Patterns of international business cycles

Early in 2020, a long upswing in the global economy came to an abrupt end. The novel coronavirus spreading around the world and the measures taken to contain it were accompanied by a dramatic slump in activity and culminated in a crisis of historic proportions. The root causes of earlier economic downturns were often less obvious. Analysing suitable indicators in order to identify signs of a cyclical downturn at an early stage is, however, a key task for a forward-looking monetary policy. Recessions are, for example, often preceded by signs of overheating that are likely to be associated with a heightened vulnerability to crises. Relevant warning signals can provide valuable insights for predicting cyclical turning points.

Indeed, empirical studies suggest that cyclical turning points – at least when seen with the benefit of hindsight – often announced themselves in advance. For example, the longer an upswing lasted, the greater was the probability that it would soon end. In most cases, a period of higher-than-average aggregate rates of expansion was followed by a soft patch in which GDP growth fell below its trend, and only rarely by a severe recession. Recessions in advanced economies were often indicated by a flattening of the yield curve, or followed sharply accelerating oil prices. The inclusion of such variables improves the accuracy of models for recession forecasting. Even so, the models would not have identified some crises in advance and have forecast recessions that failed to materialise.

Quantitative models can therefore send important warning signals before cyclical turning points. Economic observers will still be taken by surprise by downturns in the future, however. But this should not be viewed as a failure of empirical business cycle research. Even economies that previously appeared to be fairly resilient can be plunged into recession by shocks of sufficient magnitude. This year's global economic crisis is one example of this.

Introduction

Pandemic brings an end to multi-year global upswing

At the beginning of 2020, the coronavirus pandemic brought an extended upswing in the global economy to a sudden end. The spread of the virus and the measures taken to contain the number of infections led within a matter of weeks to a dramatic slump in activity, finally culminating in an economic crisis of historic proportions. Although the easing of the restrictions saw activity picking up rapidly, the recovery has remained incomplete so far given the ongoing risks of infection and constraints that remain in place.

Recessions call for swift monetary policy intervention

Even in the past, growth paths did not run along straight lines. Rather, they were repeatedly interrupted by soft patches – in other words, minor setbacks or periods of below average rates of expansion. Dramatic declines in macroeconomic activity – recessions – are also on record for almost every economy. Periods of high macroeconomic underutilisation are typically accompanied by deflationary pressure on consumer prices. This may call for timely monetary policy intervention, especially given its time-lagged effects. Against this backdrop, the analysis and forecasting of macroeconomic fluctuations – also known as the business cycle – have always been a key focus of applied macroeconomics.

Shocks the cause of cyclical fluctuations

For economic forecasting and the formulation of recommendations for monetary policy, an understanding of macroeconomic processes and their key drivers is essential. Modern business cycle models represent recessions mainly as the outcome of unexpected events known as shocks.[1] These include, say, unanticipated policy measures, technological advances, natural disasters, changes in preferences as well as modified expectations and risk assessments. Other possible triggers include unexpected international developments that can be transmitted through various channels, such as international trade and cross-border financial relationships. This means that cyclical swings are very difficult to predict. Price rigidities, financial market imperfections and other frictions can delay the effects of shocks, prolong them and also amplify them. It is, above all, the delays that give economic observers the opportunity to identify nascent downturns at an early stage.

Significance of fragilities

Moreover, during a period of expansion there is often an increase in vulnerabilities owing, for example, to exaggerations in the financial system. This means that, in mature upswings, comparatively small shocks could trigger major turmoil.[2] Timely identification of vulnerabilities would then make it possible to predict cyclical turning points or, at least, estimate their probability.

Identification of cyclical turning points

Recessions often defined by way of declining economic activity

Quantitative analysis of macroeconomic downturns and estimating the probability of their occurrence require not only an understanding of macroeconomic processes but also an empirical definition. In the traditional classification of business cycle phases, a recession describes a period of declining economic activity. This definition is used as the basis for business cycle dating, for example, by the National Bureau of Economic Research (NBER) for the United States and the Centre for Economic Policy Research (CEPR) for the euro area, both of which are widely recognised as official. A recession follows a peak in aggregate output and, after a trough, moves into an expansion. In order to be classified as a recession, the contraction also has to last at least a few months, be broad-based and must not be confined to a small

1 Slutzky (1937) and Frisch (1933) laid the groundwork for the interpretation of economic processes as a sequence of shocks, which was then incorporated into modern economic models by Brock and Mirman (1972), Lucas (1972), as well as Kydland and Prescott (1982). The Bundesbank's Dynamic Stochastic General Equilibrium (DSGE) model is one instance of a more comprehensive model of this class. For a more detailed description, see Hoffmann et al. (2020).

2 For recent approaches that capture this in macroeconomic models, see Gorton and Ordoñez (2014), Boissay et al. (2016) as well as Paul (2020).

Measuring classical business cycles

Classical business cycles are characterised by alternating periods of increasing and declining economic activity. To date these cycles, the literature often applies a rule-based procedure developed by Bry and Boschan (1971) to an indicator of macroeconomic activity.[1] Expert-based methods are an alternative approach in which special committees identify the phases of the business cycle on the basis of several statistical procedures and a subjective assessment of a number of macroeconomic indicators. In the United States, for example, the Business Cycle Dating Committee at the National Bureau of Economic Research (NBER), founded in 1978, employs a generally accepted classification of economic activity into expansionary and recessionary phases.[2] The Business Cycle Dating Committee at the Centre for Economic Policy Research (CEPR) has been determining economic peaks and troughs for the euro area since 2003.[3] A comparable classification of business cycle phases in Germany was presented by the German Council of Economic Experts (SVR) in 2017.[4]

Given the conceptual disparities, the question arises as to how the dates determined using mechanical methods differ from expert assessments. In order to make a comparison possible, the cyclical turning points for the economic areas mentioned above are calculated using the Bry-Boschan algorithm. The respective seasonally adjusted quarterly values of real gross domestic product (GDP) for the period from the first quarter of 1970 to the second quarter of 2020 are used as an indicator of economic activity.[5]

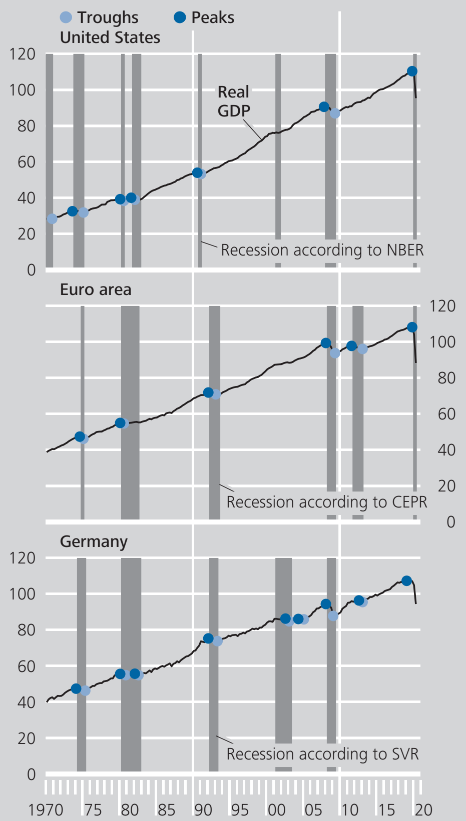
On balance, the dating of the cycles according to the Bry-Boschan algorithm is broadly in line with the experts' assessment.[6] This is particularly true of the United States and the euro area. Differences exist only in the identification of individual turning points and the classification of phases with low and, in some cases, negative GDP growth rates. For example, the recession in the United States identified by NBER experts in 2001 is not recognised. Furthermore, the algorithm shows a brief downturn for the euro area in the early 1980s, while the CEPR Committee registers a prolonged contraction.[7] A similar picture emerges for Germany in the first half of the 1980s, although the Bry-Boschan algorithm identifies two short periods of contraction during the longer-lasting recession identified by the SVR. There are further deviations for Germany in the first half of the 2000s and around the end of 2012 and the beginning of 2013.

The Bry-Boschan algorithm, in line with the NBER experts' assessment, dates the start of the economic downturn in the United

1 The procedure recognises peaks and troughs in a time series if their level was lower or higher in the period before and after. Further conditions ensure a minimum cycle length and guarantee that each peak is preceded by a trough.
2 See National Bureau of Economic Research (2020b).
3 See Centre for Economic Policy Research (2020).
4 See German Council of Economic Experts (2017).
5 The data on macroeconomic activity for the euro area aggregate for the period prior to the establishment of the monetary union are taken from the Euro Area Business Cycle Network's Area Wide Model (AWM) database. GDP data for Germany are data for West Germany up to and including the year 1991.
6 The version of the Bry-Boschan algorithm adapted by Harding and Pagan (2002) for use in quarterly time series is used to date the turning points. It is customarily assumed that a business cycle comprises at least five quarters and that a cyclical expansion or recession each last at least two quarters.
7 Developments in investment and employment, which, in contrast to real GDP, recorded a significant and steady decline in the period in question, were a key factor in the CEPR experts' decision; see Centre for Economic Policy Research (2003).

A comparison of cyclical turning points for the United States, the euro area and Germany*

2015 = 100, quarterly data, seasonally adjusted



Sources: Bureau of Economic Analysis, Area Wide Model database of the Euro Area Business Cycle Network, Eurostat, German Federal Statistical Office, NBER, CEPR and SVR recession chronologies, Haver Analytics and Bundesbank calculations. * Cyclical turning points are identified using the Bry-Boschan algorithm.
Deutsche Bundesbank

States as a result of the coronavirus pandemic to the first quarter of 2020. The algorithm also shows a cyclical peak for the euro area in the final quarter of 2019 in line with the decision of the CEPR Committee. Interestingly, according to the mechanical method, the German economy has been in a contractionary phase since the second quarter of 2019. In actual fact, the slight decline in economic output was not followed by a recovery, meaning that the first quarter of 2019 marks the most recent peak in economic output.

Overall, this comparison shows that although the Bry-Boschan algorithm does not fully replicate the expert-based dating of cyclical phases, it does come quite close. One advantage of the Bry-Boschan procedure over expert dating is that it is easy to use. Also, experts classify cyclical phases only after a certain time lag.[8] However, when turning points at the current end are calculated in an "automated" manner, it should be borne in mind that the results may also change again as GDP data are revised.

8 For instance, a clear time lag between the onset of a recession and the official reporting by the NBER or CEPR is standard. For the last two past recessions, the time lag for NBER was between three and four quarters, and for CEPR between four and five quarters.

number of sectors or regions of the economy.[3] As a preferred measure for aggregate economic activity, both the NBER and the CEPR therefore use gross domestic product (GDP) adjusted for seasonal effects and price movements. However, other quarterly time series are additionally taken into consideration – such as gross national income in the United States or the production and expenditure-side GDP components as well as employment in the euro area. As the NBER aims at a monthly chronology of the business cycles, selected higher-frequency indicators are also analysed.[4] On both sides of the Atlantic, this is the basis on which a committee of experts defines cyclical peaks and troughs – otherwise known as cyclical turning points.[5]

Both expert judgements and quantitative dating methods common

In cyclical analysis as well as academic research, expert-based dating as well as heuristic techniques and quantitative methods are used for defining turning points. The latter have the advantage that they can be applied in accordance with uniform criteria to a large group of countries. In some cases, cyclical movements can be classified more rapidly on this basis. This is especially true when it comes to the widespread concept of a "technical" recession, which is defined as two or more consecutive quarters of negative (seasonally adjusted) GDP growth.[6] Often, the Bry-Boschan algorithm is applied as an alternative.[7] This approach identifies peaks in a time series if the level was previously and subsequently lower. When analysing quarterly GDP time series, the two preceding and subsequent quarters are typically taken into consideration. Furthermore, the specification of the algorithm ensures a minimum cycle length and the sequence of peaks and troughs.[8] Even though the procedure is quite simple, the recession dates obtained in this way for major economies largely correspond to the judgement of experts (see the box on pp. 43 f.).

Alternative dating method also identifies milder downturns …

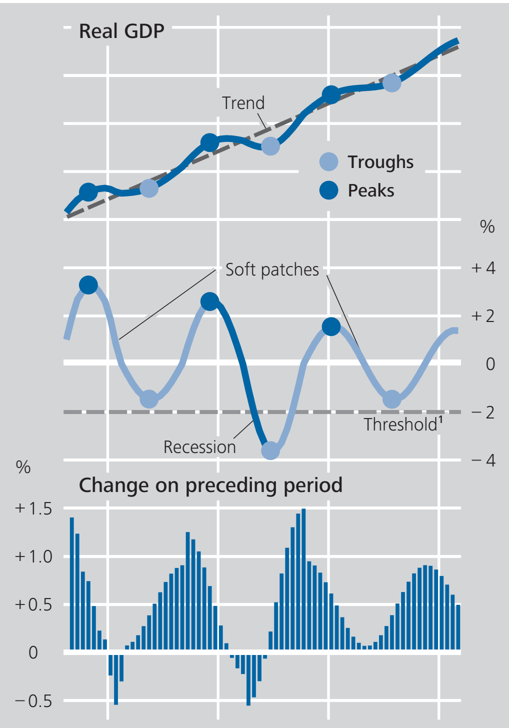
Even when there is no major crisis, the macroeconomic growth process seldom takes a steady course. Instead, there are typically alternating periods of rapid and slow growth. If phases of slow economic expansion – known as soft patches – persist for an extended period, the associated welfare losses can in fact be greater than those experienced in brief recessions. With this in mind, greater attention has been paid over the past few years to analysing cyclical patterns of trend-adjusted time series, especially of real GDP.[9] As defined in this way, a downturn would set in as soon as economic output – following a period of high growth rates – begins to move back to its trend level, then finally falling below it.[10] This process, which ends when the cyclical trough is reached, is not necessarily associated with a decline in economic output but perhaps merely with below average rates of expansion.

… but requires trend adjustment

Identifying such cycles necessitates a trend adjustment of the time series under consideration. There are various statistical procedures available for this, although these occasionally

3 This definition has already been applied in the United States for almost 75 years; see Burns and Mitchell (1946). In its modern interpretation, the three cited criteria are regarded as somewhat interchangeable. Hence, the decline in GDP in March and April of the current year – which was arguably only brief, albeit severe and broadly based – was also classified as a recession; see National Bureau of Economic Research (2020a).
4 These include, in particular, real disposable income adjusted for transfer payments as well as employment. Other indicators, such as private consumption, retail and wholesale turnover, industrial output as well as initial claims for unemployment benefits play a somewhat less important role.
5 For a description of the dating methods, see Centre for Economic Policy Research (2012) and National Bureau of Economic Research (2020a).
6 In its definition, the CEPR likewise points to the fact that recessions are generally characterised by two consecutive quarters of declining GDP growth. See Centre for Economic Policy Research (2012).
7 See Bry and Boschan (1971).
8 For a description of the methodology and its application to quarterly GDP time series, see Harding and Pagan (2002).
9 A discussion of the advantages and drawbacks of this practice may be found inter alia in Canova (1998) as well as Burnside (1998).
10 In this instance, a downturn is characterised by growth rates that lie below the longer-term trend, whereas an upturn is associated with above average rates of expansion. That is the reason why such upward and downward movements are also called growth cycles. See Zarnowitz and Ozyildirim (2006).

Stylised business cycles



1 Threshold value of -2%. A deviation from trend real GDP below this threshold is defined as a recession.
Deutsche Bundesbank

produce differing cyclical patterns.[11] A further problem is the unreliability of the trend estimations at the start and end of the sample. This means that additional data points can have a major impact on the estimation of the trend.[12] This can also affect the dating of turning points. The frequently used Hodrick-Prescott (HP) filter seems to display quite favourable properties in this respect. This is especially the case if the data series are extrapolated by suitable forecasting methods.[13]

Dating turning points for industrial countries …

Below, the HP filter is used to identify and analyse business cycles for a total of eight industrial countries[14] as well as for the euro area and the OECD group as a whole. Local peaks and troughs in trend-adjusted GDP mark the transition between upturns and downturns. To mitigate the problems of trend estimation for the most recent quarters, the time series were extrapolated using OECD growth forecasts.[15] The Bry-Boschan algorithm was used for dating the cyclical turning points.[16] In a small number of cases, the resulting cyclical chronology – often dating back to the 1960s – was also adjusted slightly.[17]

… permits distinction between soft patches and recessions

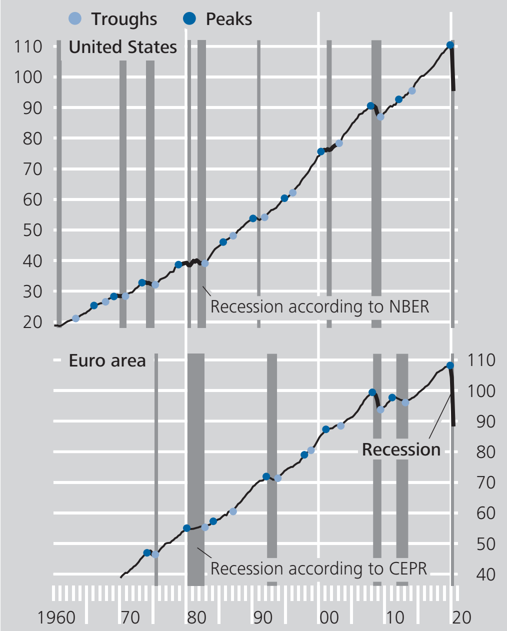
Looking at cycles of trend-adjusted GDP time series leads to a significantly higher number of turning points being identified than when using the traditional definition of business cycle phases. This is also true of the United States and the euro area. As is to be expected, virtually all the recessions identified by the NBER and the CEPR were associated with a sharp downturn in the cyclical component of real GDP.[18] Before taking a turn for the better, economic output in these periods was in fact often more than 2% below its trend. With this in mind, this mark is set as a threshold here for the definition of recessions in the context of trend-based cycles.[19] In addition, however, nu-

11 Added to this is the risk that the smoothing of volatile series will create misleading correlation patterns that mask the true characteristics of the cycles. For a discussion of the relative merits of various filtering methods giving due regard to these aspects, see Hamilton (2018) and Hodrick (2020).
12 See Orphanides and Van Norden (2002).
13 For a comparison of alternative trend adjustment methods with regard to the timely and robust identification of cyclical turning points, see Nilsson and Gyomai (2011). For a presentation of the HP filter, see Hodrick and Prescott (1997).
14 These are the United States, the United Kingdom, Japan, Sweden, Norway, Switzerland, Canada and Australia.
15 To do this, data from the June Economic Outlook were used; see OECD (2020). For the euro area, additional data from the Area Wide Model database of the Euro Area Business Cycle Network (EABCN) were also used. This makes it possible to extend the GDP time series going back only as far as early 1991 by a further 21 years into the past. For a description of the dataset and the model, see Fagan et al. (2005).
16 For one complete cycle, a minimum length of 12 quarters was specified, with each of its upturns and downturns having to have a minimum length of two quarters.
17 The cyclical component having to display a positive (negative) sign at the upper (lower) turning point was thus introduced as an additional condition. Moreover, four datings in total were shifted, as there was a significantly deeper lower or higher upper turning point in the immediate vicinity which was not selected by the dating procedure solely on account of the specified cycle length.
18 Only one of these "official" recessions is not identified as a separate downturn using the method applied here. The NBER dating for the United States for the early 1980s shows two recessions in quick succession. As defined here, this double-dip recession is identified as a single longer-lasting downturn.
19 For an alternative approach to the empirical classification of economic activity into traditional phases and more short-lived cycles, see European Central Bank (2019).

merous soft patches are also identified, in which economic output fell only slightly below its trend. For the United States, for example, the onset of such a soft patch is found most recently for the beginning of 2012.[20] The period of slow aggregate economic growth thus coincided with the euro area recession following the sovereign debt crisis. For the most recent period, recessions are diagnosed for both the United States and the euro area in the wake of the coronavirus pandemic. Overall, quite a high degree of cyclical co-movement can be identified for other periods and countries, too (see the box on p. 48 ff.).

Real GDP and cyclical turning points for the United States and the euro area*

2015 = 100, quarterly data, seasonally adjusted



Sources: OECD Economic Outlook (2020), Euro Area Business Cycle Network Area Wide Model database, NBER and CEPR recession chronologies, Haver Analytics and Bundesbank calculations. * Cyclical turning points in trend-adjusted GDP are identified using the Bry-Boschan algorithm.
Deutsche Bundesbank

Cyclical fluctuations show repeating patterns …

A look at the statistical features of the identified cycles underlines the fact that economic developments in advanced economies generally run along similar lines. In almost all the industrial countries analysed, nine or ten complete economic cycles since the 1960s were counted. Just about half of them ended in a recession. In the other cases, economic output was no more than slightly down on its trend. Economic downturns were mostly significantly shorter than upward movements. Between these cyclical turning points, which separated the phases of the business cycle from each other, real GDP generally moved within a range of just over 2% above and below its trend.

… but also exceptional movements

Even so, these common features should not make us lose sight of the fact that individual cycles do indeed deviate very significantly from the typical pattern. There are, for example, instances of short upturns and longer-lasting downturns. In particular, however, there are variations in how deep the slumps are. In this regard, the economic slump of the first half of 2020 is likely to turn out to be the severest in recent history everywhere.[21]

Do upswings die of old age?

In many places, the most recent crisis was preceded by an extended macroeconomic upswing. Against this background, concerns that the next recession had to be imminent have been expressed repeatedly over the past few years. However, amongst economists, the hypothesis that an upswing might end simply as a result of its long lifespan is highly controversial.

The impact of the duration of an upswing on the probabilities of cyclical downturns …

Empirical studies have come to fairly different conclusions. Diebold and Rudebusch (1990) and Rudebusch (2016), for example, show that the recession probabilities in the United States are not dependent on the duration of the preceding upswing. Using a comparable approach, however, the cross-country study in Castro (2010) finds that the probability of a turnaround does in fact rise the longer a given cyclical phase continues. This means that upswings would indeed “die of old age”.

20 The years 2018 and 2019, which were characterised by merely subdued upward momentum in the global economy, are not interpreted as soft patches when this approach is applied.
21 As only business cycle phases that are definitively concluded are under consideration, the recovery from the global economic crisis triggered by the pandemic does not form part of this analysis.

International business cycles

In the wake of the COVID-19 pandemic, economic output collapsed in almost all economies within a few weeks. Likewise, the global financial and economic crisis of 2008-09 hit most industrial countries almost simultaneously. The same was true for the two oil price crises in 1973 and 1979-80. This high degree of international co-movement is not typical of all crisis periods, however. One counterexample is the bursting of the dotcom bubble in 2000, which triggered a recession only in some countries. Similarly, the European sovereign debt and banking crisis between 2010 and 2012 saw economic output collapse in some euro area Member States, whilst other countries merely experienced soft patches. Against this backdrop, the question arises as to how strong the cyclical co-movement between the industrial countries actually is.

A variety of descriptive statistics point to a fairly close international cyclical relationship.[1] For example, according to an indicator that shows the share of periods in which business cycle phases are aligned,[2] the United States and Germany are highly synchronised. The business cycle phases of these two global economic heavyweights show strong overlap with those of other advanced economies, too. Correlation coefficients tend to confirm this finding.[3] In a direct comparison with the United States and Germany, a positive relationship between business cycle phases can be observed for almost all countries included in the analysis. In many cases, the point esti-

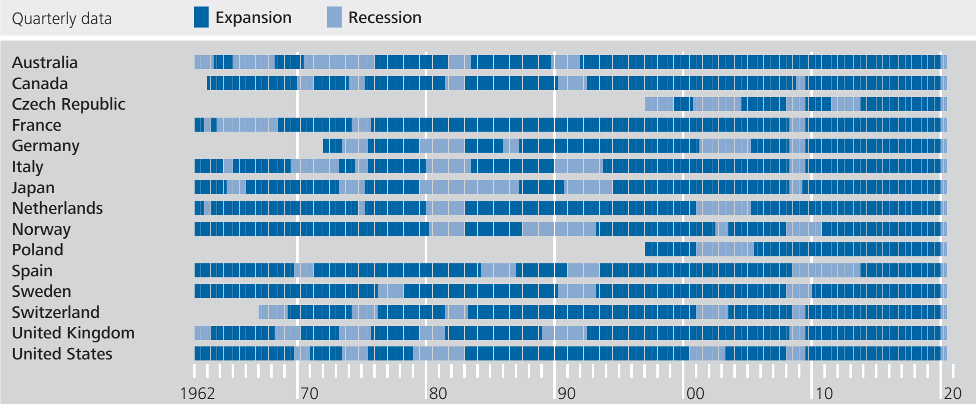
1 Cyclical turning points, which separate recessions from expansions, were dated in the following by applying the Bry-Boschan algorithm to trend-adjusted GDP time series. In this context, only those troughs that entailed high levels of aggregate underutilisation are considered recessions. For a similar study based on a classical dating of cyclical turning points, see Grigoraş and Stanciu (2016).
2 The "concordance index" draws on the binary classification of the economic situation into expansions ($S=0$) and recessions ($S=1$). The index value for two countries x and y over T time periods is then calculated as

$$Ixy = \frac{1}{T}\left(\sum_{t=1}^{T} S_{x,t}S_{y,t} + \sum_{t=1}^{T}(1-S_{x,t})(1-S_{y,t})\right).$$

Pairs of countries with perfectly synchronised business cycle phases thus show an index value of 1. If there is no synchronisation at all, the value is 0.
3 The estimation was calculated using the generalised method of moments (GMM), taking into account heteroscedasticity and autocorrelation-consistent standard errors.

Business cycle phases* in selected countries

Quarterly data



Sources: OECD Economic Outlook (2020), Haver Analytics and Bundesbank calculations. * Cyclical turning points were dated by applying the Bry-Boschan algorithm to trend-adjusted GDP series. Only downturns that fall short of the trend by at least 2% are dated as recessions.
Deutsche Bundesbank

mators are also statistically significantly different from zero. Only Sweden and Spain, as well as the commodity-producing economies of Australia and Norway, appear to largely follow distinct business cycles.

There are indications of particularly strong cyclical synchronisation within Europe. For Germany's immediate neighbours France, the Netherlands, Poland and Switzerland, the respective correlation with the German cycle is more pronounced than the co-movement with the United States. Geographical proximity, closer trade relations and interlinked production chains are likely to be key factors in this regard. However, the negative, albeit insignificant, correlation between the Spanish and German business cycles is probably influenced by the fact that Spain, like other European periphery countries, experienced a convergence boom with high growth rates in the 1990s and 2000s and, unlike Germany, avoided a recession at the beginning of the millennium when the dotcom bubble burst. By contrast, Germany recovered fairly quickly after the global financial and economic crisis, while the southern European euro area countries were drawn into the maelstrom of the sovereign debt crisis.[4]

Measures of business cycle synchronisation

Country	Concordance index[1]		Correlation	
	Germany	United States	Germany	United States
Australia	0.72	0.68	0.16	0.08
Canada	0.78	0.82	0.31*	0.40**
Czech Republic	0.74	0.74	0.48**	0.50**
France	0.80	0.74	0.38*	0.10
Germany	1.00	0.90	1.00***	0.73***
Italy	0.74	0.78	0.30	0.38**
Japan	0.76	0.73	0.41**	0.28
Netherlands	0.90	0.85	0.73***	0.49**
Norway	0.70	0.75	0.21	0.26
Poland	0.92	0.82	0.78**	0.40
Spain	0.61	0.66	− 0.07	− 0.02
Sweden	0.66	0.72	− 0.07	0.01
Switzerland	0.85	0.82	0.56***	0.45***
United Kingdom	0.78	0.79	0.36*	0.38**
United States	0.90	1.00	0.73***	1.00***

Sources: OECD Economic Outlook (2020), Haver Analytics and Bundesbank calculations. Significance of the correlation: *<0.01; **<0.05; ***<0.1. **1** The concordance index measures the share of periods with synchronised business cycle phases.

Deutsche Bundesbank

That said, a comparison that is limited to contemporaneous correlations may overlook international cyclical relationships. This is particularly true when economic downturns do not have a common, direct cause, but originate from a specific country and then spread after a certain delay. In this case, business cycle phases would be more likely to be aligned with a lead or lag in time. Indeed, for a number of industrial countries, the correlation with the US cycle is estimated to be somewhat stronger if the comparison of developments accounts for a time shift. These countries, including Canada, appear to lag behind the US business cycle, usually by one to two quarters, while Germany's business cycle is synchronous with that of the United States. Within Europe, most countries have business cycles that are in step with or lag only slightly behind the German cycle.

The conclusion that, on the whole, international business cycles correlate fairly closely is confirmed by further robustness studies.[5] This is also consistent with the academic literature. Global and common regional factors therefore probably account for a considerable portion of national cyclical fluctuations.[6] However, their impact does not appear to have been constant

4 For more information, see Grigoraş and Stanciu (2016), and Deutsche Bundesbank (2014).
5 For example, looking at alternative classifications of international business cycles and comparing cyclical GDP components produces similar results.
6 See Kose et al. (2003).

over time. For example, they did not play a significant role in the period of the "Great Moderation" prior to the financial and economic crisis of 2008-09. In any case, the impact of severe international shocks on national economic developments seems to have increased over time,[7] probably due in large part to the deepening of trade relations as a result of globalisation.[8] Given the current shift towards greater protectionism, it thus remains to be seen whether cyclical fluctuations will display a stronger national influence in the future.

7 For more information, see Kose et al. (2008). In line with this finding, counterfactual VAR simulations show that the synchronicity of international business cycles would have increased from the mid-1980s to shortly after the turn of the millennium if global shocks of a similar magnitude to those in previous decades had occurred; see Stock and Watson (2005). Recently, however, country-specific shocks in particular appear to spill over to other economies to a greater extent than previously; see Carare and Mody (2012).
8 This is supported by the fact that the influence of international trade links on the synchronisation of business cycles is confirmed in a variety of different regression specifications; see Baxter and Kouparitsas (2005). Cross-border value chains appear to be the main reason for this finding; see Ng (2010).

… can be investigated using a survival model

Based on these studies, this article applies a simple parametric survival model to the group of advanced economies.[22] This approach estimates the impact of the duration of an upswing on the probability that the upswing will soon come to an end.[23] In this context, upswings dated using the Bry-Boschan algorithm, which can also be ended by soft patches, are taken into consideration. In addition, upswings that occur between recessions are investigated separately. Other explanatory variables are initially excluded from the analysis.[24]

Probability of a cyclical turnaround rises with the duration of the upswing

Overall, the results suggest that the probability of an upswing coming to an end increases the longer the upswing continues. This holds especially true if upswings ended by soft patches are also taken into consideration. While there is a negligible risk of a young macroeconomic upswing leading to a cyclical downturn in the following quarter, the probability of a downturn rises sharply as the duration of the upswing increases.[25] On this basis, around one in every three upswings lasting more than ten years would end in the following quarter. Similar results to those in the overall sample can also be observed for most countries, although the relationship between the duration of an upswing and the probability of a downturn seems to be

22 The countries and economic areas featured in this analysis are the euro area, the United States, the United Kingdom, Japan, Sweden, Norway, Switzerland, Canada and Australia.
23 This kind of methodology is appropriate if mortality is a factor (i.e. observation units are successively eliminated). In medical research, for example, comparable models are used to estimate the efficacy of clinical treatments. The event being observed does not necessarily need to be death, but can be selected at will; other typical examples include recovery or the onset of complications.
24 With regard to the number of quarters in which an economy has been in an upswing at any given point in time, it is assumed that this variable follows a Weibull distribution. This distribution is consistent with very different hazard functions that could, in principle, generate probabilities of failure that rise or fall with the duration of the upswing. For an overview and other applications, see Cleves et al. (2008), pp. 248 ff. and Lancaster (1992), pp. 269 ff.
25 Specifically, this refers to the conditional probability that an upswing that has lasted until the time of observation will end in the following quarter.

Descriptive statistics on the business cycles of major advanced economies*

Observation period: Q1 1960 to Q2 2020

Economy	Number		Average duration in quarters[1]			Average amplitude in percentage points[1,2]		
	Cycles	Recessions[3]	Upturns	Downturns	Recessions[3]	Upturns	Downturns	Recessions[3]
Australia	9	5	11.2 (7.9)	12.7 (4.6)	12.8 (6.7)	4.0 (2.0)	− 3.8 (2.4)	− 6.1 (1.5)
Canada	10	5	14.6 (7.1)	6.4 (2.6)	5.6 (2.2)	4.3 (1.8)	− 4.1 (1.9)	− 5.5 (1.8)
Euro area	8	2	15.3 (7.6)	7.6 (2.9)	5.0 (0.0)	3.5 (1.5)	− 3.3 (1.7)	− 5.5 (0.8)
Japan	9	5	14.1 (6.6)	9.4 (8.9)	12.8 (11.0)	5.0 (1.5)	− 5.1 (2.1)	− 6.3 (1.7)
Norway	9	4	11.8 (5.2)	11.8 (5.6)	12.3 (7.9)	4.2 (2.0)	− 4.1 (2.3)	− 6.0 (2.2)
Sweden	10	3	10.9 (5.0)	8.8 (3.7)	9.3 (2.3)	4.2 (1.4)	− 4.0 (2.2)	− 6.6 (2.0)
Switzerland	9	5	13.8 (5.6)	7.2 (2.5)	7.3 (2.5)	4.5 (2.9)	− 4.1 (3.1)	− 6.4 (3.2)
United Kingdom	9	6	14.2 (10.4)	9.4 (4.8)	9.0 (3.3)	5.0 (2.5)	− 4.7 (2.8)	− 6.5 (2.3)
United States	10	5	13.2 (4.9)	8.1 (3.2)	9.6 (4.0)	4.2 (2.0)	− 4.1 (2.5)	− 6.1 (1.8)
Memo item: OECD	10	3	13.1 (5.8)	8.3 (3.7)	9.3 (4.2)	3.0 (1.2)	− 2.9 (1.8)	− 5.2 (0.7)

Sources: OECD Economic Outlook (2020), Euro Area Business Cycle Network Area Wide Model database, Haver Analytics and Bundesbank calculations. * Identified by applying the Bry-Boschan algorithm to trend-adjusted real GDP time series. **1** Standard deviations are shown in parentheses. **2** Change in cyclical components between two turning points. **3** Downturns with a negative deviation from the trend of at least 2%.

Deutsche Bundesbank

especially pronounced in the United States.[26] However, a considerably different picture is obtained if soft patches are disregarded when defining cyclical phases.[27] If only recessions are taken into consideration, the probability of crisis rises only slightly over time.[28] The answer to the question of whether an upswing's duration has an impact on its probability of soon coming to an end is highly dependent on how cyclical phases are defined.

Model-based forecasts of cyclical downturns

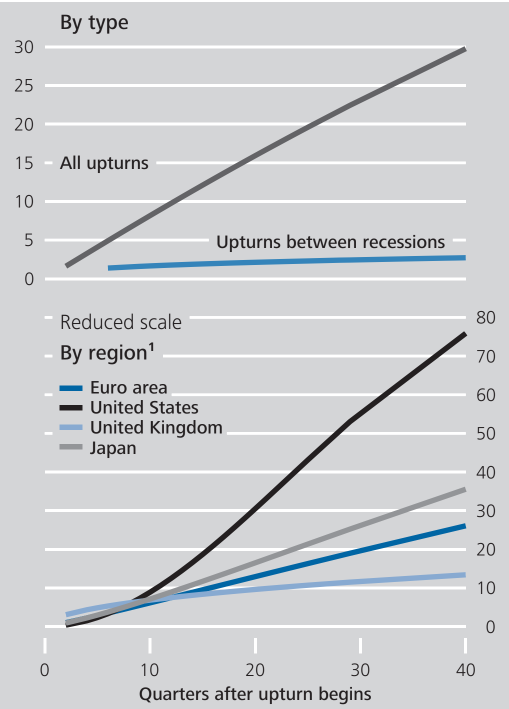
Analyses of additional determinants

Alongside just the duration of an upswing, the academic literature and business cycle research also discuss additional indicators that can be relevant to forecasting cyclical turning points. In this context, new perspectives could be offered by focusing on variables that have anticipated macroeconomic cyclical patterns in the past. Within the group of advanced economies, such variables appear to include house prices, sentiment indicators and financial market variables, for example. Furthermore, dedicated indicators developed specifically for this purpose, such as the Bundesbank's leading indicator or the OECD composite leading indicator, provide timely information on cyclical developments at the international level.[29] Finally, the literature also makes use of more complex statistical methods for forecasting cyclical turn-

26 In robustness studies, the model was also estimated using dummy variables for the various countries following Castro (2010). However, the associated coefficients were only significant in a small number of cases.
27 In this specification, a country-specific analysis is not possible due to the even smaller number of observations.
28 In this case, the results are consistent with those produced by Diebold and Rudebusch. Unlike in these studies, however, the hypothesis that the probability of a recession does not depend on the duration of the upswing can be rejected on a statistical basis. See Diebold and Rudebusch (1990) and Rudebusch (2016).
29 See Deutsche Bundesbank (2010). The Bundesbank leading indicator's time series is available at: https://www.bundesbank.de/dynamic/action/en/statistics/time-series-databases/time-series-databases/759784/759784?listId=www_s3wa_inet_bbli

Probability that an upturn will end*

%



Sources: OECD Economic Outlook (2020), Haver Analytics and Bundesbank calculations. * Probability that an upturn will end in the following quarter given its duration. **1** All upturns.

Deutsche Bundesbank

ing points. In country-specific analyses, time series models, such as regime-switching models or smooth transition autoregressive models, are typically used for this purpose.[30] The Bundesbank also utilises these approaches to assess the state of the German economy (see the box on pp. 54 f.).

Focus on cross-country logit estimates

In the following section, panel regression models are estimated; this approach allows the wealth of information contained in an international dataset to be utilised.[31] As the dependent variables in question can only take one of two values – zero when an economy is in an upturn, or one when a cyclical expansion reaches its peak – binary regression models are appropriate here.[32] One advantage of the logit models used here is that they have comparatively simple structures, even when additional explanatory variables are incorporated.[33] Furthermore, they enable historical probabilities of cyclical peaks to be calculated.

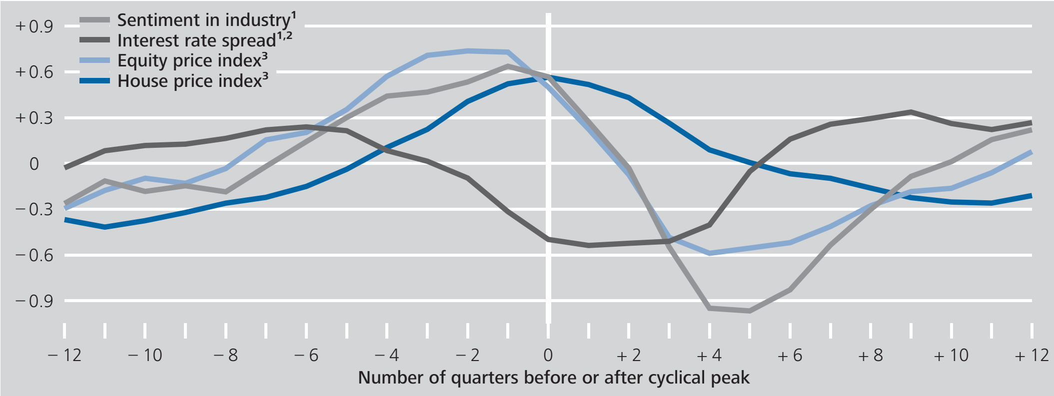
Variable selection guided by cyclical patterns, literature and quantitative selection criteria

In order to take transmission channels and causes of upturns into account as comprehensively as possible, the first step is to preselect variables by analysing the explanatory power of a number of variables, alongside the duration of the upturn thus far, using a bivariate version of the logit model. This factors in indicators that other studies have found to signal the run-up to a cyclical peak; these include, for example, interest rate spreads between assets with different maturities, equity and house prices, oil prices, and sentiment indicators.[34] Fiscal policy and monetary policy variables are additionally taken into account as, in the past, fiscal consolidation or restrictive monetary policy stances have been considered to have triggered macroeconomic downturns.[35] Labour market variables and industrial capacity utilisation, which could be indicative of "overheating" in the economy, were also assessed with regard to their suitability for predicting cyclical peaks. The final selection of variables aims to achieve the highest possible goodness of fit for

30 See, for example, Tian and Shen (2019), Carstensen et al. (2020), Eraslan and Nöller (2020) as well as Fornari and Lemke (2010) for forecasting turning points using binary vector autoregressions.
31 This approach is also used by Estrella and Mishkin (1997) and Borio et al. (2019).
32 Observations corresponding to downturns are removed from the sample.
33 As discrete dependent variables are problematic in traditional regression analyses, these are replaced by continuous variables in logit models – the logarithm of the odds ratio for the occurrence of a cyclical peak.
34 For example, Rudebusch and Williams (2009) highlight the ability of interest rate spreads to predict imminent recessions. In the case of the United States in particular, extreme scenarios with negative interest rate spreads are typically seen as signs of a looming recession (see Bauer and Mertens (2018)). House prices and credit data are factored into the turning point forecast in Borio et al. (2019) by way of an aggregate indicator. The role of equity prices as a predictor of recessions and cyclical movements is also discussed in the literature (see, inter alia, Mills (1988), Estrella and Mishkin (1998) and Andersson and D'Agostini (2008)). For more information on the properties of oil prices as a leading indicator, see Kilian and Vigfusson (2017).
35 For example, the tightening of monetary policy in the United States in the early 1980s is considered to be one of the causes of the 1981-82 recession (see, inter alia, Goodfriend and King (2005)). Heimberger (2017), however, attributes the double-dip recession in many euro area countries from 2011 to 2013 to the strong fiscal consolidation in these countries.

Development of selected indicators in the periods before and after cyclical peaks

Standardised and averaged across all business cycles in the sample



Sources: OECD Economic Outlook (2020) and Bundesbank calculations. **1** The underlying series for the sentiment indicator and interest rate spread are measured in index points and percentage points, respectively. **2** The interest rate spread measures the difference between ten-year government bond yields and the three-month interbank rate. **3** Trend-adjusted.

Deutsche Bundesbank

the regression models.[36] The resulting models therefore also include explanatory variables with coefficients that are not statistically different from zero, but which slightly improve the coefficient of determination.[37]

case, a rise in oil prices is an important indicator of an imminent turning point into a downturn. The duration of the respective upswing and the interest rate spread also prove to be robust indicators of approaching recessions in

Determinants of cyclical peaks

Different variables relevant for forecasting all downturns …

If, initially, cyclical phases are again defined in such a way that even mild downward movements are considered downturns, the results of the survival analysis are confirmed. Regardless of the forecast horizon under analysis,[38] the duration of an upswing so far has a statistically significant positive impact on the probability of a cyclical peak.[39] A narrower interest rate spread, i.e. a flatter yield curve, is also linked to an increased probability of an upswing soon coming to an end. This applies similarly to above average levels of debt in the private non-financial sector, dampened house prices, and particularly exuberant sentiment in industry. Factoring in equity prices, consumer sentiment and the domestic inflation rate measured by the GDP deflator also improves the model's ability to predict cyclical peaks.[40]

… and for forecasting recessions

However, the interrelationships appear somewhat different if the focus is placed on upswings that occur between recessions. In this

36 In total, more than 20 variables are counted among the group of indicators considered to have potential for identifying cyclical peaks. Depending on the characteristics of their time series, the variables are factored into the regression models in levels, as changes on the preceding quarter or preceding year, or as deviations from the trend. The majority of the indicators were obtained from the June 2020 edition of the OECD Economic Outlook and the OECD Main Economic Indicators. The data on outstanding loans originate from the BIS. National sources were used to obtain fiscal variables.

37 The measure of quality used is McFadden's adjusted R^2, which penalises the incorporation of additional explanatory variables in order to prevent the model from becoming overfitted to the data. Other common information criteria produce similar results. Optimising the coefficient of determination in the strict sense is made more difficult by the fact that selecting regressors also often changes the composition of the sample. Nevertheless, this has no bearing on this analysis' statements regarding the predictive power of the models used.

38 Forecast horizons of between one and four quarters were analysed. The probability of an upswing ending within the following four quarters was also estimated.

39 The statistical significance of the regression coefficients is discussed below. These describe the effects of marginal changes in each of the explanatory variables on the logarithm of the odds ratio for the occurrence of a cyclical peak.

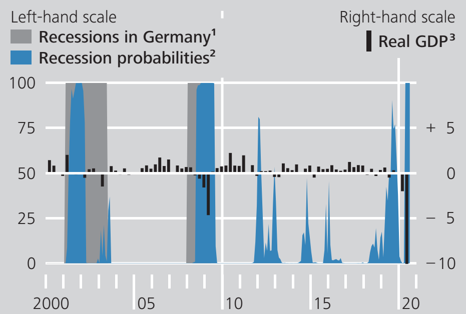
40 Nevertheless, the occurrence of cyclical peaks is not correlated with equity prices or the GDP deflator to a statistically significant degree.

A model for the timely identification of turning points in the business cycle and recession probabilities for Germany

Models used to identify probabilities of recession and associated turning points in the business cycle are often based on only a single highly aggregated indicator.[1] As an alternative, it is possible to look at a large variety of indicators, each of which captures different aspects of economic activity.[2] A new kind of modelling framework is presented below. This is based on cross-sectional information from a large dataset comprising numerous macroeconomic and financial indicators,[3] in order to estimate probabilities of recession and thus predict turning points in the business cycle.[4] The procedure, a smooth transition autoregressive model,[5] is based on the idea of a classic two-phase business cycle and allows a gradual transition between the two regimes. Expansions and recessions are distinguished from one another by turning points in the business cycle. In a first step, indicator-specific probabilities of assignment to a recession phase are estimated for a large number of macroeconomic and financial variables. These are then condensed into an aggregate probability of recession. The median of the indicator-specific probabilities is used as a measure of this.

Recession probabilities for Germany

%



Sources: German Council of Economic Experts, Federal Statistical Office and Bundesbank calculations. **1** Dating by German Council of Economic Experts. **2** Bundesbank calculations based on Eraslan and Nöller (2020). **3** Quarter-on-quarter change.

Deutsche Bundesbank

To assess the suitability of this model, a simulation study was performed with a pseudo real-time dataset[6] for Germany. The original estimation period runs from January 1993 to December 1999. The evaluation period runs from January 2000 to August 2020. The model not only determines the probability of recession at the respective point in time, but also predicts the probabilities of recession for the coming months. The ex post recession dating by the German Council of Economic Experts serves as a reference for determining the forecast accuracy.[7]

The model is fairly reliable in identifying the last two recessions in Germany as dated by the German Council of Economic Experts. Nevertheless, the start of the recession which was triggered by the bursting of the dotcom bubble and which, according to the Council, lasted from February 2001 through June 2003, as well as the onset of the Great Recession, which the Council now dates to between January 2008 and April 2009, are both identified by the model only with a lag of several months.[8] In the

1 See Hamilton (2011).
2 See Stock and Watson (2010, 2014).
3 The dataset consists of approximately 100 indicators. Alongside real economic indicators such as industrial output and new orders, the analysis also considers financial market variables such as stock price indices and interest rate variables as well as indicators of sentiment.
4 See Eraslan and Nöller (2020).
5 The modelling approach is based on smooth transition autoregressive (STAR) models, which were introduced and refined by Teräsvirta and Anderson (1992) and Teräsvirta (1994). The momentum threshold autoregressive (MTAR) threshold adjustment type was proposed by Enders and Granger (1998). See Eraslan and Nöller (2020) for the model variant applied here (ST/MTAR).
6 Data as at 8 August 2020. The respective data vintage and the delay in publication for the individual indicators were replicated in the recursive estimates. However, the estimates are based on data that contained possible revisions since the initial release.
7 See German Council of Economic Experts (2017).
8 Another factor is that many economic indicators are published with a certain time lag.

first case, the model pinpoints the start of the recession four months later, as May 2001 (and the end as early as March 2002). In the second case, the median nowcast indicates a recessionary phase from July 2008 to July 2009, i.e. with a time lag of six months (start of recession) and three months (end of recession). In this comparison, however, it should be noted that these recessionary phases were not dated until a much later point in time. At the time of the recessions, the assessment was nowhere near as clear. This was particularly true of the Great Recession of 2008-09, the start of which often went undetected until later. By comparison, the model would have delivered an early warning. Furthermore, for the downturn from 2001 to 2003 the model pointed to a dramatically rising risk of recession as early as March 2001, with a nowcast of 10% as well as forecasts of almost 50% for April and nearly 80% for May.

The model gave warning signals more recently, too. In the second half of 2019, it indicated elevated recessionary risks, which then declined sharply at the beginning of 2020, however, owing to positive macroeconomic data for January and February. At the current end, the estimated probability of recession did not increase until early May, but then did so abruptly, surging to 100%. However, the sweeping measures taken to contain the coronavirus pandemic were already being introduced in March. It was immediately clear that this would inevitably result in a slump in economic activity. In this case, the delay in signalling a recession was due to the fact that the model – unlike business cycle analysts – was unable to take into account the economic impact of the measures until early May, when the macroeconomic indicators for March were released. This illustrates once again the special nature of the current crisis.

these cases.[41] An above average rate of inflation is also associated with a heightened probability of a cyclical peak in the following quarter. The sign of the effect of house and equity prices as well as outstanding loans – each measured as deviations from their growth trends – is highly dependent on their lag. In addition, lagged values for the selected variables significantly improve the informative value of the model, even if they have no statistically significant impact on the probability that a cyclical peak will occur when viewed in isolation.

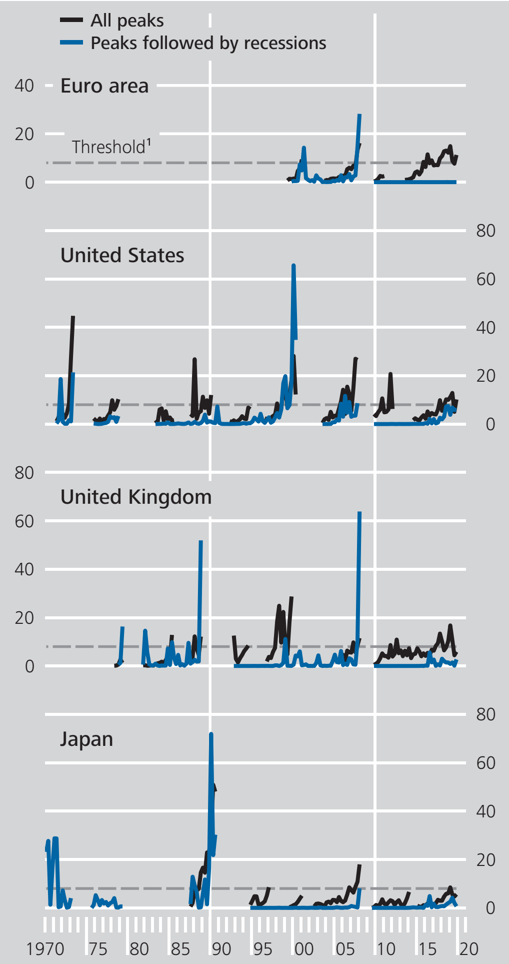
Results should be interpreted with caution

In some cases, the regression coefficients vary greatly depending on the way in which cyclical peaks are identified, the selection of explanatory variables, the underlying group of countries, and the forecast horizon. One reason for this may be that many indicators contain similar information on imminent cyclical turning points. Country-specific regressions largely confirm the impression that the duration of the upswing and the interest rate spread are good predictors of imminent cyclical peaks. For peaks that are followed by recessions, this holds true for the interest rate spread. In this context, it should also be noted that the coefficients only reflect historical correlation patterns. These are likely to contain indications of the driving forces behind cyclical turnarounds. For example, the 1973 oil crisis can also be interpreted as a cause of the subsequent downturn. By contrast, financial market variables as well as survey-based indicators probably only react in the run-up to cyclical slumps because market participants and respondents anticipate a downturn in many cases. Furthermore, the possibility that uncaptured factors are significant for the occurrence of cyclical peaks cannot be ruled out. For these reasons, the statistical impact of indi-

41 In the case of upswings that end in recessions, the relationship between the duration of the upswing and the probability that a cyclical peak will occur is weaker than for upswings that transition into soft patches. This is consistent with the results of the survival analysis.

Historical probabilities of cyclical peaks in selected regions*

%, quarterly data



***** Each estimation period begins with the first recorded probability. **1** Threshold value of 8%. Projected probabilities above this threshold are interpreted as signalling a cyclical peak in the respective quarter.

Deutsche Bundesbank

vidual variables must be interpreted with caution.

Forecasting economic downturns

Models indicate that upswings are usually increasingly fragile prior to crises

A key factor in predicting economic downturns is the model's forecast of the probability of an upturn coming to an end. This probability tends to rise sharply before soft patches, but especially before recessions. For example, models indicated that the upswing prior to the global financial and economic crisis was increasingly fragile for almost all major advanced economies. Flat yield curves, high levels of private debt and falling equity prices, but also the above average duration of the upswing so far, indicated a turning point ahead. Even clearer fluctuations were seen in the probabilities of recession for the United States at the turn of the millennium (i.e. before the economic slump triggered by the bursting of the dotcom bubble) and in Japan in the run-up to the severe economic crisis in the early 1990s.

More accurate model evaluation hinges on establishing signals for recession

The binary regressions therefore appear to provide valuable information about approaching peaks and impending downturns. To assess the quality of a forecast model more accurately, its predictions are usually compared with events that have actually occurred. This involves deriving warning signals from the forecast model probabilities and comparing them with the actual cyclical turning points. To this end, a threshold is sought which, when exceeded, means that the forecast probability sends the most reliable signal possible for a forthcoming downturn. If it is set too high, potential signals for downturns are missed. If it is set too low, a high proportion of false signals is to be expected. For peaks that mark the beginning of soft patches as well as those that are followed by deep recessions, threshold optimisation techniques suggest setting the threshold for sending a signal at 8%.[42]

Although early warning signals are often also incorrect, …

Beginning with the broad definition of a turning point, for this threshold, the model correctly classifies just over three-quarters of all observations into those with and without peaks. The error rate is only slightly higher when looking exclusively at the peaks themselves. Only one-third failed to be identified. However, in many cases, the model raises an alarm where there was no turnaround in economic activity. Nonetheless, it can be noted

42 The information content of signals is established here by determining a ratio between the probability of a signal being triggered at a peak and the probability of a signal being a false alarm. To identify warning signals, it is more important to avoid type I errors (missed peaks). As a result, fairly low thresholds are therefore selected. See also Bussière and Fratzscher (2006).

Accuracy of signals and associated probabilities of a cyclical peak

Threshold for sending a signal: 8%

Status	All peaks			Peaks followed by recessions		
	No signal	Signal	Total	No signal	Signal	Total
No peak	535	152	687	1,112	54	1,166
Peak	17	32	49	5	21	26
Total	552	184	736	1,117	75	1,192
Proportion of correctly identified observations			77.0%			95.1%
Proportion of correctly identified peaks			65.3%			80.8%
Proportion of false signals			82.6%			72.0%
Unconditional probability of a peak			6.7%			2.2%
Probability of a peak if signal sent			17.4%			28.0%
Probability of a peak if no signal sent			3.1%			0.4%

Deutsche Bundesbank

that the probability of a peak is significantly higher if the model sends a signal than if it does not. Compared with a naive forecast, which sets the unconditional probability of a peak for each quarter, the model-based forecast represents a clear improvement.

… recessions, in particular, are frequently recognised in advance

The binary regression model is even more informative if the forecast is limited to recessions. Here, almost all observations are identified correctly. The share of correctly identified peaks is also significantly higher than in the previous case. At the same time, however, the clear majority of the signals remain false. Nevertheless, the model is considerably more informative than naive forecasts. Although not every announcement was actually followed by a recession, the start of a recession was often clearly signalled.[43]

Pandemic-related economic crisis unforecastable

The global economic slump in the first quarter of 2020 can be used as a counter-example. Although there were increasing signs of an imminent soft patch in many countries last year, the risk of a recession in the near future was considered to be low. Only in the United States did the probability of recession rise slightly, owing to a negative interest rate spread. The COVID-19 pandemic itself and its consequences, however, could only be diagnosed, but not forecast with a greater lead.

Summary

Not all recessions can be predicted

In summary, quantitative business cycle analysis can be used to identify fragile macroeconomic upturns and also to predict downturns. Recessions, in particular, often appear to be signalled in advance – at least when looked at with hindsight. All the same, it must be acknowledged that the models presented here failed to recognise a few (sometimes severe) downturns. Turning points could even be missed more frequently in day-to-day business cycle analysis, not least because the characteristics of downturns often differ in their details from the patterns observed in previous cycles. However, it is precisely the particularities of the situation prevailing at a given time that are not yet reflected in the estimated forecast equations.

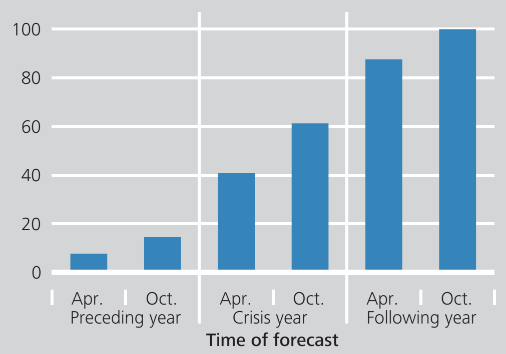
Even professional business cycle analysts are often surprised by crises

A look at the accuracy of judgements made by experts confirms how challenging it can be to predict economic downturns. In June 2008, for example, the Bundesbank was still anticipating fairly brisk growth in its forecasts for 2008 and 2009.[44] Six months later, the outlook was for

43 In almost half of all cases, an increase in the probability of a turning point interpreted as a false signal was indeed followed by a recession after a few quarters. The forecast models would therefore have indicated that the upturn was highly fragile in these situations, too.
44 See Deutsche Bundesbank (2008a).

Accuracy of IMF recession forecasts*

Percentage of correctly forecast GDP declines



Sources: IMF and Bundesbank calculations. * All forecasts for all countries and groups of countries from the April and October editions of the World Economic Outlook since 1991 have been taken into consideration. The October edition for the following year is used to determine GDP outcomes.

Deutsche Bundesbank

little growth in GDP over the course of 2009.[45] However, the current data show that, in the wake of the global financial and economic crisis, German GDP fell markedly from as early as the second quarter of 2008, decreasing by 3.3% over the course of 2009. Similarly, the International Monetary Fund has seldom forecast a decline in GDP in its published projections over the past 30 years. Even during crisis periods, its assessments for the current year were still too optimistic in around half of all cases. Other national and international organisations and private sector analysts have performed similarly poorly in the past.[46]

Explanatory approaches

Various explanatory approaches are put forward for this patchy overall performance. Some suggest that people generally tend to stick to an assessment once it has been made and do not initially assign enough importance to new information that challenges it.[47] It may also be the case that a recession – especially one that is less severe – is initially difficult to identify from the preliminary data delivered by the economic indicators. Macroeconomic forecasts would therefore be adjusted too slowly, despite signs of a deterioration in the situation. Other explanations are based on the incentives for business cycle forecasters. For instance, they might be reluctant to predict a recession if misjudgements could potentially result in major costs such as reputational damage.[48] In addition, the projections of international organisations might be influenced by political motives or concerns that a pessimistic forecast could become "self-fulfilling".[49] Finally, however, it is also possible that the picture may be clouded by the fact that, in some cases, impending downturns are detected early on and prevented by means of forward-looking economic policy measures. Recessions avoided in this way would not be included in the statistics.

Forecast models an important tool for identifying vulnerabilities

Although these factors certainly play something of a role, there is still much to suggest that, in the end, some downturns simply cannot be predicted. Even economies that previously appeared to be fairly resilient can be plunged into recession by shocks of sufficient magnitude. The latest global economic crisis resulting from the coronavirus pandemic underlines this once again. The fact that no warnings of an imminent economic turnaround are issued in situations like this should not therefore be considered a failure on the part of the experts. Business cycle research can, however, identify undesirable developments or potential excesses and thus an increased risk of recession. Quantitative methods are an important tool in this regard.

45 See Deutsche Bundesbank (2008b).
46 For more information, see Loungani (2001) and An et al. (2018).
47 This argument was first put forward by Nordhaus (1987).
48 See Zellner (1986).
49 For instance, an independent review of IMF forecasts published in the context of large support programmes found that assessments of the economic outlook were systemically overoptimistic. See Independent Evaluation Office of the International Monetary Fund (2014).

List of references

An, Z., J.T. Jalles and P. Loungani (2018), How well do economists forecast recessions?, International Finance, Vol. 21 (2), pp. 100-121.

Andersson, M. and A. D'Agostino (2008), Are sectoral stock prices useful for predicting euro area GDP?, ECB Working Paper Series, No 876.

Bauer, M.D. and T.M. Mertens (2018), Economic Forecasts with the Yield Curve, FRBSF Economic Letter, No 7.

Baxter, M. and M.A. Kouparitsas (2005), Determinants of business cycle comovement: A robust analysis, Journal of Monetary Economics, Vol. 52 (1), pp. 113-157.

Boissay, F., F. Collard and F. Smets (2016), Booms and Banking Crises, Journal of Political Economy, Vol. 124 (2), pp. 489-538.

Borio, C., M. Drehmann and D. Xia (2019), Predicting recessions: financial cycle versus term spread, BIS Working Paper, No 818.

Brock, W.A. and L.J. Mirman (1972), Optimal Economic Growth And Uncertainty: The Discounted Case, Journal of Economic Theory, Vol. 4 (3), pp. 479-513.

Bry, G. and C. Boschan (1971), Cyclical Analysis of Time Series: Selected Procedures and Computer Programs, National Bureau of Economic Research, New York.

Burns, A.F. and W.C. Mitchell (1946), Measuring Business Cycles, National Bureau of Economic Research, New York.

Burnside, C. (1998), Detrending and business cycle facts: A comment, Journal of Monetary Economics, Vol. 41 (3), pp. 513-532.

Bussière, M. and M. Fratzscher (2006), Towards a new early warning system of financial crises, Journal of International Money and Finance, Vol. 25 (6), pp. 953-973.

Canova, F. (1998), Detrending and business cycle facts, Journal of Monetary Economics, Vol. 41 (3), pp. 475-512.

Carare, A. and A. Mody (2012), Spillovers of Domestic Shocks: Will They Counteract the 'Great Moderation'?, International Finance, Vol. 15 (1), pp. 69-97.

Carstensen, K., M. Heinrich, M. Reif and M.H. Wolters (2020), Predicting ordinary and severe recessions with a three-state Markov-switching dynamic factor model: An application to the German business cycle, International Journal of Forecasting, Vol. 36 (3), pp. 829-850.

Castro, V. (2010), The duration of economic expansions and recessions: More than duration dependence, Journal of Macroeconomics, Vol. 32 (1), pp. 347-365.

Centre for Economic Policy Research (2020), Chronology of Euro Area Business Cycles, https://eabcn.org/dc/chronology-euro area-business-cycles, accessed on 10 August 2020.

Centre for Economic Policy Research (2012), Euro Area Business Cycle Dating Committee: Methodological note, https://cepr.org/Data/Dating/Dating-Methodology-Nov-2012.pdf, accessed on 19 October 2020.

Centre for Economic Policy Research (2003), Dating Committee Findings 22 September 2003, https://cepr.org/PRESS/Dating-Committee-Findings-22-September-2003.pdf, accessed on 12 October 2020.

Cleves, M., W. Gould, R. Gutierrez and Y. Marchenko (2008), An Introduction to Survival Analysis using Stata, 2nd edition, Stata Press, College Station, TX.

Deutsche Bundesbank (2014), Real economic adjustment processes and reform measures, Monthly Report, January 2014, pp. 19-37.

Deutsche Bundesbank (2010), Constructing a new leading indicator for the global economy, Monthly Report, May 2010, pp. 18-19.

Deutsche Bundesbank (2008a), Outlook for the German economy: macroeconomic projections for 2008 and 2009, Monthly Report, June 2008, pp. 17-30.

Deutsche Bundesbank (2008b), Outlook for the German economy: macroeconomic projections for 2009 and 2010, Monthly Report, December 2008, pp. 17-29.

Diebold, F. X. and G. D. Rudebusch (1990), A Nonparametric Investigation of Duration Dependence in the American Business Cycle, Journal of Political Economy, Vol. 98 (3), pp. 596-616.

Enders, W. and C. W. J. Granger (1998), Unit-Root Tests and Asymmetric Adjustment With an Example Using the Term Structure of Interest Rates, Journal of Business & Economic Statistics, Vol. 16 (3), pp. 304-311.

Eraslan, S. and M. Nöller (2020), Recession probabilities falling from the STARs, Deutsche Bundesbank Discussion Paper, No 08/2020.

Estrella, A. and F. S. Mishkin (1998), Predicting U.S. Recessions: Financial Variables as Leading Indicators, The Review of Economics and Statistics, Vol. 80 (1), pp. 45-61.

Estrella, A. and F. S. Mishkin (1997), The predictive power of the term structure of interest rates in Europe and the United States: Implications for the European Central Bank, European Economic Review, Vol. 41 (7), pp. 1375-1401.

European Central Bank (2019), Characterising the current expansion across non-euro area advanced economies: where do we go from here?, Economic Bulletin, 2/2019, pp. 39-43.

Fagan, G., J. Henry and R. Mestre (2005), An area-wide model for the euro area, Economic Modelling, Vol. 22 (1), pp. 39-59.

Fornari, F. and W. Lemke (2010), Predicting recession probabilities with financial variables over multiple horizons, ECB Working Paper Series, No 1255.

Frisch, R. (1933), Propagation problems and impulse problems in dynamic economics, in Economic Essays in Honour of Gustav Cassel, Allen & Unwin, London.

German Council of Economic Experts (2017), Konjunkturzyklen der deutschen Volkswirtschaft, Annual Economic Report 2017/18: Für eine zukunftsorientierte Wirtschaftspolitik (Towards a forward-looking economic policy), November 2017, pp. 134-135.

Goodfriend, M. and R.G. King (2005), The incredible Volcker disinflation, Journal of Monetary Economics, Vol. 52 (5), pp. 981-1015.

Gorton, G. and G. Ordoñez (2014), Collateral Crises, American Economic Review, Vol. 104 (2), pp. 343-378.

Grigoraş, V. and I.E. Stanciu (2016), New evidence on the (de)synchronisation of business cycles: Reshaping the European business cycle, International Economics, Vol. 147, pp. 27-52.

Hamilton, J.D. (2018), Why You Should Never Use the Hodrick-Prescott Filter, The Review of Economics and Statistics, Vol. 100 (5), pp. 831-843.

Hamilton, J.D. (2011), Calling recessions in real time, International Journal of Forecasting, Vol. 27 (4), pp. 1006-1026.

Harding, D. and A. Pagan (2002), Dissecting the cycle: a methodological investigation, Journal of Monetary Economics, Vol. 49 (2), pp. 365-381.

Heimberger, P. (2017), Did fiscal consolidation cause the double-dip recession in the euro area?, Review of Keynesian Economics, Vol. 5 (3), pp. 439-458.

Hodrick, R.J. (2020), An Exploration of Trend-Cycle Decomposition Methodologies in Simulated Data, NBER Working Paper, No 26750.

Hodrick, R.J. and E.C. Prescott (1997), Postwar U.S. Business Cycles: An Empirical Investigation, Journal of Money, Credit and Banking, 29 (1), pp. 1-16.

Hoffmann, M., M. Kliem, M. Krause, S. Moyen and R. Sauer (2020), Rebalancing the euro area: Is wage adjustment in Germany the answer?, Deutsche Bundesbank Discussion Paper, No 17/2020.

Independent Evaluation Office of the International Monetary Fund (2014), IMF Forecasts: Process, Quality, and Country Perspectives, Evaluation Report.

Kilian, L. and R.J. Vigfusson (2017), The Role of Oil Price Shocks in Causing U.S. Recessions, Journal of Money, Credit and Banking, Vol. 49 (8), pp. 1747-1776.

Kose, M.A., C. Otrok and C.H. Whiteman (2008), Understanding the evolution of world business cycles, Journal of International Economics, Vol. 75 (1), pp. 110-130.

Kose, M.A., C. Otrok and C.H. Whiteman (2003), International Business Cycles: World, Region, and Country-Specific Factors, American Economic Review, Vol. 93 (4), pp. 1216-1239.

Kydland, F.E. and E.C. Prescott (1982), Time to Build and Aggregate Fluctuations, Econometrica, Vol. 50 (6), pp. 1345-1370.

Lancaster, T. (1992), The Econometric Analysis of Transition Data, Econometric Society Monographs, No 17, Cambridge University Press.

Loungani, P. (2001), How accurate are private sector forecasts? Cross-country evidence from consensus forecasts of output growth, International Journal of Forecasting, Vol. 17 (3), pp. 419-432.

Lucas, R.E. (1972), Expectations and the Neutrality of Money, Journal of Economic Theory, Vol. 4 (2), pp. 103-124.

Mills, L. (1988), Can Stock Prices Reliably Predict Recessions?, Business Review, Federal Reserve Bank of Philadelphia, pp. 3-14.

National Bureau of Economic Research (2020a), The NBER's Recession Dating Procedure, https://www.nber.org/cycles/recessions.pdf, accessed on 15 September 2020.

National Bureau of Economic Research (2020b), US Business Cycle Expansions and Contractions, https://www.nber.org/cycles.html, accessed on 10 August 2020.

Ng, E.C.Y. (2010), Production fragmentation and business-cycle comovement, Journal of International Economics, Vol. 82 (1), pp. 1-14.

Nilsson, R. and G. Gyomai (2011), Cycle Extraction: A Comparison of the Phase-Average Trend Method, the Hodrick-Prescott and Christiano-Fitzgerald Filters, OECD Statistics Working Papers, No 2011/04.

Nordhaus, W. (1987), Forecasting Efficiency: Concepts and Applications, The Review of Economics and Statistics, Vol. 69 (4), pp. 667-674.

OECD (2020), OECD Economic Outlook, Vol. 2020 (1), OECD Publishing, Paris.

Orphanides, A. and S. van Norden (2002), The Unreliability of Output-Gap Estimates in Real Time, The Review of Economics and Statistics, Vol. 84 (4), pp. 569-583.

Paul, P. (2020), A macroeconomic model with occasional financial crises, Journal of Economic Dynamics and Control, Vol. 112, pp. 1-21.

Rudebusch, G.D. (2016), Will the Economic Recovery Die of Old Age?, FRBSF Economic Letter, No 2016-03.

Rudebusch, G.D. and J.C. Williams (2009), Forecasting Recessions: The Puzzle of the Enduring Power of the Yield Curve, Journal of Business & Economic Statistics, Vol. 27 (4), pp. 492-503.

Slutzky, E. (1937), The Summation of Random Causes as the Source of Cyclic Processes, Econometrica, Vol. 5 (2), pp. 105-146.

Stock, J. H. and M. W. Watson (2014), Estimating turning points using large data sets, Journal of Econometrics, Vol. 178 (2), pp. 368-381.

Stock, J. H. and M. W. Watson (2010), Indicators for Dating Business Cycles: Cross-History Selection and Comparisons, American Economic Review, Vol. 100 (2), pp. 16-19.

Stock, J. H. and M. W. Watson (2005), Understanding Changes in International Business Cycle Dynamics, Journal of the European Economic Association, Vol. 3 (5), pp. 968-1006.

Teräsvirta, T. (1994), Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models, Journal of the American Statistical Association, Vol. 89 (425), pp. 208-218.

Teräsvirta, T. and H. M. Anderson (1992), Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models, Journal of Applied Econometrics, Vol. 7 (1), pp. 119-136.

Tian, R. and G. Shen (2019), Predictive power of Markovian models: Evidence from US recession forecasting, Journal of Forecasting, Vol. 38 (6), pp. 525-551.

Zarnowitz, V. and A. Ozyildirim (2006), Time series decomposition and measurement of business cycles, trends and growth cycles, Journal of Monetary Economics, Vol. 53 (7), pp. 1717-1739.

Zellner, A. (1986), Biased predictors, rationality and the evaluation of forecasts, Economics Letters, Vol. 21 (1), pp. 45-48.

The tables accompanying this article are printed on pp. 64 f.

Regression table for forecasting cyclical peaks over various time horizons (all peaks)°

Item	(1) Peak in $t+1$	(2) Peak in $t+2$ 5	(3) Peak in $t+3$ 5	(4) Peak in $t+4$ 5	(5) Peak in $t+1$ to $t+4$
Duration	0.094** (0.046)	0.100** (0.042)	0.095** (0.038)	0.093** (0.041)	0.096** (0.047)
Interest rate spread$_t$ 1	− 0.405*** (0.113)	− 0.213* (0.128)	− 0.127 (0.165)	− 0.135 (0.165)	− 0.269* (0.143)
Equity price index$_t$ 2	− 0.044 (0.032)	− 0.014 (0.023)	0.013 (0.028)	0.013 (0.035)	− 0.009 (0.012)
Industry sentiment$_t$	0.069*** (0.018)	0.032 (0.034)	0.002 (0.032)	0.024 (0.033)	0.036** (0.014)
Industry sentiment$_{t-1}$	− 0.031** (0.015)	− 0.003 (0.036)	0.021 (0.033)	− 0.001 (0.030)	− 0.006 (0.014)
Consumer sentiment$_t$	− 0.082* (0.045)	− 0.058 (0.047)	− 0.030 (0.026)	0.084** (0.042)	− 0.013 (0.036)
Consumer sentiment$_{t-1}$	0.083** (0.038)	0.086*** (0.031)	0.079*** (0.026)	− 0.036 (0.036)	0.044* (0.025)
GDP deflator$_t$ 2	− 0.183 (0.175)	− 0.231 (0.329)	− 0.282 (0.236)	0.136 (0.361)	− 0.107 (0.256)
GDP deflator$_{t-1}$ 2	− 0.275 (0.323)	− 0.155 (0.222)	0.205 (0.327)	0.132 (0.162)	0.043 (0.211)
Credit-to-GDP$_t$ 3	0.045*** (0.014)	0.052*** (0.010)	0.054*** (0.009)	0.052*** (0.010)	0.063*** (0.012)
House price index$_t$ 4	− 0.021*** (0.005)	− 0.022*** (0.005)	− 0.021*** (0.005)	− 0.022*** (0.006)	− 0.027*** (0.006)
Constant	− 3.320*** (0.900)	− 3.443*** (0.875)	− 3.438*** (0.809)	− 3.577*** (0.840)	− 1.741** (0.848)
Countries	9	9	9	9	9
Country dummies	Yes	Yes	Yes	Yes	Yes
Observations	736	734	732	729	736
McFadden's adjusted R^2	0.042	0.011	0.009	0.009	0.099

o Robust and clustered standard errors shown in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **1** Difference between long-term and short-term interest rates. **2** Rate of change over preceding quarter. **3** Deviation from linear trend. **4** Deviation from log-linear trend. **5** Assuming that an upturn continues until that point in time.
Deutsche Bundesbank

Regression table for forecasting cyclical peaks over various time horizons (only peaks followed by recessions)°

Item	(1) Peak in $t+1$	(2) Peak in $t+2$ 5	(3) Peak in $t+3$ 5	(4) Peak in $t+4$ 5	(5) Peak in $t+1$ to $t+4$
Duration	0.042** (0.017)	0.036** (0.017)	0.020 (0.016)	0.024 (0.016)	0.029* (0.015)
Interest rate spread$_t$ 1	– 1.614*** (0.450)	– 1.438*** (0.349)	0.054 (0.346)	– 0.427 (0.371)	– 0.767*** (0.104)
Interest rate spread$_{t-1}$ 1	0.521*** (0.198)	1.199*** (0.363)	– 0.668 (0.579)	– 0.274 (0.873)	0.124 (0.183)
Interest rate spread$_{t-2}$ 1	0.339 (0.415)	– 0.296 (0.453)	0.332 (0.308)	0.374 (0.755)	0.134 (0.279)
GDP deflator$_t$ 2	0.673* (0.353)	1.166** (0.500)	0.432 (0.360)	0.244 (0.223)	0.564** (0.276)
GDP deflator$_{t-1}$ 2	0.856* (0.497)	0.198 (0.431)	0.385** (0.176)	0.061 (0.362)	0.331 (0.232)
GDP deflator$_{t-2}$ 2	0.207 (0.290)	0.114 (0.187)	– 0.032 (0.286)	0.579*** (0.154)	0.350 (0.216)
House price index$_t$ 3	– 0.070 (0.072)	0.179 (0.138)	– 0.025 (0.113)	0.198*** (0.073)	0.050 (0.050)
House price index$_{t-1}$ 3	0.222* (0.119)	– 0.254 (0.247)	0.212 (0.199)	– 0.206 (0.133)	0.026 (0.051)
House price index$_{t-2}$ 3	– 0.112 (0.104)	0.110 (0.130)	– 0.160* (0.091)	0.034 (0.070)	– 0.047 (0.034)
Credit-to-GDP$_t$ 4	0.031 (0.138)	0.498*** (0.124)	0.083 (0.076)	0.016 (0.095)	0.169** (0.082)
Credit-to-GDP$_{t-1}$ 4	0.561*** (0.162)	– 0.584** (0.232)	0.031 (0.084)	0.119 (0.151)	0.005 (0.063)
Credit-to-GDP$_{t-2}$ 4	– 0.688*** (0.241)	0.007 (0.177)	– 0.183* (0.101)	– 0.200*** (0.073)	– 0.242*** (0.069)
Equity price index$_t$ 3	– 5.505 (4.591)	– 5.040* (2.728)	2.849 (3.228)	2.221 (4.995)	– 0.357 (1.727)
Equity price index$_{t-1}$ 3	2.039 (8.054)	5.930 (4.794)	– 1.492 (5.548)	0.803 (7.835)	0.807 (1.250)
Equity price index$_{t-2}$ 3	6.084 (4.068)	1.870 (4.054)	1.346 (4.543)	– 0.153 (3.208)	2.311 (1.505)
Oil price$_t$ 3	0.038*** (0.009)	0.012 (0.016)	0.001 (0.010)	0.006 (0.019)	0.012*** (0.004)
Oil price$_{t-1}$ 3	– 0.014 (0.018)	0.000 (0.013)	0.006 (0.018)	– 0.006 (0.015)	– 0.005 (0.006)
Oil price$_{t-2}$ 3	0.029** (0.014)	0.001 (0.024)	– 0.016 (0.020)	0.014 (0.012)	0.002 (0.010)
Constant	– 11.329*** (2.973)	– 9.899*** (2.539)	– 7.382*** (2.062)	– 8.016*** (2.036)	– 7.232*** (2.013)
Countries	9	9	9	9	9
Country dummies	Yes	Yes	Yes	Yes	Yes
Observations	1,192	1,187	1,182	1,147	1,192
McFadden's adjusted R^2	0.195	0.101	– 0.044	– 0.029	0.227

o Robust and clustered standard errors shown in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. **1** Difference between long-term and short-term interest rates. **2** Rate of change over preceding quarter. **3** Deviation from log-linear trend. **4** Deviation from linear trend. **5** Assuming that an upturn continues until that point in time.
Deutsche Bundesbank