Is it high time?

Estimating the probability of an upcoming recession in Germany using a probit model approach

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Abstract

In particular in light of the recent past, being knowledgeable about what seems most likely to happen in the future is of high value. Therefore, this paper adopts a widely used methodological technique to estimate the probability of an upcoming recession in Germany in response to the Covid-19 measures. Using financial, macroeconomic, and sentiment data from the past two decades we estimate and compare a static and a dynamic probit model, the latter including lags of a binary recession indicator variable. We first find that the dynamic specification of the probit model outperforms the static probit model in-sample, but not out-of-sample. We then use our two best performing models to estimate the recession probability in Germany. Our results suggest a recession in April and May 2020 and point towards a recessionary period in winter 2020/2021.

1 Introduction

Disposing of reliable information about what will happen in the future is of great interest and value to researchers, decision makers and alike. This is particularly true in light of the current pandemic. Unsurprisingly, gathering this information is far from trivial since what lies beyond the current edge remains unknown. To the various reasons that induce fuzziness when working empirically, e.g. assumptions or approximations, adds another dimension of inherent uncertainty, that is even the most appealing and convincing predictions cannot yet be verified. In other words, it is ex ante not possible to evaluate the accuracy of a forecast of a forward looking econometric model as tomorrows data do not exist today.

Certainly, studying future economic events such as potentially upcoming crises cannot liberate itself from these conditions. However, economists have taken numerous attempts to do so by designing econometric models that are able to estimate what seems most likely to happen in the future. Of particular interest have been two broadly definable strands. On the one hand the future evolution of certain variables such as GDP, and on the other hand the probability that an economy at some point in the future is in a recession or boom, respectively. This paper aims at contributing to the latter. It adopts a probit model approach to estimate the probability of an upcoming recession in Germany in response to the Covid-19 measures under real-time conditions.

Despite its relative simplicity compared to other popular approaches in this field (e.g. Markov switching models, dynamic factor models), probit models have shown to be successful in tracing recessionary periods. It is at least in part thanks to this rather intuitive notion in conjunction with the ability of providing competitive results that probit models have been and remain widely used among researchers. Hence, accounting both for the sake and the limited scope of this paper, the probit model serves as an appropriate framework that does not lack any empirical relevance.

The remainder of this paper is organized as follows: section 2 reviews some of the most important literature findings on estimating recession probabilities with probit models, section 3 presents the methodological approach that this paper takes. The fourth section elaborates on the data, its sources and on the data selection choices that have been made. Section 5 discusses the main results and section 6 summarizes potential limitations. The last section concludes.

2 Literature Review

To estimate recession probabilities the probit model was first introduced by Estrella & Hardouvelis (1991). In this paper, the authors conducted an analysis of U.S. recessions using a static probit model, which means that a binary recession indicator is explained only by lagged explanatory variables. They find that including the yield curve (the difference between a long-term and short-term yield) results in improved estimations. In the following years, probit models with financial variables like the yield curve became fairly popular in the context of estimating recessions (e.g. Estrella and Mishkin 1998, Moneta 2005).

Dueker (1997) confirms the relevance of the yield curve for estimating recession probabilities using a probit model. However, he extended the static probit model that had been used so far by a dynamic element, i.e. a lag of the binary dependent variable. He finds that this extension provides better results than its static competitors. The improved performance of the dynamic probit model compared to the static probit model has since then been found in a number of studies (e.g. Nyberg 2010, Ng 2012).

More recently, Kauppi & Saikkonen (2008) modified the dynamic model to the dynamic autoregressive model. Next to the dynamic element they add a lag of the underlying linear index function. Performing rather equally in-sample and worse out-of-sample, the dynamic autoregressive model seems to not significantly improve the estimates in comparison to the dynamic model. Furthermore, Kauppi & Saikkonen (2008, p. 781) find that iterative forecasts provide better results than direct forecasts. This means that an iterative estimation based on a one-step ahead forecast of a future value, say in three periods, appears to be more accurate than estimating this future value directly, i.e. with a three-step ahead forecast.

The studies mentioned until here focused on U.S. recessions. Regarding Germany various studies applied a static model in a cross-country comparison, providing evidence for the high predictive power of the term spread (Bernard & Gerlach 1998, Ahrens 2002, Estrella, Rodrigues & Schich 2003). While they focus on interest rates, there are other variables that also appear to contribute to the overall accuracy of probit model estimations of recession probabilities. Schreiber et. al (2012, p.177) for instance provide evidence that the CDAX seems to be important for estimations for Germany. In addition, Proaño (2017, p.35) indicates that the 3-month Euribor may contain relevant information. Interestingly, macroeconomic indicators in turn seem to perform rather badly (Proaño 2010, p.15). Note that Proaño (2017) uses an ordered probit model for his estimations which differentiates between three states of the economy instead of two.

Estimating recession probabilities for the U.S., Christiansen, Eriksen & Moller (2014) show that sentiment data contributes to the predictive accuracy. Using both consumer sentiment and businsess confidence data they find that including these data in addition to the before mentioned slope of the yield curve and some other financial indicators has a positive effect on the model's performance. Sentiment data have also been included in some of the above mentioned studies for Germany, e.g. Schreiber et. al (2012) and Proaño (2010), and have proved to add additional information to the respective model.

In addition to the discussion of the explanatory variables it is equally important to briefly summarize the discussion of the dependent variable, i.e. the recession variable. In general, there are two common ways to determine this variable. Researchers can either calculate recessionary periods by themselves, employing for instance the widely used Bry-Boschan algorithm (Proaño 2017, Nissilä 2020), or they could refer to institutions that externally determine recession dates. For Germany turning points are externally defined by the Economic Cycle Research Institute (ECRI). According to Nissilä (2020, p.5) the ECRI follows the same judgement for turning point dating as the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER). Many of the above mentioned studies on the U.S. refer to NBER recession dates for their estimations (e.g. Nyberg 2010, Ng 2012). ECRI turning dates have been used in Fornari & Lemke (2010) and Nyberg (2010).

To summarize, a large number of studies show that the term spread is a main leading indicator. However, note that the predictive power seems to have decreased over the past few years in the euro zone (Fendel, Mai & Mohr 2018, p.10). Furthermore, the results mentioned above suggest that models which include a broader set of information outperform single predictor models. Also, previous findings indicate that the dynamic probit model is able to provide better results than the static probit model. In general, a rather small number of studies has focused on Germany of which to the best of our knowledge the most recent has been published more than three years ago.

3 Methodology

When using a probit model the object of interest is p_t which in the context of this study describes the probability that the German economy is in a recession at time t. This probability is conditional on the information set Ω_{t-h} containing all the information available at time $t-h$, with h being the forecast horizon (Proaño 2010, pp.5). Hence, $p_t \equiv P_{t-h}(y_t = 1) = E_{t-h}(y_t)$, where y_t is a binary recession indicator and is defined as:

$$y_t = \begin{cases} 1, & \text{if the economy is in a recession at time } t \\ 0, & \text{if the economy is in an expansion at time } t. \end{cases}$$

Conditional on the information set Ω_{t-h} it is assumed that y_t follows a Bernoulli distribution:

$$y_t | \Omega_{t-h} \sim B(p_t).$$

The standard normal cumulative distribution function Φ ensures that $0 \leq p_t \leq 1$, that is, $p_t = \Phi(\pi_t)$. In other words, $\Phi(\cdot)$ serves as a transformation of the so-called index function π_t onto the $[0;1]$ interval, where π_t is a linear function of the included explanatory variables that lie in the information set Ω_{t-h}. Based on these properties, the static probit model for estimating recession probabilities can be written as (see Estrella & Hardouvelis 1991):

$$\pi_t = \omega + x'_{t-h}\beta$$

where ω is a constant, x'_{t-h} contains lagged explanatory variables that are available at $t-h$, and β is a vector of coefficients.

Note that according to Dueker (1997, p.44) the static probit model has one important limitation which is that it does not account for potential autocorrelation within the binary dependent variable y_t. Therefore, Dueker (1997) added a lagged value of the dependent variable to the model. However, he argues that not any lagged value of the binary dependent variable can be included into the model equation. This constraint is referred to as the recession recognition lag r. It describes the phenomenon that people in general require some time to recognize changes in the state of the economy and will therefore adjust their expectations and behavior with delay. Thus including y_{t-j} with $j \geq h+r$ the static probit model turns into the dynamic probit model:[1]

$$\pi_t = \omega + \delta y_{t-j} + x'_{t-h}\,\beta.$$

Estimating such a model under real-time conditions requires to account for another constraint which arises due to data availability problems. More precisely, not all the data that is of interest or shall be included in the estimation may be immediately available (Proaño 2010). In particular macroeconomic data are published with delay. Generally, this restricts some data to be available with a data availability lag s. Taking this lag into account the index of the vector of explanatory variables is then bounded by $t-k$ where $k \geq h+s$. To make clear how the recession recognition lag and data availability lag affect the indices of the explanatory variables we write our final equations in sum notation. Hence, the dynamic probit model is:

$$\pi_t = \omega + \sum_{j=h+r}^{p} \delta_j y_{t-j} + \sum_{k=h+s}^{q} x'_{t-k}\beta$$

and the static probit model being the same formula without the second summand, thus

$$\pi_t = \omega + \sum_{k=h+s}^{q} x'_{t-k}\beta.$$

4 Data

For our estimation we used monthly data from January 1999 to January 2021 from Bundesbank (2021), ifo Institute (2021) and the European Cycle Research Institute (2021). To provide the models with a broad set of information we included financial, macroeconomic and sentiment data. The financial variables are the Composite DAX (CDAX), which compared to the DAX contains a broader selection of listed German stocks, the 3-month Euribor (Euribor 3m), and the term spread (Termspread 10y). We calculated the latter as the difference of the yield of the German government bond with maturity of 10 years and the 3-month

[1]The dynamic probit model as presented by Dueker (1997) is only able to account for potential autocorrelation for lags $j \geq h+r$. One modification that solves this problem is the dynamic autoregressive probit model introduced by Kauppi & Saikkonen (2008).

Euribor. All these data stem from the Bundesbank database and have shown to improve estimation results (see section 2).

As a macroeconomic indicator we use industry production without the building sector (Production). The reason to use this variable is because GDP is published quarterly. However, since we want to keep the data availability lag as small as possible we use industry production without the building sector as a proxy for GDP (e.g. Proaño 2010). Nevertheless, data on industry production without the building sector is published with a lag of two months, $s = 2$ (Proaño 2017, p.31). In contrast, the financial data are published with no delay, their data availability lag is $s = 0$. The data on industry production without the building sector is also provided by Bundesbank (2021).

Furthermore, to represent the category of sentiment variables for Germany we included the ifo business climate index for industry and trade (Ifoindex) published by ifo Institute (2021). Note that since 2018 the ifo Institute publishes a new business climate index in addition to the ifo business climate index for industry and trade, which was formerly known as ifo business climate index. However, the new ifo business climate index does not provide data for the entire length of our sample. Therefore, we decided to work with the ifo business climate index for industry and trade. Fortunately, the ifo data which we used is published without delay, that is, here the data availability lag is $s = 0$ again.

To determine the values of our binary recession indicator (Recession) we refer to data provided by the European Cycle Research Institute (ECRI). The ECRI publishes a list of business cycle peak and trough months for 22 countries, among these Germany. Table 1 lists the six turning points that the ECRI has dated for Germany for our sample period from 1999 to 2021.[2] For the purpose of this study we define a recession as the time between a peak and a trough, and the time between a trough and a peak as an expansion, respectively. Based on these definitions we construct our binary indicator variable using the so-called trough method (Nissilä 2020, p.5). With the trough method the first recession in Germany starts in February 2001 and ends in August 2003. The subsequent expansion then starts in September 2003 and lasts until April 2008, and so on. Following Nyberg (2010, p.218) we assume that the ECRI has a recession recognition lag of 9 months, i.e. $r = 9$.[3]

Table 1: ECRI turning points for Germany, 1999 - 2021

Peak	Trough
2001M1	2003M8
2008M4	2009M1
2019M7	2020M4

[2] Note that beyond April 2020 the ECRI has not yet identified neither peak nor trough months.

[3] An ECRI list from August 2020 did not include the trough in April 2020. However, in the first week of February 2021 a new list was published which now dated April 2020 as a trough. In our view, this supports the assumption of Nyberg (2010).

Table 2: Dickey-Fuller test results for explanatory variables

Variable	Transformation	p-value (DF test)
CDAX	level	0.9470
	log-difference	0.0000
Euribor 3m	level	0.9156
	difference	0.0000
Termspread 10y	level	0.2837
	difference	0.0000
Production	level	0.1902
	log-difference	0.0000
Ifoindex	level	0.2871
	log-difference	0.0000

Notes: The Dickey-Fuller tests were conducted for the entire sample.

Table 3: List of variables

Variable	Source	Abbreviation	Transformation	Availability
Binary recession indicator	ECRI	Recession	-	$r = 9$
Financial				
Composite DAX	Bundesbank	CDAX	log-difference	$s = 0$
3 month Euribor rate	Bundesbank	Euribor 3m	level difference	$s = 0$
Term spread between the yield of the German government bond with maturity of 10 years and 3 month euribor rate	Bundesbank	Termspread 10y	level difference	$s = 0$
The yield of German government bond with maturity of 10 years	Bundesbank	Term 10y	-	$s = 0$
Macroeconomic				
Production in the manufacturing industry without construction, seasonally adjusted, 2015 = 100	Bundesbank	Production	log-difference	$s = 2$
Sentiment				
ifo business climate index for industry and trade, Germany, 2015 = 100	ifo Institute	Ifoindex	log-difference	$s = 0$

Notes: Term 10y has not been transformed. Instead, we used it to calculate Termspread 10y which is the difference between Term 10y and Euribor 3m (before transformation). Data Sources: European Cycle Research Institute (2021), Bundesbank (2021), ifo Institute (2021).

Since our data is time series data it is crucial to cope with potential non-stationary. Table 2 shows the p-values of the Dickey-Fuller unit root test for the included explanatory variables. Before transformation, the null hypothesis of non-stationarity cannot be rejected for any of our variables. However, after taking (log) differences the p-values reduce such that the null is rejected. Therefore, we use the (approximate) growth rates of each of the included explanatory variables for our estimations. Table 3 summarizes the most important information of this section.

5 Results

We performed a forward model selection to determine four different models, each a static and a dynamic probit model with forecast horizon $h = 1$ and $h = 3$, to later compare their performance in section 5.1 and 5.2. To guard ourselves against potential overfitting biases when identifying the best model within our probit framework we referred to the Bayesian information criterion (BIC). Note that some previous studies performed likelihood ratio tests for model selection (e.g. Proaño 2010, Schreiber et. al 2012). However, we decided not to do so to circumvent potential biases from α-error accumulation. Instead, following a self-imposed forward selection scheme we tested from lag 1 to 12 of each variable, taking the availability constraints under real-time conditions into account (see section 3).

The selection procedure starts at the first stage of the first lag, which is subject to the forecast horizon h. We compare a model that only contains the constant to four different models. Each of them includes the first lag of one of the four variables that are available at this point (e.g. L1.CDAX, L1.Euribor 3m, L1.Ifoindex, L1.Termspread 10y) plus the constant. This makes five models in total in the first stage. The model with the lowest BIC value at the first stage moves to the second stage of the first lag. Then, for the second (and each following) stage of the first lag we compare the best model from the previous stage, say model B, against models that extend this model B by one variable each, i.e. by one lag of one variable in the next stage. For the second stage of the first lag this gives four models in total, for the third stage three models, and so on. The last stage of each lag is reached when further extensions do not reduce the BIC any more. Following this scheme up until lag 12 for each of the four models gives the combination of lags that minimizes the BIC value.[4] Note that the variables Production and Recession are added during the procedure once the availability constraints allow so.

5.1 In-sample results

The sample period for the in-sample results runs from February 2000 until April 2020. It is defined such that it allows to test for relevant information within the previous year (12 lags of monthly data), and ends in the last month the ECRI determined as a turning point. Table 4 summarizes the included variables in each of the four models which result from our model selection algorithm.

[4]Clearly, the resulting models, i.e. the combinations of lags do not globally minimize the BIC value. Another selection algorithm might perfectly identify another model.

Table 4: In-sample performance results

Sample: February 2000 - April 2020 (T=243)				
	sta1 (h=1)	dyn1 (h=1)	sta3 (h=3)	dyn3 (h=3)
CDAX	5;6;7; 8;10;11	5;6;7; 8;11	5;6;7; 8;10;11	5;6;7; 8;10;11
Euribor 3m	1	1	-	-
Ifoindex	1;9	1;9	3;9	3;9
Production	-	-	-	-
Recession	-	10	-	12
Termspread 10y	-	-	-	-
Estrella ps.-R^2	0.3284	0.3725*	0.2597	0.2949
Estrella adj. ps.-R^2	0.2462	0.2903*	0.1857	0.2128
AIC	184.42	173.69*	199.15	192.57
BIC	219.35	208.62*	230.59	227.50
PCP	0.8519	0.8848*	0.8231	0.8436

Notes: In the table * denotes the best performance.

Across the four models the CDAX plays an important role for tracing the recessionary months in our sample. Interestingly, all but one lag of the CDAX are identical for all specifications. This is also true for the ninth lag of the ifo business climate index for industry and trade. However, the other lag of the Ifoindex that enters all four models depends on the forecast horizon. More precisely, each model includes the first lag of the Ifoindex that is available under the particular forecast horizon. Regarding the 3-month Euribor interest rate, one can see from table 4 that it only enters once each in the static (sta1) and in the dynamic (dyn1) model. This suggests a rather minor importance of the Euribor 3m for estimating recession probabilities in our probit models. Note that it only is included in the models that have a forecast horizon of one month.

Nevertheless, the Euribor 3m is still more relevant than the macroeconomic indicator, not showing up in any of the four models. Surprisingly, also the Termspread 10y never is included. This finding is somewhat inconsistent to what has been discussed in section 2 where many of the earlier studies found the term spread to be particularly important. However, more recent research suggests that the predictive power of the term spread seems to have diminished over the past few years for the euro zone (Fendel, Mai & Mohr 2018, p.10).[5]

Note that the inclusion of a lag of the binary recession variable in the dynamic models increases their in-sample performance compared to their static siblings, which confirms previous findings (see section 2). This becomes visible in the bottom part of table 4 where we calculated five standard in-sample performance measures. First, we calculated the commonly used *pseudo*-R^2 goodness of fit measure from Estrella & Mishkin (1998, p.47):

$$pseudo\text{-}R^2 = 1 - \left(\frac{logL_u}{logL_c}\right)^{(2/T)logL_c}$$

where $logL_u$ is the unconstrained maximum, $logL_c$ is the constrained maximum of the log-

[5]Clearly, using another term spread, e.g. the spread to a 5 year bond, might have given other results.

likelihood function, and T denotes the sample size. However, the *pseudo*-R^2 does not account for the number of explanatory variables k. Therefore, we also included Estrella's adjusted *pseudo*-R^2 (Estrella 1998, p.203). It is defined as:

$$\text{adj. } pseudo\text{-}R^2 = 1 - \left(\frac{(logL_u - k)}{logL_c}\right)^{(2/T)logL_c}.$$

In addition, based on Wooldridge (2009, p.581) we calculated the PCP (percent correctly predicted). It is the share of correctly estimated recessionary and expansionary months over all observations that lie in the sample. Choosing $p = 0.5$ as a threshold value, any month in which the estimated probability passes this threshold is classified as a recessionary month, that is, an estimated binary equals 1, and vice versa 0 for an expansionary month. Whenever the difference between the binary variable (based on the ECRI) and the estimated binary variable (based on one of the four models) is zero, the model has assigned the same realization of the binary variable to a given month as the ECRI. Moreover, we used the Akaike (1974) and the Schwarz (1978) information criterion.

As can be seen from table 4, the dynamic probit model with forecast horizon $h = 1$ outperforms the other three specifications in all of the five listed in-sample measures. It also becomes apparent that the static probit model with a forecast horizon of three months has the worst performance across all specifications and performance measures. Overall, the shorter forecast horizon of one month improves the in-sample fit of the model.

Figure 1 and figure 2 plot the estimated recession probabilities of the two models with $h = 1$ and $h = 3$ that have been selected by our self-imposed BIC forward selection algorithm. The recession months as dated by the ECRI are shaded in grey and the threshold value of 0.5 is marked in red. In general, the static and the dynamic probit model draw a similar picture in both figures. All estimated probabilities fluctuate rather strongly which may be due to the fact that all four model specifications rest to a large extent on lags of the CDAX. However, as one can see from figure 1 the static probit model fluctuates slightly more in recessionary periods than the dynamic probit model. Similarly, the static probit model indicates more recessions in non-recessionary periods. Therefore, overall it appears that the dynamic probit model performs better which is in line with the results in table 4.

Comparing figure 1 to figure 2, one immediately sees that both models for $h = 3$ react rather sluggishly. Both series are characterized by less fluctuation compared to the models in figure 1. However, the static model for $h = 3$ also indicates more false positives than the dynamic probit model. Overall, both models in figure 2 do not detect the three recessions in the sample period immediately, but only with a delay, if at all.

Figure 1: In-sample recession probabilities for h=1, February 2000 - April 2020

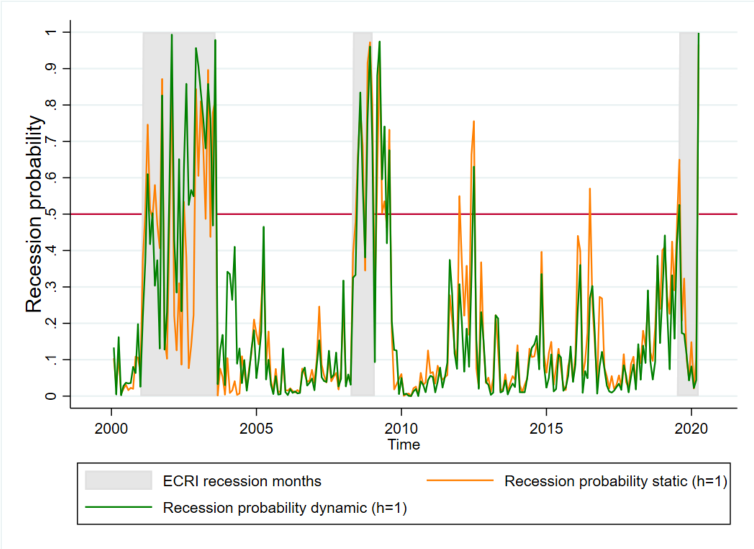
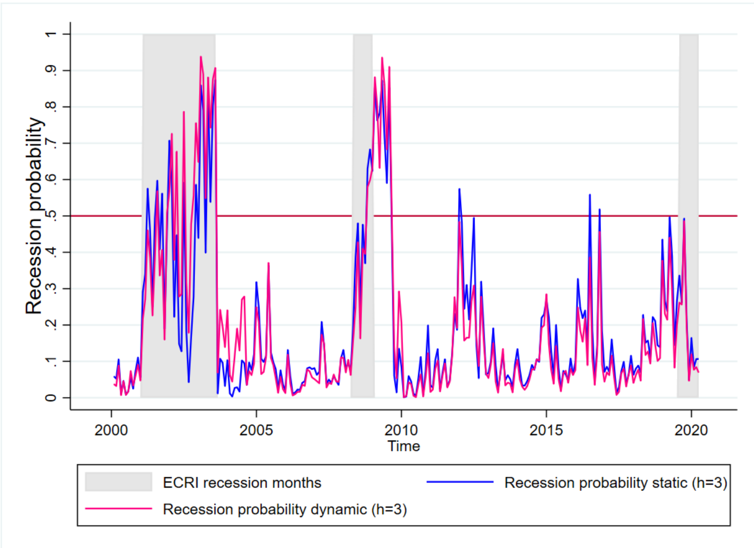


Figure 2: In-sample recession probabilities for h=3, February 2000 - April 2020



5.2 Out-of-sample results

To perform the out-of-sample estimations we determine a time period of two years. We compute the recession probabilities between May 2018 and April 2020 with an expanding window. More precisely, we run all four probit models under pseudo real-time conditions, that is, based on the underlying data available at each point. Afterwards the monthly probabilities of a recession were manually recorded from each calculation point. To evaluate the out-of-sample goodness of fit of a probit model M at a forecast horizon h, we apply three measures that are commonly used in the literature to determine the accuracy of the forecasts (Rudebusch & Williams 2009, p.498):

the mean absolute error (MAE)

$$MAE(M,h) = \frac{1}{T}\sum_{t=1}^{T} |P^M_{t|t-h} - y_t|,$$

the root mean squared error (RMSE)

$$RMSE(M,h) = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (P^M_{t|t-h} - y_t)^2},$$

as well as from Bliemel (1973, p.444) the Theil inequality coefficient (Theil)

$$Theil(M,h) = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T} (P^M_{t|t-h} - y_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} (P^M_{t|t-h})^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T} y_t^2}}.$$

The Theil inequality coefficient lies in the interval [0;1] where zero implies a perfect forecast and one no explanatory power. All pseudo out-of-sample performance results are presented in table 5. Only looking at the MAE the dynamic probit models perform better in comparison to the static probit models. However, overall the static model outperforms the dynamic models as it does so in the RMSE and Theil. In addition, the forecast error for the models with forecast horizon $h = 1$ is lower than for those with $h = 3$.[6]

Table 5: Pseudo out-of-sample performance results

Sample: May 2018 - April 2020 (T=24)				
	sta1 (h=1)	dyn1 (h=1)	sta3 (h=3)	dyn3 (h=3)
MAE	0.4178	0.3922*	0.4334	0.4115
RMSE	0.5251*	0.5390	0.5427	0.5476
Theil	0.5605*	0.6022	0.6503	0.6922

Notes: In the table * denotes the best performance.

Figure 3 shows the pseudo out-of-sample recession probabilities for all four probit models with their respective forecast horizons. For the shorter forecast horizon both the static and the dynamic model estimate probabilities pass the threshold value of 0.5 in August 2019, which coincides with the beginning of the latest recession dated by the ECRI. With a forecast horizon of three months, none of the two models passes the red line at any point in time. Overall, unlike the in-sample results we do not observe any false positives here which is likely to be due to the specific period here, i.e. May 2018 to April 2020. Interestingly, while the most recent recession ended in April 2020 according to the ECRI, two of our four models indicate a strong increase in the recession probability towards April 2020. Note that this pattern can also be observed in figure 1 for the in-sample recession probabilities.

[6] As a robustness check we extended the pseudo out-of-sample time period to three years from May 2017 to April 2020. The pseudo out-of-sample performance results were remarkably similar.

Figure 3: Pseudo out-of-sample recession probabilities, May 2018 - April 2020

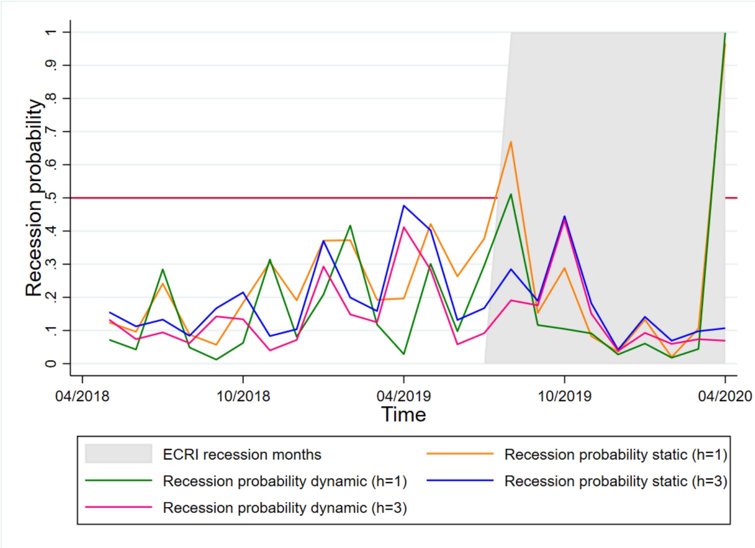
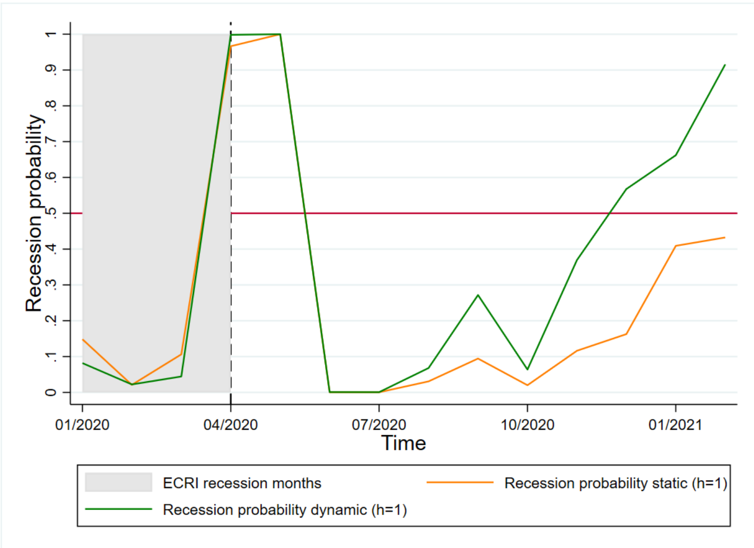


Figure 4: Nowcast of recession probabilities for h=1, January 2020 - February 2021



Following the in-sample and out-of-sample performance results we use the two best models to estimate a nowcast beyond April 2020 - which is the last month the ECRI has defined as a turning point. However, since data for our explanatory variables is provided monthly we can do this nowcasting exercise for May 2020 to February 2021. The results are shown in figure 4. Both models seem to capture the recessionary effect of the ”first lockdown” in Germany, indicated by high recession probabilities in April and May 2020. In fact, our nowcast results suggest that the ECRI shall revise its recession dates. After May 2020 the two models send rather weak recession signals until October, while from November on a new increase in both models probabilities is visible. However, the static model remains slightly below the 0.5 threshold, whereas the dynamic model clearly passes it, thus indicating a recession from December 2020 on. This coincides with the beginning of the ”second lockdown”.

6 Limitations

It should be clear that the results presented in the previous section are conditional on a number of limitations. In fact, for our model to become traceable we had to simplify and restrict it at various ends. First, our binary recession indicator is constructed using the recession dates as defined by the European Cycle Research Institute (ECRI). While referring to recession dates that are externally provided is common practice, using ECRI recession dates may bias the results for two reasons.

On the one hand, it is relatively unclear how the ECRI determines the recession dates. Nissilä (2020, p.5) states that the ECRI uses the same turning point dating procedure as the NBER (see also Moneta 2005, p.289). However, to the best of our knowledge the ECRI itself does not provide any more information in this regard on their website. This may cast doubts about the reliability of the ECRI dates. One may for instance want to raise the question why the ECRI determined the period between August 2019 and April 2020 as a recession. Note that more concerns in this regard are discussed in Nissilä (2020, p.4). On the other hand, the ECRI defined recessions are based on leading indicators, i.e. explicitly not on econometric modeling. However, for this paper we do use an econometric model. This may give rise to distortions since its performance crucially depends on the recession dates. A somewhat related concern regards the rather arbitrary choice of the trough method which we used to transform the ECRI turning point months into a binary recession variable.

To overcome these potential shortcomings, one could calculate the recession dates on one's own instead of using pre-defined dates, e.g. by the commonly used Bry-Boschan algorithm. This could possibly help to solve another problem our estimations suffer from, that is the length of the recession recognition lag. As has been stated in section 4 the recession recognition lag of the ECRI is nine months. While nine months appears to not be an overly long recession recognition lag (Dueker 1997, p.45), using the Bry-Boschan algorithm may allow to reduce it and thus, the model performance could increase.

However, even if one was to use ”own” recession dates, other issues remain. Regarding our model selection procedure it is important to highlight that opting for the Bayesian information criterion (BIC) is neither the only nor necessarily the better option. In fact, using the Akaike information criterion (AIC) or even the Hannan-Quinn information criterion (HQC) for model selection may be equally suitable. Since we test through a large number of lags we decided to use the BIC as it is known to penalize the inclusion of additional variables rather strongly, thus reducing potential overfitting biases. However, note that our selection algorithm does not globally minimize the BIC (see footnote 4). Therefore, one could decide to apply shrinkage techniques such as LASSO. Eventually, it could be that a model selected by the AIC may perform better and not suffer from overfitting.

One downside of including lagged coefficients restricted to the last 12 months is that it could miss out relevant information. The risk of not including what would have been valuable and thus positively affect the model's performance can actually never be entirely eliminated. Hence, our decision to only include the information from the last year comes at some unknown cost which we have to bear and be conscious about.

Finally, it is worth mentioning that autocorrelation of the errors may also bias the results. However, we have seen only some studies that explicitly corrected for autocorrelation within the errors. Among these, most of them used Newey-West standard errors (e.g. Estrella & Mishkin 1998, Rudebusch & Williams 2009). While autocorrelation of the errors indeed results in distorted standard errors, and thus in wrong significance of the coefficients, this is only of minor interest in the context of this paper. Therefore, we here decided to not correct for autocorrelated errors and pay the price of biased coefficient estimations.

7 Conclusion

Particularly in light of the current Covid-19 pandemic, being knowledgeable about the most likely scenarios that are about to happen is of high value. Macroeconomic literature shows that economists have come up with a broad set of models to estimate the future state of an economy. Among these models, the probit model is regularly and successfully implemented to perform that task. However, the number of new publications applying a probit model to determine recession probabilities seems to have decreased over the last few years. Therefore, in this paper we adopted a probit model approach to estimate the probability of an upcoming recession in Germany in response to the Covid-19 measures.

Using European Cycle Research Institute turning point months, financial and macroeconomic data from the Bundesbank and sentiment data from the ifo Institute on the past two decades we estimated both a static and a dynamic probit model with two different forecast horizons for Germany. We find that financial market data (such as the CDAX) and sentiment data (such as the ifo business climate index for industry and trade) have strong explanatory power for recessions in Germany in the last 20 years. In contrast, macroeconomic data seem to not contain any relevant information. This appears to also be true for the term spread, which may be somewhat surprising. However, note that earlier studies have emphasized the diminishing ability of the term spread to detect recessions within the euro zone. Thus, our findings for Germany to a large extent confirm what has been shown in previous research.

With respect to the inter-model comparison we find that the dynamic probit model specification outperforms the static probit model only in the in-sample evaluation. In contrast, the static model has a higher out-of-sample accuracy. While most of the probit literature suggests that an inclusion of a lag of the binary recession variable improves the results in general, this has shown to be only partly true in our setup. Additionally, our estimation results indicate that models with a one-step ahead forecast horizon trace recessionary periods significantly better than models with a three-step ahead forecast horizon.

Looking at the most recent past our two best performing models show clear recession signals around the time of the ”first lockdown” in spring 2020 in Germany, while only the dynamic model is determined in indicating a recession for winter 2020/2021. Nonetheless, regarding our research question we conclude that it indeed is high time. Clearly, whether or not a recession in early 2021 is about to come remains unknown. However, based on our estimation results one should at least pay high attention to the evolution of the German economy, and on sudden events such as virus mutations.

Finally, note that our results necessarily depend on various limitations. In particular the quality of the recession data should be mentioned here, as it is crucial for the accuracy of this kind of forward looking estimations. Besides, the data as well as the model selection decisions can be questioned. Furthermore, the ideal combination of explanatory variables may differ strongly depending on the period and the economy under study. This and more needs further analysis and clarification. To close, note that the presented findings result from comparing different specifications *within* one model class. Therefore, our paper by no means claims to provide any insights to be used for evidence based policy decisions.

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Eidesstaatliche Erklärung

Ich versichere, dass ich die Seminararbeit selbstständig verfasst habe. Andere als die angegebenen Hilfsmittel und Quellen wurden nicht benutzt. Die Arbeit hat keiner anderen Prüfungsbehörde vorgelegen. Es ist mir bekannt, dass ich bei Verwendung von Inhalten aus dem Internet diese zu kennzeichnen habe und einen Ausdruck davon mit Datum und Internet-Adresse (URL) als Anhang der Seminararbeit beizufügen habe.

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Berlin, den 15.03.2021