Reconciling Survey Expectations and Asset Prices

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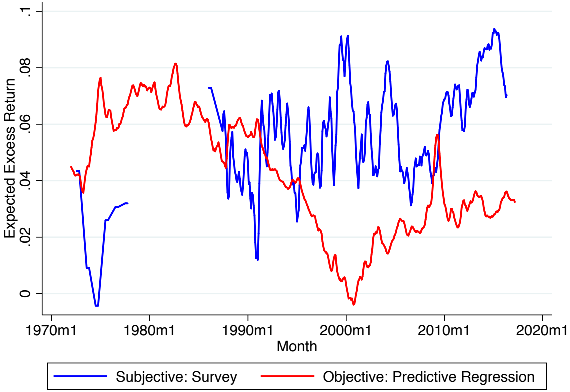
Subjective expectations and asset pricing

- Rational expectations (RE) asset pricing:
  - Subjective expectations = objective expectations
  - Beliefs not an object of empirical study
- Example: IID dividend growth

$$\Delta d_t = \mu + \sigma \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0, 1)$$

  Imposing RE:
  - Investors know μ and σ.
  - Tweak preferences and technology, not beliefs, to match asset pricing moments
- Issues:
  - How did investor acquire knowledge of μ, σ?
  - Any evidence that subjective = objective expectations?
  - How are subjective beliefs formed?

Disconnect between objective and subjective expected stock market excess returns



Source: Subjective = one-year expected stock market returns in excess of one-year Treasury yield from various individual investor surveys in Nagel and Xu (2018). Objective = Fitted value from predictive regression of stock market excess returns on log price-dividend ratio estimated on quarterly data 1927-2015.

Reconciling survey expectations and asset prices

Agenda:

1. Do individuals report expectations under distorted probability measures?
2. Models of expectations formation
3. Micro-evidence on expectations formation
4. Asset pricing models that match subjective belief dynamics from survey expectations

Talk draws on

1. Adam, K., D. Matveev, and S. Nagel. 2018. Survey Expectations and Stock Price Theories. Working paper.
2. Das, S., C. Kuhnen, and S. Nagel, 2018. Socioeconomic Status and Macroeconomic Expectations. Working paper.
3. Malmendier, U., and S. Nagel, 2011. Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking? *Quarterly Journal of Economics* 126, 373–416.
4. Malmendier, U., and S. Nagel, 2016. Learning from Inflation Experiences. *Quarterly Journal of Economics* 131, 53–87.
5. Nagel, S. and Z. Xu. 2018. Asset Pricing with Fading Memory. Working paper.

1. Do individuals report expectations under distorted probability measures?

Interpreting the disconnect between survey expectations and objective expectations

Survey expectations $\neq$ objective expectations

- Do RE asset pricing models get something fundamentally wrong?
- Or is the problem that preferences/risk-adjustments distort the expectations reported in surveys?
- Risk-neutral expectations hypothesis

> *If people report the risk-neutral expectation, then many surveys make sence [sic]. — Cochrane (2011)*

Risk-neutral expectations hypothesis

- RNE hypothesis asserts that people report marginal-utility (SDF) weighted expectation of returns

$$\mathcal{E}_{i,t}[R_{t+1}] = E_{i,t}\left[\frac{M_{i,t+1}}{E_{i,t}\left[M_{i,t+1}\right]} R_{t+1}\right],$$

  - Idea: Good times $\Rightarrow$ lower risk aversion $\Rightarrow$ lower weight on bad outcomes $\Rightarrow$ Optimism

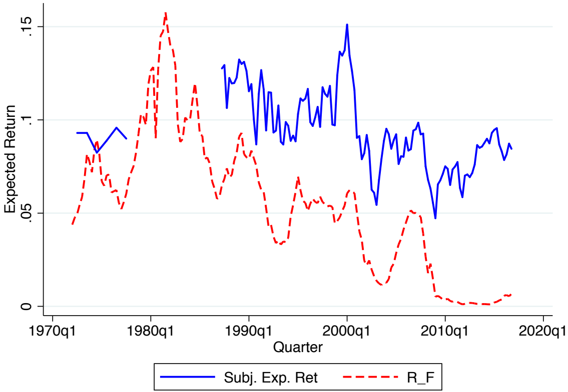
- But, in the absence of trading frictions,

$$\begin{aligned} 1 &= E_{i,t}[M_{i,t+1} R_{t+1}] \\ 1 &= E_{i,t}[M_{i,t+1}] R_{f,t}, \end{aligned}$$

- And so RNE hypothesis implies

$$\mathcal{E}_{i,t}[R_{t+1}] = R_{f,t},$$

Risk-neutral expectations: Unconditional test



Source: Subjective expected return = one-year expected stock market returns from various individual investor surveys in Nagel and Xu (2018). R_F = one-year Treasury yield

Risk-neutral expectations: Unconditional test

$$\mathcal{E}_{i,t}[R_{t+1}] - R_{f,t} = a + \varepsilon_{i,t},$$

Survey Source			a	t-statistic	p-value for $H_0 : a = 0$
CFO		mean	3.89	9.47	0.0000
		median	3.55	8.43	0.0000
UBS, own	all	mean	6.55	12.53	0.0000
		median	4.52	9.99	0.0000
	$>$100k	mean	6.40	12.36	0.0000
		median	4.79	10.82	0.0000
UBS, market	all	mean	6.64	13.31	0.0000
		median	4.61	14.13	0.0000
	$>$100k	mean	6.36	12.29	0.0000
		median	4.74	15.80	0.0000
UBS extended			5.80	20.10	0.0000

Based on Adam, Matveev, and Nagel (2018).

Risk-neutral expectations: Unconditional test

Survey Source			a	t-statistic	p-value for $H_0 : a = 0$
Shiller, individual	3m	mean	1.00	4.71	0.0000
		median	1.45	6.73	0.0000
	6m	mean	2.29	7.98	0.0000
		median	2.86	11.22	0.0000
	1yr	mean	5.02	9.26	0.0000
		median	5.81	13.14	0.0000
	10yr	mean	8.90	2.34	0.0194
		median	-5.33	-1.19	0.2341
Shiller, professional	3m	mean	0.68	2.28	0.0223
		median	1.48	5.19	0.0000
	6m	mean	2.16	3.82	0.0001
		median	3.86	8.94	0.0000
	1yr	mean	5.24	5.23	0.0000
		median	7.43	8.41	0.0000
	10yr	mean	42.47	10.79	0.0000
		median	28.88	7.88	0.0000

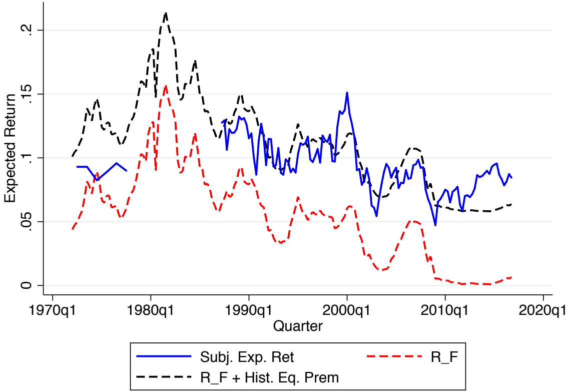
Based on Adam, Matveev, and Nagel (2018).

Pessimism hypothesis

- Ambiguity aversion, preference for robustness: Make **decisions** under pessimistically distorted probability measure
- Pessimism hypothesis: Individuals **survey responses** reflect this pessimistically distorted probability measure
- Prediction

$$\mathcal{E}_{i,t}[R_{t+1}] < E_t[R_{t+1}],$$

Pessimism hypothesis: Unconditional test



Source: Subjective expected return = one-year expected stock market returns from various individual investor surveys in Nagel and Xu (2018). R_F = one-year Treasury yield. Historical equity premium: Average return of CRSP value-weighted index in excess of one-year Treasury yield 1926-2016.

Summary: Do individuals report expectations under distorted probability measures?

- No support for risk-neutral expectations hypothesis
  - Unconditionally and conditionally
- No evidence of pessimism bias in average expectations
  - But: cross-sectionally, low socioeconomic status associated with pessimism (Das, Kuhnen, and Nagel 2018)
- Conclusion: Average survey respondent reports beliefs that
  - are not distorted by marginal utility / risk-adjustments
  - are subject to
    - time-varying biases with long-run mean zero
    - personal characteristics based biases that are cross-sectional mean zero

  relative to objective expectations

2. Models of expectations formation

Survey expectations and asset pricing

- Take survey expectations as individuals' forecasts under perceived physical distribution
  - i.e., not risk-adjusted, pessimistically distorted
- Goal: asset pricing models consistent with subjective belief dynamics from surveys
- Approach 1: Take expectations as exogenous input into asset pricing model
  - Period-by-period temporary equilibrium given expectations
  - e.g., Piazzesi and Schneider (2006)
- Approach 2: Endogenize expectations
  - Requires model of expectations formation
  - Helps eliminate noise in expectations survey data
  - Allows policy analysis in macro models

Models of expectations formation

- Candidate approaches
  - Bayesian learning
  - Adaptive learning
  - Learning from personal / cohort experience
  - Diagnostic expectations
  - Adaptive expectations
- Traditional criticism:

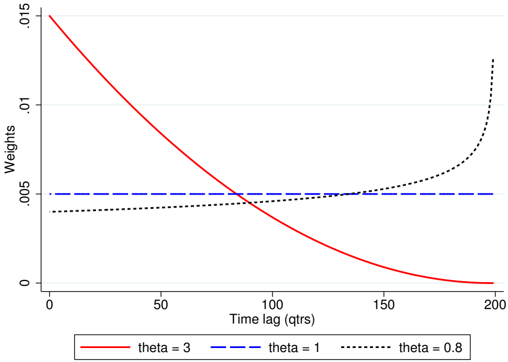
  Deviation from RE = lack of model "discipline"
- Response: Use subjective expectations data
  - as additional "moments" that model should match
  - to pin down parameters of belief dynamics

Learning from experience

- Example: investor learning about μ in stock cash flow growth

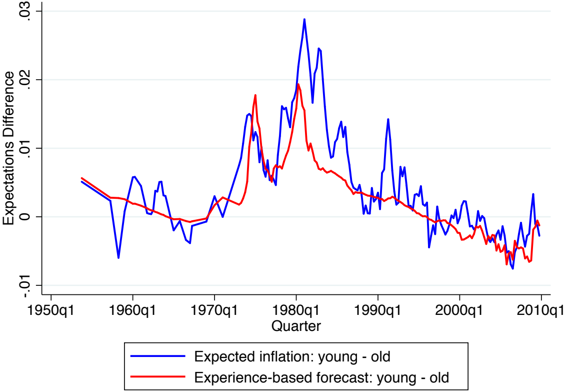
$$\Delta d_t = \mu + \epsilon_t, \qquad \epsilon_t \sim \mathrm{IID}$$

- Bayesian: Estimate μ with sample average of $\Delta d_0, \Delta d_1, ..., \Delta d_{t-1}$
- Learning from experience: Estimate μ with **weighted** average of **lifetime** data



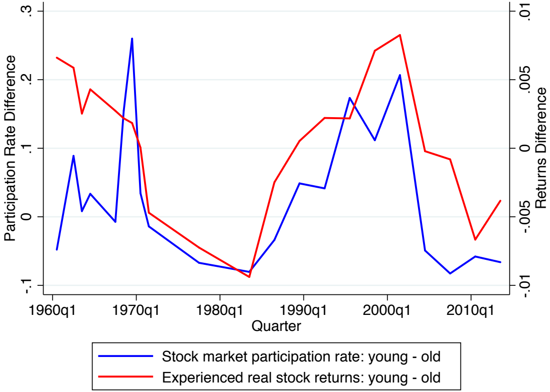
3. Micro-evidence on expectations formation

Learning from experience: Inflation



Based on Malmendier and Nagel (2016). **Inflation Expectations**: Michigan Survey of Consumers, one-year expected inflation rate. **Experience-based forecast**: AR(1) model forecast estimated based on weighted life-time inflation data for each survey respondent. Figure shows **differences**: average for individuals of age <40 minus average for individuals of age >60.

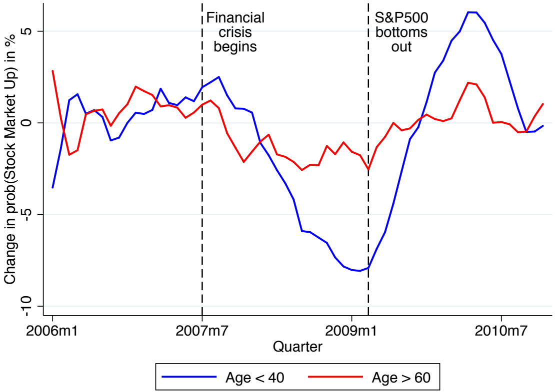
Learning from experience: Stock market participation



Based on Malmendier and Nagel (2011). **Stock market participation**: Survey of Consumer Finances, proportion of households owning stocks and stock mutual funds. **Experienced returns**: Weighted average of life-time real stock market returns for each survey respondent. Figure shows **differences**: average for individuals of age < 40 minus average for individuals of age > 60.

Update on MN (2011): Heterogeneity in belief updating during financial crisis

Six-month change in survey respondents' subjective probability of a rise in the stock market



Source: Michigan Survey of Consumers. Respondents' stated probability that stock market index will rise over the next 12 months compared to their response to the same question in the survey six months earlier. Averaged within age groups (< 40 and > 60) and over 12-month moving windows.

4. Asset pricing models that match subjective belief dynamics from survey expectations

Asset pricing with subjective beliefs

- What are investors learning / forming expectations about?
  - Returns?
  - Fundamentals (dividends)?
- Return expectations tricky: endogenous, depend on current asset price
- Example: Representative agent, constant risk aversion, constant risk $\Rightarrow$ Constant subjective expected returns
  - Optimism leads to higher current price, not higher expected returns
- Here: Focus on expectations about exogenous fundamentals
  - Return expectations determined in equilibrium along with asset price
  - Compare these implied return expectations with survey data

Asset Pricing with fading memory

- **Objective**: capture the essence of learning from experience that memory fades, but without the complications of cross-cohort heterogeneity
- Focus on dynamics of **average** belief: learning about mean endowment growth with fading memory
  - Simpler and quantitatively more realistic than OLG models in Collin-Dufresne et al. (2017), Ehling et al. (2018), Schraeder (2015), Malmendier et al. (2017)
- Yields asset pricing model that explains asset prices and expectations puzzles in simple setting
  - IID endowment growth
  - Recursive utility with constant risk aversion

Constant-gain learning

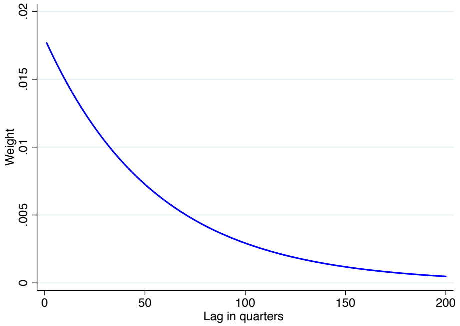
- Investor perceives stock payout growth as IID:

$$\Delta d_t = \mu_d + \epsilon_t, \qquad \epsilon_t \sim \mathrm{IID}$$

- Learns about μ_d with constant gain

$$\tilde{\mu}_{d,t+1} = \tilde{\mu}_{d,t} + \nu(\Delta d_{t+1} - \tilde{\mu}_{d,t})$$

- MN (2011, 2016): $\nu \approx 0.018$ (quarterly) for macro expectations & stock return beliefs



Simple approximation of subjective and objective expected returns

- Suppose for now: constant **subjective** risk premium θ and a constant risk-free rate r_f
- Campbell-Shiller present-value identity under investors' **subjective** expectations, $\tilde{\mathbb{E}}[.]$, yields

$$r_{t+1} = \left(1 + \frac{\rho\nu}{1-\rho}\right)(\Delta d_{t+1} - \tilde{\mu}_{d,t}) + \theta + r_f.$$

- Taking **objective** expectations: returns predictable with $\tilde{\mu}_{d,t}$

$$\mathbb{E}_t r_{t+1} - r_f = \theta + \left(1 + \frac{\rho\nu}{1-\rho}\right)(\mu_d - \tilde{\mu}_{d,t}),$$

- **Subjective** expectations **error**: predictable with $\tilde{\mu}_{d,t}$

$$\mathbb{E}_t r_{t+1} - \tilde{\mathbb{E}}_t r_{t+1} = \left(1 + \frac{\rho\nu}{1-\rho}\right)(\mu_d - \tilde{\mu}_{d,t}).$$

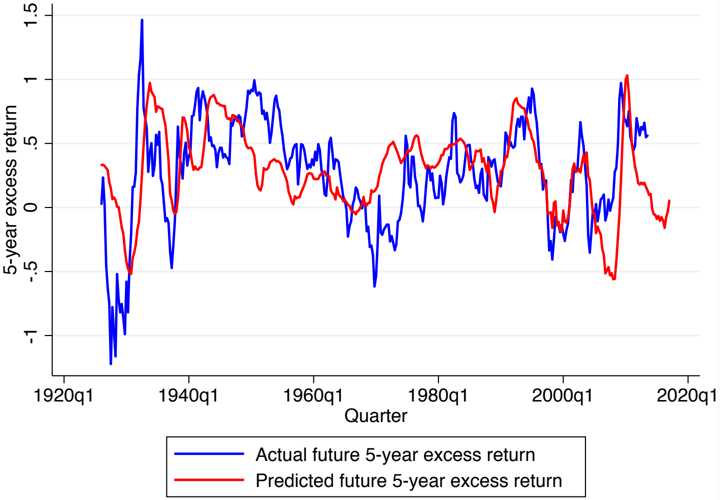
Measuring experienced payout growth

- Need long sample to compute Δd, back to 19th century
  - CRSP value-weighted index dividends and repurchases 1926-2016
  - Piketty et al. tax return data on aggregate household dividends 1913-1926
  - Aggregate nonfinancial dividends from Wright (2004) for 1900-1913
  - GDP growth 1871-1900
- Alternative proxy $\tilde{\mu}_r$: Weighted average of past real returns using returns data back to 1871 (Shiller S&P, then CRSP)
- For both, fix $\nu = 0.018$ based on MN (2016)
- Simulations of PV model: $\tilde{\mu}_{r,t}$ and $\tilde{\mu}_{d,t}$ have correlation 0.82.

Predicting Excess Returns with Experienced Payout Growth

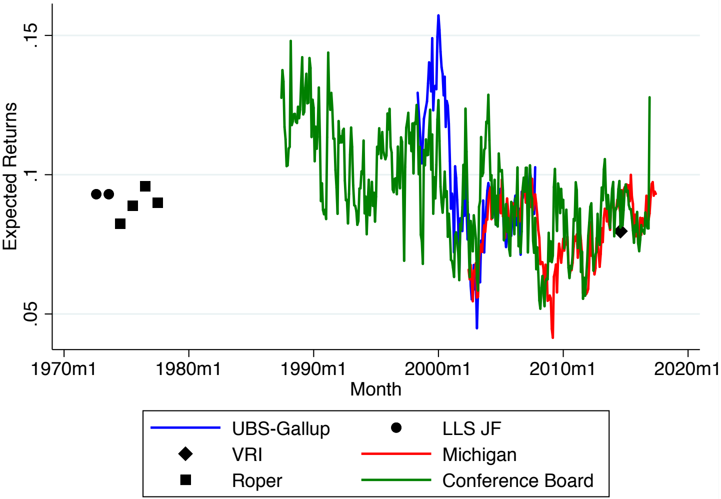
	(1) 1927-2016	(2) 1927-2016	(3) 1927-2016	(4) 1946-2016	(5) 1946-2016
Experienced real payout gr.	-5.79	-6.25	-5.82	-2.99	-1.29
[bias-adj. coeff.]	[-5.71]	[-6.14]	[-5.40]	[-2.82]	[-1.14]
(p-value)	(0.00)	(0.00)	(0.00)	(0.04)	(0.29)
Inflation		-0.73	-0.71	-1.60	-2.13
[bias-adj. coeff.]		[-0.75]	[-0.73]	[-1.68]	[-2.14]
(p-value)		(0.10)	(0.13)	(0.01)	(0.00)
$p - d$			-0.01		-0.04
[bias-adj. coeff.]			[0.01]		[-0.02]
(p-value)			(0.56)		(0.04)
Observations	360	360	360	284	284
R^2	0.033	0.037	0.034	0.027	0.044

Predicted five-year excess returns and subsequent actual cumulative five-year excess returns



Based on Nagel and Xu (2018).

Subjective return expectations: Directly measured and imputed



Based on Nagel and Xu (2018).

Survey Excess Return Expectations and Experienced Real Returns

	(1)	(2)	(3)
Panel A: Subjective expected excess returns			
Experienced real payout growth	0.35		0.42
	(0.99)		(0.93)
Lagged one-year return		0.03	0.03
		(0.01)	(0.01)
Constant	0.05	0.05	0.05
	(0.01)	(0.00)	(0.01)
Observations	126	126	126
Adj. R^2	-0.004	0.075	0.074

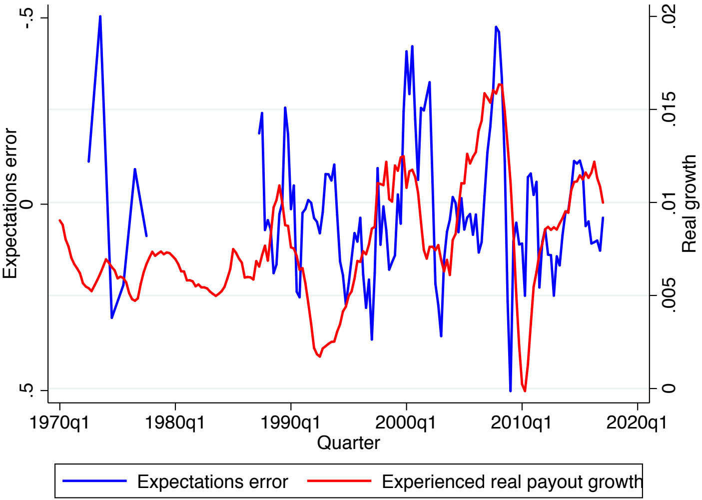
Based on Nagel and Xu (2018).

Survey Return Expectations and Experienced Real Returns

	(1)	(2)	(3)
Panel B: Expectation error: Realized - subj. expected			
Experienced real payout growth	-12.31		-12.55
	(6.75)		(6.80)
Lagged one-year return		-0.10	-0.12
		(0.14)	(0.15)
Constant	0.12	0.03	0.14
	(0.06)	(0.03)	(0.06)
Observations	126	126	126
Adj. R^2	0.055	0.002	0.059

Based on Nagel and Xu (2018).

Expectation Error Predictability



Based on Nagel and Xu (2018).

Learning with fading memory

- Endowment growth

$$\Delta c_{t+1} = \mu + \sigma\varepsilon_{t+1}, \qquad \varepsilon_t \sim \mathcal{N}(0,1)$$

  where representative agent knows σ but not μ
- Uses history $H_t \equiv \{\Delta c_0, \Delta c_1, \ldots, \Delta c_t\}$, to estimate μ.
- Posterior is formed with *weighted* likelihood

$$p(\mu|H_t) \propto p(\mu) \prod_{j=0}^{\infty} \left[\exp\left(-\frac{(\Delta c_{t-j} - \mu)^2}{2\sigma^2} \right) \right]^{(1-\nu)^j},$$

  where $\nu > 0$ induces fading memory.

Learning with fading memory

- With flat prior $p(\mu)$, posterior mean is

$$\tilde{\mu}_t = \nu \sum_{j=0}^{\infty} (1-\nu)^j \Delta c_{t-j},$$

- Equivalently,

$$\tilde{\mu}_t = \tilde{\mu}_{t-1} + \nu(\Delta c_t - \tilde{\mu}_{t-1}).$$

  i.e., updating with constant gain ν: perpetual learning.
- Subjective long-run risk: uncertainty about μ
- $S = 1/\nu$ is effective sample size
  - $S \approx 56$ quarters with $\nu = 0.018$

Predictive distribution

- Dividends levered, but cointegrated with endowment

$$\Delta d_{t+1} = \lambda \Delta c_{t+1} - \alpha(d_t - c_t - \mu_{dc}) + \sigma_d \eta_{t+1}, \quad \alpha > 0,$$

  ensures finite price of dividend claim.
- Epstein-Zin preferences with EIS $\psi = 1$.
- Following approach of Hansen, Heaton, and Li (2008), we get log SDF

$$m^1_{t+1|t} = \tilde{\mu}_m - \tilde{\mu}_t - \xi \sigma \tilde{\varepsilon}_{t+1},$$

Subjective and objective risk premia

- **Subjective** risk premium on "infinite-horizon" dividend strip

$$\log \tilde{\mathbb{E}}_t[R^{\infty}_{t+1}] - r_{f,t} = \left[1 + \nu \frac{\lambda - 1}{\alpha}\right] \xi \sqrt{1+\nu}\sigma^2,$$

  i.e., **constant**.

- **Objective** risk premium on "infinite-horizon" dividend strip

$$\begin{aligned} \log \mathbb{E}_t[R^{\infty}_{t+1}] - r_{f,t} =& \text{subj. prem.} + \text{const.} \\ & + \left(1 + \nu \frac{\lambda - 1}{\alpha}\right)(\mu - \tilde{\mu}_t), \end{aligned}$$

  i.e., **counter-cyclical**.

Baseline calibration

Parameter	Symbol	Value	Source
Belief updating			
Gain	ν	0.018	MN (2016) (survey data)
Endowment process			
Leverage ratio	λ	3	CJL (2017)
Dividend cointegration parameter	α	0.001	
Mean consumption growth	μ	0.45%	CJL (2017)
Consumption growth volatility	σ	1.35%	CJL (2017)
Dividend growth volatility	σ_d	1%	
Preferences			
Risk aversion	γ	4	
EIS	ψ	1	
Time discount factor	δ	0.9967	BKY (2012)

Unconditional moments

	Data 1927-2016	Model
$\mathbb{E}(\Delta c)$	1.84	1.80
$\sigma(\Delta c)$	2.72	2.70
$\mathbb{E}(\Delta d)$	2.38	1.80
$\sigma(\Delta d)$	13.31	8.35
$\sigma(\tilde{\mu}_d)$	1.32	1.55
$\rho(\tilde{\mu}_d)$	0.97	0.98
$\mathbb{E}(R_m - R_f)$	8.11	7.16
$\sigma(R_m - R_f)$	22.41	13.31
$SR(R_m - R_f)$	0.36	0.54
$\mathbb{E}(p - d)$	3.40	2.81
$\sigma(p - d)$	0.44	0.14
$\rho(p - d)$	0.97	0.91
$\mathbb{E}(r_f)$	0.67	1.64
$\sigma(r_f)$	2.47	0.51

Predicting Excess Returns in Simulated Data

		1Q (1)	1Y (2)	5Y (3)
$\tilde{\mu}_d$	mean	-2.43	-9.35	-38.67
	median	-2.17	-8.51	-36.90
$\tilde{\mu}_r$	mean	-1.51	-5.80	-23.82
	median	-1.35	-5.27	-22.77
$p-d$	mean	-0.06	-0.22	-0.93
	median	-0.05	-0.21	-0.92

Based on Nagel and Xu (2018).

Comparison for col. (1): Empirical point estimate -5.79, 1927-2016

Subjective Excess Return Expectations in Simulated Data

	coef.	(1)	(2)	(3)
Panel A: Subjective expected excess returns				
$\tilde{\mu}_d$	mean	0.83		0.83
	median	0.83		0.83
$r_{t-3,t}$	mean		0.006	0.000
	median		0.006	0.000
R^2_{adj}	mean	0.93	0.08	0.93
	median	0.94	0.07	0.94

Based on Nagel and Xu (2018).

Comparison for col. (1): Empirical point estimate 0.34 (Economically, ≈ 0)

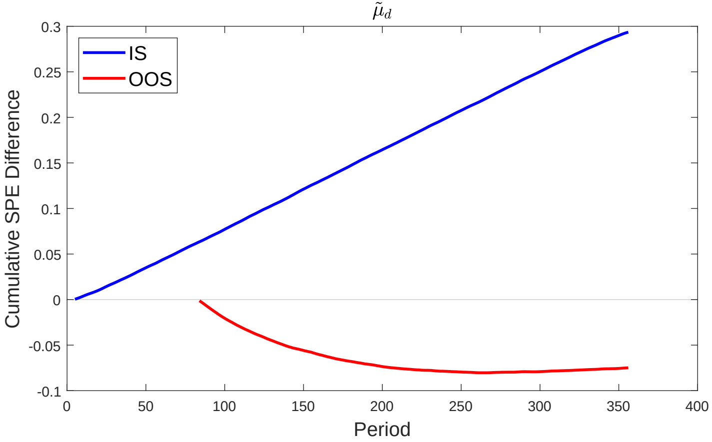
Subjective Expectations Errors in Simulated Data

	coef.	(1)	(2)	(3)
Panel B: Expectation error: Realized - subj. expected				
$\tilde{\mu}_d$	mean	-10.88		-11.17
	median	-9.98		-10.13
$r_{t-3,t}$	mean		-0.057	0.018
	median		-0.057	0.019
R^2_{adj}	mean	0.05	0.01	0.06
	median	0.05	0.00	0.05

Based on Nagel and Xu (2018).

Comparison for col. (1): Empirical point estimate -12.31

Lack of Out-of-Sample Return Predictability



Based on Nagel and Xu (2018).

Conclusion

- Survey expectations data informative about investor expectations
  - No marginal-utility weighting / risk-adjustment
  - No asymmetric loss in forecast construction
- Subjective beliefs data useful to inform about and constrain belief dynamics in asset pricing models
- Low-frequency cycles in asset prices and subjective expectations errors predictable by experienced stock market payout growth
- Learning with fading memory can reconcile survey expectations and explain asset pricing puzzles
  - with simple IID DGP and constant risk aversion (unlike CC and BY models)
  - in highly tractable framework (unlike OLG models)
  - with rate of memory loss calibrated to microdata