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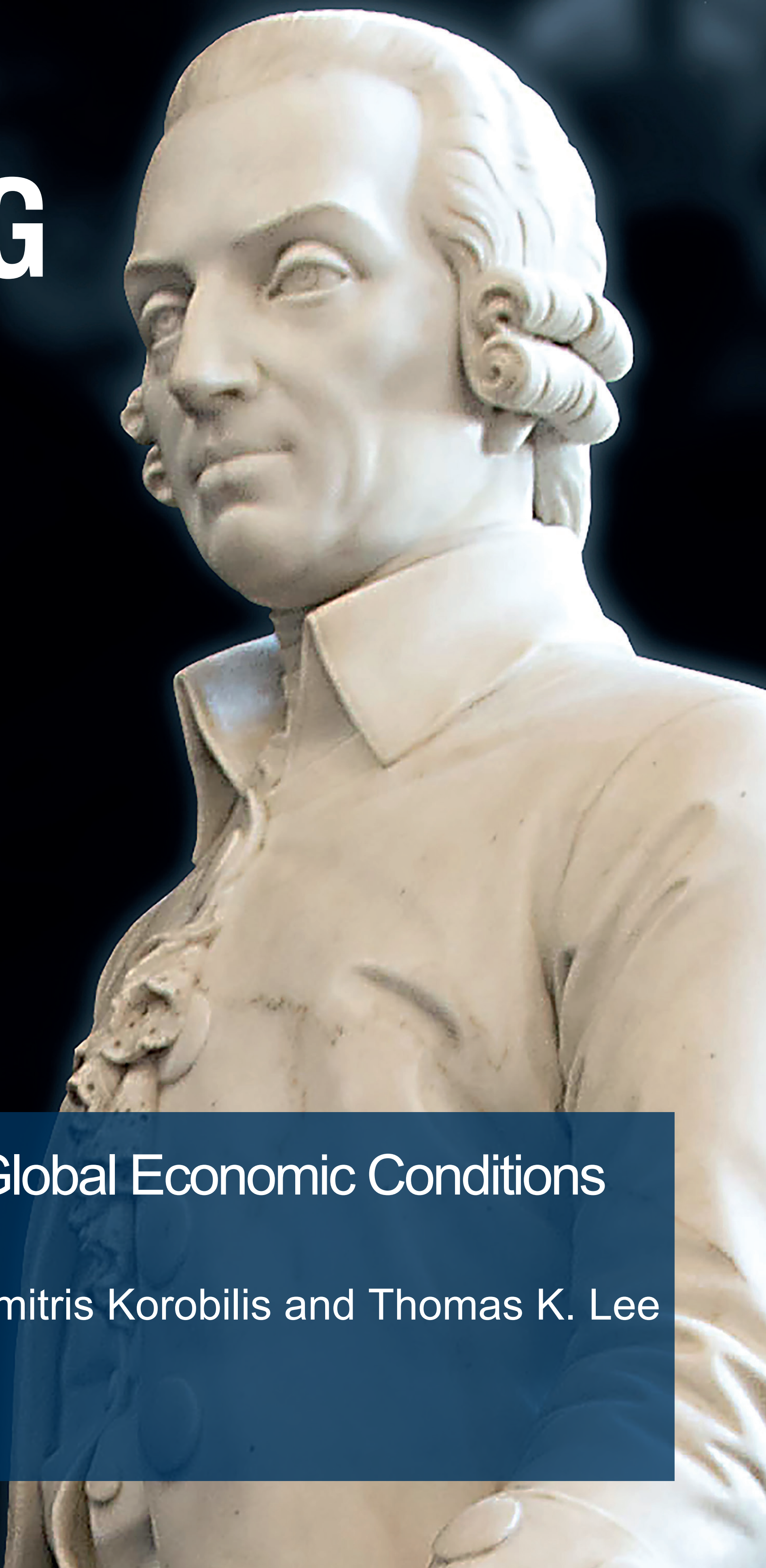

Energy Markets and Global Economic Conditions

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Paper no. 2020-08
February 2020

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February 4, 2020
Revised February 24, 2020

Abstract

This paper evaluates alternative indicators of global economic activity and other market fundamentals in terms of their usefulness for forecasting real oil prices and global petroleum consumption. We find that world industrial production is one of the most useful indicators that has been proposed in the literature. However, by combining measures from a number of different sources we can do even better. Our analysis results in a new index of global economic conditions and new measures for assessing future tightness of energy demand and expected oil price pressures.

JEL classification: C11, C32, C52, Q41, Q47

Keywords: Energy demand, forecasting, stochastic volatility, oil price pressures, petroleum consumption, state of the world economy

*We thank Nida Çakır Melek, Todd Clark, Ferre De Graeve, and James Hamilton for many insightful discussions and useful suggestions, and Scott Brave, Pierre Guérin, Francesco Ravazzolo, James Stock, and participants at the EIA 2019 Annual Workshop on Financial and Physical Energy Market Linkages for additional helpful comments. Special thanks to James Ng and Mark Robison at the Hesburgh Library for their valuable assistance with obtaining access to the shipping data. Part of this research was conducted while Christiane Baumeister was visiting KU Leuven and Bocconi University whose hospitality is gratefully acknowledged. Aram Derdzyan and Qian Li provided excellent research assistance. The work of Christiane Baumeister was supported by grant DE-EI0003240 from the U.S. Energy Information Administration. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the U.S. Energy Information Administration. Corresponding author: Christiane Baumeister, Department of Economics, 3060 Jenkins Nanovic Hall, Notre Dame, IN 46556, email: cjsbaumeister@gmail.com

1 Introduction

What are the key drivers of world energy markets? This question is of vital interest not just to academic researchers but also to business and government planners around the globe. Financial analysts, energy companies, budget agencies, central banks, and organizations like the International Monetary Fund, the International Energy Agency, and the U.S. Energy Information Administration devote a considerable amount of resources in an effort to assess the current and future outlook for production, consumption, and prices of major sources of energy.

A large academic literature has sought to contribute to these efforts by developing models of energy market dynamics that generate usable forecasts of energy prices. Prominent contributions include Alquist, Kilian, and Vigfusson (2013), Alquist, Bhattarai, and Coibion (2019), Baumeister and Kilian (2014a, 2015), Baumeister, Kilian, and Lee (2017), Bernard, Khalaf, Kichian, and Yelou (2018), Ferrari, Ravazzolo, and Vespignani (2019), and Manescu and van Robays (2016). This literature has concluded that although a random walk is hard to beat in out-of-sample oil-price forecasting exercises, careful attention to the economic fundamentals that are driving energy markets can lead to practical improvements in forecasts.

A key step in this effort is to find a useful summary of the global economic conditions that influence energy demand.[1] One of the promising early proposals for this purpose was a measure of dry-cargo shipping rates developed by Kilian (2009). This measure is available monthly in real time, is forward looking, and was found by Alquist, Kilian, and Vigfusson (2013) and Baumeister and Kilian (2012) to produce promising forecasts of the refiner acquisition cost (RAC) of crude oil imports. However, since these studies were published, there has been tremendous turbulence in the shipping index that does not seem to reflect changes in world economic activity. Although Kilian and Zhou (2018) have tried to defend continuing the use of shipping costs in modeling commodity price dynamics, they do not provide any statistical evidence or formal criteria in support of that conclusion. A growing number of researchers are suggesting alternative measures based on world industrial production (Baumeister and Hamilton, 2019; Hamilton, 2019), commodity prices more broadly (Alquist, Bhattarai, and Coibion, 2019; Delle Chiaie, Ferrara, and Giannone, 2017; West and Wong, 2014), or global steel production (Ravazzolo and Vespignani, 2019).

One of the objectives of our paper is to revisit this evidence using updated data and to compare the measures that have been proposed by other researchers with those developed from a broad set of observations on global variables that we assembled for the purpose of this study. We begin by reproducing the success of early models at forecasting real RAC over the period 1992-2010, but document how these break down badly for subsequent data. We note that they perform even more poorly for forecasting alternative measures of oil prices such as Brent. We find that models based on alternative measures of global economic conditions such as world industrial production

[1] Studies stressing the importance of the measure of global economic conditions used include Alquist, Bhattarai, and Coibion (2019), Baumeister and Kilian (2014a), Delle Chiaie, Ferrara, and Giannone (2017), Funk (2018), Manescu and van Robays (2016), and Ravazzolo and Vespignani (2019).

or a common factor extracted from a panel of real commodity prices lead to substantially better forecasts, even for forecasting RAC over the original sample period.

We also examine the usefulness of Bayesian shrinkage priors, allowing for time-varying volatility, and pooling multiple sources of information. We find that Bayesian shrinkage is beneficial in every specification, and introducing stochastic volatility improves long-horizon forecasts substantially. Although many researchers have reported that pooling leads to superior forecasts in a number of different settings, we do not find evidence of that here.

One of the features that distinguishes our effort from earlier studies is that we investigate potential measures of energy market fundamentals not only in terms of their ability to predict prices but also to predict changes in world oil consumption. We find that none of our baseline specifications perform very well for forecasting global petroleum consumption. We investigate alternative measures that add additional determinants of energy demand including measures of geopolitical risk, developments in transportation, oil price uncertainty, and weather-related indicators. We find that constructing an indicator of global economic conditions that includes these variables along with world industrial production helps improve the forecast accuracy for petroleum consumption considerably.

Our analysis results in some new measures for characterizing energy demand and quantifying oil price risks. We use real-time joint forecasts obtained from our model of oil prices and petroleum consumption to construct an energy demand indicator that signals market tightness and anticipated future demand pressures. We complement this analysis with measures that signal the likelihood of a build-up of upward or downward oil price pressures relative to the recent past and forecast the probabilities that the oil price will remain within the range of values experienced recently, rise above or fall below this range over a two-year horizon. Our analysis suggests that these measures may be very helpful for the private and public analysts who are constantly trying to assess the implications of current developments in energy markets for purposes of making their own budgeting and planning decisions.

The remainder of the paper is structured as follows. Section 2 provides a systematic comparison of the usefulness of alternative indicators of global economic activity based on their forecasting performance for the real price of oil. This evaluation takes place within existing models of the global oil market as well as a new set of forecasting models that focus more on the demand side of the market and allow for time variation in volatilities. Section 3 extends the analysis to global petroleum consumption to gain a more complete understanding of future developments in energy markets. Section 4 proposes a new indicator of global economic conditions that covers a diverse range of variables tied to future energy demand. Section 5 illustrates how price and consumption forecasts can be used to gauge the current and expected state of energy markets by introducing some new real-time monitoring tools. Specifically, we develop measures that provide policymakers and markets with a quantitative assessment of future energy demand conditions and expected oil price pressures. Section 6 offers some concluding remarks.

2 Forecasting Oil Prices

2.1 Forecasting with Vector Autoregressive Models

A widely followed approach to forecasting oil prices is the dynamic model of the global oil market proposed by Alquist, Kilian, and Vigfusson (2013) and Baumeister and Kilian (2012). Their analysis is based on the following reduced-form vector autoregression (VAR) that contains the fundamental drivers of the real price of oil,

$$\mathbf{y}_t = \mathbf{c} + \mathbf{\Phi}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{\Phi}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\mathbf{y}_t$ is a 4×1 vector of monthly data, $\mathbf{c}$ is a 4×1 vector of intercepts, $\mathbf{\Phi}_i, i = 1, ...p$, are 4×4 coefficient matrices with p indicating the number of lags, and $\boldsymbol{\varepsilon}_t$ are white-noise innovations. The four variables included in their VAR are the percent change in global crude oil production, an estimate of the change in global crude oil inventories, the log of the real price of crude oil as measured by the U.S. refiner acquisition cost of imported crude oil (RAC) deflated by the U.S. consumer price index, and an index of global real economic activity (REA) developed by Kilian (2009).[2] This measure of real economic activity is based on single-voyage dry-cargo freight rates. The idea behind the Kilian index is that changes in real shipping costs expressed in deviations from a linear time trend capture the cyclical component of demand for industrial commodities. Given that shipping of raw industrial materials is linked to future production of manufacturing goods, Kilian (2009) and subsequent researchers have treated this index as a proxy for the state of the global business cycle. Baumeister and Kilian (2012) found this model did an excellent job of predicting oil prices over the period 1992.1 to 2010.6.

2.1.1 Evaluating Forecasts Based on the Kilian Index

Our first step is to reproduce the results in Alquist, Kilian, and Vigfusson (2013) and Baumeister and Kilian (2012). In doing so, we use the global real activity measure now recommended by Kilian (2019) which corrects a coding error in the calculation of his original index noted by Hamilton (2019).[3] We set the lag length $p = 12$, which has been shown to deliver the most accurate out-of-sample forecasts for the real RAC (see Baumeister and Kilian, 2012, 2015). We estimate the

[2] All oil-related data were obtained from the U.S. Energy Information Administration's *Monthly Energy Review* and *International Energy Portal*. Monthly world oil production data measured in thousands of barrels of oil per day and monthly U.S. crude oil stocks measured in millions of barrels (which include the Strategic Petroleum Reserve) are available from January 1973 onward. We obtain a proxy for global oil stocks by multiplying the U.S. crude oil inventories by the ratio of OECD inventories of crude oil and petroleum products to U.S. inventories of crude oil and petroleum products. Given that data on OECD petroleum inventories are only recorded since January 1988, we assume that the ratio before January 1988 is the same as in January 1988. The monthly U.S. refiner acquistion cost of imported crude oil only goes back until January 1974. We follow Baumeister and Kilian (2012) to extrapolate it back to 1973.1. The U.S. consumer price index for all urban consumers was taken from the FRED database.

[3] In order to linearly detrend the deflated index only using data available to the forecaster at the time the forecast is made, we use the series of the log nominal shipping index provided on Jim Hamilton's webpage (http://econweb.ucsd.edu/~jhamilto/shipping_costs.xlsx).

VAR parameters recursively and evaluate the mean-squared prediction error (MSPE) of the oil price forecasts in levels for horizons $h = 1, 3, 6, 9, 12, 18, 24$ months ahead. We first estimate the parameters using data from 1973.2 to 1991.12 to forecast the log of the oil price for 1992.1 for $h = 1$, 1992.3 for $h = 3$, and so on, and then exponentiate to get a forecast of the level of the real oil price. We then re-estimate parameters using data through 1992.1 to forecast 1992.2 for $h = 1$, 1992.4 for $h = 3$, and so on. Following Alquist et al. (2013), we use the random walk without drift as the benchmark for evaluating the forecasting ability of alternative models (which essentially amounts to postulating that the real oil price is unpredictable). All MSPE results are normalized relative to the no-change forecast. A ratio below 1 indicates that the model does better than a random walk, while a value above 1 indicates that it does worse. To gauge the statistical significance of differences in forecasting performance, we follow Carriero, Clark, and Marcellino (2015) who suggest using the Diebold and Mariano (1995) test for equal mean-squared forecast error, compared against standard normal critical values, even for nested models. They base their recommendation on Monte Carlo evidence provided in Clark and McCracken (2015) that shows that, in the case of nested models, the Diebold-Mariano (DM) test based on normal critical values can be considered a conservative choice in finite samples.

Table 1, panel (a) presents the recursive MSPE ratios for the same evaluation period as in Baumeister and Kilian (2012) which runs from 1992.1 to 2010.6. Column 1 reproduces Baumeister and Kilian's conclusion that the VAR offers better forecasts at near horizons of the real RAC than does a random walk, with MSPE reductions of 32% at the 1-month horizon and 22% at the 3-month horizon.[4]

However, since 2010 the Kilian index has exhibited some erratic behavior that is difficult to attribute to the overall level of global economic activity. Figure 1 shows that in early 2016 the index reached an all-time record low of 159% below trend, suggesting a far weaker global economy than at the trough of the financial crisis in 2009, when the real shipping index was only 75% below the linear trend (marked with a vertical line in the figure). After a recovery back to trend the index again dropped sharply to 88% below trend in February 2019. As discussed by Hamilton (2019), these sharp contractions in the Kilian index in the post-financial crisis period are at odds with common understanding and other available measures of recent fluctuations in global economic activity. The excessive swings and increased volatility of this index have raised concerns about its reliability as an indicator of world economic activity and its usefulness for forecasting. For example, Hamilton (2019) provides in-sample evidence that the Kilian index has little predictive power for a range of real commodity prices and no statistically significant correlation with annual world real GDP growth rates, casting doubts on its ability to identify shifts in demand in industrial commodity markets. Our focus here is on out-of-sample forecasts of real RAC.

In panel (b) of Table 1 we update the analysis using data through 2018.8. The first column shows that the model does not do quite as well when the evaluation period is extended to include

[4] Interestingly, Kilian's original REA index produced slightly better forecasts at longer horizons than does the new index that corrects for the coding error.

more recent data, which may reflect the fact that oil prices were harder to forecast over 2011-2018 as well as problems with using the detrended shipping cost index as a measure of real economic activity (see Hamilton, 2019). Notwithstanding, the VAR continues to beat the random walk for near-term forecasts of real RAC but with much smaller reductions in MSPE. The improvements one and three months ahead are only 13% and 4%, respectively.

For many oil-market participants, predicting other oil prices like Brent may be a higher priority than predicting RAC. In fact, the Brent price has evolved into the global benchmark for oil and oil products with about two-thirds of oil purchases worldwide using it as a reference price according to the Intercontinental Exchange (ICE).[5] It is also closely followed by policymakers and frequently referred to in the media. For these reasons, we evaluate the usefulness of the framework for forecasting Brent, replacing the RAC with the Brent price as a more relevant measure for the global price of crude oil. Since the monthly Brent spot price is available only from 1987.5 onward, we extend it back to 1973.1 using the growth rate of RAC. Table 1, panel (c), shows that if our goal is to forecast the real price of Brent rather than RAC, the VAR is completely unsuccessful. The VAR forecast does not beat the random walk at any horizon.

2.1.2 Alternative Indicators of Global Real Economic Activity

We next explore alternative monthly measures of global real economic activity that have been proposed in the literature. Details on the different measures we investigate are summarized in Table 2.

Real shipping cost factor. One possibility is that composite measures of shipping costs other than that proposed by Kilian (2009) may provide better forecasts. Hamilton (2019) argues that removing a deterministic linear time trend is a poor way to isolate the cyclical component in real shipping costs and is not supported by the data. A natural alternative is to use the unbalanced panel of disaggregated data underlying the Kilian index and extract a common factor from the cross-section of real shipping costs in growth rates.[6] The dataset consists of a cross-section of 61 freight rates for individual shipping routes for a set of industrial commodities such as coal, iron ore, and fertilizer which we manually digitized from Drewry's *Shipping Insight* up to August 2018.[7] Changes in shipping routes and in the composition of freight lead to missing observations which we fill by recursively applying the expectation-maximization (EM) algorithm of Stock and Watson (2002).[8] The resulting real shipping cost factor for the period 1973.2 to 2018.8 is shown in the top panel of Figure 2. Visually this series appears to be a far more plausible proxy for global economic

[5] See https://www.theice.com/article/brent-crude/the-worlds-leading-crude-oil-benchmark.

[6] Before conducting the principal component analysis, each growth rate is standardized by subtracting the mean and dividing by its standard deviation.

[7] Table 1A in the online appendix provides detailed information on the shipping routes and the commodity shipped.

[8] The algorithm is initialized by replacing missing values with the unconditional mean of the observations available for each series before extracting the first K principal components where K is determined by the Bai and Ng (2002) information criterion. We use the estimated factors to impute the missing observations and repeat the factor analysis with the updated values until the estimates do not change.

activity than the corrected Kilian index in Figure 1. The measure in the top panel of Figure 2 also addresses some of the weaknesses of Kilian's real economic activity index as summarized by Kilian and Zhou (2018). For example, they document that freight rates are increasingly subject to idiosyncratic shocks in the markets for commodities shipped as dry bulk cargo. A case in point is the large supply shock in iron ore in late 2015 which contributed to the substantial deterioration in the Kilian index in early 2016 as discussed by Kilian and Zhou (2018). By contrast, the factor approach filters out commodity-specific noise and may provide a better characterization of the cyclical component of world economic activity.

Column 2 of Table 1 shows that the real shipping cost factor does not perform quite as well as the Kilian index for RAC at short horizons over the original sample. But it does better over longer horizons in the original sample period (panel a) and substantially better for forecasting RAC over any horizon when using the extended evaluation period (panel b). It is also substantially better for purposes of forecasting Brent at all horizons (panel c). Thus this alternative approach to summarizing shipping costs not only gives a more plausible proxy for global economic activity since 2010 but also offers a significant improvement for purposes of forecasting oil prices.

World industrial production. Column 3 of Table 1 repeats the analysis replacing the Kilian index with the index of world industrial production developed by Baumeister and Hamilton (2019). Their measure remains closer to the traditional concept of economic activity as measured by the physical volume of output generated in the industrial sector. They constructed an updated version of a monthly index of industrial production covering OECD countries and six major emerging markets (Brazil, China, India, Indonesia, the Russian Federation and South Africa) that was originally reported in the OECD Main Economic Indicator (MEI) database from 1958.1 to 2011.10 by applying the same methodology used by the OECD.[9] The index is plotted in growth rates in the second panel of Figure 2. The VAR using world industrial production does considerably better at predicting the real price of both RAC and Brent over every evaluation period compared to either of the shipping-based indicators (see column 3 of Table 1). Using world industrial production leads to notable improvements in forecast accuracy relative to the no-change forecast for the real Brent price at the shortest and longest horizons. In particular, it reduces the MSPE by about 5% at horizons 1 and 3, and by 6% at horizon 24.

Real commodity price factor. Alquist, Bhattarai, and Coibion (2019), Delle Chiaie, Ferrara, and Giannone (2017), and West and Wong (2014) extract a global factor related to business cycle fluctuations from a large cross-section of growth rates of monthly real commodity prices. The idea is that the source of common variation in commodity prices stems from demand-induced changes in economic activity which tend to move all prices in the same direction, while supply-side developments in specific commodity markets show up as idiosyncratic shocks that are unlikely to have pervasive effects. Our commodity price dataset consists of 23 basic industrial and agricultural commodities listed in Table 2 whose markets are sensitive to changes in global economic conditions. The selection of the set of commodity prices is guided by the same criteria as in Alquist et al.

[9] This series is regularly updated and can be downloaded at https://sites.google.com/site/cjsbaumeister/research.

(2019). The primary purpose of commodities included in the construction of the global factor should relate to aggregate output in the form of inputs in the production of final goods. This rules out commodities that behave more like financial assets such as gold and other precious metals. The commodities should be freely traded on liquid spot markets. There should be no periods of infrequent price adjustments due to long-term contractual agreements. The commodities should also not be vertically integrated to avoid idiosyncratic shocks to be propagated along the supply chain. Following Alquist et al. (2019), we do not include any energy commodities. The third panel of Figure 2 shows the real commodity price factor constructed from the first principal component of the balanced panel of percent changes of real commodity prices. Column 4 of Table 1 reports the results when this measure is used as the global economic activity indicator. The real commodity price factor does almost as well as world industrial production for short horizons and somewhat better at longer horizons. For example, it improves the forecast accuracy of the real Brent price by 3% at horizon 18 and by 8% at horizon 24 relative to the no-change forecast.

Global steel production factor. Ravazzolo and Vespignani (2019) suggest using monthly world steel production as an indicator of global real economic activity. They argue that steel is an important input for many industries including construction, transportation, and manufacturing, and that it is a relatively homogenous commodity that is traded freely worldwide. The World Steel Association provides an aggregate measure of the level of steel production reported by member countries. One important drawback is that a consistent series is only available since 1994 at monthly frequency due to changes in the number of reporting countries. Given that this measure is an aggregate of the physical amount of steel produced, an increase in the number of steel-producing countries leads to discrete jumps, as pointed out by Kilian and Zhou (2018). We propose an alternative way to construct a measure of global steel production that enables us to extend the series all the way back to 1973 without encountering the problem of structural breaks due to aggregation, while preserving the broadest possible coverage. In its *Steel Statistical Yearbook*, the World Steel Association publishes monthly data on crude steel production for individual countries and groups of countries. The earliest available issue dates back to 1978, then released by the International Iron and Steel Institute, and contains data for 29 reporting countries for the period 1968-1977. In the early years, the data are grouped into four blocks: European Community (EC), United States, Japan, and other reporting countries.[10] To maintain consistency across time, it is necessary to consolidate EC and other reporting countries since some of the countries included in the latter group later join the European Union. Over time the breakdown gets more detailed and monthly data for individual countries are reported. We manually digitize the disaggregated data and expand coverage to China, Eastern Europe, and the Middle East in 1990.1 and to Russia and Ukraine in 1992.1 resulting in an unbalanced panel of seven time series for monthly production of crude steel measured in thousands of tons (see Table 2). We extract the common component using

[10] European Community refers to the following 8 countries: Belgium, Denmark, Federal Republic of Germany, France, Italy, Luxembourg, the Netherlands, and the United Kingdom. Other reporting countries include Austria, Finland, Norway, Portugal, Spain, Sweden, Turkey, Yugoslavia, Canada, Argentina, Brazil, Chile, Mexico, Venezuela, Australia, India, Republic of Korea, South Africa, and Taiwan.

the EM algorithm to obtain a global steel production factor which is plotted in the bottom panel of Figure 2. Aggregating information in this way not only circumvents discontinuities but also deals with the concern of Kilian and Zhou (2018) that world steel production is prone to idiosyncratic supply shocks in steel-producing countries. It also takes care of other potential sources of noise such as measurement error and small data revisions. The last column of Table 1 shows that at short horizons the steel index does not perform quite as well as world industrial production and the commodity price factor for the extended evaluation period for either real RAC or Brent, but it performs much better than the Kilian index. At longer horizons its forecasting performance is comparable to that of world industrial production with MSPE reductions of up to 6%.

Summary. Taking stock, any of the three alternative measures for global real economic activity do significantly better than the Kilian index for forecasting either real RAC or Brent. While the forecasts obtained with the alternative indicators achieve gains in average forecast accuracy of up to 23% in the near term and up to 8% in the long term relative to the no-change forecast for the longer evaluation period, none of these models beats the random walk at the intermediate horizons of 9 and 12 months ahead. Overall, forecasting oil prices with VAR models has become more difficult since 2010 and forecasting the real price of Brent poses additional challenges.

To get a better sense of where the differences across evaluation periods come from, we take a look at the recursive mean-squared prediction errors for the real RAC. For illustrative purposes, we focus on the three-month forecast horizon and compare the VAR forecasts produced with the Kilian (REA) index to those produced with world industrial production (WIP).[11] Figure 3 shows that prior to the financial crisis both VAR forecasts are essentially tied with the no-change forecast and among each other. The top panel highlights that the model with the Kilian index gets a lot of mileage out of the volatile 2009-2011 period with most of the MSPE reductions happening during this time. These gains in accuracy vanish during the 2012-2014 period when oil prices were relatively stable. The sharp drop in oil prices in mid-2014 puts the model again at a slight advantage relative to the random walk. The middle panel indicates that the VAR forecast with WIP has outperformed the no-change forecast since the financial crisis consistently generating smaller forecast errors. This implies that world industrial production is a reliable indicator of global economic activity and a useful predictor of oil prices both during crisis times when oil prices move a lot and during normal times when oil prices are relatively calm. The bottom panel directly compares the recursive MSPEs of the two VAR forecasts and shows that while initially the relative ranking alternates, since 2011 the model with WIP clearly dominates. It is noteworthy that the deterioration of the forecast accuracy of the model with the Kilian index coincides with the unusual post-crisis behavior of this index as documented above.

[11] The same pattern as for WIP is found for the real commodity price factor and the global steel production factor.

2.2 The Role of Bayesian Shrinkage

All VAR models in Table 1 have been estimated by unrestricted least squares. It is widely known that the proliferation of parameters in VARs tends to hurt the out-of-sample forecasting performance of these models. One remedy is to apply Bayesian shrinkage which has been shown to lead to more precise forecasts across a wide range of applications in macroeconomics and finance (see, e.g., Carriero, Clark, and Marcellino, 2015; Giannone et al., 2014; Litterman, 1986). We examine whether Bayesian methods help reduce the MSPE of our VAR forecasts by using informative priors that shrink our highly-parameterized unconstrained models toward a parsimonious benchmark, and thus reduce estimation uncertainty. As in Baumeister and Kilian (2012), we rely on the data-based procedure proposed in Giannone, Lenza, and Primiceri (2015) for selecting the optimal degree of shrinkage in our recursively estimated Bayesian VARs (BVARs) based on the marginal data density.

Panel (a) of Table 3 compares VAR and BVAR forecasts for the real price of Brent obtained with the same five models that we considered before.[12] We find that Bayesian shrinkage leads to substantial improvements for every specification with additional MSPE reductions of up to 7% at short and long horizons relative to the unrestricted VAR.[13] Among the set of alternative activity indicators, column 6 shows that the BVAR forecast based on world industrial production is the only one that outperforms the no-change forecast at every horizon. Using the commodity price factor results in similar forecasts as world industrial production, a little better at longer horizons and a little worse at short horizons, as can be seen in column 8. In particular, both models greatly improve on the accuracy of medium-term forecasts of 6- to 12-months ahead with gains of up to 3% relative to the random walk. A comparison of columns 2 and 4 reveals that the BVAR with the real shipping cost factor does much better than the one with the Kilian index which is dominated by the random walk except at the 1-month horizon. Bayesian shrinkage also helps the performance of the steel factor, though it is still dominated by world industrial production and the commodity price factor.

While it is customary to model the global oil market from a supply-side perspective, given our interest in developing an energy demand indicator, our goal is to develop a forecasting model that emphasizes the final demand for petroleum products. For this purpose we replace global oil production with a measure of petroleum consumption. The broadest available measure at the global level is monthly total world consumption of liquid fuels provided in the *Short-Term Energy Outlook* database of the U.S. Energy Information Administration. Since this time series is only available from 1990.1 onward, we extend it back to 1982.1 using the growth rate of OECD petroleum consumption and further back until 1973.1 at the rate of change of global crude oil production.[14]

[12] Given that our main focus for the remainder of the paper is on forecasting the real price of Brent, we only discuss the findings for Brent. Results on the forecast accuracy of BVAR models for real RAC can be found in Table 2A, panel (a), in the online appendix.

[13] The only exception is the model with the Kilian index where the ranking of the forecast performance between VAR and BVAR alternates across horizons.

[14] Alternatively we could have used U.S. petroleum consumption which is available all the way back to 1973 but given that global supply and demand have to balance eventually world oil production seems more relevant for global

With the shift in focus from oil production to petroleum consumption, the pertinent measure for inventories are OECD petroleum stocks which, as before, are backcast before 1988 with the growth rate of U.S. petroleum stocks. The most important factor determining prices of petroleum products are crude oil prices since they account for the largest share of the production costs.[15] Thus, the real Brent price remains the relevant price measure given that it serves as a global reference for pricing petroleum products. This consumption-based VAR model is new to the oil price forecasting literature and adds to the suite of models that are derived based on economic grounds. The notion is that fluctuations in the demand for refined products will translate into changes in the demand for crude oil and thus have predictive power for the future path of the real price of crude oil. We evaluate the forecasting performance of this new model using all five indicators of global real economic activity.

Table 3, panel (b), reports the MSPE results for the consumption-based models estimated by unrestricted least squares and Bayesian shrinkage methods. Using oil consumption instead of oil production leads to better forecasts of oil prices for most indicators and most horizons. Comparing different indicators and estimation methods, the overall pattern is similar to the production-based models. The BVAR forecasts dominate the VAR forecasts across almost all models and horizons, and world industrial production is a very useful indicator of world economic activity for purposes of any forecast, with significant gains in forecast accuracy of 12% at the 1-month horizon, 6% at the 6-month horizon, and 8% at the 24-month horizon. Forecasts using the commodity price factor are almost as good as industrial production for short horizons and a little better for long horizons. Using oil consumption instead of oil production generally leads to additional MSPE reductions of up to 4% for 6-months-ahead forecasts. The improvement from using consumption instead of production is more modest at longer horizons, with less than a 1% improvement for Bayesian 1- to 2-year-ahead forecasts. Three out of five BVAR models consistently beat the random walk at all forecast horizons (see columns 4, 6, and 10).

We conclude that Bayesian shrinkage can help improve forecasts in this setting and that using petroleum consumption in place of oil production is promising. World industrial production and the real commodity price factor are the most useful indicators of global economic activity.

2.3 The Role of Time Variation in Volatilities

Another important consideration is that energy markets have undergone substantial transformations over time that can affect the forecasting ability of our models. Examples include shifts in the energy intensity of production and consumption, changes in the energy mix, technological progress, capacity constraints in petroleum inventory holdings, and market turmoil that induces bouts of

consumption. Moreover, U.S. fuel consumption was experiencing strong fluctuations during the 1970s which are not necessarily representative of the rest of the world.

[15] For example, in 2013 crude oil accounted for 68% of the average retail price of gasoline, while taxes (12%), refining (11%), and distribution and marketing (9%) accounted for the rest (see U.S. Energy Information Administration, *Gasoline and Diesel Fuel Update*, February 2014).

volatility which are all likely to have an influence on the models' predictive accuracy. In addition, Baumeister and Peersman (2013) document that heteroskedasticity is a pervasive feature in oil market data.

The importance of modeling time variation in the volatilities for the forecasting performance of macroeconomic variables is well established in other data sets (see, e.g., Carriero, Clark, and Marcellino, 2019; Clark and Ravazzolo, 2015; D'Agostino, Gambetti, and Giannone, 2013). Clark and Ravazzolo (2015) provide extensive empirical evidence that models with stochastic volatility increase the accuracy of point forecasts relative to models assuming homoskedasticity. Earlier evidence for forecasting energy prices is more mixed. Baumeister and Kilian (2014a) find that adding time-varying parameters and stochastic volatility to the four-variable VAR model in column 1 of Table 1 did not lead to better forecasts of quarterly RAC compared to the (monthly) no-change forecast. On the other hand, Baumeister, Kilian, and Lee (2017) find that the unobserved component stochastic volatility model, originally proposed by Stock and Watson (2007) for forecasting inflation, does great for forecasting retail gasoline prices, especially at longer horizons. The question is thus whether a more accurate modeling of time-varying uncertainty, while not explicitly modeling changes in the reduced-form coefficients, leads to improvements in out-of-sample forecasting of oil prices. As pointed out by Primiceri (2005), stochastic volatility is meant to capture possible heteroskedasticity of the shocks and potential nonlinearities in the dynamic relationships of the model variables, which are related to low-frequency changes in volatility.

To allow for time variation in the variance of the VAR residuals, we postulate that the error term $\boldsymbol{\varepsilon}_t$ in equation (1) is normally distributed with mean zero and time-varying covariance matrix $\boldsymbol{\Omega}_t$. We factor the latter as $\boldsymbol{\Omega}_t = \mathbf{A}^{-1}\boldsymbol{\Sigma}_t(\mathbf{A}^{-1})'$ where $\mathbf{A}^{-1}$ is a lower triangular matrix with ones on the main diagonal and $\boldsymbol{\Sigma}_t$ is a diagonal matrix that contains the stochastic volatilities such that $\boldsymbol{\varepsilon}_t = \mathbf{A}^{-1}\mathbf{u}_t$ with $\mathbf{u}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_t)$. Carriero, Clark, and Marcellino (2019) show these assumptions allow the VAR to be written as a system of n univariate equations with the i^{th} equation taking the form:

$$y_{it} = c_i + \sum_{j=1}^{p} \boldsymbol{\Phi}_{i,j}\mathbf{y}_{t-p} + \sum_{\ell=1}^{i-1} a^*_{i,\ell} u_{\ell t} + u_{it}, \qquad u_{it} \sim N(0, \sigma^2_{it}) \tag{2}$$

where $\boldsymbol{\Phi}_{i,j}$ is the i^{th} row of the matrix $\boldsymbol{\Phi}_j$, $a^*_{i,1}, ..., a^*_{i,(i-1)}$ denotes the parameters in the i^{th} row of the triangular matrix $\mathbf{A}^{-1}$ for $i = 2, ..., n$, $u_{\ell t}$ are the residuals from the previous $i-1$ equations, and σ^2_{it} are equation-specific time-varying variances. The benefit of this reparametrization is that we can estimate the model equation by equation which is convenient for modeling stochastic volatility and allows to specify independent priors for the reduced-form coefficients across equations. The law of motion for the stochastic volatilities is $\ln \sigma_{it} = \ln \sigma_{it-1} + \eta_{it}$ with the vector of innovations $\eta_t \sim N(0, \boldsymbol{\Lambda})$ where $\boldsymbol{\Lambda}$ is a full covariance matrix as in Primiceri (2005). Specification of the prior distributions for the VAR parameters follows the Minnesota prior tradition (Doan, Litterman, and Sims, 1984) that shrinks coefficients on persistent endogenous variables toward a univariate random walk and those on variables in growth rates toward independent white noise, and at the same time penalizes more distant lags of all endogenous variables. For details on the choices of priors and hyperparameters that control the amount of shrinkage, see Appendix A; for the Gibbs sampling algorithm, the reader is referred to Carriero et al. (2019).

Table 4 compares the forecasting performance of specifications that allow for stochastic volatility (SV-BVAR) with the homoskedastic BVAR from Section 2.2.[16] Allowing for stochastic volatility substantially improves the forecasting performance of the models based on shipping costs, but only the one using the shipping cost factor is competitive with any of the other three indicators of global economic activity. The most striking result is that stochastic volatility achieves impressive gains in forecast accuracy at longer horizons for the four competitive models. Carriero et al. (2019) make the case that time-varying volatilities should improve the point forecasts especially at longer horizons. The reason is that the heteroskedastic model will provide more efficient estimates given that the predictive means will gradually deviate from their homoskedastic counterparts as the predictive densities cumulate nonlinearly with the forecast horizon. This is consistent with what we find. The reductions in MSPE range between 10-14% at the one-year horizon and 23-29% at the two-year horizon compared to only 2-3% and 6-10% in models without stochastic volatility. These large MSPE reductions for long-run forecasts come at the expense of a small loss of at most 3% in predictive accuracy at near horizons for the models using world industrial production and the commodity price factor relative to forecasts with constant variance.[17] In contrast, the forecasts based on the global steel production factor benefit at all horizons from adding stochastic volatility. We also see from Table 4 that consumption-based models still generally outperform production-based specifications for purposes of forecasting oil prices. We conclude that stochastic volatility is an important ingredient for long-horizon forecasts of the real Brent price.[18]

2.4 Pooling Forecasts and Information

Another approach to guard against forecast failures due to structural change and other model misspecifications is to pool forecasts. It has long been known that combining forecasts not only can lead to superior forecasting performance but also hedges against varying accuracy of individual forecasting models over time (see, e.g., Timmermann, 2006). There is ample evidence that forecast combinations work well for oil price forecasting and help improve forecast accuarcy especially at longer horizons (see, e.g., Baumeister and Kilian, 2014a, 2015; Baumeister et al., 2014; Funk, 2018; Garrett et al., 2019; Manescu and van Robays, 2016). This section explores the benefits of pooling in our setting in three ways.

[16] Point forecasts for the SV-BVAR are based on the mean of the predictive density generated from a sample of $4,000$ draws from the posterior distribution of the VAR parameters; for the stochastic volatility component, we use the univariate volatility estimates of the latest in-sample period as an estimate of the out-of-sample variances.

[17] A similar pattern arises if forecasts are generated with the homoskedastic counterpart of the SV-BVAR model, i.e., using the exact same Minnesota-style prior instead of data-driven shrinkage; see Table 3A in the online appendix for a direct comparison. This is in line with Carriero et al. (2015) who note that on average changes in forecast accuracy from optimally selecting the shrinkage parameters tend to be rather small.

[18] For completeness we report the results for real RAC for the production-based models with stochastic volatility in Table 2A, panel (b), in the online appendix.

First, we consider an equal-weighted average of the forecasts from the five consumption-based BVARs with stochastic volatility whose individual results were reported in Table 4(b).[19] The MSPE for this combination of forecasts is reported in the first column of Table 5. For short horizons, these pooled forecasts are always dominated by the individual BVAR forecasts coming from either world industrial production or the commodity price factor. For long horizons, the combination forecasts are always dominated by the individual SV-BVAR forecasts coming from either industrial production or commodity prices. We conclude that although simple averaging has often been found to be a useful strategy, its success in the current setting is not convincing.

Why does forecast pooling fail to improve on the forecast accuracy of individual models? One possible explanation is that the models only differ in the measure of global economic activity, while existing evidence on the superiority of forecast combinations is based on a more diverse set of forecasting models. Pooling in this case amounts to treating shipping-based measures of world economic activity as on a par with the other measures we have investigated. If the goal is to forecast oil prices, they do not appear to be.

This interpretation motivates a second way we might try to pool information, which is by aggregating alternative proposed indicators of global economic activity directly before including that measure in the VAR. To investigate this, we consider the cross-section of variables underlying the different indicators in Table 2 and extract the first principal component from this unbalanced dataset containing a total of 93 variables using the EM algorithm. We then include this factor in the SV-BVAR in place of the individual economic indicators. The forecasting result of combining information sets is reported in column 2 of Table 5. This specification again turns out typically to be dominated by the BVAR or SV-BVAR based on industrial production alone. The interpretation may again be that the world industrial production index is itself a broad aggregate with weights guided by the importance of different sectors in different countries. Using those weights for aggregation may be superior to simple principal components.

Third, we explore a market-based approach to pooling information. Some might argue that the futures market is already pooling in a rational, optimal way all the information that could be relevant for forecasting the price of oil. We follow Baumeister and Kilian (2012, 2014a) and use the following futures-spread model:

$$R_{t+h|t} = R_t \; (1 + f_t^h - s_t - E_t(\pi_{t+h}))$$

where R_t denotes the current level of the real Brent price, f_t^h denotes the log of the current Brent futures price for a contract with maturity h, s_t denotes the log of the Brent spot price, and $E_t(\pi_{t+h})$ denotes the expected inflation rate over the next h periods.[20] We approximate expected inflation

[19] We also allowed the weights for the forecast combinations to evolve over time based on each model's recent forecasting performance. Using inverse MSPE weights based on recursive MSPEs of each model did not improve the forecast accuracy relative to constant equal weights, however.

[20] We use the monthly average of daily Brent futures prices obtained from Bloomberg and of the daily Brent spot prices obtained from the U.S. EIA website for the period 1991.12 to 2018.8. Data for Brent futures contracts with maturity $h = 12$ start in 1994.4 and for $h = 18, 24$ in 1998.2.

by the average inflation rate over the post-1986 period which is updated recursively. Our question is how does $R_{t+h|t}$ perform as a predictor of the real Brent price compared to the other methods we have considered.

The results are reported in column 3 of Table 5. The Brent futures spread actually does a worse job at forecasting the real price for near horizons than one would get from a random walk. The futures market does a reasonable job at longer horizons, but still is outperformed by the information-combination approach. For example, at the 2-year horizon the futures-spread model reduces the MSPE by 16% relative to the no-change forecast, while the SV-BVAR model with the common factor from all existing activity measures improves the MSPE by 29%.

This evidence suggests that some popular ideas about pooling information from different sources using either a model-based or a market-based approach do not work particularly well in our context. We will explore in Section 4 some alternative approaches to pooling that may hold more promise. Before doing so, however, we first evaluate our set of models in terms of an alternative dimension that has received little attention in the literature, which is forecasting petroleum consumption.

3 Forecasting Global Petroleum Consumption

Up to this point in the paper we have been considering using models like the SV-BVAR for purposes of forecasting a single variable, which is the real price of oil. However, price forecasts are only one aspect of future developments in energy markets. Government agencies like the U.S. Energy Information Administration (EIA), intergovernmental organization like the International Energy Agency (IEA) and OPEC, and oil companies such as BP also regularly release short-term and long-term projections for oil and liquid fuels consumption as a complement to their price outlook and key component of their overall assessment of global energy demand. For example, the EIA publishes monthly consumption forecasts in its *Short-Term Energy Outlook* but the length of the forecast horizon varies each month from a maximum of 24-months-ahead to a minimum of 13-months-ahead. However, it is not clear how these forecasts are generated. To the best of our knowledge, there are currently no model-based forecasts for global petroleum consumption available. We use the set of VAR models that have been shown to work well for forecasting the real Brent price to also produce forecasts for global petroleum consumption. While it would seem natural to evaluate the accuracy of our forecasts against those of the EIA, this is not possible since there are no publicly available records of the EIA's historical forecasts of monthly global petroleum consumption for our entire evaluation period that would enable such a comparison. Moreover, their maximum forecast horizon that is consistently available each month from October 2007 onward is one year, while we focus on a forecast horizon of two years. Absent an alternative forecast as benchmark, we follow the macroeconomic forecasting literature and consider a univariate linear autoregressive (AR) model which is the standard when evaluating forecasts of real economic variables (see, e.g., Chauvet and

Potter, 2013; Alquist et al., 2013).[21] We set the lag length to $p = 12$ to be consistent with our VAR models. While all models are estimated with petroleum consumption entering in growth rates, we evaluate the forecasts in levels since both the EIA and the IEA report their consumption forecasts in terms of million barrels per day.

Table 6 presents the recursive MSPE ratios for forecasts of global petroleum consumption obtained with the BVAR models with and without stochastic volatility using the same five economic activity indicators as before and the two model-based pooling methods. Panel (a) shows that none of the BVAR models beats the AR(12) benchmark. All the MSPE ratios are above 1, and their performance quickly deteriorates as the forecast horizon lengthens. Adding stochastic volatility improves the forecast accuracy considerably but the models still only outperform the benchmark at the one-month-ahead horizon with MSPE reductions between 3% and 7% as summarized in panel (b). The only model showing any promise beyond the one-month horizon is the one that features the world industrial production index which consistently produces the lowest MSPE ratios being essentially tied with the benchmark model for horizons 3 months to a year. The WIP model is also more accurate than either forecast combination or a specification exploiting the large dataset of all disaggregated data underlying the existing economic activity indicators (panel c). This disappointing forecasting performance suggests that our vector autoregressions may be missing important predictor variables that carry useful information for future global petroleum consumption, a possibility that we explore in the next section.

4 Towards A New Indicator of Global Economic Conditions

So far the literature has focused on developing indicators that capture cyclical variation in global real economic activity. These measures are rather limited in scope since they are all constructed based on a single category of variables such as shipping freight rates, commodity prices, steel production or industrial production. The question to which we now turn is whether global economic conditions as they relate to energy markets can be represented by any narrow set of variables or combinations thereof or whether there is value in diversifying the basket of variables to include new categories that cover additional dimensions of the global economy. While the forecasting success for the real price of Brent suggests that the information contained in existing activity measures is sufficient, there is reason to believe that considering other types of data might help improve the forecast accuracy for global petroleum consumption. Moreover, since the predictive content of different variables can change over time, relying on a more diverse dataset reduces the risk of obtaining results that are too heavily affected by the idiosyncratic behavior of individual measures in specific periods. Using a broader variety of predictor variables to form a global indicator also exonerates

[21] This standard was suggested to us by James Stock. We also evaluated our model forecasts relative to a random-walk benchmark, using which the superiority of our model becomes even more stark. Since some of that superiority may come from seasonality and mean reversion that one sees in the consumption data, we use the AR(12) as a tougher benchmark.

the forecaster from having to choose one specific measure of economic activity.

The next section describes the set of variables that we investigate for whether they could capture important information about the global economy as it relates to energy markets.

4.1 A Multi-Dimensional Approach

We compile the set of 16 indicators summarized in Table 7 that cover a broad spectrum of variables tied to energy demand.[22] The variable selection is guided by four principles. First, the set of variables should represent different categories of data in order to span multiple dimensions of the global economy. We broadly define eight categories: real economic activity, commodity prices, financial indicators, transportation, uncertainty, expectations, weather, and energy-related measures. Second, each individual variable should matter for energy demand on economic grounds. Third, it should have the broadest possible coverage geographically, conceptually and in time. Fourth, the number of variables should be kept at a manageable size to ensure that the dataset can be easily updated in a real-time setting. In fact, many energy market analysts, financial traders, investment banks, and government institutions tend to track a relatively small number of indicators to assess the current and future state of economic conditions related to energy markets. For example, the EIA's December 2019 *Short-Term Energy Outlook* considers developments of U.S. real GDP, China's Purchasing Managers' Index, the S&P500 equity index, and the copper-to-gold ratio as a measure of market sentiment on global economic growth as important factors in their assessment of energy markets. Investment banks like Morgan Stanley and Merrill Lynch often base their outlook on global manufacturing indicators, measures of business confidence, sales of commercial vehicles, and U.S. leading economic indicators, among others.

Real economic activity. As discussed above, current and future economic activity are a key determinant of global economic conditions and energy demand. We include the world industrial production index as the broadest measure of real output in the industrial sector at a global scale. The world industrial production index is also important to include because it includes production measures from manufacturing, mining, and utilities, sectors that are closely tied to energy in that they use oil and refined petroleum products in the production process. We also include the Conference Board Leading Economic Index. This is a closely watched leading indicator with a proven track record of signaling peaks and troughs in the business cycle. While it is U.S.-specific, it consists of a range of measures that are key for capturing future economic trends. A third measure we use is the OECD consumer confidence index, which is the broadest available measure to gauge future outlook for households' consumption spending and savings. This survey-based indicator summarizes whether the attitude of consumers is optimistic or pessimistic by asking households about their expected financial situation, their sentiment about the general economic situation, unemployment and capability of savings.

[22] Please refer to Table 7 for the start date of each series, the data transformation, and the data source.

Commodity prices. Among commodity prices, copper stands out in its importance in manufacturing, construction, and infrastructure. Copper prices have been used in a number of studies as a representative commodity price and barometer of future global growth (see, for example, Hu and Xiong, 2013; Hamilton, 2015; Bernanke, 2016). The nominal price of copper is deflated by the U.S. consumer price index.

Financial indicators. Our two main financial indicators are foreign exchange and stock returns. Exchange rate fluctuations reflect trade and financial flows and changes in economic activity. They also are tightly linked to energy demand (see, for example, De Schryder and Peersman, 2015). We select the broad real trade-weighted U.S. dollar index not only because this series extends furthest back in time, but also because oil prices are quoted in dollars and changes in the exchange rate often translate into changes in petroleum consumption in oil-importing countries. Our measure for stock returns is based on the MSCI world index which contains stocks from companies throughout the world and represents a broad cross-section of global markets. We also use a third financial indicator that is more specific to energy demand, which is the excess return earned on the Fama-French (FF) portfolio for the transportation sector. The transportation sector is obviously the most energy-intensive sector, so excess returns in this sector should provide forward-looking information for energy consumption.

Transportation. We also use two real indicators of transportation demand. Registrations of vehicles are indicative of the future demand for gasoline and diesel. The longest available series with the broadest coverage is for passenger cars in OECD countries which covers the number of newly registered private cars and commercial vehicles. Given that the automobile industry is a large sector in many major economies, car sales which precede registration also matter for aggregate fluctuations. To complement this stock variable, we also include a flow measure of traffic volume represented by U.S. total vehicle miles traveled.

Uncertainty measures. Crude oil production and prices are often driven by geopolitical events. These events can matter not just for the oil market but can also influence the global economy more broadly. We use the geopolitical risk index developed by Caldara and Iacoviello (2018). This should reflect increasing supply disruption risks and translate into rising concerns about the future availability of oil which will influence energy demand behavior worldwide. Long-run oil price uncertainty is another important determinant of energy-related spending by consumers and businesses (see, e.g., Bernanke, 1983; Pindyck, 1991; Jo, 2014). Here it is defined as realized volatility computed based on daily returns for WTI futures contracts with a maturity of 12 months.

Expectations measures. Our set of variables also includes the index of consumer expectations from the University of Michigan Consumer Survey which aggregates households' assessment of the short-term and long-term outlook of the general economy. We also construct a measure of oil price expectations based on the difference between WTI futures prices with 3 and 12 months to maturity. This market-based measure should signal the direction of expected price changes which will likely influence spending on energy-dependent goods and services.

Weather indicators. A key global weather-related variable is El Niño. We use the Oceanic

Niño Index (ONI) which is available from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center.[23] Cashin, Mohaddes, and Raissi (2017) discuss the importance of this complex weather phenomenon for global macroeconomic performance. It also has direct implications for energy demand as higher temperatures associated with El Niño episodes lead to more fuel demand for power generation. Another weather-related indicator provided by NOAA is the Residential Energy Demand Temperature Index (REDTI) which is based on population-weighted heating and cooling degree days in the United States, and as such, is a valuable tool for measuring fluctuations in energy demand for residential heating and cooling.

Energy-related indicators. The broadest energy-specific measure is energy production and electricity distribution for the EU28. This is not only directly tied to energy demand but is also an indicator for the overall intensity of economic activity since the production of most goods and services requires electricity (see Arora and Lieskovsky, 2014).

We extract the first principal component from this unbalanced panel of 16 variables by applying the EM algorithm recursively and use this estimated factor to replace the economic activity measure in our four-variable consumption-based BVAR(12) model with stochastic volatility. Row 1 of Table 8 shows that this factor-augmented model produces forecasts of the real Brent price that are marginally less accurate than forecasts from the set of models with existing measures of global real activity. At horizons up to 9 months MSPEs are at most 3% higher compared to the best-performing individual model in Table 4(b). This difference shrinks to at most 1% for longer horizons with the factor-augmented VAR being the most accurate 24 months ahead. This small loss in forecasting performance for oil prices is more than made up for by the dramatic improvement in forecasts of global petroleum consumption. Row 6 of Table 8 shows that the factor-augmented model outperforms the AR(12) benchmark at all horizons with impressive MSPE reductions between 6% and 13% some of which are statistically significant.

We conclude that while the forecasting performance for the real Brent price is comparable across indicators, the forecasting success for global petroleum consumption confirms our earlier conjecture that existing global economic activity measures miss information that is relevant for determining energy demand. The obvious next question is whether including additional variables from each data category can improve the joint forecast accuracy further.

4.2 Is More Information Better?

To address this question, we collect an additional 150 variables listed in Table 9 to form a very large dataset, which substantially expands the coverage of each of the 8 broad categories in Table 7.[24] We also add all the disaggregated data from the existing real economic activity indices, bringing

[23]The term El Niño refers to the large-scale ocean-atmosphere climate interaction linked to a periodic warming in sea surface temperatures across the central and east-central Equatorial Pacific. The ONI is NOAA's primary indicator for monitoring El Niño and La Niña, which are opposite phases of this climate pattern and it is based on the average sea surface temperature in the Niño region.

[24]Note that the cross-section of commodity prices is already included in Table 2.

the total up to 256 variables. Row 2 of Table 8 shows that substantially increasing the size of the panel does not improve the usefulness of the first principal component for forecasting the real Brent price, and row 7 shows that it leads to a deterioration of the forecast performance for petroleum consumption for all but the one-month-ahead forecast. At the one to two-year horizons relying on a factor extracted from the larger dataset results in an increase in the MSPE of 6%.

It is conceivable that for such a large cross-section of variables one factor is simply not sufficient to capture the features influencing oil prices and consumption. We therefore extract additional factors and include them in our forecasting model. As can be seen from rows 3 and 4 of Table 8, adding more factors worsens the forecast accuracy for the real Brent price considerably. In particular, the model with three factors implies a loss of 10-15% in MSPE reductions beyond the one-year horizon. Rows 8 and 9 show that for global petroleum consumption the forecasting gains vanish from horizon 6 onward with all MSPE ratios above 1. One potential issue with using more factors to construct the forecasts is that the informational advantage of incorporating additional factors can be outweighed by the increased parameter uncertainty which penalizes out-of-sample forecasting accuracy. Overall these findings are in line with Boivin and Ng (2006) who show that factors extracted from a larger panel do not necessarily improve forecasting performance and can actually lead to inferior forecasting performance. The reason why it is not always optimal to use all available data to extract factors is that as more series from the same data category are added, the possibility of cross correlation in the idiosyncratic errors increases which leads to a loss in forecast efficiency. We conclude that what matters most for the joint forecasting success is the composition not the size of the dataset.

The 16 variables in Table 7 were chosen based on their economic relevance and broadness of coverage to be representative of different aspects of the global economy. Our larger 256-variable dataset offers an alternative possibility for selecting the most relevant variables using statistical criteria. Specifically, we use the 16 variables with the highest loadings in absolute value on the first principal component. To mimic the choice a forecaster would have made at the beginning of the evaluation period, the dataset from which the factor is extracted ends in 1991.12.[25] Row 5 of Table 8 shows that the statistical variable selection leads to additional gains for the real Brent price forecasts yielding further MSPE reductions of up to 3% at long horizons. However, these gains come at the expense of the forecast accuracy for petroleum consumption (row 10). This model has much higher MSPE at all horizons and from horizon 12 onward it no longer beats the AR(12) benchmark.

Based on this analysis, we conclude that our smaller, economically-motivated set of 16 variables

[25] This reduces the number of series to 191. The variables selected are the following in the order of the magnitude of loadings: long-run oil price uncertainty, spread of oil price expectations, real freight rates for fertilizer (potash) from Germany to India, short-run gasoline price uncertainty, Conference Board Leading Economic Index, FF industry portfolio: utilities, MSCI world index, FF industry portfolio: chemicals, FF industry portfolio: oil, FF industry portfolio: transportation, FF industry portfolio: cars, Composite Leading Indicator for Japan, OECD business confidence index, real freight rates for fertilizer (phosrock) from West Africa to India, Australian unemployment rate, and Chinese consumer confidence index.

gives the most reliable signal and results in the best overall forecasts.

4.3 A Global Economic Conditions Indicator

Panel A of Figure 4 displays the first principal component of the 16 variables in Table 7 over the period 1973.2 to 2019.8. We will refer to this series as our global economic conditions indicator (GECON).[26] The series is normalized so that it has a mean of zero and a standard deviation of one which facilitates the interpretation. Thus a value of zero corresponds to economic conditions characterized by normal trend growth. Given that the underlying monthly data series are somewhat volatile we report the 6-month moving average to get a better summary of the persistent movements in the global economy. The indicator tracks known episodes of worldwide contractions and expansions well. The downturn related to the 2008-2009 financial crisis is the most severe with the indicator being five standard deviations below its long-run average followed by the worldwide recession of 1974-75. The second half of the eighties and the mid-2000s are periods of strong economic conditions. The indicator signals an improvement in global economic conditions in 2013 followed by a period of sluggish growth in 2015-17.

It is useful to take a closer look at the contributions of different data categories to the movements in the global indicator to appreciate the value of a diverse dataset. This decomposition can be found in panel B of Figure 4 which shows the contributions of the four most important categories over time. As can be seen, the relative importance of different categories varies over time. For example, most of the boom in the mid-80s is captured by the financial indicators. Real activity accounts for the largest share of the downturns in 1974-75 and the early 1980s as well as in the Great Recession, while financial indicators also help identify the early 2000s slowdown. Uncertainty is a major factor in the early 1990s slump. Financial indicators and uncertainty are the most important measures of the most recent fluctuations. Transportation contributes a small share overall and matters more in the early part of the sample than in more recent times.

4.4 The Role of Real-Time Data Constraints

Up to this point in the paper our forecasts have been generated using a pseudo real-time setting which relies on the most recent vintage of data and assumes that all data are available up to the point in time when the forecasts are produced. In practice, forecasters often face real-time data constraints in the form of data becoming available only with a lag and preliminary data being revised for some time after the first release. One concern is that not accounting for delays and revisions in data releases may result in overly optimistic assessments of the ability to forecast oil prices (see Alquist et al., 2013).

How severe are real-time data constraints for oil price forecasting? Baumeister and Kilian (2012) address this question by developing a real-time dataset for the oil market and investigating for which

[26] This series is available at https://sites.google.com/site/cjsbaumeister/research.

variables the real-time data aspects matter most. They provide evidence that having more accurate and timely data for the refiner acquisition cost of imported oil has the highest payoff in terms of out-of-sample forecasting performance, while both data revisions and lags in data availability for global oil production and OECD crude oil inventories play a negligible role. They confirm this finding by replacing the RAC with the West Texas Intermediate (WTI) spot price which is available in final form in real time and conclude that abstracting from real-time data constraints has little effect on the measures of forecast accuracy for the real WTI. Since we are using the Brent price, which is also available in real time and not subject to revisions, we would not expect differences in forecast accuracy to be driven by the energy market variables.

This leaves us with the series underlying the global economic conditions indicator which are released with varying degrees of delay. Six out of the 16 series are available in real time and based on data that are not subsequently revised.[27] The broad real trade-weighted U.S. dollar index is also released without delay but is subject to some minor revisions due to the inflation component. The update of the Fama-French industry portfolio is lagging by two months, but data for this series are final. The remaining eight series become available with a delay and are subsequently revised.[28] Baumeister and Kilian (2012) show that lags in data availability are a much bigger concern than revisions to preliminary data. This is reassuring since we can assess the relevance of publication delays, while it is not feasible to construct a true real-time version of our dataset that tracks data revisions over time. Moreover, it is likely that for the variables underlying the global economic conditions indicator data revisions would be picked up as idiosyncratic noise that is filtered out by extracting a principal component.

We investigate the role of lags in data releases by assuming that the most recent value for variable i for month t (y_{it}) is the value observed for $y_{i,t-m_i}$ where m_i is the delay parameter associated with that variable indicated in Table 7. This parameter was determined based on the number of missing observations for each series at the end of April 2019 when this dataset was originally assembled. To fill in gaps at the end of the sample, we follow Baumeister and Kilian (2012, 2014a) who show that simple nowcasting techniques based on the time series properties of the data perform best.[29]

Table 10 compares the recursive MSPE ratios for forecasts of the real Brent price and global petroleum consumption using observed and nowcasted values at the end of the sample for all forecast horizons from 1 to 24 months. As can be seen, taking data delays into account makes little difference overall. The forecast accuracy for the real Brent price suffers slightly for horizons up to

[27] These include the MSCI world index, copper prices, long-run oil price uncertainty, the index of consumer expectations, the spread between short-run and long-run oil price expectations, and the geopolitical risk indicator.

[28] For details on the delays in data availability for each variable, see Table 7.

[29] Please refer to Table 7 for a summary of the nowcasting rules for each variable entering the GECON index. Alternatively, we could make use of the EM algorithm to fill in the missing data. While the results turn out to be very similar for the price forecasts, the simple rules work slightly better for consumption forecasts. For petroleum consumption which becomes available with a delay of 2 months and for OECD petroleum stocks which are lagging 3 months, we extrapolate the missing values based on their average growth rates. While the nominal Brent price is available in real time, the release of the U.S. CPI is delayed by 1 month. To deflate the Brent price, we nowcast the CPI based on past average inflation.

9 months when nowcasted data are used registering an average loss of 2% in MSPE reductions, but is basically unaffected at longer horizons. Interestingly, the real-time nature of the data has a positive effect on global petroleum consumption forecasts leading to gains in MSPE ratios of up to 3% for short horizons. In contrast to the pseudo real-time setting, these MSPE reductions are highly statistically significant. The likely reason for this finding is that in the case of petroleum consumption, the gaps in data availability not only affect the SV-BVAR model forecast but also the AR benchmark so that it is not clear a priori which way the MSPE ratios go. From the results it is clear that the nowcasted data for consumption are putting the benchmark model at a slight disadvantage in the short run. In the medium term, this ranking is reversed and the pseudo real-time model performs slightly better.

5 Assessing Energy-Market Conditions

Based on our preferred forecasting model that takes real-time data constraints into account, we propose a set of monitoring tools to summarize expected future conditions in energy markets. First we introduce an energy demand indicator based on our preferred model's forecast of global petroleum consumption. Next we quantify oil price risks by forming an oil price pressure index.

5.1 A Barometer for Future Energy Demand

An important concern for energy market participants, industry analysts, policymakers, government agencies like the EIA, and international organizations like the IEA and the IMF is how demand for energy will evolve in the near term. How can we gauge what demand conditions are expected to prevail in the future? We propose to look at the difference between the 13-month-ahead forecast of the level of consumption and the 1-month-ahead forecast of the level of consumption. This measure summarizes the slope of the forecasts as a function of horizon. An increase in this forecast measure can be viewed as signaling rising demand pressures over the next year. Figure 5 shows the 6-month moving average of our energy demand indicator over the period 1992.1 to 2019.8. Each point in the graph tells us whether demand conditions are expected to be tight or loose relative to the past. The figure shows strong anticipated growth in demand after the East Asian crisis in 1997. A sharp tightening in demand conditions is also evident before the Great Recession. Demand pressures ease with the recession but growth in energy demand is predicted to pick up again afterwards. Demand conditions are anticipated to loosen as a result of the European double-dip recession. Expected demand pressures have been mounting again since 2012 with steep predicted growth in demand in mid-2014 when oil prices fell dramatically. Recently there is an indication that energy demand growth in the world is expected to slow down amid weakening economic conditions.

5.2 Measuring Oil Price Risks

Policymakers and other users of oil price forecasts are typically not only interested in the expected future path of the real oil price but would also like to assess the likelihood that prices exceed a certain upper threshold or fall below a certain lower threshold. This matters because a predicted increase in the probability of higher or lower prices relative to the recent past can affect firms' and consumers' spending plans with the potential to influence macroeconomic performance in the short run (see, e.g., Hamilton, 1996, 2003). Our Bayesian forecasting model delivers an entire distribution of forecasts for each horizon based on which we compute the probability that the forecast will fall outside a specific price range. While oil companies, households, and firms may differ in the thresholds they care about, we calculate probabilities that the oil price will end up outside the upper and lower bounds of recent experience.[30]

5.2.1 The Construction of Oil Price Pressure Measures

We propose a new measure that signals the likelihood of a build-up of upward and downard oil price pressures relative to the recent past. Specifically, we compute the probabilities that the expected price will remain within the range of values experienced recently, rise above or fall below this range. For this purpose, we estimate the predictive density and allow for dynamically-changing cutoff points based on the minimum and maximum values of oil price levels over the past year. The resulting measures will indicate the risk of unusually high or low prices.

Our model implies a probability based on information I_t observed in month t that oil prices h months from now will exceed the highest value seen over the last year:

$$\Pr([p_{t+h}^{oil} > \max\{p_t^{oil}, p_{t-1}^{oil}, p_{t-2}^{oil}, ..., p_{t-11}^{oil}\}]|I_t].$$

Following Jackson, Kliesen, and Owyang (2015), we can calculate an average value of this probability over the coming year,

$$PPM_t^{oil,+} = (1/12)\sum_{h=1}^{12}\Pr([p_{t+h}^{oil} > \max\{p_t^{oil}, p_{t-1}^{oil}, p_{t-2}^{oil}, ..., p_{t-11}^{oil}\}]|I_t].$$

This measure is plotted in the middle panel of Figure 6. Similarly we can calculate a probability that prices on average over the next year will fall below the lowest value seen over the last 12 months:

$$PPM_t^{oil,-} = (1/12)\sum_{h=1}^{12}\Pr([p_{t+h}^{oil} < \min\{p_t^{oil}, p_{t-1}^{oil}, p_{t-2}^{oil}, ..., p_{t-11}^{oil}\}]|I_t].$$

This measure is plotted in the last panel of Figure 6. The probability of staying within the recent range is

$$PPM_t^{oil,neutral} = 1 - PPM_t^{oil,+} - PPM_t^{oil,-},$$

[30] Baumeister and Kilian (2014b) also conduct an analysis of the risks embodied in oil price forecasts, but they propose a different set of risk measures based on a structural model of the global oil market. In particular, they focus on risks associated with hypothetical events about future oil supply and demand conditions summarized in probability-weighted predictive densities.

plotted in the top panel of Figure 6.

A number of well-known historical episodes stand out in Figure 6. In the aftermath of the Asian financial crisis, the probability that oil prices would fall below the lowest price over the past 12 months remained consistently high at 40% over a period of two years before plummeting to zero in early 2000. After oil prices reached a record low in December 1998, the likelihood of upward price pressures spiked resulting in a 55% probability that the Brent price will on average surpass its highest value during the past year over a 12-month horizon. At the onset of the Great Recession the average probability that the Brent price would exceed the previous year's price maximum over the next 12 months dropped from around 40% to essentially zero, while chances of prices falling below the lower threshold jumped up to 50% followed by an all-time high of staying within the new lower price range of close to 80% in mid-2009. From 2012 onward, the odds that the Brent price would drop below its most recent lower bound gradually increased reaching a peak of 70% in early 2015. Starting in 2016 it becomes more and more likely that oil prices will top the price ceiling in place during the preceding 12 months in the coming year. As of August 2019, the price pressure measures indicate on average a 20% probability of the Brent price exceeding the recent upper threshold of $81 and a 30% probability of falling below the recent lower threshold of $57 in the period up to August 2020.

5.2.2 A Historical Perspective on Expected Oil Price Pressures

So far we have focused on the average probability that oil prices will rise above or drop below a recent price band over the next 12 months. It is also useful to look at the risk assessment implied by the model over a two-year horizon at a given point in time. Figure 7 displays the probabilities based on the forecast distributions for the real Brent price up to 24 months ahead for three selected historical episodes. 'Status quo' refers to the probability of the future oil price fluctuating within last year's price range, 'upward price pressure' indicates the probability of exceeding the maximum price of last year, and 'downward price pressure' measures the probability of falling below the minimum price of last year. While the forecasts are produced for the real price, in what follows we discuss historical episodes in terms of dollar prices since they are more easily remembered.

Panel A shows the expected price pressures as of May 2004, just before the oil price started its gradual ascent to new highs. Between June 2003 and May 2004 the Brent price fluctuated between $27 and $38. The predictive probabilities signal elevated risks that the oil price will surpass the upper bound remaining consistently above 50% throughout the forecasting horizon. While the odds of oil prices staying within the previous price range increase slightly during the first three months, this tendency is reversed and probabilities decrease from a high of 40% to about 20%. The model assigns a fairly low chance of oil prices dropping below the lower bound of $27. In May 2006 the Brent price was $70.

Another interesting point in time is June 2014. In the year before the onset of the oil price slump, Brent prices were pretty stable and fluctuated narrowly between $107 and $112. Panel

B indicates a rapid build-up of downward price pressures which surpasses 50% after the first six months and reaches a probability as high as 75% at the end of the two-year forecasting horizon. The probability for oil prices continuing their calm ride subsides quickly falling from 60% at the one-month horizon to below 10% in the long run. The odds for upward price pressures remain fairly constant at around 20%. The observed price for Brent crude in June 2016 turned out to be $48.

After bottoming out in early 2016, the Brent price showed strong signs of recovery which in June 2016 led to the question of how likely it was that oil prices would continue to climb, hold steady around that new level, or begin another slide. In the year preceding this third episode, the Brent price ranged from $31 to $57. As can be seen in Panel C, our model attaches a very high probability to the status quo in the short run which declines gradually over the next two years to a low of 40%. Instead, the chances for upward oil price pressures increase steadily reaching about 40% after one year. Risks for oil prices falling below $31 are predicted to be minimal for the first couple of months but rise to a robust 20% in the medium to long run. In June 2018 the Brent price reached $74.

This analysis illustrates that the model can be used to derive accurate and timely measures of risks related to future price developments and of the expected tightness of energy demand conditions. These measures should help guide policymakers, market analysts, firms, and consumers in their assessment of the likely future state of energy markets.

6 Conclusions

Global economic conditions are a key driver of energy markets. In this paper we evaluated the usefulness of several existing measures of global real economic activity that have been proposed in the literature in terms of their out-of-sample forecasting performance for the real price of oil and global petroleum consumption. We also compared them to alternative measures derived from a diverse set of observations on global variables that influence energy demand collected specifically for this study. Our results imply the following main takeaways. First, for short-horizon oil price forecasts consumption-based models using world industrial production perform best. Second, for long-horizon oil price forecasts allowing for stochastic volatility leads to considerable improvements in forecast accuracy across all indicators. Third, for forecasting the real price of Brent and global petroleum consumption jointly, the most accurate model uses our newly-developed global economic conditions indicator based on a set of 16 variables that cover multiple dimensions of the global economy. We show how the real-time forecasts for price and consumption generated by this model can be used to derive measures that provide policymakers and markets with a quantitative assessment of expected oil price pressures and future energy demand conditions.

A Prior Specifications

To estimate the model in equation (2), we need to form priors for the unobserved volatility states σ_{it} and the set of coefficients $\mathbf{\Pi} = \{\mathbf{B}, \mathbf{A}, \mathbf{\Lambda}\}$ where $\mathbf{B}_i = [c_i, \mathbf{\Phi}_{i,1}, ..., \mathbf{\Phi}_{i,p}]'$ for $i = 1, ...n$ contains the VAR coefficients, $\mathbf{A}_i = [a^*_{i,1}, ..., a^*_{i,(i-1)}]'$ for $i = 2, ..., n$ contains the covariances of the reduced-form residuals, and $\mathbf{\Lambda}$ is the full covariance matrix of the vector of innovations $\boldsymbol{\eta}_t$ to the law of motion of the volatilities. Following Carriero, Clark, and Marcellino (2019), we postulate the following prior distributions: $\mathbf{B}_i \sim N(\mathbf{m}_B, \mathbf{V}_B)$, $\mathbf{A}_i \sim N(\mathbf{m}_A, \mathbf{V}_A)$, and $\mathbf{\Lambda} \sim IW(\nu \mathbf{S}, \nu)$.

The prior mean $\mathbf{m}_B$ and prior variance $\mathbf{V}_B$ for the VAR coefficients $\mathbf{B}_i$ in equation i are set according to the Minnesota prior beliefs:

$$\mathbf{m}_B = \begin{cases} \delta & \text{for first own lag} \\ 0 & \text{otherwise} \end{cases}, \quad \mathbf{V}_B = \begin{cases} \frac{\lambda_1}{j^{\lambda_3}} & \text{for own lags} \\ \frac{\lambda_1 \lambda_2}{j^{\lambda_3}} \frac{s_i^2}{s_k^2} & \text{for all other lagged predictor variables } (k \neq i) \\ s_i^2 \lambda_4 & \text{for intercept} \end{cases},$$

where $k = 1, ..., n$ are the number of endogenous variables ($n = 4$), $j = 1, ..., p$ indicates the lag length ($p = 12$), and s_i and s_k denote the estimated standard deviations of the residuals from a univariate autoregression fit to variables i and k (see, for example, Litterman, 1986; Sims and Zha, 1998). The ratio s_i^2/s_k^2 accounts for the possibility that variables y_i and y_k may have different scales. We set the prior mean for the real price of oil to $\delta = 0.99$ given its persistence and for all other endogenous variables to $\delta = 0$ given that they enter either in growth rates or changes. The hyperparameter λ_1 controls the overall tightness of the prior and $\lambda_2 \leq 1$ allows for additional shrinkage on the coefficients of lagged endogenous variable k in VAR equation i for $k \neq i$ (cross shrinkage). We set $\lambda_1 = 0.05$ and $\lambda_2 = 0.5$ as recommended by Carriero et al. (2019). The shrinkage parameter λ_1 is scaled by j^{λ_3} such that it gets smaller with increasing lag length which incorporates the belief that coefficients on more distant observations are more likely to be zero. The hyperparameter λ_3 governs the rate of the lag decay. For $i = 2, ..., n$, we postulate a quadratic decay by setting $\lambda_3 = 2$, and for $i = 1$, we set $\lambda_3 = 1$ for own lags which amounts to a linear decay, and $\lambda_3 = 6$ for variables other than the dependent variable. λ_4 determines the tightness of the prior for the constant term and is set to 10 which is pretty uninformative.

The prior mean $\mathbf{m}_A$ for the covariances of the error terms is set to 0 and and the prior variance $\mathbf{V}_A$ is a diagonal matrix with entries on the diagonal set to 10^6 which implies an uninformative prior on the coefficients in $\mathbf{A}_i$.

The prior for the covariance matrix $\mathbf{\Lambda}$ is inverse Wishart with scale matrix $\nu \mathbf{S}$ and ν degrees of freedom. We set the degrees of freedom equal to $\nu = n + 3$ and $\mathbf{S} = 0.15\mathbf{I}_n$ where $\mathbf{I}_n$ is an $(n \times n)$ identity matrix.

As in Carriero et al. (2019), the model is closed by forming a prior for the initial value of the state variables which is set to independent Gaussian: $\sigma_i^2 \sim N(0, 100)$.

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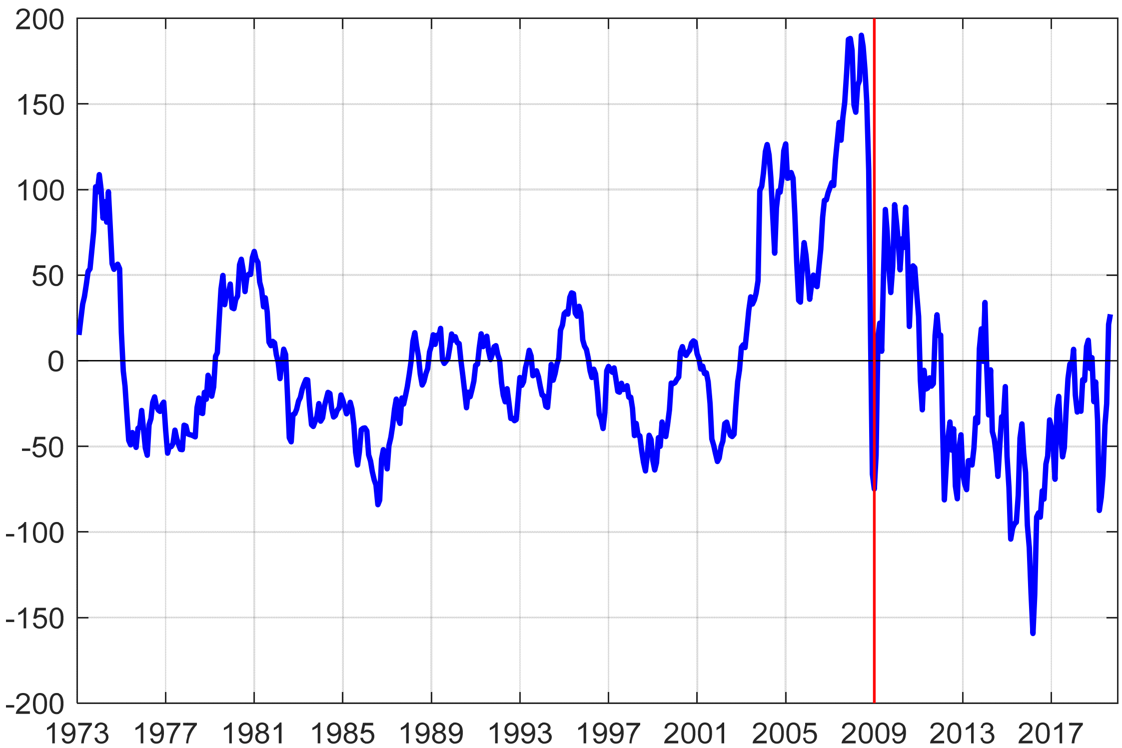
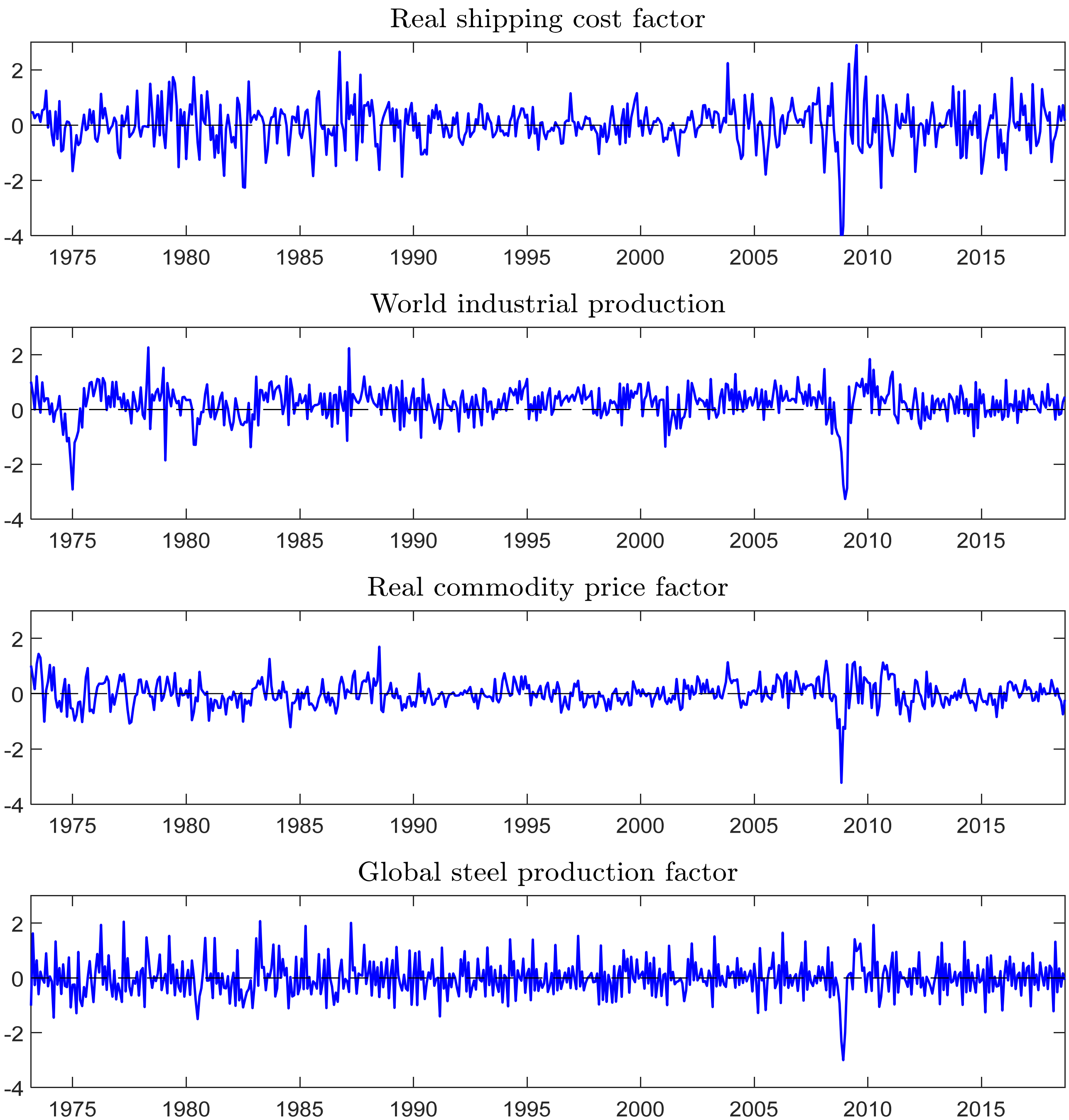
Figure 1: Kilian's corrected real economic activity index (REA), 1973.1-2019.8



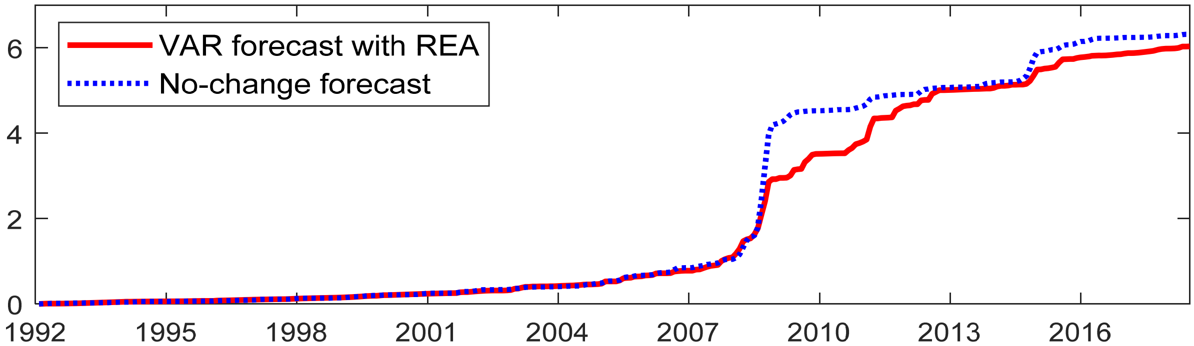
NOTES: Linearly detrended real shipping cost index. The vertical line indicates the trough of the financial crisis.

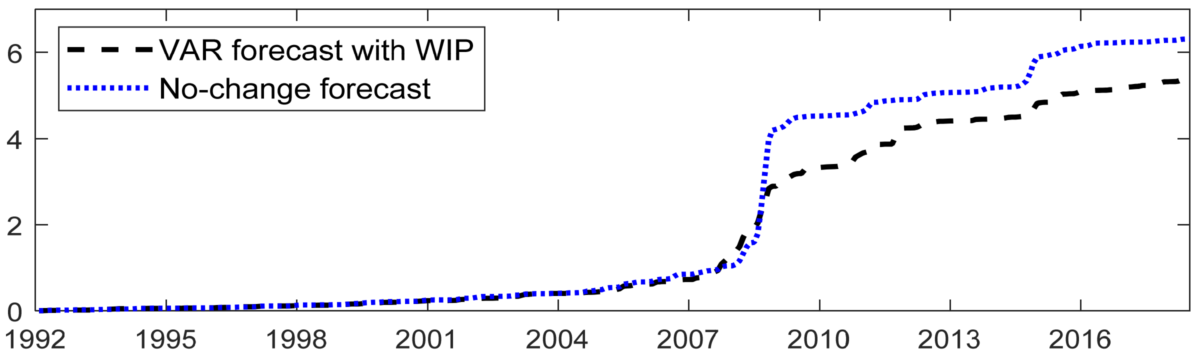
Figure 2: Alternative monthly indicators of global real economic activity, 1973.2-2018.8

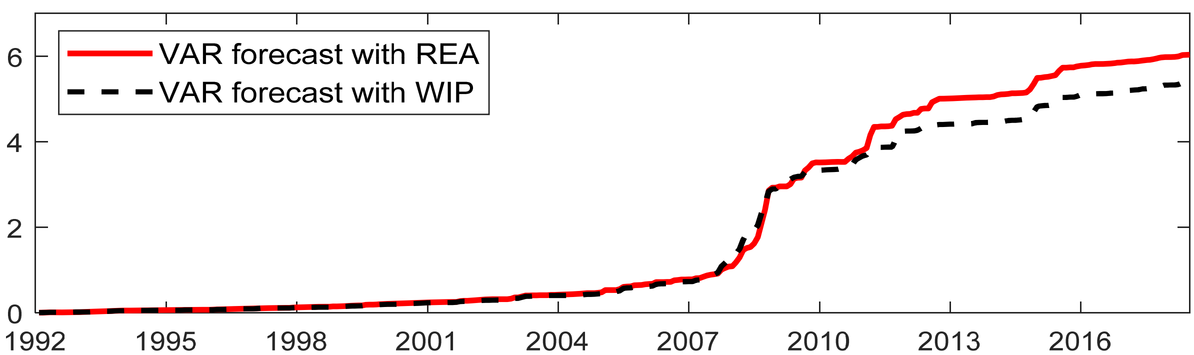


NOTES: The real shipping cost factor is extracted from an unbalanced panel of the monthly growth rates of freight rates for different shipping routes deflated by the U.S. CPI. World industrial production is shown in month-on-month growth rates. The real commodity price factor is extracted from a balanced panel of monthly growth rates of industrial and agricultural commodity prices deflated by the U.S. CPI. The global steel production factor is extracted from a cross-section of monthly growth rates of crude steel production data for individual and groups of countries with different starting dates. See Table 2 for more details on the data underlying these global economic activity indicators.

Figure 3. Recursive mean-squared prediction errors for 3-month-ahead forecast of the real refiner acquisition cost, 1992.1-2018.8







NOTES: The VAR forecasts are generated with a VAR(12) model estimated recursively by least squares using either the Kilian index (REA) or the world industrial production index (WIP) as indicator of global real economic activity.

Figure 4: Global Economic Conditions Indicator (panel A) and its main contributors (panel B), 1973.2-2019.8, 6-month moving average, expressed in standard deviations from long-run average

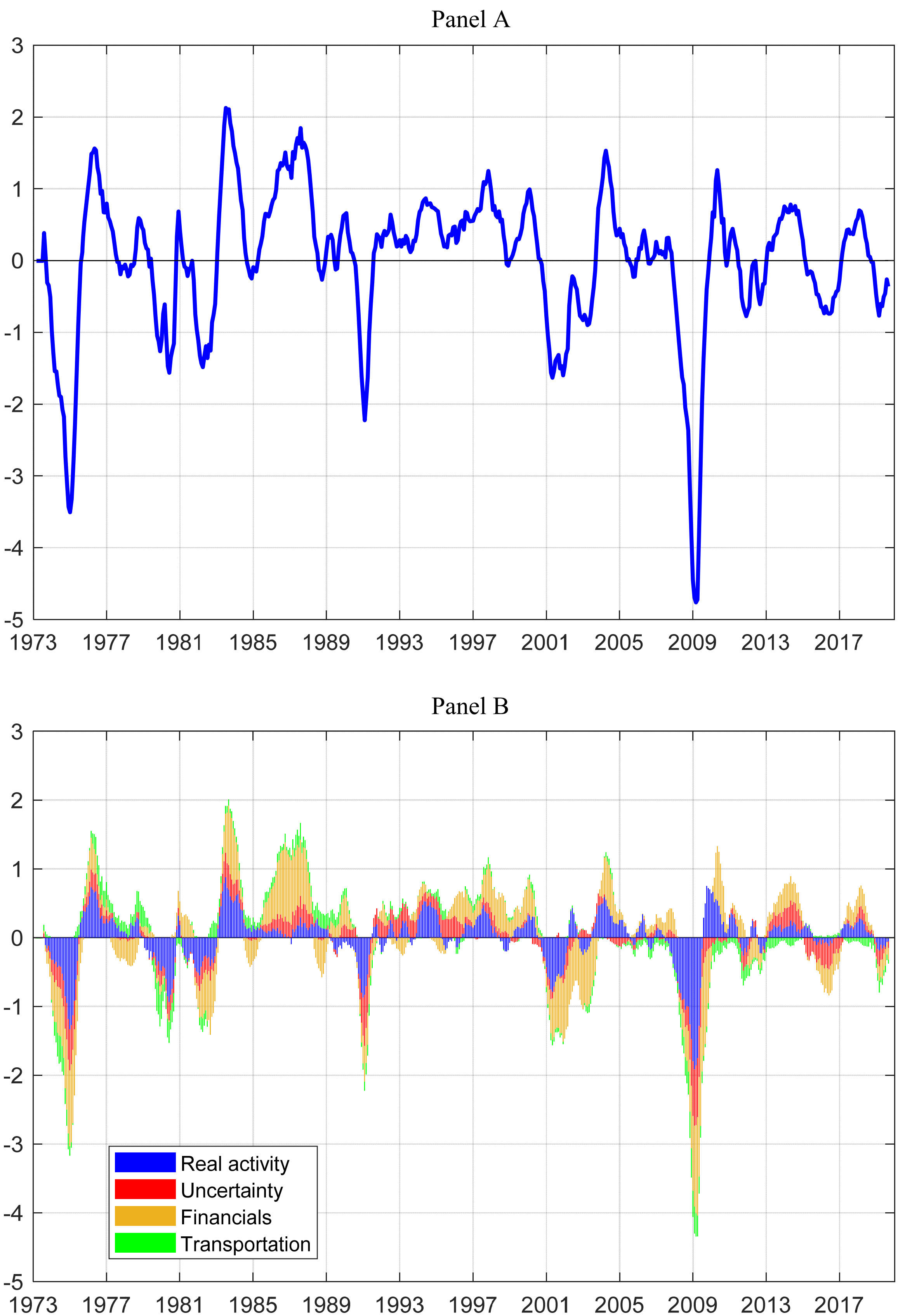
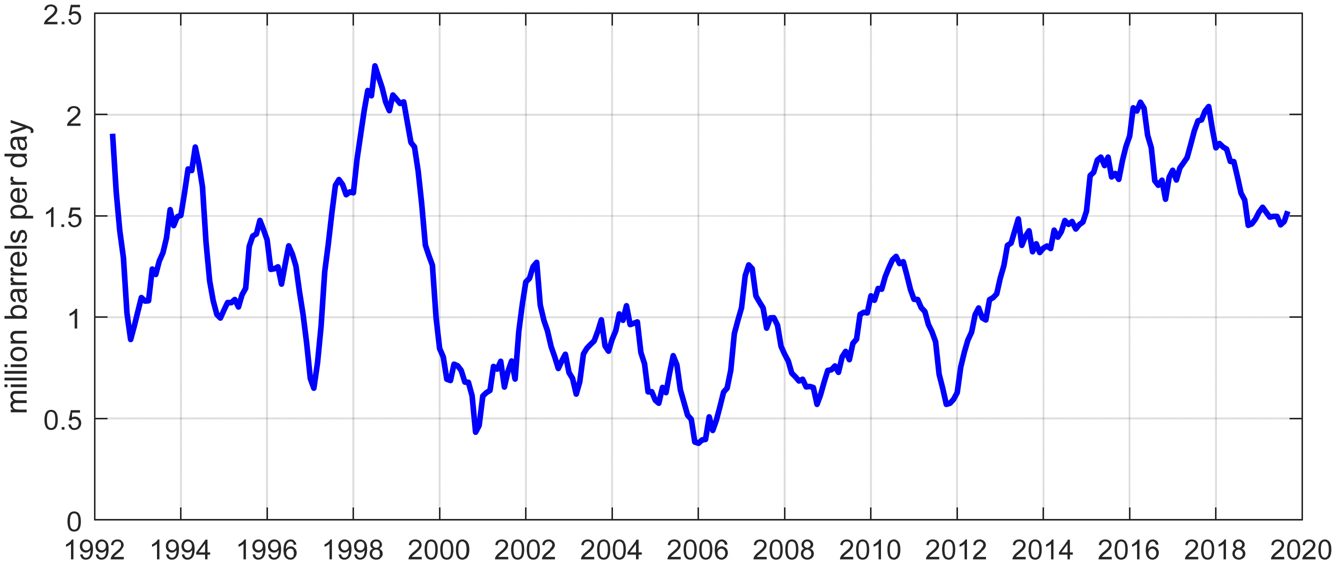
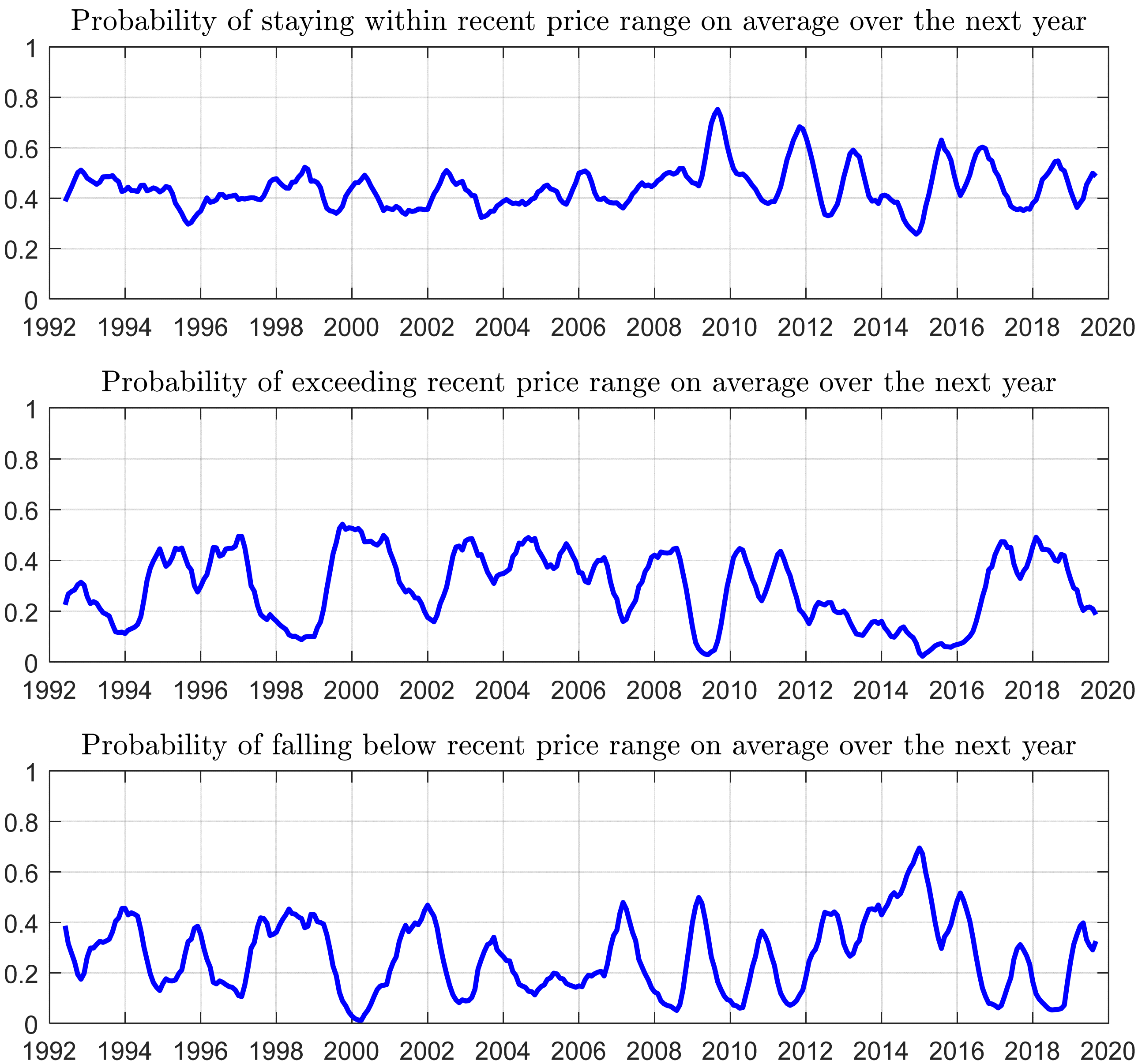


Figure 5: Energy demand indicator, 1992.1-2019.8



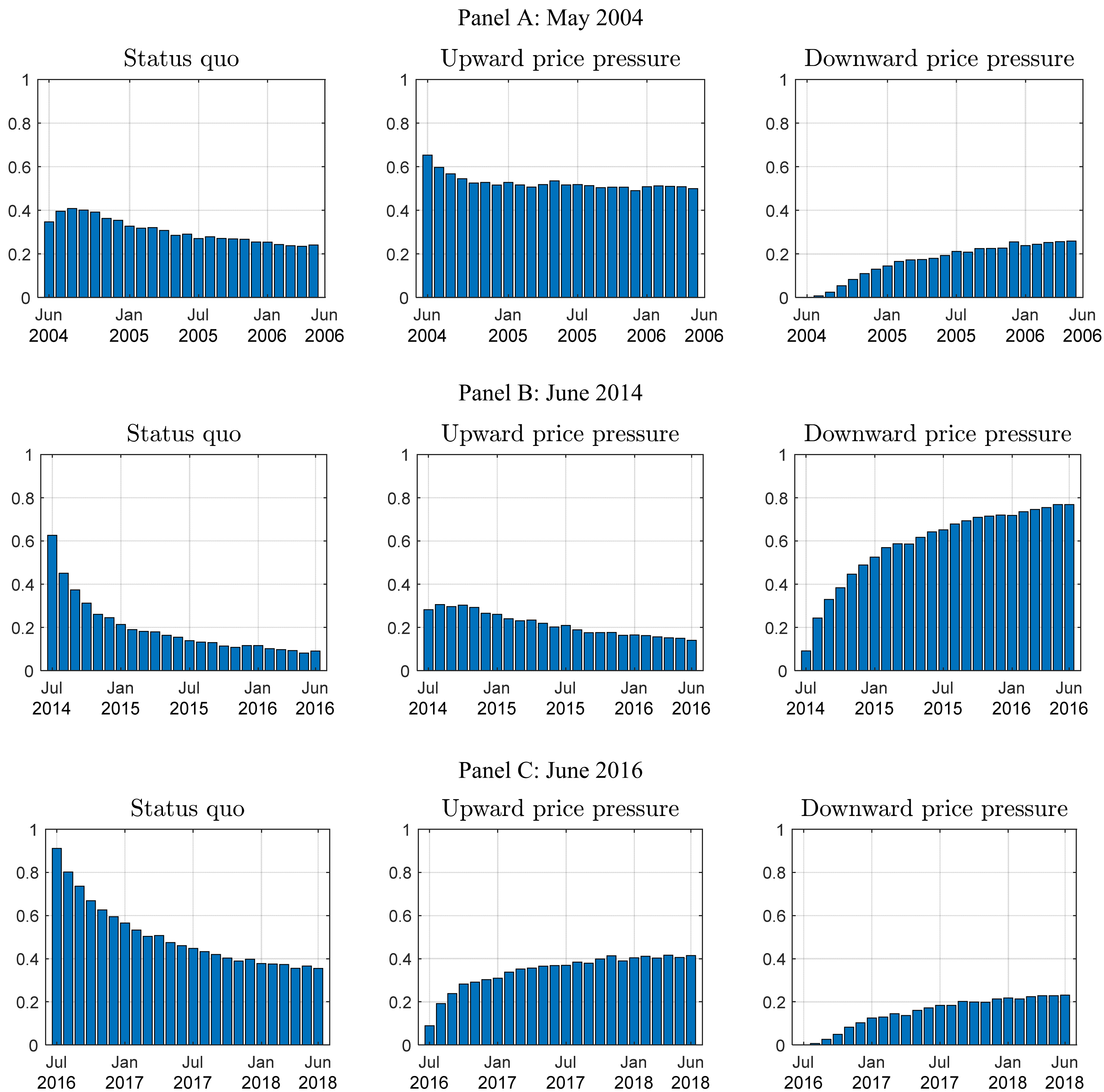
NOTES: This indicator of expected demand pressures is computed as the difference between the 13-month-ahead and the 1-month-ahead forecast of global petroleum consumption. The plot shows the six-month moving average.

Figure 6: Price pressure measures, 1992.1-2019.8



NOTES: These price pressure indices measure the average probability that the expected price level for Brent crude oil over the next 12 months stays within, exceeds or falls below the range of oil price fluctuations over the past year. The plots show the six-month moving average.

Figure 7: Expected price pressures over the next 24 months for selected historical episodes



NOTES: This figure is based on the real-time forecasts obtained with the SV-BVAR(12) model using the Global Economic Conditions Indicator. Status quo refers to the probability of the oil price staying within the price range over the past year, upward price pressure indicates the probability of exceeding the maximum price over the past year, and downward price pressure indicates the probability of falling below the minimum price over the past year.

Table 1. Recursive MSPE Ratios Relative to No-Change Forecast of Real Oil Prices in VAR(12) Models with Alternative Monthly Indicators of Global Real Economic Activity

Monthly horizon	**Kilian index (REA)**	**Real shipping cost factor**	**World IP index (WIP)**	**Real commodity price factor**	**Global steel production factor**
	(1)	(2)	(3)	(4)	(5)
	(a) Real refiner acquisition cost of crude oil imports: 1992.1-2010.6				
1	**0.679****	**0.703****	**0.657****	**0.723****	**0.694****
3	**0.779**	**0.806**	**0.728**	**0.780**	**0.776**
6	**0.989**	**0.956**	**0.867**	**0.912**	**0.925**
9	1.115	1.025	**0.988**	1.048	1.000
12	1.099	**0.992**	**0.975**	1.021	**0.940**
18	1.083	**0.962**	**0.975**	**0.956**	**0.946**
24	1.122	1.071	1.095	**0.995**	1.054
	(b) Real refiner acquisition cost of crude oil imports: 1992.1-2018.8				
1	**0.865**	**0.804***	**0.765****	**0.781****	**0.795****
3	**0.955**	**0.911**	**0.852**	**0.841**	**0.911**
6	1.074	1.008	**0.972**	**0.933**	1.025
9	1.154	1.044	1.061	1.036	1.067
12	1.159	1.031	1.069	1.038	1.045
18	1.087	**0.997**	**0.979**	**0.948**	**0.967**
24	1.045	1.000	**0.941**	**0.925**	**0.946**
	(c) Real Brent price of crude oil: 1992.1-2018.8				
1	1.075	**0.998**	**0.946**	**0.961**	**0.997**
3	1.072	1.027	**0.953**	**0.970**	1.044
6	1.172	1.087	1.060	1.021	1.105
9	1.208	1.065	1.088	1.069	1.101
12	1.215	1.045	1.070	1.037	1.052
18	1.161	1.031	**0.994**	**0.965**	**0.990**
24	1.095	1.019	**0.938**	**0.922**	**0.944**

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among the shipping-based indices and blue the best model among the three alternative indicators.

Table 2. Monthly Indicators of Global Real Economic Activity and Underlying Disaggregated Data

Global Economic Activity Indicator	Components	Transformation	Data source	Start date
Kilian index (REA)	Log of the nominal shipping cost index calculated as described in Hamilton (2019)	Deflated with U.S. CPI and linearly detrended (recursively)	JDH	1968.1
Real shipping cost factor	Freight rates for 61 shipping routes for different commodities (grain, coal, fertilizer, iron ore, scrap metal, oilseeds) – see Table 1A for details	Nominal dollar prices deflated with U.S. CPI, growth rates computed as first log differences, and missing observations filled with EM algorithm	SI	1973.1
World industrial production index (WIP)	Industrial production of OECD, Brazil, China, India, Indonesia, the Russian Federation and South Africa aggregated as described in Baumeister and Hamilton (2019)	First log difference	BH	1958.1
Real commodity price factor	Aluminum	Nominal dollar prices deflated with U.S. CPI and growth rates computed as first log differences	WB	1972.5
	Barley		WB	1960.1
	Beef		WB	1960.1
	Coffee, Arabica		WB	1973.1
	Coffee, Robusta		WB	1973.1
	Copper		WB	1964.1
	Cotton, A Index		WB	1971.1
	Lead		WB	1960.1
	Logs, Malaysian		WB	1971.5
	Maize		WB	1972.1
	Nickel		WB	1973.1
	Palm Oil		WB	1964.1
	Rice, Thai 5%		WB	1960.1
	Rubber, SGP/MYS		WB	1960.1
	Sawnwood, Malaysian		WB	1971.5
	Soybeans		WB	1973.1
	Soybean Meal		WB	1973.1

	Soybean Oil		WB	1971.1
	Sugar, US		WB	1973.1
	Sugar, World		WB	1973.1
	Tin		WB	1960.1
	Wheat, US HRW		WB	1973.1
	Zinc		WB	1973.1
Global steel production factor	Crude Steel Production, US	Growth rates computed as first log differences and missing observations filled with EM algorithm	WSA	1968.1
	Crude Steel Production, Japan		WSA	1968.1
	Crude Steel Production, EU and other reporting countries (29 in total)		WSA	1968.1
	Crude Steel Production, China		WSA	1990.1
	Crude Steel Production, Eastern Europe		WSA	1990.1
	Crude Steel Production, Middle East		WSA	1990.1
	Crude Steel Production, Russia and Ukraine		WSA	1992.1

NOTES: The codes for the data sources are as follows: BH – Baumeister and Hamilton (2019) update of discontinued OECD series (https://sites.google.com/site/cjsbaumeister/OECD_plus6_industrial_production.xlsx?attredirects=0&d=1), JDH – Hamilton (2019) (http://econweb.ucsd.edu/~jhamilto/shipping_costs.xlsx), SI – Drewry's *Shipping Insight*, WB – World Bank Commodity Price Data, The Pink Sheet (http://pubdocs.worldbank.org/en/561011486076393416/CMO-Historical-Data-Monthly.xlsx), WSA – World Steel Association, Steel Statistical Yearbook (https://www.worldsteel.org/). The groupings for the crude steel production data comprise the following countries: EU and other reporting countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom, former Yugoslavia (now consisting of Bosnia-Herzegovina, Croatia, Macedonia, Serbia, and Slovenia), Canada, Argentina, Brazil, Chile, Mexico, Venezuela, Australia, India, Republic of Korea, South Africa, and Taiwan; Eastern Europe includes the Czech Republic, Hungary, Poland, and the Slovak Republic; Middle East includes Egypt, Iran, and Saudi Arabia. The start date indicates the earliest available observation; however, in estimation the common start date is 1973.1.

Table 3. Recursive MSPE Ratios Relative to No-Change Forecast of Real Brent Price in VAR(12) and Bayesian VAR(12) Models
Evaluation Period: 1992.1-2018.8

Monthly horizon	**Kilian index (REA)**		**Real shipping cost factor**		**World IP index (WIP)**		**Real commodity price factor**		**Global steel production factor**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) Production-based models									
	VAR	BVAR	VAR	BVAR	VAR	BVAR	VAR	BVAR	VAR	BVAR
1	1.075	**0.983**	**0.998**	**0.930**	**0.946**	**0.893***	**0.961**	**0.896***	**0.997**	**0.934**
3	1.072	1.063	1.027	**0.965**	**0.953**	**0.910**	**0.970**	**0.918**	1.044	**0.983**
6	1.172	1.158	1.087	1.003	1.060	**0.972**	1.021	**0.967**	1.105	1.032
9	1.208	1.211	1.065	1.006	1.088	**0.999**	1.069	1.006	1.101	1.033
12	1.215	1.237	1.045	**0.974**	1.070	**0.971**	1.037	**0.968**	1.052	**0.983**
18	1.161	1.179	1.031	**0.954**	**0.994**	**0.947**	**0.965**	**0.932**	**0.990**	**0.955**
24	1.095	1.092	1.019	**0.927**	**0.938**	**0.922**	**0.922**	**0.898**	**0.944**	**0.927**
	(b) Consumption-based models									
	VAR	BVAR	VAR	BVAR	VAR	BVAR	VAR	BVAR	VAR	BVAR
1	1.078	**0.964**	**0.986**	**0.918***	**0.932**	**0.884****	**0.943**	**0.888****	**0.951**	**0.904***
3	1.075	1.045	**0.984**	**0.942**	**0.892**	**0.888**	**0.938**	**0.906**	**0.950**	**0.943**
6	1.164	1.138	1.019	**0.966**	**0.962**	**0.932**	**0.978**	**0.938**	**0.984**	**0.978**
9	1.237	1.219	1.032	**0.987**	1.028	**0.976**	1.061	1.002	1.001	**0.994**
12	1.287	1.267	1.041	**0.979**	1.033	**0.979**	1.061	**0.985**	**0.980**	**0.977**
18	1.242	1.209	1.022	**0.957**	**0.945**	**0.943**	**0.978**	**0.934**	**0.943**	**0.955**
24	1.152	1.114	1.018	**0.938**	**0.911**	**0.919**	**0.934**	**0.903**	**0.928**	**0.932**

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among the shipping-based indices and blue the best model among the three alternative indicators. Green indicates whether the VAR or the Bayesian VAR (BVAR) performs better.

Table 4. The Role of Stochastic Volatility for the Accuracy of Recursive Forecasts of the Real Brent Price in BVAR(12) Models
Evaluation Period: 1992.1-2018.8

Monthly horizon	Kilian index (REA)		Real shipping cost factor		World IP index (WIP)		Real commodity price factor		Global steel production factor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) Production-based models									
	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR
1	**0.983**	**0.911****	**0.930**	**0.913****	**0.893***	**0.905****	**0.896***	**0.919****	**0.934**	**0.924***
3	1.063	**0.972**	**0.965**	**0.942**	**0.910**	**0.942**	**0.918**	**0.954**	**0.983**	**0.952**
6	1.158	1.024	1.003	**0.949***	**0.972**	**0.966**	**0.967**	**0.963**	1.032	**0.972**
9	1.211	1.039	1.006	**0.931***	**0.999**	**0.939***	1.006	**0.952**	1.033	**0.943**
12	1.237	1.046	**0.974**	**0.899****	**0.971**	**0.910***	**0.968**	**0.913****	**0.983**	**0.906***
18	1.179	**0.940**	**0.954**	**0.837****	**0.947**	**0.839****	**0.932**	**0.831****	**0.955**	**0.844****
24	1.092	**0.827**	**0.927**	**0.765****	**0.922**	**0.768****	**0.898**	**0.767****	**0.927**	**0.762****
	(b) Consumption-based models									
	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR
1	**0.964**	**0.920***	**0.918***	**0.907****	**0.884****	**0.905****	**0.888****	**0.911****	**0.904***	**0.912****
3	1.045	**0.958**	**0.942**	**0.909**	**0.888**	**0.918***	**0.906**	**0.939***	**0.943**	**0.929**
6	1.138	1.018	**0.966**	**0.910****	**0.932**	**0.926***	**0.938**	**0.943***	**0.978**	**0.925***
9	1.219	1.063	**0.987**	**0.897***	**0.976**	**0.911***	1.002	**0.937***	**0.994**	**0.909***
12	1.267	1.072	**0.979**	**0.874****	**0.979**	**0.869****	**0.985**	**0.887****	**0.977**	**0.864****
18	1.209	**0.951**	**0.957**	**0.789****	**0.943**	**0.790****	**0.934**	**0.783****	**0.955**	**0.791****
24	1.114	**0.821**	**0.938**	**0.719****	**0.919**	**0.710****	**0.903**	**0.718****	**0.932**	**0.710****

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among the shipping-based indices and blue the best model among the three alternative indicators. Green indicates whether the BVAR or the BVAR with stochastic volatility (SV-BVAR) performs better.

Table 5. The Role of Pooling for the Accuracy of Recursive Forecasts of the Real Brent Price
Evaluation Period: 1992.1-2018.8

	Model-Based Pooling: SV-BVAR(12)		**Market-Based Pooling**
Monthly horizon	Equal-weighted forecast combination (5 models)	Factor from disaggregated data of all existing indices	Brent futures spread
1	**0.903****	**0.919****	1.052
3	**0.921**	**0.921***	1.064
6	**0.943**	**0.923****	1.034
9	**0.948**	**0.902***	**0.973**
12	**0.925**	**0.870****	**0.920***
18	**0.878**	**0.782****	**0.854****
24	**0.833**	**0.710****	**0.836***

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. The evaluation period for Brent futures for h=12 starts in 1994.4 and for h=18, 24 in 1998.2 due to data availability.

Table 6. Recursive MSPE Ratios Relative to AR(12) Forecast for Global Petroleum Consumption
Evaluation Period: 1992.1-2018.8

	Monthly horizon						
	1	3	6	9	12	18	24
(a) BVAR(12)							
Kilian index (REA)	1.103	1.445	2.062	2.558	3.131	3.838	4.122
Real shipping cost factor	1.046	1.134	1.310	1.421	1.521	1.781	2.055
World IP index (WIP)	1.002	1.252	1.511	1.532	1.635	1.870	2.043
Real commodity price factor	1.054	1.173	1.335	1.440	1.523	1.759	1.977
Global steel production factor	1.255	1.609	1.794	1.834	2.007	2.437	2.553
(b) SV-BVAR(12)							
Kilian index (REA)	**0.968**	1.073	1.213	1.274	1.369	1.561	1.645
Real shipping cost factor	**0.962***	1.036	1.064	1.087	1.114	1.178	1.208
World IP index (WIP)	**0.933****	**0.984**	1.009	**0.995**	1.013	1.048	1.052
Real commodity price factor	**0.949****	1.017	1.070	1.108	1.154	1.245	1.304
Global steel production factor	**0.954****	1.026	1.059	1.065	1.095	1.130	1.141
(c) Model-based pooling using SV-BVAR(12)							
Equal-weighted forecast combination (5 models)	**0.946****	1.016	1.066	1.086	1.128	1.213	1.258
Factor from disaggregated data of all existing indices	**0.955***	1.028	1.072	1.095	1.129	1.208	1.266

NOTES: Boldface indicates improvements relative to AR(12) forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test.

Table 7. Key Indicators Affecting Energy Markets

Data category	Variable	Geographic coverage	Start date	Tcode	Data source	Data delay	Nowcast rule	Data revisions
Real economic activity	World Industrial Production Index	OECD + 6 non-member countries	1973.1	5	Baumeister-Hamilton (2019)	2	AG	Y
	Conference Board Leading Economic Index	US	1973.1	5	Datastream	1	AG	Y
	Consumer Confidence Index	OECD	1974.1	5	OECD MEI	1	RW	Y
Commodity prices	Copper Price	World	1973.1	5	World Bank	0		N
Financial indicators	Real Trade-Weighted U.S. Dollar Index: Broad	World	1973.1	5	FRED	0		Y
	MSCI World Stock Price Index	World	1972.1	7	Global Financial Data	0		N
	Excess Returns on Fama-French Portfolio: Transportation	World	1973.1	7	Ken French's website	2	RW	N
Transportation	Passenger Car Registrations	OECD	1973.1	5	OECD MEI	8	AG	Y
	Total Vehicle Miles Travelled	US	1973.1	5	FRED	2	AG	Y
Uncertainty measures	Caldara-Iacoviello Geopolitical Risk Index	World	1973.1	5	Caldara-Iacoviello (2018)	0		N
	Long-Run Oil Price Uncertainty	World	1989.4	1	Bloomberg	0		N
Expectations measures	University of Michigan Index of Consumer Expectations	US	1978.1	5	Michigan Survey	0		N
	Spread between Long-Run and Short-Run Oil Price Expectations	World	1988.11	1	Bloomberg	0		N
Weather indicators	Oceanic Niño Index	World	1973.1	1	NOAA	2	RC	Y
	Residential Energy Demand Temperature Index	US	1973.1	1	NOAA	1	RW	Y
Energy-related indicators	Energy Production and Electricity Distribution	EU28	1991.1	5	FRED	3	AG	Y

NOTES: Tcode indicates the transformation of the variable where 1 indicates the variable is included in its original units, 5 refers to taking first log differences, 7 stands for annual growth rates. The delay in data release is measured in months. Nowcasts are based on the average growth rate (AG), the most recent change (RC), and no change (RW).

Table 8. The Role of Different Information Sets for the Accuracy of Recursive Forecasts of the Real Brent Price and Global Petroleum Consumption in Bayesian VAR(12) Models with Stochastic Volatility Evaluated over 1992.1-2018.8

		Monthly horizon						
		1	3	6	9	12	18	24
		(a) Real Brent Price						
(1)	Global Economic Conditions Indicator	**0.918****	**0.930**	**0.940**	**0.920**	**0.876***	**0.795****	**0.704****
	Large dataset							
(2)	1 factor	**0.922****	**0.939**	**0.947**	**0.932**	**0.886***	**0.802***	**0.715****
(3)	2 factors	**0.939***	**0.947***	**0.955**	**0.950**	**0.934**	**0.835****	**0.756****
(4)	3 factors	**0.939***	**0.967**	**0.982**	**0.987**	**0.976**	**0.930**	**0.857****
(5)	Statistical variable selection	**0.915****	**0.925**	**0.930***	**0.906***	**0.854***	**0.766****	**0.686****
		(b) Global Petroleum Consumption						
(6)	Global Economic Conditions Indicator	**0.934****	**0.945**	**0.926**	**0.880***	**0.875**	**0.907**	**0.884**
	Large dataset							
(7)	1 factor	**0.921****	**0.973**	1.005	**0.965**	**0.936**	**0.968**	**0.949**
(8)	2 factors	**0.926****	**0.981**	1.048	1.081	1.156	1.349	1.461
(9)	3 factors	**0.937****	**0.985**	1.076	1.104	1.180	1.378	1.530
(10)	Statistical variable selection	**0.946****	**0.997**	1.004	**0.981**	1.023	1.049	1.045

NOTES: Boldface indicates improvements relative to no-change forecast (panel a) or AR(12) forecast (panel b). ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. The Global Economic Conditions Indicator is based on 16 variables covering different dimensions of the global economy as they relate to energy markets (see Table 7). The large dataset contains 256 variables (see Tables 2, 7 and 9 for details). The statistical variable selection uses the 16 variables with the highest loadings on the factor extracted from the large dataset. The variables selected are the following in the order of the magnitude of loadings: long-run oil price uncertainty, spread of oil price expectations, real freight rates for fertilizer (potash) from Germany to India, short-run gasoline price uncertainty, Conference Board Leading Economic Index, FF industry portfolio: utilities, MSCI world index, FF industry portfolio: chemicals, FF industry portfolio: oil, FF industry portfolio: transportation, FF industry portfolio: cars, Composite Leading Indicator for Japan, OECD business confidence index, real freight rates for commodity/route 2, Australian unemployment rate, and Chinese consumer confidence index (see Table 9 for more details on each variable).

Table 9. Extended Dataset

No	Variable description	Units	Tcode	Data source	Start date
REAL ECONOMIC ACTIVITY					
1	Leading Indicator: Business Situation, Canada	Percent	1	FRED	1973.1
2	Composite Leading Indicator, Japan	Index	5	CEIC	1985.1
3	Leading Indicator: Sales Expectations, Japan	Percent	1	FRED	1985.1
4	Leading Indicator, Korea	Index	4	CEIC	1973.1
5	Leading Indicator: Business Situation, Korea	Percent	1	FRED	1991.7
6	Leading Indicator: Production, UK	Percent	1	FRED	1975.1
7	Leading Indicator: Order Books, Brazil	Percent	1	FRED	1980.1
8	Leading Indicator: Production, Brazil	Percent	1	FRED	1980.1
9	Composite Leading Indicator, Mexico	Index	1	CEIC	1980.1
10	Composite Leading Indicator, Russia	Percent	1	CEIC	1997.9
11	Composite Leading Indicator, South Africa	Index	1	CEIC	1973.1
12	U.S. Recession Indicator[a]	Index	1	DS, UMS	1978.1
13	Chicago Fed National Activity Indicator	Index	1	FRED	1973.1
14	U.S. Index of Consumer Sentiment	Index	5	UMS	1978.1
15	Eurocoin	Index	1	CEPR	1999.1
16	Euro Area Business Climate Indicator	Index	1	TE	1985.1
17	Euro Area Economic Sentiment Indicator	Index	1	EC	1980.1
18	ISM Manufacturing PMI, US	Index	5	B	1973.1
19	PMI Manufacturing, EA	Index	5	B	1997.6
20	Developed Markets PMI: Manufacturing	Index	5	B	1998.1
21	Emerging Markets PMI: Manufacturing	Index	5	B	2004.4
22	ISM U.S. Manufacturing: New Export Orders	Index	5	B	1988.1
23	Global PMI Manufacturing: New Export Orders	Index	5	B	1998.1
24	Consumer Confidence, Brazil	Index	5	OECD	1994.6
25	Consumer Confidence, China	Index	5	OECD	1990.1
26	Consumer Confidence, Russia	Index	5	OECD	1998.11
27	Consumer Confidence, South Africa	Index	5	OECD	1982.6

[a] This recession indicator is constructed as the difference between the index of consumer sentiment from the Michigan survey and the Conference Board consumer confidence index. This composite indicator typically reaches a low prior to recessions.

28	Business Confidence, OECD	Index	5	OECD	1974.6
29	Business Confidence, Brazil	Index	5	OECD	1995.4
30	Business Confidence, China	Index	5	OECD	2000.2
31	Business Confidence, Russia	Index	5	OECD	1992.9
32	Business Confidence, South Africa	Index	5	OECD	1974.6
33	Sales: Retail Trade, OECD	Index	5	OECD	1973.1
34	Sales: Retail Trade, Russia	Index	5	OECD	1994.12
35	Sales: Retail Trade, South Africa	Index	5	OECD	1977.1
36	Unemployment Rate, Australia	Percent	1	OECD	1978.2
37	Unemployment Rate, EU18	Percent	1	EC	1998.4
38	Unemployment Rate, Japan	Percent	1	OECD	1973.1
39	Unemployment Rate, UK	Percent	1	FRED+EC	1973.1
40	Unemployment Rate, US	Percent	1	FRED	1973.1
41	Real Disposable Personal Income, US	Billions of chained 2012 dollars	5	FRED	1973.1
42	Real PCE: New Motor Vehicles, US	Quantity index	5	BEA	1973.1
43	Real PCE: Motorcycles, US	Quantity index	5	BEA	1973.1
44	Real PCE: Pleasure Boats, Aircraft and Other Recreational Vehicles, US	Quantity index	5	BEA	1973.1
45	Real PCE: Motor Vehicle Fuels, US	Quantity index	5	BEA	1973.1
46	Real PCE: Fuel Oil and Other Fuels, US	Quantity index	5	BEA	1973.1
47	Real PCE: Motor Vehicle Services, US	Quantity index	5	BEA	1973.1
48	Real PCE: Public Transportation, US	Quantity index	5	BEA	1973.1
49	Current Buying Conditions, Durables, US	Index	5	UMS	1978.1
50	Current Buying Conditions, Vehicles, US	Index	5	UMS	1978.1
51	IP: Consumer Energy Products, US	Index	5	FRB	1973.1
52	IP: Commercial Energy Products, US	Index	5	FRB	1971.1
53	IP: Oil and Gas Well Drilling, US	Index	5	FRB	1973.1
54	IP: Petroleum and Coal Products, US	Index	5	FRB	1973.1
55	IP: Motor Vehicles and Parts, US	Index	5	FRB	1973.1
56	IP: Aerospace and Transportation Equipment, US	Index	5	FRB	1973.1
57	IP: Mining, US	Index	5	FRB	1973.1
58	IP: Autos (Consumer),US	Index	5	BEA	1973.1

59	IP: Fuels (Consumer), US	Index	5	FRB	1973.1
60	IP: Converted Fuel (Materials), US	Index	5	FRB	1973.1
61	IP: Primary Energy (Materials), US	Index	5	FRB	1973.1
62	PPI: Motor Vehicles and Equipment, US	Index	5	BLS	1973.1
63	PPI: Aircraft and Aircraft Equipment, US	Index	5	BLS	1973.1
64	Real Manufacturing Inventories: Petroleum Products, US	Millions of chained 2012 dollars	5	BEA	1973.1
65	Real Manufacturing Inventories: Motor Vehicles, US	Millions of chained 2012 dollars	5	BEA	1973.1
66	Real Value of Manufacturer's New Orders: Motor Vehicles and Parts, US	Millions of chained 2012 dollars	5	FRED	1992.2
67	Capacity Utilization: Petroleum and Coal Products, US	Percent	5	FRB	1973.1
68	Capacity Utilization: Mining, US	Percent	5	FRB	1973.1
69	Capacity Utilization: Automobile and Light Duty Vehicle, US	Percent	5	FRB	1973.1
FINANCIAL INDICATORS[b]					
70	S&P GSCI Energy Index	Index	7	GFD	1983.1
71	S&P 500 Utilities	Index	7	GFD	1972.1
72	S&P 500 Energy	Index	7	GFD	1972.1
73	S&P 500 Air Freight and Logistics	Index	7	GFD	1972.1
74	S&P 500 Airlines	Index	7	GFD	1972.1
75	S&P 500 Railroad	Index	7	GFD	1972.1
76	S&P 500 Automobiles	Index	7	GFD	1972.1
77	S&P 500 Oil, Gas and Consumable Fuels	Index	7	GFD	1972.1
78	Dow Jones: Transportation	Index	7	B	1972.1
79	Dow Jones: Utilities	Index	7	B	1972.1
80	Dow Jones: Industrials	Index	7	B	1972.1
81	FF: Oil	Index	7	FF	1972.1
82	FF: Chemicals	Index	7	FF	1972.1
83	FF: Cars	Index	7	FF	1972.1
84	FF: Utilities	Index	7	FF	1972.1
85	NYSE Arca Oil Index	Index	7	GFD	1984.11

[b] All returns for sub-categories of S&P 500, DJ, and FF are calculated as excess returns relative to the respective overall market performance.

86	Real Broad Effective Exchange Rate: Australia	Index	5	FRED	1994.1
87	Real Broad Effective Exchange Rate: Canada	Index	5	FRED	1994.1
88	Real Broad Effective Exchange Rate: Chile	Index	5	FRED	1994.1
89	Real Broad Effective Exchange Rate: Norway	Index	5	FRED	1994.1
90	Real Broad Effective Exchange Rate: South Africa	Index	5	FRED	1994.1
91	Real Broad Effective Exchange Rate: New Zealand	Index	5	FRED	1994.1
92	Real Broad Effective Exchange Rate: Euro Area	Index	5	FRED	1994.1
93	Real Broad Effective Exchange Rate: China	Index	5	FRED	1994.1
94	Real Broad Effective Exchange Rate: India	Index	5	FRED	1994.1
95	Real Broad Effective Exchange Rate: UK	Index	5	FRED	1994.1
96	Real Broad Effective Exchange Rate: Japan	Index	5	FRED	1994.1
97	Chicago Fed Adjusted Financial Conditions	Index	1	FRED	1973.1
98	10Y/1Y Treasury Yield Spread	Percent	1	FRED	1973.1
99	Moody’s Baa/Aaa Corporate Bond Yield Spread	Percent	1	FRED	1973.1
100	Real Rate: 1Y Treasury Constant Maturity Rate – CPI Inflation Rate Over Preceding Year	Percent	1	FRED	1973.1
TRANSPORTATION					
101	Passenger Car Registrations, EU28	Index	5	OECD	1973.1
102	Passenger Car Registrations, US	Index	5	OECD	1973.1
103	Passenger Car Registrations, Canada	Index	5	OECD	1973.1
104	Passenger Car Registrations, Japan	Index	5	OECD	1974.1
105	Passenger Car Registrations, Norway	Index	5	OECD	1973.1
106	Passenger Car Registrations, New Zealand	Index	5	OECD	1974.1
107	Passenger Car Registrations, South Africa	Index	5	OECD	1973.1
108	Passenger Car Registrations, India	Index	5	OECD	2001.5
109	Passenger Car Registrations, Korea	Index	5	OECD	1993.1
110	Passenger Car Registrations, Turkey	Index	5	OECD	1989.1
111	Vehicle Production, Brazil (de-trended)	Quantity	1	CEIC	1984.1
112	Vehicle Production, China*	Quantity	5	CEIC	1986.1
113	Vehicle Production, Mexico*	Quantity	5	CEIC	1983.1
114	U.S. Real Transportation Costs	Index	5	FRED	1973.1
115	U.S. Truck Sales	Index	5	BEA	1973.1
116	U.S. Electric Car Sales	Number	5	EV	2010.12

117	Rail Freight Intermodal Traffic, US	Ton miles	5	FRED	2000.1
118	Rail Freight Carloads, US	Carloads	5	FRED	2000.1
119	Truck Tonnage, US	Index	5	FRED	2000.1
120	Tonnage Carried on Internal U.S. Waterways	Millions of short tons	5	FRED	2000.1
UNCERTAINTY MEASURES					
121	Global Economic Policy Uncertainty Index	Index	5	BBD	1997.1
122	OPEC Newspaper Index	Index	5	P	1986.1
123	CBOE S&P 500 Volatility Index	Index	5	GFD	1986.1
124	Short-Run Gasoline Price Uncertainty[c]		1	B	1987.1
125	Long-Run Natural Gas Price Uncertainty[c]		1	B	1990.6
EXPECTATIONS MEASURES					
126	Expected Change in Personal Financial Situation, US	Index	5	UMS	1978.1
127	Expected Change in Real Family Income, US	Index	5	UMS	1978.1
128	Expected Change in Interest Rates, US	Index	5	UMS	1978.1
129	Expected Change in Unemployment, US	Index	5	UMS	1978.1
130	Expected Change in Business Conditions, US	Index	5	UMS	1978.1
131	Expected Average Increase in Gasoline Prices Over the Next 5 Years, US	Cents per gallon	5	UMS	1992.11
132	Spread between Long-Run and Short-Run Heating Oil Price Expectations[d]		1	B	1989.8
133	Spread between Long-Run and Short-Run Natural Gas Price Expectations[d]		1	B	1990.6
WEATHER INDICATORS					
134	Global Temperature Anomalies	Degrees Celsius	5	NOAA	1973.1
135	Heating Degree Days, US*	Index	1	EIA MER	1973.1
136	Heating Degree Days, EU28*	Index	1	EC	1974.1

[c] Price uncertainty is defined as realized volatility and is calculated as follows: $vol_p^m = 100 * \sqrt{\frac{252}{n} * (\sum_{d=1}^{n}(\Delta f_d^m)^2)}$ where Δf_d^m is the daily return for the oil futures contract on day d in month m computed as the log difference between the futures price on day d and $d-1$, and n is the number of trading days in a given month. Long-run refers to futures with 12-month maturity and short-run to futures with 3-month maturity.

[d] Price expectations are proxied by log futures prices where short-run refers to contracts with 3 months to maturity and long-run refers to contracts with 12 months to maturity.

137	Cooling Degree Days, US*	Index	1	EIA MER	1973.1
138	Cooling Degree Days, EU28*	Index	1	EC	1974.1
139	Heating Degree Days, Deviation from Normal, US	Index	1	HA	1997.5
140	Cooling Degree Days, Deviation from Normal, US	Index	1	HA	1998.7
141	Temperature Fluctuations for 48 US States	Index	1	HA	1973.1
ENERGY-RELATED INDICATORS					
142	Electricity Consumption, China*	Billion kWh	5	CEIC	1986.4
143	Electricity Consumption, India*	Million kWh	5	CEIC	1987.9
144	Electricity Consumption, Korea*	Million kWh	5	CEIC	1979.1
145	Electricity Consumption, South Africa*	GWh	5	CEIC	1985.1
146	Electricity Consumption, UK*	TWh	5	UKBEIS	1995.1
147	Electricity Consumption, US*	Million kWh	5	EIA MER	1973.1
148	Total Energy Carbon Dioxide Emissions*	Million metric tons	5	EIA MER	1973.1
149	U.S. Motor Gasoline Stocks	Million barrels	5	EIA MER	1973.1
150	U.S. Total Petroleum Stocks	Million barrels	5	EIA MER	1973.1

NOTES: The end of the sample for all data series is 2018.8. If data are available at a frequency higher than monthly, we obtain monthly data by averaging. Tcode indicates the stationarity transformation code for each variable where Tcode = 1 indicates that the variable is included in its original units, Tcode = 4 stands for log-levels, Tcode = 5 refers to taking first log differences, and Tcode = 7 stands for year-on-year growth rates. An asterisk indicates that the series has been seasonally adjusted using the X13-ARIMA procedure. The codes for the data sources are as follows: B – Bloomberg, BBD – Baker, Bloom, and Davis (2016) (http://www.policyuncertainty.com/), BEA – Bureau of Economic Analysis, BLS – Bureau of Labor Statistics, CEIC (https://www.ceicdata.com), CEPR – Centre for Economic Policy Research (https://cepr.org/data), DS – Datastream, EC – European Commission Eurostat, EIA MER – U.S. Energy Information Administration *Monthly Energy Review*, EV – Monthly Plug-In Electric Vehicles Sales Scorecard (https://insideevs.com/monthly-plug-in-sales-scorecard/), FF – Fama-French 17 Industry Portfolios (average value-weighted returns) (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), FRB – Federal Reserve Board of Governors Database, FRED – Federal Reserve Bank of St. Louis Economic Database, GFD – Global Financial Database, HA – Haver Analytics, UMS – Survey of Consumers, University of Michigan (http://www.sca.isr.umich.edu/), NOAA – U.S. National Oceanic and Atmospheric Administration, National Climatic Data Center (https://www.noaa.gov/), OECD – OECD Main Economic Indicators Database, P – data generously updated and provided by Mike Plante from Plante (2019), TE – Trading Economics, UKBEIS – U.K. Department of Business, Energy & Industrial Strategy.

Table 10. The Role of Real-Time Data Constraints for the SV-BVAR(12) with the Global Economic Conditions Indicator
Evaluation Period: 1992.1-2018.8

	Real Brent Price		**Global Petroleum Consumption**	
Monthly horizon	Pseudo real time	Real-time data	Pseudo real time	Real-time data
1	**0.918****	**0.925***	**0.934****	**0.937****
2	**0.921***	**0.937**	**0.924****	**0.904****
3	**0.930**	**0.945**	**0.945**	**0.957***
4	**0.941**	**0.951**	**0.927**	**0.913****
5	**0.940**	**0.953**	**0.936**	**0.912****
6	**0.940**	**0.955**	**0.926**	**0.919***
7	**0.940**	**0.955**	**0.912**	**0.865****
8	**0.929**	**0.948**	**0.891**	**0.864****
9	**0.920**	**0.932**	**0.880***	**0.905***
10	**0.911**	**0.926**	**0.891**	**0.890****
11	**0.892***	**0.906**	**0.904**	**0.909***
12	**0.876***	**0.881***	**0.875**	**0.922**
13	**0.870***	**0.877***	**0.889**	**0.901**
14	**0.850***	**0.856***	**0.883**	**0.912**
15	**0.832***	**0.835***	**0.884**	**0.910**
16	**0.817****	**0.822****	**0.896**	**0.889**
17	**0.808****	**0.800****	**0.910**	**0.932**
18	**0.795****	**0.792****	**0.907**	**0.935**
19	**0.785****	**0.784****	**0.901**	**0.906**
20	**0.771****	**0.764****	**0.913**	**0.919**
21	**0.750****	**0.746****	**0.892***	**0.911**
22	**0.730****	**0.727****	**0.890**	**0.908**
23	**0.721****	**0.713****	**0.877**	**0.895**
24	**0.704****	**0.703****	**0.884**	**0.899**

NOTES: Boldface indicates improvements relative to no-change forecast (left panel) or AR(12) forecast (right panel). ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test.

NOT-FOR-PUBLICATION APPENDIX

Table 1A. Dry Cargo Single Voyage Rates

No	Commodity shipped	Shipping route	First observation
1	Dry cargo index	n/a	1973.1
2	Dry cargo index	n/a	1975.12
3	Grain	USG Japan (20-40)	1979.12
4	Grain	USG-Japan (50-60)	1982.1
5	Grain	USG-ARA (50-65)	1984.4
6	Grain	USG-AH Range (65-85)	1982.1
7	Grain	USNP-Japan (45-55)	1984.4
8	Grain	USNP-Japan (50-55)	1990.7
9	Grain	USG-EC Mexico (20-25)	1998.10
10	Grain	USG-Venezuela (15-30)	1993.4
11	Grain	USG-Algeria (20-25)	1993.4
12	Grain	USG-Casablanca/Agadir (25-30)	1993.4
13	Grain	Australia-Taipei, Chinese (55)	2015.2
14	Grain	EU-North Africa (55)	2015.2
15	Coal	USG-Taiwan (50-60)	1990.6
16	Coal	Richards Bay-ARA (100-150)	1990.6
17	Coal	Richards Bay-ARA (150)	2015.2
18	Coal	East Australia-South Korea (120-160)	1995.6
19	Coal	Hay Pt.-Japan (100-150)	2010.12
20	Coal	East Australia-ARA (100-150)	1988.1
21	Coal	Puerto Bolivar-ARA (100-150)	1993.7
22	Coal	HR-Japan (50-60)	1979.12
23	Coal	USAC-ARA (100-150)	1998.7
24	Coal	USNH-ARA (80-100)	1990.6
25	Coal	HR/RB-Japan (100-150)	1984.4
26	Coal	USAC-South Korea (120-160)	1998.9
27	Coal	East Australia-Japan (100-150)	1990.8
28	Coal	USNH-Cont. (60-80)	1982.1
29	Coal	Richards Bay-China (160)	2015.2
30	Coal	Queensland-Netherlands (150)	2015.2
31	Coal	Bolivar-China (150)	2015.2
32	Coal	USG-Rotterdam (65)	2015.2
33	Coal	Indonesia-India (70)	2015.2
34	Coal	Newcastle-Qingdao (74)	2014.7
35	Coal	East Australia-Japan (60-70)	2007.1
36	Coal	Richards Bay-Mediterranean (60-70)	2007.1
37	Iron ore	Narvik-ARA (100-150)	1990.10
38	Iron ore	Brazil-ARA (100-150)	1990.6
39	Iron ore	Brazil-China (100-150)	1995.5
40	Iron ore	West Australia-China (120-160)	1998.7
41	Iron ore	West Australia-ARA (120-160)	1990.6

42	Iron ore	Saldanha Bay-China (100-150)	1993.5
43	Iron ore	Nouadhibou-ARA (80-120)	1990.6
44	Iron ore	East Canada-ARA (80-125)	1998.5
45	Iron ore	Monrovia-Cont. (60-90)	1982.1
46	Iron ore	Brazil-Cont. (60-80)	1979.12
47	Iron ore	Brazil-Cont. (125-175)	1982.1
48	Iron ore	Brazil-South Korea (100-140)	1984.4
49	Iron ore	Brazil-Japan (120-160)	1988.5
50	Iron ore	West Australia-Japan (100-150)	1990.7
51	Iron ore	West Australia-UK (100-140)	1984.4
52	Oilseeds	British Columbia-Japan (20-30)	1988.1
53	Fertilizer (dap)	USG-India (15-25)	1984.4
54	Fertilizer (potash)	Germany-India (15-25)	1984.4
55	Fertilizer (phosrock)	Aqaba-India (10-15)	1984.4
56	Fertilizer (dap)	USG-West Coast India (20-30)	1990.6
57	Fertilizer (phosrock)	West Africa-India (15-25)	1990.6
58	Fertilizer (dap)	RS/AG-India (10-15)	1995.5
59	Scrap	G-H Range-Turkey (25-35)	1995.5
60	Scrap	WCUS-South Korea (30-40)	1999.12
61	Scrap	USAC-South Korea (30-50)	1993.5

NOTES: The numbers in brackets indicate Deadweight Cargo Tons (DWCT) or the weight of cargo to be transported under a charter party. The abbreviations for the shipping routes are as follows: ARA: Antwerp-Rotterdam-Amsterdam range of ports; Cont.: Continent or Europe; G-H Range: Gibraltar-Hamburg range of ports; HR/RB: Hampton Roads or Richards Bay; RS/AG: Red Sea or Arabian Gulf; USAC: United States Atlantic Coast; USG: United States Gulf of Mexico; USNH: United States North of (Cape) Hatteras; USNP: United States North Pacific; USWC: United States West Coast; WCUS: West Coast United States. The first two series are dry cargo indices compiled by Drewry's Shipping Consultants.

Table 2A. Recursive MSPE Ratios Relative to No-Change Forecast of Real Refiner Acquisition Cost of Imported Crude Oil Evaluation Period: 1992.1-2018.8

Monthly horizon	**Kilian index (REA)**	**Real shipping cost factor**	**World IP index (WIP)**	**Real commodity price factor**	**Global steel production factor**
	(1)	(2)	(3)	(4)	(5)
			(a) BVAR(12)		
1	**0.820****	**0.781****	**0.750****	**0.745****	**0.770****
3	**0.964**	**0.892**	**0.835**	**0.835**	**0.886**
6	1.080	**0.970**	**0.939**	**0.930**	**0.986**
9	1.169	1.002	**0.998**	**0.998**	1.019
12	1.174	**0.968**	**0.972**	**0.971**	**0.979**
18	1.109	**0.936**	**0.922**	**0.923**	**0.944**
24	1.048	**0.927**	**0.918**	**0.901**	**0.927**
			(b) BVAR(12)-SV		
1	**0.784****	**0.763****	**0.788****	**0.787****	**0.800****
3	**0.906****	**0.867***	**0.885***	**0.895****	**0.900***
6	**0.981**	**0.914***	**0.937***	**0.937****	**0.937***
9	**0.998**	**0.904****	**0.923****	**0.930****	**0.923***
12	1.001	**0.864****	**0.897****	**0.884****	**0.871****
18	**0.887**	**0.802****	**0.815****	**0.801****	**0.808****
24	**0.759****	**0.699****	**0.702****	**0.698****	**0.705****

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among the shipping-based indices and blue the best model among the three alternative indicators.

Table 3A. The Role of Stochastic Volatility for the Accuracy of Recursive Forecasts of the Real Brent Price When the Same Prior is Used
Evaluation Period: 1992.1-2018.8

Monthly horizon	**Kilian index (REA)**		**Real shipping cost factor**		**World IP index (WIP)**		**Real commodity price factor**		**Global steel production factor**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(a) Production-based models									
	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR
1	**0.950**	**0.911******	**0.878***	**0.913******	**0.886******	**0.905******	**0.885******	**0.919******	**0.905***	**0.924***
3	1.026	**0.972**	**0.930**	**0.942**	**0.896**	**0.942**	**0.909**	**0.954**	**0.952**	**0.952**
6	1.102	1.024	**0.972**	**0.949***	**0.942**	**0.966**	**0.946**	**0.963**	**0.985**	**0.972**
9	1.163	1.039	**0.975**	**0.931***	**0.967**	**0.939***	**0.986**	**0.952**	**0.985**	**0.943**
12	1.191	1.046	**0.944**	**0.899******	**0.950**	**0.910***	**0.955**	**0.913******	**0.948**	**0.906***
18	1.135	**0.940**	**0.933**	**0.837******	**0.932**	**0.839******	**0.917**	**0.831******	**0.930**	**0.844******
24	1.041	**0.827**	**0.909**	**0.765******	**0.908**	**0.768******	**0.886**	**0.767******	**0.902**	**0.762******
	(b) Consumption-based models									
	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR	BVAR	SV-BVAR
1	**0.933**	**0.920***	**0.856******	**0.907******	**0.868******	**0.905******	**0.870******	**0.911******	**0.881******	**0.912******
3	1.020	**0.958**	**0.923**	**0.909**	**0.899**	**0.918***	**0.900**	**0.939***	**0.932**	**0.929**
6	1.109	1.018	**0.949**	**0.910******	**0.936**	**0.926***	**0.927**	**0.943***	**0.957**	**0.925***
9	1.183	1.063	**0.966**	**0.897***	**0.960**	**0.911***	**0.969**	**0.937***	**0.969**	**0.909***
12	1.225	1.072	**0.944**	**0.874******	**0.951**	**0.869******	**0.956**	**0.887******	**0.949**	**0.864******
18	1.158	**0.951**	**0.935**	**0.789******	**0.928**	**0.790******	**0.918**	**0.783******	**0.928**	**0.791******
24	1.045	**0.821**	**0.910**	**0.719******	**0.905**	**0.710******	**0.892**	**0.718******	**0.903**	**0.710******

NOTES: Boldface indicates improvements relative to no-change forecast. ** denotes significance at the 5% level and * at the 10% level based on the Diebold-Mariano test. Red indicates the best model among the shipping-based indices and blue the best model among the three alternative indicators. Green indicates whether the BVAR or the BVAR with stochastic volatility (SV-BVAR) both using the *same* Minnesota-style prior performs better.