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Research Report

The psychology of investment behavior: (De)biasing financial decision-making one graph at a time☆

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Abstract

Consumers' welfare largely depends on the soundness of their financial decisions. To this effect, the present research examines how people process graphical displays of financial information (e.g., stock-prices) to forecast future trends and invest accordingly. In essence, we ask whether and how visual biases in data interpretation impact financial decision-making and risk-taking. Five experiments find that the last trading day(s) of a stock bear a disproportionately (and unduly) high importance on investment behavior, a phenomenon we coin *end-anchoring*. Specifically, a stock-price closing upward (downward) fosters upward (downward) forecasts for tomorrow and, accordingly, more (less) investing in the present. Substantial investment asymmetries (up to 75%) emerge even as stock-price distributions were generated randomly to simulate times when the market conjuncture is hesitant and no real upward or downward trend can be identified. Allying experimental manipulations to eye-tracking technology, the present research begins to explore the underpinnings of end-anchoring.

Keywords: Visual-processing biases; Perceptual salience; Judgment and decision-making; Financial risk-taking; End-anchoring

Financial decision-making can take many forms (e.g., negotiating a mortgage; arbitraging between daily consumption, healthcare, and insurance; funding education vs. retirement). As varied as they may be, financial decisions often constitute important milestones whose outcome can substantially promote or impair personal welfare (Duclos, Wan, & Jiang, 2013). The present research investigates one particular form of financial decisions: asset trading (e.g., stocks, bonds, ETFs). Broadly speaking, we examine the process by which investors process visual information to (i) predict the future value of financial assets and (ii) invest accordingly.

Societal and managerial importance of the research

Forty-one percent of Americans give themselves a C, D, or F on their knowledge of personal finance (Harris Interactive Inc, 2011). Whereas low competence should foster restraint, the proportion of lay (i.e., nonprofessional) investors trading equities is skyrocketing. As of 1999, US households held 40% of all corporate equities in America (+ 71% in 10 years; Vogelheim, Schoenbachler, Gordon, & Gordon, 2001). Similarly, as of 2006, 40% of the Nikkei index was held by individual Japanese investors (+ 100% since 2002; Tanaka, 2006).

In principle, most people understand that financial decisions hinge on balancing risk and returns over time. In practice, however, how do investors weigh the pros and cons of a particular stock? How does one predict future price fluctuations? And accordingly, how does one decide when to buy, hold, or sell equities? Given their self-acknowledged inexperience, individual investors largely rely on outside recommendations to make such decisions. Typically, these recommendations originate from banks, brokers, and financial-data providers (e.g., Bloomberg, Reuters). But given

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the indigestible magnitude of information afforded by modern technologies, financial-services providers usually summarize their so-called 'market intelligence' to ease its interpretation. The method used most commonly to convey performance over time is graphs (Raghubir & Das, 2010). In fact, most industry players enable consumers to customize the visual representation of data relevant to them. Stocks, debt, commodities, and foreign-exchange markets can thus be reviewed at a glance, thanks to sophisticated yet user-friendly graphic interfaces.

Given the implications of financial decision-making for individual as well as societal welfare, the present enquiry examines how graphic representation of quantitative information may bias information processing and, ultimately, investment decisions. In the next section, we briefly review the extant literature on visual processing of financial information before deriving our own hypotheses for investment behavior.

Conceptual development

Many long-held beliefs in finance and economics were challenged in recent years by evidence coming out of the judgment and decision-making literature. Investors are not as rational, unbiased utility-maximizers as once thought (Huang, Zhang, Hui, & Wyer, 2014; Kahneman, 2003; Raghubir & Das, 1999; Shefrin, 1999). Similarly, anomalies such as loss aversion, inaccurate inference-making, and the widespread use of heuristics contradict assumptions underlying many classic models of decision under uncertainty (Benartzi & Thaler, 1995; Huberman, 2001; Shefrin & Statman, 1985, 1993; Yan & Duclos, 2013). To date, however, Raghubir and Das (2010) work remains the first and only to examine how investors process graphical financial information.

Effects of graphical displays of financial information

Our ever-increasing reliance on graphs to represent financial performance over time begs the question of whether and how visual biases in data interpretation impact investment behavior. Surprisingly, however, the finance and economics literatures offer scant research in the area. Historically, these fields operated at an aggregate level by modeling large-scale, market-level datasets to infer individual behavior (Raghubir & Das, 2010). Noting this gap, Raghubir and Das (2010) initiated a line of research dedicated to studying how visual displays of quantitative information influence investors. The authors' main contribution lies in documenting how stocks' run-lengths influence risk perceptions (i.e., shorter [longer] run-lengths signal lesser [greater] risk).

The present article leaves aside risk perceptions to examine instead how graphic representation of financial information biases (i) asset-value forecasting and (ii) investment decisions. In a nutshell, we argue that recent fluctuations of a given asset's price can unduly anchor (upward or downward) investors' future-price predictions for the said asset and, in turn, bias their investing.

A rich literature in social psychology dating back to the 1960s suggests that people operate (largely nonconsciously) under the assumption that past behavior (particularly one's most recent behavior) is predictive of future behavior (Jones & Harris, 1967). Applied to human, animal, as well as inanimate objects (Nisbett, 2003), this lay theory (sometimes referred to as a cognitive bias) entails that proximal past takes precedence over distal past to extrapolate/infer/predict future outcomes.

Drawing on this research, we posit that consumers may overweigh the importance of recent information and neglect prior/base-rate information (DeBondt & Thaler, 1985, 1987), which in turn may impair asset-value forecasting and investment behavior. We further conjecture that this end-anchoring bias is more likely to occur when quantitative information is reviewed graphically (as is usually the case in the real world). Indeed, we suggest that lines on a graph instill a greater sense of continuity over time since each new day is visibly and directly linked to its predecessor (visually speaking, two consecutive days on a graph are in fact hardly dissociable from each other). This sense of continuity may in turn make it easier to expect and/or visualize consistency from one day to the next. In contrast, tabular displays, which report numbers standing alone in separate cells, may reduce perceptions of continuity over time to underscore instead the discrete, separate, and/or relatively independent nature of each stock-price.

To summarize, our contention is that, when experiences are made of successive episodes spanning from past to future, consumers rely on the end of one episode to predict what will happen in the next. With respect to financial decision-making, we posit that the graphical representation of a stock-price can unduly anchor investment behavior. As they contemplate the retrospective performance of a stock, investors rely disproportionally on the most recent trade-activity (i.e., the end of a series) to infer how the stock will fare today. As a result, stocks whose last price-fluctuation followed an upward (downward) trajectory foster upward (downward) expectations for the future; hence increase (decrease) one's willingness to purchase shares in the present.

By documenting the moderating impact of data-presentation format (graphic vs. numeric), these findings also shed light on a prevalent yet not-fully-understood phenomenon in behavioral finance: momentum investing (i.e., buying and selling stocks rapidly to capitalize on emerging market trends; for a review, see Crombez, 2001).

Study 1: End-anchoring

Per our theorizing, study 1 tests whether recent price-fluctuations can bias asset-value forecasting and investment decisions. We examine this proposition under two conditions: when the uncertainty (i.e., standard deviation) surrounding stock-prices is small or large.

Method

Participants and design

Of 158 participants recruited via M-Turk, three (2%) were discarded for failing our attention tests (i.e., What is the result of 7–5?; If you're reading this question, please select 2 below).

Table 1
Participants (studies 1–5).

	Study 1	Study 2	Study 3	Study 4	Study 5
Recruited	158	209	49	50	162
Discarded	3 (2%)	7 (3%)	1 (2%)	0	0
(per condition)	*1 (down*large SD)*	*2 (down*graph)*	*0 (downward)*		
	*2 (up*large SD)*	*1 (up*graph)*	*1 (upward)*		
	*0 (down*small SD)*	*0 (down*table)*			
	*0 (up*small SD)*	*4 (up*table)*			
Sample	155	202	48	50	162
Average age	35	31	30	–	30
Female/Male	56/44	45/55	47/53	–	57/43

The resultant 155 participants (Table 1) were randomly assigned to one of four conditions following a 2 (Last trade-direction: downward vs. upward) by 2 (SD: small vs. large) between-subjects design.

Procedure

Participants viewed a graph reporting the stock-price of an alleged company for the last 30 days. To preempt alternative explanations, these 30 stock-prices were generated randomly around predetermined characteristics (i.e., mean = \$60; SD = 10 or 20, depending on condition; kurtosis = −1; skewness = 0). To keep these properties constant across conditions, we then reversed this distribution to create a perfect mirror image around the mean. For instance, as one distribution would move from \$48 (i.e., \$12 below mean) to \$63 (i.e., \$3 above mean) to \$45 (i.e., \$15 below mean), its mirror counterpart would move from \$72 (i.e., \$12 above mean) to \$57 (i.e., \$3 below mean) to \$75 (i.e., \$15 above mean). Overall, then, participants reviewed the same financial information (e.g., same mean, SD, kurtosis, skewness, and same run-length (i.e., 1.5)). The only differences resided in our two manipulations: (i) whether the sequence ended upward or downward and (ii) whether the uncertainty surrounding stock-prices was small or large (web appendix A).

Upon reviewing their respective graph, participants (i) predicted the company's stock-price by day's end and (ii) indicated how much of their own money they would be willing to spend to acquire this stock.

Importantly, our price distributions followed no upward or downward trend over time (i.e., slopes were virtually flat). But in any case, slopes were always in the *opposite* direction of the last price-movement. Hence, the rational thing would be to predict prices in the *opposite* direction of the last trade-direction. This subtle characteristic may go unnoticed but it allows for a more conservative test of our hypotheses.

Predicted stock-price

An ANOVA revealed a main effect of the last trade-direction ($F(1,151) = 16.188$, $p = .000$, $\eta^2 = .097$). On average, if the trading sequence ended downward (upward), participants expected a lower (higher) stock-price by day's end ($M_{\text{down}} = \$56$ vs. $M_{\text{up}} = \$63$; Table 2). No main effect of standard deviation ($p = .776$) and no interaction ($p = .301$) emerged. In other words, the influence of the previous day's trade-direction remained the same regardless of the uncertainty surrounding the company's stock-price.

Amount invested

Mirroring the above results, an ANOVA revealed a main effect of the last trade-direction ($F(1,151) = 12.481$, $p = .001$, $\eta^2 = .076$). If the sequence ended downward (upward), participants were willing to invest less (more) of their own money to buy stock from the company ($M_{\text{down}} = \$236$ vs. $M_{\text{up}} = \$377$). This was again true regardless of the uncertainty characterizing the company's stock-price distribution (i.e., no main effect of standard deviation ($p = .163$) and no interaction ($p = .851$)). Mediation analyses confirmed that the impact of the last trade-direction on investment decisions was mediated by price predictions (Table 3).

Discussion

These findings support our theorizing. Graphic displays of data seem able to bias consumers' evaluation of financial information and, consequently, their investment decisions. Once again, we stress here that our stock-price distributions were constructed so they followed no real upward or

Table 2
Means, SDs, and cell sizes (study 1).

DV	Last trade-direction	Standard deviation	Mean	SD	N
Predicted price	Upward	Small (10)	62	8	41
		Large (20)	63	12	37
		Total	63	10	78
	Downward	Small (10)	57	7	37
		Large (20)	55	10	40
		Total	56	9	77
	Total	Small (10)	60	8	78
		Large (20)	59	12	77
		Total	60	10	155
Invested amount	Upward	Small (10)	346	226	41
		Large (20)	411	282	37
		Total	377	254	78
	Downward	Small (10)	211	283	37
		Large (20)	260	216	40
		Total	236	250	77
	Total	Small (10)	282	262	78
		Large (20)	332	259	77
		Total	307	261	155

Table 3
Mediation results (study 1).

				Unstdized		Stdized		
	Step	IVs	DVs	B	SE	Beta	t	Sig
Study 1								
	1	Last trade-direction[a]	Invested amount	71.585	20.263	0.275	3.533	0.001
		SD[b]		28.415	20.263	0.109	1.402	0.163
		Last trade-direction*SD		3.82	20.263	0.015	0.189	0.851
	2	Last trade-direction[a]	Predicted price	3.127	0.777	0.31	4.023	0.000
		SD[b]		−0.222	0.777	−0.022	−0.285	0.776
		Last trade-direction*SD		0.807	0.777	0.08	1.038	0.301
	3	Predicted price	Invested amount	9.723	1.933	0.377	5.031	0.000
	4	Last trade-direction[a]	Invested amount	45.125	20.234	0.174	2.23	0.027
		SD[b]		30.292	19.235	0.116	1.575	0.117
		Last trade-direction*SD		−3.007	19.298	−0.012	−0.156	0.876
		Predicted price		8.461	2.013	0.328	4.203	0.000
	Goodman test: 3.181, SE = 9.558, p = .001							

[a] −1 = down; 1 = up. [b] −1 = small; 1 = large.
No covariates were used in any of the above analyses.

downward trend over time. This important property implies that recent price movements were no more informative than earlier ones. Yet, the present results suggest that recent stock-price fluctuations influenced investors substantially.

Study 2: Visual bias

We theorized end-anchoring as more likely to occur when information is reviewed visually (i.e., graphically, as is often the case in the real world) than numerically. Indeed, we reckon lines on a graph foster a greater sense of continuity over time (than tabular displays) since each new day is visibly/directly linked to its predecessor. This sense of continuity makes it in turn easier to expect and/or visualize consistency from one day to the next. Study 2 examines this proposition by comparing data-presentation formats.

Method

Participants and design

Participants (N = 202) were randomly assigned to one of four conditions following a 2 (Last trade-direction: downward vs. upward) by 2 (Data display: graph vs. table) between-subject design.

Procedure

The procedure followed study 1's with one difference. Rather than testing the uncertainty surrounding stock-prices, we examined the moderating role of data display. To this end, participants processed data either visually (i.e., in graphs) or numerically (i.e., in tables; web appendix B).

Results

Predicted stock-price

An ANOVA revealed a main effect of the last trade-direction ($F(1,198) = 16.621$, $p = .000$, $\eta^2 = .077$). If the trading sequence ended downward (upward), participants expected a lower (higher) stock-price by day's end (M_{down} = \$58 vs. M_{up} = \$63; Table 4). As predicted, however, this main effect was moderated by data display (interaction term: $F(1,198) = 38.941$, $p = .000$, $\eta^2 = .164$). When stock-prices were processed graphically, a trading sequence ending downward (upward) led participants to expect lower (higher) prices (M_{down} = \$55 vs. M_{up} = \$65; $p < .001$). In contrast, when stock-prices were processed numerically (i.e., from a table listing prices chronologically), participants predicted the same price by day's end whether the trading sequence ended downward or upward (M_{down} = \$61 vs. M_{up} = \$59; NS). No main effect of the presentation format emerged ($p = .809$).

Amount invested

A similar interaction emerged with the amount of money participants sought to invest ($F(1,198) = 10.026$, $p = .002$, $\eta^2 = .048$). When stock-prices were processed graphically, a

Table 4
Means, SDs, and cell sizes (study 2).

DV	Last trade-direction	Data display	Mean	SD	N
Predicted price	Downward	Graph	55	10	48
		Table	61	7	53
		Total	58	9	101
	Upward	Graph	65	5	55
		Table	59	7	46
		Total	63	7	101
	Total	Graph	60	9	103
		Table	60	7	99
		Total	60	8	202
Invested amount	Downward	Graph	375	352	48
		Table	481	354	53
		Total	431	355	101
	Upward	Graph	600	328	55
		Table	396	358	46
		Total	507	355	101
	Total	Graph	495	356	103
		Table	441	357	99
		Total	469	356	202

sequence ending downward (upward) led participants to invest less (more) (M_{down} = \$375 vs. M_{up} = \$600; p = .001). In contrast, when stock-prices were processed numerically, participants exhibited equivalent investment decisions (M_{down} = \$481 vs. M_{up} = \$396; NS).

In short, end-anchoring occurred with graphical processing but disappeared with numerical processing. These results lend credence to our "visual bias" account. Mediation analyses confirmed that the 'last trade-direction' by 'data display' interaction on investment decisions was driven by price predictions (Table 5).

Discussion

Intended to facilitate and improve information processing, graphs can sometimes backfire and bias financial decision-making. To this effect, we find that recent stock-price activity (i.e., downward/upward price movements) swayed respondents' price predictions and, in turn, their willingness to invest in a company they otherwise knew little about. This bias faded, however, when participants processed data numerically (i.e., reviewing numbers rather than graphs).

Study 3: Consequential stakes

Though instructions in studies 1–2 stressed to participants to approach the task as they would with their own money, the present experiment sought to go a step further by affording participants a chance for real financial gain.

Method

Participants and design

Forty-eight volunteers were randomly assigned to one of two conditions (Last trade-direction: downward vs. upward) following a between-subjects design.

Procedure

The procedure resembled study 2's graphical-display condition. To make the task consequential, however, we endowed participants with \$1000 of house money. This money was theirs to invest as they saw fit. Whoever had the most money left in his/her hands at the end of the study was to win \$100.

Table 5
Mediation results (studies 2–4).

			Unstdized		Stdized		
Step	IVs	DV	B	SE	Beta	t	Sig
Study 2							
1	Last trade-direction[a]	Invested amount	34.880	24.514	.098	1.423	.156
	Data display[b]		−24.554	24.514	−.069	−1.002	.318
	Last trade-direction*Data display		−77.620	24.514	−.218	−3.166	.002
2	Last trade-direction[a]	Predicted price	1.680	.488	.206	3.444	.001
	Data display[b]		−.326	.488	−.040	−.667	.505
	Last trade-direction*Data display		−3.061	.488	−.375	−6.275	.000
3	Predicted price	Invested amount	9.634	3.066	.217	3.142	.002
4	Last trade-direction[a]	Invested amount	22.627	25.394	.064	.891	.374
	Data display[b]		−25.280	24.394	−.071	−1.036	.301
	Last trade-direction*Data display		−58.865	26.682	−.165	−2.206	.029
	Predicted price		5.976	3.447	.135	1.734	.085
Goodman test: −2.838, SE = 10.390, p = .005							
Study 3							
1	Last trade-direction[a]	Invested amount	129.545	52.931	0.339	2.447	0.018
2	Last trade-direction[a]	Predicted price	3.243	1.145	0.385	2.833	0.007
3	Predicted price	Invested amount	18.179	6.127	0.401	2.967	0.005
4	Last trade-direction[a]	Invested amount	82.909	55.121	0.217	1.504	0.140
	Predicted price		14.381	6.551	0.317	2.195	0.033
Goodman test: 2.112, SE = 27.908, p = .035							
Study 4							
1	Last trade-direction[a]	Invested amount	84	26.379	0.306	3.184	0.002
2	Last trade-direction[a]	Predicted price	2.75	1.223	0.221	2.248	0.027
3	Predicted price	Invested amount	9.842	1.998	0.446	4.926	0.000
4	Last trade-direction[a]	Invested amount	59.871	24.838	0.218	2.41	0.018
	Predicted price		8.774	2	0.397	4.386	0.000
Goodman test: 2.081, SE = 13.004, p = .037							

[a] −1 = down; 1 = up. [b] −1 = graph; 1 = table.
No covariates were used in any of the above analyses.

Table 6
Means, SDs, and cell sizes (studies 3–4).

Study	DV	Last trade-direction	Mean	SD	N
3 (between-subjects)	Predicted stock-price	Downward	57	9	26
		Upward	63	6	22
	Invested amount	Downward	350	377	26
		Upward	609	352	22
4 (within-subjects)	Predicted stock-price	Downward	43	13	50
		Upward	49	12	50
	Invested amount	Downward	286	253	50
		Upward	454	274	50

Results and discussion

An ANOVA revealed a main effect of the last trade-direction on both price prediction (M_{down} = \$57 vs. M_{up} = \$63; $F(1,46) = 8.026$, $p = .007$, $\eta^2 = .149$; Table 6) and investment decision (M_{down} = \$350 vs. M_{up} = \$609; $F(1,46) = 5.990$, $p = .018$, $\eta^2 = .115$). Once more, the impact of the last trade-direction on investment decisions was mediated by price predictions (Table 5).

Even when real money is at stake, graphic displays of stock-prices seem able to bias consumers' assessment of future trends and, accordingly, their willingness to invest. Given the random nature of our stock-price distributions (i.e., in absence of any real/significant downward or upward trend), these results stress again the irrationality and harmful potential of end-anchoring for investors.

Study 4: Eye-tracking

To articulate end-anchoring, we posited that investors focus more readily on recent than on earlier price-points, which in turn biases asset-value forecasting. While studies 1–3 are supportive of this account, experiment 4 seeks convergent evidence by tracking participants' gaze as they review stock-prices. Per our theorizing, we predicted that participants would attend more (i.e., longer) to the last trade-direction.

Method

Participants and design

Fifty undergraduate students were assigned to two successive conditions (Last trade-direction: downward vs. upward; sequence determined randomly) following a within-subjects design.

Procedure

Participants reviewed not one but two graphs which depicted the stock-price of two alleged companies for the last 10 days (web appendix C). Once again, the price distributions were perfect reflections of each other around the mean so as to ensure constant statistical properties across conditions (i.e., mean = \$46; SD = 12; kurtosis = -2; skewness = 0; run-length = 1.3; Fig. 1).

Results and discussion

Stock-price and investment

Paired-samples t-tests revealed a main effect of the last trade-direction on both price prediction (M_{down} = \$43 vs. M_{up} = \$49; $t(49) = 2.410$, $p = .02$; Table 6) and investment decision (M_{down} = \$286 vs. M_{up} = \$454; $t(49) = 3.424$, $p = .001$). Once again, the impact of the last trade-direction on investment decisions was mediated by price predictions (Table 5).

Gaze duration

Nine rectangular areas of interest (AOIs) were determined ex ante to test our theorizing. Equal in size and shape, these AOIs were positioned contiguously (with no space in between

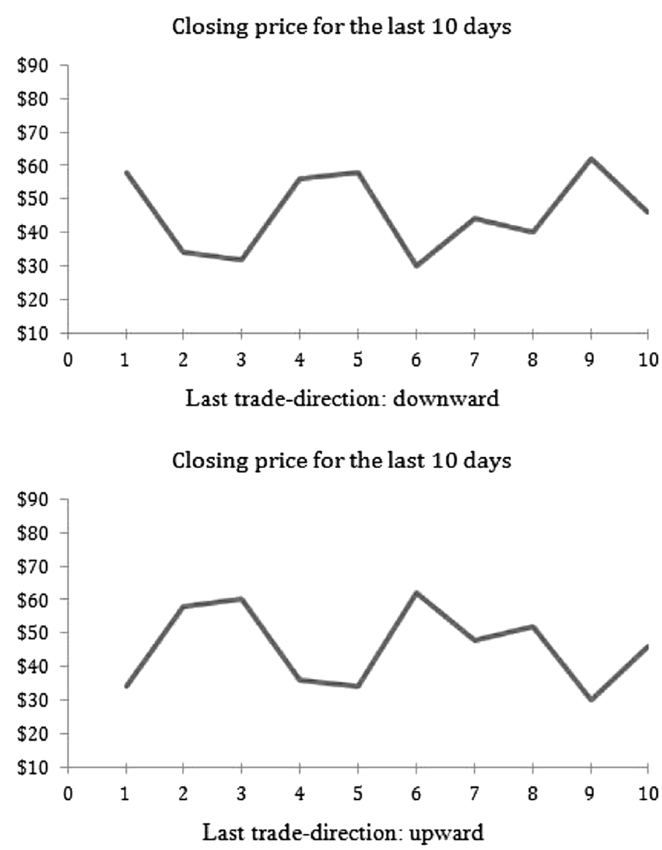

Fig. 1. Study 4 stimuli.

and no overlap) so as to capture the nine paths linking each of the ten stock-prices to one another. To assess the total amount of time spent examining each price movement, time stamps were summed for each AOI (O'Keefe et al., 2014; van der Lans, Pieters, & Wedel, 2008; van der Lans, Wedel, & Pieters, 2011). As expected, paired-samples t-tests revealed that the ninth AOI (which captured the last trade-direction) was gazed the longest (i.e., 1.45 (1.25) second in the downward (upward) condition) and significantly more than each of the previous eight AOIs which ranged from .31 to .94 second ($ps \leq .004$; Table 7).

Gaze duration itself did not correlate with our financial DVs (Table 8). This absence of correlation may relate to the fact that the time spent examining AOI9 can reflect a variety of mental processes: integrating the information sampled in previous AOIs; visualizing how the graph will look like (e.g., where [and how far] the line goes next); confidence in forecasting abilities; etc. Consequently, two people who spent different amounts of time on the last trade-direction may end up with the same forecast. Conversely, two people who spent the same amount of time on the last trade-direction may ultimately generate different forecasts. This echoes Chandon, Hutchinson, Bradlow, and Young's (2009) finding that (i) consumers gaze longer at and choose more often items that occupy central positions on shelves but that (ii) gaze duration itself does not mediate choice. More analyses of our eye-tracking data are available in web appendix D. Among other, we show that *when* participants look at AOI9 (e.g., early or late) does not influence their subsequent estimates and decisions.

Study 5: Run-length

Studies 1–4 examined end-anchoring while controlling (i.e., keeping constant) run-length across conditions. In contrast, study 5 examines whether different levels of run-length may alter end-anchoring.

Table 7
Total gaze duration (in seconds) for each AOI (study 4).

Condition		AOI9	t	df	Sig.
Upward	AOI1 = .42 s vs.	1.25 s	−4.497	49	0.000
	AOI2 = .50 s vs.		−4.848	49	0.000
	AOI3 = .44 s vs.		−5.138	49	0.000
	AOI4 = .59 s vs.		−3.838	49	0.000
	AOI5 = .43 s vs.		−5.375	49	0.000
	AOI6 = .65 s vs.		−3.692	49	0.001
	AOI7 = .51 s vs.		−5.269	49	0.000
	AOI8 = .55 s vs.		−5.112	49	0.000
Downward	AOI1 = .39 s vs.	1.45 s	−7.683	49	0.000
	AOI2 = .36 s vs.		−8.129	49	0.000
	AOI3 = .31 s vs.		−8.201	49	0.000
	AOI4 = .83 s vs.		−3.339	49	0.002
	AOI5 = .69 s vs.		−5.209	49	0.000
	AOI6 = .69 s vs.		−5.299	49	0.000
	AOI7 = .74 s vs.		−5.524	49	0.000
	AOI8 = .94 s vs.		−3.046	49	0.004

Table 8
Correlation between AOI9's gaze time and the DVs (study 4).

Condition	r(AOI9 gaze time, predicted stock-price)	r(AOI9 gaze time, amount invested)
Upward	r = −.142, p = .325, NS	r = −.165, p = .252, NS
Downward	r = .083, p = .567, NS	r = .068, p = .641, NS

Method

Participants and design

Participants (N = 162) were assigned to one of three conditions following a 2 (Last trade-direction: downward vs. upward) by 3 (Run-length: 1.0 vs. 1.3 vs. 3.0) mixed-design. The last trade-direction was manipulated within subjects (i.e., participants saw both downward- and upward-ending graphs); run-length was manipulated between subjects.

Procedure

A run-length corresponds to the number of consecutive periods over which stocks move monotonically upward (or downward). For instance, in the sequence {+ + − − 0 + 0 0 −}, the run-lengths are 2, 2, 1, 1, 1, 1. Since run-lengths are defined by movement, the absence of movement (e.g., the two consecutive 0s in the preceding sequence) is given a length of 1, not 2. In the real world, 86% of stocks have run-lengths ranging between 1.0 and 3.0 (Raghubir & Das, 2010). Accordingly, we generated price distributions whose run-lengths varied within this range but whose mean ($55), SD (5), kurtosis (0), and skewness (0) remained identical across conditions (web appendix E). Short of eye-tracking, the rest of the procedure resembled study 4's.

Results and discussion

No main effect of run-length and no run-length*last-trade-direction interactions emerged ($ps > .5$). As predicted, however, paired-samples t-tests revealed a main effect of the last trade-direction within each of the three run-length conditions (Tables 9 and 10). Graphs depicting a sequence ending downward (upward) led participants to (i) expect lower (higher) prices by day's end, and in turn (ii) invest less (more)

Table 9
Means, SDs, and cell sizes (study 5).

Run-length	DV	Last trade-direction	Mean	SD	N
1.0	Predicted stock-price	Downward	53	7	52
		Upward	58	7	
	Invested amount	Downward	246	262	
		Upward	335	327	
1.3	Predicted stock-price	Downward	53	6	57
		Upward	59	7	
	Invested amount	Downward	260	288	
		Upward	423	365	
3.0	Predicted stock-price	Downward	53	4	53
		Upward	58	6	
	Invested amount	Downward	240	299	
		Upward	419	354	

Table 10
Paired-samples statistics by run-length condition (study 5).

Run-length	DV	Last trade-dir. M_{Down}		M_{Up}	t	df	Sig
1.0	Predicted stock-price	$53	<	$58	−3.060	51	0.004
(N = 52)	Amount invested	$246	<	$335	−1.807	51	0.077
1.3	Predicted stock-price	$53	<	$59	−4.818	56	0.000
(N = 57)	Amount invested	$260	<	$423	−3.060	56	0.003
3.0	Predicted stock-price	$53	<	$58	−4.883	52	0.000
(N = 53)	Amount invested	$240	<	$419	−2.627	52	0.011

in the company. In other words, end-anchoring seems to operate for run-lengths up to 3 days long (i.e., 86% of all stocks).

General discussion

Hoping to contribute at the intersection of the finance, economics, and marketing literatures, this research drew on psychological processes to examine how investors process visual information to forecast asset-value and invest accordingly. Building on Raghubir and Das (2010) and Jones and Harris (1967), we theorized that certain datapoints on a graph are more likely to draw attention and, in turn, impair financial decision-making. To this effect, five studies allying experimental manipulations to eye-tracking technology showed that a stock-price closing upward (downward) fosters upward (downward) forecasts for tomorrow and, accordingly, more (less) investing in the present. As noted earlier, our stock-price distributions were generated randomly to simulate times when the conjuncture in real-world markets is hesitant (i.e., trendless). In such times, recent price-movements are no more diagnostic than earlier ones. Yet, we find they do bias decision-making and, ultimately, can be quite harmful for investors. These findings contribute to several literatures.

Methodological and theoretical contributions

Financial decision-making

Many times in the past have financial markets been erratic (e.g., 1980s' Japanese bubble, 1987's market crash, 1997's Asian crisis, 2008's subprime burst). Every time, individual-level behaviors aggregated to form market-level meltdowns. On a daily basis, traders take only seconds to review large amounts of data and commit large sums of money. Methodologically, behavioral finance operates at an aggregate level and has yet to translate into clinical experimentation of how individuals process information to make judgments (Raghubir & Das, 1999, 2010). As a result, the field is ill-equipped to examine the psychological underpinnings of market-level volatility. The present research takes one step in this direction by documenting how spatial judgments based on visual cues influence financial judgments based on graphical stimuli. So doing, we show that graphs, tools intended to improve decision-making, can actually backfire and hurt investors.

To explain why trading volumes increase sharply when stock-prices cross a 52-week high or low, Raghubir and Das (2010) conjectured that perceptual biases may be at play. In absence of direct evidence, however, the authors called for eye-tracking research to examine this process. In this spirit, the present findings show that graphic displays of quantitative information do indeed foster attention biases among investors. Facing large amounts of data, people seem to simplify their decision-making by focusing on specific datapoints. When these datapoints are attended to because of their salience (not their representativeness of a series), however, investment decisions can go awry.

Anchoring

The essence of anchoring research consists of showing that early/initial pieces of data have consequences on subsequent tasks (e.g., predictions, calculations). In Tversky and Kahneman's (1974) seminal demonstration, for instance, participants commenced the experiment by witnessing a numbered wheel land seemingly randomly on either 10 or 65. Next, when asked what proportion of African nations are part of the UN, participants in the low (high) anchor condition answered 25% (45%) on average. In a separate study, students asked to compute mentally 1*2*3*4*5*6*7*8 (8*7*6*5*4*3*2*1) provided median estimates of 512 (2250). Because participants in the first (second) condition started their computation with low (high) anchors before guess-combining the remaining factors, they came further (closer) to the right answer of 40,320. Similar demonstrations have since emerged with distances (Kwong & Wong, 2006), prices (Mussweiler, Strack, & Pfeiffer, 2000; Yan & Duclos, 2013), and probability assessments (Plous, 2006).

By showing that anchoring can happen spontaneously (i.e., without the need for any heavy-handed manipulations), our experiments suggest that consumers can automatically and spontaneously latch on to numbers to inform the decision at hand (i.e., without being explicitly asked to). Moreover, by showing how investors zero in predictably on the last trade-direction, the present work identifies conditions wherein recent (rather than early) datapoints may serve as anchors, a phenomenon not yet accounted by the literature.

Managerial and societal implications

As alluded earlier, despite moderate financial literacy, trading by private (i.e., lay, nonprofessional) investors is growing rapidly in America and abroad. As of 2004, 250,000 people in the US alone were already trading every single day (Karz, 2004). Like their professional counterparts, private investors rely on readily accessible graphs to interpret past market-performance and forecast future trends. The present findings should thus sound a tune of caution for consumers as much as for industry players and regulators. Indeed, biases such as end-anchoring can easily lead to precipitated sale (or purchase) of assets, lopsided portfolio allocations, or other irrational behaviors. It is thus important, both managerially and societally, to understand how displays of data impact investment behavior. To this effect, study 2 found that graphic (numeric) displays encourage (mitigate) end-anchoring. As such, it may sometimes be beneficial to convey quantitative information in less "perceptual" ways. Because of their visual nature, graphs may indeed be more likely to foster perceptual processing and heuristic decision-making. In contrast, numeric displays may be less prone to such a pitfall.

We conclude by hoping this work will help spur interest in how people process quantitative information. Given our ever-increasing reliance on graphs to convey financial information, understanding how visual biases in data interpretation (like end-anchoring) impact investment behavior seems important. It will help (i) financial-services providers refine their presentation of performance data; (ii) lay and professional investors free themselves from detrimental heuristics; and (iii) policymakers organize the dissemination of financial information so as to avoid panics in the market. Mirroring the rules governing product packaging, the present findings may help inform (and perhaps regulate) communications around financial products (Raghubir & Das, 2010).

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jcps.2014.11.005.

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