Time-Frequency Functional Models: An Approach for Identifying and Predicting Economic Recessions in Real-Time

David S. Matteson
Department of Statistical Science
Cornell University

matteson@cornell.edu
www.stat.cornell.edu/~matteson

Joint work with: Scott H. Holan & Christopher K. Wikle (Missouri Statistics) and Wen-Hsi Yang (CSIRO)

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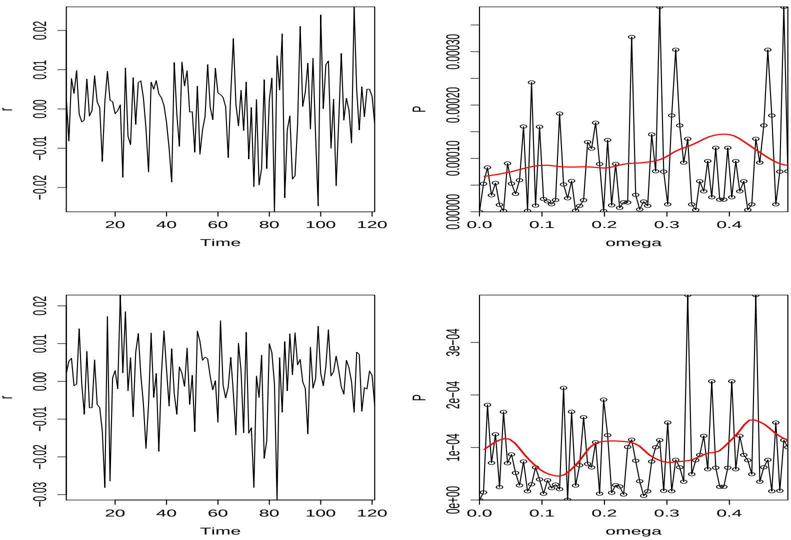
Outline

- Introduction
  - Why consider time-frequency?
  - The spectrogram (short-time Fourier transform – STFT)
- Time-Frequency Functional Models
- Economic Motivation & Preliminary Analysis
- Dimension Reduction
  - Basis function expansions
  - Karhunen-Loève expansion (EOFs)
- Feature Extraction
  - Stochastic Search Variable Selection (SSVS)
- Bayesian mixed data frequency model (MIDAS)
- Case Study: Identifying and Predicting Recessions
- Summary

Time-Frequency Covariates

- Many non-stationary time signals are high dimensional, but wanted for inference and prediction
- Time-frequency (T-F) representations can extract important features
  - But, there are MANY T-F elements (pixels)
- Consider T-F representation as a random field (image) covariate
- Apply reduced rank representation / perform model selection

NASDAQ index daily log returns: series vs. spectral density



Time-Frequency Representations

- Consider short-time Fourier transform (STFT) of signal, a local frequency (spectral) representation
- Local frequency spectrum: Fourier transform signal in given interval
- Simple segmentation has discontinuities, and undesirable artifacts
- Mitigate via windowing, c.f. Gröchenig (2001), e.g., Hamming window

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Let $g \neq 0$ denote a fixed window function. The STFT of a function f with respect to g, at time ℓ and frequencies ω ($\ell, \omega \in \mathbb{R}^d$) is defined as

$$V_g f(\ell, \omega) = \int_{\mathbb{R}^d} f(t) \overline{g(t - \ell)} e^{-2\pi i \cdot \omega} dt,$$

where $i = \sqrt{-1}$, and $\overline{g(-\ell)} = g^*(\ell)$ denotes complex conjugation. Assuming $||g||_2 = 1$ for window function $g \in L^2(\mathbb{R}^d)$

$$\text{SPEC}_g f(\ell, \omega) \equiv |V_g f(\ell, \omega)|^2$$

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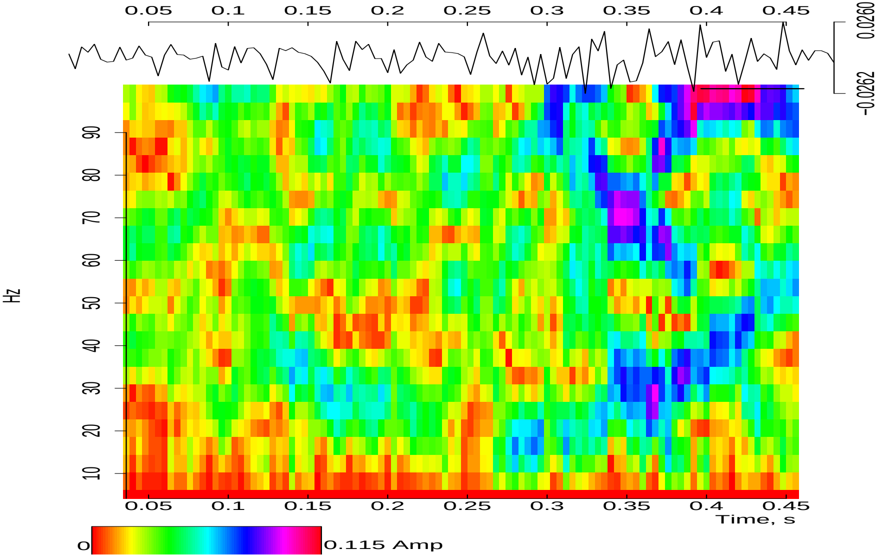
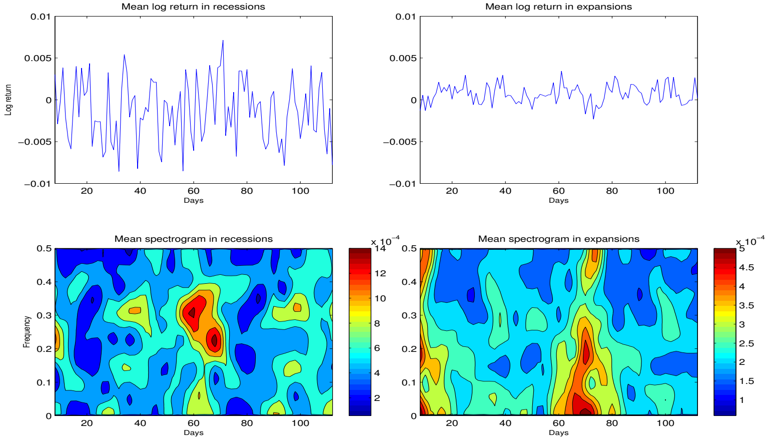


Economic Recessions – NASDAQ



Mean NASDAQ log returns for periods of recession and expansion along with their corresponding spectrograms (Holan, Yang, Matteson and Wikle, 2012)

Time-Frequency Functional Models

- Time-frequency representation is high-dimensional
- The previous displays consist of $J = 7,258$ potential T-F covariates
- Consider image as continuous 2D Gaussian process
- Let $S_t(\ell, \omega) = S_t(\mathbf{u})$ denote a mean-zero T-F process
  - t-th quarter
  - ℓ-th intra-quarter day; $\ell \in [1, K]$
  - ω frequency; $\omega \in [0, 0.5]$.

Time-Frequency Functional Models

- Let $S_t(\ell, \omega) = S_t(\mathbf{u})$ denote a mean-zero T-F process
  - t-th quarter; ℓ-th intra-quarter day; ω frequency
- Let $C_S(\mathbf{u}, \widetilde{\mathbf{u}}) = \mathrm{Cov}(S_t(\mathbf{u}), S_t(\widetilde{\mathbf{u}})), \quad \mathbf{u}, \widetilde{\mathbf{u}} \in D = [1, K] \times [0, 0.5]$

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- If $C_S(\mathbf{u}, \widetilde{\mathbf{u}})$ is continuous and square integrable, then

$$C_S(\mathbf{u}, \widetilde{\mathbf{u}}) = \sum_{j=1}^{\infty} \lambda_j \, \phi_j(\mathbf{u}) \phi_j(\widetilde{\mathbf{u}}),$$

  - $\lambda_1 \geq \lambda_2 \geq \cdots$ are eigenvalues
  - $\{\phi_j(\cdot) : \; j = 1, 2, \ldots\}$ are eigenfunctions

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  - Solutions to the Fredholm integral equation

$$\int_D C_S(\mathbf{u}, \widetilde{\mathbf{u}}) \phi_j(\widetilde{\mathbf{u}}) \, \partial \widetilde{\mathbf{u}} = \lambda_j \, \phi_j(\mathbf{u}), \quad \mathbf{u} \in D; \quad j = 1, 2, \ldots$$

(e.g., see Papoulis, 1965).

Time-Frequency Functional Models

$$C_S(\mathbf{u}, \widetilde{\mathbf{u}}) = \sum_{j=1}^{\infty} \lambda_j \phi_j(\mathbf{u}) \phi_j(\widetilde{\mathbf{u}}),$$

- Assuming completeness of the eigenfunctions, $S_t(\mathbf{u})$ can be written as

$$S_t(\mathbf{u}) = \sum_{j=1}^{\infty} \alpha_{t,j}\, \phi_j(\mathbf{u}), \quad (1)$$

  - Karhunen-Loève expansion
  - $\alpha_{t,j} \sim N(0, \lambda_j)$
  - $\{\phi_j(\cdot)\}$ are eigenfunctions

Time-Frequency Functional Models Cont.

- In practice, consider vectorized sample spectrogram (image)
- Find empirical orthogonal functions (EOFs).
- Denote discretized spectrogram for J T-F pixels, $\{\mathbf{u}_j : j = 1, \ldots, J\}$ as $\mathbf{S}_t \equiv (S_t(\mathbf{u}_1), \ldots, S_t(\mathbf{u}_J))'$, then
-
$$\mathbf{S}_t = \sum_{j=1}^{J} \phi_j \alpha_{jt} = \boldsymbol{\Phi}\boldsymbol{\alpha}_t, \quad t = 1, \ldots, T, \tag{2}$$
  - $\boldsymbol{\phi}_j \equiv (\phi_j(\mathbf{u}_1), \ldots, \phi_j(\mathbf{u}_J))'$ $\qquad \boldsymbol{\Phi} = (\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_J)$
  - $\boldsymbol{\alpha}_t \equiv (\alpha_{t,1}, \ldots, \alpha_{t,J})' = \boldsymbol{\Phi}^{-1}\mathbf{S}_t$ are the spectral expansion coefficients (i.e., principal components). Note $\boldsymbol{\Phi}^{-1} = \boldsymbol{\Phi}'$
- Sample version: $\widetilde{C}_S = \tilde{\boldsymbol{\Phi}}\tilde{\boldsymbol{\Lambda}}\tilde{\boldsymbol{\Phi}}'$, here, ℓ is measured daily.

Dimension-Reduced Spectrogram Models

- EOFs in order of decreasing variance explained in spectrogram
- Consider first k EOFs (where $k \ll K$) for some dimension reduction
- Here, first 10 EOFs & 40 EOFs explained 85% & 95% variation

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- Which remaining EOFs are useful in identifying & predicting periods of recession & expansion?

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- Consider first k EOFs (where $k \ll K$) for some dimension reduction
- Here, first 10 EOFs & 40 EOFs explained 85% & 95% variation
- Which remaining EOFs are useful in identifying & predicting periods of recession & expansion?
- First components may not be the best covariates, in general (unsupervised vs. supervised)
- We propose a hierarchical Bayesian probit model with SSVS (George and McCulloch, 1993, 1997).

Dimension-Reduced Spectrogram Models

- Response $Y_t = \{0, 1\}$ and covariates $\mathbf{x}_t$ for quarter t
- $Y_t = 1$ denotes an economic recession and $Y_t = 0$ denotes expansion
- $\mathbf{x}_t$ includes both the T-F signal & quarterly macroeconomic covariates
- Define a continuous latent variable Z_t such that

$$Y_t = \begin{cases} 1 & \text{if } Z_t > 0, \\ 0 & \text{if } Z_t \leq 0 \end{cases}$$

  - $Z_t | \boldsymbol{\beta} \sim N(\boldsymbol{\beta}' \mathbf{x}_t, 1)$
  - $\mathbf{x}_t$ and $\boldsymbol{\beta}$ both $p \times 1$

- Equivalent to probit model with a Bernoulli response
- Formulation is computationally advantageous (Albert and Chib, 1993)

Dimension-Reduced Spectrogram Models

- Consider Bayesian SSVS prior for the components of $\boldsymbol{\beta}$

  Let

$$\beta_i | \gamma_i \sim \gamma_i N(0, c\tau^2) + (1 - \gamma_i) N(0, \tau^2), \quad i = 1, \ldots, p, \tag{3}$$

  - $\gamma_i | \pi \sim \text{Bernoulli}(\pi)$
- π is prior probability that β_i is included in the model
- $\gamma_i = 1$ indicates that the i-th variable is included
- In general, c, τ, and π are fixed hyperparameters;

  George and McCulloch (1993, 1997) describe alternative specifications

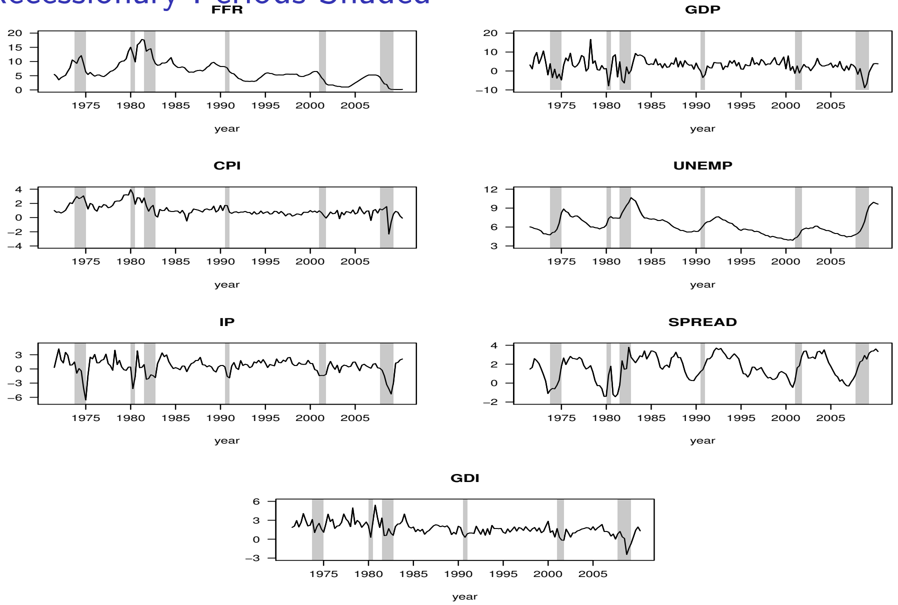
Preliminary Analysis

- Consider several quarterly macroeconomic indicators vs. recessions
- Consider functional relationship between daily log returns for various market indices and recessions
- Only results for the NASDAQ index are shown
- The dichotomous response is quarterly indicator of recession NBER Business Cycle Dating Committee (http://www.nber.org/data/)

Quarterly macroeconomic covariates:

- (FFR) nominal federal funds rate
- (CPI) percentage change in the U.S. consumer price index
- (UNEMP) seasonally adjusted U.S. national unemployment rate percentage
- (GDP) percentage change in U.S. real gross domestic product
- (GDI) percentage change in U.S. real gross domestic income
- (IP) percentage change in the U.S. industrial production index
- (SPREAD) difference between yields on 10-year Treasury bonds and 3-month Treasury bills

Recessionary Periods Shaded



Preliminary Analysis

- Recessionary periods are associated with peaks in the FFR series.
- Troughs are evident in the GDP, GDI, IP and SPREAD series during periods of recession.
- Peaks in the UNEMP series are evident immediately following an economic recession.
- The relationship between the CPI series and recessions appears inconclusive.

Preliminary Analysis

We also note:

1. When recessions occur, they last multiple quarters. Hence, the likelihood of a recession in a given period may be a useful predictor of the likelihood in future periods.

2. The number of quarters since the previous period of recession may have predictive power for the current level of economic activity.

We consider including both of these features in our model implementation.

Model Implementation

- Daily log NASDAQ index return signals from two quarters (current and previous quarter)
- Begin Q4 of 1971. End Q2 of 2010.
- $T = 155$ quarters; 29 were recessions
- In `R`, STFT functions available in `e1071`, `RSEIS`,...
- Moving Hamming window, length 16, with overlap of 14 (insensitive?)

Model Implementation

- Spectrogram and EOFs are calculated
- First 40 standardized EOFs considered (95% variation)
- We evaluated the model performance using various hyperparameters
- Fixed $\pi = 0.5$, various combinations of (τ, c) considered
- For both identification & prediction, $\tau = 0.01$ & $c = 10$ selected

Model Implementation

- SSVS sampler: 40,000 iterations with 5,000 burn-in
- Classification was set to 1 (recession) if posterior probability ≥ 0.5
- This classification represents "model averaging" over covariate combinations
- Accounts for their relative importance via the stochastic search

Model Implementation

In order to define the specific models for Z_t , consider the following two general models:

$$Z_{t+h} = \delta V_t + \boldsymbol{\beta}'\mathbf{x}_t + \epsilon_t, \qquad \text{(w/count)} \tag{4}$$

and

$$Z_{t+h} = \theta Z_t + \boldsymbol{\beta}'\mathbf{x}_t + \epsilon_t \qquad \text{(w/lag)} \tag{5}$$

- $h = 0, 1, 2, 3$ denotes a nowcast, 1-, 2-, and 3-step ahead forecasts
- $\epsilon_t \sim N(0, 1)$
- V_t equals the number of quarters since the previous recession
- $\boldsymbol{\beta}'\mathbf{x}_t$ includes both macroeconomic and EOF covariates (time-frequency daily NASDAQ log return predictor)

Model Implementation

Seven models total:

- M1 macroeconomic covariates ONLY
- M2 version of Equation (4) with no T-F NASDAQ covariate
- M3 version of Equation (5) with no T-F NASDAQ covariate
- M4 (EOF) T-F daily NASDAQ log return covariate ONLY
- M5 (EOF) T-F daily NASDAQ log return covariate and macroeconomic covariates
- M6 is equal to Equation (4), (w/ count)
- M7 is given by Equation (5) (w/ lag)

Evaluate classification and predictive performance

Identifying and Predicting Recessions – Results

Confusion Matrix (2×2 table) for each model:
false positives, false negatives, true positives, and true negatives.

		Classify To: Nowcast		1-Step Ahead		2-Step Ahead		3-Step Ahead	
		0	1	0	1	0	1	0	1
M1:	0	63.95%	36.05%	53.49%	46.51%	51.16%	48.84%	53.49%	46.51%
	1	0%	100%	0%	100%	14.29%	85.71%	21.43%	78.57%
	AUROC	.9743		.8331		.7002		.7483	
M2:	0	63.95%	36.05%	58.14%	41.86%	51.16%	48.84%	55.81%	44.19%
	1	7.14%	92.86%	14.29%	85.71%	28.57%	71.43%	28.57%	71.43%
	AUROC	.9061		.7583		.5864		.6262	
M3:	0	55.81%	44.19%	41.86%	58.14%	53.49%	46.51%	55.81%	44.19%
	1	0%	100%	64.29%	35.71%	71.43%	28.57%	57.14%	42.86%
	AUROC	.9012		.4402		.3945		.5141	
M4:	0	56.34%	43.66%	58.85%	41.15%	52.31%	47.69%	43.55%	56.45%
	1	28.57%	71.43%	35.71%	64.29%	35.71%	64.29%	21.43%	78.57%
	AUROC	.7616		.7143		.6626		.6118	
M5:	0	61.97%	38.03%	66.18%	33.82%	50.77%	49.23%	48.39%	51.61%
	1	0%	100%	7.14%	92.86%	0%	100%	0%	100%
	AUROC	.9266		.8718		.7703		.7535	
M6:	0	66.20%	33.80%	67.65%	32.35%	52.31%	47.69%	50%	50%
	1	7.14%	92.86%	14.29%	85.71%	14.29%	85.71%	0%	100%
	AUROC	.9225		.8540		.7549		.7396	
M7:	0	84.51%	15.49%	88.24%	11.76%	86.15%	13.85%	80.65%	19.35%
	1	7.14%	92.86%	14.29%	85.71%	14.29%	85.71%	14.29%	85.71%
	AUROC	.9537		.9160		.8934		.9286	

Identifying and Predicting Recessions – Results

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	AUROC	.9743		.8331		.7002		.7483	
M4:	0	56.34%	43.66%	58.85%	41.15%	52.31%	47.69%	43.55%	56.45%
	1	28.57%	71.43%	35.71%	64.29%	35.71%	64.29%	21.43%	78.57%
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M5:	0	61.97%	38.03%	66.18%	33.82%	50.77%	49.23%	48.39%	51.61%
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Identifying and Predicting Recessions – Results

AUROC

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Identifying and Predicting Recessions – Results

- Results vary across BOTH models and forecast horizons
- Some perfect classifiers of recessions, but high false positive rates
- (M7) overall best: consistent identification and prediction $\geq 80\%$, even for forecasts three quarters ahead!
- The same model with the NASDAQ signal predictor excluded (M3) was arguably the worst predictive model.
- Under all three EOF basis constructions various EOFs are among the top 6 variables selected by the SSVS

Identifying and Predicting Recessions – Results

Period 1							
Nowcast		1-Step Ahead		2-Step Ahead		3-Step Ahead	
Variable	% of models	Variable	% of models	Variable	% of models	Variable	% of models
EOF 3	77	GDP	72	SPREAD	76	SPREAD	79
IP	75	FFR	72	FFR	71	FFR	63
GDP	73	EOF 3	68	EOF 22	61	CPI	56
EOF 10	66	CPI	62	EOF 15	58	EOF 15	54
CPI	58	SPREAD	59	CPI	58	EOF 23	54
EOF 12	58	EOF 10	59	EOF 16	52	EOF 19	54

Period 2							
Nowcast		1-Step Ahead		2-Step Ahead		3-Step Ahead	
Variable	% of models	Variable	% of models	Variable	% of models	Variable	% of models
IP	84	GDP	77	SPREAD	84	SPREAD	86
GDP	77	FFR	68	FFR	68	EOF 10	61
EOF 3	67	SPREAD	68	EOF 10	65	FFR	60
CPI	61	EOF 3	65	CPI	57	UNEMP	58
EOF 10	58	EOF 10	64	EOF 28	57	EOF 16	57
EOF 5	57	CPI	63	EOF 16	56	EOF 3	55

Period 3							
Nowcast		1-Step Ahead		2-Step Ahead		3-Step Ahead	
Variable	% of models	Variable	% of models	Variable	% of models	Variable	% of models
IP	89	GDP	83	SPREAD	76	SPREAD	91
GDP	85	SPREAD	69	FFR	71	FFR	57
EOF 34	67	FFR	65	CPI	61	CPI	55
EOF 12	64	CPI	65	EOF 1	58	EOF 1	55
CPI	62	EOF 34	62	EOF 9	58	EOF 32	53
EOF 25	59	EOF 1	60	EOF 22	53	EOF 4	51

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EOF 5	57	CPI	63	EOF 16	56	EOF 3	55

Period 3							
Nowcast		1-Step Ahead		2-Step Ahead		3-Step Ahead	
Variable	% of models	Variable	% of models	Variable	% of models	Variable	% of models
IP	89	GDP	83	SPREAD	76	SPREAD	91
GDP	85	SPREAD	69	FFR	71	FFR	57
EOF 34	67	FFR	65	CPI	61	CPI	55
EOF 12	64	CPI	65	EOF 1	58	EOF 1	55
CPI	62	EOF 34	62	EOF 9	58	EOF 32	53
EOF 25	59	EOF 1	60	EOF 22	53	EOF 4	51

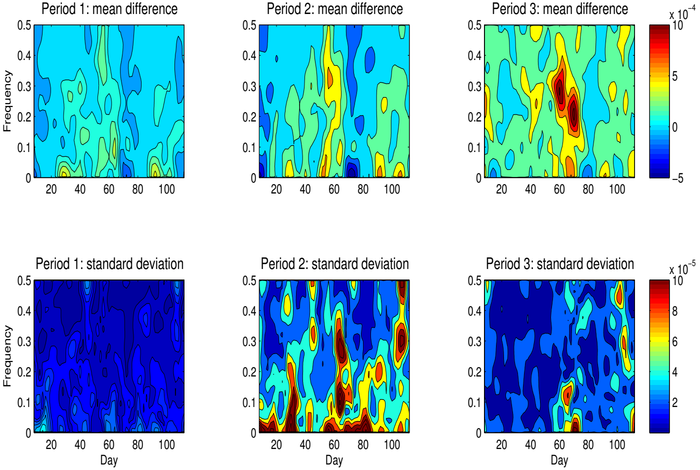
Identifying and Predicting Recessions – Results

- Reconstruct the posterior mean and standard deviation for the differenced spectrogram (e.g., the mean spectrogram for the recessions minus the expansions) one-step ahead.

- We see that the volatility in the daily NASDAQ log returns roughly lagged one quarter is a key predictor of recession.

- More recent recessionary periods, timing is approximately the same, but the high-frequency behavior becomes more pronounced
(i.e., exhibits stronger energy in the spectrogram).

Identifying and Predicting Recessions – Results



Posterior mean and standard deviation of the reconstructed differenced-spectrograms that results from back projecting each quarter in the training and forecast period on the EOFs.

Summary

- Nowcasting/predicting recessions extensively researched & still challenging
- We propose an approach based on T-F functional models of daily NASDAQ index log returns.
- Model M7 (AR model w/ macroeconomic and T-F predictors) 85% and 80% out-of-sample forecasting accuracy for recessions and expansions respectively, even 3 quarters ahead.
- The proposed approach may be viewed as a Bayesian mixed data frequency model (MIDAS)
- Many possible extensions!

Thank You!

matteson@cornell.edu

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