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Breaking Bad: Parameter Uncertainty Caused by Structural Breaks in Stocks

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Introduction

Role of stock specific uncertainty and some of its drivers are not yet clearly understood:

- What type of uncertainty (on a stock level) is important for investors?
- How to measure (proxy for) uncertainty in stocks?
- What is the impact of uncertainty on individual stocks?

We argue that:

- Agents avoid uncertain stocks until uncertainty is resolved
- Parameter uncertainty is difficult to measure → Suggested proxy: Stock age since last time series break (aka Break Age)
- We check its validity by testing whether break age offers higher CARs relative to firm age

Why break age?

- Break points co-occur with earnings releases and stock-related news (dividend payments, stock-splits and buyback announcements) (Lleo et al., 2020)
- Time series breaks occur frequently and impar predictive relationships (Dangl and Halling, 2012; Smith and Timmermann, 2021)
- Regime shifts are difficult to verify, regimes may be unknown, even advanced prediction models cannot exploit the induced uncertainty (Ang and Timmermann, 2012, Stöckl, 2020)

We test the following research hypotheses:

1. Directly after a break in the time series, stocks offer higher expected returns that diminish with the resolution of uncertainty
2. This phenomenon is more pronounced for smaller stocks as they are less researched by analysts

Data and Methodology

Data:

- Monthly delisting adjusted- stock returns from CRSP as of 1925
- 33'460 PERMNO, 4.4 Mio PERMNO-DATE observations
- Abnormal returns calculated using Fama-French-Carhart-Factors (CAPM, FF3, FFC4 based on 12-month rolling regressions)

$$AR_{i,t} = R_{i,t} - \beta_{m,i,t}R_{m,t} - \beta_{smb,i,t}R_{smb,t} - \beta_{hml,i,t}R_{hml,i,t} - \beta_{mom,i,t}R_{mom,t}$$

R-package cpm allows online break detection for multiple different methods:

- Student: Gaussian (change in mean)
- Bartlett: Gaussian (change in variance)
- GLR: Gaussian (change in mean and/or variance)
- Mann-Whitney: Non-Gaussian (change in location)
- Mood: Non-Gaussian (change in scale)
- Lepage: Non-Gaussian (general changes)
- Kolmogorov-Smirnov: Non-Gaussian (general changes)
- Cramer-von-Mises: Non-Gaussian (general changes)

Cumulative **A**bnormal **R**eturns (equally/value-weighted) for each month after break detection against IPO returns:

$$AR_t = \sum_{i=1}^{N} w_{i,t}AR_{i,t}$$

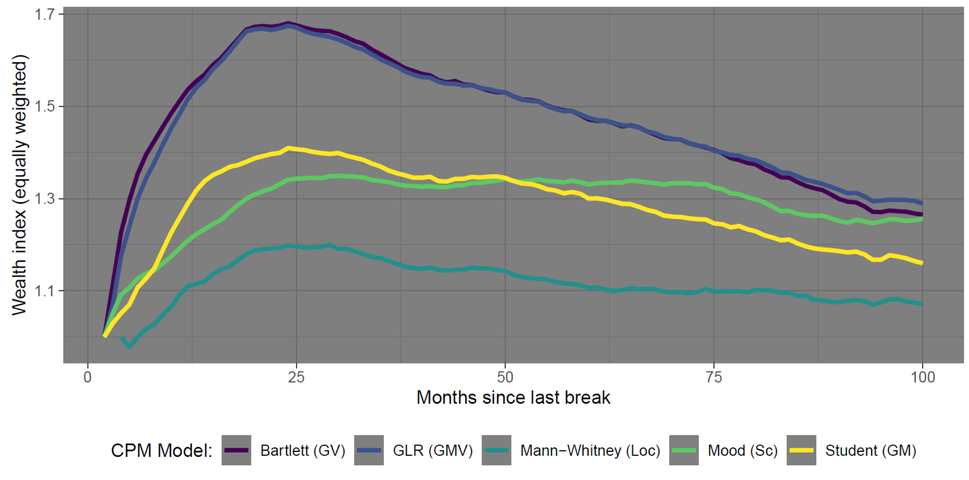
$$CAR_t = \prod_{k=0}^{t}\left(1 + (AR_t^{BP} - AR_t^{IPO})\right) - 1$$

Breakpoint Statistics CPM

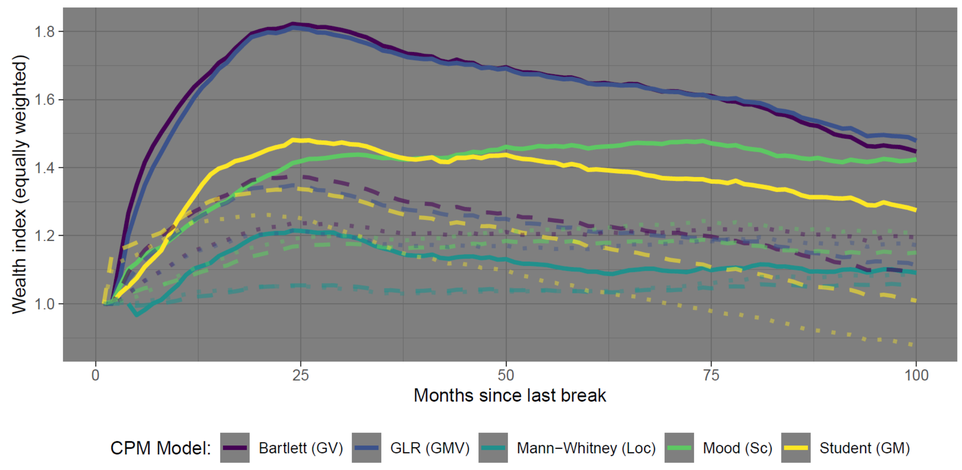
	% of stocks with BPs	Median No of BPs per stock	Median time to detect BP	Median time between BPs
Mann-Whitney	30.28	2.00	33.00	32.00
Mood	53.32	2.00	36.00	33.00
Student	57.80	2.00	34.00	32.00
Bartlett	73.02	3.00	24.00	20.00
GLR	68.30	3.00	27.00	21.00

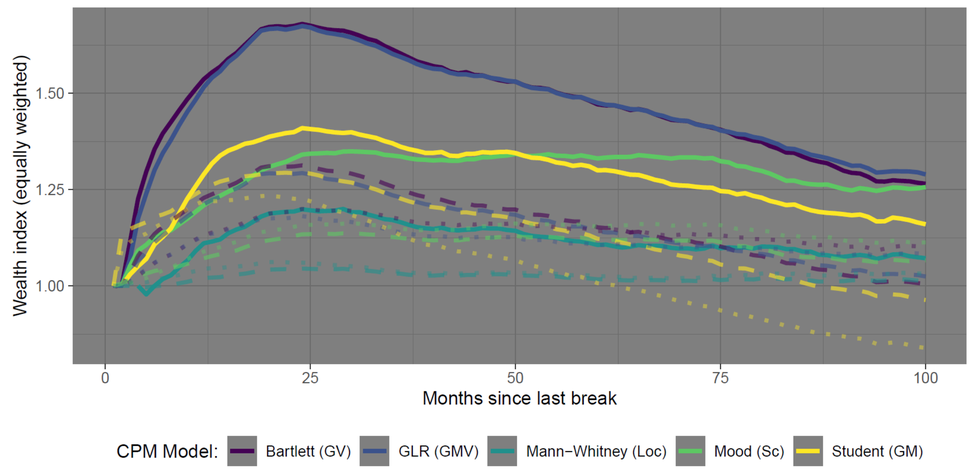
Table: Break-point detection statistics depicting percentage of stocks with detected breakpoints, the median number of breakpoints per stock, the median breakpoint detection time as well as the median time between breakpoints

Results – CAR, Equally-Weighted Over Full Sample

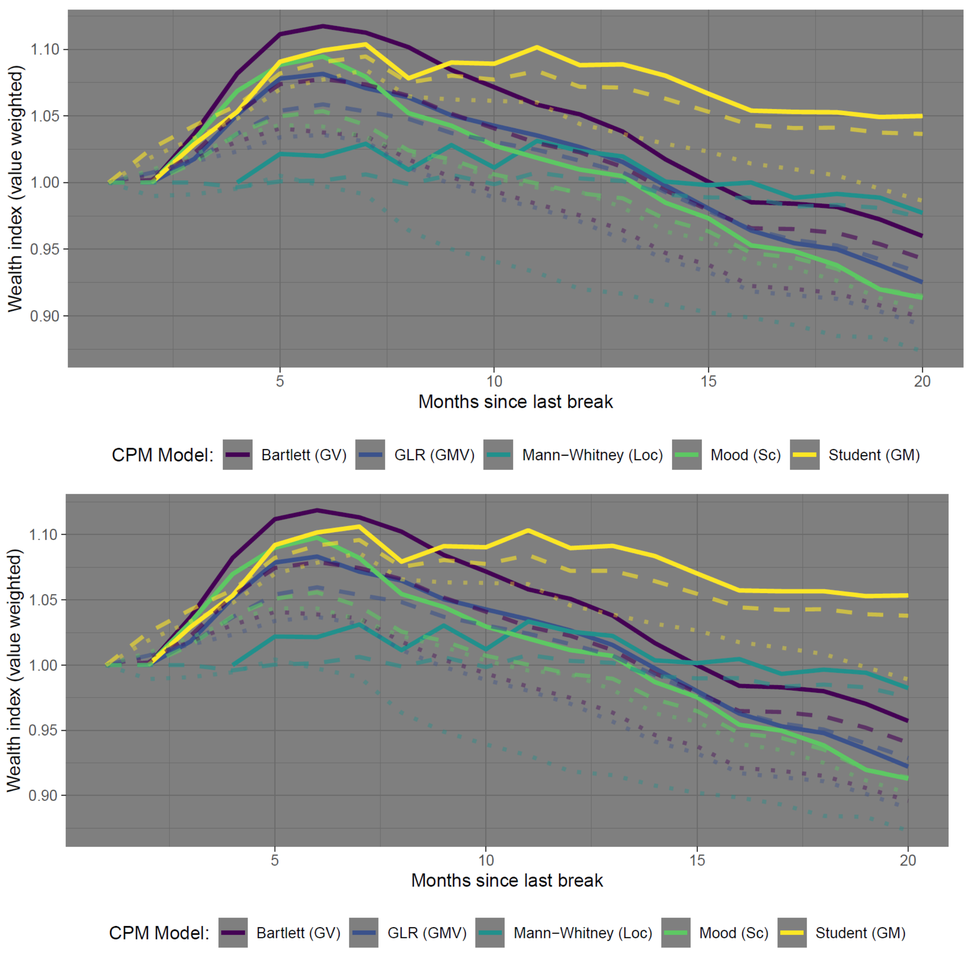


Results –CAR Equally-Weighted Since 1980





Results –CAR Value-Weighted Over Full Sample



Conclusion

- There is a substantial premium for assets with recent breaks in their time series
- This premium is strongest (among the implemented models) for breaks in the variance and mean-variance relationship
- The premium is driven by smaller stocks (as they are potentially less covered by analysts)
- Open topics:
  - What about other breakpoint detection models (i.e. for detecting breakpoints in regression coefficients)
  - What is a more suitable benchmark than IPO stocks
  - Distinguish between market wide and stock specific breaks
  - Apply CAR over various size quantiles
  - Verify relationship by studying trading volume

Forschungsförderungsfonds

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