Heterogeneous Overreaction in Expectation Formation: Evidence and Theory

Heng Chen (HKU), Guangyu Pei (CUHK), Qian Xin (HITSZ), Xu Li (HKU)

EEA-ESEM Barcelona 2023

Jul 30, 2023

Introduction

- Testing theories of expectation formation using survey data on expectations:
  - rational expectations hypothesis $\Rightarrow \mathbb{COV}\left(\text{FE}, \text{FR}\right) = 0$
  - Bordalo, Gennaioli, Ma, and Shleifer (BGMS,2020)
    - ★ $\mathbb{COV}\left(\text{FE}_{i,t}, \text{FR}_{i,t}\right) < 0$: individual forecasts overreact to information
- This paper
  - a set of empirical evidence on heterogenous over-reactions
  - a theory of asymmetric and non-monotone expectation formation

This Paper I: Cross-Sectional Evidence

- Heterogenous overreaction in the cross-section of *Info. Surprise* $\equiv$ Info. $-$ Prior
  - **sign:** overreaction is stronger when the surprises are negative
  - **size:** overreaction tends to be weaker when the surprises are larger in size
- Forecast revisions are asymmetric and non-monotone in surprises

$$\text{FR} = \kappa\left(\text{Surp}\right) \cdot \text{Surp}$$

  - response to surprises is asymmetric: $\kappa\left(\text{Surp}_{-}\right) > \kappa\left(\text{Surp}_{+}\right)$
  - FR is non-monotone in Surp: $\frac{\partial \text{FR}}{\partial \text{Surp}} < 0$ for large $|\text{Surp}|$

Noisy RE: Kalman Filter

This Paper II: Theory and Quantitative Analysis

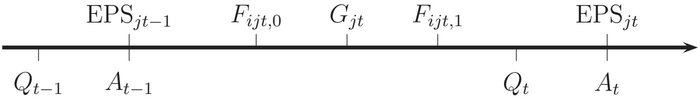
- A theory of expectation formation to rationalize the empirical facts that features
  - uncertain information quality $\rightarrow$ non-monotonicity
  - ambiguity averse analysts $\rightarrow$ asymmetry
- Quantitatively discipline the model with the data
  - a reasonable degree of ambiguity aversion can rationalize the empirical facts
  - heterogeneous overreaction originates from ambiguity and ambiguity aversion

Contributions Literature

The Empirical Evidence

Empirical Environment

- Financial analysts forecast earnings of the firms in each quarter



$\text{FR}_{ijt} = F_{ijt,1} - F_{ijt,0}$ $\text{FE}_{ijt} = \text{EPS}_{jt} - F_{ijt,1}$ $\text{Surprise}_{ijt} = G_{jt} - F_{ijt,0}$

Data and Sample Summary Statistics

Over-Reaction: FE-on-FR

$$\text{FE}_{ijt} = b_0 + b_1 \text{FR}_{ijt} + \delta_i + \delta_j + \delta_t + \omega_{ijt}.$$

	Outcome Variable: Forecast Error FE_i					
	Winsorization at the 1% and 99%			Winsorization at the 2.5% and 97.5%		
	Baseline	Control	Unscaled	Baseline	Control	Unscaled
	(1)	(2)	(3)	(4)	(5)	(6)
FR_i	-0.0952***	-0.0954***	-0.0964***	-0.0926***	-0.0926***	-0.0793***
	(0.0146)	(0.0147)	(0.0124)	(0.0119)	(0.0119)	(0.0102)
Earnings of the Last Quarter		0.0023			-0.0004	
		(0.0073)			(0.0050)	
Quarter FEs	YES	YES	YES	YES	YES	YES
Analyst FEs	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Obs.	110,895	110,895	110,895	110,895	110,895	110,895
Adj. R-sq	0.2429	0.2429	0.2170	0.2298	0.2298	0.2236

The standard errors are clustered on firm and calendar year-quarter.*** p<0.01, ** p<0.05, * p<0.1

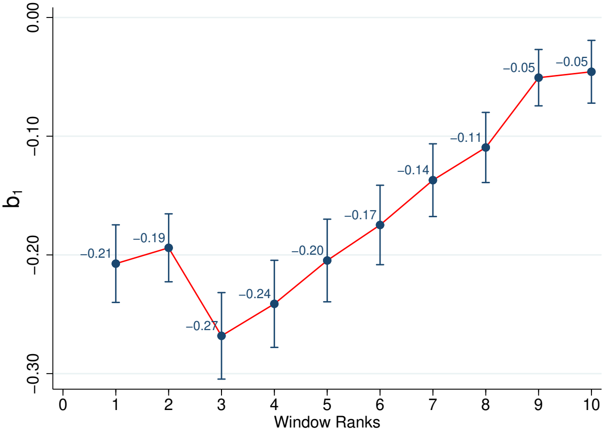
Robustness I: Subsamples   Robustness II: Trimming

Heterogeneous Over-Reactions

$$\text{FE}_{ijt} = b_0 + b_1 \text{FR}_{ijt} + \delta_i + \delta_j + \delta_t + \omega_{ijt}.$$

- One important feature of our empirical setting:
  - the guidance $G_{j,t}$ is common for all analysts,
  - but surprises Surpise_{ijt} contained in the guidance are heterogeneous across analysts
- FE-on-FR regression on running decile windows:
  - trimming the data set at the 2.5% and 97.5%
  - rank surprises from the most negative to the most positive and break them into deciles
  - construct a running decile window j covers decile $j-1$, j, and $j+1$
  - run FE-on-FR regression on each running decile window

Heterogeneous Over-Reactions



Robustness I: Trimming 1-99 | Robustness II: Decile Regression

Heterogeneous Over-Reactions: Mechanism

- FR-on-Surprise: marginal effect of Surprise on FR is state (surprise) dependent

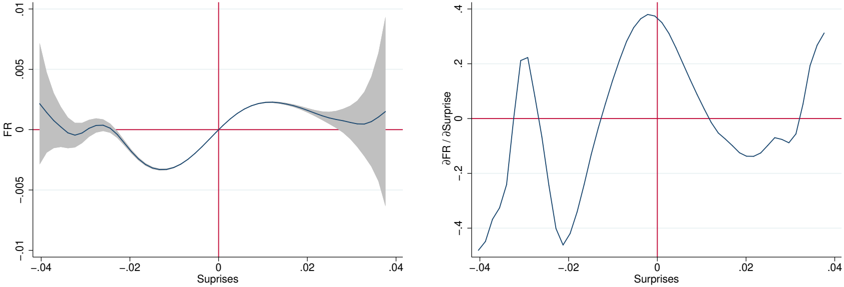
$$\frac{\partial \text{FR}}{\partial \text{Surprise}} = \kappa\left(\text{Surprise}\right) > 0$$

Noisy RE: Kalman Filter

FR-on-Surprise: Non-parametric Estimation

- Local polynomial regression with
  - Epanechnikov kernel and third degree of the polynomial smoother
- FR and Surp trimed at 2.5% and 97.5%
- FR and Surp residualized by controlling for quarter, firm, and analyst fixed effects

FR-on-Surprise: Non-parametric Estimation



(a) Non-parametric estimation

(b) Derivative: marginal effect

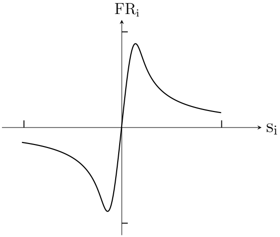
Trim at the 2.5% and 97.5%.

Robustness I: Trim. 1-99 | Robustness II: Winsorizing 1-99 | Robustness III: Consecutive Guidances | Robustness IV: Excluding Financial Crisis | Binscatter Plots

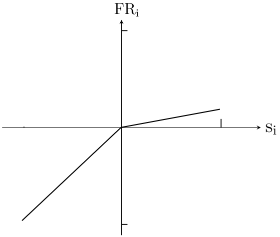
A Simple Forecasting Model

Asymmetric and Non-monotone Expectation Formation

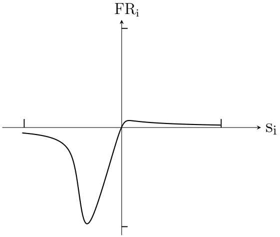
- Uncertain information quality → Bayesian updating → non-monotonicity
- Ambiguity aversion → pessimistic beliefs (as if) → asymmetry



(a) Ambiguity Neutral $\lambda = 0$



(b) Maxmin $\lambda \to +\infty$



(c) Ambiguity Aversion $\lambda > 0$

Model Setup and Characterization

A Summary: Non-monotonicity and Asymmetry

- If analysts have ambiguity neutral preferences ($\lambda = 0$),
  - non-monotone but symmetric
- If analysts have Wald (1950) maxmin criterion ($\lambda \to +\infty$),
  - asymmetric but monotone
- Qualitatively: the smooth model is in between, two competing forces
- Quantitatively: how much degree of ambiguity aversion is needed?

Average Overreaction

Quantitative Analysis

Connecting Theory to Data

- The challenge of unobservable private information of the analysts
- Is our model informative for the observable relationship quantitatively?

Disciplining Model with Data: Simulated Method of Moments

- Simulating our model and non-parametric estimation
- Construct a "distance" between simulated and empirical relationships

$$\Lambda(\Theta) = \frac{1}{N} \left[\hat{m} - m(\Theta)\right]' \hat{W} \left[\hat{m} - m(\Theta)\right]$$

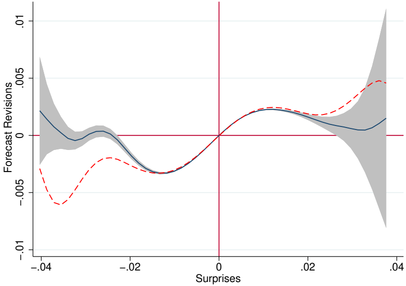
  - σ_θ is calibrated to match the standard deviation of realized earnings
  - $\Theta = \{\lambda, \beta, L, U, \sigma_\theta, \sigma_x, \sigma_Y, \sigma_z\}$
  - $\hat{m}$: a vector of N targeted moments from non-parametric estimation of the data
  - m: the vector of simulated moments as a function of the set of parameters Θ
  - $\hat{W}$ is the weighting matrix with diagonal elements being the precision of moments $\hat{m}$
- Choose parameters Θ to minimize the distance:
  - Laplace type estimator using MCMC with the Metropolis-Hasting algorithm
    - Chernozhukov and Hong (2003)
  - as if IRF matching [CEE (2005), ACEL (2011)]

Estimated Parameters

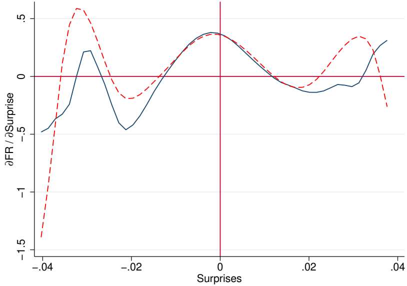
Table: Estimated Model Parameters

	Mean	90% HPDI	95% HPDI
λ	449.9	$(411.9, 504.0)$	$(379.5, 504.2)$
β	1.379	$(0.773, 1.971)$	$(0.694, 2.092)$
U	0.772	$(0.676, 0.855)$	$(0.674, 0.875)$
L	0.082	$(0.036, 0.119)$	$(0.030, 0.121)$
$100\sigma_x$	0.472	$(0.332, 0.593)$	$(0.305, 0.625)$
$100\sigma_z$	0.186	$(0.140, 0.234)$	$(0.137, 0.240)$
$100\sigma_Y$	0.435	$(0.416, 0.453)$	$(0.411, 0.453)$

Disciplining Model with Data: Non-Parametric Regression

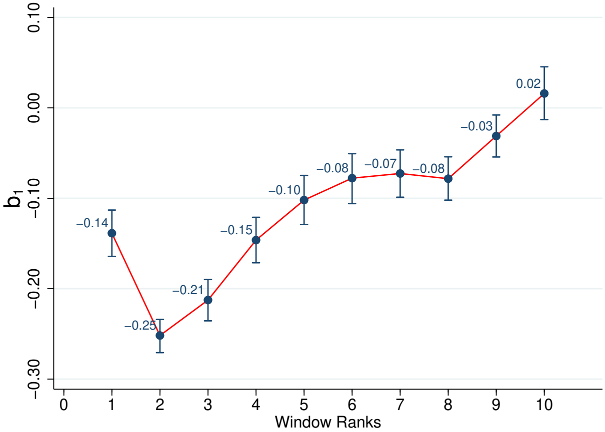


(a) $\lambda = 449.9$, Non-parametric estimation



(b) $\lambda = 449.9$, Derivative: marginal effect

Heterogeneous Over-Reaction and Ambiguity Aversion



Ambiguity Neutral | Max-Min | Average Overreaction

Discussions:

- Behavioural alternatives: Diagnostic Expectations; Over-Confidence; Loss Aversion.

- Agency Issues: Skewed Information Reliability; "Walk-down to beatable".

Dynamic Models | Exploiting Heterogeneity of Firms

Conclusion

- Empirical evidence expectation formation that features $\cdots$
  - heterogeneous over-reaction, asymmetry and non-monotonicity
  - the strategy of "FR-on-Surprise"
  - hard to be rationalized by existing theories of expectation formation
- A theory of expectation formation to rationalize the empirical facts that features
  - uncertain information quality and ambiguity aversion
- Quantitatively discipline the model with the data
  - a reasonable degree of ambiguity aversion can rationalize the empirical facts
  - heterogeneous overreaction originates from ambiguity and ambiguity aversion

Contributions

Contributions

- **Empirically**, evidence of expectation formation that features
  - heterogeneous over-reaction, asymmetry and non-monotonicity
  - cannot be rationalized by most of the existing theories of expectation formation
- **Methodologically,** the empirical strategy of "FR-on-Surprise"
  - a powerful test for asymmetry and non-monotonicity
  - complement to the "FE-on-FR" approach in the literature
- **Theoretically,** a theory of asymmetric and non-monotone expectation formation
  - rationalize the empirical facts qualitatively and quantitatively

Return-Intro Return-Conclusion

Literature Review I: Empirical Evidence of Expectation Formation

- Using survey data to test theories of expectation formation
  - Coibion and Gorodnichenko (2015)
    - "FE-on-FR", consensus forecasts of macroeconomic variables, under-reaction
  - Bordalo, Gennaioli, Ma, and Shleifer (2020)
    - "FE-on-FR", individual forecasts of macroeconomic variables, over-reaction
  - Bordalo, Gennaioli, Porta, and Shleifer (2019)
    - over-reaction in forecast data of firms' long-term earnings growth
  - Broer and Kohlhas (2019), Kohlhas and Walther (2021)
    - "FE-on-FR" and "FE-on-Info" at individual level, macroeconomic survey
    - mixed evidence on over- and under-reaction
  - Bouchaud, Krueger, Landier, and Thesmar (2019)
    - "FE-on-FR" and "FE-on-Info", consensus + individual, firm level earning forecasts
    - under-reaction in forecast data of short-term earnings growth
  - Angeletos, Huo, and Sastry (2020)
    - consensus forecasts initially under-react before over-shooting later on
  - Afrouzi, Kwon, Landier, Ma, and Thesmar (2021)
    - heterogeneous overreaction: persistence of DGP and forecast horizons matter

Return

Literature Review II: Theories of Expectation Formation

- Theories of expectation formation outside full information rational expectations:
  - rational inattention [Sims (2003)]
  - sticky information [Mankiw and Reis (2002)]
  - higher-order uncertainty [Morris and Shin (2002), Woodford (2003), Angeletos and Lian (2016)]
  - asymmetric attention [Mackowiak and Wiederholt (2009), Kohlhas and Walther (2021)]
  - diagnostic expectations [BGS (2018), BGMS (2020), Bianchi, Ilut, and Saijo (2022)]
  - over-confidence [Kohlas and Broer (2019)]
  - cognitive discounting [Gabaix (2020)]
  - level-K thinking [Garcia-Schmidt and Woodford (2019), Farhi and Werning (2019)]
  - narrow thinking [Lian (2020)]
  - autocorrelation averaging [Wang (2021)]
  - over-extrapolation + dispersed info [Angeletos, Huo, and Sastry (2020)]
  - **Loss aversion** [Capistran and Timmermann (2008), EKT(2008), ET(2008)]
  - **multiple prior preferences** [Epstein and Schneider (2008), Baqaee (2020)]
  - **uncertain info. quality** [Gentzkow and Shapiro (2006), Chen, Lu, and Suen (2016)]
  - . . .

Return

Literature Review III: Ambiguity Averse Preferences

- Smooth model of ambiguity and its applications under incomplete information
  - Klibanoff, Marinacci, and Mukerji (2005)
  - Pei (2023), Huo, Pedroni, and Pei (2023)
- Multiple prior preferences and its applications
  - Epstein and Schneider (2008), Baqaee (2020)
  - Ilut (2012), Ilut and Schneider (2014), Ilut and Saijo (2021)

Return

Data and Sample

- I/B/E/S Guidance and I/B/E/S Estimates data on firm EPS
  - firm-quarter data from 1994 - 2017 for guidance
  - analysts-firm-quarter data from 1994 - 2017 for EPS forecasts (sell-side)
  - EPS, its guidance and forecasts are
    - ★ manually split adjusted to ensure consistency with realized earnings
    - ★ deflated by stock price at the beginning of the quarter (CRSP)
  - sample selection:
    - ★ manager guidance with point or range forecasts (midpoint)
    - ★ exclude observations with bundled guidance
    - ★ exclude observations with the stock price less than $1 to avoid small price deflator problem
    - ★ multiple guidances—the latest guidance before earnings announcement

Return

Summary of Statistics

- Our final sample includes ···
  - 3226 different firms, each with 5.03 quarters on average;
  - about 6.83 analysts issue forecasts for a specific firm-quarter;
  - 6,987 individual analysts, each on average issues forecasts for 6.74 firms.

	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Initial forecasts	110,895	0.0120	0.0129	0.0070	0.0123	0.0180
Revised forecasts	110,895	0.0104	0.0149	0.0057	0.0113	0.0173
Forecast revision	110,895	-0.0016	0.0055	-0.0017	0.0000	0.0000
Forecast errors	110,895	-0.0000	0.0047	0.0000	0.0003	0.0011
Unfavorable	110,895	0.6256	0.4840	0.0000	1.0000	1.0000
Surprise	110,895	-0.0040	0.0171	-0.0062	-0.0012	0.0003
Managerial guidance	16,241	0.0067	0.0293	0.0027	0.0089	0.0160
Earnings	16,241	0.0089	0.0197	0.0044	0.0112	0.0177

Return

FE-on-FR: Robustness I

	Outcome Variable: Forecast Error FE_i					
	Winsorization at the 1% and 99%			Winsorization at the 2.5% and 97.5%		
	Excl Pre-anc	Excl Multiple	Excl Both	Excl Pre-anc	Excl Multiple	Excl Both
	(1)	(2)	(3)	(4)	(5)	(6)
FR_i	-0.0733**	-0.1561***	-0.1545***	-0.0731***	-0.1536***	-0.1540***
	(0.0284)	(0.0217)	(0.0469)	(0.0228)	(0.0171)	(0.0352)
Quarter FEs	YES	YES	YES	YES	YES	YES
Analyst FEs	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES
Obs.	50,558	46,493	17,606	50,558	46,493	17,606
Adj R-sq.	0.2675	0.3020	0.3412	0.2727	0.2842	0.3285

The standard errors are clustered on firm and calendar year-quarter.*** p<0.01, ** p<0.05, * p<0.1

Return

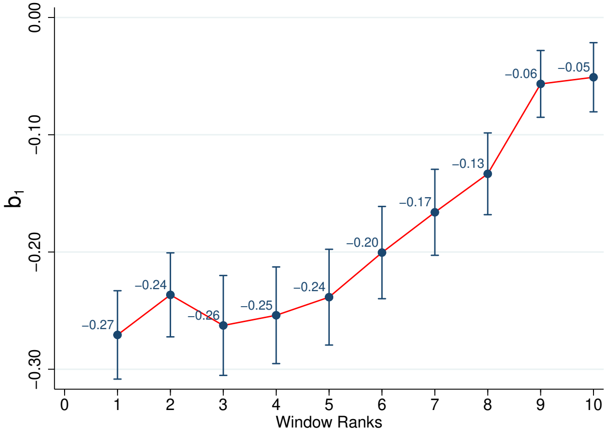
FE-on-FR: Robustness II

	Outcome Variable: Forecast Error FE_i							
	Trimmed at 1% and 99%				Trimmed at 2.5% and 97.5%			
	Full	Excl Pre-anc	Excl Multiple	Excl Both	Full	Excl Pre-anc	Excl Multiple	Excl Both
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FR_i	-0.1024***	-0.0942***	-0.1627***	-0.1774***	-0.0854***	-0.0819***	-0.1492***	-0.1568***
	(0.0105)	(0.0208)	(0.0137)	(0.0287)	(0.0082)	(0.0137)	(0.0107)	(0.0186)
Quarter FEs	YES	YES	YES	YES	YES	YES	YES	YES
Analyst FEs	YES	YES	YES	YES	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	106,614	48,950	43,756	16,738	100,308	46,363	40,148	15,484
Adj R-sq.	0.2250	0.2762	0.2817	0.3336	0.2110	0.2748	0.2654	0.3139

The standard errors are clustered on firm and calendar year-quarter.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

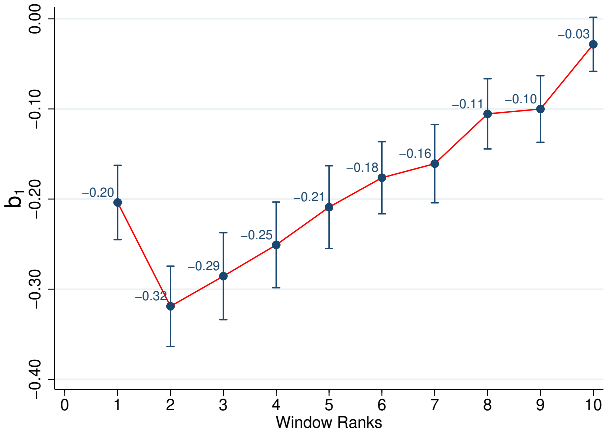
Return

Heterogeneous Over-Reaction: Trim at 1% and 99%



Return

Heterogeneous Over-Reaction: Regressions on Deciles



Return

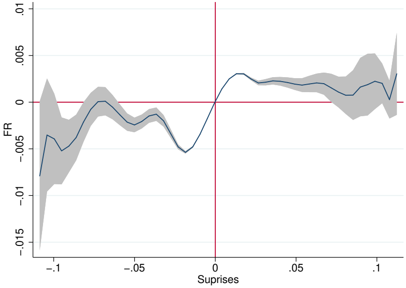
Robustness: Definition of Large Surprises

	Outcome Variable: Forecast Revision FR_i			
	Winsorization at 1% and 99%		Winsorization at 2.5% and 97.5%	
	(1) $n = 1.5$	(2) $n = 2$	(3) $n = 1.5$	(4) $n = 2$
Surprise$_i$	0.4311***	0.3971***	0.4575***	0.4193***
	(0.0188)	(0.0184)	(0.0162)	(0.0169)
Large	-0.0060***	-0.0046***	-0.0020***	-0.0019***
	(0.0006)	(0.0007)	(0.0003)	(0.0003)
Surprise$_i$ × Large	-0.3502***	-0.3203***	-0.2852***	-0.2655***
	(0.0194)	(0.0182)	(0.0167)	(0.0175)
Constant	0.0001	-0.0001	0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Quarter FEs	YES	YES	YES	YES
Analyst FEs	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Obs	110,895	110,895	110,895	110,895
Adj R-sq.	0.4819	0.4811	0.5019	0.5032

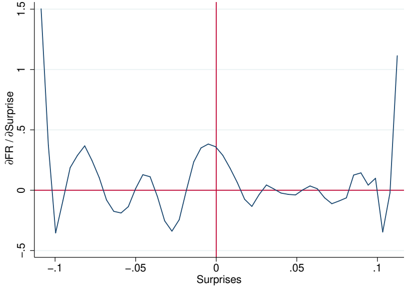
The standard errors are clustered on firm and calendar year-quarter. ***p<0.01, **p<0.05, *p<0.1

Return

Non-parametric Estimation: Robustness I



(a) Non-parametric estimation

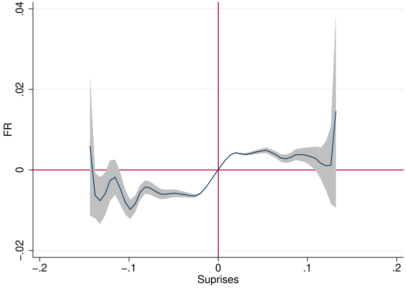


(b) Derivative: the marginal effect

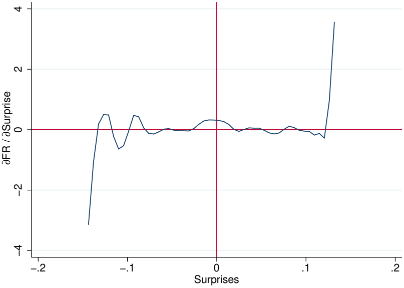
Trim at the 1% and 99%.

Return

Non-parametric Estimation: Robustness II



(a) Winsorization, Non-parametric estimation

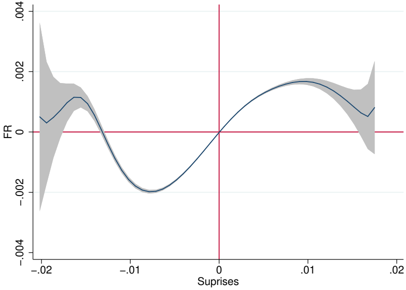


(b) Trimming, Non-parametric estimation

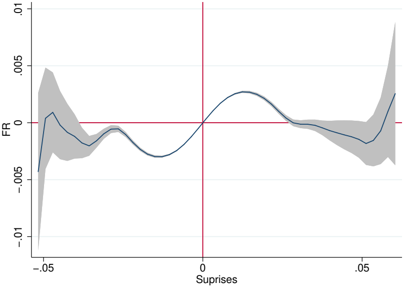
Winsorizing at the 1% and 99%.

Return

Non-parametric Estimation: Robustness III



(a) 5% Triming, Non-parametric estimation

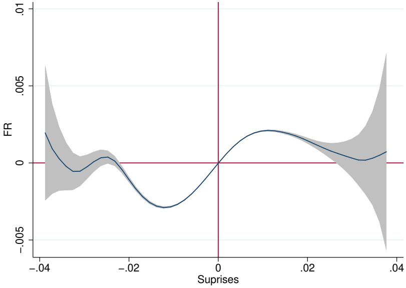


(b) 2% Trimming, Non-parametric estimation

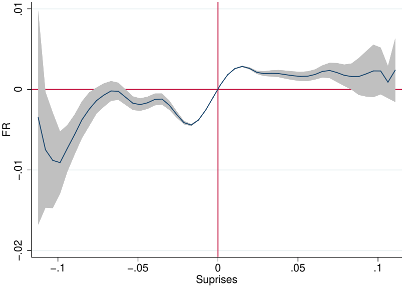
Subsample of Firms that Issued at Least 12 Consecutive Guidances.

Return

Non-parametric Estimation: Robustness IV



(a) 5% Triming, Non-parametric estimation

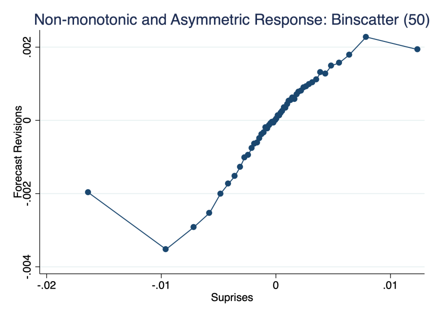


(b) 2% Trimming, Non-parametric estimation

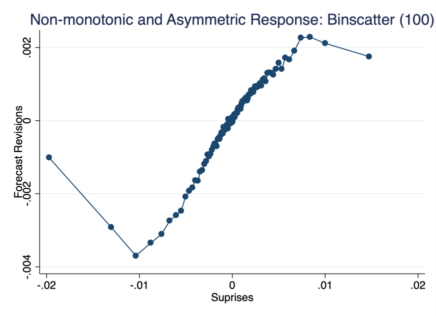
Subsample that Excludes the Period of the Financial Crisis.

Return

Binscatter Plots I



(a) Binscatter (50 bins)

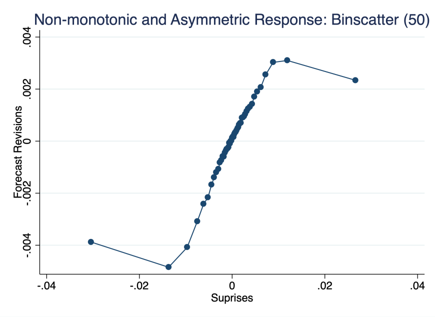


(b) Binscatter (100 bins)

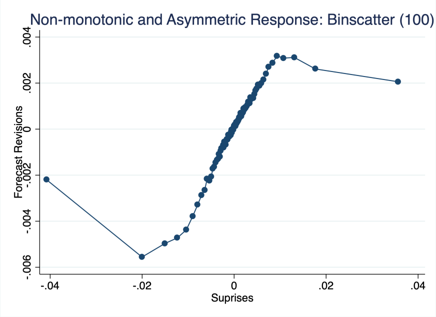
Trim at the 2.5% and 97.5%.

Return

Binscatter Plots II



(a) Binscatter (50 bins)



(b) Binscatter (100 bins)

Trim at the 1% and 99%.

Return

Over-Reaction I

Proposition: if analysts are ambiguity neutral, i.e., $\lambda = 0$,

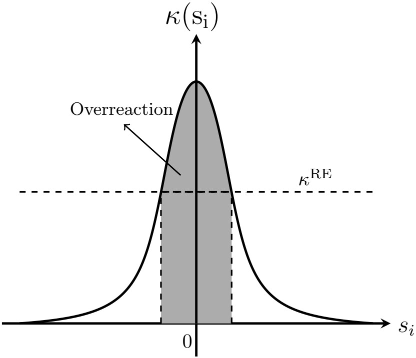
$$\text{sign}\left\{\frac{\mathbb{COV}\left(\text{FE}_i, \text{FR}_i\right)}{\mathbb{V}\left(\text{FR}_i\right)}\right\} = \text{sign}\left\{\kappa^{\text{RE}} - \hat{\mathbb{E}}\left[\kappa\left(s_i\right)\right]\right\}.$$

- $\kappa^{\text{RE}} = \frac{\tau_Y}{\tau_\theta + \tau_z + \tau_Y}$ denotes the FR's response to surprise under rational expectation.
- $\hat{\mathbb{E}}\left[\cdot\right]$ is an expectation operator under the adjusted belief $\hat{p}\left(s_i\right)$,

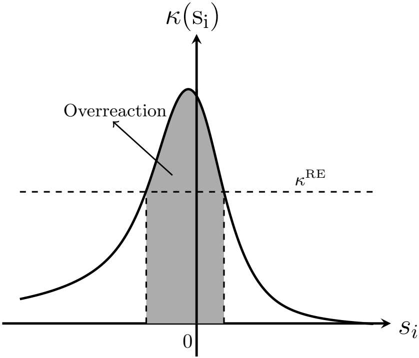
$$\hat{\mathbb{E}}\left[\kappa\left(s_i\right)\right] \equiv \int_{\mathbb{R}} \kappa\left(s_i\right)\hat{p}\left(s_i\right) \mathrm{d}s_i; \qquad \hat{p}\left(s_i\right) \propto \Omega(s_i) p\left(s_i\right); \qquad \Omega(s_i) \equiv \frac{\kappa\left(s_i\right) s_i^2}{\mathbb{E}\left[\kappa\left(s_i\right) s_i^2\right]}.$$

Return

Over-Reaction II



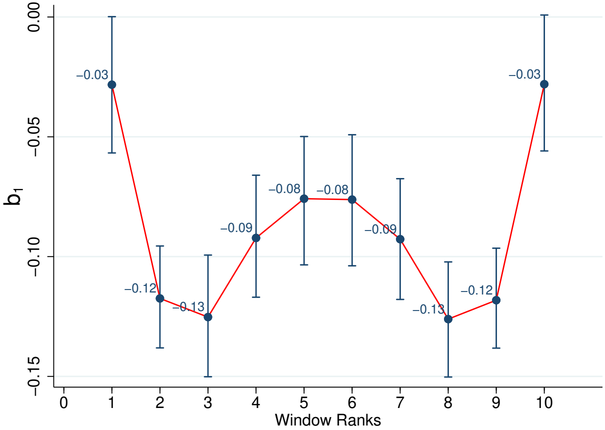
(a) Ambiguity Neutral $\lambda = 0$



(b) Ambiguity Averse $\lambda > 0$

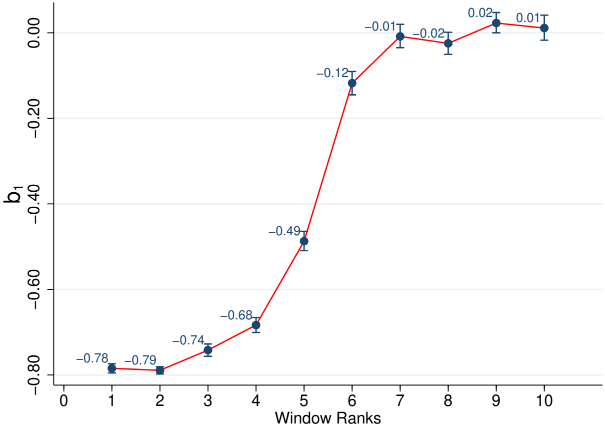
Return

Heterogeneous Over-Reaction and Ambiguity Neutrality



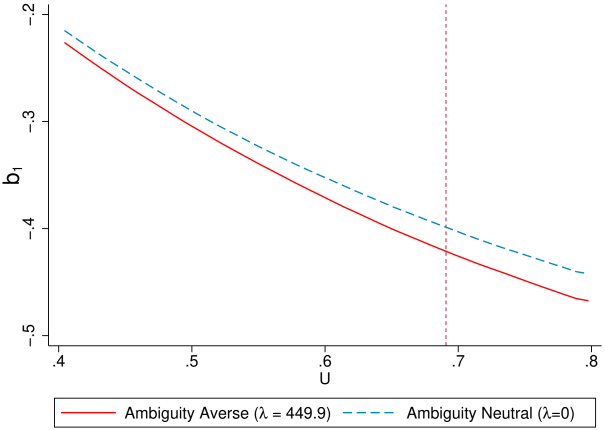
Return

Heterogeneous Over-Reaction and Max-Min Criterion



Return

Average Over-Reaction and Ambiguity Aversion



Return

Diagnostic Expectations and Over Confidence

- Diagnostic Expectations

$$\mathsf{FR}_i^{\mathsf{DE}} = (1+\psi)\,\kappa^{\mathsf{RE}}\left(y - \mathsf{F}_{0i}^{\mathsf{DE}}\right) + \psi\left[\kappa^{\mathsf{RE}} - \frac{1}{1+\psi}\right]\mathsf{F}_{0i}^{\mathsf{DE}},$$

- Over Confidence

$$\mathsf{FR}_i^{\mathsf{OC}} = \kappa_y^{\mathsf{OC}}\left(y_i - \mathsf{F}_{0i}\right) \qquad \kappa_y^{\mathsf{OC}} > \kappa^{\mathsf{RE}}$$

Return

Loss Aversion

- The parsimonious setup [Capistrán and Timmermann (2009)]
  - asymmetric loss function

$$L\left(F_i, \theta; \phi\right) = \frac{1}{\phi^2}\left[\exp\left(\phi\left(\theta - F_i\right)\right) - \phi\left(\theta - F_i\right) - 1\right],$$

  - biased optimal forecasts

$$F_i^* = \mathbb{E}_i\left[\theta\right] - \frac{1}{2}\phi \mathsf{Var}_i\left[\theta\right].$$

  - forecast revisions are still linear in surprises.
  - no overreactions: $\mathbb{COV}\left(\mathsf{FE}_i, \mathsf{FR}_i\right) = 0$
- The flexible setup [Elliott and Timmermann (2008), Elliott, Komunjer, and Timmermann (2008)]
  - potentially non-linear but globally monotone FR-on-Surp relation

Return

Agency Issues: Skewed Information Reliability

- Agency issues between analysts and the managerial teams:
  - managers spinning information in self-serving ways to cater to investors and analysts
  - delayed disclosure of bad news
- Asymmetry ✓; Non-monotonicity ✗

Return

Agency Issues: Skewed Information Reliability

	Outcome Variable: Absolute Difference between Guidance and Earnings			
	Sample: Full		Exclude Conforming	
	1% and 99%	2.5% and 97.5%	1% and 99%	2.5% and 97.5%
	(1)	(2)	(3)	(4)
Negative Guidance	0.0012***	0.0008***	0.0010***	0.0003
	(5.1339)	(3.7038)	(3.1044)	(1.2632)
Constant	0.0050***	0.0048***	0.0057***	0.0056***
	(35.1519)	(38.5143)	(26.4874)	(30.2028)
Quarter FEs	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Observations	15,528	15,528	13,476	13,500
Adjusted R-squared	0.6105	0.5395	0.6151	0.5428

Notes: The observation numbers in columns (3) and (4) vary because the numbers of conforming cases vary due to Winsorization. The standard errors are clustered on firm and year-quarter. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Return

Agency Issues: Walk-Down to Beatable

- Manager's incentives to manage guidance downwards before the earning releases
  - e.g., Matsumoto (2002), Cotter et al., (2006), Johnson et al., (2020)
- The expectation management index (EMI): Johnson et al. (2020)
  - higher EMI indicates stronger incentives for driving down earning expectations
- Adding EMI as additional control for our empirical analysis
  - estimated coefficients are barely affected in terms of magnitude and significance.

Return

Dynamic Models

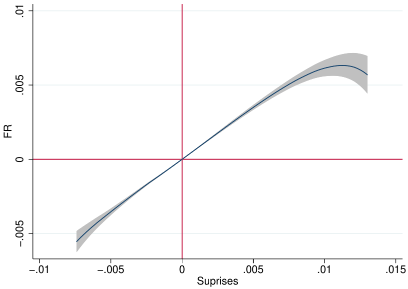
	Outcome Variable: in Quarter t for Firm j, Analyst i's			
	Forecast Errors		Forecast Revisions	
	1% and 99%	2.5% and 97.5%	1% and 99%	2.5% and 97.5%
	(1)	(2)	(3)	(4)
Earnings in the Last Quarter $(t-1)$	0.0008	-0.0010	-0.0048	-0.0058
	(0.0070)	(0.0049)	(0.0066)	(0.0053)
Surprise$_i$			0.1468***	0.2445***
			(0.0125)	(0.0128)
Constant	-0.0000	0.0001**	-0.0009***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Quarter FEs	YES	YES	YES	YES
Analyst FEs	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Obs.	110,895	110,895	110,895	110,895
Adj. R-sq	0.2341	0.2202	0.3943	0.4588

The standard errors are clustered on firm and calendar year-quarter.*** p<0.01, ** p<0.05, * p<0.1

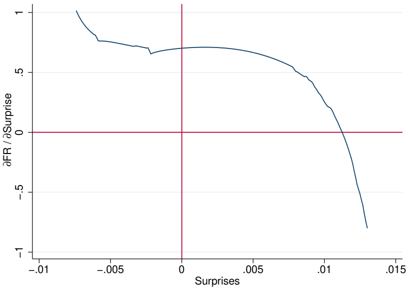
Return

Exploiting Firm Heterogeneity

- For firms with low or no uncertainty in earnings guidance quality,
    - analysts' forecast revisions should be close to linear in guidance surprise



(a) Non-parametric estimation



(b) Derivative: marginal effect

Return

Linear FR-on-Surp Relation

- Noisy RE with AR(1) fundamental θ_t and Gaussian signals $\mathcal{I}_{i,t} = \mathcal{I}_{i,t-1} \cup \{x_{i,t}, y_t\}$
  - standard Kalman filter implies that

$$\mathbb{E}_{i,t}[\theta_t] = (1 - \delta_x)\,\mathbb{E}_{i,t-1}[\theta_t] + \delta_x x_{i,t} + \delta_y y_t$$

  - or equivalently a linear FR-on-Surp relation

$$\mathsf{FR}_{i,t} \equiv \mathbb{E}_{i,t}[\theta_t] - \mathbb{E}_{i,t-1}[\theta_t] = \delta_x\left(x_{i,t} - \mathbb{E}_{i,t-1}[\theta_t]\right) + \delta_y\left(y_t - \mathbb{E}_{i,t-1}[\theta_t]\right).$$

- Extends to behavioural models such as
  - diagnostic expectations, over-confidence, and loss aversion

Return I Return II

The Model: A Static Setup

- A continuum of analysts, indexed by $i \in [0, 1]$ and a firm with fundamental θ
- Each analyst makes a forecast F about firm fundamental θ with utility given by:

$$U(F_i, \theta) = -(F_i - \theta)^2 + \beta\theta + \alpha\theta^2$$

  - quadratic approximation around complete information solution
  - restriction: $F_i^* = \theta$, under complete information
  - β plays no roles with noisy rational expectations: $F_i^* = \mathbb{E}_i[\theta]$
  - β plays important roles with ambiguity averse analysts
  - abstract out quadratic terms for simplicity: $\alpha = 0$

Return

Information Structure

- The firm fundamental θ is normally distributed with mean 0 and precision τ_θ:

$$\theta \sim N\left(0, 1/\tau_\theta\right)$$

- At stage 0, each analyst i is endowed with private information about the earning

$$z_{0i} = \theta + \iota_i, \qquad \iota_i \sim N\left(0, 1/\tau_z\right)$$

- At stage 1, each analyst i receives a managerial guidance released by the firm:

$$y = \theta + \eta, \qquad \eta \sim N\left(0, 1/\tau_Y\right)$$

Return

Ambiguity in Quality

- Analysts possess ambiguity about the quality of manager guidance τ_y

$$\tau_y \in \Gamma_y, \qquad p\left(\tau_y\right)$$

  - e.g. $\Gamma_y = \left[\tau_{y,\min}, \tau_{y,\max}\right]$ and $p\left(\tau_y\right) = \frac{1}{\tau_{y,\max} - \tau_{y,\min}}$

Return

Ambiguity Averse Analysts

- The smooth model of ambiguity - Klibanoff, Marinacci, and Mukerji (2005)

$$F_i^* = \arg\max_F \int_{\Gamma_y} \phi\left(\mathbb{E}^{\tau_y}\left[U\left(F, \theta\right) | \mathcal{I}_i\right]\right) p\left(\tau_y | \mathcal{I}_i\right) \mathrm{d}\tau_y$$

  - CAAA specification: $\phi(t) = -\frac{1}{\lambda}\exp(-\lambda t)$
    - $\lambda = 0$, ambiguity neutral
    - $\lambda \to +\infty$, max-min criterion of Wald (1950)
  - Bayesian updating

$$p\left(\tau_y | \mathcal{I}_i\right) \propto p\left(\mathcal{I}_i | \tau_y\right) p\left(\tau_y\right)$$

Return

Ambiguity Averse Analysts

- The smooth model of ambiguity - Klibanoff, Marinacci, and Mukerji (2005)

$$F_i^* = \arg\max_F \int_{\Gamma_y} \phi\left(\mathbb{E}^{\tau_y}\left[U(F,\theta)\,|\mathcal{I}_i\right]\right) p\left(\tau_y|\mathcal{I}_i\right) \mathrm{d}\tau_y$$

  - CAAA specification: $\phi(t) = -\frac{1}{\lambda}\exp(-\lambda t)$
    - $\lambda = 0$, ambiguity neutral
    - $\lambda \to +\infty$, max-min criterion of Wald (1950)
  - Bayesian updating

$$p\left(\tau_y|\mathcal{I}_i\right) \propto p\left(\mathcal{I}_i|\tau_y\right) p\left(\tau_y\right)$$

Return

Ambiguity Averse Analysts

- The smooth model of ambiguity - Klibanoff, Marinacci, and Mukerji (2005)

$$F_i^* = \arg\max_F \int_{\Gamma_y} \phi\left(\mathbb{E}^{\tau_y}\left[U(F,\theta)\,|\mathcal{I}_i\right]\right) p\left(\tau_y|\mathcal{I}_i\right) \mathrm{d}\tau_y$$

  - CAAA specification: $\phi(t) = -\frac{1}{\lambda}\exp(-\lambda t)$
    - $\lambda = 0$, ambiguity neutral
    - $\lambda \to +\infty$, max-min criterion of Wald (1950)
  - Bayesian updating

$$p\left(\tau_y|\mathcal{I}_i\right) \propto p\left(\mathcal{I}_i|\tau_y\right) p\left(\tau_y\right)$$

Return

Ambiguity Averse Analysts

- The smooth model of ambiguity - Klibanoff, Marinacci, and Mukerji (2005)

$$F_i^* = \arg\max_F \int_{\Gamma_y} \phi\left(\mathbb{E}^{\tau_y}\left[U(F,\theta)\,|\mathcal{I}_i\right]\right) p\left(\tau_y|\mathcal{I}_i\right) \mathrm{d}\tau_y$$

  - CAAA specification: $\phi(t) = -\frac{1}{\lambda}\exp(-\lambda t)$
    - $\lambda = 0$, ambiguity neutral
    - $\lambda \to +\infty$, max-min criterion of Wald (1950)
  - Bayesian updating

$$p\left(\tau_y|\mathcal{I}_i\right) \propto p\left(\mathcal{I}_i|\tau_y\right) p\left(\tau_y\right)$$

Return

Optimal Forecasts

$$F_{0i} = \arg\max_F \mathbb{E}\left[U\left(F,\theta\right)|z_{0i}\right] = \mathbb{E}\left[\theta|z_{0i}\right] = \frac{\tau_z}{\tau_\theta + \tau_z} z_{0i}$$

$$F_i = \int_{\Gamma_y} \underbrace{\left(\frac{\tau_z z_{0i} + \tau_y y}{\tau_\theta + \tau_z + \tau_y}\right)}_{\mathbb{E}^{\tau_y}\left[\theta|z_{0i},y\right]} \tilde{p}\left(\tau_y|z_{0i},y;F_i\right) \mathrm{d}\tau_y$$

$$\tilde{p}\left(\tau_y|z_{0i},y;F_i\right) \propto \underbrace{\phi'\left(\mathbb{E}_i^{\tau_y}\left[U\left(F_i,\theta\right)\right]\right)}_{\text{Pessimistic Distortion}} \underbrace{p\left(z_{0i},y|\tau_y\right)p\left(\tau_y\right)}_{\text{Bayesian Kernel}}.$$

Return

Optimal Forecasts (Cont.)

$$\mathrm{FR}_i \equiv F_i - F_{0i} = \kappa\left(s_i\right) \cdot \underbrace{\left(y - F_{0i}\right)}_{s_i}$$

$$\kappa\left(s_i\right) = \left[\int_{\Gamma_y} \left(\frac{\tau_y}{\tau_\theta + \tau_z + \tau_y}\right) \tilde{p}\left(\tau_y | s_i; \kappa\left(s_i\right)\right) \mathrm{d}\tau_y\right]$$

Proposition: (Existence and Uniqueness)

If analysts are ambiguity averse ($\lambda > 0$), there always exists a unique optimal forecast $F_i^*\left(X_i, s_i\right)$ and a unique optimal response $\kappa^*\left(s_i\right)$ associated with it.

Return

Asymmetry

- For $s_i^- < 0 < s_i^+$ and $s_i^- + s_i^+ = 0$

$$\text{sign}\left[\kappa^*\left(s_i^-\right) - \kappa^*\left(s_i^+\right)\right] = \text{sign}[\beta]$$

- Upon aggregation:

$$\text{sign}[\kappa_-^* - \kappa_+^*] = \text{sign}\,[\beta]\,,$$

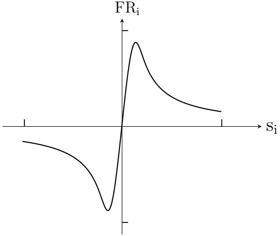
in which

$$\kappa_-^* \equiv \int_{\mathbb{R}^-} \kappa^*\left(s_i\right) \mathrm{d}P_s\left(s_i | s_i < 0\right); \qquad \kappa_+^* \equiv \int_{\mathbb{R}^+} \kappa^*\left(s_i\right) \mathrm{d}P_s\left(s_i | s_i > 0\right).$$

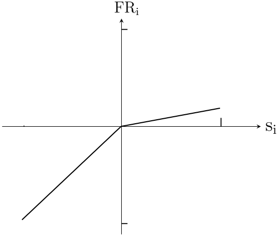
Return

Non-Monotonicity

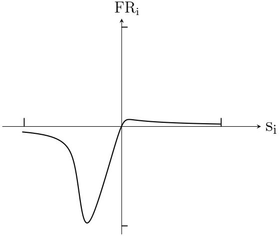
$$\frac{\partial \mathsf{FR}_i}{\partial s_i} = \kappa\left(s_i\right) + \frac{\partial \kappa\left(s_i\right)}{\partial s_i} \cdot s_i$$



(a) Ambiguity Neutral $\lambda = 0$



(b) Maxmin $\lambda \to +\infty$



(c) Ambiguity Aversion $\lambda > 0$

Return