Decision weights for experimental asset prices based on visual salience

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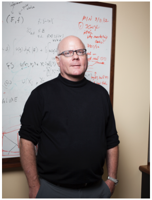

NBER Behavioral Finance Meetings, May 2020

Introduction

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- Trained on large N, varied images
- Calibrated using eyetracked 3-5 sec fixations
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- We apply off-the-shelf algorithms to asset price charts

Price Charts

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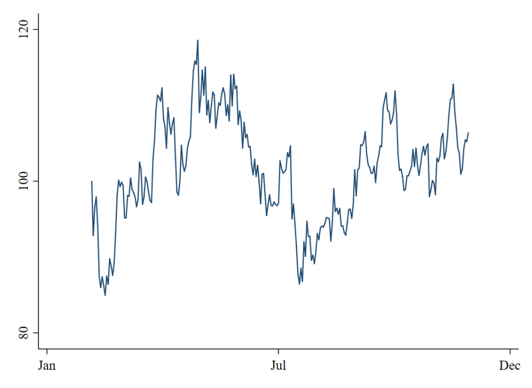
- Two kinds of information:
    - Visual properties: Peaks, troughs, jumps...
    - "Distilled" features: Returns, variance, extrapolation...

Expectations



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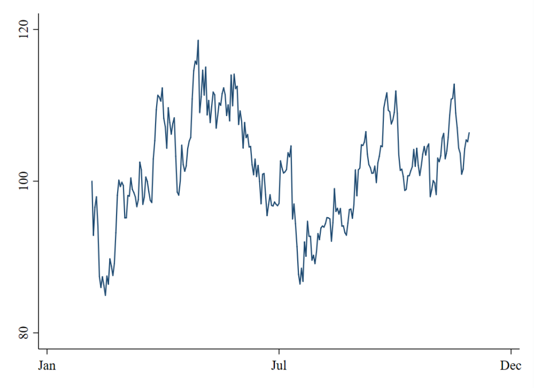
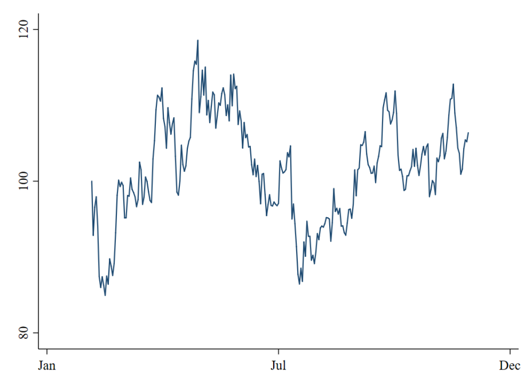


- Use past returns to form expectations

Expectations



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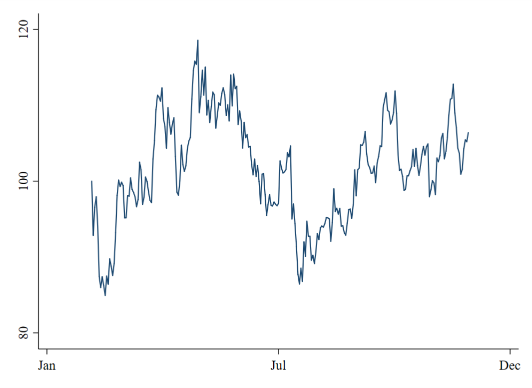

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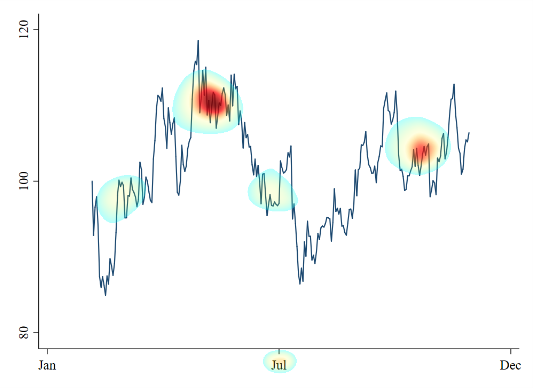

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  - Weight returns by *visual* salience

HYPOTHESES

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- (Hypothesis) VS weights returns when forming expectations
- VS $\rightarrow$ expectations $\rightarrow$ experimental investment decisions

Visual Salience

Saliency Attentive Model (Cornia et al., IEEE 2018)

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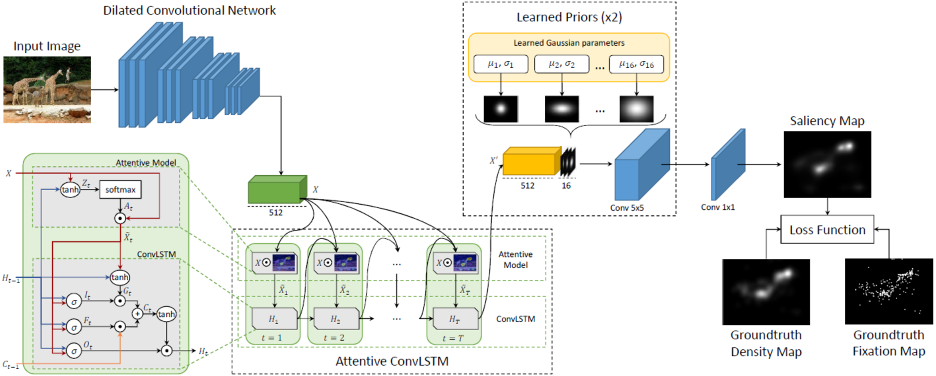
- Predictive power in Schelling matching, hider-seeker games (Li, Camerer, 2019)

Saliency Affective Model (Cornia et al., IEEE 2018)



SAM Training Images

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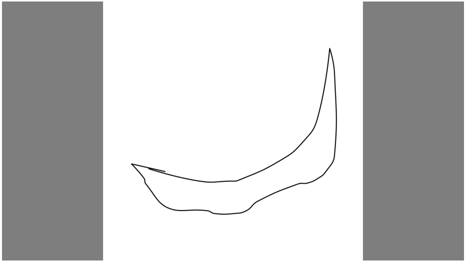

SAM's performance for price paths

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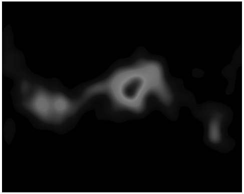
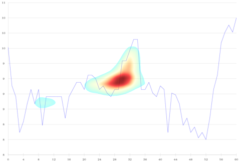
- Memory task at the end to force attention (standard)
- "Ground-truth" density maps of human fixations
- Compare fixations with SAM prediction

SAM Price Paths Performance

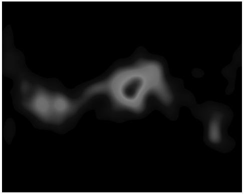


Fixation map



SAM heatmap

SAM Price Paths Performance



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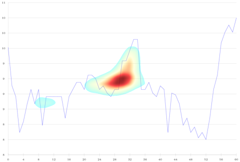

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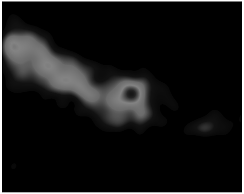

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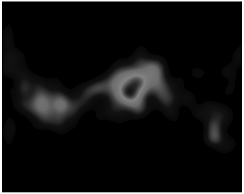

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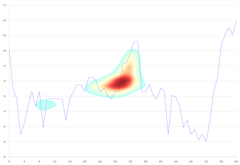
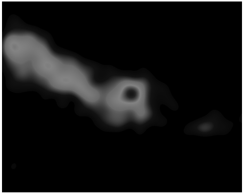


SAM heatmap

TABLE: Evaluation metrics

	AUC	Corr
SAM (domain-neutral)	0.87	0.78
SAM vs fixations (price paths)	0.81	0.52
Random vs fixations (price paths)	0.50	0.07

Explanation of Metrics
SAM and Price Path Characteristics



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Framework

Investors' value function

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- $Corr(x_k, \pi_k)$ measures association of decision weights with x_k

Different Decision Weight Theories

- Visual salience to prices (π_k^{VS}) for return x_k

Formulae for Weights

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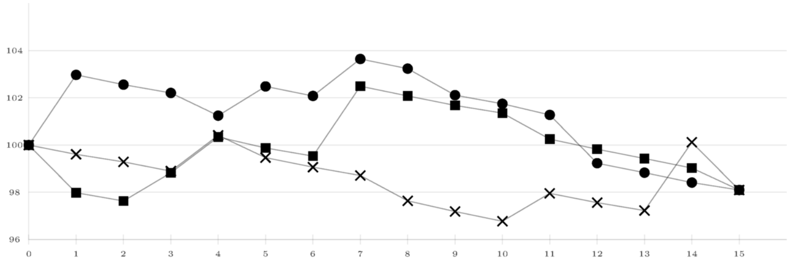
Formulae for Weights

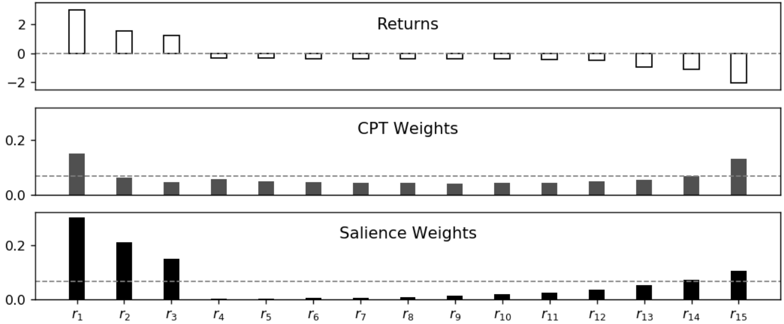
Different Decision Weight Theories

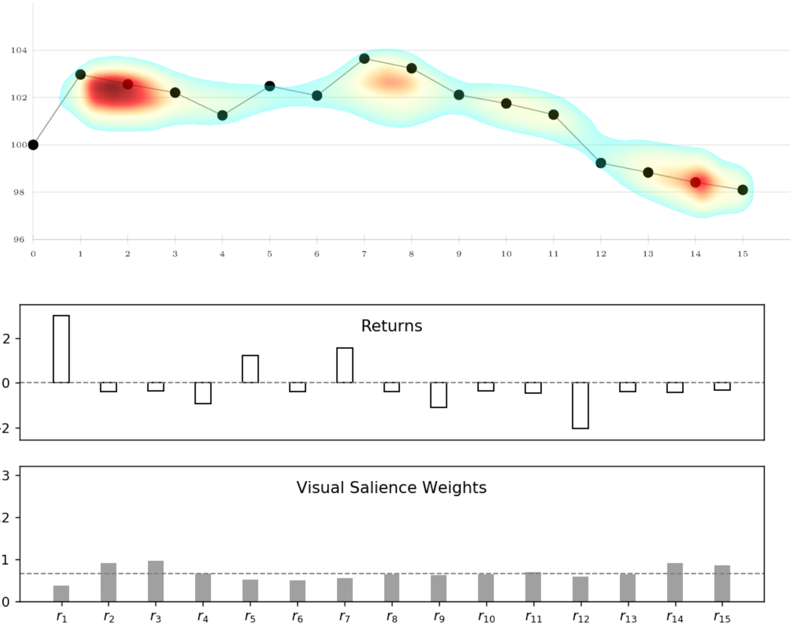
- Visual salience to prices (π_k^{VS}) for return x_k
- Compare with two well-established models in the literature:
  - CPT decision weights π_k^{CPT} (Barberis, Mukherjee & Wang, RFS 2016)
  - Decision weights using high-low salience - π_k^{S} (Bordalo, Gennaioli & Shleifer, QJE 2012, AER 2013, etc.)

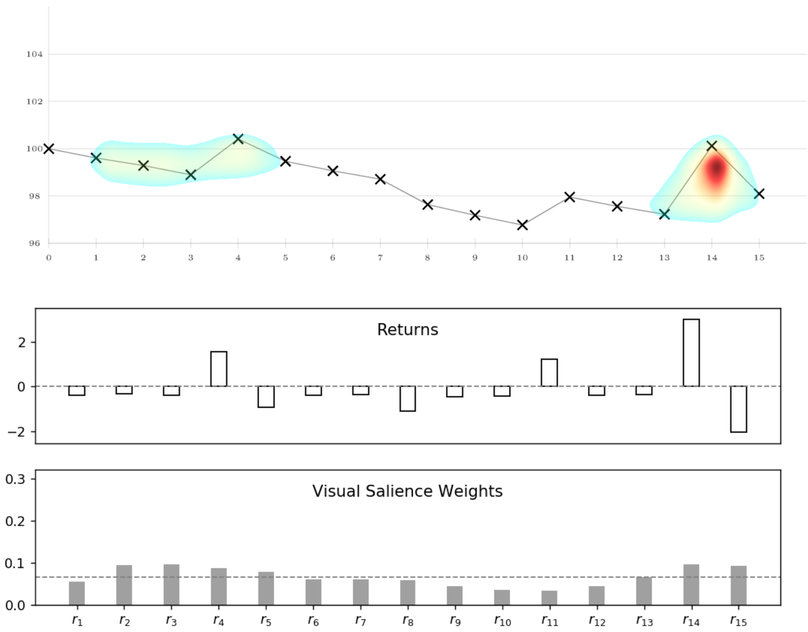
Formulae for Weights

Illustrative price paths (not used in experiments)






104
102
100
98
96
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
Returns
2
0
−2
Visual Salience Weights
0.3
0.2
0.1
0.0
r_1
r_2
r_3
r_4
r_5
r_6
r_7
r_8
r_9
r_{10}
r_{11}
r_{12}
r_{13}
r_{14}
r_{15}



Returns
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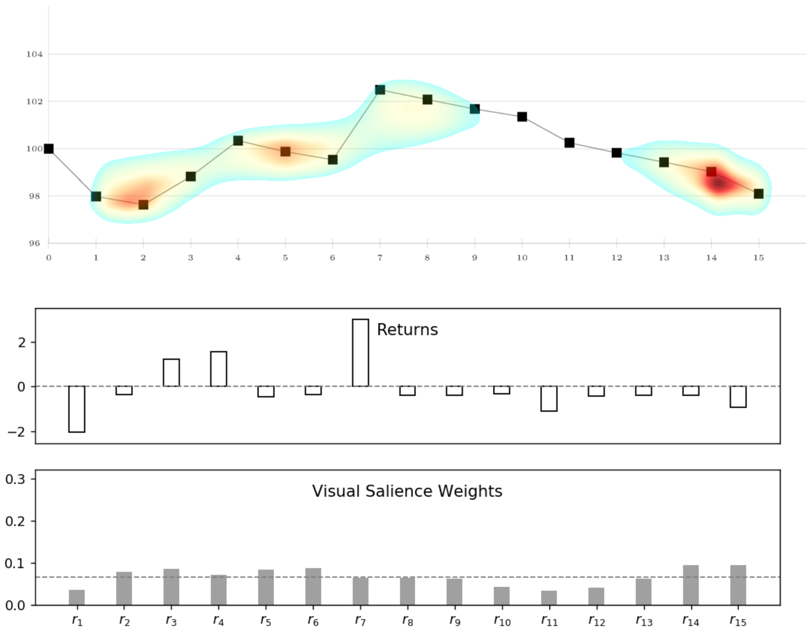

Returns
Visual Salience Weights
r_1 r_2 r_3 r_4 r_5 r_6 r_7 r_8 r_9 r_{10} r_{11} r_{12} r_{13} r_{14} r_{15}

Distance and correlation between three theories

Sum of absolute distance from equal return weights

	Path1	Path2	Path3
CPT	0.36	0.36	0.36
Sal	1.01	1.01	1.01
VS	0.20	0.29	0.26

Correlations between theories

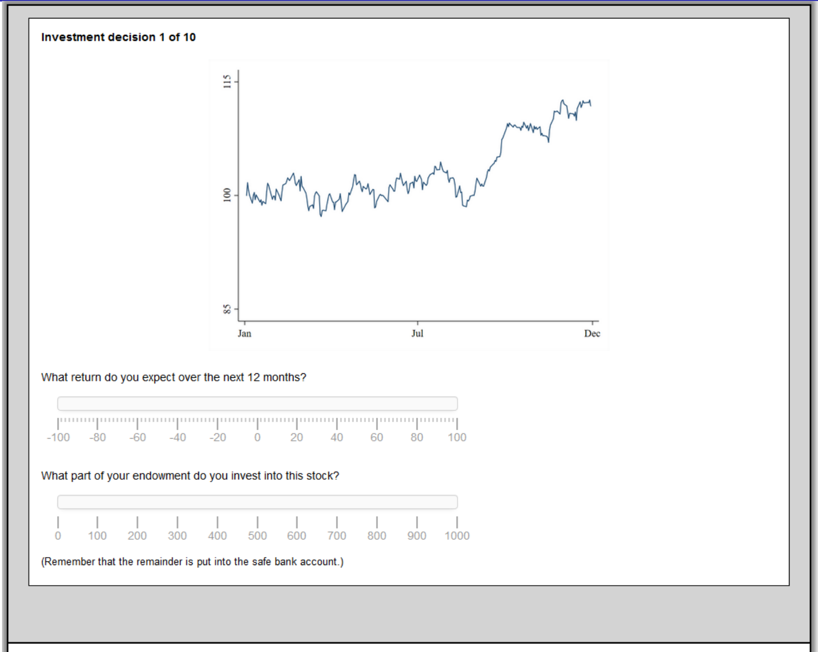
	Path1	Path2	Path3
CPT - Sal	0.68	0.68	0.68
CPT - VS	-0.47	0.48	-0.39
VS - Sal	-0.67	0.33	-0.04

Experimental Data

Three experimental studies

Table: Experimental studies summary

	Study I	Study II	Study III
Objective	Test VS against realistic price paths	Study temporal ordering effects	Test VS in simplified, controlled setting
Platform	M-Turk	M-Turk	Laboratory
Price Path Types	Empirical (CRSP 2017)	Constructed (same returns, jumbled order)	Constructed (only two possible returns)
# of Subjects	500	500	275
# of Price Paths	1000 (evaluated four times)	300 (evaluated twice)	15 (dynamic paths with 15 periods)
	Details	Details	


Investment decision 1 of 10
115
100
85
Jan
Jul
Dec
What return do you expect over the next 12 months?
-100 -80 -60 -40 -20 0 20 40 60 80 100
What part of your endowment do you invest into this stock?
0 100 200 300 400 500 600 700 800 900 1000
(Remember that the remainder is put into the safe bank account.)

Empirical Strategy

Decision weights and value functions

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  - Use $Corr(x_k, \pi_k)$ as a proxy for isolating the effects of decision weights on $V(X)$
- Step 2: Regress invested amounts (IA) on $V(X)$ (or proxy) and compare coefficients

Results

Study I - Correlational Measure

Table: Regressions for IA, Study I: Correlation Measure

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]
Corr (x,π_{VS})	0.670**			0.635**
	(0.235)			(0.237)
Corr (x,π_{CPT})		0.289		0.984**
		(0.242)		(0.434)
Corr (x,π_{S})			-0.0271	-0.249**
			(0.0689)	(0.121)
Controls	ON	ON	ON	ON
Observations	4000	4000	4000	4000
R^2	0.162	0.160	0.160	0.163

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

- Controls include average returns, standard deviation, skewness and individual fixed effects

Study I - CPT Value Function

Table: Regressions for IA, Study I: Gain-Loss

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]
$V_{CPT}(x,\pi_{VS})$	0.0955***			0.106**
	(0.0357)			(0.0415)
$V_{CPT}(x,\pi_{CPT})$		0.0184		-0.0489
		(0.0590)		(0.0809)
$V_{CPT}(x,\pi_{S})$			-0.0117	0.00768
			(0.0242)	(0.0285)
Controls	ON	ON	ON	ON
Observations	4000	4000	4000	4000
R^2	0.162	0.160	0.160	0.162

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Study I - CPT Value Function (Price Differences)

Table: Regressions for IA, Study I: Gain-Loss (Reference Level = 0)

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]
$V_{CPT}(x,\pi_{VS})$	0.286***			0.211**
	(0.0318)			(0.0347)
$V_{CPT}(x,\pi_{CPT})$		0.281***		0.122**
		(0.0386)		(0.0482)
$V_{CPT}(x,\pi_{S})$			0.143***	0.0559*
			(0.0269)	(0.0308)
Controls	ON	ON	ON	ON
Observations	4000	4000	4000	4000
R^2	0.183	0.179	0.167	0.188

Standard errors in parentheses
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Table: Regressions for IA, Study II: Recency Bias

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]	(5) IA[%]
$V_{CPT}(x,\pi_{VS})$	0.205*				0.217**
	(0.107)				(0.107)
$V_{CPT}(x,\pi_{CPT},\rho = 0.95)$		0.00417			
		(0.0418)			
$V_{CPT}(x,\pi_{CPT},\rho = 0.85)$			0.0362		
			(0.0393)		
$V_{CPT}(x,\pi_{CPT},\rho = 0.50)$				0.0961*	0.104*
				(0.0583)	(0.0585)
Controls	ON	ON	ON	ON	ON
Observations	600	600	600	600	600
R^2	0.030	0.011	0.015	0.024	0.045

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

- Controls include individual fixed effects

Conclusion

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- BGS salience is high-low contrast (”salience for decision”)
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- Prediction fairly robust across experimental studies that vary:
  - CRSP paths, and shuffled paths

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- Train finance-SAM on CRSP paths
- Visually "makeover" paths to maximize $V_{CPT}(x, \pi_{VS})$
  - Y-axis, time period to center "good" VS returns...

Thank You

Principal Component Analysis

Statistical Feature	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp 10	Comp11	Comp12
Eigenvalue	5.6443	4.7121	3.8542	2.1882	1.8790	1.4644	1.0494	1.0058	0.9989	0.9757	0.8988	0.8631
min price	0.4708											
average price	0.4646											
max price	0.4483											
distance from starting price	0.3252											
min price in % of path min price	0.2994											
loss domain	-0.3139											
spread in % of max price		0.4542										
std. dev.		0.4385										
spread		0.3859										
max return		0.3358	0.2627									
min return		-0.3778	0.2634									
skewness			0.4791	-0.3375								
momentum relative to path momentum			0.4081									
momentum			0.4001									
average return			0.3987									
max return in % of path max return			0.2737		0.4907							
min return in % of path min return			-0.2605		0.527							
no. of gains				0.5989								
Relative Strength Index (RSI)				0.587								
std. dev. in % of path std. dev.					0.5967							
max price in % of path max price						0.694						
spread in % of path spread						0.6533						
runlength							0.6934					
autocorrelation r_t, r_{t-1}							0.6778					
period								0.9525				
jump									0.9905			
autocorrelation r_t, r_{t-1} in % of path autocorrelation										0.9979		
skewness in % of path skewness											0.9985	
average return in % of path average return												0.9996

The table reports rotated factor loadings of the 12 factors with Eigenvalues greater than 0.8. Eigenvalues are listed in the first row of the table. Loadings smaller than 0.25 are blanked out to enhance readability of the table. Statistical features are ordered by their loadings on the respective components, prioritizing components with a larger Eigenvalue.

Metrics Details

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  - Calculate True Positive rate (TP rate)
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  - AUC measures the area under this curve

Metrics Details

- Pearson's Correlation Coefficient (PCC)

Back

Metrics Details

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  - Pixel-wise correlation coefficient

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Metrics Details

- Pearson's Correlation Coefficient (PCC)
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  - Ideally want correlation to be positive and close to 1

Back

SAM and Price Path Characteristics

- Split price path with 250 daily returns into 10 equal blocks, calculate relative SAM weight for each block

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  - Metrics can only explain about 20% of variance in weights, SAM is capturing more than combination of traditional metrics can

Principal Component Analysis

⏩ Back

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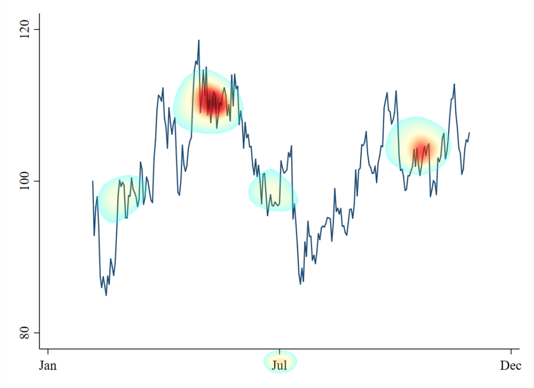

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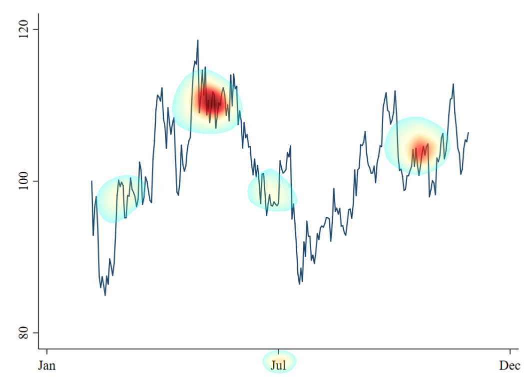

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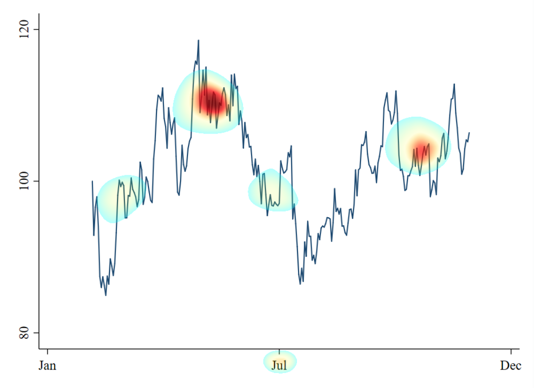

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  - $\pi_k^{VS} = \frac{p_k \times I_k}{\sum_{k'} p_{k'} \times I_{k'}}$ with the salience weight $I_k = \frac{SAM(P_{k-1}) + SAM(P_k)}{2}$

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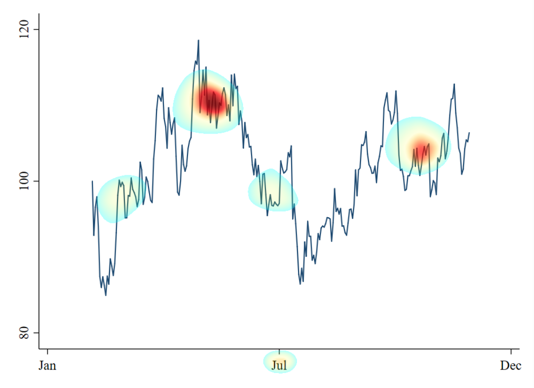

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  - where $SAM(P_k)$ denotes the visual salience of price P_k as predicted by SAM

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CPT (Barberis et al, RFS 2016)

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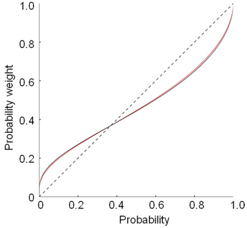

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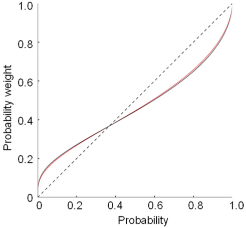

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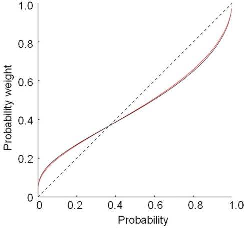

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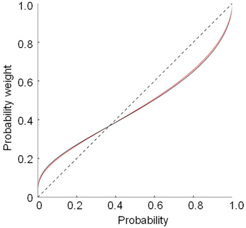

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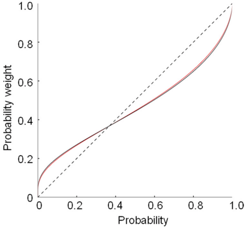

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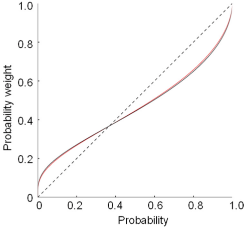

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- Check if recency parameter can account for temporal ordering effects

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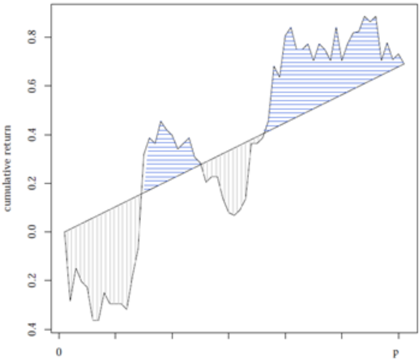
Convexity Score Details



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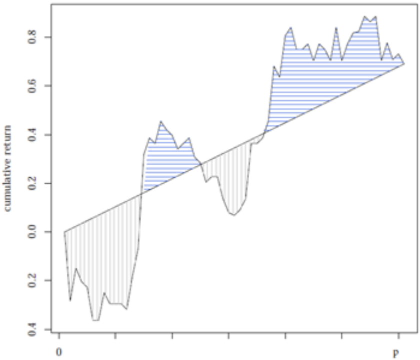

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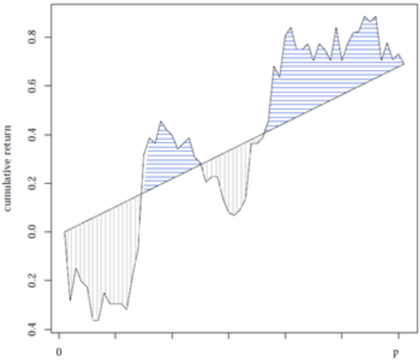

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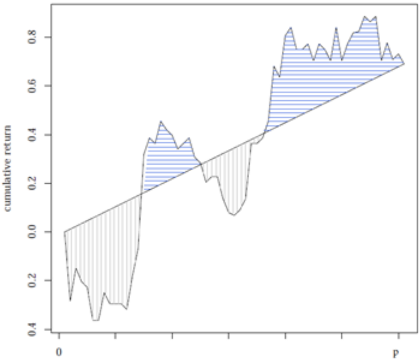

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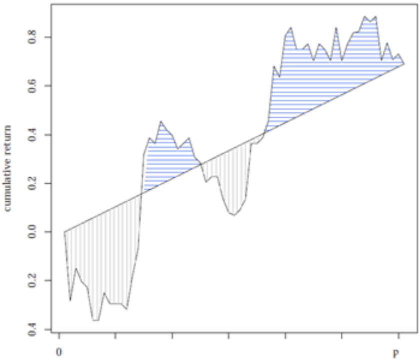

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- $CS = \frac{H^{+} - H^{-}}{max_i(x_i) - min_i(x_i)} \left(\prod_{i=1}^{p} (1 + x_i) - 1 \right)$

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  - 2 constructed paths (Study II)
- Evaluate attractiveness, expected future return, perceived risk, and percentage to invest (incentivized)

Summary - Study I and II

- Questionnaire on demographics, risk preferences, financial literacy, CRT

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- Average completion time 24min 15s

Descriptive Statistics

Table: Descriptive statistics

Variable	US-Population (2017) $N = 321,004,407$	MTurk Sample $N = 500$
Age [years; median]	37.2	30.0
Gender [female=1]	50.2	32.2
Education [%]		
No degree	12.6	0.2
High School	27.3	23.4
College incl. BA	48.2	64.2
Graduate or higher	11.8	12.2
Full employment [%]	77.2	85.6
Household size [mean]	2.58	3.08

Paths for Study I

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Back

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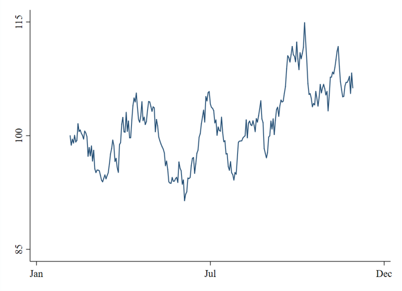
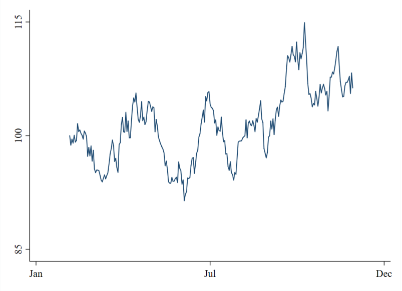
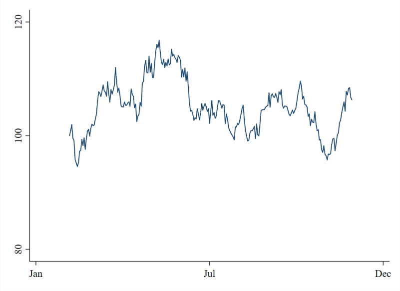
- Rearrange sub-periods of drawn path to form 100 shapes of same path
- Participants paid based on random draw of GBM

Paths for Study II - Same Returns



Paths for Study II - Same Returns





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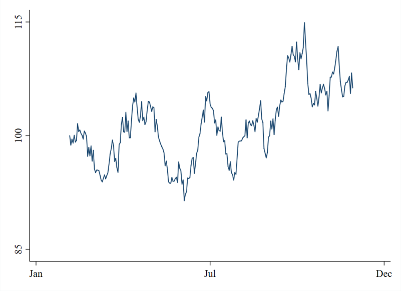

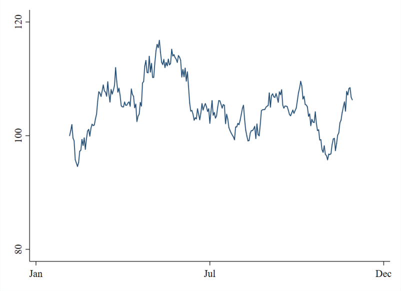

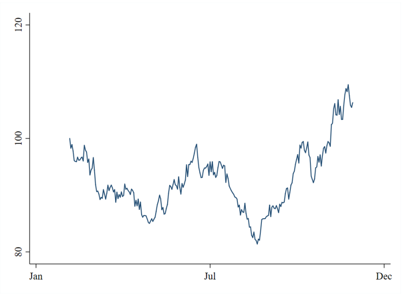

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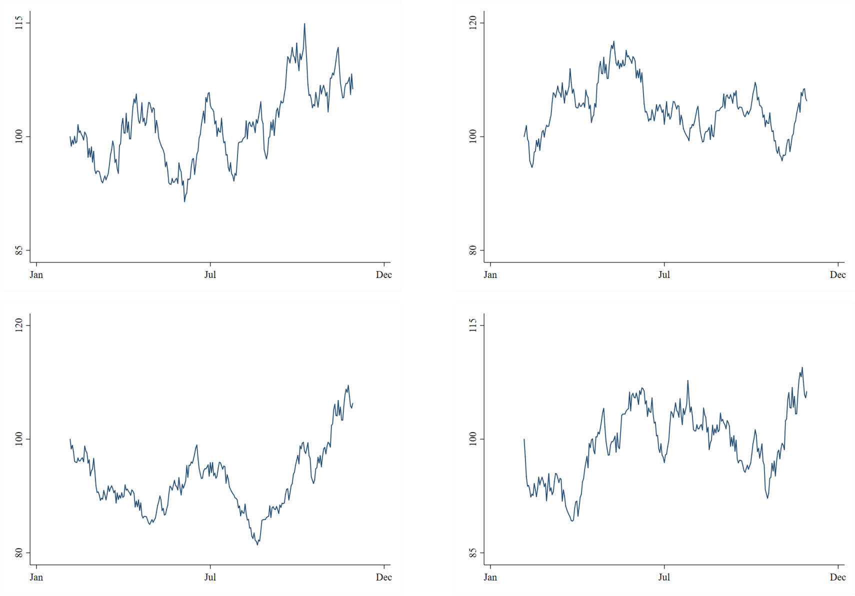
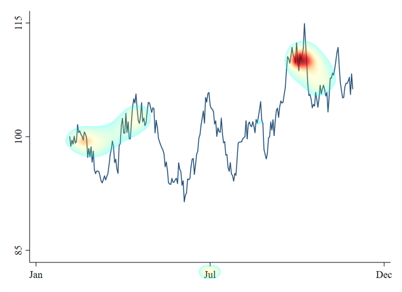


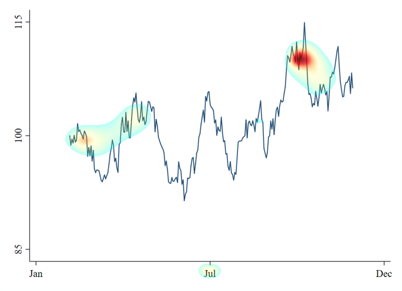
SAM Predictions - Same Returns

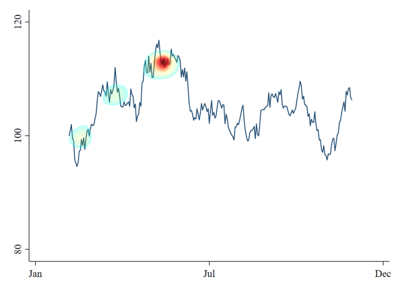
Back

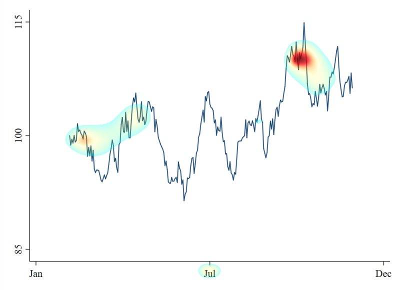


SAM Predictions - Same Returns

◂ Back



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100
85
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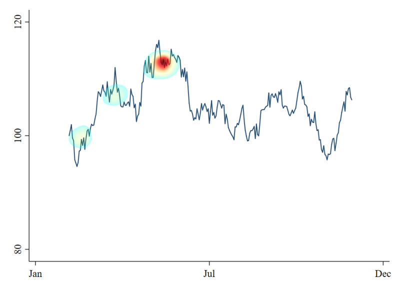
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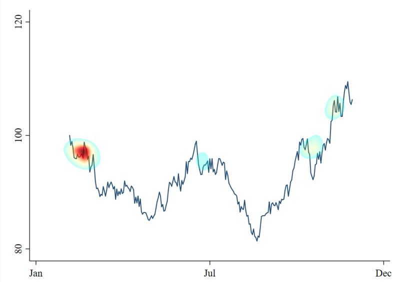
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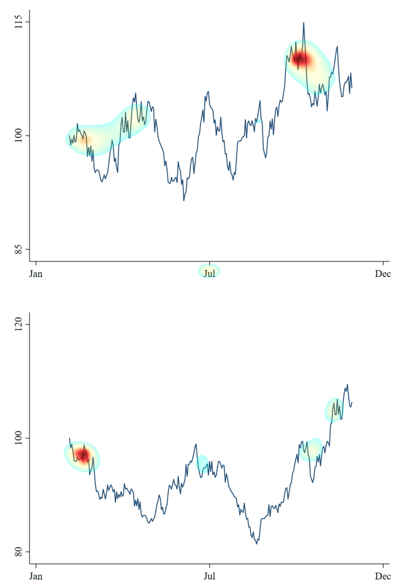

Study I - Correlational Measure

Table: Regressions for IA, Study I: Correlation Measure

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]
Corr (x,π_{VS})	0.579**			0.537**
	(0.236)			(0.236)
Corr (x,π_{CPT})		0.296		0.760*
		(0.239)		(0.420)
Corr (x,π_{S})			-0.0083	-0.195
			(0.0688)	(0.120)
Controls	ON	ON	ON	ON
Observations	4000	4000	4000	4000
R^2	0.162	0.160	0.160	0.163

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

- Controls include average returns, standard deviation, skewness and individual fixed effects

Table: Regressions for IA, Study II: Recency Bias

	(1) IA [%]	(2) IA [%]	(3) IA [%]	(4) IA [%]	(5) IA[%]
$V_{CPT}(x,\pi_{VS})$	0.192*				0.177*
	(0.105)				(0.103)
$V_{CPT}(x,\pi_{CPT},\rho = 0.95)$		-0.00534			
		(0.0455)			
$V_{CPT}(x,\pi_{CPT},\rho = 0.85)$			0.0394		
			(0.0432)		
$V_{CPT}(x,\pi_{CPT},\rho = 0.50)$				0.137**	0.127**
				(0.0690)	(0.0678)
Controls	ON	ON	ON	ON	ON
Observations	600	600	600	600	600
R^2	0.026	0.011	0.014	0.028	0.041

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

- Controls include individual fixed effects