

MEASURING AGGREGATE AND SECTORAL UNCERTAINTY

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The views expressed in this presentation are ours and do not necessarily reflect the position of the Bank of Canada.

MOTIVATION

- The world has been going through extreme uncertainty
 - Since the Great Recession, we see countless studies on uncertainty
Bloom (2009), Jurado, Ludvigson, and Ng (2015), Ludvigson, Ma, and Ng (2015), Baker, Bloom, and Davis (2016), Carriero, Clark, and Marcellino (2018), Jo and Sekkel (2019), Mumtaz and Musso (2019)
 - They focus predominantly on **aggregate** measures of uncertainty
 - Sectors usually face **additional sector-specific** uncertainty shocks on top of the economy-wide uncertainty
 - E.g. transportation, retail stores, health care during Covid-19.
 - We know that aggregate uncertainty is countercyclical and contractionary.
- ▶ But what do we know about sectoral uncertainty?
And, how different is it from the aggregate one?

MOTIVATION

- Are sectoral dynamics important? Yes!
 - Great Moderation reflected a decline in the importance of aggregate shocks relative to sector-specific shocks.
[Foerster, Sarte, and Watson \(2011\)](#), [Atalay \(2017\)](#), [Garin, Pries, and Sims \(2018\)](#)
 - Macro tail-risk during recessions are due to sectoral-dominance
[Acemoglu et al. \(2012\)](#), [Acemoglu et al. \(2017\)](#)
 - Microeconomic shocks may not 'average out' due to, e.g., the nonlinear nature of the disaggregated production structure.
[Baqae and Farhi \(2019\)](#)
- What about sectoral uncertainty? Empirical evidence is scant.
 - The effect of sector-level uncertainty on unemployment is more persistent than the aggregate uncertainty ([Choi and Loungani \(2015\)](#))
 - Consumption and investment TFP volatility shocks have different implications for macroeconomic and financial variables. ([Segal \(2019\)](#))
 - Aggregate and sectoral uncertainty based on median forecast error of earnings-per-share ratios. ([Ma and Samaniego \(2019\)](#))

- Provide an empirical framework that allows for joint estimation of aggregate and sector-specific uncertainty in data-rich environments
- Provide new measures of macroeconomic uncertainty at different levels of aggregation of economic activity
- Show the heterogeneity of aggregate & sectoral uncertainty in their
 - evolutions over time
 - roles as drivers of the business cycle

- U.S. Industrial Production data between 1972Q1 – 2019Q3
- Similar to the data of [Foerster, Sarte, and Watson \(2011\)](#)¹
- 212 Industries under 4 Sectors (note that an industry is a subset of a sector)
- Production series are transformed into growth rates.

TABLE 1: The IP dataset

Sectors	# Industries
Energy (Mining, Oil and Gas)	14
Utilities	13
Manufacturing - Nondurables	80
Manufacturing - Durables	105

We will estimate 1 aggregate (common) and 4 sector-specific volatility factors

¹Compared to FSW (2011), we omit some sectors with very few industries

A MULTISECTOR DFM WITH COMMON SV

Measurement equation: $y_t = \Lambda_f f_t + \Sigma_t^{1/2} \Psi_t^{1/2} e_t$

- ▶ $\Sigma_t^{1/2} = \text{diag}(\exp(h_{t,1}/2), \dots, \exp(h_{t,N}/2))$ is the stochastic volatility component containing **our measure of uncertainty** h_t .
- ▶ $\Psi_t = \text{diag}(\Psi_{1t}, \dots, \Psi_{Nt})$: latent scaling factor that turns Gaussian errors e_t into Student-t ($\Psi_t^{1/2} e_t$), **capturing the outliers**.
- ▶ f_t follows a VAR model with its own stochastic volatility.

Decomposing uncertainty h_t into **aggregate** (v_t^a) and **sector-specific** (v_t^s)

$$\begin{bmatrix} h_{t,1} \\ \vdots \\ h_{t,N} \end{bmatrix} = \Lambda_v v_t = \Lambda_v^a v_t^a + \Lambda_v^s v_t^s \quad \text{and} \quad \begin{bmatrix} v_t^a \\ v_t^s \end{bmatrix} = \Phi_v \begin{bmatrix} v_{t-1}^a \\ v_{t-1}^s \end{bmatrix} + \eta_{t,v}$$

- ▶ An industry's uncertainty is driven by aggregate and sector-specific uncertainty.
- ▶ v_t^a is common to all industries while v_t^s is common only to the sector s .
- ▶ Allow for uncertainty spillovers among different uncertainty measures.

VOLATILITY LOADINGS

- Recall: $h_t = \Lambda_v v_t = \Lambda_v^a v_t^a + \Lambda_v^s v_t^s$.
- The loading matrices for the aggregate and sectoral volatility factors are

$$\Lambda_v^a = \begin{bmatrix} 1 \\ \lambda_{v,2}^a \\ \vdots \\ \lambda_{v,N}^a \end{bmatrix} \quad \text{and} \quad \Lambda_v^s = \begin{bmatrix} \lambda_{v,1}^s & 0 & \cdots & 0 \\ 0 & \lambda_{v,2}^s & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & & \lambda_{v,\mathcal{S}}^s \end{bmatrix}$$

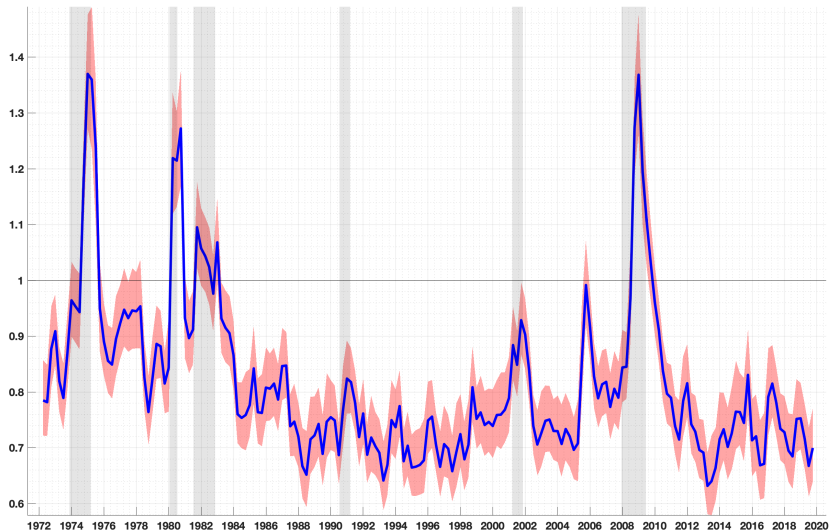
$\lambda_{v,j}^s$ for $j = 1, \dots, \mathcal{S}$ denotes a vector of loadings for each sector with the first entry equals to 1. (\mathcal{S} = number of sectors)

- Parameterization of Λ_v^a and Λ_v^s implies that the (conditional) second-moment for each industry is driven by an aggregate and a sectoral component.
 - Why not also idiosyncratic uncertainty?
 \implies Computationally infeasible with such a large N ($= 212$).

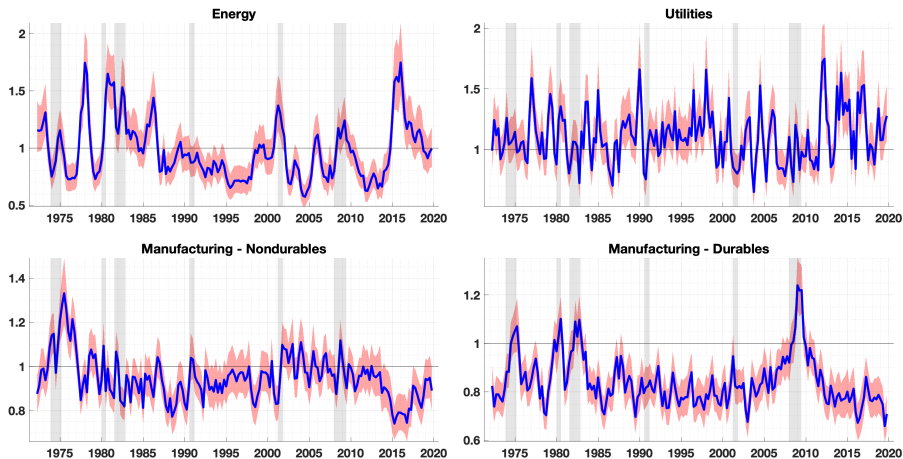
- Bayesian methods (15-step Gibbs sampler)
- Level-factors estimated using precision sampling techniques as in [Chan and Jeliazkov \(2009\)](#)
- Volatility-factors estimated combining precision sampling with the auxiliary mixture sampling method from [Omori, Chib, Shephard, and Nakajima \(2007\)](#)
- Algorithm is efficient and reasonably fast (running 10K iterations takes around 1 hour)

AGGREGATE UNCERTAINTY

FIGURE 1: Aggregate uncertainty



SECTOR-SPECIFIC UNCERTAINTY MEASURES



Notes: This figure plots the sector-specific volatility. The solid line denotes the posterior median for $\exp(v_t^S/2)$ together with its equitailed 67% posterior credible interval. Shaded vertical bars correspond to NBER recession dates.

AGGREGATE VS SECTOR-SPECIFIC UNCERTAINTY

- ▶ During “normal times”: Sector-specific uncertainty dominates (esp. during **GM**)
- ▶ During recessions: Aggregate uncertainty dominates

TABLE 2: Relative Magnitude of Aggregate versus Sector-Specific Uncertainty

	Great Inflation 72Q2–83Q4	Great Moderation 84Q1–07Q4	Recessions
Average ratio			
Aggregate/Energy	0.93	0.88	0.97
Aggregate/Utilities	0.91	0.74	1.08
Aggregate/Nondurables	0.97	0.81	1.06
Aggregate/Durables	1.08	0.93	1.08
Frequency (in %) for			
Aggregate > Energy	36%	26%	40%
Aggregate > Utilities	31%	13%	56%
Aggregate > Nondurables	41%	11%	56%
Aggregate > Durables	63%	32%	61%

CORRELATIONS

- Aggregate and Durables uncertainties are
 - countercyclical
 - highly correlated with other macro uncertainty measures
 - but less correlated with financial and policy uncertainties
- Cyclicity and correlations of other sectoral uncertainties are not strong

TABLE 3: Unconditional Correlation Coefficients

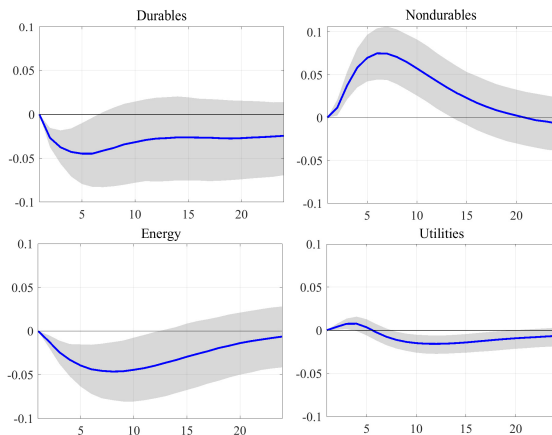
	Aggregate	Energy	Utilities	Nondurables	Durables
real GDP	-0.25	-0.01	0.11	-0.12	-0.23
IP Index	-0.38	-0.19	0.08	-0.06	-0.29
Employment	-0.39	-0.07	0.17	-0.11	-0.41
NBER	0.62	0.21	-0.12	0.20	0.50
JLN Macro U	0.73	0.33	-0.14	0.20	0.56
LMN Real U	0.75	0.27	-0.02	0.27	0.51
LMN Fin U	0.39	0.12	-0.14	0.17	0.31
VIX	0.52	0.11	-0.09	0.20	0.36
EPU	0.18	-0.01	-0.02	0.08	0.12

EFFECTS ON REAL ECONOMY - REVISITING JLN

- Let's assess the effects of our aggregate and sector-specific uncertainty measures on the real economy
- We revisit [Jurado, Ludvigson, and Ng \(2015\)](#):
11-variable VAR where uncertainty is placed last (recursive identification)
 $\{\log(IPI), \log(Emp), \log(real\ cons), \log(PCE\ defl), \log(real\ new\ orders), \log(real\ wage), hours, FFR, \log(S\&P\ 500), growth\ of\ M2, \mathbf{Uncertainty}\}$
- We repeat the exercise by replacing the **Uncertainty**, one-by-one, by our 4 sector-specific uncertainty measures.
- Result: Not all uncertainty measures are alike!
Some sector-specific uncertainties have very different real effects

RESPONSES OF PRODUCTION

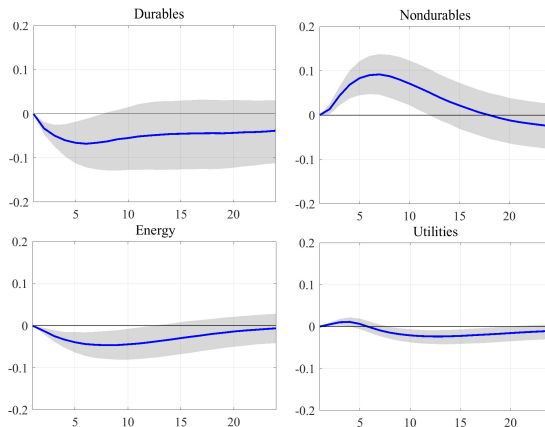
FIGURE 2: Impulse Responses of Production to Sector-Specific Uncertainty Shocks



Notes: Impulse responses denote a one standard deviation surprise movement in the sector-specific uncertainty measure. Solid lines denote posterior medians and the shaded areas represent the 67% equal-tailed posterior credible interval.

RESPONSES OF EMPLOYMENT

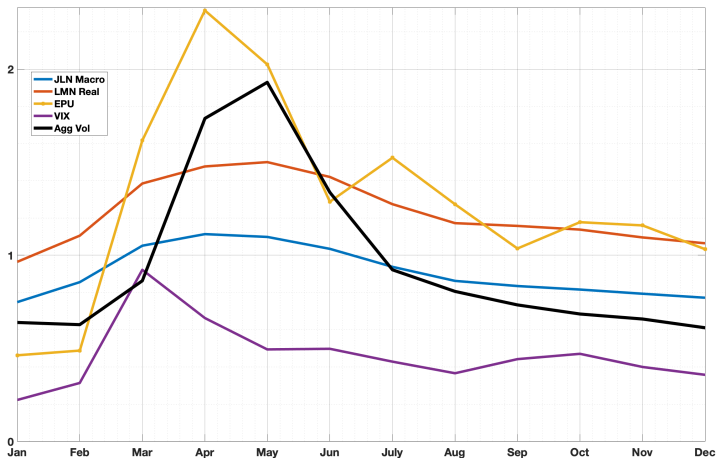
FIGURE 3: Impulse Responses of Employment to Sector-Specific Uncertainty Shocks



Notes: Impulse responses denote a one standard deviation surprise movement in the sector-specific uncertainty measure. Solid lines denote posterior medians and the shaded areas represent the 67% equal-tailed posterior credible interval.

UNCERTAINTY DURING THE COVID-19 PANDEMIC

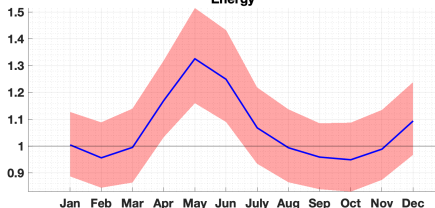
- Monthly data (72m2 – 20m12), 165 industries instead of 212 (data lag).
- Uncertainty measures are normalized by the peak uncertainty during GFC
 - Peak uncertainty during the pandemic is $2\times$ as large as GFC
 - Uncertainty peaked around Apr-May and subdued in summer and fall.



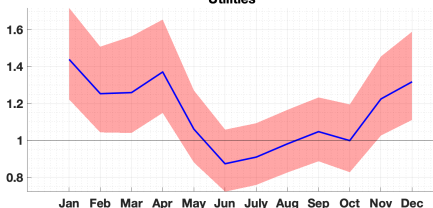
UNCERTAINTY DURING THE COVID-19 PANDEMIC

- Peak times are different. Consistent with the household spending behavior in the US and UK ([Chetty et al. \(2020\)](#) and [Surico et al. \(2020\)](#))
- Uncertainty in Nondurables sector is prolonged.
- Unevenness in uncertainty.

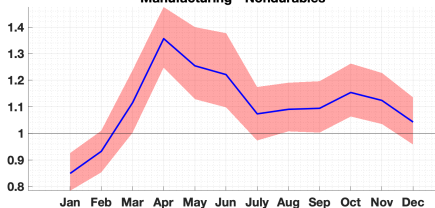
Energy



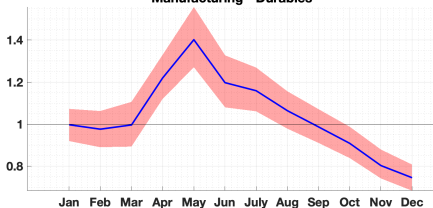
Utilities



Manufacturing - Nondurables



Manufacturing - Durables

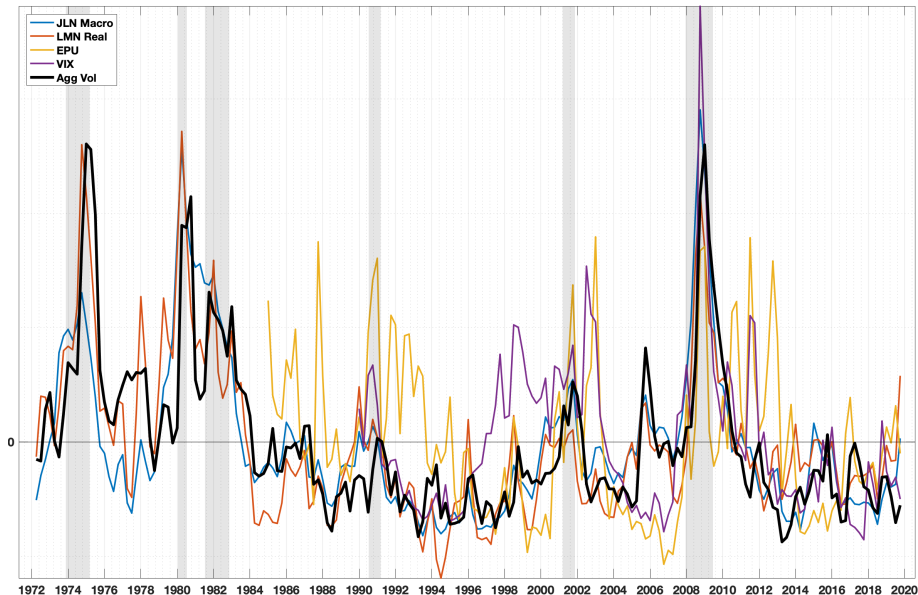


CONCLUSION

- In this paper, we proposed a new framework for extracting aggregate and sector-specific uncertainty.
- We showed that there are significant heterogeneities among different uncertainty measures (both in terms of evolution and effects)
- We shed some light on the elevated uncertainty during the Covid-19 period.

APPENDIX

COMPARISON WITH OTHER VOLATILITY MEASURES



EFFECTS OF VOLATILITY ON INDUSTRY PRODUCTION

TABLE 4: Regressing each industry production on all volatility factors
(sector-level average estimates)

	Aggregate	Energy	Utilities	Nondurables	Durables
Energy	-0.19	-0.03	0.03	-0.39	-0.37
Utilities	-0.12	-0.06	-0.09	0.17	-0.31
Nondurables	-0.29	-0.09	-0.02	0.10	-0.34
Durables	-0.72	-0.20	0.01	-0.47	-0.46

FEVD RESULTS: INDUSTRY VOLATILITY

TABLE 5: FEVD: Decomposing industry-level variance by volatility factors
(sector-level average FEVD)

	Aggregate	Energy	Utilities	Nondurables	Durables
<hr/> Horizon = 0 <hr/>					
Energy	13%	87%	0%	0%	0%
Utilities	15%	0%	85%	0%	0%
Nondurables	44%	0%	0%	56%	0%
Durables	41%	0%	0%	0%	59%
<hr/> Horizon = 20 <hr/>					
Energy	10%	81%	2%	1%	6%
Utilities	12%	47%	35%	1%	6%
Nondurables	15%	64%	3%	10%	9%
Durables	9%	76%	4%	1%	11%

FEVD RESULTS: VOLATILITY FACTORS

TABLE 6: FEVD: Decomposing volatility factor variance

	Aggregate	Energy	Utilities	Nondurables	Durables
<hr/> Horizon = 1 <hr/>					
Aggregate	77%	6%	1%	10%	7%
Energy	0%	100%	0%	0%	0%
Utilities	0%	5%	95%	0%	0%
Nondurables	5%	1%	7%	87%	1%
Durables	1%	67%	3%	0%	29%
<hr/> Horizon = 20 <hr/>					
Aggregate	21%	64%	3%	4%	9%
Energy	1%	98%	1%	0%	1%
Utilities	0%	10%	89%	0%	0%
Nondurables	8%	46%	4%	36%	6%
Durables	3%	81%	4%	0%	12%

ALTERNATIVE DATASET: BEA

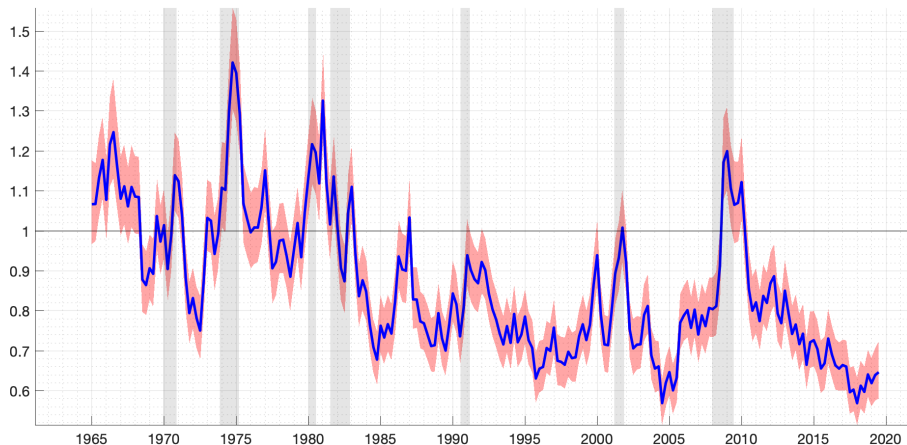
- Annual real personal consumption expenditure for 31 industries

TABLE 7: U.S. Bureau of Economic Analysis (BEA) Data (1964Q4 – 2019Q3)

	Sector	# Industry
Consumption	Durables	4
	Non-Durables	4
	Services	7
Investment	Non-Residential (Structures)	5
	Non-Residential (Equipment)	8
	Residential (Structures)	3

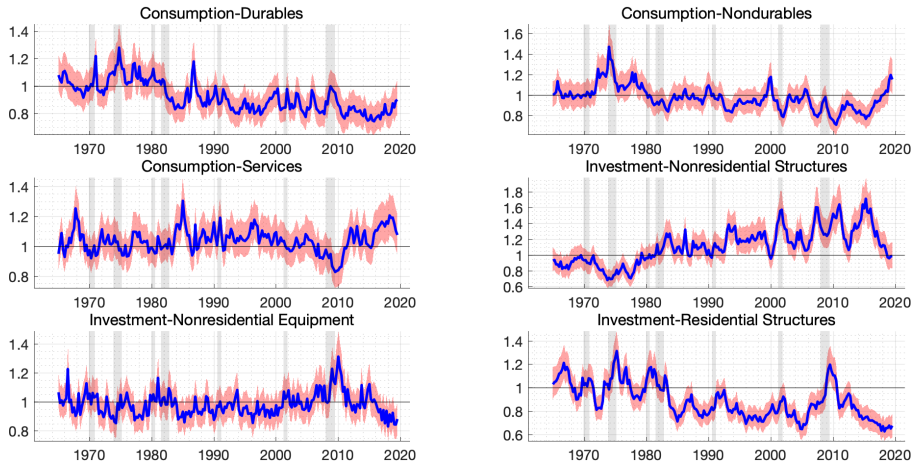
ALTERNATIVE DATASET: BEA

FIGURE 4: Aggregate Uncertainty (BEA)



ALTERNATIVE DATASET: BEA

FIGURE 5: Sectoral Uncertainty (BEA)



RESULTS: CORRELATIONS (BEA)

TABLE 8: Correlations between uncertainty measures and some important macro-financial variables

	Agg	ConsDur	ConsNonDur	ConsServ	InvNonResidStr	InvNonResidEq	InvResidStr
real GDP	-0.12	0.00	0.05	0.09	-0.10	-0.09	-0.08
IP Index	-0.17	-0.05	0.03	0.09	-0.09	-0.09	-0.08
Employment	-0.16	0.01	0.16	0.19	-0.20	-0.19	-0.12
NBER	0.43	0.22	0.06	-0.16	-0.07	0.12	0.33
JLN Macro U	0.51	0.28	0.06	-0.24	-0.07	0.20	0.38
LMN Real U	0.69	0.44	0.21	-0.20	-0.32	0.16	0.56
LMN Fin U	0.37	0.25	0.17	-0.18	-0.13	0.09	0.26
EPU	0.38	0.08	-0.07	-0.08	0.02	0.13	0.31
VIX	0.47	0.21	0.00	-0.20	0.03	0.19	0.28