

Financial Risk Meters in Taiwan's High-Cap Sectors

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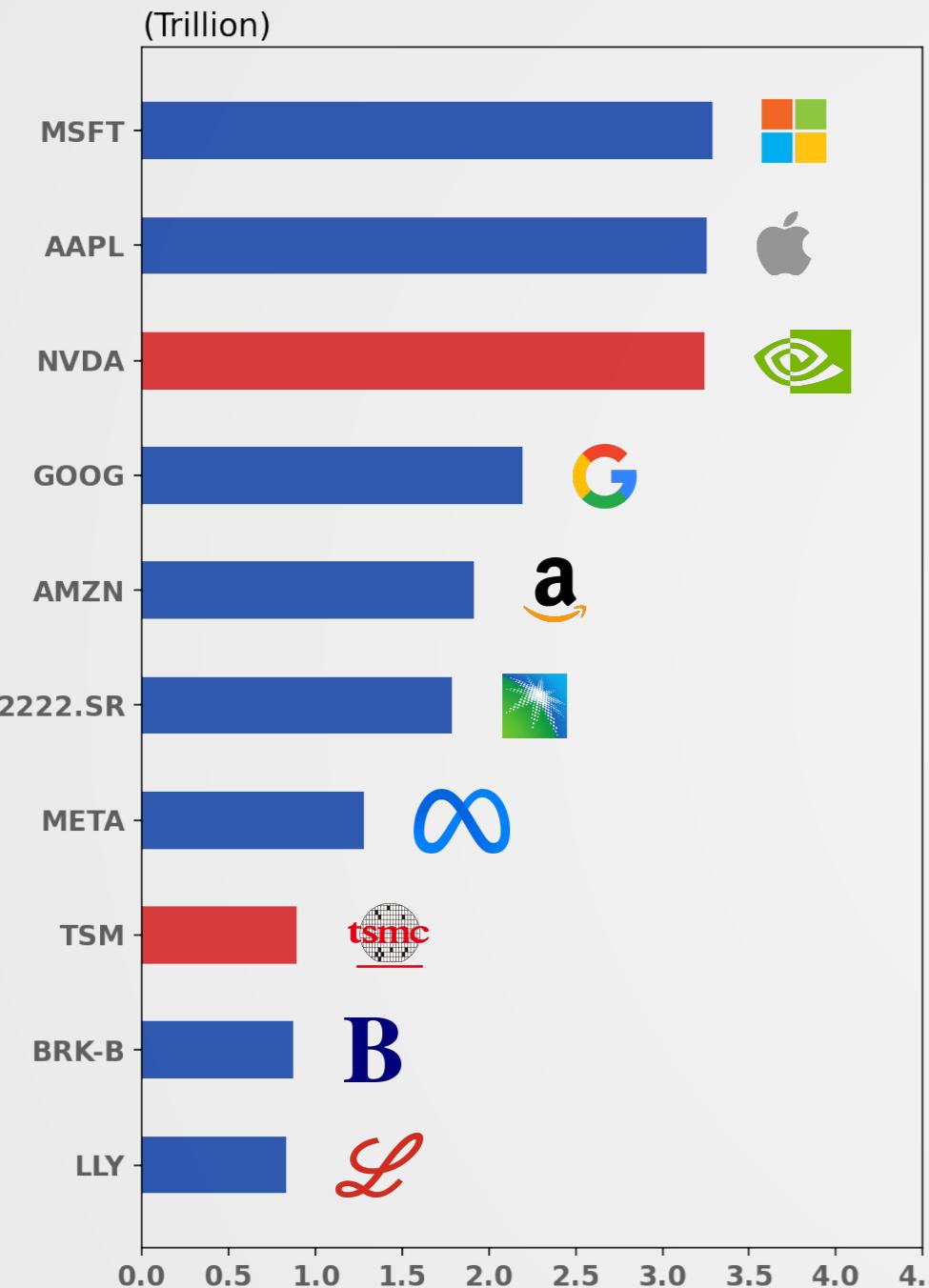
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IDA Institute
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FRM quantlet

2024/6/17

<https://companiesmarketcap.com/>

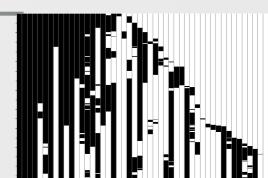
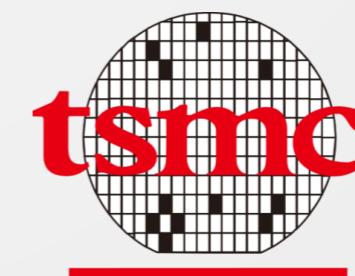
Generative AI



NVLink



UALink



“Taiwan and our partnership has created the world’s AI infrastructure.”

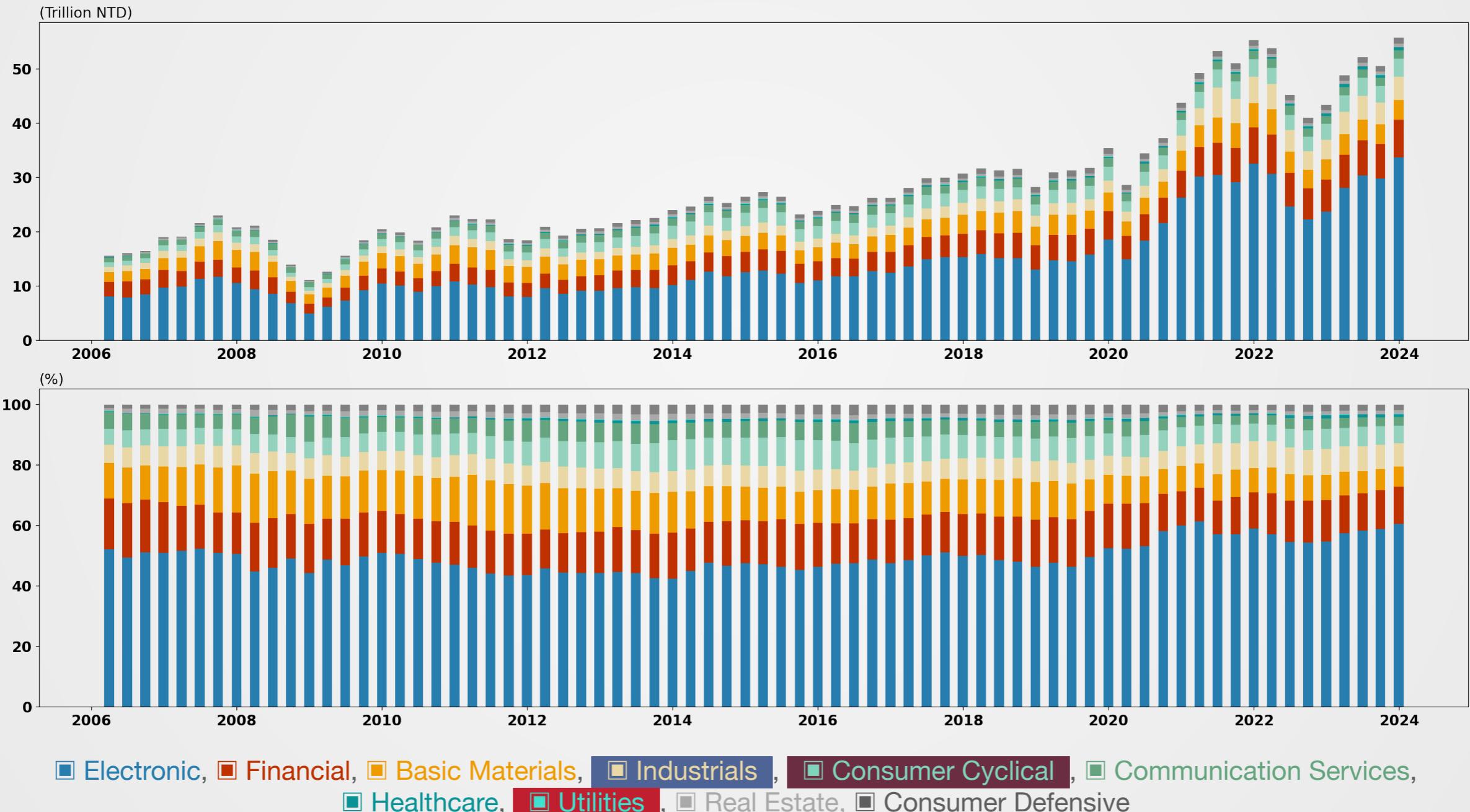
— Jensen Huang



2024/06/03, Computex 2024, Keynote by NVIDIA CEO Jensen Huang



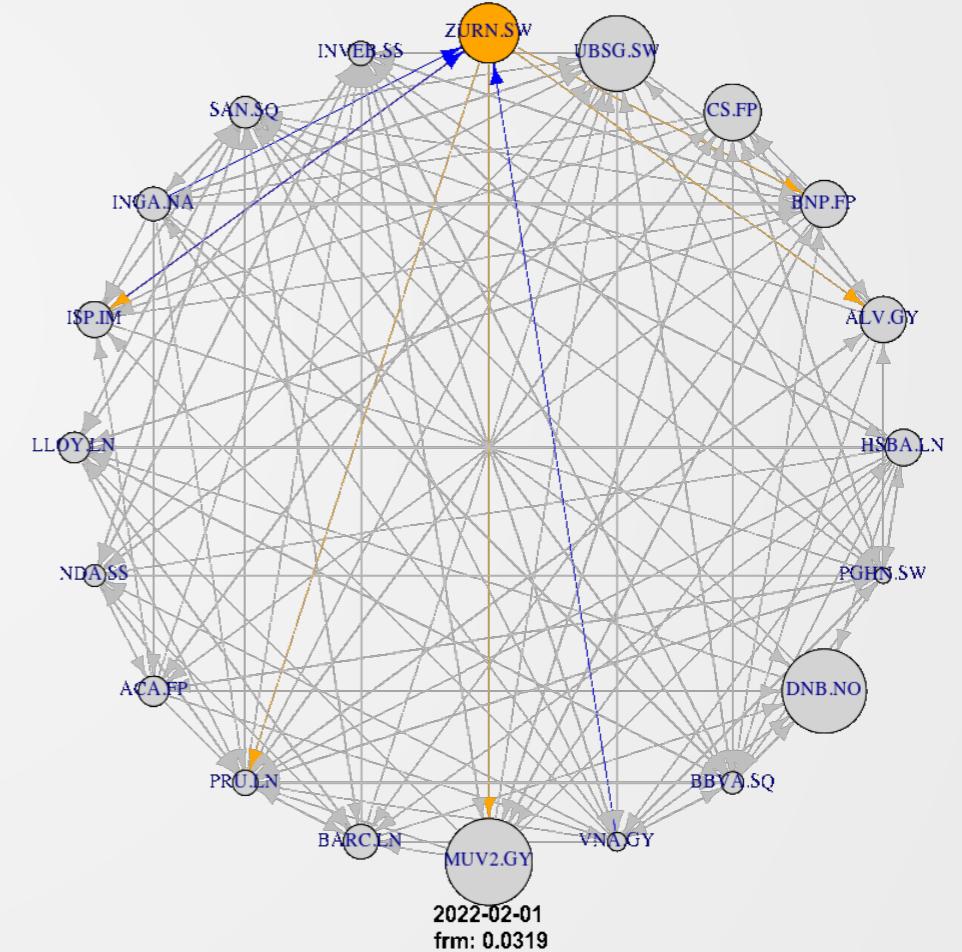
Unique Market Cap Structure



FRM FinancialRiskMeter



- Identify different systemic risk levels in the market over time
- Capture tail event co-movements
- Predict recession probabilities



Outline

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1. Motivation ✓
2. Preliminaries
3. Design of Analysis
4. Empirical Results
5. Recession prediction
6. Conclusion

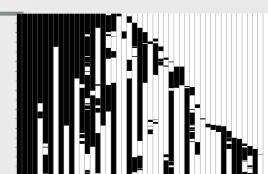
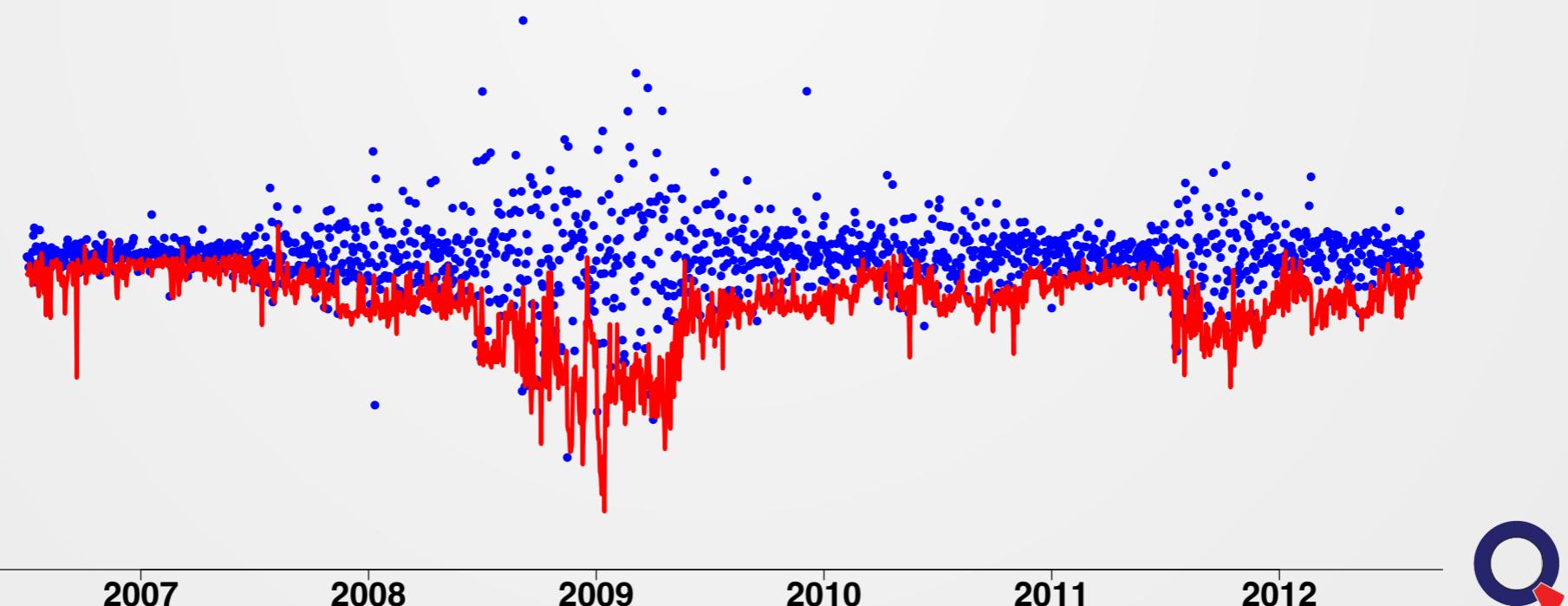


Value at Risk (VaR)

- Probability measure based

$$P(X_{i,t} \leq \text{VaR}_{i,t,\tau}) \stackrel{\text{def}}{=} \tau, \quad \tau \in (0,1)$$

- $X_{i,t}$ log return of asset i at t



Conditional Value at Risk (CoVaR)

- CoVaR of a company j at $\tau \in (0, 1)$ at time t , $\text{CoVaR}_{j,t,\tau|\mathbb{C}(X^i)}$, satisfies

$$P\left\{X_{j,t} \leq \text{CoVaR}_{j,t,\tau|\mathbb{C}(X^i)} \mid \mathbb{C}(X^i)\right\} \stackrel{\text{def}}{=} \tau$$

- $\mathbb{C}(X^i)$: The information set which includes $X_{i,t} = \text{VaR}_{i,t,\tau}$ and M_{t-1} .
 - ▶ M_{t-1} : A vector of macro-state variables reflecting the general state of the economy.
- Represents the potential losses that another company may face when one company experiences VaR.



CoVaR

- CoVaR technique

$$X_{i,t} = \alpha_i + \gamma_i^\top M_{t-1} + \varepsilon_{i,t}$$

$$X_{j,t} = \alpha_{j|i} + \beta_{j|i} X_{i,t} + \gamma_{j|i}^\top M_{t-1} + \varepsilon_{j,t}$$

- Assume $F_{\varepsilon_{i,t}}^{-1}(\tau | M_{t-1}) = 0$ and $F_{\varepsilon_{j,t}}^{-1}(\tau | M_{t-1}, X_{i,t}) = 0$

$$\widehat{VaR}_{i,t}^\tau = \widehat{\alpha}_i + \widehat{\gamma}_i^\top M_{t-1}$$

$$\widehat{CoVaR}_{j|i,t}^\tau = \widehat{\alpha}_{j|i} + \widehat{\beta}_{j|i} \widehat{VaR}_{i,t}^\tau + \widehat{\gamma}_{j|i}^\top M_{t-1}$$

CoVaR: First calculate VaRs, then compute the CoVaR given a stressed risk factor.



Linear Quantile Regression

- The log return series $X_{j,t}$ in a window of H days is given by

$$X_{j,t} = \alpha_j + A_{j,t}\beta_j + \varepsilon_{j,t}, \quad j \in \{1, 2, \dots, J\} \quad (1)$$

with N financial institutions and m macroeconomic variables.

- ▶ $A_{j,t} = [X_{-j,t}, M_{t-1}]$: a $p = (J + M - 1)$ dimensional vector of covariates.
- ▶ T : the total number of observations and $t \in \{1, \dots, H\}$.
- ▶ $X_{-j,t}$: the log return of all the FIs except the j -th FI on day t .
- ▶ M : the number of macroeconomic variables.
- ▶ β_j : a $p \times 1$ vector of coefficients.



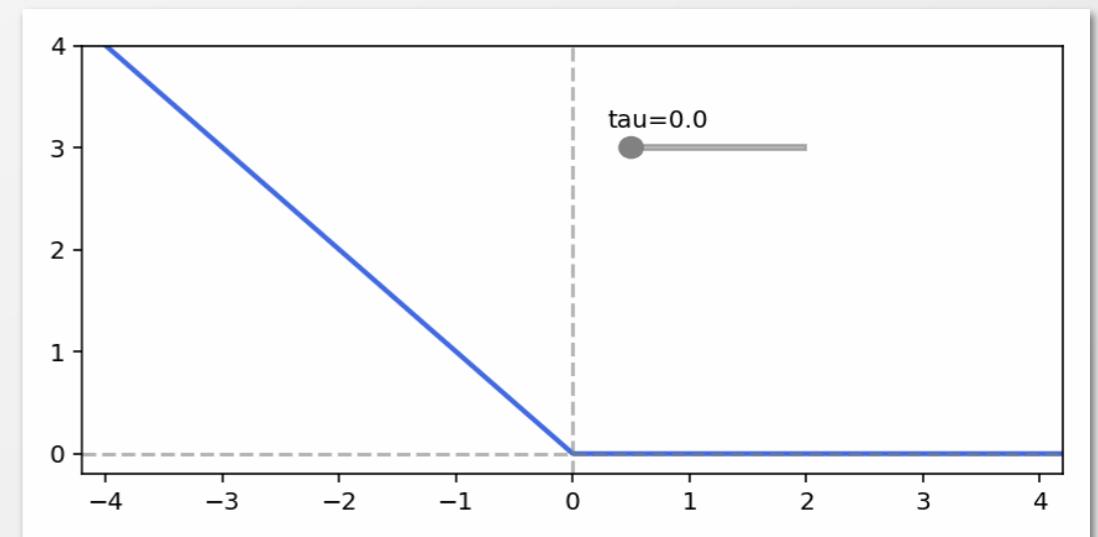
Linear Quantile Regression

- The estimation of the coefficient $\hat{\beta}_\tau$

$$\hat{\beta}_{j,\tau} = \arg \min_{\alpha_j, \beta_j} \mathbb{E}_{X_j, A_j} \left[\rho_\tau(X_j - \alpha_j - A_j \beta_j) \right]$$

with the quantile loss function, given tail risk level τ , denoted as

$$\begin{aligned} \rho_\tau(u) &= |\tau - I\{u \leq 0\}| |u| \\ &= \begin{cases} \tau |u|, & \text{if } u > 0 \\ |\tau - 1| |u|, & \text{if } u \leq 0 \end{cases} \end{aligned}$$



Linear Quantile Lasso Regression

$$\widehat{\alpha}_j(\lambda_j), \widehat{\beta}_j(\lambda_j) = \arg \min_{\alpha_j, \beta_j} \left\{ \frac{1}{H} \sum_{t=1}^H \rho_\tau \left(X_{j,t} - \alpha_j - A_{j,t} \beta_j \right) + \lambda_j \|\beta_j\|_1 \right\} \quad (3)$$

- Generalized Approximate CrossValidation

$$\text{GACV}(\lambda_j) = \frac{\sum_{t=1}^H \rho_\tau \left(X_{j,t} - \alpha_j(\lambda_j) - A_{j,t} \beta_j(\lambda_j) \right)}{H - df}$$

↑ Window size
 ↑ Number of non-zero β

- λ_j^* minimizes GACV (Yuan, 2006)

$$\lambda_j^* = \arg \min \text{GACV}(\lambda_j) \quad (4)$$



FRM

- FRM daily index at time t

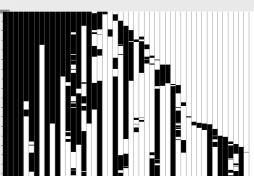
$$\text{FRM}_t = \frac{1}{J} \sum_{j=1}^J \lambda_{j,t}^* \quad (5)$$

the average of the penalties of the quantile lasso regression.

- The evolution of averaged λ_j represents the dynamic systemic tail risks
- FRM thus measures joint tail events.



FRM courselet



Linear Quantile LASSO Regression

- Incorporate the linear quantile regression with an L_1 -norm constraint

$$\|\beta_j\|_1 \leq b$$

- The optimization of the constraint level b :

$$b^* = \arg \min_b \left\{ \mathbb{E}_{X_j, A_j} \left[\rho_\tau(X_j - \hat{\alpha}_{j,\tau} - A_j \hat{\beta}_{j,\tau}(b)) \right] \right\}$$



Constrained Optimization Problem

- The convex programming problem that quantile LASSO solves

$$\arg \min_{\alpha_j, \beta_j} \left\{ \mathbb{E}_{X_j, A_j} \left[\rho_\tau(X_j - \alpha_j - A_j^\top \beta_j) \right] \right\} \quad \text{s.t.} \quad \|\beta_j\|_1 \leq b$$

- Denoted the expected gain $R(\beta_j)$ and the constraint function $B(\beta_j)$

$$R(\beta_j) = - \mathbb{E}_{X_j, A_j} \left\{ \rho_\tau(X_j - \alpha_j - A_j \beta_j) \right\}$$

$$B(\beta_j) = \|\beta_j\|_1$$

- The lagrangian formulation of the optimization objective is

$$\mathfrak{L}(\beta_j, \lambda_j) = R(\beta_j) - \lambda_j \left\{ B(\beta_j) - b \right\}$$



Constrained Optimization Problem

- View $\mathfrak{L} \left\{ \beta_j(b), \lambda_j(b), b \right\}$ as a function of the budget constraint b .
- λ_j becomes a derivative with respect to b when evaluated at the solution $\left\{ \beta_j^*(b), \lambda_j^*(b) \right\}$
- Due to KKT conditions and the chain rule,

$$\frac{d}{db} \mathfrak{L} \left\{ \beta_j^*(b), \lambda_j^*(b), b \right\} = \underbrace{\frac{d\mathfrak{L}}{d\beta_j} \frac{d\beta_j^*}{db}}_{=0} + \underbrace{\frac{d\mathfrak{L}}{d\lambda_j} \frac{d\lambda_j^*}{db}}_{=0} + \frac{d\mathfrak{L}}{db} = \lambda_j^*(b) \quad (2)$$



Constrained Optimization Problem

- ◻ Note that at the optimal value the Lagrangian equals the expected gain R :

$$\mathfrak{L}(\beta_j^*, \lambda_j^*, b) = R(\beta^*) - \underbrace{\lambda_j^* \left\{ B(\beta_j^*) - b \right\}}_{=0} = R^*(b) \quad (3)$$

- ◻ Combing Eq. (2) and (3), we can regard λ_j as the rate of change of the expected gain with respect to the budget constraint:

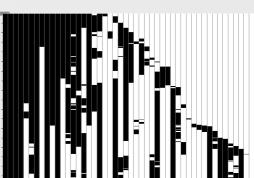
$$\lambda_j^*(b_0) = \frac{dR^*}{db} \Big|_{b=b_0}$$

- ◻ When considering a regression model as a predictive tool, λ_j can be seen as a **shadow price**. (Marginal predictability gain)

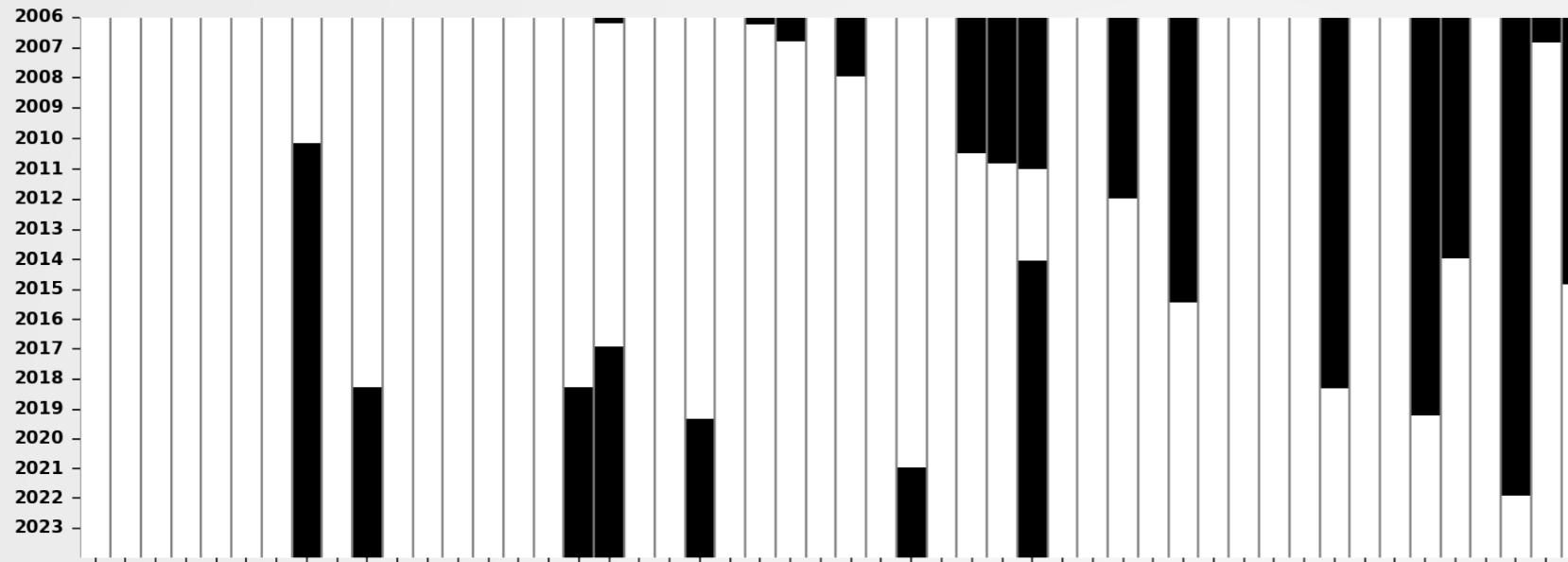


Data

- Time period: 2006/12/31~2023/12/31
- Company selected
 - ▶ FRM^C - Top 20 largest companies from the market
 - ▶ FRM^F - Top 20 largest companies from the financial sectors
 - ▶ FRM^E - Top 20 largest companies from the electronic sectors
 - ▶ FRM^{FE} - Top 10 electronics and top 10 financial
- Window size: 63, 126 days

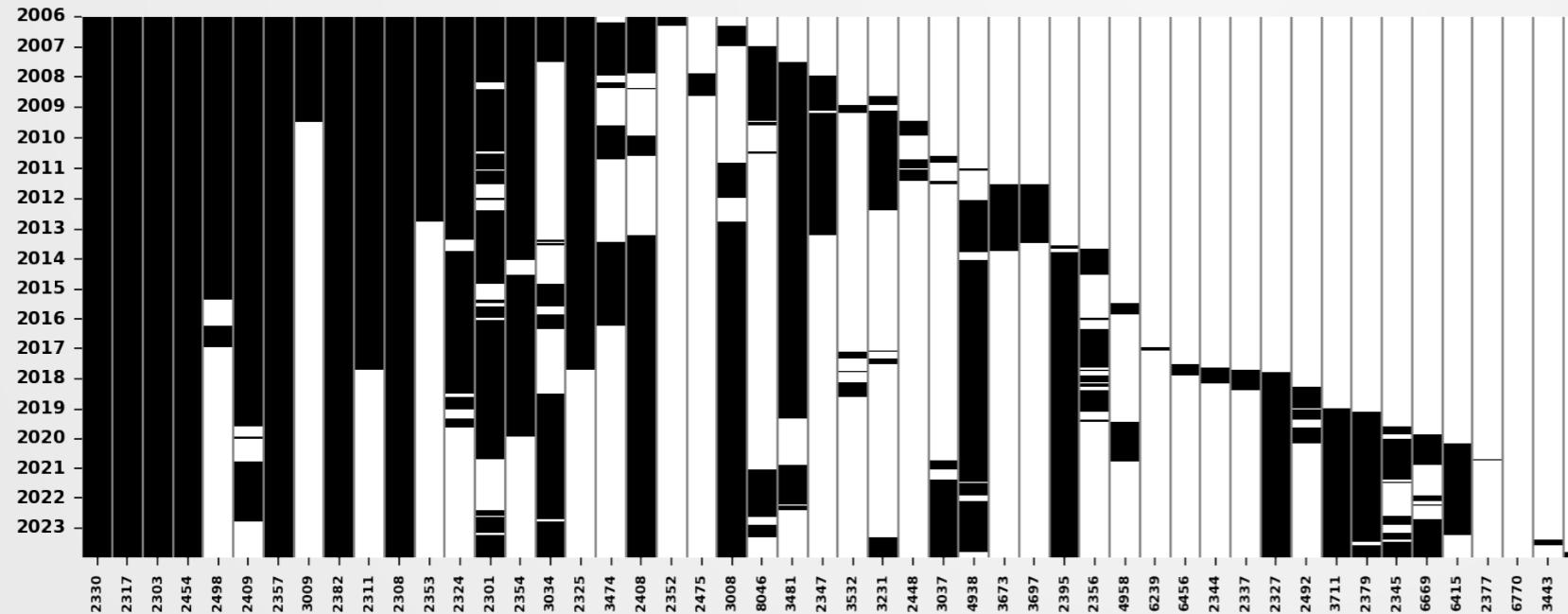


Dynamic Selection (FRM^E)



Black block

Missing data caused by companies delisting



Black block

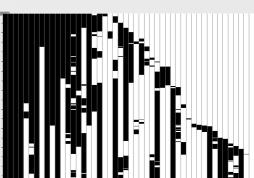
Selected top 20 capitalization companies in each day



Macroeconomic Variables

- Select ten macroeconomic variables from developed market risk factors.

Ticker	Description
TAIEX	Taiwan Stock Exchange Capitalization Weighted Stock Index
TELI	TAIEX Electronic Sub-Index
TFNI	TAIEX Finance and Insurance Sub-Index
SP500	Standard & Poor's 500 Index
REITs	Average of Taiwan's 10 REIT
TW2Y	Taiwan 2-year Treasury Note rate.
Slope	Spread between 2-year and 10-year Taiwan Treasury Bonds
VIXTWN	TAIEX Options Volatility Index
USDTWD	USD/TWD Exchange Rate
ONIR	Taiwan's Overnight Interbank Offer Rate



Data - Macroeconomic Variables

- Select four macroeconomic variables with the weakest correlations

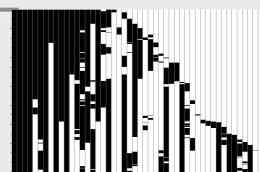
	TAIEX	Electronic	Financial	SP500	REITs	TW2Y	Slope	VIXTWN	USDTWD	ONIR
TAIEX	1.00	0.96***	0.85***	0.17***	0.28***	0.02	0.10***	-0.51***	-0.45***	-0.03*
Electronic	0.96***	1.00	0.72***	0.16***	0.26***	0.00	0.09***	-0.49***	-0.42***	-0.03*
Financial	0.85***	0.72***	1.00	0.13***	0.27**	0.01	0.08***	-0.39***	-0.38***	-0.02
SP500	0.17***	0.16***	0.13***	1.00	0.02	0.00	0.12***	-0.10***	-0.10***	0.02
REITs	0.28***	0.26***	0.27**	0.02	1.00	0.01	0.16***	-0.13***	-0.16***	-0.01
TW2Y	0.00	0.00	0.01	0.00	0.01	1.00	-0.04**	-0.01	0.03**	0.01
Slope	0.10***	0.09***	0.08***	0.12***	0.16***	-0.04**	1.00	-0.02	-0.06***	-0.01
VIXTWN	-0.51***	-0.49***	-0.39***	-0.10***	-0.13***	-0.01	-0.02	1.00	0.22***	-0.02
USDTWD	-0.45***	-0.42***	-0.38***	-0.10***	-0.16***	0.03**	-0.06***	0.22***	1.00	-0.02
ONIR	-0.03*	-0.03*	-0.02	0.02	-0.01	0.01	-0.01	-0.02	-0.02	1.00



Business Cycle Monitor Indicators (MI)



- 9 Indicators, each indicator's score is from 1 to 5.
 - ▶ Monetary Aggregate, M1B
 - ▶ Stock Price Index
 - ▶ Industrial Production Index
 - ▶ Non-agricultural Sector Employment
 - ▶ Customs Export Value
 - ▶ Import Value of Machinery and Electrical Equipment
 - ▶ Manufacturing Sales Volume Index
 - ▶ Wholesale, Retail, and Food Service Sales
 - ▶ Manufacturing Business Climate Survey Point



Business Cycle Monitor Indicators (MI)

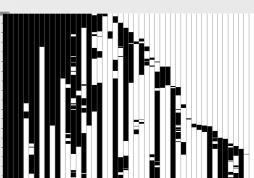


- The calculation of MI is $\sum_{i=1}^9 \text{Indicator}_i$
- Therefore the MI $\in [9, 45]$
 - ▶ **Blue light (Sluggish; Recessions):** MI $\in [9, 16]$
 - ▶ **Blue yellow light (Transitional):** MI $\in [17, 22]$
 - ▶ **Green light (Stable):** MI $\in [23, 31]$
 - ▶ **Yellow red light (Transitional):** MI $\in [32, 37]$
 - ▶ **Red light (Booming):** MI $\in [38, 45]$
- Announce at the end of next month.

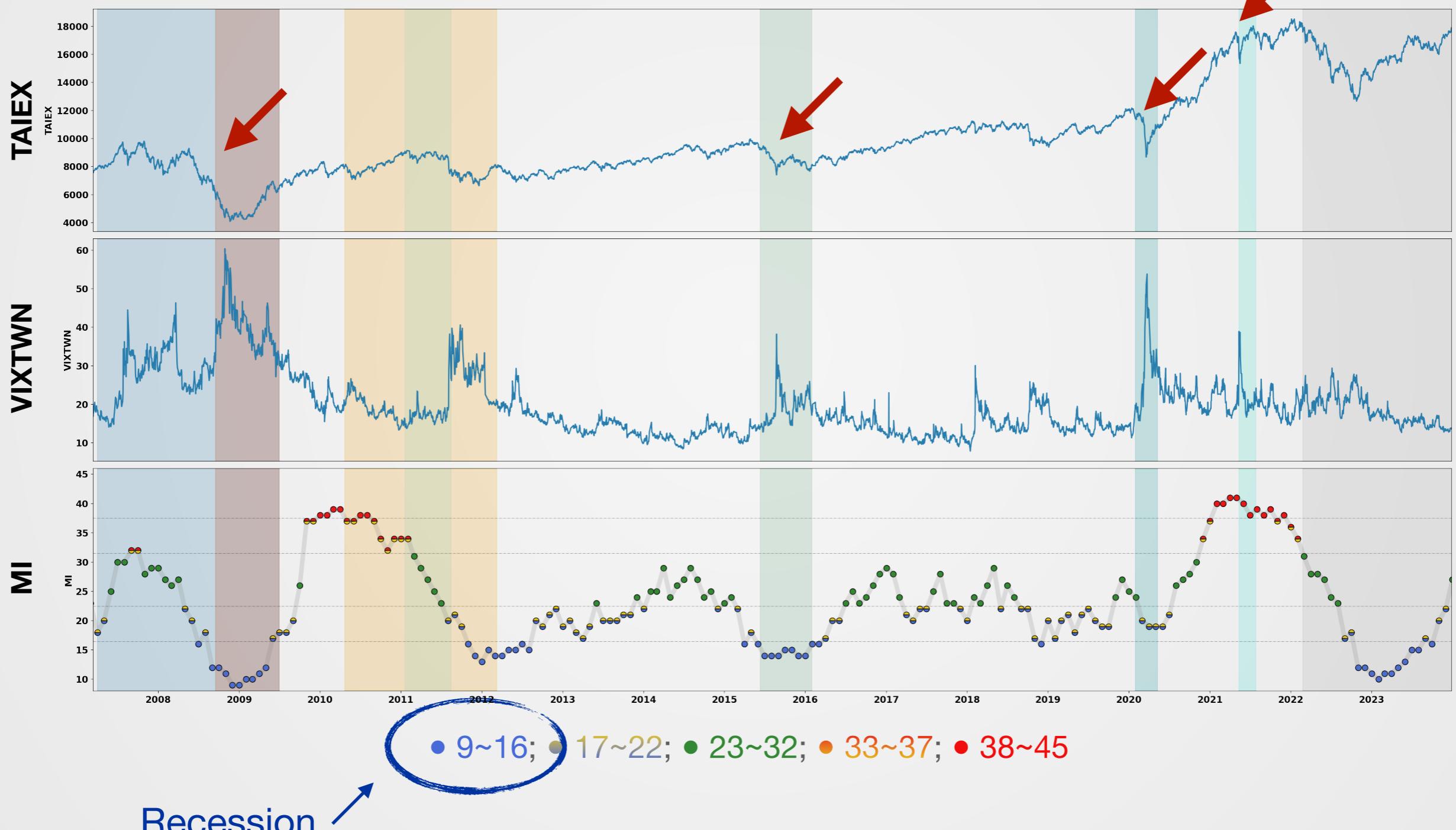


Defining Periods of Economic Turmoil

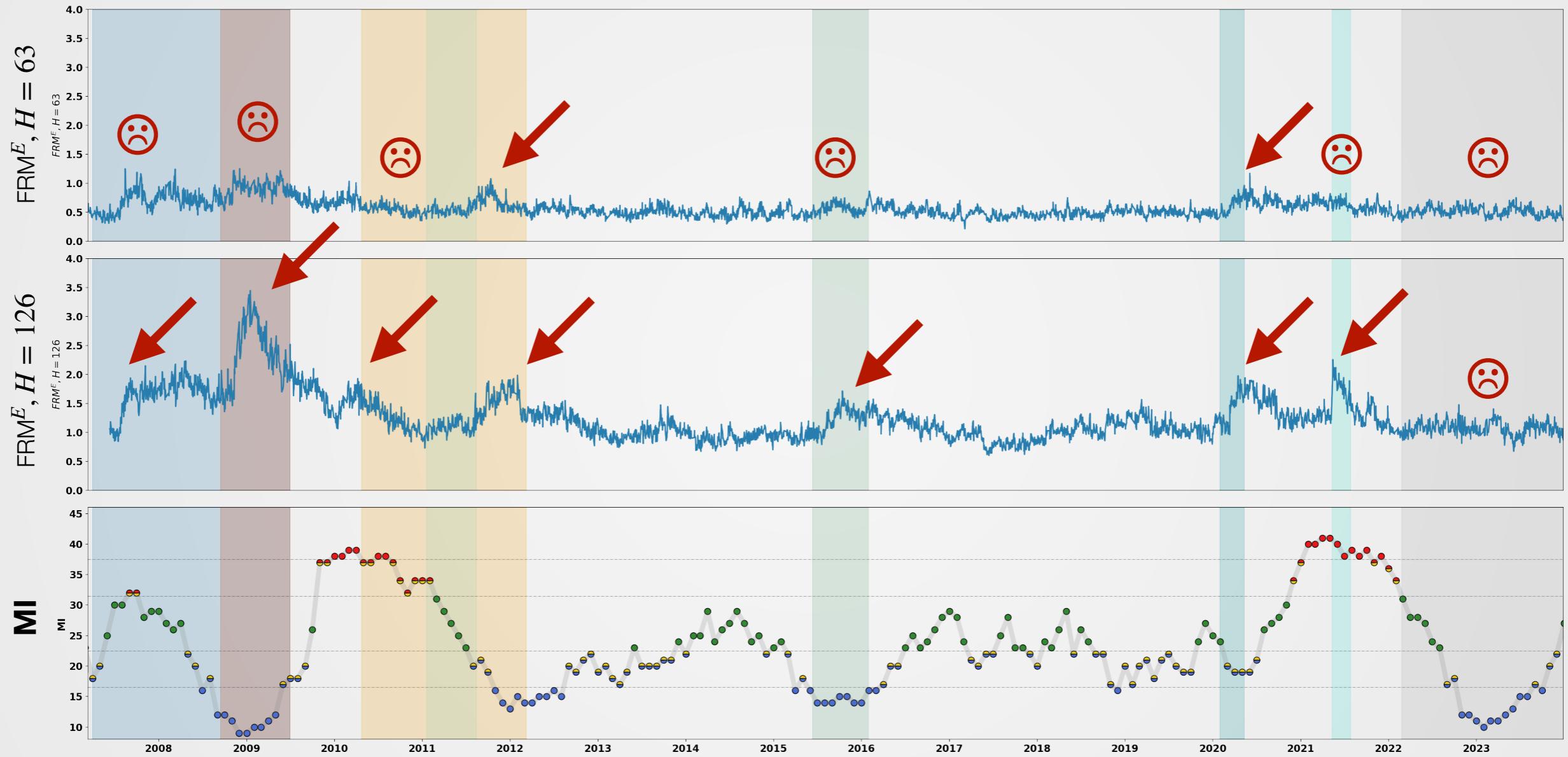
Start Date	End Date	Event
2007-04-02	2009-06-30	Subprime Mortgage Crisis
2008-09-15	2009-06-30	Lehman Brothers Bankruptcy
2010-04-23	2012-03-09	European Debt Crisis
2011-01-19	2011-08-15	US Debt Crisis
2015-06-12	2016-01-31	Chinese Stock Market Crash
2020-01-30	2020-05-10	First Taiwan's COVID-19 Outbreak
2021-05-11	2021-07-27	Second Taiwan's COVID-19 Outbreak
2022-02-24	2023-12-29	Russia-Ukraine War and US Interest Rate Hikes



TAIEX, VIXTWN, MI



Empirical Results - FRM^E



Cross-validation with 5-fold splits

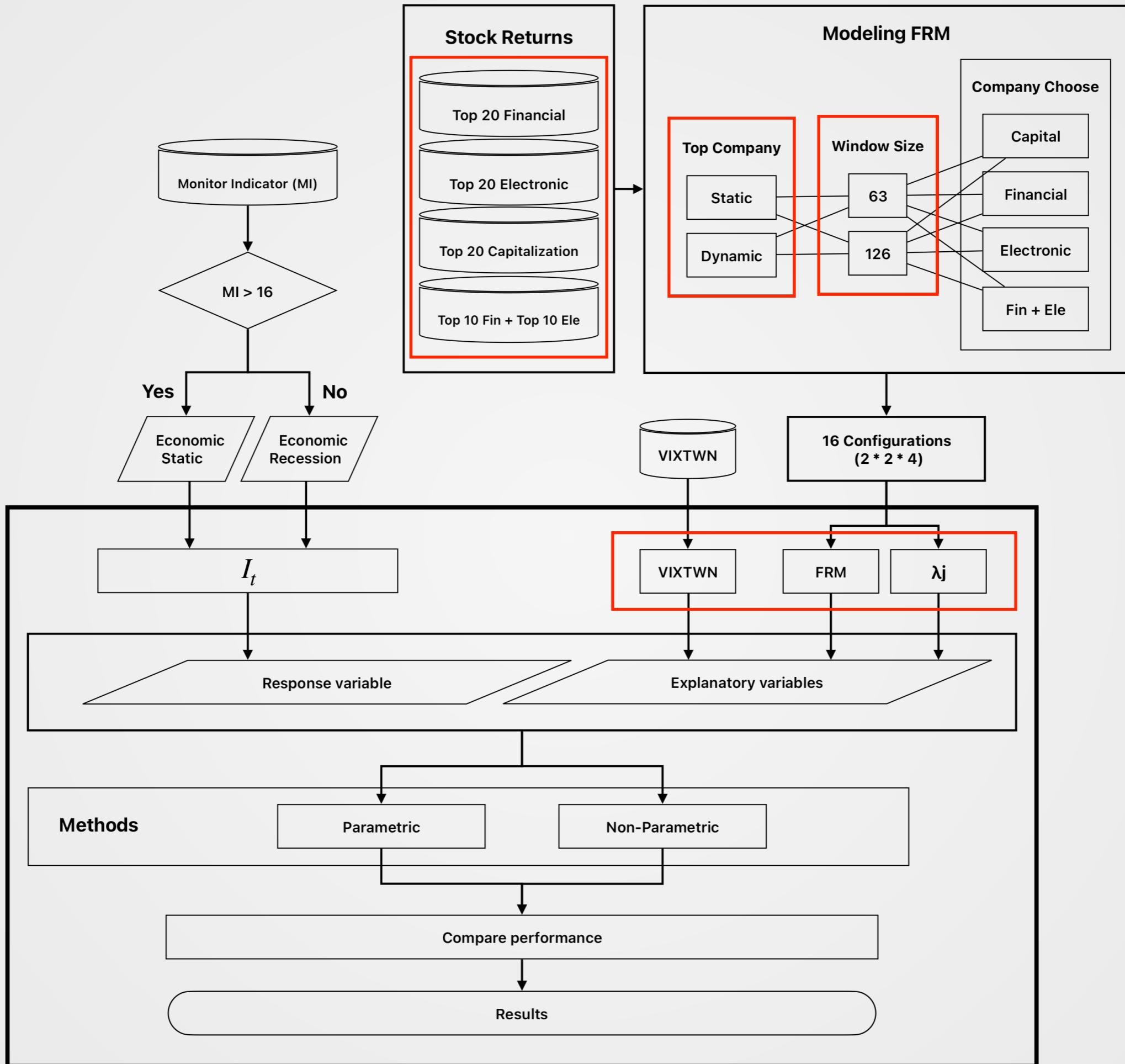
- Response variable: $I_t^{(M)}$ represents the recession at the end of the month M , t

$$I_t^{(M)} = \begin{cases} 1, & \text{MI}_t^{(M+1)} \in [9, 16] \\ 0, & \text{o.w.} \end{cases}$$

- Three sets of explanatory variables, $W = 63$

- λ_j for $j = 1, \dots, J$: $\mathbb{F}_t^{(M)} = \left\{ \lambda_{1,t}^{(M)}, \lambda_{1,t-1}^{(M)}, \dots, \lambda_{1,t-W}^{(M)}, \dots, \lambda_{J,t}^{(M)}, \lambda_{J,t-1}^{(M)}, \dots, \lambda_{J,t-W}^{(M)} \right\}$
- FRM: $\text{FRM}_t^{(M)} = \left\{ \text{FRM}_t^{(M)}, \text{FRM}_{t-1}^{(M)}, \dots, \text{FRM}_{t-W}^{(M)} \right\}$
- VIXTWN: $\mathbb{V}_t^{(M)} = \left\{ \text{VIX}_t^{(M)}, \text{VIX}_{t-1}^{(M)}, \dots, \text{VIX}_{t-(H+W)}^{(M)} \right\}$
- Estimate $P(I_t^{(M)} = 1 | X_t^{(M)})$
 - Parametric method: Logistic Regression
 - Nonparametric method: XGBoost





Performance (AUC)

Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.94		1.00		0.94		1.00	
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.54		0.41		0.54		0.41	
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.98		1.00		0.98		1.00	
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.54		0.45		0.54		0.43	
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50



Performance (AUC): In-Sample

Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.94		1.00		0.94		1.00	
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.54		0.41		0.54		0.41	
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.98		1.00		0.98		1.00	
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.54		0.43		0.54		0.43	
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50

Performance (AUC): Out-of-Sample, Dynamic vs. Static

Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.94		1.00		0.94		1.00
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.54		0.41		0.54		0.41	
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.98		1.00		0.98		1.00
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.54		0.43		0.54		0.43	
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50

Performance (AUC): Out-of-Sample, Parametric vs. Non-Parametric

Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.94		1.00		0.94		1.00
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.54		0.41		0.54		0.41
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.98		1.00		0.98		1.00
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.54		0.43		0.54		0.43
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50

Performance (AUC): Out-of-Sample, FRM, λ_j vs. Benchmark

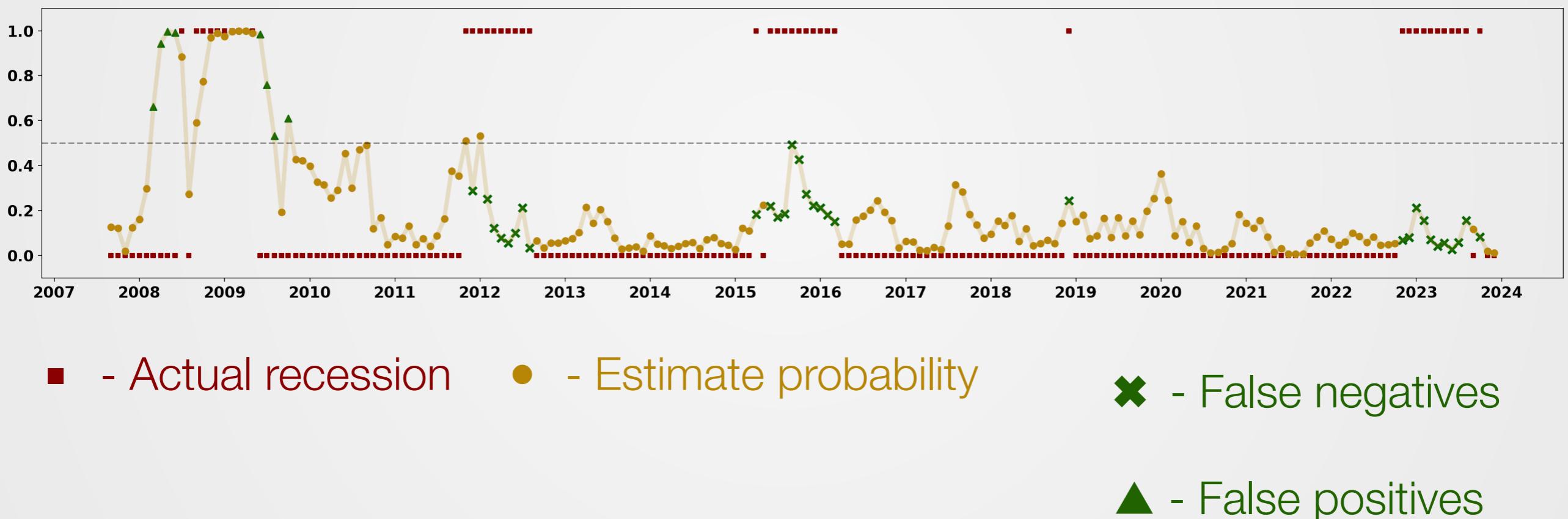
Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.94		1.00		0.94		1.00
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.54		0.41	A	0.54		0.41
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.98		1.00		0.98		1.00
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.54		0.43	A	0.54		0.43
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50

Performance (AUC): Out-of-Sample, FRM vs. λ_j

Company Choose	Window Size	Dynamic Selection				Static Selection			
		Parametric		Non-parametric		Parametric		Non-parametric	
		FRM	λ_j	FRM	λ_j	FRM	λ_j	FRM	λ_j
<i>In-sample analysis, H=63</i>									
VIXTWN	0 + 126		0.94		1.00		0.94		1.00
Cap	63 + 63	0.76	1.00	1.00	1.00	0.67	1.00	1.00	1.00
Fin	63 + 63	0.72	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Ele	63 + 63	0.79	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	63 + 63	0.73	1.00	1.00	1.00	0.70	1.00	1.00	1.00
<i>Out-of-sample analysis, H=63</i>									
VIXTWN	0 + 126	0.54		0.41		0.54		0.41	
Cap	63 + 63	0.61	0.46	0.46	0.59	0.69	0.57	0.54	0.52
Fin	63 + 63	0.71	0.63	0.41	0.50	0.71	0.64	0.50	0.59
Ele	63 + 63	0.69	0.53	0.57	0.65	0.75	0.52	0.68	0.64
Fin + Ele	63 + 63	0.67	0.70	0.45	0.66	0.72	0.73	0.49	0.65
<i>In-sample analysis, H=126</i>									
VIXTWN	0 + 189		0.98		1.00		0.98		1.00
Cap	126+63	0.87	1.00	1.00	1.00	0.72	1.00	1.00	1.00
Fin	126+63	0.81	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Ele	126+63	0.85	1.00	1.00	1.00	0.74	1.00	1.00	1.00
Fin + Ele	126+63	0.83	1.00	1.00	1.00	0.76	1.00	1.00	1.00
<i>Out-of-sample analysis, H=126</i>									
VIXTWN	0 + 189	0.54		0.43		0.54		0.43	
Cap	126+63	0.57	0.55	0.33	0.39	0.61	0.65	0.48	0.65
Fin	126+63	0.59	0.59	0.51	0.41	0.73	0.31	0.46	0.32
Ele	126+63	0.70	0.80	0.47	0.78	0.63	0.48	0.28	0.56
Fin + Ele	126+63	0.70	0.46	0.58	0.49	0.67	0.52	0.64	0.50

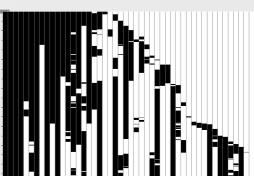
Predict Performance (Dynamic, Ele, ws=126, parametric, λ_j)

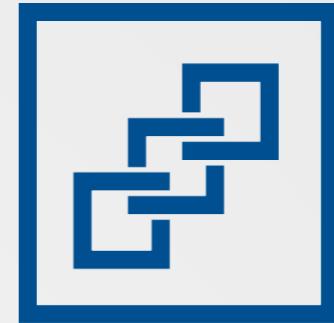
- Merged results in the 5-fold test sets



Summary

- Results
 - ▶ Dynamic ~ Static
 - ▶ Parametric > Non-parametric
 - ▶ $\text{FRM} \sim \lambda_j > \text{VIXTWN}$
- Best configuration to predict recession (AUC = 0.8037)
 - ▶ Dynamic selection
 - ▶ Using stocks from high-cap electronic sectors
 - ▶ $H = 126$
 - ▶ Parametric method
 - ▶ Using all λ_j





Financial Risk Meters in Taiwan's High-Cap Sectors

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FRM quantlet