Machine Learning in Finance

Overview

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Forecasting vs. In-Sample Fitting

Forecasting vs. In-Sample Fitting

- We are often more interested in forecasting than in understanding the past data
- For this reason we turn to the out-of-sample forecasting properties of various models
- We will take as our benchmark model the basic linear model
- Linear models in the easiest to use
- In forecasting it is useful to understand regime changes
- People behave differently in recession and in times of boom
- They also behave differently in times of high inflation than in low inflation or deflation

STRS and NNRS Models, Part I

- The **Smooth Transition Regime Switching Model** (STRS) has the following functional form:

$$y_t = \alpha_1 x_t \Psi(y_{t-1}; \theta, c) + \alpha_2 x_t [1 - \Psi(y_{t-1}; \theta, c)]$$

- The matrix x_t is the set of regressors at time t, α_1 represents the parameters in state 1, while α_2 is the parameter vector in state 2. The transition function Ψ, which determines the influence of each regime or state, depends on the value of y_{t-1} as well as a "smoothness" parameter vector θ and a threshold parameter c.
- We use a logistic or logsigmoid specification for $\Psi(y_{t-1}; \theta, c)$:

$$\Psi(y_{t-1}; \theta, c) = (1/(1 + exp[-\theta(y_{t-1} - c)]))$$

- We see that the STRS model is a special case of a neural network.

STRS and NNRS Models, Part I

- One way to model a "smooth transition" regime-switching framework with neural networks is to adapt the feedforward network with jump connections.
- In addition to the direct linear links from the inputs or regressors x to the dependent variable y, holding in all states, we can model the regime-switching as a jump-connection neural network with one hidden layer and two neurons, one for each regime.
- These two regimes are weighted by a logistic connector which determines the relative influence of each regime or neuron in the hidden layer.

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STRS and NNRS Models, Part II

STRS and NNRS Models, Part II

- This system appears in the following equations:

$$y_t = \alpha x_t + \beta\{[\Psi(y_{t-1}; \theta, c)]G(x_t; \kappa)$$

$$+[1 - \Psi(y_{t-1}; \theta, c)]H(x_t; \lambda)\} + \eta_t$$

- x_t is the vector of independent variables at time t, and α represents the set of coefficients for the direct link.
- The functions $G(x_t; \kappa)$ and $H(x_t; \lambda)$, which capture the two regimes, are logsigmoid and have the following representations:

$$G(x_t; \kappa) = (1/(1 + exp[-\kappa x_t]))$$
$$H(x_t; \lambda) = (1/(1 + exp[-\lambda x_t]))$$

- κ and λ are the coefficients for the vector x_t in the two regimes, $G(x_t; \kappa)$ and $H(x_t; \lambda)$.

STRS and NNRS Models: Part II

- As above, transition function Ψ, which determines the influence of each regime, depends on the value of y_{t-1} as well as the parameter vector θ and a threshold parameter c.
- The parameter θ determines the smoothness of the change in the value of this function, and thus the transition from one regime to another regime.
- This neural network regime switching system encompasses the linear smooth-transition regime switching system.
- If nonlinearities are not significant, then the parameter β would close to zero.
- The linear component may represent a "core process" which is supplemented by nonlinear regime switching processes.

STRS and NNRS Models: Part II

- Of course, there may be more regimes than two, and this system, like its counterpart above, may be extended to incorporate three or more regimes.
- However, for most macroeconomic and financial studies, we usually consider two regimes, for example recession and recovery in business cycle models, or inflation and deflation in models of price adjustment.
- As in the case of linear STRS regime-switching models, the most important payoff of this type of modeling is that we can forecast more accurately not only the dependent variable, but also the probability of continuing in the same regime.
- If the economy is in deflation or recession, given by the $H(x_t; \lambda)$ neuron, we can determine if the likelihood of continuing in this state, $1 - \Psi(y_{t-1}; \theta, c)$,is close to zero or one, and whether this likelihood is increasing or decreasing over time.

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Forecasting Automobile Demand, Part I

Forecasting Automobile Demand, Part I

- This market for automobiles is a well developed one, and there is a wealth of research on the theoretical foundations and the empirical behavior of this market.
- Manufacturers evaluate and forecast the demand for the stock of automobiles, the number of retirements, and their market share. Adding a dose of strategic planning, they decide how much to produce.
- These decisions occur well before production and distribution take place.
- Consumers decide at the time of purchase, based on their income, price and utility requirements, what stock is optimal.
- To the extent that consumer decisions to expand the stock of the asset coincide with or exceed the amount of production by manufacturers, prices will adjust to revise the optimal stock and clear the market.

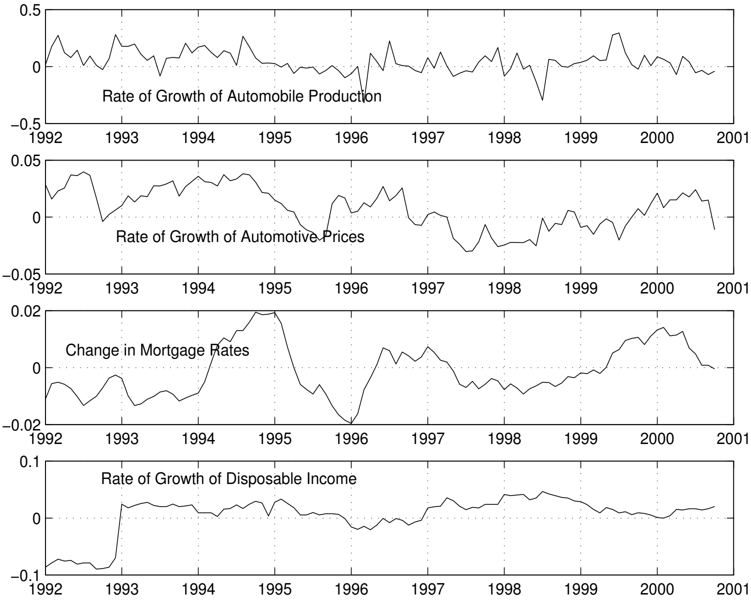
Forecasting Automobile Demand, Part I

- To the extent they fall short, the number of retirements of automobiles will increase and the price of new vehicles will fall to clear the market. Both the general stability in the underlying market structure, as well as the recursive nature of producer versus consumer decision making, have made this market amenable to less complex estimation methods.
- Since research suggests this is precisely the kind of market where linear time series forecasting will perform rather well, it is a good place to test the usefulness of the alternative of neural networks for forecasting.
- We make use of quantity and price data for automobiles, as well as an interest rate and a disposable income as aggregate variables.
- The quantity variable represents the aggregate production of new vehicles excluding heavy trucks and machinery, obtained from the Bureau of Economic Analysis of the Department of Commerce. The price variable is an index appearing in the Bureau of Labor Statistics.

Forecasting Automobile Demand, Part I

- The interest rate argument is the home mortgage rate available from Board of Governors of the U.S. Federal Reserve System, while the income argument is personal disposable income, also obtained from the Bureau of Economic Analysis of the Department of Commerce.
- Home mortgage rates were chosen as the relevant interest rate following Hess (1977), who shows consumers consider housing and automobile decisions jointly. Personal disposable income was generated from consumption and savings data.
- The consumption series was the average over the quarter to reflect more accurately the permanent income concept.

Forecasting Automobile Demand, Part I



- We see that for the decade as a whole, there has been about a four and a half percent annual growth in automobile production.
- The price growth has been slightly less than one percent and disposable income growth has been about one-half of a percent.
- We also do not see a strong contemporaneous correlation between the variables.

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Forecasting Automobile Demand, Part II

Forecasting Automobile Demand, Part II

- We use three models: a linear model, a smooth-transition regime-switching model, and a neural network smooth-transition regime-switching model
- We are working monthly data. We are interested in the year-on-year changes in these data.
- When forecasting, we are interesting in the annual or twelve-month ahead forecast of the quantity of automobiles produced.
- Letting Q_t represent the quantity of automobiles produced at time t, we forecast the following variable:

$$\Delta_h q_{t+h} = q_{t+h} - q_t$$

$$q_t = ln(Q_t), h = 12$$

- Regressors: $x_t = [\Delta_{12} q_t, \Delta_{12} p_t, \Delta_{12} r_t, \Delta_{12} y_t]$
- where P_t, R_t, Y_t signify the price index, the gross mortgage

Foreasting Automobile Demand, Part II

- Linear model:

$$\Delta q_{t+h} = \alpha x_t + \eta_t$$

$$\eta_t = \varepsilon_t + \gamma(L)\varepsilon_{t-1}$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

- STRS model:

$$\Delta q_{t+h} = \Psi_t \alpha_1 x_t + (1 - \Psi_t)\alpha_2 x_t + \eta_t$$

$$\Psi_t = \Psi(\theta \Delta y_t - c)$$

$$= 1/[1 + exp(\theta \Delta y_t - c)]$$

- The error terms η, ε have the same meaning as in the linear model

Foreasting Automobile Demand, Part II

- NNRS model:

$$\Delta q_{t+h} = \alpha x_t + \beta[\Psi_t G(x_t;\alpha_1)$$

$$+(1-\Psi_t)H(x_t;\alpha_2)] + \eta_t$$

$$\Psi_t = \Psi(\theta\Delta y_t - c) = 1/[1 + exp(\theta\Delta y_t - c)]$$

$$G(x_t;\alpha_1) = 1/[1 + exp(-\alpha_1 x_t)]$$

$$H(x_t;\alpha_2) = 1/[1 + exp(-\alpha_2 x_t)]$$

- The error terms η, ε have the same meaning as in the linear model

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Forecasting Automobile Demand, Part III

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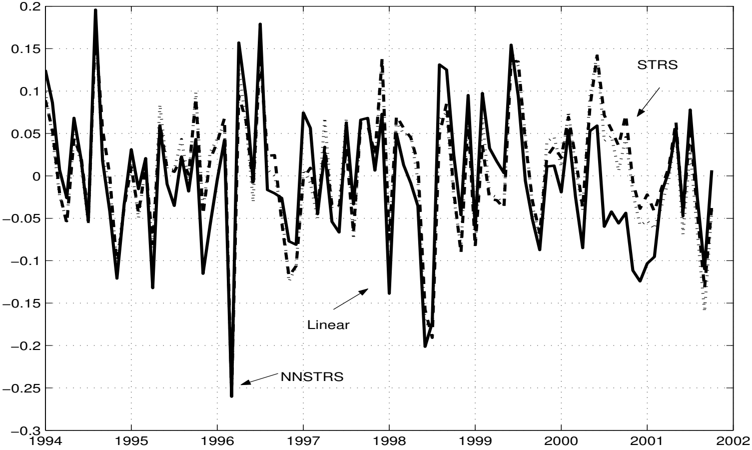
- In-sample performance



Foreasting Automobile Demand, Part III

- In-sample diagnostics and HQ criterion:

	Model		
	Linear	STRS	NNRS
Diagnostic			
SSE	.615	.612	.502
R^2	.528	.612	.645
HQIF	-25.34	-22.71	-32.98

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Forecasting Automobile Demand, Part IV

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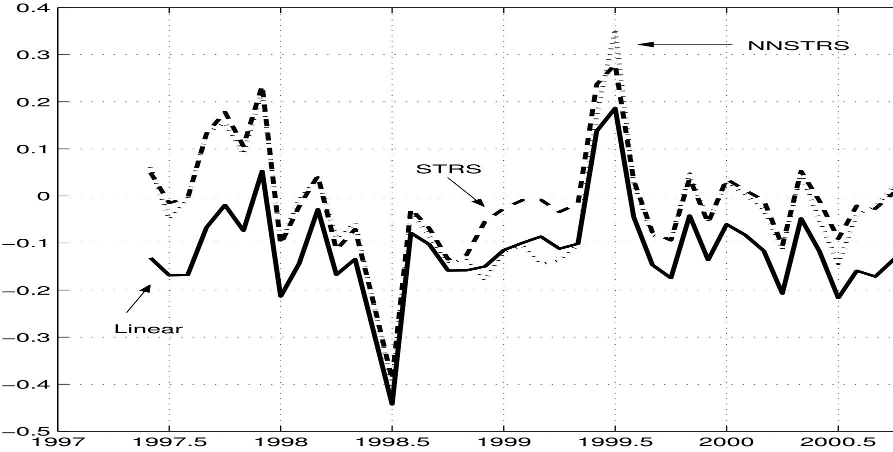
- Out-of-sample performance, forecast errors for the last 53 observations: rolling-window forecasts:



Foreasting Automobile Demand, Part IV

- Out-of-Sample Forecast Accuracy Tests

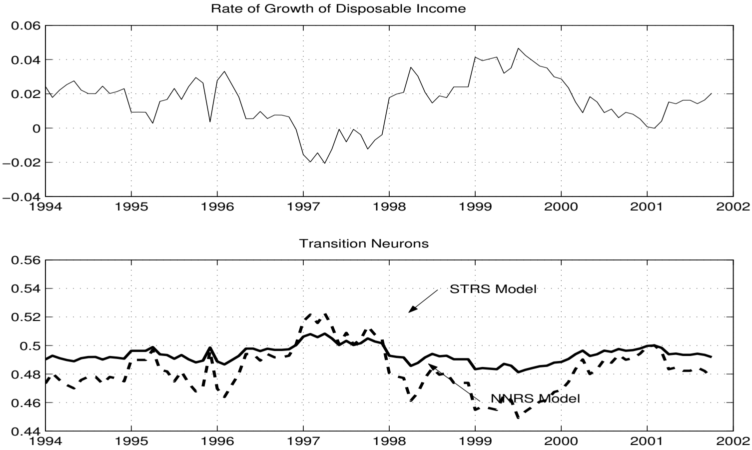
	Model		
	Linear	STRS	NNRS
Diagnostic			
Root Mean Squared Error	.180	.122	.130
Directional Accuracy	.491	.679	.698
Diebold-Mariano P-Value	Linear vs. SRTS	Linear vs. NNRS	STRS-vs. NNRS
(5-lags)	0.000	0.013	0.853

- DA test tells us that the Linear Model does no better than flipping a coin for predicting sign changes

STRS and the NNSTRS errors are significantly better than the linear model, but they are significantly different from each other.

Foreasting Automobile Demand, Part IV

- Nonlinearity evidence: Adjustment of the Neurons



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Forecasting Spreads, Part I

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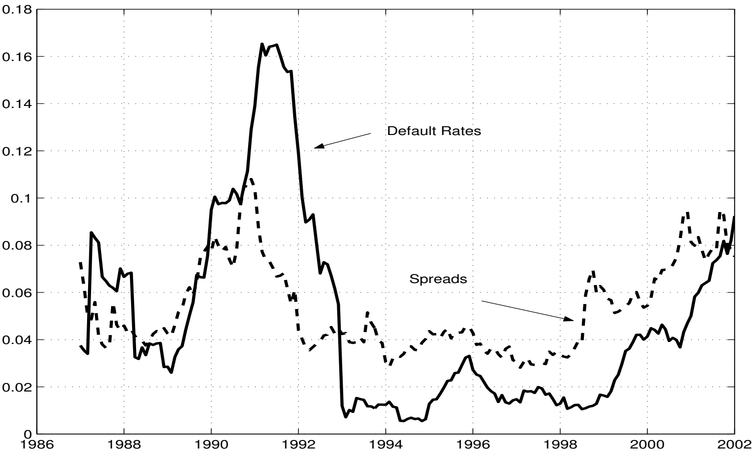
- One fact emerges: the spreads declined rapidly in the early 90's, after the Gulf War recession, and started to increase in the late 1990's, after the onset of the Asian crisis in late 1997.
- The same is true of the default rates. What is the cause of the decline in the "spreads", as well as the subsequent upswing of this variable?
- The process of financial market development may lead to increased willingness to take risk, as lenders attempt to achieve gains by broader portfolio diversification, which could explain a gradual decline, as lenders become less risk averse.
- Another factor may be the "spillover effects" from increases or decreases in the share market, as well as increased optimism or pessimism from the rate of growth of industrial production or from changes in "confidence" in the economy. These latter two variables represent "business climate" effects.

Foreasting Spreads, Part I

- Spreads and Default rates



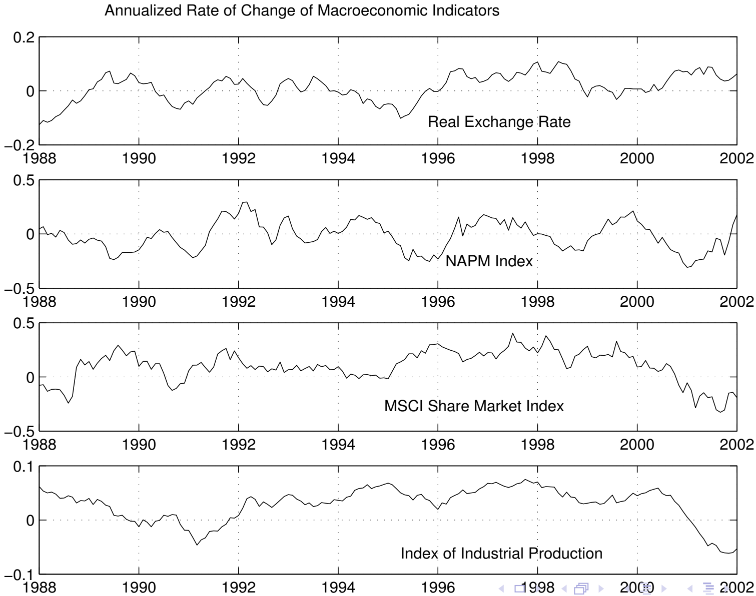
Forecasting Spreads, Part I

- We are interested in determining how these spreads respond to their own and each other's lagged values, to "bond specific shocks" such as default rates
- We also look at macroeconomic variables often taken as "leading indicators" of aggregate economic activity or the "business climate":

1. the real exchange rate (REXR)
2. index of industrial production (IIP),
3. the National Association of Product Manufacturer's Index (NAPM),
4. Morgan Stanley Capital International Index of the US Share Market (MSCI).

Forecasting Spreads, Part I

- Evolution of REXR, IIP, NAPM, MSC



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Forecasting Spreads, Part II

Forecasting Spreads, Part II

- We transform the spreads and default rates as annualized changes.
- Letting s_t represent the spread between corporate and US government bonds at time t, we forecast the following variable:$\Delta s_{t+h} = s_{t+1} - s_t$
- The regressors are the following variables: $x_t = [\Delta_{12} dr_t, \Delta s_t, \Delta_{12} rex_t, \Delta_{12} iip_t, \Delta_{12} msci_t, \Delta_{12} napm_t]$

Forecasting Spreads, Part II

- We follow the same setup as in the automobile demand with a linear, STRS and NNRS model
- The transition function depends on the rate of growth of industrial production

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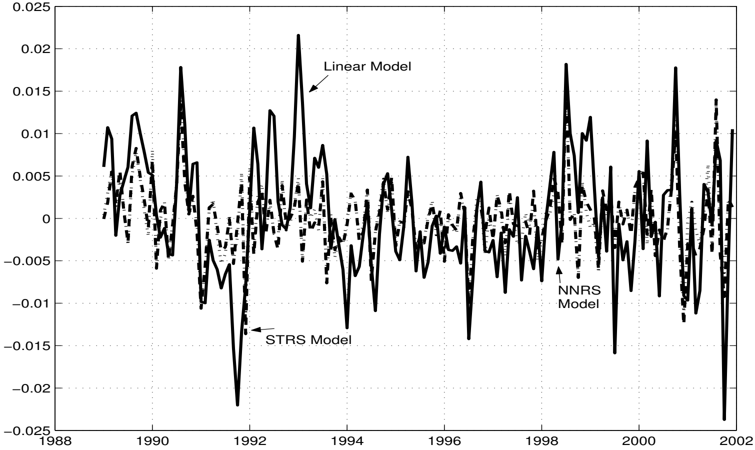
Forecasting Spreads, Part II

- In-sample performance:



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Forecasting Spreads, Part II

- In-sample diagnostics for the Spreads:

	Model		
	Linear	STRS	NNRS
Diagnostic			
SSE	.009	.003	.003
R^2	.826	.940	.943
HQIF	-63.65	-932.23	-937.39

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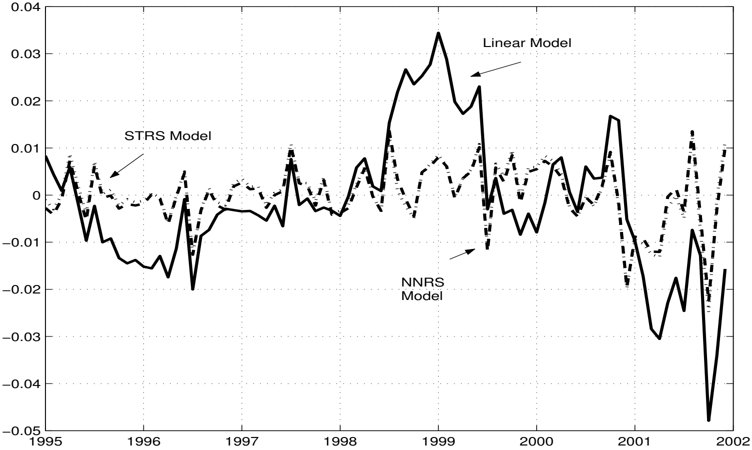
Forecasting Spreads, Part III

Forecasting Spreads, Part III

- Out-of-sample prediction errors (86 observations with rolling regressions):



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Forecasting Spreads, Part III

- Out-of-sample diagnostics:

	Model		
	Linear	STRS	NNRS
Diagnostic			
Root Mean Squared Error	.016	.008	.007
Directional Accuracy	.738	.917	.905
Diebold-Mariano P-Value	Linear vs. SRTS	Linear vs. NNRS	STRS-vs. N
(5-lags)	0.002	0.001	0.897

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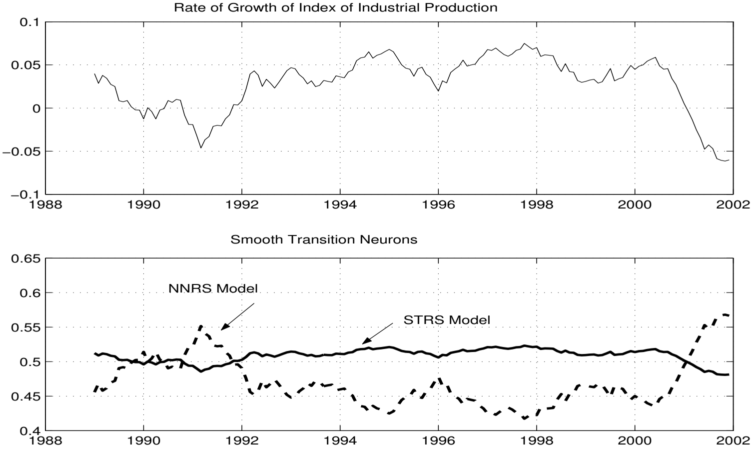
Forecasting Spreads, Part III

- Smooth-transition neurons and rate of growth of industrial production



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Forecasting Spreads, Part IV

Forecasting Spreads, Part IV

- What information can we glean from the behavior of the "smooth transition" neurons in the two "regime switching" models?
- We see sharper changes in the IIP index than in disposable income above.
- The NNSTRS and STRS neurons give about equal weight to the growth/recession" states, but the NNSTRS neuron shows slightly more volatility, and thus more information, throughout the sample, about the likelihood of switching from one regime to another.

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