Current Biology

Report

Variance After-Effects Distort Risk Perception in Humans

Highlights

- After-effects are shown for the feature of variance
- The variance after-effects generalize across markedly different displays of variance
- This suggests high-level cognitive adaptation

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In Brief

Here Payzan-LeNestour et al. show that risk perception is susceptible to after-effects. After looking at a risky stock, a medium-risk stock looks safer, whereas after looking at a safe bond, the same medium-risk stock seems riskier. These variance after-effects generalize across markedly different displays of variance, suggesting high-level adaptation.

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Variance After-Effects Distort Risk Perception in Humans

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SUMMARY

In many contexts, decision-making requires an accurate representation of outcome variance—otherwise known as "risk" in economics. Conventional economic theory assumes this representation to be perfect, thereby focusing on risk preferences rather than risk perception per se [1–3] (but see [4]). However, humans often misrepresent their physical environment. Perhaps the most striking of such misrepresentations are the many well-known sensory after-effects, which most commonly involve visual properties, such as color, contrast, size, and motion. For example, viewing downward motion of a waterfall induces the anomalous biased experience of upward motion during subsequent viewing of static rocks to the side [5]. Given that after-effects are pervasive, occurring across a wide range of time horizons [6] and stimulus dimensions (including properties such as face perception [7, 8], gender [9], and numerosity [10]), and that some evidence exists that neurons show adaptation to variance in the sole visual feature of motion [11], we were interested in assessing whether after-effects distort variance perception in humans. We found that perceived variance is decreased after prolonged exposure to high variance and increased after exposure to low variance within a number of different visual representations of variance. We demonstrate these after-effects occur across very different visual representations of variance, suggesting that these effects are not sensory, but operate at a high (cognitive) level of information processing. These results suggest, therefore, that variance constitutes an independent cognitive property and that prolonged exposure to extreme variance distorts risk perception—a fundamental challenge for economic theory and practice.

RESULTS AND DISCUSSION

To measure the effects of prior adaptation on the perception of variance, we devised several novel techniques to precisely control the nature and degree of variance across numerous different visual representations. The first is the most common representation of financial variance, the volatility of a stock market index. We developed a stylized version of what traders routinely experience on a typical Bloomberg terminal. Brownian motion depicting trajectories of a stock market index was displayed as a moving line plot that was dynamically re-drawn on screen from right to left (Figure 1A; Supplemental Experimental Procedures).

56 participants underwent a period of prolonged (50 s) passive exposure (henceforth, the "exposure period") to the Bloomberg stimulus. In 16 experimental trials, the exposure period in half of the trials consisted of high volatility (45%), and in the other half low volatility (2%). Each exposure period was immediately followed by a test phase, which featured a 20 s medium-volatility (10%) Bloomberg stimulus. Two "diversion trials" featuring medium volatility during the exposure period and high or low variance in the test phase, as well as three "control trials" in which exposure and test stimuli both had medium volatility, were randomly interspersed between standard trials. The mean level of the Bloomberg stimulus index systematically varied across all trials (see the Supplemental Experimental Procedures). Participants had to rate the perceived volatility of the test stimulus on a five-point scale, using the mouse pointer to click the relevant button. See Movie S1 and Figure 1A.

Figure 1B shows the test data for each individual participant. All participants except two showed an after-effect in the predicted direction. The reported variance was significantly higher after exposure to low variance than after exposure to high variance, according to our battery of statistical tests (Welch t test: $t = 7.52$, $p \approx 0$, one-sided; Wilcoxon signed-rank test: $z = 6.44$, $p \approx 0$; see Tables S1A and S1B). Formal regression analysis revealed no relationship between response latency and the after-effect (see the Supplemental Experimental Procedures).

Participants thus had a systematic bias to report the Bloomberg test stimuli as being lower in variance after exposure to high variance than after exposure to low variance, although variance in all experimental test stimuli was the same. To test the robustness of this effect, we ran a replication of the experiment with another group of participants ($N = 31$) using a different set of volatility parameters (high: 40%; low: 7%; medium: 13%; chosen to closely reflect real-world volatility—high, low, and medium volatility levels of the S&P 500 ~40%, 5%–7%, and 13%, respectively [12]). The previous results were fully replicated (Welch t test: $t = 3.2$, $p = 0.001$; see Figure S1).

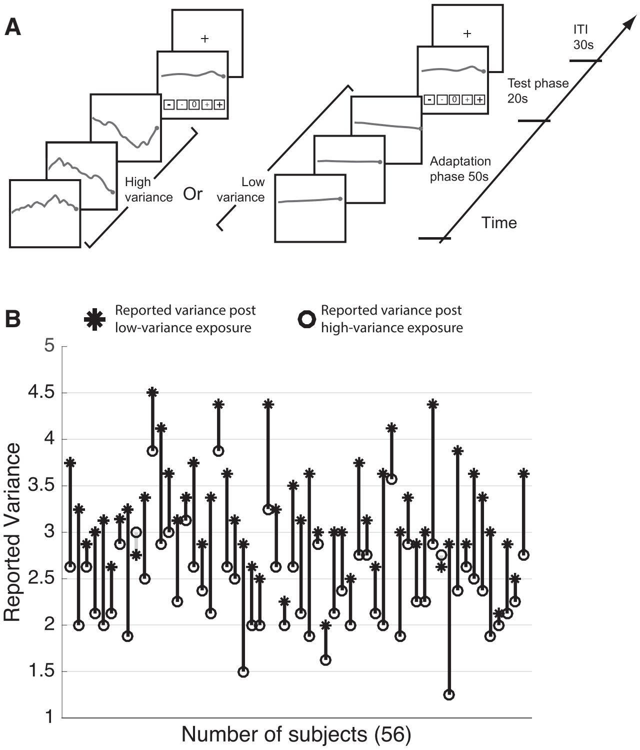

Figure 1. Variance After-Effect for a Bloomberg Line Plot of Variance

(A) Timeline for the Bloomberg experiment. In the exposure phase, Brownian motion with either high (45% volatility) or low (2% volatility) variance level was displayed for 50 s. In the test phase, the medium variance was depicted by a 10% volatility Brownian motion display, and subjects reported their perceived variance using the mouse pointer. ITI, 30 s inter-trial interval.

(B) Measure of the after-effect for each task participant. *, reported variance post low-variance exposure, averaged across experimental trials. 0, reported variance post high-variance exposure, averaged across experimental trials. Black vertical line, after-effect is in the predicted direction (reported variance after low > reported variance after high). Gray line, absence of after-effect (reported variance after low < reported variance after high).

See also Movie S1, Figure S1, Table S1 for stats, and Table S2 for response time analysis and mean variance reports from the diversion trials.

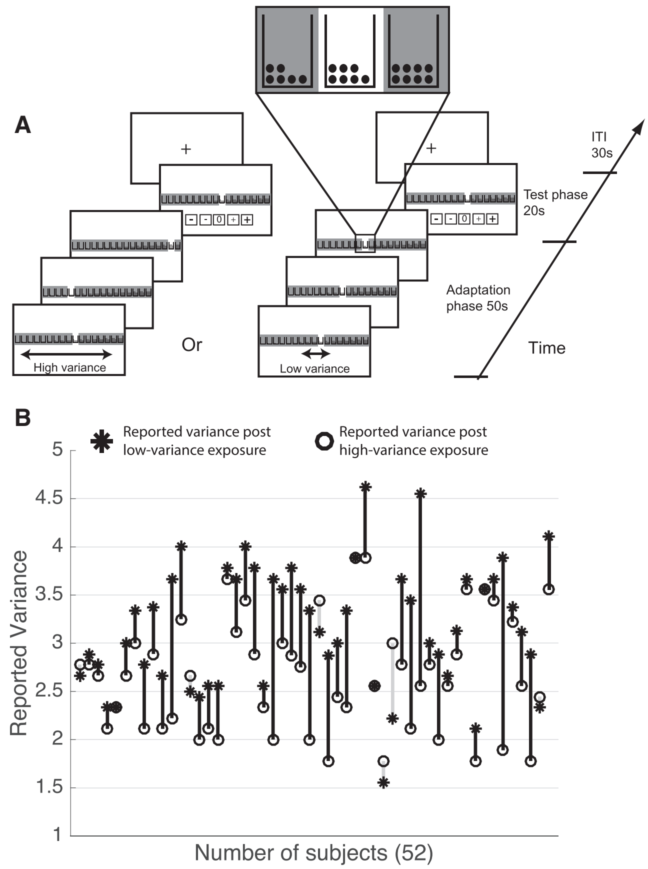

Figure 2. Variance After-Effect for the Balls-in-Buckets Depiction of Variance

(A) Timeline for the multi-bucket experiment. In the exposure phase, a single bucket was highlighted at any one time, the highlight jumped from bucket to bucket to show the given numerical distribution over time. In the test phase, the medium variance was depicted by the same multiple-bucket design, and subjects reported their perceived variance using the mouse pointer. ITI, 30 s inter-trial interval.

(B) Graphical depiction of the data from experiment 2; see Figure 1 for a description.

See also Movie S2, Figure S2, Table S1 for stats, and Table S2 for response time analysis and mean variance reports from the diversion trials.

Next we assessed whether the after-effect we observed using the Bloomberg variance stimulus was specific to this particular motion-based representation of variance or whether it would generalize to other, categorically different, depictions of variance. Generalization to other different representations of variance would suggest that the adaptation and after-effects were not particular to a specific perceptual feature, such as motion, suggesting a high-level cognitive after-effect.

To probe variance after-effects in a categorically different representation of variance, we designed a new experiment that conceptually replicated our original experiment except for the depiction of variance. Our new stimulus displayed a row of 17 buckets, each holding a different number of balls (ordered from 0–16). Variance was depicted by moving a highlighted segment left and right over each bucket (Figure 2A). Participants passively watched a sequence of highlighted numbers drawn from a normal distribution with either high variance (SD = 3.0) or low variance (SD = 0.3) for 50 s, followed by a test stimulus, in which they were required to report their perceived variance of a medium variance sequence (SD = 1.0) on a scale of 1–5 (see Movie S2 and Figure 2A).

Figure 2B shows the results from 52 participants. We observed the predicted after-effects, i.e., higher ratings of variance after exposure to low variance than after exposure to high variance, in most of our participants (Figure 2B, black vertical lines). The data are somewhat noisier than in the original experiment, which was expected given that variance judgments are harder to make under this abstract representation of variance. Nevertheless, the statistics clearly showed a significant after-effect (Welch t test: $t = 4.19$, $p < 0.0001$). Again, to test robustness, we replicated the results of the multi-bucket experiment with a fresh 31 participants using a different set of SDs chosen to closely reflect real-world variance (high: 4; low: 0.5; medium: 1.3) and found similar results (Welch t test: $t = 3$, $p = 0.002$; see Figure S2).

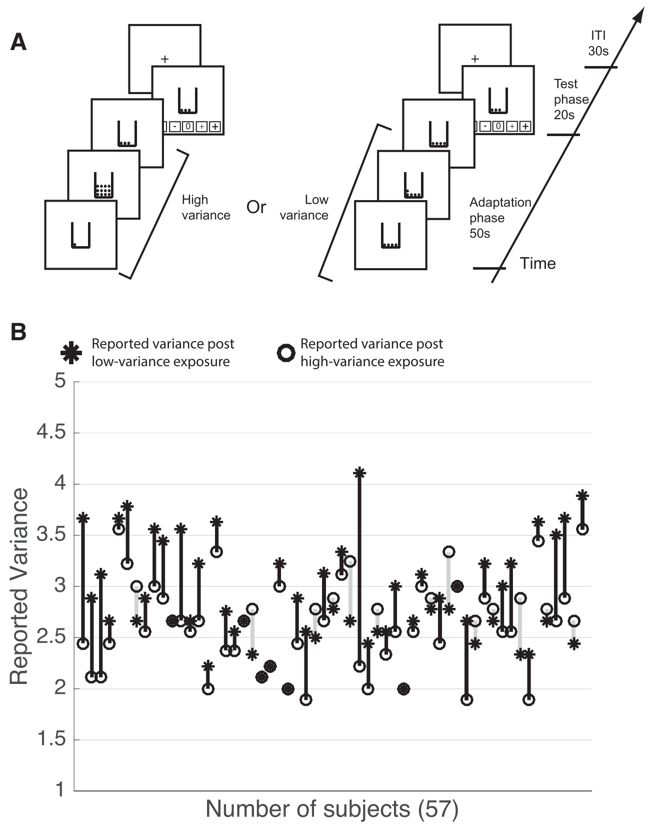

Figure 3. Variance After-Effect for the Single-Bucket Depiction of Variance

(A) Timeline for the single-bucket experiment. In the adaptation phase, a single bucket was shown for 50 s; the number of balls in it varied across frames, showing the given numerical distribution over time. In the test phase, the medium variance was depicted by the same single-bucket design, and subjects reported their perceived variance using the mouse pointer. ITI, 30 s inter-trial interval.

(B) Graphical depiction of the data from experiment 3; see Figure 1 for a description.

See also Movie S3, Table S1 for stats, and Table S2 for response time analysis and mean variance reports from the diversion trials.

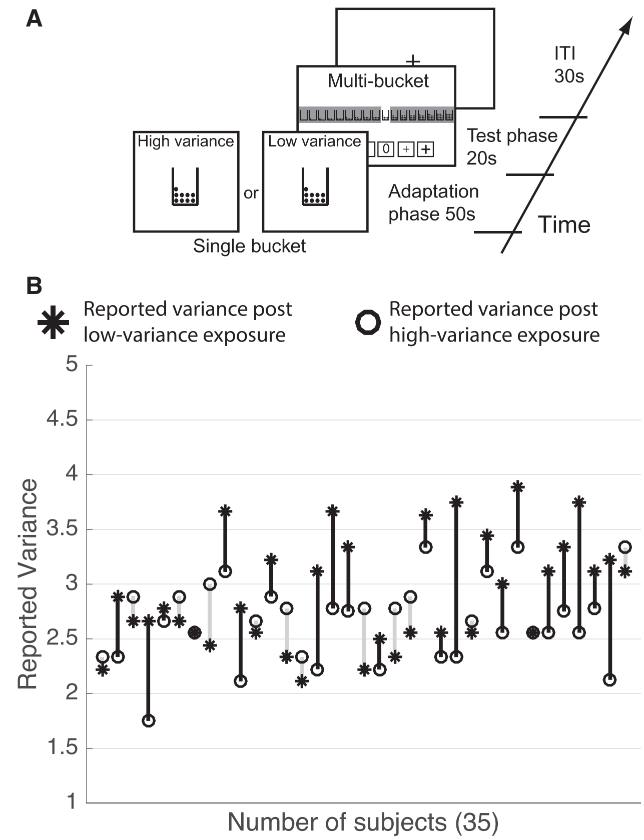

Figure 4. Variance After-Effect for the Mixed Generalization Experiment

(A) Timeline for the mixed, single-then-multi-bucket experiment. The exposure phase consisted of the single-bucket depiction of variance as in the third experiment. The test phase consisted of the multi-bucket design as described in the second experiment. ITI, 30 s inter-trial interval.

(B) Graphical depiction of the data from experiment 4; see Figure 1 for a description.

See also Movie S4, Table S1 for stats, and Table S2 for response time analysis and mean variance reports from the diversion trials.

Although this new multi-bucket representation of variance markedly differed from our prior Bloomberg stimulus, both depictions of variance involved overt motion (up/down motion of the Bloomberg stimulus, left/right motion in the highlighted buckets). Therefore, without further experiments, we cannot exclude that eye muscle fatigue caused the after-effect. To control for this and learn whether the variance after-effect would persist without motion in the display, we devised a new variance display that consisted of only a single bucket on screen at any one time. Here, only the number of balls in the single bucket changed over time to represent sequences of numbers drawn from normal distributions with SDs of 4 (high), 0.5 (low), and 1.3 (medium). The task thus required only central fixation by the participants; no eye movement (up/down or left/right) was involved. The task was otherwise the same as the multi-bucket experiment. See Movie S3 and Figure 3A.

57 subjects participated in the new experiment, and again the majority showed the predicted after-effect (Figure 3B). The reported variance was unambiguously higher after low than after high according to our tests (Welch t test: $t = 2.91$, $p = 0.002$).

Our data thus far show an after-effect in three different visual depictions of variance (Bloomberg, multi-bucket, and single bucket). Although this suggests that adaptation emerges after sensory processing, it remains possible that two visual features, visual motion [6] and numerosity [10, 13], were carrying these after-effects within each of our three different paradigms. To assess whether this was true, we combined the single- and multi-bucket paradigms, one in the exposure phase and the other in the test phase, to measure any generalization between these two different depictions of variance. If, with this heterogeneous experimental design, the after-effect generalizes from one representation of variance to the other, then it is unlikely that the after-effect reflects adaptation to a visual feature like motion or numerosity. A new group of 44 participants first viewed the single-bucket representation during the exposure period followed by the multi-bucket stimulus in the test phase. See Movie S4 and Figure 4A.

Figure 4B shows the data from the mixed-design generalization experiment. Again the majority of participants showed the variance after-effect, i.e., they rated perceived variance in the test phase as being lower after exposure to high variance than after exposure to low variance (Welch t test: $t = 2.51$, $p = 0.007$). There was also an effect of response latency in the mixed generalization experiment. However, response latency alone cannot explain the after-effect in these data (see Table S2A).

In summary, using three different representations of variance, a test of generalization across different depictions of variance, and two robustness checks, we provide strong and consistent evidence that after-effects exist for the property of variance.

Adaptation after-effects are commonly thought to imply the existence of neurons that respond selectively for the adapted feature [14], which is supported by data showing that adaptation and after-effects for basic visual features parallel the established selectivity of single neurons in early visual areas [15, 16]. To provide behavioral evidence for neurons selective for the high-level feature of variance, one must demonstrate that adaptation to variance is not contingent on a single low-level feature, but rather transpires across several low-level features (e.g., color, motion, and orientation). Here we demonstrate the invariance of the variance after-effect to changes in low-level visual features. For three different multi-feature displays, and indeed across two different forms of variance representation, our findings demonstrate that perceived variance is subject to adaptation occurring beyond the level of sensory motion or numerosity processing.

Our results raise a number of further questions. First, the neural underpinnings of this behavioral after-effect are unclear. Recent work hints at the possibility that motion variance might be susceptible to after-effects, by reporting adaptation to motion variance in neural coding of fly cells [11]. However, these findings are only indicative of potential variance after-effects in human judgment of variance, inasmuch as the strength of adaptation appears quite muted for prolonged adaptation durations (e.g., ~40 s); in our study, we see marked after-effects for adaptation periods of 50 s. Furthermore, the variance after-effect that we demonstrate operates across multiple visual features, e.g., motion and numerosity, whereas adaptation to variance in [11] concerns only motion. Hence, it remains unclear whether such adaptation could generate the behavioral after-effects that we report here. Accordingly, more work is needed to uncover the neural mechanism of variance after-effects.

Uncovering the neural underpinnings of variance after-effects would also help flesh out its mechanisms. Plausible mechanisms include imbalance in the firing rate of neurons coding in opponent directions as a result of neuronal adaptation or "fatigue," as described by opponent process theory (for a review, see [17]); adaptation as norm-based encoding, in which neurons adjust to the mean stimulus level, which confers a number of functional advantages to the observer [18, 19]; and homeostasis [20], in which the brain tries to maintain balance, so when pushed into a high variance state, the brain tries to counter-balance this by inducing the opposite representation (namely, low variance).

Of note, the current findings cannot be explained by most standard learning models (e.g., [21, 22]), which all predict the occurrence of positive priming [23, 24] in the current paradigm, i.e., a congruent bias in variance assessment (high variance exposure leads the agent to judge variance as high), not opponency as we observe here (an exception is the standard operating procedures [SOP] theory [25], which in our setting predicts neither priming nor opponency, but uniformly biased perception of the test stimulus—variance reports would be likely to be biased on average both upward and downward). The agent in such learning models adjusts the most recent variance expectation based on the prediction error (difference between realized and expected variance), thereby expecting high variance after prolonged exposure to high variance. Similarly, after prolonged exposure to low variance, variance assessment of the test stimulus is biased downward. In this account, learning and adaptation are thus two antagonistic forces, distorting variance assessment of the test stimulus in opposite directions.

Another implication of our findings is that variance after-effects may impact investor behavior and hence have a meaningful impact on asset prices and market dynamics. Preliminary results show that such after-effects are evident in investors' perception of S&P 500 volatility and cause significant distortions of S&P 500 options prices [12]. This contrasts with conventional economic theory, which assumes no biases in risk perception. Importantly, almost all risk measures, including systematic risk in the capital asset pricing model [26, 27] and downside risk measures such as value at risk [28], are related to variance and therefore should be affected by variance perception. Thus, our results have wide-reaching implications for the business community.

That the after-effect prevails in real-world financial markets is also important as reassurance that our after-effect does not reflect a "decisional bias" from explicit stimulus ratings [29]. Unlike our task designs, which involve subjects rating the variance of stimuli, the real-world data are ratings free. When using a rating paradigm, as we have in our experiments, there is always the possibility that subjects' reports of the test stimulus could be anchored to the adapting stimulus, which may serve as a reference point. Although we specifically designed the task instructions to avoid such a bias (see the Supplemental Experimental Procedures), one cannot exclude it without further analysis, such as the follow-up finding that the after-effect also occurs outside of the lab. Another indication that our data are not driven by anchoring is that variance reports in the diversion trials were almost always correct (see Table S2B), which further suggests that subjects categorized the stimuli using the definitions that we provided and not the prior adapting stimulus.

Finally, the current study may help to understand the phenomenon of "rogue trading," which has received considerable attention in recent years. It has been proposed that rogue traders have an exacerbated appetite for risk fuelled by management oversights and regulatory pitfalls. Our findings point to a complementary root cause, namely, adaptation to chronically high levels of risk and possible subsequent "risk blindness."

SUPPLEMENTAL INFORMATION

Supplemental Information includes Supplemental Experimental Procedures, two figures, two tables, and four movies and can be found with this article online at http://dx.doi.org/10.1016/j.cub.2016.04.023.

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AUTHOR CONTRIBUTIONS

E.P.-L.N. conceived and designed the experiment. E.P.-L.N., T.B., and J.P. performed the experiment and analyzed the data. E.P.-L.N., J.P., and B.W.B wrote the paper.

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REFERENCES

1. Holt, C.A., and Laury, S.K. (2005). Risk aversion and incentive effects: new data without order effects. Am. Econ. Rev. *95*, 902–904.
2. Holt, C.A., and Laury, S.K. (2002). Risk aversion and incentive effects. Am. Econ. Rev. *92*, 1644–1655.
3. Laury, S.K., and Holt, C.A. (2008). Payoff scale effects and risk preference under real and hypothetical conditions. In Handbook of Experimental Economics Results, C.R. Plott, and V.L. Smith, eds. (North Holland), pp. 1047–1053.
4. Christopoulos, G.I., Tobler, P.N., Bossaerts, P., Dolan, R.J., and Schultz, W. (2009). Neural correlates of value, risk, and risk aversion contributing to decision making under risk. J. Neurosci. *29*, 12574–12583.
5. Barlow, H.B., and Hill, R.M. (1963). Evidence for a physiological explanation of the waterfall phenomenon and figural after-effects. Nature *200*, 1345–1347.
6. Glasser, D.M., Tsui, J.M.G., Pack, C.C., and Tadin, D. (2011). Perceptual and neural consequences of rapid motion adaptation. Proc. Natl. Acad. Sci. USA *108*, E1080–E1088.
7. Webster, M.A., Kaping, D., Mizokami, Y., and Duhamel, P. (2004). Adaptation to natural facial categories. Nature *428*, 557–561.
8. Leopold, D.A., O'Toole, A.J., Vetter, T., and Blanz, V. (2001). Prototype-referenced shape encoding revealed by high-level aftereffects. Nat. Neurosci. *4*, 89–94.
9. Jordan, H., Fallah, M., and Stoner, G.R. (2006). Adaptation of gender derived from biological motion. Nat. Neurosci. *9*, 738–739.
10. Burr, D., and Ross, J. (2008). A visual sense of number. Curr. Biol. *18*, 425–428.
11. Fairhall, A.L., Lewen, G.D., Bialek, W., and de Ruyter Van Steveninck, R.R. (2001). Efficiency and ambiguity in an adaptive neural code. Nature *412*, 787–792.
12. Payzan-LeNestour, E., Pradier, L., and Putniņš, T.J. (2015). Volatility after-effects: evidence from the field. UNSW Business School research paper no. 04. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2553526.
13. Dakin, S.C., Tibber, M.S., Greenwood, J.A., Kingdom, F.A., and Morgan, M.J. (2011). A common visual metric for approximate number and density. Proc. Natl. Acad. Sci. USA *108*, 19552–19557.
14. Blakemore, C., and Campbell, F.W. (1969). On the existence of neurones in the human visual system selectively sensitive to the orientation and size of retinal images. J. Physiol. *203*, 237–260.
15. Desimone, R., Albright, T.D., Gross, C.G., and Bruce, C. (1984). Stimulus-selective properties of inferior temporal neurons in the macaque. J. Neurosci. *4*, 2051–2062.
16. Gross, C.G., Bender, D.B., and Rocha-Miranda, C.E. (1969). Visual receptive fields of neurons in inferotemporal cortex of the monkey. Science *166*, 1303–1306.
17. Clifford, C.W., and Rhodes, G. (2005). Fitting the Mind to the World: Adaptation and After-Effects in High-Level Vision (Oxford University Press).
18. Webster, M.A., McDermott, K., and Bebis, G. (2007). Fitting the world to the mind: transforming images to mimic perceptual adaptation. Adv. Vis. Comput. *4841*, 757–768.
19. Webster, M.A. (2011). Adaptation and visual coding. J. Vis. *11*, 3.
20. Solomon, R.L., and Corbit, J.D. (1974). An opponent-process theory of motivation. I. Temporal dynamics of affect. Psychol. Rev. *81*, 119–145.
21. Rescorla, R.A., and Wagner, A.R. (1972). A theory of Pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement. In Classical Conditioning II: Current Research and Theory, A.H. Black, and W.F. Prokasy, eds. (Appleton-Century-Crofts), pp. 64–99.
22. Pearce, J.M., and Hall, G. (1980). A model for Pavlovian learning: variations in the effectiveness of conditioned but not of unconditioned stimuli. Psychol. Rev. *87*, 532–552.
23. Epstein, W., and Rock, I. (1960). Perceptual set as an artifact of recency. Am. J. Psychol. *73*, 214.
24. Kahneman, D. (1973). Attention and Effort, First Edition (Prentice Hall).
25. Wagner, A.R. (1981). SOP: a model of automatic memory processing in animal behavior. In Information Processing in Animals: Memory Mechanisms, N.E. Spear, and R.R. Miller, eds. (Erlbaum), pp. 5–47.
26. Sharpe, W.F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. J. Finance *19*, 425–442.
27. Markowitz, H. (1952). Portfolio selection. J. Finance *7*, 77–91.
28. Jorion, P. (2007). Value at Risk: The New Benchmark for Managing Financial Risk (McGraw-Hill).
29. Storrs, K.R. (2015). Are high-level aftereffects perceptual? Front. Psychol. *6*, 157.