Make hay while the sun shines: An empirical investigation of maximum price and its effect on regret and trading decisions

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JEEA Teaching Material

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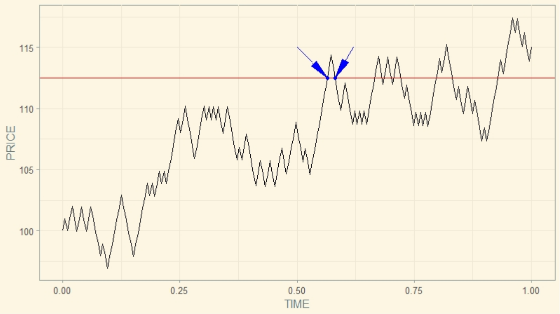
Dynamic Regret



- An Expected Utility maximizer gets the same Utility by stopping at any point where the price reaches the threshold, highlighted in red.
- A Regret agent gets more Utility by stopping the 1^{st} time the price reaches the threshold *bu* w.r.t. the 2^{nd} time (see arrows in blue) More

Dynamic Regret in the Lab

- Strack and Viefers (2021): Regret over past decisions increases as the distance from past maximum increases and it lowers the probability of selling.
- Fioretti et al. (2022): when future prices are available, investors avoid regret about expected after-sale high prices (future regret).
- We test Regret Theory in a dynamic context on field data and make connections with Strack and Viefers (2021) and Fioretti et al. (2022) explanation.

Conclusions of Strack and Viefers (2021)

Experimental subjects did not follow a threshold strategy and for any given level of the price process, they were less likely to sell the further the price was from running maximum price.

Data

- We use the LDB (Large Discount Brokerage) data-set.
- Data contains information on trading activities of American individual investors in the period 1991-1996 (trading activities and some characteristics of individuals).
- It is widely studied in the Economic community (Barber and Odean, 2013).
- Threshold analysis refers to the sample of investors where demographics are available (15,624 bank accounts with gains, 11,390 bank accounts with losses, 8,674 bank accounts with both).
- Investment episodes shorter than 300 days, i.e. 209 trading days (Benartzi and Thaler, 1995).

Data

- Price information at daily level.
- $t = 0$ is the starting point of an investment episode, a date t is obtained as the difference in days between a given date and the starting point.
- We introduce the distance from extreme, distance for brevity

$$d_t = \begin{cases} \frac{t - t_{max}}{t}, & \text{if episode ends up as a gain} \\ \frac{t - t_{min}}{t}, & \text{if episode ends up as a loss} \end{cases}$$

- We introduce the sufficient condition for an investment episode to be defined as a threshold investment:
  A trading episode is said to be a threshold strategy episode if $d_\tau = 0$ with τ being the selling date in an investment episode.

Threshold strategy

- The theory is only defined for gains but we also look at losses.
- We find that 31.6% of gains and 25.8% of losses were sold at a threshold (disposition effect implication). We reject the hypothesis that investors follow a threshold strategy.
- We regress the number of time an investor stopped at a threshold on investors' characteristics. Each observation is at bank account level.

Threshold strategy identification

Negative binomial model to investigate heterogeneity of threshold consistency at investor level

$$\mu_i = \exp(\log(n_i) + \beta \mathbf{x_i})$$

- μ_i is the number of threshold episodes in bank account i
- $\log(n_i)$ is an offset equal to the logarithm of the number of episodes in bank account i
- Vector $\mathbf{x_i}$ of bank account characteristics: account type, investor category, income, gender, occupation.

Threshold Consistency More

Dep. var.	Rate of Threshold Consistency (Odds Ratios)		
	Gain	Loss	All
Account Type (ref. Cash)			
Account Type IRA	1.068*	1.097*	1.105***
	(0.997,1.143)	(0.998,1.207)	(1.031,1.185)
Account Type Keogh	1.111	1.267*	1.238**
	(0.900,1.367)	(0.980,1.628)	(1.025,1.494)
Account Type Margin	1.194***	1.237***	1.289***
	(1.119,1.274)	(1.135,1.350)	(1.210,1.373)
Account Type Schwab	1.129***	1.152***	1.202***
	(1.068,1.194)	(1.069,1.244)	(1.137,1.270)
Client Segment (ref. General)			
Client Segment Affluent	0.905***	0.871***	0.863***
	(0.851,0.962)	(0.798,0.950)	(0.810,0.920)
Client Segment Active	1.036*	1.059**	1.076***
	(0.998,1.076)	(1.009,1.111)	(1.040,1.113)
McFadden Adj. R^2	0.24	0.25	0.25
Bank Accounts	15,624	11,390	8,674
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Threshold Consistency

- Investors do not follow consistently a threshold strategy (Strack and Viefers, 2021).
- Sophisticated investors and active traders are more consistent with a threshold strategy (Barber and Odean 2000; Dhar and Zhu 2006; Barber and Odean, 2008).
- Affluent and older investors are less consistent than general investors with a threshold strategy (Korniotis and Kumar 2011).
- Males are more willing to realize losses at a threshold than females (Barber and Odean, 2001).

Maximum identification

Proportional hazard model to estimate the probability of selling the stock

$$h_i j\left(t\right) = h_j\left(t\right) \exp\left(\beta^t x_{ijt}\right)$$

- We stratify the model at bank account level: each bank account j has a different baseline hazard function (bank account fixed effects idea).
- $\mathbf{x}_{ijt}$ is the covariate vector for the position i in bank account j on day t.
- We control for time effects (month and year).
- We check the Proportional hazard assumption.
- We report Xu and O'Quigley (1998) pseudo R squared

Maximum and Regret

- We refer to a sample of 13000 investments from 8,704 bank accounts. Max analysis does not take into account 10% most volatile episodes.
- Expected Utility prediction is that the propensity to sell is independent from past maximum.
- Regret Theory predicts that the propensity to sell is lower, the higher is the distance from past maximum.
- We only look at stocks which were sold for a gain and we estimate propensity to sell only on days when they were trading at a gain.

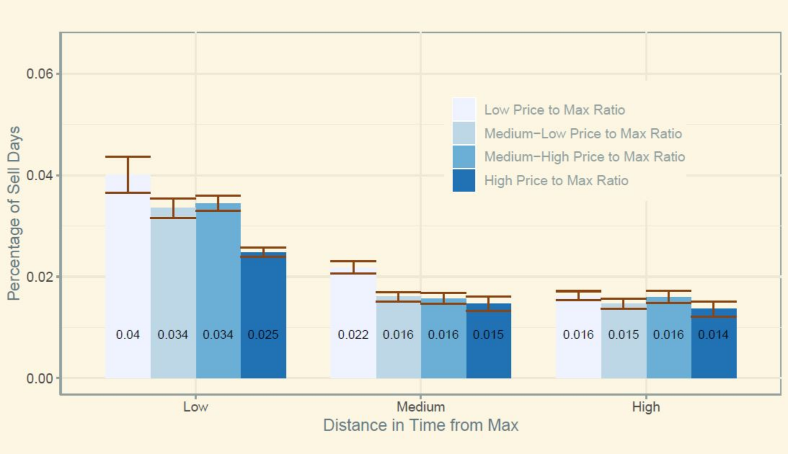
Maximum covariates

- Distance: it is the rescaled distance from maximum day, $\frac{t - t_{max}}{t}$. t_{max} is the day when maximum price between day 0 and day t realized. We split it into tertiles: low [0; 0.07]; medium [0.07; 0.34) and high [0.34; 1];
- Ratio to Max Price (Ratiomax) is the ratio of daily closing price to maximum price (on selling date, ratio of selling price to maximum price). We split it into quartiles: low [0.349; 0.918]; medium-low (0.918; 0.957]; medium-high (0.957; 0.981] and high (0.981; 1].
- Return is the ratio of daily closing price to the purchase price in the investment episode (on selling date, ratio of selling price to purchase price).We split it into tertiles: low [0.58; 1.01]; medium (1.06; 1.17]; high (1.17, 5.53] Summary Dist.

	Odds Ratio of the probability to sell		
Ratio Price to Max Price (ref. Low)			
Medium-Low	0.909		
	(0.792,1.043)		
Medium-High	1.062		
	(0.932,1.210)		
High	0.720***		
	(0.619,0.837)		
Dist. in Time from Max Day (ref. Low)			
Medium		0.877**	
		(0.786,0.979)	
High		0.430***	
		(0.385,0.481)	
Return (ref. Low)			
Medium			2.719***
			(2.435,3.035)
High			3.435***
			(2.988,3.949)
Xu-O'Quigley R^2	0.020	0.061	0.10
Concordance	0.57	0.61	0.64
PH Assumption Valid (0.05)	YES	YES	YES
Time Controls	YES	YES	YES
Number of Trading Episodes	13,000	13,000	13,000
Number of Bank Accounts	8,704	8,704	8,704
Observations	621,849	621,849	621,849

Note: *p<0.1; **p<0.05; ***p<0.01

Short time distance reverts regret predictions



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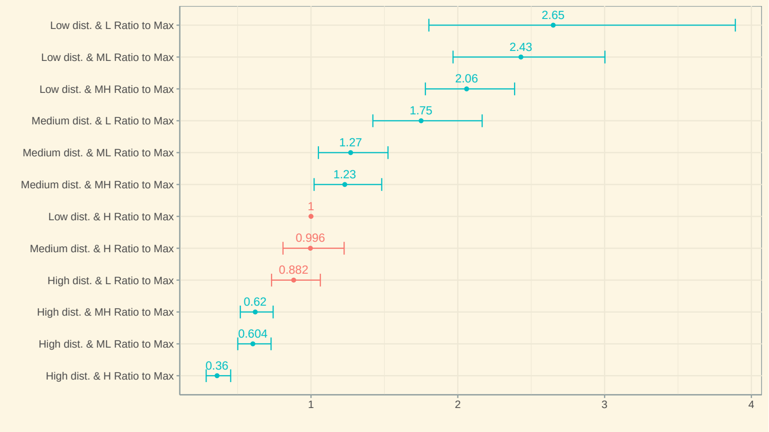

Absolute # days PH model

Channel and robustness

- We hypothesise that selling behavior can be attributed to anticipated regret (Fioretti et al., 2022): panic when stock is dropping
- An alternative explanation is due to belief updating. It should be noticed that stocks sold further in price but closer in time to past max tend to be both more profitable and more volatile Plot
- We check if our results are automatically produced by the underlying price process. We simulate selling dates, following Hobson and Zeng (2020), who assume that stopping times are event times of an independent Poisson process. However, our results disappear Plot

Take home

- Threshold strategy does not describe average investor behaviour. It better describes sophisticated investors' behaviour.
- Regret works in a different way from Strack and Viefers (2021) predictions. No regret about price distance from past maximum.
- Time matters a lot. Investors don't forget past maximum; relevant when designing investment platforms and for financial consulting.
- Regret about time should be incorporated in a theory about dynamic regret.

Regret in Dynamic Decisions

- A decision maker observes realization of a stochastic process (in our case the price process) X and she has the possibility to stop at any stopping time s in the set S. She actually stops at τ.

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- A threshold strategy $\tau(b)$ prescribes that agent stops at time t if the value of the process X_t exceeds the cut-off b and continues otherwise, where b is a given constant. If the agent uses the cut-off strategy $\tau(b)$ she will stop at the time $\tau(b, X) = min\{t \geq 0 : X_t \geq b\}$. An Expected Utility maximizer stops the process at a threshold.

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- **For a regret agent the probability of continuation is decreasing in the current value of the process x and increasing in the past maximum s.** Back

Regret Theory in practice

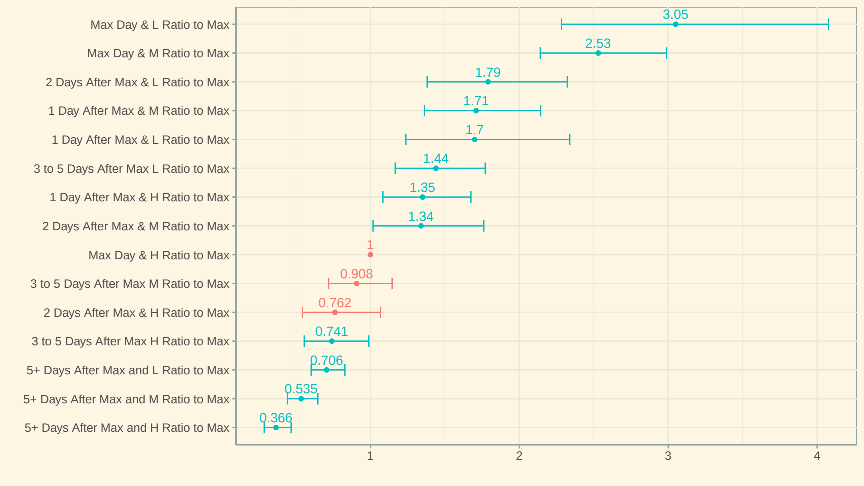
Action	1 25	26 50	51 75	76 100
A_d	£30	£20	£10	£0
人				
A_n	£20	£10	£0	£30

- There is a urn containing 100 balls numbered from 1 to 100. One ball is drawn at random from the urn and a given payoff is attached to every realization.
- The two actions A_d and A_n are equivalent for and Expected Utility maximizer but they are not for a Regret Theory maximizer. Back

Threshold Consistency (Extra Analysis) Back

Dep. var.	Rate of Threshold Consistency (Odds Ratios)		
	Gain	Loss	All
Account Type IRA (ref. Cash)	1.044	1.082	1.096**
	(0.965,1.129)	(0.971,1.206)	(1.012,1.187)
Account Type Keogh (ref. Cash)	1.180	1.144	1.262**
	(0.917,1.516)	(0.840,1.545)	(1.014,1.570)
Account Type Margin (ref. Cash)	1.186***	1.195***	1.275***
	(1.099,1.280)	(1.080,1.324)	(1.184,1.374)
Account Type Schwab (ref. Cash)	1.092***	1.130***	1.169***
	(1.023,1.167)	(1.033,1.236)	(1.094,1.248)
Client Segment Affluent (ref. General)	0.951	0.952	0.911**
	(0.884,1.023)	(0.860,1.053)	(0.844,0.981)
Client Segment Active (ref. General)	1.092***	1.078**	1.117***
	(1.045,1.142)	(1.017,1.142)	(1.073,1.163)
Age (decades)	0.921***	0.958***	0.932***
	(0.906,0.936)	(0.938,0.978)	(0.919,0.946)
Income	0.990*	0.977***	0.985***
	(0.979,1.000)	(0.964,0.991)	(0.976,0.995)
Male	1.008	1.141**	1.058
	(0.931,1.093)	(1.021,1.277)	(0.979,1.144)
Non Professional Occupation	1.060	1.004	1.031
	(0.977,1.150)	(0.898,1.121)	(0.954,1.113)
Professional Occupation	1.015	0.956	0.994
	(0.971,1.061)	(0.901,1.014)	(0.954,1.036)
McFadden Adj. R^2	0.46	0.46	0.46
Observations	11,477	8,315	6,280
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Short days distance reverts regret predictions (PH model)



Back

Maximum Regression Back

Dist. in time from Max and Ratio to Max (ref. Low and High)	
Low dist. and Low Ratio to Max	2.649***
	(1.803,3.891)
Medium dist. and Low Ratio to Max	1.755***
	(1.421,2.166)
High dist. and Low Ratio to Max	0.882
	(0.731,1.064)
Low dist. and Medium-Low Ratio to Max	2.430***
	(1.968,3.002)
Medium dist. and Medium-Low Ratio to Max	1.266**
	(1.051,1.524)
High dist. and Medium-Low Ratio to Max	0.604***
	(0.501,0.728)
Low dist. and Medium-High Ratio to Max	2.061***
	(1.779,2.387)
Medium dist. and Medium-High Ratio to Max	1.230**
	(1.021,1.482)
High dist. and Medium-High Ratio to Max	0.620***
	(0.519,0.742)
Medium dist. and High Ratio to Max	0.996
	(0.809,1.226)
High dist. and High Ratio to Max	0.360***
	(0.286,0.453)
Xu-O'Quigley R^2	0.095
Concordance	0.65
PH Assumption Valid (0.05)	YES
Time Controls	YES
Number of Trading Episodes	13,000
Number of Bank Accounts	8,704
Observations	621,849
Note:	*p<0.1; **p<0.05; ***p<0.01

Ratiomax and Distance distribution Back

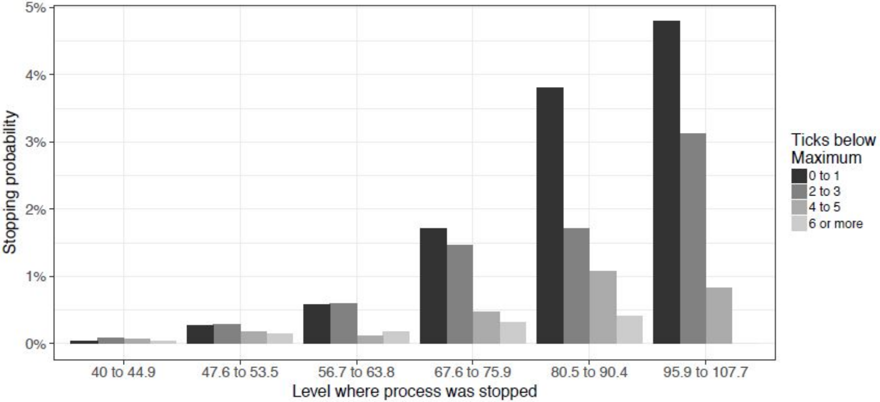
	Low Distance	Medium Distance	High Distance
Low Price Ratio to Max	0.02	0.10	0.13
Medium-Low Price Ratio to Max	0.05	0.10	0.10
Medium-High Price Ratio to Max	0.09	0.09	0.07
High Price Ratio to Max	0.17	0.04	0.04

	Max Day	1 Day After	2 Days A.	3 to 5 Days A.	5+ Days A.
Low Price Ratio to Max	0.01	0.02	0.02	0.06	0.39
Medium Price Ratio to Max	0.04	0.03	0.02	0.05	0.11
High Price Ratio to Max	0.13	0.03	0.02	0.03	0.05

Distance in days (PH model) Back

Dist. from Maximum Day (ref. Max Day)	
1 Day	1.093
	(0.943,1.266)
2 Days	0.929
	(0.783,1.101)
3 to 5 Days	0.742***
	(0.640,0.860)
More than 5 Days	0.413***
	(0.363,0.470)
Xu-O'Quigley R^2	0.061
Concordance	0.61
PH Assumption Valid (0.01)	NO
Time Controls	YES
Number of Trading Episodes	13,000
Number of Bank Accounts	8,704
Observations	621,849
Note:	*p<0.1; **p<0.05; ***p<0.01

Results from Strack and Viefers (2021)



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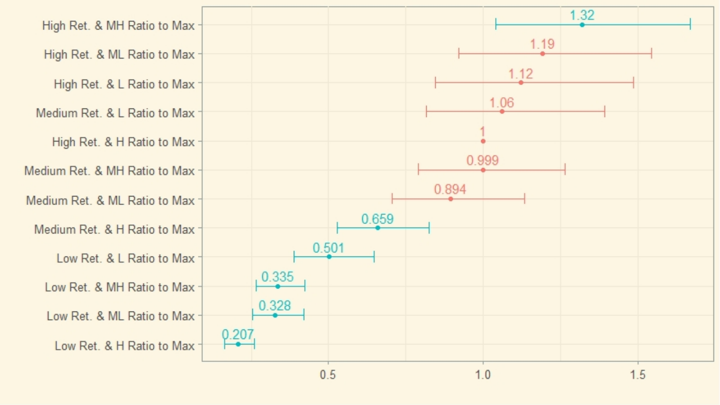
Ratiomax and return (PH model)



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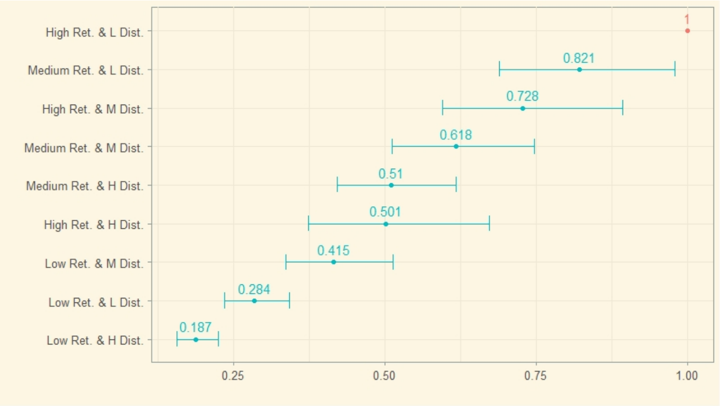
Distance and return (PH model)



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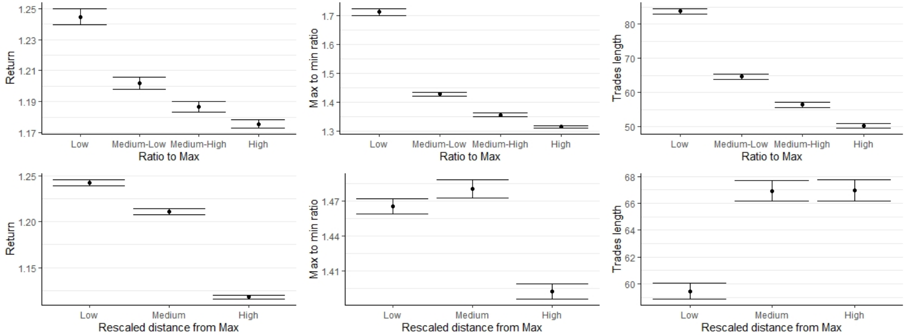
Xu and O'Quigley (1998) pseudo R squared

The coefficient aims at explaining the variability on the outcome looking at the distribution of time to events, given covariates. It has the following properties:

- When a covariate is unrelated to survival, and the corresponding regression coefficient it is equal to zero, it is equal to zero;
- When the effect of at least a coefficient is different from 0, it is between 0 and 1;
- It is invariant under linear transformations of covariates and under monotone increasing transformations of time Back

Stock characteristics by RatioMax and Distance



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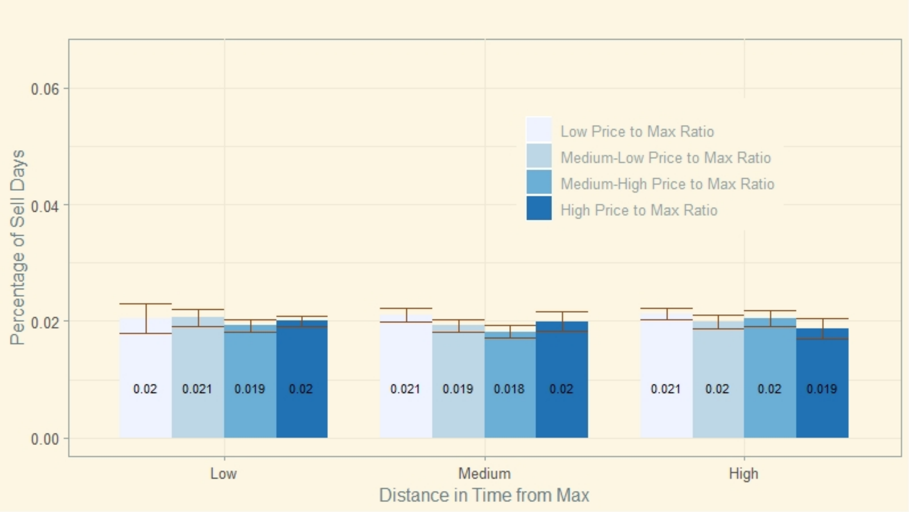

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