Recovering Price Informativeness from "Nonfundamental" Shocks

Julien Cujean Samuel Jaeger

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<u>Conceptual and practical challenges:</u>

- **1.** What is the fundamental value? (which proxy, horizon,..)
- **2.** Earnings impose a low frequency on regressions, which thus speak to long term, low frequency information, as opposed to rapid changes in info flow.

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- **1.** We proxy for noise instead of fundamental value (Dessaint et al., 2018; Honkanen and Schmidt, 2021).
  - Using large mutual fund outflows.
  - *MFFlow* measures the "intensity" at which a stock is fire-sold in a given month (Edmans et al., 2012; Wardlaw, 2020).
  - MFFlow is monthly and horizon-independent .

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↑

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⇒ **Main idea:** Move away from **1.** earnings data and **2.** regressions.

- **2.** We use MFFlow to identify (presumed) non-fundamental price shocks.
  - Each month, we use MFFlow to collect a subset of stocks that fall in the lowest decile of the cross-sectional MFFlow distribution.
  - Form portfolios of shocked stocks and calculate the CAR after the shock.

Recovery from Shocks

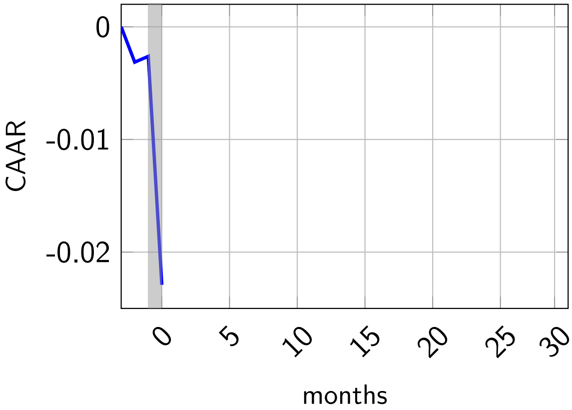

figure 1. CAARs (panel approach).

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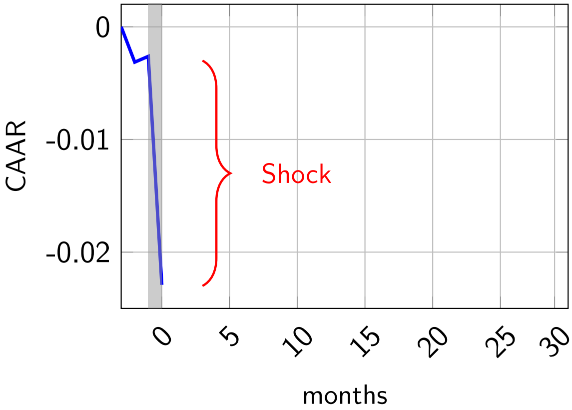

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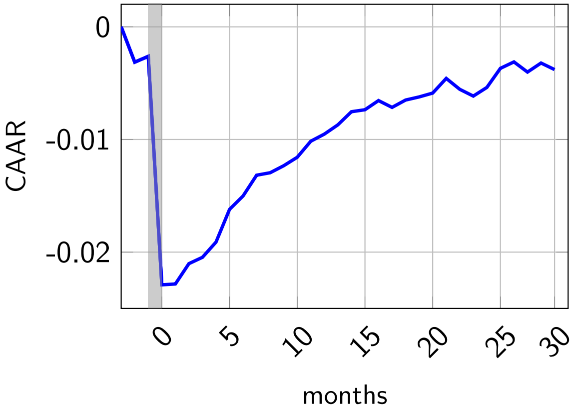

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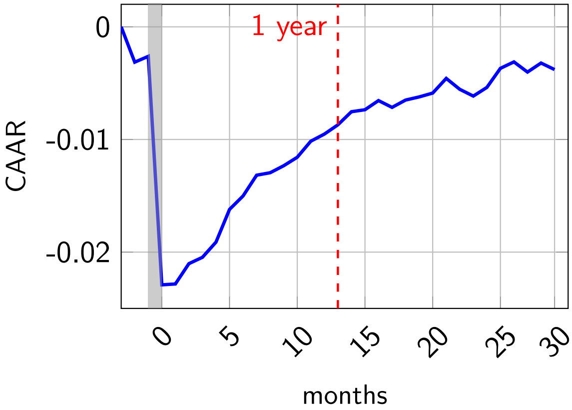

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  $\Rightarrow$ *[...] Over time, the conditional probability that the price drop was due to the arrival of adverse private information would decline and the price would recover in expectation [...] a suitable specialization of the neoclassical model of He and Wang (1995) could be used to analyze price dynamics in this setting* **(Duffie, 2010)**.

A simple one-shot model

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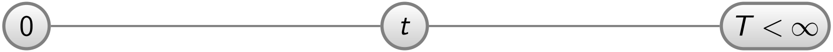
Continuous trading on $[0, T)$



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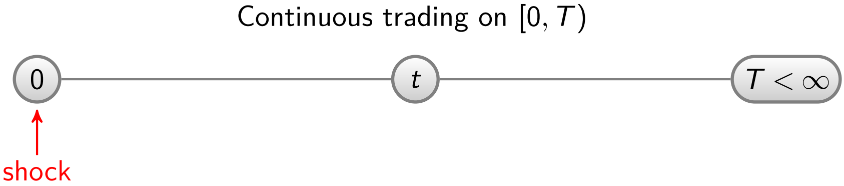

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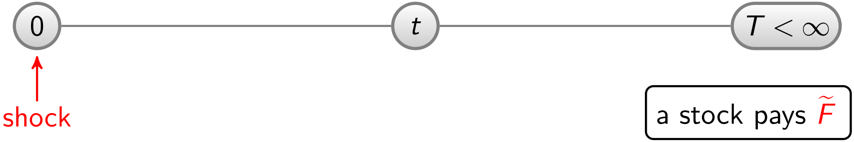

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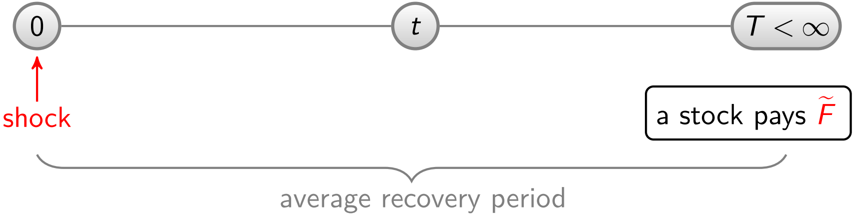

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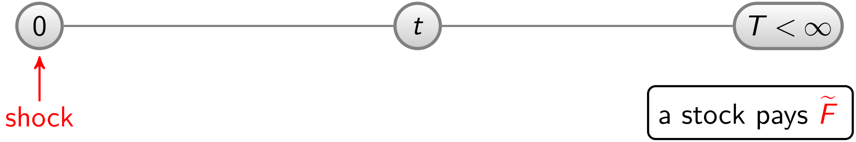

Total number of shares of stock $\widetilde{m}_t$ available:
$\mathrm{d}\widetilde{m}_t = \tau_m^{-1/2}\mathrm{d}B_{m,t}, \quad \widetilde{m}_0 \sim \mathcal{N}(0, \tau_{m,0}^{-1})$

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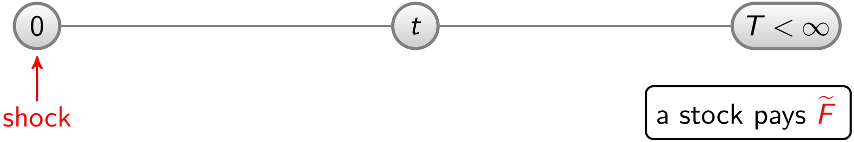

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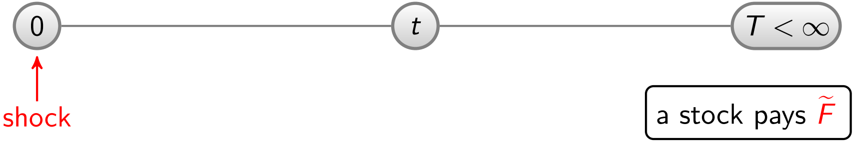

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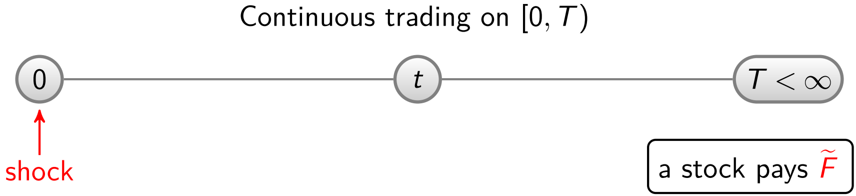

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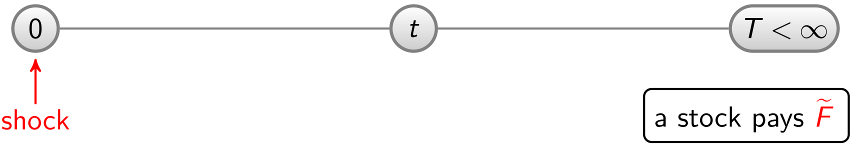

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We define ϕ_t as the private information flow, which corresponds to the cross-sectional average number of private signals.

The model's key insight for price informativeness

Theorem 1 In equilibrium, price informativeness at time t is (**Formula A**):

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Main message: The speed at which information flows from prices is proportional to *the square of the speed at which private information accumulates.*

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$\Rightarrow$ Therefore, the task of recovering the flow of price informativeness is one of recovering the flow of private information, $(\phi_t)_{t>0}$, and the three remaining parameters:

$$\mathbf{\Theta} \equiv \left(\begin{array}{ccc} \frac{\tau_m}{\gamma^2} & \tau_F & \phi_0 \end{array} \right).$$

Recovering the Shape of Learning from Prices

1.) Recovering Private Information Flow ϕ_t:

- The diffusion of CAR (σ_t) in equilibrium is a function of ϕ'_t:

$$\sigma_t \equiv \sqrt{\mathrm{d}\langle P_t \rangle / \mathrm{d}t} = a^{-1/2} \cdot \tau_t^{-1} \cdot \left(1 + a \cdot \phi'_t\right).$$

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- Then, differentiate and solve for ϕ_t (**formula B**):

$$a \cdot \phi_t(\mathbf{\Theta}) = c - b + \int_0^t \left(\frac{\exp\left(-\int_0^s \sigma_u / a^{1/2}\,\mathrm{d}u\right) \sigma_s / a^{1/2}}{1/c - \int_0^s \exp\left(-\int_0^v \sigma_u / a^{1/2}\,\mathrm{d}u\right) \sigma_v^2 / a\,\mathrm{d}v} - 1 \right) \mathrm{d}s$$

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- The resulting log-likelihood is given by the following expression:

$$\mathscr{L}_T \equiv -\frac{1}{2}\sum_{n=1}^{N}\left(\log(2\cdot\pi)+\log(\sigma^2_{n\cdot\Delta}\cdot\Delta)-\left(\frac{P_{n\cdot\Delta}-\mu_{n\cdot\Delta|(n-1)\cdot\Delta}}{\sigma_{(n-1)\cdot\Delta}\sqrt{\Delta}}\right)^2\right)$$

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- Which we maximize to find the parameters which make the observed data (CAR) most likely.

Illustration of Methodological Steps

- Ilustrative example: Shock 231, occured on February 2016.

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- Recovery period runs from March 2016 through February 2017.

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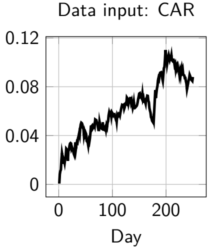

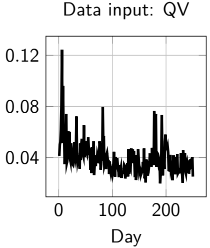

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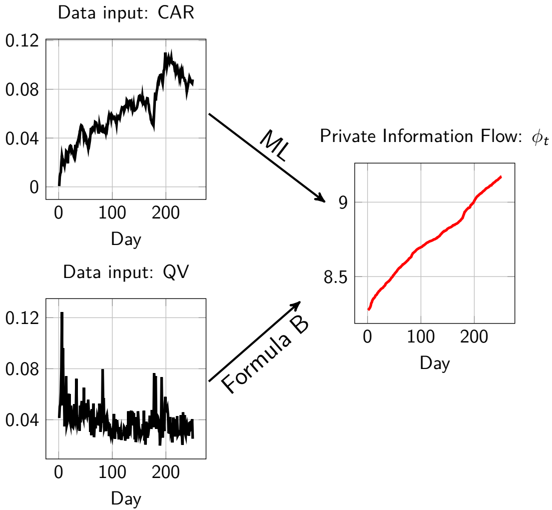

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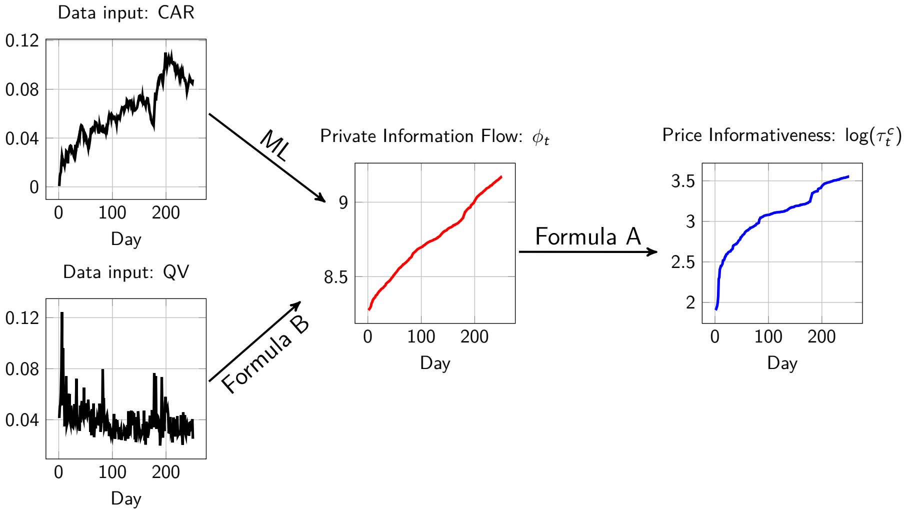

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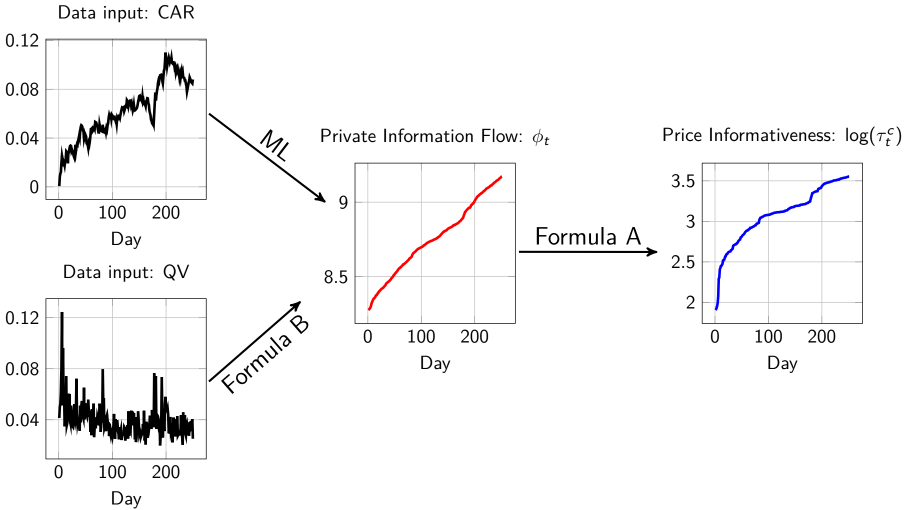
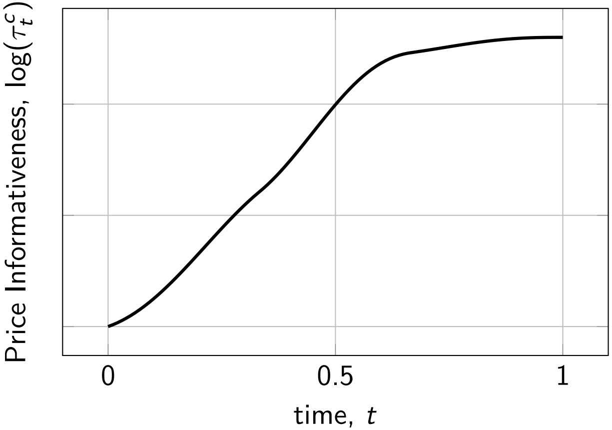


We get as many curves of price informativeness as there are recoveries (300).

Inspiration from the fixed-income literature

We get as many curves as there are shocks (300):



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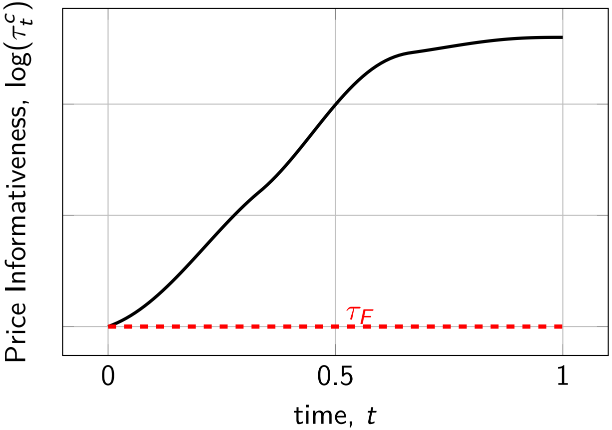

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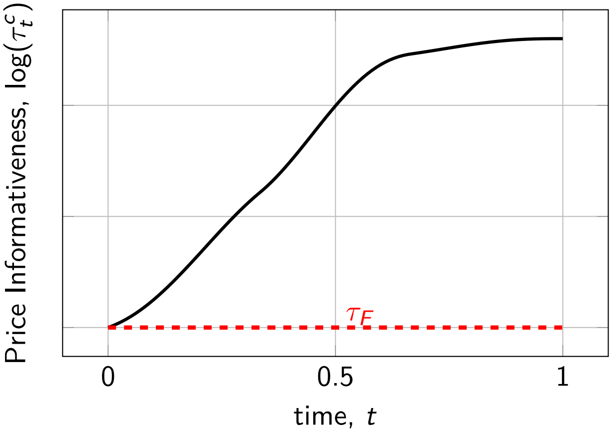
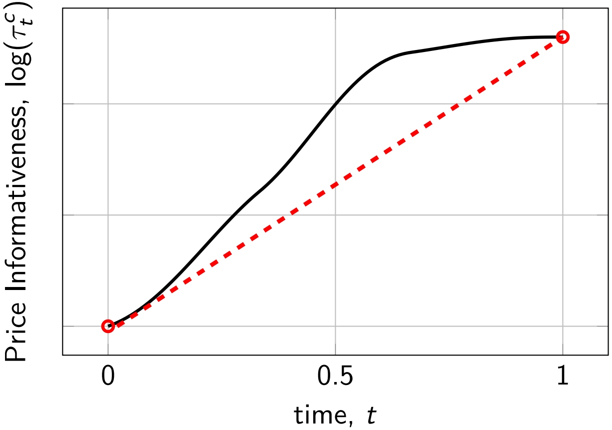


- We capture these shapes with their **1.**

$$L_t \equiv \log(\tau_F)$$

Inspiration from the fixed-income literature

We get as many curves as there are quarters (300 shocks):



- We capture these shapes with their **2.**

$$Slope_t = log(\tau_T^c) - log(\tau_F)$$

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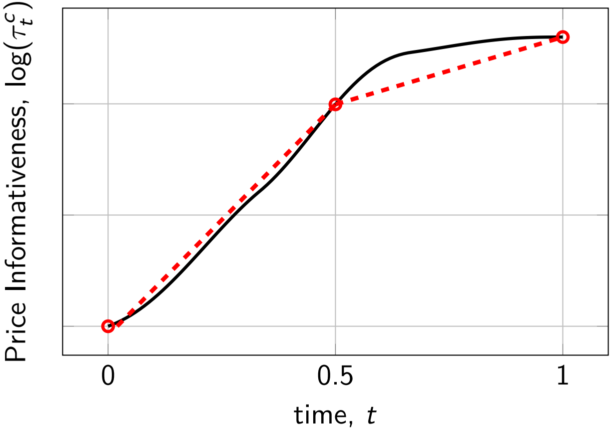

- We capture these shapes with their **3.**

$$\textit{Curvature}_t = \tau_T^c - 2\tau_{T/2}^c + \tau_F$$

The shape of price informativeness over two decades

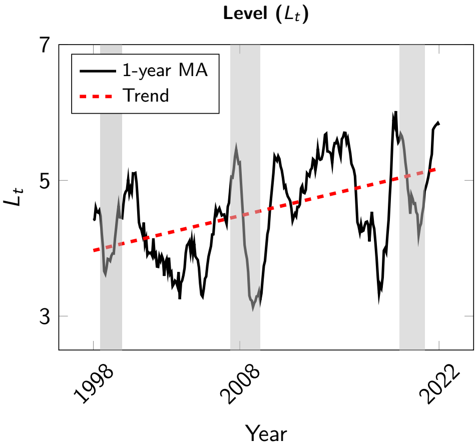

figure 3. Level of price informativeness over time.

The shape of price informativeness over two decades

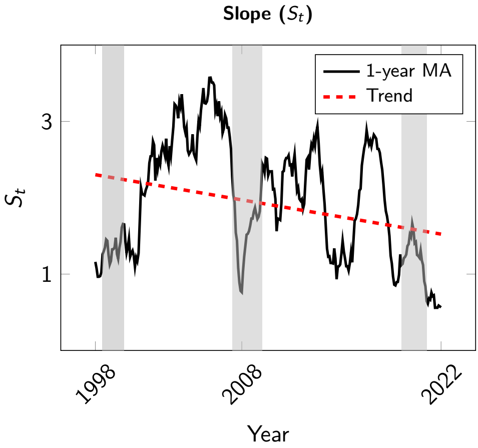

figure 4. Slope of price informativeness over time.

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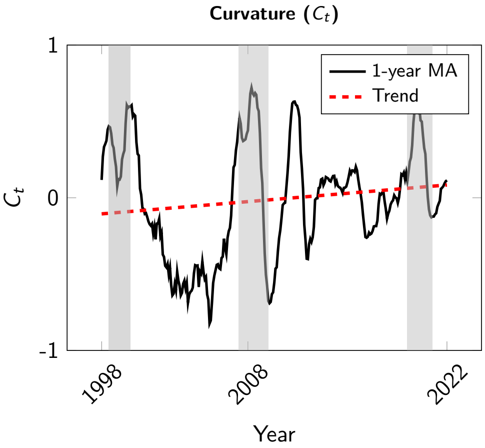

figure 5. Curvature of price informativeness over time.

- END -

The shape of price informativeness in the cross-section

	Size	Value	Liquidity$^{\perp}$	Coverage$^{\perp}$
L_t	1.22***	-0.27**	-0.97***	-0.20
	(9.22)	(-2.46)	(-8.13)	(-1.49)
S_t	-0.84***	0.40***	0.62***	0.04
	(-5.28)	(3.04)	(4.30)	(0.33)
C_t	0.13***	-0.06	-0.10**	-0.01
	(2.64)	(-1.54)	(-2.19)	(-0.41)

Table 1. Cross-sectional differences in price informativeness.

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Implications for market efficiency

- *"Almost all markets are efficient", meaning"price is within a factor 2 of value" at least 90% of the time* ***(Black, 1986)***

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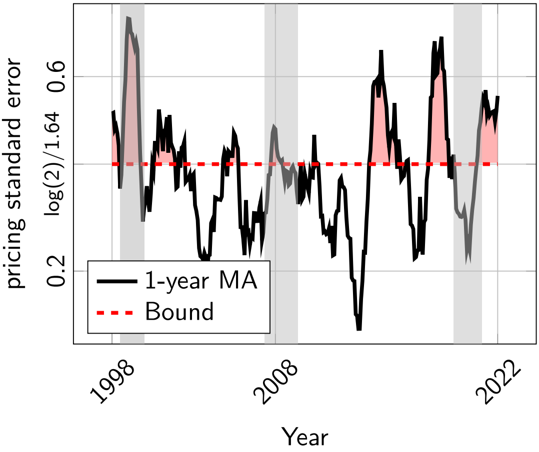

figure 6. Fischer Black's bound.

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