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GDP Forecast Accuracy During Recessions*

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Abstract

This paper proposes a simple nonlinear framework to produce real-time multi-horizon forecasts of economic activity as well as conditional forecasts that depend on whether the horizon of interest belongs to a recessionary episode or not. It is hence particularly well-suited for the actual (post-)pandemic crisis that the world is facing. Moreover, it can be applied easily to any country and measure of economic activity. The forecasting model takes the form of an autoregression that is augmented with either a probability of recession or an inverse Mills ratio. The method is applied to US data over the 1959-2016 sample. The most parsimonious augmented autoregressive model delivers more accurate out-of-sample forecasts of GDP growth than the linear and nonlinear benchmark models considered, and this is particularly true during recessions. Our approach suits particularly well for the real-time prediction of final releases of economic series before they become available to policy makers. Moreover, standard probit models are used to generate the Term Structure of recession probabilities. Interestingly, the dynamic patterns of these Term Structures are informative about the business cycle turning points.

JEL Classification: C35, C53, E27, E37

Keywords: Augmented Autoregressive Model, Conditional Forecasts, Economic Activity, Inverse Mills Ratio, Probit, Recession.

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1 Introduction

This paper proposes a framework to perform multi-horizon, real-time and nonlinear forecasting of macroeconomic variables (typically, the GDP growth). Our workhorse is an Augmented Autoregressive (AAR) model, which is a direct autoregressive (AR) model of order one augmented with probabilities of recession and/or Inverse Mills Ratios (IMR). The probability of a recession at a given horizon h is predicted conditionally on the information available (in real time) at period t using a Probit model. A forecast that is conditional on an expansion at the horizon of interest is termed optimistic and a forecast computed conditionally on a recession scenario is termed pessimistic. Methods are proposed to infer the business cycle turning points from the dynamics of the term structure of recession probabilities.

Optimistic and pessimistic forecasts can in principle be obtained by splitting the sample according to whether there is a recession or not, as done in an illustrative example presented in Hamilton (2011). Here, we follow an alternative approach that involves IMR corrections. Dueker (2005) and Dueker and Wesche (2005) propose a Qual VAR model, which is a VAR system that includes a latent variable that governs the occurrence of a binary outcome. This approach is not favored here because it does not naturally lead to state-dependent forecasts of economic activity in real time.[1] Our AAR model falls within the broad family of conditional forecasting models studied by Clark and McCracken (2013). This family includes all forecasting models that assume a particular policy path (e.g., announced inflation target) or a scenario for the future path of given macroeconomic variables (e.g., low inflation and high unemployment)[2]. Conditional forecasting models are used by major financial institutions and regulatory agencies worldwide to perform Stress Tests, see e.g. Grover and McCracken (2014). Typically, the goal of a Stress Testing exercise is to predict the impact of a more or less strong adverse shocks affecting one sector or the overall business environment on a particular outcome. The methodology developed in this paper can be useful in that context as

[1]Our paper assumes that recession dates are observed up to the most recent official turning point. Studies that attempt to predict the business cycle turning points include: [Chauvet (1998), Chauvet and Hamilton (2006), Chauvet and Piger (2008), Stock and Watson (2010), Berge and Jorda (2011) Stock and Watson (2013) or Ng (2014)]. Other studies attempt to identify the variables that lead future economic activity, e.g. [Stock and Watson (1989), Issler and Vahid (2006), Ng and Wright (2013)].

[2]For instance, Giannone et al. (2010) perform an inflation forecasting exercise conditional on pre-specified paths for oil price indicators. Schorfheide and Song (2013) produce inflation and growth forecasts conditional on forecasts that are obtained from judgmental sources. Other references on conditional forecasts include Sims (1982), Doan et al. (1984), Meyer and Zaman (2013) and Aastveit et al. (2014).

well. Indeed, our pessimistic forecast can serve as input for a wide range of Stress Testing models.

To implement our models empirically, we first need an operational definition of a recession. Obviously, a recession is a period running between a peak and the next trough of economic activity while an expansion is a period between a trough and the next peak.[3] We assume that the peaks and troughs of economic activity are observed (with a release lag) and that they coincide with the NBER dates.[4] Second, we need a model to predict the probability of a recession h quarters ahead. Sophisticated models that account for structural breaks and state dependence in the dynamics of the probability of a recession could have been used, as for example in Chauvet and Potter (2002) and Chauvet and Potter (2005). Here, we advocate a simple Probit model that allows us to obtain parsimonious closed form expressions for our conditional forecasts.

Our empirical application starts with a set of *in-sample* performance evaluation exercises. We find that a static Probit model that uses only Term Spread (TS) as regressor compares favorably to those that use more regressors, and to dynamic version of the model, especially at horizons three quarters and beyond. We compare the AAR to a simple AR model, an Augmented Distributed Lag (ADL) model and a Markov Switching (MS) model in terms of their ability to forecast GDP growth a few quarters ahead. The ADL model is a version of the AAR model that implicitly assumes a linear structure for the probability of a recession. The AR model produces uninformative forecasts as soon as the horizon exceeds three quarters. The MS model does well at horizons 1 and 2 but its performance deteriorates fast as h increases. The ADL model is less and less resilient than the AAR model as the forecast horizon increases.

We compare our model and the benchmarks above in a real-time out-of-sample forecasting exercise covering 1981Q1 - 2016Q4 period. Our AAR model outperforms the AR over the whole evaluation period and particularly during recessions. The performance is maximized at one-year horizon. The non-linearity of the Probit probability boosts the forecasting accuracy over the ADL model, but the improvement is tiny during NBER downturns. When compared to Markov switching

[3] The previous definition of a recession raises two practical issues. The first issue concerns the precise meaning of the expression "*economic activity*". The Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) does not provide a precise definition to this expression. Rather, it defines a recession as "*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.*" The second issue concerns the identification of the business cycle turning points (i.e., peaks and troughs of real economic activity) from the observed data. The Business Cycle Dating Committee does provide a precise response to the latter issue by regularly publishing recession dates with approximately one year lag.

[4] The business cycle dates can be found at http://www.nber.org/cycles.html.

models, our approach dominates uniformly over all forecast horizons during the whole evaluation period, and at horizons $h = 3$ and $h = 4$ quarters during recessions. Overall, the AAR model improves the forecast accuracy of GDP growth by up to 30% during recessions compared to the best nonlinear benchmark. Our method suits particularly well to produce real-time predictions of final releases of economic data before they become available, which is of great importance for policy makers.

Our finding that the predictability of economic series varies across the business cycle is not new in the literature. For instance, Rapach and Zhou (2010) and Gargano and Timmermann (2014) find that the predictability of the stock market and commodity prices is stronger during recessions. Kotchoni et al. (2019) document instabilities in the predictability of real activity variables, stock market returns, exchange rates and inflation growth. Chauvet and Potter (2013) use a methodology that is similar to ours and find an improvement in forecasting performance at short horizon. Our approach provides a simple and flexible nonlinear framework to forecast economic series in real time. Moreover, our first step Probit models captures recession signals quite well up to four quarters ahead. As a result, our AAR model improves the accuracy of GDP growth forecasts over the benchmark at longer horizons.

Finally, we use our model to conduct a real-time analysis of the Great Recessions.[5] Our results suggest that the AAR model delivers more accurate real-time forecasts than the benchmark models. We also find that the dynamics of the term structure of recession probabilities are quite informative about the business cycle turning points. Indeed, the shape of the term structure of recession probabilities switches from convex to concave before a recession and from concave to convex after a recession.

The remainder of the paper is organized as follows. Section 2 details the construction of the AAR model. Section 3 motivates the static Probit model used for the probability of recessions and discusses alternative approaches. Section 4 presents our strategy to infer turning points from the term structure of the probability of recession in real time. Section 5 presents the empirical application, and section 6 concludes. A separate document contains supplementary material.

[5]First, we estimate a static Probit model for the probability of a recession and an AAR model for the GDP growth using a sample that stops at the latest official turning point before the recession. Second, the estimated parameters and the most recent release of GDP are plugged into the AAR model to obtain forecasts of the probability of a recession and of GDP growth rate at different horizons. Finally, benchmark models are estimated and their out-of-sample predictions compared to those of the AAR model.

2 Modeling the Economic Activity

Let y_t denote an economic activity variable (e.g., GDP growth, unemployment rate, etc.), $R_t \in \{0,1\}$ the indicator of recession[6] at time t and X_t a set of potential predictors of recessions. Our main objective is to produce multi-horizon forecasts of the variables y_t. For that purpose, we consider using a family of Augmented AutoRegressive (AAR) models specified at a quarterly frequency.

The intended models normally take the form:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + \delta_h R_{t+h} + v_{t+h}, \tag{1}$$

for $t = 1, ..., T-h$, where $h \geq 1$ is the forecast horizon and $v_{t+h} \sim N(0, \sigma_h^2)$ is a Gaussian error term. This error is assumed potentially correlated with R_{t+h} but uncorrelated with lagged realizations of y_t. Unfortunately, these models cannot be used for real time forecasting as the right hand side contains a regressor that is not yet observed at period t.

Taking the expectation of y_{t+h} conditional on the information available at time t yields:

$$E\left(y_{t+h}|y_t, X_t\right) = \rho_{h,0} + \rho_{h,1} y_t + \delta_h \Pr\left(R_{t+h} = 1|y_t, X_t\right).$$

Historical values of the economic activity variable y_t might have been used by the economists of the NBER to produce the series R_t. Therefore, there is a risk that a model that forecasts the probability of a recession at period $t+h$ conditional on an information set that includes y_t be spuriously good in-sample and bad out-of-sample. To avoid this issue, we posit that the probability of a recession at period $t+h$ depends on X_t only. Moreover, we advocate a functional form that leads to a Probit model:

$$\Pr\left(R_{t+h} = 1|y_t, X_t\right) = \Pr\left(R_{t+h} = 1|X_t\right) = \Phi\left(X_t \gamma_h\right), \tag{2}$$

where Φ is the cumulative distribution function (CDF) of the standard normal random variable. Therefore, an equation that expresses the expected value of y_{t+h} in terms of quantities that depends

[6] That is, $R_t = 1$ if the NBER dating committee designated period t as a recession time and $R_t = 0$ otherwise.

on the information available at time t is given by:

$$E\left(y_{t+h}|y_t, X_t\right) = \rho_{h,0} + \rho_{h,1} y_t + \delta_h \Phi\left(X_t \gamma_h\right) \equiv \widehat{y}_{t+h}, \tag{3}$$

Accordingly, y_{t+h} may be represented as an Augmented Autoregressive (AAR) process as follows:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + \delta_h \Phi\left(X_t \gamma_h\right) + \widetilde{v}_{t+h}, \tag{4}$$

where $\widetilde{v}_{t+h} \equiv v_{t+h} + \delta_h \left(R_{t+h} - \Phi\left(X_t \gamma_h\right)\right)$ is a zero mean error term.

Interestingly, our AAR model can be casted in the neural network framework as depicted in Figure 1. The inputs for the Probit part feed the one neuron hidden layer with normal CDF as activation function. Then, the signal is sent to the output layer together with other inputs, the lagged values of y_t. Of course, the neural network can be much more flexible by selecting among many forms of architectures: more than one hidden layer and neurons, different activation functions, recurrent framework and back-propagation among others. Nevertheless, our framework does not require fixing a huge number of hyperparameters nor numerical optimization of highly non-convex objective function with a large number of parameters. It requires only simple estimation procedures and few data. Since it is very parsimonious, it is not prone to overfitting contrary to machine learning and time-varying parameters methods. Therefore, it is appealing for practitioners who want to monitor the economic activity in real time.

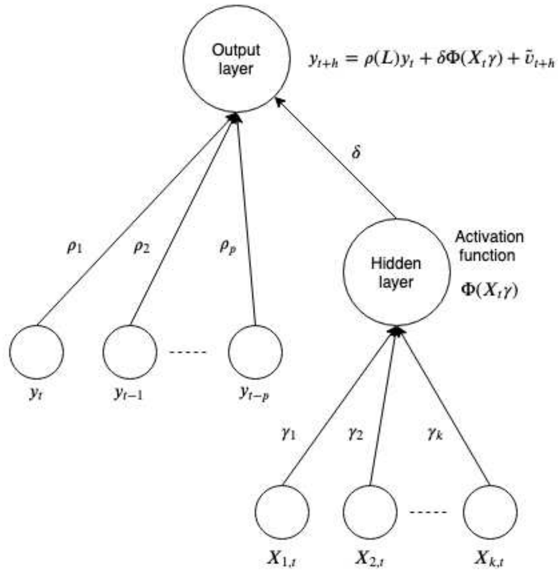
Note that the forecasting formula (3) exploits the information content of X_t in a nonlinear manner. This suggests an alternative ADL model where X_t enters linearly in the right hand side. That is:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + X_t \beta_h + \varepsilon_{t+h}, \tag{5}$$

where ε_{t+h} is an error term. The model above implicitly assumes a linear structure for the probability of a recession. ADL models similar to this have been explored, among others, in Gilchrist et al. (2009), Chauvet and Potter (2013) and Ng and Wright (2013). The valued added of the AAR model (4) vis-à-vis the ADL model (5) is attributable to nonlinearity.

It is possible to go one step beyond the average forecast (3) by taking advantage of the observability of the recession dates (R_t). Indeed, a forecast can be generated based on the pessimistic

Figure 1: Neural network representation of the AAR model



scenario that the economy will experience a recession at horizon $t+h$, i.e.:

$$E\left(y_{t+h}|y_t, X_t, R_{t+h}=1\right) = \rho_{h,0} + \rho_{h,1}y_t + \overline{\delta}_h + \delta_{h,1}E\left(\widetilde{v}_{t+h}|y_t, X_t, R_{t+h}=1\right).$$

Under a joint normality assumption on v_{t+h} and the error term $(u_{h,t})$ of the latent equation underlying the Probit (2), we obtain:

$$E\left(y_{t+h}|y_t, X_t, R_{t+h}=1\right) = \rho_{h,0} + \rho_{h,1}y_t + \overline{\delta}_h + \delta_{h,1}\frac{\phi\left(X_t\gamma_h\right)}{\Phi\left(X_t\gamma_h\right)} = \underline{y}_{t+h}, \tag{6}$$

where $\delta_{h,1} = Cov\left(u_{h,t}, v_{t+h}|R_{t+h}=1\right)$, ϕ is the probability distribution function (PDF) of the standard normal random variable, $\overline{\delta}_h$ is a constant shift and $\delta_{h,1}\frac{\phi(X_t\gamma_h)}{\Phi(X_t\gamma_h)}$ stems from a "break" in the structure of dependence between y_{t+h} and X_t due to the recession. Note that this break is absent when v_{t+h} is uncorrelated with recessions so that $\delta_{h,1}=0$. The pessimistic forecast may be used to assess how severe a recession is expected to be if it were to effectively occur at the forecast horizon. This kind of formula can be used to perform a wide range of stress testing exercise in the banking sector, anticipate extreme losses on a portfolio or assess the fragility of the housing sector.

Likewise, another forecast based on the optimistic scenario of no recession at horizon $t+h$ can be computed as:

$$E\left(y_{t+h}|y_t, X_t, R_{t+h}=0\right) = \rho_{h,0} + \rho_{h,1} y_t + \delta_{h,0} \frac{-\phi\left(X_t \gamma_h\right)}{1-\Phi\left(X_t \gamma_h\right)} = \overline{y}_{t+h}, \tag{7}$$

where $\delta_{h,0} = Cov\left(u_{h,t}, v_{t+h}|R_{t+h}=0\right)$ and $\delta_{h,0}\frac{\phi(X_t\gamma_h)}{1-\Phi(X_t\gamma_h)}$ is a break that marks expansion periods. This optimistic forecast can be used to assess how favorable the economic conjuncture is expected to be if an expansion were to occur at the forecast horizon.

The variables $\frac{\phi(X_t\gamma_h)}{\Phi(X_t\gamma_h)}$ and $\frac{-\phi(X_t\gamma_h)}{1-\Phi(X_t\gamma_h)}$ are the well-known IMRs. The parameters $\overline{\delta}_h$, $\delta_{h,0}$ and $\delta_{h,1}$ are all expected to be negative if y_t is pro-cyclical (that is, if y_t increases during expansions and shrinks during recessions). In our framework, the terms $\delta_{h,1}\frac{\phi(X_t\gamma_h)}{\Phi(X_t\gamma_h)}$ and $\delta_{h,0}\frac{-\phi(X_t\gamma_h)}{1-\Phi(X_t\gamma_h)}$ capture the combined effects of factors that are hard to measure such as supply and demand shocks, policy responses to these shocks, investors sentiments, consumer confidence, agents anticipations, etc.

Pooling the forecasting formulas (6) and (7) yields:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + \overline{\delta}_h R_{t+h} + \delta_{h,0} IMR_{t,h,0} + \delta_{h,1} IMR_{t,h,1} + \widetilde{\widetilde{v}}_{t+h}, \tag{8}$$

where $\widetilde{\widetilde{v}}_{t+h}$ is a zero mean error term and:

$$IMR_{t,h,1} = \begin{cases} \frac{\phi(X_t\gamma_h)}{\Phi(X_t\gamma_h)} & \text{if } R_{t+h}=1, \\ 0 & \text{otherwise.} \end{cases},$$

$$IMR_{t,h,0} = \begin{cases} \frac{-\phi(X_t\gamma_h)}{1-\Phi(X_t\gamma_h)} & \text{if } R_{t+h}=0, \\ 0 & \text{otherwise.} \end{cases}.$$

To implement the AAR model empirically, we first estimate a Probit model for the probability of recessions to obtain $\widehat{\gamma}_h$. This estimate is used to compute fitted values for the probability of recession $\widehat{P}_{t,h} = \Phi\left(X_t \widehat{\gamma}_h\right)$ and for the IMRs $\widehat{IMR}_{t,h,1}$ and $\widehat{IMR}_{t,h,0}$. The average forecasts are obtained as the fitted values of the following OLS regression:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + \delta_h \widehat{P}_{t,h} + e_{t+h}, \tag{9}$$

where e_{t+h} is an error term. Finally, the parameters used to compute the optimistic and pessimistic forecasts are deduced from the following OLS regression:

$$y_{t+h} = \rho_{h,0} + \rho_{h,1} y_t + \overline{\delta}_h \widehat{P}_{t,h} + \delta_{h,0} \widehat{IMR}_{t,h,0} + \delta_{h,1} \widehat{IMR}_{t,h,1} + \widetilde{e}_{t+h}, \tag{10}$$

where $\widetilde{e}_{t+h}$ is an error term. Recall that R_{t+h} is replaced by $\widehat{P}_{t,h}$ above as a means to avoid endogeneity biases.

An alternative framework to produce state-dependent forecast of economic activity is provided by the Markov Switching (MS) model of Hamilton (1989). The simplest version of this model allows only the intercept to be state-dependent as follows:

$$y_{t+h} = \mu_{R_t} + \rho y_t + \varepsilon_{t+h} \tag{11}$$

where $\varepsilon_{t+h} \sim N(0, \sigma_\varepsilon^2)$. In a more flexible specification, the autoregressive root is allowed to be state-dependent as well:

$$y_{t+h} = \mu_{R_t} + \rho_{R_t} y_t + \varepsilon_{t+h} \tag{12}$$

It is further possible to let the variance of ε_{t+h} depend on R_t. However, we restrict (11) and (12) to the homoskedastic case in our empirical applications.

Chauvet and Potter (2013) obtained a model that is similar to our AAR model by augmenting an autoregression with the probability of recession as predicted by a dynamic factor regime switching model. Our approach differs from the one of Chauvet and Potter (2013) in that we treat the recession indicator R_t as observed (up to a release lag) and we specify its probability as a function of the lags of other explanatory variables rather than the lags of R_t itself. Another important contributon of our approach is that it explicitly takes the endogeneity of recessions into account when computing the optimistic and pessimistic forecast. This endogeneity is reflected in the correlation between the latent variable of the Probit and the error term of the equation that is used to forecast the economic activity variables.

3 Modeling the Probability of Recession

In the previous section, we have chosen to model the probability of a recession using a static Probit for three reasons. First, this model has a structural flavor as it emerges naturally from assuming the existence of a latent lead indicator $Z_{h,t}$ that takes the form:

$$Z_{h,t} = X_t \gamma_h + u_{h,t}, \text{ for all } t \text{ and } h, \tag{13}$$

with $u_{h,t} \sim N(0,1)$, and which satisfies:

$$R_{t+h} = \begin{cases} 1 & \text{if } Z_{h,t} > 0, \\ 0 & \text{otherwise.} \end{cases} . \tag{14}$$

Second, our optimistic and pessimistic forecasting formulas depends on the expressions of $E\left(v_{t+h}|X_t, R_{t+h}\right)$. These expressions are easily calculated by assuming that $(u_{h,t}, v_{t+h})$ are jointly Gaussian, for all $h \geq 1$.[7] The third argument in favor of the static Probit model is that it is transparent and easy to replicate.[8]

The IMR terms resulting from the calculation of $E\left(v_{t+h}|X_t, R_{t+h}\right)$ have the usual interpretation of Heckman (1979)'s sample selection bias correction. Indeed, the Probit model (13)-(14) may be viewed as an attempt to infer the behavior of the NBER dating committee from historical data. The AAR model attempts to capture patterns in the data that prompted the NBER committee to label certain dates as recessionary and others as expansionary. Business cycle turning points are announced with up to four quarters lags. As suggested by Wright (2006), a probabilistic model like the one above is interesting in its own as it can be trained on historical data and used to infer the next tuning point pending an NBER official announcement.

The exercise which consists of predicting the probability of recessions is not new in the literature. Stock and Watson (1989) use a probabilistic framework to construct a coincident and a leading index of economic activity as well as a recession index. Estrella and Mishkin (1998) examine

[7]Note that it is not clear how one would generate conditional forecasts analogue to (6) and (7) in the context of the ADL model.

[8] Kauppi and Saikkonen (2008) and Hao and Ng (2011) find that dynamic Probit models improve upon the static Probit, especially when predicting the duration of recessions. However, the dynamic feature of these models makes them unsuitable for a real-time forecasting exercise as R_t is usually observed with at least one-year lag. A static Probit that uses financial predictors released at high frequency does not suffer from this shortcoming.

the individual performance of financial variables such as interest rates, spreads, stock prices and monetary aggregates at predicting the probability of a recession. They find that stock prices are good predictors of recessions at one to three quarters horizon while the slope of the yield curve is a better predictor beyond one quarter. The forecasting power of the yield curve is also documented in Rudebusch and Williams (2009), who find that professional forecasters do not properly incorporate the information from the yield spread. Nyberg (2010) advocate a dynamic Probit model and find that in addition to the TS, lagged values of stock returns and foreign spreads are important predictors of a recession. Anderson and Vahid (2001) apply nonlinear models to predict the probability of U.S. recession using the interest-rate spread and money stock (M2) growthWright (2006) estimates several Probit models and finds that adding the FFR to the TS outperforms the model of Estrella and Mishkin (1998) that used the TS only. Christiansen et al. (2013) find that sentiment variables have predictive power beyond standard financial series.

Of course, the predictors' set, X_t, could be large and various data-rich approaches can be used to model and predict the probability of a recession, see for instance Stock and Watson (2013) and Ng (2014). These methods can be easily adapted to our framework but for the sake of simplicity and tractability we stick to the simplest, and the most robust, static Probit model with a small set of leading financial indicators.

4 Predicting Turning Points in Real Time

There is a difference between the prediction of the probability of a recession and the prediction of the beginning and the end of a recession. The latter exercise is slightly more difficult as it requires decision science tools in addition to a probabilistic model. This section discusses how to infer turning points from the predicted probabilities of the recession in real time.

At a quarterly frequency, the first release of GDP is available with one lag while the 'final' value is released with approximately one year lag.[9] The NBER turning points are released with at least four lags. These aspects may be ignored if we are interested only in assessing the *in-sample* performance of the Probit and AAR models based on historical data. However, a strategy to deal with release lags is needed if one wishes to conduct a real time analysis.

[9] In the realm of real time data, the "final value" of a variable is a release that is unlikely to be revised in the future. Strictly speaking, there is actually no final value.

If the current period is t^* and the latest turning point occurred at period $t^* - l$, then the final releases of NBER recession dates are available in real time only up to period $t^* - l$. Therefore, we can use fully revised data covering the periods $[1, t^* - l]$ to estimate the probability of recessions at any horizon h. We have:

$$\Pr\left(R_{t+h} = 1 | X_t\right) = \Phi\left(X_t \gamma_h\right), \; t \in [1, t^* - l - h].$$

The estimate $\widehat{\gamma}_h$ of γ_h obtained from above can be used to generate out-of-sample forecasts of the probability of recession. As we choose to include only high frequency financial variables in X_t, this out-of sample exercise does not suffer from release lag issues. We therefore can compute $\widehat{P}_{t,h} = \Phi\left(X_t \widehat{\gamma}_h\right)$ as well as the variables $\widehat{IMR}_{t,h,0}$ and $\widehat{IMR}_{t,h,1}$ for periods $t \in [1, t^*]$. Note that the out-of-sample periods run from $t^* - l - h + 1$ to t^* for this Probit.

The next step is to estimate the AAR model for an economic activity variable based on the available information. At a quarterly frequency, the first release of economic activity variables is generally available with only one lag. Nonetheless, we constrain the in-sample period to be the same as for the Probit model. That is, we estimate Equations (9) and (10) by OLS using the sample covering the periods $t \in [1, t^* - l - h]$. At time t^*, the most recent release of the GDP growth is for the period $t^* - 1$. Equations (3), (6) and (7) take this latest release and the estimates $\widehat{\gamma}_h$ as input to return nowcasts ($h = 1$) and forecasts ($h > 1$) of economic activity. A similar strategy is employed for the ADL and MS models.

Using our static Probit model, we can calculate the term structure of the probability of recession at a given period t as the mapping $P_t : h \mapsto \Phi\left(X_t \widehat{\gamma}_h\right)$, $h \geq 1$. As we move forward from period t to periods $t+1$, $t+2$, etc., the term structure of recession probabilities is updated to P_{t+1}, P_{t+2}, etc. Our empirical experiments show that the sequence $P_t, t > 1$ is clustered into successive blocs of convex and concave curves. This suggests two possible strategies to identify turning points.

The first strategy relies on the upper envelope of the concave blocks and the lower envelope of the convex blocs. Suppose that at period t the term structure of recession probabilities P_t is concave. At that period, the next business cycle peak is predicted to occur at $t + h_t$, where h_t is the horizon where P_t is maximized. If P_t, P_{t+1}, ..., P_{t+H}, $H \geq 1$ is a block of concave term structure of recession probabilities, then we can compute an upper envelope curve for this bloc and predict the beginning of the next recession as the maximum of this curve. Business cycle troughs are predicted similarly. If P_t is convex, then the next business cycle trough is expected to occur at $t + \tau_t$, where τ_t is the horizon that minimizes P_t. Considering a bloc P_t, P_{t+1}, ..., $P_{t+L}, L \geq 1$ of convex term structure of recession probabilities, we can compute a lower envelope curve for this bloc and predict the end of the next recession as the minimum of this curve.

The second strategy relies on the timing of the changes in the shape of the term structure of recession probabilities. Indeed, a convex term structure curve of recession probabilities suggests that recession is less and less likely for some time. If this curve suddenly switches from convex to concave, this suggests that a new signal that raises the prospects of a recession just came in. One might therefore want to predict the beginning of the next recession as $t+h_t$, where h_t is the horizon that maximizes P_t, and P_t is the beginning of a concave block. Likewise, the end of a recession may be predicted as $t + \tau_t$, where τ_t is the horizon that minimizes P_t and P_t is the beginning of a convex block.

5 Empirical Application

For this application, we use the quarterly NBER recession indicator available in the FRED2 database. Data on TS, CS and FFR are also obtained from the same source.[10] The real time vintages of GDP data are obtained from Federal Reserve Bank of Philadelphia real-time data sets for macroeconomists. The time span starts in 1959Q1 and ends in 2016Q4. We consider three different designs for X_t. In the first design, X_t is restricted to contain TS only. In the second design, X_t contains TS and CS. In the third design, X_t contains TS, CS as well as FFR. It is found that the addition of CS and FFR to TS generally adds little to the predictive power of our Probit models, especially at horizons beyond $h = 2$ quarters. Therefore, most of the results presented here are for the case where X_t reduces to TS. Additional results are in the supplementary material.

[10]The TS is defined as difference between a 10-Year Treasury Constant Maturity Rate (labelled GS10 in FRED2) and a 3-Month Treasury Bill: Secondary Market Rate (TB3MS). The credit spread (BAA10YM) is Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity.

5.1 Full-Sample Analysis

This section presents in-sample forecasts based on models that are estimated on the full sample. The sample used here consists of historical data. Accordingly, release lag issues are ignored.[11]

5.1.1 Term Structure of recession probabilities

Figure 2 shows a 3-D plot of the term structures of the probabilities of recession. The two horizontal axes are respectively the time stamp of the information set used to compute the term structure curves and the horizons to which the predicted probabilities of recessions belong. We see that this figure consists of clusters of concave and convex curves. Indeed, the term structure curves are concave in the neighbourhood of and during recessions while they are convex during expansions. The shape of the term structure curves conveys a more reliable signal than its level about the prospects of a recession. This claim is better illustrated by other 2-D plots that are shown in subsequent analyses.

One possible approach to reduce the dimensionality of the information contained in this 3-D plot is to summarize each term structure curve into a single number measuring its shape: the Term Spread of recession probabilities. Here, we consider the spreads obtained by respectively taking the probabilities of recession three, four and five quarters ahead minus the probability of recession one quarter ahead. Figure 3 shows the results. We see that the beginning of each recession is immediately preceded by a large peak in the Term Spread curves.

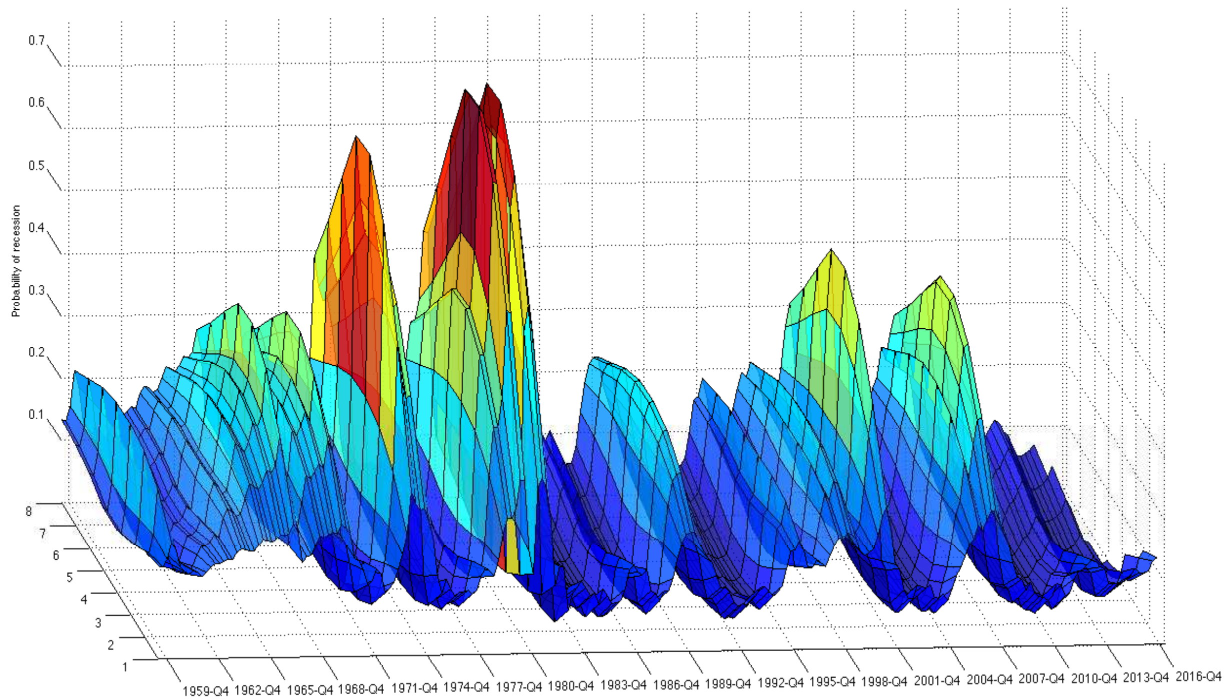
A few peaks of the Term Spread of recession probabilities are observed at periods that have not been declared recessionary by the NBER. Such peaks may be indicating short episodes during which the economy underperformed or recessions that have been avoided due to timely and adequate policy responses. It is interesting to note that the Term Spread of recession probabilities exhibits no significant peak since 2010Q4.

5.1.2 In-sample prediction of GDP growth

We now compare the performance of the AAR model to that of the benchmark models (namely the AR, ADL and MS) at predicting GDP growth. Figure 4 shows the adjusted R-squared of the AR, ADL and AAR models on the left vertical axis and the Student t-stat associated with $\widehat{\delta}_h$ on the

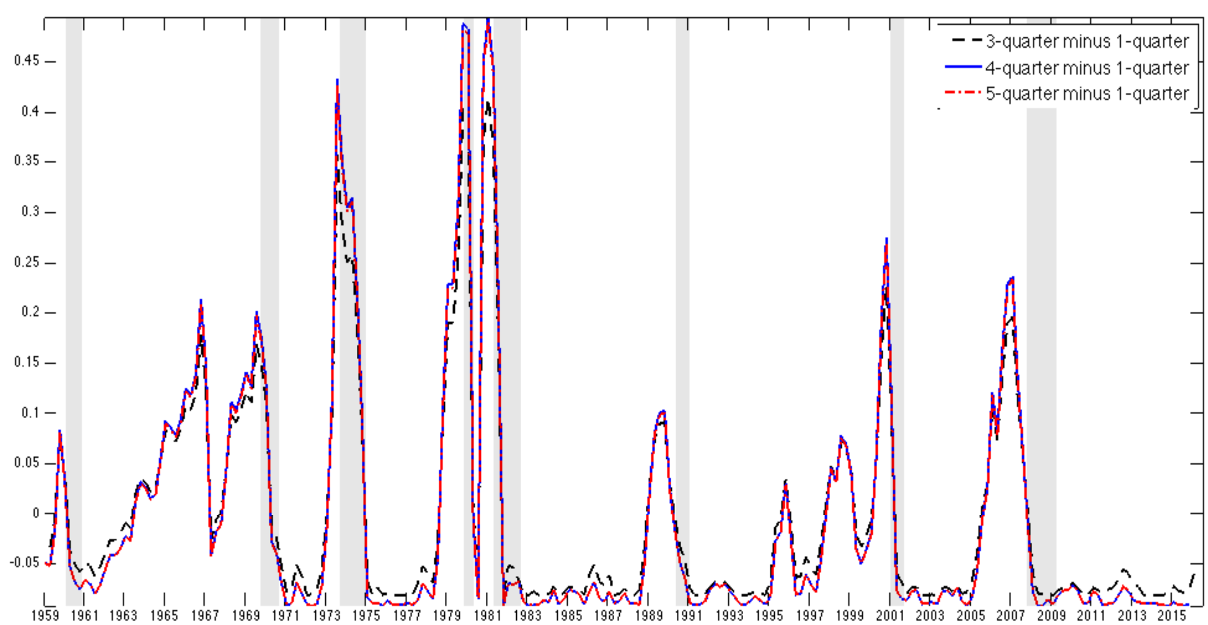
[11] Hence, the full sample ends on 2016Q4 and contains only the most recent values of GDP, as obtained from the 2017Q1 vintage.

Figure 2: Full-sample Term Structure of recession probabilities



This figure plots the full-sample Term Structure of recession probabilities, 1 to 8 quarters ahead, from static Probit model having the term spread as the only predictor. The periods correspond to information set when the forecasts have been constructed.

Figure 3: Full-sample Term Spread of recession probabilities

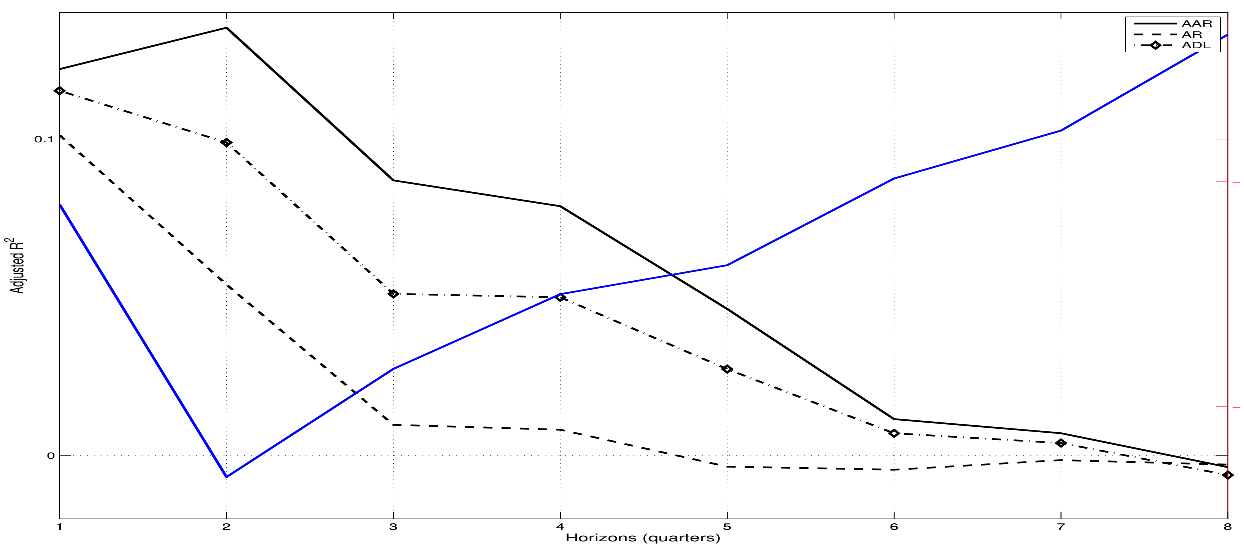


This figure shows the full-sample Term Spread of recession probabilities from static Probit model having the term spread as the only predictor. 3-quarter minus 1-quarter *stands for 3-quarter minus 1-quarter ahead forecasted recession probabilities.*

right vertical axis. Recall that the AAR models reduces to an AR model when $\delta_h = 0$. We see that the adjusted R-squared is larger for the AAR model than for the AR at horizons $h = 1$ to $h = 7$. Accordingly, the parameter δ_h is estimated to be significant for these lags (i.e., t-stat larger than 2 in absolute value). The gap between the adjusted R-squares of the two models decreases with h and the AR model underperforms the historical average at lags beyond $h = 4$.

The ADL model fits that data better than the AR model but underperforms the AAR model. This suggests that the nonlinear transformation applied to X_t prior to its inclusion in the right hand side of Equation (4) matters. Putting it differently, the probability of recession at a given horizon is a relevant predictor of GDP growth at that horizon.[12]

Figure 4: Predicting GDP growth: In-sample goodness-of-fit



This figure shows the adjusted R^2 of the AAR, AR and ADL models on left vertical axis (full black line and dotted lines respectively), and the Student t-stat associated with $\widehat{\delta}_{i,h}$ on the right vertical axis. The probabilities of recession have been estimated from the static Probit model conditioned on TS only.

5.2 Real-Time Out-of-Sample Analysis

We now explore the performance of our forecasting strategies in a real-time out-of-sample forecast exercise. The OOS evaluation period spans 1981:Q4-2015:Q4. We stop the sample at the end of 2015 in order to have all data releases available. First, we re-examine the performance of our method to predict turning points based on term structures of recession probabilities that are computed out-of-sample. Next, we examine the performance of the AAR model at predicting GDP growth.

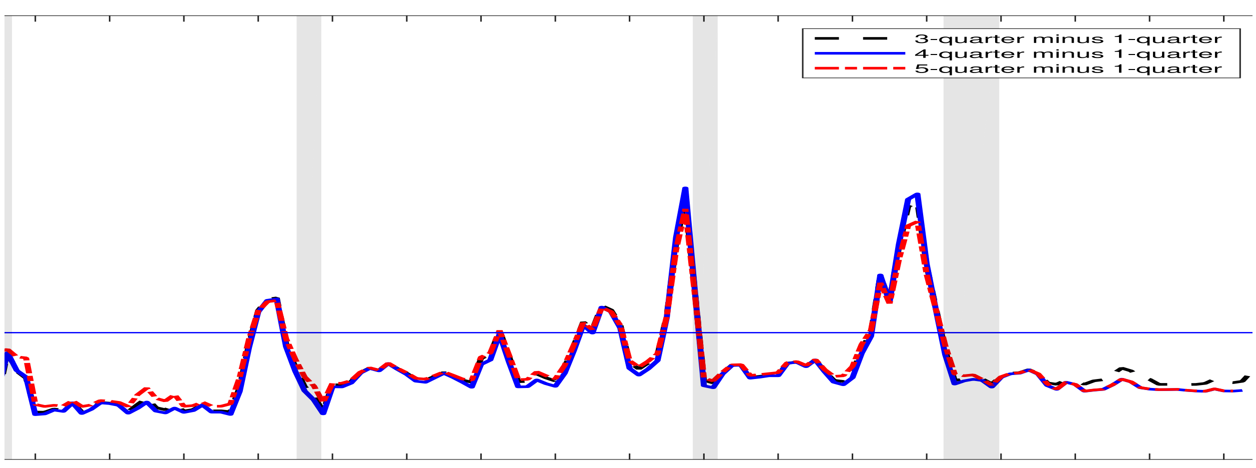
[12]The supplementary material contains graphical comparisons of in-sample forecasts of all predictive models.

5.2.1 Predicting Recessions in Real Time

Figure 2 and Figure 3 were computed using in-sample predictions of models that are estimated using final releases. We redo the same exercise in real time. That is, we estimate Probit models for the probability of recession using a sample that stops at the latest official NBER turning point. The parameter estimates obtained from these models are then used to make out-of-sample predictions. Figure 5 shows the out-of-sample predictions of the Term Spread of recession probabilities over the whole out-of-sample period. We see that the results are qualitatively similar to what we have found in the in-sample analysis. Recessions are always announced by a large peak in the term spread of recession probabilities. Quantitatively, the out-of-sample predictions of the term spreads tends to be uniformly lower than their in-sample counterparts.

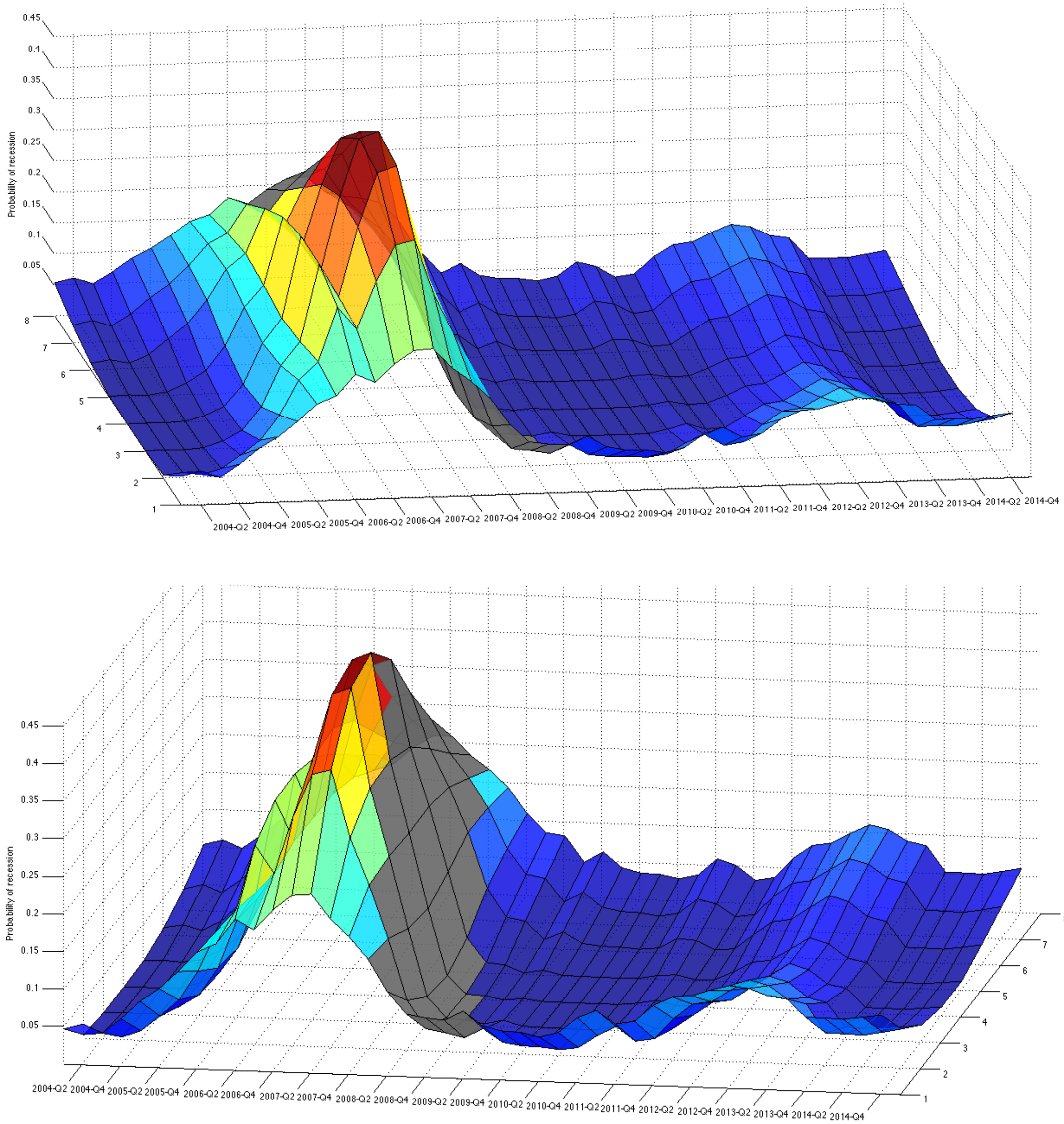
Figure 6 shows a 3-D plot of the term structure of recession probabilities that focuses on the most recent recession. Clearly, the switching of the term structure curve from convex to concave has been a warning sign of the recession. Likewise, as the recession approached its end, the term structure curve moved slowly from concave to convex. The level of the term structure curves have been changing since 2010, but its shape remains convex. The fact that the out-of-sample predictions of the term structure of recession probabilities behaves qualitatively as the in-sample predictions is quite reassuring but not surprising. This is attributable to the parsimonious parameterization of the probit models on which the predictions are based.

Figure 5: Out-of-sample Term Spread of recession probabilities



This figure shows the out-of-sample Term Spread of recession probabilities from static Probit model having the term spread as the only predictor. 3-quarter minus 1-quarter *stands for 3-quarter minus 1-quarter ahead forecasted recession probabilities.*

Figure 6: Out-of-sample Term Structure of recession probabilities



This figure plots the out-of-sample Term Structure of recession probabilities, 1 to 8 quarters ahead, from static Probit model having the term spread as the only predictor. The periods correspond to information set when the forecasts have been constructed.

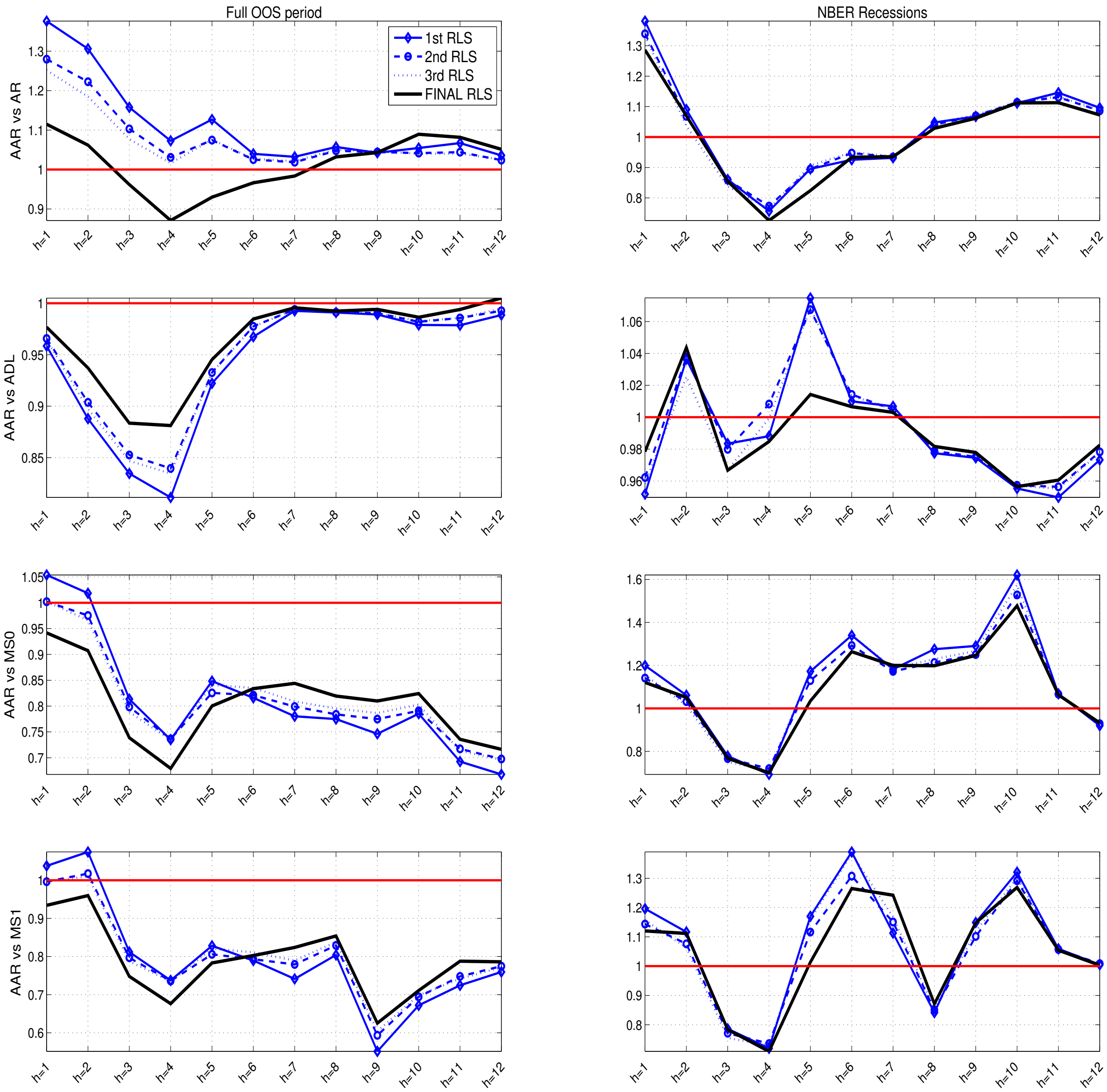
5.2.2 Forecasting GDP Growth

In this section we compare the forecasting performance of our AAR model versus the linear and nonlinear benchmarks. The analysis is done in real time and on an out-of-sample (OOS) basis. The OOS evaluation period spans 1981:Q4-2015:Q4. The models are estimated recursively from 1959:Q1 and are updated only at the NBER announcements. We consider forecasting economic activity variables 1 to 12 quarters ahead. The performance metrics advocated is the mean squared error (MSE). In all tables, we always show the ratio of MSEs between the AAR and the competing model. If this ratio is lower than 1, this means that the AAR produces more accurate forecasts than the competing model. In the main text, we show the results that are based on the Probit model that uses the TS only as predictor.

Figure 7 shows the performance of the models on the full out-of-sample period and during recession periods only. As the analysis is done in real time, we are able to construct forecast errors with respect to the first, second, third and the final release of the GDP. The final releases are the best approximations of the actual data of interest which, in the realm of real-time analysis, are considered latent. Therefore, it is important to assess the ex-post accuracy of real-time forecasts for subsequent releases.

Comparing the AAR to the AR model on the period 1981-2015 (Figure 7, upper left panel), we see that adding the probability of recession to the AR improves its forecasting accuracy for final releases by more than 10% at one-year horizon. The AAR model delivers a smaller relative MSE for horizons 3 to 7 quarters for final releases, but it is outperformed at all horizons when predicting the initial releases. As expected, the relative out-of-sample performance of the AAR improves significantly during NBER recessions (Figure 7, upper right panel). The largest performance improvements are observed at horizons between 3 and 7 quarters. At one-year horizon, the relative efficiency of the AAR is as large as 30%. The results are qualitatively similar across releases, but the relative efficiency of the AAR is maximized for the final release. This is an important result given that revisions tends to be important during recession (see the section on the Great Recession in the sequel). Having an approach in hand to predict accurately the final releases in real-time is crucial for policy makers, investors and statistical agencies that are in charge of nowcasting and revision of the national accounts forecasts.

Figure 7: Out-of-sample performance of AAR model



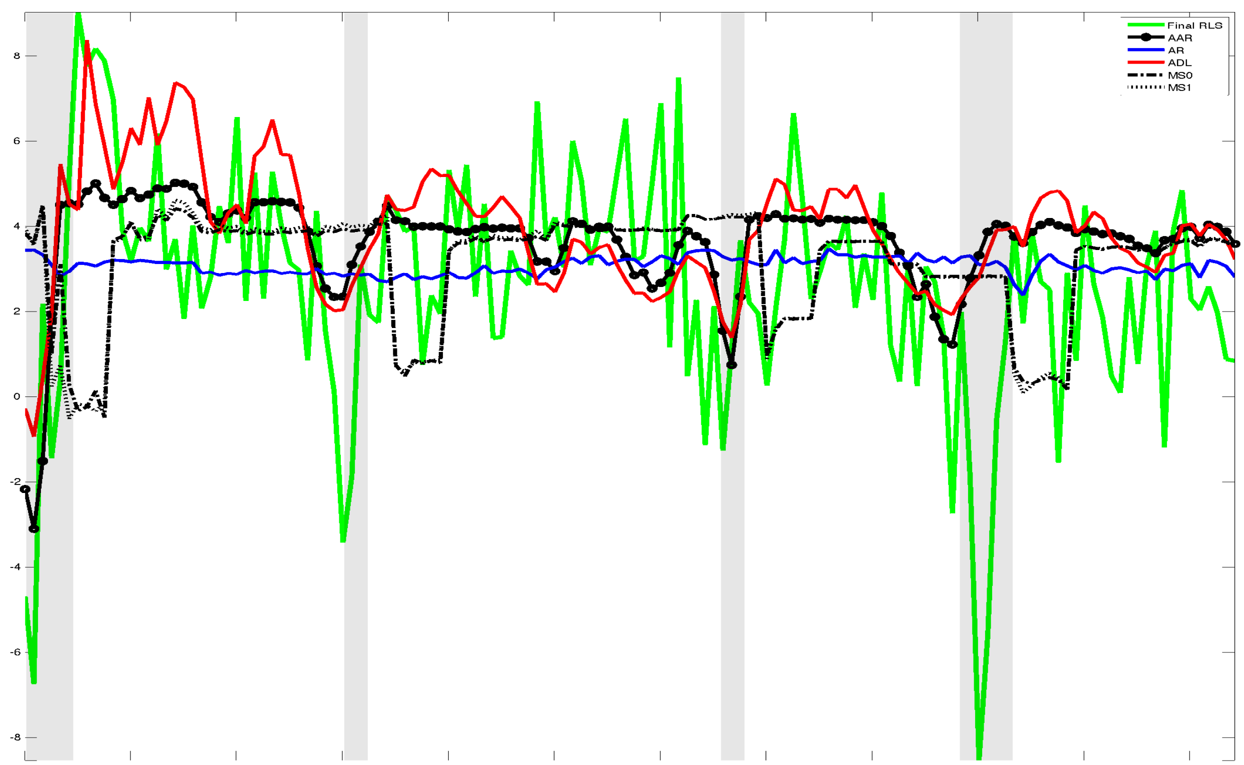
This figure shows the ratio of the AAR mean squared errors over the competing models for the full out-of-sample period, the left column, and during the NBER recessions, the right column. ADL correspond to model in (5). MS0 and MS1 are the Markov Switching models (11) and (12) respectively. 1st RLS, 2nd RLS, 3th RLS *and* Final RLS *stand for data releases.*

The second row of Figure 7 compares the AAR and ADL model. Recall that the difference between the AAR and the ADL rests on the treatment of the Term Spread (i.e., nonlinear for the AAR and linear for ADL). Considering the full out-of-sample period, the AAR outperforms the ADL uniformly over the forecast horizons with the smallest relative MSE occurring around horizons 3 and 4 quarters (12% for the final release and nearly 20% for the 1st release). This good performance of the AAR is attributable to the non-linear treatment of the TS done via the probability of recessions. In fact, the contribution of Term Spread to the predictions of the AAR is negligible during no-recession periods where the probability of a recession is close to zero while the ADL always imposes the same marginal effect for TS. Note however that the AAR does not uniformly dominate the ADL across horizons during NBER recession periods. The AAR still displays a smaller relative MSE at several horizons for the final release.

Finally, the last two rows of Figure 7 compares the AAR model to two popular nonlinear alternatives. MS0 is the two-state Markov switching model (11) where only the intercept is state dependent. The AAR model outperforms the Markov switching models on the full OOS period and at all forecast horizons for the final release. The improvement attains more than 30% at one-year horizon compared to MS0 and nearly 40% at $h = 9$ with respect to MS1. During recessions, the Markov switching models perform better except at horizons 3 to 4 quarters where the predictive power of the Probit model is maximized (hence the good performance of AAR at these horizons). Indeed, the AAR model delivers predictions that are up to 20% more accurate than the forecasts made by MS models at horizons 3 and 4. The reason is rather simple. The AAR model relies on a first step probabilistic model that exploits the forward looking information contained in the TS. This forward looking information is brought into the forecasting equation much earlier than in the MS model, where a rather large change in GDP must occur before we observe a change in the value of the state variable. Moreover, GDP data are available with one quarter lag and subject to large revision during crises. The observability of the NBER recessions therefore gives some milage to the AAR approach at horizons where the signal that leads recessions (i.e., the probability of recessions) is maximized.

Figure 8 plots the real-time out-of-sample forecasts of the GDP growth 4-quarters ahead as well as the final release. Table (1) presents the usual statistics: MSPE, bias and variance ratio of the AAR model over the alternative models and the p-values of Diebold-Mariano's accuracy test. The AR forecast is weakly oscillating around the unconditional average of the GDP growth, hence the bias is low but the variance of the forecast error is high. The ADL is closer to the AAR during recessions but is more biased otherwise. The AAR performs better than Markov Switching for a reason that was mentioned previously. Namely, the signal that leads recessions is taken into account early by the AAR via the first step probit that conditions the probability of recessions on forward looking financial variables. The MS models relies more on a delayed signal. Table (1) shows that over the full out-of-sample, the AAR model outperforms significantly the MS models in terms of MSPE. This good performance of the AAR model compared to the AR and Markov Switching models is mainly attributable to the variance. With respect to ADL, the AAR produce more than 20% less biased forecasts. During NBER recessions, the over-performance of the AAR is attributable to bias reduction.[13] This is again relevant for policy makers since the bias is very important during economic downturns.

Figure 8: Out-of-sample 4-quarter ahead forecasts



This figure shows the real-time 4 quarters ahead forecasts of the GDP growth. ADL correspond to model in (5). MS0 and MS1 are the Markov Switching models (11) and (12) respectively. Final RLS *stand for the final data release.*

5.3 Real-Time Analysis of the Great Recession

Policy makers and investors attach a high value to forecast accuracy during recession episodes. Typically, recession episodes are shorter than expansion episodes and characterized by rapid changes in the values of many economic indicators. Moreover, economic activity data that are released

[13]Diebold-Mariano p-values should be taken with a grain of salt since there are only 16 periods of recessions.

Table 1: Performance statistics for 4-quarter ahead forecasting

	Full out-of-sample				NBER Recessions			
AAR w/r	MSPE	DM	Bias	Variance	MSPE	DM	Bias	Variance
AR	0.8709	0.0459	2.3169	0.7588	0.7260	0.0811	0.7165	1.2968
ADL	0.8812	0.0370	0.7873	0.9520	0.9847	0.4256	0.9052	1.2537
MS0	0.6793	0.0468	1.9161	0.5940	0.7002	0.0946	0.6946	1.3463
MS1	0.6763	0.0450	1.9205	0.5911	0.7090	0.1067	0.7194	1.1686

Note: This table shows the real-time out-of-sample forecasting statistics of the AAR model against the alternatives. Forecasting errors are calculated with final release data. MSPE stands for the ratio of AAR mean squared predictive error over the alternative. DM stands for p-value of Diebold-Mariano test (Clark-West adjustment has been used for comparison between AAR and AR because the models are nested). Bias (Variance) stand for ratio of bias (variance) of AAR over the alternative models.

during recession episodes tend to undergo more or less important revisions. It is therefore of interest to assess how well our models perform during those periods where economic data are harder to track than usual.

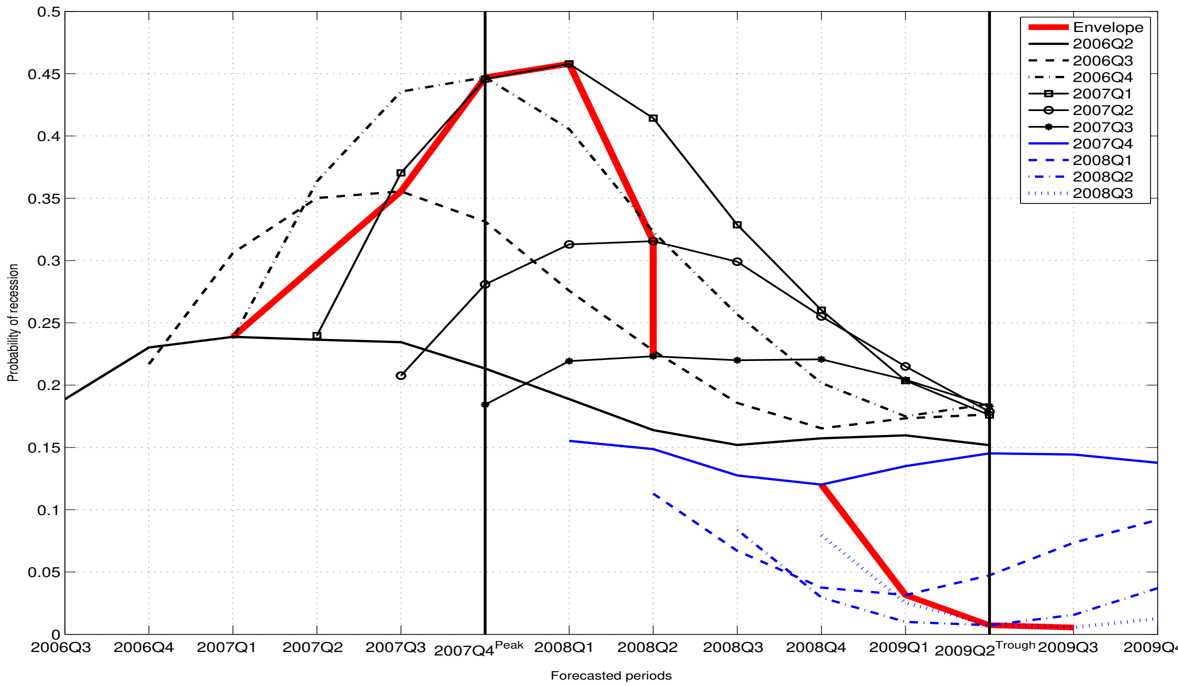
In this section, we conduct a real-time analysis of the last recession experienced by the U.S. economy.[14] We define a time window that starts around four periods before the recession and ends around two periods after the recession. We generate the term structure of probabilities of recession for each period on the selected window. Second, we compare the term structure of forecasts of the AAR versus AR and ADL models on two separate figures. Third, we compare the term structure of forecasts of the AAR and MS models on another graph. The MS model considered here is the one with changing intercept and constant autoregressive coefficient. Finally, we generate trajectories of recursive forecasts for the AAR model at fixed horizons. The analysis is done in real time, meaning that the forecasts are generated using the most recent GDP release and parameters that are estimated from a sample that stops at the previous official NBER turning point.

Figure 9 shows ten curves, each of them representing the term structure of the probability of recession at a given date. Two bold red lines are superimposed in order to ease the visualization of the upper envelope of the six concave curves that are at the beginning of the recession and the lower envelope of the four convex curves that are at the end of the recession. The maximum of the upper envelope curve is located at 2008Q1, one quarter only after the date officially designated by the NBER as the peak of the business cycle. Likewise, the minimum of the lower envelope curve is

[14]The supplementary material contains the real-time analysis of every recession since 1981.

located one quarter after the official end of the recession. This suggests that the upper and lower envelope curves are informative about the business cycle turning points as hypothesized previously.

Figure 9: Forecasting the Great Recession turning points in real time



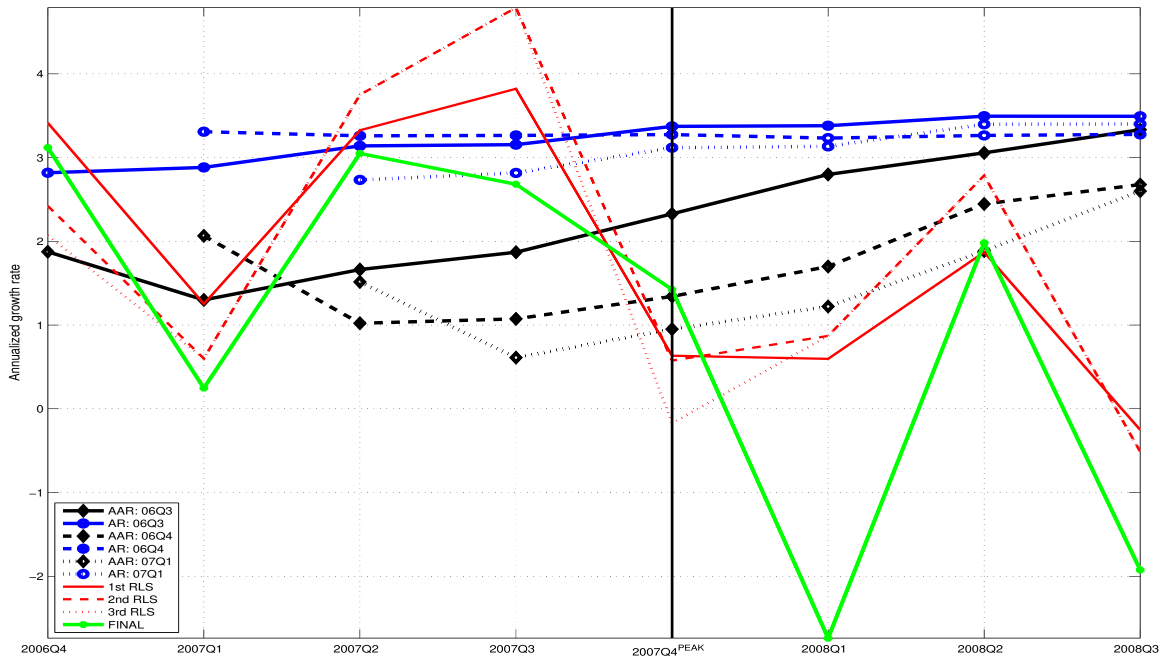
This figure shows out-of-sample predictions of the term structure of recession probabilities obtained from the static Probit model that uses TS only as predictor around the great recession. The black line 2006Q2 corresponds to the forecasts conditional on 2006Q2 information, the black dotted line forecasts is made conditional on 2006Q3, and so on. Thick red lines stand for the upper and lower envelopes of the predicted term structures of recession probabilities.

Figure 10 compares the term structures of out-of-sample predictions for the AAR and AR models. The term structures of out-of-sample forecasts produced by the AR model are roughly flat while those produced by the AAR model exhibit more correlation with the actual data. Clearly, the out-of-sample forecasts of the AR model are more disconnected from reality that those of the AAR model.

Figure 11 compares the term structure of forecasts of the AAR and ADL models. The forecasts of the ADL model are more responsive to the actual data than those of the AR model, but less responsive than those of the AAR model. The gap between the term structures of forecasts of the AAR and ADL models increases with the horizon.

Figure 12 compares the term structures of out-of-sample predictions for the AAR and MS models. All term structure of forecasts are flat for the MS model. Their levels a few quarters before and through the middle of the recession are quite deceptive about reality. Indeed, one has to wait until 2009Q1 (one quarter before the official end of the recession) before seeing a sudden

Figure 10: Direct OOS forecasts of GDP growth during the Great Recession: AR vs. AAR

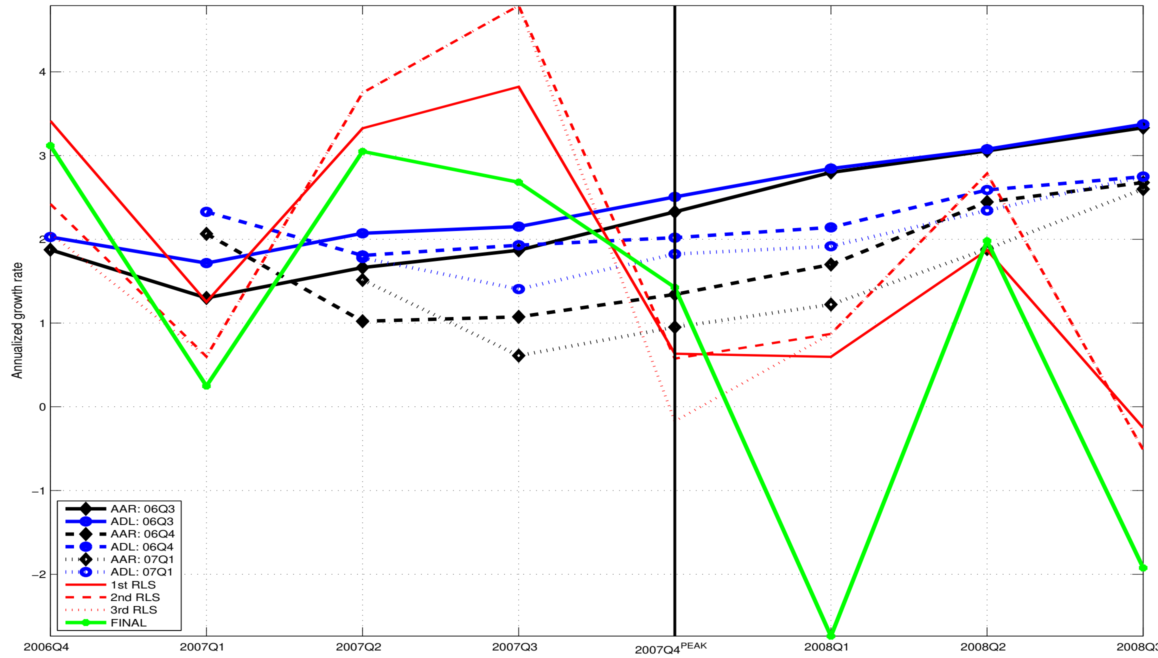


This figure shows out-of-sample forecasts of GDP growth at different horizons obtained from the AR and AAR models around the great recession. For instance, AAR: 06Q3 stands for the forecasts of the AAR model based on the first release of 2006Q3 GDP, as it was available in 2006Q4, and so on. The other lines represent the 1st, 2nd and 3rd releases in real time as obtained from the corresponding vintages. The final data are the most recent values of the 2015Q1 vintage.

drop in the level of the term structure of forecasts of the MS model. Overall, the term structure of out-of-sample forecasts of the MS model has an uninformative shape while its level signals the recession quite late.

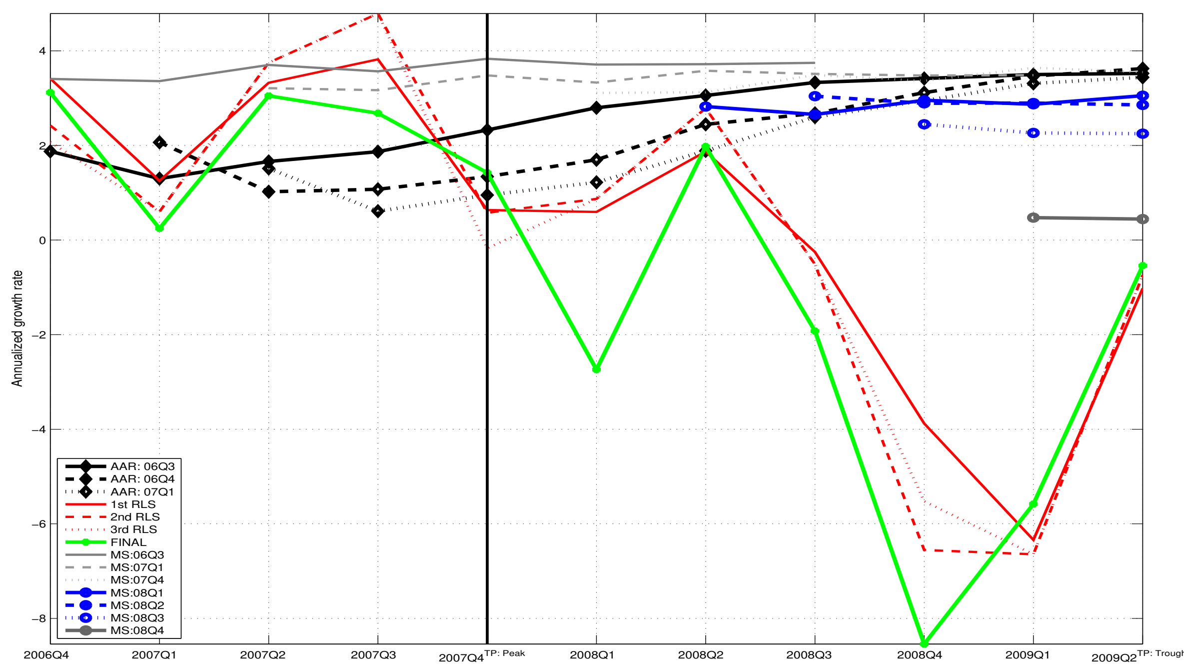
Figure 13 shows the trajectories of recursive forecasts of the AAR model for $h = 3$ and $h = 4$ along with the corresponding optimistic and pessimistic scenarios. The results are quite similar for both horizons. The average forecasts are upward trending during the recession periods while the optimistic and pessimistic forecasts are decreasing. The actual realizations of GDP growth are much lower than the average forecasts. Indeed, actual realizations are closer to the pessimistic forecasts between 2008Q4 and 2009Q1. Having a pessimistic scenario available in advance can help mitigate the impact of bad surprise during recessions.

Figure 11: Direct OOS forecasts of GDP growth during the Great Recession: AAR vs. ADL



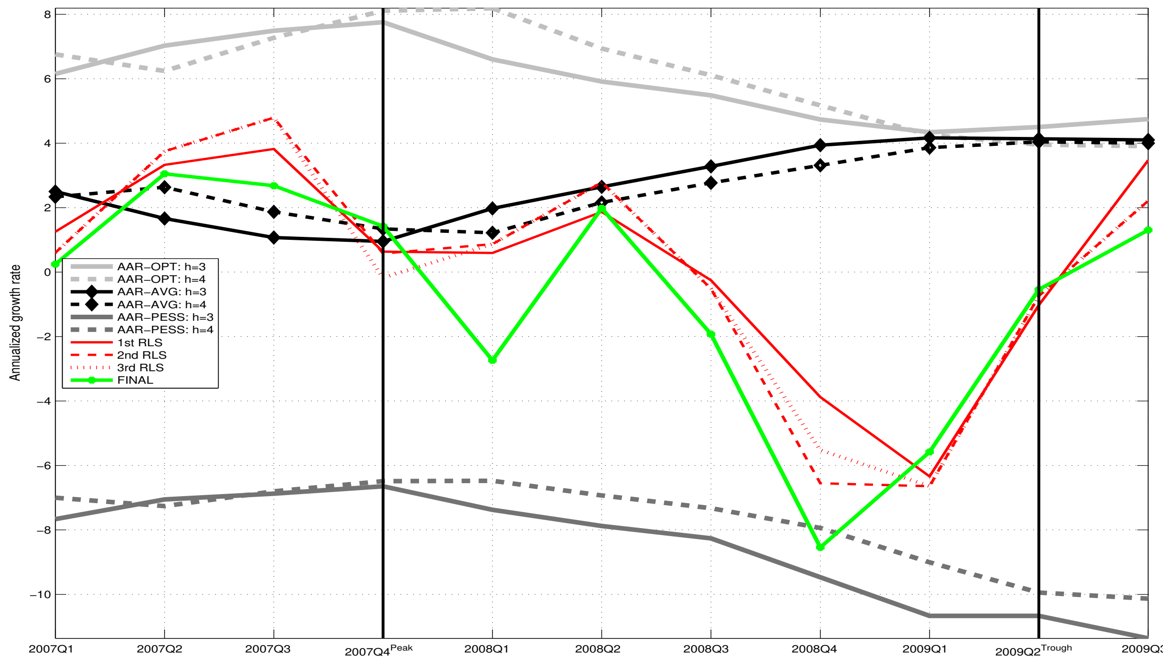
This figure shows out-of-sample forecasts of GDP growth at different horizons obtained from the AAR and ADL models around the great recession. For instance, AAR: 06Q3 stands for the forecasts of the AAR model based on the first release of 2006Q3 GDP, as it was available in 2006Q4, and so on. The other lines represent the 1st, 2nd and 3rd releases in real time as obtained from the corresponding vintages. The final data are the most recent values of the 2015Q1 vintage.

Figure 12: Direct OOS forecasts of GDP growth during the Great Recession: AAR vs. MS



This figure shows direct out-of-sample forecasts of GDP growth at different horizons obtained from the AAR model and the MS model with state-dependent intercept around the great recession.

Figure 13: Recursive OOS forecasts of GDP growth during the Great Recession: average, optimistic and pessimistic scenarios



This figure shows the trajectories of recursive forecasts of the AAR model for $h = 3$ and $h = 4$ along with the corresponding optimistic (AAR-OPT) and pessimistic (AAR-PESS) scenarios around the great recession.

6 Conclusion

This paper explores an approach based on augmented autoregressive models (AAR) to forecast future economic activity. Average forecasts are obtained from an AR(1) model that is augmented with a variable that measures the probability of a recession conditional on forward-looking financial variables. AR(1) models augmented with IMRs are used to produce forecasts of economic activity that are conditional on whether the horizon of interest is a recession period (pessimistic forecast) or not (optimistic forecast). The implementation of these models require a prior estimation of a Probit model for the probability of a recession. Overall, our methodology is simple, parsimonious and easy to replicate. It can be easily adapted to other contexts by replacing the economic activity variable by another variable of interest (unemployment rate, credit volume, etc.) and adding more predictors to the first step Probit model. In particular, our pessimistic forecast can be used as input for stress testing exercises in the banking and real estate sectors.

We find that the dynamic patterns of the term structure of recession probabilities are informative about the business cycle turning points. Indeed, these term structure curves switch from convex to concave near to the beginning of recessions and from concave to convex near to the end of recessions. Our most parsimonious AAR model delivers better out-of-sample forecasts of GDP growth than the AR, ADL and Markov Switching models.

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