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

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Motivation

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- In a dynamic regret setting (Strack and Viefers, 2020) an investor trading stocks experiences regret by comparing the trading price of the stock she is trading to past maximum price since the stock was purchased.

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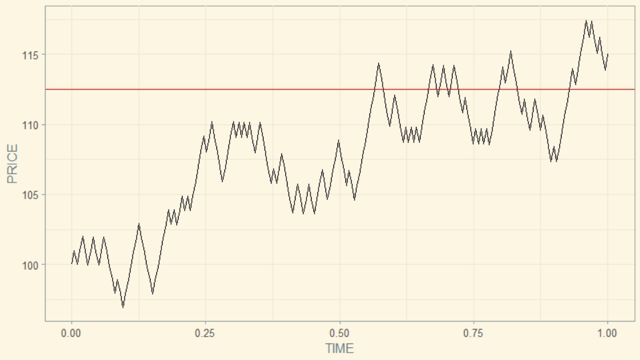
- In a dynamic regret setting (Strack and Viefers, 2020) an investor trading stocks experiences regret by comparing the trading price of the stock she is trading to past maximum price since the stock was purchased.
- We test Dynamic regret using trading data of individual investors.

An illustrative example



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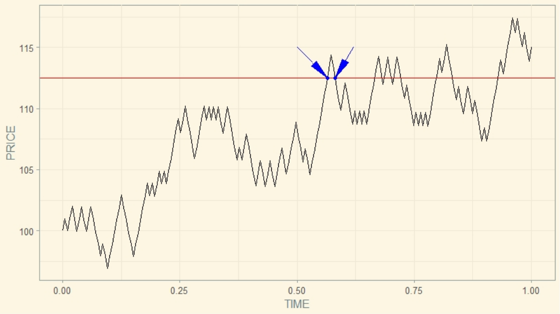

- An Expected Utility maximizer gets the same Utility by stopping at any point where the price reaches the threshold, highlighted in red.
- A Regret agent gets more Utility by stopping the 1^{st} time the price reaches the threshold *bu* w.r.t. the 2^{nd} time (see arrows in blue).

Contribution 1: Threshold strategy

*D*o investors follow a threshold strategy (Expected Utility optimal strategy?

The vast majority of investments are not threshold investments, consistent with experimental evidence.

*W*hich category of investors are more likely to follow a threshold strategy?

More sophisticated and younger investors are more likely to follow a threshold strategy.

Contribution 2: Past Maximum

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- *Propensity to sell a stock declines as the distance in time from past maximum increases (Regret about time distance).*

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- *Propensity to sell a stock declines as the distance in time from past maximum increases (Regret about time distance).*
- *Joint effect: investors are more willing to realize stocks which are closer in time but further in price from past maximum. When time distance from past maximum is short, investors are more willing to realize stocks, the further is the price from maximum (anticipated Regret).*

Roadmap

- Link with the literature.
- A primer on Regret intuition for static decisions.
- Regret in dynamic decisions.

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- **Maximum price and regret in the field**.

Investors' behaviour

- The behaviour of individual investors:
  - Investors show investment biases, like the disposition effect (realize gains at a faster rate than losses, Odean, 1998);
  - Investment frequency is correlated with worse investment performance (Barber and Odean, 2001);
  - Older investors and less sophisticated investors are likely to show investment biases (Korniotis and Kumar, 2011; Grinblatt and Keloharju, 2001, Dhar and Zhu, 2006, Huang, 2019).
- We look at investors' consistency with a threshold strategy and heterogeneity in following it.

Past Maximum and Regret in financial decisions

- The effect of maximum level of a stream of payoffs on decision making:
  - Baucells et al. (2011) in the lab (reference point formation);
  - Grinblatt and Keloharju (2001), local maxima and stock selling;
  - Barber and Odean (2008) and Huddart et al. (2009), trading volume;
  - Heat et al. (1999) on stock option and last year's peak.
- Regret Theory can explain financial decisions on: asset pricing and portfolio choice (Gollier and Salanié, 2006; Muermann et al., 2006); insurance markets (Braun and Muermann, 2004); why people invest too little in stocks (Barberis et al., 2006); currency risk (Michenaud and Solnik, 2008); disposition effect (Muermann and Volkman, 2006).
- We look at the impact of past maximum on regret and on the propensity to sell common stocks.

Dynamic Regret in the Lab

- Regret Theory in a dynamic context has only been tested in laboratory experiments:
  - Strack and Viefers (2020): Regret over past decisions increases as the distance from past maximum increases and it lowers the probability of selling.
  - Fioretti et al. (2018): when future prices are available, investors avoid regret about expected after-sale high prices (future regret).
  - Descamps et al. (2016): participants deviate from the optimal strategy in a systematic manner: information is either mostly over-sampled or mostly under-sampled, depending on the cost of information.
- We test Regret Theory in a dynamic context on field data and make connections with Strack and Viefers (2020) and Fioretti et al. (2018) explanation.

Regret Theory

- Regret Theory relaxes the transitivity axiom.
- A decision maker makes choices between acts (actions): L_i and L_j.
- Act L_i leads to consequence x_{iR} in State of the world R.
- Utility of consequence x_{iR} is a function $\Phi(x_{iR}, x_{jR})$ which is increasing in x_{iR} and decreasing in x_{jR}.
- Utility from x_{iR} is suppressed by regret if $x_{iR} < x_{jR}$; Utility from x_{iR} is enhanced by rejoicing if $x_{iR} > x_{jR}$.
- Decision Maker maximizes: $\sum_R p_r \Phi(x_{iR}, x_{jR})$., where p_r is the probability that state of the world r realizes.

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.

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- The two actions A_d and A_n are equivalent for and Expected Utility maximizer but they are not for a Regret Theory maximizer.

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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- Disutility she has to incur due to regret is the utility difference between her strategy and the strategy that turns out to be ex-post optimal $R = u\left(\max_{s \in \mathcal{S}} X_s\right) - u\left(X_\tau\right)$.

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- A threshold strategy $\tau\left(b\right)$ 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 $\tau\left(b\right)$ she will stop at the time $\tau\left(b, X\right) = min\left\{t \geq 0 \, : \, X_t \geq b\right\}$. 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.

Regret in Dynamic Decisions

- We test predictions of Regret Theory in Dynamic Decisions (Strack and Viefers, 2020) on real data.
- They conducted a laboratory experiment where they simulated a stock market and tested their predictions.

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Conclusions of Strack and Viefers (2020)

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

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- 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

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 (Extra Analysis)

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

Threshold Consistency

- Investors do not follow consistently a threshold strategy (Strack and Viefers, 2020).
- 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];

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- 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].

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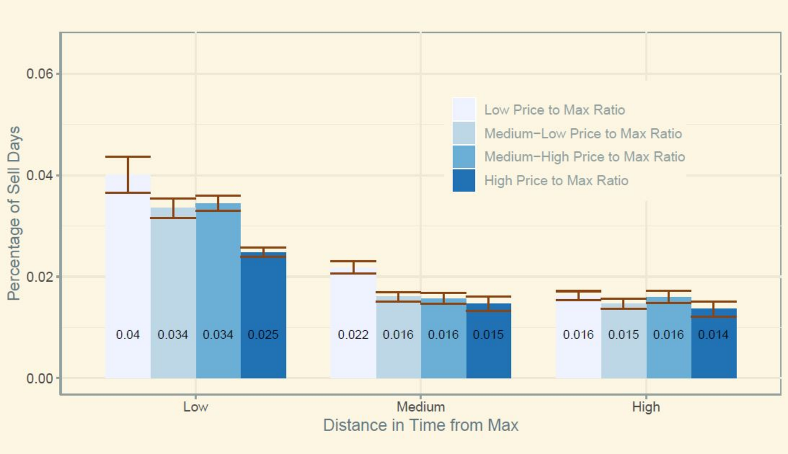
- Return is the ratio of daily closing price to the purchase price in the investment episode (on selling date, ratio of selling price to purchase price).We split it into tertiles: low [0.58; 1.01]; medium (1.06; 1.17]; high (1.17, 5.53].

Maximum results

	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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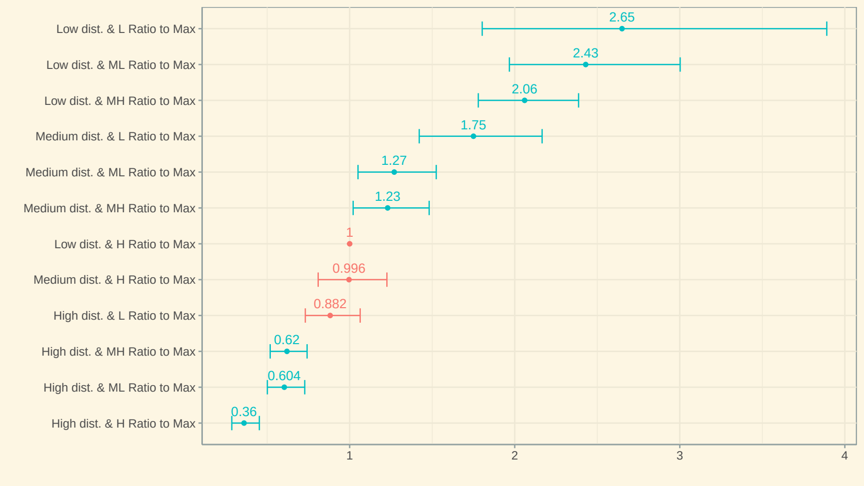

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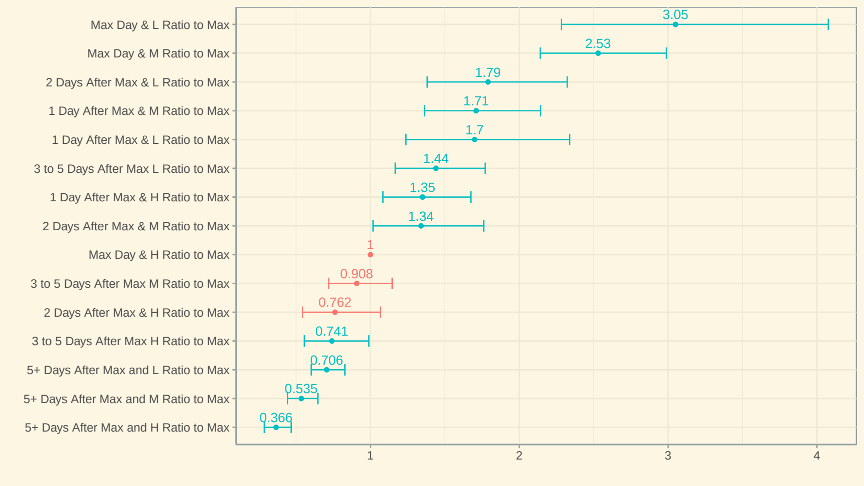
- Threshold strategy does not describe average investor behaviour. It better describes sophisticated investors' behaviour.
- Regret works in a different way from Strack and Viefers (2020) predictions. No regret about price distance from past maximum.
- Time matters a lot. Investors don't forget past maximum; relevant when designing investment platforms and for financial consulting.
- Regret about time should be incorporated in a theory about dynamic regret.

Short days distance reverts regret predictions (PH model)



Maximum Regression

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

	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)

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
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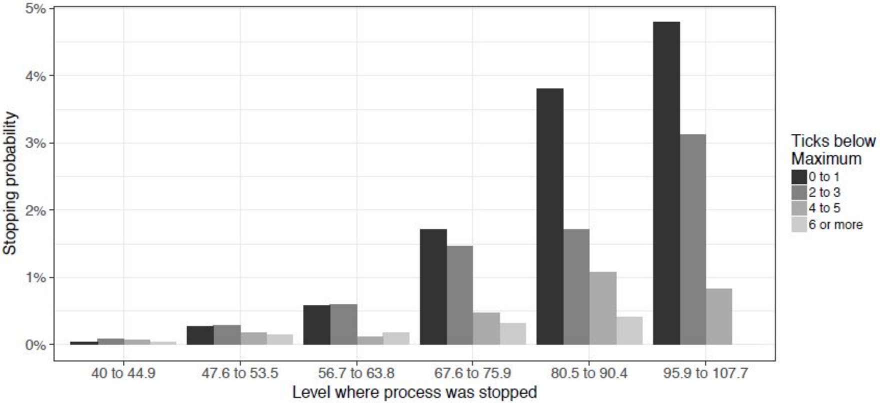
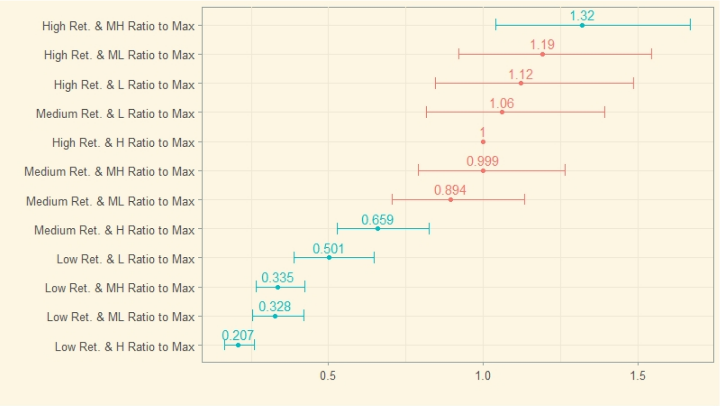
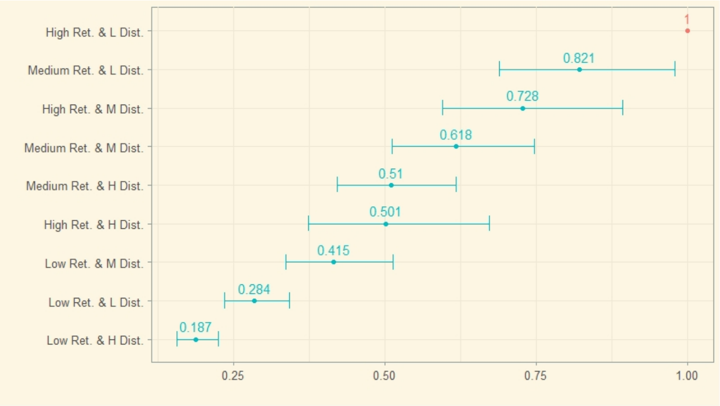
Results from Strack and Viefers (2020)



Ratiomax and return (PH model)



Distance and return (PH model)



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.

Threshold Consistency: Logit model

Dep. var.	1+ threshold investments					
	Gain		Loss		All	
Account Type (ref. Cash)						
Account Type IRA	1.173	1.170	1.030	1.054	0.999	0.981
Account Type Keogh	1.710	1.652	1.684	1.566	1.669	1.818
Account Type Margin	1.323**	1.401***	1.189	1.214	1.161	1.260
Account Type Schwab	1.576***	1.580***	1.230*	1.267**	1.461***	1.494***
Client Segment (ref. General)						
Client Segment Affluent	0.894	0.902	0.731***	0.745***	0.784**	0.799*
Client Segment Active	2.496***	2.573***	1.991***	2.032***	2.564***	2.604***
Age (decades)	0.872***	0.875***	0.984	0.991	0.826***	0.839***
Income	0.977	0.975	0.965*	0.971	0.978	0.979
Male	1.021	1.017	1.153	1.157	0.886	0.880
Occupation (ref. Other (also NA)						
Non Professional Occupation	0.831	0.866	0.926	0.987	0.878	0.957
Professional Occupation	0.850**	0.849***	0.919	0.924	0.839**	0.836**
Experience (ref. Good)						
Experience Extensive	0.911		1.189*		0.945	
Experience Low	0.916		0.995		0.900	
Experience None	1.137		0.674*		1.310	
Knowledge (ref. Good)						
Knowledge Extensive		0.837*		1.124		0.887
Knowledge Low		0.895		0.923		0.885
Knowledge None		0.950		0.901		0.918
McFadden Adj. R^2	0.03	0.29	0.029	0.29	0.038	0.31
Observations	4,713	4,911	3,531	3,663	2,701	2,809

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