

Online Appendix to: Forecasting Low Frequency Macroeconomic Events with High Frequency Data

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Abstract

High-frequency financial and economic indicators are usually time-aggregated before computing forecasts of macroeconomic events, such as recessions. We propose a mixed-frequency alternative that delivers high-frequency probability forecasts (including their confidence bands) for low-frequency events. The new approach is compared with single-frequency alternatives using loss functions for rare-event forecasting. We find: (i) the weekly-sampled term spread improves over the monthly-sampled to predict NBER recessions, (ii) the predictive content of financial variables is supplementary to economic activity for forecasts of vulnerability events, and (iii) a weekly activity index can date the 2020 business cycle peak in real-time using a mixed-frequency filtering.

keywords: mixed frequency models, recession, financial indicators, weekly activity index, event probability forecasting.

JEL Codes: C25, C53, E32

A Convergence Analysis

We check the convergence of the proposed sampler described in the main text Appendix for the empirical exercise in Section 4.1, that is, using a MIDAS-Probit specification for one-year-ahead, $h = 12$, predicted probabilities of a NBER recession using the spread. We consider the specification with $K = 32$. The hyperparameter, Δ , required to obtain draws for the weighting function parameters θ_1^h and θ_2^h are set such that acceptance rates are around 30%. Figure A1 shows draws for the intercept and slope parameters ($\beta_0^{h=12,j}$ and $\beta_1^{h=12,j}$), and also for the parameters of the weighting function ($\theta_1^{h=12,j}$ and $\theta_2^{h=12,j}$). These are presented for $j = 1, \dots, 15,000$ computed for 4 independent chains. We also compute the implied logscore for each draw of the parameters and include them in Figure A1. The logscore is computed as $\frac{1}{\tau-h} \sum_{t=1}^{\tau-h} -\ln \left| 1 - S_{t+h} - \Phi[\mathbf{Z}_t(\Theta_{h=12}^j)' \beta_{h=12}^j] \right|$. Finally, we compute the potential scale reduction factor for each parameter.

There is clear evidence that the sampler converges after 5,000 draws. Draws for the slope $\beta_1^{h=12}$ are more strongly serially correlated than the draws of the other parameters as indicated by the effective sample size included computed for each coefficient. We treat Figure A1 as evidence that the sampler described in the main text Appendix converges if care is taken to set the hyperparameters Δ_i .

B Computation of High Frequency Probability Forecasts

We describe here the results of a comparison between our benchmark approach described in (7) to compute high-frequency probability forecasts using the MIDAS-Probit with an approach that would estimate the forecasting model for each high-frequency horizon $(\beta_{h+(j/m)}, \Theta_{h+(j/m)})$ for $j = 1, \dots, m-1$.

Figure A3 shows 68% intervals for the predicted probabilities computed every week for a one-quarter ahead event with a mixed-frequency model that combines different frequencies (described in detail in Section 4.2, see eq. (8)). We show the results using the approach in (7) in the top panel and the case where parameters are re-estimated for each $j = 0, \dots, m-1$ in the bottom panel.

One can clearly see that the re-estimation leads to predicted probability intervals with higher

variability (as one fits the weighting function and slope for each horizon), but it does not seem to improve the accuracy of the event probabilities, as the effect on the ability of the posterior mean probability to classify the event is small (AUROC changes from 0.937 to 0.943). The re-estimation each week has the disadvantage of significantly increasing the computation time to obtain the weekly-updated forecasts.

Figure A1: Convergence Analysis: Draws over 4 chains of 15000 draws

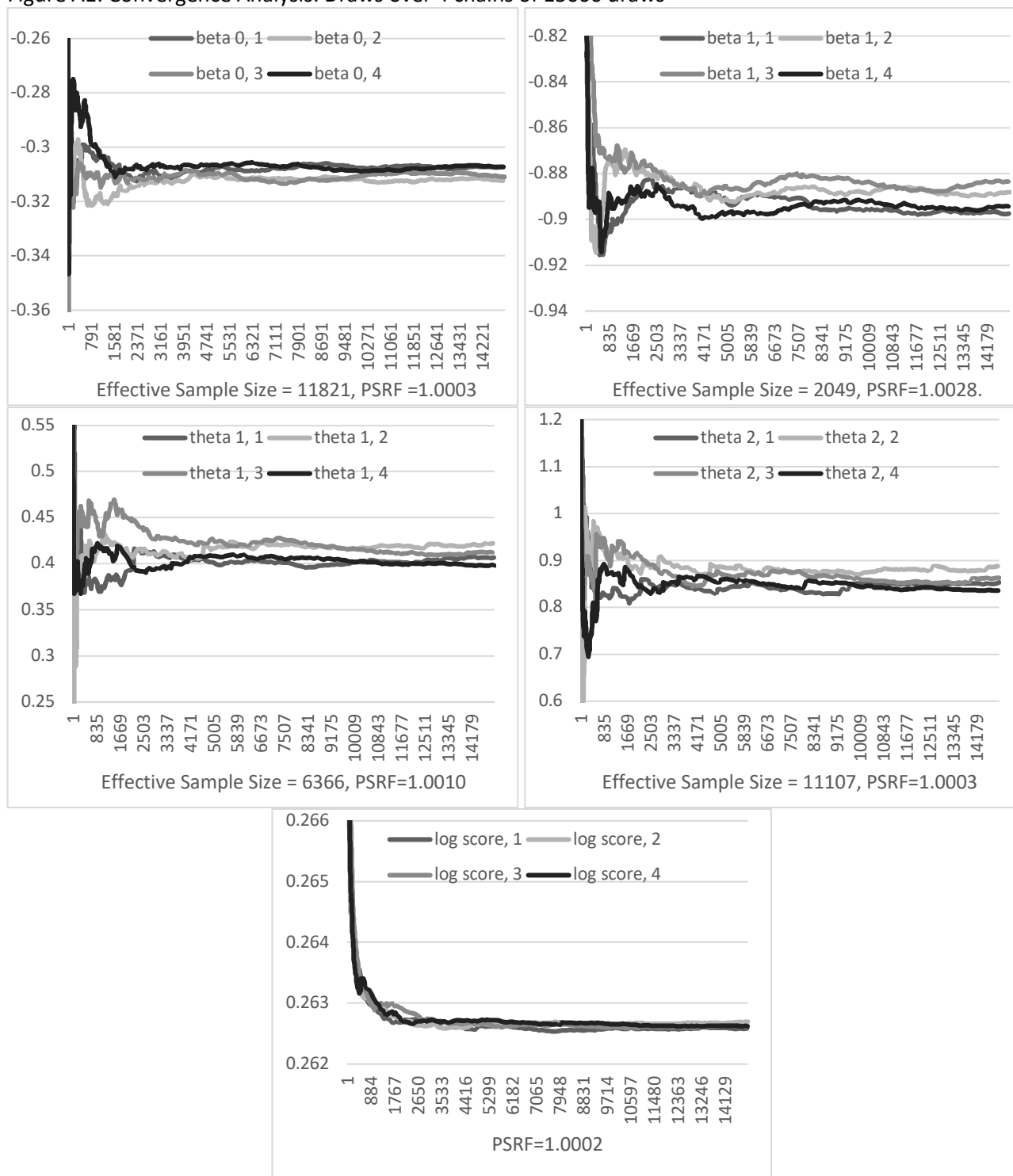
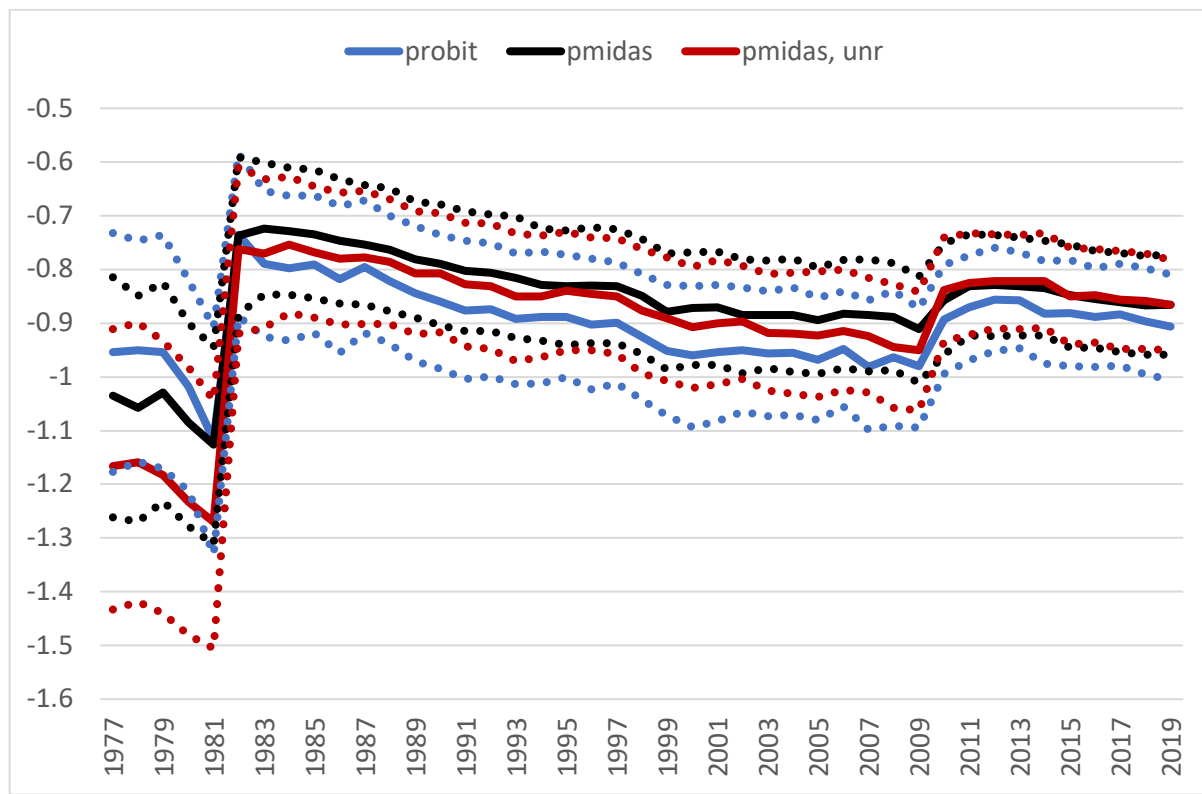
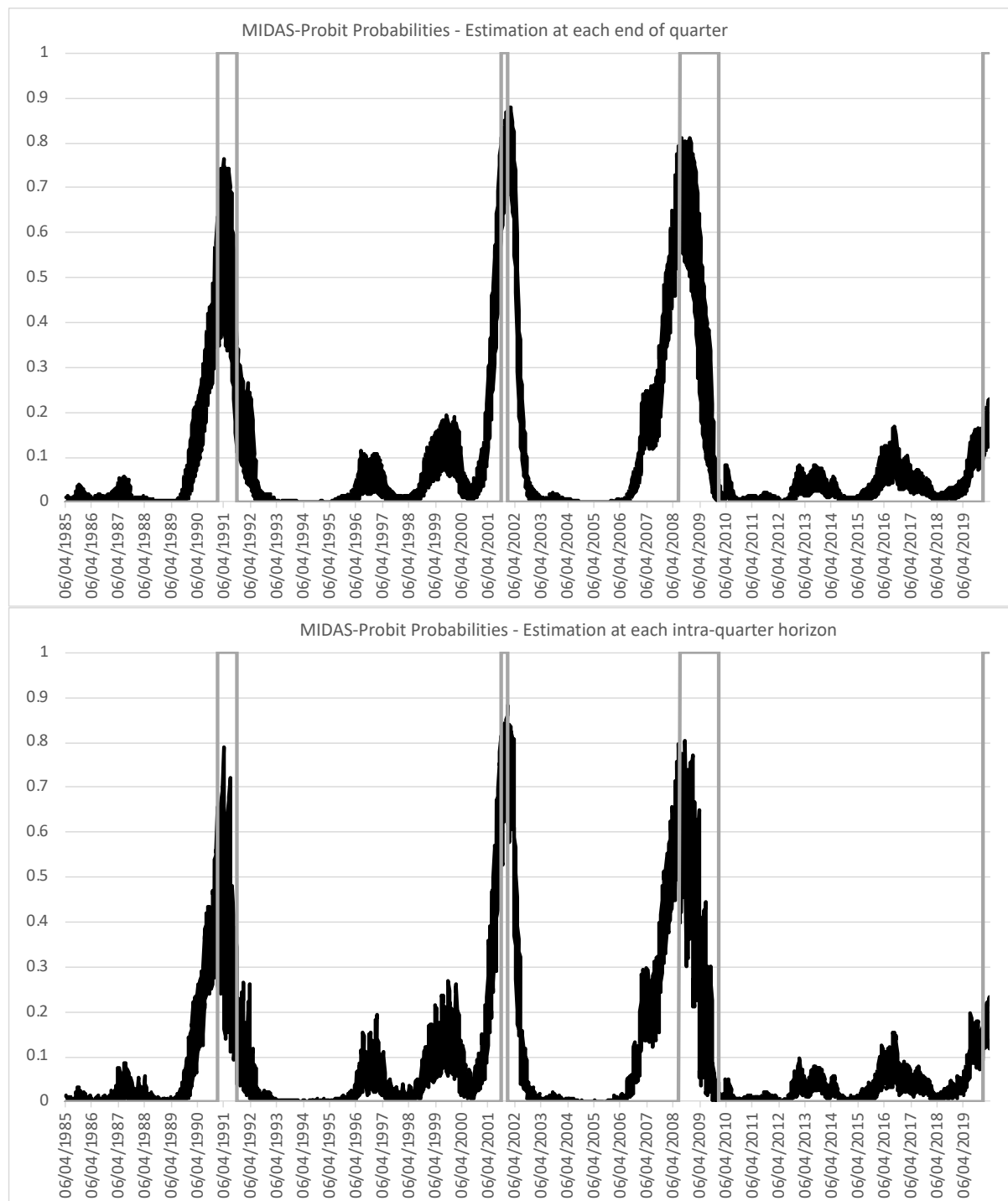


Figure A2: Slope Parameter Posterior Distribution over successive forecast origins (re-estimated every year from 1977 to 2019 with increasing windows of data): Probit, MIDAS-Probit with beta weighting function (pmidas) and MIDAS-Probit with unrestricted weights (pmidas, unr).



Notes: Dotted lines are 68% Credible Intervals. Line is the posterior mean. The values are the sum of all slope coefficients in the case of the Probit and MIDAS-Probit with unrestricted weights.

Figure A3: Comparing the Effects of Intra-Quarter Re-estimation for MIDAS-Probit in Eq. (7) with the Spread as the monthly variable and $h=1$: 68% Intervals for the Probability of a Vulnerable Growth



Note: Dates refer to $t+(j/13)$. Re-estimation every week is employed to compute results in the bottom panel, while the parameters employed in the top panel are estimated only when full quarter information is available. These are based on 4,000 draws (after 500 are discarded).