Financial Volatility and Economic Activity

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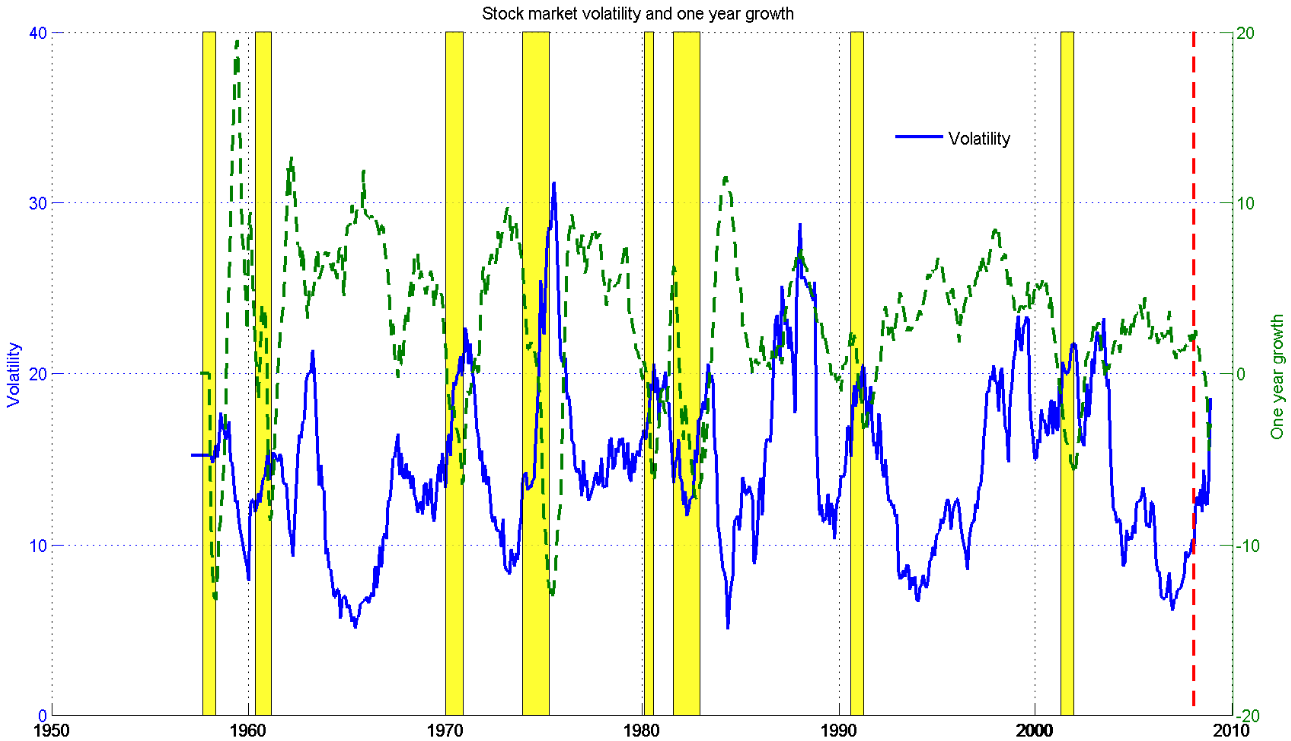
Does capital markets uncertainty affect the business cycle?

- Stock market fluctuations partly reflect changes in the expectations about the underlying real economic activity.
  - Do capital markets also help anticipate movements in the real economy?
  - An old issue.

- And, why should capital markets volatility help predict economic activity?

- We know stock market volatility is higher in bad times than in good. But if stock market volatility is countercyclical, it might convey information about future economic activity!

S&P 500 volatility



Rolling estimates, obtained as $\sqrt{\frac{\pi}{2}}\sum_{i=1}^{12}\frac{abs(\mathrm{Return}_{t+1-i})}{\sqrt{12}}$. Monthly data. Annualized, percent. Shaded areas: NBER recessions. Avg: 14.18. Avg during expansions: 13.50 (−4%). Avg during recessions: 17.39 (+23%)

Two key issues

- That capital markets uncertainty is countercyclical does not immediately lead to conclude that financial volatility **anticipates** real economic activity. Moreover, correlation is not causation. In general,
  - Does aggregate stock market volatility affect investment decisions in the real sector of the economy?
  - Does volatility help predict the business cycle?
- These issues have outstanding policy implications, even in the simple case where a sustained stock volatility merely anticipates, without affecting, the business cycle.

This paper's results

We find that:

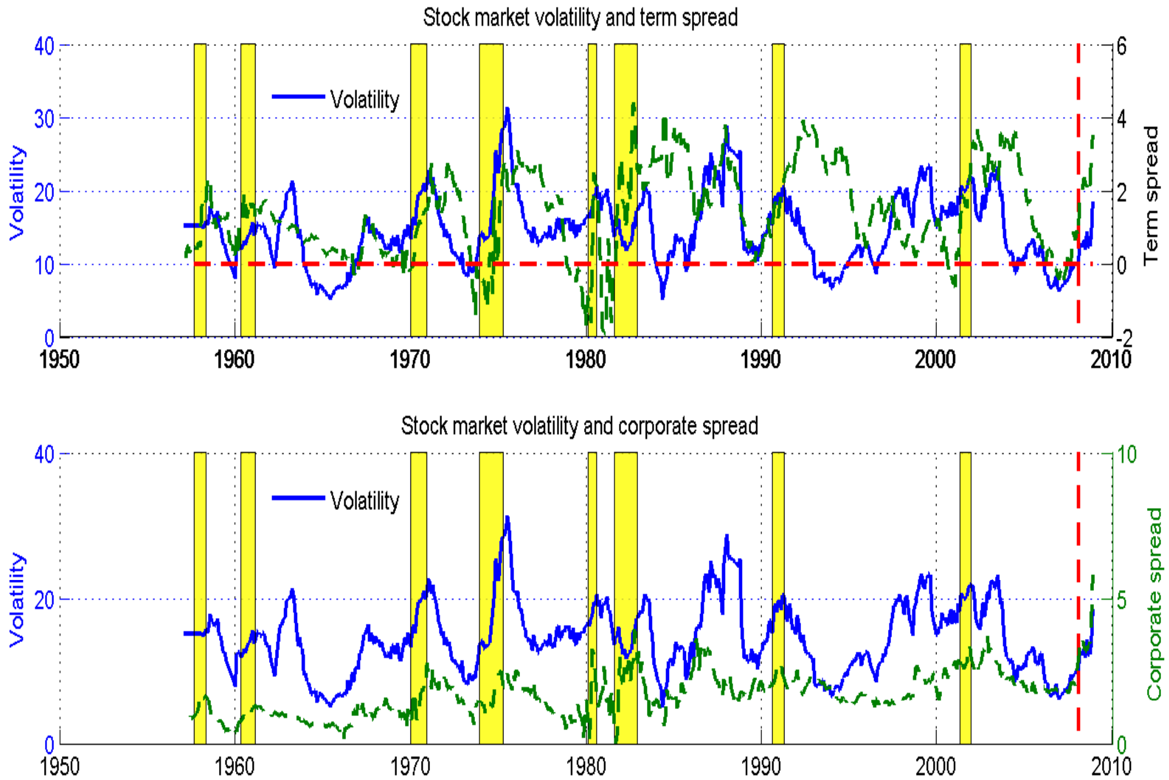
- Financial volatility predicts roughly 30% of after-war economic activity in the United States (one year Industrial Production growth)

- This number increases to roughly 50% when indicators of financial volatility are used in conjunction with indicators of macroeconomic volatility.

- These findings are robust to the sampling period, and are particularly significant over the Great Moderation era.

- At the heart of our analysis is a notion of volatility based on a **slowly changing measure of returns variability**. This volatility measure captures **long-run uncertainty in capital markets**, and is particularly successful at explaining trends in the economic activity at horizons of six months and one year.

Comparison with some leading indicators



Stock volatility and the term spread

- The predicting power of stock market volatility has increased in the last twenty-five years:
  - Over the Great Moderation, stock market volatility explains, $alone$, between 35% and 55% of future real economic activity, at horizons of one and two years.
  - Over the same period, stock volatility has a predictive power that is quite comparable to that of a traditional leading indicator: the term spread.

- In fact, we find that combining the term spread with aggregate stock market volatility leads to a predicting block that anticipates the business cycle reasonably well, delivering quite isolated false signals of economic slowdowns, with no such false signals over the Great Moderation period.

- Combining aggregate stock volatility and the term spread leads to a proxy for:

  (i) risk-premiums and monetary policy developments (term spread)

$\Longrightarrow$ (ii) **aggregate risk** (stock volatility)

- We undertake out-of-sample experiments and submit these findings to reality checks.

  – In these experiments, developments in the term spread and stock market volatility anticipate all the NBER-dated recessions that are left by the data and our estimation constraints, including the recession episode related to the 2007 subprime crisis.

Plan

1. Why does financial volatility help predict real economic activity?

2. Data, measurement methods and competing predictors

3. In-sample results

4. Out-of-sample experiments

5. Conclusion

Part 1

Why does financial volatility help predict real economic activity?

We consider four explanations

(i) Information-related reasons, not necessarily causality reasons. An example of a production economy and incomplete information
   – correlation

(ii) Time-varying risk premiums
   – correlation

(iii) Uncertainty and irreversible investments
   – causation

(iv) Procyclicality of capital markets and financial distress
   – causation

(i) Production and incomplete information

- Simple production-based explanation. Two-period economy. First period: production by a monopolist. In the second period, the producer faces a linear inverse demand,

$$D^{-1}(Q) = a + \tilde{v} - \lambda Q,$$

for some positive constants a and λ. The variable $\tilde{v}$ captures a random shock in the demand. We assume that $\tilde{v} \sim N\left(0, \sigma^2\right)$, and that prior to production decisions, the firm observes a signal s on $\tilde{v}$,

$$s = \tilde{v} + \epsilon, \quad \epsilon \sim N\left(0, \sigma_\epsilon^2\right).$$

- Linear technology $\Leftrightarrow$ total costs $C(Q) = zQ$ for some positive constant z.
- Firm's managers are risk-neutral, and maximize the value of the firm.
- Safe assets are elastically supplied so as to make the safe interest rate zero.

Possible to show that,

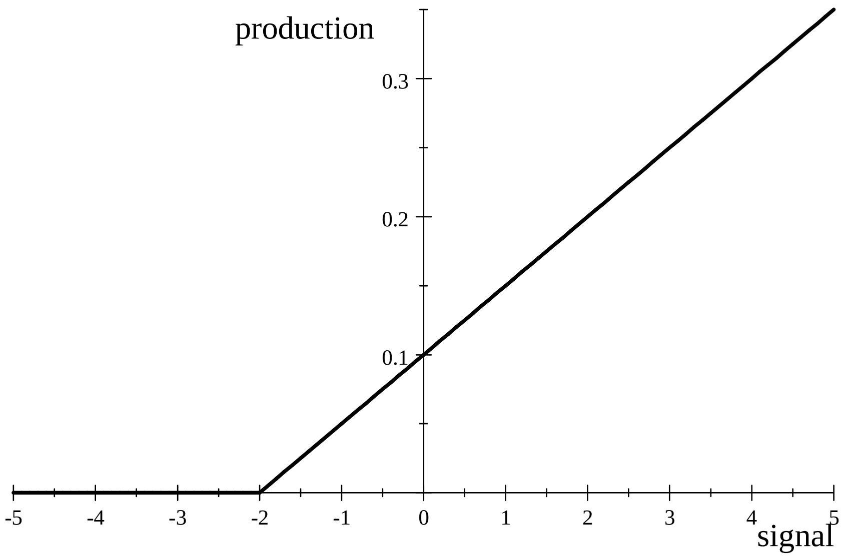
- Production takes place only when the signal s takes a sufficiently favourable cutoff value $\hat{s} \equiv -\frac{a-z}{\theta}$, where $\theta = \frac{n-1}{n}$, and n is the signal-to-noise ratio.

- Stock price P, production Q and returns volatility Vol (say) are all functions of the current signal s, and equal

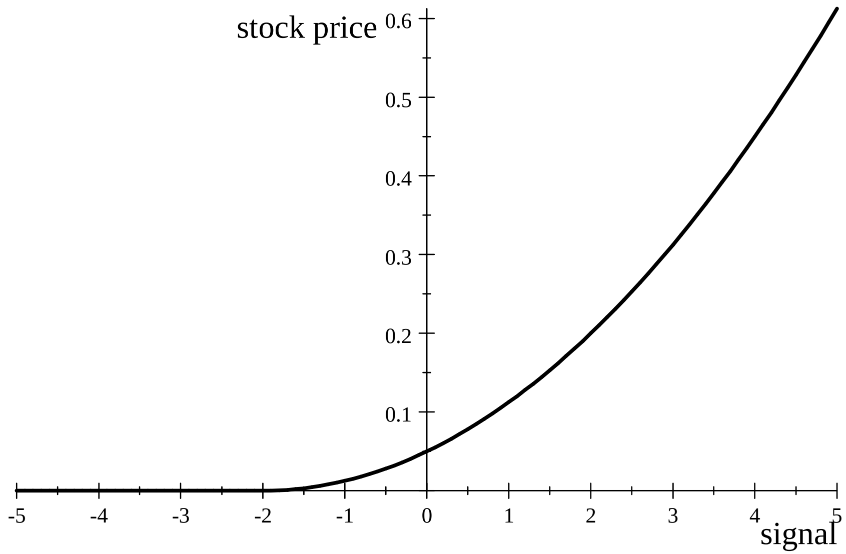
$$P(s) = \frac{\theta^2}{4\lambda}(s-\hat{s})^2 \mathbb{I}_{s>\hat{s}};\ \ Q(s) = \frac{\theta}{2\lambda}(s-\hat{s})\mathbb{I}_{s>\hat{s}};\ \ \text{and Vol}(s) = \frac{2\sigma\sqrt{1-\theta}}{a-z+\theta s},$$

where $\mathbb{I}$ is the indicator function, and where returns volatility is only defined when economic activity takes place, i.e. when $s > \hat{s}$.

Production and stock prices

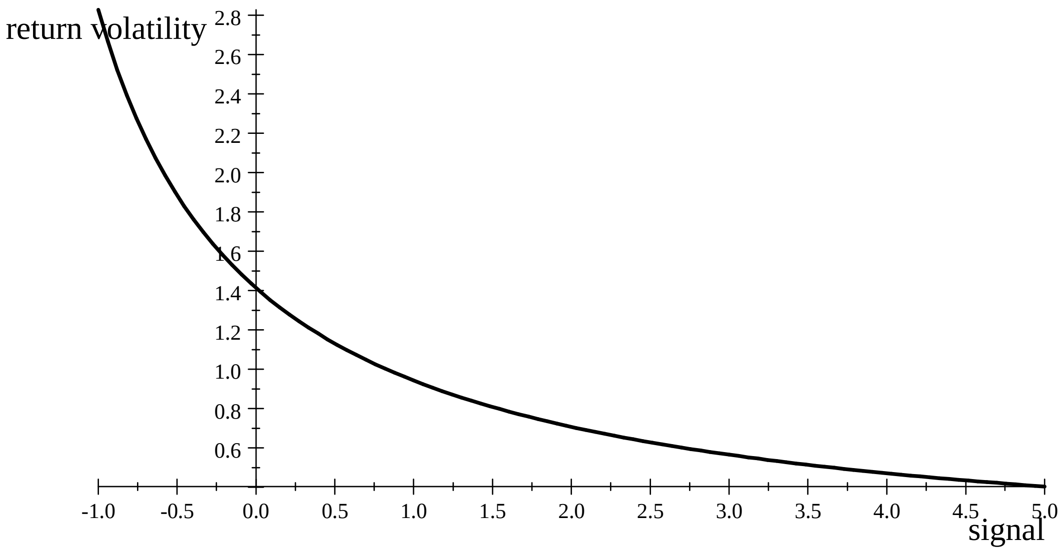


Production and signals of economic activity



Stock price and signals of economic activity

Return volatility



Return volatility and signals about future economic activity

Regressions in a Monte Carlo experiment

	const	Vol	R^2	const	Price	R^2	const	Vol	Price	R^2
estim	0.32	−0.17	0.91	0.08	0.55	0.97	0.17	−0.06	0.36	0.99
t-stat	100.88	−53.61		100.16	99.92		153.05	−71.86	14.45	

(iii) Uncertainty and irreversible investments

- Option pricing theory predicts that uncertainty raises the value to wait.
- Bloom (2009) models time-varying uncertainty of business conditions, assuming that total factor productivity has stochastic volatility.
  - His model, which includes irreversible investments and nonconvex adjustment costs, predicts that firms freeze investments during uncertain times, as the value to waiting increases in such periods.
  - Bloom, Floetotto and Jaimovich (2009) reach a similar conclusion within a calibrated real business cycle model: uncertainty shocks are impulses that generate rich propagation mechanisms.

Part 2

Data, measurement methods and competing predictors

Economic activity

Monthly data, January 1957 - September 2008

- First, we predict the growth of industrial production at horizons of three, six, twelve and twenty-four months:

$$G_{t\to t+k} = \ln\left(\frac{\mathrm{IP}_{t+k}}{\mathrm{IP}_t}\right), \qquad k \in \{3, 6, 12, 24\},$$

  where IP_t is the industrial production index as of month t.

- Second, we predict probabilities of recessions, by utilizing the NBER-dating series as a recession variable,

$$\mathrm{Rec}_t \equiv \mathbb{I}_{\mathrm{NBER}_t=1},$$

  which equals one if US economy is in recession at t, and zero otherwise.

Volatility

- Given an asset price P_t and dividend D_t, we decompose the total return as of time t as,

$$R_t^{tot} \equiv \ln\left(\frac{P_t + D_t}{P_{t-1}}\right) = \underbrace{\ln\left(\frac{\mathrm{P/D}_t + 1}{\mathrm{P/D}_{t-1}}\right)}_{\equiv R_t^p \text{ (price-induced returns)}} + \underbrace{\ln\left(\frac{D_t}{D_{t-1}}\right)}_{\equiv R_t^d \text{ (dividend-induced returns)}}$$

where $\mathrm{P/D}_t$ is the price-dividend ratio as of time t.

- We calculate volatility as a long-run moving average of past absolute *price-induced* returns,

$$\sigma_t^p \equiv \sqrt{6\pi}\frac{1}{12}\sum_{i=1}^{12}\left|R_{t+1-i}^p\right|. \tag{1}$$

Stock volatility as a leading indicator: a preliminary scrutiny

We regress:

$$\sigma_t = c + \sum_{i\in\{3,12,24,36\}} b_i \sigma_{t-i} + \gamma_1 \mathbb{I}_{t\in\mathcal{O}(\mathrm{NBER}_t=1)} + \gamma_2 \mathbb{I}_{\mathrm{NBER}_t=1} + u_t^{\sigma},$$

Panel A: Full sample, 1957-2008

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	3.11	0.94	-0.15	-0.01	-0.01	0.48	1.51
t-stat	7.18	40.10	-6.48	-0.65	-0.98	2.52	5.80

Panel B: 1957-1982

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	3.60	0.98	-0.24	0.02	-0.04	0.34	1.87
t-stat	6.19	27.83	-8.85	1.07	-1.91	1.41	5.50

Panel C: 1983-2008

	c	b_3	b_{12}	b_{24}	b_{36}	γ_1	γ_2
estimate	2.88	0.94	-0.09	-0.05	-0.01	1.01	1.22
t-stat	4.76	32.56	-2.28	-1.86	-0.41	3.35	3.36

Predictors

- Financial volatility might be countercyclical, and anticipate the business cycle, because it merely reflects information conveyed by other factors. To assess if financial volatility accounts for additional pieces of information, we need to specify sets of control variables.

Individual predictors

- **Financial Volatility**
  (i) stock market volatility; (ii) volatility of the term spread; (iii) volatility of the corporate spread; (iv) volatility of stock market volatility

- **Macroeconomic Volatility**
  (v) volatility of oil return; (vi) volatility of industrial production growth; (vii)volatility of inflation; (viii) volatility of unemployment rate; (ix) volatility of metal return

- **Traditional Predictors**
  (x) term spread; (xi) corporate spread; (xii) stock returns; (xiii) oil return; (xiv) index of leading indicators, growth; (xv) 3 month interest rate; (xvi) inflation; (xvii) dividend yield; (xviii) lagged industrial production growth

Predicting blocks, main

Block B1: *Term spread, corporate spread, and 12 month stock market returns*

Block B2: $\boxed{\textit{Term spread, short-term rate}}$

Block B3: *Stock market volatility, term spread volatility*

Block B4: $\boxed{\textit{Stock market volatility, term spread}}$

Block B5: *Volatility of stock market volatility, short-term rate*

Block B6: *Volatility of stock market volatility, term spread*

Block B7: *Volatility of stock market volatility, stock market volatility, term spread*

Block B8: *Volatility of stock market volatility, stock market volatility, interaction term, term spread*

Predicting blocks, macroeconomic controls

Block B9: *Volatilities of: oil return, industrial production growth, inflation, metal return*

Block B10: *Oil return, index of leading indicators (growth), inflation, dividend yield*

Part 3

In-sample results

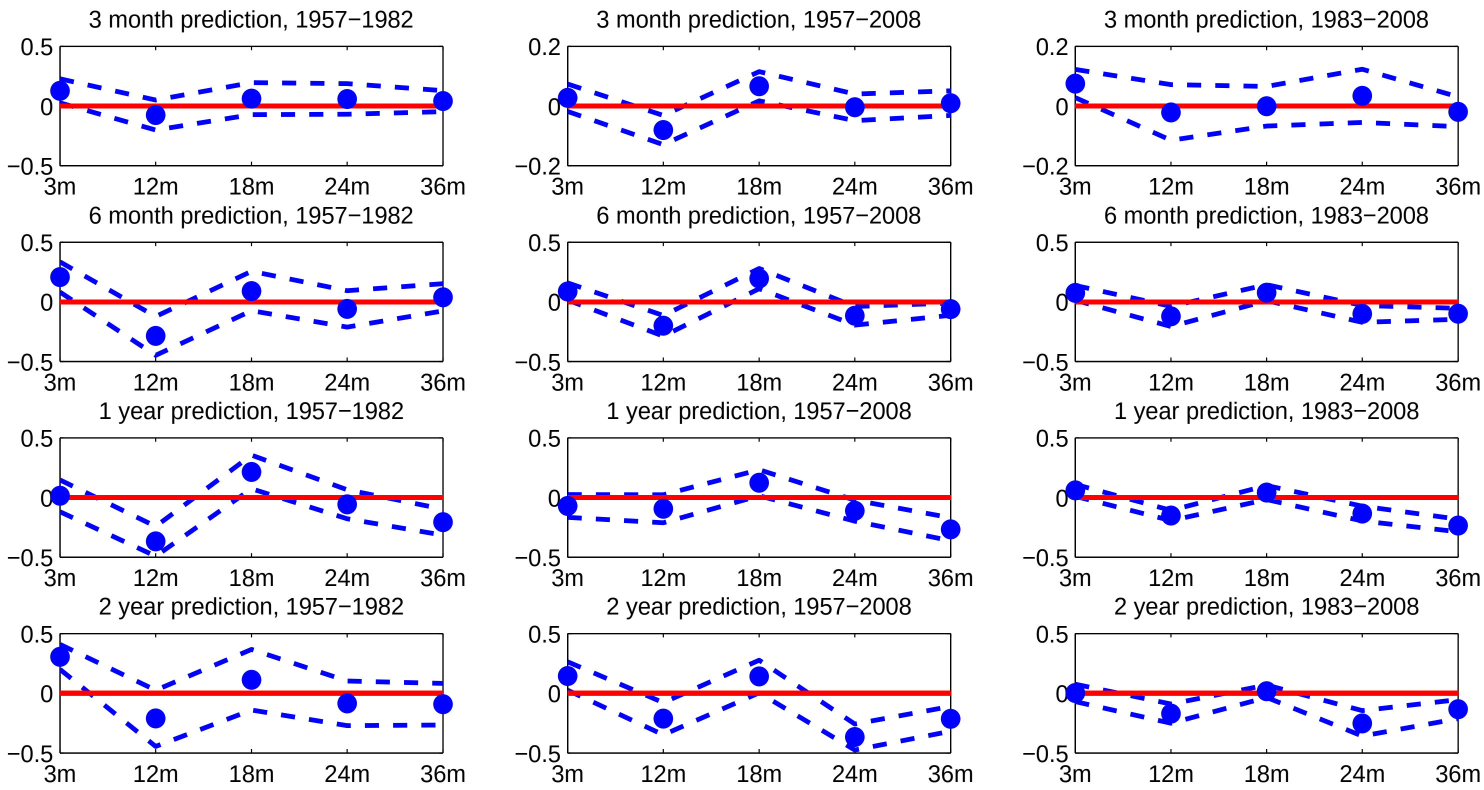
Linear regressions

For each predicting horizon $k \in \{3, 6, 12, 24\}$, we regress industrial production growth on to the previous predicting variables or blocks:

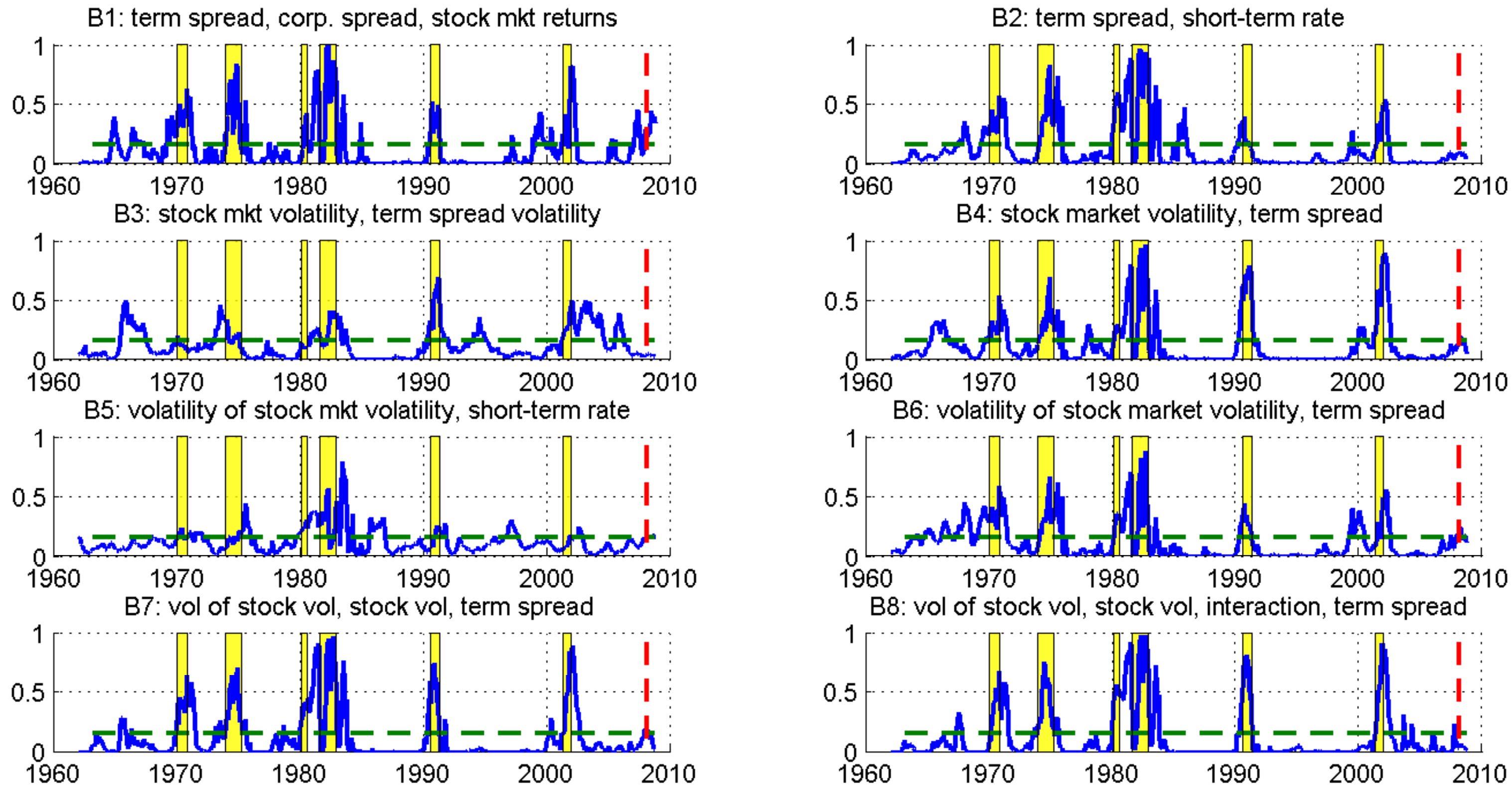
$$G_{t \to t+k} = \alpha^k + \sum_{j=1}^{P_i} \sum_{\text{lag} \in \left\{0, l_1^k, \cdots, l_4^k\right\}} \beta_j^k (\text{lag}) \cdot \text{Regressor}_j (t - \text{lag}) + \text{Error} (t + k),$$

where P_i is the number of regressors, and $\alpha^k, \{\beta_j^k (\text{lag})\}_{\text{lag} \in \left\{0, l_1^k, \cdots, l_4^k\right\}}$ are the parameters to be estimated.

Volatility loadings



Probabilities of recession



Part 4

Out-of-sample experiments

- Rolling estimates with estimation window equal to $M = 120$ months or 90 months. Needed to cope with the non-stationarity of the data
  - For example, we showed, in sample, that a structural break in the linkages between financial volatility and the business cycle, occurred around the inception of the Great Moderation.
  - Yet with Probit models, we need wider windows, given that NBER recessions are "rare," and use $M = 360$ months.

- Let $\epsilon_{t,k}^{i}$ be any predicting error as of time t, arising out-of-sample, using the predicting block i at forecasting horizon k.

- **Unconditional predictive ability**. We use the standard Diebold-Mariano (1995) test, relying on:

$$\bar{d}^{i,j}_{T,k} = \frac{1}{T} \sum_{t=1}^{T} \left(\left| \epsilon^i_{t,k} \right| - \mid \epsilon^j_{t,k} \mid \right).$$

- **Conditional predictive ability**. We use Giacomini-White testing strategy. Let $\Delta\epsilon^{i,j}_{t,k} \equiv \mid \epsilon^i_{t,k} \mid - \mid \epsilon^j_{t,k} \mid$. Regress $\Delta\epsilon^{i,j}_{t+1,k}$ on some vector of variables $h^{i,j}_{t,k}$, deemed to explain the failure of equal conditional predictive ability stemming from any two blocks:

$$\Delta\epsilon^{i,j}_{t+1,k} = \delta^{i,j}_k \cdot h^{i,j}_{t,k} + u^{i,j}_{t+1,k}, \quad t = M-1, \cdots, N-k, \tag{1}$$

where for any two predicting blocks i and j, and predicting horizon k, $\delta^{i,j}_k$ is a vector of constants, and, finally, $u^{i,j}_{t+1,k}$ is a residual term.

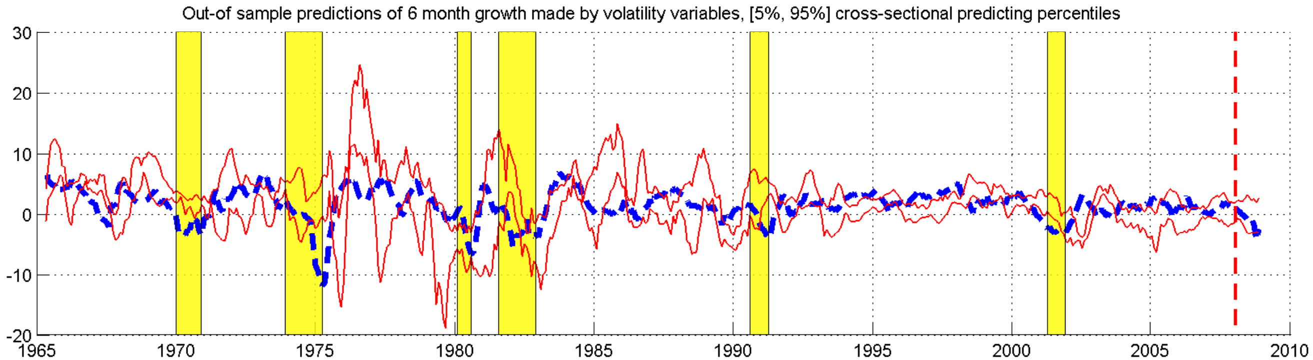
- In Monte Carlo experiments, Giacomini and White show that test has both reasonable size and power, once $h_{t,k}^{i,j} = [1\ \Delta\epsilon_{t,k}^{i,j}]^\top$. We make this choice.

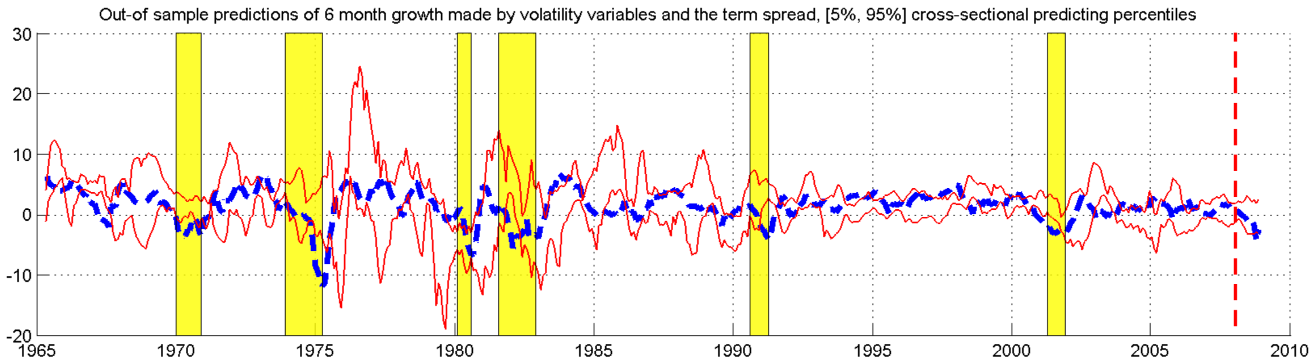
- The GW test can be used to implement an adaptive decision rule for selecting a predictive block over the others, thus exploiting the best conditional predictive power of any block. We report the frequency at which we reject block i for block j, over the entire out-of-sample period,

$$\frac{1}{N-M-1}\sum_{t=M-1}^{N-1}\mathbb{I}(E_N(\Delta\epsilon_{N+1,k}^{i,j}) > 0) \approx \frac{1}{N-M-1}\sum_{t=M-1}^{N-1}\mathbb{I}(\hat{\delta}_k^{i,j} \cdot h_{t,k}^{i,j} > 0),$$

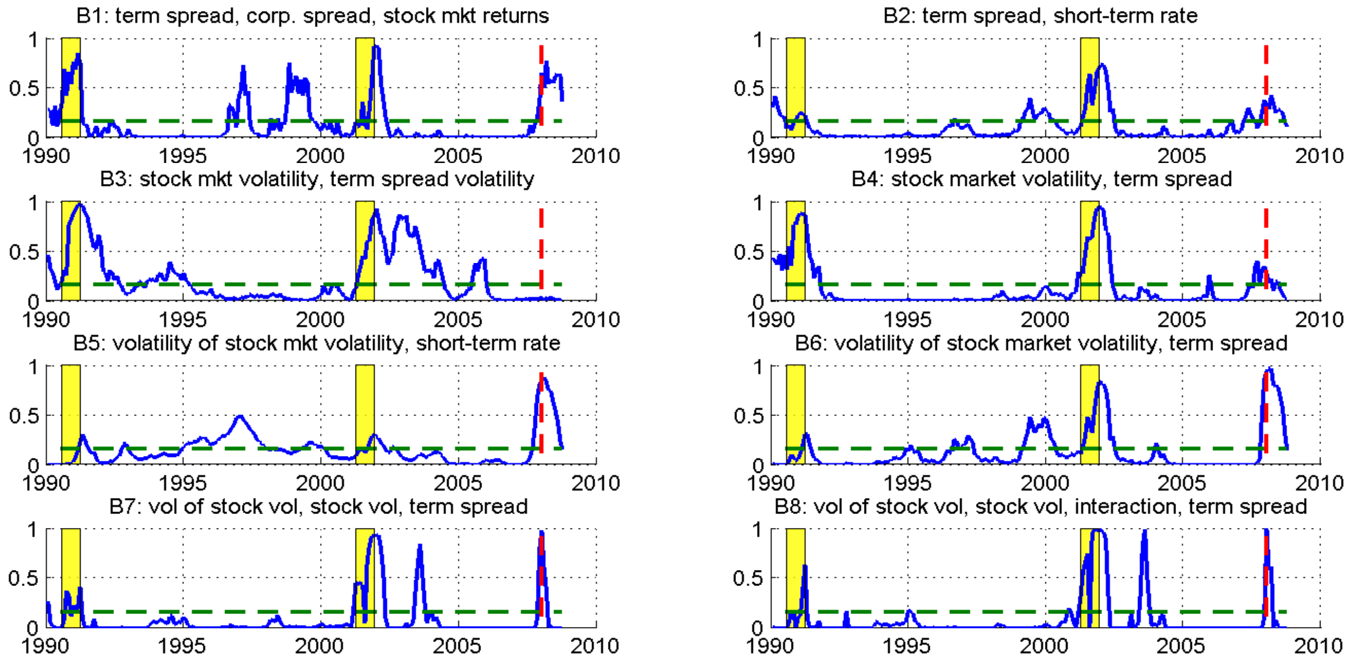
where $\mathbb{I}$ is the indicator function.

Linear predictions

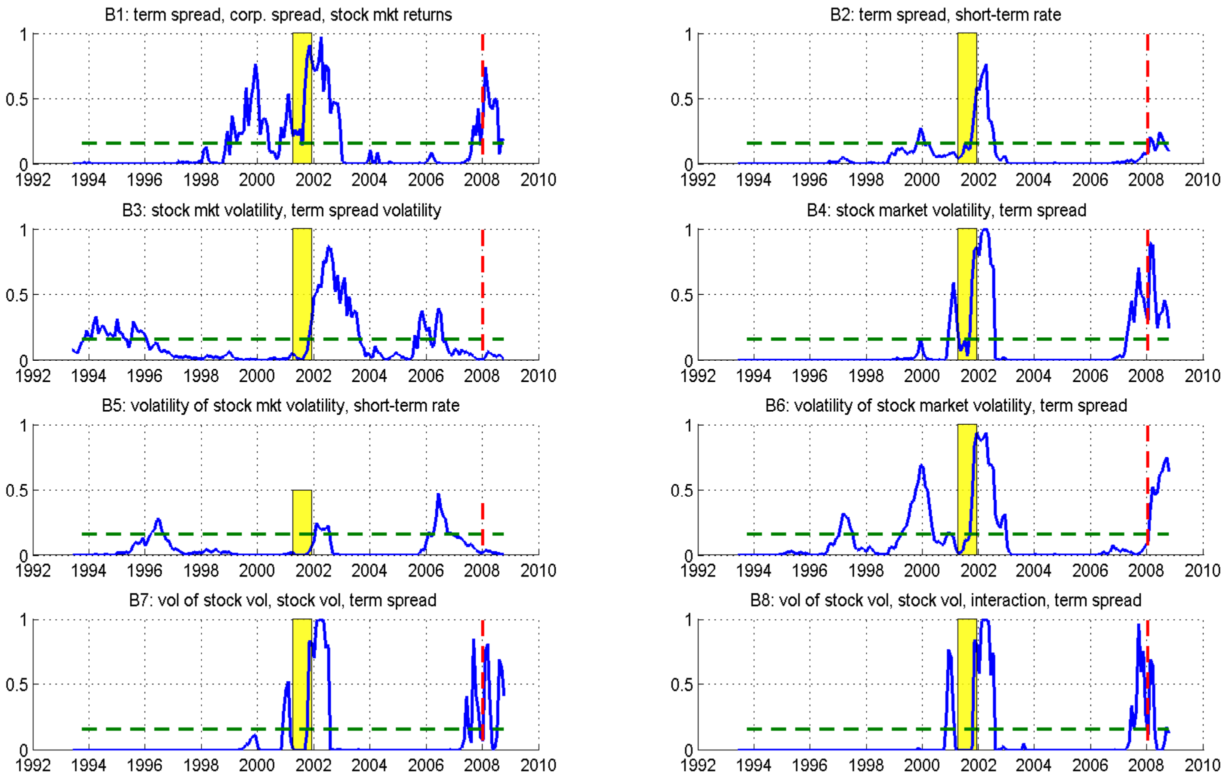




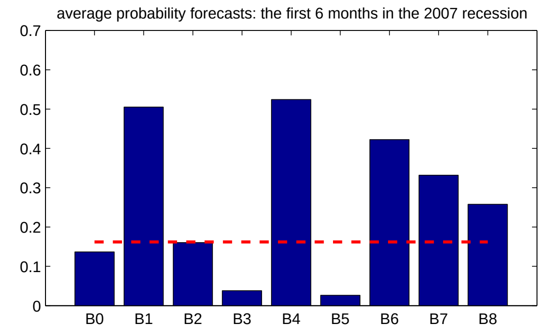
Probit, out-of-sample, coincident

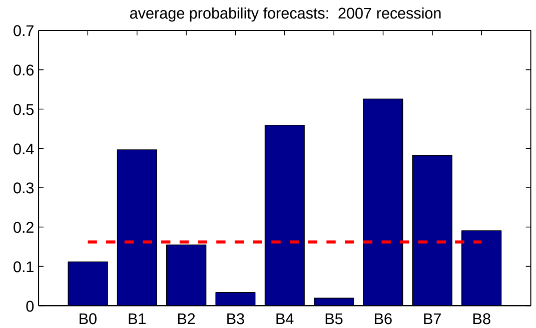


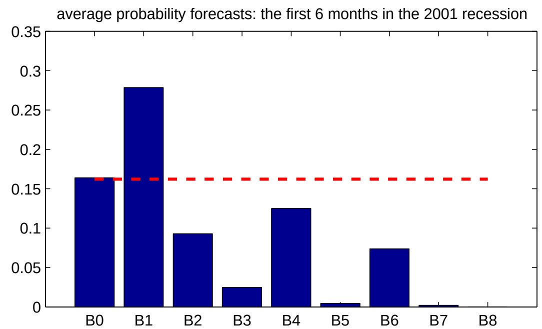
Probit, out-of-sample, six-month projections

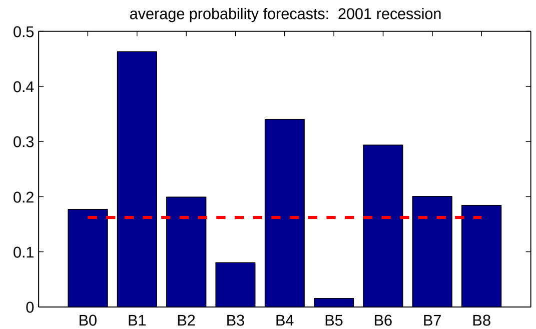


A tale of two recessions









Conclusion

- If financial volatility is countercyclical, it might encode information about the development of the business cycle.

- Our conclusion, based on an array of measurement methods, is that stock volatility does indeed help predict the business cycle.
  - We rely on predictions of both industrial production growth and NBER-dated recessions, utilizing in-sample projections and submitting our findings to reality checks and other out-of-sample experiments.
  - We control the significance of these predicting relations, by looking at alternative predicting blocks of economic activity, which include:
    (i) traditional leading indicators
    (ii) financial variables such as the term spread or the corporate spread

(iii) additional volatility variables, such as the volatility of the term spread, the volatility of stock market volatility or the volatility of real aggregates.

– We find that combining stock volatility with the term spread leads to a predicting block of economic activity, which tracks, and anticipates, the business cycle reasonably well. For instance, this predicting block would have considerably helped predict at least the last three recessions, with no "false positive" signals.

- While we have outlined a few theoretical explanations for these findings, we still lack a systematic explanation of them.
  – The next challenging step is to integrate financial volatility into a plausible propagation mechanism that includes realistically calibrated asset prices.