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A Contribution to the Chronology of Turning Points in Global Economic Activity (1980-2012)*

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Abstract

The Database of Global Economic Indicators (DGEI) of the Federal Reserve Bank of Dallas is aimed at standardizing and disseminating world economic indicators for the study of globalization. It includes a core sample of 40 countries with available indicators and broad coverage for quarterly real GDP, and the monthly series of industrial production (IP), Purchasing Managers Index (PMI), merchandise exports and imports, headline CPI, CPI (ex. food and energy), PPI/WPI inflation, nominal and real exchange rates, and official/policy interest rates (see Grossman, Mack, and Martínez-García (2013)). This paper aims to codify in a systematic way the chronology of global business cycles for DGEI. We propose a novel chronology based on IP data for a sample of 84 countries at a monthly frequency from 1980 until now, and assess the turning points obtained as a signal of the underlying state of the economy as tracked by the indicators of DGEI. We conclude by proposing and also evaluating global recession probability forecasts up to 12 months ahead. The logit model proposed uses the DGEI aggregate indicators to offer advanced warning of turning point in the global cycle—by this metric a global downturn in 2013 does not appear likely.

JEL codes: C14, C82, E32, E65

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"Data! Data! Data!" he cried impatiently. "I can't make bricks without clay."
The Adventure of the Copper Beeches (1892),
in *The Adventures of Sherlock Homes*,
by Sir Arthur Conan Doyle (1859-1930).

1 Introduction

The Database of Global Economic Indicators (DGEI) aims to provide a broad perspective on the world economy that is indicative of common developments and less subject to idiosyncratic country factors. With that as its main purpose, DGEI reflects a major effort of the working group on international statistics at the Globalization and Monetary Policy Institute of the Federal Reserve Bank of Dallas—to which the aforementioned authors of this document belong (see Grossman, Mack, and Martínez-García (2013)).

DGEI aims to standardize and facilitate the extraction and documentation of common features of the international data. It channels a variety of data sources—going back to 1980 whenever possible—for the compilation of monthly and quarterly time series at the country level and the construction of world aggregates. With this database, the Federal Reserve Bank of Dallas wants to both contribute and promote research in international macroeconomics that deepens our understanding about the role of globalization and international business cycles—the latter topic is discussed in this paper.

The preoccupation with business cycles has its origins in the study of crises, so it is no surprise that renewed interest followed the financial recession of 2007-08. As economies have become more integrated since the 1980s, interest in international business cycles also has increased. However, global recessions are by no means a new phenomenon. Jorda, Schularick, and Taylor (2011) document no less than four global financial crises involving countries that accounted for more than 50 percent of global GDP during the period from 1870 to 1929.

It was precisely against this backdrop that the National Bureau of Economic Research (NBER) was created in 1920 for the purpose of examining the "business cycle and long-term growth" of the U.S. economy. Among the early research sponsored by the NBER, Burns and Mitchell (1946) laid the foundations for the study of business cycles and greatly influenced the NBER approach to dating turning points in the U.S. The NBER-sponsored work of Bry and Boschan (1971) formalized a widely-used algorithm for the identification of turning points in the business cycle (see also Harding and Pagan (2002)).

The NBER created a standing Business Cycle Dating Committee (BCDC) in 1978 to institutionalize the dating of U.S. recessions, which has produced a historical series of turning points going back to 1854. Other institutions and international organizations have slowly moved towards establishing their own chronologies at the national, supra-national, or international level using a variety of methods. Among these it is worth pointing out the International Business Cycle Dates of the Economic Cycle Research Institute (ECRI) for a selection of 22 countries which implement the same methodology used to determine business cycle dates for the U.S. by the NBER.[2]

We recognize that a chronology of global business cycles is as important nowadays as it ever was for the study of international macroeconomic fluctuations and for policy analysis. With that idea in mind, we adopt the Bry and Boschan (1971) algorithm—as reinterpreted by Harding and Pagan (2002)—to date global business cycle turning points in a consistent manner following in the NBER and ECRI traditions. The Bry and Boschan (1971) algorithm is not the official procedure for dating U.S. business cycles used by the NBER, but it provides a set of turning points that closely matches the NBER-determined dates. The Bry and Boschan (1971) algorithm has the additional advantage of codifying the definition of a chronology of business cycle turning points in a systematic, transparent, and objective way—removing all subjective judgment from the process.

To compare the chronology established under our Bry and Boschan (1971) methodology, we also adopt a more structural approach to date business cycles following on the seminal work of Hamilton (1989). Under this alternative approach, we characterize the stochastic process of the growth rates in economic activity (which are reasonably thought of as stationary) as being generated by two possibly different distributions—one for expansions and another for contractions. The actual state of the economy is unobservable, but the transitions between states of this econometric model can be characterized as a hidden-Markov process and estimated by standard state-space procedures (see, e.g., Kim and Nelson (1999)). Then, the recovered recession probability can be used to date turning points in the business cycle as well.

Each method—the Bry and Boschan (1971) algorithm and the Hamilton (1989) model—can be applied to different variables and to a different selection of countries to establish a comparison across multiple chronologies. Each method can also be used under an aggregate-then-date approach, or alternatively under a date-then-aggregate approach. Country business cycles and even different time series indicators within each country do not always fluctuate synchronously—which tends to favor the date-then-aggregate approach (see, e.g., Stock and Watson (2010)). We follow that approach in our implementation of the Bry and Boschan (1971) method.

The more structural approach derived from Hamilton (1989) is implemented with different variables from the Dallas Fed's Database of Global Economic Indicators (DGEI)—see Grossman, Mack, and Martínez-García (2013) for reference—other than the industrial production (IP) series that we use for our preferred chronology. It also is applied with data at quarterly as well as monthly frequencies, and with data that has been aggregated-then-dated. The purpose of exploring all those alternatives to our preferred method is to offer a contrast, and to evaluate the extent to which widespread turns in the business cycle picked up by our chronology are reflected in the aggregate indicators reported in DGEI.

[2] Geoffrey H. Moore, one of the ECRI co-founders, was directly involved in determining recession dates on behalf of the NBER from 1949 to 1978, and then served at the NBER as the BCDC's senior member until passing away in 2000. Geoffrey H. Moore brought his NBER experience to define the ECRI methodology on business cycles, which facilitates the comparison of business cycle turning points for all 22 countries monitored by ECRI which is methodologically consistent with that of the NBER.

However, the different classification methods leave us with a number of discrepancies across chronologies to deal with. To statistically assess the quality of our chronology, we adopt simple tools from the theory of networks and signal detection. Berge and Jorda (2011) and Berge and Jorda (2013) highlight these techniques to classify data in periods of expansions and contractions for the cases of the U.S. and Spain, and use them to evaluate competing chronologies. After evaluating our proposed chronology for the global business cycle, we go a step further and exploit some of the data collected by DGEI to assess their potential for predicting future turning points of the global cycle.

The remainder of the paper proceeds as follows: Section 2 outlines the time series indicators in DGEI, the taxonomy applied for the purposes of country classification, and the aggregation methods. Further details can be found in Grossman, Mack, and Martínez-García (2013). In Section 3 we provide an extensive discussion and further details on the Bry and Boschan (1971) procedure used to construct our chronology of global business cycles with IP data for 85 countries, as implemented with the Dallas Fed's DGEI. Then we present alternative chronologies based on the econometric model of Hamilton (1989) and the main DGEI indicators for contrast. In Section 4 we assess the statistical quality of the chronologies, while in Section 5 we consider different indicators from DGEI that can be evaluated as predictors of future turning points of the global business cycle. Section 6 provides some additional discussion on the insights gained in building a global chronology, and concludes.

2 The Database of Global Economic Indicators (DGEI)

2.1 Main Global Economic Indicators

The time series listed in Table 1 represent the current selection of (monthly and quarterly) indicators in DGEI, which includes a number of the most relevant macro variables used to check the pulse of the global economy and gauge real and nominal developments. See Grossman, Mack, and Martínez-García (2013) for details on the sources for each variable.

Table 1. Main Economic Indicators in DGEI

Variables	Frequency
Real Economic Activity Indicators	
GDP	Quarterly
Industrial Production	Monthly
Purchasing Managers Index (PMI)	Monthly
Price Indicators	
Headline CPI Inflation	Monthly
PPI/WPI Inflation	Monthly
Core CPI Inflation	Monthly
Nominal Exchange Rates	Monthly
Real (CPI-based) Exchange Rates	Monthly
Real (PPI-based) Exchange Rates	Monthly
Trade Indicators	
Merchandise Exports to World	Monthly
Merchandise World Imports	Monthly
Financial Indicators	
Short-term Policy Rates	Monthly

Note: The GDP series is computed as an index, and expressed in levels in PPP-adjusted terms in international U.S.$. Among the 12 indicators listed in this table, nine of them are considered to be core indicators for which all countries in DGEI must have some data at least as far back as 2005. Of the three non-core indicators of reference, PPI/WPI inflation and real (PPI-based) exchange rates have nearly complete country coverage in DGEI, and only the PMI series is subject to significant data limitations.

2.2 Country Classification and Selection

Our development classification for DGEI is based on a relative income threshold. We classify countries as <u>advanced</u> or <u>emerging</u> based on PPP-adjusted real GDP per capita from the IMF World Economic Outlook (WEO), using annual data from 1980 until 2012 for 183 countries and overseas/dependent territories.[3] Countries that fell below the upper quartile of the cross-country distribution of PPP-adjusted GDP per capita at least 20 percent of the time since the 1980s are classified as emerging. This relative threshold accounts for changes in distribution over time, as

[3] Nielsen (2011) describes the methodologies for the classification of countries by their development attainment used by the U.N. Development Programme (UNDP), the World Bank, and the International Monetary Fund (IMF). Further discussion on how those taxonomies compare with the one adopted here can be found in Grossman, Mack, and Martínez-García (2013), which also proposes an alternative country classification based on the differences in the degree of trade openness across countries.

GDP per capita has trended upwards over this sample period. The classification is further adjusted to separate advanced countries from high-income countries whose economies are especially dependent on commodities. In particular, high-income, oil-producing countries are reclassified as emerging.

There is readily available data on all key macro indicators listed in Table 1 for at least 58 countries starting in 2005 or earlier, although the coverage is not complete for all going back to 1980. Out of the 58 countries, DGEI selects 40 countries by: (a) their economic size, and (b) representativeness. Representativeness is attained when the countries account for at least 75 percent of the advanced (ex. the U.S.) and emerging shares of world PPP-adjusted GDP in 2005. In DGEI, the country sample ends up including 19 advanced countries (including the U.S.) and 21 emerging countries, reported in Table 2 below according to our country classification.

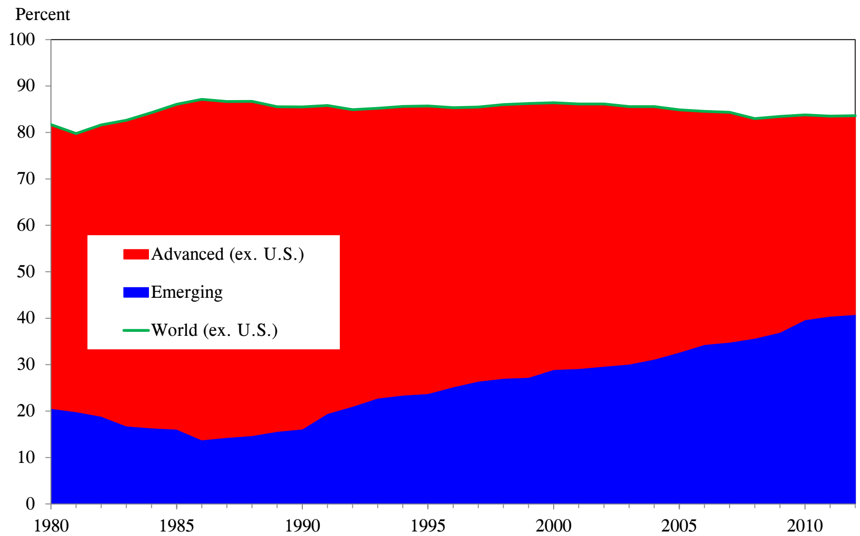
Table 2. Country Sample in DGEI

Advanced Countries	PPP-adj. GDP Shares (2005)	Emerging Countries	PPP-adj. GDP Shares (2005)
U.S.	22.16	China	9.42
Japan	6.83	India	4.26
Germany	4.38	Russia	2.98
U.K.	3.42	Brazil	2.78
France	3.27	Mexico	2.28
Italy	2.88	Turkey	1.31
Spain	2.08	Indonesia	1.24
Canada	2.04	Poland	0.91
S. Korea	1.93	Thailand	0.78
Australia	1.21	Argentina	0.74
Taiwan	1.07	S. Africa	0.71
Netherlands	1.00	Colombia	0.55
Belgium	0.59	Malaysia	0.55
Sweden	0.53	Venezuela	0.46
Austria	0.49	Philippines	0.46
Switzerland	0.48	Nigeria	0.43
Greece	0.48	Chile	0.36
Portugal	0.38	Peru	0.31
Czech Rep.	0.38	Hungary	0.30
		Bulgaria	0.14
		Costa Rica	0.07

Note: PPP-adjusted GDP shares are from the IMF World Economic Outlook (WEO) database.

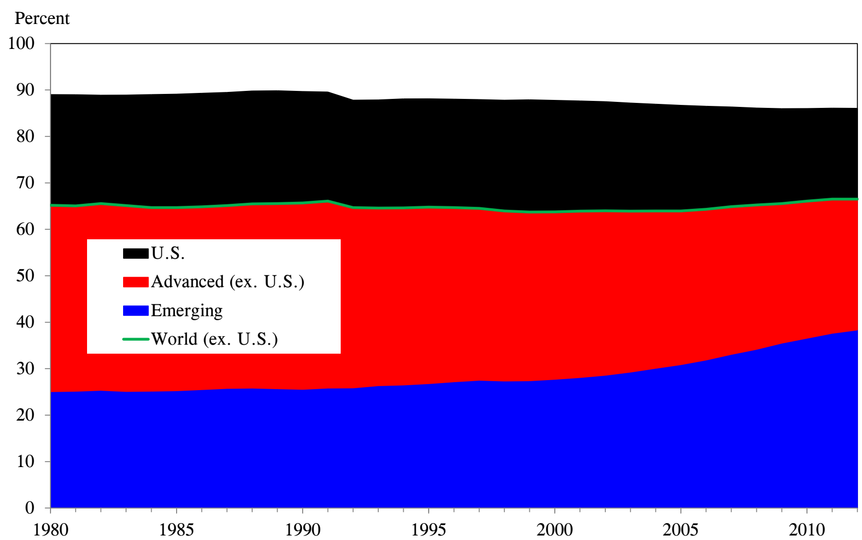
The country selection of DGEI represents a fairly stable share of U.S. trade for the period of reference since 1980 (as can be seen in Figure 1), as well as a stable share of world GDP in PPP-adjusted terms (as shown in Figure 2). Moreover, it also accounts for—and is representative of—two major structural changes that have occurred since the 1980s: (a) the share of U.S. trade accounted for by emerging countries has more than doubled since 1987; and (b) the share of world GDP accounted for by emerging countries has significantly increased since 2000.

Figure 1. G40 Share of U.S. Trade (1980-2012)



Source: Trade data comes from the IMF Direction of Trade (DOT) database.

Figure 2. G40 Share of PPP-adjusted World GDP (1980-2012)



Source: PPP-adjusted GDP shares are from the IMF World Economic Outlook (WEO) database.

2.3 Pre-processing the Data (at the Country Level)

Seasonal adjustment is performed with the X12-ARIMA using a multiplicative specification as the default, unless the series has negative or zero values or is expressed in percent in which case we adopt the additive model. Linear interpolation is used to fill gaps in the time series. The quadratic-match average method is used for temporal disaggregation to adjust the frequency of the time series indicators to monthly (except for real GDP which is adjusted to quarterly), while constant interpolation is used with the annual weight data.

Unless otherwise noted, we always use exact growth rates in all calculations.[4] DGEI uses the exact growth rates of historical series, for instance, to splice the current time series backwards. The historical series may need to be temporally disaggregated and/or linearly interpolated to fill in the gaps before it can be spliced together with the most current series. To correct for jumps that occur due to countries entering the sample, DGEI follows this simple procedure: say country *k* enters into the sample at time *t*, then the aggregate series calculated without country *k* is spliced together with the aggregate series calculated with the country included when the country enters into the sample at time t.

2.4 Aggregation Method

Consistent with the practice of constructing National Accounts followed by most statistical offices and the OECD (2011)'s Economic Outlook methodology, all reported aggregate series are computed on the basis of time-varying, annual weights to better capture the structural changes that occur in the data. We consider two alternative weighting schemes depending on the variable to be aggregated:

- *Weighting scheme 1*: weights are applied to the variable in levels – to be preferred with diffusion indexes (PMIs) or rates of interest (the official/policy interest rates),

$$\sum_{i=1}^{N} Y_t^i w_t^i , \qquad time\ t,$$

  where w_t^i is the weight of country *i* in period *t* among the *N* countries to be combined, and Y_t^i is the variable to be aggregated.

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[4] The rate of growth of a variable Y_t^i for country *i* in period *t* over the preceding period *t-1* expressed in percentage terms is computed as $100\left({Y_t^i}/{Y_{t-1}^i} - 1\right)$, while the annualized growth rate is given by $100\left(\left({Y_t^i}/{Y_{t-1}^i}\right)^s - 1\right)$, where *s* defines the periodicity (s=4 for quarterly data, s=12 for monthly). The year-on-year growth of a variable Y_t^i for country *i* in period *t* over the preceding period *t-s* of the previous year expressed in percentage terms is computed as $100\left({Y_t^i}/{Y_{t-s}^i} - 1\right)$, where *s* again defines the periodicity (s=4 for quarterly data, s=12 for monthly).

- *Weighting scheme 2*: weights are applied to the variable in exact growth rates – to be preferred with indexed (industrial production, core and headline price indexes) or variables expressed in absolute units (real GDP, exports and imports, nominal and real exchange rates),

$$\sum_{i=1}^{N}\left(Y_t^i \big/ Y_{t-1}^i - 1 \right) w_t^i, \qquad time\ t,$$

where w_t^i is the weight of country *i* in period *t* among the *N* countries to be combined, and Y_t^i is the variable to be aggregated. The resulting weighted average growth rate series is then transformed into an index with a base year of 2005=100.

Annual weights for PPP-adjusted GDP-weighted aggregation are calculated as follows,[5]

$$w_{t,k} = \frac{GDP_{t,k}}{\sum_{k=1}^{N} GDP_{t,k}}, \qquad country\ k$$

Data for the PPP-adjusted GDP weights comes from the IMF's World Economic Outlook (WEO). GDP weights put the emphasis on the economic size of a country, assigning a larger share to countries whose economies account for a larger fraction of world output.

DGEI adopts the rule that group aggregates are calculated (and reported) only if countries representing 80 percent or more of the weight of the group are included in the subsample of countries with available data at a given point in time. This rule is also used to determine when the most recent observations ought to be included in the time series.

2.5 Sources of Data Revisions

The country data are released with varying lags and are subject to data revisions. The most recent observations of the aggregate series are likely to exclude data from some countries with missing data points. In subsequent updates when these missing country observations become available, correcting the initial aggregate series becomes a source of revisions in DGEI. The country series themselves are systematically revised by the original reporting sources which becomes another source of revisions for the aggregates in DGEI. Finally, the weighting data used for aggregation can also be revised by the original reporting sources affecting the DGEI aggregates. However, we notice that weight data revisions tend to be less frequent and produce smaller changes on the aggregates (most of the time) than the other two sources of data revisions.

[5] DGEI gives preference to trade weights with the U.S. in weighting the variables for reporting, but allows for a number of alternative aggregation schemes to be used. Among them, we use annual PPP-weights for tracking global business cycles in this paper. For additional details on the aggregation methods and weights used by DGEI, see Grossman, Mack, and Martínez-García (2013).

3 Dating Global Turning Points

Classical business cycles were extensively analyzed by Arthur Burns and Wesley Mitchell in their classic 1946 book *Measuring Business Cycles*. The key insight of their work is that many economic indicators co-move along the business cycle, so expansions and contractions can be detected more easily if we observe a cross-section of economic indicators expanding or contracting over a prolonged period of time. Burns and Mitchell adopted the working definition proposed earlier by Mitchell to characterize a classical recession in the following terms,

> "Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitude approximately their own." Mitchell (1927:p. 468).

This view became the core principle in the NBER methodology for dating U.S. recessions. While vaguely stated, it clearly places restrictions on both the duration and amplitude in order to separate business cycle episodes within a given period of time. We use a similar view of business cycles to determine global turning points, but remove all judgment in the identification with the implementation of the Bry and Boschan (1971) algorithm. This algorithm comes closest to translating the NBER's methodological principles and the working definition of Burns and Mitchell (1946) into a mechanical classification rule placing the emphasis on making concrete the duration features of Mitchell's definition.

The statistical approach based on the Bry and Boschan (1971) algorithm has the advantage that data does not have to be detrended in order to detect turning points, even when the data generating process is only stationary around a trend. However, in our attempts to formalize a chronology of global turning points we also explore measures of economic activity in growth rates—so the data would be stationary—as well. An econometric model for the rate of growth can be postulated that allows the data generating process to be driven by different processes in periods of expansion and contraction. The transitions between the two processes can be modeled with a hidden-Markov process along the lines of Hamilton (1989), which can be estimated and used to make inferences about the likelihood of a turning point having occurred.

In this section, we briefly discuss both methodologies while the rest of the paper provides empirical evidence in support of our preferred chronology based on the implementation of the Bry and Boschan (1971) algorithm. We also evaluate the potential of the DGEI aggregate indicators to forecast turning points in the global cycle at different forecasting horizons.

3.1 *Bry and Boschan (1971)*

Let X_t denote a univariate time series for which we want to detect turning points and characterize a classical cycle. The Bry and Boschan (1971) algorithm starts by removing seasonals from the data X_t in levels (without detrending), so that pronounced seasonality patterns could not be confounded as turning points. Next, the seasonally-adjusted time series X_t^{sa} is smoothed out slightly using a moving average filter to remove outliers, breaks, or other irregular patterns in the data.

Finally, the algorithm searches for and identifies local minima and maxima in the resulting time series $X_t^{sa,ma}$ under a number of constraints on the duration of the cycle (or censoring rules). The censoring rules on local minima and maxima guarantee that the classical business cycles recovered with the Bry and Boschan (1971) algorithm occur at the appropriate frequency. To be more precise, they ensure that classical cycles have a certain duration for each phase (contraction and expansion), that they alternate between phases, and that complete cycles with an expansion and contraction phase last for a minimum amount of time that rules out short-lived ups-and-downs in the data.

The censoring rules for the algorithm were adapted to monthly/quarterly data by King and Plosser (1994), Harding and Pagan (2002), Kose, Prasad, and Terrones (2003), and Kose, Otrok, and Whiteman (2008) among others. We use the following censoring rules for monthly/quarterly data in our search for turning points of the global cycle:

- Turn-phase is 5 months/2 quarters on either side;
- The minimum length of the phase (contraction or expansion) is 4 months/2 quarters; and
- The minimum length of a full cycle is 12 months/4 quarters.

The output of the algorithm is summarized in a pair of binary indicators: P_t takes the value of 1 if at time *t* there is a peak in the series (local maximum), 0 otherwise; and, similarly, T_t equals 1 if at time *t* there is a trough in the series (local minimum), 0 otherwise. The period between trough and peak is an expansion, and the period from peak to trough is a recession. We construct a classical recession indicator S_t that assigns the value of 1 from peak to trough, 0 otherwise, to capture the most relevant information about the cycle extracted with the Bry and Boschan (1971) algorithm.

We exploit the cross-section of one particular monthly indicator of the strength of the manufacturing sector that is available for a broad range of countries through DGEI, rather than attempt to build a cross-section of different indicators that could be only sparsely collected across time and across countries. IP tends to be more sensitive to changes in the business cycle than other economic activities included in real GDP, so it can give us a cleaner chronology of the cycle in each country.

Total IP excluding construction is our preferred series for this purpose. This measure includes the mining, manufacturing, and utilities sector and has broad cross-country and time series coverage. We exclude the construction sector whenever possible because it tends to display patterns that are different than those of the other sectors. If the preferred series is not available, manufacturing production is used instead as a proxy (with total IP being the last resort). When IP data are reported at a quarterly—instead of monthly—frequency, the series are interpolated to a monthly frequency with the quadratic-match average method.

Our indicator of turning points is constructed applying the Bry and Boschan (1971) method—in the version of Harding and Pagan (2002)—to a sample of 84 countries representing more than 96 percent of world output (as of 2005). See Appendix A. Industrial Production Data Coverage for further details on the country sample and coverage. The 40 countries tracked by DGEI are a subset of those included in this paper for the determination of global cycles. We choose to employ the largest country sample with data available in order to incorporate as much information as possible for the identification of turning points.

Dating of global recessions is based on a weighted diffusion index D_t obtained from the turning points identified for each one of the 84 countries in the sample. For each period *t*, we calculate a weighted percentage of the countries in recession using time-varying PPP-adjusted GDP weights as indicated in Section 1 above, i.e.,

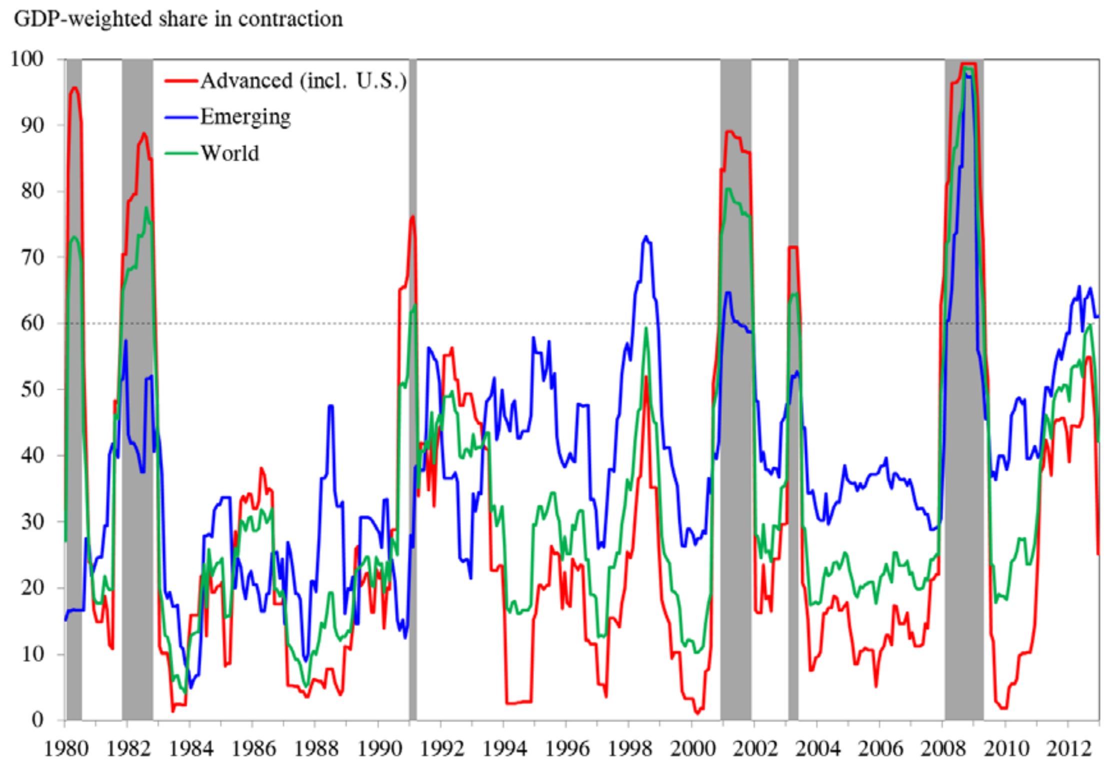
$$D_t = \sum_{i=1}^{N} \omega_{it} S_{it} \quad \sum_{i=1}^{N} \omega_{it} = 1.$$

Applications of similar diffusion indexes can be found in Artis, Marcellino, and Proietti (2004), Crone (2006), and Stock and Watson (2010) among others.

Turning points for global recessions are said to occur when IP contraction is more widespread around the world. We declare that a global recession has occured when the countries simultaneously experiencing an IP contraction according to the Bry and Boschan (1971) algorithm represent at least 60 percent of world output as measured by PPP-adjusted GDP (i.e., $D_t > 0.6$ or 60 if calculated in percentages). An illustration of the diffusion index for all countries and with our country groupings by level of development (advanced versus emerging countries) can be found in Figure 3 for the period between 1980 and 2012.

The 60 percent threshold identifies up to six global recessions in this sample, as highlighted by the shaded areas in Figure 3. The turning points dating exercise also reveals other relevant stylized facts. First, we notice that a larger share of emerging than advanced countries have been in contraction since the early 1990s (except during global downturns). Secondly, the global recessions generally correspond with advanced country recessions, but less frequently global recessions occur when there is an emerging market recession based on the 60 percent threshold. For instance, the diffusion index picks up the effects of the Asian financial crisis of 1997 and the Russian default of 1998 as an emerging markets recession which does not become a global recession since the advanced countries were less affected.

Figure 3. Date-stamping the Global Cycle (1980-2012) with Industrial Production



Note: The shaded areas represent a chronology of global recessions. The indicator of contraction periods in industrial production (IP) is weighted with time-varying PPP-adjusted GDP shares.

The chronology of global turning points that results from our dataset of IP series is compared with the dates obtained with IP and real GDP data from the sample of 40 countries covered in DGEI in Table 3 below. Our preferred chronology is based on the approach of dating each individual series first, and then aggregating all recession indicators. When we apply the same procedure to IP data for the subset of countries in DGEI, we obtain a chronology that is almost identical to the preferred one with only minor differences of at most one month. This suggests that the DGEI sample is fairly representative for dating global business cycles.

For contrast, we also report in Table 3 a similar exercise for dating turning points, but applied to quarterly real GDP data that includes only the time series available for the sample of 40 countries covered in DGEI. The turning points for real GDP are obtained under the censoring rules indicated before for quarterly data. We interpolate the quarterly contraction indicator for real GDP to a monthly frequency using quarterly values of the indicator as mid-values, and set the threshold to declare a global recession at a lower level of 50 percent. The evidence suggests that a lower threshold is needed as the measure of real GDP is less sensitive than IP data to changes in the business cycle, so detecting turning points becomes more difficult.[6] As a result, the global

[6] In the particular case of China, for example, we cannot detect a turning point with the available real GDP series—so the entire sample period is classified as an expansion—but we detect more marked phases of contraction and expansion in IP data.

recessions of 1991, 2000-01, and 2003 that we identify with IP data do not get picked up with real GDP.

Alternatively, we also explore the dating of turning points with DGEI data on IP and real GDP that previously has been aggregated with time-varying PPP-adjusted GDP weights. The aggregate-then-date approach appears to be fairly popular at present—an example being Stock and Watson (2010). The patterns are broadly consistent with those of the preferred chronology and those derived under the date-then-aggregate approach, but do not exactly coincide. With the aggregated IP series, the chronology now differs with respect to our preferred one by several months. Moreover, the episode of 1997-98 reaches the category of a global recession. With real GDP, however, the aggregate series that we obtain is so smooth that we can only detect one global downturn in the entire sample since the 1980s. In light of results like these, we prefer to use the date-then-aggregate approach to be able to exploit the cross-sectional differences that could otherwise be obscured with aggregated data in order to identify turning points in the global cycle more precisely.

Table 3. Global Recession Chronologies (1980-2012)

	Global Recessions	Date-then-Aggregate Approach		Aggregate-then-Date Approach	
	IP (84)	IP (40)	Real GDP (40)	IP (40)	Real GDP (40)
1980s	1980:Feb-1980:Jul	1980:Jan-1980:Jul	1980:Feb-1980:Oct	1980:Feb-1980:Sep	
	1981:Nov-1982:Oct	1981:Nov-1982:Nov	1982:Feb-1982:Apr	1981:Oct-1983:Feb	
1990s	1991:Jan-1991:Mar*	1991:Jan-1991:Mar		1992:Feb-1992:Dec	
				1997:Oct-1998:Aug	
2000s	2000:Dec-2001:Nov	2000:Dec-2001:Dec		2000:Dec-2001:Dec	
	2003:Feb-2003:May*	2003:Feb-2003:May			
	2008:Feb-2009:Apr	2008:Jan-2009:Apr	2008:Feb-2009:Jul	2008:Apr-2009:Feb	2008:Aug-2009:Apr

Note: The global recessions are dated using an indicator of the incidence of IP contractions for 84 countries from Haver Analytics. The asterisk denotes short-lived global recessions of at most four months. All other chronologies are based on IP and real GDP data from the DGEI database - Haver Analytics.

3.2 Hamilton (1989)

Suppose X_t^g refers to the stationary one-year percentage change (4-period change for quarterly data, 12-period change for monthly data) of a given time series. The stochastic process driving X_t^g depends on the value of an unobserved discrete state variable s_t which evolves over time. The X_t^g process switches between different regression specifications for each possible state according to some transition probabilities across states. Hamilton (1989) proposed a switching model of this type, to capture the differences between periods of contraction and expansion, in order to date business cycles. We also assume 2 possible unobserved states for s_t to distinguish between periods of recession and periods of contraction in the aggregate monthly IP and in the aggregate quarterly real GDP series constructed in DGEI.

The switching model variant introduced by Hamilton (1989), which we use, specifies the transition between states as a first-order hidden-Markov process. In that sense, the probability of being in a given state during the current period depends solely on the state reached in the previous period, i.e., $P(s_t = j|s_{t-1} = i) = p_{ij}(t)$ represents the probability of transitioning from state i in period $t-1$ to state j in period t and does not depend on the history leading to state i in period $t-1$. These transition probabilities are assumed to be time-invariant, so that $p_{ij}(t) = p_{ij}$ for all t.

The Markov-switching model of Hamilton (1989) is also dynamic as the regression postulated follows an AR specification of order p given by,

$$X_t^g = \mu_t^g(s_t) + \sum_{z=1}^{p} \theta_z(s_t)\left(X_{t-z}^g - \mu_{t-z}^g(s_{t-z})\right) + \sigma^g(s_t)\varepsilon_t,$$

where ε_t is i.i.d. normally distributed with mean zero and variance of one. The standard deviation σ^g may be state-dependent, as well as the conditional mean μ_t^g and the autoregressive coefficients $\theta_z, z = 1, \dots, p$. We specify the two-state Markov switching model as in Hamilton (1989) allowing only the mean growth rate to be subject to switching, but not the standard deviation or the autoregressive coefficients. Hamilton (1989) assumes an AR(4) process for the regression model on quarterly GNP data. We similarly use $p = 4$ quarter lags for real GDP, and $p = 12$ month lags for IP data.

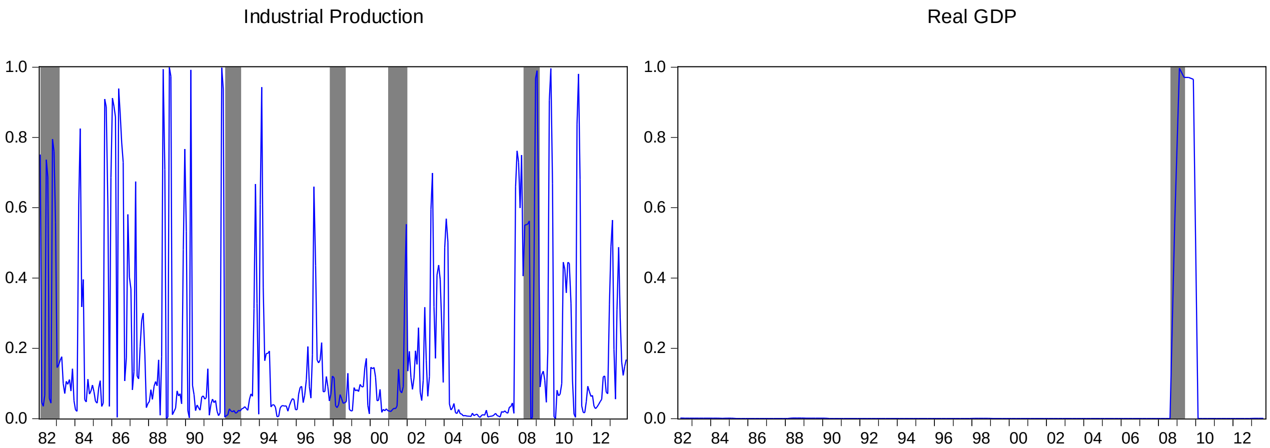
This particular specification is widely known as the "Hamilton model" of Markov switching with dynamics. We cast the Hamilton model in state-space form in order to draw inferences about the unobserved states. The model can then be estimated by maximum likelihood and the transition probabilities derived through a backward smoothing algorithm. Kim and Nelson (1999:Ch. 4) offer a detailed description of the lagged-state filtering procedure used to evaluate the likelihood function and estimate dynamic models like this one. The resulting smoothed transition probability estimates are what we report for the purpose of dating the phases of the business cycle. We illustrate our findings in Figure 4 below, and identify the implied chronologies in Table 4.

The findings with the aggregate IP series show that the Hamilton model picks up a lot more periods of low growth in the early part of the sample and misses some of the later recessions identified with the Bry and Boschan (1971) algorithm. As can be seen in Figure 4, periods of low growth tend to be short-lived according to the smoothed probabilities inferred from the model. In that sense, imposing a minimum length of 4 months/2 quarters for each phase of the cycle and a cut-off of 0.5 on the probability of low growth seems a reasonable benchmark on which to date the turning points—that is how the chronology reported in Table 4 is obtained.

There is still considerable state dependence in the transition probabilities inferred from the aggregated IP series with a relatively higher probability of remaining in the origin state: 0.92 for the high growth state, 0.68 for the low growth state. The corresponding expected durations in each state are approximately 12.4 and 3.1 quarters, respectively. While this pattern appears plausible with periods of high growth expected to last 4 times longer than periods of low growth, the 1998 and early 2000 recessions would be missed by this metric while a lot more recessionary periods would be declared prior to 1996. In some respect, we could say that the Hamilton (1989) filter became more conservative in dating contractions after 1996.

Our results with the DGEI aggregated real GDP series show that there is considerable state dependence in the transition probabilities with a relatively higher probability of remaining in the origin state: 0.99 for the high growth state, 0.77 for the low growth state. The corresponding expected durations in each state are approximately 123.4 and 4.4 quarters, respectively. The Hamilton model picks up only one global recession in the 2008-10 episode in the entire sample. The smoothed probability for the low growth regime aligns with the Bry and Boschan (1971) chronology derived on the same aggregated real GDP series as can be seen in Figure 4.

Figure 4. A Comparison of Business Cycle Chronologies on Aggregated Data



Note: The Hamilton (1989) smoothed transition probabilities (blue line) against the contraction periods identified with the Bry and Boschan (1971) algorithm (shaded areas). Based on one-year percentage changes of the aggregate IP and aggregate real GDP series in DGEI from 1981 until 2012, then interpolated linearly to monthly in the case of quarterly real GDP.

Table 4. Alternative Global Recession Chronologies (1980-2012)

	Global Recessions	Aggregate-then-Date Approach: Bry and Boschan (1971)		Aggregate-then-Date Approach: Hamilton (1989)	
	IP (84)	IP (40)	Real GDP (40)	IP (40)	Real GDP (40)
1980s	1980:Feb-1980:Jul	1980:Feb-1980:Sep			
	1981:Nov-1982:Oct	1981:Oct-1983:Feb		1982:Feb-1982:Dec	
				1985:Aug-1986:Nov	
				1988:Oct-1989:Mar	
1990s	1991:Jan-1991:Mar*	1992:Feb-1992:Dec		1989:Dec-1990:Apr	
		1997:Oct-1998:Aug		1993:Oct-1994:Feb	
2000s	2000:Dec-2001:Nov	2000:Dec-2001:Dec			
	2003:Feb-2003:May*				
	2008:Feb-2009:Apr	2008:Apr-2009:Feb	2008:Aug-2009:Apr	2007:Nov-2009:Feb	2008:Nov-2009:Nov

Note: The global recessions in the first column are the same ones reported in Table 3 for our preferred methodology. The asterisk denotes short-lived global recessions of at most three months. The second and third columns are also reported in Table 3 using the Bry and Boschan (1971) algorithm on aggregated data. The fourth and fifth columns record the peak and trough dates using Hamilton (1989)'s smoothed recession probabilities, a cutoff recession probability of 0.5, and a pair of censoring rules to ensure the minimum length of each phase (contraction and expansion) is at least 4 months/2 quarters.

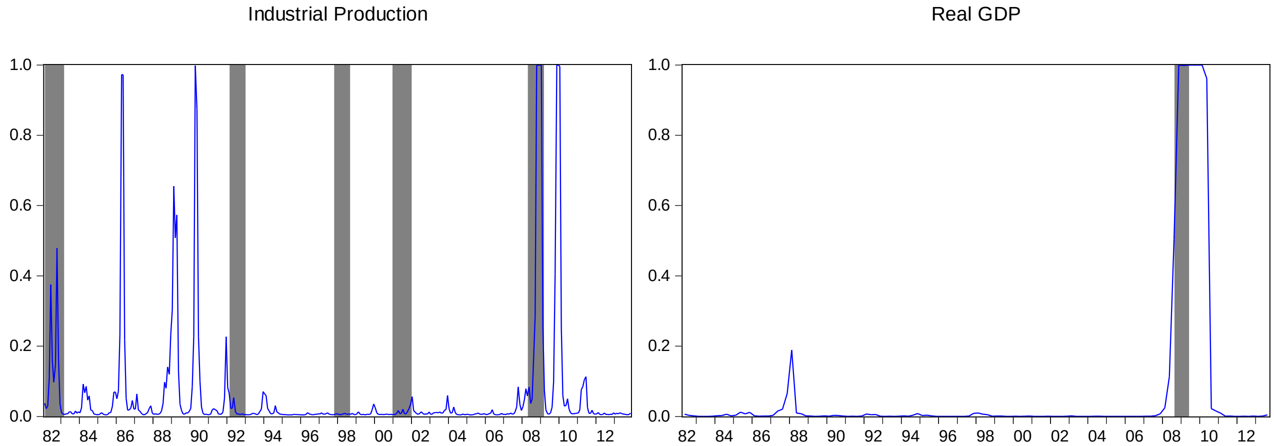
We have also estimated the Hamilton switching mean specification for aggregate IP data, but with time-varying transition probabilities as in Filardo (1994). We use the aggregate Purchasing Managers Index (PMI), a measure of manufacturing activity also included in DGEI, as a business-cycle predictor. We also consider aggregate exports and aggregate imports and the PPI-based real exchange rate as alternative business-cycle predictors exploiting more of the data collected and aggregated in DGEI. We use the one period lag of these predictor variables as our probability regressor so that their value at time t is what influences the transition probability from $t-1$ to t. In all cases, the smoothed probability for the low growth regime replicates the finding on the aggregated real GDP series—picking up only one distinct global contraction in the 2008-10 period. These results are available from the authors upon request.

Looking only at aggregate real GDP data—or the Filardo (1994)-type models of IP noted before—seems clearly insufficient to provide a chronology of the global business cycle. In turn, IP data contains more information that can be exploited to date the global cycle even when it is aggregated. It would be quite difficult to come up with a statistical model to extend the Hamilton variant estimated here that would be rich enough to describe a sample period like ours. Significant structural change may have occurred during the 1990s, and data/methodological breaks affecting the aggregate IP indicator cannot be excluded either. In this sense, we remain convinced that the Bry and Boschan (1971) algorithm can be a more useful tool to construct a business cycle chronology as it is unaffected by those unmodelled features of the data.

We can attempt to improve the fit of the Hamilton model by modelling explicitly some of the features that the original specification may not have taken into account. In this paper we explore the possibility of regime heteroskedasticity. We introduce regime heteroskedasticity in the Hamilton model allowing for standard deviations σ^g to be state-dependent. This alternative specification maintains the rest of the assumptions including Markov-switching probabilities on 2 states, constant transition probabilities, and autoregressive coefficients with 12 lags that are independent of the state.

Our estimates show that the differences in the mean between the two states are not statistically large, so the two states differ primarily because of the differences in the error volatility. The figure below represents the smoothed probability of a period of high volatility estimated on aggregated IP and real GDP data from DGEI. We observe that aggregate IP went through several periods of high volatility prior to 1990, and did not experience anything similar until the 2008-10 episode. Periods of elevated volatility, however, do not necessarily correspond with periods of global contractions as implied by the same underlying aggregate IP series using the Bry and Boschan (1971) algorithm. This suggests that regime heteroskedasticity is not helpful to distinguish turning points of the cycle because the association between high volatility and economic downturns is not very strong, as illustrated in our sample.

Figure 5. Business Cycle Chronologies on Aggregated Data with Regime Heteroskedasticity



Note: The smoothed transition probabilities (blue line) of the Hamilton (1989) model with state-dependent standard deviations are plotted against the contraction periods identified with the Bry and Boschan (1971) algorithm (shaded areas). Based on one-year percentage changes of the aggregate IP and aggregate real GDP series in DGEI from 1981 until 2012, then interpolated linearly to monthly in the case of quarterly real GDP.

3.3 Towards a Chronology of Global Business Cycles

Each approach we have considered so far produces a different chronology of the global business cycle. We have found that different underlying measures of economic activity identify different turning points and generate different business cycle features. Our preferred methodology remains that of the Bry and Boschan (1971) algorithm for a number of reasons: (a) because it is straightforward to implement; (b) because it is broadly consistent with the methodology of the NBER and ECRI and, therefore, more comparable in cataloguing basic empirical facts and features of the business cycle; (c) because it does not require us to detrend the data or model explicitly the key features of the data generating process; and (d) because the chronology derived from our implementation of the Bry and Boschan (1971) algorithm will not change over time as more data becomes available, although it can still change as a result of revisions to the underlying data.

The main disadvantage of the Bry and Boschan (1971) algorithm is timeliness. The procedure cannot date a turning point as it happens because it requires a few additional observations before it can detect the change of phase. In turn, the Hamilton model that we have investigated can produce more timely pronouncements. In this sense, the method is less practical for real time analysis as it identifies and declares turning points only with a lag. We shall elaborate later on the possibility of forecasting turning points to help provide more timely indications about the state of the business cycle using the Bry and Boschan (1971) recession indicator.

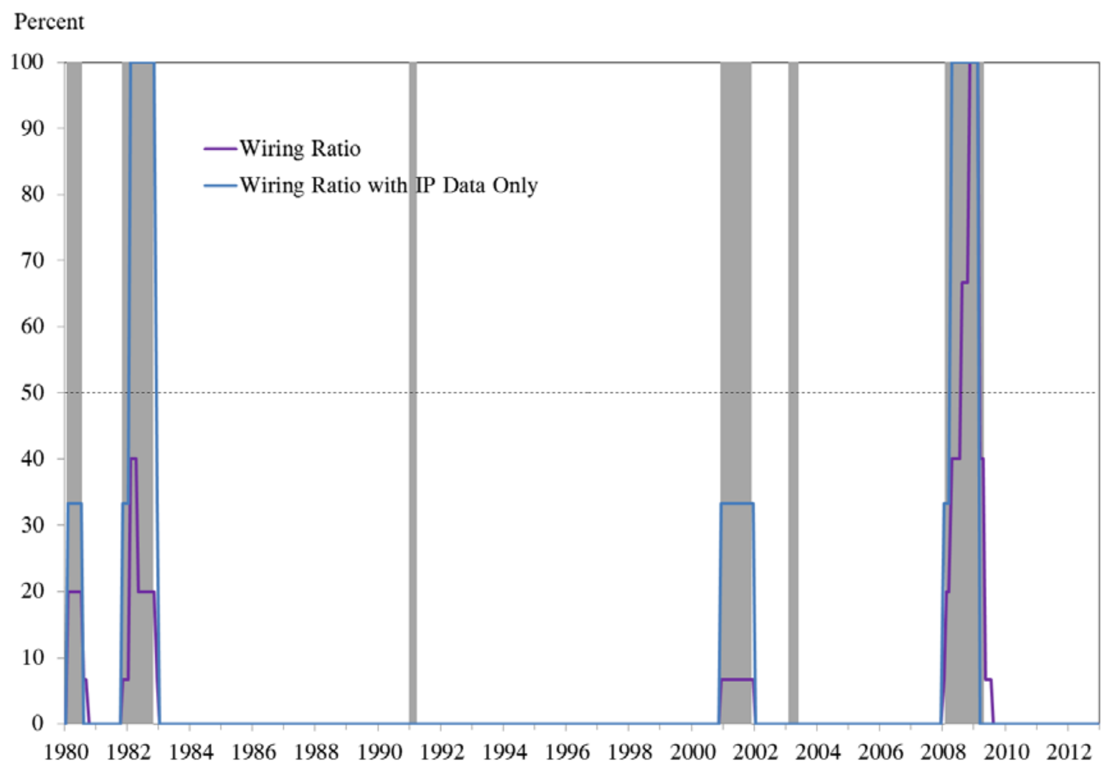
To reconcile the multiplicity of competing dates that we have uncovered in order to validate a single chronology, we adopt as our metric the wiring ratio used by Berge and Jorda (2011) and Berge and Jorda (2013), among others. Against our preferred chronology of global recessions based on a broad sample with 84 countries, we have constructed 6 alternative chronologies based on IP and real GDP data using the Bry and Boschan (1971) method and then aggregating the recession indicators, aggregating and then applying the Bry and Boschan (1971) method, and finally aggregating and using the Hamilton (1989) model. The alternative chronologies are summarized in Table 3 and Table 4. Having established that, we need a way to combine the information contained in all of these competing chronologies in order to contrast that against our preferred business cycle chronology.

We construct a binary recession indicator $S_{jt}, j = 1, \dots, m$ for each of the $m = 6$ competing models that we have illustrated here, and then calculate the number of indicators pointing to recession in each month, i.e., $R_t = \sum_{j=1}^{m} S_{jt}$. The wiring ratio then calculates the number of pair-wise indicators signaling a recession in each period relative to the total number of all pair-wise combinations that could possibly indicate recession as follows,

$$W_t = \frac{R_t(R_t - 1)}{m(m-1)}, \text{for all t.}$$

This wiring ratio is computed for all six competing chronologies and also for the subset of three chronologies derived with IP data. Figure 6 displays the two wiring ratios along with the global recessions implied by our preferred chronology using the Bry and Boschan (1971) algorithm and IP data on 84 countries.

Figure 6. A Single Chronology of Global Business Cycles



Note: The shaded areas represent our preferred chronology of global recessions without adjusting them to remove the short-lived ones.

We have set an ad-hoc threshold of 50 for reference, but we see that the wiring ratio tends to be above one-third whenever our chronology indicates a global recession except in two cases. Both exceptions occur for short-lived downturns that last no more than three months. We interpret the evidence here as suggesting that our preferred chronology is broadly consistent with alternative ways to date turning points whenever we impose the additional constraint that a global recession must last at least 4 months (or 2 quarters if working with quarterly data). We shall follow that rule going forward and, therefore, no longer consider the 1991 and 2003 episodes indicated by our method as global downturns.

4 Evaluation of Global Chronology

We have refined our preferred chronology by comparing it against a series of competing models. The wiring ratio is a measure of network connectivity that signals which episodes are most commonly occurring across different methods and economic variables. That gives some validation for our classification of periods of global expansion and contraction, and in the process, we learned how to refine our selection of dates by excluding the short-lived recessions. However, it is also important to judge the resulting classification of global turning points by other standards and, in particular, according to the information content it uncovers about the true underlying state of the economy.

Our discussion here borrows heavily from the work of Berge and Jorda (2011) and Jorda and Taylor (2011) on applications of the theory of signal detection to economics. A chronology of business cycles, including our preferred one, can be described as a choice from a family of ordinal classifier functions based on an indicator Y_t. The classifier together with a threshold δ defines a binary prediction for the unobserved state s_t of expansion/contraction: that is, it predicts $S_t = 1$ (contraction) whenever $Y_t \leq \delta$, and $S_t = 0$ (expansion) whenever $Y_t > \delta$.

Associated with each classifier, there are four possible outcome pairs for (s_t, S_t) where $S_t = 1_{\{Y_t \leq \delta\}}$ is the indicator function that takes the value of 1 whenever $Y_t \leq \delta$ and 0 otherwise: true contraction rate $P(Y_t \leq \delta | s_t = 1)$, false contraction rate $P(Y_t \leq \delta | s_t = 0)$, true expansion rate $P(Y_t > \delta | s_t = 0)$, and false expansion rate $P(Y_t > \delta | s_t = 1)$. Clearly, there is a tension in each classifier that we specify similar to statistical error trade-offs that arise in hypothesis testing. Hypothesis testing is almost never free of error by its own probabilistic nature—to be more precise, one can distinguish between type I error and type II error. Similarly the classifier is subject to error by declaring either a false contraction or a false expansion. The choice of δ can reduce one type of error, but that occurs at the expense of increasing the other type of classification error.[7]

Conditional on a particular choice of δ that defines the chronology we want to evaluate, we can judge the classifier by the rate of classification error that we attain in a given sample. The fact that the true state is unobservable, however, complicates the direct evaluation approach. An indirect strategy for the evaluation of classifiers emerges from the same idea that motivated the Hamilton (1989) model and subsequent variants: the data generating process differs between periods of contraction and expansion, hence a good classifier would have to pick up on those

[7] The optimal classification would have to select δ in order to maximize a given objective function subject to these constraints, as indicated in Berge and Jorda (2011) and Jorda and Taylor (2011).

differences. That is the basis on which we evaluate the significance of our preferred chronology of global business cycles.

To be more precise, if the candidate chronology $\{S_t\}_{t=1}^{T}$ does a good job predicting the unobserved state $\{s_t\}_{t=1}^{T}$, then we would expect that cyclical variables $\{Y_t\}_{t=1}^{T}$—whether they underlie the classifier function or not—would be sorted out in periods of expansion and contraction that have empirical distributions clearly differentiated from each other. In turn, if the candidate chronology $\{S_t\}_{t=1}^{T}$ contains no useful information about the unobserved state $\{s_t\}_{t=1}^{T}$, then sorting the data accordingly would produce two conditional empirical distributions that largely overlap so that any given observation would be as likely to have been drawn in a period of expansion as in a period of recession.

The statistical measure that we use to compare the conditional empirical distributions on a number of cyclical variables (indicators) from DGEI is the AUC measure proposed by Berge and Jorda (2011) and Jorda and Taylor (2011). For a summary of the existing literature on this statistic in medical testing and prediction, the interested reader is referred to Pepe (2003). In order to calculate this statistic, first we express the one-year percentage change (4-period change for quarterly data, 12-period change for monthly data) of the given time series Y_t^g to remove the trend component if one is present. Secondly, we sort out the $\left\{Y_t^g\right\}_{t=1}^{T}$ in predicted periods of expansion and contraction according to the classifier $\{S_t\}_{t=1}^{T}$ that summarizes our chronology.

Let us denote $\left\{Y_t^{g0}\right\}_{t=1}^{T}$ the random variable associated with all T_0 observations $y_t \in \{Y_t\}_{t=1}^{T}$ drawn when $S_t = 0$, and $\left\{Y_t^{g1}\right\}_{t=1}^{T}$ the random variable associated with all other T_1 observations in the sample. Then, finally, the statistic $AUC = P\left(Y_t^{g0} > Y_t^{g1}\right)$ can be non-parametrically estimated as,

$$\widehat{AUC} = \frac{1}{T_0 T_1} \sum_{i=1}^{T_0} \sum_{j=1}^{T_1} 1\left(y_i^{g0} > y_j^{g1}\right),$$

where $1\left(y_i^{g0} > y_j^{g1}\right)$ is an indicator function that takes the value of 1 if observations in periods classified as expansionary are higher than observations in contractionary periods, 0 otherwise.

We consider a number of DGEI aggregate indicators and ask how well our preferred chronology of global business cycles classifies that data into two differentiated empirical distributions for expansions and contractions allowing leads and lags of up to 12 months in the dependent variable in order to explore the classification more extensively. We do this in order to locate the horizon at which the AUC statistic is maximized, recognizing that the main cyclical indicators available in DGEI may not be coincident with the global business cycle. Furthermore, we investigate the indicators in levels (whenever their time series does not display a trend) as well as in growth rates, and detect significant differences in the strength of the classifier and the optimal horizon across the different measures. All our results are summarized in Table 5 below.

Table 5. Assessing Global Business Cycle Chronology Against DGEI Indicators

	Horizon (Lag = - & Lead = +)																								
	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5	+6	+7	+8	+9	+10	+11	+12
IP																									
mo/mo	0.396	0.429	0.476	0.516	0.516	0.564	0.599	0.608	0.647	0.686	0.695	0.737	**0.746**	0.721	0.722	0.712	0.678	0.631	0.595	0.577	0.575	0.517	0.513	0.485	0.461
yr/yr	0.772	0.822	0.866	0.907	0.939	0.969	**0.977**	0.964	0.947	0.925	0.885	0.848	0.799	0.747	0.697	0.652	0.596	0.548	0.499	0.455	0.422	0.387	0.352	0.320	0.289
Exports																									
mo/mo	0.463	0.486	0.484	0.528	0.512	0.563	0.577	0.558	0.621	0.599	0.582	**0.638**	0.635	0.615	0.625	0.612	0.599	0.582	0.561	0.521	0.505	0.498	0.519	0.512	0.505
yr/yr	0.665	0.718	0.767	0.817	0.854	**0.885**	0.885	0.872	0.853	0.815	0.781	0.758	0.726	0.692	0.667	0.639	0.604	0.579	0.548	0.508	0.503	0.510	0.498	0.489	0.478
Imports																									
mo/mo	0.469	0.494	0.506	0.548	0.521	0.554	0.582	0.559	0.607	0.576	0.563	**0.619**	0.614	0.589	0.594	0.607	0.596	0.588	0.568	0.532	0.533	0.515	0.525	0.506	0.505
yr/yr	0.728	0.773	0.813	0.848	0.872	**0.898**	0.898	0.877	0.856	0.825	0.799	0.770	0.732	0.694	0.659	0.627	0.582	0.546	0.504	0.462	0.448	0.438	0.412	0.394	0.377
Real (PPI-based) Exchange Rate																									
Level	**0.629**	0.625	0.619	0.614	0.608	0.603	0.597	0.592	0.586	0.578	0.576	0.573	0.565	0.561	0.558	0.553	0.545	0.538	0.534	0.526	0.519	0.515	0.508	0.501	0.494
mo/mo	0.521	0.554	0.537	0.533	0.521	0.521	0.530	0.555	0.573	0.567	0.589	**0.607**	0.589	0.577	0.581	0.588	0.581	0.579	0.580	0.573	0.548	0.527	0.522	0.523	0.548
yr/yr	0.628	0.654	0.670	0.689	0.713	0.740	0.751	0.766	**0.775**	0.767	0.751	0.733	0.716	0.703	0.693	0.680	0.662	0.644	0.625	0.602	0.576	0.565	0.551	0.535	0.523
Purchasing Managers Index (PMI)																									
Level	0.629	0.678	0.727	0.768	0.809	0.846	0.878	0.903	**0.922**	0.920	0.900	0.866	0.825	0.773	0.714	0.651	0.592	0.534	0.474	0.418	0.359	0.312	0.276	0.246	0.215
mo/mo	0.246	0.226	0.284	0.306	0.325	0.353	0.372	0.397	0.462	0.524	0.572	0.627	0.679	0.724	0.737	0.746	**0.767**	0.753	0.727	0.724	0.673	0.623	0.602	0.597	0.561
yr/yr	0.374	0.451	0.529	0.597	0.660	0.723	0.785	0.843	0.896	0.928	**0.935**	0.927	0.913	0.886	0.857	0.821	0.781	0.739	0.691	0.644	0.597	0.555	0.518	0.478	0.436

Note: This table reports the AUC statistic favored by Berge and Jorda (2011). For our preferred chronology of global turning points (corresponding to the dates summarized in Table 3 and Table 4 excluding the short-lived global downturns), we calculate the AUC contemporaneously and at different leads and lags up to 12 months on each side for the main cyclical indicators in DGEI. We look at each indicator as a classifier in levels (if the variable does not display a trend), in month-to-month growth rates, and in monthly year-on-year growth rates. We highlight the horizon that maximizes the classification ability of our preferred chronology in bold. The data in this exercise includes all observations available for each aggregate indicator in DGEI between January 1980 and November 2013—not all indicators have the same length, with PMI being the shortest series as it only starts in January 1992.

Broadly speaking, we find that our preferred global business cycle chronology delivers results that are, in many cases, quite strong and clearly better than the null of no distinction between expansions and contractions. Our proposed chronology tends to do better with aggregate IP, and aggregate exports and imports in monthly year-on-year growth rates. Generally the strength of the classification is weaker for those same indicators if we measure them in month-over-month growth rates. Similarly for the aggregate Purchasing Managers Index (PMI), although in this case the strength of the classification is also pretty robust in levels. In turn, the real (PPI-based) exchange rate is the indicator that attains the weakest AUC profiles whether it is measured in levels or month-over-month growth rates (it does better in monthly year-on-year growth rates).

Looking at the horizon at which our proposed chronology maximizes the AUC, we aim to evaluate our proposed chronology while revealing whether the DGEI aggregates work better as coincident, lagging, or leading indicators. We note that lags between 1 and 7 months tend to generate higher AUCs—especially for variables measured either in levels or in monthly year-on-year growth rates. How do we interpret the lead/lag results reported in Table 5? For example, the month-on-month growth rate of aggregate IP achieves its maximum AUC of 0.746 contemporaneously. However, the monthly year-on-year growth rate of the same indicator attains its maximum AUC at a more robust 0.977 value with a six month lag. What this means is that the monthly year-on-year growth rate 6 months ahead is the best classifier for our preferred chronology contemporaneously. In other words, this measure of aggregate IP tends to be a lagging indicator of the global business cycle relative to our proposed chronology.

We observe that while the maximum AUC for the aggregate Purchasing Managers Index (PMI) in levels is lagged four months (AUC=0.922) and in monthly year-over-year growth rates is lagged two months (AUC=0.935), the maximum AUC for the month-over-month growth rate is attained at 0.767 with a lead of four months. This means that the monthly year-on-year growth rate on the aggregate PMI 4 months prior is the best classifier for our preferred chronology contemporaneously. While all other indicators in DGEI perform best contemporaneously or with a lag in the different measures that we consider, PMI appears to display some leading properties in this case. We find that these lagged/coincident/leading features of the aggregate DGEI indicators add additional information that can be valuable to help us later on in our efforts to forecast turning points of the global business cycles.

5 Predicting Turning Points of the Global Business Cycles

As noted before, the Bry and Boschan (1971) algorithm that we use to date turning points in a systematic way cannot detect turning points in real time because it requires observations on both sides of a given period in order to make a determination. Moreover, due to the possibility of data revisions affecting the phase classification, it is also sensible to delay the announcement of a turning point in order to ensure that its classification remains unchanged after the initial data revisions are incorporated to minimize the possibility of having to adjust the dates afterwards. Furthermore, even if a turning point has been detected, a delay in the announcement may be warranted in order to disregard downturn episodes that turn out to be short-lived—as we've argued before. For all those reasons, a lag of up to 12 months (and perhaps a bit longer) usually is found to be appropriate before calling a global recession.

We have explored a number of aggregate indicators from DGEI in Section 4, and evaluated their ability to signal the current state of the global economy. Our evidence suggests that most of these indicators (measured in different ways) can be better described as coincident or lagging relative to our proposed chronology of global business cycles. There is only some evidence of leading behavior in the aggregate PMI. However, looking at the AUC optimal horizon in Table 5, we noted that a 1 to 7 month lag usually gave us the strongest results for these classifiers. In other words, even the lagged indicators considered here can detect turning points in the global business cycle in a more timely manner than the procedure we use to make the formal determination. This offers one potential avenue to resolve a major problem of our preferred methodology.

Following on Berge and Jorda (2013), we explore the ability of the DGEI indicators to predict turning points in global cycles using a logit model. Taking into account that the optimal lead-lag differs across variables (as illustrated with the AUC statistics for the main DGEI indicators in Table 5), indicator variables can be good classifiers in the short-run but poor classifiers in longer horizons and vice versa. Therefore, we put different loadings on the indicators included in the model whenever forecasting at different horizons. In other words, we prefer the forecasting model to vary with the horizon—a practice known as direct forecasting—rather than use a one-period ahead model iterated forward up to the desired horizon—a practice referred to as indirect forecasting.

The choice of cyclical indicators to predict global turning points is constrained by those variables currently available in DGEI. This is by no means an exhaustive list of global economic indicators, but data availability is a major factor limiting our ability to incorporate more variables of potential interest at this time. We expect other variables with a stronger leading profile to be added to the DGEI database in the future, and exploited for the prediction of turning points as our efforts are ongoing. The dependent variable that we seek to model is the global recession indicator $\{S_t\}_{t=1}^{T}$ derived by the date-then-aggregate method with the Bry and Boschan (1971) algorithm and IP data for a sample of 84 countries—which is our preferred signal about the unobserved true state of the economy $\{s_t\}_{t=1}^{T}$.

The global recession indicator $\{S_t\}_{t=1}^{T}$ may take on only two values: 1 if the period is classified as a global contraction, 0 otherwise. The ultimate goal of the model is to quantify the relationship between time-varying macroeconomic conditions and the probability of being in a global recession contemporaneously or at leads of up to 12 months. Such a model would extract the most relevant information from the main indicators in DGEI listed in Table 1 and provide us with predictions about turning points that could occur up to 12 months into the future. Therefore, it can bridge the gap between the time at which a turning point occurs and the time it is recognized, and offer some warning signals about the next year.

We model the posterior probabilities of observing a value of zero/one in our global recession indicator (which is a binary dependent variable), i.e., $P(S_{t+h} = s|x_t, \theta_h)$ at different horizons $h = 0,1, \dots ,12$ and for $s = 0,1$, as follows,

$$P\left(S_{t+h} = 0 \middle| Y_{h,t}, \theta_h\right) = F\left(-\theta_h' Y_{h,t}\right), h = 0,1, \dots ,12,$$
$$P\left(S_{t+h} = 1 \middle| Y_{h,t}, \theta_h\right) = 1 - F\left(-\theta_h' Y_{h,t}\right), h = 0,1, \dots ,12,$$

where F is a continuous, strictly increasing function that takes a real value and returns a value ranging from zero to one.

The binary model presented here is often motivated as a latent variable specification. Suppose there is an unobserved latent variable $\{S_t^*\}_{t=1}^T$ that is linearly related to the vector of characteristics $Y_{h,t}$ as $S_{t+h}^* = \theta_h' Y_{h,t} + \epsilon_{h,t}$, where $\epsilon_{h,t}$ is a random disturbance. The observed binary dependent variable $\{S_t\}_{t=1}^T$ at horizon h is determined by whether $\{S_t^*\}_{t=1}^T$ exceeds a given threshold, i.e., $S_{t+h} = \begin{cases} 1 \; if \; S_{t+h}^* > \alpha \\ 0 \; if \; S_{t+h}^* \leq \alpha. \end{cases}$ The choice of the threshold is of no consequence so long as we include a constant among the regressors $Y_{h,t}$ in this model, which we do by default in all our specifications.

If the binary dependent variable is defined as a one-zero indicator, then the expected value of S_{t+h} implies that $E\left(S_{t+h} \middle| Y_{h,t}, \theta_h\right) = P\left(S_{t+h} = 1 \middle| Y_{h,t}, \theta_h\right)$. As a conditional mean specification, the binary choice model has a regression representation given by,

$$S_{t+h} = 1 - F\left(-\theta_h' Y_{h,t}\right) + \varepsilon_{h,t}, h = 0,1, \ldots ,12,$$

where $\varepsilon_{h,t}$ is a random residual capturing the deviations of the binary variables from its conditional mean. We shall assume that the index specification is linear in the parameters taking the form $\theta_h' Y_{h,t}$, and that the F is based on the cumulative distribution for the logistic distribution (i.e., $F\left(-\theta_h' Y_{h,t}\right) = \frac{exp\left(-\theta_h' Y_{h,t}\right)}{1+exp\left(-\theta_h' Y_{h,t}\right)}$). This binary choice model specification is generally referred to as the logit model.

At each horizon, we shall include as potential predictors $Y_{h,t}$ in the logit model all main DGEI indicators reported in Table 1 aggregated across all countries, and let the data sort out which indicators work best to predict global turning points. Given the evidence reported in Table 5 for the main cyclical indicators, we shall include in $Y_{h,t}$ the IP and trade (exports and imports) indicators measured in monthly year-to-year growth rates rather than levels or month-to-month rates. The other regressors added to $Y_{h,t}$ are a constant, the aggregate policy/short term rate in levels, the CPI-based and PPI-based real exchange rate value of the dollar, and the monthly year-on-year rate of change in the aggregate CPI and PPI. This highly aggregated model—which we refer to as model A—is estimated over the entire sample from January 1980 till December 2012. We also estimate an augmented variant of the model that includes the aggregate PMI as well, but due to data availability it covers the shorter sample that starts in January 1992 and ends in December 2012—we refer to this one as model B. The prediction results for both models at each forecasting horizon from 0 to 12 are summarized in Table 6 below.

Table 6. Performance Forecasting Turning Points with DGEI Aggregates at Different Horizons

	Forecasting Horizon																									
	0		+1		+2		+3		+4		+5		+6		+7		+8		+9		+10		+11		+12	
	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
Goodness-of-Fit Tests (P-value)																										
Andrews	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.071	0.000	0.000	0.000	0.053	0.000	0.258	0.000	0.294	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Classification Table (Cutoff=0.5)																										
S=0																										
Total	344	225	344	225	344	225	344	225	344	225	344	225	344	225	344	225	344	225	344	225	345	225	346	225	347	225
% Correct	98.55	99.11	98.55	98.67	98.84	97.78	99.13	98.22	99.42	99.56	99.13	99.11	99.71	99.11	99.71	98.22	99.71	98.22	99.13	97.78	98.55	97.33	98.55	97.78	98.56	97.33
Total Gain	-1.45	-0.89	-1.45	-1.33	-1.16	-2.22	-0.87	-1.78	-0.58	-0.44	-0.87	-0.89	-0.29	-0.89	-0.29	-1.78	-0.29	-1.78	-0.87	-2.22	-1.45	-2.67	-1.45	-2.22	-1.44	-2.67
S=1																										
Total	39	27	39	27	39	27	39	27	39	27	39	27	39	27	39	27	39	27	39	27	38	27	37	27	36	27
% Correct	23.08	59.26	12.82	48.15	7.69	37.04	2.56	33.33	0.00	33.33	0.00	33.33	0.00	29.63	0.00	37.04	0.00	29.63	10.26	33.33	18.42	40.74	18.92	51.85	19.44	59.26
Total Gain	23.08	59.26	12.82	48.15	7.69	37.04	2.56	33.33	0.00	33.33	0.00	33.33	0.00	29.63	0.00	37.04	0.00	29.63	10.26	33.33	18.42	40.74	18.92	51.85	19.44	59.26
S=0,1																										
Total	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252	383	252
% Correct	90.86	94.84	89.82	93.25	89.56	91.27	89.30	91.27	89.30	92.46	89.03	92.06	89.56	91.67	89.56	91.67	89.56	90.87	90.08	90.87	90.60	91.27	90.86	92.86	91.12	93.25
Total Gain	1.04	5.56	0.00	3.97	-2.56	1.98	-0.52	1.98	-0.52	3.17	-0.78	2.78	-0.26	2.38	-0.26	2.38	-0.26	1.59	0.26	1.59	0.52	1.98	0.52	3.57	0.52	3.97

Note: This table reports the p-value on the Andrews test statistic as a measure of goodness of fit, as well as a classification table with a threshold of 0.5 where the results of the predicted response are classified against the 0.5-cutoff and compared against the observed binary dependent variable. The goodness-of-fit measure as well as the classification table are reported at each horizon from h=0 to 12 and for two distinct models. Two variants of the logit model are estimated at each horizon: model A includes a constant, IP and trade (exports and imports) indicators measured in monthly year-to-year growth rates, the aggregate policy/short term rate, the CPI-based and PPI-based real exchange rate value of the dollar, and the monthly year-on-year rate of change in the aggregate CPI and PPI; model B augments model A with aggregate PMI. The data for model A includes all observations available for each aggregate indicator in DGEI between January 1980 and December 2012, while the data for model B which incorporates the PMI has a shorter time series coverage that goes from January 1992 till December 2012.

Table 6 reports the p-value on Andrews (1988a) and Andrews (1988b) x^2-type goodness-of-fit test showing evidence generally supportive of both model specifications at most forecasting horizons. These tests compare the fitted expected values to the actual values of the binary dependent variable. If the regressors were to provide an insufficient fit to the data, then the differences would become “statistically too large” leading us to reject the model specification. This is, for instance, what happens with model variant A at forecasting horizons of 7 and 8 months ahead at all conventional significance levels and at the forecasting horizon six months ahead at the 5 percent significance level. In general, we observe that the fit of the model is better at short horizons (1 month ahead) and long horizons (12 months ahead) than at most forecasting horizons in between.

The problem of choosing good predictors for classification purposes is not resolved merely by attaining a good fit to the data. Therefore, we evaluate the in-sample performance of the forecasting models A and B at each horizon with a classification table that helps us summarize and assess the strength of the models’ predictions as a classifier for turning points of the global business cycle. Observations are classified as contractions ($\hat{S}_{t+h} = 1$) if their predicted probability, given the information set $Y_{h,t}$, lies above our set 0.5 threshold level. Otherwise, observations are classified as expansions ($\hat{S}_{t+h} = 0$). The classification table also produces an alternative classification based on a restricted model that computes the predicted probabilities with only the constant intercept as regressor (the constant probability model) for contrast.

In the more economically-relevant case where we are forecasting 12-months ahead, model A correctly classifies 98.56 percent of the 347 observations in expansion and model B attains a success rate of 97.33 percent on 225 observations in expansion. In turn, the classification of observations in contraction is less accurate and significantly different across models. We see that model A classifies only 19.44 percent of the 36 observations in contraction correctly, while model B does better reaching an accurate classification rate of 59.26 of the 27 observations in contraction. Overall, the correct classification rate for all observations is 91.12 percent for model A and 93.25 for model B. However, the correct classification rate does not give us a clear way to assess the performance of our proposed models.

We look at the total gain in the classification attained as a measure of predictive ability by using a fully-specified model relative to the classification attained under a restricted model with solely an intercept as explanatory variable (the constant probability model)—that is our metric to assess the model performance. From that perspective, the classification of contractions improves 19.44 percentage points in our proposed model A relative to the constant probability model, and 59.26 percentage points for model B. Both model specifications do slightly worst predicting expansions (-1.44 percentage points for model A, and -2.67 percentage points for model B). Overall, our proposed model A is 0.52 percentage points better at predicting responses than the constant probability model, while model B is 3.97 percentage points better.

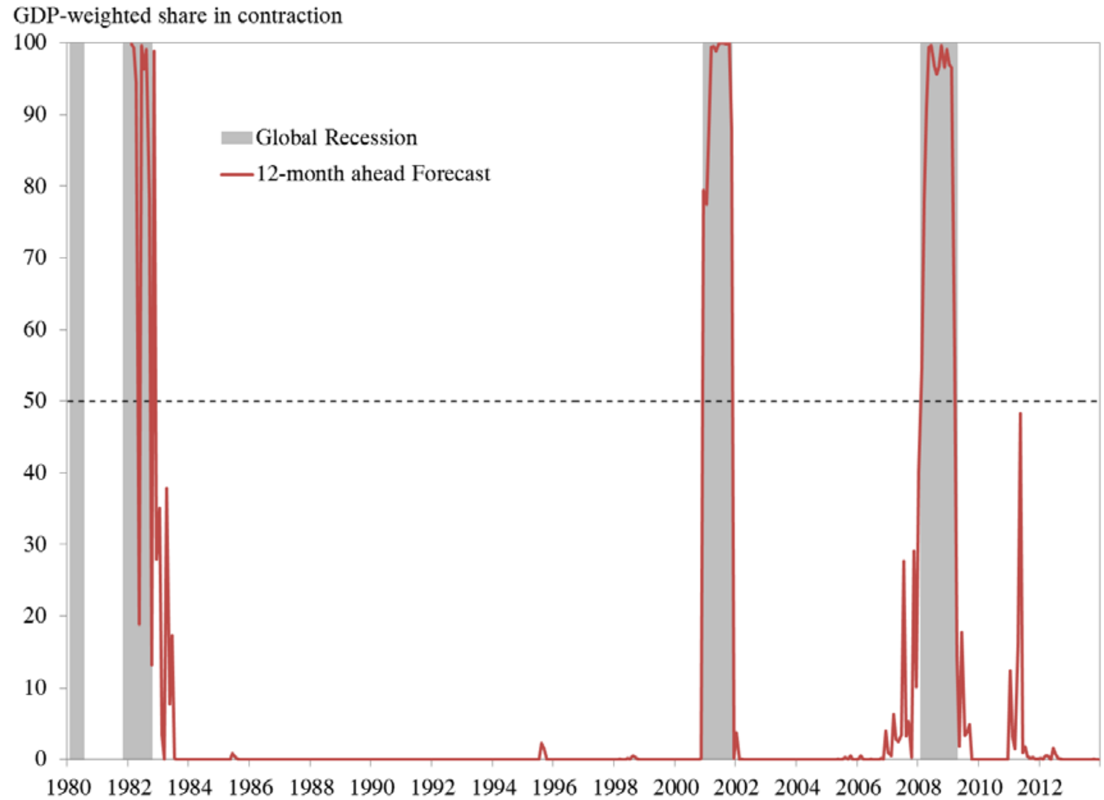
We have described the results of the classification table reported in Table 6 using the 12-month ahead forecast as an illustration. The same interpretation applies to the classification tables presented here at all other forecasting horizons. However, when we look at all results in this perspective, it is relevant to notice that the total gains attained by the proposed model A tend to be smaller than those of model B. In some instances, , we even see that overall model A performs worst in classifying expansions and contractions at 2-7 month forecasting horizons than the alternative constant probability model. Finally, we observe that the forecasting horizons with strongest total gains from model B are to be found at short-horizons (0, 1-month ahead) and long-horizons (12-month ahead).

We interpret the results of Table 6 as encouraging because they show that the DGEI aggregate indicators have some statistical value in helping predict turning points at the 12-month range. This is most relevant because it provides us with a tool for advance signaling of possible turning points in the global business cycle, which may have occurred over the last year but have not yet been picked up by our methodology based on the Bry and Boschan (1971) algorithm. We also appreciate that PMI data may have additional information content that can improve the overall fit of the model and its ability to better classify expansions/contractions than the constant probability model although at the expense of covering a much shorter period.

What we find next, however, is that our main model (model A) can be massively improved if we use indicators at a disaggregated level—distinguishing between advanced (ex. U.S.) and emerging countries—rather than aggregates of all countries tracked in DGEI (which is what we have used for Table 6). We concentrate in the most relevant case of forecasting turning points 12-months ahead to illustrate this point. Not all indicators end up being significant; we include a constant, the policy rates for advanced (ex. U.S.) and emerging countries, the year-on-year growth rate of IP for emerging economies, export and import year-on-year growth from the advanced (ex. U.S.) countries, the real (CPI-based and PPI-based) value of the dollar for the emerging economies, and year-on-year CPI and PPI inflation for both advanced (ex. U.S.) and emerging countries. However, we find that in goodness-of-fit terms—with a McFadden R-squared of 0.852 and a p-value on Andrews test of 0.000—and in terms of the total classification gains attained relative to the constant probability model—with a total gain of 8.36—this more disaggregated model performs significantly better in predicting turning points than models restricted to more aggregated data.

Figure 7 below shows the predicted probability from our model against the background of a cutoff of 50 percent probability and the global recessions dated with our preferred methodology excluding the short-lived ones (represented here by the shaded areas). The lesson that we learn from this exercise is two-fold: on one hand, the indicators in DGEI contain valuable information that can be used to help us predict turning points in the cycle and provide advance signaling before our dating methodology can reach the determination that a turning point has occurred; on the other hand, very aggregate indicators are not always the best signal for the current state of the global economy. More disaggregated data may contain relevant information about the global cycle that we would not be able to detect in overall aggregates that mask that information. We acknowledge this in our preference for the date-then-aggregate approach, and also find useful to maintain country groupings (such as the advanced and emerging aggregates) when working with DGEI indicators.

Figure 7. Predicting Turning Points of the Global Cycle 12-Months Ahead with Disaggregated Data



Note: The shaded areas represent our preferred chronology of global recessions without adjusting them to remove the short-lived ones. The 50 percent line represents the standard cutoff to classify observations as corresponding to periods of contraction (above) or expansion (below). The figure include the 12-month ahead predicted probabilities of a model based on a constant, the policy rates for advanced (ex. U.S.) and emerging countries, the year-on-year growth rate of IP for emerging economies, export and import year-on-year growth from the advanced (ex. U.S.) countries, the real (CPI-based and PPI-based) value of the dollar for the emerging economies, and year-on-year CPI and PPI inflation for both advanced (ex. U.S.) and emerging countries.

6 Concluding Remarks

Business cycle theory seeks to understand the causes and consequences of business cycles. One of the major areas of research in international macroeconomic is on international business cycles that aims to explain the common factors driving the business cycles across countries as well as the potential channels through which local cycles are interconnected and lead to spillovers. At its core, business cycle research recognizes that episodes of expansion and contraction are inherently different, and those differences can be tracked in the data in order to set a chronology of business cycles. In the case of the U.S., this has a long tradition going back to the work of Mitchell (1927) and Burns and Mitchell (1946) that was inherited by the NBER. Our paper makes a contribution to the literature by proposing a methodology, consistent with the NBER practice, to construct a chronology of expansions and contractions for the global economy.

We exploit data collected in the Database of Global Economic Indicators (DGEI) of the Federal Reserve Bank of Dallas for the purpose of construction our preferred chronology from 1980 onwards, and follow the Bry and Boschan (1971) method of dating turning points that closely tracks the NBER business cycle dating methodology. The indicators calculated by DGEI illustrate the common patterns of the data using a representative sample of 40 countries, both advanced and emerging, and multiple real and nominal variables. Our preferred chronology is based on a broader selection of 84 countries, and IP data which we find to be more sensitive to turns in the cycle that other broader output measures. We also adopt a methodology that starts dating the cycle country by country, and then construct an aggregate indicator of turning points from the country expansions and contractions.

In this paper, we evaluate different classification methods including chronologies based on real GDP data or on aggregates constructed with the DGEI sample. The different methods leave us with a number of discrepancies across chronologies to deal with. To statistically assess the quality of our chronology, we adopt tools from the theory of signal detection. Berge and Jorda (2011) and Berge and Jorda (2013) highlight these techniques to classify data in periods of expansions and contractions for the cases of the U.S. and Spain, and use them to evaluate competing chronologies as well. Our findings suggest that short-lived global recessions probably should not be included among the episodes of global recessions—and we adjust our methodology accordingly. Furthermore, we also find evidence about the strength of the aggregates produced by DGEI as classifiers for our preferred chronology at different leads and lags.

After evaluating our proposed chronology for the global business cycle, we go a step further and exploit the aggregate data produced by DGEI to assess the potential of these indicators for predicting future turning points of the global cycle. We recognize that the Bry and Boschan (1971) method cannot identify turning points in real time since the method requires data on both sides of the observation before it can identify whether a turning point has occurred. In this sense, our proposed logit model that exploits data disaggregated by country groupings (advanced and emerging) is fairly accurate at predicting turning points 12-months ahead, showing promise as an advanced warning tool that can help us assess the probability of a turning point before the Bry Boschan (1971) methodology is able to detect it.

As Berge and Jorda (2013) noted in their work, "(…) the last word on the past, present and future of the (…) business cycle has not yet been written." Like them, we hope that our contribution to the debate on dating business cycles (and our efforts to develop economically-relevant global indicators) will instead be seen as a step in the direction of further deepening and improving our understanding of international business cycles.

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Appendix A. Industrial Production Data Coverage

Country	Time Coverage
U.S.	1921M1-present
U.K.	1960M1-present
Austria	1960M1-present
Belgium	1980M1-present
Denmark	1974M1-present
France	1960M1-present
Germany	1960M1-present
Italy	1960M1-present
Luxembourg	1957M1-present
Netherlands	1960M1-present
Norway	1960M1-present
Sweden	1960M1-present
Switzerland	1959Q1-present
Canada	1957M1-present
Japan	1953M1-present
Finland	1960M1-present
Greece	1962M1-present
Iceland	1998M1-present
Ireland	1975M7-present
Malta	1997M1-present
Portugal	1960M1-present
Spain	1965M1-present
Turkey	1985M1-present
Australia	1957Q3-present
New Zealand	1977Q2-present
South Africa	1963M1-present
Argentina	1993M1-present
Brazil	1975M1-present
Chile	1990M1-present
Colombia	1980M1-present
Ecuador	1973M1-present
Mexico	1980M1-present
Nicaragua	1994M1-present
Peru	1979M1-present
Venezuela	1957M1-present
Trinidad & Tobago	1969M1-present
Cyprus	1988M1-present
Iran	1957M1-present
Iraq	1969M1-present
Israel	1957M1-present
Jordan	1971M11-present

Country	Time Coverage
Kuwait	1965M1-present
Oman	1967M7-present
Qatar	1957M1-present
Saudi Arabia	1964M5-present
UAE	1974M1-present
Egypt	2004M2-present
Bangladesh	1973M7-present
Sri Lanka	2003M2-present
Taiwan	1960M1-present
Hong Kong	1982Q1-present
India	1971M1-present
Indonesia	1986M1-present
Korea	1970M1-present
Malaysia	1971M1-present
Pakistan	1977M7-present
Philippines	1981M1-present
Singapore	1966M1-present
Thailand	1987M1-present
Algeria	1971M1-present
Gabon	1978M1-present
Libya	1965M1-present
Morocco	1959Q1-present
Tunisia	1993M1-present
Armenia	1996M1-present
Kazakhstan	1998M12-present
Bulgaria	2000M1-present
Russia	1993M1-present
China, PR	1991M1-present
Ukraine	2002M1-present
Czech Republic	1990M1-present
Slovakia	1989M1-present
Estonia	1994M1-present
Latvia	1996M1-present
Serbia	1994M1-present
Montenegro	2002M1-present
Hungary	1980M1-present
Lithuania	1995M12-present
Croatia	1991M1-present
Slovenia	1992M1-present
Macedonia	1993M1-present
Bosnia and Herzegovina	2002M1-present
Poland	1985M1-present
Romania	1990M5-present