News-Driven Systemic Tail Risk at High Frequency*

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- Financial markets are often vulnerable to tail shocks driven by news.
  - → Some examples: the crash of "Black Monday" (October 19, 1987), the bailout rejection (September 29, 2008), flash crash (May 6, 2010), FOMC rate cut (December 11, 2007), the COVID-19 crash (March 16, 2020), ...
- When news-induced shocks hit, asset and portfolio managers are exposed to large financial losses associated with tail risks.
- The potential losses due to realized tail episodes may pose severe challenges:
  - → Asset managers/investors/traders: When does the tail risk occur? How frequently? What triggers that? Is it diversifiable? Is it priced?
  - → Policymakers/regulators: How "bad" is the financial distress? Is it a short-term market reaction or is it linked to policy decisions?

Prior Research

- Idiosyncratic and systematic jump risks matter:
  Pelger (2020, *JF*), Chan et al. (2017, *JEF*), Bollerslev et al. (2013, 2008, *JoE*)
- Tail risk is systematic and priced in the market:
  Andersen et al. (2020, *JBES*), Weller (2019, *RFS*), Van Oordt and Zhou (2016, *JFQA*), Bollerslev and Todorov (2014, *JoE*), Bollerslev et al. (2013, *JoE*), ...
- Ongoing debate on the link between news announcements and jump risk:
  Lahaye et al. (2011, *JAE*), Amengual and Xiu (2018, *JoE*), Bajgrowicz et al. (2016, *MS*), ...

Our Focus

- Identification and financial implications of systemic tail risk:
  (*risk that occurs when financial assets jump or crash together at the same time*)

  → Das and Uppal (2005, *JF*):
  "Weak evidence" that systemic risk matters for international asset allocation

  → Caporin et al. (2017, *JFE*):
  "Strong evidence" that systemic risk matters, reveals return predictability

This Paper: Contributions and Findings

(1) Methodological:

- We develop a new methodology to measure news-induced systemic tail risk:
  - → Conditional testing and inference based on news release times
  - → Exploiting time-varying jump intensity dynamics to capture tail risk
  - → Accurate identification (systemic volatility risk versus systemic jump risk)
  - → Conservative bias control for spurious detection + bootstrap consistency

(2) Empirical:

- We use a panel of HF data on individual stocks and sector portfolios to study if U.S. monetary policy (FOMC) announcements lead to systemic tail risk:
  - → We find strong evidence of "Fed-driven" systemic tail risk.
  - → Left tail (systemic crash) risk occurs frequently over the business cycle.
  - → Results hold for both individual stocks and sector (ETF) portfolio indices.
  - → We identify which Fed events are systemically important as tail events.
  - → We construct a simple proxy for systemic tail risk:
    - – Helps explain the pre-FOMC announcement drift puzzle
    - – Predicts intraday stock returns ahead of the upcoming Fed meeting
  - → No clear evidence that macro news creates HF systemic tail risk.

Outline

Outline

The General Form

Jump-Diffusion with Time-Varying Intensity

Log-prices $X := [X_1, \ldots, X_N]'$ of N assets:

$$dX_{i,t} = b_{i,t}dt + \sigma_{i,t}dW_{i,t} + \xi_{i,t}dJ_{i,t}, \qquad i = 1, \ldots, N, \tag{1}$$

Our focus is on J_t which has the form

$$d\lambda_{i,t} = \tilde{\alpha}_i(\lambda_{i,\infty} - \lambda_{i,t})dt + \tilde{\beta}_i dJ_{i,t}, \qquad i = 1, \ldots, N, \tag{2}$$

where the stochastic jump intensity $\lambda_{i,t}$ helps control for the time-varying intensity of the extreme tail shocks at high frequency.

- Boswijk et al. (2018, *JoE*), Dungey et al. (2018, *JoE*), Aït-Sahalia et al. (2015, *JFE*)
- Maheu and McCurdy (2004, *JF*), Chan and Maheu (2002, *JBES*)

Our Extension:

Goal: Systemic (simultaneous) response of assets to specific events

Motive: Traders monitoring markets awaiting for FOMC news to assess positions

Idea: **Going from general (calendar time) form to localized (event time) form**

Intuition: **Analogous to conventional event studies based on high-frequency data**

Localized Form:

Consider the simple localized version of (2):

$$d\lambda_{i,t}^{event} = \tilde{\alpha}_i(\lambda_{i,\infty}^{event} - \lambda_{i,t}^{event})dt + \tilde{\beta}_i dJ_{i,t}, \qquad i = 1, \ldots, N, \tag{3}$$

where $\lambda_{i,t}^{event} := [\lambda_{1,t}^{event}, \ldots, \lambda_{N,t}^{event}]'$ denotes the stochastic intensities around each FOMC event.

Tail Risk and News Events

- We can use (3) to characterize the dynamics of news-induced shocks that simultaneously hit all assets.
- Systemic tail risk can stem from the common jumping behavior of many stocks, governed by $\lambda_{i,t}^{event}$ in (3), conditional on event times.
- Event times act as reference points for testing/detection.

Schematic Representation

Outline

Our variable of interest λ^{event} is latent.

Estimating intensity "before" and "after" news event:

For each stock ($i = 1, \dots, N$) and event ($s = 1, \dots, S$), estimate λ^{event} via

$$\widehat{\lambda}_i(k_n)^{\text{event}} \begin{cases} \widehat{\lambda}_i(k_n)^{\text{pre}} := \frac{\Delta_n^{\varpi \widehat{\beta}_i}}{k_n \Delta_n} \sum_{j=1}^{k_n} g\left(\frac{|\Delta_j^n X_i^{(\text{pre})}|}{\alpha \Delta_n^{\varpi}}\right) \frac{\alpha^{\widehat{\beta}}}{C_{\widehat{\beta}_i}(k_n)} & \Longrightarrow \textbf{(pre-event)} \\ \widehat{\lambda}_i(k_n)^{\text{post}} := \frac{\Delta_n^{\varpi \widehat{\beta}_i}}{k_n \Delta_n} \sum_{j=1}^{k_n} g\left(\frac{|\Delta_j^n X_i^{(\text{post})}|}{\alpha \Delta_n^{\varpi}}\right) \frac{\alpha^{\widehat{\beta}}}{C_{\widehat{\beta}_i}(k_n)} & \Longrightarrow \textbf{(post-event)} \end{cases}$$

where $\widehat{\beta}$ controls the vibrancy of sharp fluctuations (jump activity).

$\longrightarrow$ choose $g(\cdot)$
$\longrightarrow$ set the window length surrounding events
$\longrightarrow$ obtain the estimates $\widehat{\lambda}_i(k_n)^{\text{pre}}$ and $\widehat{\lambda}_i(k_n)^{\text{post}}$

Testing idea:

Does $\widehat{\lambda}_i(k_n)^{\text{post}}$ change sharply compared to "benchmark" $\widehat{\lambda}_i(k_n)^{\text{pre}}$?

Considering the entire set of events, null and alternative hypotheses:

$$\mathbf{H}_0 : \quad \omega \in \Omega_T^{\textbf{noSCOJ}} := \Omega_t^{\lambda^{\textbf{event}},0} = \{\omega : \lambda(\omega)_{i,t}^{\textbf{pre}} = \lambda(\omega)_{i,t}^{\textbf{post}}\}, \qquad i = 1, \ldots, N,$$

vs.

$$\mathbf{H}_a : \quad \omega \in \Omega_T^{\textbf{SCOJ}} := \Omega_t^{\lambda^{\textbf{event}}} = \{\omega : \lambda(\omega)_{i,t}^{\textbf{pre}} \neq \lambda(\omega)_{i,t}^{\textbf{post}}\}, \qquad i = 1, \ldots, N,$$

where ω denotes a specific outcome, $\omega \in \Omega$.

Under the null, the event-based test statistic:

Test statistic

$$\mathcal{T}_{i,t}^{(\text{event})} = \sqrt{\frac{k_n \Delta_n}{\Delta_n^{\varpi \widehat{\beta}_i}}} \frac{\widehat{\lambda}_{i,t}^{\text{post}} - \widehat{\lambda}_{i,t}^{\text{pre}}}{\left(\sqrt{\alpha^{\widehat{\beta}_i} C_\beta(2)(\widehat{\lambda}_{i,t}^{\text{post}} + \widehat{\lambda}_{i,t}^{\text{pre}})}\right) \Big/ C_\beta(1)}, \qquad i = 1, \ldots, N, \qquad (4)$$

which can be computed given $\widehat{\lambda}_{i,t}^{\text{post}}$, $\widehat{\lambda}_{i,t}^{\text{pre}}$, $\widehat{\beta}_i$, k_n, Δ, α and C_β.

Asymptotic behavior of (4) is not reliable due to multiple testing bias.

We deal with the multiple testing problem in three respects:

- Accounting for the news-induced dependence of test statistics given by (4)
- Asymptotically controlling for the FWE at a given nominal level
- Seeking for high power: better ability to identify false discoveries:

$\Longrightarrow$ Eliminate as many "spurious" systemic cojumps as possible

$\Longrightarrow$ Detect as many "real" systemic cojumps as possible

We propose an event-based extension of the stepwise method of Romano and Wolf (2005, *Ecta*).

We implement the following procedure to detect event-based systemic cojumps:

Algorithm 1: Event-based StepM

1. For each event (define as $s = 1, \dots, S$), use high-frequency data to estimate $\widehat{\lambda}_i^{\text{pre}}$ and $\widehat{\lambda}_i^{\text{post}}$ for all assets ($i = 1, \dots, N$).
2. Compute the test statistic $\mathcal{T}_{i,t}^{(\text{event})}$ in Equation (4) conditional on time (t) of each event ($s = 1, \dots, S$) for all assets ($i = 1, \dots, N$). The testing data matrix is $N \times S$.
3. Relabel the assets (for a given event) in descending order of all $\mathcal{T}_{i,t}^{(\text{event})}$: asset r_1 corresponds to the largest test statistic and asset r_i to the smallest.
4. Set $j = 1$ and $R_0 = 0$ (the number of null hypothesis initially rejected).
5. For $R_{(j-1)} + 1 \leq i \leq N$, if $0 \notin [\mathcal{T}_{r_i,t}^{(\text{event})}$ - $\hat{c}_j$, $\infty)$, reject the null hypothesis $H_0^{(r_i)}$.
6. (a) If no (further) null hypotheses are rejected, stop.

   (b) Otherwise, denote by R_j the total number of hypotheses rejected so far and, afterward, let $j = j + 1$. Then, return to step 5.

Event-Based StepM Method (Cont)

In Algorithm 1, $\hat{c}_j$ denotes the quantiles that we compute directly from the estimated (probability) distribution by using bootstrap.

Under certain assumptions, we have the following result.

Theorem 2: Asymptotic control and consistency

The following statements pertaining to Algorithm 1 are true.

(i) When the null hypothesis is false, the event-based StepM algorithm will reject the null hypothesis with probability 1 as $n \to \infty$.

(ii) The event-based StepM algorithm asymptotically controls the familywise error rate (FWE) at level α; that is, $\lim_n \mathrm{FWE}_{\mathbb{P}} \leq \alpha$,

which ensures that bootstrap consistently estimates the limiting distribution of our test statistic.

Final tasks for implementation:

$\Longrightarrow$ Use bootstrap to approximate the critical values
$\Longrightarrow$ Reject/accept each null for all assets, given the arrival times of events
$\Longrightarrow$ The procedure works well: reasonable power and computationally feasible

Monte Carlo Study

Outline

High-Frequency Data

- A cross-sectional panel of 22 individual DJ stocks and 9 sector ETF indices
- Raw data: tick-by-tick (WRDS) and equally-spaced 15-sec sampling frequency
- Noise correction via price bounceback filtration (Aït-Sahalia et al., 2011, *JoE*)
- Conventional HF data adjustments and cleaning procedures implemented
  (excessively low trading activity, missing/constant prices, empty intervals, constant transactions, etc.)
- The sample period: January 31, 2006 through January 30, 2019

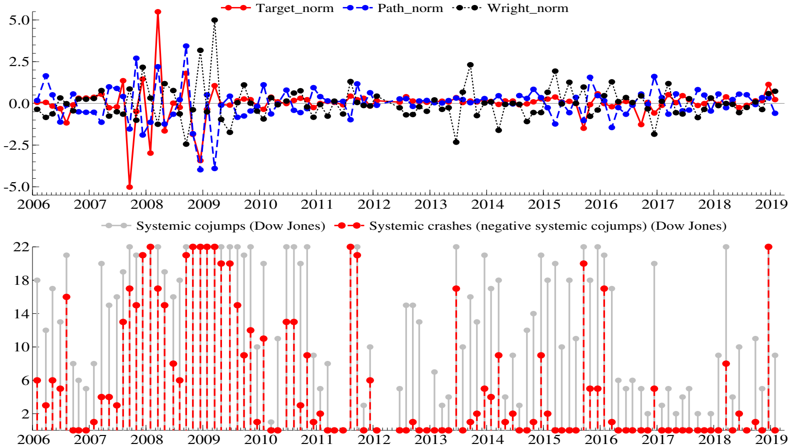
FOMC Announcements and Monetary Policy (MP) Shocks

- Scheduled announcements of the Federal Open Market Committee (FOMC)
- Source: Federal Reserve Bank, Bloomberg and media articles (for cross-check).
- Dates/times of the FOMC news releases (106 events over 2006-2019)
- MP surprise factors: target/path/zero-bound (henceforth Wright factor).
- Construct a revision factor (times when FOMC changes the fed funds target)

Discussion on Noise

Main Results

Monetary Policy Shocks, Systemic Cojumps and Crashes (Dow Jones)



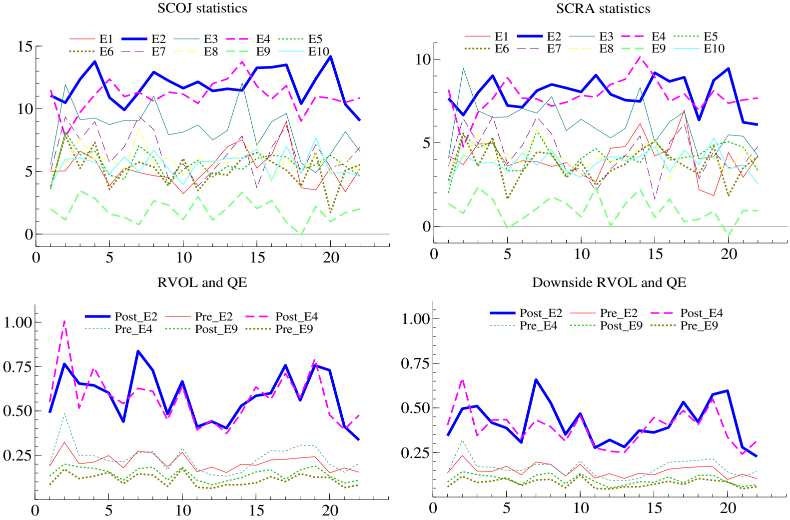
Searching for Systemically Important Fed Events

Dow Jones Stocks

Date	Rank	SCOJ	Frac_SCOJ	SCRA	Frac_SCRA	Target	Path	Wright
2008-01-30	1	22	1.00	22	1.00	-2.983	-1.134	0.321
2008-10-29	2	22	1.00	22	1.00	-1.859	-1.816	-0.383
2008-12-16	3	22	1.00	22	1.00	-3.433	-3.979	3.178
2009-01-28	4	22	1.00	22	1.00	-0.359	0.511	-0.508
2009-03-18	5	22	1.00	22	1.00	1.060	-3.904	4.991
2011-08-09	6	22	1.00	22	1.00	0.433	-0.978	1.307
2018-12-19	7	22	1.00	22	1.00	1.135	0.333	0.587
2008-09-16	8	22	1.00	21	0.95	1.802	3.438	-2.443
2011-09-21	9	22	1.00	21	0.95	0.218	1.170	0.053
2009-04-29	10	22	1.00	20	0.91	-0.072	-0.109	-0.959
2009-06-24	11	22	1.00	20	0.91	-0.106	0.431	-1.735
2015-09-17	12	22	1.00	20	0.91	-1.492	-1.033	0.979
2007-09-18	13	22	1.00	17	0.77	-5.019	-1.533	0.861
2008-03-18	14	22	1.00	17	0.77	5.490	2.195	-1.252
2013-06-19	15	22	1.00	17	0.77	0.345	0.317	-2.326
2009-08-12	16	22	1.00	15	0.68	0.157	-0.835	0.039
2010-06-23	17	22	1.00	13	0.59	-0.012	0.794	0.138
2010-08-10	18	22	1.00	13	0.59	0.179	-0.415	0.619
2009-11-04	19	22	1.00	12	0.55	0.222	-0.460	0.010
2010-11-03	20	22	1.00	9	0.41	0.219	-0.318	-0.211

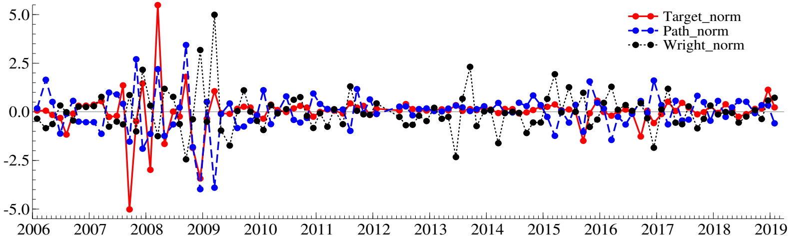
Systemic Effects of Quantitative Easing (QE)

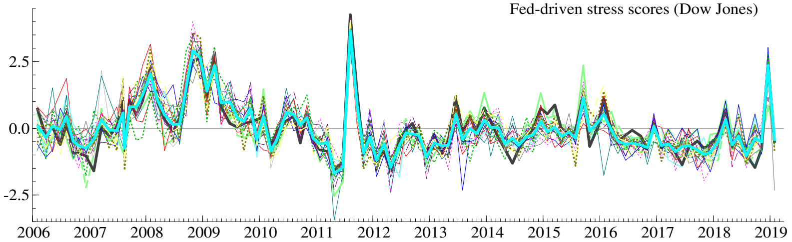
QE Events, Systemic Cojumps and Crashes



News-Driven Realized Tail Risk

"Fed-Driven" Risk Scores Computed from the Test Statistics (Dow Jones)





Does Systemic Tail Risk Explain the Pre-FOMC Drift?

Lagged Regressions for Pre-FOMC Returns

We estimate the following regression model:

$$r_t^{(\text{pre})} = \beta_0 + \beta_x X_{t-1} + \epsilon_t \tag{5}$$

$r_t^{(\text{pre})}$: Cumulative pre-FOMC high-frequency log-returns
RS_{t-1}: Lagged realized tail risk scores
WRS_{t-1}: Lagged weighted realized tail risk scores
$SCOJ_{t-1}$: Fraction of assets that cojump together at *previous meeting*'s event time

Table: Lagged regressions for pre-FOMC announcement returns

	Dependent variable: pre-FOMC announcement returns											
	Panel A. All returns				Panel B. Only positive				Panel C. Only negative			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(RV(t-1))	0.158***				0.118**				0.041			
	(0.055)				(0.046)				(0.040)			
RS(t-1)		0.027***				0.018**				0.009		
		(0.011)				(0.009)				(0.007)		
WRS(t-1)			0.019**				0.014**				0.005	
			(0.009)				(0.007)				(0.005)	
SCOJ(t-1)				0.140*				0.081*				0.059
				(0.080)				(0.045)				(0.060)
Constant	0.255***	−0.120**	−0.062*	−0.081	0.269***	0.001	0.035*	0.033	−0.014	−0.121***	−0.096***	−0.114**
	(0.087)	(0.054)	(0.037)	(0.057)	(0.082)	(0.034)	(0.020)	(0.024)	(0.059)	(0.044)	(0.028)	(0.046)
Obs.	105	105	105	105	105	105	105	105	105	105	105	105
R^2	0.079	0.079	0.059	0.039	0.131	0.101	0.092	0.039	0.011	0.020	0.010	0.015
Res. Std. E.	0.242	0.242	0.245	0.247	0.136	0.138	0.139	0.143	0.170	0.170	0.170	0.170
F Statistic	8.894***	8.850***	6.401**	4.205**	15.544***	11.599***	10.418***	4.208**	1.182	2.152	0.996	1.577

Outline

Conclusions

Overview

- A new methodology for quantifying systemic tail risk in a large panel of assets
- High-frequency approach that exploits time-varying jump intensity
- Conditional testing based on the arrival times of news events
- Controlling for spurious detection across assets and limiting data snooping

Main takeaways and findings

- Severe news-induced systemic tail risk that occurs at high frequency
- Systemic market reaction to Fed (FOMC) announcements
- Strong evidence of systemic tail risk in forms of cojumps and crashes

  $\rightarrow$ cannot be easily diversified away
  $\rightarrow$ sector rotation strategies are likely to be limited
- Systemic risk helps explain the pre-FOMC drift: significant and sizeable
- Macro news does not create systemic tail risk at high frequency.

Future work / extensions

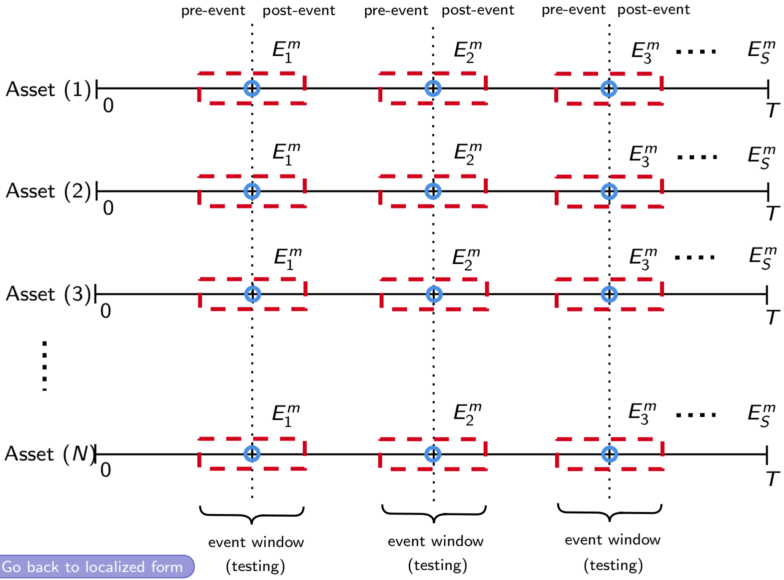
- Systemic tail risk, monetary policy news and international portfolio choice

  $\rightarrow$ A high-frequency approach? $\Longrightarrow$ Revisiting Das and Uppal (2005, *JF*)?
- Exploring further via market microstructure data (LOB/MBO)?
  Deep learning for systemic tail risk monitoring?

Outline

Extensions and Robustness Checks

Schematic Representation of the Detection Approach



Go back to localized form

Tail risk $\Rightarrow$ probability of extremely large losses

Left tail risk $\Rightarrow$ left skewness of returns

Given (3), how does the tail probability change at high frequency in response to news?

If the news creates a jump with a certain magnitude ξ, we can compute the news-induced tail probability ratio as

$$\frac{\mathbb{P}(|(\lambda_{i,\infty}^{event} + \xi)\Delta_n J_i| \geq \alpha \Delta_n^{\varpi})}{\mathbb{P}(|\lambda_{i,\infty}^{event} \Delta_n J_i| \geq \alpha \Delta_n^{\varpi})} \approx \left(\frac{\lambda_{i,\infty}^{event} + \xi}{\lambda_{i,\infty}^{event}}\right)^{\beta_i} = (1 + \xi/\lambda_{i,\infty}^{event})^{\beta_i}, \quad i = 1, \ldots, N, \tag{6}$$

where $\beta_i := [\beta_1, \ldots, \beta_N]'$ is the vector of jump activity indices controlling the vibrancy of fluctuations, serving as a tail measure.

This measure is analogous to the estimator of Hill (1975, *AoS*).

Go back to localized form

Simple Example:

- For a given value of λ^{event}, if the news generates a jump with large magnitude (e.g., $\xi = 12$), the tail probability ratio is around 1.8.
- In practical terms, this implies that the FOMC event that induces a large jump in each asset will increase the tail probability by 80%.
- Put differently, the likelihood that the investor will be exposed to extreme loss (both left- and right-tails) due to *FOMC-driven* jumps is now 80% higher than that in the case of no jumps.
- Such a change in the tail probability amplified by news is rather substantial, thereby assets that cojump together pose systemic tail risk.

For each stock ($i = 1, \dots, N$), the underlying DGP for log-returns:

$$dX_{i,t} = \sigma_{i,t} dW_{i,t} + \lambda_\infty dJ_{i,t} \tag{7}$$

$$d\sigma^2_{i,t} = \kappa(\theta - \sigma^2_{i,t}) + \eta\sigma_{i,t}(\phi dW_{i,t} + \sqrt{(1-\phi^2)} dB_{i,t}) + \theta 1_{\{S=JT\}} \tag{8}$$

$$d\lambda_{i,t} = \kappa_\lambda(\lambda_{i,\infty} - \lambda_{i,t})dt + \eta_\lambda dB'_{i,t} + \xi 1_{\{S=JT\}}, \tag{9}$$

where the vector of Brownian motion ($W_{i,t}$, $B_{i,t}$, $B'_{i,t}$) and the vector of β-stable jump processes $J_{i,t}$ are independent from each other.

Implementation

- Select the parameters and calibration values,
- Generate data based on the dynamics given in (8)-(10),
- For each replication, simulate testing time points (representing event times S) that are same for all N asset. Let each asset jump at these pre-determined time points, that is, when jump times (JT) coincide with event times $S = JT$ in (9),
- Determine the pre- and post-event window, (e.g., within hour before and after the event times),
- Compute the estimators, test statistic and apply the StepM detection procedure.

Go back to StepM

MONTE CARLO STUDY: SIMULATION RESULTS (POWER)

Table: Power of the uncorrected and bias-corrected tests based on StepM

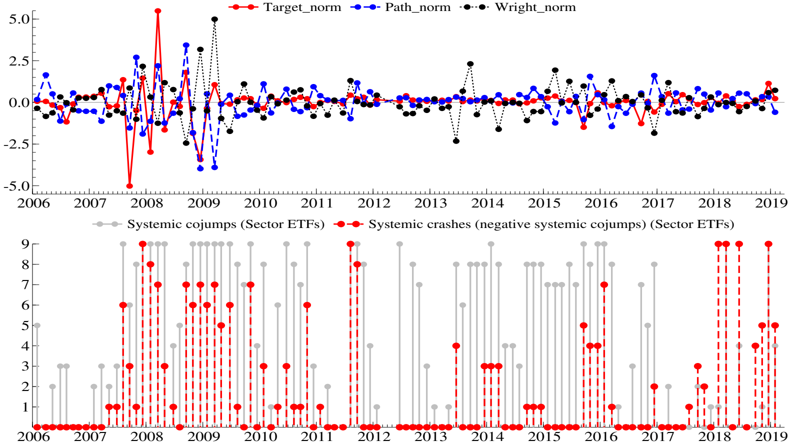
		$S = 1$			$S = 10$		
Panel A.		Uncorr	Step-1	Step-M	Uncorr	Step-1	Step-M
$(N = 200)$	15-sec	99.95%	99.70%	99.95%	99.91%	95.77%	99.61%
	1-min	99.20%	92.15%	96.85%	95.51%	69.53%	73.67%
Panel B.							
$(N = 20)$	15-sec	100.00%	99.70%	100.00%	97.37%	74.20%	87.19%
	1-min	98.10%	93.30%	98.20%	97.87%	94.40%	97.54%
Panel C.							
$(N = 20)$	15-sec	85.70%	71.20%	76.10%	92.86%	62.52%	79.70%
	1-min	94.50%	82.40%	89.70%	76.94%	34.86%	45.58%

"FED-DRIVEN" SYSTEMIC COJUMPS AND CRASHES

	Events	Assets	Mean	Frac	Stdev	Max	Min	Thr
Panel I. Dow Jones stocks								
SCOJ	106	22	12.77	0.58	7.76	22	0	0.48
SCRA	106	22	5.75	0.26	7.61	22	0	0.20
Panel II. Sector ETFs								
SCOJ	106	9	4.93	0.55	3.51	9	0	0.50
SCRA	106	9	2.08	0.23	2.91	9	0	0.18

Extensions and Robustness Checks

Monetary Policy Shocks, Systemic Cojumps and Crashes (Sector ETFs)



In Search of Systemically Important Events (Sector ETFs)

Date	Rank	SCOJ	Frac_SCOJ	SCRA	Frac_SCRA	Target	Path	Wright
2007-12-11	1	9	1.00	9	1.00	1.459	-1.898	2.164
2011-08-09	2	9	1.00	9	1.00	0.433	-0.978	1.307
2018-03-21	3	9	1.00	9	1.00	0.391	-0.259	-0.006
2018-12-19	4	9	1.00	9	1.00	1.135	0.333	0.587
2008-01-30	5	9	1.00	8	0.89	-2.983	-1.134	0.321
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2009-11-04	10	9	1.00	7	0.78	0.222	-0.460	0.010
2016-01-27	11	9	1.00	7	0.78	-0.013	0.163	0.462
2007-08-07	12	9	1.00	6	0.67	1.361	0.414	-0.646
2008-10-29	13	9	1.00	6	0.67	-1.859	-1.816	-0.383
2009-01-28	14	9	1.00	6	0.67	-0.359	0.511	-0.508
2009-06-24	15	9	1.00	6	0.67	-0.106	0.431	-1.735
2010-11-03	16	9	1.00	6	0.67	0.219	-0.318	-0.211
2009-04-29	17	9	1.00	5	0.56	-0.072	-0.109	-0.959
2015-09-17	18	9	1.00	5	0.56	-1.492	-1.033	0.979
2015-12-16	19	9	1.00	4	0.44	0.574	0.465	-0.399
2008-04-30	20	9	1.00	3	0.33	-1.652	-1.239	1.182

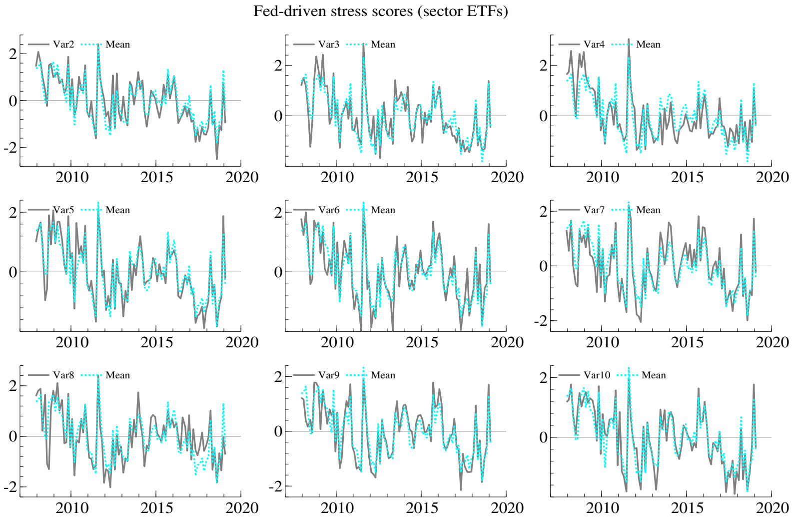
Extensions and Robustness Checks

QE Events, Systemic Cojumps and Crashes

Dates	Time	Type	Description of event	G2011	W2012	SCOJ-stat	SCOJ	SCRA-stat	SCRA	RV ratio	DRV ratio
20081125	8:15	QE1	Type of event: FOMC statement – Expansion of QE. Initial LSAP announcement. The Fed announces purchases of $100 billion in GSE debt and up to 500 billion in MBS. Creation of the Term Asset-Backed Security Loan Facility (TALF)	-22	0.75	NA	NA	NA	NA	NA	NA
20081201	13:45	QE1	Type of event: Bernanke Speech – Expansion of QE. Chairman Bernanke mentions that the Fed could purchase long-term Treasuries.	-19	0.84	5.24	22	4.06	20	1.41	1.44
20081216	14:15	QE1	Type of event: FOMC statement – Expansion of QE. The FOMC "evaluates" the potential benefits of purchasing longer-term Treasury securities. Also FED funds target rate reduced to the range 0- 0.25	-26	2.22	**(11.80)**	22	**(7.92)**	22	2.78	2.86
20090128	14:15	QE1	Type of event: FOMC statement – Expansion of QE. The Fed is ready to expand agency debt and MBS purchases, as well as to purchase long term treasuries.	14	-0.23	8.35	22	6.09	22	2.27	2.45
20090318	14:15	QE1	Type of event: FOMC statement – Expansion of QE. The Fed will purchase an additional $750 billion in agency MBS and an additional $100 billion in Agency Debt. Moreover, the FOMC decided to purchase up to $300 billion of longer-term Treasury securities over the following six months.	-47	3.41	**(11.05)**	22	**(7.78)**	22	2.53	2.45
20090812	14:15	QE1	Type of event: FOMC statement – Phase out of QE. The Fed will slow the pace of the LSAP by purchasing the full amount by the end of October instead of mid- September.	5	0.15	5.57	22	4.23	21	2.11	2.30
20090923	14:15	QE1	Type of event: FOMC statement – Phase out of QE. The Fed will slow the purchases of agency MBS and agency debt, finishing the purchases by the end of 2010Q1. Treasury purchases will still be finished by October 2009.	-3	0.85	5.14	21	3.73	20	2.23	2.26
20091104	14:15	QE1	Type of event: FOMC statement– Phase out of QE. The amount of agency debt will be halted at $175 billion, instead of $200 billion.	6	0.12	6.52	22	4.38	20	2.40	2.27
20100810	14:15	QE2	Type of event: FOMC statement – Expansion of QE. The Fed will reinvest principal payments from agency debt and agency mortgage-backed securities in longer-term Treasury securities. Holdings of Treasury securities will be rolled over as they mature.	NA	0.57	5.85	22	4.14	22	2.62	2.55
20100827	10:00	QE2	Type of event: Bernanke speech – Expansion of QE. Bernanke mentions potential policy options for further easing, including additional purchases of long term securities.	NA	-0.83	NA	NA	NA	NA	NA	NA
20101015	14:15	QE2	Type of event: Bernanke speech – Expansion of QE. The Fed is prepared to provide additional accommodation if needed to support the economic recovery.	NA	-0.21	**[1.88]**	8	**[1.01]**	3	1.32	1.26
20101103	14:15	QE2	Type of event: FOMC statement – Expansion of QE. The Fed will purchase a further $600 billion of longer-term Treasury securities by the end of the second quarter of 2011, a pace of about $75 billion per month.	NA	-0.05	5.55	22	3.81	22	2.37	2.11

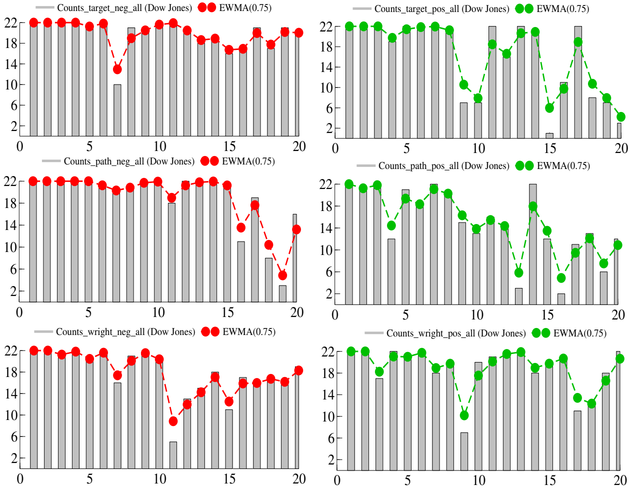
Extensions and Robustness Checks

"Fed-Driven" Risk Scores Computed from the Test Statistics (Sector ETFs)



Extensions and Robustness Checks

Negative versus Positive Monetary Policy Shocks (Dow Jones)



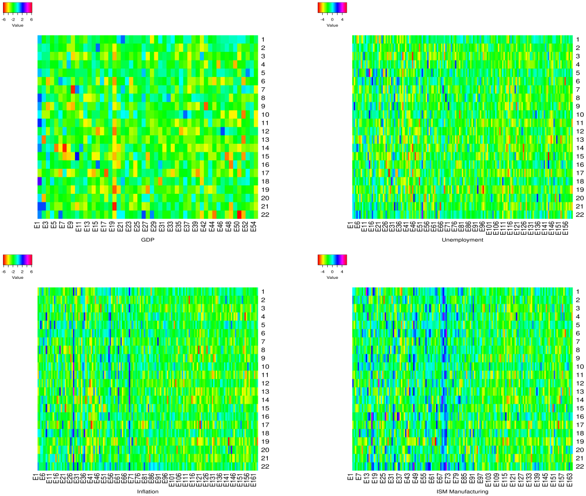
Extensions and Robustness Checks

Macroeconomic News Announcements

News type	News ticker	Release time	Frequency	Relevance	Events
GDP Annualized QoQ	CQOQ	8:30	Quarterly	96.81	54
Unemployment Rate	USURTOT	8:30	Monthly	89.28	163
CPI MoM	CPI CHNG	8:30	Monthly	95.41	163
ISM Manufacturing	NAPMPMI	10:00	Monthly	95.83	163
New Home Sales	NHSLTOT	10:00	Monthly	90.44	163

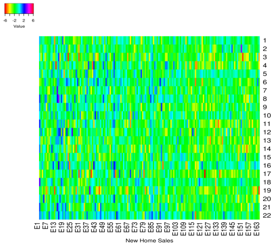
Extensions and Robustness Checks

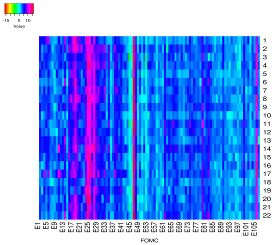
Systemic Reaction Heat Maps for News Announcements



Extensions and Robustness Checks

Systemic Reaction Heat Maps for News Announcements (Cont)





"Why not using pre-averaging method to remove noise?"

- Pre-averaging method has been widely shown as a very effective tool in eliminating the impact of noise in the estimation of realized quantities (and jump detection). → e.g. Hautsch and Podolskij (2013, *JBES*), Podolskij and Vetter (2009, *Bernoulli*)
- Despite its viable usefulness for noise reduction, pre-averaging method might be of limited help in our context for estimating jump compensator related quantities → Bücher and Vetter (2013, *AoS*).
- Recall our variable of interest λ (stochastic jump intensity) which belongs to Lévy measure.
- The challenge: Bücher and Vetter (2013, *AoS*) show pre-averaging does not yield a consistent estimator of the tail of a Lévy measure.
- See Bücher and Vetter (2013, *AoS*) and Boswijk et al. (2018, *JoE*) for the discussion.
- We instead use price bounceback filtration (as in Aït-Sahalia et al., 2011, *JoE*) to eliminate the potential impact of noise.

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