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Recession probabilities falling from the STARs

Sercan Eraslan
(Deutsche Bundesbank)

Marvin Nöller
(University of Bonn and Bonn Graduate School of Economics)

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
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Non-technical summary

Research Question

The existing literature on dating and forecasting business cycle turning points mainly relies on detecting such turning points based on a single highly aggregated indicator. However, there is a small number of recent studies revealing that considering a broad range of indicator-specific turning points may be beneficial to identifying business cycle turning points. In this study we provide a comprehensive comparison of the two approaches to identifying business cycle turning points.

Contribution

We utilise cross-sectional information from a large dataset comprising many US macroeconomic and financial indicators to improve recession probability forecasts. Moreover, we compare the forecast performance of both approaches employing real-time data. Finally, we propose a novel smooth transition framework which exploits the interconnection of business and growth cycles to forecast recession probabilities and, thus, business cycle turning points.

Results

Our forecast evaluation reveals that (i) cross-sectional information is beneficial to predicting recession probabilities; (ii) aggregating indicator-specific turning point forecasts clearly outperforms such predictions based on a single aggregated indicator in forecasting recession probabilities; and (iii) the proposed smooth transition modelling framework is able to provide accurate and timely recession probability forecasts in the US.

Nichttechnische Zusammenfassung

Fragestellung

Die bestehende Literatur zur Datierung und Prognose von konjunkturellen Wendepunkten stützt sich häufig auf nur einen hochaggregierten Indikator. Eine kleine Anzahl neuerer Studien zeigt jedoch, dass die Betrachtung vieler verschiedener, indikatorspezifischer Wendepunkte gut geeignet ist, um konjunkturelle Wendepunkte zu ermitteln. In dieser Studie stellen wir einen umfassenden Vergleich dieser beiden Ansätze zur Ermittlung von konjunkturellen Wendepunkten vor.

Beitrag

Wir nutzen Querschnittsinformationen aus einem großen Datensatz mit einer Vielzahl makroökonomischer und finanzieller Indikatoren für die USA, um die Prognosen von Rezessionswahrscheinlichkeiten zu verbessern. Zudem verwenden wir für den Vergleich der Prognosegüte beider Ansätze Echtzeitdaten. Schließlich schlagen wir einen neuartigen Modellierungsrahmen vor, der die Wechselbeziehung von Konjunktur- und Wachstumszyklen nutzt, um Rezessionswahrscheinlichkeiten und somit konjunkturelle Wendepunkte vorherzusagen.

Ergebnisse

Unsere Evaluation zeigt, dass (i) die Nutzung von Querschnittsinformationen aus einem großen Datensatz für die Vorhersage von Rezessionswahrscheinlichkeiten von Vorteil ist; (ii) die Betrachtung vieler indikatorspezifischer Wendepunktprognosen deutlich präzisere Vorhersagen ermöglicht als Wendepunktprognosen auf Grundlage eines einzigen aggregierten Indikators und (iii) der vorgeschlagene Modellrahmen in der Lage ist, genaue und zeitnahe Prognosen der Rezessionswahrscheinlichkeit in den USA zu liefern.

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Recession probabilities falling from the STARs*

Sercan Eraslan†
Deutsche Bundesbank

Marvin Nöller‡
University of Bonn, Bonn Graduate School of Economics

Abstract

We follow the idea of exploiting cross-sectional information to improve recession probability forecasts by aggregating indicator-specific turning point predictions to obtain economy-wide recession probabilities. This stands in contrast to most of the relevant literature, which relies on an aggregated economic indicator to identify business cycle turning points. Using smooth transition regressions we compare the forecast performance of both approaches to business cycle dating in a comprehensive real-time forecasting exercise for recessions in the US. Moreover, we propose a novel smooth transition modelling framework which makes use of the interrelation between business and growth cycles to forecast recession probabilities. Our real-time out-of-sample forecast evaluation reveals that (i) using cross-sectional information is beneficial to predicting recession probabilities, (ii) aggregating indicator-specific turning point forecasts clearly outperforms turning point predictions based on a single indicator and (iii) the proposed smooth transition framework is able to provide informative recession probability forecasts for up to three months in the US.

Keywords: Business cycles, forecasting, recessions, STAR models, turning points

JEL classification: C24, C53, E37

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†Contact address: Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main, Germany. Email: sercan.eraslan@bundesbank.de.

‡Contact address: Bonn Graduate School of Economics, Kaiserstr. 1, 53113 Bonn, Germany. Email: marvin.noeller@uni-bonn.de. This paper was partly written while he was visiting the Deutsche Bundesbank, whose hospitality is gratefully acknowledged.

1 Introduction

Reliable forecasts for business cycle turning points are of paramount interest to firms, households and policy makers. Having timely information about the current state of the economy, firms and individuals can better manage their investment activities and consumption plans. Policy makers can more effectively adapt fiscal policy, often with long-term effects, to future economic conditions. Finally, central bankers can gear monetary policy toward imminent business cycle turning points and thereby dampen the volatility of the business cycle. However, business cycle turning points are announced with a considerable delay, mostly one to two years after they have occurred, widening the gap between the time when this information is needed and obtained.

This information gap gives rise to a growing academic literature on identifying and predicting business cycle turning points in real-time. So far, the major part of the existing studies focused on highly aggregated economic indicators, such as GDP or an unobserved factor describing the state of the economic activity, in dating business cycle turning points.[1] This dating strategy is considered as the "*aggregate-then-date*" approach. By contrast, Burns and Mitchell (1946) document that business cycle fluctuations, such as expansions and recessions, occur among widely spread economic aggregates synchronously. Thus, they aim at identifying business cycle turning points based on clusters of turning points of a set of disaggregated economic time series which is referred to as the "*date-then-aggregate*" approach. However, this approach attracted little attention in the literature and hence, the number of studies following the date-then-aggregate approach is still very limited. In this context Harding and Pagan (2006) develop a nonparametric algorithm to identify the reference cycle by clustering a set of indicator-specific cycles. More recently, Stock and Watson (2010, 2014) and Camacho, Gadea, and Loscos (2019) propose two distinct methods to identify business cycle turning points based on the population distribution of indicator-specific turning points.[2]

In this paper, we build on this literature by estimating and forecasting recession probabilities using parametric smooth transition models based on a large cross-section of macroeconomic and financial indicators in the US. In doing so, we contribute to the existing literature on identifying and predicting business cycle turning points by (i) exploiting cross-sectional information from a large dataset to improve recession probability forecasts; (ii) providing the literature with a comprehensive comparison of the forecast performance of both approaches to dating business cycle turning points in real-time and (iii) proposing a smooth transition framework to identify and predict recession probabilities.

First, we follow Stock and Watson (2014) and aim to exploit cross-sectional information to improve recession probability predictions. To this end, we use a large real-time dataset consisting of a broad set of macroeconomic and financial indicators for the US. With more than hundred time series our dataset is considerably larger than those used in Harding and Pagan (2006) and Camacho et al. (2019) focusing on a small number of economic indicators which have been considered by the NBER Business Cycle Dating

[1] The reader is referred to Hamilton (2011) for a detailed overview of the literature on identifying and predicting business cycle turning points.

[2] We borrow the terms "*aggregate-then-date*" and "*date-then-aggregate*" referring to the two business cycle dating approaches from Stock and Watson (2010).

Committee (2003, 2010), respectively. Moreover, series in our dataset are not subaggregates of a few economic indicators and thereby cover a broader range of the economic and financial activity compared to that covered in the dataset employed by Stock and Watson (2010, 2014) which comprises subcomponents of four economic indicators such as employment, industrial production, personal income and sales.

Second, we examine the predictive accuracy of date-then-average and aggregate-then-date approaches to dating business cycle turning points in a comprehensive real-time forecasting exercise. To this end, we consider both equally- as well as performance-based weighted forecast combination schemes in aggregating indicator-specific recession probability forecasts within the scope of the date-then-aggregate approach. In a similar manner we apply two distinct factor extraction methods in the aggregate-then-date approach to consolidate the information contained in the dataset into a single indicator representing the state of the economy. Moreover, we utilise three distinct datasets in comparing both business cycle dating approaches. First, we use our entire real-time dataset comprising over a hundred indicators. Thus, it is considerably larger than those utilised in Chauvet and Piger (2008) and Clements and Galvão (2006) that respectively use four and ten preselected variables for such a comparison. Accordingly, our second dataset consist of only four preselected coincident indicators which are mostly used in related studies. While such studies tent to pick a tiny set of informative indicators, our third dataset makes use of a variable selection algorithm in real-time. It consist of a small number of automatically selected predictors from a large cross-section of macroeconomic and financial time series and hence is also of similar size with those used in related studies. In this way, we are also able to investigate the role of real-time variable selection in both business cycle dating approaches.

Finally, we utilise parametric smooth transition autoregressive (STAR) models, introduced by Teräsvirta and Anderson (1992), to predict recession probabilities in real-time. Despite its simple nature and large potential the STAR framework has surprisingly been neglected in the literature on detecting business cycle turning points so far. To the best of our knowledge Anderson and Vahid (2001) (using a univariate STAR model) and Camacho (2004) (proposing a vector smooth transition regression model) are the only studies which employ such a framework for identifying business cycle turning points and predicting the probabilities of a recession. Against this background, we aim at highlighting the capability of this model class in capturing the alternation of the different phases of the business cycle in a comprehensive empirical study. Moreover, the flexibility of the STAR framework allows us to address a recent discussion introduced by Harding and Pagan (2005) on the interrelation between classical business cycles and growth cycles as well as on its implications for identifying turning points of such cycles.

Our real-time out-of-sample forecast evaluation reveals that information from a large cross-section of macroeconomic and financial indicators can improve the accuracy of recession probability predictions. Comparing both business cycle dating approaches, our results indicate that the date-then-aggregate approach tends to outperform the aggregate-then-date approach in terms of forecast accuracy. Therefore, combining indicator-specific recession probability forecasts (date-then-aggregate) seems to be superior to aggregating information on the economic activity into a common factor for business cycle dating based on a single indicator (aggregate-then-date). The superiority of the date-then-aggregate approach over the latter holds in both forecasting exercises based on the large as well as on the small dataset. Moreover, variable selection via elastic net appears to bring only modest gains in forecast accuracy with such improvements being limited to the aggregate-then-date approach. Though, such models perform mostly better than those relying on a fixed set of small number of indicators. Thus, we suggest utilising real-time variable selection if a small number of indicators are preferable for forecasting business cycle turning points. In addition, we show that performance based forecast combination schemes are partly able to outperform equally weighted combined forecasts with respect to turning point predictions which challenges the well-known forecast combination puzzle. Finally, our proposed smooth transition modeling framework is able to provide informative recession probability forecasts for up to three months in the US.

The remainder of this paper is set out as follows. The next section provides an overview of the data and the reference business cycle turning points used in this study. Section 3 introduces the econometric methodology. Section 4 describes the forecasting exercise and discusses our empirical findings. Section 5 concludes.

2 Data and reference recession dates

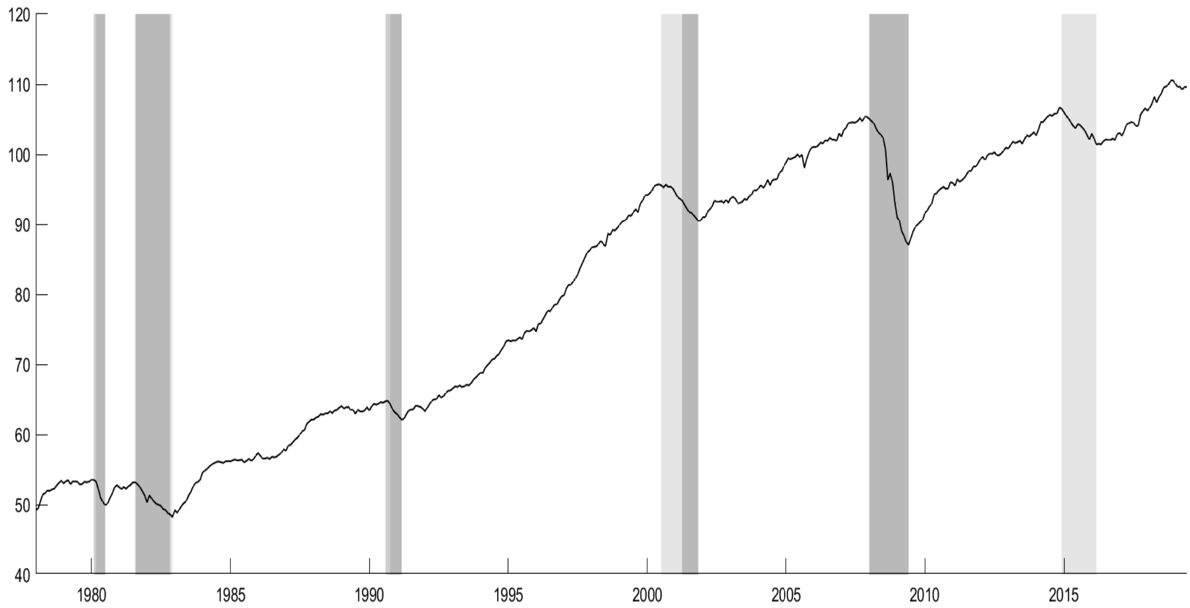
We use a large dataset consisting of GDP and monthly indicators covering a wide range of economic and financial activity in the US. Our dataset spans from 1978M1 to 2019M7, while we make use of the real-time data vintages from 2000M1 to 2019M7 for the recursive forecasting exercise. We obtain the monthly dataset as well as its historical vintages from the Federal Reserve Bank of St. Louis FRED-MD which is described by McCracken and Ng (2016). In addition, we get quarterly GDP data and its historical vintages from the ALFRED provided by the Federal Reserve Bank of St. Louis. Lastly, we retrieve reference recession periods which is the NBER recession indicator, from the FRED, Federal Reserve Bank of St. Louis. Appendix A provides a detailed overview of the dataset.

Against the background of various definitions of a cycle in business cycle analysis[3] we collect data on reference periods for classical business cycle recessions in the US in order to evaluate our forecasts for recession probabilities. Historical business cycle turning points as well as associated expansions and recessions are announced by the NBER's Business Cycle Dating Committee for the US economy. The committee, however, releases business cycle turning points with a considerable time lag, mostly one to two years after they have already occurred. While these reference dates can be considered for an ex-post forecast evaluation, the utilisation of such turning points in a real-time forecasting exercise is subject to a large delay between occurrence and announcement. For this reason we employ the Bry and Boschan (1971) algorithm[4] in order to obtain real-time estimates for business cycle turning points during our recursive forecasting exercise. Along similar lines to the literature we use industrial production (in levels, unsmoothed) as the underlying indicator to calculate reference recessionary periods in the US.

[3]The reader is referred to Harding and Pagan (2005) for an in-depth discussion on the difference between classical business cycles (based on the level of the underlying series), growth cycles (determined by deviations from trend growth of the underlying series) and cycles in growth rates (which is also referred to as acceleration cycles, studied based on the in growth rates of the underlying series) as well as on turning points obtained from such cycles.

[4]We thank Emanuel Mönch for kindly sharing the replication code of Mönch and Uhlig (2005) with us.

Figure 1: Reference recession dates in the US



Notes: The figure plots industrial production (black solid line) and reference recession dates estimated by the Bry and Boschan (1971) algorithm (grey shaded area) as well as those based on the NBER's business cycle turning point announcements (dark grey shaded area) in the US.

Figure 1 plots industrial production and reference recession dates estimated by the Bry and Boschan (1971) algorithm (grey shaded area) as well as those based on the NBER's business cycle turning point announcements (dark grey shaded area) from 1978M01 to 2019M06. Overall the Bry and Boschan (1971) algorithm - albeit being a purely mechanical approach based on a single indicator - is able to match recessions based on turning point announcements of the NBER's Business Cycle Dating Committee quite well.

3 Econometric methodology

In this paper we employ two-regime smooth transition autoregressive (STAR) models to estimate and forecast recession probabilities based on a large set of macroeconomic and financial indicators. While the STAR framework is able to capture the different characteristics of expansionary and recessionary periods, it allows for a smooth transition between these two regimes. In the first step we specify the linear autoregressive (AR) models for each state. Then we estimate the parameters of the transition function and the STAR model. Finally, we use the estimated model for out-of-sample forecasts for recession probabilities. These steps are described in Section 3.1.

After having introduced the STAR framework we describe the two factor extraction methods which we utilise within the aggregate-then-date approach (Section 3.2) as well as the various forecast combination schemes on which we rely in the date-then-aggregate approach (Section 3.3). Finally, we shortly describe a penalised regression framework in Section 3.4 that we apply in order to select the informative predictors from our large dataset in real-time during the empirical exercise.

3.1 Smooth transition models

The STAR modelling framework was initially introduced by Teräsvirta and Anderson (1992) and further discussed by Teräsvirta (1994), while van Dijk, Teräsvirta, and Franses (2002) and Teräsvirta, Tjøstheim, and Granger (2010) provide a review of various extensions and specifications of this model class. In general, two-regime STAR models consist of two piece-wise linear AR models which are interlinked with a transition function. Therefore, a univariate STAR model can be specified as

$$y_t = [F(\cdot)](\beta_{0,1} + \sum_{i=1}^{p} \beta_{i,1} y_{t-i}) + [1 - F(\cdot)](\beta_{0,2} + \sum_{i=1}^{p} \beta_{i,2} y_{t-i}) + \epsilon_t, \qquad (1)$$

where y_t is a given indicator. The coefficients $\beta_{0,1}$ and $\beta_{0,2}$ are the intercepts in each state, while the $\beta_{i,1}$ and $\beta_{i,2}$ for $i = 1, ..., p$ are the coefficients of the lagged dependent variables in both regimes. Moreover, ϵ_t is the error term with $\epsilon \sim N(0, \sigma^2)$. A key element of the STAR model is the transition function, denoted as $F(\cdot)$, which is bounded between zero and one. In fact, it assigns a weight to each state of the model and is therefore the variable of interest in our analysis. Teräsvirta and Anderson (1992) consider two possible transition functions: (i) an exponential one; and (ii) a logistic transition function for $F(\cdot)$ in Eq. (1). In our study we employ a logistic transition function which takes the following form:[5]

$$F(\gamma, c, \tau_{t-d}) = \frac{1}{1 + exp(-\gamma(\tau_{t-d} - c)\sigma^{-1}_{\tau_{t-d}})}, \qquad (2)$$

where $\gamma > 0$ is the smoothness parameter. Moreover, τ_{t-d} is the threshold series which can usually be either a lagged value of the dependent variable (y_{t-d}) or the i^{th} difference of the lagged dependent variable ($\Delta_i y_{t-d} \equiv y_{t-d} - y_{t-d-i}$) with d being the delay parameter. While the former is referred to as a TAR-type adjustment, the latter is called a momentum TAR-type (MTAR) adjustment and was introduced for $i = 1$ by Enders and Granger (1998). Skalin and Teräsvirta (2002) use $\Delta_{12} y_{t-d}$ as the potential threshold series.[6] Furthermore, c is the threshold value triggering the regime switches once τ_{t-d} hits the c. Finally, $\sigma_{\tau_{t-d}}$ is the unconditional standard deviation of the threshold series and is used to standardise the smoothing parameter in order to make it scale-free. Overall, the STAR model, as it is set up in Eqs. (1) and (2), can be considered as a weighted average of two piece-wise linear AR models representing expansions and recessions in which the smooth transition function determines the weights of these regimes in each point of time.

We follow Teräsvirta (1994) in model building and estimation which broadly consists of the following steps: (i) Specifying a linear AR(p) model; (ii) setting the parameters of

[5] The alternative exponential transition function is given by $F(\gamma, c, \tau_{t-d}) = 1 - (exp(-\gamma(\tau_{t-d} - c)^2))$. However, the exponential transition function is rather used for modelling an intermediate regime with two extreme regimes sharing the same dynamics around. Thus, it is not able to determine two states with different dynamics, such as expansions and recessions. Against this backdrop, exponential STAR (ESTAR) models are not discussed further in this paper.

[6] In fact, any exogenous variable can be the threshold series in a more general smooth transition modeling framework. However, if such model is used for forecasting exercise, this would introduce the problem of predicting the threshold series exogenously to obtain forecasts for $F(\cdot)$ over the forecast horizon. Thus, we prefer to utilise STAR models which are not subject to an additional forecasting problem for an exogenous threshold series.

the transition function; (iii) estimating the parameters of the STAR model; and (iv) using the estimated model for forecasting.[7] Starting with the first step we use the Bayesian Information Criterion (BIC) to choose the optimal lag length of a simple linear AR model, that determines the lag length in both regimes. The next step is related to the transition function and its components as determined in Eq. (2). We choose a (M)TAR-type adjustment and set the threshold series τ_{t-d} to (the first difference of) the lagged dependent variable $(\Delta)y_{t-d}$. Moreover, we use a three-dimensional grid search over γ, c and d,[8] which provides us with starting values for both the parameters of the logistic transition function and the coefficients of the two linear AR models. In the third step we use these starting values for the nonlinear optimization in order to estimate the final parameters of the STAR model. Accordingly, the model coefficients can be estimated as

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{t=1}^{T} (y_t - g(x_t, \theta))^2, \tag{3}$$

with $g(x_t, \theta) = [F(\gamma, c, \tau_{t-d})]\phi_1' x_t + [1 - F(\gamma, c, \tau_{t-d})]\phi_2' x_t$, $x_t = (1, y_{t-1}, ..., y_{t-p})'$ and $\hat{\theta} = (\phi_1', \phi_2', \gamma, c)'$.

In the final step, we use the estimated model for forecasting recession probabilities. To this end, we first calculate the iterated h-step ahead point forecasts of the underlying indicator, denoted by $\widehat{y}_{t+h|t}$. In a linear modeling framework the optimal point forecast of a time series can be determined by its conditional expectation

$$\widehat{y}_{t+h|t} = E[y_{t+h}|\Omega_t], \tag{4}$$

with h and Ω_t respectively being the forecast horizon and the information set up to time t in which the forecast is made. While this may also hold for nonlinear time series models under a squared error loss function, computing the conditional expectation analytically may be generally difficult in such models.[9] In fact, Mariano and Brown (1983) and Brown and Mariano (1989) show that this approach may lead to asymptotically biased forecasts when the underlying model is a nonlinear system. Accordingly, using STAR and TAR models for multi-step ahead forecasts Lin and Granger (1994) and Clements and Smith (1997) show that bootstrap and Monte Carlo methods yield better predictions compared to those obtained from a simpler approach, such as the one determined in Eq. (4). Against this backdrop, we employ bootstrap methods[10] for h-step ahead forecasts to approximate

[7]Note that the modeling approach proposed by Teräsvirta (1994) also involves testing for nonlinearity as well as model evaluation and modification if it is necessary. The reader is referred to Teräsvirta (1994) and van Dijk et al. (2002) for a more detailed discussion on this modeling approach.

[8]We use the following intervals for γ, c and d during the grid search: The interval $\gamma_{grid} = [5\ 6\ 7\ 8\ 9\ 10\ 15\ 20\ 25\ 50]$ captures various switching dynamics from a rather gradual transition to a sudden jump, while c_{grid} can take non-positive (if none existing, below average) values located in the middle 70% of $\tau_{1:t}$ allowing for at least 15% of observations being in both regimes. Finally, the grid for the delay parameter is set to $d_{grid} = 1, ..., p$.

[9]See Franses and van Dijk (2000) p. 117-124 and van Dijk et al. (2002) for a detailed discussion on the issue why the implementation of this approach may not follow straightforward in a nonlinear modelling framework.

[10]While in bootstrap methods errors are drawn from the models' own past prediction errors, they are drawn from a theoretical distribution in Monte Carlo simulations. The former may capture greater-than-average errors made in turbulent times, whereas such errors may not be considered when drawing from a Gaussian or t distribution in the latter case. Considering our aim at forecasting future recessions we

the conditional expectations for horizons $h > 1$. The bootstrapped forecasts take the following form:

$$[\widehat{y}^{boot}_{t+h|t}]^k_{i=1} = g(\widehat{x}_{t+h|t}, \theta) + \widehat{\epsilon}_i, \tag{5}$$

where $\widehat{\epsilon}_i$ denotes the residuals drawn (with replacement) from those of the estimated model for $t = 1, ..., T$ with $i = 1, ..., k$ representing the i^{th} draw out of k total bootstrap draws. Note that we are not interested in point forecasts $[\widehat{y}^{boot}_{t+h|t}]^k_{i=1}$ per se, but need them for calculating recession probabilities over the forecast horizon in the next step. Given the autoregressive nature of our model, such that the transition function depends on lagged values of $\widehat{y}^{boot}_{t+h|t}$, we also obtain k bootstrapped recession probability forecasts $[1 - \widehat{F}(\cdot)]^k_{i=1}$ through iterating the model over the forecast horizon. Accordingly, (bootstrapped) point forecasts translate into (bootstrapped) recession probability forecasts through the transition function as

$$[1 - \widehat{F}_{t+h|t}(\cdot)]^k_{i=1} = \begin{cases} [1 - \widehat{F}_{t+h|t}(\gamma, c, \tau_{t+h-d})] & \text{for } h \leq d \\ [1 - \widehat{F}_{t+h|t}(\gamma, c, \widehat{\tau}^{boot}_{t+h-d})]^k_{i=1} & \text{for } h > d, \end{cases} \tag{6}$$

where $[1 - \widehat{F}_{t+h|t}]^k_{i=1}$ stands for bootstrapped recession probability forecasts in each forecast horizon. Moreover, $\widehat{\tau}^{boot}_{t+h-d}$ is the bootstrapped threshold series for horizons $h > d$, whereas we use the observed values of the τ_{t+h-d} for forecast horizons $h \leq d$. Finally, we calculate our indicator specific forecast for recession probabilities as the mean of the k bootstrapped predictions, such that $[1 - \widehat{F}_{t+h|t}(\cdot)]^{boot} = \frac{1}{k}\sum^k_{i=1}[1 - \widehat{F}_{t+h|t}(\cdot)]_i$.

3.1.1 Discussion on the threshold type

This section discusses the choice of the type of the threshold series within our modeling framework. Different choices on TAR- and MTAR-type adjustments in combination with different data transformations allow us to link our model to various types of cycles, such as classical business cycles and growth cycles. To see the difference between these cycle definitions, let us decompose (the level of) a time series y_t as

$$y_t = y^{tr}_t + y^c_t + \epsilon_t, \tag{7}$$

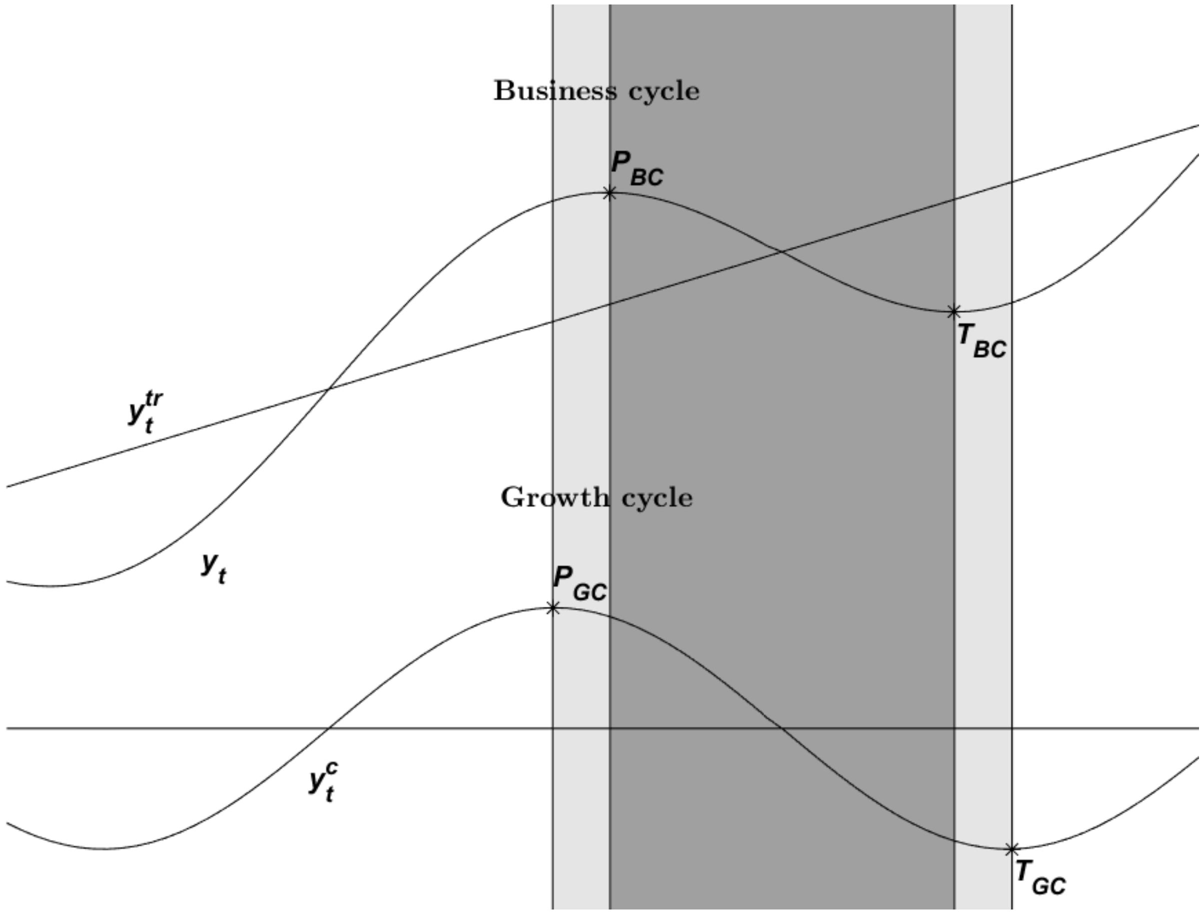
where y^{tr}_t and y^c_t are the long-run trend and the cyclical component of a time series, respectively, while ϵ_t is the irregular fluctuation around the cyclical component. Accordingly, Harding and Pagan (2005) emphasis that turning points obtained from the level y_t and from its cyclical component y^c_t refer to those of a classical business cycle and a growth cycle, respectively. In order to obtain the turning points in the underlying series, they outline to study the dynamics of the first difference (which can be either Δy_t or Δy^c_t) as the changes in its sign are associated with the turning points in the underlying series.

In our parametric STAR modeling approach the combination of the transformation of the underlying series and the type of the threshold series enables us to identify and interconnect turning points in both business as well as growth cycles in a unified framework. Let us illustrate this on the basis of an indicator y_t representing the state of the economy in the following. In order to identify classical business cycle turning points we

prefer bootstrapping over Monte Carlo simulations in our forecasting exercise.

can set the dependent variable to Δy_t and the threshold series to $\tau_{t-d} = \Delta y_{t-d}$ which is referred to as the TAR-type threshold series, i.e. we use the lagged dependent variable as threshold series. Then, changes in its sign, captured at $\tau_{t-d} = \Delta y_{t-d} = c = 0$ in the transition function as denoted in Eq. (2), will determine the turning points in the level of the underlying indicator y_t. Similarly, we can set the dependent variable to Δy_t^c and the threshold series to $\tau_{t-d} = \Delta y_{t-d}^c$ to identify growth cycle turning points at $\tau_{t-d} = c = 0$. In both settings a STAR model with TAR-type threshold series and a fixed threshold value at $c = 0$ can detect peaks and troughs of (the former) business and (the latter) growth cycles. Alternatively, given the fact that the cyclical component y_t^c is already stationary, we can also fit a STAR model directly to y_t^c. In this case, using a MTAR-type threshold series, denoted as $\tau_{t-d} = \Delta y_{t-d}^c$, growth cycle turning points will correspond to sign changes in its first difference which are captured at $\tau_{t-d} = \Delta y_{t-d}^c = c = 0$ as above.

Figure 2: Business cycle recessions and growth cycle slowdowns



Notes: This figure (which is based on a similar illustration by Anas and Ferrara (2004)) plots classical business cycle recessions (dark grey shaded area) and growth cycle slowdowns (grey shaded area) as well as their turning points in the top and bottom panel, respectively. The level of the underlying series y_t and its long-run trend y_t^{tr} are shown in the upper part, while its cyclical component y_t^c is displayed in the lower part.

Figure 2 plots the level of y_t and its long-run trend y_t^{tr} in the upper part, while its cyclical component y_t^c is displayed in the lower part.[11] The figure also visualises classical business cycle recessions (dark grey shaded area) and growth cycle slowdowns (grey shaded area) as well as their peaks P_i and throughs T_i, where $i \in \{BC, GC\}$ represents business cycle (BC) and growth cycle (GC) turning points, in order to illustrate the interconnection between such turning points.

While turning points in classical business cycles and growth cycles do not need to coincide necessarily, they are closely interconnected with each other. A positive long-run trend in economic activity translates into a positive intercept in the growth rate (the first difference) of the underlying indicator. Against this backdrop, the peak of the business cycle, captured at P_{BC} with $\Delta y_t = 0$, corresponds to a negative value in the first difference of the detrended indicator, that is $\Delta y_t^c < 0$. In comparison with the business cycle peak, however, the growth cycle peak is already identified at P_{GC} with $\Delta y_t^c = 0$. Thus, classical business cycle turning points tend to follow those of the growth cycle as illustrated in Figure 2. Therefore, a STAR model using a MTAR-type threshold series, which is fitted to the cyclical component of the underlying indicator, can capture turning points both in the growth cycle when the threshold value is set to $c = 0$ and in the classical business cycle when the threshold value is estimated as $\hat{c} \leq 0$. Hence, such STAR models, especially the latter specification, may be able to identify business cycle recessions short after the growth cycle has passed its peak leading to an earlier warning of a looming recession. In this study, we aim at examining the potential of a STAR model with MTAR-type threshold series over a TAR-type one to model the alternation of expansions and recessions.

3.2 Factor extraction methods

In line with the aggregate-then-date approach to business cycle dating we impose a factor structure to the predictors in order to obtain a single highly aggregated indicator from a large dataset. The idea of applying factor extraction methods to large datasets in economics goes back to Stock and Watson (1989, 1991) and is based on the assumption that a large number of macroeconomic variables representing the overall economic activity may be driven by a smaller number of common factors. In general, the forecasting equation takes the following form:

$$\begin{aligned} \widehat{y}_{t+h|t} &= \beta' \boldsymbol{f_t} \\ x_t &= \Lambda' \boldsymbol{f_t} + \epsilon_t, \end{aligned} \tag{8}$$

where y_t and x_t are the target variable and the large dataset consisting of N predictors, respectively. Moreover, $\boldsymbol{f_t} = (f_{1,t}, ..., f_{1,t})'$ is the r-dimensional vector of unobserved common factors with Λ being an $r \times N$ matrix of factor loadings relating the predictors to the common factors, while ϵ_t is the vector of idiosyncratic components of the predictors which is not explained by the common factors.

Our smooth transition factor model specification follows a two-step estimation approach, similar to that of Diebold and Rudebusch (1996). The first step consists of extracting a factor (in our framework) from a balanced dataset. In doing so we consider principal component analysis (PCA) as well as partial least squares (PLS) in order to

[11] For illustrative purposes we set the irregular component to zero $\epsilon_t = 0$.

obtain the common factor from the dataset. Principal component analysis, popularised by Stock and Watson (2002a,b) in macroeconomic forecasting, extracts factors explaining the overall variance of the dataset, denoted as x_t in Eq. (8). Alternatively, partial least squares, initially introduced by Wold (1985) and adopted to macroeconomic forecasting by Groen and Kapetanios (2008, 2016), considers the covariance between factors and a target variable to calculate the factor. We use GDP as the target variable. In the second step, we substitute y_t in Eq. (1) with the first common factor, f_t, and call this model specification smooth transition factor model, denoted as STFM$_i$ with i being PCA or PLS.

3.3 Forecast combination schemes

Within the scope of the date-then-aggregate approach we rely on univariate STAR model specifications for generating indicator-specific predictions of turning points. Then we aggregate these predictions to obtain aggregated probability forecasts for economy-wide recessions. Accordingly, a combined forecast takes the following form:

$$(1 - \widehat{F}_{t+h|t})^c = \sum_{i=1}^{n} w_i (1 - \widehat{F}_{i,t+h|t}), \tag{9}$$

where $(1 - \widehat{F}_{t+h|t})^c$ denotes the combined probability forecast for each horizon h with w_i being the weight each point forecast gets in combining such predictions. We consider equal weighting and performance-based weighting schemes to pool indicator-specific forecasts. Regarding the equal weighting scheme we first calculate a simple mean forecast, denoted as $(1-\widehat{F}_{t+h|t})^{mean}$, where the corresponding weights are simply given as $w_i^{mean} = 1/n$, with n being the number of predictors considered for forecast combination. Second we calculate a median forecast, referred to as $(1-\widehat{F}_{t+h|t})^{median} = median[(1-\widehat{F}_{i,t+h|t})]_{i=1}^{n}$, as it may be less affected by outliers and may reduce the noise in the combined forecasts. Concerning the performance based weighting schemes, we use weights which are based on the in-sample accuracy of indicators in matching past business cycle turning points. Thus, we utilise the in-sample quadratic probability score (QPS) which is the binary outcome equivalent to mean squared errors as a measure of model fit. It can be calculated simply as $QPS_T^{ins} = \frac{1}{T}\sum_{t=1}^{T}[(1-\widehat{F}_t) - r_t]^2$, where T is the month when the forecast is made and r_t is a binary variable taking the value 1 during reference recession dates and 0 otherwise. The QPS can range over an interval of $[0, 1]$ with lower values indicating a better in-sample fit of the underlying model. Consequently, the weight an indicator i gets is inversely proportional to its model fit and can be determined as $w_i^{qps} = \frac{(QPS_i{}^{ins})^{-1}}{\sum_{i=1}^{n}(QPS_i{}^{ins})^{-1}}$. Moreover, we use weights based on the ranking of the in-sample model fit of individual predictors in a similar manner as proposed by Aiolfi and Timmermann (2006). Accordingly, we rank our indicators based on their in-sample QPS, where the indicator with the lowest QPS gets the rank of 1 and the worst one with the highest QPS the rank of n. Again the weight of indicator i is inversely proportional to its rank and can be calculated as $w_i^{rank} = \frac{rank_i{}^{-1}}{\sum_{i=1}^{n} rank_i{}^{-1}}$. This leaves us with four different weighting schemes when aggregating indicator-specific probability forecasts in order to generate our combined forecasts for recessionary periods.

Note that we use the same set of indicators for forecast combinations and factor extractions. This enables us to compare the forecast performance of imposing factor structure to potential predictors (aggregate-then-date) and forecast combination methods aggregating univariate model predictions (date-then-aggregate) in terms of forecast accuracy.

3.4 Indicator selection: elastic net

In a data rich environment the number of potential predictors of economic activity can be considerably large, whereas the information content of such indicators can vary substantially. Consequently, selecting those with higher predictive power for future business cycle turning points from a large macroeconomic dataset may be of paramount interest for analysts and forecasters. In this context, Boivin and Ng (2006) investigate the role of the number of potential indicators for factor analysis in economic forecasting and conclude that factors extracted from a low number of preselected predictors often lead to better forecasts than those obtained from the entire dataset. Similarly, Camacho, Perez-Quiros, and Poncela (2015) find out that adding more indicators with similar information content in Markov-switching dynamic factor models yields decreasing gains in predicting business cycle turning points. Against this background, we apply a statistical variable selection technique in order to pick the informative indicators for economic activity out of the entire dataset. Based on the above studies, the selection of informative indicators may be especially beneficial for the accuracy of our estimated factors. But in general this selection enables us to examine the potential contribution of such methods to the accuracy of recession probability forecasts in any of either business cycle dating approaches.

We utilise a penalised regressions which take the following form:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} |\boldsymbol{y} - \boldsymbol{X\beta}|^2 + \lambda_i L_i, \tag{10}$$

where y is the dependent variable representing the economic activity, $\boldsymbol{\beta}$ and $\boldsymbol{X}$ are the k-dimensional vector of coefficients and a $T \times k$ matrix of regressors, respectively, and k is the number of predictors. While the first part of Eq. (10) represents the OLS estimator, the second part $\lambda_i L_i$ for $i = 1, 2$ refers to the penalty added into the regression with λ_i being the tuning parameter controlling the weight of the penalty term L_i. For $i = 1$ the L_1 penalty is determined as $|\beta|_1 = \sum_{j=1}^{k} |\beta_j|$ and the penalised regression becomes a least absolute shrinkage and selection operator (lasso) introduced by Tibshirani (1996). In a similar vein, for $i = 2$ the L_2 penalty gets the form $|\beta|^2 = \sum_{j=1}^{k} \beta_j^2$ with the Eq. (10) shaping a ridge regression proposed by Hoerl and Kennard (1970). While the ridge estimator shrinks the coefficients of uninformative predictors towards zero without setting them exactly to zero, the lasso regression sets such coefficients to zero generating a sparse model. Thus the latter may be the better suitable approach to reduce the number of potential predictors. However, Tibshirani (1996) finds out that the ridge regression has a superior prediction performance compared to the lasso when the potential predictors are (highly) correlated. Against this background, Zou and Hastie (2005) introduce the elastic net (EN) regularisation technique which combines both lasso and ridge penalisation. Accordingly, the elastic net estimator can be written as

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} |\boldsymbol{y} - \boldsymbol{X\beta}|^2 + \alpha \sum_{j=1}^{k} \beta_j^2 + (1-\alpha) \sum_{j=1}^{k} |\beta_j|, \tag{11}$$

where the elastic net penalty, denoted as $J(\beta) = \alpha \sum_{j=1}^{k} \beta_j^2 + (1-\alpha) \sum_{j=1}^{k} |\beta_j|$ for $\alpha = \frac{\lambda_2}{\lambda_2+\lambda_1}$, is a convex combination of L_1 (lasso) and L_2 (ridge) penalty terms. While the lasso part of the elastic net penalty generates sparsity in reducing the number of predictors, the L_2 penalty supports the "*grouping effect*" considering the correlation among predictors. Moreover, the elastic net estimator reduces to the lasso for $\alpha = 0$, while it becomes a simple ridge regression for $\alpha = 1$.

We make use of the elastic net regularisation in order to select the informative predictors for the business cycle phases from our large dataset. In doing so, we use GDP as the dependent variable for the elastic net penalised regressions. Subsequently, we conduct a grid search for α over the interval $[0, 1)$ and select the predictors using the BIC adapted to the lasso as suggested by Zou, Hastie, and Tibshirani (2007). Lastly, we use the same set of selected indicators both for forecast combinations as well as for factor extraction to test their performance in detecting business cycle turning points.

4 Forecasting exercise

4.1 Forecast setup

We conduct a real-time out-of-sample forecasting exercise to assess the accuracy of recession probability predictions obtained from the two business cycle dating approaches in the US. Our initial estimation sample spans from 1980M01 to 1999M12, while the evaluation period is between 2000M01 and 2019M06. We carry out recursive estimations with an expanding window utilising historical real-time data vintages for the US. In our dataset, we only include those variables which are available over all vintages across the entire forecast evaluation period. This yields a real-time dataset which consists of 106 macroeconomic and financial indicators for the US.[12] Note that the ragged-edge structure of the dataset has no direct implications for our estimation steps, as we rely on univariate model specifications. It only determines the number of backcasts (predictions for past months in which data has not been published yet) at the current edge of the sample, which we need to calculate the now- and forecasts iteratively. For both factor extraction and variable selection, we cut our dataset to the variable with the highest publication delay and apply such procedures with a balanced dataset.

We use two model specifications during our forecasting exercise. On the one hand, we use a STAR model with a MTAR-type threshold with y_t^c and $\tau_{t-d} = \Delta y_{t-d}^c$ being the dependent variable and the threshold series, respectively. With this combination of the transformation of the underlying indicator and the type of the threshold series we aim at forecasting classical business cycle recessions exploiting their interconnection with growth cycle turning points as discussed in Section 3.1.1. On the other hand, we fit a STAR model with a TAR-type threshold to the first difference of the underlying series. In this specification the dependent variable is Δy_t and its lagged value $\tau_{t-d} = \Delta y_{t-d}$ is the threshold series. This combination aims at identifying classic business cycle recessions

[12]Note that an update of GDP data is missing in vintages October 2013 and January 2019. Moreover, time series for real personal income, real personal income ex transfers receipts and nonrevolving consumer credit to personal income have some missing observations in the December 1981 vintage. Similarly, the series for real manufacturing and trade industries sales is missing some data points in the August 1993 vintage. In all these cases we take the last available series for such indicators from previous vintages.

directly by means of turning points of the first difference of the underlying series as emphasised by Harding and Pagan (2005).

For the first model specification in which we use y_t^c as the dependent variable we need to extract the cyclical component of the underlying indicator. In this context Nilsson and Gyomai (2011) show that a double Hodrick and Prescott (1997) (HP) filter outperforms that of Christiano and Fitzgerald (2003) in terms of providing stable business cycle turning point predictions. Against this background, we adopt the double HP filter with a 12-120 month frequency band as employed by the OECD for its coincident leading indicators. In this filter method, the first step removes the long-run trend, denoted as y_t^{tr}, which is defined as developments above 10 year frequency, while the second step smoothes the time series eliminating short-term fluctuations determined in a frequency less than 1 year. As a result, the cyclical component y_t^c represents the dynamics of the underlying time series in a 12-120 month frequency band which is also in line with the observation of Burns and Mitchell (1946) that the duration of business cycle may range from one to ten or twelve years.

For the second model specification we simple use the first difference[13] of the underlying series, denoted as Δy_t, as the dependent variable. While - compared to dating with quarterly data - this enables a more timely identification of business cycle turning points in real-time, monthly data may exhibit more erratic movements which may have no information on the cyclical properties of the underlying indicator. In this regard, Burns and Mitchell (1946) and Bry and Boschan (1971) note that eliminating such movements may be beneficial to dating business cycle turning points. A common approach may be to use moving averages of monthly indicators to smooth the time series. However, moving average series' tend to be lagging the dynamics of the underlying indicators and hence may have unfavourable consequences for identifying business cycle phases. Considering the importance of the timeliness of indicators' business cycle dynamics in dating turning points we make use of the Hodrick and Prescott (1997) filter to smooth the monthly series under study. We eliminate erratic movements, defined as such below 1-year frequency, in a similar manner as done above.

In the context of trend-cycle decomposition, Orphanides and van Norden (2002) emphasise that utilisation of the HP and comparable filters may result in unreliable (end-of-sample) estimates of the output-gap in real-time. They attribute this to data revisions of the underlying series and to unreliable estimation results of the chosen filtering technique at the current edge of the sample. While this may have a considerable impact on the results when the point estimate of a single series, such as output-gap, is the variable of interest under study, the drawback of using such filters may be less evident in our framework which is based on aggregating recession probability forecasts obtained from a large set of indicators. Nevertheless, we take such potential drawbacks into account by utilising real-time data and applying the double HP-filter in each iteration over the recursive estimations.

In order to comply with the requirements of a real-time forecast evaluation, in each iteration of the recursive forecasting exercise, we

(1) use the Bry and Boschan (1971) algorithm with industrial production being the underlying series to obtain reference recessionary periods in real-time;
(2) smooth and transform the time series with the double HP-filter;

[13]See the third column of Table A.1 for the transformation of each series in this model specification.

(3) make use of elastic net regularisation technique for variable selection in real-time;
(4) specify the indicator specific model and get the coefficients of the model as well as of the transition function via three-dimensional grid search which are used as starting values for the nonlinear optimisation;
(5) generate bootstrapped indicator-specific recession probability forecasts based on STAR models;
(6) pool (i) all forecasts and (ii) those of via elastic net selected indicators with equal- (mean, median) and performance-based-weighting (inverse QPS/rank) schemes to obtain economy-wide recession probability forecasts;
(7) estimate ST factor models (pca, pls) and generate recession probability forecasts based on factors which are extracted from (i) all indicators and (ii) via elastic net selected indicators.

We evaluate the performance of our specifications by using the horizon-specific out-of-sample QPS as a measure of forecast accuracy. It takes the following form:

$$QPS_h^{oos} = \frac{1}{T-h-t_0+1}\sum_{t_0}^{T-h}[(1-\widehat{F}_t)-r_t]^2, \tag{12}$$

where t_0 and T are the beginning and the end of the evaluation period, respectively. Similar to its in-sample counterpart QPS_h^{oos} lies also within an interval of $[0,1]$ with lower values pointing at a better forecast accuracy of the underlying predictor. Note that we use recessionary periods based on the announcements of the NBER's Business Cycle Dating Committee as reference recessions r_t during the ex-post evaluation of the out-of-sample recession probability forecasts.

4.2 Forecast evaluation results

During our recursive forecasting exercise we utilise our real-time dataset and employ various data transformations, forecast combination schemes, factor extraction methods and a variable selection technique for the comparison of the date-then-aggregate and aggregate-then-date approaches to dating business cycle turning points.

Table 1 presents forecast evaluation results of two distinct model specifications. While the left panel reports the results obtained from smooth transition models with MTAR-type threshold series (ST/MTAR) using the cyclical component of underlying indicators, the middle panel displays those generated by smooth transition models with TAR-type threshold series (ST/TAR) using the first difference of underlying indicators. The right panel ($|\Delta|$) denotes the difference in forecast performance between the two model specifications. Moreover, $STAR$ refers to combined forecasts weighted with the scheme denoted in the subscript (*mean*, *median*, *qps*, *rank*). These four STAR model specifications represent the date-then-aggregate approach to business cycle dating. By contrast $STFM$ denotes predictions made by the common factor extracted by the method described in the subscript (*pca*, *pls*). These two ST factor model specifications act for the aggregate-then-date approach to dating business cycle turning points. Furthermore, $(\cdot)$ indicates either the entire dataset (all) or a subset of it which consists of a set of (i) via elastic net selected indicators (enet); or (ii) four indicators (real personal income excluding transfer receipts, industrial production, total nonfarm payroll employment and real manufacturing

Table 1: Forecast performance of selected ST/MTAR and ST/TAR models in real-time

	ST/MTAR models				ST/TAR models				$\|\Delta\|$			
$h =$	0	1	3	6	0	1	3	6	0	1	3	6
STAR_{mean} (*all*)	0.10	0.10	0.10	0.12	0.14	0.15	0.16	0.17	0.04	0.05	0.06	0.05
STAR_{median} (*all*)	0.03	0.04	0.07	0.13	0.08	0.08	0.11	0.14	0.05	0.04	0.04	0.01
STAR_{qps} (*all*)	0.07	0.07	0.08	0.10	0.10	0.11	0.12	0.13	0.02	0.03	0.04	0.02
STAR_{rank} (*all*)	0.06	0.06	0.07	0.10	0.09	0.11	0.12	0.14	0.03	0.05	0.06	0.03
STFM_{pls} (*all*)	0.19	0.21	0.23	0.27	0.20	0.20	0.19	0.26	0.01	0.01	0.04	0.01
STFM_{pca} (*all*)	0.26	0.26	0.25	0.23	0.23	0.25	0.26	0.29	0.03	0.01	0.01	0.06
STAR_{mean} (*enet*)	0.08	0.08	0.10	0.13	0.08	0.10	0.11	0.14	0.00	0.01	0.02	0.01
STAR_{median} (*enet*)	0.08	0.08	0.08	0.14	0.05	0.06	0.10	0.13	0.04	0.02	0.02	0.01
STAR_{qps} (*enet*)	0.07	0.08	0.09	0.12	0.07	0.09	0.11	0.14	0.01	0.01	0.02	0.01
STAR_{rank} (*enet*)	0.07	0.08	0.09	0.12	0.07	0.10	0.13	0.15	0.00	0.02	0.03	0.03
STFM_{pls} (*enet*)	0.15	0.15	0.16	0.21	0.28	0.30	0.31	0.32	0.13	0.15	0.15	0.11
STFM_{pca} (*enet*)	0.16	0.15	0.15	0.12	0.11	0.13	0.20	0.23	0.05	0.02	0.06	0.12
STAR_{mean} (4)	0.13	0.13	0.12	0.14	0.08	0.09	0.11	0.12	0.05	0.03	0.01	0.02
STAR_{median} (4)	0.14	0.12	0.10	0.14	0.07	0.08	0.10	0.12	0.06	0.04	0.00	0.03
STAR_{qps} (4)	0.10	0.10	0.09	0.12	0.08	0.10	0.11	0.12	0.02	0.00	0.02	0.00
STAR_{rank} (4)	0.10	0.10	0.10	0.13	0.09	0.10	0.12	0.13	0.02	0.00	0.03	0.01
STFM_{pls} (4)	0.18	0.19	0.20	0.25	0.19	0.21	0.24	0.25	0.01	0.02	0.04	0.00
STFM_{pca} (4)	0.18	0.17	0.18	0.25	0.31	0.33	0.36	0.41	0.13	0.16	0.18	0.16
STAR_{gdp}	0.28	0.29	0.33	0.42	0.10	0.11	0.16	0.30	0.17	0.18	0.17	0.12

Notes: This table presents the QPS' of selected models based on the ST/MTAR and ST/TAR specifications as well as their absolute differences $|\Delta|$ between the two model specifications. The grey cells highlight that the QPS of selected models is statistically significantly lower than that of the benchmark at least under 10% significance level based on a one-sided DM-test for forecast evaluation based on historical vintages of the real-time dataset. For $|\Delta|$ grey cells indicate that the difference in forecast performance between the two model specifications is statistically significant at least under 10% significance level based on a two-sided DM-test.

and trade industries sales) which are closely monitored by the NBER's Business Cycle Dating Committee (4). The bottom line presents the performance of the benchmark, which is a STAR model estimated with monthly GDP.[14] We report forecast evaluation results for all the above-mentioned model specifications in both business cycle dating approaches in terms of QPS as well as the absolute difference in forecast performance, denoted as $|\Delta|$, between the two distinct model specifications. Lastly, grey coloured cells highlight either that the QPS of the selected model is significantly lower than that of the benchmark or $|\Delta|$ is statistically different then zero under 10% significance level based on

[14] We estimate the STAR_{gdp} model with monthly GDP as follows: First we extrapolate the quarterly value of GDP to every month of the related quarter which yields a monthly time series. Then we apply the double HP-filter in order to obtain the cyclical component of the GDP in a monthly frequency and, at the same time, to eliminate the stepped structure of the artificially created monthly series. In addition, we replicate the ragged-edge structure of GDP throughout recursive estimations. Finally, recession probability forecasts are generated in the same way as with monthly indicators.

one- and two-sided Diebold and Mariano (1995) (DM) tests, respectively.

Table 1 shows that the best performing model is clearly the STAR_{median} (all) with a MTAR-type threshold series. Thus, the combination of a large dataset with a date-then-aggregate approach and taking into account the interrelation between the classical business cycle and the growth cycle seems to be beneficial to forecasting recession probabilities in the US. In addition, our forecast evaluation results reveal interesting facts on the importance of cross-sectional information in forecasting turning points, the performance of the two different dating approaches and the role of variable selection. On top of that, they unveil the potential of smooth transition models in forecasting recession probabilities. We take a closer look at all these insights in the following.

The importance of cross-sectional information

Following Stock and Watson (2014) we utilise a large set of macroeconomic and financial indicators to predict business cycle turning points. Our results confirm that cross-sectional information may be beneficial to forecasting recession probabilities as selected model specifications utilising such information are mostly able to outperform model specifications based on four preselected variables as well as the single indicator benchmark model. This holds true for both dating approaches.

On "*date-then-aggregate*" vs. "*aggregate-then-date*"

Table 1 shows that the date-then-aggregate approach clearly outperforms the aggregate-then-date approach in predicting recession probabilities over the entire forecast horizon. Specifically, combining indicator-specific recession probability predictions tends to yield more accurate recession forecasts than those based on a single aggregated indicator representing the state of economic activity. This holds irrespective of the size of the dataset. Even if we just use four preselected variables or a smaller set of predictors obtained from a variable selection algorithm, combining indicator specific turning points always outperforms the smooth transition factor models. In line with the findings of Boivin and Ng (2006) and Camacho et al. (2015), however, factor models representing the aggregate-then-date approach yield better forecast performance using a relatively small set of indicators, whereas date-then-aggregate models perform better when applied to a large dataset. This is in line with the definition of business cycle turning points of Burns and Mitchell (1946) arguing that such turning points occur among a large set of widely spread indicators synchronously. Clements and Galvão (2006), who compared the two approaches on business cycle dating based on a small dataset of ten variables and only focusing on the 2001 recession, did not find a clear pattern which approach performs better. With the information of an additional recessionary period, namely the 2008/2009 downturn, we by contrast can clearly show that the date-then-aggregate approach outperforms the aggregate-then-date approach remarkably. Chauvet and Piger (2008) evaluate both approaches for various recessionary periods but by only using four variables. They show that a parametric Markov-Switching factor model outperforms the non-parametric date-then-aggregate approach of Harding and Pagan (2006). However, by using both types of business cycle dating parametrically, we show the superiority of the date-then-aggregate approach.

The role of variable selection in real-time

Many studies following the aggregate-then-date approach use a tiny set of preselected coincident indicators which are emphasised by the NBER's Business Cycle Dating Committee in order to identify business cycle turning points. These indicators are proven to perform reasonably well in identifying recessionary periods as shown in several studies, such as Chauvet (1998), Kim and Nelson (1998), Chauvet and Piger (2008) and Camacho, Perez-Quiros, and Poncela (2018) among others, as well as in the bottom panel of Table 1. Though, they only represent a limited subset of the information on economic activity and hence are far away from being a large cross-section in the sense of Burns and Mitchell (1946). Against this backdrop we suggest - if a small number of indicators are preferable for forecasting - to apply statistical variable selection techniques to pick the informative predictors from a large dataset in real-time. In this regard a comparison of the middle and bottom panel of Table 1 indicates that model specifications based on via elastic net selected indicators mostly have a better forecast performance than those relying only on the four preselected coincident indicators in both business cycle dating approaches.

A closer look at the "*date-then-aggregate* model specifications

Within the scope of the date-then-aggregate approach, we consider both equally- as well as performance-based forecast combination schemes to aggregate indicator-specific recession probability predictions. Starting with the former an equally-weighted forecast combination often turns out to be too hard to beat in empirical applications.[15] Accordingly, the median forecast also seem to be hard to beat with respect to recession probability forecasts. Nevertheless, forecasts combined with a simple performance-based weighing scheme are partly able to beat the equally-weighted mean forecast combination. However, this comparison should be considered with caution for a couple of reasons. In macroeconomic forecasting exercises model weights are mostly calculated according to their out-of-sample prediction performance in the recent past. This may be an appropriate approach to estimate optimal weights when the target variable is an indicator with a frequent release calender, such as monthly or quarterly. However, this approach might suffer from lack of recent and timely available observations in predicting business cycle turning points due to a less frequent occurrence of recessions. Therefore, we rely on the in-sample fit of the univariate models when we utilise performance-based weighting schemes for aggregate indicator-specific forecasts. This enables us to endorse more weights to indicators which, at least in our framework, exhibit a higher degree of coincidence with historical business cycle fluctuations. Finally, relatively stable weights - supposing that the performance of indicators coinciding with the business cycle do not change as frequent as their out-of-sample predictive accuracy - may partly explain our findings on the comparison between equally- and performance-based weighting schemes.

[15] This (repeated) finding is called "forecast combination puzzle" by Stock and Watson (2004). While the reader is referred to Aiolfi and Timmermann (2006) and Timmermann (2006) for a more comprehensive overview of various forecast combination schemes, Smith and Wallis (2009), Claeskens, Magnus, Vasnev, and Wang (2016) and Chan and Pauwels (2018) provide possible empirical and theoretical explanations of the forecast combination puzzle.

A closer look at the "*aggregate-then-date* factor extraction methods

In the aggregate-then-date approach, we use two different factor extraction methods to aggregate the cross-sectional information into a single indicator which is then used for business cycle turning points dating. While the PCA aims at explaining the overall variance of the dataset, PLS considers the covariance between factors and the target variable. According to Table 1 PLS seems to be the favourable factor extraction method, especially when the dataset is large. Considering smaller datasets both methods lead to similar forecast performance based on the ST/MTAR model specifications, whereas the results are rather mixed applying ST/TAR models.

On ST/MTAR vs. ST/TAR model specifications

First of all, the STAR framework - despite its simple nature - is able to provide reasonably well business cycle turning point predictions. This holds mainly in both business cycle dating approaches under study. The flexibility of the STAR model allows us to consider two model specifications based on the discussion of Harding and Pagan (2005) during our forecasting exercise. To begin with, both model specifications are able to outperform the benchmark with a few ST/TAR model specifications being an exception. Comparing both model specifications, however, we show that smooth transition models with an MTAR-type threshold series fitted to the cyclical component of the underlying series tend to generate more accurate recession probability forecasts than those made by the ST/TAR models. This indicates that considering the interconnection between business and growth cycle in model building seems to be favourable to forecasting classical business cycle recession probabilities within the smooth transition framework.

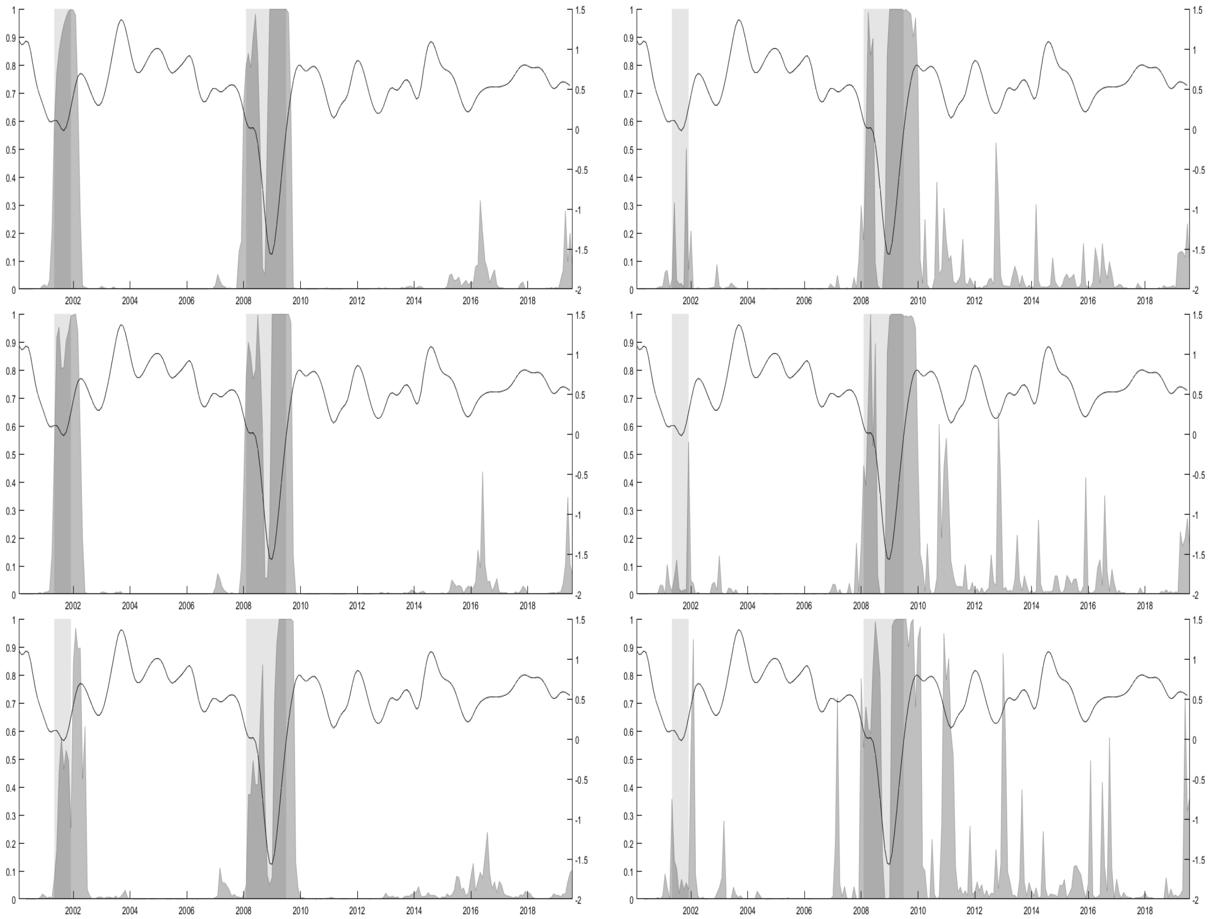
A graphical illustration

Our out-of-sample forecast evaluation shows that the $\text{STAR}_{median}(all)$ is the best performing model to forecast recessionary periods, at least from a purely statistical point of view. In order to visualise its strong performance, Figure 3 presents recession probability estimates for the current month (top panel) as well as 1- and 3-months-ahead (middle and bottom panel) recession probability forecasts of the $\text{STAR}_{median}(all)$ models for the ST/MTAR (left panel) and ST/TAR (right panel) specifications over the entire evaluation period from 2000 January to 2019 June. Shaded areas correspond to past recession periods based on the NBER's business cycle turning point announcements, while black solid line refers to the smoothed 3-month growth rate of the monthly GDP (right axis) to illustrate the state of the economic activity.

Our now- and forecasts shows that the ST/MTAR $\text{STAR}_{median}(all)$ model (left panel) is able to identify both recessions quite accurately in real-time. Moreover, we again want to stress that we forecast recessionary periods out-of sample, that is the model anticipates both recessions up to 3-months in advance, whereas the NBER's Business Cycle Dating Committee announced related turning points up to 20 months after they occurred. By contrast, the ST/TAR $\text{STAR}_{median}(all)$ specification (right panel) seems to miss the recession in 2001 and generates slightly more false recession signals, especially in the aftermath of the Great Recession in 2008/9.

In general, the graphical illustration underpins the strong forecast performance of our

Figure 3: Real-time recession probability forecasts for the US



Notes: This graph plots the nowcast (upper panel) as well as 1- and 3-month-ahead recession probability forecasts (middle and lower panel) of the $\text{STAR}_{median}(all)$ models for the ST/MTAR (left panel) and ST/TAR (right panel) specifications over the entire evaluation period from 2000 January to 2019 June. Shaded areas and black solid line correspond to the reference recession periods based on the NBER's Business Cycle Dating Committee's turning point announcements and to the (smoothed) 3-month growth rate of monthly GDP.

proposed ST/MTAR model specification. It is not only able to provide reliable out-of-sample recession predictions, but it also sends very few (if any) false signals, i.e. whenever the model generates a positive recession probability forecast, there is at least a small dip in the GDP growth pointing at an economic slowdown. Against this background, one may ask "when does the predicted probabilities signal a looming recession?". In this regard, 50% and above is widely considered as a threshold for recessions, whereas Chauvet and Piger (2008) suggest a two-step approach using 80% for three consecutive months as a signal for recessions and the first month with above 50% probability prior to crossing 80% as the turning point. While the former may give rise to more frequent false recession signals, the latter may suffer from lack of timeliness of the recession warning. With respect to our proposed framework, a probability forecast of around 50% seems to be a reasonable cut-off to distinguish between expansions and recessions.

Finally, Figure 3 illustrates that the probability of a recession mostly starts to increase (decrease) gradually prior to (after) recessions. While this property provides the forecaster with timely information on soaring economic conditions and hence may be desirable by practitioners, it generates forecast errors for several months and may be disadvantageous for the statistical properties of the model under study. Consequently, one may consider the pattern of recession probability forecasts in addition to statistical model comparison methods, especially between models with similar forecast performance but different patterns, when selecting the appropriate model for the analysis.

5 Concluding remarks

We propose a novel approach to forecast recession probabilities based on a large set of macroeconomic and financial indicators for economic activity using smooth transition models. Following Stock and Watson (2010, 2014) we exploit a large cross-section of macroeconomic and financial variables and show that the use of such a large dataset in combination with a date-then-aggregate approach is able to provide informative recession forecasts for up to three months in advance. Moreover, we demonstrate that the smooth transition framework - which is surprisingly neglected in the related literature so far - performs very well in forecasting recession probabilities, especially when we take into account the interrelation between classical business cycles and growth cycles in our modeling strategy. To sum up, we contribute to the existing literature by (i) examining the importance of cross-sectional information on predicting recession probabilities; (ii) providing the literature with a comprehensive comparison of the date-then-average and average-then date approaches to business cycle dating in real-time and (iii) unveiling the capability of smooth transition regressions to forecast recession probabilities.

It is worth to mention that our adopted methodology follows a slightly different approach for modelling regime switches than those in the related literature. In this context we utilise ST regressions to model the alternation between the two business cycle phases, whereas related studies mostly employ binary response or Markov-switching factor models. The smooth transition framework offers practitioners some advantages compared to other model classes. For instance, in the STAR framework, an estimated transition function determines the alternation between the two states making its drivers observable for the analyst, whereas regime changes are driven by an unobserved process in Markov-switching models. Therefore, the smooth transition framework is able provide valuable insights into dynamics of its underlying indicator over different phases of the business cycle. In fact, it allows to model regime switches explicitly enabling us to take into account the interrelation between classical business- and growth cycles. Besides that, binary response models mostly rely on the assumption that past business cycle turning points are known. This may have an impact on the forecasting properties of the model under study. Unlike such models, however, estimation process of the STAR approach requires no information on past recessionary periods. Historical recession dates are only used to evaluate (in- and) out-of-sample forecast performance of these models (while the former is only of interest, if a performance-based weighting scheme based on in-sample fit to past recessions is desirable for combining indicator-specific forecasts). Thus, recession probability predictions made by this class of models tend to be more robust to potentially different assessments of past business cycle turning points.

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Appendix A

For a detailed overview of the time series, the reader is referred to McCracken and Ng (2016) for the FRED-MD, to https://fred.stlouisfed.org/series/USREC for the recession indicator (USREC) and to https://alfred.stlouisfed.org/series?seid=GDPC1 for the GDP.

The column data transformation (tra.) denotes: (0) no transformation, (3) 1-month difference, (5) 1-month log growth rates, (8) 3-months log growth rates, (13) 12-months growth rates, (14) 12-months log growth rates. Note that data transformations only apply to ST/TAR model specifications.

Table A.1: US dataset

Series	Description	tra.	Source
Recession indicator			
USREC	NBER based Recession Indicators for the United States from the Period following the Peak through the Trough	0	FRED
GDP			
GDPC1	Real Gross Domestic Product	8	ALFRED
Output and income			
RPI	Real Personal Income	5	FRED-MD
W875RX1	Real personal income ex transfer receipts	5	FRED-MD
INDPRO	IP Index	5	FRED-MD
IPFPNSS	IP: Final Products and Nonindustrial Supplies	5	FRED-MD
IPFINAL	IP: Final Products (Market Group)	5	FRED-MD
IPCONGD	IP: Consumer Goods	5	FRED-MD
IPMAT	IP: Materials	5	FRED-MD
IPMANSICS	IP: Manufacturing (SIC)	5	FRED-MD
CUMFNS	Capacity Utilization: Manufacturing	5	FRED-MD
Labour market			
CLF16OV	Civilian Labor Force	5	FRED-MD
CE16OV	Civilian Employment	5	FRED-MD
UNRATE	Civilian Unemployment Rate	5	FRED-MD
UEMPMEAN	Average Duration of Unemployment (Weeks)	5	FRED-MD
UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	5	FRED-MD
UEMP5TO14	Civilians Unemployed for 5-14 Weeks	5	FRED-MD
UEMP15OV	Civilians Unemployed - 15 Weeks & Over	5	FRED-MD
UEMP15T26	Civilians Unemployed for 15-26 Weeks	5	FRED-MD
UEMP27OV	Civilians Unemployed for 27 Weeks and Over	5	FRED-MD
CLAIMSx	Initial Claims	5	FRED-MD
PAYEMS	All Employees: Total nonfarm	5	FRED-MD
USGOOD	All Employees: Goods-Producing Industries	5	FRED-MD

Continued on next page

Series	Description	tra.	Source
CES1021000001	All Employees: Mining and Logging: Mining	5	FRED-MD
USCONS	All Employees: Construction	5	FRED-MD
MANEMP	All Employees: Manufacturing	5	FRED-MD
DMANEMP	All Employees: Durable goods	5	FRED-MD
NDMANEMP	All Employees: Nondurable goods	5	FRED-MD
SRVPRD	All Employees: Service-Providing Industries	5	FRED-MD
USWTRADE	All Employees: Wholesale Trade	5	FRED-MD
USTRADE	All Employees: Retail Trade	5	FRED-MD
USFIRE	All Employees: Financial Activities	5	FRED-MD
USGOVT	All Employees: Government	5	FRED-MD
CES0600000007	Avg Weekly Hours : Goods-Producing	5	FRED-MD
AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	5	FRED-MD
AWHMAN	Avg Weekly Hours : Manufacturing	5	FRED-MD
CES0600000008	Avg Hourly Earnings : Goods-Producing	5	FRED-MD
CES2000000008	Avg Hourly Earnings : Construction	5	FRED-MD
CES3000000008	Avg Hourly Earnings : Manufacturing	5	FRED-MD
Housing			
HOUST	Housing Starts: Total New Privately Owned	0	FRED-MD
HOUSTNE	Housing Starts, Northeast	0	FRED-MD
HOUSTMW	Housing Starts, Midwest	0	FRED-MD
HOUSTS	Housing Starts, South	0	FRED-MD
HOUSTW	Housing Starts, West	0	FRED-MD
PERMIT	New Private Housing Permits (SAAR)	0	FRED-MD
PERMITNE	New Private Housing Permits, Northeast (SAAR)	0	FRED-MD
PERMITMW	New Private Housing Permits, Midwest (SAAR)	0	FRED-MD
PERMITS	New Private Housing Permits, South (SAAR)	0	FRED-MD
PERMITW	New Private Housing Permits, West (SAAR)	0	FRED-MD
Consumption, orders and inventories			
CMRMTSPLx	Real Manu. and Trade Industries	5	FRED-MD
RETAILx	Retail and Food Services Sales	5	FRED-MD
AMDMNOx	New Orders for Durable Goods	5	FRED-MD
ANDENOx	New Orders for Nondefense Capital	5	FRED-MD
AMDMUOx	Unfilled Orders for Durable Goods	5	FRED-MD
BUSINVx	Total Business Inventories	5	FRED-MD
ISRATIOx	Total Business: Inventories to Sales	5	FRED-MD
UMCSENTx	Consumer Sentiment Index	5	FRED-MD
Money and credit			

Continued on next page

Series	Description	tra.	Source
M1SL	M1 Money Stock	14	FRED-MD
M2SL	M2 Money Stock	14	FRED-MD
M2REAL	Real M2 Money Stock	14	FRED-MD
AMBSL	St. Louis Adjusted Monetary Base	14	FRED-MD
TOTRESNS	Total Reserves of Depository Institutions	14	FRED-MD
NONBORRES	Reserves Of Depository Institutions	13	FRED-MD
BUSLOANS	Commercial and Industrial Loans	14	FRED-MD
REALLN	Real Estate Loans at All Commercial Banks	14	FRED-MD
NONREVSL	Total Nonrevolving Credit	14	FRED-MD
CONSPI	Nonrevolving consumer credit to Personal Income	14	FRED-MD
MZMSL	MZM Money Stock	14	FRED-MD
DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	14	FRED-MD
DTCTHFNM	Total Consumer Loans and Leases Outstanding	14	FRED-MD
INVEST	Securities in Bank Credit at All Commercial Banks	14	FRED-MD
Interest and exchange rates			
FEDFUNDS	Effective Federal Funds Rate	3	FRED-MD
CP3Mx	3-Month AA Financial Commercial Paper Rate	3	FRED-MD
TB3MS	3-Month Treasury Bill:	3	FRED-MD
TB6MS	6-Month Treasury Bill:	3	FRED-MD
GS1	1-Year Treasury Rate	3	FRED-MD
GS5	5-Year Treasury Rate	3	FRED-MD
GS10	10-Year Treasury Rate	3	FRED-MD
AAA	Moody's Seasoned Aaa Corporate Bond Yield	3	FRED-MD
BAA	Moody's Seasoned Baa Corporate Bond Yield	3	FRED-MD
COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	3	FRED-MD
TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	3	FRED-MD
TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	3	FRED-MD
T1YFFM	1-Year Treasury C Minus FEDFUNDS	3	FRED-MD
T5YFFM	5-Year Treasury C Minus FEDFUNDS	3	FRED-MD
T10YFFM	10-Year Treasury C Minus FEDFUNDS	3	FRED-MD
AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	3	FRED-MD
BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	3	FRED-MD

Continued on next page

Series	Description	tra.	Source
TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	5	FRED-MD
EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	5	FRED-MD
EXJPUSx	Japan / U.S. Foreign Exchange Rate	5	FRED-MD
EXUSUKx	U.S. / U.K. Foreign Exchange Rate	5	FRED-MD
EXCAUSx	Canada / U.S. Foreign Exchange Rate	5	FRED-MD
Prices			
OILPRICEx	Crude Oil, spliced WTI and Cushing	14	FRED-MD
PPICMM	PPI: Metals and metal products:	14	FRED-MD
CPIAUCSL	CPI : All Items	14	FRED-MD
CPIAPPSL	CPI : Apparel	14	FRED-MD
CPITRNSL	CPI : Transportation	14	FRED-MD
CPIMEDSL	CPI : Medical Care	14	FRED-MD
CUSR0000SAC	CPI : Commodities	14	FRED-MD
CUSR0000SAS	CPI : Services	14	FRED-MD
CPIULFSL	CPI : All Items Less Food	14	FRED-MD
CUSR0000SA0L5	CPI : All items less medical care	14	FRED-MD
Stock market			
S&P 500	S&P's Common Stock Price Index: Composite	5	FRED-MD
S&P: indust	S&P's Common Stock Price Index: Industrials	5	FRED-MD
S&P div yield	S&P's Composite Common Stock: Dividend Yield	5	FRED-MD
S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	5	FRED-MD