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Detecting turning points in global economic activity

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Abstract

We present non-linear models to capture the turning points in global economic activity as well as in advanced and emerging economies from 1980 to 2017. We first estimate Markov Switching models within a univariate framework. These models support the relevance of three business cycle regimes (recessions, low growth and high growth) for economic activity at the global level and in advanced and emerging economies. In a second part, we find that the regimes of the Markov Switching models can be well explained with activity, survey and commodity price variables within a discrete choice framework, specifically multinomial logit models, therefore reinforcing the economic interpretation of the regimes.

Keywords: Global GDP, Markov Switching, multinomial logit, turning points

JEL Classification: C34, C35, E32

Non-technical summary

In this paper, we propose the use of non-linear models to get an indication about the probability of being at different stages of the business cycle. For that purpose, we estimate Markov Switching models for the period 1980 to 2017, allowing for *three* regimes, specifically recession, low growth and high growth. We differentiate between the world economy (global) and advanced (AE) as well as emerging (EME) economies. The explanatory variables considered include only lagged GDP growth rates and regime-specific constants. All models appear to capture the dynamics of GDP rather well and clearly identify the global recessions of the mid/late 1990s as well as the Great Recession. The most volatile model is that for emerging market economies. Moreover, we find that for the global economy and for AEs, the high growth regime generally follows recessions, but was also in place over the "Great Moderation" and in the late 1980s. The model indicates that the world economy is in a low growth regime since 2012, showing some incipient, although still low, probability of switching into the high growth regime.

The results also point to some interesting differences in the business cycles for the global economy, AEs and EMEs: (i) the Great Recession was unprecedented for AEs, being the only significant downturn that occurred in our sample period; meanwhile, recessions are more common in EMEs, particularly before the 2000s; (ii) outside recessions, AEs have been in a high growth regime most of the time, although since 2010 they are found to be in the longest low growth regime since the start of our sample. In contrast, EMEs have been mainly in a low growth regime, the main exception being the intermittent high growth periods in advance of the financial crisis; (iii) there are signals of an increase in the probability of a transition to higher growth in AEs, but EMEs are expected to remain in a low growth regime for the time being.

As an additional exercise, we account for changes in estimated potential output at a global level. This is motivated by the fact that the above-mentioned baseline results are purely statistical, while there may be economic reasons that have led to a decline in global potential growth after the Great Recession. In this adjusted model, estimated recessionary periods remain the same, while the model indicates in this case that global GDP has been in a low growth regime for most of the sample, including the post-Great Recession period (accounting for lower potential growth). As changes in potential growth are inherently difficult to detect in real time, the three-regime model may help to inform about possible changes in potential growth, for example when showing an unusually persistent period of low or high growth.

In the final part of the paper, we use the Markov regimes to estimate discrete choice models for the three GDP aggregates, namely multinomial logit models. This can be interpreted as a crosscheck and further validating of the economic interpretation of the regimes found. For that purpose, a set of independent variables is used to identify and explain the (probabilities of) different regimes. Our results show that not only activity related variables and surveys play an important role, but also oil prices in some specifications. Although these models have sometimes problems in capturing the recession regimes correctly, their forecasting accuracy is quite good.

1. Introduction

One of the greatest challenges of empirical business cycle research is the detection and modelling of business cycle turning points. In the US and the euro area, there are the Business Cycle Dating Committees of the NBER and the CEPR, respectively, which date the turning points in the dynamics of economic activity. However, at a global level - be it world-wide, advanced economies, emerging market economies - such dating does not exist and business cycle analysis is quite limited. To detect as well as model the turning points in a global context, we make use of dynamic and non-linear methods, namely the Markov Switching approach and multinomial discrete choice models.

Since the seminal paper by Hamilton (1989), Markov Switching models (see for recent applications Levanon et al 2011 for the US, Fritsche & Kuzin 2005 for Germany, Krznar 2011 for Croatia) have been intensively used for this kind of business cycle analysis on a national level.[1] These models define and estimate two or more regimes (e.g. expansions and recessions) where the evolution of economic activity is regime-dependent. This enables to derive regime probabilities.

There are only few papers that aim at nowcasting or detecting turning points in *global* economic activity. Ferrara & Marsilli's (2014) approach builds on a Factor-Augmented Mixed Data Sampling model that enables to account for a large monthly dataset including various countries and sectors of the global economy and to nowcast low-frequency world activity using higher-frequency information. More specifically, they use 392 indicator variables from 37 countries, both advanced and emerging. Pseudo real-time exercises yield reliable and timely nowcasts of world GDP on a monthly basis, especially at the beginning of each year when only little information about the current year is available.[2] Ravazzolo & Vespignani (2015) also concentrate on growth rates and evaluate the quality of world steel production compared to Kilian's index of global real economic activity and the index of OECD world industrial production as monthly indicators of global economic activity on a quarterly basis. Based on long-term, distance, correlation and mixed-frequency predictability properties, they find that both world steel production and Kilian's index of global real economic activity equally accurately predict world GDP growth rates.

Stratford (2013) uses *linear* models to investigate several global indicators' ability to nowcast world trade and world GDP. His indicator set is composed of variables directly related to activity (e.g. world goods trade, OECD composite leading indicator, IfO World Economic Climate) as well as others where the link to activity is more indirect (Baltic Dry Index, Brent oil price, S&P global stock price index). He finds that the indicators are most helpful during periods of large swings in world

[1] On forecast combination schemes for predicting turning points of business cycles see Billio et al (2012).

[2] Several authors have also developed bridge models to forecast world GDP growth rates based on monthly indicators, see, e.g., Golinelli & Parigi (2014).

growth, as seen since the onset of the financial crisis. However, their usefulness has fluctuated greatly over time. Interestingly, since 2010, the nowcasts of world GDP and world trade using only export orders have the smallest nowcast errors.

The contributions that address turning points directly at a global level, in part within a non-linear framework, are Camacho & Martinez-Martin (2015) and Martinez-Garcia et al (2015). Camacho & Martinez-Martin (2015) propose a two-state *Markov-switching* dynamic factor model to produce short-term forecasts of world GDP and to compute business cycle probabilities. The model is able to handle mixed frequencies, publication delays and different starting dates in the economic indicators. The variables included are world GDP, global industrial production, the global manufacturing Purchasing Manager Index, employment, export orders and the CBOE volatility index. Their pseudo real-time results reveal that this approach provides reliable and timely inferences of quarterly global growth and of the world state of the business cycle on a monthly basis. Martinez-Garcia et al (2015) construct a chronology of global business cycles using the Bry & Boschan (1971) algorithm and industrial production data. As the authors point out, however, the main drawback of using the Bry & Boschan algorithm is its timeliness, in that it requires a number of additional observations before it can detect a change of a business cycle phase. For this reason, the authors combine their approach with a forecasting exercise to predict global turning points using a logit model.

Our analysis differs in several aspects from these papers. First, in contrast to Ferrara & Marsilli (2014), Ravazzolo & Vespignani (2015) and Stratford (2013), we concentrate solely and directly on turning points of global GDP growth. Second, we estimate the Markov Switching models with three regimes, namely recessions as well as low and high growth, whereas Camacho & Martinez-Martin (2015) and Martinez-Garcia et al (2015) only consider two regimes. Third, we use the Markov Switching regimes to estimate Multinomial Logit models to get further insights on the determinants of turning points in economic activity. And fourth, while focusing on economic activity at a world level, we also distinguish between that in advanced and emerging economies.

Our findings support the relevance of three regimes of economic growth at the global level in a sample from 1980 to 2017. In particular, one regime clearly identifies the global recessions of the mid and late 1990s as well as the Great Recession, while another regime detects the high growth phase that generally follows recessions, but that was also in place for a more prolonged period prior to the recent financial crisis ("Great Moderation"). By contrast, a third regime captures periods of low growth that tend to precede global recessions, but also prevails at a global level since 2012. Our estimates point, at the same time, to some growing probability, although still modest, for global growth to switch into the high growth regime since the end of 2016.

The remainder of the paper is structured as follows. Section 2 describes the independent and dependent variables used. Following this, Section 3 introduces the Markov Switching models and presents their results. Section 4 uses the regimes derived within the Markov approach to estimate Multinomial Logit models. Section 5 summarises and concludes.

2. Data

We use seasonally adjusted quarterly data for the sample 1980Q1-2017Q2. World activity is measured by real quarterly world GDP, derived from a PPP-weighted aggregation of national GDP data based on national sources. We also distinguish between real quarterly GDP for advanced economies and emerging economies (see Appendix A for further details on the data sources and construction).

The independent variables considered in the Multinomial Logit models can be grouped as follows:

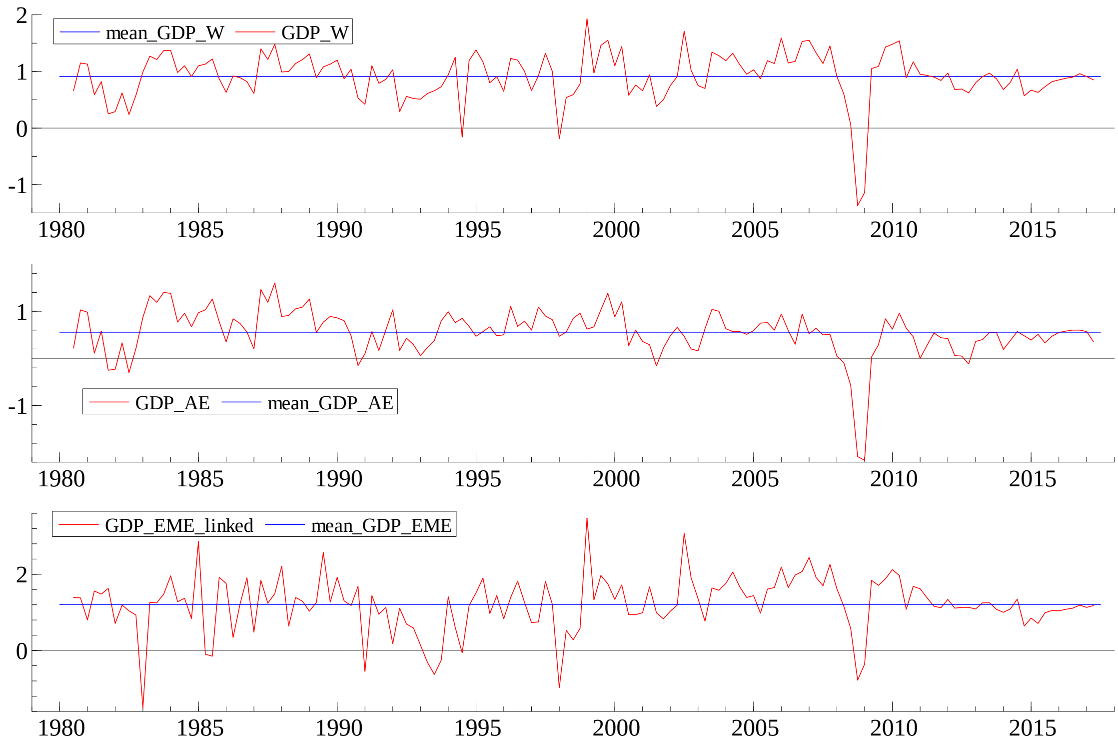
- *Activity data*: these include industrial production in OECD countries and emerging market economies, world steel production, the Kilian index of real world economic activity, the Goldman Sachs Global Leading Indicator, the Composite Leading Indicator by the OECD, a global factor derived by Delle Chiaie et al (2017) and the Conference Board US Leading Economic Index.
- *Survey data*: consumer confidence in OECD countries and in the US.
- *Financial data*: the US term spread, the US BBB bond spread, S&P500, M1 and M3 for OECD countries, and a global monetary policy rate.
- *Commodity prices*: oil prices in USD and indices of metal prices and non-oil commodity prices.

Chart 1 plots quarterly world, advanced economy and emerging economy real GDP growth from 1980Q1 to 2017Q2. Visual inspection suggests that world GDP can be characterised by three types of periods with different mean growth rates: (i) global recessions or brief periods of negative growth rates, of which there have been only three in the sample period considered (in the mid-1990s, the late-1990s and the Great Recession in 2008-09); (ii) periods of robust growth, either briefly following recessions or on a more prolonged basis, such us around the Great Recession (2006-07 and 2010); and (iii) low growth episodes, like the post-Great Recession years. When comparing advanced (AEs) and emerging market economies (EMEs) developments, not only average growth rates differ significantly, but recessions also have a different dating. The only exception is the Great Recession, which affected both AEs and EMEs, although to a lesser extent the latter group. Still, it is possible to identify in both groups high and low growth periods.

The economic rationale for considering three regimes of economic growth is particularly evident in the wake of the financial crisis, with a very timid recovery in advanced economies, partly linked to low investment and productivity growth. As regards emerging market economies, low post-crisis growth is related to the rebalancing in China's growth model and its spillovers particularly in commodity producers. In line with that, various international organisations have been alerting in recent years of the possibility of a low growth trap and have advised on the right policy mix to avoid it. Moreover, academic work has concentrated on the long-term effects of the Great Recession, including areas like productivity, the labour market and potential growth.[3]

In what follows, our aim is to use model-based techniques (combined with economic rationale) to detect these alternative episodes, and thereafter to estimate probabilities of staying in a regime or moving to a different one.

Chart 1: Real GDP – world, advanced (AE) and emerging economies (EME)
(quarter-on-quarter percentage change)



Sources: IMF, ECB and author's calculations.

3. Markov-switching models

3.1 Econometric framework

To model the dynamics of global, AEs and EMEs GDP growth, we employ a dynamic Markov-switching model (see Hamilton 1989), where we allow the intercept to be regime dependent. Assuming a random variable, $S_t \epsilon \{0,1,\ldots N\}$ where N denotes the unobserved regimes, the model can be written as follows:

(1) $$y_t = \vartheta(S_t) + \alpha_k \sum_{k=1}^{K} y_{t-k} + \varepsilon_t, \qquad \varepsilon_t \sim N(0,\sigma^2), t = 1 \ldots T,$$

[3] See, for instance, Ball (2014) and Hall (2014).

where y_t is real quarterly world GDP growth, $\vartheta(S_t)$ is the mean of regime S_t. Due to the quarterly frequency of the data, we take up to four lags of GDP into account. S_t follows a Markov chain defined by the following transition probabilities $p_{i|j}$ between regimes:

(2) $$p_{i|j} = P[S_{t+1} = i \mid S_t = j], \quad i,j = 0,1 \dots N-1, \; with \; \sum_{i=0}^{S-1} p_{i|j} = 1,$$

This approach leaves the determination of the different regimes to the estimated econometric model. The (transition) probability of being in a certain regime depends only on the previous regime and the available data, and thus has a Markovian structure. Transition probabilities and other model parameters are estimated using Maximum likelihood and the sequential quadratic programming approach (SQP) for optimisation (see Doornik 2013).[4]

An important issue with regime switching models is to specify the number of regimes. As this is often difficult to determine solely from data, it is useful to combine a data-driven approach with a meaningful economic interpretation (see Ang & Timmermann 2012). As motivated in section 2, in the case of global, AEs and EMEs GDP growth, we identify three different regimes: recession, robust growth and low growth episodes.[5] We are mainly interested in the evolution of the probabilities of a regime (change) and in understanding the dynamics of regimes.[6]

3.2 Estimation results for global growth

The model for global GDP includes as explanatory variables the regime-switching constants, as well as four lags of global growth (GDP_W). We do not include other variables as regressors in the equations, because these would act as additional filters which renders the interpretation of the Markov Switching activity difficult.[7] As shown in Chart 2, this model specification, allowing for three regimes (recession, high and low growth), appears to capture the dynamics of global GDP rather well. Regime 1 clearly identifies the global recessions of the mid and late 1990s as well as the Great Recession, as reflected by a sharp rise in transition probabilities of regime 1, but for a very short duration. According to the model, the high growth regime 2 generally immediately follows recessions, but was also in place for a more prolonged period prior to the recent financial and economic crisis ("Great

[4] In addition, we assume uniform probabilities to start the recursion.

[5] The choice of three regimes is largely confirmed by the model estimates in terms of significance of different means. Still, we have tested the robustness of our results to assuming only 2 states. For world GDP, we find a stable model also when assuming two regimes, which identifies the three recessions versus expansionary periods. For AEs and EMEs, however, the models with two regimes were clearly inferior. In AEs, a two-state model identifies only the Great Recession versus other periods, while in EMEs, a two-state model identifies pre vs post-2000 states which lack a clear economic interpretation.

[6] Guérin & Leiva-Leon (2017) present a different approach and use dynamic model averaging to combine business cycle forecasts from a large set of Markov Switching models. They find that standard weighting schemes based only on the models' likelihood are not necessarily appropriate in a context of regime classification.

[7] We are indebted to G. Perez-Quiros for this hint.

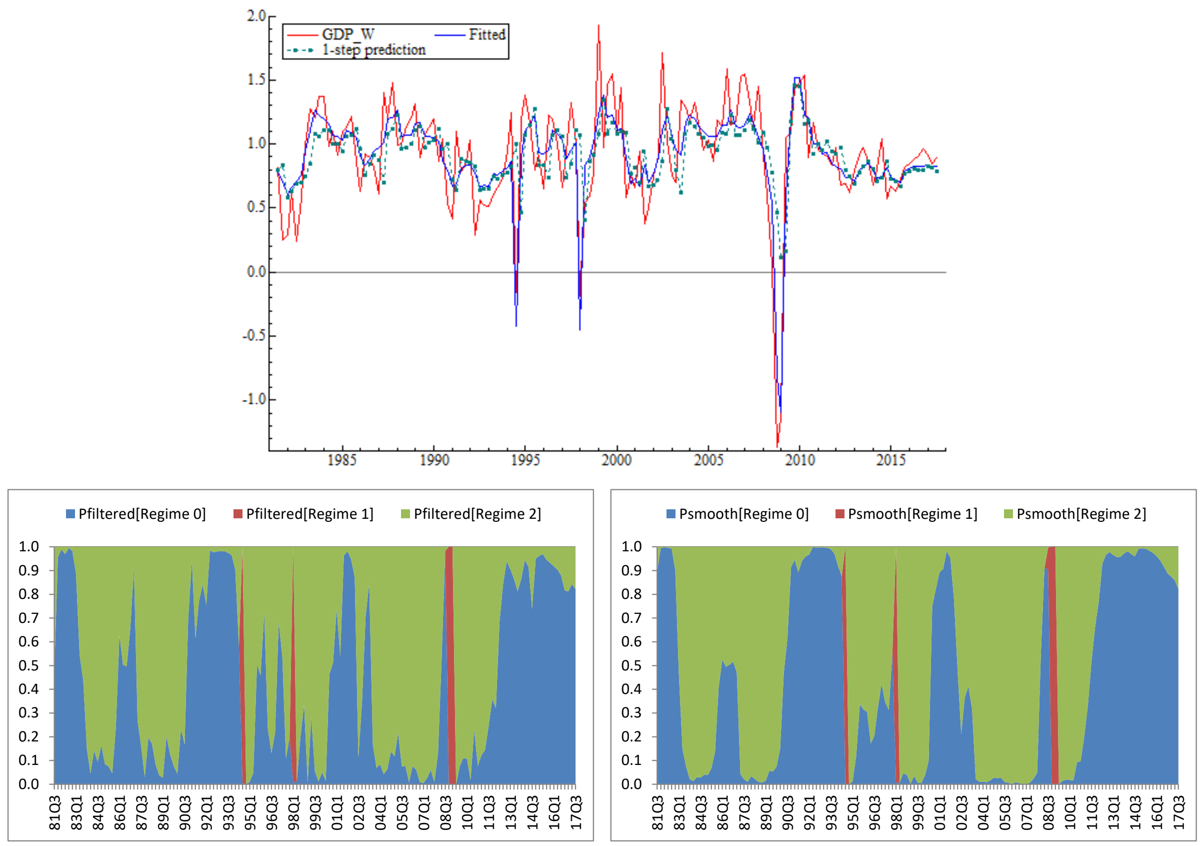
Moderation") as well as in the late 1980s. Since the first quarter of 2012, the world economy is in a low growth regime 0 (an unusually long period compared with the past), albeit with some emerging, although still low, probability of switching into the high growth regime. Low growth regimes also tend to be in place prior to all of the global recessions since the early 1980s. However, before the Great Recession 2009, the periods of low growth regimes had a relatively short duration. Our results differ from those by Martinez-Garcia et al (2015), who - as a robustness to their main business cycle dating procedure with global industrial production data using the Bry & Boschan (1971) algorithm - also apply a two-state AR(4) Markov switching model for global GDP growth (without additional explanatory variables) to identify business cycle turning points. Their model identifies only the Great Recession episode as one of their regimes.[8] As a result, they argue that looking at aggregate real GDP growth is not sufficient to provide a chronology of the global business cycle. By contrast, our results show that allowing for three regimes helps in the detection of turning points in the global business cycle.

The parameter estimates and transition probabilities are shown in Tables 1 and 2. Given their statistical significance, the first and fourth lags of global GDP growth contain valuable information for the detection of turning points in global activity. The results indicate that the world economy was in a high growth regime (with an intercept slightly above 1.0) for around 55% of the time since 1980, while being in a low growth regime (with an intercept of 0.7) 42% of the time. The frequency of recessions (intercept of -0.6) is naturally low at below 3%. The estimated transition probabilities are intuitively plausible in that global growth first moves from the high growth (2) to the low growth (0) regime before turning into a recession (1), while it directly moves to a high growth regime after recessions. The probabilities of staying in the high and low growth regime (both around 0.90) are significantly higher than that of staying in the recession regime (0.26).

[8] The main approach used by the authors to identify business cycles, based on global industrial production and the Bry & Boschan algorithm, also detects slightly different dates of global recession periods compared with our results (two recessions in the early 1980s, the 2000/01 recession and the Great Recession). However, we are interested in determining turning points in global GDP and not the global industrial cycle, and our model picks up well the key global recessions as reflected in declines in global real GDP.

Chart 2: Markov-switching model for world GDP

(first chart: quarter-on-quarter percentage change; other charts: filtered and smoothed probabilities)



Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

Table 1: Markov-switching preferred model: global GDP growth

	Coefficient (standard error)	Regime frequency (%)
GDP_W lag 1	0.229***	
	(0.065)	
GDP_W lag 2	0.044	
	(0.064)	
GDP_W lag 3	-0.020	
	(0.066)	
GDP_W lag 4	-0.147**	
	(0.059)	
Constant (0) low	0.682***	42.1
	(0.075)	
Constant (1) recession	-0.634***	2.8
	(0.147)	
Constant (2) high	1.004***	55.2
	(0.093)	
log-likelihood	-36.371	
AIC	0.681	
SC	0.948	
Linearity LR-test Chi^2(7) =	48.973 [0.0000]**	

Source: Authors' calculations.

*Notes: ***/**: significant at the 1%/5% level.*

Table 2: Estimated transition probabilities

	Regime 0,t	Regime 1,t	Regime 2,t
Regime 0,t+1	0.89	0.00	0.09
Regime 1,t+1	0.04	0.26	0.01
Regime 2,t+1	0.07	0.74	0.90

Source: Authors' calculations.

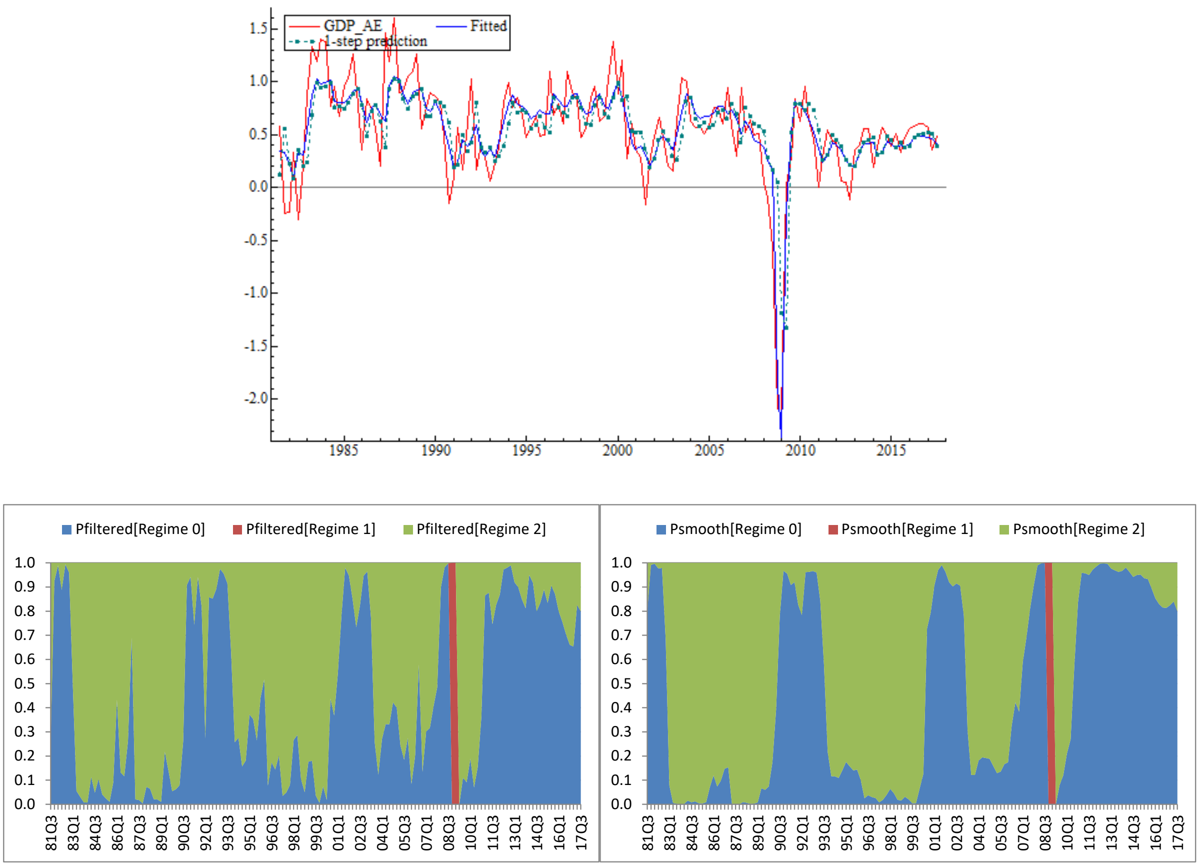
Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

3.3 Results for advanced economies

Of interest is also whether the preferred model setup is similar for advanced (AEs) and emerging (EMEs) economies, respectively, as for the world economy as a whole. Starting with AEs, the model includes three lags of advanced economy growth rates.[9] The model also detects three regimes with different mean growth rates (see Chart 3). However, the Great Recession was clearly unprecedented for AEs, as the model assigns regime 1 only to this observation. The results indicate that the probabilities of AEs being in high growth and low growth are very similar to those of the global economy, while it is lower for the recession regime. While most of the past 35 years was spent in the high growth regime, AEs have entered a low growth regime since the last quarter of 2010. Since early 2015, the (filtered) probability of returning to the high growth regime has increased steadily, from 4% in 2015Q1 to 18% in 2016Q4, but has declined marginally in 2017.[10]

Chart 3: Markov-switching model for GDP in advanced economies

(first chart: quarter-on-quarter percentage change; other charts: filtered and smoothed probabilities)



Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

[9] This is similar to the model Hamilton (1989) selected for the US.

[10] In a framework with regime-switching mean and variance, McConnell & Perez-Quiros (2000) have found a structural break in the volatility of GDP growth in the US in 1984Q1. In our sample, by contrast, we find no support for a model with regime-switching variance for advanced economies or the global economy.

Table 3: Markov-switching preferred model: AE GDP growth

	Coefficient (standard error)	Regime frequency (%)
GDP_AE lag 1	0.291***	
	(0.078)	
GDP_AE lag 2	0.104	
	(0.075)	
GDP_AE lag 3	-0.089	
	(0.066)	
Constant (0) low	0.233***	45.5
	(0.057)	
Constant (1) recession	-1.701***	1.4
	(0.217)	
Constant (2) high	0.573***	53.1
	(0.068)	
log-likelihood	-40.334	
AIC	0.708	
SC	0.934	
Linearity LR-test Chi^2(6) =	41.597 [0.0000]**	

Source: Authors' calculations.

*Notes: ***/**/*: significant at the 1%/5%/10% level.*

Table 4: AE - estimated transition probabilities

	Regime 0,t	Regime 1,t	Regime 2,t
Regime 0,t+1	0.91	0.00	0.08
Regime 1,t+1	0.02	0.48	0.00
Regime 2,t+1	0.07	0.52	0.92

Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth.

Overall, the timing of the high growth/recession regimes does not coincide exactly with those of the global regimes, but is rather close (as can be seen further in Charts B1 to B6 in Appendix B). However, the estimated transition probabilities and their interpretation are rather similar to the results for the global growth model. At the same time, the persistence of the high growth regime for AEs is slightly higher than for global growth.

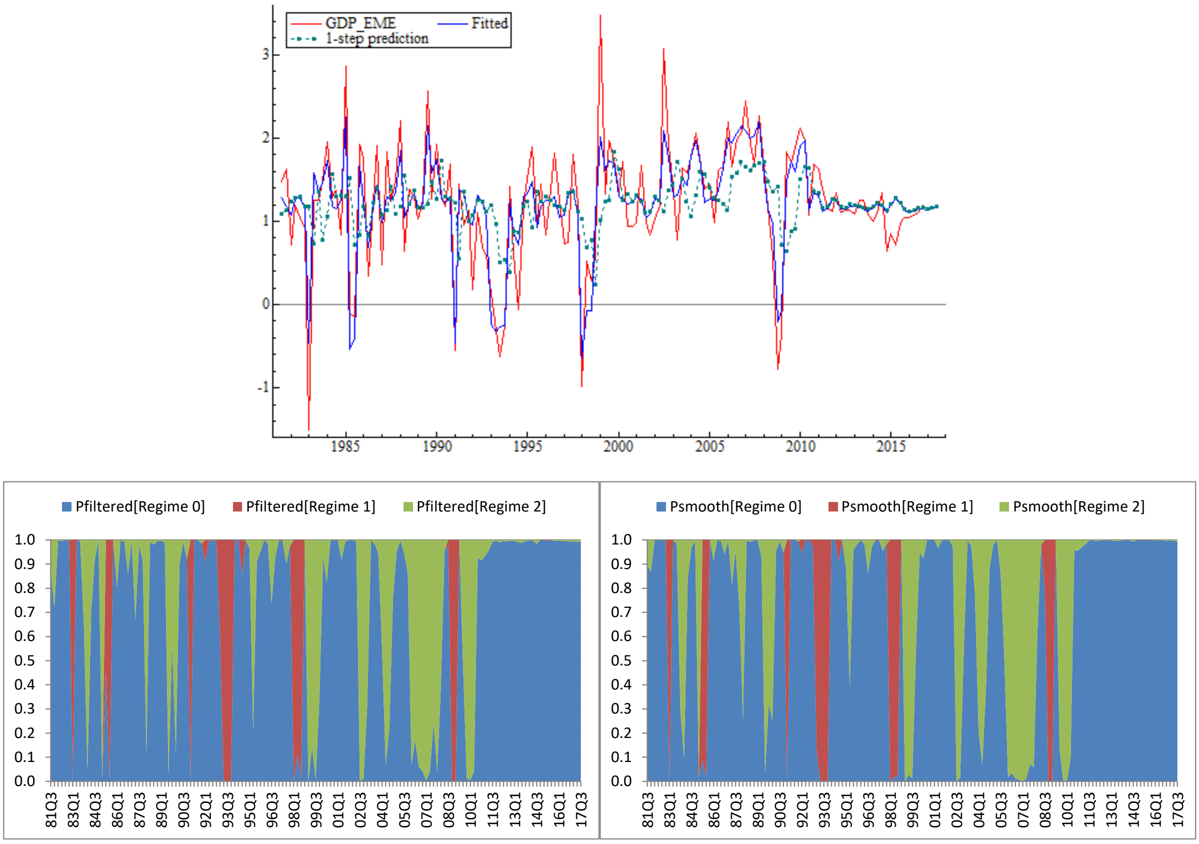
3.4 Results for emerging economies

In the case of EMEs, the model once again includes four lags of growth in EMEs and three regimes. Chart 4 depicts the estimated periods for the different regimes as well as the transition probabilities. A first observation is that, compared to the models for global and AEs growth, there is more volatility across regimes. Still and interestingly, the results suggest that emerging markets have spent most of their time in the "low growth" regime 0. The "high growth" regime 2 occurs only about a fifth of the time (around 20%). This is less than half the time than the estimates for the global economy or AEs, having occurred briefly following the Great Recession and the late 1990s recession, as well as during most of the period between 2002 and 2008. The latter appears to be a rather exceptional period. It coincided with the credit and investment boom in several large EMEs including the BRIC countries. Since the second quarter of 2011, EMEs have returned to a "low growth" regime (reflecting the slowing down of investment growth), which is the predominant regime for EMEs (accounting for around 72% of the sample period). Overall, the results for EMEs are less robust than the global and AEs models.[11]

The timing of the recession regimes, apart from the Great Recession, also adds various episodes in the 1980s and 1990s (see Appendix B) that are partly captured by the global model, too. The estimated transition probabilities also show some differences between AEs and EMEs that are worth mentioning. The probability of the transition from recession to low growth in EMEs is higher than to high growth, contrary to AEs, and EMEs are more likely to transit from high growth to recession.

Chart 4: Markov-switching model for GDP in EMEs

(first chart: quarter-on-quarter percentage change; other charts: filtered and smoothed probabilities)



Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

[11] We have also investigated a model with switching variance. There is limited statistical support for a switching variance, but the economic interpretation is less intuitive. Although the model identifies high volatility versus low volatility regimes, allowing for a regime-switching variance is not helpful in distinguishing turning points in activity. As pointed out by Martínez-García et al (2015), this may be due to the loose link between high volatility and low growth or recession phases.

Table 5: Markov-switching preferred model: EME GDP growth

	Coefficient (standard error)	Regime frequency (%)
GDP_EME lag 1	-0.158***	
	(0.068)	
GDP_EME lag 2	-0.091	
	(0.062)	
GDP_EME lag 3	0.132**	
	(0.070)	
GDP_EME lag 4	0.099	
	(0.067)	
Constant (0) low	1.175***	71.7
	(0.125)	
Constant (1) recession	-0.454***	9.0
	(0.157)	
Constant (2) high	2.156***	19.3
	(0.161)	
log-likelihood	-137.887	
AIC	2.081	
SC	2.348	
Linearity LR-test Chi^2(7) =	29.769 [0.0001]**	

Source: Authors' calculations.

*Notes: ***: significant at the 1% level; d: quarterly lag operator.*

Table 6: EME - estimated transition probabilities

	Regime 0,t	Regime 1,t	Regime 2,t
Regime 0,t+1	0.85	0.48	0.32
Regime 1,t+1	0.05	0.52	0.03
Regime 2,t+1	0.10	0.00	0.64

Source: Authors' calculations.

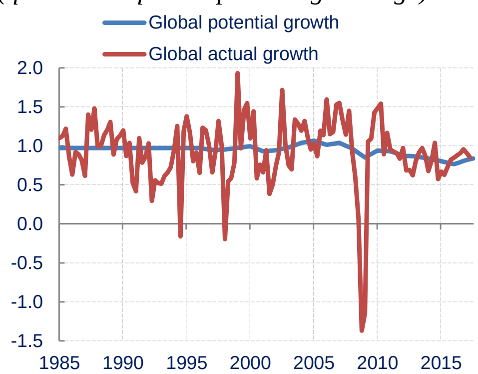
Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

3.5 Accounting for a slowdown in global potential output growth

The Markov Switching model is purely statistical and therefore does not provide any information on whether high or low growth regimes are structural or cyclical. Real-time assessments about structural changes in the economy are often difficult and estimates of potential growth heavily revised in subsequent years. The finding of an unusual and persistently low growth episode, such as the one the global economy is experiencing since 2012, using the above model, may help to assess whether structural factors could be playing a role.

As shown in Chart 5, available estimates of potential output (see Appendix A for details) show a decline in potential growth for the global economy since the global financial crisis. While actual growth fluctuated substantially during and immediately after the financial crisis, our finding of being in a low growth regime since around 2011 could be explained by weaker potential growth. To investigate further the role of structural versus cyclical factors for the current

Chart 5: Global growth – actual and potential
(quarter-on-quarter percentage change)

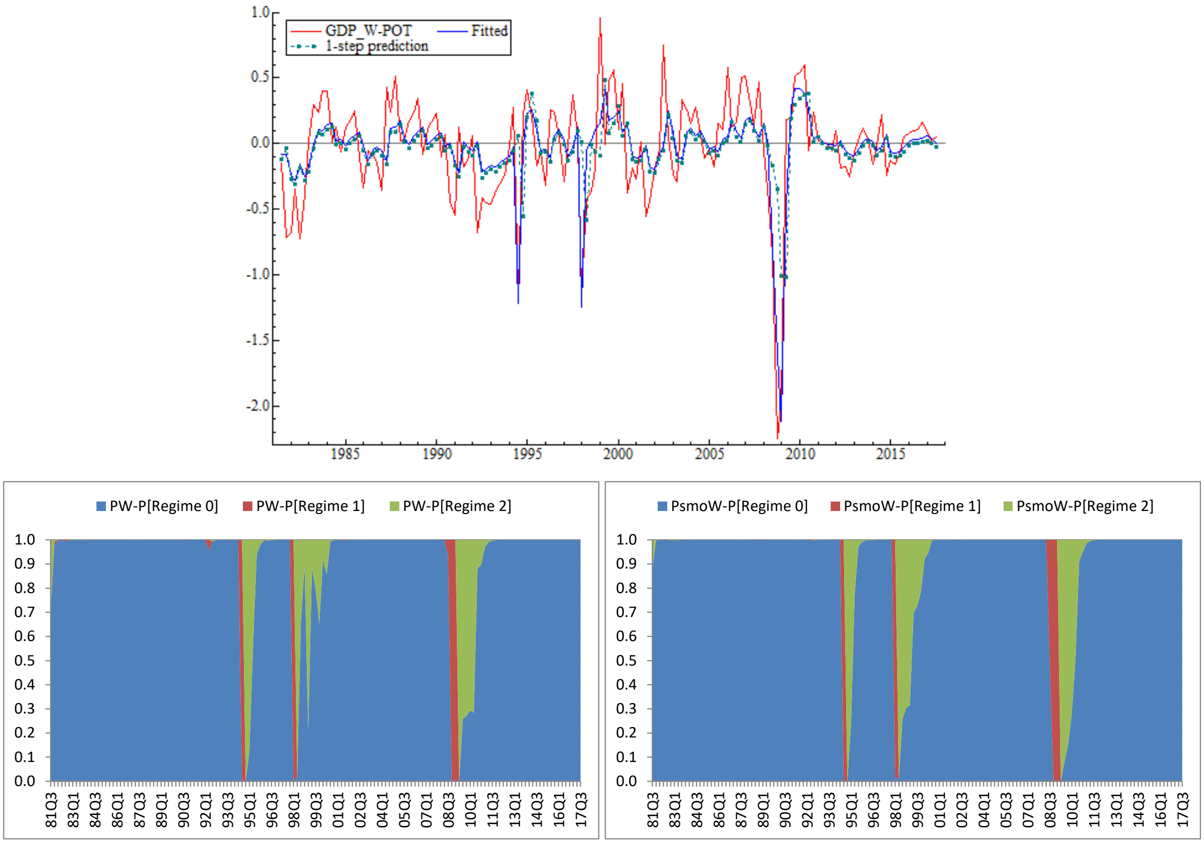


Sources: IMF WEO and authors' calculations.

low global growth episode – and bearing the caveats about real-time estimates of potential growth in mind –, we estimate an alternative model, where we take the difference between actual and potential global growth as dependent variable.[12]

Chart 6: Markov-switching model for global – actual less potential GDP

(first chart: quarter-on-quarter percentage change; other charts: filtered and smoothed probabilities)



Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

Table 7 shows the estimation results. The model includes three lags and we again find evidence of three regimes. However, the regime-switching constants take on lower values than in the baseline model for global growth, except for the recession regime, as we are using deviations from potential growth. The transition probabilities are broadly similar to the previous model, although the persistence in the high growth regime is lower and the probability to transit to a lower growth regime is higher.

The different regimes are shown graphically, together with the regime probabilities, in Chart 6. The results suggest that when taking into account the estimated slowdown in potential growth, the model does not point to a switch to a high growth regime after 2011. In fact, the high growth regime is limited to recovery phases following recessions.

[12] All these points are equally relevant for AEs and EMEs. However, to illustrate and exemplify the argument, we concentrate on the global case.

Table 7: Markov-switching model: global actual less potential GDP growth

	Coefficient (standard error)	Regime frequency (%)
GDP_W-Pot lag 1	0.331***	
	(0.070)	
GDP_W-Pot lag 2	0.080	
	(0.073)	
GDP_W-Pot lag 3	-0.027	
	(0.073)	
Constant (0) low	-0.003	90.3
	(0.026)	
Constant (1) recession	-1.311***	2.8
	(0.166)	
Constant (2) high	0.339**	6.9
	(0.132)	
log-likelihood	-37.895	
AIC	0.661	
SC	0.866	
Linearity LR-test Chi^2(5) = 44.416 [0.0000]**		

Source: Authors' calculations.

Table 8: Estimated transition probabilities

	Regime 0,t	Regime 1,t	Regime 2,t
Regime 0,t+1	0.98	0.00	0.31
Regime 1,t+1	0.02	0.33	0.00
Regime 2,t+1	0.00	0.67	0.69

Source: Authors' calculations.

Note: Regime 0 is the low growth regime, regime 1 the recession regime and regime 2 the high growth regime.

4. Multinomial discrete choice models

4.1 Methodology

In what follows, we use the Markov regimes of section 3 to estimate discrete choice models. As we have three regimes (recession, low growth, robust growth), we revert to multinomial models. A natural candidate is to estimate the determinants of the probabilities with a Multinomial Logit model in which we treat regime 1 (recession) as the reference regime.[13] The probabilities (*Pr*) have the following characteristics

$$\text{(3)} \qquad \Pr(Y_i = j) = \frac{\exp(x_i^{'}\beta_j)}{1+\exp(x_i^{'}\beta_1)+\exp(x_i^{'}\beta_2)}, \; j=0,1,2; \;\; 0 \le \Pr(Y_i = j) \le 1; \;\; \sum_{j=0}^{2} \Pr(Y_i = j) = 1$$

To solve an identification problem and to make the probabilities sum to 1 as well as the marginal effects sum to 0, the parameters of one regime, in our case those specific to regime 1 (recession), are set to zero. Thus, the sign of $ß_j$ tells us whether a change in x_i will make the jth (j=0,2) regime more or less likely relative to the recession regime 1. Estimation of this model is by maximum likelihood and with the Newton method to find convergence.[14] However, as every subvector of the coefficient matrix ***ß*** enters every marginal effect, the coefficients per se of the Multinomial Logit model are difficult to interpret. Therefore, we present the derivatives of probabilities at regressor means.

[13] As in our preferred Markov Switching models the regimes only differ with respect to the means, it is quite common to get different probability determinants in discrete choice models.

[14] For a textbook exposition see Greene (2017), ch 18.2.

4.2 Results

The various variables that we consider (outlined in section 2) and the possibility of different combinations of these variables leads to a large number of possible models out of which we need to choose the best ones. We use both statistical and economic criteria for model selection. The statistical criteria are (i) the statistical significance of the variables; (ii) Akaike information criterion); (iii) the forecasting performance (see Tables B2 and B3 in Appendix B). For that purpose and for the sake of parsimony, we take at most one of the variables of each category (see section 2) up to lag 1 into account. To select the variables entering the final model, we use the General-to-Specific methodology.[15] Statistics are summarised in the following tables and Appendix B. The economic criterion to be fulfilled by variables entering the final model is that the signs of the coefficients should be in line with economic theory.

Table 9 summarizes the estimation results for the three aggregates (global, AEs, EMEs) in the Multinomial Logit case. As already mentioned, the models presented are chosen on the basis of statistical (significance, information criteria, forecast performance) and economic (sign in line with economic theory) criteria. Especially, activity-oriented variables have explanatory power for the regime probabilities. In general, the statistical fit of all the models is satisfactory. For instance, the χ^2(Likelihood Ratio)-test on the overall significance of the economic variables taken into account is in any case highly significant.

For the *global* economy, our preferred model includes the changes in oil prices (*OIL_USD*) and industrial production (lagged one quarter) at the OECD level (*IP_OECD*), both with a positive sign (see Table 9). This means that the probability of the low and high regime increases (relative to the recession regime) with rising oil prices and a higher level of industrial activity. Therefore, in this respect, oil prices are capturing the demand-side component of the indicator, instead of the supply-side. However, industrial production is only significant for the second regime (high growth). As the individual coefficients are not equal to marginal effects as they depend on all regressors taken on board, the derivatives at regressor means are shown in Table 10. It is evident that at this level of regressors an increase in both variables decreases the probability of regime 0 and 1 and increases the probability of regime 2 in a significant way. The preferred model is only able to capture two of the four recession regimes and also underestimates the number of low growth regimes (correct = 86 %), but overestimates slightly the number of high growth regimes, see Table B2 in Appendix B.

For the *advanced* economies, the chosen model is one with OECD consumer confidence (*CONS_OECD*), in both regimes with a significant positive sign (see Table 9). Again, at regressor

[15] Optimally, these exercises should be conducted in a real-time setting. However, real-time data sets are only available for very few advanced countries. Therefore, we rely on the data as published at the end of our sample.

means an increase in consumer confidence increases the probability of regimes 0 and particularly 2. The model is not able to identify the two recession regimes, but predicts over 83 % of the low growth regimes correctly while overestimating the high growth regimes.

Table 9: Multinomial logit models for global, advanced and emerging economies

	global	**AE**	**EME**
	Preferred model	**Preferred Model**	**Preferred Model**
Constant(0)	3.59 (*4.24*)	4.64 (*3.55*)	1.50 (*5.06*)
Constant(2)	3.51 (4.*11*)	4.76 (*3.65*)	-0.20 (0.*46*)
Δlog OIL_USD$_t$(0)	0.06 (2.*16*)		
Δlog OIL_USD$_t$(2)	0.10 (3.*26*)		
Δlog IP_OECD$_{t-1}$(0)	37.67 (*1.51*)		
Δlog IP_OECD$_{t-1}$(2)	80.50 (2.*48*)		
Δlog CONS_OECD$_t$(0)		3.88 (1.77)	
Δlog CONS_OECD$_t$(2)		6.43 (2.82)	
GS_GLI$_t$(0)			0.55 (*2.27*)
GS_GLI$_t$(2)			1.38 (*4.24*)
sample	1985.3-2017.2	1981.2-2017.2	1985.2-2017.2
observations	128	145	129
LL	-89.66	-98.18	-104.10
AIC	191.32	204.35	216.20
χ^2	27.02 [0.00]	22.15 [0.00]	25.14 [0.00]

Notes: LL: Log-likelihood: AIC: Akaike information criterion; χ^2: Likelihood ratio test on the overall fit of the model; the test statistic is χ^2-distributed with the degrees of freedom depending on the number of regressors and states. Absolute t-values in brackets below coefficients.

For *emerging* markets, we found three models which performed relatively well. Our preferred one includes the Goldman Sachs Global Leading Indicator (*GS-GLI*).[16] At regressor means, the same interpretation as for the other two country groupings holds. Also in line with the other two cases is the underestimation of the number of recession regimes (correct only about 13 %). However, this time there are many more recession regimes. In contrast to "*global*" and "*advanced*", the number of low

[16] The other two models (see the last two columns in Table B1 in appendix B) substitute *GS-GLI* by the Kilian index (*KILIAN*) and oil prices (again as a demand indicator), respectively. Lagged GDP growth rates would enter all models significantly. However, this might create some circularity in the estimates as these are also components of the dependent variable of the Markov-Switching model itself. Therefore, we disregard this alternative. Due to poor data quality on financial and survey data in the case of emerging markets as a group (see the data section 2), we were not able to find convincing models with these variables alone.

growth regimes is overestimated, whereas the number of high growth regimes is underestimated (correct about 50 %).[17]

Table 10: Derivatives at regressor means: preferred models

	global			AE			EME		
	Reg 1	**Reg 0**	**Reg 2**	**Reg 1**	**Reg 0**	**Reg 2**	**Reg 1**	**Reg 0**	**Reg 2**
Δlog OIL_USD$_t$	-0.001 (*2.88*)	-0.01 (*2.55*)	0.01 (*2.72*)						
Δlog IP_OECD$_{t-1}$	-0.63 (*2.24*)	-10.26 (*1.90*)	10.89 (*1.97*)						
Δlog CONS_OECD$_t$				-0.02 (*2.37*)	-0.62 (*3.63*)	0.64 (*3.73*)			
GS_GLI$_t$							-0.07 (3.*12*)	-0.09 (*2.30*)	0.16 (*3.82*)

Notes: Absolute t-values in brackets below derivatives.

To get an idea on the forecasting performance of the models, we divide the total sample into two sub-samples. The estimation sample ends just before the latest regime switch. The forecasting sample starts in the quarter afterwards. Optimally, the models should pick-up the change in the regime. Let us exemplify this in-sample forecasting procedure for the case of world GDP, i.e. "global", and the preferred model. Until the third quarter of 2011, our regime classification indicated a strong growth regime which changed to a low growth regime from the fourth quarter of 2011 until the end of the sample. Therefore, the estimation sample ends in 2011Q3 and we let the model forecast the regimes until 2017Q2 on the basis of the data available for the explanatory variables (oil prices and OECD industrial production).[18] The results indicate that the model does a very good forecasting job in that the forecasted regime 0 corresponds to the actual regime for all 23 quarters until 2017Q2 (see Table B3 of Appendix B).[19]

5. Summary and conclusions

In this paper, we propose the use of non-linear models to provide an indication of the probability of being at different stages of the business cycle at a global level. For that purpose, we first estimated Markov Switching models allowing for three regimes, for the sample covering the period 1980 to 2017. The global model appears to capture the dynamics of global GDP rather well. It clearly identifies the global recessions of the mid and late 1990s as well as the Great Recession. Moreover, it shows that the high growth regime generally follows recessions, but was also in place over the “Great Moderation” and in the late 1980s. The model also indicates that the world economy is in a low

[17] As we have a natural ordering in our discrete regime variable (negative growth, low growth, high growth), an ordered models might also be an alternative. The results of ordered probit (logit) models confirm in principle the results of the multinomial logit case (results available upon request).

[18] The model is s still a valid one for that specific sample.

[19] The forecasting results for advanced and emerging economies are similarly good (available upon request).

growth regime since 2012, showing some incipient, although still low, probability of switching into the high growth regime.

Taking into account changes in potential output at a global level, the recessionary periods remain the same, whereas the model indicates that global GDP has been in a high growth regime most of the sample, including the post-Great Recession period. This finding can be explained by the fact that the model now accounts for a post-crisis decline in potential growth. As changes in potential growth are inherently difficult to detect in real time, the three-regime baseline model (that is not adjusted for potential growth) may help to inform about possible changes in potential growth in case of unusually persistent periods of low (or high) growth.

The paper also explored the business cycles for advanced (AEs) and emerging market economies (EMEs), the results pointing to some interesting differences. First, the Great Recession was unprecedented for AEs, the only significant downturn, while recessions are more common in EMEs, particularly before the 2000s. Second, outside recessions, AEs have been in a high growth regime most of the time during our sample, although since 2010 they are in the longest low growth regime. By contrast, EMEs have been mainly in a low growth regime, the main exception being the intermittent high growth periods in advance of the financial crisis. Lastly, while there are signals of an increase in the probability of a transition to higher growth in AEs, EMEs growth is expected to remain in a low growth regime much longer.

The regimes from this Markov Switching exercise can be well explained within a multinomial discrete choice framework in a second step, therefore reinforcing the economic interpretation of the regimes found. In this case, not only activity related variables and surveys play an important role, but also oil prices in some specifications. In general, the statistical and forecasting quality is quite good, although the recession regimes were sometimes difficult to identify, especially in the case of global and emerging economies.

Our modelling approach with three-regimes seems to be better suited for the classification of the business cycles in the last decades at a global level than the usual two-regime case. This leaves plenty of room for future research: First, is this also true on an individual country basis? Second, what are the main regime change drivers (countries, variables) in this respect, both statistically in economically in terms of magnitudes? Third, how robust are the results with respect to different econometric methodologies? And finally, might the relationships change against the background of widespread digitalisation and trade restrictions?

Appendix A: Variable definitions

Activity data:

- real GDP growth, national accounts at country level weighted using PPP shares of world total, ECB and WEO databases
- the EME GDP aggregate is based on ECB data after 1995, which are linked up to IMF International Financial Statistics data (in year-on-year growth rates) before 1995
- potential growth rate, global economy, global potential growth between 2001-2017; a weighted average of potential growth of the US, Japan, China, India, Russia, Turkey, Korea, Brazil and Mexico for the period 1996-2000 and assuming constant potential growth at the 1996 value before that; data are taken from annual IMF WEO data that are linearly interpolated
- industrial production in OECD countries, index excluding construction, OECD
- industrial production in emerging market economies (EMEs), indices excluding construction at country level weighted using PPP shares of EMEs total, country statistical offices
- world steel production, crude steel production in thousand tonnes, World Steel Association
- index of real world economic activity, based on Kilian (2009)
- composite leading indicator, OECD total, OECD
- global leading indicator (GLI), Goldman Sachs. The GS GLI is a leading indicator derived from ten timely and relevant component series, namely (i) Korean exports, (ii) GS industrial metals index; (iii) US initial jobless claims, (iv) G4 consumer confidence, (v) Japanese inventory-to-sales ratio, (vi) AUD and CAD trade weighted index, (vii) Belgian and Dutch manufacturing confidence survey, (viii) Global PMI new orders less inventories, (ix) Baltic Dry Index, (x) Global PMI. Before aggregation, the components are de-trended and double-smoothed with the Hodrick-Prescott filter. The aggregate cyclical series is constructed by weighting the double-smoothed components with equal (10%) weight, see also O'Neill et al (2002) and Stupnytska et al (2010).
- global factor of economic activity, based on Delle Chiaie et al (2017)
- leading economic index, US, Conference Board

Survey data:

- consumer confidence, OECD total, OECD
- consumer confidence, US, OECD

Financial data:

- term spread, US, the 10-year Treasury Note yield minus the 3-month Treasury Bill yield, Federal Reserve Board

- bond spread, US, the Baa corporate bond yield minus the 10-year Treasury Note yield, Federal Reserve Board
- stock price index, S&P500 composite, Standard & Poor’s
- monetary aggregates, OECD M1 and M3, OECD
- policy rate, world, based on King and Low (2014)

Commodity prices:

- oil prices, Avg Crude Price of UK Brt Lt/Dubai Med/Alaska NS heavy (US$/Bbl), IMF
- metal prices, Commodity Price Index: Metals, IMF
- non-oil commodity prices, Non-fuel Primary Commodities Index, IMF

Classification of advanced (AEs) and EMEs:

- AEs include: US, Japan, UK, Canada, euro area, Switzerland, Sweden, Denmark, Poland, Czech Republic, Romania, Hungary
- EMEs include: China, India, South Korea, Russia, Brazil, Mexico, Argentina, Turkey

Appendix B: Additional charts and tables

Charts B1-B6: Estimated probabilities of recession and high growth regimes, Markov models

Chart B1-B3: Estimated (filtered) probabilities of recession regimes	Chart B4-B6: Estimated (filtered) probabilities of high growth regimes

Chart B1

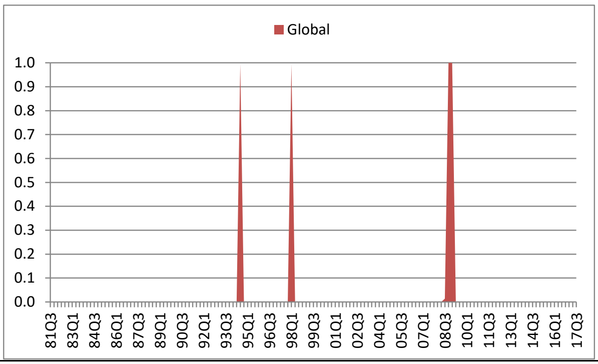


Chart B4

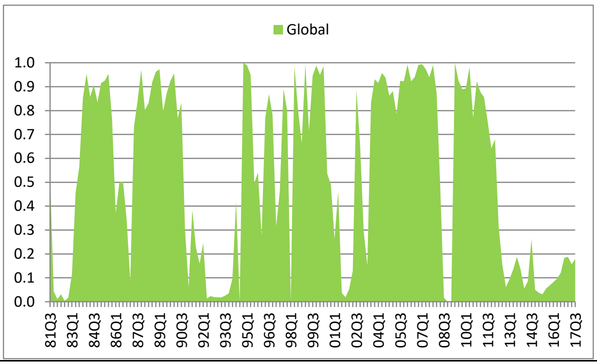


Chart B2

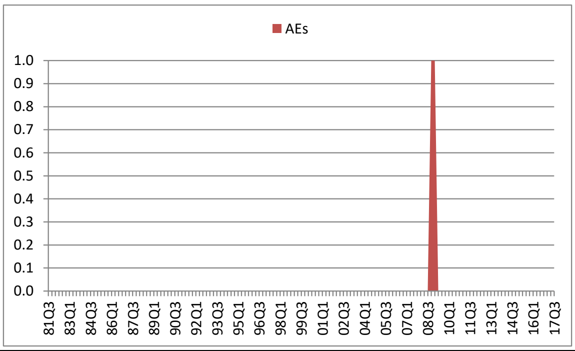


Chart B5

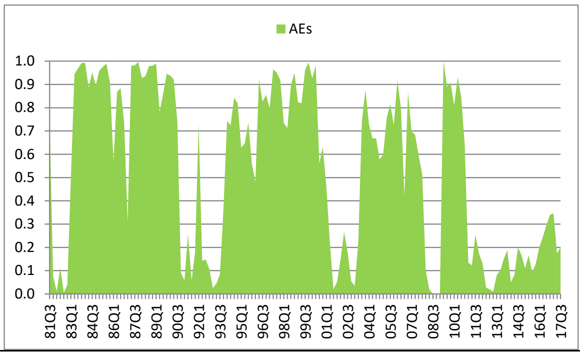


Chart B3

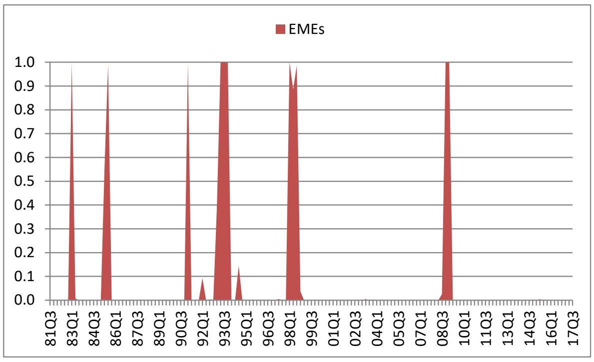


Chart B6

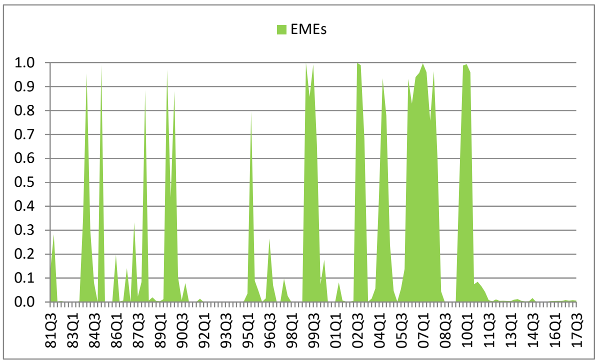


Table B1: Alternative multinomial logit models for emerging economies

	EMEs	
	Alternative model 1	**Alternative model 2**
Constant(0)	1.90 (6.*00*)	2.11 (6.*48*)
Constant(2)	0.38 *(0.95)*	0.88 (2.37)
Δlog OIL_USD$_t$(0)		0.05 (3.00)
Δlog OIL_USD$_t$(2)		0.11 (4.43)
KILIAN$_t$(0)	0.01 (*0.74*)	
KILIAN$_t$(2)	0.08 (*4.80*)	
sample	1980.4-2017.2	1980.4-2017.2
observations	147	147
LL	-96.77	-113.77
AIC	201.55	235.53
χ^2	59.69 [0.00]	25.70 [0.00]

Notes: LL: Log-likelihood: AIC: Akaike information criterion; χ^2: Likelihood ratio test on the overall fit of the model; the test statistic is χ^2-distributed with the degrees of freedom depending on the number of regressors and states. Absolute t-values in brackets below coefficients.

Table B2: Share of actual versus predicted outturns: preferred models

	global		AE		EME	
	Actual	**Predicted**	**Actual**	**Predicted**	**Actual**	**Predicted**
Regime 1 - recession	4	2	2	0	15	2
Regime 0 - low growth	56	48	66	55	79	110
Regime 2 - high growth	68	78	77	90	35	17

Table B3: Pseudo out-of-sample forecasting of the latest regime change: Global economies

	Recession	Low growth	High growth	**Sum actual**
Regime 1 - recession	0	0	0	0
Regime 0 - low growth	0	23	0	23
Regime 2 - high growth	0	0	0	0
Sum predicted	0	23	0	

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