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On Perceptions of Financial Volatility in Price Sequences

Darren Duxbury [a] and Barbara Summers [b]
(both authors contributed equally)

[a] *Newcastle University Business School*
[b] *Leeds University Business School*

Abstract

Stock prices in financial markets rise and fall, sometimes dramatically, thus asset returns exhibit volatility. In finance theory, volatility is synonymous with risk and as such represents the dispersion of asset returns about their central tendency (i.e. mean), measured by the standard deviation of returns. When individuals make investment decisions, influenced by perceptions of risk and volatility, they commonly do so by examining graphs of historic price sequences rather than returns. It is unclear, therefore, whether standard deviation of return is foremost in their mind when making such decisions. We conduct two experiments to examine the factors that may influence perceptions of financial volatility, including standard deviation along with a number of price-based factors. Also of interest is the influence of price sequence regularity on perceived volatility. While standard deviation may have a role to play in perception of volatility, we find evidence that other price-based factors play a far greater role. Furthermore, we report evidence to support the view that the extent to which prices appear irregular is a separate aspect of volatility, distinct from the extent to which prices deviate from central tendency. Also, while partially correlated, individuals do not perceive risk and volatility as synonymous, though they are more closely related in the presence of price sequence irregularity.

Keywords: volatility; risk, price sequence, mean absolute price change, standard deviation
JEL classifications: G02, G11

On Perceptions of Financial Volatility in Price Sequences

1. Introduction

Stock prices in financial markets rise and fall, sometimes dramatically, thus asset returns exhibit volatility.[1] In standard finance theory, with its roots in portfolio theory (Markowitz, 1952), volatility is synonymous with risk and as such represents the dispersion of returns around their central tendency (i.e. mean) as measured by standard deviation (Schwert, 2011). Such a view, however, has been challenged in recent years, not just by other academic disciplines but within finance itself. Santos and Haimes (2004), for example, argue that equating risk with volatility can be problematic, particularly during periods of extreme market movements. Similarly, Jones et al. (2004) call into question whether standard deviation of return is an adequate measure of volatility (viewed as synonymous with risk), finding that a simple measure based on extreme-day returns is a better metric of stock market risk than standard deviation, more accurately explaining investor behaviour.[2] Furthermore, Raghubir and Das (2010, p.975) note that "the statistical moments of a return distribution do not completely capture investor's perceptions of risk" (a view supported by prior experimental evidence, e.g. Duxbury and Summers, 2004). Finally, Goldstein and Taleb (2007) report that individuals, even those with a background in financial markets, err in their interpretation, misconstruing mean absolute return (a linear measure) to be equivalent to standard deviation of return (a non-linear measure). They recommend the adoption of a more natural metric than standard deviation.

[1] The study of volatility has long held academic interest and has witnessed many advances over the years, as exemplified by the rapidly growing literature on modelling and forecasting "realized volatility" using intra-day data to obtain more accurate and efficient forecasts. See, for example, the many papers published in the "realized volatility" special issue of the *Journal of Econometrics* edited by Meddahi, Mykland, and Shephard (2011) and more recent studies including Fuertes et al. (2015), Andrada-Félix et al. (2016) and Kourtis et al. (2016), among others.
[2] Earlier, Parkinson (1980) and Kunitomo (1992) propose price-based, extreme value methods for estimating volatility. Such models are shown to provide more efficient volatility estimators than commonly used return-based estimators such as standard deviation.

This paper contributes to the search for a more natural metric, providing insight into perceptions of financial volatility. We address two questions: *first*, how do individuals perceive volatility, and *second*, do they perceive risk and volatility as synonymous? [3] To this end, we examine experimentally the factors that drive investors' perceptions of financial volatility using stylised price sequences, comparing the explanatory powers of price-based measures of volatility to those of standard return-based measures. We conduct two experiments; one where price sequences have systematic patterns (i.e. regularity) and a second where price sequences are irregular and without pattern. In doing so, we are able to differentiate two aspects of volatility, the extent to which prices deviate from central tendency and the extent to which prices appear irregular or unpredictable (Pincus and Kalman, 2004), thus gaining further insight concerning perceptions of volatility and the synonymy between risk and volatility.

To motivate our approach, we consider briefly recent developments in the financial markets, and the nature of the information investors typically use in their financial decision making, before turning to consider how volatility is portrayed in the financial media. Over the 1990s, the number of individuals investing in the US stock market increased dramatically (Vogelheim et al., 2001) and recent evidence suggests the numbers remain high.[4] Vogelheim et al. (2001) put the high level of individual participation down to the bull market of the 1990s, the move away from defined benefit to defined contribution pension schemes[5] and the rise of the Internet, offering individual investors access to a profusion of financial information and to relatively low cost trading. While individual investors have a wealth of information available to them, via websites

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[3] While it is common to use the terms risk and volatility interchangeably in the finance literature, we do not do so here. Our approach is not to adopt specific definitions of risk or volatility, but to let participants reveal, via their ratings of graphical price sequences, what these concepts mean to them. That is, their *perceptions* of risk and of volatility, whatever they may be. We are then interested in finding which characteristics of the price sequences, individually or in combination, best explain the experimental data. Where no confusion arises we use the terms perception and rating interchangeably when discussing risk and volatility. When reviewing other studies we adopt the nomenclature used in the original study.

[4] Gallup poll [http://www.gallup.com/poll/147206/stock-market-investments-lowest-1999.aspx, accessed on 05-09-15]

[5] Comparable changes to pension systems have been witnessed in other developed countries such as the UK (Duxbury et al., 2013)

such as Yahoo! Finance, arguably the most prevalent and widely used is the historic price sequence, typically observed graphically. Indeed, Duclos (2015, p.324) claims "[l]ike their professional counterparts, private investors rely on readily accessible graphs to interpret past market-performance and forecast future trends", while Raghubir and Das (2010) report that individuals find graphical display of price sequences most useful.

Popular representations of stock market volatility, such as those reported in the financial media or popular press, are commonly couched in terms stock *prices* not stock returns. For example, discussing the likely impact of economic and political developments in Greece and China, The Motley Fool website states; "it's quite possible that the situation will spark stock price volatility".[6] Other examples abound to support this populist view of volatility. For example, in evaluating the growth prospects of Royal Mail, an article on the Interactive Investor website states; "In the New Year, Royal Mail effused as high as 617p, turning volatile briefly in a 560p to 605p range".[7]

In light of the widespread use of price sequence graphs by investors and the populist depiction of volatility as related to stock prices, we examine experimentally the factors that drive investors' perceptions of financial volatility when presented with sequences of historic prices. In our first experiment, we use stylised price sequences, all with systematic patterns (i.e. regularity), to manipulate the dispersion of prices around the mean, along with a number of other price sequence characteristics. We find that the mean absolute price change explains most of the variation in volatility perception, with standard deviation playing only a minor role. While we find some evidence of a relationship between perceptions of risk and volatility, the two are not perfectly synonymous. A second experiment, in which we introduce irregularity into the price sequences, supports the view that the extent to which prices appear irregular is a separate aspect

[6] The Week Ahead: Greece, China, and the Fed, The Motley Fool, [http://www.fool.com/investing/general/2015/07/06/the-week-ahead-greece-china-and-the-fed.aspx, accessed 04-09-15]
[7] Edmond Jackson's Stockwatch: Is Royal Mail's growth prospect limited?, Interactive Investor, [http://www.iii.co.uk/articles/168701/edmond-jacksons-stockwatch-royal-mails-growth-prospect-limited, accessed 04-09-15]

of volatility, distinct from the extent to which prices deviate from central tendency. Furthermore, when irregularity is present we find that returns now play a role in risk perception and that risk and volatility ratings are more positively related, though still not perfectly so. We conclude, therefore, that perceptions of volatility have more to do with price-based factors than the dispersion of returns around the mean. Furthermore, investors do not perceive risk and volatility as synonymous.

2. Related literature

Given our interest in volatility perception in the presence of graphically depicted price sequences, we review briefly literature on sequences of outcomes, graphical presentation and prior studies of volatility, the findings from which inform our experimental approach.

In an early experiment, Lathrop (1967) examines notions of variability in groups of lines of varying length. Of interest is the impact of line sequence, holding constant mean and standard deviation. The results support the view that perceptions of variability are influenced not just by a mathematical definition of variability (i.e. standard deviation), but by sequence or order effects, which persist even in the face of instructions to ignore. Lathrop (1967, p.502) concludes; "Events do not normally occur as distributions defined by a mean and standard deviation, but rather occur in sequences." These findings provide strong motivation for our focus on perception of volatility in stock price sequences, in particular the impact of the size and direction of change between consecutive prices.

Evidence suggests individuals have a preference for sequences of outcomes such that utility (disutility) is increasing (decreasing) over the sequence (e.g., Kahneman et al., 1993; Loewenstein and Prelec, 1991, 1993; Redelmeier and Kahneman, 1996; Varey and Kahneman, 1992). In the context of monetary outcomes, as is the case with stock prices, the evidence also indicates a preference for improving sequences albeit with some exceptions (Chapman, 1996; Guyse et al., 2002; Hoelzl et al., 2011). Dolansky and Vandenbosch (2012) compare sequences with identical variance, but where one is the mirror image of the other thus changing sequence directionality. They find that sequences of increasing utility are judged to be less variable than sequences of decreasing utility, suggesting there may be an impact of trend on perceptions of stock price volatility whereby falling prices are perceived as more volatile.

Turning to presentational format, Weber et al. (2005) investigate the extent to which the format in which *returns* are presented, either by way of historical sequence or probability density function, influences expectations and investment decisions. The two formats make salient different facets of the same past-return information, with the time-series highlighting trends in returns, while the probability density function emphasizes distributional features. While presentation format impacted volatility forecasts, with return-distributions eliciting higher volatility forecasts than time-series, there was no effect on perceived risk. Though not a direct test of whether risk and volatility are synonymous, the evidence suggests this may not be the case. We investigate this directly by first examining the price-based factors that influence volatility perceptions and then evaluating the relationship between perceptions of volatility and risk.

While Weber et al. (2005) vary mode of graphical presentation format, they do so only for returns. In contrast, Diacon and Hasseldine (2007) examine differences in risk perception when information is presented in the form of price sequences or returns. They find a discernible impact on perceptions of risk and return, with respondents exhibiting heightened risk perception for returns than prices. More recently, Stössel and Meier (2015) investigate differences in perceptions of risk, which they take as being synonymous with volatility, when information is graphically presented as price-levels, returns or a combination of the two, while also examining the effect of direction of the past performance path. They report a framing effect whereby participants who view returns report lower levels of volatility than those viewing price sequences.

Despite the wide spread use of graphical information as a basis of investment decisions, it is likely that investors are unable to absorb fully the wealth of information that such charts depict and as such focus on perceptually salient points to simplify the information-processing task (Raghubir and Krishna 1996, 1999). The question, of course, is what information is most salient in a price sequence chart and how does this influence perceptions, and so inform expectations, of risk and return? Mussweiler and Schneller (2003) conjecture that the extreme points on a price chart are likely to be highly influential, acting as comparison standards when forming expectations of future stock prices. They find that investor expectations are related to salient highs or lows, with extreme highs (lows) leading to expectations of higher (lower) future performance.

Noting that the two main summary features of price sequences are i) the trend or pattern and ii) the noise or dispersion around the trend or pattern, Raghubir and Das (2010) suggest that individuals sample the local maxima and minima of a price sequence to infer variation around the trend and use this to estimate risk. They conjecture, the higher the run length in stock prices (i.e. consecutive price changes in the same direction), the more extreme the local maxima and minima, thus the higher the estimate of noise and hence the higher the perception of risk. In line with their theorizing, Raghubir and Das (2010) find that stocks with shorter run lengths are perceived as less risk, and so preferred by investors, than those with longer run lengths.

Continuing the search to identify salient features of graphical price sequences, Duclos (2015) investigates end-anchor effects, examining whether recent price changes exert undue influence on forecasts and investment decisions. In a between-subjects experiment, participants view one of four graphs of stock prices with the same mean, standard deviation, kurtosis, skewness, and run-length, but that differ with respect to last trade direction (downward vs. upward) and uncertainty level (standard deviation low vs. high). Forecasts of future performance and levels of investment were higher for stocks ending on an upward move than for those ending on a downward move. Surprisingly, from a finance perspective, there was no effect of uncertainty (i.e. standard deviation) on either forecasts or levels of investment.

There has been an upsurge in interest in financial volatility, perhaps in part fuelled by recent market events, and we turn now to briefly review recent survey and experimental findings. Examining investors' risk taking behaviour, Nosic´ and Weber (2010) contrast subjective measures of volatility (risk) and returns with objective, or historical, measures. Faced with historical price charts, subjective expectations are constructed by asking individuals to specify a median stock price forecast, along with upper and lower bounds for 90% confidence intervals. While treating risk and volatility as synonymous, Nosic´ and Weber (2010, p.296) find that risk taking can be explained more by investors' subjective risk attitudes and perceptions, than by objective return and volatility measures. They also report very low levels of correlation between participants' risk perceptions and their subjective expected volatility. Employing a similar approach, Weber et al. (2013) survey UK investors from September 2008 to June 2009. They too find low correlations between objective and subjective measures of risk and return expectations, concluding that risk taking is better predicted by subjective than by objective expectation measures.

In an experiment requiring participants to divide their investment between a risk-free asset and a risky asset, Ehm et al. (2014) modify the risk-return profile of risky assets across three conditions in such a way that they have comparable Sharpe ratios and so define the same capital market line in combination with the risk-free asset. The experimental design is such that volatility and return differ across the risky asset conditions, but the optimal risk–return trade-off is independent of treatment condition. While mean allocations to the risky asset across the three conditions of 51.7% (basic), 56.3% (low risk), and 54.8% (high risk) do not differ statistically, the resulting portfolio volatilities of 11.5%, 6.4% and 15.9%, respectively, do. Ehm et al. (2014) conclude their evidence supports the view that investors adopt two mental accounts, a risk-free account and a risky account, allocating a fixed percentage to each and disregarding portfolio volatility. In a similar vein, Heuer et al. (2015) present survey-based evidence that individuals fail to take account of volatility (risk) when evaluating past performance of fund managers and are, therefore, likely to confuse risk taking with fund manager skill.

Noting that financial price series have a fractal structure, Sobolev and Harvey (2016) use real price data to experimentally investigate sensitivity to the Hurst exponent, H, which is negatively correlated with standard deviation. Participants either observe graphs of price sequences alone or graphs of both price sequences and price changes. In the price sequence only condition participants fail to distinguish between the risk inherent in price series with different Hurst exponents, despite being perceptive to the degree of randomness in the prices series (confirmed by a discrimination task), perhaps suggesting they did not see connections between risk and randomness (volatility). In the prices sequences and price changes condition, however, participants are able to differentiate between graphs of different Hurst exponent, interpreting this in the context of risk. Sobolev and Harvey (2016) also report that risk perceptions were driven more by the Hurst exponents than by other common measures of financial volatility, including standard deviation.

Pincus and Kalman (2004) distinguish between two ways in which price sequences may depart from constancy: i) the extent to which prices deviate from central tendency and ii) the extent to which prices appear irregular or unpredictable. They propose an approximate entropy (ApEn) measure of irregularity or unpredictability, with higher (lower) values of the measure associated with greater irregularity (regularity) in the price sequence. That irregularity of a price sequence captures a distinct aspect of notions of volatility plays an important role in our experimental approach, to which the discussion now turns.

3. Experiment One – Systematic Patterns

3.1. Design

We conduct an experiment to examine the factors that may influence perceptions of financial volatility, including standard deviation along with a range of price-based factors which are salient graphically (e.g. number of changes in direction, number of peaks and troughs, number of highs and lows, mean absolute price change etc.). It is impossible to manipulate all price-based explanatory variables independently, hence a full factorial design is not possible. We produce 16 price sequences (graphs), each with 24 price observations that vary with respect to value and order to produce graphs that differ with respect to the above price-based factors, but all with an average price of 12. See Table 1 for definitions of these price-based factors,[8] along with two standard return-based measures, and a summary of their values in each of the 16 graphs.

We present participants with graphs of price sequences that differ with respect to the above characteristics and ask them to rate the graphs for risk and volatility (0-10 scales).[9] While other studies may assume, explicitly or implicitly, that risk and volatility are synonymous, in this paper we examine whether this is the case. We employ a within-subjects design, with graph order randomised and counterbalanced. A total of 78 students participated in the experiment, all drawn from a leading UK Business School and all with prior training in statistics.

In using stylized price sequences in our experiment, we depart from the approach elsewhere of investigating volatility using real price or return data (e.g., Heuer et al. 2015; Nosic´ and Weber, 2010; Sobolev and Harvey, 2016). While it is conceivable that there may be some loss in realism associated with stylized price sequences, we believe the increased experimental control that this

[8] Many of the price-based factors we examine have their roots in early work by Pinches and Kinney (1971).
[9] The exact phrasing used in the experiments was: “We would like you to tell us how risky you think these investments are. Please rate each graph on a scale from 0 (no risk at all) to 10 (highest possible risk).” and “We would also like you to tell us how volatile you think the investments are. Please rate each graph on a scale from 0 (not at all volatile) to 10 (extremely volatile).” Note also, the experimental instrument contained no mention of such terms as “dispersion”, “standard deviation”, “variance” or any other such statistical term associated with dispersion. Thus, participants were free to adopt their own interpretations of “risky” and “volatile”. This was essential given our intention of examining factors that influence perceptions of risk and volatility.

affords is necessary to identify the factors that influence perceptions of volatility and risk.[10] In designing the price sequences we are conscious of the fact that graphs convey such a large volume of data "that people simplify their task by sampling points from a financial instrument's price history to estimate trend and noise" leading to perceptual biases (Raghubir and Das, 2010, p.965). The use of long price sequences would require inference to be drawn about the salient information and heuristics used by participants to form their perceptions. To avoid the need for such inference, we construct relatively short price sequences. As such participants will likely have no need for sampling or using heuristics, thus removing the potential for visual and perceptual biases to distort risk and volatility perceptions. Furthermore, Pincus and Kalman (2004) state that the extent to which prices appear irregular is a separate aspect of volatility, distinct from the extent to which prices deviate from central tendency. In experiment one, we remove the influence of irregularity on volatility perception by constructing price sequences that follow clear and systematic patterns. In doing so we avoid DeBondt's (1998) concern that while investors attempt to spot trends and turning points in stock prices, they often see patterns where there are none. We also eliminate the possibility that biases in judgmental forecasting of time series (e.g., Harvey, 1995; Harvey and Reimers, 2013; Reimers and Harvey, 2011) might distort volatility perception.

Given our interest in perception of, and not preference for, volatility, we ask participants to rate the price sequence and not to choose between them, as such we cannot adopt standard incentive compatible financial rewards whereby participants play out their preferred price sequence for real. The systematic patterns present in the price sequences would also make such an approach problematic. To ensure participants engage meaningfully with the task, however, we employ a financial incentive that is in part related to their perceptions of the price sequences. In addition

[10] See Jiménez-Buedo and Miller (2010) for a convincing argument that the commonly held view of a trade-off between internal and external validity need not hold true. Indeed, they conclude that problems of external or internal validity "do not necessarily nor crucially depend …. on the artificiality of experimental settings" (p.318). It need not be the case, therefore, that external validity, or the generalisability of results, is compromised by the pursuit of experimental control (internal validity).

to rating risk and volatility, participants also rate the attractiveness of the price sequences. We offer a cash prize draw whereby 1 in every 25 participants is selected at random to win a cash prize, the value of which is determined by selecting the graph they rate as most attractive and then drawing a random point from the 24-point price sequence and multiplying the selected point by £2 to determine the cash prize. Participants are paid in cash at the end of the experiment.

3.2. Results

Table 2 reports descriptive statistics (mean and standard deviation) for the perceptions of volatility and risk for each of the graphs in experiment one (and two). It is difficult to draw inference concerning the influence of the price sequence characteristics on participants' ratings from the descriptive statistics. To facilitate such an inference, Figure 1 presents an overview of volatility perception, depicting the groupings of graphs with no significant difference in volatility rating. That it takes 9 areas of no significant difference to enclose all 16 graphs shows the high degree of differentiation between volatility rating across the price sequences. The average mean volatility rating grouped by graphs in the same enclosed area ranges from 8.77 for graphs 1 and 16 combined to 2.95 for graphs 11 and 15 combined. Casual observation of Figure 1 reveals that those graphs where price swings are frequent and dramatic (e.g. graph 1, 16 etc.) are perceived to be more volatile than those where price changes from period to period are infrequent (e.g. graph 11, 15 etc.). It is also apparent that price sequences with the same price dispersion (StDev, see Table 1), are often viewed as differing with respect to volatility. For example, graphs 2 and 11 have the same StDev=7.66, but their volatility ratings differ significantly (7.06 vs 2.95, respectively, $p<0.01$, Bonferroni adjusted) and they are not enclosed in the same coloured area in Figure 1. In contrast, there are instances, for example graph 2 and 12 , where price sequences with disparate price dispersion are viewed as equally volatile (7.06 vs 7.45, respectively, $p=1.00$, Bonferroni adjusted). Clearly, there appears to be more to volatility than simply price dispersion.

Univariate correlations (Table 3) show that the standard deviation of returns (Returnsd) and its natural log (LnReturnsd) have the weakest correlation with volatility ratings and the second and third weakest correlations, respectively, for risk rating. Most price-based factors are significantly correlated to both dependent variables (NumAccelChg being the exception), although the correlation coefficients differ. With volatility perception, all of the significant price-based variables have a higher correlation coefficient than the returns variables with the largest correlations being with the mean absolute price change over the sequence (MeanAbsChg), the number of changes in direction over the sequence (NumChgD) and the number of peaks and troughs in the sequence (NumPeak and NumTrough).

The price sequence characteristics also include the standard deviation of prices (StDev), which would be the usual statistical measure of price dispersion, but while this variable is significantly correlated to risk and volatility (with a correlation coefficient much higher than either returns variable, Returnsd or Lnreturnsd), it is not the most highly correlated variable. With volatility perception, 5 out of 7 significant variables have a higher correlation coefficient than StDev, with the largest correlations being with the mean absolute price change over the sequence (MeanAbsChg), the number of changes in direction (NumChgD) and the number of peaks and troughs (NumPeak and NumTrough). All these have correlation coefficients over twice that of StDev. For risk, MeanAbsChg again has a higher correlation coefficient than StDev, but Range is the only other price-based factor with a higher correlation. These results would support a view that volatility and risk are not synonymous, but also that the conventional measures of dispersion do not capture volatility.

To explore volatility in more detail regression models were used. Correlations between independent variables (i.e. price sequence characteristics) are shown in Table 4, splitting the variables into two groups of characteristics; *Directly Observable Characteristics*, those that can be directly observed via visual inspection (e.g. number of changes of direction in the price sequence), and *Indirectly Observable Characteristics*, those that cannot be directly observed, but that can be detected or perceived indirectly (e.g. standard deviation, which might be perceived as a form of spread). Many of the variables are significantly correlated with each other, some inevitably so (e.g., number of peaks and troughs with each other and with number of changes of direction), thus shaping the approach we take in the empirical analyses below.

Running regression models[11] on the two groups of variables separately shows that both sets of characteristics produce models with similar predictive powers, with Directly Observable Characteristics producing an adjusted r^2 of 35.5% and Indirectly Observable Characteristics an adjusted r^2 of 37.4%. Running a model with all characteristics included gives an adjusted r^2 of 39.6%. Although these models all have collinearity problems (identified by, for example, high VIF), with some variables inevitably highly correlated (see Table 4), and hence problems associated with coefficient interpretatation, they serve as an indication of the relative explanatory power of the two groups of variable, directly and indirectly observable.

To identify the variables with best explanatory power, while addressing collinearity issues, stepwise procedures were used to identify the most parsimonious model (Table 5), with an adjusted r^2 of 39.4% and variables entering in the order MeanAbsChg, Outside10pct, NumAccelChg, StDev and NumChgD. The only difference between the variables in this parsimonious model and the significant variables from the model including *all* variables is the inclusion of Outside10pct rather than Range. Outside10pct has a lower VIF than Range (1.083 vs 2.640) making it more attractive for inclusion due to reduced collinearity issues. The two variables clearly measure related aspects.

As observed in Table 3, all variables in the most parsimonious model are significantly correlated with volatility perception except NumAccelChg. Investigation of this variable's role shows that it

[11] Results are untabulated, but are available from the authors on request.

produces an enhancement effect (see, for example, Currie and Korabinski, 1984) on MeanAbsChg and StDev,[12] increasing their coefficients and improving explanatory power.

We also investigated the relationship between MeanAbsChg, as the variable most highly correlated with volatility perception, and StDev, the classic measure of dispersion. MeanAbsChg is significantly correlated with StDev (see Table 4), so the relationship between these was therefore explored using hierarchical regression and analysis of shared and unique variance. The initial model introduced StDev at step 1, adding MeanAbsChg at step 2. This initial model shows[13] that StDev has a significant positive coefficient, but only explains 4.2% of the variation in perceived volatility (as expected from the univariate correlation coefficient). The addition of MeanAbsChg at step 2 brings the variation explained to 33.9% (adjusted R^2). This is, however, only 1% more than would be provided by MeanAbsChg alone (based on its correlation with perceived volatility), suggesting substantial shared variance, and indeed StDev moves to a negative sign in this model supporting such a conclusion. Analysis of shared and unique variance shows that for StDev the shared variance with MeanAbsChg represents 74% of the explanatory power it contributes to the model, whereas for MeanAbsChg the shared variance represents only 10% of its contribution to explanatory power. When repeating the above with dispersion of returns replacing dispersion of prices, Returnsd is not significant in the two variable model, and the unique variance for MeanAbsChg is more than 99% of its contribution to the explanatory power. MeanAbsChg is therefore showing more unique explanatory power for perception of volatility than traditional types of dispersion measure based on either prices or returns.

[12] With enhancement the proportion of variation explained by a regression with a particular pair of independent variables is greater than the sum of the proportions of variation explained in regressions with each alone. The terminology in this area is somewhat confusing in that enhancement is also referred to in some literatures as suppression. The intuition behind this name is that the variable that gives rise to the enhancement acts to suppress variance in another variable (say, X_1), enhancing its explanatory power. This comes about because the variable producing enhancement is correlated with elements of X_1 which are not correlated with Y. NumAccelChg actually fulfils the requirement for a classic suppression effect (Horst, 1941), having no significant relationship with the outcome itself.

[13] Results are untabulated, but are available from the authors on request.

Moving on to consider risk perception, ratings for perceptions of volatility and risk are significantly correlated (0.567, $p<0.001$), indicating that each explains just over 32% of variation in the other. This contrasts with the assumption in finance theory that volatility and risk are synonymous. The univariate correlations in Table 3 provide further evidence, indicating that each has a different pattern of relationships with the price-based factors and the return-based measures in particular.

Regression models[14] on the Directly and Indirectly Observable characteristics separately again show that both sets of characteristics produce models with predictive powers in a similar range, with Directly Observable Characteristics giving an adjusted r^2 of 17.3% and Indirectly Observable Characteristics giving an adjusted r^2 of 19.0%. Running a model with all characteristics included gives an adjusted r^2 of 22.4%. As with the volatility models, all these models have substantial collinearity problems. Using stepwise regressions to produce the most parsimonious model of risk produces a model that can explain 21.5% of variation in risk perception (Table 6a). The natural log of the returns is the only dispersion measure in the model, and it does not make a substantial contribution, adding less than 1% to variation explained when it enters the model. The most parsimonious model has fewer significant variables in common with the model including *all* variables than is the case for the volatility models. However, here significant variables in the "all variables" model include NumPeak, NumTrough and NumChgD, despite their fundamental correlation with one another, giving particular collinearity problems.

Adding perception of volatility to the model improves the model substantially, with 37.6% of variability explained (Table 6b). The perceived volatility of the graph is therefore an important component in risk perception, despite the evidence that volatility and risk are not synonymous. Rerunning the model forcing volatility in initially as step 1 followed by a stepwise regression on the price sequence characteristics factors cannot improve on this explanatory power.

[14] Results are untabulated, but are available from the authors on request.

4. Experiment Two – Irregularity

4.1. Design

As discussed above, Pincus and Kalman (2004) note that irregularity of a price sequence represents a unique aspect of volatility, distinct from the extent to which prices deviate from central tendency. In experiment one, we removed this from consideration by constructing price sequences that follow clear and systematic patterns (i.e. regularity). However, "if an investor were assured that future prices would follow a precise sinusoidal pattern, even with large amplitude, this perfectly smooth roller coaster ride would not be frightening, because future prices and resultant strategies could be planned" (Pincus and Kalman, 2004, p.13709). In experiment two, we add back irregularity to the price sequences to further examine perceptions of volatility.

The design of experiment two mirrors that of experiment one with a notable exception; we randomise the order of the prices in the original sequences so as to remove the systematic patterns, replacing regularity with irregularity. In experiment one, six unique sets of price observations were used to construct the 16 price sequences. Here we randomise the order of the each of the unique sets twice, hence the number of graphs in experiment two is 12 (6 pairs of random price sequences, with each pair from the same unique set of original price observations). Note, the new price sequences have the same mean and price-based standard deviation (StDev) as their experiment one counterparts, hence we are able to compare irregularity of price sequence while holding constant concepts of classical variability (Pincus and Kalman, 2004). See Table 1 for a summary of the values of the price sequence characteristics in each of the 12 graphs.[15]

[15] As the graphs had been numbered consecutively from 1 in each experiment, numbers for the graphs in experiment two were adjusted to give unique references by adding 20 to each value (so 1 becomes 21, etc.).

We employ the same financial incentive mechanism as in experiment one and a total of 67 students, again drawn from a leading UK Business School and all with prior training in statistics, participated in experiment two.

4.2. Results

Table 2 reports descriptive statistics (mean and standard deviation) for the perceptions of volatility and risk for each of the graphs in experiment two. Again, it is difficult to draw inference concerning the influence of the price sequence characteristics on participants' ratings from the descriptive statistics. To provide insight, Figure 2 depicts the groupings of graphs with no significant difference in volatility rating. Relative to Figure 1, three observations emerge; i) the least volatile graphs (graphs 22 and 32) are rated as more volatile than the least volatile graphs in experiment one (note also from Table 2, that the average mean volatility rating across all graphs in experiment two is higher than that in experiment one – 6.50 vs 5.98, respectively), ii) there is less differentiation between volatility rating across the graphs as can be inferred from the fact that all graphs are enclosed by only 5 areas of no significant difference, while the number of equivalent areas in Figure 1 is 9 (while the number of graphs in experiment one is higher than in experiment two, this does not account for the near halving of the number of areas required to encompass all graphs), and iii) those graphs where price range is high (e.g. graphs 25, 28 etc.) are perceived to be more volatile than those where price range is low (e.g. graphs 22, 32 etc.). This latter observation perhaps suggests participants adopt a range-based heuristic in the presence of price sequences with little discernible systematic pattern, thus supporting the descriptive validity of the price-based, extreme value methods of Parkinson (1980) and Kunitomo (1992).

Univariate correlations of perceptions of volatility and risk with the independent variables (i.e. price sequence characteristics), reported in Table 7, show that a high percentage of the variables are correlated with risk and volatility, although the pattern of correlations differs from that in experiment one, and in this experiment the correlations coefficients across the two dependent variables are more similar than was the case previously. Given that the correlations for volatility were higher than those for risk in experiment one, this suggests that the irregularity of the price sequences in experiment two is affecting risk perception. Whether price sequences exhibit systematic patters or irregularity seems, therefore, to affect the extent to volatility and risk perception depart from one another.

The correlation coefficients for usual measures of dispersion (Returnsd, Lnreturnsd, StDev) are also much higher in these results, with only Range having a stronger correlation. The correlation for Range is more than twice the size observed in experiment one, suggesting that if sequences are irregular then the range over which they seem to vary becomes more important. MeanAbsChg is still strongly correlated, however, with a correlation coefficient just below that of Returnsd. Models comparing the impact of Returnsd and StDev versus MeanAbsChg, as expected from the findings above, show both variables are now significant in a 2 variable model ($p<0.01$), but the additional impact of MeanAbsChg is low, suggesting more shared variation.

Correlations between the independent variables in this experiment are shown in Table 8. While the patterns of correlation differ from experiment one due to the random ordering, many are still high and significant. A model[16] using the Directly Observable Characteristics as independents gives an adjusted r^2 of 27.7%, while using the Indirectly Observable Characteristics produces a model with an adjusted r^2 of 33.8%. The Indirectly Observable Characteristics show a higher explanatory power in experiment two, to a greater extent than was the case in experiment one. A model containing *all* potential independent variables gives an adjusted r^2 of 37.4%. As in experiment one all models have collinearity problems, so a stepwise regression was again used to develop a parsimonious model of volatility perception, while addressing collinearity issues, producing the model reported in Table 9, with 35.7% of variation explained by, in order of entering the model, Range, NumAccelChg, MeanAbsChg, Lnreturnsd and NumChgD.

[16] Results are untabulated, but are available from the authors on request.

To evaluate the explanatory power of the two parsimonious models (Tables 5 and 9), we conduct out-of-sample tests by running the experiment one model on the experiment two data and vice versa. The experiment one model explains 34.7% of variation in the experiment two data. While this is a lower explanatory power than the model had in experiment one, 39.4%, the reduction is not large. The experiment two model explains 34.1% of variation in the experiment one data. Overall the models are not as dissimilar in performance as might be expected and while the variables in both models differ, there are some similarities, with both containing MeanAbsChg and a measure of dispersion (LnReturnsd or StDev), along with NumChgD (changes of direction) and a measure related to range (Range or Outside10pct). It seems, however, that models built on more systematic patterns can exploit the regularity in the price sequences to achieve better predictive performance.

Moving on to risk, ratings for perceptions of volatility and risk are significantly correlated (0.595, $p<0.001$), as in experiment one, with each explaining 35.4% of variation in the other. This is comparable to the variation explained in the experiment one results, again suggesting risk and volatility are less than perfectly synonymous, though, as can be seen in comparison with the univariate correlations in Table 7, there is a greater degree of similarity in the pattern of correlations across risk and volatility ratings in experiment two than was observed in experiment one.

Individual models using the Directly and Indirectly Observable characteristics as independents give adjusted r^2 values of 19.3% and 21.8%, respectively, while a model including *all* potential independents gives an adjusted r^2 of 24.4%.[17] Using stepwise regressions to produce the most parsimonious model of risk indicates that price sequence characteristics can explain 30.7% of variation in risk perception (Table 10a), which is considerably more than the stepwise model produced on the experiment one data (Table 6a). Two out of three variables are in both models,

[17] Results are untabulated, but are available from the authors on request.

with StDev being the exception (although the experiment one model contains Lnreturnsd and MeanAbsChg by way of measures of dispersion).

As before, adding perception of volatility as an independent variable improves the model, with 41.8% of variability now explained (Table 10b), though the improvement is less than in the equivalent model in experiment one, presumably because the explanatory power of the model with price sequence characteristics alone is better. As above, we conduct out-of-sample tests by running the experiment one model on the experiment two risk perception data and vice versa. The experiment one model explains 28.8% of the variation in the experiment two data, with MeanAbsChg being at the forefront. In stark contrast, the experiment two model explains only 11.9% of the variation in the experiment one data, suggesting that models built on price sequences with systematic patterns have better explanatory power at different levels of regularity as found above.

Overall, we find irregularity results not only in a higher correlation between perceptions of volatility and risk, but also in an increased similarity in the pattern of correlations with the independent variables, supporting the view that irregularity represents perhaps the risky aspect of volatility (Pincus and Kalman, 2004). Our models predicting volatility and risk indicate that models built on the more systematic data are more robust to variations in regularity, the less regular sequences perhaps suffering from decreased signal to noise ratio.[18]

5. Analysis of Comparator Price Sequences across Experiments

Pincus and Kalman (2004) advocate the separation of concepts of classical variability and irregularity in the context of volatility. Given the experiment two price sequences are randomised versions of the experiment one sequences, they have the same mean and price-based standard deviation as their experiment one counterparts. Comparisons of ratings for counterpart

[18] Similar phenomena have been found in stock market data (Summers et al., 2004).

graphs across experiment one and experiment two, therefore, enables us to examine the influence of irregularity of price sequence on perceptions of volatility, while holding constant concepts of classical variability (i.e. price-based standard deviation). In addition some graphs have direct counterparts in another set exhibiting the same systematic pattern, for example graphs which go from one extreme to another in consecutive periods, and these again can give insights.

A univariate ANOVA was therefore run examining volatility perception across all graphs from experiments one and two, and the results are discussed below in the context of the sets of graphs containing the same price points, but in varying sequences. Significant differences in volatility rating were explored using pairwise comparisons with Games-Howell adjustment for multiple comparisons.

5.1 Group 1 (Figure 3a)

Graph 11, with its single change in level is seen as least volatile and is significantly different from all others in the group. Graphs 24, 27 and 2 form a group not seen as significantly different from each other. Two of these are from the random set of graphs, with 2 being regular but changing across the range of values with each time period. They are all significantly different from graphs 7 and 11, the least volatile. Graphs 5 and 24 form another group of non-significance, as do graphs 5 and 7, following a pattern of consecutively ranked graphs with no significant differences.

Overall the pattern in this group suggests that the number of changes of direction is driving volatility *ceteris paribus*. This value (NumChgD) is significantly correlated with MeanAbsChg, with both being significantly correlated with volatility.

5.2 Group 2 (Figure 3b)

Group 2 follows a similar pattern to group 1 with the most volatile graph having the most number of changes in level, and the least volatile graph the least. Only the least and most volatile graphs are different from each other. The most volatile graph in this group (graph 9) is comparable to the most volatile graph in group 1 (graph 2), with consecutive changes in direction across the range of values (i.e. low run length), but with a lower amplitude to its changes in level. Graph 2 with its higher amplitude is seen as significantly more volatile than graph 9, indicating that amplitude of variation also contributes to perceptions of volatility.

5.3 Group 3 (Figure 3c)

This group contains the three most volatile graphs in the design; the most volatile graph in the systematic sequences (graph 1) and two random re-orderings (graphs 25 and 28). These three are not significantly different from each other, although the two graphs with some static values across 2-3 periods do get lower volatility ratings. Graph 1 is comparable to Graphs 2 and 9 in the previous groups, with all graphs having values that go from one extreme to the other in consecutive periods (low run length). Inspection shows that these three (graphs 1, 2 and 9) are all significantly different, with amplitude of variation driving perceptions of volatility.

5.4 Group 4 (Figure 3d)

This group has points varying across three levels. The only significant difference here is between the least and most volatile graphs (29 and 23). Although both are random sequences, graph 29 does have a separation of two groups of points, one group oscillating between the middle and lowest values and a second group oscillating between middle and highest values, giving the look at a systematic change. Graph 23 is much less predictable looking, so this would seem to provide evidence for the impact of predictability/ pattern.

5.5 Group 5 (Figure 3e)

This group has points varying across 4 levels. Comparing graph 10 and 12, which are significantly different, supports the importance of the number of changes of direction put forward for group 1.

5.6 Group 6 (Figure 3f)

This group has four subsets of no significant difference, with three of these overlapping, and contains systematic graphs which address trend. Graphs 15 and 13, and graphs 3 and 8 are upward trending and downward trending versions of a pattern. In both cases the volatility of the downward trending item is rated more highly, but the difference is not significant. Graphs 15 and 13 have the value moving from one level to the next, with values forming three horizontal runs. These two graphs are judged as significantly less risky than all the others. Graph 26 is a random version which has visual similarities to graphs 3 and 8, with points tending to move between two values at a higher level for part of the pattern and at a lower level for the rest (similar to graph 29, though with a higher range overall). The random graph follows a generally upward trend and is ranked between the two systematic graphs, although the differences are not significant. The two graphs rated as most volatile are a random sequence with no clear pattern and a systematic graph which moves up and down across the full range. This latter would support the importance of amplitude of change, and indeed the three most volatile graphs involve several movements across the full range in one or two steps.

6. Discussion and conclusions

In our first experiment, we use stylised price sequences that follow systematic patterns and manipulate the dispersion of prices around the mean, along with a number of other price sequence characteristics. While standard deviation may have a role to play in perception of volatility, we find evidence that other price-based factors, for example mean absolute price change, play a far greater role. Also, while partially correlated, individuals do not perceive risk and volatility as synonymous.

While our second experiment, in which we remove regularity of the price sequence via random ordering of the price observations, supports the robust nature of our initial results, we find that returns now play a role in risk perception and that risk and volatility are more positively related.

In addition, we are able to examine the influence of regularity vs irregularity of the price sequence, by examining perceptions of volatility between comparator graphs from across the two experiments. On average, price sequences with systematic patterns are viewed as less volatile than comparator price sequences in which irregularity is present, supporting Pincus and Kalman (2004) in their view that irregularity plays a distinct role in volatility, above and beyond concepts of classical variability related to price dispersion, such as standard deviation. Irregularity results not only in a higher correlation between perceptions of volatility and risk, but also in an increased similarity in the pattern of correlations with the independent variables, suggesting irregularity represents perhaps the risky aspect of volatility, further supporting Pincus and Kalman (2004) in their view that investors would not see risk in stocks that exhibit extreme price movements that follow perfectly smooth roller coaster rides (i.e. systematic patterns).

Our results also shed light on findings in other recent studies. For example, the evidence that standard deviation of prices plays little or no role in perceptions of volatility may explain the lack of effect of uncertainty (i.e. standard deviation) on either forecasts or levels of investment reported by Duclos (2015) when participants are presented with graphs of stock prices. Also, the low correlations between numeric and subjective measures of risk and return expectations reported in Weber et al. (2013) may be explained by our findings that volatility perception is little influenced by standard deviation and that perceptions of risk and volatility not highly correlated. A possible explanation for the apparent disregard of volatility reported in Ehm et al. (2014) and Heuer et al. (2015) might also be that perceptions of risk and volatility bear little relation to mathematical measures of dispersion.

Volatility remains a key concept in finance (Kourtis et al., 2016) and understanding it has implications for many important applications, including, for example, portfolio selection and option pricing. We find that when individuals make investment evaluations informed by graphical displays of historic price their perceptions of volatility have more to do with price-based factors, along with the regularity of patterns in the price sequence, than the dispersion of returns around the mean. Goldstein and Taleb (2007, p.86) suggest "[e]ither we have the wrong intuition about the right volatility, or the right intuition but the measure of volatility is the wrong one". Our evidence suggests that the search for such intuitive metrics should begin with price-based characteristics, as opposed to traditional return-based ones, and that there is more to volatility than dispersion around central tendency, with irregularity associated closely with perceptions of volatility. Periods of financial crises are characterised by heightened uncertainty (Schwert, 2011) and hence with price sequences exhibiting greater irregularity. As such, our findings help explain the drop in predictive ability of traditional volatility forecasting models during periods of financial crises (Kourtis et al., 2016). Future developments in volatility forecasting might usefully augment traditional models by incorporating measures of irregularity or unpredictability.

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Table 1: Experimental Parameters – Price Sequence Characteristics

Exp	*Graph Num*	*St Dev*	*Mean AbsChg*	*Num ChgD*	*Num Accel Chg*	*Num Peak*	*Num Trough*	*Range*	*Outside 10pct*	*Return sd*	*Ln Return sd*
One	1	11.24	22.00	22	0	11	11	22	24	11.73	3.20
	2	7.66	15.00	22	0	11	11	15	24	2.10	1.50
	3	7.95	10.52	22	2	10	10	22	12	5.02	1.81
	4	7.95	11.00	18	15	6	5	22	12	7.22	1.97
	5	7.66	7.83	22	22	6	5	15	24	1.65	1.08
	6	5.42	7.50	11	0	6	5	15	12	0.93	0.78
	7	7.66	4.57	14	14	3	3	15	24	1.36	0.82
	8	7.95	10.52	22	2	10	10	22	12	4.77	1.81
	9	4.09	8.00	22	0	11	11	8	24	0.77	0.71
	10	4.89	5.00	7	0	4	3	15	8	0.58	0.52
	11	7.66	0.65	2	2	0	0	15	24	0.70	0.31
	12	4.89	6.52	14	14	7	7	15	8	0.70	0.68
	13	7.95	0.96	4	4	0	0	22	12	0.21	0.53
	14	4.09	1.04	6	6	1	1	8	24	0.31	0.25
	15	7.95	0.96	4	4	0	0	22	12	2.29	0.53
	16	7.95	11.00	11	0	6	5	22	12	5.04	1.82
Two	21	4.89	4.79	17	14	5	3	15	8	0.58	0.60
	22	4.09	4.00	20	14	3	3	8	24	0.58	0.53
	23	5.42	5.30	18	14	4	4	15	12	1.03	0.77
	24	7.66	7.50	21	11	4	6	15	24	1.85	1.25
	25	11.24	11.00	20	14	3	3	22	24	10.06	2.41
	26	7.95	7.78	20	11	4	6	22	12	4.33	1.61
	27	7.66	7.50	20	14	3	3	15	24	1.67	1.13
	28	11.24	11.00	21	11	4	6	22	24	10.97	2.67
	29	5.42	5.30	20	9	5	7	15	12	0.81	0.71
	30	7.95	7.78	18	14	4	4	22	12	6.04	1.80
	31	4.89	4.79	19	17	4	6	15	8	0.99	0.73
	32	4.09	4.00	21	11	4	6	8	24	0.65	0.59

Notes:

Exp = Experiment identifier

GraphNum = Graph identifier – to differentiate graphs across experiments we start numbering at 21 (i.e. 20+n) in experiment two, hence identifiers 17-20 are not used

StDev = Standard deviation of prices over the sequence

MeanAbsChg = Mean absolute price change over the price sequence

NumChgD = Number of changes in direction over the price sequence

NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change

NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence

Range = Range of the price sequence - i.e. max-min

Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max

Returnsd = Standard deviation of returns

LnReturnsd = Standard deviation of natural log returns

Table 2: Mean and Standard Deviation of Volatility and Risk Rating by Graph

		Volatility		Risk		
Experiment	***Graph Num***	***Mean***	***S.D.***	***Mean***	***S.D.***	***N***
One	1	8.77	1.746	7.90	1.991	77
	2	7.06	1.831	6.11	1.740	76
	3	6.60	1.640	6.00	1.967	77
	4	7.29	1.668	6.96	1.848	78
	5	5.90	1.619	5.79	1.533	77
	6	5.95	1.603	5.65	1.510	78
	7	5.58	1.791	5.69	1.731	78
	8	6.87	1.797	6.76	1.722	78
	9	5.55	2.562	4.17	2.206	78
	10	5.79	1.783	5.51	1.756	78
	11	2.95	2.063	3.88	2.486	78
	12	7.45	1.877	6.01	1.848	78
	13	4.32	1.903	6.60	2.281	78
	14	4.14	1.734	4.37	1.766	78
	15	3.46	2.106	3.95	2.496	78
	16	7.95	1.72	7.27	1.726	78
Two	21	6.39	1.585	5.96	1.561	67
	22	4.31	1.588	4.25	1.795	67
	23	6.37	1.465	5.93	1.480	67
	24	6.69	1.690	6.01	1.796	67
	25	8.03	1.696	7.81	1.828	67
	26	6.78	1.496	6.42	1.339	67
	27	6.82	1.230	6.36	1.544	67
	28	8.09	1.621	7.57	2.304	67
	29	5.49	1.364	5.28	1.265	67
	30	7.51	1.397	7.01	1.387	67
	31	6.87	1.313	5.99	1.376	67
	32	4.64	1.649	4.03	1.595	67

Notes:

GraphNum = Graph identifier – to differentiate graphs across experiments we start numbering at 21 (i.e. 20+n) in experiment two, hence identifiers 17-20 are not used

S.D. = Standard deviation

N = Number of observations

Table 3: Correlations of the Price Sequence Characteristics with Perceptions of Volatility and Risk – Experiment One

	Volatility	***p***	***Risk***	***p***
Directly Observable Characteristics				
NumChgD	0.461	0.000	0.236	0.000
NumAccelChg	0.010	0.729	0.023	0.418
NumPeak	0.510	0.000	0.241	0.000
NumTrough	0.485	0.000	0.223	0.000
Range	0.214	0.000	0.325	0.000
Indirectly Observable Characteristics				
StDev	0.206	0.000	0.299	0.000
MeanAbsChg	0.574	0.000	0.372	0.000
Outside10pct	-0.112	0.000	-0.135	0.000
Returnsd	-0.059	0.038	0.056	0.048
LnReturnsd	-0.003	0.915	0.101	0.048

Notes:

Directly Observable Characteristics
NumChgD = Number of changes in direction over the price sequence
NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change
NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence
Range = Range of the price sequence - i.e. min-max
Indirectly Observable Characteristics
StDev = Standard deviation of the prices over the sequence
MeanAbsChg = Mean absolute price change over the price sequence
Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max
Returnsd = Standard deviation of returns
LnReturnsd = Standard deviation of natural log returns
Dependent Variables
Volatility = Volatility perception
Risk = Risk perception

p = Statistical significance level

Table 4: Pearson Correlations between Price Sequence Characteristics – Experiment One

	Num ChgD	Num AccelChg	Num Peak	Num Trough	Range	StDev	Mean AbsChg	Outside 10pct	Return sd	LnReturn sd
Directly Observable Characteristics										
NumChgD	1	.152**	.913**	.906**	.066*	.246**	.782**	.229**	-.025	.085**
NumAccelChg	.152**	1	-.188**	-.210**	-.076**	-.006	-.173**	.097**	-.275**	-.212**
NumPeak	.913**	-.188**	1	.993**	.052	.147**	.850**	.084**	.022	.119**
NumTrough	.906**	-.210**	.993**	1	.041	.158**	.831**	.121**	.034	.120**
Range	.066*	-.076**	.052	.041	1	.775**	.319**	-.503**	.265**	.310**
Indirectly Observable Characteristics										
StDev	.246**	-.006	.147**	.158**	.775**	1	.518**	.132**	.066*	.156**
MeanAbsChg	.782**	-.173**	.850**	.831**	.319**	.518**	1	.135**	-.099**	-.002
Outside10pct	.229**	.097**	.084**	.121**	-.503**	.132**	.135**	1	-.305**	-.263**
Returnsd	-.025	-.275**	.022	.034	.265**	.066*	-.099**	-.305**	1	.952**
LnReturnsd	.085**	-.212**	.119**	.120**	.310**	.156**	-.002	-.263**	.952**	1

* <= 0.05, ** <= 0.01 (2-tailed).

Notes:

Directly Observable Characteristics

NumChgD = Number of changes in direction over the price sequence

NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change

NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence

Range = Range of the price sequence - i.e. min-max

Indirectly Observable Characteristics

StDev = Standard deviation of the prices over the sequence

MeanAbsChg = Mean absolute price change over the price sequence

Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max

Returnsd = Standard deviation of returns

LnReturnsd = Standard deviation of natural log returns

Table 5: Most Parsimonious Model of Volatility Perception – Experiment One

	B	*Std. Error*	*Beta*	*t*	*Sig,*
(Constant)	6.046	0.272		22.199	0.000
MeanAbsChg	0.341	0.022	0.782	15.628	0.000
Outside10pct	-0.071	0.009	-0.191	-8.296	0.000
NumAccelChg	0.063	0.010	0.176	6.667	0.000
StDev	-0.197	0.038	-0.148	-5.203	0.000
NumChgD	-0.032	0.015	-0.098	-2.193	0.028

Adjusted R^2 = 0.394

Notes:

StDev = Standard deviation of the prices over the sequence
MeanAbsChg = Mean absolute price change over the price sequence
NumChgD = Number of changes in direction over the price sequence
NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change
NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence
Range = Range of the price sequence - i.e. min-max
Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max
B = Unstandardized regression coefficients
Std. Error = Standard error
Beta = Standardized regression coefficients
t = t-value
Sig = Statistical significance level

Table 6: Models of Risk Perception – Experiment One

6a) Most parsimonious model from price sequence characteristics

	B	Std. Error	Beta	t	Sig,
(Constant)	5.121	0.218		23.447	0.000
MeanAbsChg	0.279	0.020	0.691	14.137	0.000
NumAccelChg	0.041	0.009	0.124	4.713	0.000
Outside10pct	-0.062	0.009	-0.180	-6.812	0.000
NumPeak	-0.183	0.028	-0.324	-6.596	0.000
LnReturnsd	0.345	0.078	0.120	4.398	0.000

Adjusted R^2=0.215

6b) Most parsimonious model plus volatility

	B	Std. Error	Beta	t	Sig,
(Constant)	2.725	0.236		11.524	0.000
MeanAbsChg	0.166	0.019	0.412	8.896	0.000
NumAccelChg	0.019	0.008	0.056	2.359	0.018
Outside10pct	-0.024	0.008	-0.069	-2.858	0.004
NumPeak	-0.210	0.025	-0.371	-8.464	0.000
LnReturnsd	0.407	0.070	0.141	5.807	0.000
Volatility	0.473	0.026	0.511	17.872	0.000

Adjusted R^2=0.376

Notes:

StDev = Standard deviation of prices over the sequence
MeanAbsChg = Mean absolute price change over the price sequence
NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change
NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence
Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max
LnReturnsd = Standard deviation of natural log returns
Volatility = Perceived volatility rating
B = Unstandardized regression coefficients
Std. Error = Standard error
Beta = Standardized regression coefficients
t = t-value
Sig = Statistical significance level

Table 7: Correlations of the Price Sequence Characteristics with Perceptions of Volatility and Risk – Experiment Two

	Volatility	*p*	*Risk*	*p*
Directly Observable Characteristics				
NumChgD	-0.066	0.061	-0.063	0.073
NumAccelChg	0.116	0.001	0.084	0.017
NumPeak	-0.054	0.125	-0.075	0.033
NumTrough	-0.043	0.222	-0.085	0.016
Indirectly Observable Characteristics				
StDev	0.512	0.000	0.500	0.000
MeanAbsChg	0.460	0.000	0.436	0.000
Range	0.544	0.000	0.522	0.000
Outside10pct	-0.039	0.273	-0.017	0.636
Returnsd	0.464	0.000	0.459	0.000
LnReturnsd	0.497	0.000	0.484	0.000

Notes:

Directly Observable Characteristics

NumChgD = Number of changes in direction over the price sequence

NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change

NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence

Range = Range of the price sequence - i.e. min-max

Indirectly Observable Characteristics

StDev = Standard deviation of the prices over the sequence

MeanAbsChg = Mean absolute price change over the price sequence

Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max

Returnsd = Standard deviation of returns

LnReturnsd = Standard deviation of natural log returns

Dependent Variables

Volatility = Volatility perception

Risk = Risk perception

p = Statistical significance level

Table 8: Pearson Correlations between Price Sequence Characteristics – Experiment Two

	Num ChgD	Num AccelChg	Num Peak	Num Trough	Range	StDev	Mean AbsChg	Outside 10pct	Return sd	Lnreturn sd
Directly Observable Characteristics										
NumChgD	1	.335**	.657**	.747**	-.007	.160**	.675**	.236**	.033	.107**
NumAccelChg	.335**	1	-.308**	-.253**	-.110**	-.050*	-.131**	.050*	-.135**	-.122**
NumPeak	.657**	-.308**	1	.949**	.069**	.080**	.715**	-.003	-.027	.055*
NumTrough	.747**	-.253**	.949**	1	.048*	.099**	.734**	.060**	.009	.088**
Range	-.007	-.110**	.069**	.048*	1	.793**	.404**	-.379**	.481**	.497**
Indirectly Observable Characteristics										
StDev	.160**	-.050*	.080**	.099**	.793**	1	.610**	.240**	.490**	.499**
MeanAbsChg	.675**	-.131**	.715**	.734**	.404**	.610**	1	.225**	.189**	.229**
Outside10pct	.236**	.050*	-.003	.060**	-.379**	.240**	.225**	1	-.029	-.038
Returnsd	.033	-.135**	-.027	.009	.481**	.490**	.189**	-.029	1	.955**
Lnreturnsd	.107**	-.122**	.055*	.088**	.497**	.499**	.229**	-.038	.955**	1

* <= 0.05, ** <= 0.01 (2-tailed).

Notes:

Directly Observable Characteristics

NumChgD = Number of changes in direction over the price sequence

NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change

NumPeak, NumTrough = Number of peaks or troughs, respectively, over the price sequence

Range = Range of the price sequence - i.e. min-max

Indirectly Observable Characteristics

StDev = Standard deviation of the prices over the sequence

MeanAbsChg = Mean absolute price change over the price sequence

Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max

Returnsd = Standard deviation of returns

LnReturnsd = Standard deviation of natural log returns

Table 9: Most Parsimonious Model of Volatility Perception – Experiment Two

	B	***Std. Error***	***Beta***	***t***	***Sig,***
(Constant)	3.802	2.050		1.855	0.064
Range	0.168	0.030	0.430	5.558	0.000
NumAccelChg	0.159	0.033	0.178	4.828	0.000
MeanAbsChg	0.406	0.064	0.686	6.349	0.000
Lnreturnsd	-1.191	0.329	-0.445	-3.624	0.000
NumChgD	-0.196	0.087	-0.131	-2.260	0.024

Adjusted $R^2 = 0.357$

Notes:

MeanAbsChg = Mean absolute price change over the price sequence
NumChgD = Number of changes in direction over the price sequence
NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change
Range = Range of the price sequence - i.e. min-max
LnReturnsd = Standard deviation of natural log returns
B = Unstandardized regression coefficients
Std. Error = Standard error
Beta = Standardized regression coefficients
t = t-value
Sig = Statistical significance level

Table 10: Models of Risk Perception – Experiment Two

10a) Most parsimonious model from price sequence characteristics factors

	B	Std. Error	Beta	t	Sig,
(Constant)	2.366	0.453		5.221	0.000
StDev	0.483	0.026	0.594	18.741	0.000
NumAccelChg	0.108	0.028	0.117	3.847	0.000
Outside10pct	-0.059	0.009	-0.206	-6.341	0.000

Adjusted R^2=0.307

10b) Most parsimonious module plus volatility

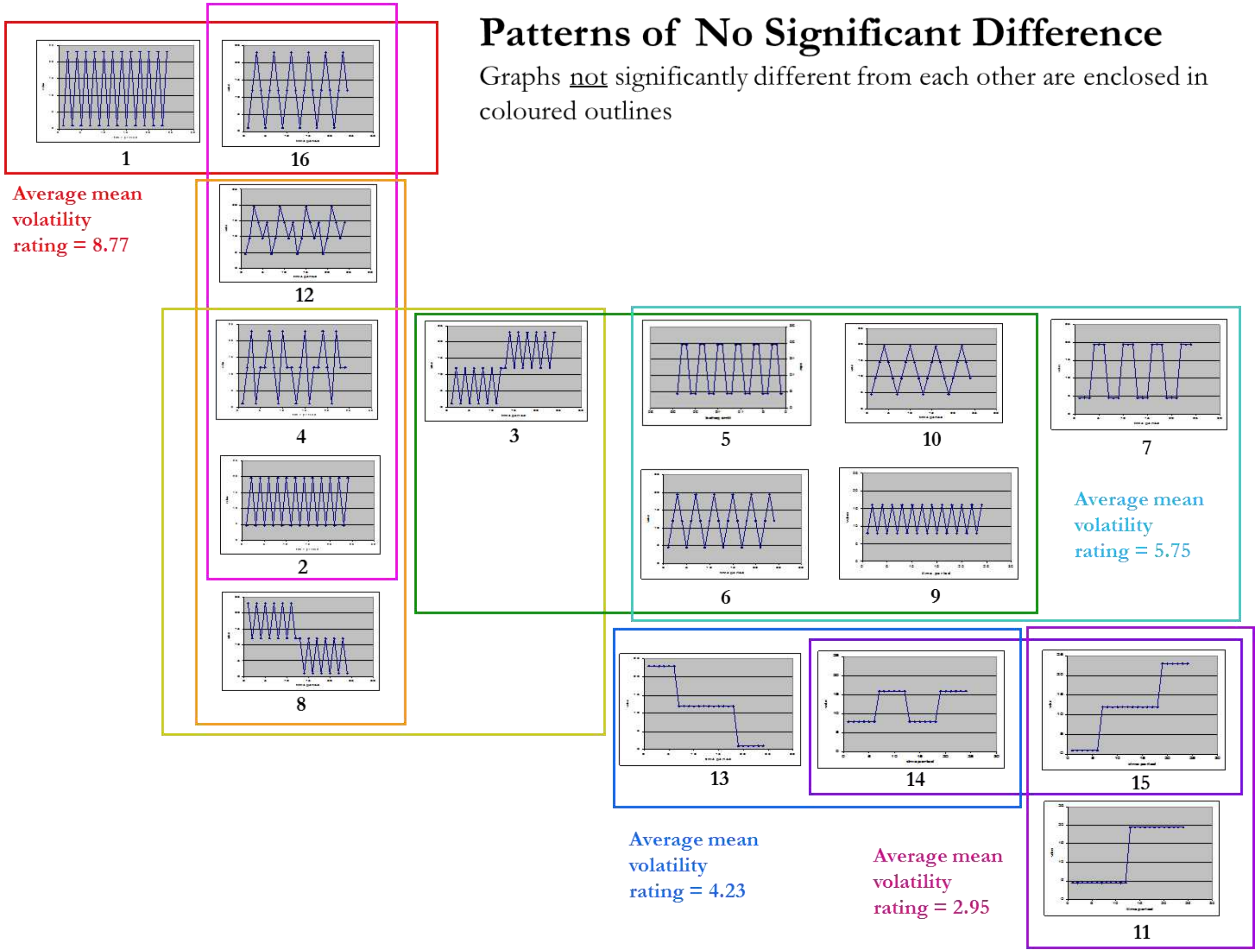
	B	Std. Error	Beta	t	Sig,
(Constant)	1.265	0.425		2.977	0.003
StDev	0.277	0.029	0.340	9.562	0.000
NumAccelChg	0.053	0.026	0.057	2.015	0.044
Outside10pct	-0.032	0.009	-0.112	-3.64	0.000
Volatility	0.425	0.034	0.410	12.344	0.000

Adjusted R^2=0.376

Notes:

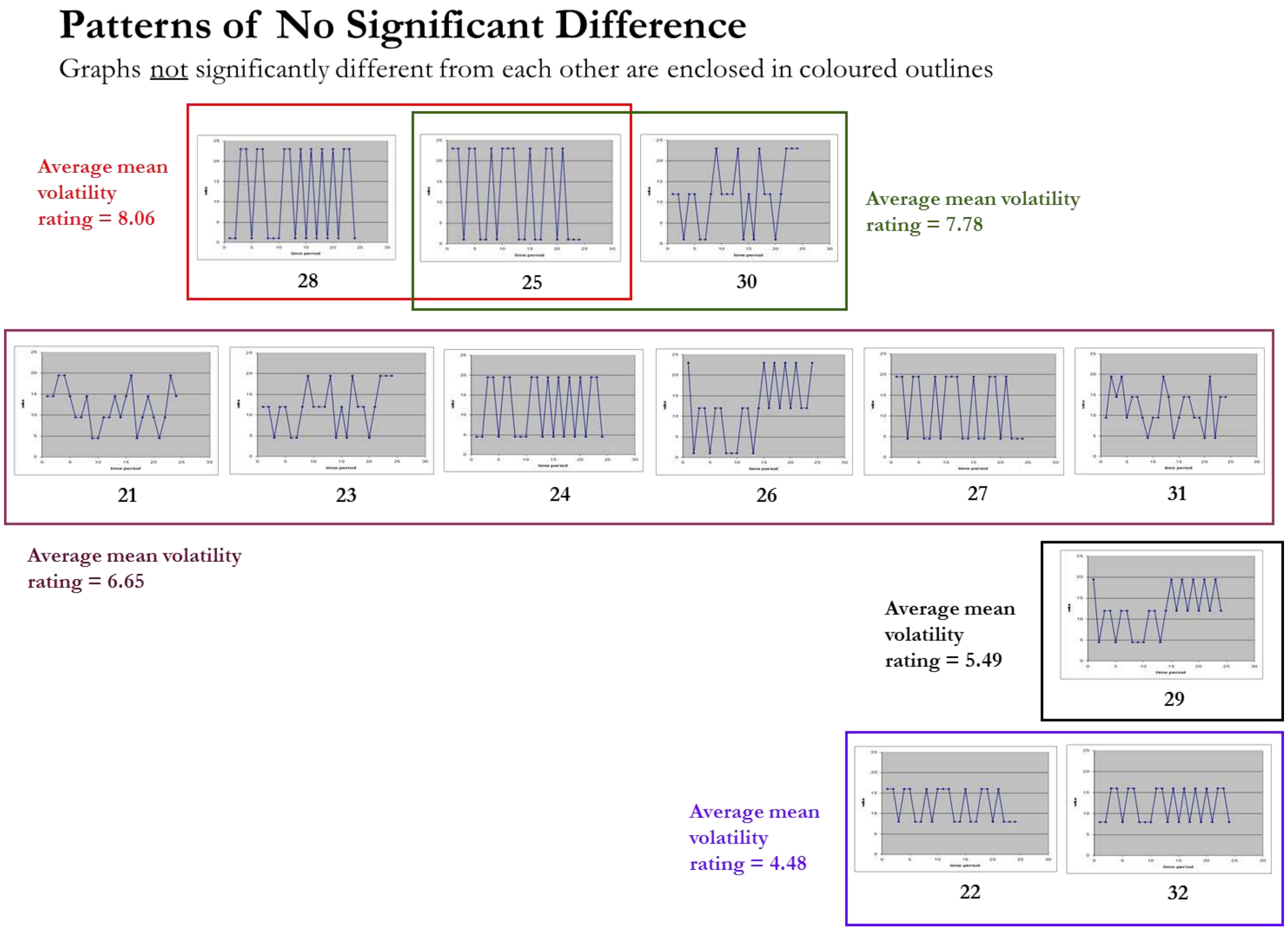
StDev = Standard deviation of prices over the sequence
NumAccelChg = Number of acceleration changes over the price sequence, i.e. change in the rate of change
Outside 10pct = Number of observations in the extremes of the price sequence, i.e. within 10% of min/max
Volatility = Perceived volatility rating
B = Unstandardized regression coefficients
Std. Error = Standard error
Beta = Standardized regression coefficients
t = t-value
Sig = Statistical significance level

Figure1: Overview of Experiment One Results for Volatility Perception



Notes: *Average mean volatility rating* = mean volatility rating across participants, averaged across graphs enclosed in the area
No significant difference = based on Bonferroni adjusted pairwise comparisons where p>0.10

Figure2: Overview of Experiment Two Results for Volatility Perception



Notes: *Average mean volatility rating* = mean volatility rating across participants, averaged across graphs enclosed in the area
No significant difference = based on Bonferroni adjusted pairwise comparisons where p>0.10

Figure 3: Comparisons across Graphs with the Same Data Points

Figure 3a: Group 1

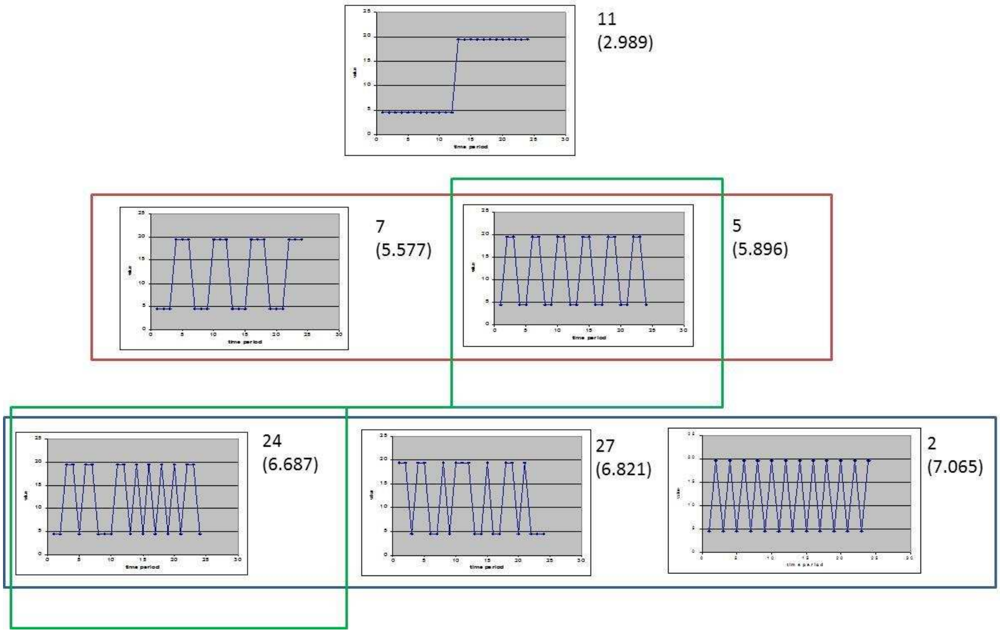


Figure 3b: Group 2

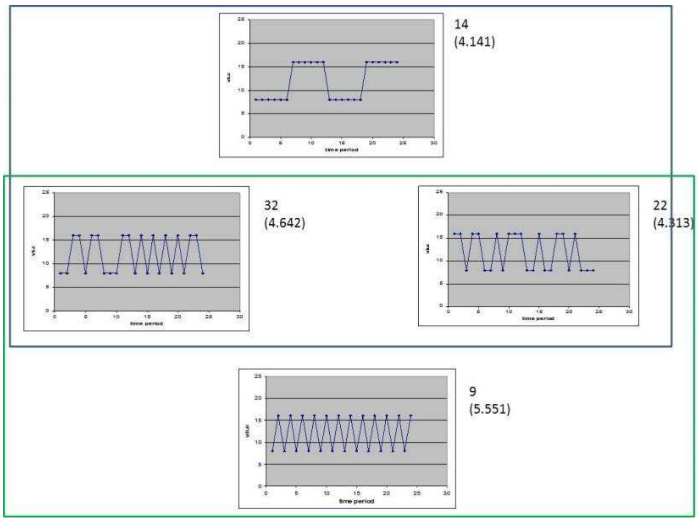


Figure 3c: Group 3

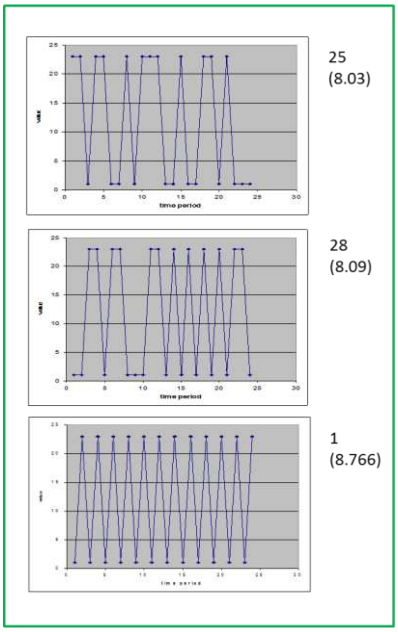


Figure 3d: Group 4

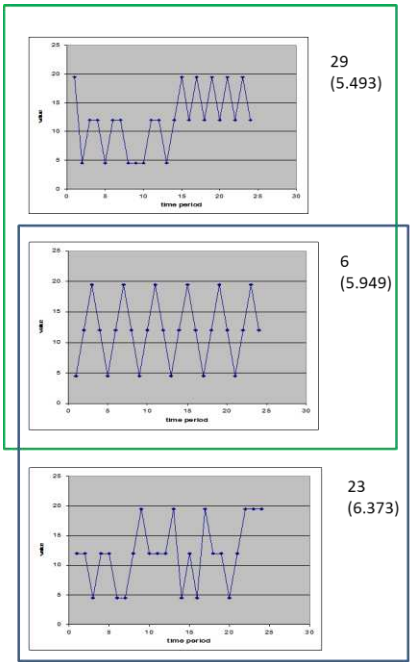


Figure 3e: Group 5

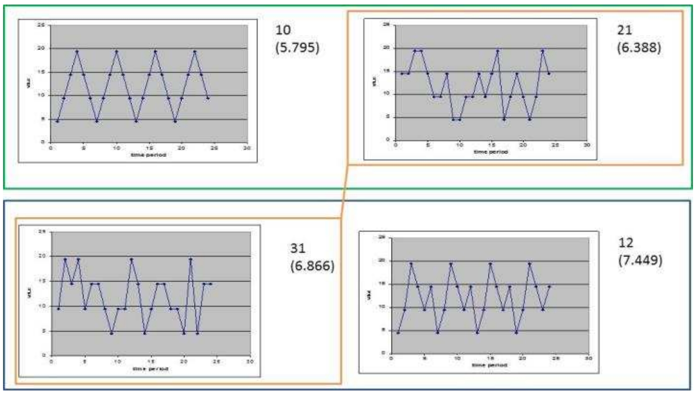


Figure 3f: Group 6