Leading Economic Indicators. *NBER Macroeconomics Annual*, 1989 (4), National Bureau of Economic Research, 351-409.

Watson, M., and Engle, R. 1983. Alternative algorithms for the estimation of dynamic factor, mimic and varying coefficient regression models. *Journal of Econometrics*, 23 (3), 385-400

Welch, I., and Goyal, A. 2008. A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *The Review of Financial Studies*, 21 (4), 1455–1508.

West, K. D. 1996. Asymptotic Inference about Predictive Ability. *Econometrica*, 64, 1067-1084.

West, K. D., and Wong, K-F. 2014. A factor model for co-movements of commodity prices. *Journal of International Money and Finance*, 42, 289-309.

White, H. 1982. Maximum Likelihood Estimation of Misspecified Models. *Econometrica*, 50 (1), 1-25.

Yin, L., and Han, L. 2015. Co-movements in Commodity Prices: Global, Sectoral and Commodity-specific Factors, *Economics Letters*, 126 (C), 96-100.

Table 1: Descriptive Statistics of Data for Estimating Global Factors and Source

Type of Indicators	Number of Series	Pooled Mean	Average S. D.	Source and Details
Industrial Production growth	7	0.68	14.83	OECD, Main Economic Indicators. G7 countries.
Real Commodity Index Returns	8	0.70	58.46	IMF Primary Commodity Prices. Deflated by US CPI.
Commodity Currency Exchange Rate Returns	6	0.14	2.56	FRED database at Federal Reserve Bank of St. Louis. National Currency to US Dollar Exchange Rate: Average of Daily Rates.

Note: The data is monthly, from 1992:2 to 2019:12. S. D. implies standard deviation.

Table 2: Key Parameter Estimates for the Global Economic Factors

	Global Factors	Output Factors	Commodity Factors	Currency Factors
$\boldsymbol{\phi}$	0.767 (0.05)	0.859 (0.04)	0.724 (0.05)	0.465 (0.06)
$\boldsymbol{\lambda_{1,P}}$	0.301 (0.04)	0.310 (0.04)	-	-
$\boldsymbol{\lambda_{2,P}}$	0.203 (0.04)	0.125 (0.03)	-	-
$\boldsymbol{\lambda_{3,P}}$	0.224 (0.04)	0.214 (0.04)	-	-
$\boldsymbol{\lambda_{4,P}}$	0.220 (0.04)	0.128 (0.03)	-	-
$\boldsymbol{\lambda_{5,P}}$	0.263 (0.04)	0.168 (0.04)	-	-
$\boldsymbol{\lambda_{6,P}}$	0.270 (0.04)	0.183 (0.04)	-	-
$\boldsymbol{\lambda_{7,P}}$	0.273 (0.04)	0.186 (0.04)	-	-
$\boldsymbol{\lambda_{8,P}}$	0.204 (0.05)	-	0.230 (0.05)	-
$\boldsymbol{\lambda_{9,P}}$	0.261 (0.04)	-	0.310 (0.05)	-
$\boldsymbol{\lambda_{10,P}}$	0.303 (0.05)	-	0.298 (0.06)	-
$\boldsymbol{\lambda_{11,P}}$	0.106 (0.05)	-	0.160 (0.05)	-
$\boldsymbol{\lambda_{12,P}}$	0.173 (0.04)	-	0.358 (0.06)	-
$\boldsymbol{\lambda_{13,P}}$	0.253 (0.04)	-	0.291 (0.05)	-
$\boldsymbol{\lambda_{14,P}}$	0.151 (0.04)	-	0.221 (0.05)	-
$\boldsymbol{\lambda_{15,P}}$	0.281 (0.04)	-	0.385 (0.05)	-
$\boldsymbol{\lambda_{16,P}}$	-0.284 (0.07)	-	-	0.703 (0.10)
$\boldsymbol{\lambda_{17,P}}$	-0.241 (0.06)	-	-	0.650 (0.05)
$\boldsymbol{\lambda_{18,P}}$	-0.221 (0.05)	-	-	0.513 (0.05)
$\boldsymbol{\lambda_{19,P}}$	-0.228 (0.05)	-	-	0.639 (0.06)
$\boldsymbol{\lambda_{20,P}}$	-0.266 (0.06)	-	-	0.627 (0.07)
$\boldsymbol{\lambda_{21,P}}$	-0.198 (0.05)	-	-	0.557 (0.05)
Log Likelihood	-9140.338	-3140.534	-3608.469	-2362.466

Note: Standard errors are reported in the parentheses. The estimated loadings of the non-persistent factors and the estimated variances of the idiosyncratic components are not reported due to space concerns.$\lambda_{1,P} - \lambda_{7,P}$ denote factor loadings of output from U.S., U.K., Canada, France, Germany, Italy, and Japan respectively. $\lambda_{8,P} - \lambda_{15,P}$ denote factor loadings of commodities using food and beverage, agricultural raw materials, base metals, precious metals, fertilizer, crude oil, natural gas, and coal respectively. $\lambda_{16,P} - \lambda_{21,P}$ denote factor loadings of currencies from Australia, Canada, Chile, Norway, New Zealand, and South Africa respectively.

Table 3: Correlations between the Global Economic Measures

Measures	Persistent Global Factor	Persistent Output Factor	Persistent Commodity Factor	Persistent Currency Factor
World Industrial Production	0.756	0.681	0.456	-0.234
World Steel Production	0.348	0.255	0.289	-0.238
Kilian Index	0.222	0.018	0.431	-0.148
Real Commodity Price Factor	0.574	0.245	0.593	-0.645
Global Economic Condition	0.715	0.811	0.402	-0.289
Persistent Global Factor	1.000	-	-	-
Non-persistent Global Factor	0.092	-0.259	0.198	-0.835
Persistent Output Factor,	0.813	1.000	-	-
Persistent Commodity Factor	0.774	0.427	1.000	-
Persistent Currency Factor	-0.562	-0.192	-0.509	1.000

Note: The Persistent Global Factor and the Non-Persistent Global Factor are from the model using 21 data series with data on output growth, real commodity returns and commodity currency returns. The Persistent Output Factor is from the model using G7 output growth data series. The Persistent Commodity Factor is from the model using eight real commodity index returns data series. The Persistent Currency Factor is from the model using six commodity currency returns data series. The correlations between the five other measures of global economy, in the first five rows, range from 0.0 to a high of 0.62 (between World Industrial Production and Global Economic Condition).

Table 4: Adjusted R^2s in Predictive Regressions with Global Economic Measures

Measures	1 Month	3 Months	6 Months	12 Months
	All Commodity Price Index			
World Industrial Production	0.068	0.079	0.056	0.012
World Steel Production	0.028	0.012	0.006	-0.002
Kilian Index	0.017	0.018	0.010	0.006
Real Commodity Price Factor	0.120	0.144	0.115	0.036
Global Economic Condition	0.050	0.040	0.025	0.005
Persistent Global Factor	0.216	0.220	0.140	0.043
Non-persistent Global Factor	0.011	0.010	0.022	0.026
Persistent Three Factors	0.253	0.229	0.144	0.077
Non-persistent Three Factors	0.018	0.030	0.041	0.043
	All Commodity Price Index Excluding Gold			
World Industrial Production	0.070	0.080	0.057	0.013
World Steel Production	0.028	0.012	0.006	-0.001
Kilian Index	0.016	0.016	0.008	0.004
Real Commodity Price Factor	0.117	0.143	0.114	0.036
Global Economic Condition	0.053	0.042	0.027	0.008
Persistent Global Factor	0.219	0.226	0.145	0.047
Non-persistent Global Factor	0.009	0.010	0.021	0.025
Persistent Three Factors	0.255	0.235	0.150	0.080
Non-persistent Three Factors	0.017	0.030	0.040	0.042

Note: The numbers represent adjusted R^2 values for predictive regressions of real all commodity returns (with and without Gold) at each horizon on each global economic measure(s). The regressions include an intercept.

Table 5: Adjusted R^2s in Predictive Regressions with Global Economic Measures on Energy

Measures	1 Month	3 Months	6 Months	12 Months
	Fuel (Energy) Index			
World Industrial Production	0.053	0.061	0.052	0.014
World Steel Production	0.032	0.016	0.010	-0.001
Kilian Index	0.008	0.006	0.001	-0.001
Real Commodity Price Factor	0.059	0.090	0.092	0.029
Global Economic Condition	0.042	0.036	0.029	0.014
Persistent Global Factor	0.161	0.183	0.138	0.052
Non-persistent Global Factor	0.002	0.004	0.016	0.018
Persistent Three Factors	0.185	0.190	0.139	0.075
Non-persistent Three Factors	0.012	0.020	0.031	0.024
	Crude Oil (Petroleum) Price Index			
World Industrial Production	0.034	0.024	0.018	-0.001
World Steel Production	0.028	0.012	0.002	-0.003
Kilian Index	0.000	-0.002	-0.003	-0.003
Real Commodity Price Factor	0.048	0.071	0.064	0.009
Global Economic Condition	0.031	0.014	0.005	0.000
Persistent Global Factor	0.104	0.107	0.064	0.014
Non-persistent Global Factor	0.005	0.016	0.023	0.020
Persistent Three Factors	0.123	0.121	0.073	0.045
Non-persistent Three Factors	0.017	0.029	0.031	0.017

Note: The numbers represent adjusted R^2 values for predictive regressions of real fuel (energy) returns and real crude oil (based on spot price average of Brent, WTI, and Dubai Fateh) returns at each horizon on each global economic measure(s). The regressions include an intercept.

Table 6: Average adjusted R^2s in Predictive Regressions with Global Economic Measures

Measures	1 Month	3 Months	6 Months	12 Months
	Average R^2s from 16 Commodity Price Indexes			
World Industrial Production	0.028	0.043	0.033	0.018
World Steel Production	0.014	0.004	0.003	0.000
Kilian Index	0.012	0.019	0.021	0.021
Real Commodity Price Factor	0.066	0.075	0.060	0.028
Global Economic Condition	0.018	0.019	0.017	0.025
Persistent Global Factor	0.095	0.107	0.077	0.043
Non-persistent Global Factor	0.010	0.006	0.015	0.017
Persistent Three Factors	0.121	0.114	0.090	0.073
Non-persistent Three Factors	0.016	0.017	0.027	0.030

Note: The numbers represent average of adjusted R^2 values for predictive regressions of real commodity returns on 16 indexes, excluding real all commodity returns (with and without Gold), at each horizon on each global economic measure(s). The regressions include an intercept.

Table 7: Average adjusted R^2s in Predictive Regressions on Disaggregated Commodity Prices

Measures	1 Month	3 Months	6 Months	12 Months
	Average adjusted R^2s from 54 Commodity Prices			
World Industrial Production	0.016	0.025	0.022	0.016
World Steel Production	0.008	0.005	0.003	0.001
Kilian Index	0.008	0.016	0.021	0.031
Real Commodity Price Factor	0.032	0.043	0.038	0.020
Global Economic Condition	0.014	0.018	0.018	0.020
Persistent Global Factor	0.046	0.060	0.050	0.034
Non-persistent Global Factor	0.007	0.007	0.009	0.009
Persistent Three Factors	0.061	0.073	0.071	0.064
Non-persistent Three Factors	0.007	0.011	0.016	0.015

Note: The numbers represent average of adjusted R^2 values for predictive regressions of real commodity returns on 54 commodity prices at each horizon on each global economic measure(s). The regressions include an intercept.

Table 8: MSPE-adjusted Equal Accuracy Test on Commodity Price Indexes

Commodity Indexes	1 Month	3 Months	6 Months	12 Months
All Commodity Price Index	2.497*	1.358*	2.017*	0.032
All Commodities Index excluding Gold	2.523*	1.357*	2.020*	0.120
Non-Fuel Price Index	2.129*	0.430	0.207	-0.275
Food and Beverage Price Index	0.774	-0.483	-0.239	-0.619
Food Price Index	0.603	-0.615	-0.293	-0.631
Beverage Price Index	0.661	1.322*	0.782	0.518
Industrial Inputs Price Index	2.584*	1.239	-0.223	-0.857
Agriculture Price Index	1.285*	-0.109	-0.029	-0.484
Agricultural Raw Materials Index	2.644*	1.804*	1.698*	0.251
All Metals Index	1.365*	0.156	-0.874	-0.752
Base Metals Price Index	2.284*	1.094	-0.409	-0.991
Precious Metals Price Index	-0.634	-1.177	-0.398	0.825
All Metals Ex Gold Index	2.192*	0.969	-0.438	-1.081
Fertilizer Index	3.017*	2.723*	2.021*	3.790*
Fuel (Energy) Index	2.459*	1.397*	1.922*	1.809*
Crude Oil (petroleum) Price index	1.544*	0.370	0.457	-0.254
Natural Gas Price Index	2.632*	2.032*	1.721*	1.810*
Coal Price Index	2.378*	1.757*	3.454*	3.303*

Note: The numbers represent MSPE-adjusted t-statistics to test for equal accuracy of out-of-sample forecasts in nested models as presented in Clark and West (2007) for real commodity returns on 18 indexes. The benchmark is the mean, and the alternative is the forecast average using inverse squared prediction errors from three persistent factors. * indicates statistically significant at 10 percent level using one-sided tests.

Table 9: MSPE-adjusted Equal Accuracy Test on Commodity Price Indexes from 2010

Commodity Indexes	1 Month	3 Months	6 Months	12 Months
All Commodity Price Index	2.989*	1.658*	2.184*	2.580*
All Commodities Index excluding Gold	2.965*	1.684*	2.242*	2.719*
Non-Fuel Price Index	3.618*	1.222	1.316*	1.338*
Food and Beverage Price Index	1.555*	0.862	0.976	0.079
Food Price Index	1.374*	0.788	0.886	0.102
Beverage Price Index	1.273	1.042	1.405*	-0.466
Industrial Inputs Price Index	3.977*	1.428*	1.730*	2.059*
Agriculture Price Index	1.955*	1.047	1.078	0.351
Agricultural Raw Materials Index	3.112*	1.407*	1.140	3.380*
All Metals Index	3.255*	1.019	1.277	1.128
Base Metals Price Index	3.760*	1.316*	1.723*	1.964*
Precious Metals Price Index	1.109	-0.690	-1.491	-0.043
All Metals Ex Gold Index	3.731*	1.273	1.618*	1.811*
Fertilizer Index	5.281*	2.344*	1.860*	2.746*
Fuel (Energy) Index	2.301*	1.724*	2.534*	2.828*
Crude Oil (petroleum) Price index	1.895*	1.188	2.373*	3.753*
Natural Gas Price Index	1.631*	1.991*	2.471*	2.156*
Coal Price Index	2.656*	1.295*	1.896*	4.269*

Note: The numbers represent MSPE-adjusted t-statistics to test for equal accuracy of out-of-sample forecasts in nested models as presented in Clark and West (2007) for real commodity returns on 18 indexes. The benchmark is the mean, and the alternative is the forecast average using inverse squared prediction errors from three persistent factors. * indicates statistically significant at 10 percent level using one-sided tests.

Table 10: MSPE Ratios Relative to Mean from 2010

Commodity Indexes	1 Month	3 Months	6 Months	12 Months
All Commodity Price Index	0.926	0.948	0.932	0.963
All Commodities Index excluding Gold	0.929	0.948	0.933	0.963
Non-Fuel Price Index	0.927	0.967	0.972	0.986
Food and Beverage Price Index	0.984	0.986	0.987	1.003
Food Price Index	0.986	0.988	0.989	1.002
Beverage Price Index	0.991	0.987	0.978	1.008
Industrial Inputs Price Index	0.927	0.964	0.964	0.977
Agriculture Price Index	0.974	0.979	0.983	0.999
Agricultural Raw Materials Index	0.939	0.958	0.977	0.986
All Metals Index	0.941	0.980	0.977	0.986
Base Metals Price Index	0.934	0.970	0.961	0.977
Precious Metals Price Index	0.991	1.006	1.013	1.003
All Metals Ex Gold Index	0.933	0.972	0.964	0.979
Fertilizer Index	0.830	0.944	0.932	0.806
Fuel (Energy) Index	0.952	0.956	0.936	0.960
Crude Oil (petroleum) Price index	0.965	0.978	0.959	0.973
Natural Gas Price Index	0.980	0.950	0.920	0.924
Coal Price Index	0.953	0.974	0.970	0.967

Note: The numbers represent out-of-sample MSPE ratios for real commodity returns on 18 indexes. The denominator is the MSPE from forecasts using the historical mean. The numerator is the MSPE from forecast average using inverse squared prediction errors from three persistent factors and an intercept.

Table 11: MSPE Ratios of Disaggregated Commodity Prices Relative to the Mean from 2010

Commodities	1 Month	3 Months	6 Months	12 Months
Aluminum	0.993	0.992	0.950	0.976
Bananas	1.011	0.981	0.977	1.014
Barley	0.993	0.972	0.989	0.998
Beef	1.002	1.000	1.007	1.010
Coal, Australian	0.950	0.962	0.955	0.958
Coal, South African	0.972	0.991	0.988	0.983
Cocoa	0.989	0.998	1.004	0.999
Coffee, Arabica	0.998	0.999	0.989	1.007
Coffee, Robusta	0.986	0.945	0.933	1.010
Rapeseed oil	0.960	0.991	0.988	1.019
Copper	0.961	1.020	0.978	0.978
Cotton	0.988	0.980	0.993	1.005
Fishmeal	1.000	0.999	0.989	1.038
Groundnuts	0.994	0.984	0.987	0.991
Hides	0.989	1.011	1.018	0.977
Iron Ore	0.984	0.992	0.981	0.975
Lamb	0.972	0.983	1.002	1.000
Lead	0.993	0.990	0.993	0.977
Soft Logs	1.006	1.000	1.008	1.063
Hard Logs	1.018	1.023	0.994	0.998
Maize (corn)	0.993	0.977	0.985	0.980
Natural Gas, Netherlands	0.983	0.952	0.922	0.900
Natural Gas, Japan	0.996	0.965	0.942	0.954
Natural Gas, Henry Hub	1.009	0.998	0.992	1.009
Nickel	0.960	0.978	0.979	1.009
Crude Oil, Brent	0.955	0.972	0.957	0.974
Crude Oil, Dubai Fateh	0.945	0.968	0.956	0.976
Crude Oil, WTI	0.979	0.993	0.966	0.978

Commodities	1 Month	3 Months	6 Months	12 Months
Olive Oil	1.003	1.013	1.004	0.998
Swine (pork)	1.000	0.997	0.973	1.007
Poultry (chicken)	0.998	1.003	0.994	0.999
Rice	0.988	0.960	0.986	0.972
Rubber	0.922	0.970	0.996	0.982
Fish (salmon)	1.002	1.011	1.001	0.972
Hard Sawnwood	0.986	0.990	0.992	0.997
Soft Sawnwood	0.995	0.998	0.996	1.000
Shrimp	0.988	1.007	1.037	1.015
Sunflower oil	0.969	0.991	0.966	1.026
Tea	1.003	0.997	1.014	1.009
Tin	0.972	1.013	0.999	1.001
Uranium	1.002	0.983	0.977	0.963
Wheat	0.995	0.997	0.977	0.974
Sorghum	0.995	0.991	0.985	0.980
Wool, coarse	0.978	0.995	1.014	1.044
Wool, fine	0.960	0.978	0.986	1.010
Zinc	0.991	0.991	0.985	0.976
Cobalt	0.951	0.976	0.962	0.978
Gold	0.996	1.007	1.009	1.001
Silver	0.986	1.002	1.027	1.007
Palladium	0.976	0.994	1.002	1.022
Platinum	0.965	0.999	1.002	0.997
Urea	0.866	0.966	0.968	0.878
Potassium Chloride	1.008	1.010	0.963	0.866
Diammonium phosphate	0.806	0.820	0.774	0.840

Note: The numbers represent out-of-sample MSPE ratios for real commodity returns on 54 commodity real returns. The denominator is the MSPE from forecasts using the historical mean. The numerator is the MSPE from forecast average using inverse squared prediction errors from three persistent factors and an intercept.

Table 12: MSPE Ratios Relative to Persistent Global Factor

Commodity Indexes	1 Month	3 Months	6 Months	12 Months
All Commodity Price Index	0.894	0.884	0.982	0.935
All Commodities Index excluding Gold	0.900	0.888	0.985	0.944
Non-Fuel Price Index	0.919	0.897	0.942	0.894
Food and Beverage Price Index	0.967	0.909	0.951	0.994
Food Price Index	0.973	0.919	0.962	1.003
Beverage Price Index	0.955	0.892	0.880	0.924
Industrial Inputs Price Index	0.938	0.942	0.930	0.859
Agriculture Price Index	0.966	0.912	0.945	0.970
Agricultural Raw Materials Index	0.968	0.985	0.954	0.895
All Metals Index	0.927	0.944	0.944	0.819
Base Metals Price Index	0.935	0.934	0.925	0.842
Precious Metals Price Index	0.970	0.989	0.988	0.855
All Metals Ex Gold Index	0.924	0.930	0.939	0.861
Fertilizer Index	0.772	0.900	1.082	1.113
Fuel (Energy) Index	0.916	0.911	0.991	0.954
Crude Oil (petroleum) Price index	0.883	0.850	0.929	0.920
Natural Gas Price Index	1.036	1.011	1.037	1.047
Coal Price Index	1.012	1.057	1.067	1.007

Note: The numbers represent out-of-sample MSPE ratios for real commodity returns on 18 indexes. The denominator is the MSPE from forecasts using Persistent Global Factor and an intercept. The numerator is the MSPE from forecast average using inverse squared prediction errors from three persistent factors and an intercept.

Table 13: MSPE Ratios with World Industrial Production

Commodity Indexes	1 Month	3 Months	6 Months	12 Months
	With Persistent Commodity Factor			
All Commodity Price Index	1.003	1.001	1.015	1.068
All Commodities Index excluding Gold	1.001	1.002	1.015	1.066
Industrial Inputs Price Index	1.010	1.034	1.025	1.066
Agricultural Raw Materials Index	1.003	1.031	1.031	1.014
All Metals Index	1.017	1.016	1.012	1.074
Base Metals Price Index	1.012	1.029	1.021	1.074
Fertilizer Index	0.793	0.937	1.001	1.023
Fuel (Energy) Index	0.996	1.003	1.010	1.051
Crude Oil (petroleum) Price index	0.990	0.982	0.993	1.039
Coal Price Index	1.004	1.020	1.035	1.075
	With Persistent Currency Factor			
All Commodity Price Index	0.938	0.957	0.943	0.976
All Commodities Index excluding Gold	0.941	0.960	0.946	0.976
Industrial Inputs Price Index	0.964	0.967	0.942	1.001
Agricultural Raw Materials Index	0.988	0.994	0.977	0.977
All Metals Index	0.962	0.956	0.935	1.005
Base Metals Price Index	0.964	0.963	0.934	1.002
Fertilizer Index	0.940	0.962	1.006	0.971
Fuel (Energy) Index	0.949	0.971	0.952	0.971
Crude Oil (petroleum) Price index	0.955	0.961	0.947	0.977
Coal Price Index	0.974	0.997	0.957	0.969

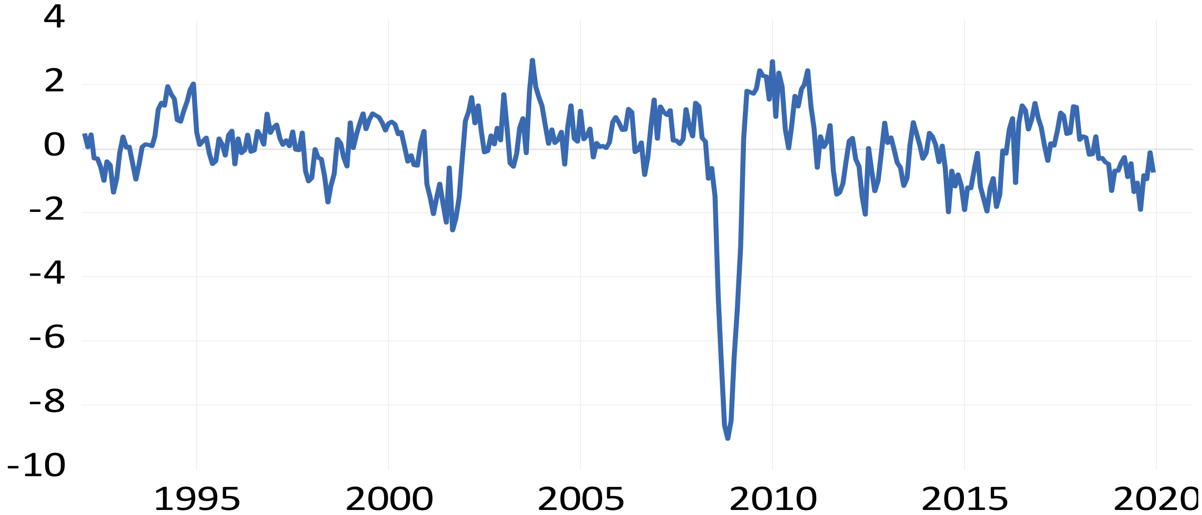
Note: The numbers represent out-of-sample MSPE ratios for real commodity returns on 10 selected indexes. The denominator is the MSPE from forecasts using World Industrial Production and an intercept. The numerator is the MSPE from forecast average using inverse squared prediction errors from the specific persistent factor, World Industrial Production and an intercept.

Table 14: MSPE Ratios with Real Commodity Price Factor

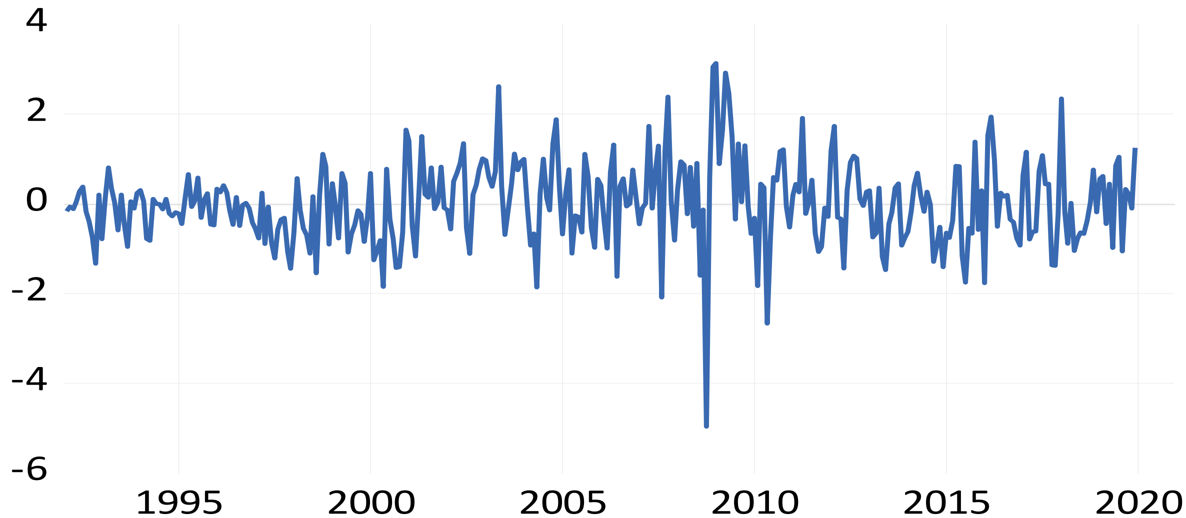
Commodity Indexes	1 Month	3 Months	6 Months	12 Months
	With Persistent Output Factor			
All Commodity Price Index	1.048	1.089	1.069	0.994
All Commodities Index excluding Gold	1.045	1.087	1.067	0.996
Industrial Inputs Price Index	1.033	1.057	1.087	0.959
Agricultural Raw Materials Index	1.020	1.040	1.033	0.988
All Metals Index	1.043	1.050	1.073	0.912
Base Metals Price Index	1.032	1.055	1.094	0.957
Fertilizer Index	1.034	1.005	0.989	0.957
Fuel (Energy) Index	1.027	1.062	1.049	1.004
Crude Oil (petroleum) Price index	1.046	1.092	1.070	1.009
Coal Price Index	1.005	1.045	1.076	1.003
	With Persistent Currency Factor			
All Commodity Price Index	1.009	1.026	0.995	0.973
All Commodities Index excluding Gold	1.010	1.030	0.996	0.974
Industrial Inputs Price Index	1.008	1.006	0.981	0.967
Agricultural Raw Materials Index	1.014	1.027	1.002	0.981
All Metals Index	1.010	0.994	0.972	0.962
Base Metals Price Index	1.006	1.002	0.977	0.965
Fertilizer Index	1.006	1.000	1.017	0.985
Fuel (Energy) Index	1.001	1.030	0.998	0.977
Crude Oil (petroleum) Price index	1.001	1.024	0.991	0.976
Coal Price Index	1.002	1.026	1.006	0.980

Note: The numbers represent out-of-sample MSPE ratios for real commodity returns on 10 selected indexes. The denominator is the MSPE from forecasts using a common component of 54 real commodity returns and an intercept. The numerator is the MSPE from forecast average using inverse squared prediction errors from the specific persistent factor, the common component of 54 real commodity returns, and an intercept.

Figure 1: Two-sided Estimates of Global Economic Factors



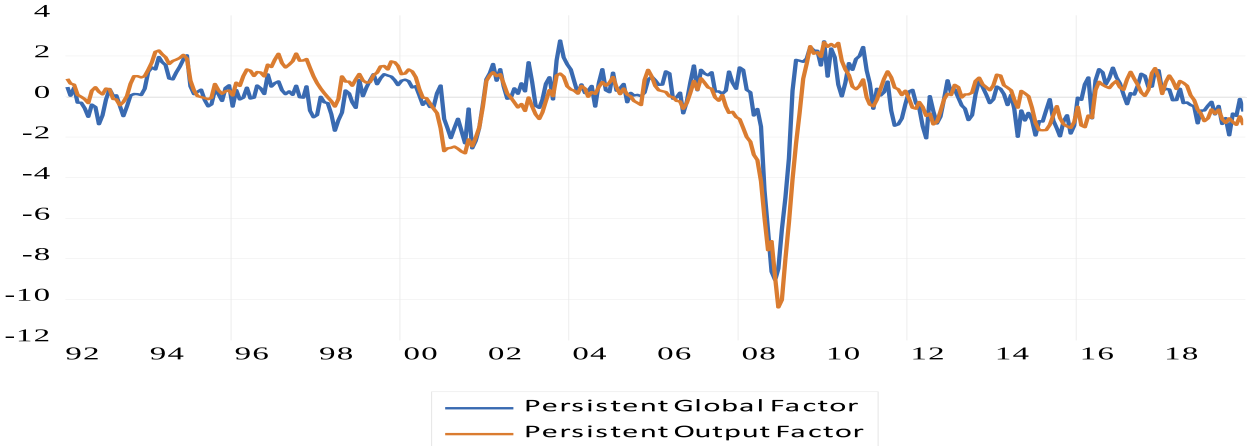
Persistent Global Factor

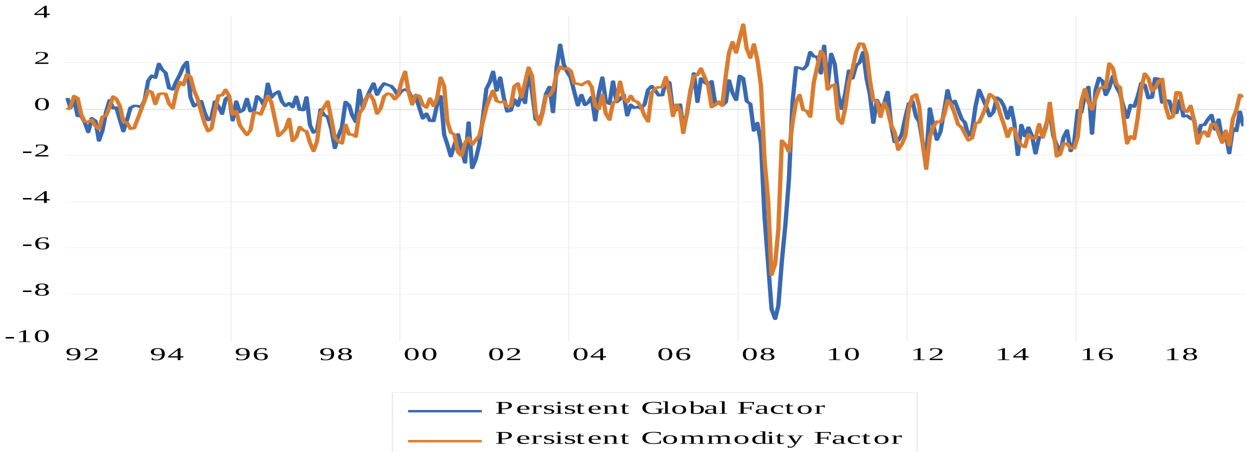


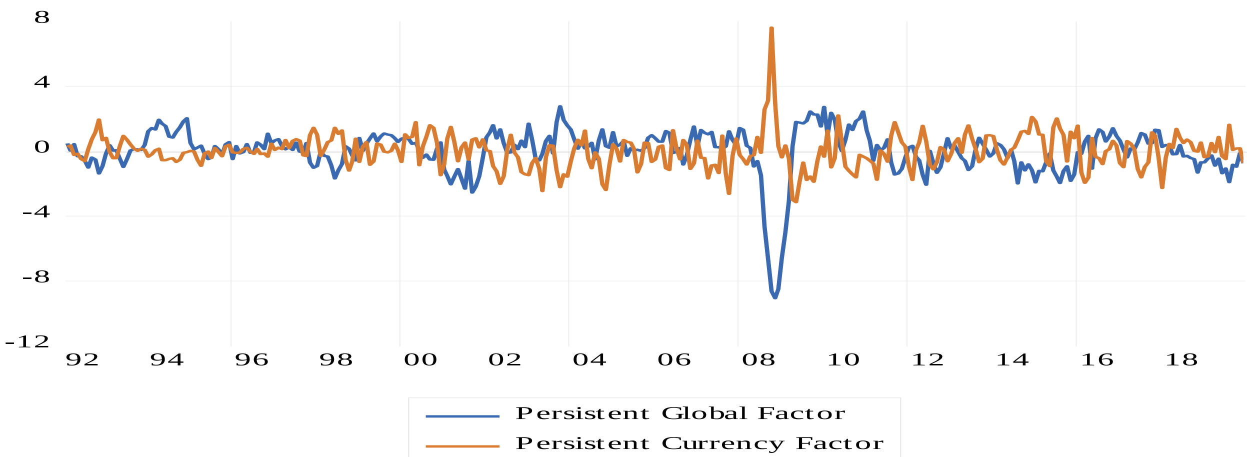
Non-persistent Global Factor

Note: The two-sided (smoothed) monthly estimates of the Persistent Global Factor and the Non-Persistent Global Factor are from the model using 21 data series. The data includes G7 industrial production, real commodity price index returns (8 sectors), and 6 commodity currency exchange rate returns.

Figure 2: Persistent Factors from Output, Commodity, and Currency Models

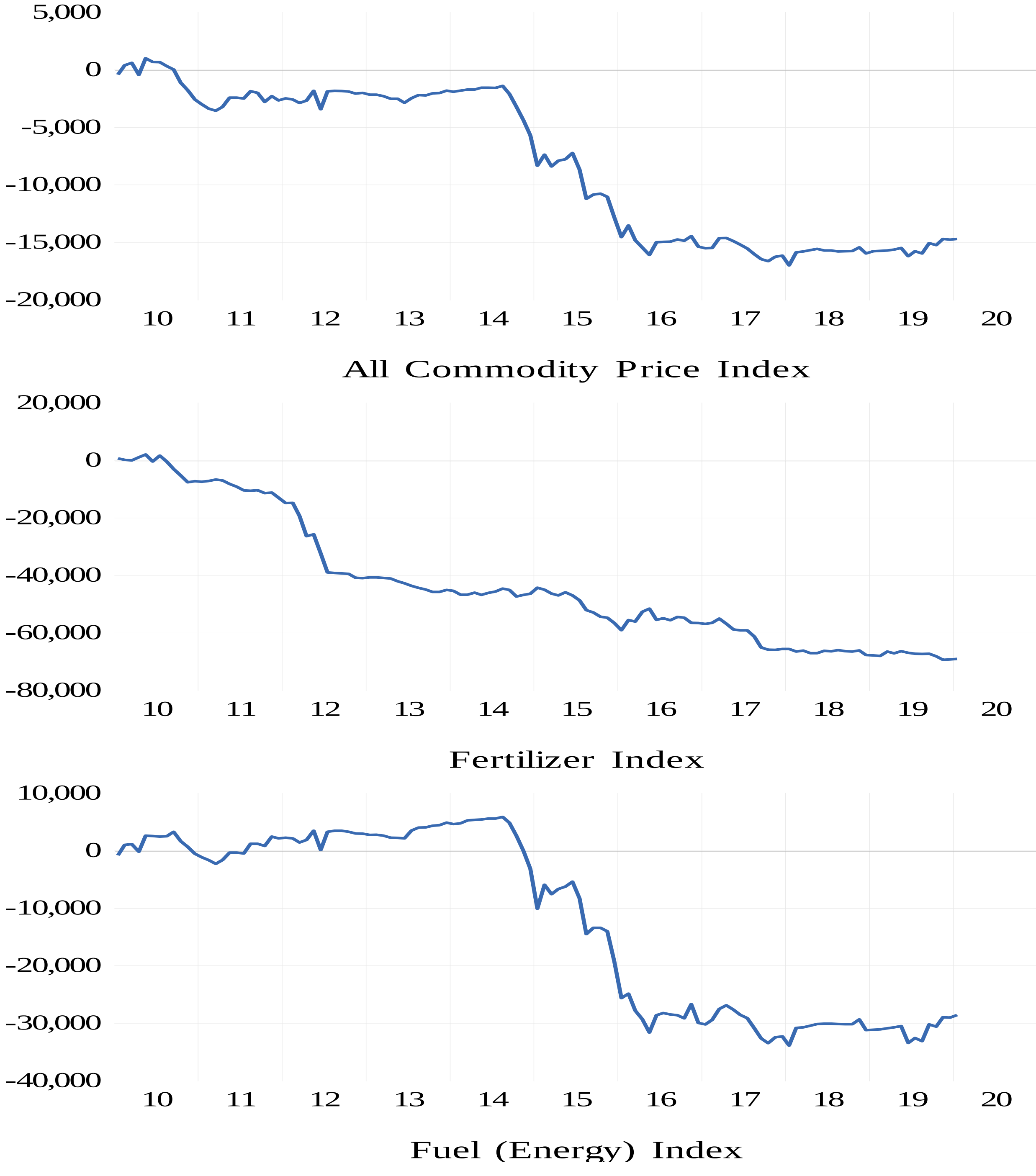






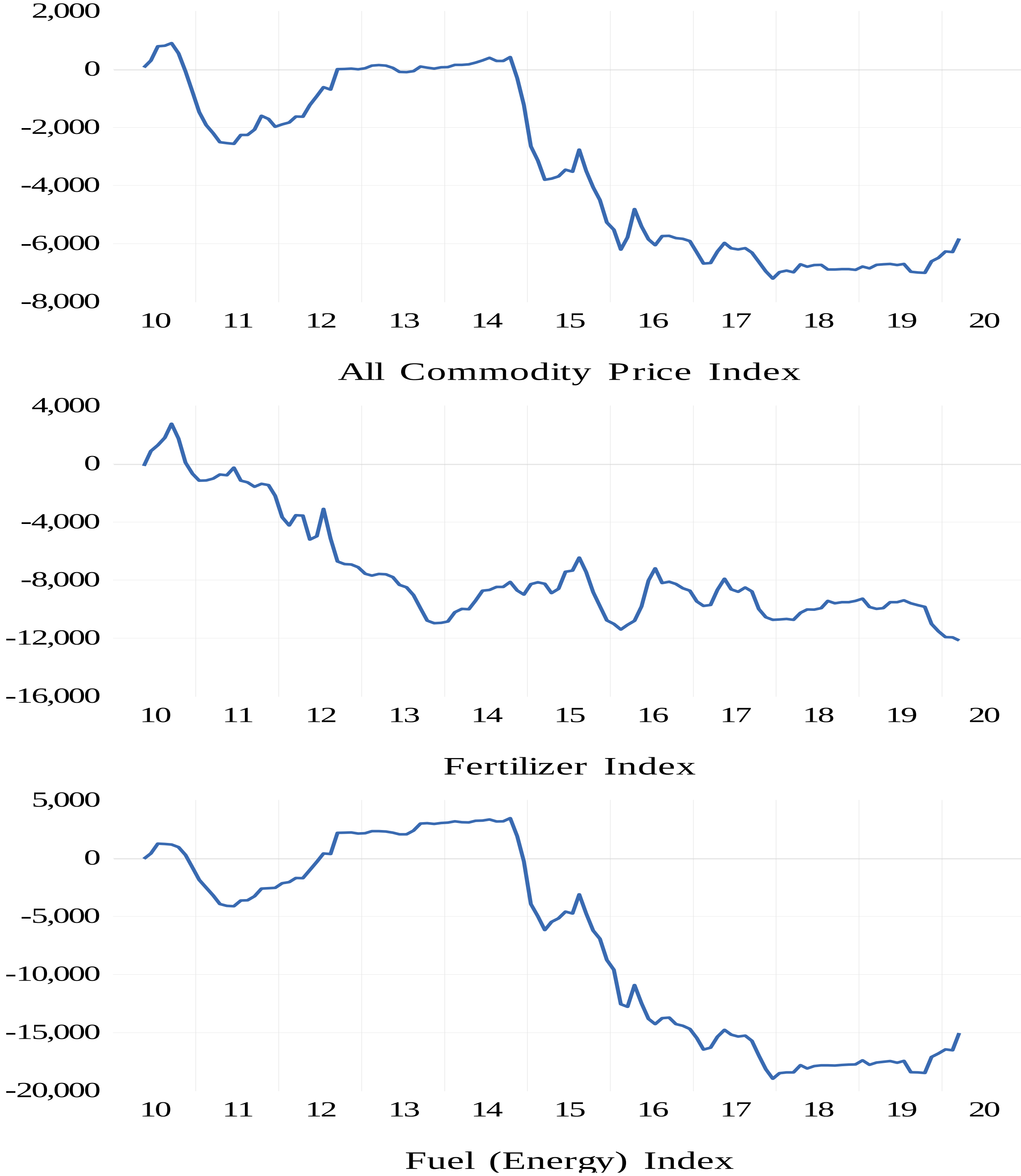
Note: The two-sided estimates of the Persistent Global Factor are from the model using 21 data series. The two-sided estimates of the Persistent Output Factor are from the model using G7 industrial production data series. The two-sided estimates of the Persistent Commodity Factor are from the model using 8 sectoral commodity index real returns data. The two-sided estimates of the Persistent Currency Factor are from the model using 6 commodity currency returns data.

Figure 3: Cumulative Forecast Error Squared Difference, 1-month



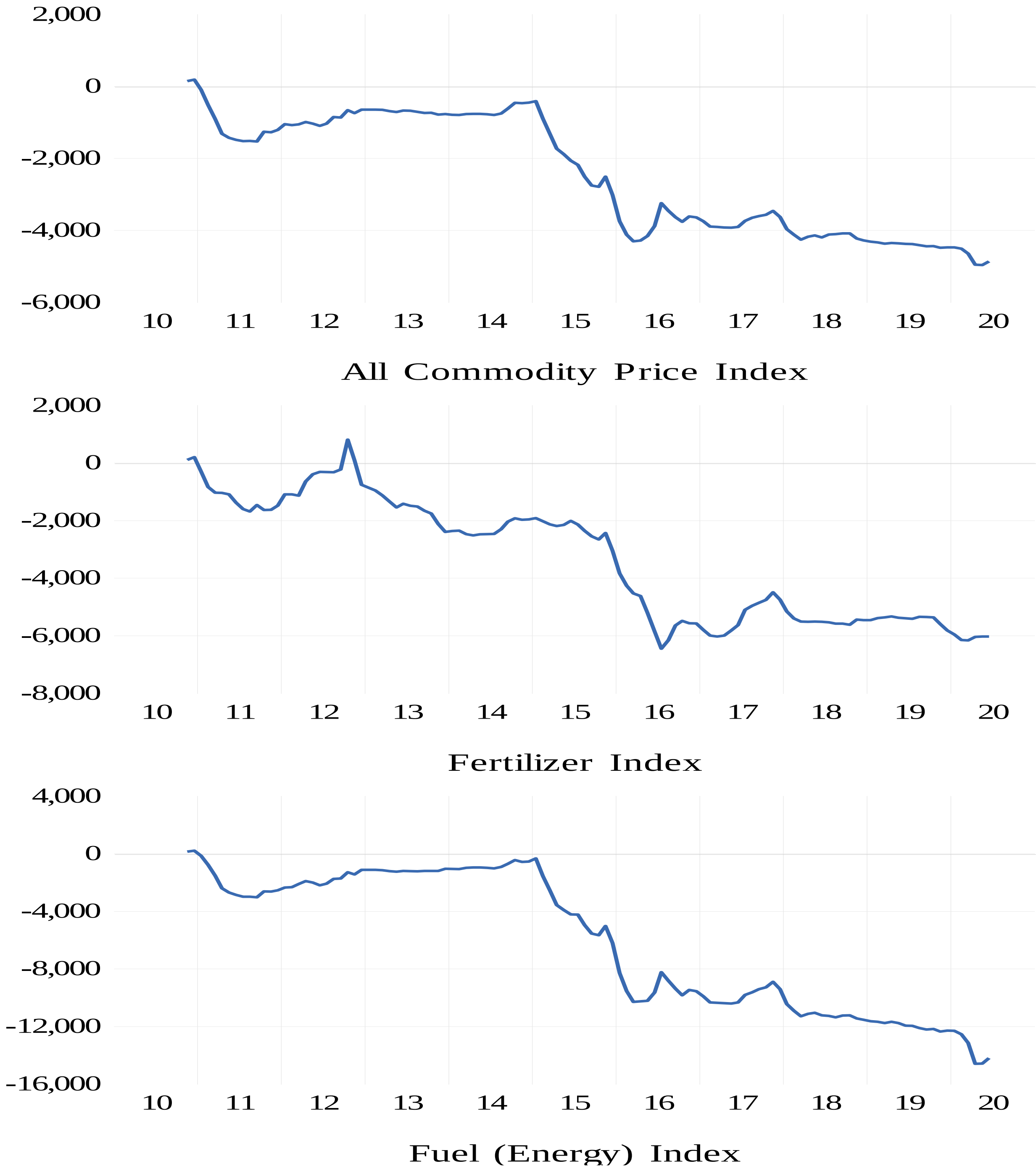
Note: The line in each panel represent the difference between the cumulative forecast error squared of the specified commodity returns at the 1 month horizon for two forecasts. The difference is measured as the cumulative forecast error squared of the forecast average of the three persistent factors minus the cumulative forecast error squared of the mean benchmark.

Figure 4: Cumulative Forecast Error Squared Difference, 3-months



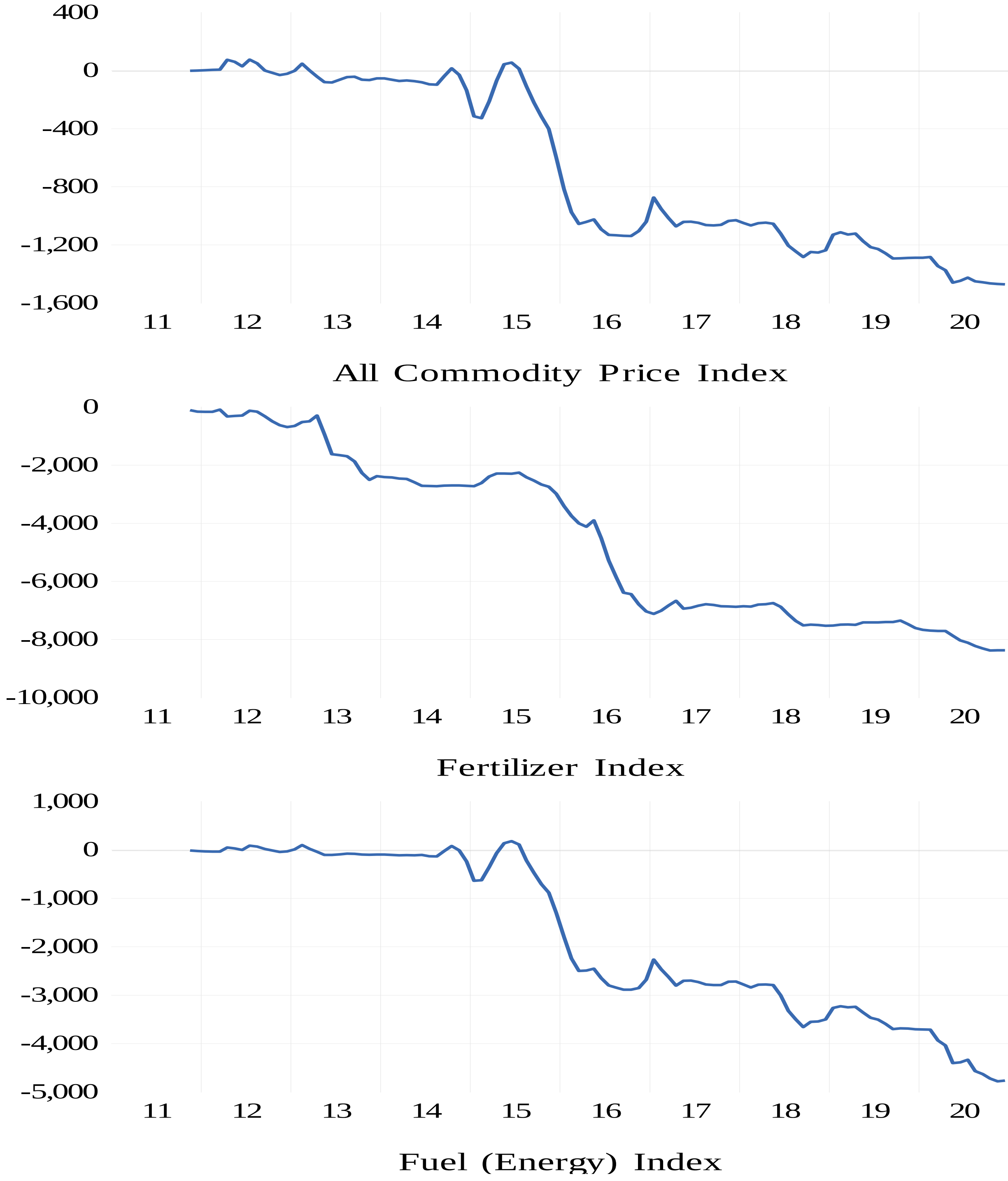
Note: The line in each panel represent the difference between the cumulative forecast error squared of the specified commodity returns at the 3 months horizon for two forecasts. The difference is measured as the cumulative forecast error squared of the forecast average of the three persistent factors minus the cumulative forecast error squared of the mean benchmark.

Figure 5: Cumulative Forecast Error Squared Difference, 6-months



Note: The line in each panel represent the difference between the cumulative forecast error squared of the specified commodity returns at the 6 months horizon for two forecasts. The difference is measured as the cumulative forecast error squared of the forecast average of the three persistent factors minus the cumulative forecast error squared of the mean benchmark.

Figure 6: Cumulative Forecast Error Squared Difference, 12-months



Note: The line in each panel represent the difference between the cumulative forecast error squared of the specified commodity returns at the 12 months horizon for two forecasts. The difference is measured as the cumulative forecast error squared of the forecast average of the three persistent factors minus the cumulative forecast error squared of the mean benchmark.

Not for Publication Appendix:

Table A1: Data Description and Sources

Variable Categories	Countries	Transformation	Sources
Production of Total Industry, Seasonally Adjusted, Index, 2015 = 100.	G7	Monthly growth rate, annualized.	OECD, Main Economic Indicators
Sectoral Commodity Price Indexes, Index, 2016 = 100.	Global Index	Real (deflated by US CPI) monthly returns, annualized.	IMF Primary Commodity Prices
National Currency to US Dollar Exchange Rate: Average of Daily Rates	Australia, Canada, Chile, New Zealand, Norway, South Africa	Monthly returns.	FRED, Federal Reserve Bank of St. Louis
Commodity Prices, in US Dollars.	Global	Real (deflated by US CPI) returns, annualized.	IMF Primary Commodity Prices
Consumer Price Index for All Urban Consumers (CPIAUCSL), Seasonally Adjusted.1982-84=100.	US	Used as a deflator	FRED, Federal Reserve Bank of St. Louis
Monthly Global Economic Indicators	Global	As listed in Christiane Baumeister's website: https://sites.google.com/site/cjsbaumeister/datasets	

Table A2: List of Commodity Price Indexes

Commodity Prices Indexes (18)	Sectoral Commodity Price Indexes (8)
All Commodity Price Index	Food and Beverage Price Index
Commodities for Index: All, excluding Gold	Agricultural Raw Materials Index
Non-Fuel Price Index	Base Metals Price Index
Food and Beverage Price Index	Precious Metals Price Index
Food Price Index	Fertilizer Index
Beverage Price Index	Crude Oil (petroleum), Price index
Industrial Inputs Price Index	Natural Gas Price Index
Agriculture Price Index	Coal Price Index
Agricultural Raw Materials Index	
All Metals Index	
Base Metals Price Index	
Precious Metals Price Index	
All Metals EX GOLD Index	
Fertilizer Index	
Fuel (Energy) Index	
Crude Oil (petroleum), Price index	
Natural Gas Price Index	
Coal Price Index	

Note: All commodity prices indexes use 2016 as the base year with value equal to 100.

Table A3: List of Disaggregated Commodity Prices

Commodities	
Aluminum	Olive Oil
Bananas	Hogs
Barley	Poultry (Chicken)
Beef	Rice
Coal, Australian	Rubber
Coal, South African	Fish (Salmon)
Cocoa beans	Hard Sawnwood
Coffee, Arabicas	Soft Sawnwood
Coffee, Robusta	Shrimp
Rapeseed oil	Sunflower oil
Copper	Tea
Cotton	Tin
Fishmeal	Uranium
Groundnuts (Peanuts)	Wheat
Hides	Sorghum
China Iron Ore	Wool
Lamb	Wool, fine
Lead	Zinc
Soft Logs	Cobalt
Hard Logs	Gold
Maize (Corn)	Silver
Natural Gas, Netherlands	Palladium
Natural Gas, Japan	Platinum
Natural Gas, Henry Hub	Urea
Nickel	Potassium Chloride
Crude Oil Brent	Diammonium Phosphate
Crude Oil Dubai	
Crude Oil WTI	

Further data notes:

Our records show that the data from IMF Primary Commodity Prices database was downloaded on 3/17/2021. It had prices on 68 disaggregated commodities. We removed some of them based on two considerations. One, some prices were based on forward or futures contracts, and not exactly spot prices as others. Sugar (2 varieties) and Soybean (3 varieties), Oat, Palm oil, and Generic 1st 'JO' Future would be examples of this issue. Two, some commodity prices were not available from 1992:1. Examples would be Apple (priced in Euro), Milk, Tomatoes (priced in Euro), Chana (priced in Indian Rupees), Molybdenum, Propane.

In our previous version we had a Natural Gas, Indonesian, commodity. The description for that commodity was stated in the data table as "Natural Gas, Indonesian Liquefied Natural Gas in Japan, US$ per Million Metric British Thermal Unit". However, we noted that in the technical document of IMF Primary Commodity Price Index (dated January 25, 2019), this commodity is listed as Natural Gas, Japan. We accordingly altered our description in this version of the paper.