Asymmetric detection of changes in volatility: Implications for risk perception

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Abstract

Variance of the outcomes associated with an option often provides a measure of the riskiness of that option. Hence, it is important for organisms are able to detect any sudden changes in outcome variance. In Experiment 1, we presented people with graphs of share price time series or water level time series. In half the graphs, variance (financial or flooding risk) changed at some point. People were better at detecting increases than decreases in risk - maybe because it is more important to detect increases in danger than decreases in it. However, in Experiment 2, people were still better at detecting increases than decreases in variance even when those changes did not reflect altered levels of risk. Our findings may reflect the fact that the actual change in variance exceeds the change needed to identify a regime change in variance by a larger amount for upward than for downward changes.

Keywords: volatility; variance; risk; change detection; judgment

Introduction

In many domains, variance of outcomes associated with an option is taken as a measure of level of risk of that option. For example, in modern finance theory, level of risk associated with an asset is defined as the standard deviation of the returns on that asset (Jorion, 2006). Similarly, as variability in water levels increases, so does the risk of flooding or drought (Crowell, Coulton, Johnson, Westcott, Bellomo, Edelman, and Hirsh, 2010). Finally, in foraging theory, the risk associated with different food sources is defined in terms of the variance of the energy gains that an animal can derive from those sources (Kacelnik and Bateson, 1996). In all these cases, higher variance in the data is treated as a signal that risk levels are higher.

Most work in these and other domains has been based on the assumption that the riskiness of different options remains constant over time. For example, Diacon and Haseldine (2007), Duxbury and Summers (2004, 2017), Sobolev and Harvey (2016), and Weber, Siebenmorgen and Weber (2005) have used various methods to examine the relation between volatility of financial indicators (e.g., returns) and financial risk perception. However, level of risk can change: variance of outcomes may increase or decrease, often quite suddenly. As far as we are aware, there have been no studies of people's ability to perceive a change in volatility and, hence, to detect onset of a new level of risk.

Here we ask how easily people are able to detect such a change when they are given a graphical record of the outcomes that have occurred. More specifically, we examine how well people are able to detect a structural break in the variance of a time series and study whether the level of their ability is influenced by whether that variance is framed as representing level of risk.

We varied task frame. In Experiment 1, any structural break in the series signified an increase or decrease in the level of risk over time. Changes in financial trading risk and water flooding risk were of this type. In Experiment 2, any structural break in the series did not represent any change or difference in risk level. Instead, participants needed to detect it because it represented an opportunity rather than a risk. These experiments were used to address two questions.

First, is there any asymmetry in ability to detect increases and decreases in volatility? Second, is any such asymmetry limited to tasks in which changes in volatility should be interpreted as temporal changes in level of risk? It can be argued that it is more important to detect an increase in risk so that protective measures can be adopted. Removing those protective measures when there is a decrease in risk is likely to be less critical.

Experiment 1

In this first experiment, participants performed the task within a temporal risk frame. They were presented with one of two scenarios: a finance scenario and a flooding scenario.

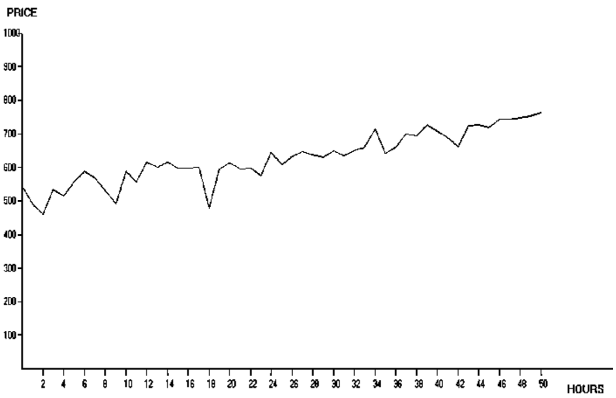
Method

Participants One hundred and sixty-five students acted as participants: 59 were assigned to the financial risk scenario and 106 were assigned to the flooding risk scenario.

Stimulus materials Each graphically presented series comprised 50 data points generated uniquely for each participant. They were drawn from a Gaussian distribution with a mean of 500 and a standard deviation of either 5.00 (low volatility) or 15.0 (high volatility). Of the 60 graphs seen by each participant, 15 were of low volatility throughout, 15 were of high volatility throughout, 15 contained a change from low volatility to high volatility, and 15 contained a change from high volatility to low volatility. The 60 graphs were presented in random order. When there was a change in volatility, it occurred between points 11 and 40 inclusive and with equal likelihood. One third of the graphs of each of the four types contained no trend, one third contained a shallow upward trend, and one third contained a shallow downward one. When there was a trend, the series still started at 500 but was then incremented or decremented by 0.1 on each successive point. Labelling of graphs depended on the task frame.

Procedure In the financial risk scenario, the vertical axis was labelled as ‘price’ and the horizontal axis as ‘hours’ (Figure 1). Participants were told that the series represented a record of recent stock prices and told that increased volatility represented increased trading risk. They needed to detect whether a change in risk had occurred because their trading strategy would need to change if it had done.

Figure 1: Example graph from the finance scenario in Experiment 1 showing prices that change every hour for a period of 50 hours and volatility shifting from high to low.



In the flooding risk scenario, the vertical axis was labelled as water depth and the horizontal axis as ‘hours’. Participants were told that each graph represented a record of water levels in various locations and that increased volatility represented increased risk of flooding. They needed to detect whether a change in flood risk had occurred in order to implement flood control measures if it had increased or to stand them down if it had decreased.

For each graph, participants first gave a yes/no response to signal whether they had detected a change in the volatility in it. They then estimated the likelihood that their response was correct on a 50-100% scale.

Results

Here we report analyses of participants’ detection responses using signal detection theory (Macmillan and Creelman, 1991). We extracted measures of sensitivity (d′) and response criterion (β) for a) trials starting with low volatility on the left of the graph that either stayed low or that changed to high volatility and b) trials starting with high volatility on the left that either stayed high or that changed to low volatility. Data were analysed in this way so that we could use the signal detection measures to compare detection of change when the series started with low volatility to that when it started with high volatility. To obtain d′ and β, the z-transformations of the hit rate (z(H)) and false alarm rate (z(F)) were first obtained. Then

$$d' = z(H) - z(F)$$
$$\beta = \exp((z(F)^2 - z(H)^2)/2)$$

The sensitivity measure d’ reflects how discriminable signal (change) trials are from noise (no change) trials, with higher values indicating better detection performance. The response criterion measure β reflects the relative strength the evidence has to reach in order for the organism to respond that the trial was a change trial, with a value of 1 indicating no response bias, while values below 1 indicating a bias towards responding ‘change’ (i.e., the evidence for ‘no-change’ has to be stronger than the evidence for ‘change’).

As we are interested only in the effect of increasing as compared to decreasing volatility, we collapse the data over the presence and types of trend. Also, note that the signal detection measures are based on both signal (change) and noise (no change) trials, and hence we cannot compare sensitivity and response bias between change and no-change trials.

Table 1: Mean values of sensitivity (d′) and response criterion (β) in the two types of scenario for detection of changes in volatility in graphs that started with low volatility and in those that started with high volatility.

	Sensitivity (d′)		Response criterion (β)	
	Low Starting Volatility	High Starting Volatility	Low Starting Volatility	High Starting Volatility
Financial risk scenario (n = 59)	.95	.26	.22	.19
Flooding risk scenario (n = 106)	.79	.43	.10	.22

Mean values of d′ and β are shown in Table 1. A two-way analysis of variance on d′ using starting volatility as a within-participant variable and temporal frame as a between-participant variable revealed a strong main effect of starting volatility ($F(1, 163) = 43.82$; $p < .001$; $\eta^2 = .21$) and some evidence of an interaction between this variable and frame type ($F(1, 163) = 4.57$; $p = .034$; $\eta^2 = .03$).

An ANOVA using the same variables on β failed to reveal any significant effects.

Discussion

The experiment showed that people find it easier to detect increases in volatility than decreases in volatility. Given that increases in volatility in the task scenarios corresponded to increases in risk, this result can be interpreted as showing that people are better at detecting increases than decreases in risk. This corresponds to what would be expected from a functional perspective: it is more important to be sensitive to increases in risk (so that protective measures can be implemented) than to decreases in risk (as removal of protective measures is less urgent). Differences in the size of the effect in the two scenarios may be related to beliefs about the nature of the risks and the ease of managing them in the two cases.

Before committing to this risk-based interpretation of the effects, it is important to ascertain whether they appear when the same graphs are presented within a scenario that does not involve risk.

Experiment 2

In this experiment, participants were presented with a version of the task in which risk assessment was not involved. Results were then compared to those obtained in the previous experiment.

Method

Participants A total of 80 new participants drawn from the same pool as before performed a risk-free version of the task.

Procedure Participants were told that the data points represented the contours of a mountain range. The vertical axis represented height in meters and the horizontal one degrees of visual angle. Mountains could be formed of soft rock that had eroded (low variance) or harder rock that had not (high variance). They were told that they needed to detect differences in the contours of the mountains because mineral deposits tended to occur at the interface of hard and soft rocks. Identifying such interfaces would trigger ground-based surveys to confirm the presence of mining opportunities. Thus, a left/right difference in variance was associated with identification of an opportunity rather than a risk.

In all other respects, the experiment was the same as Experiment 1.

Results

In the same way as before, the d′ and β values were extracted from the data (Table 2). Then an ANOVA was used to compare the values obtained from the temporal risk scenarios of Experiment 1 with those obtained from the risk-free scenario in the current experiment. Starting volatility (low versus high volatility on the left side of the graph) was a within-participants variable and task frame (risk-free versus temporal risk scenarios) was a between-participants variable.

Again, there was a strong main effect of starting volatility (F (1, 243) = 30.00; $p < .001$; $\eta^2 = .11$). However, in this case, though there was an effect of frame type (F (1, 243) = 10.34; $p = .001$; $\eta^2 = .04$), there was no interaction between frame type and starting volatility. Thus, while people were better at detecting differences in volatility in the risk-free scenario, they were better *in both types of scenario* at detecting changes in volatility from low to high (assuming left-to-right scanning in the risk-free scenario) than at detecting volatility changes from high to low.

As before, an ANOVA using the same variables on β failed to reveal any significant effects.

Table 2: Mean values of sensitivity (d′) and response criterion (β) in the two types of scenario for detection of changes in volatility in graphs that started with low volatility and in those that started with high volatility.

	Sensitivity (d′)		Response criterion (β)	
	Low Starting Volatility	High Starting Volatility	Low Starting Volatility	High Starting Volatility
Temporal risk scenario (n = 165)	.85	.37	.15	.21
Risk-free scenario (n = 80)	1.01	.75	.17	.24

Discussion

We obtained the same effect reported in Experiment 1 when participants performed the task within a risk-free scenario. Assuming left-to-right attentional scanning of the graphs (Bergen and Lau, 2012; Eviater, 1995; Maas and Russo, 2003), we can say that they were more sensitive to an increase in volatility than to a decrease in volatility. Furthermore, this was true whether or not greater volatility represented greater risk. The asymmetry uncovered in Experiment 1 is of a more general nature than we originally assumed. However, its implications for detection of changes in levels of risk remain.

There was also a main effect of scenario type on d′: sensitivity was higher in the risk-free scenario. Focusing on opportunities rather than risks appears to have made the task simpler for participants.

General discussion

The experiments show that people find it easier to detect an increase than a decrease in the variance of a graphically presented time series. Though changes in risk are realized as changes in variance in many domains, Experiment 2 indicated that increases in variance are easier to detect than decreases in variance even when changes in variance do not correspond to changes in risk level. Here we will outline two possible explanations for our findings: an explanation in terms of the processes needed to detect upward and downward changes in variance and a functional explanation based on the relative importance of upward and downward changes in variance.

A process-based account

It is possible that our findings arose because increases in variance are statistically easier to detect than decreases in variance. For example, we could ask whether it is statistically easier to detect the presence of a data point outside a given distribution (an outlier) than to detect the absence of a data point expected within that distribution. Conceivably, more data might be needed to perform the latter detection reliably.

In fact, to detect an increase in variance, it is not sufficient to detect a single anomaly: in normal distributions, we expect one in 22 data points to be more than two standard deviations away from the mean. To detect a change in variance, the presence of unexpected data points outside a reference distribution or the absence of expected data points within that reference distribution must be *persistent*. In other words, there must be evidence of a regime shift in the variance of the distribution.

There are many different approaches to detecting regime shifts in the mean of time series but relatively few have been developed for detecting shifts in the variance of series. Downton and Katz (1993) developed a non-parametric bootstrap technique to compute confidence intervals for discontinuities in variance. However, their approach requires the series containing the putative regime shift in variance to be compared to a separate reference series known to be characterized by homogeneous variance. We presented our participants with series in which variance did not change but we did not inform them of this constancy for particular series. Thus they had no series that they could treat as a reference series in the manner that Downton and Katz (1993) require.

Rodionov (2004) developed a sequential algorithm for early detection of regime shifts in the mean of series. The advantage of his approach is that it does not require large amounts of data to be accumulated and can automatically detect regime shifts in real time. Later, Rodionov (2005) extended his approach so that it could be used to detect regime changes in variance in short series in real time. These features of his approach render it a suitable one for modeling detection of variance change in our experiments.

The first step is to identify the regime length (l). In our task, this value would initially be set to 10 because participants knew there was no shift in the first 10 data points. The next step is to use an F-test to determine the critical variance ratio (F_{crit}) of two successive regimes that would be statistically significant. For an l value of 10 and a p-value of 0.05 (one-tailed), this ratio is 4. The variance of the initial l values of the series is then used to estimate the variance of the current regime (V_{cur}). For the new regime to be statistically different from the current regime, its variance (V_{new}) should be equal to or greater than the critical variance ($V_{crit\uparrow}$) if the variance is increasing or equal to or less than the critical variance ($V_{crit\downarrow}$) if the variance is decreasing, where

$$V_{crit\uparrow} = V_{cur} \cdot F_{crit}$$

$$V_{crit\downarrow} = V_{cur} / F_{crit\downarrow}$$

The variance, V_{cur}, is the sum of squares of z_i, where i spans from the first point of the current regime to $i = t_{cur} - 1$. If, at time t_{cur}, the current value z_{cur} satisfies either $z^2_{cur} > V_{crit\uparrow}$ or $z^2_{cur} < V_{crit\downarrow}$, this time is marked as a potential point where a regime shift in the variance has occurred. Subsequent values (z_{cur+1}, z_{cur+2} …) are used to verify this hypothesis by using a Residual Sum of Squares Index (RSSI).

$$RSSI = 1/l \sum_{i=t_{cur}}^{m} (z_i^2 - V_{crit}),$$

where $m = t_{cur}, t_{cur} + 1, \ldots, t_{cur} + l - 1$.

If, at any time during the testing period from t_{cur} to $t_{cur} + l - 1$, the index turns negative for the case where $V_{crit} = V_{crit\uparrow}$ or positive for the case where $V_{crit} = V_{crit\downarrow}$, the hypothesis of a regime shift in variance at time t_{cur} is rejected and z_{cur} is included in the current regime. Otherwise, time t_{cur} is taken as a break point at which a regime shift in variance occurred.

In essence, Rodionov's (2005) approach first detects an anomaly and then goes on to determine whether that anomaly *persists* over time. A regime shift in variance is identified only when it does. Because his approach is simple and requires little accumulated data, it is appropriate for the statistical detection of regime changes in variance in the type of task that our participants completed.

In our task, the value of the lower variance was 25 and, hence, $V_{crit\uparrow} = 25 \times 4 = 100$. The value of the higher variance (225) exceeded this critical value by a large amount (125). The value of the higher variance was 225 and, hence, $V_{crit\downarrow} = 225/4 = 56.25$. The value of the lower variance (25) was less than this critical value by only a small amount (31.25). However, the relative difficulty of two comparative judgments does not depend on the size of the *absolute* difference between the stimuli.

According to Weber's Law, "The stimulus increase which is correctly discriminated in any specified proportion of attempts (except 0 and 100 per cent) is a constant fraction of the stimulus magnitude" (Thurstone, 1959, p. 61). In the case of upward changes in variance, the change in variance that participants had to detect (125) as a proportion of the critical variance (100) was 1.25. In the case of downward changes in variance, the change in variance that participants had to detect (31.25) as a proportion of the critical variance (56.25) was 0.56. Hence the task of deciding whether there was evidence of a new variance regime would have been more difficult when the variance decreased from the high to the low value than when it increased from the low to the high value.

In terms of Rodionov's (2005) approach, for each current value, z_{cur}, it would have been harder to determine whether z^2_{cur} was less than $V_{crit\downarrow}$ than to determine whether it was greater than $V_{crit\uparrow}$. As a result, the initial assessment of whether a potential anomaly had occurred at t_{cur} would have been harder for a downward than for an upward anomaly. Furthermore, using the RSSI to verify whether the potential anomaly should be confirmed would have been less effective for a downward than for an upward anomaly.

We have outlined this process-based account using the parameters of our experimental task but it could be applied to any task in which comparative judgments of variance are made. Of course, other process-based accounts are possible:

the strategy outlined by Rodionov (2005) is not the only statistical approach to detecting regime change in variance. Indeed, it is possible that no unitary process-based explanation would be appropriate to account for the asymmetry in our data. We may have evolved so that the characteristics of the processes that detect upward and downward changes in variance are different. It is to this possibility that we turn next.

A functional explanation

A sudden increase in volatility can be regarded as a signal onset and a sudden decrease in volatility as a signal offset. Work in psychophysics indicates that people are better at detecting the onset of a signal than the offset of one (e.g., Ahumuda, Marken, and Sandusky, 1975). This phenomenon can be given a functional interpretation, albeit a more general one than that we proposed when discussing the results of Experiment 1. The onset of a signal is likely to be of greater importance to an organism than the offset of one. Signal onsets (e.g. the appearance of a predator) are more likely to require urgent and rapid action than signal offsets (e.g., the disappearance of a predator).

One objection to this account is that differences in signal importance should be expected to affect response bias (β) rather than sensitivity (d′). If a signal is more important, the response criterion should be shifted to the left to increase the proportion of hits. In other words, there should be no difference in d′ values for detecting signal onsets and offsets. Instead, responses should be more biased in favour of saying there is a change when signals start low but may change to high (potential signal onset) than when they start high but may change to low (potential signal offset).

The problem with this approach is that shifting the response criterion to the left will also serve to increase the proportion of false alarms. Responding to these false alarms is likely to be costly. For example, animals reacting to a non-existent predator may lose foraging time and flee into a more dangerous environment. These high costs would tend to force the response criterion rightwards and so counteract the benefit-driven increase in hit rate arising from moving it leftwards. According to this functional account, evolution resolved this dilemma over time by increasing sensitivity to signal onsets. Such a strategy would avoid the increased costs arising from the additional false alarms associated with a laxer response criterion while still assuring the benefits of a high hit rate.

Implications

Although the phenomenon that we have identified is not specific to identification of changes in risk, it still has implications for risk perception. In finance, sudden changes in series variance occur (Hammoudeh and Li, 2008; Todea and Petrescu, 2012). Although attempts to predict these changes have been made using autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models (Bollerslev, 1986; Engle, 1982), severe problems in forecasting them remain.

For Mandelbrot (1997), this was not surprising. He argued that bursts of high volatility are inherently unpredictable and emerge naturally as a consequence of the nonlinear processes responsible for generation of financial series. He claimed that these series do not meet the assumptions of modern financial theory (e.g., Markowitz, 1959; Sharpe, 1964; Black and Scholes, 1973) but are, instead, fractal. If he is correct, technical analysts and traders cannot possibly predict sudden volatility changes in financial series. Instead, all they can do is to be alert to the possibility that such changes will occur and then react to them appropriately as soon as possible.

Assuming that sudden volatility changes in financial series are not predictable, how would the asymmetry that we have identified here affect trading behavior? Increases in risk may lead investors to sell winning shares to lock in their profits but to keep losing ones in the hope that high volatility will provide an opportunity of selling them later at a higher price. Decreases in risk should lead to investors keeping their winning shares because nothing untoward will happen but to sell their losing shares because there is no chance of their bringing in a higher price later if they are retained. Easier detection of an increase than a decrease in volatility will lead responses to increases in risk to dominate responses to decreases in risk. In other words, the tendency to sell winning shares but to retain losing ones will dominate. This is the disposition effect (Shefrin and Statman, 1985). While we would not wish to claim that easier detection of increases than decreases in risk is the only driver of the effect, it may be contributory.

In our experiments, we presented time series graphically. We could explain our results by assuming a) that graphs were scanned left to right so that earlier data points were encountered before later ones, and b) that signal onsets are easier to detect than signal offsets. Both these assumptions are supported by existing evidence in the literature.

Consider now the case where the data points are encountered sequentially in real time. We would no longer need to make the first assumption: the earlier points would be encountered before later ones anyway. Hence, given that the second assumption holds, we would expect the asymmetry to be maintained. In other words, our findings could be expected to generalize to situations in which people experience data points successively over a period in real time.

For example, situations in which operators of some system receive readings in this way but assess volatility judgmentally rather than formally may produce a greater tendency to implement measures to protect against increased risk than to remove those measures once the period of increased risk has passed. Such situations could include those associated with natural hazards, such as evacuation decisions in the case of potential volcanic eruptions or hurricanes.

We would not wish to claim that asymmetric tendencies to respond to increases and decreases in risk in such cases should be characterized as cognitive biases. In line with the functional approach discussed above, they may represent sensible ways of responding to changes in risk levels.

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