

Good and Bad Uncertainty: Macroeconomic and Financial Market Implications

by Gill Segal, Ivan Shaliastovich, and Amir Yaron

Discussion

Pietro Veronesi

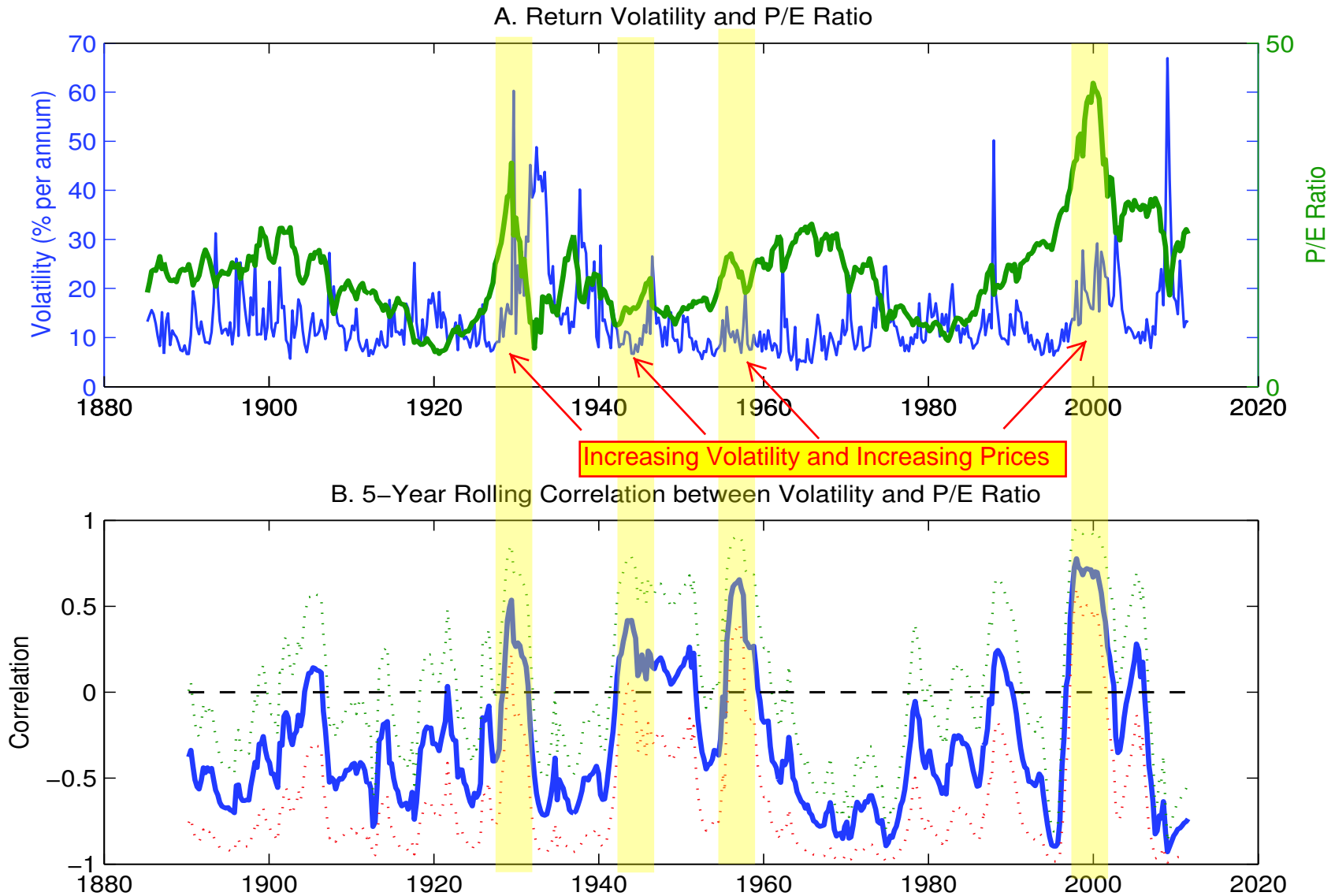
The University of Chicago Booth School of Business

Outline of Discussion (directed by the planner)

- Discuss SSY in light of my recent research.
 1. David and Veronesi (2013, JPE): “What Ties Return Volatilities to Price Valuations and Fundamentals?”
 2. Kelly, Pastor, and Veronesi (2014, WP): “The Price of Political Uncertainty: Theory and Evidence from the Option Market”
- Circle back to SSY to discuss some additional issues

Volatility and Asset Prices

- The correlation between P/E and stock volatility is strongly time varying



Log P/E is not related to return volatility.

C. Data

	EXPECTED EARNINGS				BELIEFS						
	RCP (1a)	RGDP (1b)	Boom (1c)	Model Expected (1d)	SPF($t + 1$) (2a)	SPF(t) (2b)	Model (2c)	SPF($t + 1$) (3a)	Model (3b)	(4)	(5)
Constant	18.96 (7.04)	23.15 (6.17)	41.52 (5.46)	21.90 (4.84)	12.45 (10.70)	13.27 (11.16)	12.45 (11.42)	10.41 (5.14)	12.15 (7.97)	14.28 (.99)	275.74 (3.52)
ExpInf	-.85 (-1.83)	-.95 (-2.01)	-1.37 (-3.31)	-1.51 (-1.70)							
ExpEarn	-.22 (-2.84)	-1.83 (-2.82)	-.26 (-3.56)	-1.44 (-2.15)							
P_{HI}					3.28 (1.34)	2.16 (.92)	4.21 (1.29)				
P_{ZI}					46.87 (4.03)	29.48 (3.77)	24.06 (3.41)				
UncInf								-144.02 (-1.56)	-75.01 (-1.01)		
UncEarn								50.35 (3.66)	38.76 (1.50)		
$Y(5)$										-.23 (-.38)	-8.66 (-2.75)
Log P/E										.43 (.11)	-154.97 (-3.53)
$Y(5)^2$											-.03 (-.34)
Log P/E ²											24.92 (3.74)
$Y(5)^2 \times \log P/E^2$.09 (2.94)
Adjusted R^2	.12	.19	.33	.12	.14	.10	.18	.17	.04	.00	.17

NOTE.—Regression of (Stock Volatility) $= b_0 + b_1 \mathbf{X}_t + \epsilon_t$, where Stock Volatility is the theoretical formula (panels A and B) or is estimated from daily stock returns (panel C). Explanatory variables \mathbf{X}_t are identified on each row. ExpInf and ExpEarn are expected inflation and earnings, P_{HI} and P_{ZI} are the probabilities of high inflation or zero (or lower) inflation, UncInf and UncEarn are the inflation and earnings uncertainty, and $Y(5)$ denotes the 5-year zero-coupon bond yield. In panels A and B, all the quantities are computed from the regime-switching model. In panel A, the stand-alone coefficient is the population value from a simulation of 5,000 years of quarterly data, while the brackets contain the 5th–95th percentiles of the coefficient distribution obtained from 100 samples of 200 quarters each. In panel C, these quantities are empirical proxies either directly observable ($Y(5)$ and log P/E) or computed from the SPF or from the model’s fitted probabilities, as indicated on the heading of each column. The sample in panel B is 1962–2010. The sample in panel C is also 1962–2010, except when SPF data are used (cols. 1a, 1b, 1c, 2a, 2b, and 3a), in which case the sample is 1968–2010. All t -statistics (in parentheses) are Newey-West adjusted for heteroskedasticity and autocorrelation using 12 lags.

Source: David and Veronesi “What ties return volatilities to price valuations and fundamentals?” (JPE, 2013)

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- Most models that feature time-varying volatility (habit formation, long-run risk) would imply that $\log P/E$ would be highly correlated with return volatility.
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(e.g. late 1920s, 1990s etc – good volatility)
- The model generates vast volatility variation (it is fitted to the data), but very hard to predict from observable quantities.

Model also does not explain volatility from log P/E

A. Model: Simulations

	(1)	(2)	(3)	(4)	(5)
Constant	11.52 [6.48, 20.10]	11.67 [9.43, 13.77]	9.60 [8.52, 12.27]	-.75 [-60.78, 160.58]	-1.08 [-3,599.2, 3,167.1]
ExpInf	.49 [-1.32, 2.51]				
ExpEarn	-.50 [-2.41, -.14]				
P_{HI}		7.48 [2.08, 79.01]			
P_{ZI}		2.61 [-.29, 45.95]			
UncInf			57.56 [-71.23, 110.88]		
UncEarn			29.28 [9.28, 46.56]		
Y(5)				.76 [-2.61, 2.43]	-7.11 [-70.31, 12.19]
Log P/E				3.11 [-50.93, 21.20]	33.13 [-2,200.3, 2,625.4]
$Y(5)^2$					-31.30 [-4.10, 5.85]
Log P/E^2					-8.51 [-475.49, 396.24]
$Y(5)^2 \times \text{log P/E}^2$.15 [-.75, 1.18]
Adjusted R²	.22 [.07, .85]	.13 [.06, .79]	.59 [.22, .97]	.12 [.04, .72]	.34 [.21, .94]

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Model suggest a non-linear relation between volatility and log P/E (but far from perfect)

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Non-linear relation between volatility and log P/E is found in the data (but far from perfect)

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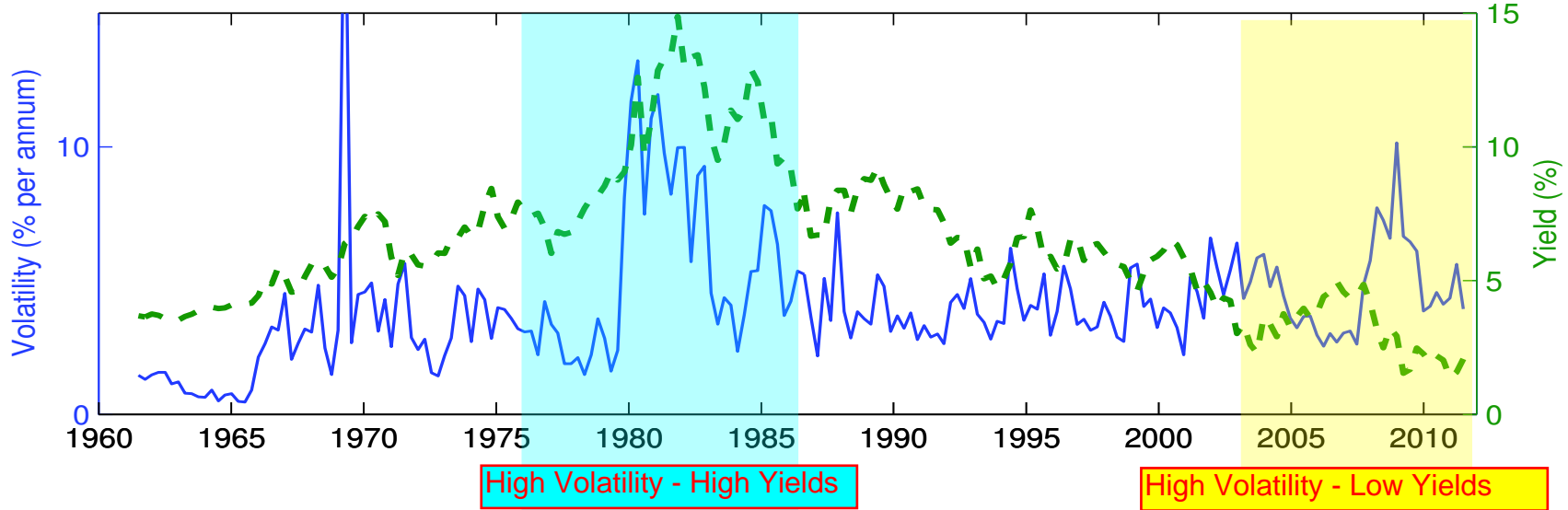
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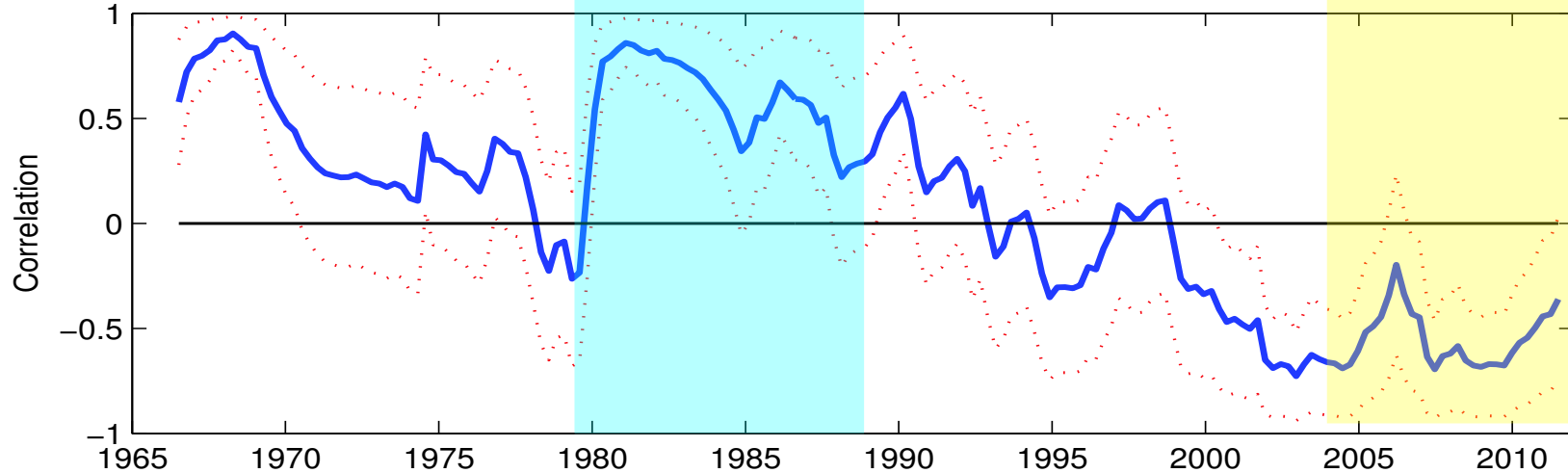
Volatility and Asset Prices

- This non-linearity between volatility and prices is there also for Treasury bonds

A. 5-Year Bond Return Volatility and Yield



B. 5-Year Rolling Correlation Between Bond Volatility and Yield

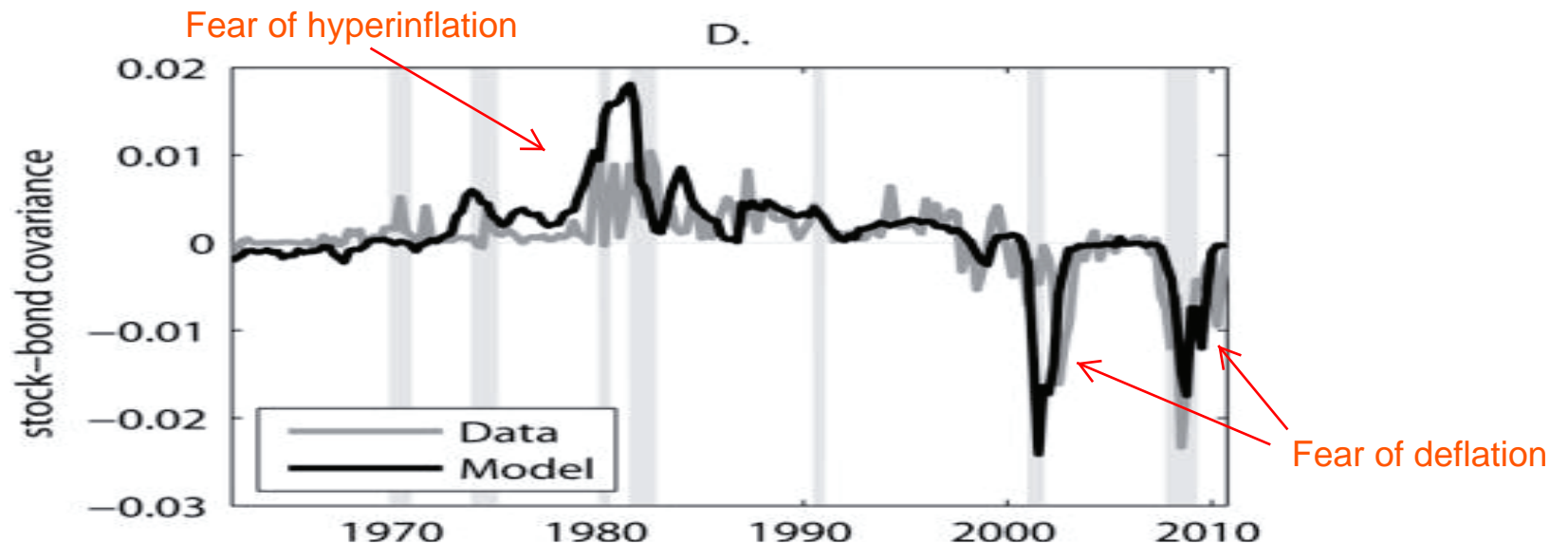


Volatility and Asset Prices

- The *same* mechanism is at play:
- Three regimes for inflation: High Inflation, Medium Inflation, Deflation
 - ⇒ Uncertainty between HI and MI ⇒ high yield and high volatility (1980s, bad volatility?)
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- In fact, the same mechanism explains the time-variation in **stock/bond covariance**



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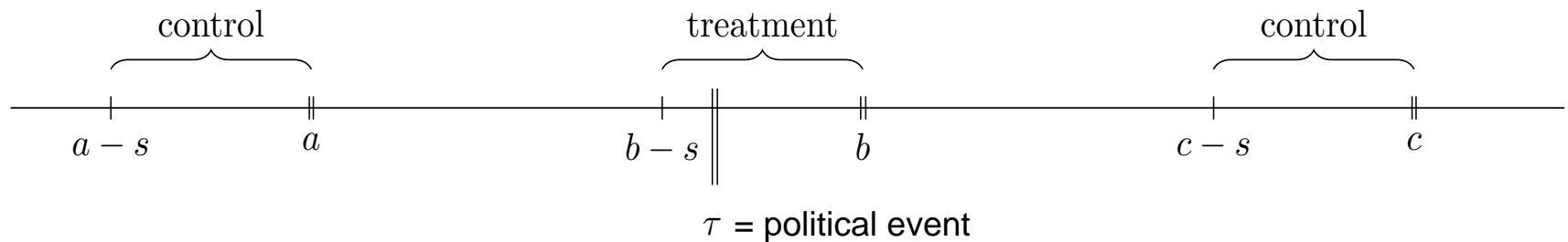
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- Analysis is guided by theory ⇒ Interpret results in light of our model.

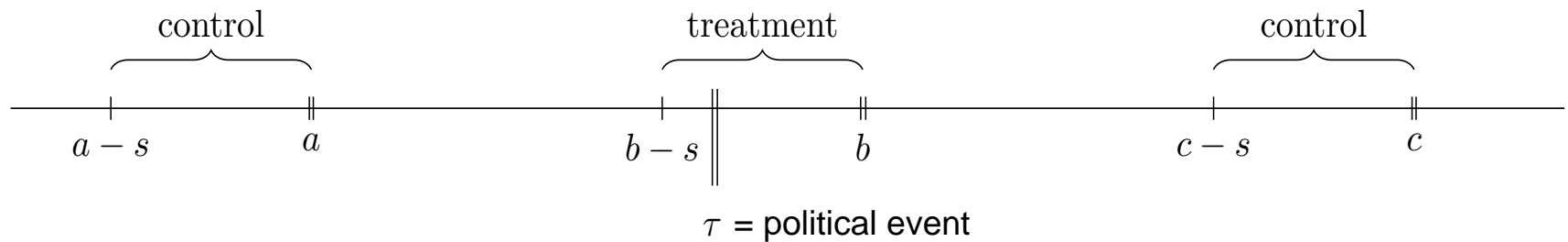
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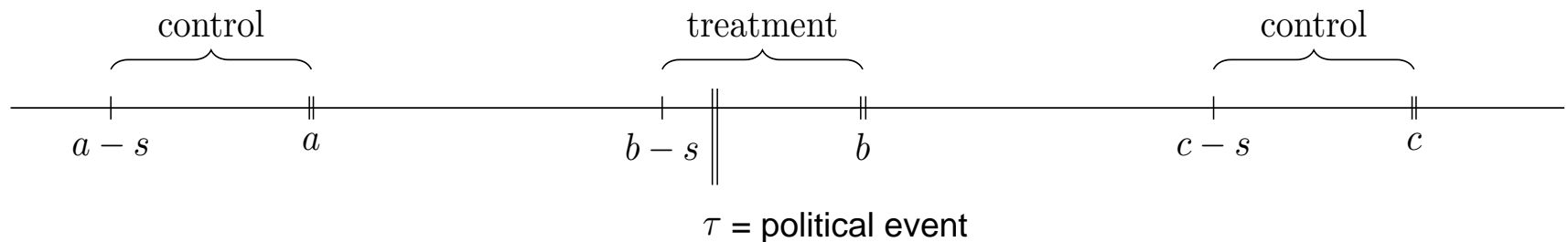


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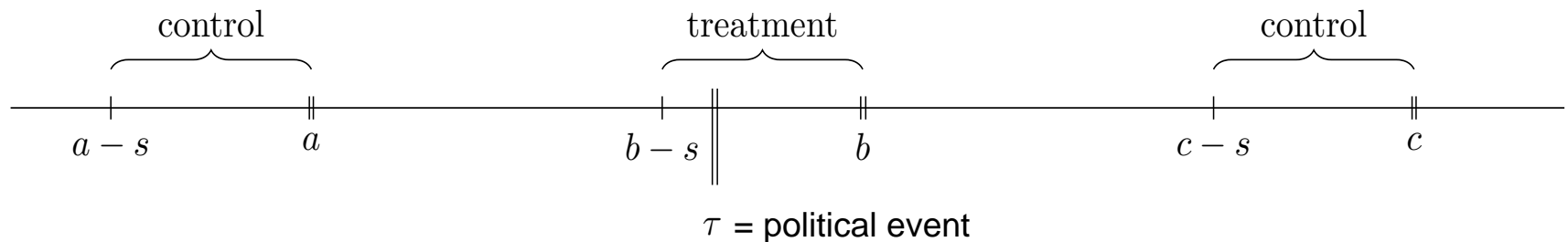


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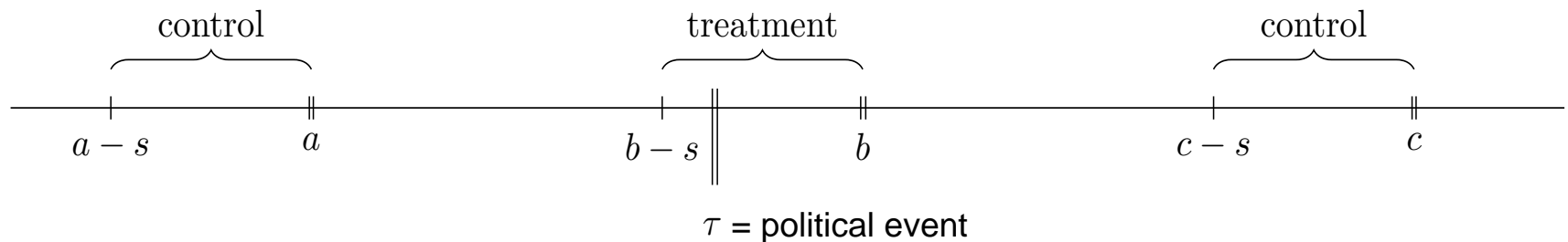


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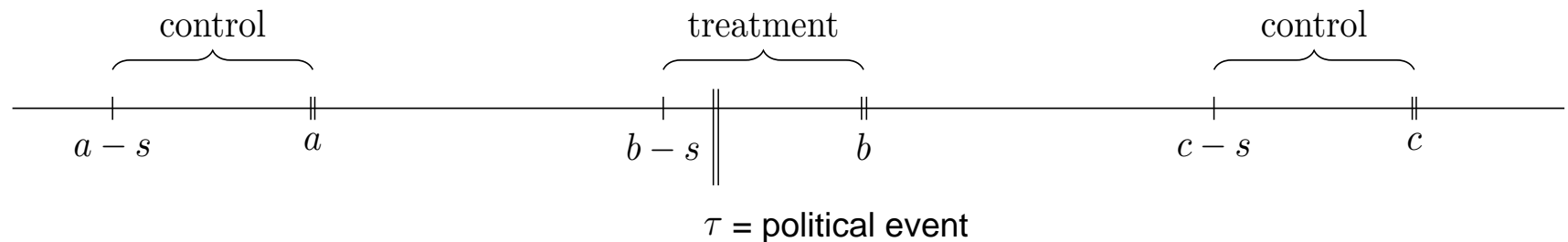


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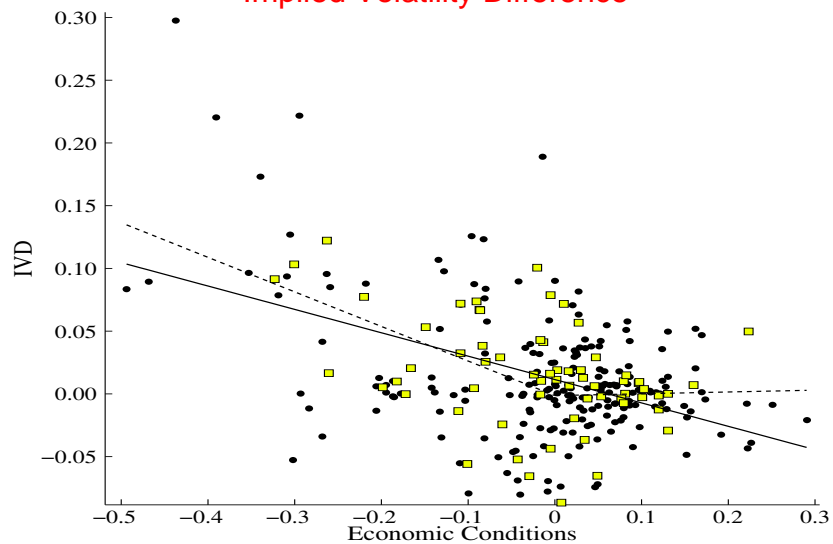
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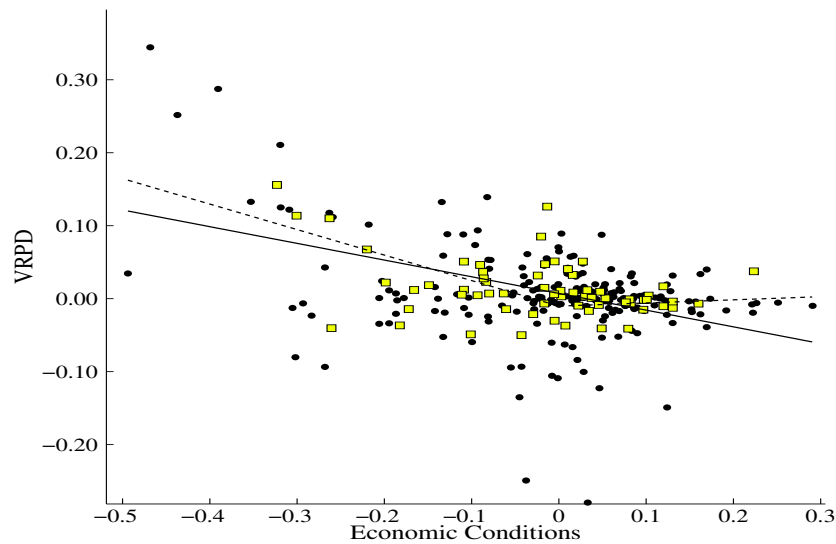
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 - * more expensive when political uncertainty is higher than options whose lives *do not* span political events.

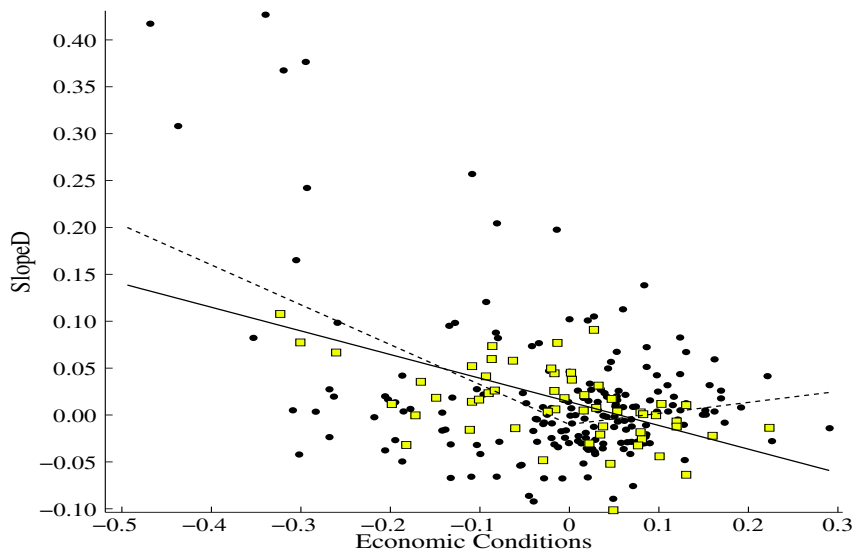
Implied Volatility Difference



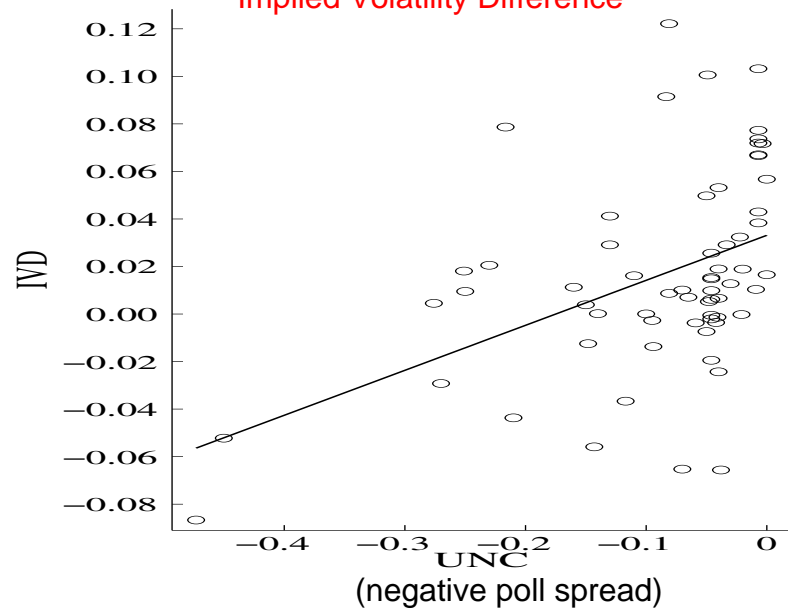
Variance Risk Premium Difference



Slope Difference



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a

Back to Segal, Shaliastovich, Yaron

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 - $\log(P/E)$ declines with high good uncertainty because of a **built-in feedback effect** from uncertainty to long-run growth:

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- Paper provides evidence of the feedback effect.
 - * Good (bad) uncertainty predicts higher (lower) future growth

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$$\begin{aligned}\Delta c_{t+1} &= \mu_c + x_t + \sigma_c(\epsilon_{g,t+1} - \epsilon_{b,t+1}) \\ x_{t+1} &= \rho x_t + \tau_g V_{g,t} - \tau_b V_{b,t} + \sigma_x(\epsilon_{g,t+1} - \epsilon_{b,t+1})\end{aligned}$$

- Paper provides evidence of the feedback effect.
 - * Good (bad) uncertainty predicts higher (lower) future growth
- Uncertainty = Realized Fundamental Volatility
 - Different from belief-based uncertainty about long-term growth

Back to Segal, Shaliastovich, Yaron

- What is the micro-foundation of good uncertainty impacting growth?
 - In investment uncertainty literature, higher uncertainty may increase value to keep the option to invest alive
 - \implies investments decrease and less growth.
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 - Such uncertainty is “bad uncertainty” in this paper.
- How does the good uncertainty work in an investment model?
 - Cross-sectional convexity effect?
 - * Cross-sectional heterogeneity increase growth rate of aggregate capital.
 - * It increase average prices.
 - * It may plausibly be generated by innovation.

The Cross-sectional Standard Deviation of Profitability: Nasdaq vs NYSE/Amex

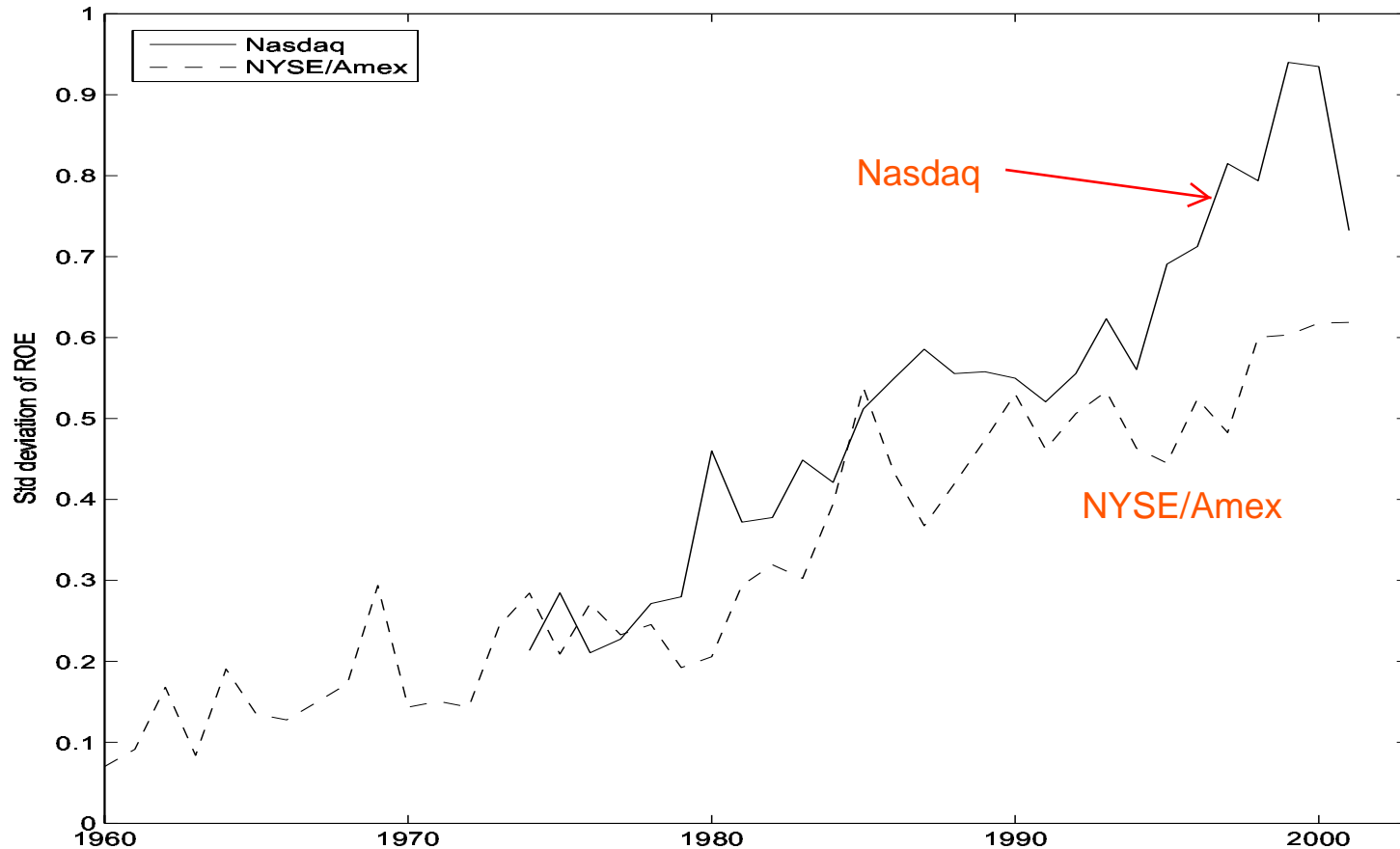


Fig. 9. Cross-sectional standard deviation of profitability for Nasdaq firms and for NYSE/Amex firms. Profitability (return on equity, ROE) of each firm in each year is computed as the firm's earnings in the given year divided by the firm's book equity at the end of the previous year. ROEs larger than 1,000% per year in absolute value are excluded.

Source: Pastor and Veronesi "Was There a Nasdaq Bubble in the late 1990s?" (JFE, 2006)

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- In this model:
 - $\sigma_\theta =$ Good uncertainty
 - $\sigma, \sigma_M =$ Bad uncertainty

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- How about the flip-flop nature of the relation between Treasury yields and bond return volatility? What is the mechanism there? good/bad monetary policy uncertainty?