How beliefs respond to news: implications for asset prices

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Discussed by
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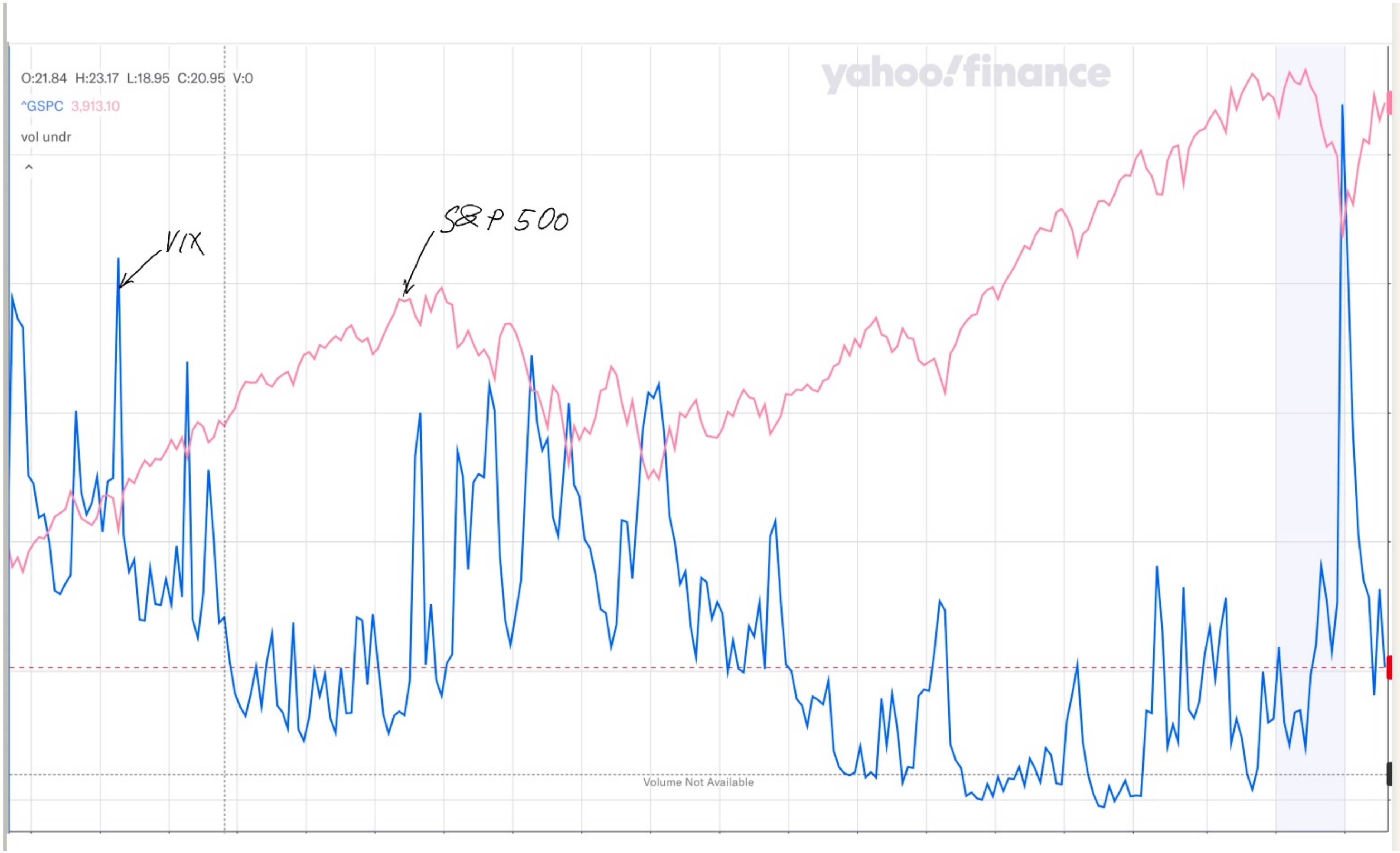
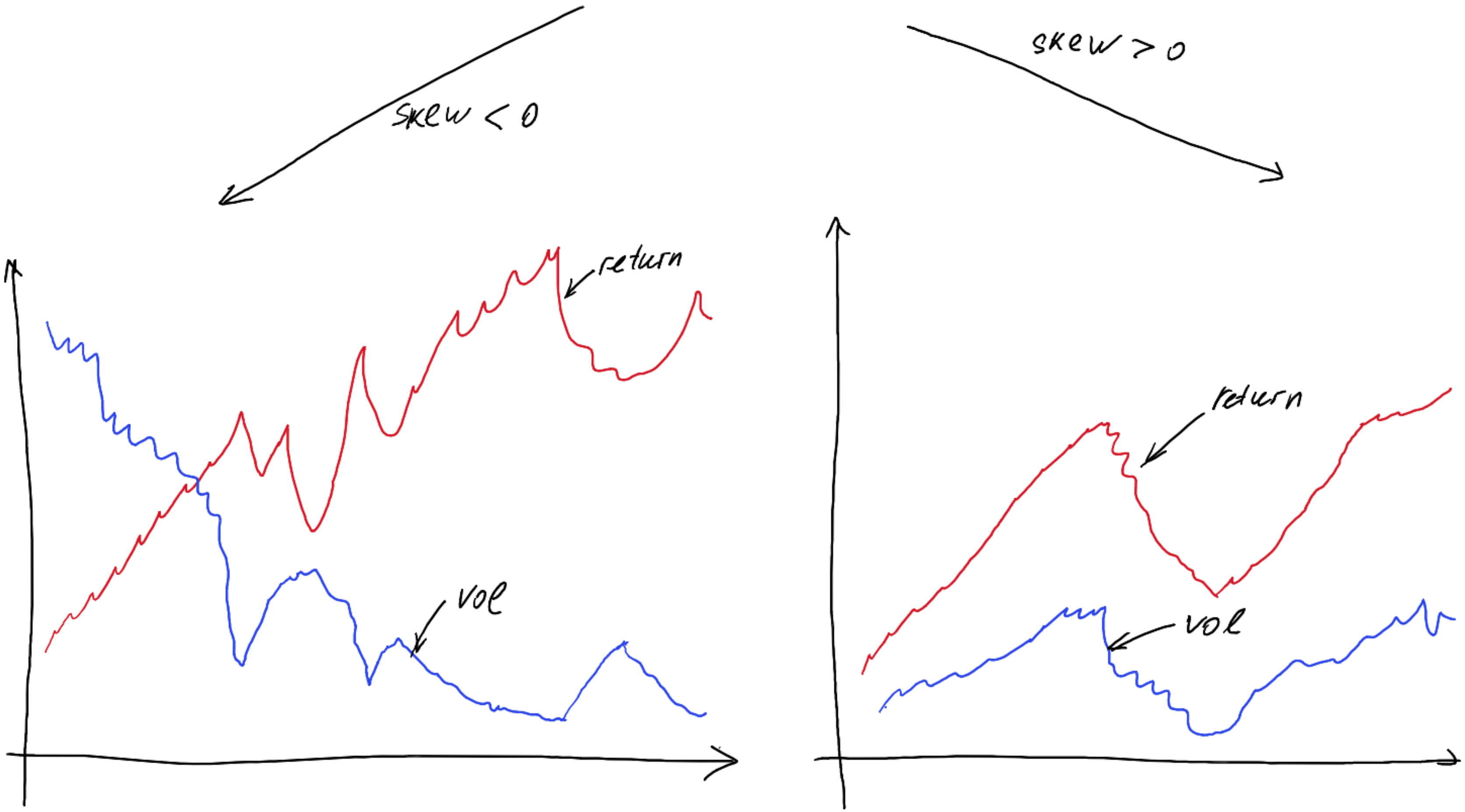
Motivation: leverage effect



This paper

Connects the sign of leverage effect to skewness

- $sign\big(corr(\Delta p_t, \Delta vol_t)\big) = sign(skew(\Delta p_t))$



This paper

Connects the sign of leverage effect to skewness

- $sign\left(corr(\Delta p_t, \Delta vol_t)\right) = sign\left(skew(\Delta p_t)\right)(*)$

Theory: when innovations in prices and vol are driven by the same news, standard Bayesian filtering yields (*).

This paper

Connects the sign of leverage effect to skewness

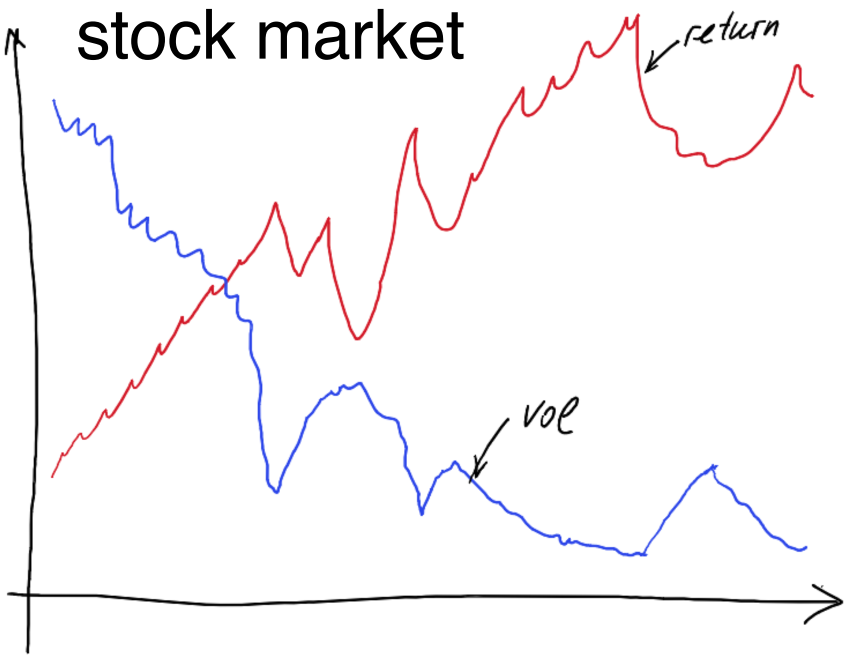
- $sign\big(corr(\Delta p_t, \Delta vol_t)\big) = sign(skew(\Delta p_t))$

Evidence:

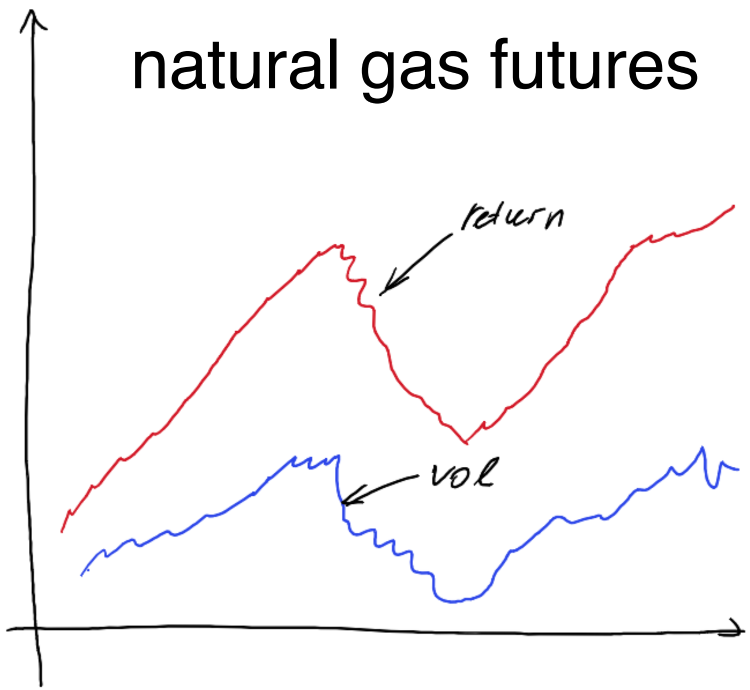
skew < 0

skew > 0

stock market



natural gas futures



This paper

Connects the sign of leverage effect to skewness

- $sign(corr(\Delta p_t, \Delta vol_t)) = sign(skew(\Delta p_t))(*)$

- $\Delta vol_t = \beta \Delta p_t + \cdots,$

Theory: prediction about the magnitude of the leverage effect

$$\beta = \left(\frac{1}{3}\Delta t^{-1/2}\right)\mathrm{skew}_t(p_{t+\Delta t})$$

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Empirics: strong support for the theory, at monthly frequency ($\Delta\mathrm{t} = 21$ days)

Plan

- A simple example to illustrate the theory
- Comments

* Hereafter, the <u>comments are underlined</u>

A simple example

- Consider an asset that pays off $f(v)$ at time $t = 1$
- Suppose, for simplicity, $\mathrm{E}[f(v)] = E[v] = 0$ and $var[v] = 1$.
- An agent learns about v from

$$ds = vdt + dB$$

- How do first and second moments react to news?
  - For simplicity, ask this question at $t = 0$.
  - Looking for x and y in

$$E[f(v)|ds] = xds + \cdots \qquad E[f(v)^2|ds] = yds + \cdots$$

A simple example

- Looking for x in

$$E[f(v)|ds] = xds + \cdots$$

- Since ds is small, $E[f(v)|ds]$ is linear in ds

- x is then given by the familiar Best Linear Predictor/ Linear Regression formula

$$x = \frac{cov(f(v), ds)}{var(ds)}$$

A very simple example

- Let $f(v) = v$. Looking for x and y in

$$E[v|ds] = x ds + \cdots \qquad\qquad E[v^2|ds] = y ds + \cdots$$

- Familiar linear regression formula yields

$$x = \frac{cov(v, ds)}{var(ds)} \ and \ y = \frac{cov(v^2, ds)}{var(ds)}$$

- $var(ds) = var(vdt + dB) = dt^2 var(v) + var(dB) = dt$

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A very simple example

- Let $f(v) = v$. Looking for x and y in

$$E[v|ds] = xds + \cdots \qquad\qquad E[v^2|ds] = yds + \cdots$$

- Familiar linear regression formula yields

$$x = var(v) \; and \; y = skew(v)$$

- $var(ds) = var(vdt + dB) = dt^2 var(v) + var(dB) = dt$
- $cov(v, ds) = cov(v, vdt + dB) = dt\, var(v)$
- $cov(v^2, ds) = cov(v^2, vdt + dB) = dt\, skew(v)$

A very simple example

- Let $f(v) = v$. Looking for x and y in

$E[v|ds] = xds + \cdots$ $\qquad$ $E[v^2|ds] = yds + \cdots$

- Familiar linear regression formula + some work yield

$$x = var(v) \ and \ y = skew(v)$$

- When $skew(v) < 0$ (> 0), the first and second moments respond to news in opposite (same) directions.

Simple example: discussion

- Let $f(v) = v$
- When $skew(v) < 0$ (> 0), the first and second moments respond to news in opposite (same) directions.
- We need to link the moments of v to the moments of price.
- In my example, it can be achieved by assuming that prices are set by a competitive RN market maker who observes ds

$$p_t = E[v|\{ds_\tau\}_{\tau \in [0,t]}]$$

Simple example: discussion

- Let $f(v) = v$
- When $skew(v) < 0$ (> 0), the first and second moments respond to news in opposite (same) directions.
- <u>I'd like to see a fully closed model in the paper</u>
  - <u>How prices are set? Is ds a private or public info?</u>
  - <u>You can have one concrete example + argue that things hold more generally</u>

A simple example

- Consider a generic, well-behaved $f(v)$. Suppose $v \sim N(0,1)$. Looking for x and y in

$$E[f(v)|ds] = xds + \cdots \qquad\qquad E[f(v)^2|ds] = yds + \cdots$$

- Familiar linear regression formula + Stein's Lemma yield

$$x = \frac{cov(f(v), ds)}{var(ds)} = var(v)E[f'(v)] \ and$$

$$y = \frac{cov(f(v)^2, ds)}{var(ds)} = var(v)2E[f(v)f'(v)]$$

* Stein's lemma:

Suppose X and Y are jointly normally distributed. Then $\mathrm{Cov}(g(X), Y) = \mathrm{Cov}(X, Y)\mathrm{E}(g'(X))$.

A simple example

- Consider a generic, well-behaved $f(v)$. Suppose $v \sim N(0,1)$. Familiar linear regression formula + Stein's Lemma yield

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- $\text{sign}\left(\frac{x}{y}\right)$ is no longer proportional to $skew\big(f(v)\big)$!

  - <u>Importance of info structure. Do we learn about discounted cashflows, or about some transformation of them (like earnings)? Maybe we learn about second moment, i.e. $ds = v^2 dt + dB$ ...</u>

  - <u>Log-linearization in the paper is perhaps not wlog</u>

Comments

- Currently, the writing overstates the generality of the results—you present them as if they were almost model-free.
  - They are not: different learning specifications will yield different results
- I think the best way to address these comments is to present a closed, equilibrium model that links the leverage effect to skewness.
- Then, you can validate this model with your empirical findings.
  - After that, it’s acceptable that another model might produce different results, since that would be considered counterfactual.

Suggestions for empirics

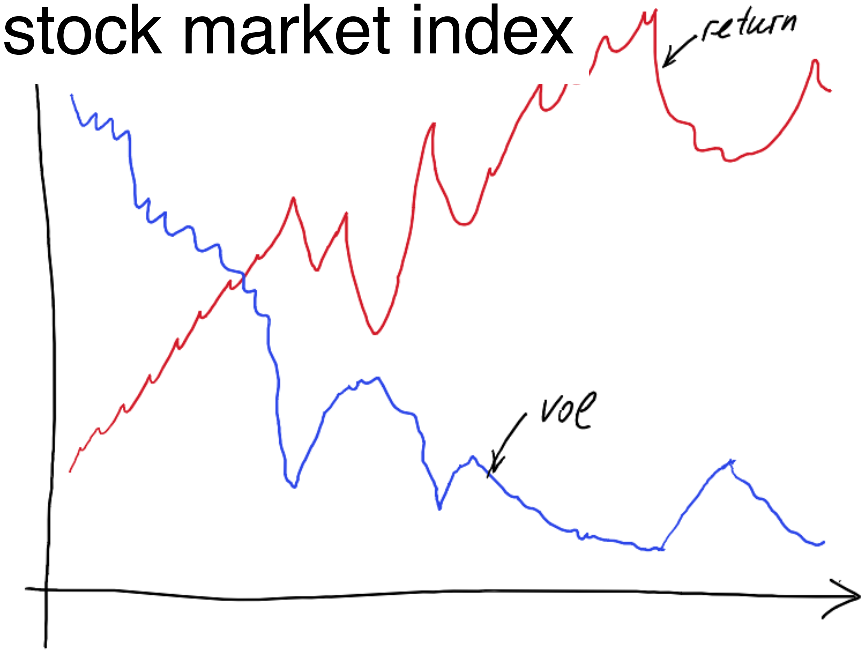
It would be nice if the evidence for the opposite signs of skew came from more similar asset classes.

Evidence:

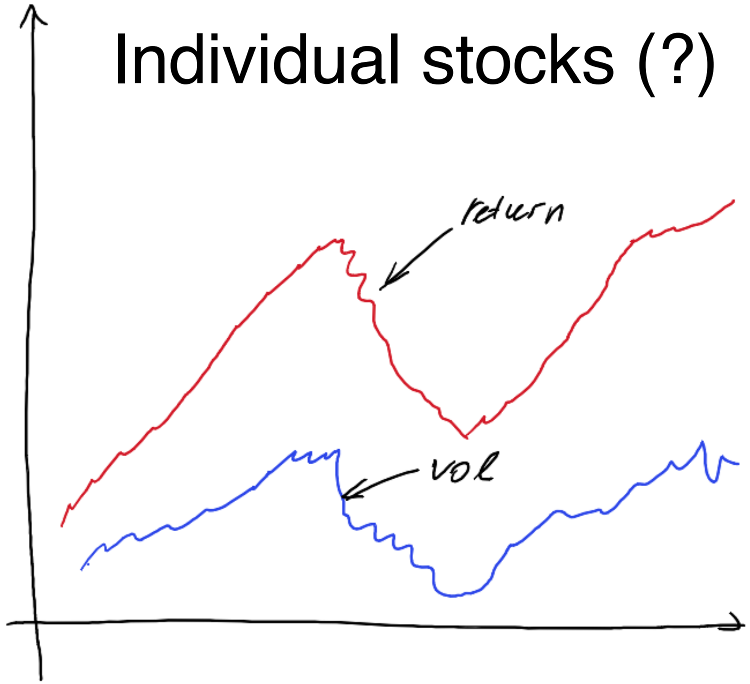
skew < 0

skew > 0

stock market index



Individual stocks (?)



Suggestion for empirics

Play with Δt in tbe prediction about the magnitude of the leverage effect

$$\beta = \left(\frac{1}{3}\Delta t^{-1/2}\right)\mathrm{skew}_t(p_{t+\Delta t})$$

- Show β aligns with theory not only for monthly frequency ($\Delta t = 21$).

- Do you get $\Delta t^{-1/2}$ scaling?

A (somewhat) related result

In my JMP, I connected (theoretically) price impact asymmetry to skewness.

(e.g., stock market index)
sells move prices more than purchases

(e.g., individual stocks)
purchases move prices more than sells

*Another mechanism for why skewness matters: many preferences are such that agents like >0 skewness.

Conclusion

This is a great paper

- Simple, intuitive idea
- Supporting evidence

I like it.

- Better packaging for more impact and easier publishing