A New Monthly Indicator of Global Real Economic Activity

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Abstract

In modelling macroeconomic time series, often a monthly indicator of global real economic activity is used. We propose a new indicator, named World steel production, and compare it to other existing indicators, precisely the Kilian's index of global real economic activity and the index of OECD industrial production. We develop an econometric approach based on desirable econometric properties in relation to the quarterly measure of World gross domestic product to evaluate and to choose across different alternatives. The method is designed to evaluate short-term, long-term and predictability properties of the indicators. World steel production is proven to be the best monthly indicator of global economic activity in terms of our econometric properties. Kilian's index of global real economic activity also accurately predicts World GDP growth rates. When extending the analysis to an out-of-sample exercise, both Kilian's index of global real economic activity and the World steel production produce accurate forecasts for World GDP, confirming evidence provided by the econometric properties. Specifically, forecast combinations of the three indices produce statistically significant gains up to 40% at nowcast and more than 10% at longer horizons relative to an autoregressive benchmark.

Keywords: Global real economic activity, World steel production, Forecasting

JEL Codes: E1, E3, C1, C5, C8

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Introduction

In time series macroeconomic analysis often an indicator of global real economic activity is used to represent the World economy. World gross domestic product (GDP), measured at quarterly frequency in United States (US) dollars using purchasing power parity, is broadly accepted and frequently used as a measure of global economic activity. However, there is a lack of degrees of freedom associated with quarterly data. To address this issue, economic modellers commonly turn to a monthly indicator of global economic activity. Consequently, several monthly indicators of activity have been used in the literature to measure real economic activity (at both country and global level).[1]

This paper develops a novel econometric approach to evaluating and choosing across existing and new proposed monthly indicators of global economic activity. We believe that an indicator shall have desirable econometric properties in relation to the quarterly measure of World gross domestic product that shall be tested before to use. We propose eight features that focus on short- and long-term properties of the indicators and their relationship with a quarterly measure of global output based on cointegration, correlation, fitting and mixed-frequency in-sample predictability considerations.

In particular, there are two measures of global real economic activity popular among empirical researchers. The first such measure, taken from the Organisation for Economic Co-operation and Development (OECD) Monthly Economic Indicators (MEI), is aggregated industrial production for OECD countries. The second measure is the global real economic activity (rea) index proposed by Kilian (2009). Industrial production has been widely used as a measure of real economic activity at both country and global level. At country level, among

[1] We concentrate our analysis on observable indicators and do not consider unobservable global factors, such as global factors extracted by large datasets. Our properties can be applied to these series too and can also be extended to account for desirable properties when, for example, extracting the factors.

others, Mullineaux (1980), Grilli and Roubini (1996), Bernanke et al. (1997), Kim (2001), and Kim and Roubini (2001) have used industrial production as a proxy for real economic activity for large developed economies. Similarly, Mackowiak (2007) measured real economic activity at country level for emerging economies using industrial production.[2] Not without controversy, the index of industrial production for aggregated OECD economies has been widely used as a proxy for global real economic activity. For example, Gerlach (1988) uses both the industrial production index for OECD countries and US industrial production as a proxy for global real economic activity in the study of World business cycles under different exchange rate regimes. Furthermore, Ciccarelli and Mojon (2010) use the industrial production index for OECD economies in studying global inflation.

Kilian (2009) developed an index of global real economic activity (rea) using data of dry cargo single voyage ocean freight rates. Since 2009, this indicator has become a popular choice to represent global real economic activity, in particular for oil price studies. Among others, Apergis and Miller (2009) model the effect of oil shocks on different country stock prices using this index. Basher et al. (2011) use this index to study the relationship between oil prices, exchange rates and emerging stock markets. Vespignani and Ratti (2013) build a SVAR model to describe the influence of global liquidity on oil prices using Kilian's rea index as a proxy for global economic activity. Baumeister and Kilian (2013) use this index, in conjunction with other variables, to forecast real oil prices.

[2] For large developed economies: Mullineaux (1980) in studying the relationship between unemployment, output and inflation for the US, Grilli and Roubini (1996) in studying liquidity models for G7 economies, Bernanke et al. (1997) in studying the effect of oil price shocks for the U.S economy, Kim (2001) in addressing international transmissions of monetary shocks for non-US G6 economies and Kim and Roubini (2001) in developing a model for exchange anomalies for non-US G7 economies. For emerging economies Mackowiak (2007) studies the transmission mechanism of US shocks to emerging economies, including the following countries Chile, Hong Kong, Korea, Malaysia, Mexico, Philippines, Singapore and Thailand.

We extend the indicator set with a new proposed indicator: World steel production. Steel is an important input component of global economic activity and we test whether it can be considered as a reliable indicator. Results indicate that World steel production is the preferred monthly indicator for our econometric properties. Kilian's rea index also does reasonably well for the properties on global output growth. Then, we extend our evidence from the in-sample econometric approach to an out-of-sample exercise. We confirm the in-sample results and find that the World steel production and Kilian's rea index produces accurate forecasts for World GDP. Therefore, our econometric approach provides accurate information for both in-sample and out-of-sample analyses. Moreover, using forecast combinations of the three indices produce statistically significant gains up to 40% at nowcast and more than 10% at longer horizons relative to an autoregressive benchmark.

The remainder of the paper is organised as follows: Section 2 provides a review of current indicators of global real economic activity used in the literature. Section 3 proposes a new indicator of global real economic activity. Section 4 proposes a new econometric approach to evaluating monthly indicators of global economic activity. Section 5 presents the results of the econometric approach proposed in the previous section. Section 6 sets up an exercise to forecast World GDP. Section 7 concludes.

2. Current indicators of global real economic activity

In this section we describe two popular choices of monthly indicators of global real economic activity: OECD industrial production and Kilian's rea index. In Figure 1, World GDP, OECD industrial production (both in log-first difference form) and the Kilian's rea index are compared using quarterly frequency.[3] It can be observed that OECD industrial production does

[3] Note that Kilian's rea index provided by the author is constructed using rates and further linearly detrend the data.

not capture the unprecedented increase in global aggregate demand registered in the late 1990s, which originated from emerging economies. World GDP, Kilian's rea index and World Steel Production (not shown in Figure 1) capture these effects. However, all these indexes seem to capture very well the Great Moderation (1985-2002), and the global financial crisis (GFC).[4]

2.1 OECD industrial production

This index is available from the OECD monthly economic indicators (MEI) database from January 1975 to the present. The popularity of using this index to represent global real economic activity can be partially attributed to the fact that prior to 2009 there were few alternative time series of reasonable length that were representative of monthly global real economic activity.

This index is constructed with data from 34 OECD countries.[5] According to the OECD MEI definition: "Area totals for industrial production are annually chain-linked Laspeyres indices. The weights for each yearly link are based on the previous year's gross domestic product in construction adjusted by GDP purchasing power parity."

The use of this index as a proxy for global real economic activity relies on two assumptions. The first assumption is that the industrial sector is a good representation of the full economy. The second assumption is that the OECD economies are representative of the World economy. Prior to 1990, both assumptions were reasonable, as manufacturing sectors were a large part of most economies and economic growth was concentrated in developed

[4] The term the Great Moderation was first coined by Ben Bernanke in 2004 based on the Stock and Watson (2002) study. Kilian (2008), Kilian (2009), Kilian and Hicks (2013) and Humphreys (2010) attribute the rise in oil prices and commodity prices from 2003 to 2008 to the rapid economic growth and demand from emerging economies respectively.

[5] These countries are: Australia, Austria, Belgium, Canada, Chile, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, the Netherlands, New Zealand, Norway, Mexico, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States.

economies. However, most recent empirical evidence indicates a diversion between industrial production and GDP.

For example, Steindel (2004) argues that the relationship between industrial production and the goods output component of GDP has diverged significantly since the 2001 recession in the US. Steindel (2004) attributes this departure to the growth of imports and the increase of services inputs of all goods. Similarly, Herrera et al. (2011) attribute the possible divergence of GDP and industrial production to two factors. First, GDP is a measure of the valued added in the economy, while industrial production measures gross output; and, second, industrial production excludes services whose contribution to GDP has increased over time in the US.

In Kilian’s (2009) influential study on oil prices, he disputes the use of this indicator as a proxy for global real economic activity. Kilian’s main critique is that OECD industrial production excludes emerging economies in Asia such as China and India, whose demand for industrial raw materials is thought to be fuelling the surge in industrial commodity and oil prices since 2002.[6] Similarly, with reference to global output, Engel and Rogers (2006) note that in terms of purchasing power parity, the combined GDP of emerging economies such as Brazil, China, India, Indonesia, Korea, Mexico, Philippines, and Thailand was 2.43 times the GDP of the US. Crucini et al. (2012) also observe that the share of global output of G7 economies has declined in recent decades while the share of emerging economies such as China and India has increased. Kose et al. (2012) indicate that emerging market economies (specifically China and India) have become major contributors to World output over the period 2003-2007. Kilian (2009) also questions the lack of clarity in which the weights of the OECD industrial index are defined, given different exchange rates across countries.

[6] Support for this view can also be found in Hamilton (2013) and Kilian and Hicks (2013).

2.2 Kilian's Index of Real Economic Activity

Focussing on the study of oil prices, Kilian (2009) proposed a monthly measure of global real economic activity by constructing an index using dry cargo single voyage ocean freight rates from "Shipping Statistics and Economics". Kilian constructs this index using monthly data published by Drewry Shipping Consultants Ltd from the period January 1968 to the present based on various bulk dry cargoes prices, including grain, oilseeds, coal, iron ore, fertilizer and scrap metal. When modelling international commodity prices or business cycles, an important advantage of this series is that it has a long span, being built from 1968 at a monthly frequency.

Klovland (2004) argues that World economic activity is by far the most important influential variable in determining demand for sea transport. Empirically, Klovland (2004) demonstrates that from 1850 to the First World War (WWI), cycles in economic activity can explain the short-term behaviour of shipping freight rates.[7] In line with this view, Kilian (2009) claims that this dry cargo single freight rate index is designed to capture changes in the demand for industrial commodities in global markets.

Kilians's rea index is constructed with quotes for different commodities, routes and ship sizes. However, due to limitations in the data, the index uses equal weights for both commodities and routes. Equal weighting may be a source of bias across time as both individual commodities and routes are expected to significantly fluctuate across time.[8]

[7] For the period preceding WWI, Tinbergen (1959), Isserlis (1938) and Meuldijk (1940) also document the positive correlation between freight rates and economic activity. Stopford (1997) studies this relationship from 1872 to 1989, finding similarities in cyclical peaks and troughs between shipment and business cycles.

[8] Note that the structure of Kilian's rea index is similar to a factor model. Factor models are also constructed from growth rates. It has been shown that in many applications ignoring cointegration in the latter context has little effect.

We first focus on routes. The shift in global demand for commodities (and potentially the shift in global routes), has been documented by several authors: Kilian (2008), Kilian (2009), Kilian and Hicks (2013) and Hamilton (2013) attributes the increase in oil prices since 1997 to the unprecedented increase in consumption of oil from newly industrialised economies.[9] Also supporting the shift in global demand for commodities, Barsky and Kilian (2004) and Humphreys (2010) observe that industrialisation increases demand for metals substantially and that developments in the economies of Brazil, Russia, India, China (BRIC) is the main factor behind the boom in metal prices from 2003 to 2008. Radetzki (2006) argues that since 2004, the increase in global demand for commodities was the highest on record over the preceding 30 years and that this was a consequence of increases in demand from developing Asian economies. The unprecedented increase in demand from Asian developing economies (particularly China and India) observed since 1997 cannot be properly captured when using equal weights, see for example Kilian and Hicks (2013) and Aastveit at al. (2014).

Kilian's rea index also uses equal weights for different shipping prices, including grain, oilseeds, coal, iron ore, fertilizer, and scrap metal. However, the relative consumption and prices of these commodities may shift across time. These inter-temporal changes in relative consumption of commodities have been well documented by several studies: Stout (2012) shows that oil consumption increased more rapidly than coal consumption between 1970 and 1980 but at a substantially slower rate than between 1980 and 1995.[10] Finally, Kilian's rea

[9] This contrasts with the period 1973-1996, when the main factor affecting the price of oil was supply shocks originating from Organization of the Petroleum Exporting Countries (OPEC) producers according to Hamilton (2013).

[10] This view is also supported by the International Monetary Fund (IMF) World Economic Outlook (2014,) which indicates that world primary energy consumption (oil, coal and gas) has grown much faster than metal and food consumption since 2001.

index is constructed using rates and further linearly detrending the data and therefore cannot be used in a cointegration framework.[11]

3 World steel production: A New indicator of global real economic activity

Crude steel is a key input for many industries, including construction, transport, energy, packaging, home goods and agriculture. Consequently a World measure of steel production is expected to track the global economy fairly well.[12] The World Steel Association (WSA) has published monthly figures for World steel production since January 1990. The series aggregates the production of crude steel for 65 countries, which was estimated to account for 98% of World steel production in 2013.[13] The unit of measurement is thousands of tonnes. The data are collected by the WSA from several sources, including WSA member companies, national statistics offices and regional steel industry associations. The data is provided by the WSA for the public only in hardcopy; therefore the data were entered manually in a spreadsheet by the authors.

[11] Nelson and Plosser (1982) show that some macroeconomic shocks cannot be explained by purely transitory (first difference) fluctuations and Engle and Granger (1987) formally proposed an error correction model to account for the long-run properties of cointegrated multivariate time series.

[12] According to the WSA, steel is a major input for the following goods: Construction (low- and high-rise buildings, housing, modular buildings, retail, industrial, education and hospital buildings, sports stadia, stations, reinforcing bars for concrete, bridge deck plates, piers and suspension cables, harbours, cladding and roofing, office, tunnels, security, coastal and flood defences.), Transport (car bodies, engine components, wheels, axles, trucks, transmissions, trains, rails, ships, anchor chains, aircraft undercarriages, jet engines components), Energy (oil and gas wells and platforms, pipelines, electricity power turbine components, electricity pylons, wind turbines.), packaging (food and beverage cans, promotional materials, aerosols, paint and chemical containers, bottle tops and caps), home goods (domestic appliances such as fridges, washing machines, ovens and microwaves, sinks, radiators, cutlery, hi-fi equipment, razors, pins.), agriculture (farm vehicles and machinery, storage tanks, tools, structures, walkways, protective equipment).

[13] The countries (by continent) are: European Union: Austria, Belgium, Bulgaria, Croatia, the Czech Republic, Finland, France, Germany, Greece, Hungary, Italy, Luxembourg, the Netherlands, Poland, the Slovak Republic, Slovenia, Spain, Sweden, the United Kingdom, Bosnia-Herzegovina, Macedonia, Norway, Serbia, Turkey, Belarus, Kazakhstan, Moldova, Russia, Ukraine, Uzbekistan, other European countries. North America; Canada, Cuba, El Salvador, Guatemala, Trinidad Tobago, the United States. South America; Argentina, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela. Africa; Algeria, Egypt, Libya, Morocco, South Africa,. Asia; China, India, Japan, South Korea, Taiwan, Iran, Qatar, Saudi Arabia the United Arab Emirates. Oceania; Australia and New Zealand.

The weighting problem associated with the OECD industrial production index and Kilian's rea index does not apply to steel production, as the latest index is aggregated in monthly basis. Another advantage is that the series does not require deflating as steel production is already a real variable.

Additionally, different rates of growth among countries do not bias this indicator as crude steel production is a relatively homogenous good that is traded freely around the World. Changes in productivity across countries are not problematic for this indicator (as may be the case for OECD industrial production index), given that production of steel generally moves from more expensive to cheaper producers (countries). For example, from 1990 Chinese steel production grew by a factor of 10.8 while the US steel production remained relatively unchanged for the full sample.

Panels a), b) and c) in Figure 2 compare the evolution of World steel production (in quarterly frequency) with World GDP from 1990:Q1 to 2013:Q3. In panel a) both series are in levels, in panel b) in log-linear detrended version and in panel c) in log-first difference. In panel a) we observe that the relatively low growth of both World steel production and GDP from 1990 to 2002 coincides with the Great Moderation (the period where major economic variables such as real GDP growth and inflation began to decline in volatility) and the mild recession observed in the US in 2001. From 2002, both series grew rapidly until the GFC, and this period of rapid growth is explained by the acceleration of economic growth and increasing demand for commodities from emerging economies. In 2008, the GFC took place and World steel production decreases faster than World GDP, and then a gradual.

Panel b) shows that using logs-linear detreded data, World steel production closely follows World GDP cycles. In particular, four cycles are observed: first a declined from 1990 to around 1994. From 1994 early 2000's it is a period of stability (the great moderation period).

From early 2000's to 2008 a sharp growth as emerging economies rapidly expanded. In 2008, the big drop characterized by the GFC is followed by a period of moderation. Finally, in panel c) the growth rates of both series are plotted. This figure shows that in general World steel production is more volatile than World GDP, however a correlation pattern emerges. World.

The use of a closely-related commodity like steel production as an indicator of real economic activity was first proposed by Macaulay (1938), who creates a series of pig iron production in the US. This indicator was used as a measure of real economic activity before 1936, when other series were not available, by several authors including Zarnowitz (1987), Gorton (1988) and Calomiris and Hubbard (1989). Miron and Romer (1990) argue that the main problem with this indicator is that it is based on only one commodity, whereas in most settings a more broadly based indicator would be desirable. This disadvantage also applies to World steel production. In addition, another drawback of World steel production, when compared with Kilian's rea index and OECD industrial production is that this index series starts only in early 1990s. Accordingly, it is unable to explain any phenomena prior to this time.[14]

4. Evaluating global indicators of real global economic activity: An econometric approach

In this section we propose 8 properties to evaluate monthly indicators of global economic activity. The idea is that an indicator should have desirable econometric and economic features in relation to the quarterly measure of World gross domestic product. Therefore, our approach is based on econometric and economic considerations and we divide

[14] We have also investigated the CPB World Trade Monitor (WTM) data. This index is constructed by the CPB (Central Planning Bureau) Netherlands Bureau for Economic and contains monthly seasonally-adjusted world trade data for 81 countries worldwide, which by 2010 jointly accounted for 99% of World trade. Similar to World steel production, the aggregation weights (value series are simply added in current dollar prices) and the fact that this data is reported at country, regional and global levels constitute very important features. The main drawbacks are that the index starts only in 1990 and it is released with a two month publication lags. Our econometric approach and the forecasting exercise in section 6 indicate that index based on the World steel production provides superior statistics than the index based on World Trade.

them into long-term, distance, correlation and mixed-frequency predictability properties. A user could be interested in applying the monthly indicators of global economic activity in level, first differences or detrended. For example, level and first differences are often used in Structural VAR analysis, see for example Kim and Roubini (2000) or Kim (2001), and a detrended transformation is often applied in Dynamic Stochastic Equilibrium models, see for example Smets and Wouters (2007). We take an agnostic approach and apply our approach to all three measures. Therefore, our ranking of the indicators is based on this assumption.[15]

We first test if the monthly indicator is stationary or not and if it is not we investigate if it is cointegrated with World GDP. If the indicator is not stationary and not cointegrated with the level of World GDP we believe it should not be considered. Then, if there is a set of indicators to choose, the best one should minimise distance from World GDP, have the highest correlation with it and finally maximise fitting, in particular when accounting for the fact that the indicators are monthly and World GDP is quarterly. A distance measure, in our case Euclidean distance, can be computed for non-stationary and stationary series; on the contrary, correlation and fitting quantities can simply be computed for stationary series to avoid spurious regression problems. Therefore, we limit the use of the level series just to the aggregate distance, and focus only on first difference and detrended indicators for the remaining properties.[16]

The common sample for all the indices is January 1990 to March 2013 for a total of 279 monthly observations. We also collect quarterly World GDP for the same sample from the IMF database, resulting in 93 quarterly observations, and we use it as final measure of World output. The series is released with one-quarter delay with respect to the monthly indicators.

[15] A user with a specific preference on the type of transformation to apply can restrict the econometric properties to his/her assumption.
[16] Fitting measures could be computed with non-stationary level series in Vector Error Correction models, but we omit that analysis as we do not consider that it lies within the scope of the paper.

Therefore, even if an indicator is available in the first or following months in the quarter, World GDP is never available in the same quarter and must be nowcasted.

Long-run properties

Property 1: The global monthly indicator of real economic activity ($GREA_t^q$), when converted to quarterly frequency, has to be cointegrated with World GDP ($GGDP_t$). If both series are non-stationary and integrated of the same order and there exists a parameter α such that:

$$u_t = \log(GREA_t^q) - \alpha\log(GGDP_t) \quad (1)$$

is a stationary process.

Where: u_t is the error term, $GREA_t^q$ is the global monthly indicator of real aggregate demand. The superscript q is used to denote that the monthly series was converted to a quarterly series using the simple average. $GGDP_t$ is World GDP and α is a parameter to be estimated.

Aggregate distance properties

Property 2: When $GGDP_t$ and $GREA_t^q$ are indexed from the same start period, the square aggregated distance between these two series should be minimised. Formally;

$$Min \sum_{i=1}^{n} \sqrt{\left(\log(GGDP)_t - \log(GREA_t^q)\right)^2} \quad (2)$$

Property 3: When $GGDP_t$ and $GREA_t^q$ are first differenced and indexed from the same start period, the square aggregate distance between these two series should be minimised. Formally;

$$Min \sum_{i=1}^{n} \sqrt{\left(\Delta\log(GGDP_t) - \Delta\log(GREA_t^q)\right)^2} \quad (3)$$

Where: Δ is the first difference operator and log is short for logarithm.

Property 4: When $GGDP_t$ and $GREA_t^q$ are detrended and indexed from the same start period, the square aggregate distance between these two series should be minimised. Formally;

$$Min \sum_{i=1}^{n} \sqrt{\left[(GGDP_t - \beta t) - (GREA_t^q - \delta t)\right]^2} \quad (4)$$

Where $t = (1,2, \dots, n)$ is a time trend and β and δ are parameters to be estimated using ordinary least square regression.

Correlation properties

Property 5: Maximise correlation between $\Delta GGDP_t$ and $\Delta GREA_t^q$.

Formally;

$$Max \left[\frac{n \sum \Delta GGDP_t * \Delta GREA_t^q - (\sum \Delta GGDP_t) * (\sum \Delta GREA_t^q)}{\sqrt{n \sum (\Delta GGDP_t)^2 - \sum (\Delta GGDP_t)^2} \sqrt{n \sum \left(\Delta GREA_t^q\right)^2 - \sum \left(\Delta GREA_t^q\right)^2}} \right] \quad (5)$$

Property 6: Maximise correlation between d$GGDP_t$ and $dGREA_t^q$.

Formally:

$$Max \left[\frac{n \sum dGGDP_t * dGREA_t^q - (\sum dGGDP_t) * (\sum dGREA_t^q)}{\sqrt{n \sum (dGGDP_t)^2 - \sum (dGGDP_t)^2} \sqrt{n \sum \left(dGREA_t^q\right)^2 - \sum \left(dGREA_t^q\right)^2}} \right] \quad (6)$$

Where $dGGDP_t = GGDP_t - \beta T$ and $dGREA_t^q = GREA_t^q - \delta T$, where T is a lineal trend.

Predictability Properties

Property 7: This property states that: a desirable feature of the global real economic activity monthly indicator is to be able to predict quarterly World GDP when both series are transformed to a stationary process by using first difference transformation. The R^2 and adjusted R^2 are used as an indicator of predictive power. We notice that different frequencies of the variables require mixed-frequency analysis.

Formally,

$$Max\ R^2\left[\Delta GGDP_t = \beta_0 + \beta_1 B(L^{1/m};\theta)\Delta GAD_{t-h}^{(m)} + \varepsilon_t\right] \quad (7)$$

Where $\left(L^{1/m};\theta\right) = \sum_{k=1}^{K} b(k;\theta)L^{(k-1)/m}$, and $L^{s/m}GAD_{t-1-s/m}^{(m)}$, and t is indexes at quarterly frequency and $m = 3$ and is the higher sampling frequency. Δ is the first difference operator.

Property 8: This property states that: a desirable feature of the global aggregate demand monthly indicator is to be able to forecast quarterly World GDP when both series are transformed to a stationary process by detrending both series. The R^2 and adjusted R^2 are used as indicator of nowcating power.

Formally,

$$Max\ R^2\left[dGGDP_t = \beta_0 + \beta_1 B(L^{1/m};\theta)dGAD_{t-h}^{(m)} + \varepsilon_t\right] \quad (8)$$

Where $\left(L^{1/m};\theta\right) = \sum_{k=1}^{K} b(k;\theta)L^{(k-1)/m}$, and $L^{s/m}GAD_{t-1-s/m}^{(m)}$, and t is indexes at quarterly frequency and $m = 3$ and is the higher sampling frequency. d is detrended operator.

5. Results of the econometric approach

The results of our econometric approach for OECD industrial production, Kilian's rea index and World steel production are summarised in Table 6. In this table, we rank the indicators according to the 7 numerical properties (we exclude property 1) developed in section 4. The best performance for each property is indicated by the number 1, while the worst by the number 3. Property 1 is the only non-numerical feature in this table. Results show that OECD industrial production and World steel production are individually cointegrated with World

GDP while Kilian's rea index is not (as is expected).[17] Properties 3, 5 and 7 are distinguished with a darker background to denote exercises built with data in first difference or short term.

Considering all properties, World steel production presents the most promising results out of the three indicators. This indicator yields the best results with regard to properties 2, 3, 4, 6, 7 and 8 and the second best results in property 5. Kilian's rea index yields the best results when first difference data is used, being the best indicator according to properties 5 and the second best in property 3, 7 and confirming Kilian's assertion that this index is a global business cycles index. OECD industrial production general performs badly in terms of these properties, being ranked third in properties 3, 5 and 8 and second in properties 2, 4, 6 and 7.

Rows 9, 10 and 11 in Table 6 present the average results for properties in first difference, detrended and for all numerical properties (2 to 8), respectively. World steel production outperforms all other 2 indicators in terms of first difference and detrended properties. Although, Kilian's rea also performs very well in tracking global GDP growth rates.

Finally, average results for all numerical properties also produce favourable results for World steel production revealing the lower average score of 1.14, while Kilian's rea index and OECD industrial production achieve an average score of 2.28 and 2.42 (respectively). Results in detail are discussed below.

[17] Kilian's index is already constructed using rates and further linearly detrend the data. For property 1, we have constructed a chain index from the starting period (1990:Q1=100) for the Kilian's index of global real economic activity.

5.1 Long-run properties

In Table 2 the stationary properties of the data are reported. For this purpose both the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) are estimated for all variables. For robustness purposes, both methods, which have inverse null hypotheses, have been used.[18] The null hypothesis for the ADF test is the variable has a unit root and the null hypothesis for the KPSS test is that the variable is stationary. Both tests results suggest that World GDP, OECD industrial production and World steel production are non-stationary variables. Kilian's rea index presents mixed results. However, as describe by Kilian (2009), this index is a measure of the business cycle and constructed by aggregating different growth rates (for different dry cargos and routes), consequently it is reasonable to assume that it is stationary.[19]

5.1.1 Property 1

In Table 3, results for the VAR Johansen's cointegration test are presented.[20] In this table we evaluate the cointegration relationship between World GDP and OECD industrial production, and World GDP and World steel production. Results for the Trace and Maximum eigenvalue tests are reported in Table 2 and 3 respectively. In specifying these tests with no intercept and no trend, both tests suggest only one cointegrating relationship between the three relationships tested.

[18] Testing the inverse null hypothesis can be seen as a robustness analysis to determine the stationary properties of the data, ideally both tests should agree. Jin and Frechette (2004) show that disagreement in the results of these tests is a sign that the data could be fractionally integrated.

[19] Our constructed chain index from the starting period for the Kilian's index of global real economic activity is appears to be non-stationary, but both eigenvalue and trace tests suggest no cointegration vector between Kilian's chained index and the log of world GDP.

[20] For more detail of this test, please see Enders (2004; pp. 362), and Engle and Granger (1987).

Specifically, in Table 2, it is observed that the null hypothesis of the number of cointegrating vectors is less than or equal to r is rejected when $r = 0$ at the 5% level, for the cointegrating vector between OECD industrial production and World GDP, and for World steel production and World GDP. The null hypothesis that the number of cointegration vectors is $r \leq 0$ cannot be rejected even at the 10% level for the two cases, pointing to only one cointegrating vector.

In Table 3, results for the Maximum eigenvalue confirm these results. The null hypothesis that the number of cointegrating vectors is r can only be rejected when r = 0 at the 5% level for the relationship between OECD industrial production and World GDP and for World steel production and World GDP; while the hypotheses of either r = 1 cannot be rejected even at the 10% level for both cases. Consequently, this first exercise supports the use of either OECD industrial production or World steel production as indicators of World economic activity.

5.2 Aggregate distance properties

In properties 2, 3 and 4 we evaluate the aggregate distance between World GDP and the monthly indicators to be evaluated in levels, first difference and detrended series respectively. In these 3 exercises, all indicators are re-scaled by constructing an index where the first observation is 1990:Q1=100. For comparative purposes, Kilian's rea index is not transformed to logs and previously re-scaled by dividing this index by 100 given that this index is constructed using rates. [21] The ranking of these properties 2, 3 and 4 are reported in table 6, rows 2, 3 and 4 respectively, where the indicator with lowest distance is reported as number 1, the second lowest distance number 2, and the third lowest distance number 3.

[21]We also test this property by using the chained index version of Kilian's rea index. Results for the chained index worsen significantly with respect to the unchained version of Kilian's index.

5.2.1 Property 2

In Table 6, row 2, results are presented for property 2, where the aggregate distance of the log-level of World GDP with respect to monthly indicators of World growth valued added (at quarterly frequency) is evaluated. It can be seen that World steel production ranked first with the lowest log-level distance value of 2.61, followed by OECD industrial production with a log-level distance value of 4.06, and Kilian's rea index fourth with a log-level distance value of 8.2.

5.2.2 Property 3

In the third row of Table 6, results are presented for property 3, where the aggregate distance of the first difference of World GDP with respect to monthly indicators of World growth valued added (at quarterly frequency) is evaluated. Note that World steel production indicator ranked first with the lowest distance of 0.59, followed by Kilian's rea index with second lowest distance value of 0.72 and OECD industrial production with third lowest distance value of 1.03.

5.2.3 Property 4

In the fourth row of Table 6, results are presented for property 4, where the aggregate distance of the detrended version of World GDP with respect to monthly indexes of World growth valued added (at quarterly frequency) is evaluated. It can be observed that World steel production indicator ranked first with the lowest distance with respect to World GDP of 2.68, followed by OECD industrial production with second lowest distance value of 3.12, and Kilian's rea index with fourth lowest distance value of 3.21.

5.3 Correlation properties

In this set of properties, the correlation between World GDP and monthly global indicator of growth value added is investigated.

5.3.1 Property 5

Results for property 5 are presented in the fifth row of Table 6. Kilian's rea index shows the highest correlation with World GDP with a correlation coefficient of 0.29, indicating that this index is by far the best index in terms of representing short-term global economic fluctuations. All other indicators present a small and negative correlation in first difference. World steel production has a correlation coefficient of -0.09 and OECD industrial production has a correlation coefficient of -0.10.

5.3.2 Property 6

Row 6 in Table 6 shows results of the correlation between detrended World GDP and the corresponding series for World monthly indicator of economic activity. These correlations are much higher than those observed in property 5. The detrended index of World GDP is highly correlated with World steel production (correlation coefficient of 0.96). OECD industrial production's correlation with World GDP is 0.90 while Kilian's rea index correlation is with World GDP is only 0.45.

5.4 Predictability properties

In 7 and 8, the predictability properties of monthly Global indicator of economic activity on World GDP are investigated. In 7 and 8, the first difference transformation and detrended World GDP (respectively) are predicted using monthly global indicators.

5.4.1 Property 7

In Table 4, results of property 7 are presented. In the second, third, fourth and fifth columns results of World steel production, OECD industrial production and Kilian's rea index respectively are presented. In evaluating this feature, the higher R^2 and adjusted R^2 are observed in the fifth column, showing that World steel production monthly indicator observations within a quarter (M1, M2 and M3) and its lags predict up to 58% of World GDP, following by both; OECD industrial production and Kilian's rea index with 47%.

5.4.2 Property 8

Results for property 8 are presented in Table 5. In the second column, World steel production presents by far the highest R^2 and adjusted R^2 predicting up to 75% of variation in World GDP, following by Kilian's rea index (47%) and OECD industrial production (36%).

6. Forecasting World GDP

6.1 Exercise set-up

The analysis above has focused on developing econometric properties to investigate features of monthly indicators of Global real economic activity to explain contemporaneously World GDP. We extend this by evaluating the out-of-sample predictive power of these indices. Inoue and Kilian (2004) examine the question of in-sample versus out-of-sample testing of predictability, motivated by the finding that positive in-sample evidence of predictability is often not associated with out-of-sample predictability. Ashley, Granger and Schmalensee (1980) claim that in-sample inference without out-of-sample verification is likely to be spurious, with an out-of-sample approach inherently involving less overfitting. Inoue and Kilian (2004) assert that this argument is not compelling since there is ample opportunity for the researcher to data mine in a simulated out-of-sample study, and because data snooping adjustments can be made to both tests. Therefore, we view the results we obtain as a natural complement to the set of in-sample evidence reported in the previous section. Moreover, we provide further evidence on a growing literature on out-of-sample nowcasting and forecasting of global GDP, see e.g. Ferrara and Marsilli (2014), Golinelli and Parigi (2014) and Rossiter (2010).

We split the full quarterly sample 1991Q1-2013Q1 into two periods: an initial in-sample period 1991Q1-1999Q4 and the out-of-sample (OOS) period 2000Q1-2013Q1. We use a recursive window to estimate the models and produce the forecasts over the different vintages. For each of the 53 OOS values, we produce from 1- to 8-step ahead forecasts using several different models based on the indicators of Global real economy. Precisely, we apply the following models:

$$dGGDP_t = \alpha + \beta \ dGGDP_{t-1} + \gamma \, X_{i,t-1} + \ \varepsilon_t \quad (9)$$

where $X_{i,t-1}$ is one of the three indicators of Global real economy activity, that is Kilian's rea index, OECD industrial production and World steel production; and ε_t is the error term with zero mean and σ^2 variance. Each model produces an *h*-step ahead forecast of detrended World GDP, $dGGDP_{t+h}$, our preferred measure of value added GDP, as:

$$d\widetilde{GGD}P_{i,t+h} = a + b \ dGGDP_t + c \, X_{i,t} \quad (10)$$

where *a*, *b* and *c* are the OLS estimates of unknown parameters α and β in equation (9).[22] The indicators are monthly variables and we convert them to quarterly observation $X_{i,t}$ using the most updated available information.[23] The release date of data varies between series. The

[22] We fix the autoregressive lag to 1 because this model outperforms models with more lags. Irrespectively, results are qualitative similar for models with more autoregressive lags. Moreover, the linear framework in equation (10) ignores that indicators are available at higher frequency than World GDP. We leave for future research to investigate regression methods that allows for estimation with mixed frequency data, such as MIDAS models, see e.g. Ferrara and Marsilli (2014).
[23] Since the four indicators are indices, the last observation should contain all the history information.

timeliest indicator is the World steel production that is published with a month delay. On the contrary, OECD industrial production is published with longer delays; and the Kilian's rea index depends on the author publishing the new information. We assume OECD industrial production and Kilian's rea index is available with 3-month delays, even if there is evidence of longer publication delay. World GDP is also published with delay, but the length of delay varies. In our exercise, we assume the release to be at the end of month three of the quarter and World GDP from the previous quarter is just released. Then, World steel production in month 2 of the quarter is available; whereas the most up-to-date information of the OECD industrial production and the Kilian's rea index refers to month 3 of the previous quarters.[24] World steel production is never revised; we ignore revisions for the other two indices and for World GDP. Accordingly, our analysis is a (pseudo) real-time forecasting exercise where the 1-step ahead forecast corresponds to nowcast.

We compare the three individual models to the AR(1) benchmark model where γ=0. Moreover, to account for the uncertainty with regard to choice of indicators, we apply forecast combination (FC) strategies:

$$d\widetilde{GGD}P_{c,t+h} = \sum_i w_{i,t+h}\, d\widetilde{GGD}P_{i,t+h} \quad (11)$$

where $w_{i,t} > 0$, $\sum_i w_{i,t} = 1$ are forecast combination weights. We consider two types of weights. First, we assume equal weights, $w_{i,t} = 1/3$. We label it as FC_EW. Second, we compute the weights $w_{i,t}$ as the inverse SPE of model *i* up to time (*t-1*) for horizon *h*.[25] We label it as FC_SPE. Timmermann (2006) discusses benefits of the two methods and provides

[24] Results are qualitatively similar when indicators are lagged one-month further.
[25] For the initial *h* period where the realization is not available to compute the square prediction error, we use equal weights in the FC_SPE scheme too.

several macroeconomic examples where the two methods provide accurate forecasts relative to other models.

Finally, we test for OOS population-level predictability via the Clark and West (2007) (CW) test. The test is based on a mean squared prediction error (MSPE) adjustment to account for noise induced in the OOS forecasts by way of estimation of parameters with zero population means under the null hypothesis that the benchmark model is the true DGP.

6.2 Forecasting results

Table 7 reports the OOS forecasting results for the different individual models and the forecast combinations. All the three indicators produce lower MSPE at 1-step ahead, in two cases they are statistically significant. However, only the Kilian's rea index and the World steel production produce lower MSPEs for most of the horizons and in the case of the World steel production these gains are significant relative to the AR benchmark up to 1-year ahead. Gains are economically significant, ranging from 30% to 40%.

The largest forecast improvements are, however, achieved by the forecast combination schemes. The reduction in MSPEs is for all the horizons and statistically significant up to 6-steps ahead. The gains are very large and for the FC_SPE scheme that on average provides the most accurate results over all horizons the reduction in terms of MSPE is 40% at nowcast and more than 10% at the longer horizons.

6.3 Local performance

The previous section does not provide evidence on how the OOS predictive content varies across the subsamples considered. We apply the Giacomini and Rossi (2010) Fluctuation test. This test provides a more formal framework for addressing this question; see also Ravazzolo and Rothman (2013). The test is motivated by the notion that if the OOS performance of the two models is time-varying, averaging this movement over the OOS period will result in a loss of information. In Figures 3 and 4, we provide time series plots for the Fluctuation test at h = 1 and h=8, the two horizons with higher and lower predictability, at the 10% significance level using 28 quarters rolling windows of CW test statistics (for testing the benchmark model against the alternatives). If the value of the Fluctuation test statistic is greater than the critical value at observation t, the null hypothesis that the benchmark model is the true model for the 7-year window ending at time t is rejected.

Figure 3 confirms the predictive power of the forecast combinations, which deliver statistically superior predictability over the entire sample, and it also shows that the indicators reduce the predictability after the US financial crisis, with the exception of the Steel production index, which delivers lower statistics at beginning of the sample. The combinations, in particular FC_SPE, exploit such differences and improve forecast performances. However, the predictability reductions of individual indicators for 8-step ahead in Figure 4 is substantial and even the combination schemes are not statistically significant anymore, in particular after 2009. OECD IP performs poorly for the entire sample. Bjørnland, Ravazzolo and Thorsrud (2015) discuss in a forecasting framework how the US financial crisis has been a global event, but the recovery has been different across countries and a global economic factor loses predictability from 2010.

7 Conclusions

In this paper we propose a new monthly indicator of Global real economic activity, named World steel production, and compare it to Kilian's rea index and the OECD industrial production index using a new econometric approach based on desirable properties of monthly global real economic activities. This novel approach proposes seven properties that evaluate four important features of the data: Long-term, aggregate distance, correlation and predictability properties of the data.

Averaging all the properties, World steel production is proven to be the best monthly indicator of global economic activity. In particular, in averaging results for all numerical exercises where a lower score indicates better performance, World steel production prevails with a lower average score of 1.14, while both Kilian's rea index and OECD industrial production have an average score of 2.28 and 2.42 respectively. Using either detrended or first difference data, World steel production outperforms both; Kilian's rea index and OECD industrial production index.

We test our in-sample econometric evidence in an out-of-sample exercise and confirm in-sample ranking with both Kilian's rea index and World steel production producing accurate forecasts for World GDP. Moreover, forecast combinations of the three indices produce statistically significant gains up to 40% at nowcast and more than 10% at longer horizons relative to an autoregressive benchmark. However, indicators of global real activity perform poorly at longer horizons after the US financial crisis in the recovery phase. The US financial crisis has been a global event, but the recovery has varied across countries and a global economic factor reduces predictability in such period.

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Table 1: Test for unit roots 1999:1-2012:12: Data in level

Null Hypothesis for ADF test: the variable has a unit root Alternative Hypothesis for ADF test: the variable has not a unit root					
Null Hypothesis for KPSS test: variable is stationary Alternative Hypothesis for KPSS test: variable is not stationary					
Log-Level	ADF	KPSS	First difference	ADF	KPSS
$\log(OECDIP_t)$	-1.29	1.15***	$\Delta\log(OECDIP_t)$	1.15**	0.07
$\log(\mathrm{GSTEEL}_t)$	0.56	-6.67***	$\Delta\log(\mathrm{GSTEEL}_t)$	1.20***	0.25
$\log(\mathrm{SHIP}_t)$	-2.93**	-10.08***	$\Delta\log(\mathrm{SHIP}_t)$	-0.35*	0.04
$\log(GGDP_t)$	0.12	3.13***	$\Delta\log(GGDP_t)$	1.26***	0.17

Note: The first difference of the series is indicated by Δ.The lag selection criteria for the ADF is based on Schwarz information Criteria (SIC) and for the KPSS is the Newey-West Bandwidth. One star * indicates rejection of the null hypothesis at 10% level; two stars ** at 5% level; and three stars *** at 1% level.

Table 2. Unrestricted cointegration rank test (Trace)

Null hypothesis: The number of cointegrating vectors is less than or equal to r Alternative hypothesis: There are more than r cointegrating vectors			
Hypothesized Null	Alt.	$\log(OECDIP_t)$ and $\log(GGDP_t)$	$\log(GSTEEL_t)$ and $\log(GGDP_t)$
r=0,	r≥1	0.02**	0.01**
r≤1,	r≥2	0.70	0.13

Note: Values reported are p-values MacKinnon-Haug-Michelis (1999). One star * indicates rejection of the null hypothesis at 10% level; two stars ** at 5% level; and three stars *** at 1% level. Lags are selected using Bayesian information criterion.

Table 3. Unrestricted cointegration rank test (Maximum eigenvalue)

Null hypothesis: The number of cointegrating vectors is r Alternative hypothesis: There are more than r cointegrating vectors			
Hypothesized: Null	Alt.	$\log(OECDIP_t)$ and $\log(GGDP_t)$	$\log(GSTEEL_t)$ and $\log(GGDP_t)$
r=0,	r=1	0.01*	0.03**
r=1,	r=2	0.70	0.13

Note: Values reported are p-values MacKinnon-Haug-Michelis (1999). One star * indicates rejection of the null hypothesis at 10% level; two stars ** at 5% level; and three stars *** at 1% level. Lags are selected using Bayesian information criterion.

Table 4: Predictability for World GDP (first difference)

Independent variable, first difference Global GDP	World Steel production	OECD Industrial production	Kilian's rea index
Constant	0.028*** (0.001)	0.029*** (0.001)	0.032*** (0.001)

M1 first difference	0.011	-0.207	0.005
	(0.067)	(0.268)	(0.00)
M2 first difference	0.081	0.109	0.02**
	(0.061)	(0.274)	(0.001)
M3 first difference	-0.005	-0.010	0.005
	(0.026)	(0.082)	(0.005)
M1 first difference (-1)	0.013	0.066	-0.0001
	(0.079)	(0.323)	(0.0001)
M2 first difference (-1)	0,123*	0.080	0.0001
	(0,067)	(0.312)	(0.0001)
M3 first difference (-1)	-0.032	0.106	0.0001
	(0.028)	(0.103)	(0.0001)
M1 first difference (-2)	0.001	0.302	0.0000
	(0.007)	(0.334)	(0.0002)
M2 first difference (-2)	0.145*	0.255	0.0000
	(0.075)	(0.169)	(0.0002)
M3 first difference (-2)	0.078	0.176	0.0001
	(0.051)	(0.273)	(0.0002)
M1 first difference (-3)	0.014	0.027	0.0000
	(0.059)	(0.292)	(0.0002)
M2 first difference (-3)	0.011	0.089	0.0001
	(0.007)	(0.234)	(0.0002)
M3 first difference (-3)	-0.048	0.066	-0.0001
	(0.068)	(0.323)	(0.0002)
M1 first difference (-4)	0.036	-0.276	-0.0004
	(0.044)	(0.225)	(0.0001)
M2 first difference (-4)	0.080	-0.0163	0.0002
	(0.046)	(0.261)	(0.0002)
M3 first difference (-4)	-0.073	-0.179	0.0000
	(0.068)	(0.212)	(0.0002)
R^2	0.58	0.47	0.47
Adj.R^2	0.50	0.36	0.36

Note: Four lags are used as indicated by the Akike Information Criterion. One star * indicates the coefficient is statistically different than zero at 10% level; two stars ** at 5% level; and three stars *** at 1% level.

Table 5: Predictability for World GDP (detrended)

Independent variable, first difference Global GDP	World Steel production	OECD Industrial production	Kilian's rea index
Constant	0.0002	-0.0052	-0.0129**
	(0.0034)	(0.005)	(0.0048)
M1 first difference	0.1738	-2.5007*	-0.0002
	(0.2327)	(1.4019)	(0.0009)
M2 first difference	0.1542	0.5349	0.0007
	(0.2191)	(1.3669)	(0.0008)
M3 first difference	-0.1854**	-1.5306**	-0.0004
	(0.0966)	(0.4206)	(0.0003)
M1 first difference (-1)	0.1408	-1.5265	-0.0004
	(0.2346)	(1.3376)	(0.0009)
M2 first difference (-1)	0.1127	-0.3645	0.0011
	(0.2271)	(1.3316)	(0.0008)
M3 first difference (-1)	0.1153	0.7582	0.0000
	(0.1539)	(0.7847)	(0.0004)
M1 first difference (-2)	0.0223	-1.1945	0.0000
	(0.2234)	(1.2707)	(0.0008)
M2 first difference (-2)	0.2575	0.6770	0.0009
	(0.2303)	(1.3578)	(0.0008)
M3 first difference (-2)	-0.0919	0.7470	-0.0002
	(0.2324)	(1.0909)	(0.0008)
M1 first difference (-3)	-0.10187	0.4511	-0.0011
	(0.2023)	(1.2175)	(0.0007)
M2 first difference (-3)	0.1710	-0.0675	0.0012
	(0.2040)	(1.2175)	(0.0007)
M3 first difference (-3)	-0.1582	2.0232	-0.0007
	(0.2532)	(1.2892)	(0.001)
M1 first difference (-4)	0.0130	0.3629	-0.0002
	(0.1671)	(1.3484)	(0.0006)
M2 first difference (-4)	0.2516	-0.5767	0.0014*
	(0.2022)	(1.1292)	(0.0007)
M3 first difference (-4)	-0.3363	1.8867	0.0002
	(0.2202)	(1.3227)	(0.0009)
R^2	0.75	0.36	0.44
Adj.R^2	0.70	0.26	0.32

Note: Four lags are used as indicated by the Akike Information Criterion. One star * indicates the coefficient is statistically different than zero at 10% level; two stars ** at 5% level; and three stars *** at 1% level.

Table 6: Econometric property results

	Kilian's rea index	OECD IP	Steel Production
Property 1	-	Yes	Yes
Property 2	3	2	1
Property 3	2	3	1
Property 4	3	2	1
Property 5	1	3	2
Property 6	3	2	1
Property 7	2	2	1
Property 8	2	3	1
First difference properties (average)	1.66	2.66	1.33
Detrended properties (average)	2.66	2.33	1
All properties (average)	2.28	2.42	1.14

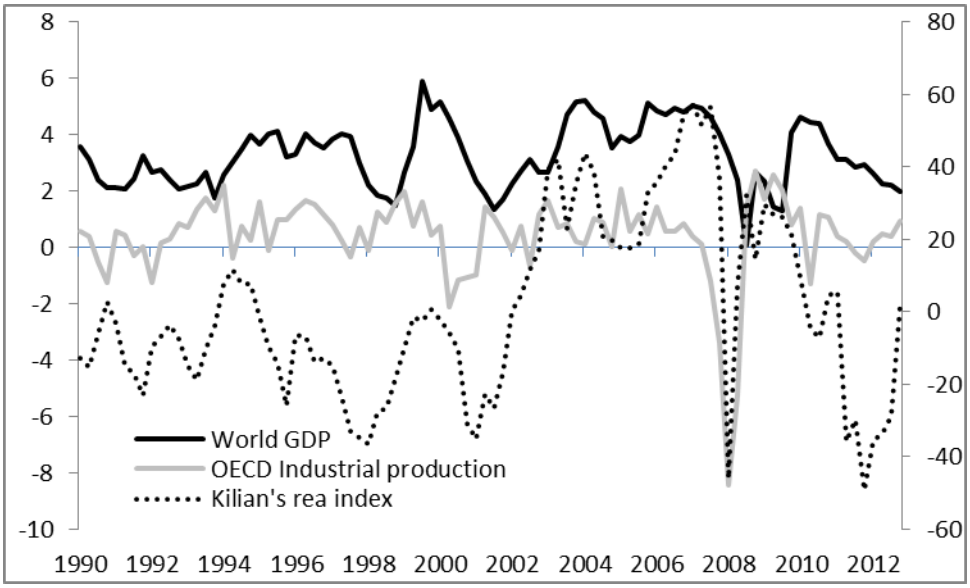
Note: For properties 1 and 2, where data in log-level is used, we have constructed a chain index from the starting period (1990:Q1=100) for the Kilian's index of global real economic activity. Although this chain index appears to be non-stationary, results for property 1 shows that both eigenvalue and trace tests suggest not cointegration vector between Kilian's rea chained index and the log of world GDP. For property 2, Kilian's rea index chained index worsens results significantly with respect to the unchained index.

Table 7: Forecasting World detrended GDP: MSPE

Hor	1	2	3	4	5	6	7	8
AR	0.017	0.065	0.134	0.211	0.284	0.347	0.402	0.455
Kilian's rea index	**0.695***	**0.708**	**0.693**	**0.715**	**0.747**	**0.763**	**0.781**	**0.816***
OECD IP	**0.828**	**0.922**	1.030	1.131	1.218	1.287	1.332	1.355
Steel Production	**0.734****	**0.732***	**0.687***	**0.664***	**0.710**	**0.828**	**0.948**	1.014
FC_EW	**0.599*****	**0.612*****	**0.627****	**0.671*****	**0.739****	**0.811***	**0.876**	**0.920**
FC_SPE	**0.596*****	**0.609*****	**0.605****	**0.624*****	**0.680****	**0.762***	**0.837**	**0.884**

Note: The table reports the Mean Square Prediction Error of the various alternative models to predict World detrended GDP over the sample 2000Q1-2013Q1. The column "AR" reports the MSPE value for the AR(1) benchmark model; the other columns present the ratio of the alternative model's MSPE to the benchmark's MSPE. Bold numbers indicate the alternative model provides lower MSPE. The alternative models refer to AR(1) model extended with one of the monthly indicators of Global real economic activity studied in the paper and combinations of them based on equal weights (FC_EW) or inverted square prediction errors (FC_SPE). We measure statistical significance relative to the benchmark model using the Clark and West (2006) tests for equality of the average loss. One star * indicates significance at 10% level; two stars ** at 5% level; and three stars *** at 1% level.

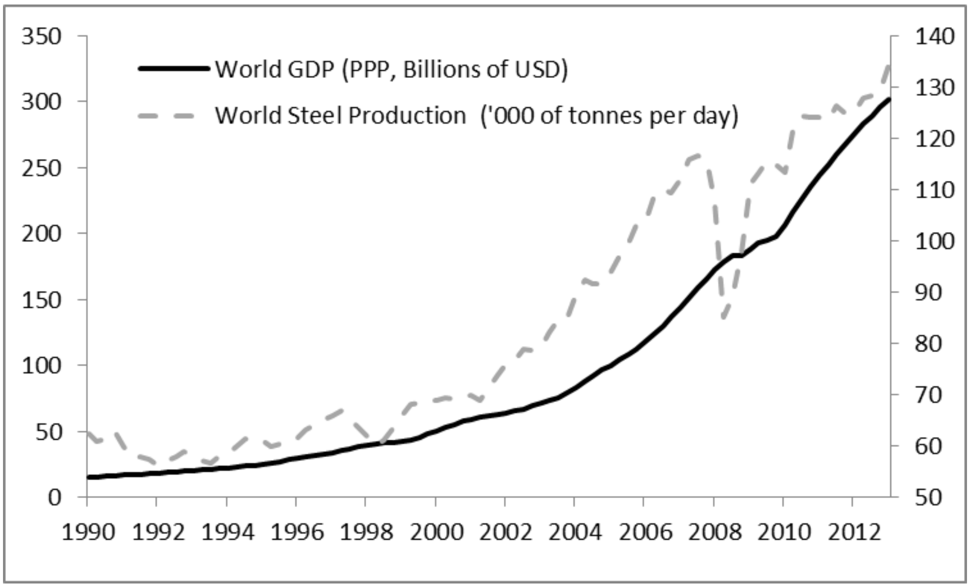
Figure 1: OECD industrial production index and World GDP in log first difference (right scale), Kilian's rea index (left scale): 1990:Q1 to 2013:Q1



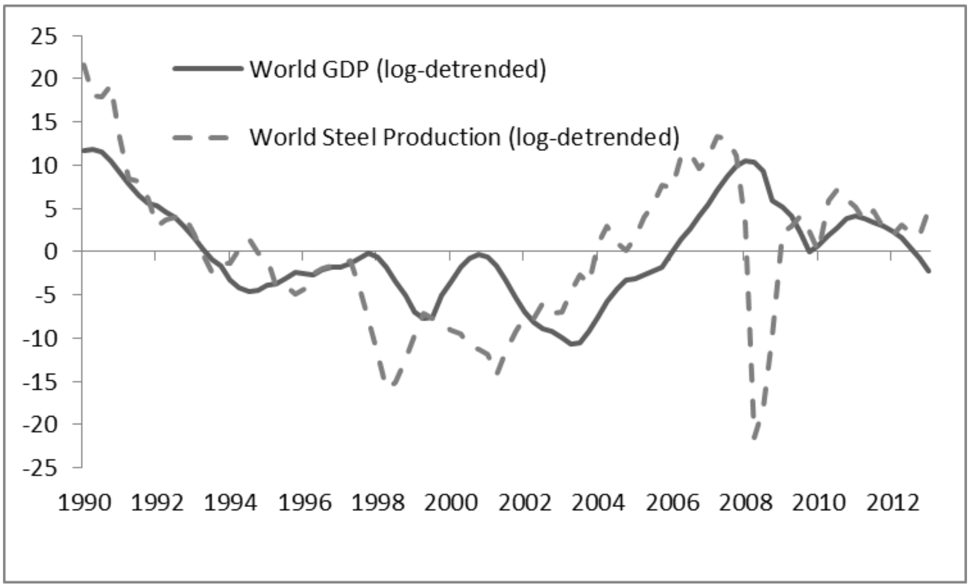
Note: The series have been seasonally adjusted by the authors using census X12 method.

Figure 2: World Steel Production (right scale) vs. World GDP (left scale): Quarterly data 1990:Q1 to 2013:Q1

a) Data in Levels



b) Logs of detrended data



c) Logs of first diffrence

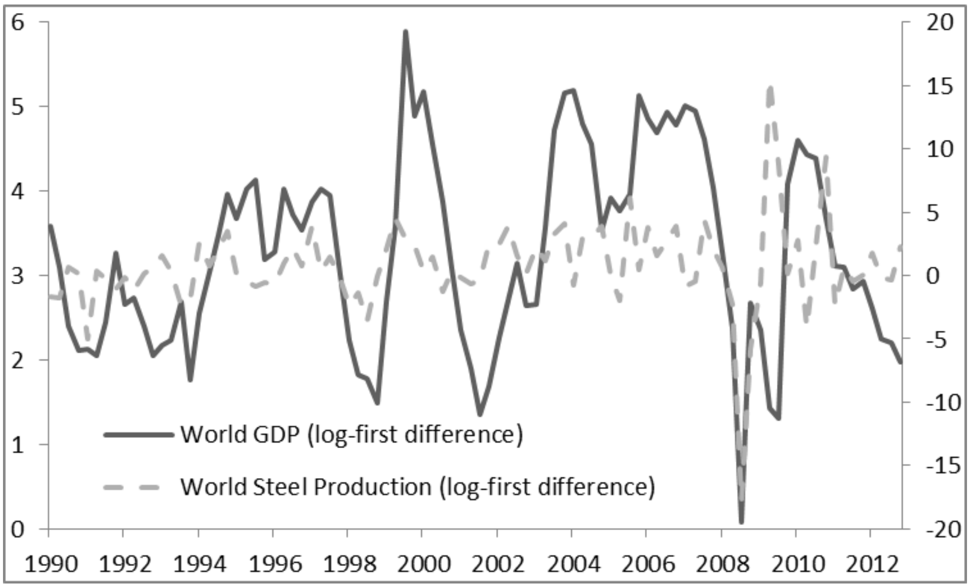
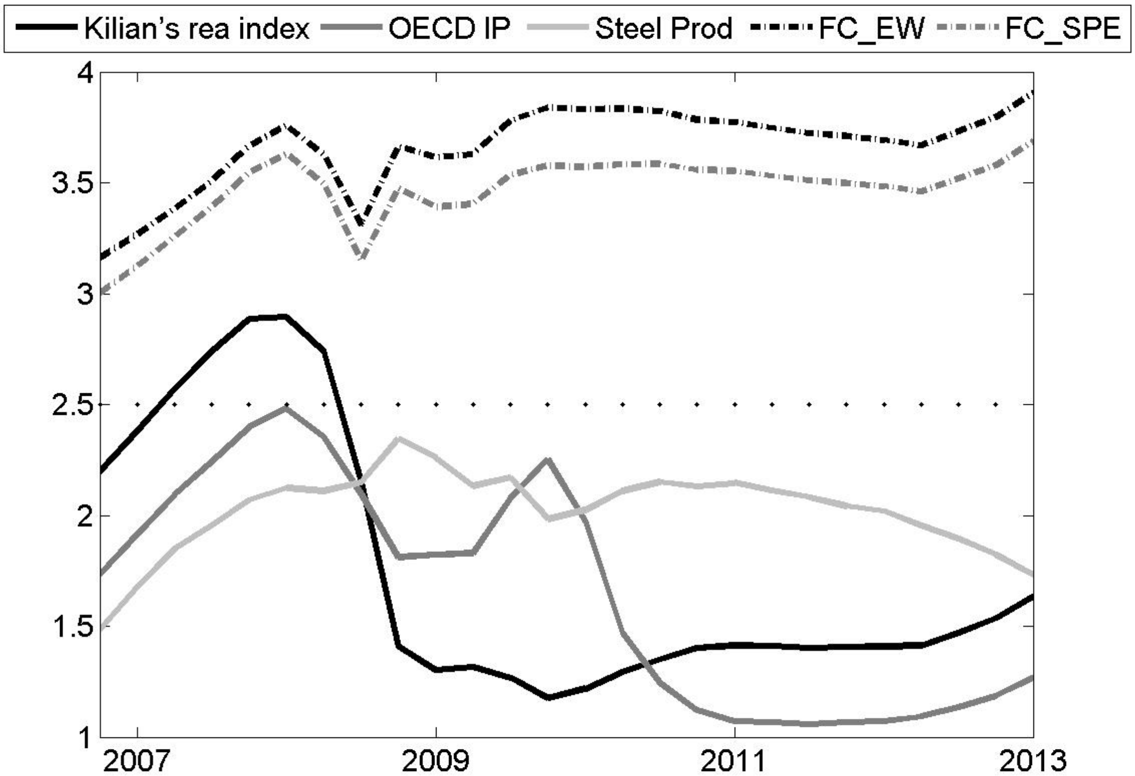
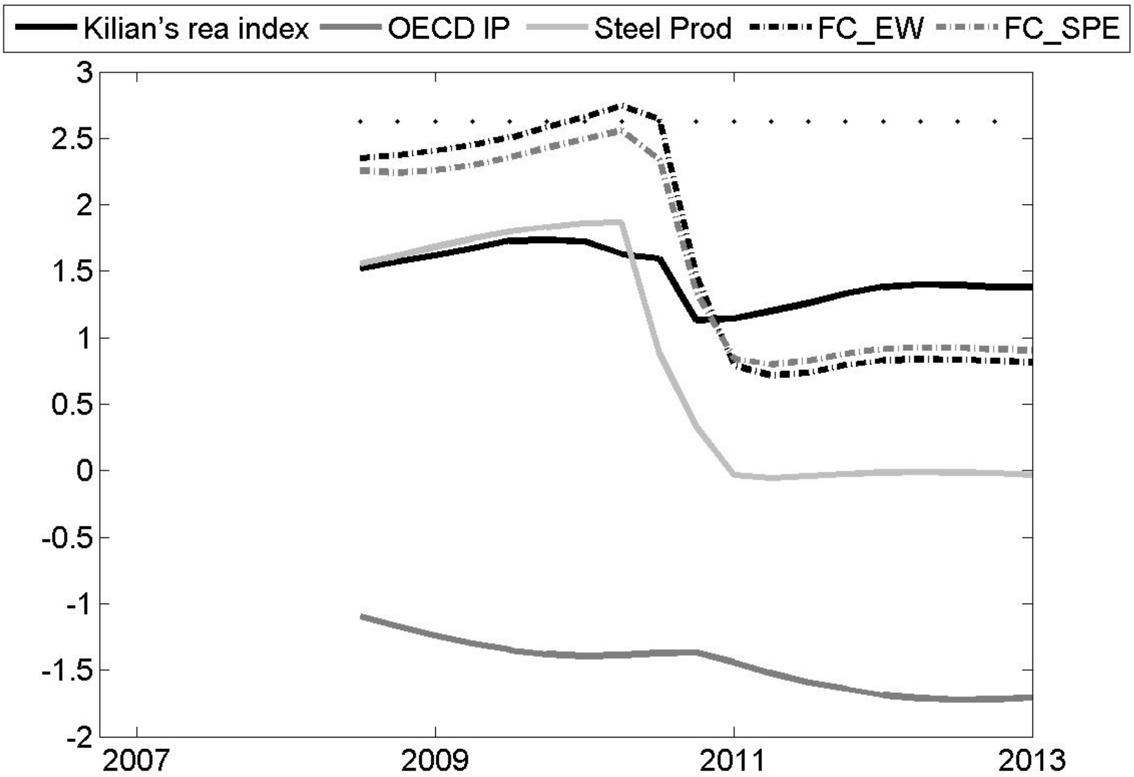


Figure 3: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability at h=1



Note: Giacomini and Rossi (2010) Fluctuation test based on sequences of Clark and West (2007) test statistics (for testing model (1) against model (2)), with μ=0.5 and m=P, where m = the size of the rolling window of CW statistics and P = the number of OOS observations, for the OOS period 2000Q1-2013Q1, such that the length of each window of CW statistics is 28 quarters, i.e., 7 years. The x-axis refers to the last value of each sample. Fluctuation test critical value at the 10% significance level in dotted lines; if the Fluctuation test statistic exceeds the critical value, the null that the benchmark model is the true model is rejected for the particular window. Benchmark model is an AR(1), alternative models in legend are defined in Section 6.

Figure 4: Giacomini and Rossi (2010) Fluctuation Test for Equal Out-of-Sample Predictability at h=8.



Note: See Figure 3.