Why Does Return Predictability Concentrate in Bad Times?

Julien Cujean Michael Hasler





Empirical Fact

 Disagreement and the content of news predict stock returns Diether, Malloy, & Scherbina (2002), Tetlock (2007)

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- MAIN FACT: This relation is concentrated in bad times Cen, Wei & Yang (2014), Garcia (2013)

Main Idea: Countercyclical disagreement (Patton and Timmermann (2010)) explains observed patterns of time-series predictability

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 \Rightarrow Predictability strengthens as economic conditions deteriorate

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If disagreement is countercyclical

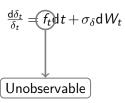
⇒ Predictability strengthens as economic conditions deteriorate

WE BUILD A MODEL CONSISTENT WITH THESE FACTS

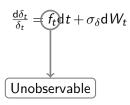
The stock is a claim to the aggregate output:

$$\frac{\mathrm{d}\delta_t}{\delta_t} = f_t \mathrm{d}t + \sigma_\delta \mathrm{d}W_t$$

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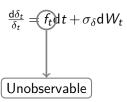


Agent A

f is mean-reverting: $df_t = \kappa(\bar{f} - f_t)dt + \sigma_f dW_t^f$

$$\mathrm{d}\mathbf{f_t} = \kappa(\mathbf{\bar{f}} - \mathbf{f_t})\mathrm{d}t + \sigma_f \mathrm{d}W_t^f$$

The stock is a claim to the aggregate output:



Agent A

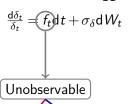
f is mean-reverting: $df_t = \kappa(\bar{f} - f_t)dt + \sigma_f dW_t^f$

Agent B

$$f$$
 is a 2-state Markov Chain:
$$f_t = \{f^h, f^l\}$$

$$\Lambda = \begin{pmatrix} -\lambda & \lambda \\ \psi & -\psi \end{pmatrix}$$

The stock is a claim to the aggregate output:



Estimate: $\hat{f}_t^A = E_t^A(f_t)$

Estimate: $\hat{f}_t^B = E_t^B(f_t)$

Agent A

f is mean-reverting:

$$d\mathbf{f_t} = \kappa(\bar{f} - \mathbf{f_t})dt + \sigma_f dW_t^f$$

Agent B

f is a 2-state Markov Chain:

$$f_t = \{f^h, f^l\}$$

$$\Lambda = \left(\begin{array}{cc} -\lambda & \lambda \\ \psi & -\psi \end{array} \right)$$

Estimation

Parameter	Symbol	Value
Mean-Reversion Speed f^A	κ	0.1911
Long-Term Mean f ^A	$ar{f}$	0.0630
_		

Agent A

$$\begin{aligned} & \quad \quad \textbf{\textit{f}} \text{ is mean-reverting:} \\ \mathrm{d} \widehat{\textbf{\textit{f}}_{t}^{A}} &= \kappa (\bar{\textbf{\textit{f}}} - \widehat{\textbf{\textit{f}}_{t}^{A}}) \mathrm{d}t + \frac{\gamma}{\sigma_{\delta}} \mathrm{d} \widehat{W}_{t}^{A} \end{aligned}$$

Estimation

Symbol	Value
κ	0.1911
Ī	0.0630
f ^h	0.0794
f ^I	-0.0711
λ	0.3022
ψ	0.3951
	$\frac{\kappa}{f}$ f^h f^l

Agent A

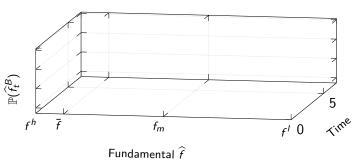
f is mean-reverting:

$$d\widehat{\mathbf{f}}_{t}^{A} = \kappa(\overline{\mathbf{f}} - \widehat{\mathbf{f}}_{t}^{A})dt + \frac{\gamma}{\sigma_{\delta}}d\widehat{W}_{t}^{A}$$

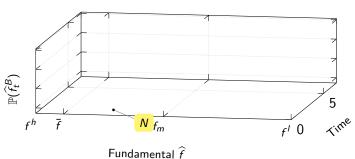
Agent B

$$f$$
 is a 2-state Markov Chain:
$$\mathrm{d}\widehat{f}_t^B = (\lambda + \psi)(f_\infty - \widehat{f}_t^B)\mathrm{d}t \\ + \frac{1}{\sigma_\delta}(\widehat{f}_t^B - f^I)(f^h - \widehat{f}_t^B)\mathrm{d}\widehat{W}_t^B$$

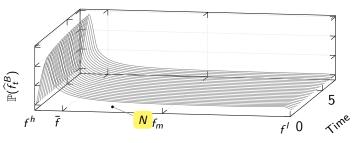
Good (G), Normal (N), Bad (B) Times



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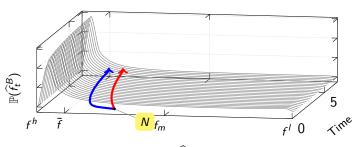


Good (G), Normal (N), Bad (B) Times

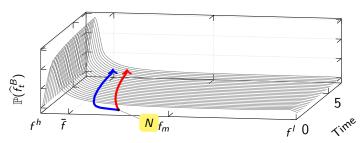


Fundamental \widehat{f}

Good (G), Normal (N), Bad (B) Times

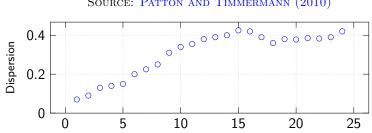


Good (G), Normal (N), Bad (B) Times

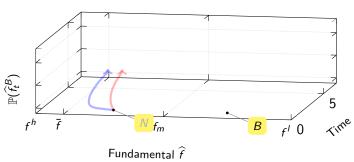


Fundamental \hat{f}

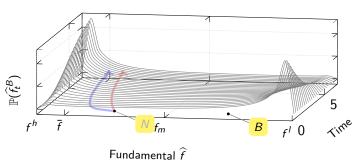
Source: Patton and Timmermann (2010)



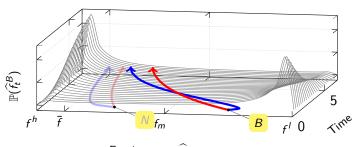
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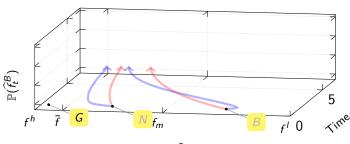


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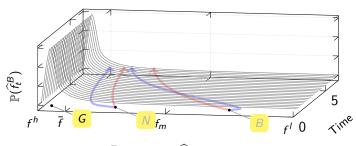
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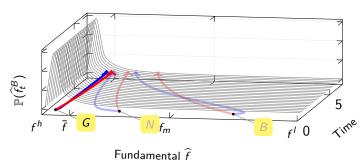


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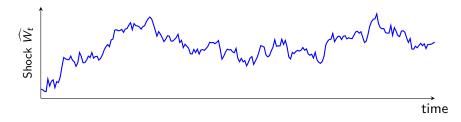


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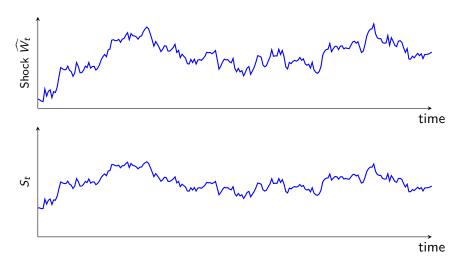


$$E_t(\mathcal{D}_t S_u)$$

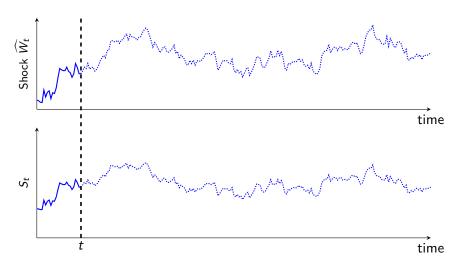
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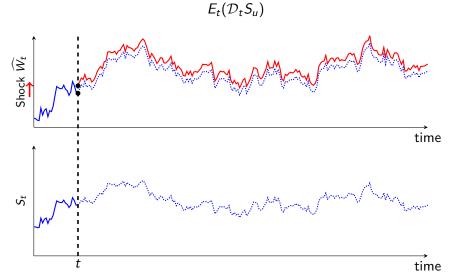






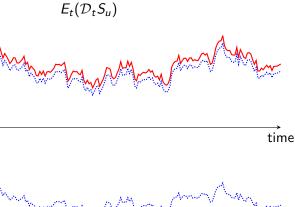
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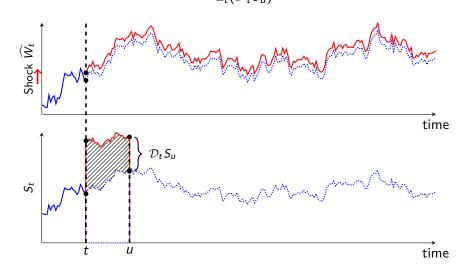
Shock $\widehat{W_t}$

We compute the expected price response to a shock \widehat{W} today:

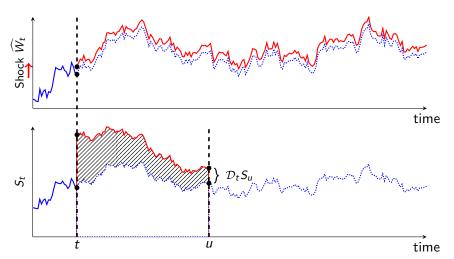


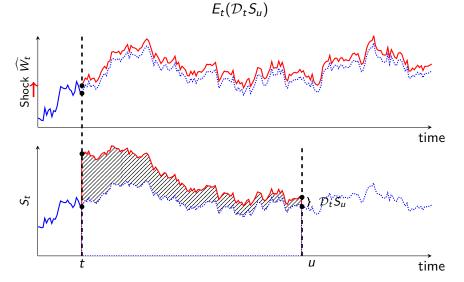
time

We compute the expected price response to a shock \widehat{W} today: $E_t(\mathcal{D}_tS_u)$

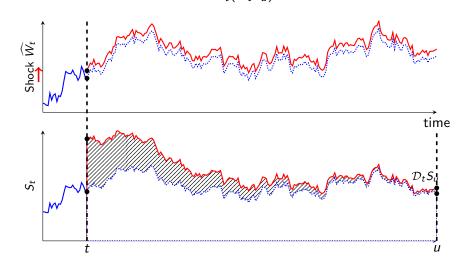




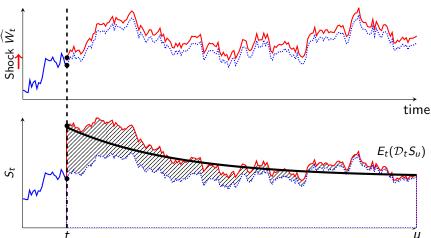




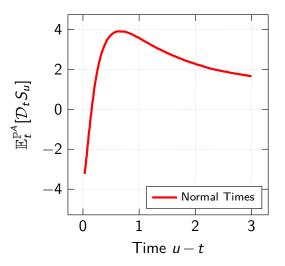
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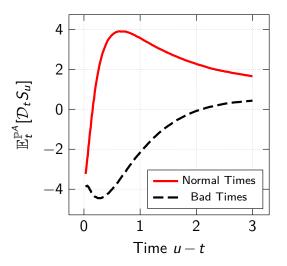




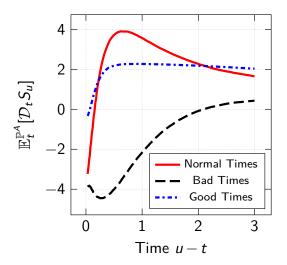
Price Impulse Response

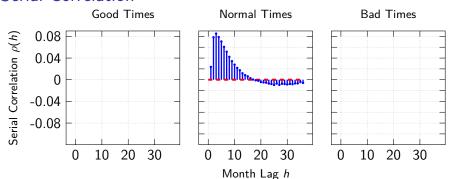


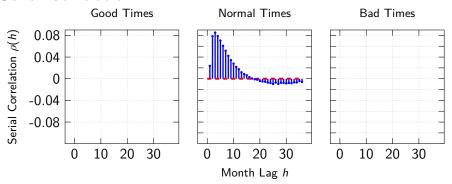
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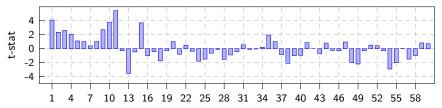
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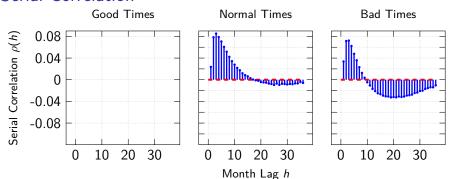


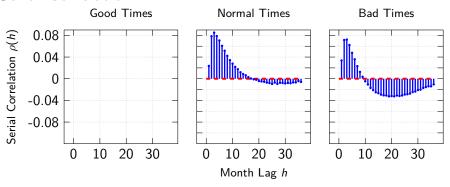


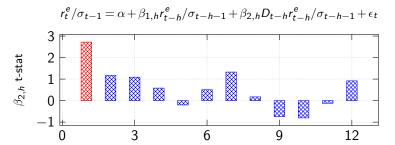


Source: Moskowitz, Ooi & Pedersen (2012)

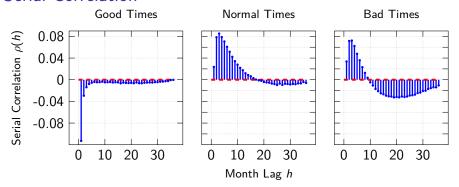








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Momentum crashes

Daniel and Moskowitz (2013), Baroso and Santa-Clara (2014)