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Keywords: Ordered probits, dynamic probit models, real-time econometrics, business cycle turning points

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Abstract

The dichotomous characterization of the business cycle in recessions and expansions has been central in the literature over the last fifty years. However, there are various reasons to question the adequacy of this dichotomous, recession/expansion approach for our understanding of the business cycle dynamics, as well as for prediction of future business cycle developments. In this context, the contribution of this paper to the literature is twofold: First, since a positive rate of growth in the level of economic activity can be considered as the normal scenario in modern economies due to both population and technological growth, it proposes a new non-parametric algorithm for the detection and dating of economic acceleration periods, trend or normal growth periods, and economic recessions. Second, it uses an ordered probit framework for the estimation and forecasting of these three business cycle phases using an automatized model selection approach using monthly macroeconomic and financial data on the German economy. The empirical results do not only show the empirical relevance of this new algorithm, but also significant asymmetries in the determinants of the different business cycle phases.

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1 Introduction

Since Burns and Mitchell's (1946) seminal contribution, the great majority of the literature on the detection and prediction of business cycle turning points has followed a dichotomous characterization of the business cycle based on a detailed characterization of economic recessions, and the definition of non-recessionary periods as economic expansions (see e.g. Bry and Boschan (1971), Sargent and Sims (1977), Geweke (1977), Stock and Watson (1989, 1993), Chauvet and Piger (2005), and Harding and Pagan (2002)). However, there are various reasons to question the adequacy of this dichotomous, recession/expansion approach for our understanding of the business cycle dynamics, as well as for prediction of future business cycle developments. From a more abstract perspective, while the occurrence of economic recessions (associated in general with periods of negative economic growth of a certain duration) can indeed be considered as an unusual event, a positive rate of growth in the level of economic activity can be considered as the normal state of modern economies due to both population and technological growth. This however does not mean that all non-recessionary periods can or should be assumed to be generated by the same data generating process (DGP). Indeed, periods of a high economic growth immediately following an economic recession (usually known as economic recoveries) are likely to have different characteristics and implications for other macroeconomic variables such as unemployment and inflation than periods of high economic growth taking place much later in the cycle. By the same token, periods of low (but positive) economic growth occurring just after a recession may have quite different macroeconomic consequences (as the sluggish recovery after the recent financial crisis shows) than periods of also low though positive economic growth occurring after a phase of significant economic expansion.

From a more empirical perspective, recent research has also shown that a classification of the business cycle in "expansions" and "recessions" may in some cases be insufficient for the characterization of the economic fluctuations in many European countries. For instance, Artis et al. (2004) estimate the real GDP growth of the nine largest European economies using a Markov-Switching (MS) approach and come to the conclusion that for the majority of countries studies, three-state Markov-Switching models are better able to explain the dynamics of the real GDP growth rate than MS models with only two unobservable states, such as the one originally proposed by Hamilton (1989). Further, using an automatized specification rule Theobald (2012) shows in a real-time setup how increasing the number of states in a univariate Markov-Switching model of the monthly industrial production growth rates can significantly improve the model's forecast, especially in episodes such as the recent global financial crisis. Indeed, the sluggish economic recovery of the U.S. economy following the 2007-08 global financial crisis represents just the most recent example of episodes which, by many criteria, would not be considered neither a recessionary period, nor a robust economic expansion.

The differentiation between a dichotomous conception of the business cycle and a more differentiated perspective is by no means trivial also from an econometric perspective. Indeed, if one understands the different business cycle phases as being indeed generated by different data-generating processes (DGP) with different characteristics in terms of means, variance and other moments, as done e.g. in Neftci (1982*a*), and one uses econometric models which allow for less business cycles phases or "states" than the ones driving the joint DGP, the resulting forecasts would be based on biased estimates resulting from a latent misspecification problem.

Against this background, the contribution of this paper to the literature is twofold: First, it proposes a new non-parametric algorithm for the detection and dating of truly expansionary periods which differentiate themselves from periods of "normal growth" in the spirit of Anas and Ferrara (2006), coupled with the modified Bry and Boschan (1971) algorithm discussed in Proaño (2010) and Proaño and Theobald (2012), which was employed to identify recessionary periods on the basis of the index of industrial production. Second, it uses a composite ordered probit model for the estimation and forecasting of these three business cycle phases using the model selection and forecast combination approach proposed by Proaño (2010) using monthly macroeconomic and financial data on the German economy.

The remainder of this study is organized as follows. In section 2 a non-parametric algorithm for the joint detection of economic accelerations and recessions in real-time is introduced and discussed in detail. The empirical relevance of this new algorithm is investigated in section 3 on the basis of ordered probit regressions using German macroeconomic and financial data. Further, possible asymmetries in the composition of the set of indicators used for the prediction of the different business cycle phases is investigated in section 4. Finally, section 5 draws some concluding remarks from this study and outlines possible further research directions.

2 Methodology

As previously pointed out, the great majority of the literature on business cycle turning points detection and prediction undertaken over the last fifty years has implicitly followed a dichotomous understanding of the business cycle, separating it into economic recessions and economic expansions. For instance, according to the NBER Business Cycle Dating Committee[1]

> A recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. A recession begins just after the economy reaches a peak of activity and ends as the economy reaches its trough. Between trough and peak, the economy is in an expansion.

[1]For a a detailed chronology of the U.S. business cycles by the NBER Business Cycle Dating Committee, see `http://www.nber.org/cycles.html`.

However, as also pointed out in the introduction, while periods of sustained negative economic growth can be indeed considered as rather unusual events in modern economies, this does not necessarily imply that all periods of non-negative economic growth may be characterized by the same statistical and economic dynamics. Indeed, it seems worthwhile to differentiate among these non-recessionary periods the ones where the business cycle experiences a true acceleration (or in other words, when a true economic boom occurs), and the ones where the economy simply grows alongside of technological progress and population growth.

The following non-parametric algorithm aims to provide a consistent framework for the detection of these three phases of the business cycle – accelerations, normal growth periods and recessions – by making use of the information on the *level* of the business cycle reference series, and the *speed* of its rate of change. This approach is not completely new. For instance, Anas et al. (2008) have differentiated between the "classical business cycle" – which is closely related with the *level* of economic activity and focuses on periods of sinking economic activity – and the "growth" or "accelerationist cycle" – defined as the deviation of the reference series (real GDP or the index of industrial production) from its long-term trend – for the detection of business cycle turning points (see also Anas and Ferrara (2004)). In this light, the following non-parametric algorithm can be considered as a consolidation of the modified Bry and Boschan (1971) algorithm as discussed in Proaño (2010) and Proaño and Theobald (2012), and the ABCD approach proposed by Anas and Ferrara (2004, 2006). This algorithm is composed by the following steps: In the first step, and following Proaño (2010) and Proaño and Theobald (2012), the binary recession series b_t is computed according to the Bry and Boschan (1971) algorithm, whereafter a peak in the business cycle is identified when

$$\{y_{t-k} < y_t > y_{t+k}, \quad k = 1, \ldots, 5\} \tag{1a}$$

while, analogously, a trough is assumed to take place when

$$\{y_{t-k} > y_t < y_{t+k}, \quad k = 1, \ldots, 5\}. \tag{1b}$$

where y_t is the two-month moving average of the German index of industrial production – the business cycle reference series.[2] Further, as an additional censoring rule for the identification of recessionary periods and thus for the generation of the binary recession indicator series b_t, the "severity" of an economic downturn j – and by extension the eventual occurrence of a recession – is assessed following Harding and Pagan (2002) according to

$$S_j = 0.5 \times Deepness_j \times Duration_j,$$

[2]Given the high volatility of monthly data, it is usual in the turning points dating literature to "smooth" the underlying business cycle reference series among other things to avoid potential outlier biases. For example, Darné and Ferrara (2009) use a low pass filter which eliminates fluctuations in the industrial production index of a frequency higher than one year.

where the *duration* are the number of months between peak and trough of the economic downturn considered,[3] and

$$Deepness_j = |y_p - y_t|/y_p,$$

with y_p and y_t are the respective values of the index of industrial production at the corresponding peak and trough (see Anas et al. (2008)). A recessionary period is identified when $S_j < 0.005$, as there is no consensus on the reference minimum duration and deepness of recessions (Darné and Ferrara, 2009, p.5).

The second step, consists of identifying among the non-recessionary periods those which could be potentially considered as true economic accelerations or booms, and those which could be normal growth periods. For this purpose, the six-month average period percent changes, as well as the first difference of this time series, are calculated. Using a given threshold value of a $\bar{g}_t^{\min} = 0.25\%$ monthly growth rate − this implies an annual growth rate of about 3%, since $(1 + 0.0025)^{12} - 1 \approx 0.03$ − the period t is identified as a potential economic acceleration period if

- the annualized *centered moving average* period growth rate in period t is higher than the growth rate considered as "normal" given population growth and technological progress, i.e.[4]

  $$\bar{g}_t = \frac{1}{6}\sum_{i=-3}^{3} g_{t-i}, \geq \bar{g}_t^{\min} \quad \text{with} \quad g_t = 100 \cdot \left(\frac{Y_t}{Y_{t-1}} - 1\right) \quad \text{and} \tag{2}$$

  where the two end-points in the sum are weighted by 0.5, and

- the change in the monthly growth rate from $t - 1$ to t is not lower than a given negative value, e.g.

  $$\Delta g_t \geq -1\%, \tag{3}$$

  where $\Delta \bar{g}_t \equiv g_t - g_{t-1}$.

Concerning this third step, it should be pointed out that one could alternatively think of a *backward-looking moving average* specification such as

$$\bar{g}_t^b = \frac{1}{6}\sum_{i=0}^{5} g_{t-i}, \tag{4}$$

or of a *forward-looking moving average* specification such as

$$\bar{g}_t^f = \frac{1}{6}\sum_{i=0}^{5} g_{t+i} \tag{5}$$

[3]According to the NBER definition of a recession as a *significant decline in economic activity* [of] *more than a few months.*

[4]Similarly, Hausmann et al. (2005) define a growth acceleration as an increase in per-capita growth of 2 percentage points or more and identify an acceleration period where the increase in growth has being sustained for at least eight years and the post-acceleration growth rate has to be at least 3.5 percent per year. In addition, to rule out cases of pure recovery, they require that post-acceleration output exceed the pre-episode peak level of income.

for the calculation of the average growth rate of the business cycle reference series. There are however various reasons why the *centered moving average* specification seems to be the most appropriate formulation for our algorithm. The *backward-looking* specification does not incorporate any information beyond period t due to its purely backward looking nature – in contrast to algorithms for the detection of recessionary periods based on the classical business cycle along the lines of Bry and Boschan (1971) and Harding and Pagan (2002) – implying a methodological inconsistency if applied together with a recession detection algorithm such as the one used in the first step. Also, the implied growth rate g_t which would make $\bar{g}_t$ fulfill the criterion described by eq.(2) would have to be extremely high in the periods immediately following a trough in the classical business cycle to counterbalance the negative growth rates observable on average prior to such a classical business cycle turning point. Due to this reason, economic booms occurring immediately after the end of a recession are not likely to be detected in due time by this specification. The exact opposite characterizes the *purely forward-looking specification*: Since it draws only from future information, this rule has the largest likelihood of detecting economic booms immediately following the end of recessions. However, it has also the longest recognition lag of the three considered specifications, and its interpretation may be not be completely straightforward.

In the light of this brief discussion of the pros and cons of the rules described by eqs. (4) and (5), the advantages of the *centered moving average* specification given by eq.(2) become particularly clear: as it is a a symmetric rule which draws from both past and future information (relative to time t), it has a similar methodological approach as the dating algorithms for the classical business cycle. This specification is also more likely to detect economic booms occurring immediately after a business cycle trough than the backward-looking one despite the fact that this specification has a longer recognition lag than the backward-looking one because it draws also on information after date t, since past growth rates have a smaller weight in the determination of $\bar{g}_t$ than in the backward-looking one, .[5]

Let us now discuss in detail how and why the business cycle dating algorithm just discussed offers a more insightful perspective on the business cycle than the predominant dichotomous expansion/recession approach. Figure 1 illustrates a stylized evolution of a business cycle reference series such as the GDP or the industrial production index. According to a dichotomous expansion/recession approach, an expansion would take place between points *I* and *III*, as well as between points *IV* and *V*, and between points *VI* or *VII* (depending on which of these two points is identified as a business cycle trough), and point *VIII*. By the same token, a recession would take place between points *III* and *IV*, as well as between points *V* and *VI* (or *VII*, depending again on which of these two points is identified as a business cycle trough).

[5]It should be noted that this feature does however not represent a constraint on the present algorithm as a whole if the computation window for the detection of economic booms is of a shorter length than the one used for the detection of turning points in the classical business cycle.

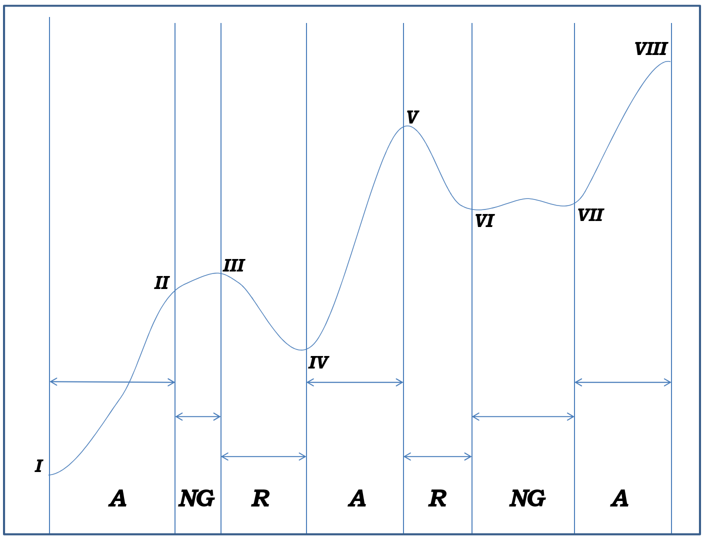

Figure 1: The ARNG Algorithm

On the basis of the distinction between the classical and the growth cycle discussed by Anas and Ferrara (2004, 2006), I propose to make a further differentiation of the business cycle phases oriented not at the *level* of the business cycle reference series, but at its *rate of change* (as in growth cycle discussed by Anas et al. (2008)). Consider for instance the periods between *II* and *III*: Under a dichotomous expansion/regression approach these periods would unequivocally belong to an expansionary phase, even though the rate of growth of the series is significantly lower than between periods *I* and *II* (as illustrated by the slope of the series). In contrast, our approach would identify these periods as *normal growth* phase, since $\bar{g}_t < \bar{g}_t^{\min}$, see eq.(2). Analogously, while the periods between *VI* and *VII* would also be identified as part of an expansion occurring between *VI* and *VIII* according to the classical business cycle, our approach would identify them also as a as *normal growth* phase by the same argument as before.

As mentioned in the introduction, such a differentiation is not trivial either from an econometric nor from a policy-oriented perspective, and would in fact imply different policy responses in the two cases just discussed. In the normal growth phase *II-III*, such a de-acceleration of the economy could even be considered as beneficial if associated with lower inflationary pressures and with high and sustained employment levels. In contrast, between points *VI-VII*, such a normal growth phase would have completely different implications in terms of inflationary pressure and unemployment dynamics, because it takes place immediately after a recession. Accordingly, the policy-maker is likely to try to stimulate the economy and thus to induce a higher rate of economic growth in such a situation.

3 Predicting Economic Accelerations, Normal Growth Periods and Recessions with Ordered Probit Models

3.1 Methodology

In the following the three different business cycle phases determined by the dating algorithm discussed in the previous section are estimated by means of an ordered probit regression model based on macroeconomic and financial indicators on the German economy. For this purpose, let c_t be a discrete variable determined as follows:

$$c_t = \begin{cases} 0, & \text{if the economy goes through an economic recession,} \\ 1, & \text{if the economy goes through a normal growth phase, or} \\ 2, & \text{if the economy experiences an accelerative economic phase at time } t, \end{cases} \tag{6}$$

with each of these outcomes being jointly determined by the non-parametric ARNG dating algorithm discussed in the previous section. Further, let Ω_{t-h} be the information set available at date $t-h$, where h represents the forecasting horizon, $\mathbf{z}_t$ the set of right-hand side explanatory variables of a particular specification i, $\boldsymbol{\beta}$ the corresponding parameter vector and φ_t a continuous unobservable latent variable which is regressed on $\mathbf{z}_t$ in a linear manner, i.e.

$$\varphi_{t+h} = \mathbf{z}_t'\boldsymbol{\beta} + u_{t+h}, \quad \text{with } \; u_{t+h} \sim N(0,1), \tag{7}$$

As discussed in Proaño (2010) and Proaño and Theobald (2012), if the forecasting regression model is meant to be implemented in real-time, then the set of possible regressors contained in the matrix $\mathbf{z}_t$ has to be specified to take into account two important restrictions: (1) the data availability or publication lag (which of course is variable-specific and ranges here between zero and two lags, see Table 1) and, (2) with respect to the discrete variable describing the different business cycle phases c_t, the recognition lag, i.e. the number of periods required by the underlying algorithm to identify the period t as a period of economic recession, which in the present case would be five months (see eqs. (1a) and (1b)).

The corresponding conditional probabilities of observing each value of c_t on the basis of a particular set of explanatory variables i are given by

$$\Pr\left(c_{t+h} = 0|\mathbf{z}_t, \boldsymbol{\beta}, \gamma\right) \quad = \quad \Phi\left(0 - \mathbf{z}_t'\boldsymbol{\beta}\right) \tag{8}$$

$$\Pr\left(c_{t+h} = 1|\mathbf{z}_t, \boldsymbol{\beta}, \gamma\right) \quad = \quad \Phi\left(1 - \mathbf{z}_t'\beta\right) - \Phi\left(0 - \mathbf{z}_t'\boldsymbol{\beta}\right) \tag{9}$$

$$\Pr\left(c_{t+h} = 2|\mathbf{z}_t, \boldsymbol{\beta}, \gamma\right) \quad = \quad 1 - \Phi\left(2 - \mathbf{z}_t'\boldsymbol{\beta}\right) \tag{10}$$

with $\gamma = (0, 1, 2)'$ being a vector containing the defining threshold values for the determination of c_t, and $\Phi(\,\cdot\,)$ a linking function between the left-hand side latent variable and the above conditional probabilities, which in an ordered probit framework is given by the normal distribution function.

Given the uncertainty linked with the use of macroeconomic data, as well as the potential misspecification of any particular and invariant ordered probit specification,[6] as in Proaño (2010) for the case of dynamic probit models, the ordered probit regression model is specified through an automatically *general-to-specific* variables- and lag selection mechanism. Starting with a relatively large set of indicators, the statistical significance of each of the lag of each explanatory variable is tested using a redundant variables Likelihood Ratio (LR) test, with the LR statistic computed as

$$LR = -2(\mathcal{L}_R - \mathcal{L}_U) \tag{11}$$

where $\mathcal{L}_R$ and $\mathcal{L}_U$ are the maximized values of the (Gaussian) log likelihood function of the unrestricted and restricted regressions. Under the H_o of this asymptotically χ^2 distributed test with one degree of freedom, the coefficient of a redundant variable (lag) is zero. A rejection of this test results in the conservation of the tested variable (lag) in the model specification. More specifically, after including six lags of each explanatory variable (its absolute position along the time dimension being determined by the real-time availability of the respective series), the last lag of each variable was tested for significance and omitted if not found significant at 5% level.

3.2 In-Sample Estimation Results

For the following real-time exercise periods were employed, from 2007:1 to 2012:12. In order to perform a true real-time forecasting analysis, as in Proaño and Theobald (2012), every time a vintage became available, a new discrete series c_t was computed and, on this basis, completely new regressions were specified and estimated using a *general-to-specific* variable and lag selection procedure as previously outlined. As in Proaño (2010) and Proaño and Theobald (2012) I use the industrial production index as the business cycle reference series for the dating algorithm previously discussed.[7]

The explanatory variables dataset used for the following analysis – shown in Figure 2 – include the following macroeconomic and financial indicators from 1991:1 to 2012:12 at a monthly frequency: the open vacancies in the productive sector, the domestic and foreign orders received by the industrial sector, the ifo business sentiment indicator (all variables as month-to-month % changes), the corporate bond spread to the average yield of public securities, the growth rate of the CDAX stock price index, the 1-, 2-, 3-, 5- and 10-year yield (calculated by the Svensson's method) spreads to the three-month EURIBOR, and the three-month EURIBOR. All financial and real economy variables stem from the Bundesbank database (`www.bundesbank.de/statistik/`), with the exception

[6] As pointed out by Croushore and Stark (2001), many macroeconomic indicators are subject to significant information lags and ex-post revisions which may directly affect the model specification, estimation and evaluation if undertaken in real-time. This problem is particularly important in the field of business cycle prediction, not only due to its natural real-time nature, but also due to the many non-linearities which may be at work at the turning points of the business cycle (Neftci, 1982*b*).

[7] In fact, this series is the only series subject to potential revisions which may ex-post deliver a different business cycle dating. However, this is not true in our case.

of the orders, which stem from the GENESIS-Online database from the German Statistical Office (`https://www-genesis.destatis.de/genesis/online`), and the ifo business cycle climate index (`http://www.cesifo-group.de`). In the real time exercise, the starting estimation sample extends from 1991:1 to 2006:12 (in-sample period), being then stepwise extended from 2007:1 to 2012:12.

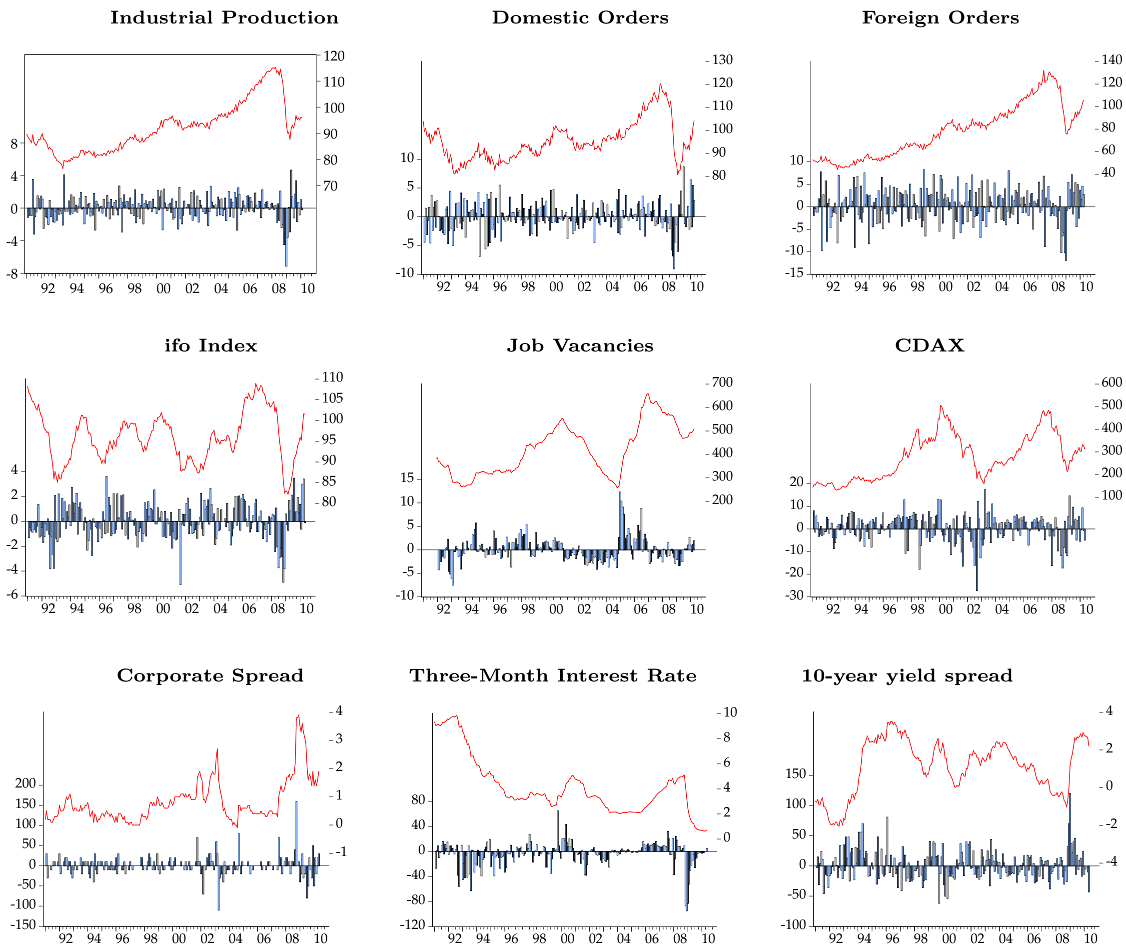

Figure 2: Seasonally and calendar-adjusted foreign orders and domestic orders received by the productive sector, industrial production index (levels and month-to-month % changes for ifo index and job vacancies), CDAX, corporate spread, three-month euribor and yield spreads of different maturities (levels and month-to-month % changes). Source: Deutsche Bundesbank and ifo Institute.

As illustrated in Table 1, in terms of real-time data availability the financial indicators have a clear advantage with respect to the real economy indicators as they are both immediately available and are not subject to revisions over time. However, an a-priori exclusion of the real-economy variables from the set of possible leading indicators would not only be difficult to justify on theoretical grounds, but may also deliver biased estimation results on practical grounds. It seems worthwhile to include both macroeconomic and financial indicator in the set of potential regressors and let the automatized model selection procedure find the most appropriate specification on statistical grounds.

Table 1: Macroeconomic and Financial Indicators

Series	Description	Vintage Data	Publication Lag
IPIDX	Index of industrial production	yes	2 months
JOBVAC	Job vacancies	no	2 months
D-ORD	Domestic orders received by the industrial sector	yes	2 months
F-ORD	Foreign orders received by the industrial sector	yes	2 months
CDAX	CDAX	no	0 months
C-SPRD	Corporate spread	no	0 months
EURIBOR	3-month euribor	no	0 months
1Y-SPRD	1-year yield spread	no	0 months
2Y-SPRD	2-year yield spread	no	0 months
3Y-SPRD	3-year yield spread	no	0 months
5Y-SPRD	5-year yield spread	no	0 months
10Y-SPRD	10-year yield spread	no	0 months

Sources: Deutsche Bundesbank, ifo-Institute.

Figure 3 illustrates the underlying industrial production series and the corresponding business cycle classification into *acceleration*, *recession* and *normal growth* periods according to the ARNG algorithm for the vintage 2012:12. As Figure 3 clearly illustrates, the ARNG algorithm delivers a quite plausible

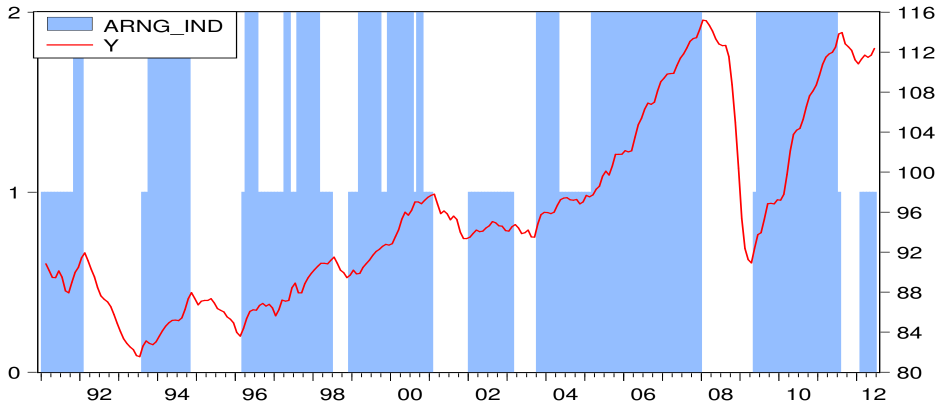

Figure 3: Dating of economic accelerations, recessions and normal growth periods based on the ARNG algorithm, and German industrial production index (two-month moving average).Source: Deutsche Bundesbank. Author's calculations.

chronology of the German business cycle, identifying the majority of periods as economic accelerations or recessionary periods, with the value-added that it also identifies a non-trivial number of periods as normal-growth periods. Indeed, as displayed in Figure 3, since some periods do not fall in one of the two traditional categories of the business cycle literature (the most descriptive ones being the periods between the 2001 and the 2003 recessionary periods) as they are characterized by positive, though low growth rates, it is advantageous to define an extra category for them, and take their specificity into account when forecasting business cycle turning points.

Table 2 illustrates the estimation results of the ordered probit specification obtained by the *general-to-specific* model selection procedure for the one-month ahead forecast horizon resulting from the estimation of the discrete variable c_t through an ordered probit regression model using the complete set of observations, i.e. 1991:1-2012:12. At the general level, Table 2 illustrates the main advantage

Table 2: Estimation Results of Ordered Probit Regression (One-Month-Ahead Forecast Horizon).

						Sample: 1991:1 – 2012:12				
Lag	ARNG_IND	IP-IDX	FOR-ORD	DOM-ORD	JOB-VAC	IFO-IDX	CRP_SPRD	CDAX	EURIBOR	B-SPRD10YG
0	-	-	-	-	-	23.289^{***} (7.685)	-	-	1.551^{***} (0.478)	1.060^{**} (0.478)
1	-	-	-	-	-	24.537^{***} (7.685)	-	-	-	-1.578^{***} (0.456)
2	-	-	-	-	-	25.685^{***} (7.309)	-	3.400^{**} (1.507)	-2.104^{***} (0.473)	-
3	-	-	-	-	-	-26.064^{***} (7.514)	-0.822^{***} (0.158)	-	-	-
4	-	-	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-
6	-0.398^{***} (0.127)	-	-	-	-	-	-	-	-	-
Pseudo-R^2: 0.327				AIC: 1.540				SIC: 1.730		
HQC: 1.617				LR-Stat: 166.204				Prob(LR-Stat): 0.000		

Note: '-' means that the coefficient of the explanatory variable was not identified as statistically significant at a 5% level, as was therefore removed by the *general-to-specific* model selection procedure. The lower part shows goodness-of-fit measures for the probit estimations. Note that these results are particularly linked to the available data and thus may change for other publication. *,** and *** represent statistical significance at the 10%, 5% and 1%, respectively.

of the automatized *general-to-specific* model procedure − which determines which (if any) lags of the considered regressors have a statistically significant predictive power and are therefore worth being included in the final specification − with respect to the ad hoc and fixed model specification used in the majority of empirical studies. For the specific sample 1991:1-2012:12, the automatized general-to-specific model selection procedure identifies at least one lag of the discrete variable c_t, the ifo-index, the three-month euribor rate and the 10-year yield spread to have a statistically significant forecasting power with respect to the discrete variable c_t. By the same token, no lag of the industrial production index (the business cycle reference series), the foreign and domestic order, and of the job vacancies is identified as having any statistically significant explanatory power, at least for the vintage 2012:12. It should be clear, however, that this particular specification does not necessarily have to be representative for other samples and/or vintages, where a complete different final set of regressors could be automatically chosen by the automatized model selection procedure. However, even though the set of explanatory variables may vary over time and/or vintage, as long as the model selection procedure remains the same, the performance of the different specification may be compared to each other, as they are the result of the same specification framework.

Figure 4 illustrates the corresponding estimated probabilities of the three different business cycle phases (accelerations, recessions, and normal growth periods). As it can be clearly observed, the ordered probit regression model seems to have a good performance in term of fit, particularly with respect to the occurrence of economic accelerations and recessionary periods as defined by the ARNG algorithm over the whole sample. Concerning the explanatory power of the newly defined normal

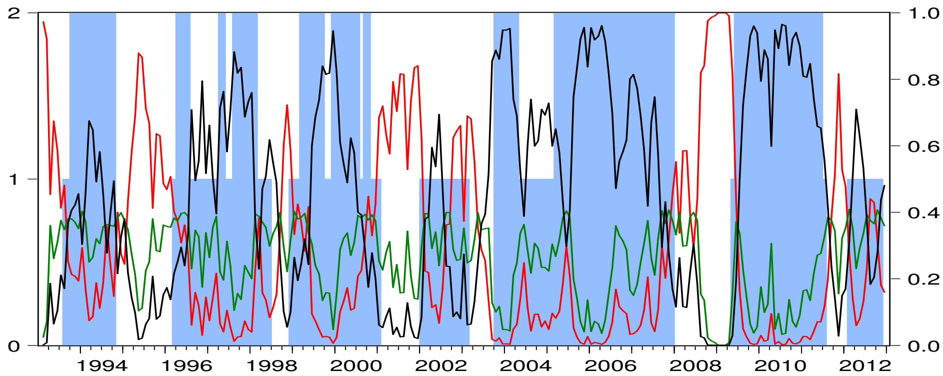

Figure 4: Estimated in-sample probabilities of accelerations (black), recessions (red) and normal growth periods (green) from ordered probit regression, one-month-ahead forecast horizon, vintage 2012:12 (estimation sample: 1991:1–2012:12), and ARNG series. Author's calculations.

growth periods, it is noteworthy that particularly during the 2002 and 2012 months, while the recession, acceleration and normal growth probabilities are mostly below the 50% threshold, the normal growth probabilities seem to be the highest on average, implicitly hinting the occurrence of a "normal growth" phase as the one sketched in Figure 1. This however is not true for the 2004 normal growth periods, where the acceleration probabilities are the highest, and above the 50% threshold, despite the fact that the economy was experiencing a normal growth phase as defined again by the ARNG algorithm.

Table 3: Expectation-Prediction Evaluations of Ordered Probit Regression (One-Month-Ahead Forecast Horizon), Estimation Sample: 1991:1–2012:12.

$c_t = 0$	% Correct	$c_t = 1$	% Correct	$c_t = 2$	% Correct	Total	% Correct
67	74.627	62	29.032	109	80.734	238	65.546

Table 3 summarizes the expectation-prediction evaluations of the considered ordered probit regression, showing in particular that this regression has a better performance in terms of fit when explaining both accelerations and recessions, than in explaining normal growth periods. Indeed, while the percentage of correctly identified accelerations and recessions is about 75% and 80%, respectively, the percentage of correctly identified normal growth periods is only about 30%. On average, the percentage of correctly predicted values of c_t (without the distinction between accelerations, recessions and normal growth periods) across all specifications is about 65%. A possible reason for this rather moderate overall performance of the ordered probit regressions may be that the different phases of the business cycle may be driven by different DGPs, so that different sets of leading indicators may be optimal for the respective prediction of such different phases. This issue is investigated in more detail in section 4.

3.3 Real-Time Evaluation

As previously pointed out, the model specification exemplarily summarized in Table 2 for the vintage 2012:12 may not necessarily be valid for other data vintages due to the use of an automatized variable and lag selection procedure every time that new data may become available. Indeed, it is possible that the final dynamic probit specifications may differ significantly across vintages due to both data revisions as well as eventual variations in the forecasting power of the explanatory variables, and that therefore the model selection procedure may deliver different specifications for different forecast horizons as the ones just discussed. In order to evaluate in a compact way the results of the five alternative probit regressions for the one-, two-, and three-ahead forecast horizons for the 72 analyzed vintages, the joint significance of all the lags of a determinate explanatory variable was tested by means of a standard likelihood ratio test (where under the null hypothesis, the restriction that the included lags' coefficients are zero does not affect in a statistically significant way the value of the likelihood function) for each data vintage.[8]

As summarized in Table 4, the industrial production index (the business cycle reference series), domestic orders received by the industrial sector, as well as the job vacancies, were not found to be statistically significant in any or mostly any vintage. In contrast, lagged values of the foreign orders received by the industrial sector, the ifo index, the corporate spread, the CDAX, the short term interest rate, the 10-year yield spread and of the discrete business cycle series c_t were found to have a significant forecasting power in the majority of the vintages, with the latter six variables being selected by the automatized selection procedure in more than 75% of the vintages. Table 7 summarizes these statistics for all estimated regressions by showing the percentage of vintage-specific regressions where the included lags of the automatically selected explanatory variables are jointly statistically significant at standard confidence levels for the one-, two-, and three-month forecast horizons.

[8]All tables and estimation results discussed in the present paper are available from the author upon request.

Table 4: Likelihood ratio test statistics of ordered probit regressions. Real-Time Sample: 2007:1–2012:12

	arng_ind	ipidx_d	aftg_inl	aftg_aus	jobvac	ifo_r1	crp_sprd	cdax	eubor_3m	yc10y
2007M01	0.0013			0.0000			0.0041	0.0005	0.0000	0.0015
2007M02	0.0117			0.0000			0.0070	0.0007	0.0000	0.0022
2007M03	0.0154			0.0000			0.0011	0.0011	0.0000	0.0001
2007M04				0.0000			0.0022	0.0043	0.0000	0.0001
2007M05	0.0030			0.0000			0.0002	0.0113	0.0000	0.0000
2007M06	0.0056			0.0000		0.0023	0.0001	0.0264	0.0000	0.0000
2007M07	0.0029			0.0000		0.0013	0.0004	0.0101	0.0000	0.0001
2007M08				0.0000				0.0013	0.0002	
2007M09				0.0000				0.0006	0.0000	0.0409
2007M10	0.0012			0.0004		0.0000	0.0000		0.0000	0.0000
2007M11	0.0028			0.0021		0.0000	0.0000		0.0000	0.0000
2007M12	0.0002			0.0184		0.0000	0.0000	0.0252	0.0000	0.0000
2008M01	0.0002			0.0173		0.0000	0.0000	0.0171	0.0000	0.0000
2008M02	0.0151			0.0000		0.0039		0.0006	0.0000	0.0000
2008M03	0.0286			0.0000			0.0008	0.0184	0.0000	0.0000
2008M04	0.0051			0.0000		0.0211	0.0000	0.0036	0.0000	0.0000
2008M05	0.0005			0.0008		0.0002	0.0000	0.0018	0.0000	0.0000
2008M06	0.0116			0.0000			0.0003	0.0066	0.0000	0.0000
2008M07	0.0045			0.0000		0.0314	0.0000	0.0038	0.0000	0.0000
2008M08	0.0089			0.0000			0.0000	0.0012	0.0000	0.0000
2008M09	0.0023			0.0001		0.0429	0.0000	0.0008	0.0000	0.0000
2008M10	0.0018			0.0000			0.0000	0.0005	0.0000	0.0000
2008M11	0.0008			0.0000			0.0000	0.0005	0.0000	0.0000
2008M12	0.0000			0.0000			0.0000	0.0002	0.0000	0.0000
2009M01	0.0000			0.0000			0.0000	0.0003	0.0000	0.0000
2009M02	0.0002			0.0000			0.0000	0.0004	0.0000	0.0000
2009M03	0.0001			0.0002	0.0073		0.0009	0.0002	0.0000	0.0000
2009M04	0.0024			0.0040	0.0044	0.0097	0.0004	0.0059	0.0000	0.0000
2009M05					0.0165	0.0001	0.0000		0.0000	0.0000
2009M06					0.0160	0.0000	0.0000		0.0000	0.0000
2009M07	0.0385					0.0000	0.0000		0.0000	0.0000
2009M08	0.0137					0.0000	0.0000		0.0000	0.0000
2009M09	0.0019					0.0000	0.0000	0.0217	0.0000	0.0000
2009M10	0.0018					0.0000	0.0000	0.0219	0.0000	0.0000
2009M11	0.0019					0.0000	0.0000	0.0243	0.0000	0.0000
2009M12	0.0034					0.0000	0.0000	0.0254	0.0000	0.0000
2010M01	0.0035					0.0000	0.0000	0.0308	0.0000	0.0000
2010M02	0.0034					0.0000	0.0000	0.0293	0.0000	0.0000
2010M03	0.0048					0.0000	0.0000	0.0060	0.0000	0.0000
2010M04	0.0031					0.0000	0.0000	0.0188	0.0000	0.0000
2010M05	0.0024					0.0000	0.0000	0.0141	0.0000	0.0000
2010M06	0.0125					0.0000	0.0000	0.0046	0.0000	0.0000
2010M07	0.0017					0.0000	0.0000	0.0004	0.0000	0.0000
2010M08	0.0008					0.0000	0.0000	0.0008	0.0000	0.0000
2010M09	0.0001			0.1685		0.0000	0.0000	0.0006	0.0000	0.0000
2010M10	0.0016			0.0230		0.0001	0.0000	0.0081	0.0000	0.0000
2010M11	0.0001					0.0000	0.0000	0.0003	0.0000	0.0000
2010M12	0.0000					0.0000	0.0000	0.0001	0.0000	0.0000
2011M01	0.0000					0.0000	0.0000	0.0001	0.0000	0.0000
2011M02	0.0022					0.0000	0.0000	0.0089	0.0000	0.0001
2011M03	0.0015					0.0000	0.0000		0.0000	0.0000
2011M04	0.0015					0.0000	0.0000		0.0000	0.0000
2011M05		0.0550				0.0000	0.0000		0.0000	0.0000
2011M06		0.1283				0.0000	0.0000		0.0000	0.0000
2011M07	0.0152					0.0000	0.0000		0.0000	0.0000
2011M08	0.0136					0.0000	0.0000		0.0000	0.0000
2011M09		0.1965				0.0000	0.0000		0.0000	0.0000
2011M10	0.0240			0.5087		0.0000	0.0000	0.0440	0.0000	0.0000
2011M11	0.0006			0.1584		0.0000	0.0000	0.0059	0.0000	0.0000
2011M12	0.0004			0.0527		0.0000	0.0001	0.0015	0.0000	0.0000
2012M01	0.0162			0.0014		0.0000	0.0061	0.0000	0.0000	0.0000
2012M02	0.0010			0.0002		0.0000	0.0016	0.0000	0.0000	0.0000
2012M03	0.0013			0.0003		0.0000	0.0017	0.0000	0.0000	0.0000
2012M04	0.0140			0.0015		0.0000		0.0000	0.0000	0.0002
2012M05	0.0034					0.0000	0.0000	0.0180	0.0000	0.0000
2012M06	0.0187					0.0000	0.0001	0.0532	0.0000	0.0000
2012M07	0.0016					0.0000	0.0000	0.0281	0.0000	0.0000
2012M08	0.0018					0.0000	0.0000	0.0274	0.0000	0.0000
2012M09	0.0012					0.0000	0.0000	0.0325	0.0000	0.0000
2012M10	0.0016					0.0000	0.0000	0.0266	0.0000	0.0000
2012M11	0.0016					0.0000	0.0000	0.0236	0.0000	0.0000
2012M12	0.0015					0.0000	0.0000	0.0233	0.0000	0.0000
Significant Periods (%)	88.88	4.10	0.00	51.38	5.55	77.77	94.44	81.94	100.00	98.10

When compared with the outcomes of previous related empirical studies, among the just discussed estimation results a particularly interesting one is the corroboration of the predictive power of stock price developments on future economic activity already documented by Harvey (1989), Stock and Watson (1999), and recently by Haltmeier (2008). Also corroborating a large number of previous studies, the 10-year yield spread seems to have a significant forecasting power, as originally suggested by Estrella and Hardouvelis (1991).

4 Is the Predictive Power of Leading Indicators Different for Recessions and Economic Accelerations?

As previously mentioned, while an estimation of different phases of the business cycle as just discussed is an advantageous venue to pursue as it correctly constraints the sum of the different estimated probabilities to be equal to one, such an approach is based on the implicit assumption that the different business cycle phases are generated by the same DGP. However, as pointed out e.g. by Neftci (1982a), it seems quite reasonable to assume that different business cycle phases are driven by different DGPs, and that turning points in the business cycle are situations where both DGPs affect equally the dynamics of the economy. Obviously, if the business cycle is driven by different DGPs, this should be reflected in a differentiated set of regressors for the prediction of the different business cycle phases as the result of the automatized model selection procedure.

In order to allow for maximal flexibility in terms of the model specification, in the following I estimate periods of economic acceleration and recessions individually by means of a standard probit regression framework, since this methodology can be in principle applied to any binary time series. Accordingly, a binary recession series b_t is set such that

$$b_t = \begin{cases} 1, & \text{if the economy goes through a recessionary phase at time } t \\ 0, & \text{if the economy experiences an expansion at time } t. \end{cases} \tag{12}$$

as done by Estrella and Hardouvelis (1991), Dueker (1997), Kauppi and Saikonnen (2008), Nyberg (2010) and more recently, Proaño and Theobald (2012), and a binary acceleration variable a_t such that

$$a_t = \begin{cases} 1, & \text{if the economy experiences an accelerative economic phase at time } t \\ 0, & \text{if the economy goes through an economic recession or is in a normal} \\ & \quad \text{growth phase at time } t. \end{cases} \tag{13}$$

according to the dating algorithm discussed in the previous section. These two binary series b_t and a_t are then estimated separately using exactly the same set of explanatory variables as potential regressors, and model selection procedure.[9] Formally, if the latent variable φ_t be given by

$$\varphi_{t+h} \quad = \quad \mathbf{z}_t^{i\prime}\beta + u_{t+h}, \quad u_{t+h} \sim N\left(0,1\right), \tag{14}$$

where $\mathbf{z}_t^i$, $i = \{b, a\}$ contains all available explanatory variables and lags considered in the estimation of b_{t+h} and a_{t+h}, respectively, the expected future value of b_{t+h} and a_{t+h} conditional on the current information set can be expressed as

$$\begin{aligned} &E\left(b_{t+h}|\mathbf{z}_t^b,\beta\right) = \Pr\left(b_{t+h}=1|\mathbf{z}_t^b,\beta\right) = \Phi\left(\mathbf{z}_t^{b\prime}\beta\right) = \Phi\left(E\left(\varphi_{t+h|t}^b\right)\right) \quad \text{and} \\ &E\left(a_{t+h}|\mathbf{z}_t^a,\beta\right) = \Pr\left(a_{t+h}=1|\mathbf{z}_t^a,\beta\right) = \Phi\left(\mathbf{z}_t^{a\prime}\beta\right) = \Phi\left(E\left(\varphi_{t+h|t}^a\right)\right) \end{aligned} \tag{15}$$

where $\Phi(\cdot)$ the linking function between φ_t^i and the conditional probabilities $\Pr\left(b_{t+h}=1|\mathbf{z}_t^b,\beta\right)$ and $\Pr\left(a_{t+h}=1|\mathbf{z}_t^a,\beta\right)$ according to the Bernoulli distribution, which in standard probit models is given by a standard normal distribution function.

Table 5 summarizes the final probit regression specifications for the estimation of the recession binary variable b_{t+1} and the acceleration binary variable a_{t+1} obtained by the *general-to-specific* model selection procedure for the vintage 2012:12. The regression statistics summarized in this table deliver a variety of findings that are worth to be highlighted. At the general level, they support the notion that economic accelerations and recessions are driven by different DGPs and thus are better explained by different sets of explanatory variables. Further the signs of the estimated coefficients of the leading indicators are by and large consistent with economic theory, as the ifo business sentiment index coefficients are negative in the *recession* probits and positive in the *acceleration probits.* Concerning specifically the *recession* regression and this specific vintage, it is interesting to note that no macroeconomic indicators seem to have significant explanatory or forecasting power, but that instead at least one lag of the ifo business climate index, the corporate spread, the three-month euribor rate and the 10-year yield spread are identified as statistically significant. By contrast, the variables which are identified as statistically significant in the *acceleration* regressions are the foreign orders, the ifo index, the CDAX and the euribor rate, and the 10-year yield spread. It is also interesting to note that the lags of these variables identified as statistically significant are quite different in the *recession* and the *acceleration* probit regressions, and that their coefficients are also rather different in their dimension. The comparison of these tables with the estimation results of the ordered probit summarized in Table 4 sheds also further insights: On the one hand, it is interesting to note that while in the ordered probit regressions the lagged discrete business cycle variable c_t was found as statistically significant, in the *recession* and *acceleration* probit regressions none of the respective lagged endogenous variables were identified as statistically significant for the vintage 2012:12.

A comparison between the expectation-prediction evaluations of the *recession* and *acceleration* regressions summarized in Table 6 seems to suggest that the *recession* probit regression has a better

[9]It should be clear that the binary recession series b_t and the economic acceleration binary series a_t are mutually exclusive by construction, as only periods not identified as economic recessions are considered in the determination of a_t.

Table 5: Summary of Dynamic *Recession* Probit Regressions (One-Month-Ahead Forecast Horizon)

Sample: 1991:1 – 2012:12

Recession Binary Variable

Lag	REC_IND	IP-IDX	FOR-ORD	DOM-ORD	JOB-VAC	IFO-IDX	CRP_SPRD	CDAX	EURIBOR	B-SPRD10YG
0	-	-	-	-	-	-39.231^{***} (11.975)	-	-	0.663^{***} (0.139)	0.416^{***} (0.162)
1	-	-	-	-	-	-37.590^{***} (11.887)	-	-	-	-
2	-	-	-	-	-	-31.280^{***} (11.664)	-	-	-	-
3	-	-	-	-	-	-	1.083^{***} (0.245)	-	-	-
4	-	-	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-	-	-

Pseudo-R^2: 0.429	AIC: 0.745	SIC: 0.848
HQC: 0.786	LR-Stat: 119.988	Prob(LR-Stat): 0.000

Acceleration Binary Variable

Lag	ACC_IND	IP-IDX	FOR-ORD	DOM-ORD	JOB-VAC	IFO-IDX	CRP_SPRD	CDAX	EURIBOR	B-SPRD10YG
0	-	-	-	-	-	-	-0.487^{***} (0.192)	-	2.045^{***} (0.533)	0.783^{***} (0.272)
1	-	-	-	-	-	-	-	6.134^{***} (2.089)	-	-
2	-	-	-	-	-	-	-	6.288^{***} (1.975)	-2.385^{***} (0.529)	-
3	-	-	11.845^{***} (3.452)	-	-	29.594^{***} (8.191)	-	-	-	-1.211^{***} (0.286)
4	-	-	10.299^{***} (3.432)	-	-	-	-	-	-	-
5	-	-	8.221^{***} (2.931)	-	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-	-	-

Pseudo-R^2: 0.371	AIC: 0.969	SIC: 1.144
HQC: 1.039	LR-Stat: 121.697	Prob(LR-Stat): 0.000

Note: '-' means that the coefficient of the explanatory variable was not identified as statistically significant at a 5% level, as was therefore removed by the *general-to-specific* model selection procedure. *,** and *** represent statistical significance at the 10%, 5% and 1%, respectively.

predictive performance (measured using a 0.5 evaluation cut-off value) than the *acceleration* regression: On average, the *recession* regressions correctly predict a recessionary period about 92% of the times in the analyzed sample 1991:1–2012:12, while the *acceleration* regressions correctly predict an acceleration period in about 78% of the times.

Table 6: Expectation-Prediction Evaluations of *Recession* and *Acceleration* Probit Regressions, Sample: 1991:1–2012:12

	Dep=0	Correct	% Correct	% Incorrect	Dep=1	Correct	% Correct	% Incorrect
Recession Probit	166	153	92.17	7.83	67	47	70.15	29.85
Acceleration Probit	129	101	78.29	21.71	109	89	81.65	18.35

In this context, let us focus on the estimated *recession* and *acceleration* probabilities of the different probit specifications obtained from the data vintage 2012:12, illustrated in Figure 5. As it can be

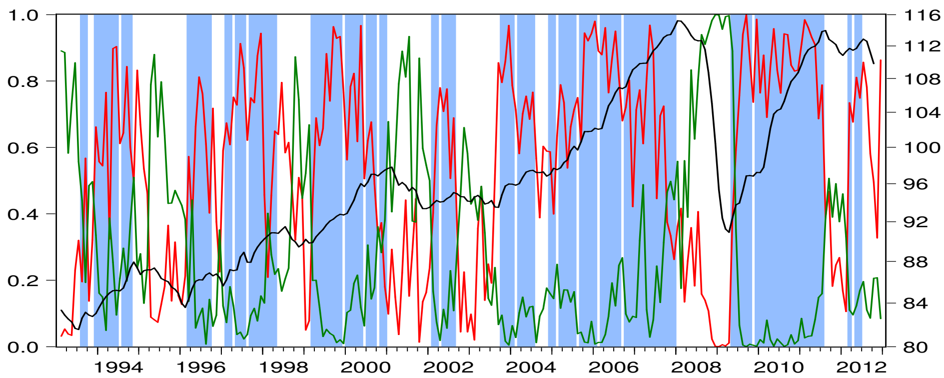

Figure 5: Estimated in-sample probabilities of accelerations (red) and recessions (green) from individual probit regressions, one-month-ahead forecast horizon, vintage 2012:12 (estimation sample: 1991:1–2012:12). Shaded areas are economic accelerations as identified by the ARNG algorithm. Author's calculations.

clearly observed in this figure, the combined estimated *recession* and *acceleration* probabilities seem to be quite consistent with each other, even though they are the result of independent estimation and combination processes, with both series not only moving in opposite directions but rising significantly above the 50% threshold level every time the corresponding business cycle phase is detected by the dating algorithm. Further, it is particularly noteworthy that during the 2002 months, as well as during the last months of 2011 and the beginning of 2012, both *recession* and *acceleration* probabilities are below the 50% threshold, implicitly hinting the occurrence of "normal growth" phases as the one sketched in Figure 1.

As previously mentioned, it should be clear that the results summarized exemplarily in Tables 2, 3, 5 and 6 should not be overinterpreted since these are a snapshot only valid for the vintage 2012:12, and may not necessarily be valid for other data vintages. Indeed, as clearly demonstrated by Table 4 with respect to the ordered probit regressions, it is possible that the final dynamic probit *recession* and *acceleration* specifications may differ significantly across vintages due to both data revisions as well as eventual variations in the forecasting power of the explanatory variables, and that therefore the model selection procedure may deliver different specifications for different forecast horizons as the ones just discussed. As in the previous case, the joint significance of all the lags of a determinate explanatory variable in the *recession* and *acceleration* probit regressions was tested through a standard likelihood ratio test for each of the 72 vintages.[10]

Table 7 summarizes the percentage of vintage-specific regressions where the included lags of the

[10] All tables and estimation results discussed in the present paper are available from the authors upon request.

automatically selected explanatory variables are jointly statistically significant at standard confidence levels for the one-month-ahead forecast horizons for both *recession* and *acceleration* regressions analogously to the last row in Table 4. The results summarized therein are by and large consistent with the

Table 7: Percentage of vintage-specific regressions with jointly statistically significant lagged values according to Likelihood-Ratio Test for estimation of binary recession series b_t, and acceleration series a_t. Real-Time Sample: 2007:1–2012:12

	bin_ind	ipidx_d	aftg_inl	aftg_aus	jobvac	ifo_r1	crp_sprd	cdax	eubor_3m	yc10y
Recession Probit	51.38	0.00	0.00	47.22	0.00	72.22	100.00	00.00	100.00	100.00
Acceleration Probit	54.16	5.55	0.00	73.61	20.83	62.50	65.27	97.22	100.00	100.00

results of Table 4 in a variety of dimensions. On the one hand, they corroborate the findings of the ordered probit that the (growth rate of the) industrial production index, the domestic orders received by the industrial sector, and the job vacancies do not have (or at least not a systematically) predictive power for both economic recessions and accelerations. Here, it is interesting to note that while none of the lagged values of the job vacancies was found to be statistically significant in the prediction of recessionary, periods, this was indeed the case in the prediction of economic accelerations in 20% of the vintages analyzed. On the other hand, at least one lagged value of the respective binary series (b_t or a_t), as well as of the foreign orders, the ifo sentiment index, the corporate spread, the three-month euribor rate and the 10-year yield spread was found to have significant predictive power of both recessions and economic accelerations in the majority of vintages, corroborating previous results in the literature which have however only focused on the prediction of recessionary periods. The corporate spread was found however as statistically significant in the prediction of recessions in 100% of the vintages, while this was the case in only 65% of the cases when predicting economic accelerations.

A final rather striking result concerns the power of the CDAX in the prediction of accelerations and recessions: According to the results in Table 7, while the CDAX was found as statistically significant in prediction accelerations in 97.22% of the vintages, this was the case in none of the vintages (0.00%) in the recession probit regression model. This crystal-clear finding stands not only in stark contrast with Bernanke (1990), who found that stock prices have a significant power in predicting U.S. economic recessions, but also highlights their significance for the real-time detection of economic accelerations, at least in Germany.

5 Concluding Remarks and Outlook

In this paper I argued for a more differentiated classification of the business cycle than the classical expansion/recession approach currently predominant in the literature, and proposed a non-parametric algorithm (labelled ARNG for acceleration, recession and normal growth periods) for the holistic real-time detection of economic accelerations, recessions and periods of normal growth. Further, using both an ordered probit regression model to estimate the resulting discrete variable from the proposed ARNG algorithm, as well as dynamic probit regressions for the estimation of both recession and acceleration binary series along the lines of Proaño (2010) and Proaño and Theobald (2012), I investigated the prediction properties of a variety of macroeconomic and financial indicators of the German economy in real time.

In general terms, the estimation results corroborated the power of well-known leading indicators such as the 10-year yield spread and the corporate spread, among others, for the prediction of German business cycles defined through the ARNG algorithm. Further, while the application of the ordered probit framework delivered satisfactory results (being the appropriate estimation method from a theoretical point of view), the application of independent probit regressions on the mutually exclusive recession and acceleration binary series seemed to deliver a somewhat superior performance, despite the obvious shortcoming that the respective estimated probabilities were independent from each other and thus could sum up to more than one, at least theoretically. However, this caveat did not seem to be binding at least in the estimation sample considered. Nonetheless, the estimation and prediction of economic accelerations, recessions and normal growth periods by means of multinomial regression models which are able to account for the asymmetric behavior of these different business cycle phases seem a promising line of research.

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