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The importance of updating: Evidence from a Brazilian nowcasting model

by
Daniela Bragoli*, Luca Metelli** *and* Michele Modugno***

How often should we update predictions for economic activity? Gross domestic product is a quarterly variable disseminated usually a couple of months after the end of the quarter, but many other macroeconomic indicators are released with a higher frequency, and financial markets react very strongly to them. However, most of the professional forecasters, including the IMF, the OECD, and most central banks, tend to update their forecasts of economic activity only two to four times a year. The Central Bank of Brazil, not only disseminates its official forecasts every quarter as other central banks, but also collects and publishes the results of professional forecasters' survey data at a daily frequency. The aim of this article is to evaluate the forecasting performance of the Central Bank of Brazil Survey and to compare it with the mechanical forecasts based on state-of-the-art nowcasting techniques. Results indicate that both model and market participant predictions are well behaved, i.e. as more information becomes available their accuracy and correlation with the actual realization increases. In terms of performance the model seems to be slightly better than the institutional forecasts in the nowcast and backcast.

Keywords: Nowcasting, Updating, Dynamic Factor Model.

JEL classification: C33, C53, E37.

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1. Introduction

Monitoring short-term economic developments, in particular real GDP growth, is the instrument through which market participants and policy institutions all over the world make their decisions on how to invest or on how to conduct monetary and fiscal policy. Real GDP growth in many countries, including Brazil, is a quarterly variable that is released by the national statistical office with a delay that could be, at times, significant. In the case of Brazil the delay is two months. In other words, real GDP growth related to the first quarter (January to March) is disclosed only in May.

Given this limitation it is nevertheless reasonable to think that it is possible to learn the current economic condition by monitoring other indicators that are linked to GDP growth and that are released at a higher frequency. Newspapers, statistical offices, and central bank websites release daily data (for instance releases on industrial production, on the number of vehicles sold, on the confidence of consumers, etc.) that can be used to produce early estimates of GDP growth. Market participants monitor these data too. Global information services, such as Bloomberg and Forex Factory, report a calendar of data releases that is highly regarded by the markets. Bloomberg and Forex Factory also assign a measure of importance to each release, which reflects the usage by markets. Bloomberg, in addition, conducts a survey and collects forecasts from analysts and economists on each release they report and publishes it the day before the release is disseminated.

Academia has also moved toward incorporating this more timely information into formal econometric forecasting models. Two seminal papers (Evans, 2005, and Giannone et al., 2006) have modeled, within the same statistical framework, the joint dynamics of GDP and the monthly indicators. According to this literature, it is worthwhile to update economic predictions often, as the incorporation of the continuous data flow makes the forecasts more and more accurate.

Professional forecasters, however, do not publish short-term economic forecasts frequently. The Organisation for Economic Co-operation and Development (OECD) and the International Monetary Found (IMF) report their forecast twice a year, many central banks (e.g. Bank of England, Bank of Canada, and the Federal Reserve Open Market Committee) four times a year and, only a few institutions update their forecasts monthly (e.g. Banque de France, Bank of Japan, Bundesbank, the Conference Board). The process through which they revise their forecasts is not clear.

The Central Bank of Brazil (BCB), not only disseminates its official forecasts every quarter as other central banks, but also collects and publishes the results of professional forecasters' survey data at a daily frequency. It is, in fact, responsible for the set up of an interesting Market Expectation System, a web interface where financial institutions, consulting firms, and universities report their expectations for various macroeconomic variables including GDP.

The aim of this paper is to understand how sensible it is for an institution, such as the BCB, to produce such regular predictions of GDP growth. The aim is to evaluate the

forecasting performance of the BCB Survey and to compare it with the mechanical forecasts based on state-of-the-art nowcasting techniques.

Results indicate that both model and market participants' predictions are well behaved, i.e. as more information becomes available their accuracy and correlation with the out-turn increases.

In addition, our results show that model based forecasts perform slightly better than institutional forecasts. According to this last result, the often-cited superiority of professional forecasts (see Ang et al., 2007, Clements, 2010, Jansen et al., 2012) turns out to be weak in our sample confirming findings in Giannone et al. (2006) and Liebermann (2011).

Recently, there has been a lot of interest in applying this statistical environment to various economies, including the United States (Lahiri and Monokroussos, 2013), the Euro Area (Angelini et al., 2010; Angelini et al., 2011; Camacho and Perez-Quiros, 2010), France (Barhoumi et al., 2010), Germany (Marcellino and Schumacher, 2010), Ireland (D'Agostino et al., 2008; Liebermann, 2012), the Netherlands (de Winter, 2011), the Czech Republic (Arnostova et al., 2011; Rusnák, 2013), New Zealand (Matheson, 2010), Norway (Aastveit and Trovik, 2012), Switzerland (Siliverstovs, 2012) and for China (Yiu and Chow, 2010). For a survey, see Bańbura et al. (2012) and Bańbura et al. (2013).

In the case of Brazil, Issler and Notini (2013) propose an interpolation method based on state-space models to estimate monthly Brazilian GDP, through the use of coincident indicators. This methodology is part of the literature on coincident indicators of economic activity, where an unobserved state of the economy is estimated from a multivariate model. Chauvet (2001) constructs an indicator of Brazilian monthly GDP through the use of a Markov switching dynamic factor model. In this article, instead, we aim at pure nowcasting, defined as timely estimation of GDP.

The rest of the paper is structured as follows. Section 2 describes the structure of the data releases in Brazil. Section 3 introduces the model and estimation technique. Section 4 describes the BCB survey and the other benchmarks. Section 5 introduces the empirical analysis and comments on the results. Section 6 concludes.

2. The data set

The Brazilian statistical office publishes real GDP growth two months after the end of the quarter. The aim of the statistical model we propose in this paper is to predict GDP before the official figures are published by taking advantage of the information in the flow of economic data releases that precede them and updating our prediction with each successive data release.

We include in our model those variables whose headline number is reported by the main statistical sources and central banks; in addition we consider those indicators monitored by financial markets and by the press. We choose the transformations that guarantee stationarity of the variables (see Table 1), which are the same as the ones reported by the media and Bloomberg, making the comparison easier. We consider only real data and surveys. We disregard prices and financial variables, nominal variables, and sector-specific series. This choice reflects the results of previous research, in which the inclusion of these variables does not improve the model's forecasting performance (see Bańbura and Modugno, 2010, and Bańbura et al., 2012).[1]

The target variable is quarterly Real GDP growth, reported as a quarter-on-quarter (QoQ) transformation, the headline series on which market participants focus their attention on.[2] The input series, which are of monthly frequency, are reported as month-on-month (MoM)

Table 1. **Series used in the model**

Name	Timing	Publishing lag	Frequency	Source	Available from	Transf.	Relevance Bloomberg
Formal employment	20th month	20 days	M	IBGE	Jan. 85	Monthly change	63.5
Merchandise exports	First days	2 days	M	MDIC	Jan. 54	MoM	40.4
Merchandise imports	First days	2 days	M	MDIC	Jan. 59	MoM	36.5
Capacity utilization	First week	one month	M	CNI	Dec. 91	Monthly change	32.7
Industrial production	First days	one month	M	IBGE	Jan. 91	MoM	90.4
Consumer confidence index	Last week	current month	M	FGV	Sept. 05	Monthly change	17.3
Economic activity index	Middle	1-2 months	M	BCB	Jan. 03	MoM	23.2
Monthly GDP	End	one month	M	BCB	Mar. 90	MoM	-
Manufacturing sales	First days	one month	M	CNI	Dec. 91	MoM	-
PMI manufacturing	First days	2 days	M	BancoRI	Feb. 06	Levels	75.0
Extended retail trade	Middle	1-2 months	M	IBGE	Jan. 03	MoM	-
Retail trade: volume	Middle	1-2 months	M	IBGE	Jan. 03	MoM	71.1
Real GDP	First days	2 months	Q	IBGE	Q1. 90	QoQ	80.1

Timing: Is approximately the number of days from the end of the reference period.
Frequency: Indicates whether the series is monthly (M) or quarterly (Q).
Available from: Indicates the starting date of the series.
Source: MTE (Ministério do Trabalho e Emprego), IBGE (Fundaçâo Instituto Brasileiro de Geografia e Estatística), MDIC (Ministério do Desenvolvimento, Indústria e Comércio Exterior), CNI (Confederaçâo Nacional da Indústria), FGV (Fundaçâo Getúlio Vargas), BCB (Banco Central do Brasil), BancoRL (Banco Real); **Bloomberg:** Reports the market relevance of each variable according to Bloomberg's relevance index, that ranges from 0 to 100.

transformations, with the exception of PMI Manufacturing, which is in levels but behaves like a MoM for how it is constructed.[3] The fact of linking the QoQ target variable with MoM input series is standard in this literature (see among others Mariano and Murasawa, 2003, Camacho and Perez-Quiros, 2010 and Bańbura and Modugno, 2014).

Table 1 reports some details on the selected series, in particular the timing of the release and the importance that the financial markets attach to the series, according to the Bloomberg index. The peculiarity of the Brazilian data set is the fact that it includes two indicators that are strictly related to the target variable (quarterly GDP). The first is the monthly nominal GDP, published by the BCB, based on monthly indicators for economic activity and prices. The second is the economic activity index (EAI), also published by the BCB. The EAI is a monthly coincident indicator based on the same methodology used to measure the Brazilian quarterly GDP, which consists of a set of proxies of economic behavior in the different economic sectors (agriculture, industry, distributive trade, transportation, services). As the EAI is a recent indicator, it still does not relate directly to the monthly nominal GDP, whose calculations follow an older methodology.

The rest of the variables can be divided into four categories: surveys, labor, production, demand, and trade indicators. Among surveys, we consider the consumer confidence index and the purchasing manager index (PMI). The consumer confidence index is very timely and it is the only piece of information in Brazil published within the reference period, though Bloomberg does not rank it as important (17.3%). The PMI is released at the beginning of the following month and is a relevant series according to the markets (75.0%).

For labour, we include formal employment (FE), which is rated fairly important by Bloomberg (63.5%). For production, we track industrial production (IP), which is rated highly for importance by Bloomberg (90.4%). For domestic demand, we track capacity utilization (CU), real manufacturing turnover (RMT), extended retail trade (ERT) and retail trade (RT). ERT, differently from RT, reports the volume of sales of formally established companies with 20 or more employed persons and whose main activity is retail trade which includes

"Vehicles, motorcycles, parts and accessories" and "Construction material". Bloomberg comments RT and rates it fairly high in terms of importance (71.1%). The trade category is particularly important for the Brazilian economy given its timeliness. Exports and Imports have the same publication lag as the PMI.

Most of the hard data series (employment, retail sales and industrial production) are published with a three to six weeks lag after the end of the reference month. Trade variables (exports and imports) are published at the beginning of the following month. Differently from other countries the statistical office, the Brazilian Institute of Geography and Statistics (IBGE), disseminates a monthly GDP indicator, which is published four weeks after the reference period.

3. The nowcasting problem and the econometric framework

The problem of nowcasting lies in estimating GDP in the interval of time between the beginning of the reference quarter and its official release, exploiting the information coming from other higher frequency variables.[4]

More formally, the nowcast of GDP (y_t^Q) can be defined as the orthogonal projection of y_t^Q on the available information set Ω_v,[5] which contains mixed-frequency variables ($x_{k_j,t_j}, j = 1,\ldots,J_{v+1}$) and is characterized by a "ragged edge" structure given that the time of the last available information varies from series to series.

Each time new information arrives, a new nowcast is produced. This nowcast can be decomposed as follows:

$$E[y_t^Q \mid \Omega_{v+1}] = E[y_t^Q \mid \Omega_v] + E[y_t^Q \mid I_{v+1}]. \tag{1}$$

The new forecast $E[y_t^Q \mid \Omega_{v+1}]$ is just the sum of the old forecast $E[y_t^Q \mid \Omega_v]$ and the revision $E[y_t^Q \mid I_{v+1}]$, where

$$I_{v+1,j} = x_{k_j,t_j} - E[x_{k_j,t_j} \mid \Omega_v], \tag{2}$$

with $j = 1,\ldots,J_{v+1}$. This revision ($I_{v+1,j}$) is the expected value of our target variable conditional to the difference between the actual release of any variable ($x_{k_j,t_j} \in \Omega_{v+1}$) and what our model was predicting for that release ($E[x_{k_j,t_j} \mid \Omega_v]$): this revision is the only element that leads to a change in the nowcast, because it is the "unexpected" (with respect to the model) part of the data release and we call it "news".

As shown by Bánbura and Modugno (2010), the revision can be decomposed as a weighted average of the news in the latest release. We can find a vector $B_{v+1} = [b_{v+1,1},\ldots,b_{v+1,J_{v+1}}]$ such that the following holds:

$$E[y_t^Q \mid \Omega_{v+1}] - E[y_t^Q \mid \Omega_v] = B_{v+1} I_{v+1} = \sum_{j=1}^{J_{v+1}} b_{v+1,j}(x_{k_j,t_j} - E[x_{k_j,t_j} \mid \Omega_v]). \tag{3}$$

The magnitude of the forecast revision depends both on the size of the news and on its relevance for the target variable, as represented by the associated weight $b_{v+1,j}$.[6]

Through this interesting mechanism, it is possible to trace the contribution of each series to the revision of the nowcast, in particular putting in relation the revision of the target with the unexpected developments of the inputs.

The model we use in order to compute the nowcast and the news is a dynamic factor model (DFM). This model produces a good representation of the data and guarantees, at the

same time, parsimony. It exploits the fact that there is a large amount of co-movement among macroeconomic data series, and hence that relatively few factors can explain the dynamics of many variables (see Sargent and Sims, 1977; Giannone et al., 2005; Watson, 2004; and Stock and Watson, 2011).

The model can be written as a system with two types of equations: a measurement equation (Equation 4) linking the observed series (i.e. GDP and all the indicators listed in Table 1) to a latent state process, and the transition equation (Equation 5), which describes the state process dynamics. Equations 4 and 5, written in a state space form, allow the use of the Kalman filter to obtain an optimal projection for both the observed and the state variables. The Kalman filter generates projections for all of the variables in the model (GDP but also all the other data releases).

The DFM model is described by the following equations:

$$y_t = \Lambda f_t + e_t, \tag{4}$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + \ldots + A_p f_{t-p} + u_t \qquad u_t \sim i.i.d.N(0,Q), \tag{5}$$

$$e_{i,t} = \rho_i e_{i,t-1} + v_{i,t} \quad v_{i,t} \sim i.i.d.N(0,\sigma_i^2), \tag{6}$$

where $y_t = [y_{1,t}; y_{2,t}; \ldots; y_{n,t}]'$ denotes a set of standardized stationary monthly variables, f_t is a vector of r unobserved common factors with zero mean and unit variance, Λ is a matrix of coefficients collecting the factor loadings for the monthly variables, and $e_t = [e_{1,t}; e_{2,t}; \ldots; e_{n,t}]'$ is a n-dimensional vector of idiosyncratic components uncorrelated with f_t at all leads and lags.

This last assumption, which means that all of the joint correlation between observables is explained by the common factors, is strong and unrealistic, however Doz et al. (2006) have shown that the effects of this mispecification on the estimation of the common factors is negligible for large sample size (T) and the cross-sectional dimension (n).

We consider only one factor and two lags in Equation 5 and an AR(1) process for the idiosyncratic components described in Equation 6.[7]

In order to incorporate quarterly variables into the model, we construct for each of them a partially observed monthly counterpart in which the value of the quarterly variable is assigned to the third month of the respective quarter. We assume that the "unobserved monthly" growth rate of GDP (y_t^{UM}) admits the same factor model representation as the monthly real variables:

$$y_t^{UM} = \Lambda_Q f_t + e_t^Q, \tag{7}$$

$$e_t^Q = \rho_Q e_{t-1}^Q + v_t^Q \qquad v_t^Q \sim i.i.d.N(0,\sigma_Q^2). \tag{8}$$

To link y_t^{UM} with the observed GDP data, we construct a partially observed monthly series and we use the approximation of Mariano and Murasawa (2003):

$$y_{i,t}^Q = y_{i,t}^{UM} + 2y_{i,t-1}^{UM} + 3y_{i,t-2}^{UM} + 2y_{i,t-3}^{UM} + y_{i,t-4}^{UM}. \tag{9}$$

The estimation procedure is quasi maximum likelihood. As shown in Doz et al. (2006), the estimator, apart from being robust to model mispecification, is feasible when n is large (as in the case of Brazil) and easily implementable using the Kalman smoother and the EM algorithm, initialized using principal components, as in traditional factor analysis.

Given that most of the indicators we include in our model are characterized by missing data at the beginning of the sample (as it is in the case of the consumer confidence index, which starts in September 2005, or the PMI, which starts in February 2006) and by a "ragged edge" structure, due to unsynchronized data releases at the end of the sample, we follow Bańbura and Modugno (2014), that propose a solution for estimating factor models in the presence of datasets characterized by arbitrary patterns of missing data.

4. The BCB Survey and other benchmarks

The BCB has set up a Market Expectation System, a web interface where financial institutions, consulting firms, and universities, which are required to have a specialized team on macroeconomic projections, report their expectations for various macroeconomic variables including GDP growth. The process through which these institutions revise their forecasts is not clear, nevertheless it is reasonable to think that these predictions are not entirely model based, but that a certain amount of judgment is also used.[8] Every business day at 5:00 pm (GMT-2) the information is consolidated and several statistics are generated: averages, medians, standard deviations, coefficients of variation, and minimum and maximum values of the projections recorded by the participants. Of the universe of qualified institutions, most of them alter their expectations weekly. For the purposes of our exercise, we consider the median projection.

The other important benchmark we consider is Bloomberg, which conducts a survey and collects forecasts from analysts and economists in order to produce predictions for GDP and other market-relevant variables before their release dates. Bloomberg publishes predictions as soon as they have at least three respondents to their questionnaire, which is generally around two weeks before the release of the relevant data series. Thereafter the prediction is continually revised until 24 hours before the release. The final number is usually close to the actual release value.

Surveys of professional forecasters are forecast combinations that have the advantage of performing better than single forecasts (see Bates and Granger, 1969; Diebold and Lopez, 1996; Newbold and Harvey, 2002; and Clements and Hendry, 2004). In addition, short term forecasts, produced by the surveys, are based on real-time information.

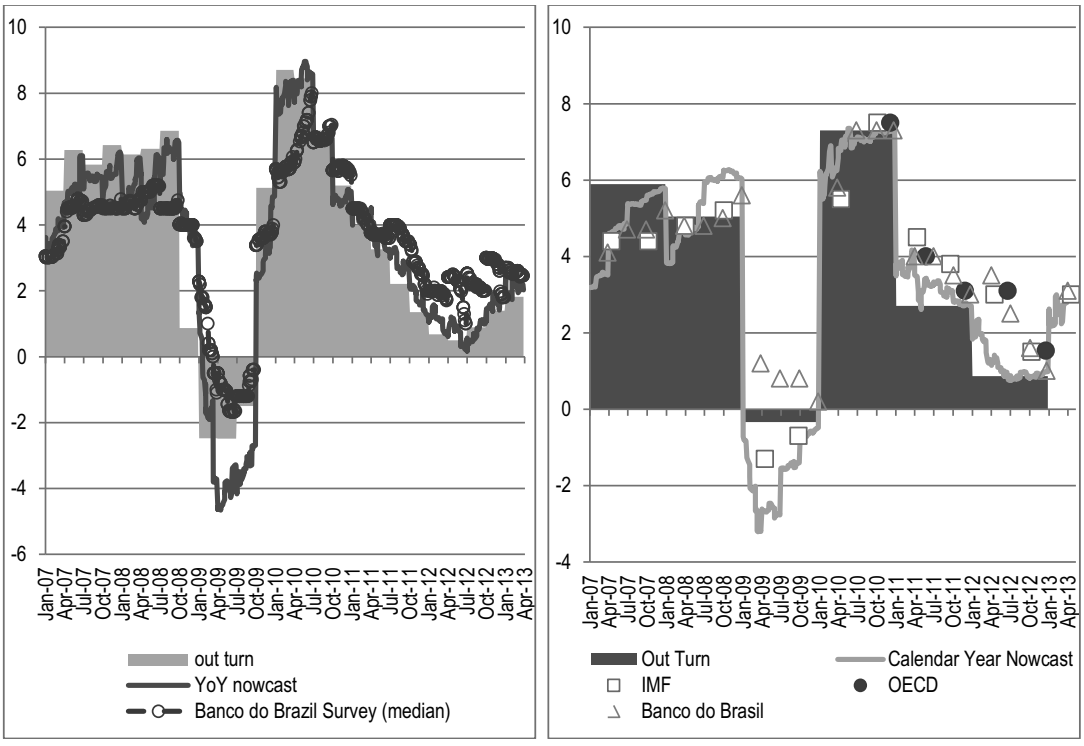
We also consider as benchmarks the OECD, IMF (released twice a year), and the BCB quarterly forecasts to compare the model results on calendar year forecasts.

5. Model evaluation

In order to evaluate the performance of the model we report a "pseudo real time" historical reconstruction from 2007:Q1 to 2013:Q1. We estimate the model recursively (the estimation period starts in January 1995) and we take account of information from each new data release (real-time), but we do not consider revisions (pseudo).[9] This last point can in principle distort the results in favour of the model, given that the BCB short term forecasts and the Bloomberg survey rely on real time information. However, given the robustness of factor models to data revision errors (see Giannone et al., 2006 and Bańbura et al., 2013), we expect this not to be the case.

The results of the historical evaluation are reported in the figures below. Figure 1 compares the year-on-year GDP nowcast and the BCB Survey with the actual realization of GDP in panel (a), and the calendar year now-cast and the IMF, OECD and BCB forecasts with

Figure 1. **GDP nowcast**



Note: Panel a), reports the comparison between GDP nowcast, GDP actual value, and the BCB survey (year-on-year). Panel b), reports the comparison between GDP nowcast, GDP actual value, OECD, IMF and Banco do Brasil forecasts (calendar year).

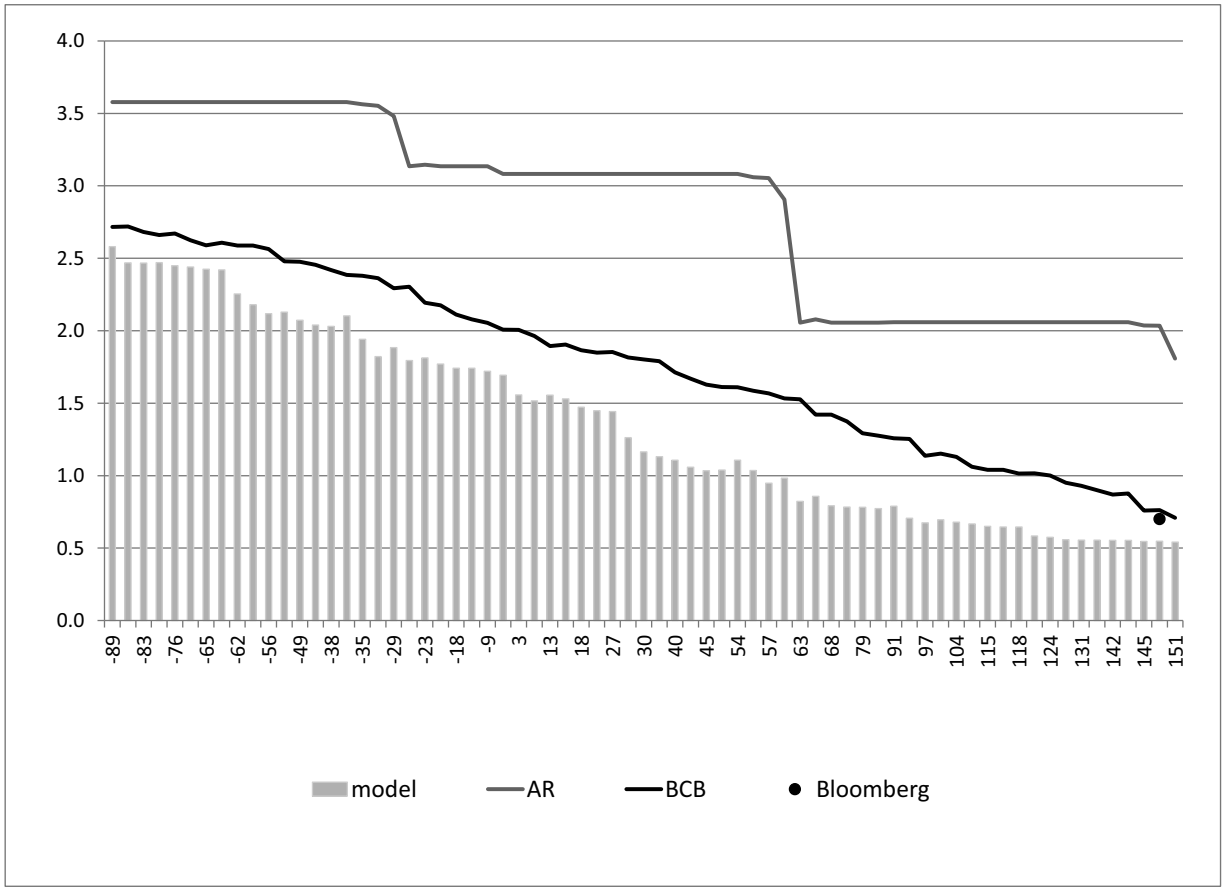
the actual realization of GDP in panel (b). Figure 1 shows that the nowcasting model mimics very well the actual realization of GDP.

Figure 2 compares the root-mean-squared forecast error (RMSFE) of the model – on average for all of the calendar quarters in the historic reconstruction period – with the short-term forecast of BCB, the Bloomberg's survey of independent forecasters (published the day before the preliminary GDP release) and an auto-regressive forecast, which changes only when GDP is released. Given that the BCB GDP Survey reports YoY figures, we evaluate the model on a YoY basis. Results do not differ significantly if we consider QoQ figures.

The model's quarterly GDP growth prediction is first made 90 days before the start of a given quarter. It is then updated with each successive data release until the release of preliminary GDP, which takes place 145 days after the start of the calendar quarter. Thereby for each calendar quarter there is a period of 235 days (the "prediction period") over which the prediction is continuously updated. This period is measured by the X-axis. The Y-axis measures the root-mean-squared forecast error (RMSFE) for each different series of predictions.

In Table 2, we report the RMSFE reduction by release, in each of the three months of the reference quarter. Specifically, real GDP, Exports, industrial production, PMI and formal employment are the data releases that have the most impact in improving the accuracy of the model's prediction.

Figure 2. **RMSFE**



Note: The Y-axis reports the root-mean-squared forecast error (RMSFE) over the period 2007:Q1 to 2013:Q1. The forecast accuracy is evaluated from the first month of the previous quarter to the time when GDP is released. The X-axis reports the distance in terms of days from the beginning of the current quarter.

Table 2. **Average MSFE reduction by variable**

	m1	m2	m3
Merchandise exports	-5.3	-29.9	0.7
Merchandise imports	-3.1	-2.4	-4.4
PMI manufacturing	6.9	-24.7	-10.3
Industrial production	-37.2	-19.6	-7.7
Manufacturing sales	-5.1	-2.3	3.9
Capacity utilisation	-5.9	0.5	-1.2
Economic activity indicator	-6.7	-6.5	-1.4
Extended retail trade	-7.3	-4.4	-6.6
Retail trade: Volume of sales	-1.5	-0.4	-0.8
Formal employment	-15.8	-11.5	-1.1
Consumer confidence index	-0.6	-0.3	0.0
Monthly GDP	-5.9	15.4	-1.6
Real GDP			-37.3

Note: These results are referred as the first (m1), second (m2), and third (m3) months of the nowcast period.

5.1. *Tests*

The BCB professional forecasts seem to be highly collinear with the nowcasts and equally accurate. In Table 3, we report the Diebold-Mariano (2002) test of equal predictive accuracy to check whether the difference in forecasting performance between models is significant. For each month, we report the sample average of the difference between the squared errors of the AR and the BCB professional forecasts both with respect to the nowcasting model (benchmark), in coincidence with the first Brazilian release (exports). We report the value of the DM test and its standard deviation estimated using heteroskedasticity and autocorrelation robust (HAC) standard errors (see Appendix A.2 for details). The test confirms better performance in terms of accuracy of the nowcasting model in comparison with the AR (in the forecast, nowcast and backcast) and a slightly better performance in comparison with the BCB forecasts (only in the nowcast and in the backcast).

Table 3. **Diebold-Mariano test of equal forecasting accuracy**

	Forecast		Nowcast		Backcast	
	AR	BCB	AR	BCB	AR	BCB
1m	6.42	0.62	6.95	1.24	3.78	1.03
	(3.37)	(1.26)	(2.95)	(0.68)	(1.45)	(0.31)
2m	8.06	1.55	8.26	1.80	3.98	0.64
	(3.76)	(1.11)	(3.21)	(0.71)	(1.50)	(0.17)
3m	9.37	1.86	8.63	1.48		
	(3.86)	(1.16)	(3.24)	(0.47)		

Note: The table reports the estimated constant and the HAC estimator of its standard error in the first, second, and third month of the forecast, nowcast, and backcast, respectively. The AR and BCB professional forecasts are compared against the nowcast model.

From Figure 2 we can see that the model's RMSFE declines more or less continuously over the prediction period, which means that new information has a monotonic and negative effect on uncertainty. In order to formally test the decline in uncertainty, as more data arrive we apply the test for forecast rationality proposed by Patton and Timmerman (2012). Table 4 reports the p-values of three monotonicity tests for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable (see the appendix for a description of the test). Monotonicity cannot be rejected by any of the three tests confirming the evidence of Figure 2 and proving the importance of incorporating new information as it arrives in the forecast update.

Table 4. **Monotonicity tests**

	$\Delta^e \geq 0$	$\Delta^f \geq 0$	$\Delta^c \geq 0$
Nowcast model	0.4965	0.4978	0.5012

Note: The table reports the p-values of three monotonicity test for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable.

5.2. *The news*

The importance of calculating the news is twofold: first, given that the news is defined as the difference between the actual value of the data release and the value predicted by

the model, it is possible to check whether the model is well specified in all of its dimensions. The average of the news for each release should be close to zero, and the standard deviation should be such that | *mean* | < 2 standard deviation. Table 5 confirms the previous statement. In addition, the table also compares the model's performance in predicting each of the series with that of the Bloomberg survey. We show that, for most series, the model's predictions are comparable to the Bloomberg survey predictions. Finally, we include in Table 5 the mean and standard deviation of the revisions for each of the series in the data set. As the means of the revisions are close to zero and the standard deviations are such that | *mean* | < 2 standard deviation, this suggests that the model's relative performance would have been similar in real time.[10]

Table 5. **Average news and standard deviation**

		Model		Bloomberg		Revisions	
	Units/Transformation	Mean	StD	Mean	StD	Mean	StD
Merchandise exports	USD/MoM	-0.32	6.97	0.74	11.68	0.85	8.95
Merchandise imports	USD/MoM	0.82	6.01	0.39	10.31	0.43	8.53
PMI manufacturing	D.I./Levels	-0.14	1.69	-0.07	0.22	0.01	0.13
Industrial production	Index/MoM	-0.12	1.98	0.38	1.09	-0.05	0.54
Manufacturing sales	Index/MoM	-0.17	2.29				
Capacity utilisation	Percentage/Diff.	-0.02	0.37	-0.81	0.68	-0.80	0.46
Economic activity index	Index/MoM	-0.07	0.81				
Extended retail trade	Index/MoM	0.08	2.62	-0.10	2.00	-0.08	2.67
Retail trade: Volume	Index/MoM	0.30	0.85	-0.05	0.85	-0.01	0.60
Formal employment	Index/Diff.	0.04	0.18				
Consumer confidence index	Index/Diff.	-0.24	3.34	-0.48	6.06	0.22	4.41
Monthly gross domestic product	Mil. reais/MoM	-0.24	2.12				
Real gross domestic product	Index/MoM	0.14	0.55	0.04	0.45	-0.07	0.56

D.I.= diffusion index; Diff.= differences; Thous. units = Thousand units; Manuf. = Manufacturing; Mil. reais = Million reais.

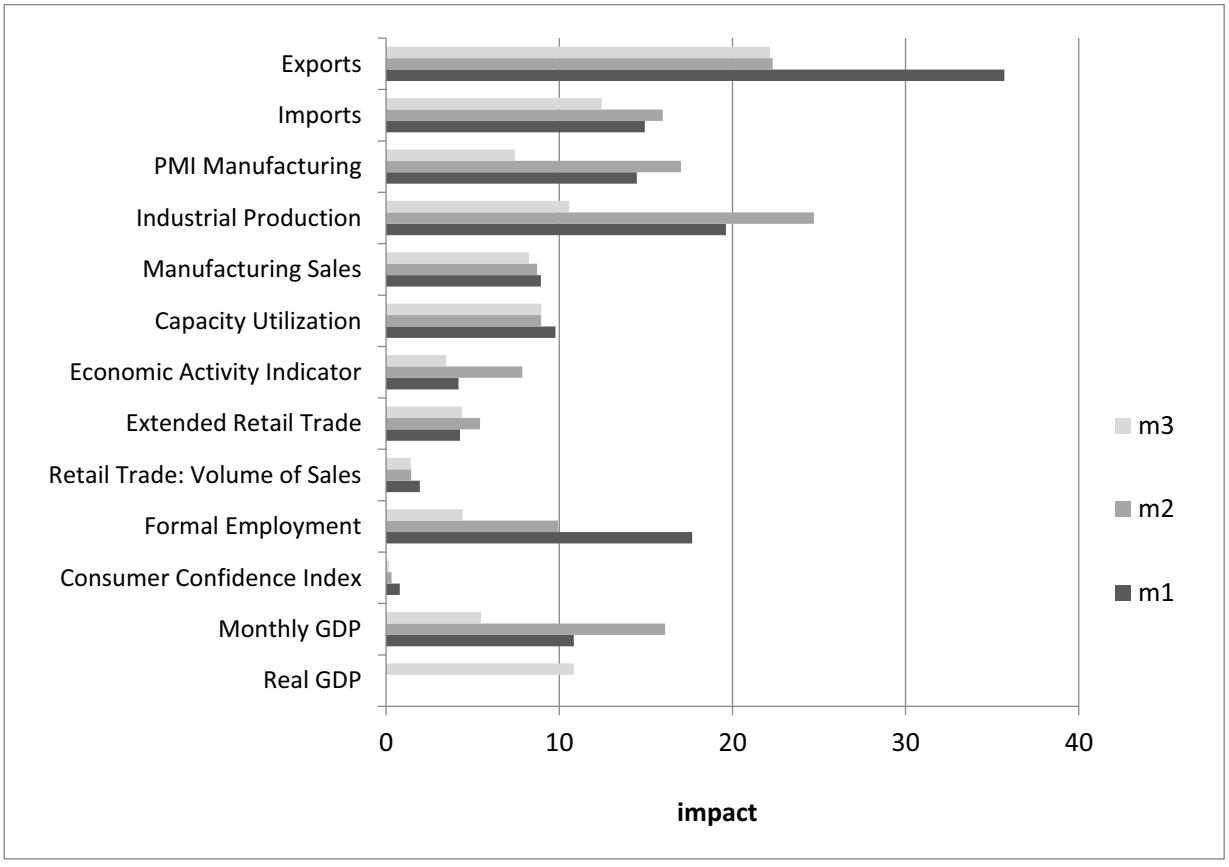
The second important feature of the news within a nowcasting framework is that it allows interpretation of all the data releases in terms of the signals they give about current economic conditions (Bańbura and Modugno, 2010). It is possible, with the use of Equation 3, to decompose the forecast revision into contributions from the news in individual series. The impact that a given release has on the GDP nowcast is the product of two variables: the news (or the unexpected component of the release value), and the relevance of the series in relation to GDP, which is expressed as its weight (i.e., impact = news standard deviation[11] x weight). Figure 3 shows the average impact of each variable in the first, second, and third month of the quarter. Trade variables have a huge impact on the forecasting revision given their timeliness, but also industrial production, PMI and employment variables seem to have a relevant contribution to the forecast revisions of GDP. See Appendix A.4 for the decomposition of the average impact.

6. Conclusions

In the nowcasting literature it has always been stressed the importance of developing models that can incorporate large information and that can be updated taking the continuous data flow into account.

In this paper we propose a model for nowcasting Brazilian real GDP, which mechanically updates the predictions as new information becomes available.

Figure 3. **Variables' relevance**



Note: Variables' average impact in the first (m1), second (m2), and third (m3) month of the nowcast.

The results of the model are compared with the survey of professional forecasts, collected by the Central Bank of Brazil at a daily frequency. The latter comparison gives a unique opportunity to relate, over the same frequency, forecasts based on a mechanical model with forecasts that incorporate some form of judgment.

Results indicate that both model and market participant predictions are well behaved, i.e. as more information becomes available their accuracy and correlation with the actual realization increases. In terms of performance the model seems to be slightly better than the institutional forecasts in the nowcast and backcast.

In addition, the nowcasting model can be a useful instrument to stress the single variable's relevance to the updating process. In Brazil, trade variables (in particular exports), given their timeliness, turn out to have a huge impact on the forecasting revisions. Industrial production, manufacturing PMI and employment variables are also relevant.

Notes

1. It is true that financial variables, which are available at very high frequency might, in principle, carry information on expectations of future economic developments (Andreou et al., 2008), however we only consider macro indicators and surveys given that other studies on this topic – see Bańbura et al. (2013), Stock and Watson (2005) and Forni et al. (2003) – indicate that "financial variables do not help improving the precision of GDP now-cast", because the news from financial

variables is highly volatile and leads to revisions in different directions. Moreover, Bańbura et al. (2013) show that there is correlation between some financial variables and GDP, but only at low frequency: this indicates that while financial variables are not important for short term forecast they could instead be important for long term forecast. This is also confirmed by the fact that market participants mostly monitor real variables.

2. Brazil also has a Nominal Monthly GDP series, but this is not the headline series, so we consider it as an input variable.
3. In order to construct the PMI index, respondents are asked to state whether business conditions for a number of variables have improved, deteriorated or stayed the same, compared with the previous month. Therefore the index is comparable to a MoM transformation. PMI is produced by Markit, see web page *www.markit.com/product/pmi*.
4. In this section we closely follow Giannone et al., 2006; Bańbura Modugno, 2010; Bańbura et al., 2012; and Bańbura et al., 2013.
5. Denotes a vintage of data corresponding to a particular release date v.
6. Equation 3 can be considered as a generalization of the usual Kalman filter update equation to the case in which new data arrive in a non-synchronous manner. See Bánbura and Modugno (2010) for further detail.
7. We use Bai Ng (2002) Information Criteria to select the number of factors in Equation 4 and Akaike Information Criteria to select the lag order of Equation 5. See the Appendix for details.
8. This statement was confirmed by a BCB forecasting expert.
9. We cannot conduct a real time analysis given that we do not have real time information for all the data series included in the model. To our knowledge only the OECD reports real time information on Brazil, but only on a small number of series, namely GDP, industrial production, retail trade, export and import. See *http://stats.oecd.org/mei/default.asp?rev=1*.
10. Note that the Bloomberg survey is conducted in real time, and the respondents whose forecasts it reflects are attempting to predict the first release of each series, whereas the reconstruction of the model's predictions is based on the last available vintage of data, ignoring revisions.
11. We consider the standard deviation instead of the mean because the latter should be close to zero and also in order to discard the sign.

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Appendix

A1. Selecting the number of factors and lags

We select the optimal number of factors using an information criteria approach. The idea is to choose the number of factors that maximizes the general fit of the model using a penalty function to account for the loss in parsimony. Bai and Ng (2002) derive information criteria to determine the number of factors in approximate factor models when the factors are estimated by principal components. They also show that their information criterion (IC) can be applied to any consistent estimator of the factors provided that the penalty function is derived from the correct convergence rate.

Table A1 reports the information criterion and the sum of the variance of the idiosyncratic components for the different specifications, which allow for a different number of factors. The IC selects the model with one factor. Given that our data set is strongly unbalanced at the top, and some series are more recent than others, we report the test on three different samples. The first (sample 1) considers a balanced panel in the estimation period 1995:Q1 to 2006:Q4 (13 series and 11 observations), the second (sample 2) a restricted balanced panel where we exclude two of the most recent series (11 series 47 observations), the third (sample 3) is a balanced panel that incorporates the whole sample (estimation and forecasting period). The choice of one factor is confirmed across the different samples.

Table A1. **Model selection (number of factors)**

	Sample 1		Sample 2		Sample 3	
	IC	V	IC	V	IC	V
1	-0.03	0.68	-0.03	0.69	-0.06	0.68
2	0.03	0.50	0.01	0.51	0.05	0.55
3	0.35	0.48	0.29	0.48	0.25	0.48
4	0.31	0.32	0.40	0.39	0.29	0.36
T	11		47		128	
N	13		11		13	

Note: IC stands for Information Criteria, V is the sum of the variance of the idiosyncratic component.

In order to select the number of lags in Equation 5 of the model, we report in Table A2 the results on the Akaike information criterion, which selects two lags.

Table A2. **Model selection (number of lags)**

Number of lags	Akaike information criteria
1	0.82
2	0.68
3	0.72
4	0.73

Note: The lag is chosen in correspondence with the minimum AIC value.

A2. Diebold-Mariano test

Denote the loss associated with forecast error e_t by $L(e_t)$ and the time-t loss differential between forecasts 1 and 2 as $d_{12t} = L(e_{1t}) - L(e_{2t})$. The Diebold-Mariano (DM) requires only that the loss differential is covariance stationary:

$$E(d_{12t}) = \mu, \forall t$$

$$cov(d_{12t}, d_{12t-\tau}) = \gamma(\tau), \forall t$$

$$0 < var(d_{12t}) = \sigma_2 < \infty$$

The key hypothesis of equal predictive accuracy (i.e., equal expected loss) corresponds to $E(d_{12t}) = 0$, in which case, under the maintained assumption DM:

$$DM_{12} = \frac{\bar{d}_{12}}{\hat{\sigma}_{\bar{d}_{12}}} \xrightarrow{d} N(0,1),$$

where $\bar{d}_{12} = \frac{1}{T}\sum_{t=1}^{T} d_{12t}$ is the sample mean loss differential and $\sigma_{\bar{d}_{12}}$ is a consistent estimator of the standard deviation of $\bar{d}_{12}$.

DM is thus an asymptotic *z – test* of the hypothesis that the mean of a constructed but observed series (the loss differential) is zero. Forecast errors, and hence loss differential, though, may be serially correlated for various reasons. In this paper, we calculate the DM statistics by regression of the loss differential on an intercept, using heteroskedasticity and autocorrelation robust (HAC) standard errors. In a fully articulated econometric model in which we have pseudo out-of-sample forecasts, following West (1996), we define the test on the sample mean quadratic loss as follows:

$$\bar{d}_{12} = \frac{\sum_{t=t^*+1}^{T} (e^2_{1,t|t-1} - e^2_{2,t|t-1})}{T - t^*},$$

where $e_{t|t-1}$ is a time-t pseudo out-of-sample one-step ahead forecast error. We do not consider a rolling scheme, so results should be taken with caution, as the test ignores estimation uncertainty.

A3. Monotonicity test

We rely on the first three tests of Patton and Timmermann (2012) based on the multivariate inequality tests in regression models of Wolak (1987, 1989). We report the p-values for the nowcast model.

Test 1: Monotonicity of the forecast errors

Let us define $\tilde{y}_t = y_{t,1}^k$ and $e_{t|\Omega_v} = \tilde{y}_t - E[\tilde{y}_t \mid \Omega_v]$ as the forecast error obtained on the basis of the information set corresponding to the data vintage Ω_v and by $e_{t|\Omega_{v+1}}$ that obtained on the basis of a larger more recent vintage $v+1$ and $v = 1,\ldots,V$.

The mean squared Error (MSE) differential is $\Delta_v^e = E[e_{t|\Omega_v}^2] - E[e_{t|\Omega_{v+1}}^2]$.

The test is: H0 : $\Delta^e \geq 0$ vs. H1 : $\Delta^e \ngeq 0$, where the $(V-1)\times 1$ vector of MSE-differentials is given by $\Delta^e \equiv (\Delta_1^e,\ldots,\Delta_{V-1}^e)'$.

Test 2: Monotonicity of the mean squared forecast

Define the mean squared forecast (MSF) for a given vintage as $E[\tilde{y}_{t|\Omega_v}^2] = E[E[\tilde{y}_t^2 \mid \Omega_v]]$ and consider the difference $\Delta_v^f = E[\tilde{y}_{t|\Omega_v}^2] - E[\tilde{y}_{t|\Omega_{v+1}}^2]$ and its associated vector Δ^f.

The test is H0 : $\Delta^f \leq 0$ vs. H1 : $\Delta^f \nleq 0$.

Test 3: Monotonicity of covariance between the forecast and the target variable

Here we consider the covariance between the forecast and the target variable for different vintages v and the difference $\Delta_v^c = E[\tilde{y}_{t|\Omega_v}\tilde{y}_t] - E[\tilde{y}_{t|\Omega_{v+1}}\tilde{y}_t]$. The associated vector is defined as Δ^c and the test is H0 : $\Delta^c \leq 0$ vs H1 : $\Delta^c \nleq 0$.

Wolak (1987, 1989) derived a test statistic whose distribution under the null is a weighted sum of chi-squared variables.

A4. Impact of the releases on the nowcast

Table A3. **Impact of the releases on the now-cast**

	A			B			C		
	m1	m2	m3	m1	m2	m3	m1	m2	m3
Merchandise exports	4.497	4.139	2.938	7.941	5.392	7.543	35.708	22.318	22.163
Merchandise imports	2.907	2.679	1.923	5.138	5.963	6.477	14.937	15.975	12.454
PMI manufacturing	10.936	8.930	4.052	1.324	1.906	1.835	14.478	17.023	7.436
Industrial production	9.970	9.606	8.799	1.969	2.573	1.202	19.629	24.712	10.575
Manufacturing sales	4.070	3.920	3.596	2.197	2.225	2.295	8.943	8.724	8.253
Capacity utilisation	25.777	25.600	23.613	0.380	0.350	0.380	9.783	8.956	8.964
Economic activity indicator	7.199	6.825	5.980	0.580	1.153	0.578	4.177	7.869	3.458
Extended retail trade	1.988	1.903	1.606	2.147	2.853	2.731	4.268	5.431	4.387
Retail trade: Volume of sales	1.988	1.880	1.716	0.981	0.771	0.828	1.950	1.450	1.420
Formal employment	75.902	66.813	30.721	0.233	0.149	0.144	17.673	9.954	4.431
Consumer confidence index	0.186	0.122	0.060	4.241	2.571	3.083	0.787	0.312	0.184
Monthly GDP	6.375	5.734	3.452	1.700	2.810	1.591	10.838	16.112	5.490
Real GDP			19.749			0.549			10.838

Note: A is the average weight; B is the news standard deviation; C is the average impact equal to $A \cdot B$.

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The world and "The world business cycle chronology"

by
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Twenty-one individual country business cycle chronologies, maintained and updated by the Economic Cycle Research Institute (ECRI), are analysed for their degree of synchronisation with a proposed "world business cycle chronology". Several key results emerge. First, perhaps not surprisingly, the world's four 20th Century locomotor economies of the US, UK, Germany and Japan are statistically significantly and reasonably strongly positively synchronised with the world cycle. Second, European countries in the sample are either positively synchronised with the world cycle at zero lag or with a lag of around three months. Third, the NAFTA countries (US, Canada and Mexico) are, perhaps again not unexpectedly, quite strongly positively synchronised with the world cycle at zero lag and with each other. Fourth, the single South American country included in the sample, Brazil, is strongly positively synchronised with the world cycle at zero lag as well as with the NAFTA countries – but behaves very differently from China and India with respect to the world cycle. Fifth, interestingly, the newly industrialized East Asian countries included in the sample appear to lead the world cycle by about three to nine months. Finally, and very interestingly, there appears to be some a priori evidence of a long leading negative *synchronisation between the commodity exporting countries in the sample and the world cycle.*

Keywords: world business cycle, synchronisation

JEL classification: E32, E37

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1. Introduction

The last decade has a seen quite a bit of research on international business cycle synchronization. Given the advent of the Economic and Monetary Union of the European Union (EMU) in 1990 and the subsequent creation of the Euro and the (now) 18-country Eurozone common currency union, much of this has perhaps quite naturally focussed on the European region. For example, one early paper showed significant timing differences – i.e., lack of cyclical synchronization – between employment cycles at the aggregate EMU level and those in Germany and France (Guha and Banerji, 1998/1999). In contrast, Artis and Zhang (1997, 1999) suggested that increased exchange rate stability had led to greater business cycle synchronization in Europe.[1]

However, Inklaar and de Haan (2001) later questioned this finding and suggested that if such synchronization was not in evidence then a common monetary policy in the Eurozone area may prove hazardous.[2, 3] Later still, Altavilla (2004) evaluated the synchronization of individual Euro area country cycles – defined by variation in real GDP – with an aggregate GDP-based Euro area regional cycle and found recessionary period synchronization, concluding the common currency union in the Eurozone was likely to lead to even stronger synchronization of members' cycles.

Recently, Artis et al. (2011) studied the behaviour of "the" international business cycle across 25 countries around the world (advanced and emerging) using 125 years of annual real GDP per capita data. They concluded the evidence supported a reasonable degree of international business cycle synchronization within a group of European and a group of English-speaking countries, while country-specific shocks remained dominant elsewhere in the world. An interesting feature of this paper was their use of per capita data which is somewhat unusual in defining and analysing business cycles (either classical cycles or growth cycles).[4] Using a somewhat different approach, namely one based on spectral transformation of the raw data, Aguiar-Conraria and Soares (2011) also studied the European situation and, perhaps unsurprisingly, found Germany and France to be the most synchronized with the rest of Europe (and to be the drivers of the region), while countries like Portugal, Greece and Ireland were much less so.[5]

In a related vein, some researchers have focussed on what factors might be associated with increased international business cycle synchronization amongst groups of countries. For example, Darvas et al. (2005) used annual data over 40 years for a panel of 21 OECD countries and found that countries whose government budgetary outcomes tended to vary over time in similar ways also exhibited increased business cycle synchronization. However, a natural question here of course is what is causing what? Calderón et al. (2003) examined the role of trade intensity amongst 147 countries, both industrialized and developing, and found that countries with increased trade intensity tended to have higher business cycle synchronization, but that this was tempered by the extent of production structure asymmetries across countries.[6] Very recently, Duval et al. (2014) also examined this issue using data on 63 advanced and emerging economies and again found trade intensity was

significant, but, in addition, they found the degree of intra-industry trade between countries was important.

Finally, Bergman and Jonung (2011) – with a primary focus on identifying changes in the degree of synchronization in the three Scandinavian countries of Sweden, Norway and Denmark before, during and after the Scandinavian Currency Union of 1873-1921 – used annual real GDP data spanning the 1800s through to 2008 for 12 OECD countries. They extracted and dated domestic business cycles for each country, used a common factor model to extract a Scandinavian international business cycle and an EU cycle, and then performed various bivariate synchronization tests between individual countries' business cycles and also between countries and the constructed aggregated international cycles. They found the degree of synchronization amongst the three Scandinavian countries had increased during the currency union, and that common Scandinavian shocks were important for their individual business cycles.

In this paper we seek to value-add to this synchronization literature in several ways, viz.:

- Rather than use real GDP or Industrial Production data – as is used in virtually all other papers in the area – we use post-WWII monthly business cycle chronologies for the US, compiled by the National Bureau of Economic Research (NBER), and 20 other countries compiled by the Economic Cycle Research Institute (ECRI) using a similar approach;
- Our focus then is to compare the timing of individual country business cycle chronologies with what we call a "world business cycle chronology" constructed from a group of so-called 20th and 21st Century locomotor countries;
- Specifically, in prosecuting the above, by calculating synchronization metrics and test statistics for not only the zero lag but also a relatively large number of leads and lags, we investigate whether countries' chronologies appear to systematically lag, lead or are contemporaneous with the world chronology.

Our motivation for pursuing this line of research has a couple of facets. First, the occurrence of a synchronized international recession is a relatively rare – but highly disruptive and painful – world phenomenon. In attempting to determine which world economies are apparently systematically synchronized with such a phenomenon, which might lead it, which may lag it, and which may, in fact, appear to have no relationship with it at all, we hope will add to our general understanding of the impact patterns around the world of such major disruptive events. Second, and deriving from the first, it is hoped that the empirical results may lead to potentially interesting economic explanations of the apparent international business cycle dynamics in evidence in the data.

In the next section we provide some discussion of our approach to the issue of business cycles and their proper measurement and dating. Following this we discuss the concept of synchronisation as it is applied in this paper and outline some approaches to determining the degree of synchronisation between two business cycle chronologies. In the fourth section we present and discuss the results, and in the final section we provide some proposed broad conclusions following from the empirics.

2. Measuring and dating business cycles

In their seminal contribution to the study of business cycles, Burns and Mitchell (p.3, 1946), stated:[7]

> 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 amplitudes approximating their own.

In the same spirit, the NBER defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales."[8] The NBER-sponsored business cycle dating committee uses this definition and turning points in a set of so-called coincident economic indicators to determine the official dates of the U.S. business cycle.[9]

ECRI uses a similar methodology as used by the NBER to track and provide analogous dates for the business cycles of some 20 countries around the world.[10] ECRI also compiles coincident indexes (CIs) and leading indexes (LIs) for the set of countries they cover.[11]

A country's business cycle chronology is the set of peak and trough dates in its measured business cycle. The phase of a business cycle between a trough and a subsequent peak is its expansionary phase and the phase of the business cycle between its peak and subsequent trough is its recessionary phase. In Table 1 we provide the NBER-determined US business cycle chronology, along with the chronologies for the other 20 countries monitored by ECRI.

As is evident from the table, expansions are typically much longer than recessions, although recessions, when they occur, are fairly painful, with rapidly rising unemployment which, even after the country has entered back into an expansionary phase, can take many years to revert to pre-recession levels.

But what about a "world" or "international" recession? Banerji, Layton and Achuthan (2012) proposed an approach to measuring what might constitute a "world business cycle" and the dating of a "world business cycle chronology". That proposed world chronology is also provided in Table 1 and was based on the economies of the so-called 20th Century locomotor countries of the US, UK, Germany and Japan, along with the emerging 21st century economies of China and India.

The rationale for choosing these six countries as the basis of a "world chronology" was outlined in detail in Banerji et al. (2012). In brief, the combined GDP of these six countries accounts for over half the world's output.[12] They also represent key economic regions of the world – the Americas, Europe and Asia, and, finally, they are major economies in their regions of the world and could be expected to be significant influences on economic growth in those regions. For these reasons we believe it is defensible to use these six in determining a "world chronology". Notwithstanding this, it must be noted that our subsequent synchronization analysis, and discussion thereto, is clearly conditional on this particular derivation of a "world chronology".

Table 1. **Business cycle peak and trough dates, WCI & 21 countries, 1948-2013**

Period	Peak or Trough	World Chronology*	WCI countries*									
			United States	Japan	China	India	United Kingdom	Germany	Canada	Mexico	Brazil	France
1948-50	P		11/48	..	..	..	..			..	..	..
	T		10/49	..	..	..	..			..	..	..
1951-52	P			..	..	..				..	..	..
	T			..	..	..	8/52			..	..	
1953-55	P		7/53	1/53	..	..			5/53	..	..	
	T		5/54	12/54	..	..			6/54	..	..	
1956-59	P		8/57		..				10/56	..	..	11/57
	T		4/58		..				2/58	..	..	4/59
1960-61	P		4/60		..					..	..	
	T		2/61		..					..	..	
1962-65	P				..	11/64				..	..	
	T				..	11/65				..	..	
1966-68	P				..	4/66		3/66		..	..	
	T				..	4/67		5/67		..	..	
1969-73	P		12/69		..	6/72				..	..	
	T		11/70		..	5/73				..	..	
1973-75	P	11/73	11/73	11/73	..	11/73	9/74	8/73		..	..	7/74
	T	5/75	3/75	2/75	..	2/75	8/75	7/75		..	..	6/75
1976-78	P				..					..	..	
	T				..							
1979-80	P	1/80	1/80		..	4/79	6/79	1/80			..	8/79
	T		7/80		..	3/80					..	6/80
1981-83	P		7/81		..				4/81	3/82		4/82
	T	11/82	11/82		..		5/81	10/82	11/82	7/83	12/83	
1984-86	P									10/85		
	T									11/86		12/84
1986-88	P				8/88						2/87	
	T										7/87	
1989-91	P		7/90			3/91	5/90	1/91	3/90		8/89	
	T		3/91		12/89	9/91						
1992-94	P			4/92						10/92		2/92
	T			2/94			3/92		3/92	10/93	3/92	8/93
1994-96	P					5/96				11/94	3/95	
	T					11/96		4/94		7/95	9/95	
1997-99	P			3/97							10/97	
	T			7/99							4/99	
2000-01	P	12/00	3/01	8/00				1/01		8/00	2/01	
	T	12/01	11/01								12/01	
2002-03	P										10/02	8/02
	T			4/03				8/03		8/03	6/03	5/03
2004-10	P	4/08	12/07	2/08			5/08	4/08	1/08	4/08	8/08	2/08
	T	6/09	6/09	3/09			1/10	1/09	7/09	5/09	1/09	2/09
	P			8/10			8/10					
	T											
2011-13	P											4/11
	T			4/11			2/12					
	P			5/12								
	T			1/13								11/12

Table 1. **Business cycle peak and trough dates, WCI & 21 countries, 1948-2013** *(cont.)*

									ASIA PACIFIC				AFRICA
Period	Peak or Trough	World Chorology	Italy	Spain	Switzerland	Sweden	Russia	Austria	Korea	Australia	Taiwan	New Zealand	South Africa
1948-50	P		..	..	..	..	..	..	..		..	..	..
	T		..	..	..	..	..	..	..		..	..	..
1951-52	P		..	..	..	..	..	..	..	6/51	..	..	..
	T		..	..	..	..	..	..	..	9/52	..	..	..
1953-55	P		..	..	..	..	..	..	..	12/55	..	..	..
	T		..	..	..	..	..	..	..		..	..	..
1956-59	P			..		..	..	..	..		..	..	..
	T			..		..	..	..	..	8/56	..	..	..
1960-61	P			..		..	..	..	..	12/60	..	..	..
	T			..		..	..	..	..	9/61	..	..	..
1962-65	P		1/64	..		..	..						
	T		3/65	..		..	..						
1966-68	P			..		..	..					6/66	
	T			..		..	..					3/68	
1969-73	P		10/70			10/70	..						
	T		8/71			11/71	..						
1973-75	P	11/73	4/74		4/74	7/75	..	8/74		6/74	12/73	4/74	
	T	5/75	4/75				..	6/75		1/75	1/75	3/75	
1976-78	P						..					3/77	6/76
	T				3/76	11/77	..					3/78	11/77
1979-80	P	1/80	5/80	3/80		2/80	..	2/80	3/79				
	T						..		10/80				
1981-83	P				9/81		..			6/82		4/82	11/81
	T	11/82	5/83		11/82	6/83	..	1/83		5/83		5/83	1/83
1984-86	P						..					11/84	6/84
	T			5/84			..					3/86	2/86
1986-88	P						..					9/86	2/89
	T						..						
1989-91	P			11/91	3/90	6/90	..			6/90			
	T						..			12/91		6/91	
1992-94	P		2/92				..	4/92					
	T		10/93	12/93	9/93	7/93	..	6/93					8/92
1994-96					12/94			5/95					
					9/96		11/96	3/96					
1997-99	P						12/97		8/97			10/97	4/97
	T						1/99		7/98			5/98	11/98
2000-01	P	12/00			3/01			1/01			8/00		
	T	12/01						12/01			9/01		
2002-03	P								12/02				
	T				3/03				9/03				
2004-10	P	4/08	8/07	2/08	5/08	4/08	5/08	2/08	7/08		2/08	11/07	4/08
	T	6/09	1/10	**12/10**	5/09	3/09	**5/09**	6/09	12/08		1/09	**12/10**	4/09
2011-13	P		4/11										
	T			7/13									

* Derived from turning points in a "world coincident index", which is a GDP weighted average of the individual countries coincident indexes for United States, Japan, United Kingdom, Germany, China and India. ... data not available.

Given this world chronology, it is of interest to ascertain whether the business cycle chronology of an individual country systematically leads or lags this world cycle, alternatively, whether it is "synchronised" with the world cycle, or whether indeed it appears not to vary in any way systematically with the identified world cycle.

This question will be addressed in subsequent sections of this paper using the country chronologies maintained by ECRI. Whilst we are necessarily limited to these 20 ECRI-covered countries and the US, nonetheless this set of countries account for almost 80% of world GDP and covers all of the world's key economic regions, so we feel this amounts to a useful exercise.[13]

3. Defining and testing for the degree of "synchronisation" between cycles

One approach to the issue of the extent to which a country's business cycle is synchronised with the world cycle is to look at the frequency with which the country's turning points (TPs) correspond in some way with the TPs in the world cycle. What we do here is to use a window of +/- 24 months around each TP in the world cycle to see whether there is a corresponding TP in the country's business cycle. We also note the lead or lag involved in any pair of apparently corresponding TPs, the median lead or lag, and the proportion of TPs for which such a correspondence appears to be in evidence. The results of this approach – denoted "TP correspondence" – are presented in the next section.[14]

Another approach to the definition of synchronisation we use here is that described in the paper by Harding and Pagan (2006).[15] In our current context we define a constructed binary variable, S_{wt}, = 1 when the world cycle is in an expansionary phase, and = 0 when it is in a recessionary phase. We similarly define S_{jt} = 1 when country j's business cycle is in an expansionary phase, and = 0 when it is in a recessionary phase.

One definition of synchronisation then is what Harding and Pagan define as the concordance index, I, computed as the ratio obtained by dividing the number of periods in which S_{wt} and S_{jt} take on the same value (indicating both cycles are in the same phase) by the total available sample size. The concordance index then has a maximum value of one – implying "perfect" synchronization – and zero – implying the absence of any synchronization at all. Clearly, observing a concordance value of zero or one is very unlikely in practice.

Despite its intuitive appeal, as pointed out by Harding and Pagan, the concordance index as just described has a significant limitation. Because most modern economies experience much longer expansions than recessions it is quite possible to get quite a high value of the concordance index – i.e., greater than 0.8 – even if the recessionary episodes of two countries do not correspond whatsoever. This would give a very misleading impression of the true strength of concordance and is simply due to both countries very often being in expansions.

One solution to this problem we propose here is to use a modified concordance index which focuses on recession phases only. More precisely, we count the number of periods in which country j is in recession conditional on the world cycle being in a recessionary phase, and divide that total by the total number of periods in which the world cycle is in recessionary phases. This calculated modified concordance statistic will also vary between zero (no concordance) and one ("full" concordance), but is uninfluenced by long periods when both the country's business cycle and the world cycle may be – purely coincidentally – in expansionary phases. The results of this second approach – denoted "recession concordance" – are also presented in the next section.[16]

Defined in this way, it should be noted that any additional recessionary episodes in a country will not reduce the value of "recession concordance". An alternative which would take this possibility into account would be to divide the total number of times when both

the country's business cycle and the world cycle were in recession in the same period by the total number of times when either the country's business cycle or the world cycle were in recession. We elected to use the method described above as we ascribed a primacy to the identified synchronized international recessions and our interest (in this paper) lay in the extent to which each country had recessions which corresponded to those identified international recessions. Of course, in other contexts, the fact that some countries may have had additional recessions to the identified synchronized international recessions could be of considerable interest.

A third and final approach to estimating synchronization we use here is also due to Harding and Pagan (2006) and involves estimating the parameter, p_j, in the following equation

$$\hat{\sigma}j^{-1} * \hat{\sigma}_w^{-1} * S_{jt} = \alpha_j + \rho_j * \hat{\sigma}_j^{-1} * \sigma w^{-1} * S_{wt} + \varepsilon_t \quad (3.1)$$

In equation, (3.1), $\hat{\sigma}_j$ and $\hat{\sigma}_w$ denote the estimated standard deviations of the constructed binary variables, S_j and S_w respectively, and ρ_j denotes the correlation between S_w and S_j which varies between –1 (perfect negative synchronization) and +1 (perfect positive synchronization).

A ρ_j value of zero equates to zero synchronization, meaning there is no tendency for the country's business cycle to have any systematic association with the world cycle. A "+" value equates to positive synchronisation, meaning the country cycle tends systematically to be in the same phase as the world cycle. And a "–" value equates to negative synchronization, meaning the country cycle tends systematically to be in the opposite phase to the world cycle.

By estimating (3.1) and testing whether $\hat{\rho}_j$ is statistically significantly different from zero, we can infer whether synchronization exists between the country's business cycle and the world cycle, and if so, the sign of $\hat{\rho}_j$ provides an indication of the nature of that synchronization. Estimation is complicated since, under the null hypothesis of $\rho_j = 0$, the error term, ε_t, is not i.i.d. and so OLS estimation would produce biased – and inflated – t statistics. Given this, Harding and Pagan recommend using Generalized Method of Moments (GMM) estimation so that the resulting calculated t statistics are approximately normally distributed.[17] The results of this third approach – denoted "econometric synchronization testing" – are also presented and discussed in the next section.[18]

There is one final important point to note in relation to the second and third approach. It will be recalled that we are also interested in the extent to which there may be any systematic leading or lagging in country chronologies vis- à -vis the world cycle. Thus, what we do is calculate "recession concordance" between a country's chronology and the world chronology at lag zero as well as a set of "+" and "–" lags, and look to see at what lag or set of lags "recession concordance" appears to be largest. This provides an indication of whether the country's chronology appears to systematically lead, lag or is concurrent with the world chronology.

In a similar way, for country j, not only do we calculate $\hat{\rho}_j$ and test its statistical significance at lag zero, but we also do this for a set of "+" and "–"lags. Looking at where $\hat{\rho}_j$ is largest (in absolute value) again provides an indication of whether the country chronology appears to systematically lead, lag or is concurrent with the world chronology.

4. Results and discussion

In Table 2 we report the results of conducting a "TP correspondence" analysis of the world cycle TPs with each of the countries listed in Table 1.

Table 2. **Pairwise lead/lag correspondence in months: WC and individual country**

Within a +/-24 months window

World chronology		Canada	Mexico	Brazil	France	Italy	Spain	Switzerland	Sweden	Austria	Korea	Australia	Taiwan	New Zealand	South Africa	Russia	United States	Japan	Germany	United Kingdom	India	China*
Peak	Trough																					
Nov. 73			...	...	8	5		5	20	9		7	1	5		...	0	0	-3	10	0	...
	May. 75		...	...	1	-1		10		1		-4	-4	-2		...	-2	-3	2	3	-3	...
Jan. 80		15		...	-5	4	2	20	1	1	-10				22	...	0		0	-7	-9	...
	Nov. 82	0	8	13		6	18	0	7	2		6		6	2	...	0		-1	-18		...
Dec. 2000			-4	2	20			3		1	24		-4				3	-4	1			
	Dec. 01		20	0	17			15		0	21		-3				-1	16	20			
Apr. 08		-3	0	4	-2	-8	-2	1	0	-2	3		-2	-5	0	1	-4	-2	0	1		
	Jun. 09	1	-1	-5	-4	7	18	-1	-3	0	-6		-5	18	-2	-1	0	-3	-5	7		
Median		0.5	0	2	1	4.5	10	4	1	1	3	6	-3.5	5	1	0	0	-2.5	0	2	-3	
No. of WC TPs in country sample		8	6	5	8	8	8	8	8	8	8	8	8	8	8	4	8	8	8	8	8	4
% correspondence with WC TPs		50	83	100	88	75	50	100	63	100	63	38	75	63	50	50	100	75	100	75	38	0

Note: ... data are not available.

To illustrate the interpretation of Table 2 we start with the six countries used to compile the world chronology. The Table presents each of the eight world chronology TPs and then, using a window of +/– 24 months around each of those TPs, indicates whether there was a corresponding TP in the country in question and, if so, the number of months lead or lag. In the Table, a + indicates the country's TP occurs after the world chronology TP by the indicated months.

Thus, for example, for the proposed world chronology trough in 05/1975, the US troughed 2 months before it, Japan and India troughed 3 months before it, while Germany and the UK troughed 2 and 3 months, respectively, after it. Median leads and lags for each country are also presented and, as can be seen, all, except China which had no TPs over the available data, are within +/- 3 months.

It is common in business cycle dating to regard a lead or lag of 3 or fewer months as coincident with the chronology. Furthermore, except for India (and China), all countries had a relatively high correspondence of TPs, as measured by the proportion of world TPs with corresponding country TPs. Thus, following this approach, we can conclude that all of these five countries' chronologies (excluding China) are concurrent and seemingly well synchronised with the world chronology. Of course, this is not surprising given these countries figured significantly in the compilation of the world chronology![19]

Now, moving to the other countries in the sample, we will just point out a few things of potential interest to readers.

First, the other two NAFTA countries of Mexico and Canada appear to be reasonably closely synchronised with the world cycle. This is no doubt due to their geographic proximity to,[20] and economic dependence on, the US, and to their increased interconnectedness with the US as a result of the FTA.

Second, all of the European countries in the sample, except for Austria, appear to lag the world cycle by a few months on average, while Austria, again probably due to its proximity to and reliance on Germany,[21] seems to be quite closely synchronised with the world cycle.

Third, consider the other two BRIC countries of Russia and Brazil. Brazil appears to be quite closely synchronised with the world cycle and with the NAFTA countries. It has 100% TP correspondence with the world cycle TPs applying to the sample data available for Brazil, with a median lead/lag less than 3 months. Russia, on the other hand, only had close correspondence to the world cycle in the most recent world recession of 2008/09. Due to limited data availability prior to the 21st century to compute its business cycle chronology, it is really too early to yet be very definitive in regard to how closely synchronized with the world cycle Russia might become.

In Table 3 we present results for "recession concordance" for each of the countries. Recall this is defined as the ratio of the number of months a country is in recession given the world cycle is in recession. A high value – say, greater than 0.5 – indicates a reasonably high level of recession concordance. This might be interpreted as meaning that, if the world cycle is in recession, it is more than 50% probable that the country in question will also be experiencing a recession.

However, rather than only calculate this statistic for a zero lag, we also calculate it out to +/- 36 months. For presentational purposes we only present the results for +/- 12 months since, except in the case of France and South Africa, the highest concordance occurred within +/- 12 months. Again a "+" means the individual country's recession tends to lag

Table 3. **Ratio of the no of months a country is in recession given the WC indicates recession, over the total no of months of recession indicated by the WC**

Lag/lead	Canada	Mexico	Brazil	France	Italy	Spain	Switzerland	Sweden	Austria	Korea	Australia	Taiwan	New Zealand	South Africa	Russia	US	Japan	UK	Germany	India	China
12	0.282	0.483	0.600	0.385	0.538	0.615	0.551	0.500	0.423	0.000	0.167	0.026	0.397	0.179	0.038	0.282	0.192	0.282	0.526	0.038	0.000
11	0.295	0.500	0.600	0.372	0.577	0.615	0.577	0.500	0.474	0.000	0.179	0.038	0.410	0.192	0.077	0.308	0.205	0.321	0.551	0.051	0.000
10	0.308	0.517	0.583	0.359	0.615	0.615	0.603	0.513	0.526	0.000	0.192	0.051	0.423	0.205	0.115	0.346	0.231	0.359	0.577	0.064	0.000
9	0.321	0.533	0.583	0.359	0.654	0.615	0.615	0.526	0.577	0.000	0.205	0.064	0.436	0.218	0.154	0.385	0.256	0.385	0.603	0.077	0.000
8	0.333	0.550	0.600	0.359	0.692	0.615	0.628	0.538	0.615	0.013	0.218	0.103	0.449	0.231	0.192	0.423	0.282	0.410	0.641	0.090	0.000
7	0.346	0.550	0.617	0.359	0.731	0.615	0.641	0.551	0.654	0.038	0.231	0.141	0.462	0.244	0.231	0.462	0.308	0.436	0.679	0.103	0.000
6	0.359	0.550	0.633	0.359	0.756	0.615	0.654	0.551	0.692	0.064	0.231	0.179	0.474	0.256	0.269	0.500	0.333	0.449	0.718	0.115	0.000
5	0.372	0.550	0.650	0.359	0.769	0.615	0.667	0.551	0.731	0.090	0.218	0.218	0.474	0.269	0.308	0.551	0.359	0.462	0.756	0.128	0.000
4	0.385	0.550	0.667	0.372	0.769	0.615	0.667	0.551	0.769	0.115	0.205	0.256	0.462	0.282	0.346	0.603	0.385	0.474	0.795	0.141	0.000
3	0.397	0.550	0.667	0.385	0.756	0.615	0.667	0.551	0.808	0.141	0.192	0.295	0.449	0.295	0.385	0.654	0.410	0.487	0.833	0.154	0.000
2	0.410	0.550	0.667	0.397	0.744	0.615	0.654	0.551	0.846	0.154	0.179	0.333	0.436	0.308	0.423	0.692	0.436	0.487	0.872	0.167	0.000
1	0.423	0.550	0.650	0.410	0.731	0.603	0.641	0.564	0.872	0.167	0.167	0.372	0.423	0.308	0.462	0.731	0.462	0.487	0.897	0.192	0.000
0	0.423	0.550	0.633	0.410	0.718	0.590	0.615	0.564	0.859	0.179	0.154	0.397	0.410	0.308	0.462	0.769	0.487	0.474	0.910	0.218	0.000
-1	0.410	0.533	0.600	0.410	0.705	0.577	0.577	0.551	0.821	0.192	0.141	0.423	0.397	0.295	0.462	0.756	0.500	0.462	0.897	0.231	0.000
-2	0.397	0.500	0.567	0.410	0.679	0.564	0.526	0.538	0.782	0.205	0.128	0.449	0.385	0.282	0.423	0.731	0.513	0.449	0.872	0.244	0.000
-3	0.385	0.467	0.533	0.397	0.654	0.538	0.474	0.526	0.731	0.218	0.115	0.462	0.359	0.256	0.385	0.692	0.513	0.436	0.846	0.256	0.000
-4	0.359	0.433	0.500	0.385	0.628	0.513	0.423	0.500	0.679	0.231	0.103	0.462	0.333	0.231	0.346	0.654	0.487	0.423	0.808	0.256	0.000
-5	0.333	0.383	0.467	0.359	0.603	0.487	0.372	0.474	0.628	0.244	0.077	0.436	0.308	0.205	0.308	0.603	0.449	0.410	0.769	0.256	0.000
-6	0.308	0.333	0.417	0.321	0.577	0.462	0.321	0.449	0.577	0.256	0.064	0.397	0.269	0.179	0.269	0.551	0.410	0.397	0.718	0.256	0.000
-7	0.282	0.283	0.367	0.282	0.551	0.436	0.269	0.423	0.526	0.256	0.051	0.359	0.231	0.154	0.231	0.500	0.372	0.385	0.667	0.269	0.000
-8	0.256	0.233	0.317	0.256	0.526	0.410	0.218	0.397	0.474	0.256	0.038	0.321	0.205	0.128	0.192	0.449	0.333	0.359	0.615	0.282	0.000
-9	0.231	0.200	0.267	0.231	0.487	0.385	0.167	0.372	0.423	0.256	0.026	0.282	0.179	0.103	0.154	0.397	0.295	0.346	0.564	0.295	0.000
-10	0.205	0.167	0.217	0.205	0.449	0.359	0.128	0.346	0.385	0.256	0.013	0.244	0.154	0.077	0.115	0.359	0.256	0.333	0.513	0.295	0.000
-11	0.179	0.133	0.200	0.192	0.410	0.333	0.090	0.321	0.346	0.244	0.000	0.205	0.128	0.051	0.077	0.321	0.218	0.321	0.462	0.295	0.000
-12	0.154	0.100	0.183	0.179	0.372	0.308	0.051	0.295	0.321	0.244	0.000	0.167	0.103	0.026	0.038	0.282	0.179	0.308	0.423	0.295	0.000
Max value	0.423	0.550	0.667	0.462	0.769	0.615	0.667	0.564	0.872	0.256	0.231	0.462	0.474	0.436	0.462	0.769	0.513	0.487	0.910	0.295	0.000
Max possible months	78	60	60	78	78	78	78	78	78	78	78	78	78	78	26	78	78	78	78	78	26
Actual max months	33	33	40	36	60	48	52	44	68	20	18	36	37	34	12	60	40	38	71	23	0

Notes:

1. Computations actually done out to +/-36 months; +/- 12 presented to save space.
2. France's maximum occured at +20 to +25 mths at a value .462 and Sth Africa's maximum occurred at +30 and 31 mths at a value of .436.
3. "Max possible" is max no of corresponding recession mths possible given country data availability. "Actual max" is the actual maximum no of mths of recession correspondence.
4. Shaded cells represent, for each country, the lags/leads at which the maximum ratio of recession correspondence occurs.

behind the world recession. In the Table 3 we have highlighted the lead(s)/lag(s) at which the largest value occurs.

We summarise Table 3 results as follows.

First, in addition to the 20th Century locomotor countries – US, UK, Germany and Japan – Canada, Mexico, Brazil and all the European countries in the sample – except for France and Italy – display a maximum value of recession concordance which is within +/- 3 months of lag 0. In most cases this maximum is > 0.5 and in all cases greater than 0.4, again suggesting a reasonably high degree of recession concordance – or synchronization – of these countries with the world cycle recessions.

In the cases of Italy and France, it can also be noted that the recession concordance at lag zero was .718 and .41, respectively. Even though the actual maximum value occurred outside the three-month window, it is nonetheless clearly the case that there is a very strong degree of recession concordance at zero lag for these two European countries also.

Second, apart from the US having a very high probability of being in recession if the world cycle is in recession (understandable given the huge size of the US economy), the other countries which have a very high probability of being in recession at the same time are Germany and Austria (and to a lesser extent Italy), these probabilities interestingly being much higher than that for the UK and Japan (the other two 20th Century locomotor countries).

Third, of particular interest is that the two East Asian Tigers – or newly industrialized countries – of Taiwan and Korea which are included in the set of countries both appear to lead world cycle recessions, apparently by between three and nine months. This apparently counterintuitive result is discussed further below.[22]

We propose the following possible explanation. The economies of Taiwan and Korea are more heavily dependent on manufacturing than the developed countries of the world – like the US, UK, Germany, Japan and other Western European countries. These developed countries have service sectors which are larger proportions of their economies than is the case in countries such as Taiwan and Korea. And, of course, it is well known the service sector is less cyclically prone than manufacturing (see Layton and Moore, 1989). This means then, for example, that as far as the economy as a whole is concerned, any emerging cyclical downswing in manufacturing may be mitigated, at least for a time, by service sector economic activity holding up.

This would then delay the occurrence of the business cycle peak for these more services-intensive countries as compared with more manufacturing-intensive countries like Taiwan and Korea whose service sectors were not large enough to mitigate the cyclical impacts on their manufacturing sectors. Thus, any cyclical impact on manufacturing arising from, for example, cyclical swings in commodity prices, would be likely to be reflected earlier in the business cycle TPs of countries such as these, than would be the case for other more economically developed countries.

The results of econometric synchronization testing are presented in Table 4. Again we not only estimate equation (3.1) for each country at lag zero, but also estimate the equation after lagging each country's chronology for a set of lags out to +/- 24 months. In Table 4 we highlight the lead/lag for each country where the maximum "local" absolute value of $\hat{\rho}_j$ occurs – and the lag closest to lag 0 if the largest value occurs more than once – provided its absolute t-ratio is > or very near 2.[23]

We summarise what we believe are the most interesting results as follows.

Table 4. **Synchronization testing estimation results**

lag/lead			24	21	18	15	12	9	6	3	0	-3	-6	-9	-12	-15	-18	-21	-24
Canada Jan. 52-Dec. 10	GMM	Coeff	0.01	0.05	0.08	0.12	0.17	0.21	0.26	0.31	0.35	0.32	0.24	0.15	0.06	-0.03	-0.12	-0.15	-0.15
		t-stat	0.08	0.41	0.68	0.96	1.34	1.70	2.01	2.30	2.46	2.24	1.81	1.25	0.59	-0.46	-2.94	-4.07	-4.03
Mexico Jan. 79-Dec. 10	GMM	Coeff	0.20	0.24	0.26	0.25	0.26	0.32	0.37	0.37	0.37	0.31	0.16	-0.04	-0.17	-0.29	-0.34	-0.33	-0.32
		t-stat	1.27	1.57	1.66	1.65	1.66	2.14	2.37	2.40	2.36	1.92	1.05	-0.28	-1.72	-4.47	-5.30	-5.28	-5.17
Brazil Jan. 81-Dec. 10	GMM	Coeff	0.12	0.25	0.28	0.29	0.28	0.25	0.37	0.51	0.56	0.48	0.36	0.14	-0.05	-0.13	-0.23	-0.34	-0.28
		t-stat	0.75	1.47	1.73	1.75	1.59	1.40	2.27	3.68	4.80	3.51	2.09	0.76	-0.28	-0.76	-1.64	-4.03	-2.24
France Jan. 53-Dec. 10	GMM	Coeff	0.41	0.38	0.35	0.33	0.29	0.24	0.24	0.26	0.30	0.30	0.24	0.12	0.04	-0.01	-0.04	-0.04	-0.04
		t-stat	2.77	2.70	2.45	2.41	2.15	1.81	1.86	2.06	2.36	2.32	1.89	1.02	0.37	-0.08	-0.40	-0.41	-0.38
Italy Jan. 56-Dec. 10	GMM	Coeff	0.02	0.06	0.13	0.24	0.38	0.52	0.66	0.70	0.66	0.60	0.50	0.41	0.27	0.15	0.06	-0.02	-0.10
		t-stat	0.19	0.48	0.99	1.75	2.84	4.12	5.46	6.33	5.89	4.66	3.65	2.86	1.96	1.15	0.54	-0.24	-1.18
Spain Jan. 69-Dec. 10	GMM	Coeff	0.31	0.39	0.47	0.50	0.50	0.50	0.50	0.50	0.49	0.44	0.35	0.26	0.17	0.08	0.01	0.00	-0.08
		t-stat	2.16	2.80	3.40	3.58	3.61	3.62	3.63	3.63	3.53	3.21	2.57	1.93	1.31	0.66	0.05	0.04	-0.84
Switzerland Jan. 56-Dec. 10	GMM	Coeff	-0.02	0.12	0.23	0.32	0.38	0.47	0.52	0.55	0.52	0.38	0.20	0.01	-0.15	-0.26	-0.26	-0.25	-0.25
		t-stat	-0.19	0.93	1.72	2.35	2.77	3.54	4.06	4.46	4.06	2.81	1.55	0.10	-2.37	-5.30	-5.41	-5.39	-5.32
Sweden Jan. 69-Dec. 10	GMM	Coeff	0.27	0.29	0.30	0.30	0.30	0.32	0.37	0.37	0.39	0.35	0.27	0.17	0.07	-0.03	-0.08	-0.13	-0.17
		t-stat	1.84	2.02	2.15	2.17	2.18	2.33	2.68	2.70	2.78	2.58	1.95	1.25	0.55	-0.20	-0.64	-1.14	-1.68
Austria Jan. 62-Dec. 10	GMM	Coeff	-0.02	0.02	0.06	0.16	0.27	0.44	0.60	0.74	0.87	0.76	0.57	0.38	0.22	0.12	0.04	0.00	-0.04
		t-stat	-0.18	0.21	0.54	1.27	2.09	3.60	5.83	9.61	10.53	7.30	4.66	2.91	1.70	1.02	0.39	0.03	-0.41
Korea Jan. 62-Dec. 10	GMM	Coeff	0.04	0.05	0.02	-0.03	-0.08	-0.09	-0.05	0.05	0.11	0.16	0.21	0.22	0.21	0.21	0.20	0.20	0.20
		t-stat	0.48	0.59	0.22	-0.61	-2.61	-3.14	-1.27	0.68	1.24	1.59	1.87	1.94	1.74	1.76	1.76	1.76	7.74
Australia Jan. 52-Dec. 10	GMM	Coeff	0.09	0.08	0.08	0.08	0.09	0.14	0.18	0.15	0.10	0.05	-0.01	-0.06	-0.10	-0.11	-0.11	-0.11	-0.11
		t-stat	0.87	0.83	0.80	0.79	0.96	1.37	1.59	1.39	1.03	0.61	-0.17	-1.34	-3.57	-3.60	-3.61	-3.61	-3.62

Table 4. **Synchronization testing estimation results** *(cont.)*

lag/lead			24	21	18	15	12	9	6	3	0	-3	-6	-9	-12	-15	-18	-21	-24
Taiwan Jan. 62-Dec. 10	GMM	Coeff	-0.08	-0.08	-0.08	-0.08	-0.06	-0.12	0.09	0.24	0.38	0.47	0.46	0.32	0.17	0.03	-0.08	-0.08	-0.08
		t-stat	-2.84	-2.84	-2.84	-2.83	-2.23	-0.31	1.26	2.30	3.17	3.73	3.47	2.68	1.86	0.62	-2.78	-2.83	-2.80
New Zealand Jan. 62-Dec. 10	GMM	Coeff	0.03	0.00	0.04	0.05	0.10	0.15	0.20	0.20	0.16	0.11	0.02	-0.10	-0.19	-0.26	-0.31	-0.33	-0.31
		t-stat	0.27	0.03	0.29	0.39	0.77	1.13	1.46	1.47	1.16	0.84	0.18	-0.89	-2.09	-3.64	-5.70	-6.54	-6.12
South Africa Jan. 62-Dec. 10	GMM	Coeff	0.23	0.17	0.05	0.00	-0.04	-0.01	0.04	0.09	0.12	0.09	-0.01	-0.11	-0.20	-0.27	-0.27	-0.27	-0.26
		t-stat	1.73	1.28	0.46	0.01	-0.40	-0.10	0.32	0.70	0.92	0.68	-0.09	-1.25	-3.58	-5.55	-5.62	-5.60	-5.51
Russia Jan. 95-Dec. 10	GMM	Coeff	-0.18	-0.19	-0.21	-0.23	-0.25	-0.12	0.01	0.14	0.27	0.22	0.07	-0.14	-0.24	-0.34	-0.35	-0.34	-0.33
		t-stat	-2.66	-2.77	-3.03	-3.17	-3.30	-0.97	0.07	0.69	1.24	1.00	0.34	-0.96	-2.34	-3.93	-4.01	-3.89	-3.70
United States Jan. 52-Dec. 10	GMM	Coeff	-0.05	-0.01	0.03	0.05	0.08	0.22	0.36	0.53	0.68	0.68	0.44	0.28	0.15	0.01	-0.10	-0.09	-0.09
		t-stat	-0.50	-0.08	0.23	0.44	0.72	1.87	3.00	4.82	6.79	6.04	3.94	2.33	1.39	0.09	-1.31	-1.27	-1.22
Japan Jan. 53-Dec. 10	GMM	Coeff	-0.14	-0.10	-0.06	-0.02	0.00	0.06	0.15	0.24	0.32	0.38	0.31	0.17	0.03	-0.11	-0.22	-0.19	-0.14
		t-stat	-2.61	-1.29	-0.67	-0.21	0.03	0.52	1.17	1.74	2.28	2.60	2.14	1.30	0.27	-1.69	-4.85	-3.41	-1.81
Germany Jan. 52-Dec. 10	GMM	Coeff	-0.01	0.08	0.16	0.25	0.34	0.43	0.56	0.70	0.82	0.79	0.66	0.48	0.30	0.02	0.06	-0.03	-0.09
		t-stat	-0.07	0.60	1.15	1.78	2.43	3.16	4.58	7.22	11.71	12.04	6.44	3.73	2.12	0.16	0.50	-0.26	-0.86
United Kingdom Jan. 52-Dec. 10	GMM	Coeff	-0.13	-0.13	-0.07	0.02	0.16	0.30	0.39	0.43	0.44	0.39	0.35	0.29	0.24	0.22	0.22	0.19	0.15
		t-stat	-3.79	-3.78	-1.54	0.27	1.49	2.35	2.90	3.14	3.15	2.94	2.62	2.14	1.86	1.63	1.64	1.48	1.24
India Jan. 56-Dec. 10	GMM	Coeff	-0.14	-0.14	-0.14	-0.14	-0.11	-0.06	-0.01	0.04	0.10	0.16	0.17	0.20	0.22	0.22	0.22	0.20	0.20
		t-stat	-4.00	-4.00	-4.00	-3.99	-2.66	-0.92	-0.13	0.36	0.87	1.34	1.45	1.72	1.90	1.91	1.81	1.69	1.66
China Jan. 84-Dec. 10	GMM	Coeff	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06
		t-stat	-1.80	-1.80	-1.80	-1.80	-1.80	-1.80	-1.80	-1.79	-1.79	-1.79	-1.80	-1.80	-1.80	-1.80	-1.80	-1.80	-1.80

Notes: Estimation results of estimating Eqn 3.1 by GMM to allow for non-iid disturbance term under the null of no synchronisation; Coeff is estimate of p (-1 <= p <= 1); GMM t-stats are considered to be approximately normally distributed under the null; shaded cells are those with the maximum "local" absolute value of p-estimate - closest to lag 0 - and provided its absolute t-ratio is > or very near 2.

First, of the six countries used to compile the world chronology, perhaps not surprisingly, the US, Germany and the UK are all positively synchronized with the world chronology with maximum value of $\hat{\rho}_j$ at lag 0. In Japan's case the maximum value of $\hat{\rho}_j$ occurs at lag -3, implying Japan may tend to lead the world cycle by a short lead of 3 months. Of course, as mentioned earlier, in business cycle analysis 3 months is within the window usually regarded as corresponding to coincidence.[24]

Second, in North America, Canada appears to be significantly positively synchronised with the world cycle at zero lag, while in Central and South America, Mexico and Brazil also appear to be significantly positively synchronized at zero lag.[25]

Third, the results suggest that other European countries' business cycles appear to be either coincident with the world cycle (Sweden and Austria) or lag behind the world cycle by just three months (Italy, Spain, Switzerland). In France's case, whilst the maximum value of $\hat{\rho}_j$ occurs at a rather long positive lag, the statistically significant positive value of $\hat{\rho}_j$ at lag zero is not very much smaller than that at the long lag, suggesting France too may be interpreted as having a strong positive synchronization with the world chronology at zero lag.

Fourth, by this approach, the two newly industrialized countries of East Asia included in the country set, namely Korea and Taiwan, again appear to lead the world cycle (with positive synchronisation) by between 3 and 9 months.[26]

Finally, we draw attention to the statistically significant negative $\hat{\rho}_j$s at relatively long negative lags for Canada, Australia, Brazil, New Zealand and South Africa. The interpretation of this is that these countries' business cycles appear to be negatively synchronized with the world cycle at long leads ahead of the world cycle. We discuss this further below.

All five of these countries are known to be significant commodity exporting countries, and whose currencies, national income and general economic activity are significantly affected by swings in commodity prices. Thus, we speculate here that it is this characteristic which is responsible for what appears to be present in the business cycle chronology data.

More specifically, we propose the following may be a reasonable explanation of what may be occurring. If the demand for, and the prices of, commodities decline – perhaps because of a recent world cyclical downturn – this will exert external downward cyclical pressure on the economies of these countries. However, such cyclically reduced commodity prices will also eventually feed through into lower input costs for the major manufacturing countries of the world, thereby allowing for the possibility of a cyclical upturn in those economies.

This mechanism, if reasonably systematic and recurring, would manifest as cyclical upturns (or downturns) in the larger manufacturing countries of the world occurring some time after cyclical downturns (or upturns) in the commodity exporting countries, or, in other words, the occurrence in the data of a leading negative synchronisation between the business cycles of the commodity exporting countries and that of the world business cycle. On this explanation of the economic forces perhaps at work, Table 4 suggests that the average delay in this process is between 15 and 21 months.

5. Conclusions

We summarise the above-described synchronization results from the three approaches into the following proposed broad findings.

First, perhaps not surprisingly, the world's four 20th century locomotor economies of the US, UK, Germany and Japan are statistically significantly and reasonably strongly positively synchronised with the world cycle. This is not – at least not yet – the case with China and India, the emerging 21st century likely powerhouse economies.

Second, European countries in the sample are either positively synchronised with the world cycle at zero lag or lag it by around three months.

Third, the NAFTA countries (US, Canada and Mexico) are, perhaps again not unexpectedly, quite strongly positively synchronised with the world cycle and with each other.

Fourth, the single South American country included in the sample, Brazil, is strongly positively synchronised with the world cycle as well as with the NAFTA countries – but – at least to date – cyclically behaves very differently from the other BRIC countries of China, Russia and India with respect to the proposed world business cycle chronology.

Fifth, the newly industrialized East Asian countries included in the sample appear to lead the world cycle by about three to nine months.

Finally, and very interestingly, there appears to be some a priori evidence of a long leading *negative* synchronisation between the significant commodity exporting countries of Canada, Australia, Brazil, New Zealand and South Africa and the world business cycle chronology.

As the last two results may appear to be somewhat counterintuitive we have also attempted in the previous section to provide possible – but admittedly quite speculative – explanations of what might be the underlying mechanisms driving the international business cycle dynamics seemingly in the chronology data. A possible future line of inquiry might therefore be to: first further confirm the veracity of the existence of such international recession chronology patterns; and, if confirmed, to determine using an appropriate framework whether the proposed explanations are supported or not. Another issue for future research would be to see how robust the broad findings in the paper are to alternative ways of defining and dating a "world chronology" or set of "synchronized international recessions". On this, there appears as yet to be no general current consensus on such a definition and dating, and it was for that reason that we proposed the definition and chronology employed in this paper.

Notes

1. The issue was subsequently revisited by Artis et al. (2004) in which they identify a common cycle in Europe, date it, and investigate the extent of relationship of each member country's cycle to it.
2. The recent extreme divergence of unemployment rates in the Eurozone area post-GFC would seem to suggest this view held, and continues to hold, considerable currency.
3. Later, in a subsequent paper, Montoya and de Haan (2007) found in favour of increased synchronization in the Euro area over the period 1975-2005, but also found that some regions in the area nonetheless exhibited little synchronization.
4. Although per capita data were also used, for example, by Antonakakis (2012) and Kose et al. (2003).
5. Yet another paper which found in favour of increased synchronization in the EU post-Euro is Furceri and Karras (2008).
6. See also, Kose et al. (2003).
7. The reader may refer to, for example, Moore (1967) and, more recently, Layton and Banerji (2003), for more detailed discussion of the definition.

8. Quoted from the NBER website, *www.nber.org/cycles/cyclesmain.html*, in July, 2014
9. The indicators comprise output, sales, employment and income measures. A turning point is a date at which an economic indicator changes from a cyclical upswing into a downswing (a peak) or from a cyclical downswing into an upswing (a trough).
10. The full list is: Australia, Brazil, Austria, Canada, China, France, Germany, India, Italy, Japan, Mexico, New Zealand, Russia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, the U.K. and the U.S.
11. A coincident index is a composite of component coincident indicators – each of which is a partial measure of the state of the business cycle – and provides one summary measure of the current state of the business cycle in any given measurement period. A leading index is similarly a composite of component leading economic indicators – movements in each of which lead the business cycle – and provides in any given measurement period one summary indicator of the likely future state of the business cycle.
12. In 2013, the percentage was 52% in USD terms.
13. In 2013, in USD terms the percentage was 77.3%.
14. Note that, using this approach our prime focus is on the TPs in the world cycle. Whilst there may well be additional TPs in an individual country's business cycle, these are not of interest in this analysis and their existence does not detract from any correspondence evident at TPs in the world cycle.
15. This Harding-Pagan approach has also recently been used by, for example, Altavilla (2004) and Bergman and Jonung (2011).
16. Some may argue that "recession concordance" involves a degree of loss of business cycle information, in that expansionary periods are also part of the business cycle! However, our view is simply that (classical) recessions are the relatively much rarer event these days for modern economies and, for two economies to be truly regarded as synchronized, the focus needs to be on the timing of their recessionary episodes.
17. The model was separately estimated with the world chronology as explanatory variable (along with a constant) with each country's chronology as the dependent variable and for each lead and lag listed in the table. In each case a one-period lag of the explanatory variable was used as an instrument in the estimation and Newey-West HAC weighting matrix was used to estimate the long-run parameter estimate covariance matrix. The Newey-West HAC weighting matrix is known to be a Heteroscedasticity and autocorrelation consistent estimator of the long-run covariance matrix. Econometric software EViews was used for the estimation.
18. This approach automatically adjusts for the expected values of the two binary variables used in the estimation – in calculating $\hat{\rho}_j$ – and so it also avoids the problems mentioned earlier with the unadjusted concordance index measure.
19. China has not experienced a classical recession since 1989 (see Table 1) and so there cannot be any TP correspondence with the WC.
20. Inter alia, Aguiar-Conraria and Soares (2011) also discussed issues of business cycle dissimilarities being correlated with geographical distance.
21. Again, Aguiar-Conraria and Soares (2011) noted this and expressed it in the rather charming way that Austria's business cycle had somewhat of a German "accent". They similarly found that Spain's business cycle had somewhat of a French "accent".
22. As previously noted, since China has not had a classical recession since 1989 its computed value of recession concordance with the WC is zero at all leads/lags. This contrasts with the other three BRIC countries (refer to Table 1).
23. Following the previous Fn, this implies the regression results in Table 4for China simply reflect this very low level of correlation between Sj_t, and S_{wt}, and that this is unaffected by the lagging process.
24. We offer no interpretation for the negative values of $\hat{\rho}_j$ at lead/lag -18 in Japan's case and +21 in the UK's case and have elected to ignore them.
25. The apparent significant negative synchronisation at long negative lags for Canada and Brazil is discussed below. The authors do not have a ready interpretation for the apparently similar situation in Mexico's case.
26. Again, the authors do not have any economic explanation of the quite small (but seemingly significant) negative $\hat{\rho}_j$ values at lags +9 (Korea) and +15 (Taiwan).

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Business cycle dynamics: A bottom-up approach with Markov-chain measurement

by
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Business cycle dynamics can be seen as footprints left by individual decision makers. Tracing those footprints we offer a novel, largely model independent and exogenous measure of the business cycle dynamics. This measure also, allows for distinguishing positive and negative shocks without prior estimation. Utilizing more than twenty-thousand observations of firms surveyed quarterly in the periods (1999-2006), we employ a Markov-chain approach combined with conventional time series econometrics for gauging the dynamics of business cycles. Since we start the analysis with firm level data we label our method the "bottom-up approach".

Keywords: Business cycle dynamics, shock identification, Markov-chain, impulse-response analysis.

JEL classification: E32, C40, C50.

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1. Introduction

Time and time again business cycles take their tolls in terms of unemployment, loss of income, inflation and other unpleasant consequences. No wonder, therefore, that business cycles are the object of intense scientific debate. Two basic research strands have been established which shed light on the sources and consequences of business cycles. One looks at the economic structures generating business cycles while the other is primarily concerned with their econometric identification. This paper contributes to both these strands of the literature by introducing a novel method for extracting business cycle information from the data and by providing a an approach that distinguishes between positive and negative shocks without prior estimation.

The literature reports two basic ways of extracting business cycles. The first is based on theoretical models where decisions such as the choice of optimal inputs in terms of quantity and prices can be modelled as equilibrium choices. The Keynesian and the monetarist branches of this literature define deviations from equilibrium as residuals, or disequilibrium situations. An example is estimates of differences between actual and potential output based on a Cobb-Douglas production function or Friedman's (1993)'s popular "plucking model".

By contrast, the classical business cycle approaches including the real business cycle (henceforth RBC) theory pose that the economy is always in states of equilibrium. Business cycles are regarded as the consequences of supply shocks changing the equilibrium level. These shifts of the equilibrium levels are observationally equivalent to the notion of business cycles.

All these approaches generally share the basic feature that their empirical implementation requires imposing the economic model structure on the data. Therefore, modelling business cycles and testing the model at the same time turns out to be methodologically very cumbersome, if not impossible (Summers, 1986).

Due to the tight entanglement of theory and empirics we denote this approach "economic filtering". The second way, in contrast to the theory-driven business cycle extraction, alternatively uses technical filters for deriving equilibrium measures. For example, the Hodrick-Prescott filter (Hodrick and Prescott, 1997) assumes a certain stochastic data generating process for the data under consideration.

This process does not need to be derived from economics but allows to decompose a time series in components such as trend, season, and noise. The trend component may henceforth be used as a numerical expression for equilibrium or potential output, for example. Shocks (the noise) are obtained as residual values given the model and data used. Other popular technical approaches in this domain are attributed to Hamilton (1989), or Beveridge and Nelson (1981).

Of course, the distinction between technical and economic filters is not that clear-cut since many technical filters can be given an economic underpinning as Kim and Nelson (1999) have nicely illustrated.

A common feature across approaches is, however, the lack of model independent, exogenous measures of business cycles. This limitation has led to a large body of literature which tries to come up with adequate answers. For example, in the context of RBC models the appropriate identification of technology shocks – a closely related problem – takes centre stage (Basu, Fernald and Kimball, 2006).

This paper contributes to the literature by proposing a novel way of describing the business cycle. This description focusses on measuring the duration of business cycles and differentiating between positive and negative shocks. At this stage we are not yet able to also use our method for dating business cycles.

Our approach rests on three pillars: first, is the consideration of individual, firm level data. Since researchers have become aware of the fact that the standard approach of learning from aggregate data is at odds with results obtained on the micro level (Caballero and Engel, 2003) we stress the importance of firm behaviour before drawing conclusions for the aggregate economy, in line with Clower (1998). The second pillar, is the semantic approach for identifying (dis)equilibrium situations. It builds on the comparison of (implied) intentions of firms to their actual behaviour. This deviation is what we call a business cycle shock (henceforth occasionally simply shock). These shocks can be numerically measured and be given a meaningful interpretation. This method of business cycle shock identification is largely model free and only relies on broad economic reasoning which we consider an advantage. To the best of our knowledge the only study which has undertaken a similar approach is Bouissou, Laffont and Vuong (1986) who look at (*ex post*) mistakes made by firms when formulating expectations about the demand for their products.[1]

Thirdly, given the identification of business cycle shocks and the characterisation of the economy we approximate the shock absorption process of the economy by a Markov-chain. We describe the movement of a firm from one defined state to the other between two periods by a multivariate, discrete Markov-chain of order one and dimension nine. We then use a vector autoregressive model (VAR) interpretation to calculate impulse-responses using the estimates of our Markov-chain model. Hence, we are able to identify the effect of each shock on the economy as well as to estimate the duration of the adjustment processes.

The backbone of our analysis is a new panel data set that combines both qualitative and quantitative information on a micro level basis. Our data set comprises hundreds of firms surveyed quarterly, namely 22 122 observatons in the period 1999-2006 – which provides a wealth of information on how firms behave. Thus, this study not only infers business cycle dynamics based on micro-level data but it also extends the literature by providing a largely model independent, exogenous, measure of the business cycle dynamics which allows to match theory and empirics. A further value added of our approach is it enables to distinguish between positive and negative shocks without prior estimation.

The remainder of the paper is structured as follows. In Section 2 the modelling framework is described, Section 3 establishes a link between the model and our data; Section 4 presents the results of the empirical exercise. Finally, Sections 5 and 6 give an outlook on further research and summarize the findings.

2. The empirical model in a bottom-up approach

We consider a firm that operates at an actual level of capacity utilisation c_t. The subscript t denotes time (e.g. quarter). Obviously, the degree of capacity utilisation for any

given level of capacity is positively associated with the level of output. A firm's output in turn depends on internal and external factors. The firm for example determines its capacities by investments but depends on labour market conditions for being able to employ the available capacities as desired. Furthermore, exogenous conditions like the market price for its output and customers' aggregate income impact actual capacity utilisation.

For determining the actual capacity utilisation level and hence the output level of a firm we assume that each firm tries to operate at a profit optimizing level of capacity utilisation in t which we denote by c_t^*. Due to external and internal shocks a firm may suffer from, the current level of capacity utilisation will very often depart from the profit maximizing level:

$$c_t - c_t^* = \varepsilon_t \tag{1}$$

$$\varepsilon_t \sim (\mu_\varepsilon, \sigma_{\varepsilon,t})$$

$$E(\sigma_{\varepsilon,t} \mid \sigma_{\varepsilon,t-1}) < \infty$$

In principle, ε_t is equivalent to the business cycle shock that draws apart desired and actual capacity utilisation. For example, according to Friedman's (1993) plucking model ε_t would be strictly non-positive and c_t^* would be equivalent to the secular output trend. In Keynesian and new Keynesian theories ε_t can be both, negative, or positive, and c_t^* would be the equivalent to the economy's potential or full employment level.

We assume that the variance of ε_t is bounded conditional on knowing its past values. The unconditional variance may grow without limits, however. In other words, we do not impose covariance stationarity on the business cycle as is often done especially with technical filter approaches, but leave this question to be answered by the data. Furthermore, it is worthwhile stressing that ε_t may or may not be predictable. By definition it is just the difference between a desired and an actual output level. Hence, ε_t summarises all unpredictable news ("shocks" in the econometric sense) and predictable gaps between intentions and achievements. Those gaps arise, for example, because a firm may expand its capacities at some projected path knowing that while so doing it does not yet operate at its optimal capacity utilisation level. We leave it to the data to tell the exact properties of ε_t, the business cycle shocks.

Replacing c_t by an observable variable such as GDP paves the way for widely used business cycle analysis tools. One might for example assume a (log-)linear time trend for GDP and estimate the trend component with actual data. Instead of (log-)linear deterministic trends, time varying and non-linear trends could likewise be used. Furthermore, various filter techniques like Baxter-King (Baxter and King, 1999) and Hodrick-Prescott (Hodrick and Prescott, 1997), or structural time series analysis (Harvey, 1989) all permit the extraction of approximations to c_t^*, or rather its GDP equivalent which can then be interpreted as potential, equilibrium, optimal, or trend output and the like.

Note that all those filter techniques usually start with some aggregated time series such as GDP, or industrial production. They are hence without explicit and direct linkage to actual firm behaviour. Moreover, the time series based extractions are necessarily built on technical assumptions such as that the empirical counterpart of ε_t add up to zero over time, or are covariance stationary.

Those assumptions often lead to undesired properties such as the need for revisions once new data is being made available. Hence, a negative deviation might turn into a

positive one when the information set is updated (see e.g. Orphanides and van Norden, 2005; Graff and Sturm, 2010). The sign of the deviation might also differ between filter methods. Of course, these properties limit the use of those techniques' output and an alternative might be worthwhile considering.

In the following the relationship (1) will be used to derive an interpretable business cycle representation based on firm level data. Let us, therefore, consider the decision making process of a firm. Note that in period t the firm has to decide about the adjustment of capacity utilisation to match next period's optimal level. The firm will adjust such that the utilisation level is optimal in the next period given all constraints it faces. It will, therefore, do so by exploiting all available information subject to information processing costs and further obstacles to adjustment. Thus, the adjustment process can be characterised by

$$c_t + \gamma_t = c^*_{t+1} + u_t \tag{2}$$

$$u_t \sim (0, \sigma_{u,t}), \tag{3}$$

$$\sigma_{u,t} < \infty$$

where γ_t represents all the activities the firm considers necessary and practically as well as economically feasible for adjusting the current level of capacity utilisation to the optimal level in the next period. Following the definition of c^*_t the activities γ_t are chosen subject to the usual restrictions such as financial constraints, information processing capacities, availability of resources at reasonable costs, implementation lags, etc. This interpretation of γ_t therefore, entails cases in which some unpredictable shock, say a sudden surge in the demand for outdoor equipment due to heavy rainfalls cannot be fully coped with within one period.[2] This may happen because it takes time before sufficient production capacities or, say distribution capacities, are available. If so, the value of γ_t will be known in $t-1$ up to some error because the adjustments started in $t-1$ will continue in t quite as planned in $t-1$.[3]

In addition to γ we allow for random measurement errors and a firm specific shock to the adjustment activity which we denote u_t. Quite plausibly, for rational managers this shock should have expectation zero. In order to limit the effect of these errors we assume that the variance of u_t is finite.

Replacing c^*_{t+1} with $c_{t+1} - \varepsilon_{t+1}$ in (1) we may write

$$c_t + \gamma_t = c_{t+1} - \varepsilon_{t+1} + u_t$$

$$c_t - c_{t+1} + \gamma_t = -\varepsilon_{t+1} + u_t$$

$$\Delta c_{t+1} - \gamma_t = -\varepsilon_{t+1} - u_t \tag{4}$$

$$\Delta c_{t+1} - \gamma_t = \eta_t \tag{5}$$

$$E(u_t, \varepsilon_{t\pm s}) = 0 \forall s, t.$$

The relationship in (4) simply states that the difference between the actual change and the desired, economically feasible adjustment in a firm's capacity utilisation is due to a shock consisting of a business cycle component (ε_{t+1}) plus some idiosynchratic, mean zero noise. Therefore, the business cycle variable can be calculated as the average of the difference of actual changes of capacity utilisation and intended adjustments to its optimal level in the next period $t+1$. The properties of η_t depend on γ_t and Δc_{t+1}. If, for

example, η_t was co-variance stationary we could use Wold's (1938) theorem to represent it as an autoregressive process consisting of the sum of two linearly independent components.

It is worthwhile noticing that upon averaging η_t over firms $\eta_t \equiv \varepsilon_{t+1} - u_t$ approaches ε_{t+1} when the sample size gets large. This follows directly from the mean zero assumption in (3) and from assuming that the u_t represent idiosyncratic shocks across firms.

Considering from now on large enough sample sizes we may neglect the influence of u_t. Hence, in the following ε_t will be referred to as the business cycle shock. Shock in this context is thought of as an impulse which potentially changes the path of the whole economy as it drives a wedge between optimal and actual production capacities. The extent to which the resulting gap widens or closes determines the path of the economy. This said, we thus expect our business cycle shock to be informative about the path of the economy but not its being a pure random event.

3. The empirical methodology

3.1. The data

Our data source is a business tendency survey in the manufacturing industry of Switzerland carried out by the KOF Swiss Economic Institute. It covers the years 1989 to 2006 on a quarterly basis. As there was a reclassification of industry branch codes in 1998, we split our sample into the two parts: 1989 to 1998 third quarter with 57 160 observations, and 1999 to 2006 third quarter (22 122 observations). For the sake of brevity we will focus on the more recent sub-sample.

The two survey questions which are most relevant for our analysis are related to the firms' capacity utilisation. One asks whether the firm's technical capacities are currently too high, just right, or too low. The other inquires the degree of the capacity utilisation within the past three months in percentage points, where the firms can choose from a range of 50% to 110% in five percentage steps. From the latter we can calculate the percentage change in production capacity from t to $t + 1$ and compare it to the judgement about capacity utilisation given by the firm in the previous period, that is in t.

Using the terminology established previously we will denote the degree of capacity utilisation by c_t and its first difference by Δc_{t+1}, which reflects the change in c between t and $t+1$. The γ_t is not that easy to translate into the given survey data. Recall that γ_t represents all the activities the firm considers necessary and economically feasible for adjusting the current level of capacity utilisation to the desired level in the next period. Therefore, this variable is hardly quantifiable for empirical investigations.

Nevertheless, from the definition that γ_t incorporates all feasible activities to accomplish the profit maximizing level of capacity utilisation in the next period it can be inferred that if no activities are considered necessary, the current capacities seem to be just right. Otherwise, if the firm feels pressure to take action in order to achieve the desired capacity utilisation, the firm's technical capacities seem to be too high or too low, respectively. These judgements about the technical capacities are well covered in the survey and can be used as a proxy of γ_t in the following way. We define

$$\delta_t \equiv \text{sign of } \gamma_t : \begin{cases} + : \text{current technical capacities are too high } (\gamma_t > 0) \\ = : \text{current technical capacities are just right } (\gamma_t \approx 0) \\ - : \text{current technical capacities are too low } (\gamma_t < 0). \end{cases}$$

Our ability to match the qualitative answer which tells whether or not firms are in need of more capacity and the change in their actual capacity utilisation holds the key for answering the research question. For example, if firms indicate that their *technical capacities* are too low (δ_t = –) actions are considered necessary to adjust capacities upwards as *capacity utilisation* seems to be too high (and therefore not at the desired level) and we observe that their degree of capacity utilisation increases, it is safe to say that this particular firm has been hit by a (positive) business cycle shock ($\varepsilon_{t+1} > 0$). As explained before, such a shock encompasses genuine news as well as afterglows of previous shocks to which the firm could not yet fully adjust.

We thereby allow for both developments that may underlie a change in capacity utilisation. On the one hand, a change in capacity utilisation can be caused by a change in capacities at a constant level of production while on the other hand a firm may adjust the level of production with capacities remaining unchanged.[4]

If capacities are, for example, too low, a firm can react by increasing capacities in order to satisfy the risen demand. As the survey explicitly asks for technical capacities, more precisely production facilities like buildings and machinery, it is perhaps not likely that capacities are adjusted within a quarter. Capacity utilisation itself, on the other hand, is more flexible in the short run and can be matched to sudden events that hit the firm rather quickly by, for example, stocking output. However, we do not know in which way firms adjust when their capacity utilisation changes.[5] For our purpose it is important *that* firms do adjust, not *how*.

3.2. Data properties

Next, we discuss the main data properties. We first examine the data by means of contingency tables as suggested by (Ivaldi, 1992). They are constructed as follows (see Table 1).

Table 1. **The principle structure of the contingency table**

		Realisation Δc_{t+1}		
		+	=	–
Judgement δ_t	+	pp	pe	pm
	=	ep	ee	em
	–	mp	me	mm

The rows describe the judgement of the firms in *t* about their current technical capacity; "+" stands for "too high", "=" for "just right", "–" for "too low". The columns list the possible outcomes in capacity utilisation changes (Δc_{t+1}). A "+" means that the level of capacity utilisation has been augmented between *t* and *t* + 1, a "=" stands for an unchanged level and "–" means a lower level.

On the basis of this table we obtain nine different states of the firms, and we are able to identify states that can be associated with either positive or negative shocks. The remaining states will be considered equilibrium situations or states during which adjustment takes place.

When looking at state *pm*, for example, firms positioned in this field consider their capacities in *t* as "too high", but from *t* to *t* + 1 their degree of capacity utilisation still declines. Using the previous arguments we can classify this state as a situation where a

severe negative shock has hit the particular firm, henceforth large negative shock. The argument for state *mp* is similar. As capacities in *t* are stated as "too low" and the capacity utilisation rises anyway in the next quarter, we can classify *mp* as a state generated by a severe positive shock, henceforth strong positive shock. The equilibrium derived from this observations is the state *ee*, where capacity is "just right" in *t* and hence there follows no change in capacity utilisation in $t + 1$.

In order to minimize firm specific effects and to be able to focus on economy wide business cycles we will calculate the share of firms which assume a certain state. Doing so averages out the effects of u_t in our measurement approach. For the sample 1999-2006 the repartition of percentage shares to the different states of the 3 × 3 matrix is composed as summarised in Table 2.

Table 2. **Contingency table – empirical frequencies of ε_t across firms and time (1999-2006)**

Sample (1999-2006)		Realisation Δc_{t+1}		
		+	=	–
Judgement δ_t	+	4.7	3.7	3.0
	=	25.5	29.9	25.6
	–	2.4	2.7	2.5

Note: The table entries report the shares of firms in % who judge their capacities according to the row labels and likewise experience a change in capacity utilisation as indicated by the column headers.

Apart from simply summarising the data properties, the table shows a few interesting features. For example, the majority of firms finds itself in a situation where capacities are sufficient. After judging their capacities as "just right" in *t*, nearly the same number of these firms report a decrease as well as an increase in their realisation of capacity utilisation one period later. Similarly, firms which have too much capacities will most likely increase their level of capacity utilisation in the following period. By contrast, respondents with too few capacities will most often report an unchanged level afterwards. Furthermore, positive as well as negative shocks do not occur very frequently (e.g. *pm* = 3.0 and *mp* = 2.4).

As regards the marginal probability for reporting a satisfactory state of affairs which averages 80%, this number is very well in line with surveys in other industries which obtain similar results. We add to our arguments here the standard caveat that all survey responses underlie an indifference range within which changes in realised quantitative figures do not translate into reported negative or positive judgements, for example.[6]

We also test for each row whether the mean of the shares of firms distributed in the three possible states per row are significantly different from each other. It shows that the means within a row are significantly different over time (test level: 0.1).[7] All in all, the contingency table points to a rather reliable and intuitively appropriate answering pattern where the responses are overall consistent with at least weak rational expectations on part of the surveyed firms.

4. Characterising business cycle dynamics

4.1. *Survey data and a discrete approximation*

The previous section has shown that (4) can be linked to standard business tendency surveys. Combining the questions regarding the use of capacities and the current level of

capacity utilisation at an individual firm level permits to infer about ε_t, the business cycle measure (see Section 3).

A key property of typical survey data is its discrete nature, however. Therefore, ε_t cannot be measured as a continuous variable but as a categorical variable only. In our case, the surveys enable us to identify nine different realisations of ε_t each of which can be given interpretations as a negative, a positive or a neutral, or a transition shock. There is no chance to quantify the shocks without reference to outside information, however. Therefore, we need other means to progress.

First of all, we note that each firm is at any time subject to one of the nine possible qualities, or rather categories of shocks. As we track the firms over time we are able to observe what category of shock the firm is subject to in any one period. This allows us to do two things. First of all we can describe the current business cycle by calculating the share of firms being subject to any one of the nine shocks.

Depending on their nature (positive, negative, or neutral) we can thus approximate the economy-wide business cycle.[8] Second, we can try to characterise the dynamics of the business cycle not only as a whole but also depending on the properties of the current state during the cycle. The focus of this paper is on this second opportunity.

4.2. *Transition probabilities and Markov-chain*

Now, the question is what are the dynamic properties of ε_t, our proxy for the business cycle? We answer this question as follows. First, we estimate the probability that some specific realisation of ε_t, say mm_t is followed by some other realisation, say mp_{t+1}. To that aim we consider (4) again and define the nine discrete states as in Table 3. This time, however, we replace the unobservable variables by their empirical counterparts. In order to facilitate estimation we then make two simplifying assumptions.

Table 3. **The nine different qualities of ε_t (shocks) and their origin**

		Δc_{t+1}		
		> 0	≈ 0	< 0
δ_t	> 0	pp	pe	pm
	≈ 0	ep	ee	em
	< 0	mp	me	mm

ASSUMPTION 1 (Markov chain). *Firms at state s_j, $1 \leq j \leq 9$ in period t will move to state s_k, $1 \leq k \leq 9$ with constant probability $p_{j,k}$.*

ASSUMPTION 2 (Homogeneity). *The firms in our sample are homogeneous with respect to their typical response pattern.*

Remark 1. An alternative way to look at assumption 1 is to assign the economy an autoregressive (AR) behaviour that will be approximated by a discrete Markov-chain. In contrast to a simple AR representation of a single state, all nine states are modelled simultaneously. As a consequence, the marginal process for a single state (e.g. the positive shock) has an autoregressive-moving average representation that allows a much richer dynamic than a simple AR process of order one (Lütkepohl, 2006).

Remark 2. Assuming homogeneity helps simplifying the analysis. While there might be arguments that imply different responses depending on the size of the firm, for example,

even our large data set does not provide enough information for sensibly estimating the required 81 transition probabilities conditional on the firm characteristics.

Interestingly, there is no need to a priori assume stationarity. Whether or not the economy behaves explosively (or implosive) can be left to the estimation of the transition matrix. In their analysis of demand shocks faced by individual firms Bouissou et al. (1986) also use a Markov-chain approximation. Their results point to a non-ergodic Markov process.

In sum, we suggest to regard the move from state $s_{j,t}$ to $s_{k,t+1}$, $1 \leq j,k \leq 9$ to be ruled by a 9-dimensional Markov-chain. We thus define

$$pj,k = Prob(s_{k,t+1} \mid s_{j,t}), j,k = 1,\ldots,9 \tag{6}$$

$$\sum_{k=1}^{9} p_{j,k} = 1 \forall j \tag{7}$$

where j and k denote either of the 9 states defined before. In order to find the adjustment paths of the firms, we have to estimate the implied 9×9 matrix of transition probabilities. To facilitate estimation we need to calculate the repartition of firms to the different states of the contingency table both for t to $t + 1$ and $t + 1$ to $t + 2$.[9] Matching these three dates leaves us 17 526 observations.

It is then checked in which state the firms are in t and where they are in t +1. As an intermediate result we obtain a 9×9 matrix, whose elements show the frequency by which firms move from a state given by the row number to the state given by the column number. Table 4 illustrates the results for our sample. For example, of all 823 firms that take position *pp* at time t, 105 will be found in state *pp* at time t +1 too, while 134 move to *ee*, the equilibrium state.

Table 4. **One-step-transition frequencies**

t /*t* +1	pp	pe	pm	ep	ee	em	mp	me	mm	sum
pp	105	95	158	124	134	187	6	6	8	823
pe	158	219	89	79	71	35	5	4	1	661
pm	198	108	57	80	36	24	11	4	2	520
ep	27	41	68	883	1 303	1 853	50	120	156	4 501
ee	56	69	71	1 222	2 458	1 251	41	90	42	5 300
em	235	126	86	1 874	1 115	833	93	52	29	4 443
mp	2	3	5	44	43	110	41	43	93	384
me	7	4	2	34	104	65	55	133	71	475
mm	13	4	2	115	63	77	72	43	30	419

Note: The cells report the number of firms in the sample which are associated with the row state in t and the columns state in t +1.

Table 4 tells a number of interesting stories about the economy. First of all, the most prominent position for a firm is equilibrium *(ee)*. Once being there it is most likely that the firm will stay there. This is only true also for positions *pe* and *me*. On the other hand, more than one half of the firms in *ee* move out of there the following period. This can be taken as an indication that shocks occur rather frequently and hence firms are constantly forced to adjust in one way or another.

Thus, measuring the time it takes before a firm gets active may not be an appropriate measure of the actual speed of adjustment since during that time span additional shocks

hit the firm making it impossible to relate the eventual action to a particular point in time. The adjustment measured should thus be regarded as the typical adjustment process in an environment that is characterised by both frequent shocks and the permanent struggle for coping with them.

Conditioning on the respective initial state, the one-step transition probabilities can be defined. The one-step probability of moving from state *pp* to state *pp* again will be denoted p_{11}. The estimated one-step-transition probabilities are collected in the matrix $A_{i=1}$ whose 81 elements $a_{j,k}$, $j, k = 1,\ldots, 9$ correspond to the p_{jk}.

For the sample period we obtain the following estimates

$$\hat{A}_1 = \begin{bmatrix} 0.1276 & 0.1154 & 0.1920 & 0.1507 & 0.1628 & 0.2272 & 0.0073 & 0.0073 & 0.0097 \\ 0.2390 & 0.3313 & 0.1346 & 0.1195 & 0.1074 & 0.1074 & 0.0076 & 0.0061 & 0.0015 \\ 0.3808 & 0.2077 & 0.1096 & 0.1538 & 0.0692 & 0.0462 & 0.0212 & 0.0077 & 0.0038 \\ 0.0060 & 0.0091 & 0.0151 & 0.1962 & 0.2895 & 0.4117 & 0.0111 & 0.0267 & 0.0347 \\ 0.0106 & 0.0130 & 0.0134 & 0.2306 & 0.4638 & 0.2360 & 0.0077 & 0.0170 & 0.0079 \\ 0.0529 & 0.0284 & 0.0194 & 0.4218 & 0.2510 & 0.1875 & 0.0209 & 0.0117 & 0.0065 \\ 0.0052 & 0.0078 & 0.0130 & 0.1146 & 0.1120 & 0.2865 & 0.1068 & 0.1120 & 0.2422 \\ 0.0147 & 0.0084 & 0.0042 & 0.0716 & 0.2189 & 0.1368 & 0.1158 & 0.2800 & 0.1495 \\ 0.0310 & 0.0095 & 0.0048 & 0.2745 & 0.1504 & 0.1838 & 0.1718 & 0.1026 & 0.0716 \end{bmatrix}$$

where each row sums up to one.

The typical adjustment pattern of firms implies that after being hit by a shock a vast majority of firms starts to adjust immediately. Most of them do so by adjusting capacity utilisation. For example, the typical path of, say, a positive shock (initial position *mp*) is $mp \rightarrow mm \rightarrow ep \rightarrow em \rightarrow ep$ .... The adjustment closes with a sustained switching between the two near equilibrium states *em* and *ep*.

The probability of jumping from a state of a positive shock to a state being regarded a negative shock (from *mp* to *pm*) and vice versa is comparably low. In general, a move from one of the more extreme situations which are given in the lower left and top right 3 × 3 sub matrices to the other extreme positions appears very unlikely. This conclusion can be inferred from the small numbers in these parts of the matrix. In other words, extreme moves are very rare which is reassuring in the sense that the data under investigation has properties that comply with straightforward economic reasoning.

The fact that most of the firms start to adjust immediately can be confirmed by looking at the probabilities of starting in a shock state and actually staying there until the next quarter. For the positive shock, these probabilities are even lower than for the negative shock. But in general, the probability to really stay in the shock position (meaning not doing any adjustments, or taking an identical hit again) are the lowest next to the possibilities to jump directly to some equilibrium state or to the opposite shock. Thus, we have evidence that adjustment starts immediately and hence firms are able to react very quickly.

Yet another argument in favour of fast adjustment provides Table 2. The percentage share of firms in states of a severe shock (*pm* or *mp*) is very low. Thus, firms only find themselves in a shock state when the shock severely hits them and they are not able to balance it immediately. Altogether, the results seem to confirm our way of identifying the shocks: Firms which state that their capacities are too high (or too low) and which cannot adjust immediately must experience a profound event.

The final state of the system is given by the marginal distribution of the Markov chain. This state exists if the Markov chain is regular (Hamilton, 1994). Regularity follows if there exists an n for which all elements of the n-step transition matrix A_n are positive. Then all A_n^t are regular for all $t \geq n$. The marginal distribution $\tilde{\pi}$ is stationary if

$$\tilde{\pi}A_n = \tilde{\pi}. \tag{8}$$

This condition holds for A. Hence, the Markov chain is ergodic. Therefore, $\lim_{t\to\infty} A_i^t = A_\infty$ exists and the matrix A_∞ has identical rows:

$$A_\infty = \begin{bmatrix} p_1 & p_2 \cdots & p_9 \\ p_1 & p_2 \cdots & p_9 \\ \cdots & \cdots & \cdots \\ p_1 & p_2 \cdots & p_9 \end{bmatrix} \tag{9}$$

This result is quite remarkable because it addresses the issue of covariance stationarity. The ergodicity of the Markov chain implies stationarity of the business cycle. It must be stressed at this point that ergodicity has not been an a priori assumption for identifying the business cycle measure but it has been obtained after identification. In contrast to this order of arguments, basically all popular technical filters use a stationarity assumption in order to identify the business cycle. Therefore, with these standard approaches stationarity of the business cycle cannot be subjected to empirical scrutiny while in our case it can. For the sample under investigation we obtain the following marginal distribution

$$\hat{A}_\infty = 1_{(9,1)} \otimes \begin{bmatrix} .046 & .039 & .031 & .254 & .304 & .252 & .022 & .029 & .025 \end{bmatrix}$$

where $1_{(9,1)}$ signifies a column of nine ones.

We find that the fifth column, which represents state *ee*, shows the highest marginal probability. Consequently, following the Markov-chain, the firms will end up in the equilibrium state with highest probability.

Here again it is interesting to observe that the final state is characterised by a non-zero proportion of firms off the equilibrium position (*ee*). The implicit conclusion would be that the economy does not move towards equilibrium as a whole but rather to a steady state with a certain share of firms being in and out of equilibrium.

4.3. Markov-chain and VAR(1) analysis

In the following we describe the path and the speed of adjustment firms undergo once they have been hit by a shock. Building on the previous section we describe the movement of a firm by the vector autoregressive model order one (*VAR*[1]) counterpart of the Markov chain:

$$e_{t+1} = Ae_t + \varepsilon_t \tag{10}$$

where A is the transition probability matrix, $e_t = (pp, mp, \ldots, mm)'$ now denotes a 9×1 vector of the nine qualitatively different realisations of ε_t at time t and ε_t is a vector of innovations with $\Sigma(\varepsilon_t) = 0_{9\times 1}$ and Σ_ε being a variance-covariance matrix.

The business cycle dynamics are then equivalent to the dynamic properties of the vector e_t. Equation (10) represents a vector autoregressive process of order one. Therefore, we can use the standard VAR(1) tool kit for interpretation and analysis. For example, according to (10) the business cycle follows a simple autoregressive process, however, its components (the various shock types) being the marginal sub processes do potentially follow rather involved autoregressive moving average processes and so does ε_t.

Further, while the dynamics of the vector represent the business cycle dynamics as a whole we can pick one particular kind of shock and trace it through the business cycle. For example we might only be interested in the effect a strongly negative impulse (*pm*) has and compare it to the effect of, say *em,* or *mp,* the latter being a strongly positive shock. Of course, while in each case the path may be different, the system as a whole will always behave in a structurally similar fashion, e.g. it will eventually return to its stationary position if there was such a state.[10]

In other words, with this methodology we can check whether or not the system responds qualitatively different to different qualities of shocks and we can determine the time it takes for the system to digest shocks. This time span yields an interpretation of the duration of a business cycle from an individual firm's perspective. By the nature of the model we are not able, however, to learn whether or not different qualities of shocks also have different quantitative impacts. The latter deficiency arises because we are at this stage not yet able to associate these different qualities with particular quantities and must leave this exercise to future research.

The respond paths and their duration are determined by impulse-response analyses. Meaningful responses can only be obtained if we can say something about their statistical significance. To that aim we have to compute confidence bands for the impulse-responses. Since we use $\hat{A}_1$ as our estimator for A, standard errors for the point estimates of the elements in A can be obtained in the following way.

Each element $a_{i,j}$ (i: row index, j: column index) in A follows a binomial distribution with $p_{i,j} = 1 - \left(\sum_{k=1}^{9} p_{i,k \neq j}\right)$. Therefore, the variance of $a_{i,j}$ is given by $p_{i,j}\,(1 - p_{i,j})$. The covariances are also easily obtained by noticing that $cov(a_{i,j}, a_{k,j}) = 0 \forall k \neq i$. We obtain $cov(a_{i,j}, a_{i,k}) = -(p_{i,j}\, p_{i,k}) \forall k \neq j$.

This is all what is needed for calculating the standard impulse-response functions and their confidence bands as described in Lütkepohl (2006, Chapter 3.7), for example. However, these confidence bands rest on the assumption that the estimates of $a_{i,j}$ are normally distributed while in our case they follow a binomial distribution. Therefore, the statistical interpretation hinges on the fact that the normal distribution is the limiting distribution of the binomial as the sample gets large. The size of our sample is certainly large enough for a reasonable approximation.

In standard VAR analyses the identification of the innovation variance-covariance matrix is an important issue. In our experiment we consider the behaviour of a representative firm as an approximation to the whole economy. Therefore, identification is not a problem. Notice that with our definitions the most sensible shock to be considered is by letting a single element in ε_t to assume the value one while restricting all others to zero. The reason is very simple. At any time a single firm may only be subject to one particular kind of shock out of the nine possible. This kind of impulse response is usually referred to as forecast error impulse response.

We may interpret the results as follows. Being hit by a particular shock the representative firm will find itself in some other shock state with a given probability in the following period. The impulse-responses show these probabilities for all possible states. Independent of the particular shock feeding into the system all impulse-responses will die out at the same time since they are part of the same dynamic system.

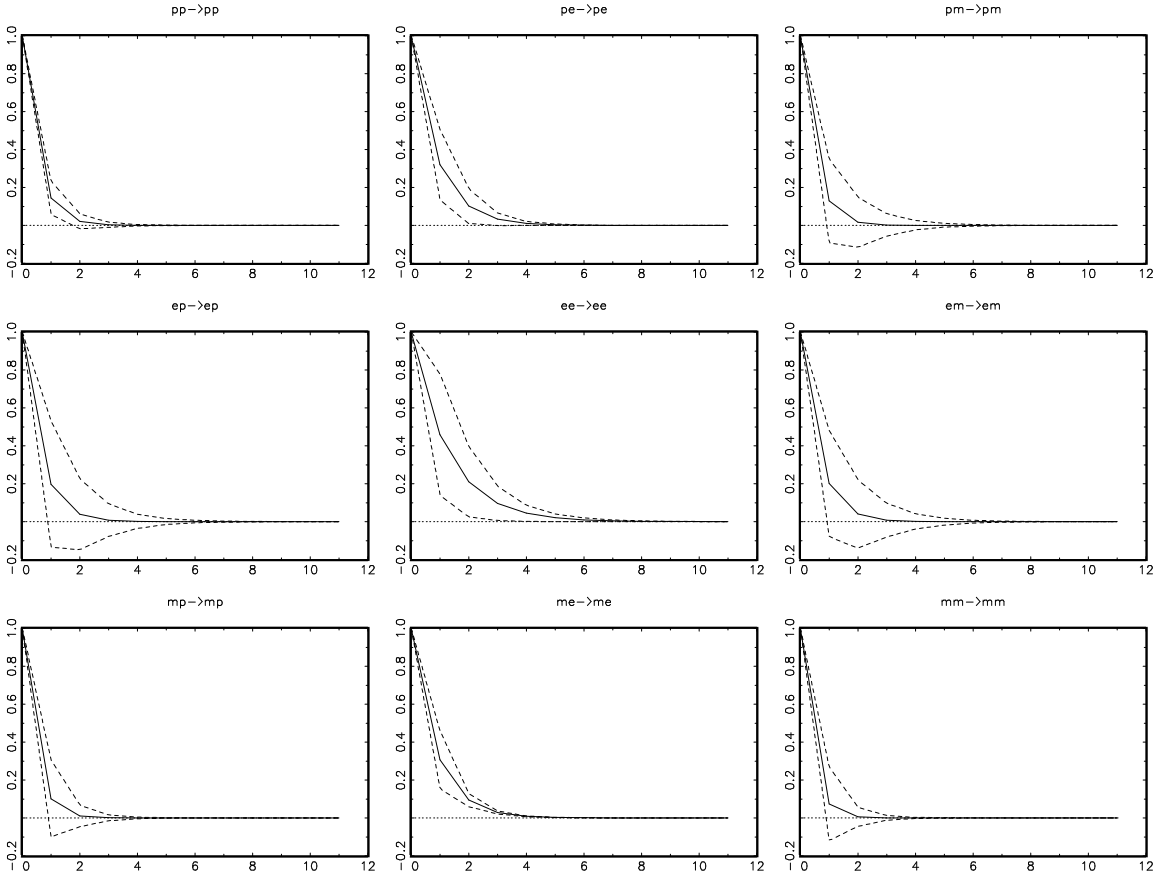
While some shocks will trigger a more balanced adjustment pattern with probabilities evenly shared between the various states, some other shocks will result in distinct

adjustment paths with high probabilities of certain shock states. The more balanced impulse-responses can be thought of as the initial shock pushing the representative firm in all possible directions with equal force to the effect that no particular reaction of the firm will stand out. In statistical terms, the impulse-responses will turn out insignificant in this case. If, however, a shock causes a certain negative or positive consecutive shock with a high probability this will present itself as a significant impulse-response and give rise to a potentially strong and distinct reaction of the firm. In the economy these distinct reactions can then be interpreted as booms or recessions. Therefore, we will focus on identifying those shock which trigger significant impulse-responses.

All in all we obtain 81 impulse-responses. We suggest to collect them in pictures with 3 × 3 panels. In Figure 1 the response of each shock to an innovation in itself is presented. For example, in the lower-left panel the response of the shock *mp* (strongly positive) to a shock in *mp* is shown.

There are two things to be learned from Figure 1. First, once disturbed the system adjusts back to the initial position, and second this adjustment is fast. After six quarters all responses become insignificant. In order to appreciate the speed of adjustment one might compare it to traditional measures of business cycle duration. Applying X12-ARIMA seasonal adjustment to the log-levels of industrial production and calculating the first difference shows that recessions lasted about four and expansions four to eight quarters ever since the 1990s.

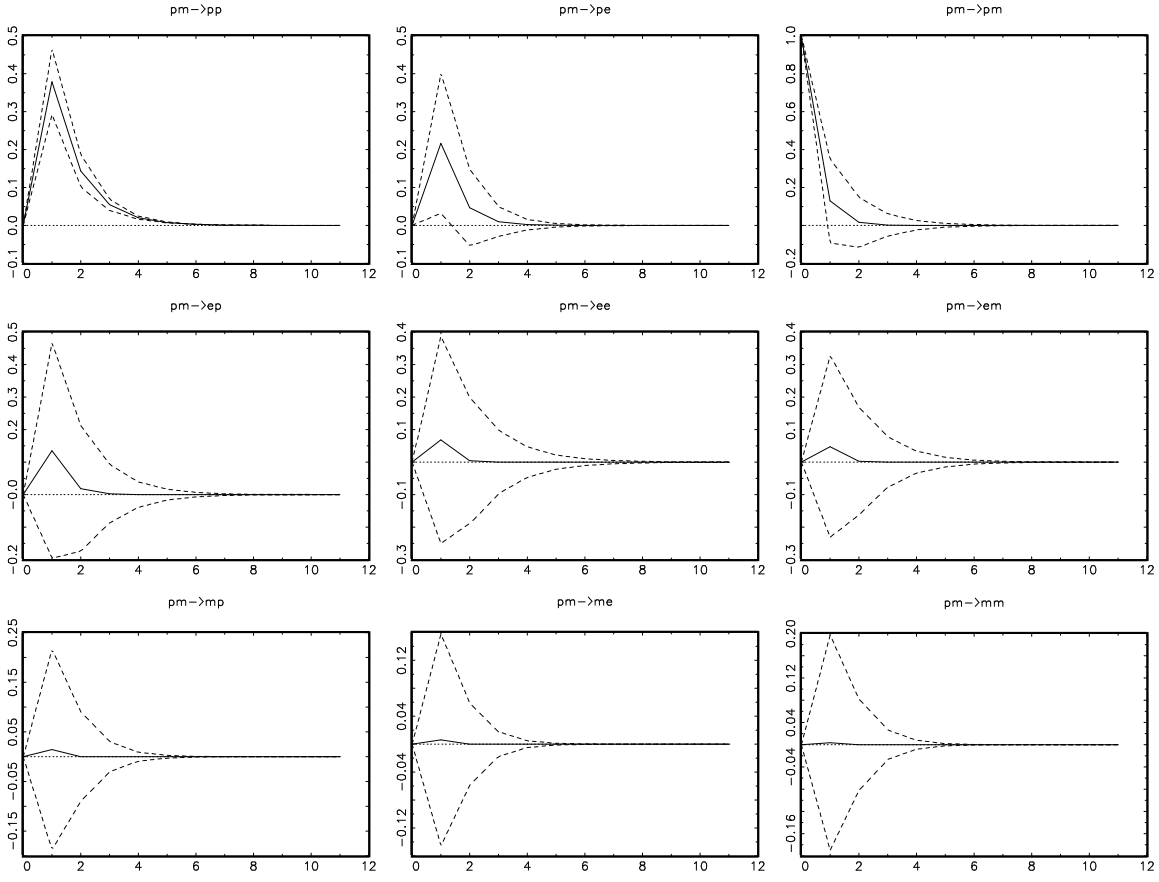
Figure 1. **Impulse response analysis: Effects of a quality i shock on quality i shock**



Turning to the question what event has the strongest impact on the system we have to look at the remaining 72 forecast impulse-responses and identify the shocks with the most pronounced impact on the system. It turns out that *pm* (strongly negative shock) is the one that triggers the most widely felt effects.

In Figure 2 we depict the impact of a shock with the following characteristics. The firm in question considers it necessary to increase the rate of capacity utilisation but instead of seeing an increase it observes a decrease in the next period. In our terminology this is equivalent to a strongly negative shock. The impulse-response analysis shows that shocks to *pp* and *pe* are significantly likely to follow a shock *pm*.

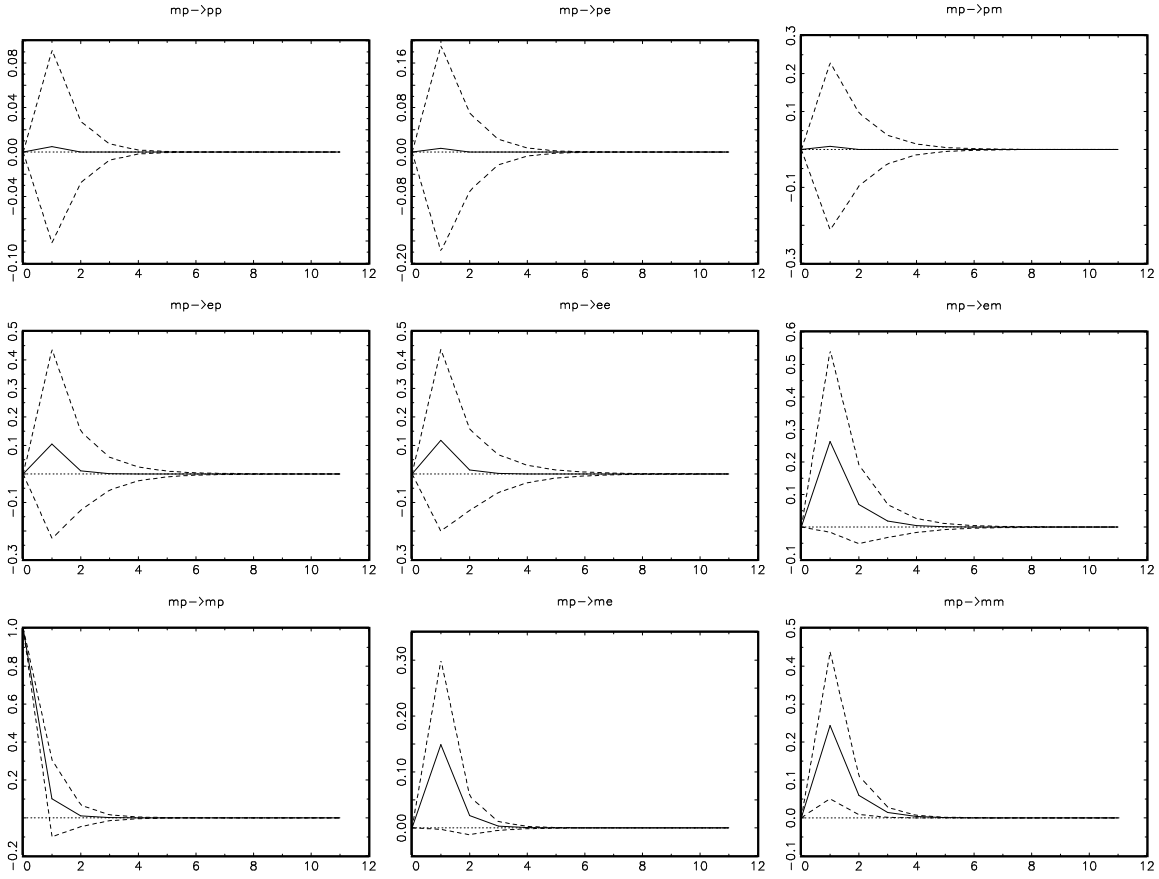
Figure 2. **Impulse response analysis: Effects of a strongly *negative* shock (*pm*)**



By contrast, its strongly positive counterpart (*mp*) does almost not leave any significant trace as Figure 3 shows.

Summing up the evidence, we observe that firms adjust to business cycle shocks within the first four quarters after a shock. The adjustment is thus faster than standard estimates on the aggregate level suggest. According to macro based estimates such as Siliverstovs's (2011) for the duration of business cycles in Switzerland indicate that recessions last 4.4 quarters on average while expansions average 14 quarters in the period 1981Q1 through 2010Q4. These estimates are obtained with a classical approach to business cycle characterisation with dating of the cycle being the main objective. It is thus interesting to note that the analysis of how firms digest business cycle shocks without prior or

Figure 3. **Impulse response analysis: Effects of a strongly *positive* shock (*mp*)**



simultaneous judgement about the actual dating of recessions and booms delivers partly differing results. It has at this stage to be left to future research to reconcile the findings of these alternative approaches.

Maybe we should also emphasize the fact that the limited duration of our business cycle shocks is not a result of the econometric technique used for identifying them like it is in procedures such as the Hodrick-Prescott filter. In our case stationarity is a purely data driven conclusion drawn from a procedure that does not predetermine stationarity as the outcome.

The second implication is that positive and negative shocks have different consequences for the economy. Negative shocks are significantly more influential than positive ones. Again, our procedure did not by any means impose symmetry or asymmetry on the results.

5. Outlook

In order to characterise the economy's shock propagation process we operate with a number of approximations such as homogeneity of firms. Therefore, a point of interest for future research is the investigation of whether or not all firms do indeed feature the same adjustment behaviour. Likewise, the first order Markov-chain restricts the effect of a shock to a firm's behaviour two periods apart to the effects transmitted by the intermediate period. It is, however, very well possible that direct effects play a role which would require the estimation of higher order Markov-chains. We leave both these extensions to future research.

Our finding that, on the micro level, negative shocks exhibit a more pronounced impact on the economy would imply that an according time series should be informative for the growth of GDP, or at least for the industrial sector. Therefore, a natural extension of the current work is to develop a business cycle indicator that is based on our measurement of shocks and the state of the adjustment process. As we have seen in this analysis, the adjustment process on the micro level is rather fast. It is therefore interesting to see whether an aggregation from the micro to the macro level leads to higher persistence in the response to shocks as, for example, not all firms might be hit by the same shock at the same time.

In the aftermath of a shock firms can react by adjusting prices or output, or both. The more readily output is adjusted the lower the impact on prices should be. Hence, our findings suggest that firm-specific prices face a significant upward pressure for at most half a year after a positive shock. This observation should be interesting for policy makers and model builders alike. The links between capacity utilisation, production constraints and prices are analysed, for example, in Lein and Köberl (2009) and Köberl and Lein (2008).

6. Summary and conclusion

This paper models the business cycle as the adjustment process of a firm to a shock as a series of states of a Markov-chain. The basis for our analysis is a micro data set of firms in the manufacturing industry that allows us to combine qualitative and quantitative information on an individual basis. We interpret the judgement of a firm about its technical capacities in combination with the effective change in capacity utilisation as the result of a business cycle shock. We are able to identify positive, negative, or no (neutral) shock depending on whether or not the implicit expectations is met.

The outcome of the investigation indicates that firms do react differently depending on whether or not the experienced shock was a negative, or a positive one. Negative shocks have more pronounced effects than positive ones.

Our bottom-up method allows to characterise business cycle dynamics "directly", that is by avoiding strong technical assumptions of standard filters. Therefore, our approach permits in principle an impartial tool for business cycle analysis at large.

Notes

1. Elstner, Sims and Bachmann (2010) pursue a similar approach which is based on a previous version of this work. They interpret shocks as a measure of uncertainty, however.
2. There is no general water-tight agreement on what exactly the necessary features of a shock are. This disagreement sometimes even extends to a single author. For example, Alesina and Fuchs-Schündeln (2007) use the term shock to characterise a situation that is *unwanted* by the majority of a population, while Fuchs-Schündeln (2008) follows the more widely used approach to regard those events a shock that are *unexpected*. In our case these two concepts are both present to some extent.
3. This inertia in capacity adjustment will in turn feed back into the properties of the business cycle shock and generates comparable inertia there.
4. Strictly speaking, various other combinations of changes in the level of production and the availability of capacities could also be thought of. Since the main message of the interpretation remains unchanged, we do not discuss these possibilities any further.
5. Another survey among the same firms also asks for changes in production and stock. This survey is conducted monthly which raises technical issues. Therefore, we did not yet exploit this information but leave it to future research.

6. See for example Carlson and Parkin (1975) for a seminal paper and Müller (2010) for a more recent approach for estimating the indifference interval.
7. See the Appendix for detailed results of the one way ANOVA procedure for each row.
8. An exercise left to future research is to calculate weights for the nine possible categories and come up with an aggregated, single time series of the business cycle.
9. Note that we obtain the capacity utilisation rate from the survey answers only, we therefore need to calculate the change in utilisation from t to $t + 1$ and from $t + 1$ to $t + 2$ to get observations of the change in utilisation for t and $t + 1$.
10. As seen before stationarity prevails in our case.

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Appendix

Table 5. **Descriptives for row δ_t = "-"**

	N	Mean	Std. dev.	Std. error	95 % confidence interval (mean)		Min.	Max.
					Lower	Upper		
mm	32	2.60	0.86	0.15	2.29	2.92	1.04	4.24
me	32	2.93	1.27	0.22	2.47	3.03	1.31	5.66
mp	32	2.38	0.78	0.14	2.10	2.66	0.72	4.32

Note: The table shows descriptive statistics of the row where firms state that their current technical capacities are too low (δ_t = "-"). In column *N*, the number of observations is shown. Next, the means that will be compared, standard deviations and standard errors are reported. Columns 6 and 7 show the lower and upper bounds of the 95% confidence intervals of each group mean. The last two columns report the minimum and maximum values of the respective group.

Table 6. **One way ANOVA for row δ_t = "-"**

	Sum of squares	df	Mean square	F	Sig.
Between groups	4.90	2	2.45	2.49	0.09
Within groups	91.45	93	0.98		
Total	96.36	95			

Note: The table shows the results of the one way ANOVA for the row where firms state that their current technical capacities are too low (δ_t = "-"). Under the null hypothesis, the group means do not differ in the population. The resulting test statistic is computed by a comparison of the sum of squares between the groups and the sum of squares within groups, adjusted by the number of groups and observations.

Table 7. **Descriptives for row δ_t = 0**

	N	Mean	Std. dev.	Std. error	95 % confidence interval (mean)		Min.	Max.
					Lower	Upper		
em	32	25.43	4.37	0.77	23.85	27.01	16.83	34.98
ee	32	30.02	4.43	0.78	28.42	31.62	15.61	37.20
ep	32	25.75	5.01	0.88	23.94	27.55	17.81	42.03

Note: The table shows descriptive statistics of the row where firms state that their current technical capacities are just right (δ_t = 0). In column *N*, the number of observations is shown. Next, the means that will be compared, standard deviations and standard errors are reported. Columns 6 and 7 show the lower and upper bounds of the 95% confidence intervals of each group mean. The last two columns report the minimum and maximum values of the respective group.

Table 8. **One way ANOVA for row $\delta_t = 0$**

	Sum of squares	df	Mean square	F	Sig.
Between groups	420.25	2	210.13	9.87	0.00
Within groups	1978.75	93	21.28		
Total	2399.00	95			

Note: The table shows the results of the one way ANOVA for the row where firms state that their current technical capacities are just right ($\delta_t = 0$). Under the null hypothesis, the group means do not differ in the population. The resulting test statistic is computed by a comparison of the sum of squares between the groups and the sum of squares within groups, adjusted by the number of groups and observations.

Table 9. **Descriptives for row δ_t = "+"**

	N	Mean	Std. dev.	Std. error	95 % confidence interval (mean)		Min.	Max.
					Lower	Upper		
pm	32	2.85	1.61	0.28	2.27	3.43	0.79	6.26
pe	32	3.53	1.23	0.23	3.09	3.97	1.54	6.04
PP	32	4.50	2.02	0.36	3.77	5.23	1.42	10.13

Note: The table shows descriptive statistics of the row where firms state that their current technical capacities are too high (δ_t = "+"). In column *N*, the number of observations is shown. Next, the means that will be compared, standard deviations and standard errors are reported. Columns 6 and 7 show the lower and upper bounds of the 95% confidence intervals of each group mean. The last two columns report the minimum and maximum values of the respective group.

Table 10. **One way ANOVA for row δ_t = "+"**

	Sum of squares	df	Mean square	F	Sig.
Between groups	44.29	2	22.14	8.11	0.00
Within groups	253.83	93	2.73		
Total	298.012	95			

Note: The table shows the results of the one way ANOVA for the row where firms state that their current technical capacities are too high (δ_t = "+"). Under the null hypothesis, the group means do not differ in the population. The resulting test statistic is computed by a comparison of the sum of squares between the groups and the sum of squares within groups, adjusted by the number of groups and observations.

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The role of oscillatory modes in US business cycles

by
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We apply multivariate singular spectrum analysis to the study of US business cycle dynamics. This method provides a robust way to identify and reconstruct oscillations, whether intermittent or modulated. We show such oscillations to be associated with comovements across the entire economy. The problem of spurious cycles generated by the use of detrending filters is addressed and we present a Monte Carlo test to extract significant oscillations. The behavior of the US economy is shown to change significantly from one phase of the business cycle to another: the recession phase is dominated by a five-year mode, while the expansion phase exhibits more complex dynamics, with higher-frequency modes coming into play. We show that the variations so identified cannot be generated by random shocks alone, as assumed in "real" business-cycle models, and that endogenous, deterministically generated variability has to be involved.

Keywords: Advanced spectral methods, comovements, frequency domain, Monte Carlo testing, time domain.

JEL classification: C15, C60, E32.

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1. Introduction

Dominated over many decades by a long-term upward drift (Solow, 1956), macroeconomic time series also exhibit smaller but still important shorter-term fluctuations often associated with business cycles. The causes and characteristics of these cycles have been extensively studied in modern economic theory (Burns and Mitchell, 1946; Kydland and Prescott, 1998, and references therein).

A number of approaches have been proposed to separate the shorter-term fluctuations from the long-term trend (Canova, 1998; Baxter and King, 1999). Morley and Piger (2012) recently attempted a classification of business cycle analyses into i) those that consider a cyclic sequence of expansions and contractions; and ii) an output-gap view, in which business cycles merely correspond to transitory fluctuations superimposed on a permanent trend level.

The definition of business cycles depends, however, on the knowledge of a trend component that cannot be observed directly. Several filters have been developed (Graff, 2011) to extract such a trend component, of which the Hodrick-Prescott (HP) filter is the most commonly used one (Hodrick and Prescott, 1997). Since there is no fundamental theory – and hence no generally accepted definition – of the trend, the resulting residuals have to be analyzed very critically, to avoid spurious results due merely to the detrending procedure itself (Nelson and Kang, 1981; Harvey and Jaeger, 1993; Cogley and Nason, 1995).

Business cycles can also be understood as comovements of transitory fluctuations in several distinct macroeconomic variables (Burns and Mitchell, 1946; Lucas, 1977). It is imperative, therefore, to analyze business cycle properties as a multivariate process.

The purpose of this paper is to apply *multivariate singular spectrum analysis (M-SSA)* – the extension of *singular spectrum analysis* (SSA) to multivariate time series – to the analysis of business cycles. Both SSA and M-SSA rely on the classical Karhunen-Loève spectral decomposition of random processes (Karhunen, 1946; Loève, 1945, 1978). Broomhead and King (1986a, b) proposed to use both in the context of nonlinear dynamics as a more robust application of the Mañé-Takens idea of reconstructing dynamics from measured time series (Mañé, 1981; Takens, 1981; Sauer et al., 1991). Ghil, Vautard and associates (Vautard and Ghil, 1989; Ghil and Vautard, 1991; Vautard et al., 1992) noticed that SSA can be used as a time-and-frequency domain method for the analysis of time series, whether they are generated by a linear stochastic process, a nonlinear deterministic one or a superposition of the two.

We propose to use M-SSA for the analysis of business cycles in a completely multivariate fashion. This method combines two useful approaches of statistical analysis: 1) it determines – with the help of principal component analysis (PCA) – major directions in the system's phase space that are populated by the multivariate time series; and 2) it extracts major spectral components by using data-adaptive filters. To get reliable information about significant oscillatory modes, we perform exhaustive statistical tests by means of Monte Carlo SSA (Allen and Smith, 1996), which allow us to deal with the problem of spurious oscillations (Nelson and Kang, 1981; Cogley and Nason, 1995).

SSA and M-SSA have already proven their advantages in a variety of applications, such as climate dynamics, meteorology and oceanography, as well as the biomedical sciences. Ghil et al. (2002) provide an overview and a comprehensive set of references to their theory and applications. In economics, this approach has received little attention so far. Recent applications to the univariate SSA analysis of business cycles include de Carvalho et al. (2012), Sella and Marchionatti (2012), and Dumas et al. (2013). The present paper introduces the M-SSA methodology into the economic literature and demonstrates its advantages for the multivariate analysis of economic activity.

The paper is organized as follows. In Section 2, we introduce the methodology and summarize its properties in terms of spectral decomposition, as well as of time-domain reconstruction. In Section 3, we apply SSA to the US gross domestic product (GDP) and M-SSA to the full data set. The reliability of the results is then discussed via Monte Carlo testing. Section 4 analyzes the cycle-to-cycle variability of the US business cycles, and we draw conclusions about the underlying dynamics in Section 5.

2. Decomposition and reconstruction

2.1. Data and pre-processing

We study here US macroeconomic data from the Bureau of Economic Analysis (BEA; see *www.bea.gov*). The nine variables analyzed are GDP, investment, employment rate, consumption, total wage, change in private inventories, price, exports, and imports; all monetary variables are in constant 2005 dollars, while the employment rate is in percentage points. The quarterly time series cover 52 years, from the first quarter of 1954 to the third quarter of 2005.

Aligning ourselves with the output-gap view of business cycle analysis, we first remove the trend of each time series separately, by using the HP filter with the common parameter value $\lambda = 1600$. Employment is the only one of the nine variables that does not exhibit an upward trend; still, we do detrend it to consistently remove periods longer than 10 years, as done for the other variables.

The restriction to the interval 1954-2005 reduces end-to-end mismatches of the remaining transitory fluctuations and minimizes spectral leakage effects, i.e. the presence of spurious oscillations in the spectral analysis. On the macroeconomic side, the years 2007-08 correspond to a well-known crisis, whose origin was financial, rather than economical. The time interval since that crisis exhibited several new characteristics, for which we do not yet have sufficiently long data sets to distinguish this interval from the previous half-a-century of data.

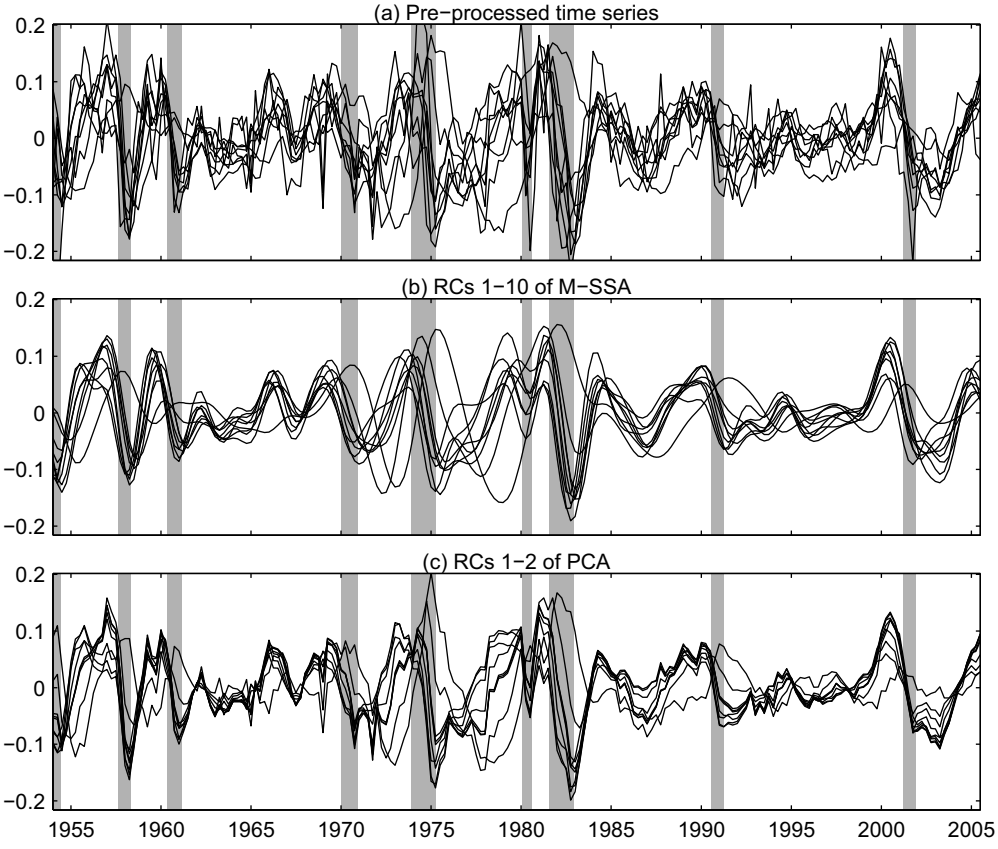
In contrast to our two-step approach – see also Dumas et al. (2013) – de Carvalho et al. (2012) have chosen to apply a single SSA analysis for the decomposition of the GDP into trend and fluctuations. Such an approach is indeed desirable as it appears to provide a more consistent separation into a permanent trend component and transitory fluctuations that are orthogonal to it (see Vautard et al., 1992; Ghil et al., 2002). In the present macroeconomic context, however, the trend dominates the SSA's variance-based phase-space decomposition and small fluctuations could be masked in such a single-sweep analysis (Granger, 1966; Sella and Marchionatti, 2012). We will return to this issue in the estimation of the covariance matrix in Section 2.2.

In line with our two-step decomposition, we next obtain trend residuals that we divide by the trend – i.e., we concentrate on relative values – and then transform to unit standard deviation.

This normalization brings all the indicators to the same scale and gives equal weight to each of them in the M-SSA analysis. One could choose to give different weights to each time series to reflect a priori ideas on their relative importance. Our choice here is one of simplicity, and the covariance matrix is transformed into a correlation matrix. Finally, we divide the normalized time series by $(DM)^{1/2}$ – with $D = 9$ is the number of variables and $M = 24$ is the window width – so that the sum of the partial variances equals one.

Figure 1a shows the results of this pre-processing. The US recessions, as defined by the NBER, are indicated by shaded vertical bars.

Figure 1. **Pre-processed macroeconomic indicators and their reconstruction**



Note: The nine time series of US macroeconomic data used in this paper; raw data from the US Bureau of Economic Analysis (BEA), 1954-2005. The figure illustrates the results of pre-processing and of applying either multivariate singular spectrum analysis (M-SSA) or principal component analysis (PCA); the shaded vertical bars in the three panels indicate NBER-defined recessions. (a) Detrended and standardized time series. (b,c) Reconstruction of the entire data set: (b) with the first 10 M-SSA components, using a window width of $M = 24$ quarters; and (c) with the first two PCA components. Both reconstructions capture 75% of the total variance, while the M-SSA reconstruction is smoother.

2.2. Singular spectrum analysis (SSA)

In this section we discuss the univariate version of SSA and present its main properties, in particular, its ability to reconstruct cyclical dynamics.

Following Mañé (1981) and Takens (1981), the starting point of SSA is to embed the time series $\{x(t) : t = 1 \ldots N\}$ into an M-dimensional *phase space* X, by using M lagged copies.

$$x(t) = (x(t), x(t+1), \ldots, x(t+M-1)), \tag{1}$$

with $t = 1\ldots N - M + 1$. The SSA procedure starts by calculating the principal directions of the embedded data set x(*t*).

Reconstructing the entire attractor of a nonlinear dynamical system from x(*t*), as originally proposed by Broomhead and King (1986a), may fail, however, even in relatively simple cases (Mees et al., 1987; Vautard and Ghil, 1989). Ghil, Vautard and several associates first proposed, instead, to apply the SSA methodology to describe cyclical behavior in short and noisy time series, for which standard methods derived from Fourier analysis do not work well (Vautard and Ghil, 1989; Ghil and Vautard, 1991; Vautard et al., 1992). The key idea in their approach was to reconstruct the "skeleton of the attractor", i.e. the most robust, albeit unstable limit cycles embedded in it.

The next step in SSA is to compute the auto-covariance matrix C of *x*. Vautard and Ghil (1989) proposed to estimate it by

$$c_{i,j} = \frac{1}{N-|i-j|} \sum_{t=1}^{N-|i-j|} x(t)x(t+|i-j|), \tag{2}$$

imposing a Toeplitz structure with constant diagonals: the entries $c_{i,j}$ of the matrix depend only on the lag $|i - j|$.

The eigenvalues λ_k and eigenvectors ρ_k of C, $k = 1\ldots M$, are obtained by solving

$$C\rho_k = \lambda_k \rho_k. \tag{3}$$

The eigenvectors, which are pairwise orthonormal, span a new coordinate system in the *M*-dimensional embedding space X, and each eigenvalue λ_k indicates the variance in the corresponding direction ρ_k. This computation helps us find, therefore, the major components of the system's dynamical behavior.

The eigenvectors of such a Toeplitz matrix are necessarily either symmetric or anti-symmetric, and the method's reliability in extracting oscillations is enhanced therewith by using this form of C (Allen and Robertson, 1996). In the presence of strong non-stationarity, the *Toeplitz approach* yields a slightly larger bias in the reconstruction of low-frequency activity than the original *trajectory approach* of Broomhead and King (1986a).

The latter approach relies on a singular-value decomposition of the trajectory matrix x and is more appropriate for the analysis of trends (Ghil et al., 2002). Our focus here is on the transitory fluctuations and we rely therefore on the Toeplitz approach for our analysis. de Carvalho et al. (2012) have found the trajectory approach to be also adequate in their one-step identification of the permanent trend and superimposed fluctuations in the US business cycles.

By convention, the eigenvalues $\{\lambda_k, k = 1\ldots M\}$ are arranged in descending order, from the largest to the smallest variance, yielding a so-called "scree diagram" of eigenvalues λ_k vs. order *k*. In this diagram, one often looks for a clear break in the slope to distinguish "signal" from "noise". Such a break, however, occurs mostly when the noise is actually white, with no temporal correlations at all. The signal-to-noise separation test has, therefore, to be modified in the presence of non-vanishing correlations, as done in Section 3 below.

Projecting the embedded time series x onto eigenvectors ρ_k yields the corresponding *principal components* (PCs),

$$A_k(t) = \sum_{j=1}^{M} x(t+j-1)\rho_k(j), \qquad k = 1\ldots M. \tag{4}$$

Note that the sum above is not defined close to the end of the time series, where $N - M \leq t \leq N$. It is customary, therefore, to consider the PCs as defined for only $N - M + 1$ indices, which could start at $t = M$ and end at N, or start at $t = 1$ but end at $N - M + 1$; most commonly they are plotted centered for $M/2 \leq t \leq N - M/2$, with M even (Ghil et al., 2002).

Finally, we can reconstruct parts of the time series that are associated with a particular eigenvector by:

$$r_k(t) = \frac{1}{M_t} \sum_{j=L_t}^{U_t} A_k(t-j+1)\rho_k(j), \qquad k = 1 \ldots M, \tag{5}$$

cf. Ghil and Vautard (1991) and Vautard et al. (1992). The values of the triplet of integers (M_t, L_t, U_t) for the central part of the time series, $M \leq t \leq N - M + 1$, are simply $(M, 1, M)$; for either end they are given in Ghil et al. (2002). Each *reconstructed component* (RC) $r_k(t)$ associated with the variance λ_k has a complete set of N indices, but with a reduced confidence in its values at either end of the time series.

Given any subset $k \in K$ of eigenelements, we obtain the corresponding reconstruction $r_k(t)$ by summing the RCs,

$$r_k(t) = \sum_{k \in K} t_k(t). \tag{6}$$

Typical choices of K are i) $K = \{k : 1 \leq k \leq S\}$, where S is the *statistical dimension* of the time series, cf. Vautard and Ghil (1989), i.e. the number of statistically significant components; or ii) a pair of components (k_0, k_1) for which $\lambda_{k_0} \approx \lambda_{k_{0+1}}$, and which may capture a cyclic mode (see Section 3). The whole set of RCs, $K = \{k : 1 \leq k \leq M\}$, gives the complete reconstruction of the time series.

In the following we refer to the common notation for the reconstructed component r_k as RC k, and for a sum of several, consecutive RCs in Eq. (6) from index k to index k' as RCs k–k'.

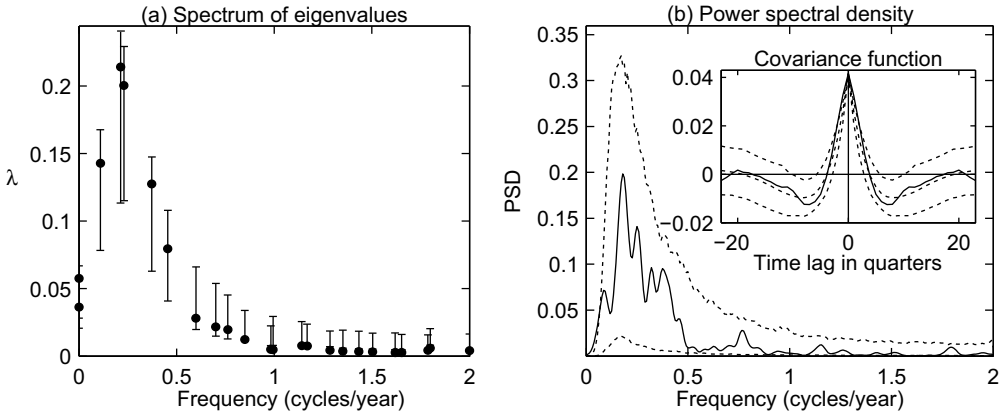
From the viewpoint of signal processing, the RCs can be considered as filtered time series, with the eigenvectors being a set of *data adaptive* filters. Both Eqs. (4) and (5) can be interpreted as a finite-impulse response (FIR) filter (Oppenheim and Schafer, 1989), with ρ_k being an FIR filter of length M. The PCs obtained in Eq. (4) are time-reversed in Eq. (5), and the FIR filter is run again through them. After this second filter pass, the correct chronological order is restored by reversing the filtered result $r_k(t)$ once more. This procedure is called *forward-backward filtering*, and it is known to preserve the phase relations. Hence, each RC k and the original time series $x(t)$ are in phase and the filtering acts only on the amplitude.

In designing an appropriate band-pass filter, Baxter and King (1999) require, in particular, that this "filter should not introduce phase shifts". Unlike their band-pass filter, with its data-independent weights chosen *a priori*, SSA is data adaptive. The M filters are the eigenvectors of the auto-covariance matrix and provide an optimal spectral decomposition of the time series, i.e. a maximum of the variance is captured by a minimal number of spectral components.

Following Vautard et al. (1992), we assign to each pair (λ_k, ρ_k) a frequency, given by the maximum of the Fourier transform of ρ_k. Plotting each eigenvalue vs. its dominant frequency provides a complementary perspective on SSA in terms of an analogy with classical spectral analysis.

This analogy becomes more obvious when analyzing the trend residuals of GDP (Figure 2). In the SSA analysis of panel (a), we observe a maximum in the spectrum of eigenvalues at the usually reported mean business cycle length of 5-6 years, which agrees with the classical estimation of the power spectral density (PSD) in panel (b). For various PSD estimation algorithms that we have tested, we observe a maximum around the same period; at this point, though, the trend residuals are still subject to the Nelson and Kang (1981) criticism of spurious cycles. Therefore, we have to perform additional significance tests before relying on the results, cf. Section 3.1.

Figure 2. **Spectral analysis of the US GDP**



Note: Univariate spectral analysis of US gross domestic product (GDP). (a) Eigenvalue spectrum of λ_k (filled circles) vs. dominant frequency of the associated eigenvector ρ_k, with window width $M = 24$ quarters; the error bars indicate the significance levels (cf. Sec. 3.1). (b) Power spectral density (PSD) estimate (solid line) using Welch's averaged periodogram method, with a Hamming window of length 128 quarters and 75% overlap (Priestley, 1991); the dashed lines indicate the significance levels. Inset: Covariance estimates (solid line) and their significance levels (dashed lines). The upper and lower significance levels in both panels and in the inset are derived from the 2.5% and 97.5% percentiles of 1 000 surrogate time series from an AR(1) null hypothesis; see Section 3.1.

2.3. Multivariate SSA (M-SSA)

M-SSA provides an extension of SSA to multivariate time series (Broomhead, 1986b; Kimoto et al., 1991; Keppenne and Ghil, 1993; Plaut and Vautard, 1994). Let $\mathrm{x}(t) = \{x_d(t): d = 1\ldots D, t = 1\ldots N\}$ be a vector time series of length N, with D channels. In generalizing (2), we use the D auto-covariances $C_{d,d}$, as well as the $D \times (D-1)$ cross-covariances $C_{d,d'}$ to form a *grand covariance matrix* $\widetilde{\mathrm{C}}$:

$$\widetilde{\mathrm{C}} = \begin{pmatrix} C_{1,1} & C_{1,2} & \cdots & C_{1,D} \\ C_{2,1} & C_{2,2} & \cdots & C_{2,D} \\ \vdots & \vdots & C_{d,d'} & \vdots \\ C_{D,1} & C_{D,2} & \cdots & C_{D,D} \end{pmatrix}, \tag{7}$$

Here $\widetilde{\mathrm{C}}$ is a $DM \times DM$ matrix and the entries of the individual matrices $C_{d,d'}$ can be estimated as

$$(c_{i,j})_{d,d'} = \frac{1}{\widetilde{N}} \sum_{t=\max\{1,1+i-j\}}^{\min\{N,N+i-j\}} x_d(t) x_{d'}(t+i-j). \tag{8}$$

The denominator $\widetilde{N}$ depends on the range of summation, namely $\widetilde{N} = min\{N, N+i-j\} - max\{1, 1+i-j\} + 1$.

As before we diagonalize the grand matrix $\tilde{C}$ to yield its eigenvalues λ_k and eigenvectors $\tilde{\rho}_k$,

$$\tilde{\mathbf{C}}\tilde{\rho}_k = \lambda_k \tilde{\rho}_k. \tag{9}$$

In contrast to SSA, the M-SSA eigenvectors $\tilde{\rho}_k$ have now length *DM*, and are composed of *D* consecutive segments ρ_k^d, $d = 1\ldots D$ of length *M*. These segments can be likewise interpreted as frequency-selective FIR filters, combined here into one multivariate filter ρ_k^d.

The associated PCs are single-channel time series that are computed by projecting the multivariate time series x(t) onto ρ_k^d,

$$A_k(t) = \sum_{d=1}^{D}\sum_{j=1}^{M} x_d(t+j-1)\rho_k^d(j), \qquad k = 1\ldots DM. \tag{10}$$

In addition to the summation *j* over time, as in Eq. (4), we get a second summation *d* over the channels. This summation involves a classical PCA. In particular, setting *M* = 1 reduces M-SSA to PCA in D variables.

Finally, one can reconstruct parts of each time series $x_d(t)$ associated with its corresponding eigenvector segment ρ_k^d by (Plaut and Vautard, 1994):

$$r_k^d(t) = \frac{1}{M_t}\sum_{j=L_t}^{U_t} A_k(t-j+1)\rho_k^d(j), \qquad k = 1\ldots DM, d = 1\ldots D. \tag{11}$$

This formula provides a set of *DM* RCs for each of the *D* time series and – depending on the information contained in the cross-covariances $C_{d,d'}$ – the RCs of different time series may or may not be correlated. In this way, M-SSA helps extract common spectral components from the multivariate data set, along with comovements of the time series.

In Figure 1, we compare the pre-processed time series in panel (a) with the M-SSA reconstruction in panel (b), using the ten leading RCs, and with PCA reconstruction in panel (c), using the two leading RCs of the data set; the latter results from Eq. (11) with *M* = 1. Both the M-SSA and PCA reconstructions capture 75% of the total variance and extract coherent behavior manifest in the nine economic variables. In contrast to PCA, the M-SSA results are much smoother, having removed irregular temporal fluctuations. It is especially the inclusion of temporal correlations that makes M-SSA superior to PCA in the extraction of dynamical behavior.

3. Oscillatory behavior and its statistical significance

The trend residuals in Figure 1 exhibit obviously more structure than pure white noise; we need, therefore, a stringent test to decide whether the visually apparent cyclical behavior can be attributed to random fluctuations or to a more regular oscillatory behavior, of possibly intrinsic origin. Cogley and Nason (1995), among others, have discussed in detail the effects of detrending, in particular the possibility that it might give rise to spurious cycles; their discussion was placed in the context of the detrending effect on a standard real business cycle (RBC) model, with no oscillatory dynamics.

We follow Cogley and Nason (1995) and test against a first-order autoregressive process, AR(1), to verify the statistical significance of oscillations; this test is already well-established in the geosciences (Allen and Smith, 1996; Ghil et al., 2002). Since AR(1) processes exhibit maximum variance at zero frequency, detrending with the HP filter may

yield a possibly spurious maximum in the PSD at other frequencies, e.g. around the commonly reported business cycle length of 5-6 years.

3.1. Univariate time series: the GDP

We first focus on GDP alone, the most widely studied macroeconomic indicator. A Monte Carlo–type test consists in first fitting an AR(1) process $X(t)$ to the scalar time series $x(t)$ of interest,

$$X(t) = \alpha X(t-1) + \sigma_0 \varepsilon(t), \tag{12}$$

with $\varepsilon(t)$ being Gaussian white noise of variance $\sigma = 1$, and then comparing the spectral properties of many realizations of $X(t)$ with that of $x(t)$.

We estimate the regression coefficient in Eq. (12) to be $a = 0.82$, and the variance $\sigma_0 = 0.04$, with the influence of the HP filter taken into account. That is, we choose the parameter a to minimize the mean-square distance between the GDP covariance function (solid line in the inset of Figure 2b) and the HP-filtered AR(1) covariance function (dotted line), while to estimate σ_0 we use the unbiased estimator proposed by Allen and Smith (1996) for short time series. Given the model parameters, we create a set of 1 000 surrogate realizations of length N from the AR(1) model, lowpass filter each with the HP filter, and normalize it to the same variance as $x(t)$. An additional division by the trend is not necessary, since the innovations in the AR(1) process have constant variance.

In Figure 2b, we compare the PSD estimate of the GDP residuals (solid line) with that of the surrogate time series. Frequency-dependent significance levels at the 2.5% and 97.5% quantiles (dashed lines) also show high power around five years, and the PSD estimate of the GDP falls entirely between them.

Other PSD estimates, such as the maximum entropy or the multi-taper method (see Ghil et al., 2002, and references therein), confirm this finding and yield the conclusion that GDP residuals alone cannot be distinguished from the null hypothesis of an HP-filtered AR(1) process. The high PSD values around five years could be due to the detrending of an otherwise stable model with exogenous excitation, in complete agreement with the findings of Cogley and Nason (1995) and Nelson and Kang (1981).

The same lack of statistical significance holds for the lag-covariance function, as expected from the Wiener-Khinchin theorem, according to which the PSD and the lag-covariance function of a time series are related by the Fourier transform (Blackman and Tukey, 1958). The swing below zero for the surrogate time series is thus likewise due to the HP filter's effect; see the inset in Figure 2b. The preliminary conclusion is that we cannot falsify the null hypothesis of an AR(1) process for the GDP residuals, as analyzed separately here.

This conclusion can also be confirmed by Monte Carlo SSA, which tests whether an eigenvalue λ_k captures more partial variance in the direction of the corresponding eigenvector ρ_k than present in the null hypothesis. To derive significance levels, the covariance matrix C_S for each surrogate time series $x_S(t)$ is projected onto the set of eigenvectors E of the original time series via

$$\Lambda_S = E^T C_S E, \tag{13}$$

here the eigenvectors ρ_k are the columns of E, and $(\cdot)^T$ denotes the transpose of a matrix.

Equation (13) is not the eigendecomposition of C_S, and Λ_S is not necessarily diagonal, as it would be for C. Instead, Λ_S provides a measure of the discrepancy between C_S and C,

and by computing quantiles of the diagonal elements' distribution from a set of Λ_S, we derive significance levels for each eigenvalue λ_k (Allen and Smith, 1996).

The resulting significance levels for the SSA analysis of GDP in Figure 2a are indicated as vertical bars and we see that all eigenvalues fall within these error bars. Hence, the observed spectrum of eigenvalues cannot falsify the null hypothesis either. In the following subsection, we show that additional information from other macroeconomic indicators helps reject the null hypothesis.

3.2. Multivariate time series

To test significance in M-SSA results, comovements should be taken into account in formulating the null hypothesis. Vector AR models, however, may support oscillations even for order one; when present, these are referred to as principal oscillation patterns (von Storch et al., 1995; Penland and Matrosova, 2001). We keep, therefore, the idea of fitting univariate AR(1) processes

$$X_d(t) = a_d X_d(t-1) + \sigma_d \varepsilon_d(t). \tag{14}$$

but build characteristics of the cross-correlations into the null hypothesis. The estimated parameters for each indicator are listed in Table 1.

Table 1. **Null-hypothesis parameters**

Variable	AR(1) a_d	Parameters σ_d	Time lag behind GDP Δ_d (quarters)
GDP	0.82	0.040	0
Investment	0.92	0.028	1
Employment	0.96	0.021	0
Consumption	0.88	0.034	0
Total wage	0.95	0.024	0
Δ (Inventories)	0.61	0.055	0
Price	0.99	0.012	7
Exports	0.95	0.023	1
Imports	0.83	0.039	1

The cross-correlation information is included by coupling the noise residuals $\varepsilon_d(t)$ at a certain temporal lag Δ_d. Relative to GDP, denoted by $x_1(t)$, we chose Δ_d so as to maximize the correlations between $x_1(t)$ and $x_d(t + \Delta_d)$. Doing so is especially necessary for the price, for which we observe a correlation maximum at seven quarters (cf. Figure 3g).

The covariance matrix R for innovation processes $\varepsilon_d(t)$ has elements

$$R_{d,d'} = \frac{1}{\widetilde{N}_{d,d'}} \sum_{t=\max\{1,1+\Delta_{d'}-\Delta_d\}}^{\min\{N,N+\Delta_{d'}-\Delta_d\}} x_d(t) x_{d'}(t+\Delta_{d'}-\Delta_d); \tag{15}$$

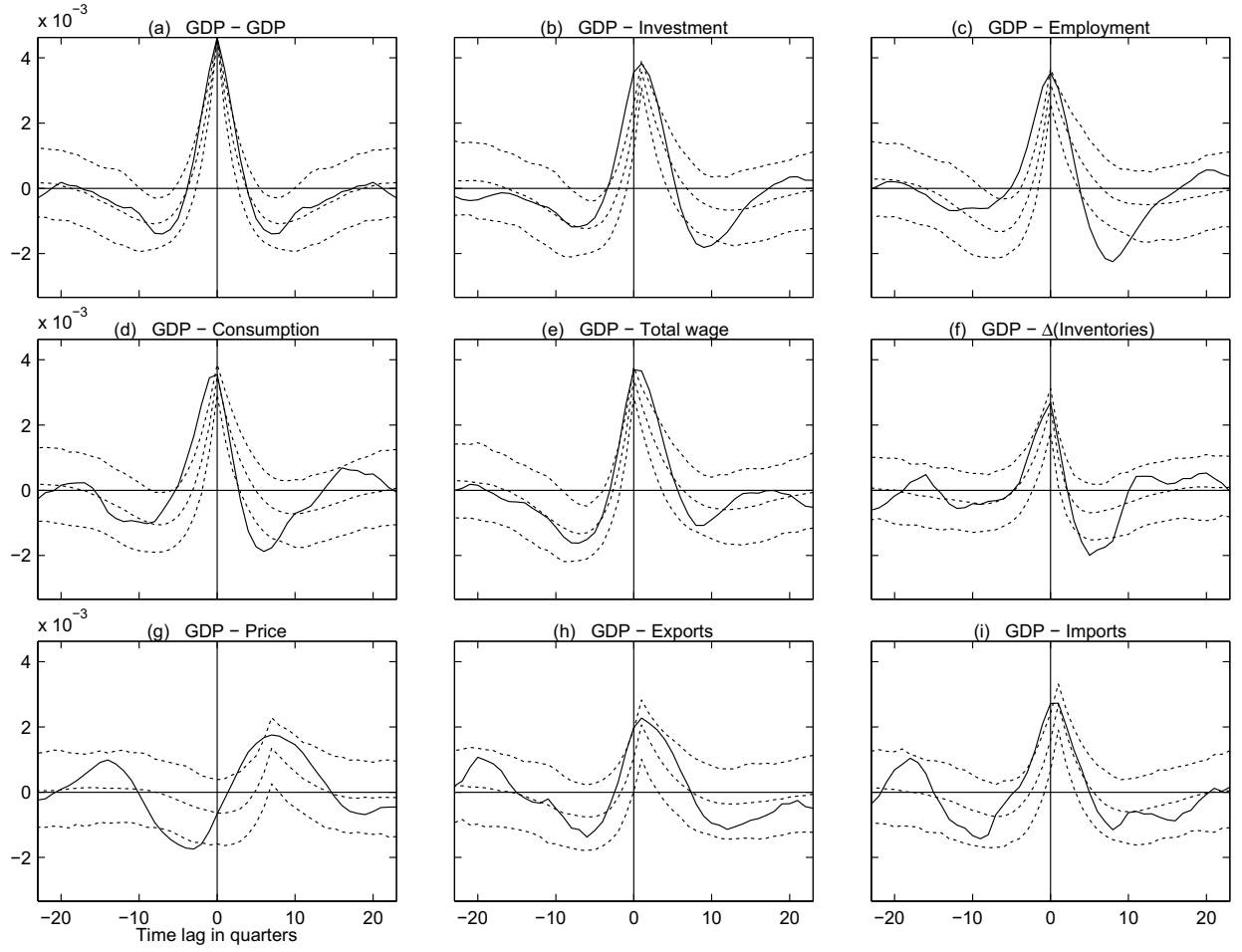
the denominator $\widetilde{N}_{d,d'}$ depends on the range of summation, namely $\widetilde{N}_{d,d'} = min\{N, N+\Delta d' - \Delta d\} - max\{1, 1+\Delta d' - \Delta d\} + 1$. Cholesky decomposition yields $R = L^T L$ and we derive correlated innovation processes from

$$(\epsilon_1(t), \ldots, \epsilon_d(t+\Delta_d), \ldots, \epsilon_D(t+\Delta_D))^T = L^T (\xi_1(t), \ldots, \xi_d(t), \ldots, \xi_D(t))^T, \tag{16}$$

with the ξ_d being independent white-noise processes. Finally, we pass the realizations through the HP filter and normalize it to the same standard deviation as the data set.

Figure 3 compares the covariance of the data with that of the null hypothesis. Lead-lag relations among economic indicators are reproduced by the null-hypothesis model, and

Figure 3. **Comovements of US economic indicators**



Note: Auto- and cross-covariance functions of the nine US economic indicators with respect to GDP (solid lines). Dashed lines indicate the significance levels 2.5% and 97.5%, as well as the median from the realization of 1 000 surrogate time series. Panels (a)-(i) are labeled directly in the figure; Δ(Inventories) in the legend of panel (f) indicates changes in inventories.

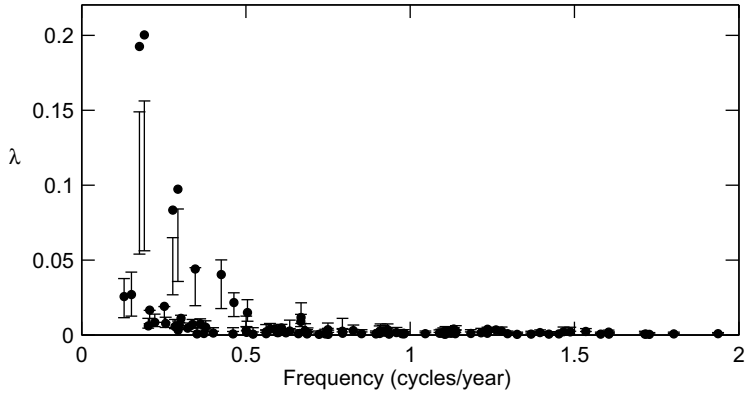
the data covariance function lies almost, but not quite, within the variability of the null hypothesis. As in the univariate case, the HP filter introduces a swing below zero and which would lead once again to spurious cycles.

Projecting the grand covariance matrix $\tilde{C}_S$ for each of the surrogate realizations onto the data eigenvectors, $\tilde{\Lambda}_S = \tilde{E}^T \tilde{C}_S \tilde{E}$, yields again a measure of the discrepancy between $\tilde{C}_S$ and C, which allows us to derive significance levels for λ_k from the distribution of the diagonal elements of $\tilde{\Lambda}_S$ (Figure 4).

As in the case of GDP alone, we observe higher significance levels near a five-year period, but this time the data eigenvalues clearly exceed the upper significance level. Hence the high variance associated with the leading pairs of eigenvalues can no longer be explained by spurious cycles induced by inappropriate detrending.

We have further tested the consistency of the present results by using different values of the window width, namely $M = 20$, 30, 40 and 50. It turns out that the leading pair describes a significant oscillation of five-year period. The three-year oscillation in the second pair is somewhat less robust, but probably still deserves further examination in future work.

Figure 4. **Collective spectral properties of the nine US aggregate indicators**



Note: Spectrum of M-SSA eigenvalues (non-dimensional, filled circles) using all nine US indicators, with M = 24. The error bars indicate the significance levels, derived from the 2.5% and 97.5% percentiles of 1 000 multivariate surrogate time series.

We have performed additional, exhaustive tests – as proposed by Allen and Smith (1996) – to cope with the problem of overestimating large eigenvalues in SSA and have found further evidence that the five-year oscillatory pair is indeed statistically significant at the 95% level. We focus, therefore, in the next section on this oscillatory mode and investigate its role in business cycle dynamics.

4. Business cycle dynamics: Phase dependence and evolution

The presence of oscillatory pairs indicates recurrent behavior in the system's dynamics. Such more-or-less regular recurrences are typically produced by the presence of an attracting or only weakly unstable limit cycle in the dynamics (Vautard and Ghil, 1989; Vautard et al., 1992; Ghil et al., 2002). On the other hand, vector AR(1) processes can possess oscillatory solutions as well, as mentioned at the beginning of Section 3.2. In practice, however, it might be hard to distinguish between purely deterministic, but chaotic oscillators and stochastically driven ones.

From the point of view of economic theory, the distinction is not that important: in fact, deterministic mechanisms – whether linear or nonlinear – are the only ones that give rise to cyclic behavior in a vector AR(1) process or in a vector random process generated by a system of linear (Arnold, 1974) or nonlinear (Arnold, 1998) stochastic differential equations as well (Schuss, 1980); for illustration purposes, we discuss the case of a vector AR(1) process in the Appendix. The stochastic forcing, if present, only contributes truly irregular fluctuations. It is, therefore, only the deterministic part of the dynamics that is of genuine interest in discussing cyclicity in macroeconomics, whether stochastic forcing is present or not.

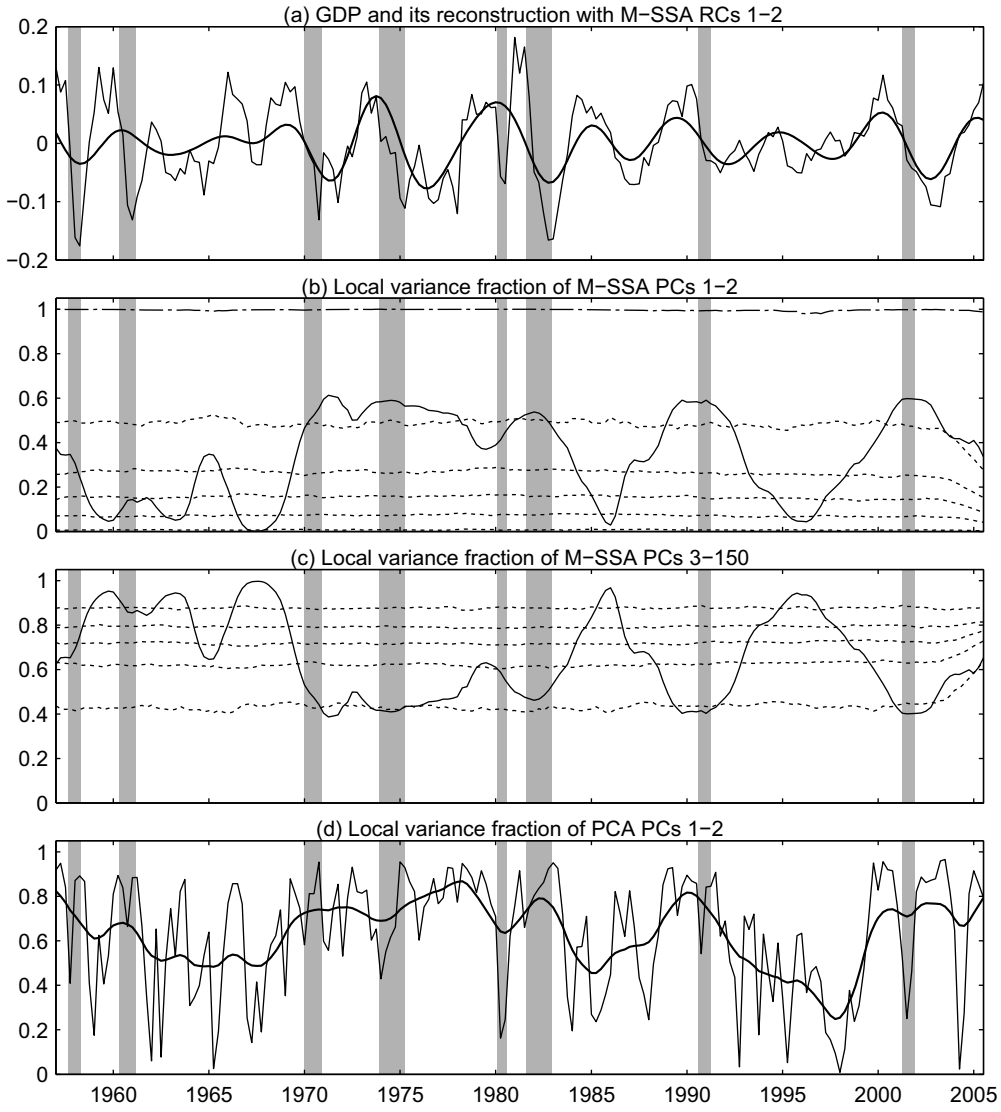
The first two eigenvalues capture 40% of the total variance, and RCs 1-2 give already a good approximation of the GDP, cf. Figure 5a.

To better understand the role of this five-year oscillatory mode in the processes of expansion and recession, we study the temporal evolution of its variance.

Plaut and Vautard (1994) introduced the concept of *local variance fraction* $V\kappa(t)$,

$$V_K(t) = \frac{\sum_{k\in K} A_k(t)^2}{\sum_{k=1}^{DM} A_k(t)^2}, \tag{17}$$

Figure 5. **Time dependence of the variance in leading and residual modes**



Note: Dependence of the (a) pre-processed GDP data set (light solid line) and its reconstruction with RCs 1-2 of our M-SSA analysis (heavy solid line). (b, c, d) Local variance fraction $V(t)$: (b) for M-SSA PCs 1-2 (solid line) and PCs 1-150 (near-total variance, dash-dotted line); (c) for M-SSA PCs 3-150 (solid line); and (d) for PCs 1-2 of a PCA analysis (light solid line), as well as after smoothing with a two-year moving average (heavy solid line). The dashed lines in panels (b) and (c) give the 2.5%, 25%, 50%, 75%, and 97.5% percentiles based on 1 000 surrogate time series. The shaded vertical bars indicate NBER-defined recessions.

which quantifies the fraction of the total variance that is described by a subset K of PCs in a window of length M. We consider the PCs as centered, i.e. starting at $M/2$, cf. Section 2.2.

Figure 5 shows this index, along with the NBER-defined recessions, for the leading PCs 1-2 in panel (b) and for PCs 3-150 in panel (c). The sum of PCs 1-150 capture 99% of the total variance; see dash-dotted line in panel (b). Starting after 1980, it is quite remarkable that the fraction of the five-year oscillatory mode in PCs 1-2 is high during recessions and low during expansions. It shows that during the recessions, the trajectory of the data set stays closer to a suspected five-year limit cycle – like the one in the Non-Equilibrium Dynamic Model (NEDyM) of Hallegatte and Ghil (2008) or in other endogenous business

cycle models (Chiarella et al., 2005) – while this trajectory reveals more complex behavior during expansions.

During the 1970s, PCs 1-2 capture roughly 50% of the variance or more over the full decade, while from 1980 on, PCs 1-2 play a significant role only during recessions. This result of our analysis suggests a change in the system's dynamics in the 1980s, a change that agrees in timing with the "great moderation", during which volatility in GDP growth diminished markedly (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2002; Kim et al., 2004).

There has been considerable debate on the cause of this shift, as well as on the expected duration of the US economy's new mode of functioning; in particular it has been proposed that this moderate behavior terminated in 2007, i.e. before and during the "great recession" of 2008-09. In any case, our results are at least consistent with the hypothesis of structural changes in the 1980s, and our M-SSA methodology can help provide sophisticated analysis tools to determine whether and when the great moderation ended, once additional BEA data become available.

To assess the significance of the local variance results, we compare their variability with that of the null hypothesis in Eq. (14). To wit, we project each surrogate realization onto the data eigenvectors $\widetilde{\rho}$ to obtain surrogate PCs in the same way as for the data set in Eq. (10). As in the significance test of the eigenvalues, the resulting surrogate PCs are not orthogonal, since their covariance matrix $\widetilde{\Lambda}_S$ is not diagonal.

For each surrogate PC we calculate the local variance fraction in the same way as for the data set in Eq. (17), and derive time-dependent significance levels from the distribution of $V\kappa(t)$ (Figs. 5b, c, dashed lines). Since the AR(1) processes are stationary, these levels are supposed to be constant; this stationarity is seen in fact in Figure 5, except near the end of the time series, i.e. starting at $t \simeq N - M$.

In contrast to the approximate constancy of $V\kappa(t)$ in the null hypothesis, the five-year oscillatory mode in the data set exhibits much greater variance during the recessions, when it does exceed the 97.5% significance level. The variance in PCs 3-150 is also larger than can be explained by the null hypothesis, with $V\kappa(t)$ values that are significantly larger than the 97.5% percentile during expansions and smaller than the 2.5% percentile during recessions, respectively.

We have further examined the variability of $V\kappa(t)$ during the whole 1954-2005 interval by using other quantities, such as standard deviation and interquartile range (not shown here). All these estimates confirm that the US macroeconomic indicators exhibit larger variability than can be explained by the random fluctuations of the null hypothesis.

It is interesting to note that a similar phenomenon can also be identified by applying PCA to the data (Figure 5d). Although, at first glance, the local variance fraction of the leading two PCs of PCA (light solid line) is rather irregular, with no apparent link to the business cycle, smoothing with a two-year moving-average filter (heavy solid line) does indeed produce a behavior comparable to that in Figure 5b. It would, however, be difficult to guess that from the raw PCA results: the moving-average filtering was only inspired by the M-SSA results in panels (b) and (c), which did not require any additional post-processing.

5. Concluding remarks

In this article, we applied multivariate singular spectrum analysis (M-SSA) to study business cycles dynamics in a consistent and multivariate way. Our M-SSA results allowed

us to reconcile and combine the NBER definition of recessions with quantitative analysis. This methodology extends, in particular, the recently proposed SSA business cycle analysis of a single macroeconomic indicator (de Carvalho et al., 2012; Sella and Marchionatti, 2012; Dumas et al., 2013). The present M-SSA analysis uses information on nine US macroeconomic indicators from the BEA for 52 years (1954-2005).

This extended business cycle analysis leads to three major conclusions: i) the presence of genuine periodicity in macroeconomic behavior and its deterministic causes; ii) the essential role of comovements of economic aggregates in the proper definition of business cycles; and iii) the dependence of economic "volatility" on the phase of the business cycle. We describe these conclusions in greater detail below.

Genuine periodicity and its deterministic causes

In their work about the "real facts" and monetary myths of business cycles, Kydland and Prescott (1998) discussed the origin of business cycles in terms of the Slutzky (1937) theory of random shocks. In the simplest RBC models, cyclicity originates exclusively from productivity shocks that can be modeled by a simple random walk. Cogley and Nason (1995) have, moreover, argued that the spurious appearance of business cycle dynamics can be generated by the HP filter even if none is present, even in a random walk.

In agreement with the findings of Cogley and Nason (1995), a simple univariate analysis of GDP does not reveal any significant oscillatory modes (see Figure 2). Our multivariate analysis, however, uses a larger amount of information about macroeconomic behavior, and allows us to identify a five-year oscillatory mode with high statistical confidence (see Figure 4). This mode cannot be explained by artificial effects due to detrending by the HP filter, and a random-walk-driven model of business cycles has to be questioned in the light of the results obtained in our paper.

A major result of our study thus points to the presence of deterministic, endogenous effects in the business cycles of the US economy and leads to the conclusion that business cycles cannot be explained by exogenous shocks alone. This conclusion does not exclude the importance of random effects in the economy, as discussed at the beginning of Section 4 and in the Appendix: it only emphasizes the role of the deterministic ones in giving rise to cyclic behavior.

Comovements of macroeconomic aggregates

The role of the additional information provided by the M-SSA analysis emphasizes the need to understand business cycles as a phenomenon that is not limited to GDP variations, but involves all aspects of the economy; it is reflected, therefore, in the comovements of several macroeconomic aggregates. In the present study, we have performed a quantitative analysis of the BEA data set that is consistent with the NBER definition of the business cycle, inasmuch as it is entirely multivariate and takes into account the lead-and-lag relationships between the various indicators present in the data (see Table 1 and Figure 3). These lead-and-lag relationships, in turn, reflect certain widely acknowledged "stylized facts" of economic cycles (Kydland and Prescott, 1998; Zarnowitz, 1985).

State-dependent fluctuations

M-SSA also allowed us to provide further insight into the underlying macroeconomic dynamics, and especially into the crucial question of the complex interplay between endogenous dynamics and exogenous shocks. We showed that the US economy changes

its behavior from one phase of the business cycle to another: the recession phase is dominated by the five-year mode, while the expansion phase exhibits more complex dynamics, with higher-frequency modes coming into play (see Figure 5). This type of behavior cannot be explained by the random fluctuations that drive a simple stationary RBC model, in the absence of endogenous oscillatory dynamics.

It thus appears that the dynamics of the US economy can indeed be decomposed into a five-year cycle and more complex, higher-frequency behavior superimposed on this cycle. The amplitude of the latter, irregular component is higher during expansions, i.e. the business cycle is more volatile during expansions than during recessions.

This phase-dependent volatility is consistent with the response to natural disasters predicted by Hallegatte and Ghil (2008) in an endogenous business cycle (EnBC) model. These authors have shown that exogenous shocks, whether positive or negative, are likely to have a bigger impact in the presence of EnBCs.

Their modeling framework (Hallegatte et al., 2008), while highly simplified, has Keynesian features and their EnBC model's predictions can be interpreted in terms of production being closer to capacity during expansions. On the other hand, the lower volatility during recessions in our analysis here is consistent with the predicted reduction in sensitivity to exogenous shocks, due to underutilized production capacity in the low phases of an EnBC. This so-called "vulnerability paradox" was also highlighted by Ghil et al. (2011) and by Dumas et al. (2013).

Such a variable-volatility pattern may seem at odds with the findings of French and Sichel (1993). But this apparent discrepancy can be explained by the fact that our analysis and theirs are not defining the fluctuations in the same manner. French and Sichel (1993) modeled the variance of the residuals on a long-term trend, without decomposing these residuals into cyclical and non-cyclical behavior, as we do here, and found higher variance during epochs of recession. In the present paper, we study the fluctuations superimposed on the sum of the long-term trend, plus a possible cyclical component. It is the variance of the fluctuations so defined that is largest during expansions.

The next step in our research program is to investigate whether the change in the economy's dynamical behavior between boom and bust also leads to different types of response to exogenous shocks. This question is fundamental in attempting to evaluate the efficiency of economic policy in different phases of the business cycle.

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Appendix

Cyclicity in deterministic and stochastic models

It is well known, as already mentioned at the beginning of Section 3.2, that vector AR(1) processes can posses oscillatory solutions, due to the presence of pairs of complex conjugate eigenvalues $(\lambda_k, \lambda_{k+1}) = (\lambda_k^{(r)} \pm \lambda_k^{(i)})$ in the spectrum of the matrix A = (a_{ij}) that characterizes such a process,

$$X(t) = AX(t-1) + \Sigma\,\varepsilon(t); \tag{1}$$

here Σ is a covariance matrix multiplying the noise vector ε. For a stationary AR(1) process, all the real parts $\lambda_k^{(r)}$ of the eigenvalues of A must be negative, and the damped oscillations are maintained at a statistically constant amplitude by the noise ε.

In practice, such a stochastically driven oscillator might be hard to distinguish from a purely deterministic, possibly chaotic one. But the term AX(t – 1) in the former case, on the right-hand side of Eq. (A.1), still captures the manifestation of a coupled pair of deterministic feedbacks, one positive, the other negative, whether linear or nonlinear, noise-driven or not, as the ultimate cause of any complex conjugate pair of eigenvalues $(\lambda_k^{(r)} \pm \lambda_k^{(i)})$.

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Report

Construction of composite business cycle indicators in a scarce data environment: A case study for Abu Dhabi

by
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Business cycle indicators are important instruments for monitoring economic development. When employing indicators one usually relies on a sound statistical database. This paper deals with indicator development in a scarce data situation. Indicator building is merged with temporal disaggregation, which is often used by statistical offices. The discussed tools are applied in a case study for Abu Dhabi. Because the economy of Abu Dhabi is very dependent on oil, real income reflects the economic situation better than real gross domestic product (GDP). For this reason a measure of real gross domestic income (GDI) was chosen as reference series.

Keywords: Business cycle indicators, temporal disaggregation, terms of trade, oil-producing countries

JEL code: E01, E32, C22

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1. Introduction

Business cycles are fluctuations in the capacity of the entire economic production potential. These cycles are referred to as *growth cycles* to distinguish them from the (*classical*) business cycle with absolute contractions. If the trend of the real gross domestic product (real GDP) is interpreted as a non-structural estimate of production potential, then the growth cycle can be measured on the basis of the deviation of GDP to its trend. The turning points are defined as the maximum distance of GDP from its trend value. Growth cycles might be approximated by cycles in the growth rate of real GDP.

Business cycle indicators should be able to describe cyclical economic development in a timely and accurate fashion. They are divided according to their chronological relationship to the respective business-cycle reference series in leading, coincident and lagging indicators. For the analysis of the present economic situation coincident indicators are of particular importance. A composite indicator combines several individual indicators to summarize the economic condition – as shown by a reference series – in a single statistic.

The construction and use of business indicators has a long history in economics. Systematic considerations that date back to the 1930s were carried out by a group of economists around Arthur Burns and Wesley Mitchell of the National Bureau of Economic Research (NBER).[1] At the time various methodological leaps hade been made. Especially the econometric tools were improved dramatically. Static and dynamic factor models were employed. Nonlinear techniques like hidden Markov models and multivariate techniques have been developed.[2] These sophisticated methods require a sound data base, however. Some of these methods are even developed to draw on huge data sets, like the factor approach of Stock and Watson.[3]

This paper deals with the development of business cycle indicators in a scarce data environment, where even a high frequency reference series is missing. Although many countries have already built up statistical reporting systems and agencies of high quality, there are still some countries where this process is ongoing and the data availability is still not sufficient for the highly sophisticated econometric methods. Even so these countries are keen to present timely business cycle indicators, perhaps as part of an information toolkit for investors so that countries are more attractive to international capital or for local actors to monitor risks for the economy.

One such country where a statistical reporting system is still in development is Abu Dhabi. As a case study, a coincident indicator for Abu Dhabi is constructed in this article. For this country a further complication arises. It is a resource rich country, relaying heavily on oil. So a business cycle concept based on capacity utilization and real production could be misleading. Cycles in real income are a more suitable benchmark for overall economic conditions and welfare in Abu Dhabi.

The paper is structured as follows. The next chapter presents the recipe and the tools used for the construction of composite indicators in the case of a scarce data environment. The applied statistical methods are well established. The innovation of this paper is that

sensible procedures for the underlying data situation are chosen and that these methods are combined in a specific new way. Indicator building is merged with temporal disaggregation, which is often used by statistical offices. Candidate indicators are classified and either abandoned, selected as candidate for the business cycle indicator or selected as candidate for the temporal disaggregation of a reference series. The procedure is then applied to the data situation in Abu Dhabi.

2. Construction procedure

In the following a general procedure for developing business cycle indicators in a scarce data environment is discussed. The data situation is characterized by only a few possible indicators and by the lack of a high frequency reference series. Business cycle indicators should be calculated at least at a quarterly time scale. Usually real gross domestic product is used as reference series. In the absence of real GDP figures, synthetic activity measures, indicators of key parts of the economy (e.g. industrial production) or measures of real domestic income could be considered. The reference series should be:

- reliable;
- contain a broad/important range of economic activity;
- available in a quarterly or monthly frequency.

Countries that are building up statistical offices usually start with statistics on an annual basis. Annual data are not suitable for a timely monitoring the business cycle development, however. Nevertheless, these data can be used as an anchor for the assessment of high frequency indicators.

The composite indicator construction algorithm consists of the following steps. First, possible indicators have to be searched for and their characteristics have to be collected. Then, a first classification of the candidates must be made. A more sound assessment of indicators requires a comparison with a reference series. Therefore available information has to be used to construct such a reference. Some of the indicators may be useful for this task. Then, the final selection of single indicators can be done and the composite indicator can be weighted as a whole.

In this procedure only well-established statistical methods are used. These methods are not explained in detail here, because they can be found in numerous papers and even textbooks.[4] As well as simple calculations like first differences or yearly growth rate, trend adjustments are often necessary. For the later task, filters are usually used. Some common filters are the Hodrick-Prescott filter, the Baxter-King filter, the Rotemberg filter, the Christiano Fitzgerald filter and the Kalman filter.[5] Since a quarterly or monthly frequency is pursued, often seasonal adjustments are required. For this task there are several standard techniques available such as the X-12-ARIMA procedure developed by the US Bureau of Census, or the TRAMO SEATS adjustment method of Maravall and Gómez (Bank of Spain).[6]

For the construction of a high frequency reference series methods of temporal disaggregation are used. Temporal disaggregation is a process of deriving high frequency data from low frequency data optionally using additional information from related series observed at the desired higher frequency. The related series approach includes, among others, the seminal procedure developed by Chow and Lin (1971) and the extensions by Fernández (1981) and Litterman (1983). More recent developments draw on unobserved components and structural time series models and Kalman filter techniques.[7]

2.1. Collecting and classification of indicators

The scarce data environment is also characterized by a lack of established and sufficient data collections. So in the first step one has to brainstorm the possible data providers: statistical offices, ministries, national banks, private banks, market data, associations, large companies, like power suppliers, harbours etc. All possible informants of economic activities should be employed. Also in countries with statistical offices in development one can find a considerable amount of alternative data providers. Providers and their data should be collected very open mindedly.

There are various pieces of information that might be considered for the construction of indicators. Some examples of possible indicators are:

- Production, stock of orders, employment, unfilled job vacancies, new car registrations, housing starts, nights spent in hotels, electricity consumption, passengers at airports, air cargo, freight managed by harbours;
- business tendency surveys;
- consumer surveys;
- various price figures and share prices, terms of trade, exchange rates, commodity prices like the copper price;
- interest rates (spreads), bank credits;
- indicators of other countries to capture foreign trade.

The indicators are enclosed step by step. This encapsulating has to be guided by the general characteristics of good indicators. Good indicators should:

- be meaningful and reliable;
- be timely available;
- not be revised considerably after publication;
- be leading or coincident for the business cycle, so that timely signals are given;
- have a stable relationship with the reference series;
- give clear signals with minor noise.

With the help of the information collected, the indicators are classified into three categories. The categories consist of data which: 1) is not considered further, 2) maybe used for the temporal disaggregation of the reference series, 3) is regarded as a candidate for the composite indicator.

Since a composite business indicator must have a timely availability, the data used must be at hand with a minor publication lag and must not suffer from large revisions after first publication. Data not fulfilling these tough criteria for Group 3 should be considered for Group 2, however. Data of Group 2 are used for the temporal disaggregation of the annual reference series. It is not necessary that the reference series is very timely, because it is used as a benchmark for the individual and for the composite indicator in the past. Meaningful, reliable, timely data which is not revised heavily is considered as a potential business cycle indicator. To assess these data with the help of statistical methods, a reference series for comparison is required. So after browsing for data and after the collection information, a reference series must be constructed for further considerations.

2.2. Construction of reference series

The scarce data situation is characterized by the lack of a high frequency reference series, e.g. a quarterly national accounts system is not available. Even when countries are just building up statistical offices and reporting systems, they often publish only annual figures. However, annual data may serve as an important anchor for a quarterly or even monthly reference series, derived by temporal disaggregation techniques.

The reference series is needed for historical comparisons with the individual candidate indicators for the composite indicators. That's why also data that is not published in a timely fashion and that is revised later can be utilized at this step. This division of variables also has the important advantage that the high frequency series used for temporal disaggregation are different from the data used for the composite indicator. This makes the statistical comparisons reliable. Only in very special cases it might be necessary to deviate from this principle and for temporal disaggregation to use high frequency series that are also candidates for the composite indicator. This means introducing some self-reference, which general should be avoided. However, with temporal disaggregation methods the annual reference is distributed to the quarters within the years. The annual figures and thus the general course of the reference series do not change. Nevertheless, turning point analyses and cross-correlations should be interpreted with care, because they may be a bit overoptimistic. In the present case study the self-reference is reduced by the fact that the oil price is used to disaggregate oil value added in current prices which is only on part of the overall reference series and which is determined to a large extend by oil prices. Oil prices are also part of the composite indicator, which is constructed with the overall reference series. The use of oil prices in the whole construction procedure is in the case of Abu Dhabi inevitable, because this economy is very dependent on oil.

2.3. Assessment of indicators

The collected indicators at this stage are already categorized by qualitative assessments, like publication lag. The candidates for the composite indicator are now assessed statistically. Before individual indicators can be compared with the reference series, it must be determined whether some transformations are needed, such as seasonal adjustment, trend adjustment with the help of filters, annual differences or first differences. Since business cycles are fluctuations around a growth trend, business cycle indicators must be trend free. Fluctuations with a period below one year (or 1.25 or 1.5 years) are not considered as business cycles.[8] Seasonal fluctuations fall in this category.

The prepared individual indicators can be analyzed statistically with cross-correlations, turning point analysis,[9] spectral and co-spectral analysis. These comparisons restrict the list of candidates further.

Individual indicators can be combined in a composite indicator in various ways. The classical approach builds arithmetic averages of standardized indicators. This corresponds to weighting indicators by the reciprocal of its standard deviation. This is often a suitable approach in a scarce data situation. Alternative principal component analysis or static and dynamic factor analysis can be used.[10] Estimation of principal components and factors is often not robust with scarce data. The estimated loadings often fluctuate with every newly available piece of data.

3. Case study: A composite indicator for Abu Dhabi

As an example for the above described procedure, a composite indicator for the business cycle in Abu Dhabi is constructed. Although the country is currently building up a high quality statistical agency that uses international best practice methods, the data situation is still characterized by a scarce data environment. Figures for GDP and it components are available only annually. For the construction of the composite indicator, various types of statistics and various data providers have been explored.

3.1. Selection of reference series

The UAE possesses nearly 10 per cent of the world's total reserves. Abu Dhabi holds currently 94% of the UAE's oil reserves, or about 92.2 billion barrels. As shown in Table 1, the share of gross value added of Abu Dhabi's oil and gas sector in 2012 was 52% of real GDP. From 2005 to 2012 the oil and gas sector in Abu Dhabi contributed on average 35% to the average growth rate of real GDP in the time-span (4.7%). According to preliminary data, oil value added accounted for 56.5 percent of GDP in current prices due to the significant rise in oil prices since 2010 (see Table 1).

Table 1. **Percentage distribution of GDP by industries in Abu Dhabi**

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012[1]
Oil value added in current prices	46.7	50.7	56.2	59.2	56.4	58.5	44.6	49.6	57.3	56.5
Non-oil value added in current prices	53.3	49.3	43.8	40.8	43.6	41.5	55.4	50.4	42.7	43.5
Total % of oil and non-oil value added to GDP (current prices)	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Oil value added in constant 2007 prices	-	-	59.3	57.7	56.4	57.0	51.6	51.8	52.9	52.0
Non-oil value in constant 2007 prices	-	-	40.7	42.3	43.6	43.0	48.4	48.2	47.1	48.0
Total % of oil and non-oil value added to GDP (constant 2007 prices)	-	-	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

1. Preliminary estimates.
Source: Statistics Centre Abu Dhabi.

Due to the large share of the oil sector and considerable trading gains due to high oil prices, a business cycle concept based on capacity utilization and production could be misleading. Cycles in real income are a more suitable benchmark for overall economic activity and welfare in Abu Dhabi. Real GDP underestimates the growth of real gross domestic income (real GDI), whenever the terms of trade improve, defined as the relation of export to import price indices.[11] An improvement in the terms of trade allows a country to import more for its exports or to export less for a given volume of imports.

Thus, it is possible to purchase more goods and services out of the incomes generated by domestic production. Real GDI measures the purchasing power of total income generated by domestic production. When the terms of trade change significantly there may be a considerable divergence between real GDP and real GDI.[12]

The distinction between real GDP and real GDI implies differences between the corresponding deflators for *nominal GDP*.[13] In order to measure real domestic income, a *common price index* should be used instead of the *implicit GDP deflator* P_{GDP}. Deflating nominal GDP with the price index of gross domestic final expenditure P_{DD}, for example, neutralizes a rise or fall of the prices of domestic demand, whereas the effects of changing terms of trade pass through. Whenever the terms of trade improve, the deflator for gross domestic final expenditure P_{DD} will show a lower inflation than the GDP deflator P_{GDP} in

comparison to a predefined base year, thus indicating an increase of purchasing power. The increase in real GDI is caused by higher entrepreneurial profits and/or lower domestic prices.

In the System of National Accounts (SNA), trading gains or losses from changes in the terms of trade are measured as the difference between exports and imports deflated by a common price index and exports and imports deflated by special export and import price indices. Thus, using the deflator of gross domestic final expenditure P_{DD} as a general price index, the *terms-of-trade effect* T_{DD} is given by the expression:

$$T_{DD} = (X - M)/P_{DD} - (X/P_X - M/P_M)$$

where *X*: nominal exports, *M* nominal imports, P_X: price index of exports, P_M: price index of imports. The *terms-of-trade effect* equals the difference between real GDI and real GDP.[14] T_{DD} is measured with reference to the price level of the *base year 0*. In the base year all price indices (such as P_X, P_M and P_{DD}) equal 100, which implies $T_{DD} = 0$. For $t > 0$ ($t < 0$) a positive (negative) value of T_{DD} denotes a trading gain in comparison to the base year.

If imports and exports of a country are large relative to gross domestic production and if the commodity composition of imports and exports is very different, the scope for *terms-of-trade effects* is generally large. Large trading gains and losses may happen, whenever exports consist mainly of primary products (such as crude oil or gas), while imports consist primarily of manufactured products.[15] For example, *positive terms-of-trade effects* contribute up to two thirds of total real GDI growth in the United Arab Emirates (2008, 2011 and 2012, see Table 2). In contrast, the *trading loss* in 2009 due to the enormous fall of oil prices contributes 70% of the decline of real GDI (-15.1%). All in all, cumulative growth of real GDI in the UAE from 2005 to 2012 was almost 30 percentage points larger than the growth of real GDP (see Figure 1a).

Table 2. **Real GDP, real GDI and terms-of-trade effect in the United Arab Emirates**[1]

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012*
Real gross domestic product (real GDP)	727.5	797.1	835.8	918.0	947.2	977.4	930.5	946.0	982.7	1 025.6
Terms-of-trade effect	-88.3	-99.3	-59.7	-16.3	0.0	63.3	-47.4	-45.1	57.8	150.9
Net exports deflated with a common index[2]	61.0	73.4	121.2	160.4	75.5	96.0	51.4	58.3	187.7	243.3
Real net exports	149.4	172.6	180.9	176.7	75.5	32.7	98.8	103.5	129.8	92.4
Real gross domestic income (real GDI)	639.1	697.8	776.0	901.7	947.2	1 040.7	883.1	900.9	1 040.6	1 176.5
Terms-of-trade[3]	76.3	79.0	88.4	97.2	100.0	108.5	93.2	93.8	106.7	115.7

* Preliminary.
1. AED bn., at constant prices of 2007.
2. Deflated with the price index of gross domestic final expenditure.
3. Index, 2007 = 100.
Source: National Bureau of Statistics, United Arab Emirates.

For this reason a measure *of real gross domestic income* was chosen as *reference* for the overall economic situation in Abu Dhabi. Due to the fact that the price index for gross domestic final expenditure P_{DD} is not yet released by the Statistics Centre Abu Dhabi, the *consumer price index* (CPI) was used as common price index for deflating GDP. Hence, *CPI deflated GDP* is chosen as a *proxy* for real GDI in Abu Dhabi (see Figure 1b).

Figure 1a. **Real GDI and Real GDP in the United Arab Emirates**

(2005 = 100)

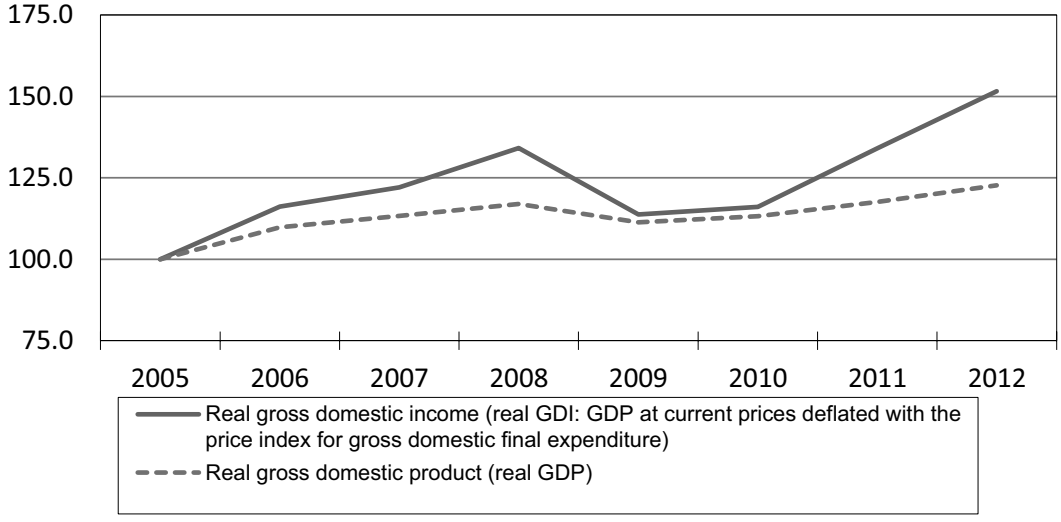
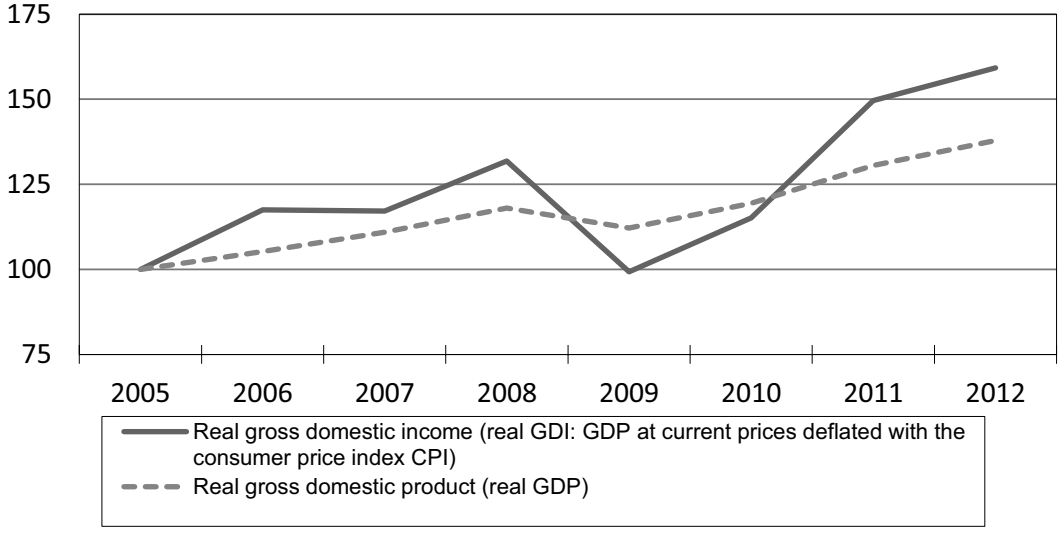


Figure 1b. **Real GDI and Real GDP in Abu Dhabi**

(2005 = 100)



3.2. Derivation of quarterly real GDI by temporal disaggregation

Quarterly SNA figures that are needed for the construction of a quarterly reference series are not yet available for Abu Dhabi. However, this problem can be overcome by temporal disaggregation methods. Temporal disaggregation is a method of deriving high frequency data from low frequency data optionally using related high frequency indicators. For the *oil-sector*, a high-frequency indicator, namely the oil price, is available. So a temporal disaggregation between the oil value added and the oil price has been carried out. It is built on the hypotheses that the movement of the quarterly oil price provides a correct description of the movement of the quarterly value added in the oil sector. For the *non-oil sector*, no predominant indicator is available. So a mathematical method for constructing quarterly figures was selected, which is based on past trends in the annual data.

For transforming annual figures into quarterly series by means of a related high frequency indicator, the *Litterman* method based on the seminal work of *Chow and Lin* was applied.[16] The idea behind this method is as follows. A relationship between annual figures Y_t and a suitable set of annualized high frequency indicators $X_{h,t}$ is estimated, usually with linear regression methods (for the particular case of disaggregating annual to quarterly data, h = 4). The high frequency indicators $X_{h,t}$ are used to estimate the unobservable high frequency series $Y_{h,t}$. The following data generating process is supposed for $Y_{h,t}$, which takes into account, that the oil price and the value added in the oil-sector are not cointegrated[17] due to varying output quotas:

$$Y_{h,t} = X_{h,t}\beta + u_{h,t}$$

subject to the aggregation constraint that the quarterly figures add up to annual figures.

$$u_{h,t} = u_{h,t-1} + v_{h,t}$$

$$v_{h,t} = \rho\, v_{h,t-1} + \varepsilon_{h,t}$$

$$\varepsilon_{h,t} \sim i.i.d.(0,\sigma^2_h),\ h = 1,\ldots,4\ t = 1,\ldots,T$$

which means that the innovation process $u_{h,t}$ follows an ARIMA(1,1,0) model. For the transformation of annual to quarter data the ECOTRIM software package by Eurostat was used.[18]

For the non-oil sector, a temporal disaggregation technique based on Boot, Feibes, and Lisman (1967) was selected. A quarterly time series is derived from annual totals using a least squares minimization technique:

$$\min \sum [Y_{h,t} - Y_{h,t-1}]^2\ h = 1,\ldots,4 \quad t = 2,\ldots,T$$

under the restriction, that the sum of the quarterly figures is equal to the observed annual data ($Y_t = \sum_{h=1,..,4} Y_{h,t}$).

For obtaining quarterly real GDI figures, the quarterly estimates for oil value added in current prices as well as the quarterly estimates for non-oil value added are deflated with the quarterly consumer price index CPI. In a final step, quarterly estimates of total real GDI in Abu Dhabi are derived by summing up the separate results for oil-based and non-oil based real GDI.

3.3. The composite indicator

After processing through the selection method explained in Section 2.1, the following indicators for Abu Dhabi were identified:

- Oil price (Murban, Y-Y change in %; source: Datastream), CPI deflated (source: SCAD and NBS).
- Securities (ADX Industrial, ADX Services, quarterly averages, Y-Y change in %; source: Abu Dhabi Security Exchange), CPI deflated.
- Business Permissions (seasonally adjusted, HP detrended, source: ADCCI).
- Personal income of private households, assessment of current situation (balances, source: DED).[19]

For oil-based real GDI, the oil price, CPI deflated, was chosen as coincident indicator:

For $t \geq$ Q1/2003:

$$I_{Oil}(t) = \textit{oil price CPI deflated (t)}$$

For the non-oil sector, a distinct indicator was built. The indicator consists of CPI deflated securities (more specifically the ADX Industrial and the ADX Services), business permissions, and – starting with the second quarter of 2009 – the assessment of personal income situation of private households, all series equally weighted. Results from surveys are internationally established, the OECD[20] uses survey results quite often in its country indicators. For this reason some results stemming from surveys are used for tracking non-oil value added real GDI:

For Q1/2003 ≤ t ≤ QI/2009:

$$CI_{Non\text{-}Oil}(t) = 1/3\ ADX\ Industrial\ CPI\ deflated\ (t) + 1/3\ ADX\ Services\ CPI\ deflated\ (t) + 1/3\ business\ permissions\ (t),$$

For t > Q1/2009:

$$CI_{Non\text{-}Oil}(t) = 1/4\ ADX\ Industrial\ CPI\ deflated\ (t) + 1/4\ ADX\ Services\ CPI\ deflated\ (t) + 1/4\ business\ permissions\ (t) + 1/4\ personal\ income\ (t)$$

Finally, the overall composite indicator for Abu Dhabi is also constructed by an equal weighting scheme:

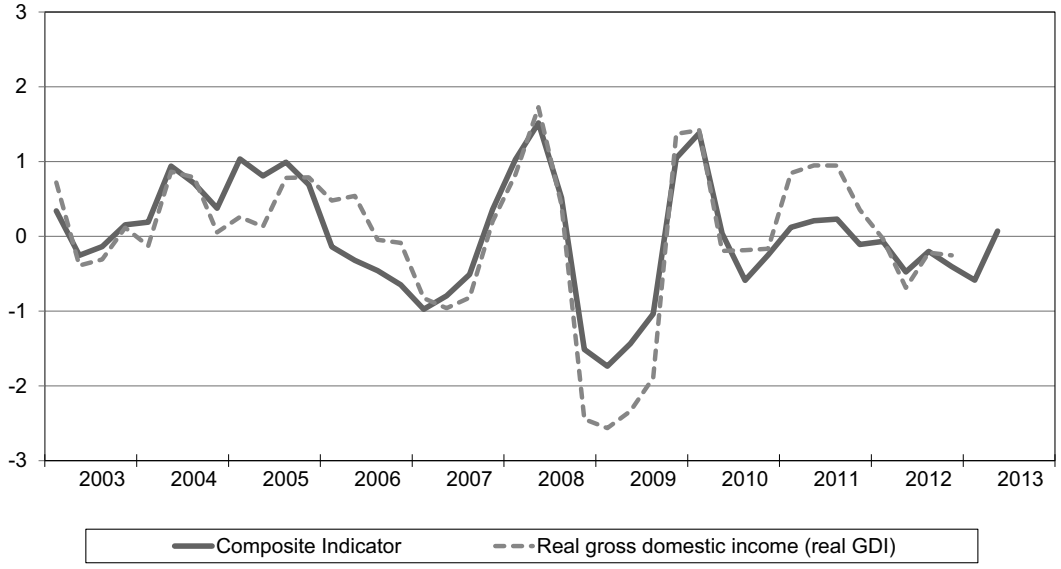
For t ≥ Q1/2003:

$$CI(t) = ½ \bullet I_{Oil}(t) + ½\ CI_{Non\text{-}Oil}(t)$$

All series are standardized meaning each indicator X is transformed to $Z = (X - \mu)/\sigma$ with μ: mean and σ: standard deviation of the observed indicator values. The transformed indicators have a zero mean and a standard deviation of one.

Figure 2 shows that the course of the composite indicator and the standardized quarterly real gross domestic income (real GDI) is quite similar. The indicator tracks closely the cyclical behavior of the reference series.

Figure 2. **Composite Indicator for Real Gross Domestic Income (Real GDI) in Abu Dhabi**



The cross-correlogram analysis for the time-span Q1/2003-Q4/2012 shows a *coincidence* between the two series; the maximum correlation coefficient is achieved accordingly at a parallel course and amounts to 0.89. Obviously, the predominant oil sector has a weight of 50 % in the composite index for Abu Dhabi corresponding to the actual percentage share of real GDP. The divergence between the composite indicator and real gross domestic income observed from 2010 to 2012 stems primarily from the assessments of the income situation of private households and from business permissions, which performed weak during the Arab Spring, whereas real gross domestic income rose visibly. If these critical years are excluded, the correlation between all variables is higher, especially in the non-oil sector (see Table 3).

Table 3. **Correlation matrices**

Correlation matrix (Q1/2003-Q4/2012)						
	CI	GDI	CI_{OIL}	GDI_{OIL}	$CI_{NON\text{-}OIL}$	$GDI_{NON\text{-}OIL}$
CI	1.00					
GDI	0.89	1.00				
CI_{OIL}	0.92	0.97	1.00			
GDI_{OIL}	0.86	0.94	0.96	1.00		
$CI_{NON\text{-}OIL}$	0.86	0.56	0.59	0.50	1.00	
$GDI_{NON\text{-}OIL}$	0.52	0.60	0.46	0.32	0.47	1.00
Correlation matrix (Q1/2003-Q4/2009)						
	CI	GDI	CI_{OIL}	GDI_{OIL}	$CI_{NON\text{-}OIL}$	$GDI_{NON\text{-}OIL}$
CI	1.00					
GDI	0.91	1.00				
CI_{OIL}	0.94	0.97	1.00			
GDI_{OIL}	0.87	0.96	0.97	1.00		
$CI_{NON\text{-}OIL}$	0.90	0.68	0.71	0.59	1.00	
$GDI_{NON\text{-}OIL}$	0.66	0.70	0.58	0.49	0.66	1.00

4. Summary

Business cycle indicators are calculated for many countries. The indicators are important for the monitoring of the economic development in economies. They are closely watched by capital markets, by politicians and by the public.

Various econometric methods have been developed for the construction and optimization of business cycle indicators. Usually one relies on a sound statistical database when employing indicators. Many recent methodological developments try to capture large data sets. However, there are still countries where the data situation is not so rich. This paper deals with indicator development in a scarce data situation. No new methods are developed in this article, but known methods are combined in a new way. Indicator development is merged with temporal disaggregation, which is often used by statistical offices. Candidate indicators are classified and either abandoned, selected as candidate for the business cycle indicator or selected as candidate for the temporal disaggregation of a reference series.

The discussed tools are applied in a case study. Despite the scarce data situation, a coincident business cycle indicator for Abu Dhabi has been developed. The indicator can be assessed with the help of a quarterly reference series. Because the economy of Abu Dhabi is very dependent on oil, a further complication occurs. Real income reflects the economic situation better than real production. For this reason a measure of real gross domestic income (CPI deflated nominal GDP) was chosen as reference for the overall economic

situation. The developed indicator is a valuable improvement for business cycle analysis in Abu Dhabi. Up to now, results of national accounts are published only annually and with a considerable publication lag. Thus, a quarterly indicator, which is published a few days after the respective quarter, is an important addition of very timely information.

Notes

1. See Mitchell and Burns (1938).
2. See Hamilton (1989) and especially for nonparametric methods Fan and Yao (2005).
3. See Stock and Watson (2005).
4. See for example The Conference Board, *Business Cycle Indicators Handbook*, 2001 or OECD, *Handbook on Constructing Composite Indicators*, OECD, 2008.
5. See Hodrick and Prescott (1997), Baxter and King (1995), Rotemberg (1998), Lawrence and Fitzgerald (1999), Kalman (1960). Some recent discussions of filters can be found in Canova and Ferroni (2011).
6. For X-12-ARIMA see Findley, Monsell, Bell, Otto and Chen (1998), for TRAMO (time series regression with ARIMA noise, missing observations and outliers) and SEATS (signal extraction in ARIMA time series) see Gómez and Maravall (2001).
7. See for example Mazzi, Moauro and Savio (2005) and Proietti (2006).
8. See also Baxter and King (1995).
9. See Bry and Boschan (1971).
10. See for example Schumacher (2007).
11. See Kohli (2004, p. 83).
12. See System of National Accounts (2008, p. 316).
13. See Kohli (2004, p. 84) and Nierhaus (2000, p. 8).
14. See Abberger and Nierhaus (2011, p. 11).
15. See System of National Accounts (2008, p. 316).
16. See Chow and Lin (1971), Litterman (1983) and Müller (2006).
17. While the basic methodology of Chow and Lin assume cointegrated variables, in the extension proposed by Litterman this is not the case. Although the oil price and oil value added move similar within the available data range, both Johansen tests, the trace test and the maximum eigenvalue test, do not reject the hypothesis of no cointegration. Also with Engle-Granger test procedure the unit root hypothesis for the regression residuals is not rejected. It might be that the sample size is too low and the power of the test is not high enough. However, it is plausible that in the long-term the oil production develops somewhat differently than the oil price. Especially, when new oil sources are exploited. That is why the Litterman procedure was applied. The authors calculated also the Chow and Lin quarterly estimates and the results were quite similar. So the disaggregation seems to be relatively robust regarding the applied method.
18. Barcellan and Buono (2002), ECOTRIM Interface, Temporal Disaggregation Techniques, *https://circabc.europa.eu/w/browse/c6049bc0-c633-4cab-9811-b476ffe08370*, Version 1.01.
19. ADCCI: Abu Dhabi Chamber of Commerce & Industry, DED: Department of Economic Development Abu Dhabi, NBS: National Bureau of Statistics United Arab Emirates, SCAD: Statistical Centre Abu Dhabi.
20. A list of the component series for the country composite indicators of the OECD can be found at: *www.oecd.org/document/29/0,3746,en_2649_34349_35725597_1_1_1_1,00.html* (July 2011).

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