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Statistical offices revise GDP values to improve earlier GDP estimates. Revisions are led by updates on data availability and methodological changes, including those required for international comparability. In this paper, we apply the Bry-Boschan Quarterly (BBQ) algorithm for dating turning points on a set of UK real GDP data vintages to assess the impact of GDP data revisions on dating UK business cycles. A peak identified in 2011Q3 suggesting a recession in late 2011/early 2012 vanishes as data revisions are incorporated to previous estimates of real GDP. We also evaluate the impact of turning point revisions on the choice of indicators to provide accurate predictions of recession probabilities. In real-time, the GFK consumer confidence index is the best, but alternative indicators such as CBI retail orders and construction indices are more accurate if recession periods are identified with the latest vintage of real GDP.

Keywords: turning point algorithms, UK business cycles, probit models, recession probabilities, real-time data.

JEL classification: E32, C35.

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Abstract

Statistical offices revise GDP values to improve earlier GDP estimates. Revisions are led by updates on data availability and methodological changes, including those required for international comparability. In this paper, we apply the Bry-Boschan Quarterly (BBQ) algorithm for dating turning points on a set of UK real GDP data vintages to assess the impact of GDP data revisions on dating UK business cycles. A peak identified in 2011Q3 suggesting a recession in late 2011/early 2012 vanishes as data revisions are incorporated to previous estimates of real GDP. We also evaluate the impact of turning point revisions on the choice of indicators to provide accurate predictions of recession probabilities. In real-time, the GFK consumer confidence index is the best, but alternative indicators such as CBI retail orders and construction indices are more accurate if recession periods are identified with the latest vintage of real GDP.

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1. Introduction

Historical analyses of business cycles characteristics usually require the identification of recession and expansion phases. As Burns and Mitchell (1946) have suggested, recessions and expansions phases are defined after turning points --peaks and troughs-- are dated in time series data of aggregate economic activity. Harding and Pagan (2002) argue that the 'Classical Business Cycles Turning Points Analysis' led by Burns and Mitchell (1946) requires the identification of turning points on the levels of aggregate measures of economic activity such as employment, industrial production and real GDP. Recessions are usually defined as the period between a peak and a trough.

Artis et al (1997) describe a chronology for UK business cycles using the Bry and Boschan (1971) algorithm that identifies turning points in monthly measures of economic activity such as industrial production. Harding and Pagan (2002) adapted the Bry and Boschan (1971) algorithm to classify turning points in monthly measures of economic activity to quarterly series, leading to the Bry and Boschan (1971) Quarterly (BBQ) algorithm. They argue that the algorithm is successful in identifying turning points for quarterly GDP time series since they match NBER turning points when applied to US data.

In this paper, we apply the BBQ algorithm to UK real GDP to identify business cycle turning points in different vintages of UK GDP data released by the Office of National Statistics. GDP data revisions aim to improve the accuracy of early estimates, which are timely but based on incomplete data, as detailed in ONS (2019). Data revisions may also be a result of methodological improvements including those that improve coherence across statistical measures and of international comparability.

Our results suggest that data revisions are in particular relevant for the identification of a trough, implying that data uncertainty plays a key role in detecting the end of recessions in real-time. In addition to evaluating the impact of data revisions on a business cycle chronology based on GDP, we also compare the most recent turning point chronology with alternative chronologies as proposed by the Economic Cycle Research Institute (ECRI) and Artis et al (1997). Our chronology, however, is not comparable with growth cycles chronologies, as the one proposed by the OECD (2019)

UK GDP data revisions add a layer of uncertainty on the identification of business cycle turning points. For example, by employing the turning point algorithm to UK GDP historical data published by the ONS in 2012, we find a peak in 2011Q3, characterising the so-called double-dip recession in early 2012. More recent vintages, which include revisions due to new information and methodological improvements, including those required for international comparability, however, do not identify turning points for observations in 2011 and 2012.

Of interest is to evaluate whether economic indicators can predict an expansion during the 2011-2012 period. As a consequence, we design an empirical exercise to assess whether or not economic indicators available in real-time can predict UK recession phases during the 1997-2019 period. Our aim is short-term forecasting of turnings points, and our choice of predictors reflects that. We employ ten candidate indicator variables and compute predicted probabilities of a recession phase using Probit models, following the methodology of Estrella and Mishkin (1998). Taylor and McNabb (2007) have exploited the ability of consumer confidence in predicting UK recessions using Probit models. Many of our candidate predictors are commonly employed to nowcast GDP (as, for example, in Anesti et al (2017)) such as car registration, orders, retail sales and business confidence. In contrast with Osborn and Sensier (2002), however, we do not exploit the predictive content of financial variables.

The remaining of this paper is organised as follows. Section 2 describes the BBQ turning point algorithm, which is then applied to UK GDP data vintages from 1983. Section 3 evaluates the recession predictive content of a set of indicators. Section 4 concludes and describes the main implications of this study.

2. UK Turning Points

We start this section by describing the BBQ algorithm. The chronology of the UK business cycle phases obtained by applying the BBQ algorithm is discussed in the second part of the section. In the last part, we assess the impact of data revisions on turning point chronologies.

2.1 The BBQ Algorithm

The algorithm to identify turning points in historical GDP data adopted in this paper is as in Harding and Pagan (2002). The algorithm relies on the classical business cycles definition of Burns and Mitchell (1946).

The first step of the algorithm requires the determination of a potential set of peaks and troughs for historical data available up to *t=T*. At each point in time *t (t=2,…,T-2)*, the algorithm checks how growth rates in a neighbourhood of two quarters around t are changing. If Y_t is the log level of real GDP, then a peak is identified at t if $(Y_t - Y_{t-2}) > 0$, $(Y_t - Y_{t-1}) > 0$, $(Y_{t+1} - Y_t) < 0$, $(Y_{t+2} - Y_t) < 0$, and a trough if $(Y_t - Y_{t-2}) < 0$, $(Y_t - Y_{t-1}) < 0$, $(Y_{t+1} - Y_t) > 0$, $(Y_{t+2} - Y_t) > 0$. The second step of the procedure ensures that peaks and troughs alternate and the final step is a censoring rule that sets the minimum duration of the cycle (expansion + recession, or recession + expansion). As in Harding and Pagan (2002), we set the minimum size of the cycle to 5 quarters, and we employ the original Gauss code written by Don Harding to the available UK GDP data.

Harding and Pagan (2002) emphasise that although the algorithm uses changes (growth rates) in the first step to identify either a local maximum or a local minimum, we are identifying classical business cycle turning points (on the log level of GDP). They also argue that the censoring step is crucial to identify turning points because censoring helps avoid the drawbacks of the classification based on the rule-of-thumb of two-consecutive negative quarters.

2.2 UK Business Cycle Turning Points

We apply the BBQ algorithm to real UK GDP real-time dataset downloaded from the Office for National Statistics website. We use quarterly vintages from 1983Q2 by classifying the monthly vintage available in the middle month of the quarter as the quarterly vintage. Figure 1 presents the recession phases for the latest available vintage, that is, 2019Q1.

The algorithm detects six recessions since 1955. There is a short recession in the early 60's, a double-dip recession in mid 70's, and a long expansionary period from 1991 up to 2007. Table 1 describes the peaks and troughs for the 2019Q1 vintage and also for the 2012Q4 vintage. The main difference between these vintages published six years apart is that in the 2012Q4 vintage, we identify two additional recessions, one in 1956 and another one that starts in 2011Q3. These recessions are revised away as the ONS improved the accuracy of earlier GDP estimates. We consider a more detailed analysis of the impact of data revisions on UK business cycle turning points in the next subsection.

Table 1 also presents peaks and troughs for UK business cycles as published by the Economy Cycle Research Institute (ECRI) in March 2019. It also includes the historical chronology computed by Artis et al (1997) using industrial production data up to mid 1990's. A comparison suggests that recessions in 1974-75, 1979-1981 and 1990-1992 are included in all chronologies, although the exact turning points dates may differ. For the last three recessions (including the one in 2008-2009), it is clear that the trough is identified earlier using the BBQ algorithm applied to real GDP. In the next subsection, we provide additional evidence that turning point chronologies based on initial GDP estimates may lead to misleading turning point chronologies.

2.3 Data Revisions and Turning Points

Figure 2 presents the recession phases for UK business cycles computed for vintages since 1986Q1 sampled at every five years. Exceptions to this are the additional results for the 2012Q4 and the 2019Q1 vintages. The turning point chronologies in Figure 2 suggest that improved GDP estimates made recessions in the 50's and 60's detected using early estimates vanish. Some vintages also indicate a short slowdown in 1984 as the one stated by Artis et al (1997) turning points presented in Table 1.

The best chronology of turning points we have is the one computed for the latest available vintage, compatible with the fact that ONS data revisions improve the accuracy of GDP estimates. In Figure 2, it is the chronology calculated with the 2019Q1 real GDP vintage. We use this chronology to compute a measure of business cycle phase disagreement for each reference quarter from 1983Q2 up to 2013Q4.

We compute business cycle phase disagreement by counting the proportion of times that a given vintage has identified a phase for reference quarter *t* that differs from the baseline chronology. Figure 3 shows the proportion of vintages that have phases that differ from the 2019Q1 vintage, assuming we evaluate turning point disagreement for 20 consecutive quarterly vintages published after the reference quarter (up to 5 years). Figure 3 also presents the recession phases for the 1983-2013 period using the latest available vintage.

The method to compute the disagreement in Figure 3 is, in detail, as follows. We first define turning points for each quarterly vintage from 1983Q3 to 2019Q1. We then extract the time series of the business cycle phases obtained from 1 up to 20 quarters from the reference quarter. Based on these 20 real-time business cycle phases (a binary variable =1 if in a recession), we compute the proportion of times that the indicated business cycle phase disagrees with the one set in 2019Q1 (Figure 1). If disagreement = 0, then, in all releases, the business cycle phase is always as in the latest vintage. If disagreement=1, then the phase is always different from the one in current vintage, that is, turning point dates have changed by benchmark revisions published by the ONS more than 5 years after the reference quarter. A disagreement of 0.5 means that we find the same business cycle phase as the one described earlier only in 50% of the quarterly releases.

An inspection of Figure 3 leads us to claim that data uncertainty has a key role in dating the end of a recession, that is, a trough. For both recessions during the period, it is clear that revisions make them shorter by moving the trough to an earlier quarter. Furthermore, the 2019Q1 data vintage revises away recessions in 1984 and 2012 that were evident in the early data vintage. As a consequence, GDP data uncertainty suggests that one should be cautious in dating UK business cycle in real-time using quarterly GDP data.

3. Predicting Recessions

In the previous section, we provide evidence of the role of GDP data revisions, that is, GDP data uncertainty, on business cycle chronologies based on quarterly GDP. In this section, we evaluate whether economic indicators have predictive content for recessions in real-time.

3.1 Design of the Empirical Exercise

We consider as target variable two chronologies. The first one is the one computed using the 2012Q4 vintage as described in Table 1. The interesting feature of this chronology is that it includes a peak in 2011Q3 but the data does not have enough information to identify the trough, so the recession phase extends to 2012Q3. The second chronology is the one based on the 2019Q1 vintage that does not include the 2012 double-dip recession. By comparing predictions for these two chronologies, we can identify indicators that were helpful for economists to say there was a recession in 2012 while in 2012, and indicators that can detect the quarters in 2012 as part of an expansion phase.

As Estrella and Mishkin (1998), Osborn and Sensier (2002) and Taylor and McNabb (2007) do, we employ Probit models to extract predictions for the probability of recession using a set of indicators. We consider the following predictive model to exploit the predictive content of predictor *x*:

$$Prob(rec_t = 1|x_{t-h}, x_{t-h-1}, \dots) = \Phi(\beta_0 + \beta_1 x_{t-h} + \beta_2 x_{t-h-1} + \cdots + \beta_m x_{t-h-m+1})$$

where $\Phi()$ is the CDF of the standard normal distribution and $rec_t = 1$ if the reference quarter t is in a recession phase as identified either by the 2012Q4 or the 2019Q1 chronologies. The autoregressive order *m* is set using AIC.

We are mainly interested in nowcasts (*h=0*) and one-step-ahead forecasts (*h=1*), so we choose a set of indicators usually employed for short-term forecasting of economic activity. These indicators are listed in Table 2. They include survey data from the European Commission Consumer and Business Confidence survey, the CBI, the Society of Motor Manufacturers and traders (SMMT) and the Bank of England. It also includes some timely economic statistics such as retail sales. Quarterly data on these indicators were computed by averaging over quarters using observations from 1997.

Estrella and Mishkin (1998) use pseudo R^2s to compare the predictive content of each indicator. In addition to the pseudo-R^2, we also employ the Kuiper Score as suggested by Pesaran and Skouras (2002). The Kuipers Score (KS) is computed using the estimated in-sample predictive probabilities of recession: $Prob(\widehat{rec_t = 1}|x_{t-h}, \dots)$ for *t=h+m+1,…,T*. If $Prob\left(\widehat{rec_t = 1}\middle|x_{t-h,}, \dots\right) \geq c$ and $rec_t = 1$, then we say we have a correct prediction. If $Prob\left(\widehat{rec_t = 1}\middle|x_{t-h,}, \dots\right) \geq c$ and $rec_t = 0$, then we say we have a false alarm. The Kuiper score for a given sample period is the difference between the proportion of correct predictions (from the total of times that $rec_t = 1$) and the proportion of false alarms (from the total of times that $rec_t = 1$). It is clear from the definition of the KS score that if the predictor makes no mistake for a given cut-off *c*, the KS will be equal to 100%. The KS score could be negative if the predictor indicates many false alarms.

A key parameter on the analysis of the KS score is the cut point *c*. We usually need a cut point that is larger than the unconditional probability of the event because otherwise, the predictive model is not better than a forecaster that always uses the unconditional predictive probability. We consider *c=0.50*, that is, the model predicts a recession if the probability of recession is larger than 50%. We also consider *c=0.2*. The reasoning for this smaller cut-off is that the unconditional probability of a recession using the turning points in Figure 1 for the period from 1997 onwards is about 8%, that is, recessions are indeed rare events. The disadvantage of this lower cut-off is that the predictive model may suggest many false alarms.[2]

3.2 Empirical Results

Table 3 presents the KS scores and the R^2s for each candidate indicator variable in Table 2. We have separated sub-tables for each horizon (h=0, 1) and also for using either the 2012 or the 2019 chronologies.

Based on the 2012 recession dates, the empirical results support consumer confidence (GFK) as the best recession predictor at both horizons. The performance deteriorates with the horizon as expected, but the achieved KS score is of 85% even with one-quarter-ahead forecasts. Because consumer confidence might be affected by current economic conditions, it is not clear whether it was uncertainty about a recession in 2012 that lowered consumer confidence or was the consumer confidence itself that led the recession that subsequently vanished in later data vintages. Based on the 2019 recession dates, other variables such as retail orders and construction have a more accurate predictive content than consumer confidence.

These empirical results imply that data uncertainty affects the choice of predictors for recession phases. Using the real-time chronology that includes a recession in 2012, our evaluation suggests that consumer confidence would be a good predictor. However, if our interest is to assert the continuing expansion phase in 2012, agreeing with the most recent business cycle chronology, then indicators, such as retail orders and construction, fare better.

A caveat of our analysis is that our empirical evaluation relies on historical data from 1997 to 2018. As a consequence, we will be only able to use the information of the top predictors in Table 3 to identify the next UK recession if the relation between the predictors and the business cycle is stable.

[2] An alternative is to evaluate turning point predictions using the ROC curve as indicated by Berge and Jorda (2011).

4. Conclusions

This paper assesses the impact of UK GDP data uncertainty in defining the UK business cycle chronology and in deciding which indicators have predictive content for UK recessions. Two main empirical contributions arise.

The first one is that data revisions to UK GDP lead to a turning point chronology that has fewer and shorter recessions than real-time chronologies that rely on an early estimate of GDP. As a consequence, data uncertainty affects the ability of an analyst in defining turning points for UK business cycle in real-time based on quarterly GDP. GDP data uncertainty suggests that one should be cautious in dating UK business cycle in real-time using quarterly GDP data. Our suggestion is to use a richer dataset, including monthly economic statistics such as index of production and services.

The second one is that retail orders and construction are better predictors for the latest vintage recession phases than consumer confidence, which is better at picking the recession dates in an early data vintage. Consumer sentiment seems to be strongly related to UK business cycle phases. Still, business confidence, particularly in the retail and construction sectors, are better indicators if one would like to predict recessions as identified with the latest available UK GDP growth data, which are the best GDP estimates currently available.

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Table 1: UK (Classical) Turning Points

	2012Q4 GDP vintage	2019Q1 GDP vintage	ECRI	Artis et al (1997)
Peak	1955Q4			
Trough	1956Q3			
Peak	1961Q2	1961Q2		
Trough	1961Q4	1961Q4		
Peak	1973Q2	1973Q2		1971M1
Trough	1974Q1	1974Q1		1972M2
Peak	1974Q3	1974Q3	1974M9	1974M6
Trough	1975Q3	1975Q3	1975M8	1975M8
Peak	1979Q2	1979Q2	1979M6	1979M6
Trough	1981Q1	1981Q1	1981M5	1981M5
Peak				1984M1
Trough				1984M8
Peak	1990Q2	1990Q2	1990M5	1990M6
Trough	1991Q3	1991Q3	1992M3	1992M5
Peak	2008Q1	2008Q1	2008M5	
Trough	2009Q2	2009Q2	2010M1	
Peak	2011Q3			
Trough				

Note: ECRI turning points are available at https://www.businesscycle.com/ecri-business-cycles/turning-points-leading-indicators. The BBQ is implemented with a minimum business cycle phase of 5 quarters.

Table 2: Candidate Predictors: Indicators

Name	Description	Source
eqretail	Retail sales	ONS
smmtsa	Car registrations	SMMT
consconf	Consumer Confidence	DG ECFIN
consconfgfk	Consumer Confidence	GFK-Markit
bus climate	Business Climate	DGECFIN
CBI retail orders	CBI Retail Orders	CBI
CBI motor trades	CBI Motor Trades	CBI
Export Orders	Export Orders	DG ECFIN
investment intentions	Investment Intentions	BofE
construction	Construction Output	BofE

Note: All indicators are sampled quarterly (by averaging over the quarter) and we use observations from 1997Q1.

Table 3: Predicting Turning Points with Economic Indicators

Table 3.1: Nowcasts for 2012 Turning Points

	R^2	% false c=0.5	% correct c=0.5	KS. c=0.5	% false c=0.2	% correct c=0.2	KS. c=0.2
eqretail	0.39	3.9	11.1	7.3	23.1	100.0	76.9
Smmtsa	0.34	5.6	33.3	27.8	16.7	88.9	72.2
consconf	0.76	5.6	77.8	72.2	5.6	100.0	**94.4**
consconfgfk	0.79	3.7	88.9	**85.2**	5.6	100.0	**94.4**
bus climate	0.40	3.7	22.2	18.5	18.5	88.9	70.4
CBI retail orders	0.43	3.7	44.4	40.7	11.1	77.8	66.7
CBI motor trades	0.15	0.0	22.2	22.2	18.5	55.6	37.0
Export Orders	0.20	0.0	11.1	11.1	25.0	66.7	41.7
investment intentions	0.26	2.0	22.2	20.2	20.0	55.6	35.6
construction	0.34	1.9	44.4	42.5	13.5	55.6	42.1

Table 3.2: One-quarter-ahead 2012 Turning Points

	R^2	% false c=0.5	% correct c=0.5	KS. c=0.5	% false c=0.2	% correct c=0.2	KS. c=0.2
eqretail	0.37	1.9	11.1	9.2	26.4	100.0	73.6
smmtsa	0.25	0.0	22.2	22.2	22.6	77.8	55.1
consconf	0.71	3.9	88.9	85.0	7.7	88.9	81.2
consconfgfk	0.73	1.9	88.9	**87.0**	3.9	88.9	**85.0**
bus climate	0.24	1.9	11.1	9.2	22.6	77.8	55.1
CBI retail orders	0.37	3.8	33.3	29.6	11.3	77.8	66.5
CBI motor trades	0.14	0.0	22.2	22.2	18.9	55.6	36.7
Export Orders	0.20	0.0	11.1	11.1	25.0	66.7	41.7
investment intentions	0.26	2.0	22.2	20.2	20.0	55.6	35.6
construction	0.31	3.9	33.3	29.4	11.8	66.7	54.9

Table 3.3: Nowcasts for 2019 Turning Points

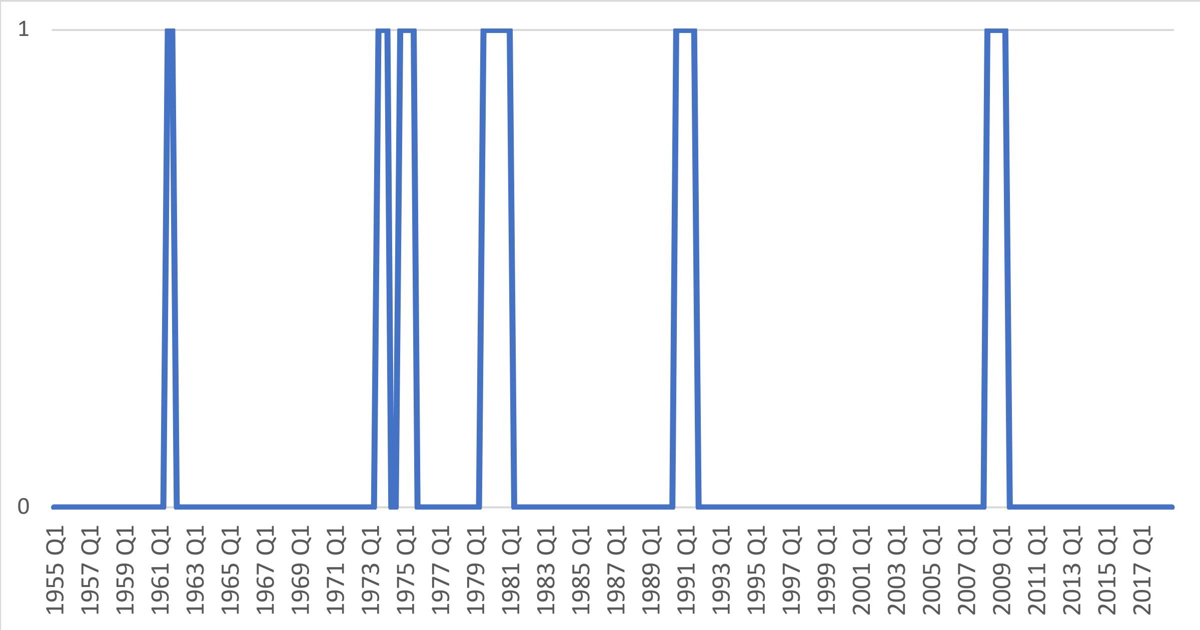
	R^2	% false c=0.5	% correct c=0.5	KS c=0.5	% false c=0.2	% correct c=0.2	KS c=0.2
eqretail	0.41	0.0	40.0	40.0	7.5	60.0	52.5
smmtsa	0.35	0.0	20.0	20.0	7.2	80.0	72.8
consconf	0.60	1.2	40.0	38.8	6.2	80.0	73.8
consconfgfk	0.62	1.2	60.0	58.8	7.2	80.0	72.8
bus climate	0.55	1.2	60.0	58.8	3.7	80.0	76.3
CBI retail orders	0.70	0.0	80.0	**80.0**	2.4	80.0	77.6
CBI motor trades	0.29	0.0	20.0	20.0	4.8	60.0	55.2
Export Orders	0.38	0.0	40.0	40.0	7.4	40.0	32.6
investment intentions	0.49	0.0	40.0	40.0	3.8	60.0	56.3
construction	0.88	0.0	80.0	**80.0**	2.6	100.0	**97.4**

Table 3.4: One-quarter-ahead 2019 Turning Points

	R^2	% false c=0.5	% correct c=0.5	KS c=0.5	% false c=0.2	% correct c=0.2	KS c=0.2
eqretail	0.31	1.3	0.0	-1.3	7.5	40.0	32.5
smmtsa	0.18	0.0	0.0	0.0	4.9	40.0	35.1
consconf	0.58	1.3	40.0	38.8	3.8	80.0	**76.3**
consconfgfk	0.66	1.3	60.0	**58.8**	3.8	60.0	56.3
bus climate	0.26	0.0	20.0	20.0	4.9	40.0	35.1
CBI retail orders	0.46	1.2	60.0	**58.8**	3.7	60.0	56.3
CBI motor trades	0.23	0.0	20.0	20.0	3.7	60.0	56.3
Export Orders	0.30	0.0	20.0	20.0	7.4	80.0	72.6
investment intentions	0.47	0.0	40.0	40.0	5.1	80.0	74.9
construction	0.58	1.3	60.0	58.7	5.1	80.0	74.9

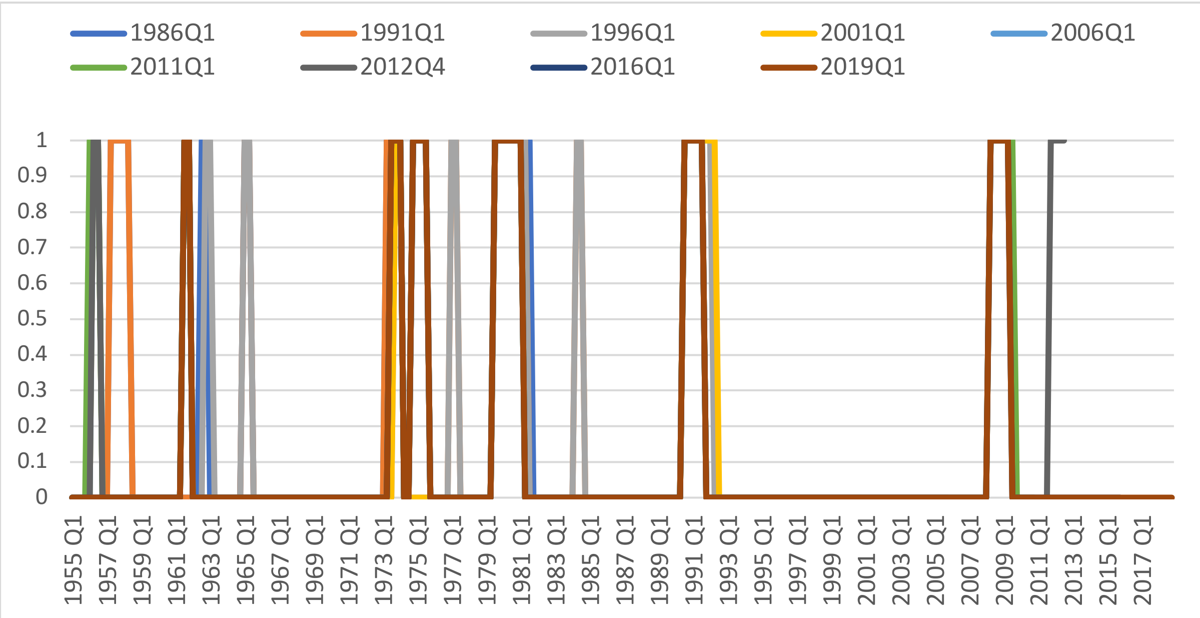
Note: These are based on single predictor Probit Models estimated with observations since 1997Q1.

Figure 1: UK Business Cycles Turning Points using the 2019Q1 real GDP vintage.



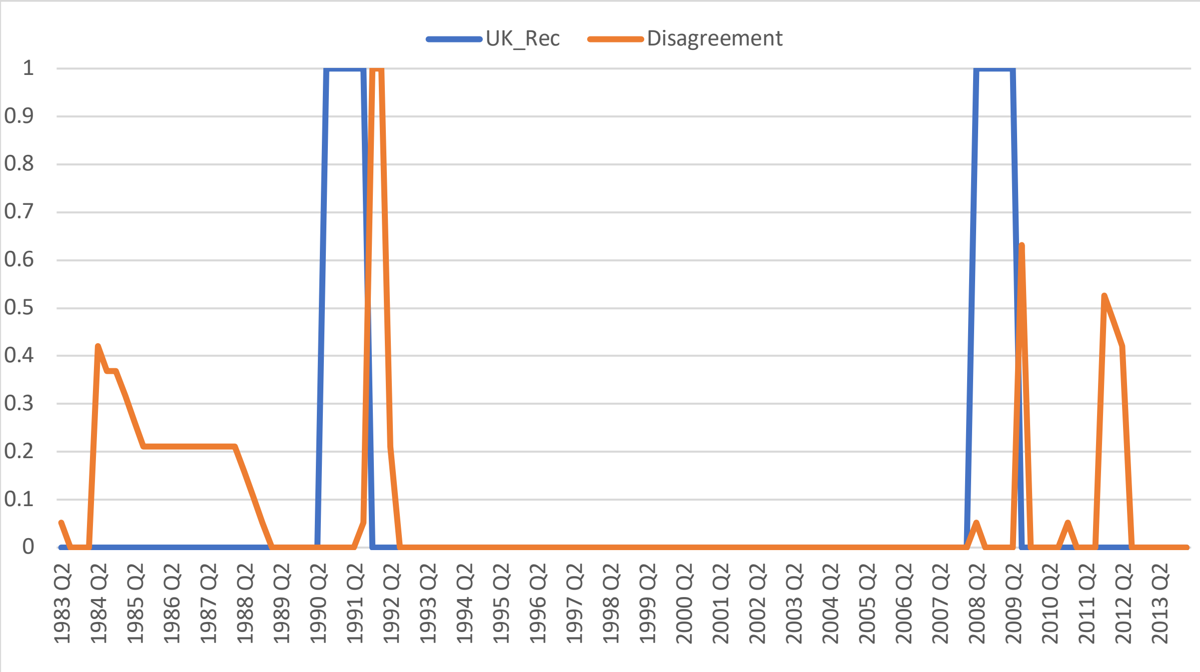
Note: Recession phases are set to 1 as expansion phases are set to zero.

Figure 2: UK Business Cycle Turning Points for historical data using 9 GDP publication dates.



Note: The BBQ algorithm is applied to vintages in the ONS real-time dataset for real GDP. We use the monthly vintage published at the middle of the quarter.

Figure 3: Business Cycle Phase Disagreement between early GDP releases and the 2019 vintage.



Note: Disagreement is the proportion of vintages (up to 20 quarters after the reference quarter) that the BBQ algorithm has identified the specific reference quarter to a business cycle phase that differs from the one in the 2019 vintage. This is based on the application of the BBQ algorithm is applied to vintages in the ONS real-time dataset for real GDP. We use the monthly vintage at the middle of the quarter.