Break Risk
by Simon Smith and Allan Timmermann

Discussion by Nancy Xu
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Objective

- Propose a new approach to forecasting stock returns in the presence of structural breaks that simultaneously affect the parameters of multiple portfolios (and thus the market portfolio).

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- Nevertheless, modeling dynamics in parameters is difficult $\Leftarrow$

Addressing statistical challenges

- Lettau and Van Nieuwerburgh (2008) point out two challenges:
    1. Slow detection of breaks in real time
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Addressing statistical challenges

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  1. Slow detection of breaks in real time
  2. Imprecise model estimates shortly before and after breaks
- This paper addresses both concerns by:
  1. Exploiting information in the cross-section of stock returns (Smith and Timmermann (2017a))
  2. Adopting a Bayesian econometric breakpoint approach (Chib (1998))

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  $\Rightarrow$ The rationale: if the predictive power of a predictor on the aggregate stock market portfolio decreases, we expect to find a similar effect on industry portfolios at approximately the same time.
- Namely, pooled breaks with portfolio-specific parameters:

$$r_{it} = \mu_{ik} + \beta_{ik} X_{t-1} + \varepsilon_{it} \tag{1}$$

$\Rightarrow$ Industry portfolios: $i = 1, ..., N$

$\Rightarrow$ Months in Regime k: $t = \tau_{k-1} + 1, ..., \tau_k$

$\Rightarrow$ Regimes: $k = 1, ..., K$

$\Rightarrow$ Shock assumption: $\varepsilon_{it} \sim N(0, \sigma^2_{ik})$

Data and estimation

- Main predictor: lagged dividend-price ratio
- 30 industry portfolios (FF)
- Monthly returns, 1926-2015
- MLE + Bayesian

Comments

Ambitious project in an important and *growing* research area

1. Review of main results - Time Series
2. Review of main results - Cross Section
3. Economic interpretations of the filtered breaks
4. Link to current theories

1. Review of main results - Time Series

- Accounting for breaks in panel return models: more accurate OOS return forecasts

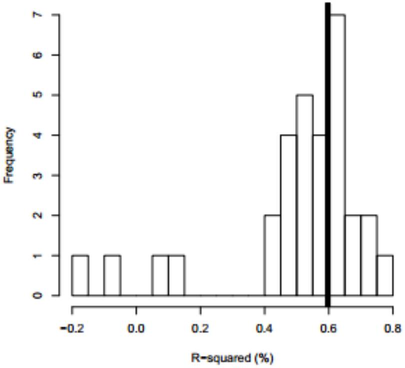

Figure: Figure 8(c) of Smith and Timmermann (2018)

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  $\Rightarrow$ Explain better the source, is it driven by a specific break identified?
- Dividend-price ratio, an annual predictor (Shillller (1984), Goyal and Welch (2003, 2008), Ang and Bekaert (2007), Golez and Koudijs, 2017)
  $\Rightarrow$ Do your results hold considering annual forecasting models?
  $\Rightarrow$ Or daily

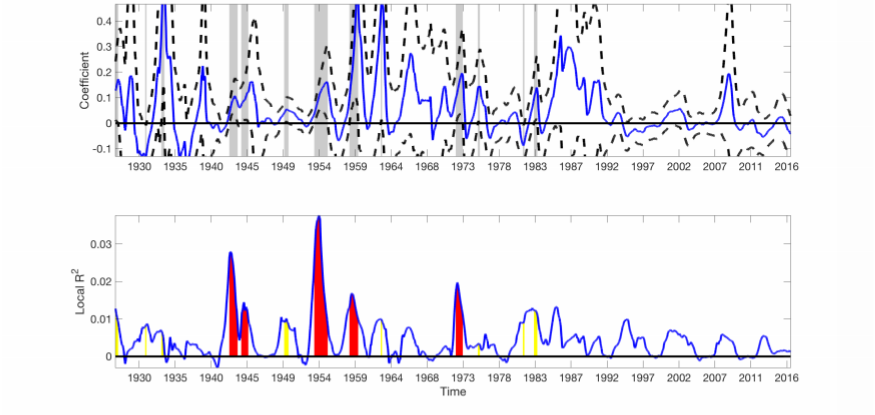

Figure 1: Local return predictability from the dividend yield. The top panel in this figure plots non-parametric kernel estimates of the local slope coefficient from a regression of daily excess stock returns on the lagged dividend yield. Dashed lines represents plus or minus two standard error bands. The bottom panel plots the local $\overline{R}^2$ measure with shaded areas tracking periods identified as pockets of return predictability using a 5% critical value. The shaded areas represent the integrated $\overline{R}^2$ inside pockets with areas colored in red representing pockets that have less than a 5% chance of being spurious, areas colored in orange representing pockets that have between a 5% and a 10% chance of being spurious, and areas colored in yellow representing pockets that have more than 10% chance of being spurious.

Figure: Farmer, Schmidt and Timmermann (2018, SSRN)

2. Review of main results - Cross Section

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- Portfolios whose excess returns are more sensitive to breaks earn significantly higher average returns than firms with lower break exposure (after controlling for FF3F)

Portfolio	r	α
Low	0.26	-0.18
	(1.98)	(-2.04)
2	0.32	-0.06
	(2.19)	(-1.99)
3	0.44	-0.01
	(2.25)	(-1.60)
4	0.46	0.02
	(1.98)	(1.01)
High	0.53	0.17
	(2.58)	(2.04)
High-low	0.27	0.35
	(2.18)	(2.97)

Figure: Table 6 of Smith and Timmermann (2018)

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- One possibility is that breaks identified here coincide with priced economic or financial shocks
  $\Rightarrow$ Need more discussions on the interpretations of breaks in this paper (e.g., thinking about the recent predictor PCA literature...)

3. Economic interpretations of the filtered breaks

- 10 breaks
- Stronger predictability over market returns after the early seventies

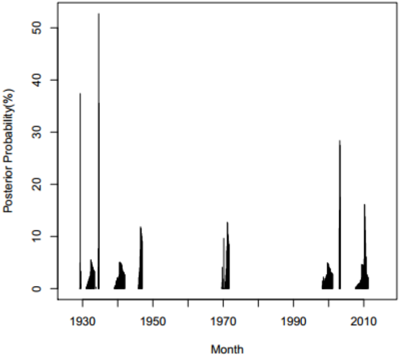

Figure: Figure 13(a) of Smith and Timmermann (2018)

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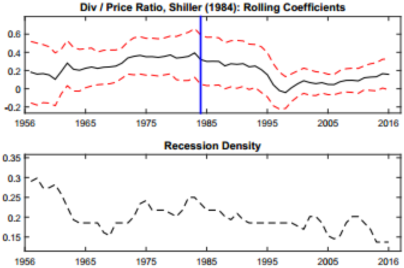
- Robustness ⇒ Multivariate predictive models? Subsamples?
- Upward trend ⇒ Conflicting with the publication / self-destruction story earlier? See some of my findings:



(Andrew Chen and Nancy Xu in prep.)

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  $\Rightarrow$ For example, long-run risk, disaster and habit formation models and their recent variants (e.g., Kilic and Shaliastovich (2018); Wachter (2013); Bekaert, Engstrom and Xu (2018))

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Conclusion

- Important question!
  New angle (of identifying market-wide breaks)!
  Well execution!

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  New angle (of identifying market-wide breaks)!
  Well execution!
- To make it more convincing:
  1. Time series result: choice of horizon?
  2. Cross section results: construct of “break risk”
  3. Economic interpretations / Link to theories

Thank You!