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Prospect Theory to the Disposition Effect in an Agent-Based Model of the Stock Market

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Abstract: We take the key equation of cumulative prospect theory and simulate its parameters from an agent-based model of the stock market. We show how the disposition effect emerges numerically in an alternative and complementary way to what is found in literature using analytical methods.

Keywords: Cumulative Prospect Theory, Disposition Effect, Agent-Based Models

JEL classification Number: G4, C63

1. Introduction

The value function v of cumulative prospect theory (Tversky and Kahneman, 1992; Barberis and Xiong, 2009) is

$$v_{i,t} = \begin{cases} x_{i,t}^{\alpha} & \text{if } x_{i,t} \geq 0 \text{ (gains)} \\ -\lambda(-x_{i,t})^{\alpha} & \text{if } x_{i,t} < 0 \text{ (losses)} \end{cases} \quad (1)$$

where $\alpha \in (0,1)$; $\lambda > 1$ and x is here interpreted as an ecology of distinct expected stock returns. The empirically determined parameter values (Tversky and Kahneman, 1992) are: $\alpha = 0.88$ and $\lambda = 2.25$. However, "if the functions associated with the theory are not constrained, the number of estimated parameters for each subject is too large" (Tversky and Kahneman, 1992). Thus, rather than assuming these parameter values, we perform numerical simulations of parameter λ by keeping α constant within the framework of an agent-based model of the stock market. The model is displayed in NetLogo at http://modelingcommons.org/ browse/one_model/5207#. This simple move suffices to generate the disposition effect from cumulative prospect theory in a way analogous to that previously found in the literature using analytical methods (Barberis and Xiong, 2009).

2. Results

We ran 900,000 trials, divided into subsets of 3,000. For three selected values of λ and $\alpha = 0.88$, Table 1 shows the averages of 10simulations, each comprising 3,000 periods and 10,000 agents. The disposition effect may emerge. The disposition effect occurs whenever the number of periods in which winners are held is lower than the number of periods in which losers are held. In particular, the disposition effect may emerge for $\lambda = 2.20$, a figure roughly equal to that found empirically (Tversky and Kahneman, 1992).

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Table 1: Possible emergence of the disposition effect from the simulations of an agent-based model

λ	Number of trades	Winners held (average number of periods)	Losers held (average number of periods)	Disposition effect?
1.00	2,083,039	46.1 (± 6.3)	46.9 (± 6.4)	No
1.50	258,974	267.2 (± 45.1)	377.6 (± 79.5)	Yes*
2.20	1,259	454.1 (±71.8)	805.3 (±103.2)	Yes*

Note: * denotes 95 percent confidence interval.

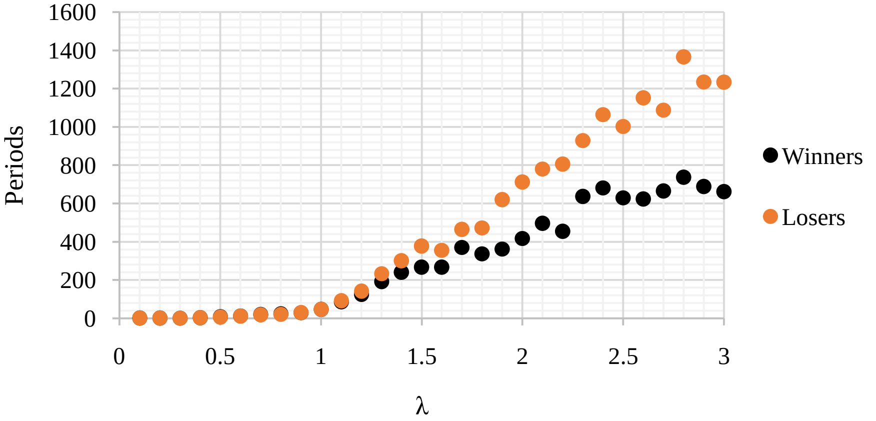
To illustrate how we determine the number of periods in which stocks are held, Table 2 considers data for $\lambda = 1.5$. As before, each simulation comprises 3,000 periods and 10,000 agents. Table 2 exemplifies over realized losses, and show how the mean number of periods in which losers are held is calculated from the realized losses.

Table 2: Example of how to determine the number of periods in which stocks are held

Simulation	λ	Realized losses (A)	Total number of periods in which a stock is held (B)	Mean number of periods in which a stock is held (C = B/A)
1	1.50	22,224	8,446,995	380.1
2	1.50	31,285	7,870,846	251.6
3	1.50	23,797	9,112,160	382.9
4	1.50	13,329	9,081,807	681.4
5	1.50	17,887	8,586,890	480.1
6	1.50	33,247	9,834,432	295.8
7	1.50	39,259	8,908,538	226.9
8	1.50	36,054	10,048,397	278.7
9	1.50	20,239	9,563,319	472.5
10	1.50	21,653	7,060,879	326.1
	Total	258,974	97,788,582	
	Mean	25,897.4	9,778,858.2	377.6

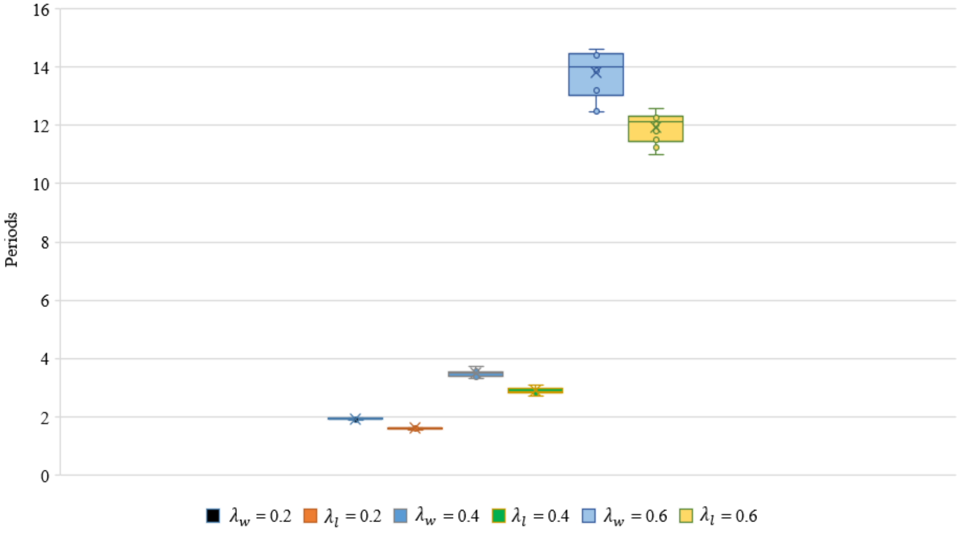
Figure 1 shows the behavior of the agents as parameter λ rises. The average time they hold stocks increases for both gains and losses, and so does the number of periods that they keep their purchases. Figure 1 shows that the more the value of λ exceeds one, the greater the disposition effect. Of note, cumulative prospect theory assumes $\lambda > 1$, which is precisely the situation where the disposition effect emerges in our simulations.

Figure 1: Holding winners and losers changes as λ increases: the disposition effect increases steadily for $\lambda > 1$



To assess whether cumulative prospect theory is really generating the disposition effect, we now focus on $\lambda < 1$, a situation ruled out by the theory. Figure 2 shows that for $\lambda = 0.2$, $\lambda = 0.4$ and $\lambda = 0.6$, the agents hold their winning stocks for longer, and thus the disposition effect vanishes.

Figure 2: For $\lambda = 0.2$, $\lambda = 0.4$ and $\lambda = 0.6$, the time that agents hold winners (λ_w) is longer than the time they hold losers (λ_ℓ), and thus the disposition effect vanishes



To be precise, the simulations show unequivocally the disposition effect for $\lambda \geq 1.4$ (Table 3). In Table 3, we ran 10 simulations for each value of λ over 3,000 periods.

Table 3: Summary of the simulations. The disposition effect emerges unequivocally for $\lambda \geq 1.4$, which are the parameter values to which cumulative prospect theory holds

λ	**Mean number of periods agents hold winners***	**Mean number of periods agents hold losers***	**Disposition effect?**
0.1	1.7 (± 0.01)	1.4(± 0.01)	No
0.2	1.9(± 0.01)	1.6(± 0.01)	No
0.3	2.4(± 0.03)	2.0(± 0.03)	No
0.4	3.5 (± 0.07)	2.9(± 0.06)	No
0.5	7.8(± 0.21)	6.6(± 0.21)	No
0.6	13.8(± 0.47)	11.9(± 0.31)	No
0.7	20.3(± 0.44)	18.6(± 0.47)	No
0.8	23.5(± 0.69)	22.2(± 0.79)	Indefinite
0.9	30.5(± 1.53)	30.0(± 1.45)	Indefinite
1.0	46.1(± 6.33)	46.9(± 6.44)	Indefinite
1.1	87.4(± 16.0)	91.7(± 16.0)	Indefinite
1.2	124.7(± 13.7)	142.1(± 16.2)	Indefinite
1.3	192.4(± 34.2)	234.4(± 43.4)	Indefinite
1.4	240.2(± 25.9)	300.3(± 29.2)	Yes
1.5	267.2(± 45.1)	377.6(± 79.5)	Yes
1.6	267.5(± 40.1)	356.4(± 38.6)	Yes
1.7	371.7(± 79.6)	463.9(± 47.2)	Yes
1.8	338.4(± 72.6)	473.5(± 106)	Yes
1.9	363.5(± 73.5)	620.2(± 150)	Yes
2.0	418.4(± 106)	712.1(± 156)	Yes
2.1	496.6 (± 90.7)	781.0(± 129)	Yes
2.2	454.1(± 117)	805.3(± 168)	Yes
2.3	636.8(± 148)	929.5(± 186)	Yes
2.4	682.3(± 142)	1,065.2(± 196)	Yes
2.5	630.7(± 74.6)	1,003.5(± 159)	Yes
2.6	622.9(± 133)	1,150.7(± 236)	Yes
2.7	664.9(± 110)	1,088.3(± 155)	Yes
2.8	736.4(± 139)	1,365.2(± 273)	Yes
2.9	688.8(± 140)	1,235.5(± 162)	Yes
3.0	661.9(± 135)	1,233.4(± 236)	Yes

Note: * denotes 95 percent confidence interval.

3. Conclusion

The disposition effect is a fundamental feature of trading, though competing theories find it difficult to explain. This prompts a more basic explanation based on prospect theory (Barberis and Xiong, 2009). Here, we provide a numerical reinforcement of this long-standing explanation. In a framework of an agent-based model where agents obey cumulative prospect theory, we show how the disposition effect emerges from the proper parametrization assumed by the theory.

References

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